

# Contagion among Central and Eastern European Stock Markets during the Financial Crisis<sup>\*</sup>

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## Abstract

*This paper contributes to the literature on international stock market comovements and contagion. The novelty of our approach lies in the application of wavelet tools to high-frequency financial market data, which allows us to understand the relationship between stock markets in the time-frequency domain. While a major part of economic time series analysis is done in the time or frequency domain separately, wavelet analysis combines these two fundamental approaches. Wavelet techniques uncover interesting dynamics of the correlations between Central and Eastern European (CEE) stock markets and the German DAX at various investment horizons. The results indicate that the connection of the CEE markets to the leading market of the region is significantly lower at higher frequencies than at lower frequencies. Contrary to previous literature, we document significantly lower contagion between the CEE markets and the German DAX after the large 2008 stock market crash.*

## 1. Introduction

International stock markets are getting increasingly interconnected. As the stock markets become more open to foreign investors, growth in the liquidity and availability of stocks of transition and emerging countries is enlarging the scope for international portfolio diversification. On the other hand, integration and comovement are becoming stronger over time and reducing this scope. The events of 2007–2009 reminded us how the potential for diversification may decrease during crises, as the interconnection of markets increased in this period.

Turning to the time dimension of market dynamics, researchers often ignore the dynamics at different investment horizons. These may be especially important, as they represent the trading frequencies of investors with heterogeneous beliefs. Starting with noise traders with an investment horizon of several minutes or hours, the spectrum of investors ranges through technicians with a horizon of several days to fundamentalists with a horizon of several weeks or months, and to investment funds with an investment horizon of several years. Thus, apart from the time domain, it is important to understand the frequency domain, which represents various investment horizons. As both domains are equally important and valid for a deeper

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understanding of financial market dynamics, one should not overlook them in the analysis. The importance of modeling events in both domains motivates us to apply wavelet analysis, which can work with both domains simultaneously.

In our work, we combine the time and frequency domain and we apply cross-wavelet analysis to study comovement and contagion on high-frequency (five-minute) data. We concentrate on the Czech (PX), Hungarian (BUX), and Polish (WIG) stock indices together with the benchmark German stock index (DAX), while we are interested mainly in the crisis period. The time frame chosen for the analysis gives us an opportunity to study the reaction of Central and Eastern European (CEE) financial markets to the large crash of September 2008.

The literature on comovement, interdependence, and contagion is broad. The largest part of the literature examines the interdependence between the U.S. and countries of Western Europe. Baele (2005) and Baele and Inghelbrecht (2010) apply switching models to show that the intensity of comovements and spillovers increased during the 1980s and 1990s with no evidence of significant contagion other than a small effect during the 1987 crash. Connolly et al. (2007) research comovements between the U.S., UK, and German stock and bond markets and show that during high (low) implied volatility periods, the comovements are stronger (weaker), whereas stock-bond comovements tend to be positive (negative) following low (high) implied volatility days. Morana and Beltratti (2008) examine the stock markets of the U.S., the UK, Germany, and Japan between 1973 and 2004 and find increasing comovements for all markets.

Research on the Central and Eastern European region is discussed in several studies. Egert and Kocenda (2007) examine high-frequency stock market comovements of the Czech, Hungarian, Polish, German, French, and UK stock markets between 2003 and 2005. They find that the correlations are much lower for high-frequency data than for daily data. Gilmore et al. (2008) study the CEE stock markets and find strong cointegration, but argue that signs of convergence to Western Europe are lacking after EU accession. Gjika and Horvath (2013) examine the correlations between the Czech stock market and the STOXX50 index on daily data and find that the correlation increased during the recent financial crisis. Hanousek and Kocenda (2009) analyze high-frequency data on the CEE stock markets and show that these are strongly influenced by developed economies.

Whereas correlations and comovements are well defined through linkages based on fundamentals, the definition of contagion varies across the literature. Calvo and Reinhart (1996) term transmission of shocks among countries because of their real financial linkages as a “fundamentals-based” contagion, whereas “pure” contagion describes the transmission of shocks among countries in excess of what should be ascribed to fundamental factors, i.e., it is characterized by excessive comovements (see Gallegati, 2012). This type of contagion is usually caused by loss of confidence and panic in financial markets after the arrival of important negative news. Forbes and Rigobon (2002) define contagion in a similar way as a significant increase in cross-market linkages after a shock.

In our analysis of contagion, we use the approach of Gallegati (2012), who identifies contagion as a change in correlation structure between two time periods defined by the large crash in September 2008. Using the wavelet correlation, we

decompose the correlation into various investment horizons. Recently, there have been numerous studies that investigate contagion and comovement across financial markets using wavelets (Aguar-Conraria et al., 2008; Rua and Nunes, 2009; Vacha and Barunik, 2012). Ranta (2013) uses rolling wavelet correlation to uncover contagion among the major world markets during the last 25 years. A similar methodology was applied by Dajcman et al. (2012) to data for the CEE countries. Contagion between oil and stock markets in Europe and the U.S. was studied by Reboredo and Rivera-Castro (2013). Their results indicate contagion between oil and stock prices in Europe and the U.S. since the onset of the global financial crisis.

In our work, we enrich the current literature by employing high-frequency data to see whether the markets studied are also strongly interconnected at higher frequencies, which represent short trading horizons. In this respect, we follow our previous work studying the time-frequency correlations between gold, oil, and stocks (Barunik et al., 2013).

The main findings of this paper are that the interconnection between all stock markets has changed considerably over time and varies across investment horizons. We confirm the contagion between the DAX and the PX, but we find unexpectedly lower correlations on high-frequency investment horizons after the 2008 crash. This finding complements the literature studying the daily data, as most of those studies find increased correlations during the crisis period (Gjika and Horvath, 2013). Another interesting result of the wavelet correlation analysis is that the CEE markets generally exhibit low correlations at high frequencies as compared to daily data. This shows that the CEE markets are connected to the leading markets in the region only in terms of longer investment horizons.

The paper is structured as follows. In the next section we present a very brief introduction to wavelet and contagion analysis. After the methodology is set, we describe the data. Next, we employ high-frequency data on the Czech (PX), Hungarian (BUX), Polish (WIG), and German (DAX) stock indices and study their comovement and contagion in the time-frequency domain. The final section concludes.

## 2. Methodology

This section briefly discusses wavelet techniques that are essential for comovement and contagion analysis. Subsequently, we introduce the concept of contagion formally.

The wavelet transform allows us to decompose time series from the time domain into the time-frequency domain. Thus, one-dimensional time series are transformed into a two-dimensional space using a localized function with a finite support, called a wavelet. It is convenient for decomposition in situations where the time series under study is non-stationary, or only locally stationary (Roueff and Sachs, 2011). An important feature of wavelet analysis is the decomposition of the time series into frequency components called scales. With this decomposition, we have an opportunity to study economic relationships on a scale-by-scale level, which gives us a broader picture. Hence, wavelets can be seen as a kind of “lens” for studying the data.

In particular, we are able to separate short-term and long-term investment horizons using wavelets. In the bivariate case, we are interested in the short-term and

long-term comovements and dependencies. As the wavelets are localized functions, we can also study the dynamics of these relations over time.

## 2.1 Wavelet Coherence

As we are studying the comovement between two time series, we introduce a bivariate wavelet technique called wavelet coherence. First, we define the cross wavelet power of two time series  $x(t)$  and  $y(t)$  as

$$|W_{xy}(u, j)| = W_x(u, s) \overline{W_y(u, j)} \quad (1)$$

where  $W_x(u, s)$  and  $W_y(u, s)$  denote the continuous wavelet transforms of time series  $x(t)$  and  $y(t)$ , respectively, the bar denotes a complex conjugate, parameter  $u$  allocates a time position, and parameter  $j$  denotes the scale parameter. A low wavelet scale identifies the high-frequency part of the time series—a short investment horizon. For example, the first scale,  $j = 1$  carries information about 10-minute investment horizons when using data with five-minute frequency. For more details about wavelet transforms, see Daubechies (1988), Mallat (1998), and Percival and Walden (2000). For the analysis of financial market comovement, we use the Morlet wavelet.

The cross wavelet power uncovers areas in the time-frequency space where the time series show a high common power. However, in the comovement analysis we search for areas where the two time series in the time-frequency space comove, but do not necessarily have high power. A useful wavelet technique for finding these comovements is wavelet coherence.

Following Torrence and Webster (1999), we define the squared wavelet coherence coefficient as

$$R^2(u, j) = \frac{|S(j^{-1}W_{xy}(u, j))|^2}{S(j^{-1}|W_x(u, j)|^2)S(j^{-1}|W_y(u, j)|^2)} \quad (2)$$

where  $S$  is a smoothing operator.<sup>1</sup> The coefficient  $R^2(u, j)$  lies in the interval  $[0, 1]$ . Wavelet coherence values close to one indicate strong correlation (denoted by dark grey color in the figures), while values close to zero (white color in the figures) indicate low or no correlation (see *Figure 2*). The areas where the wavelet coherence is significant are bordered with a thick black contour.<sup>2</sup> The squared wavelet coherence coefficient can be seen as a local linear correlation measure between two time series in the time-frequency space.

As the wavelets are in fact filters, at the beginning and the end of the dataset the filter analyzes nonexistent data. To solve this, we augment the dataset with a sufficient number of zeros. The affected area is called the cone of influence and it is graphically represented by area below the bold black line in the figures. For more details, see Torrence and Compo (1998) and Grinsted et al. (2004).

<sup>1</sup> Smoothing is achieved by convolution in both time and scale; see Grinsted et al. (2004) for more details.

<sup>2</sup> The theoretical distribution for the wavelet coherence is not known, so the statistical significance is tested using Monte Carlo methods. The testing procedure is based on the approach of Torrence and Compo (1998). In our analysis, we use the 5% significance level.

The squared wavelet coherence coefficient can have positive values only, hence we cannot distinguish between negative and positive correlation directly. This problem can be solved using the wavelet coherence phase differences. These indicate delays in the oscillation between the two time series, therefore we obtain information on whether the two time series move together in phase (zero phase difference) or whether the time series are in antiphase, i.e., they are negatively correlated. Torrence and Webster (1999) define the wavelet coherence phase difference as

$$\phi_{xy}(u, j) = \tan^{-1} \left( \frac{\Im \left\{ S \left( s^{-1} W_{zy}(u, j) \right) \right\}}{\Re \left\{ S \left( s^{-1} W_{zy}(u, j) \right) \right\}} \right) \quad (3)$$

where  $\Im$  and  $\Re$  denote an imaginary and a real part operator, respectively. Phase differences are indicated by black arrows in the wavelet coherence figures in the areas with significant coherence.<sup>3</sup> If the two time series examined move together on a particular scale, then the arrows point to the right. If the time series are negatively correlated, then the arrows point to the left. Arrows pointing down (up) indicate that the first (second) time series leads the second (first) one by  $\frac{\pi}{2}$ .

## 2.2 Wavelet Correlation

The wavelet correlation is computed using a discrete type of wavelet transform.<sup>4</sup> Unlike the continuous wavelet transform, the discrete version of the wavelet transform decomposes the time series into vectors of wavelet coefficients that represent frequency bands. For example, wavelet coefficients at scale  $j$  represent frequency band  $f \in [1/2^{j+1}, 1/2^j]$ , thus the highest frequency—the shortest investment horizon—is characterized by the first scale,  $j = 1$ . Having vectors of discrete wavelet coefficients for all scales,  $w(u, j)$ , we can define the wavelet correlation at scale  $j$  for time series  $x(t)$  and  $y(t)$  as

$$\rho_j = \frac{\text{Cov}[w_x(u, j), w_y(u, j)]}{\sqrt{\text{Var}[w_x(u, j)] \text{Var}[w_y(u, j)]}} \quad (4)$$

The wavelet correlation provides a measure between two time series on scale-by-scale basis. In our study, we use the estimator of wavelet correlation based on Eq. (4). For a more detailed treatment of wavelet correlation and the computation of confidence intervals, see Gençay et al. (2002).

## 2.3 Analysis of Contagion

Following Forbes and Rigobon (2002) and Gallegati (2012), we define contagion as a change in correlation structure in two non-overlapping time periods. Wavelet multiresolution correlation is used as the measure of correlation. Formally,

<sup>3</sup> Note that phase differences are depicted only for time-frequency areas with significant wavelet coherence.

<sup>4</sup> We use the MODWT, which is not restricted to sample sizes that are powers of two. For more details about the MODWT, see Percival and Walden (2000) and Gençay et al. (2002)

**Table 1 Descriptive Statistics for 5-min High-Frequency Data**

	DAX	PX	BUX	WIG
Mean	$-2.98577 \times 10^{-6}$	$-1.66586 \times 10^{-5}$	$-2.63242 \times 10^{-5}$	$-1.76341 \times 10^{-5}$
St.dev	0.00152547	0.00127775	0.00169863	0.0018456
Skewness	0.426297	-0.144049	0.131315	0.208045
Kurtosis	20.3099	16.3973	27.0218	12.824
Min	-0.0156048	-0.0146523	-0.0243584	-0.0177151
Max	0.0317693	0.0170459	0.0434668	0.0276198

we define a null hypothesis of no contagion at scale  $j$  as

$$H_0 : \rho_{(I),j} = \rho_{(II),j} \quad j = 1, \dots, J \quad (5)$$

where  $\rho_{(\cdot),j}$  denotes the wavelet correlation at scale  $j$  and the indices  $I$  and  $II$  indicate the time period used for the correlation estimation. Since we decompose the five-minute time series of stock market returns into eight wavelet scales,  $J = 8$ , we can study contagion at investment horizons ranging from 10 minutes to 3 days.

### 3. Data and Empirical Results

#### 3.1 Data Description

In our analysis, we use five-minute high-frequency data on the Czech (PX), Hungarian (BUX), and Polish (WIG) stock indices, with the German stock index (DAX) as a benchmark. The Central European stock market data were collected over a period of two years beginning on January 2, 2008 and ending on November 30, 2009. The data were obtained from Tick Data.

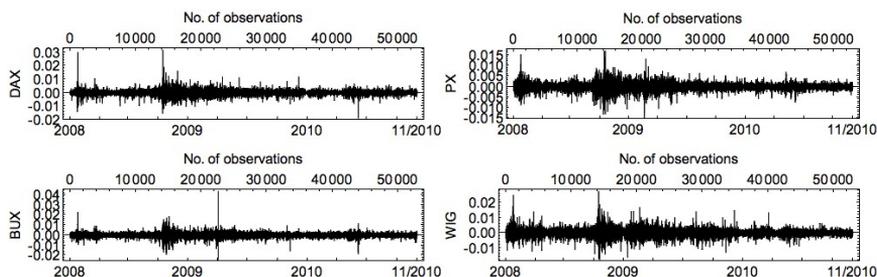
When looking at the data, one quickly observes that the number of observations for each trading day differs among the indices. This problem arises due to different stock market opening hours. The Prague Stock Exchange and the Warsaw Stock Exchange are open from 9:30 a.m. to 4:00 p.m. Central European Time (CET). The Budapest Stock Exchange is open from 9:00 a.m. to 4:30 p.m. CET. Finally, the Frankfurt Stock Exchange is open from 9:00 a.m. to 5:30 p.m. CET. Thus, we need to adjust the dataset by including only times of day when data are available for all the stock indices analyzed. We compute the logarithmic returns for the period from 9:30 a.m. to 16:00 p.m. CET for each day separately in order to avoid overnight returns. Finally, we are left with 77 return observations for each stock market for each day of the period analyzed. After discarding major public holidays, the final sample covers 450 trading days.

*Table 1* provides descriptive statistics for our final sample of five-minute high-frequency returns. *Figure 1* shows plots of the data.

#### 3.2 CEE Stock Market Comovements during the Crisis

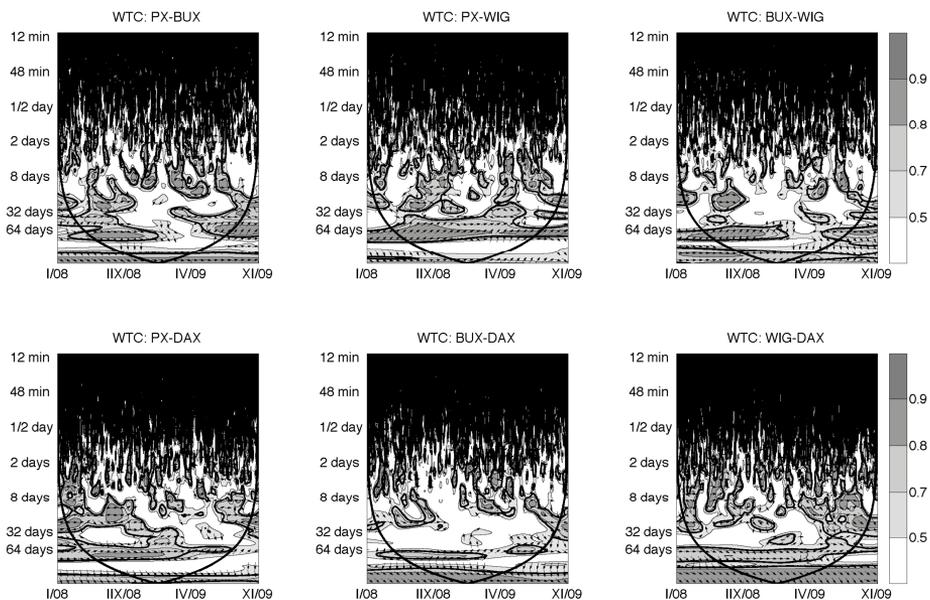
*Figure 2* shows the estimated wavelet coherence and phase difference for all the pairs of indices examined. Time is on the horizontal axis, while the vertical axis refers to frequency (the lower the frequency, the higher the scale, or period). Regions inside the black lines plotted in grey color represent regions where significant de-

**Figure 1 Plots of 5-min Logarithmic Returns for the DAX, PX, BUX, and WIG Indices**



**Figure 2 Wavelet Coherence of the PX, BUX, WIG, and DAX Index Pairs on Five-Minute High-Frequency Returns**

The horizontal axis shows time, while the vertical axis shows the period in minutes/days. The darker the region, the higher the degree of dependence between the pair.



pendence has been found. The lighter the grey color is, the less dependent the series are. White regions represent periods and frequencies with no dependence in the indices. The plot thus clearly identifies both frequency bands and time intervals where the series are highly coherent. The continuous wavelet transform at a given point uses information from its neighboring data points, so areas at the beginning and the end of the time interval should be interpreted with caution, as discussed in the methodology part. This applies especially to the time-frequency blocks inside the cone of influence at lower frequencies, where the transform does not have a sufficient number of data.

We observe interesting results from the analysis of wavelet coherence. First of all, there are large significant comovement periods in all the stock markets tested through several frequencies. As for the high-frequency patterns, these are hard to see from the figures, as the black regions consist of many small periods of significant comovement at various frequencies (10 min, 20 min, etc.). Each of the pairs also shows strong comovement periods at several daily frequencies up to two and three weeks, as well as periods where the pairs comove on a several-month scale.

When we look at the comovement of the PX, BUX, and WIG indices (*Figure 2*), we observe that the PX is positively correlated with the WIG at lower frequencies of up to several months. The PX-WIG pair also shows a very interesting pattern of changing cross-correlation from the second half of 2008 until the end of the first half of 2009. The correlations are strongly significant through this time period, but they change from a period of one month (lower frequency) to a shorter period of one week (higher frequency). These dynamics of interdependence visible from the wavelet transform of the high-frequency data are unique and allow us to understand the relationship between the stock markets analyzed in a different way than conventional analysis. Moreover, the phases—represented by arrows—reveal that the WIG is positively influenced by the PX; these markets also have the largest period of comovement through time and scales. The PX is also positively correlated with the BUX in several large time and scale periods, but the phases do not point to any directional influence. As to the dependence of these markets on the DAX, the PX-DAX pair shows the largest periods of comovement. The WIG is dependent on the DAX, while the BUX again shows the weakest dependence through different time and scale periods.

### 3.3 Contagion

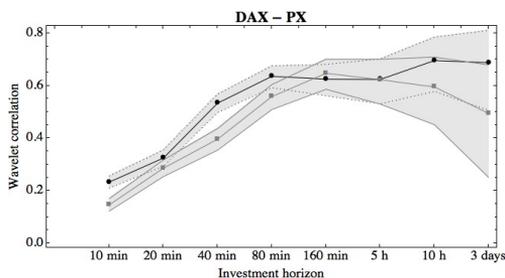
The analysis of contagion focuses on the wavelet correlation difference before and after the bankruptcy of Lehman Brothers in September 2008. The three pairs examined consist of the DAX index and the three CEE indices. We estimate the wavelet correlation on two different time windows, the first window containing observations starting on January 2, 2008 and ending on September 15, 2008, and the second window beginning on September 16, 2008 and ending on June 5, 2009. The two windows have an equal size of 12,860 five-minute high-frequency returns to make them statistically comparable.

The results of the contagion analysis indicate partial contagion only in the case of the PX index (see *Figures 3–5*). Comparing the wavelet correlation estimates, there are only two scales where the contagion is significant—scales 1 and 3—representing 10-minute and 80-minute investment horizons. To sum up the results, we can see that there is only one index out of the three for which we reject the hypothesis of no contagion. However, the result is unexpected, because after the bankruptcy of Lehman Brothers, we observe a decrease in the wavelet correlations. This result reveals that the comovement between these two markets decreased on short investment horizons.

An additional interesting aspect arising from the wavelet correlation decomposition is that the CEE markets have low correlations with the DAX at high frequencies (short investment horizons). This result is in line with the findings of

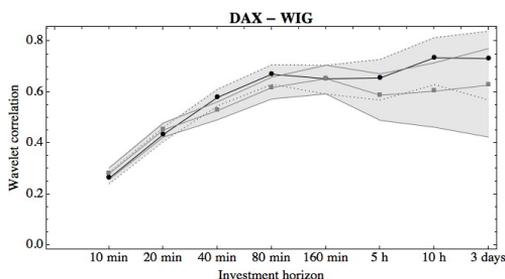
**Figure 3 Time-Frequency Correlations of the DAX and the PX.**

The Period before the Bankruptcy of Lehman Brothers is Depicted in Black (circles) and the Period after in Grey (squares). The grey region is the 95% confidence interval.



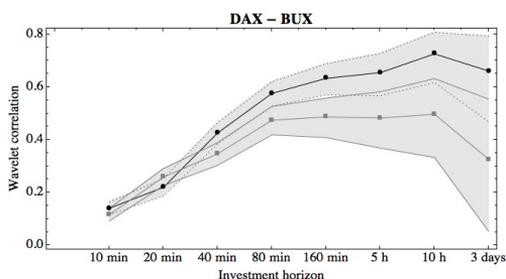
**Figure 4 Time-Frequency Correlations of the DAX and the WIG.**

The Period before the Bankruptcy of Lehman Brothers is Depicted in Black (circles) and the Period after in Grey (squares). The grey region is the 95% confidence interval.



**Figure 5 Time-Frequency Correlations of the DAX and the BUX.**

The Period before the Bankruptcy of Lehman Brothers is Depicted in Black (circles) and the Period after in Grey (squares). The grey region is the 95% confidence interval.



Egert and Kocenda (2007). Our result shows that the CEE markets are still not tightly connected to the leading markets in the region. Interestingly, after the onset of the financial crisis these market interconnections decreased even further. While this holds only for high frequencies, it complements the results from previous literature, which finds that interconnections increase at times of crisis (Gjika and Horvath, 2013).

#### 4. Conclusion

In this paper, we contribute to the literature on international stock market comovement and contagion by researching the interconnections between CEE stock markets during the recent crisis in the time-frequency space. The novelty of our approach lies in the application of wavelet tools to high-frequency financial market data, which allows us to understand the relationship between stock market returns in a different way than conventional analysis. Using the wavelet transform, we show how the correlations change continuously over time and across frequencies. In the first part of the empirical analysis, we employ wavelet coherence on high-frequency (five-minute) data on the Czech (PX), Hungarian (BUX), and Polish (WIG) stock indices together with the benchmark German stock index (DAX) in the period of 2008–2009. The second part analyzes contagion in the periods before and after the bankruptcy of Lehman Brothers accompanied by the large crash in September 2008.

The main result of the comovement analysis is the finding that the interconnection between all the stock markets changes significantly over time and varies across frequencies. Using five-minute high-frequency data, we find the strongest interdependencies between the Czech (PX) and Polish (WIG) stock markets. The comovements were significant through various frequencies, starting at the intraday period and ending at periods of up to three months. The PX-WIG pair also shows a very interesting pattern of changing comovements from the second half of 2008 until the end of the first half of 2009. The correlations are strongly significant through this time period, but they change from a period of one month (lower frequency) to a shorter period of one week (higher frequency).

Contagion analysis uncovered a partial change in the time-frequency correlation structure for the DAX–PX pair. The first and third wavelet scales changed significantly after the large 2008 crash, indicating signs of contagion. Unexpectedly, the correlation decreased rather than increased. This result shows that the connection between these two markets decreased on short investment horizons during the crisis.

Another interesting aspect arising from the correlation decomposition is that the CEE markets generally exhibit low correlation with the DAX at high frequencies. This shows that the CEE markets are still not tightly connected to the leading markets in the region. Our results complement the previous literature and open up several interesting avenues of research. Time-frequency dynamics can be exploited in both forecasting and risk management. For example, Barunik (2008) improves the forecasting ability of models on CEE data using principal component analysis, hence it would be interesting to see whether decomposition into various investment horizons improves predictive ability.

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