Shocks in capital markets – phase breakdowns in the wavelet analysis

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Abstract: In the wavelet analysis, the basis for the inference on lead/lag times of response of return rates is the phase difference between the components of two time series connected with significant coherence coefficients. In theory, the occurrence of breakdowns in the phase shift signifies interference in the interdependence. The preliminary research results presented in this article aim to address the question whether those breakdowns can be used to identify moments of the occurrence of shocks in financial markets, resulting from the behaviour of return rates in the partner market under examination. The results presented in the article reveal the significance of most square rates of return in the period preceding the occurrence of a phase break in the model for variance and the lack of significance of return rates of those moments to the concurrent change in the expected value. This article presents a methodological approach to identification of shocks.

Keywords: wavelet analysis, capital markets, shocks (jumps) in financial markets

JEL: C14, C58, F36, G01, G15

Introduction

In the literature, for many years authors have been discussing the transmission of impulses in financial markets. To a large extent, the discussion is triggered by the ambiguity of the classification of the impulses, their identification, and the variety of the research methods applied. The studies most often use tests of correlation coefficients [Lee, Kim 1993], [Calvo, Reinhart 1996], [Forbes, Rigobon 2002], ARCH and GARCH models [Edwards, Susmel 2001], [Billio, Caporin 2010], DCC-GARCH models [Cappiello, Engle and Sheppard 2006], [Frank, Gonzalez-Hermossilloand Hesse 2008], [Wang, Moore 2012], structural VAR [Favero, Giavazzi 2002] and cointegration analysis [Longin, Solnik 1995], probit and logit models [Eichengreenet al. 1996], [Kaminsky, Reinhart 2000], [Falcetti, Tudela 2006], regime-switching models [Gallo, Otranto2008], factor models [Corsetti et al. 2005], [Dungeyet al. 2005, 2007] and a copula approach [Rodriguez 2007]. A shortcoming of time series models is that it is impossible to separate simultaneous and lagged responses, and short- and long-term ones – the reason is that at any given time the results of various responses are being actualised. For this reason, research on the transmission of impulses is more and more often conducted the frequency domain by means of spectral/co-spectral analysis and wavelet analysis [Fan and Wang 2007], [Bodart, Candelon 2009], [Orlov 2009]; [Rua, Nunes 2009], [Nikkinen et al. 2011], [Gallegati 2012], [Graham et al. 2011], [Kiviaho et al. 2014], [Madaleno, Pinho 2012], [Ranta 2013], [Ftiti et al. 2014], [Barunik and Vacha 2015]. These authors focus their attention on the analysis of coherence coefficients, or coefficients of short-term correlations. In this research, the author's focus is on the analysis of phase difference and time lags in the reciprocal responses of markets. The main reason for taking such a course of research is the possibility to depart from making the comparison of correlations in periods of relative calmness and crises in financial markets, where the results of the comparison depend largely on the adopted time periods [Burzała 2015].

This article complements the author's previous works on the transmission of crisis, contagion and the interconnections governing capital markets [Burzała 2014, 2016]. The results obtained by means of the cospectral analysis and wavelet analysis allow an unambiguous classification of markets' responses into simultaneous responses (resulting from comovements), the effects of contagion (significant lagged responses over a short period of time – up to two weeks), and the transmission of a financial crisis (significant lagged responses over a medium period of time – up to two months). When analysing significant time lags/time leads in markets' responses, it was found that phase breakdowns occur quite often. Hence the question: what do those breakdowns signal, and are they relevant to the behaviour of rates of return? The aim of this article is to identify the shocks in the mutual dependencies of capital markets on the basis of phase breakdowns occurring in wavelet analysis, and their verification using time series models. Section 1 presents a brief overview of the research on jumps (shocks) in financial markets, and explains how the research relates to the fractal market hypothesis. Section 2 presents the methodology. The statistical data used and the results obtained from the wavelet analysis are discussed in Section 3. Finally, Section 4 presents the results of and conclusions on the verification of shocks (phase breakdowns) conducted by means of a modification of a method proposed by Baur [2003]. At the very end, the article offers a summary and reference list.

The fractal market hypothesis and the jumps in financial markets

Under the fractal market hypothesis, investor behaviour is influenced by the information obtained from the market and the time horizon length of their investments. A piece of information which triggers a drop in the rate of return on a stable market prompts selling over a short period of time and buying over a long period of time. A change in the behaviour of long-term investors can be sparked by a piece of information of strategic importance [Weron,

Weron 2009]. The situation in which long-term investors begin to behave like short-term ones poses a threat to maintaining market balance (everyone wants to sell, no one wants to buy). Stability and assets liquidity is guaranteed by investors' buying and selling over different time horizons. The fractal market hypothesis explains the behaviour of investors not only in times of a balanced market but also during a time of panic in the capital market. An example of losing the fractal structure of the market is the financial crisis of 2007-2009. However, determining the breakthrough point is a hard task, as the statistical drop in prices can stem from not merely one incident but a cumulation of moods and a number of incidents over a short period of time. Some authors argue that the breakthrough moment was the day on which BNP Paribas declared problems in pricing toxic assets, some others claim that it was the bankruptcy of Lehman Brothers. The biggest drop (jump – shock) in the DJIA Index was reported after the US Congress turned down a bailout plan drawn up by Paulson.

The significant jumps of prices observed (so-called shocks) in capital markets may result from breakthrough points and cause contagion effects. Sometimes, however, they are an effect of short-term, random market turmoil. Barndorff-Nielsen and Shephard [2004] put forward statistical models to measure the stochastic features of jumps. Lee and Mykland [2007] designed a non-parametric test which is used to tell a real shock from a false one. A lot of research is into the analysis of the causes, and consequences of the observed jumps. Patton and Sheppard [2015], based on an analysis of high frequency data concerning the S&P 100 Index, infer that negative jumps increase the oscillation of return rates, while positive ones decrease it. Wright and Zhou [2009] argue that the jumps average helps predict bond risk premiums. Tauchen and Zhou [2011] claim that the jumps made in financial markets can be used to predict credit spreads. Zhou and Zhu [2012] examine the possibility to use jumps in assets pricing and predicting the oscillations in Chinese shares and bonds markets.

Many authors use daily data to test the response of markets to macroeconomic news stories, for instance Lahaye, Laurent and Neely [2011], Dungey, McKenzie and Smith [2009]. Most studies deal with fully developed capital markets.

Research on emerging markets is conducted by such authors as Haw et al. [2000] and Altiok-Yilmaz and Selcuk [2010]. Those authors argue that share prices are sensitive to pay statements, and that financial reports impact price oscillations. Research results by Będowska-Sójka [2016] show that jumps happen when the market is incapable of absorbing new and large orders (so-called liquidity shocks).

Wavelet analysis allows considering the rates of return of assets on different scales corresponding to actions over different time horizons. It also allows us to examine non-stationary processes. Finding a positive answer to the question posed in this article may foster further research on the classification of the shocks detected and the consequences they bring.

Phase difference in wavelet analysis

One-dimensional wavelet analysis decomposes process x_n into orthogonal components through the translation and dilatation of the mother wavelet ψ. For the purposes of this research, Morlet wavelet was used a mother wavelet, defined as:

$$\psi_0(t) = \frac{1}{\pi^{1/4}} e^{i\omega_0 t} e^{-t^2/2} , \qquad (1)$$

where ω_0 is the centre frequency of the wavelet. When $\omega_0 = 6$, the scale in the wavelet analysis is almost equal to the period in the Fourier analysis, which makes it much easier to draw inferences [Grinsted et al. 2004]. All of the properties of the process under examination can be retained applying Discrete Wavelet Transform (DWT):

$$\psi_{j,k} = \frac{1}{\sqrt{s_0^j}} \psi\left(\frac{t - k\tau_0 s_o^j}{s_0^j}\right) . \qquad (2)$$

In Equation 2, j, k stands for discrete, complete transform coefficients. When $s_0 = 2$, $\tau_0 = 1$, we obtain so-called dyadic sampling, and calculations are made octave by octave[1]. Dyadicity is expressed by a constant scale 2^j and shift $k \cdot 2^j$. A wave family is obtained by scaling and shifting the mother wavelet $\psi_{j,k}(t) = 2^{j/2} \psi(2^j t - k)$.

In the wavelet analysis of two time series x_niy_n, the measure of lead/lagged responses is phase difference:

$$\varphi_{x,y}(u,s) = \tan^{-1}\left(\frac{\Im[S(s^{-1}W_{x,y}(u,s))]}{\Re[S(s^{-1}W_{x,y}(u,s))]}\right) . \qquad (3)$$

During research, we usually consider those mean phases which are associated with high squared wavelet coherence. A phase shift within $(0; \pi/2)$ or $(-\pi; -\pi/2)$ signals that process x_n precedes process y_n. If the phase shift is within $(\pi/2; \pi)$ or $(-\pi/2; 0)$, it must be inferred that process y_n precedes process x_n. Basically, when two time series are correlated in a stable way, phase difference ought to be constant. Hence, a sudden change in phase shift signifies interference in interdependence, especially if connected with a change of the preceding series. Then, it can be inferred that the behaviour of one of the series changed so much that it caused a shock in market interconnections. In this research, the author considered only those phase

[1] The estimation used a smoothing operator as defined by Torrence and Webster (cf. Grinsted et al., 2004).

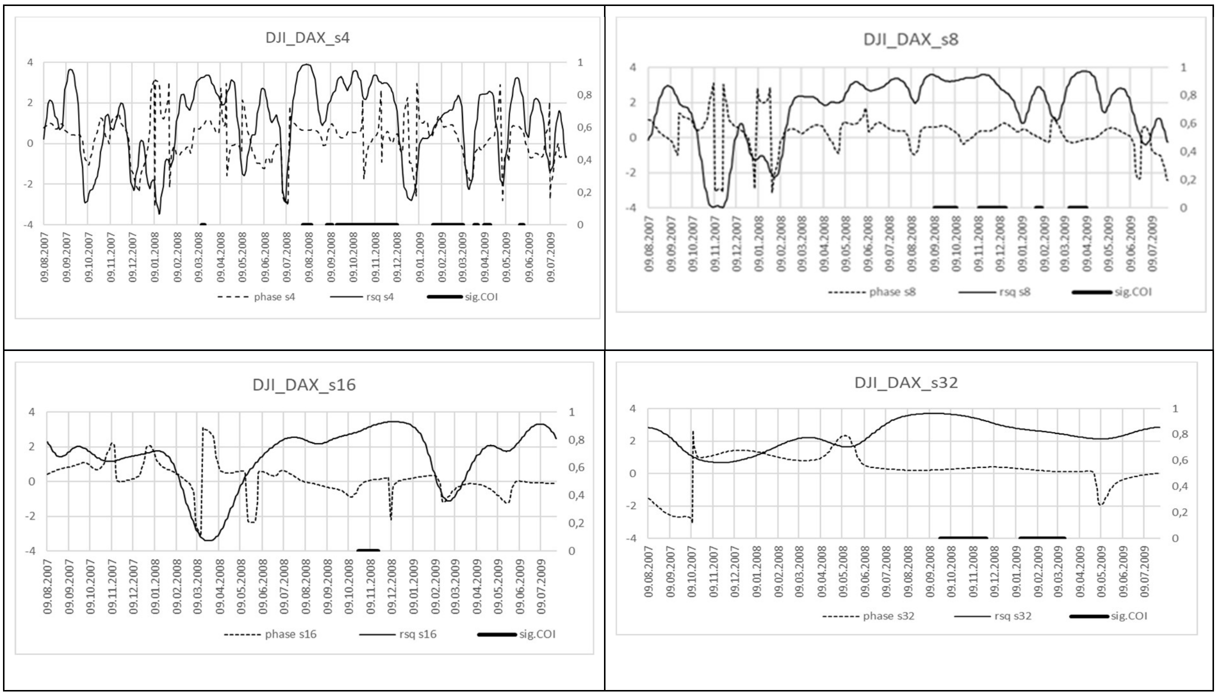
breakdowns which concerned with phase break+/- 2*s with a change preceding the market (s is the circular standard deviation).

An analysis of phase breakdowns in the interconnections between the US and German markets

In this research, the author used data from the US market (the DJIAindex) and the German market (the DAXindex) during the period of the financial crisis 9 August 2007 – 31 July 2009. Due to the different times of market quotations (resulting from different geographical time zones), the series of logarithmic rates of return were smoothed with a two-period moving average [Dungey et al. 2007]. It was assumed that the time series obtained in this way were comparable.

Figure 1 presents phase differences and squared wavelet coherence in the interconnections of the two markets on four selected scales. It is worth noting that phase breakdowns are mostly connected with a rise in squared wavelet coherence, which implies increased comovements resulting from such jumps.

Fig. 1. Squared wavelet coherence and phase difference (s = 4, 8, 16, 32)

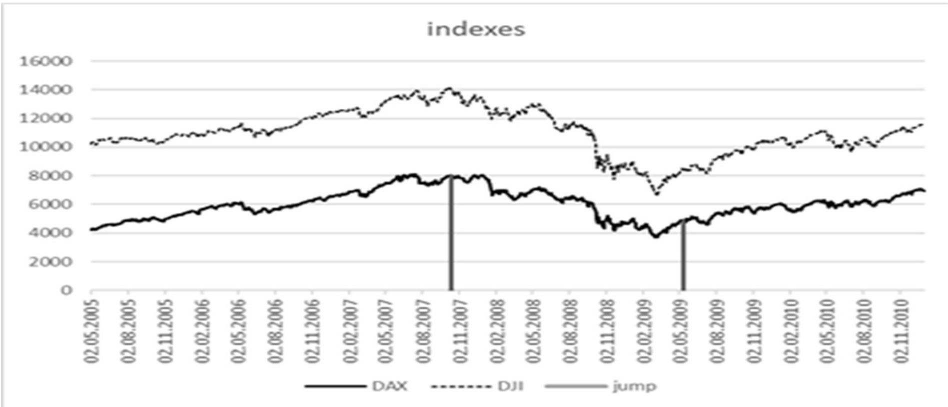


Source: own calculations and elaboration.

Most jumps (phase breakdowns on different scales) occurred before 15 September 2008, which might confirm the nervous reactions and growing anxiety that led to the outbreak of the financial crisis. More interestingly, no phase breakdowns were reported around 15 September, which in turn implies that both markets followed a “harmonious fall”.

The highest vulnerability of return rates and most breakdowns are reported over short periods of time (low scales). On higher scales, breakdowns usually occur at a different time than they would on scale s4. It can be inferred that they are formed as a result of different impact forces on rates of return from indices, and that they concern behaviours over different time horizons. On higher scales, less significant turmoils die off, and only those remain that are capable of changing the trend. Particularly interesting are two phase breakdowns on scale s16 (Figure 2). As it turns out, they signal the beginning and end of the indices' downward trend. This raises the comparison with cyclical growth, in which annual rates of return signal peak levels in advance, and bottom levels with delay. This observation can help predict changes in the capital market.

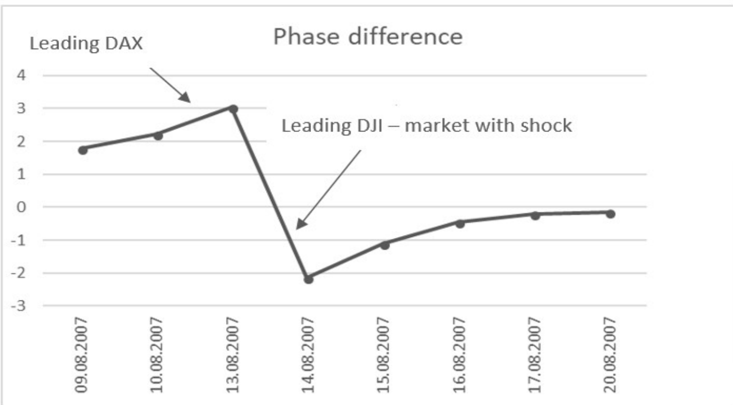
Fig. 2. The DAX and DJIA



Source: own calculations and elaboration.

As mentioned before, in the time domain, only those phase breakdowns were selected which were connected with a change in preceding responses between the markets. This inference is illustrated by Figure 3.

Fig. 3. Illustration of inferring a shock occurrence



Source: own calculations and elaboration.

The results presented in Table 1 point to significant differences in average rates of return at times of phase breakdown in comparison to the average over the whole period under examination, which stresses the need for those moments to be carefully considered and given particular attention.

Table 1. The basic description characteristics of rates of return

Period	DJI			DAX		
	Average	Standard deviation	Averagerate of change	Average	Standard deviation	Averagerate of change
crisis: 9.08.2007 – 31.07.2009	-0,077	1,416	0,003	-0,068	1,416	0,002
jumps – scale s4	-0,452	1,234	-0,081	-0,552	1,213	-0,264
jumps – scale s8	-0,472	0,860	0,130	0,061	1,210	0,078
jumps – scale s16	-0,330	0,818	-0,677	-0,020	1,357	-0,516

Source: own calculations and elaboration.

In terms of the jumps signalled on scale s4 (four-day oscillations), the average rate for both indices is considerably lower than the average for the whole period. The positive average rate of change on scale s8 signifies the efforts made by markets to regain stability, which, unfortunately, ends up in reversing the trend on scale s16. On lower scales, squeezed waves are considered, on higher scales – stretched ones. The latter help analyse a trend over a medium time period, and hence, a significantly higher average rate of decline.

The verification of shocks relevance in the AR and GJR models

For the verification of the relevance of shocks on a partner market, the author chose an approach proposed by Baur [2003] which allows the simultaneous verification of the changes in the expected value and variance, which is a measure of the insecurity in financial markets. In his research, the author used rates of return from periods of calm and crisis in financial markets. In this research, the model was referred to the time of crisis and the moments when phase breakdown occurred.

Let's assume that we are examining the relevance of the impact of shocks in the US market on the German market[2]. *The comovements of rates of return* in the period of crisis can be presented in the following form;

[2] It is assumed that the logarithmic series of rates of return from SE indices are covariantly stationary.

$$s_{DJI,t} = u_{DJI,t},$$

$$s_{DAX,t} = \mu_{DAX,t} + \beta_1 s_{DJI,t} + \beta_2 s_{DJI,t} \cdot D_{kt} + u_{DAX,t}, \quad (4)$$

Where $u_{DJI,t}$ represents the stochastic shocks in the US market that we are examining, $\mu_{DAX,t}$ stands for the expected value of the rate of return on the DAX market, β_1 is a measure of how much the rate of return from the DJIA impacts the DAX in the time of crisis, and parameter β_2 is a measure of the impact exerted by the rate of return from the DJIA at the time of phase breakdown (the shock exerting its influence). Variable $D_{kt}$is a zero-one variable that assumes value 1 for k^{th} shock at moment t, and value 0 otherwise. Hence, parameter β_1 describes the comovements of markets manifested by simultaneous changes in rates of return; β_2 is a measure of how much the shock impacts the expected value which informs about the intensified transmission mechanisms. At the time of shock in the US market, the impact exerted on the German market is the sum of the estimated parameters $\beta_1 + \beta_2$. For the expected value $\mu_{DAX,t}$ the following model was assumed: ARMA(1,0): $\mu_{DAX,t} = \alpha_0 + \alpha_1 s_{DAX,t-1}$. Similar comovements could be assigned to the German market affecting the US market.

The model describing the impact of shocks at the time of crisis due to *changing variances* assumes the following form:

$$u_{DAX,t} = \xi_{DAX,t} \sqrt{h_{DAX,t}},$$

$$h_{DAX,t} = \alpha_0 + \alpha_1 u^2_{DAX,t-1} + \alpha_2 h_{DAX,t-1} + \alpha_3 s^2_{DJI,t-1} + \alpha_4 s^2_{DJI,t-1} \cdot D_{k,t-1}, \quad (5)$$

Where $\xi_{DAX,t}$ is a stochastic variable of zero expected value and unitary variance. In the research, the variance variability model was the *GJR(1,1)* model, taking account of the additional impact exerted by negative rates of return, and which incorporated variables represent the impact exerted by the squared rates of return from the DJIA at the time of crisis and at the moment of phase breakdown. In model (5), the measure of the impacts exerted by additional shocks is parameter α_4.

The results obtained from the model for expected value (4) and variance (5) are presented in Table 2. An x in the table signifies the market from which the shock emerged. Therefore, its impact was examined in the partner market.

Table 2. Shock relevance in the model for expected value and variance

Date	Change of leading index	Scale_shocknumber	DJI to DAX		DAX to DJI	
			model 4 (β_2)	model 5 (α_4)	model 4 (β_2)	model 5 (α_4)
04.01.2008	DJI/DAX	s4_1	x	x	0,36	-0,58***
08.01.2008	DAX/DJI	s4_2	0,12	-0,57	x	x
09.01.2008	DJI/DAX	s4_3	x	x	-1,92**	-0,99***
30.01.2008	DAX/DJI	s4_4	0,17	-12,92**	x	x
09.04.2008	DJI/DAX	s4_5	x	x	-0,30	0,82*
11.04.2008	DAX/DJI	s4_6	0,15	-1,10***	x	x
04.07.2008	DAX/DJI	s4_7	-2,64	8,64**	x	x
14.07.2008	DJI/DAX	s4_8	x	x	0,17	-0,93
23.10.2008	DJI/DAX	s4_9	x	x	0,05	0,12
24.10.2008	DAX/DJI	s4_10	1,92*	-4,85	x	x
17.11.2008	DJI/DAX	s4_11	x	x	2,44**	1,30***
19.11.2008	DAX/DJI	s4_12	0,33	-0,62**	x	x
06.01.2009	DJI/DAX	s4_13	x	x	-0,77	-1,33
04.05.2009	DAX/DJI	s4_14	-0,17	-0,16	x	x
08.07.2009	DJI/DAX	s4_15	x	x	0,35	0,69***
09.07.2009	DAX/DJI	s4_16	4,25	-35,44	x	x
20.09.2007	DAX/DJI	s8_1	3,89	-23,09**	x	x
09.11.2007	DAX/DJI	s8_2	-0,84	-0,003	x	x
21.11.2007	DJI/DAX	s8_3	x	x	-16,21	-281,35
07.01.2008	DJI/DAX	s8_4	x	x	0,89	-1,63***
28.01.2008	DAX/DJI	s8_5	-43,17	896,46***	x	x
02.05.2008	DAX/DJI	s8_6	-0,32	0,22*	x	x
09.06.2008	DAX/DJI	s8_7	-0,33	0,35**	x	x
17.06.2009	DAX/DJI	s8_8	-0,21	-0,72	x	x
24.06.2009	DJI/DAX	s8_9	x	x	-0,98*	0,30*
14.11.2007	DAX/DJI	s16_1	-0,87	-0,16	x	x
27.12.2007	DJI/DAX	s16_2	x	x	-5,14	-14,40***

Date	Change of leading index	Scale_shocknumber	DJI to DAX		DAX to DJI	
			model 4 (β_2)	model 5 (α_4)	model 4 (β_2)	model 5 (α_4)
06.03.2008	DAX/DJI	s16_3	-1,25	-1,86**	x	x
17.03.2008	DJI/DAX	s16_4	x	x	-0,45	0,31***
04.04.2008	DAX/DJI	s16_5	-12,70	3014,89***	x	x
02.06.2008	DJI/DAX	s16_6	x	x	0,87	-5,71**
03.06.2008	DAX/DJI	s16_7	-0,27	0,13	x	x
10.12.2008	DJI/DAX	s16_8	x	x	-1,77**	-0,17
16.02.2009	DJI/DAX	s16_9	x	x	4,56**	-4,65***
11.10.2007	DAX/DJI	s32_1	4,09	-30,45***	x	x

Source: own calculations and elaboration.

Table 3 presents the estimates for overall parameters in both models. The results obtained confirmed the preliminary predictions that insecurity in financial markets is transmitted as a result of financial shocks, and the shocks' minor significance in terms of the expected value [Burzała 2016].

Table 3. Overall parameters in the model of excepted value (4) and variance (5)

Model for expected value (4)			Model for variance (5)		
Parameter	**DAX**	**DJI**	**Parameter**	**DAX**	**DJI**
α_0	0,02	-0,02	α_0	0,01*	0,01*
α_1	0,31***	-0,09***	α_1	-0,02	0,01
β_1	0,76***	0,76***	α_2	0,89***	0,88***
			α_3	0,04*	-0,01
			Additional effect of negative impulses in the GJR model	0,025***	0,18***
ADJ R^2	0,61	0,60	Log likelihood	-705,974	-700,922

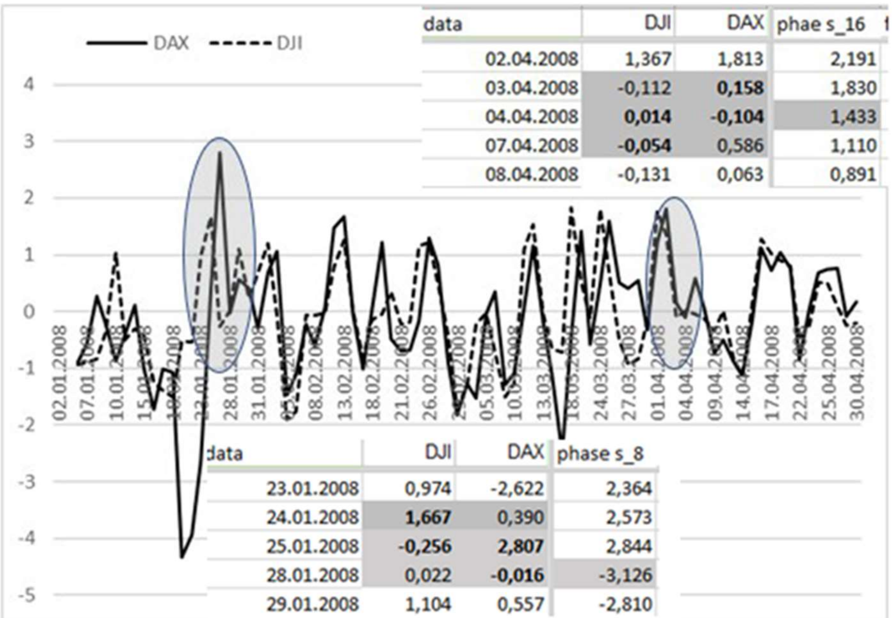
Source: own calculations and elaboration.

In model (4) for the expected value of return rates from both the DAX and DJIA, the significant parameter β_1 indicates simultaneous changes in rates of return. It confirms a massive comovement resulting from the interconnections of the two markets. The levels of rates of return are only impacted by single shocks from the two markets; however, more often, shocks from the German market were statistically significant. On the one hand, this conclusion comes as a surprise, but on the other, the information flowing from Europe did imply the scope and scale of the markets' involvement in toxic securities – hence the reactions of investors in the US market.

Then, the shocks following phase breakdowns exerted a big influence on the spreading insecurity in financial markets. Not only the positive but also the negative marks of the parameters obtained imply not only spreading insecurity but also a number of signals that, in the end, helped restore calmness in the markets. Despite the previous intentions, it was decided not to associate the moment of shock occurrence with specific incidents of that time. On the one hand, the large number of those incidents makes it difficult to associate phase breakdown with a formally made announcement, but on the other, investors react repeatedly to certain confidential information reaching the market before formal announcements are made.

Analysis of the results indicate a very powerful impact of the shock in the US market on the German market in January and April 2008. Drops in capital markets were first reported in early January 2008. The forerunners of the upcoming crisis came from the US real estate market – on 27 January, Freddie Mac, a company that refinances banks offering mortgage loans, announced their decision to stop buying the most risky securities in the real estate market.

Fig. 4. Rates of returns from indices between January – May 2008

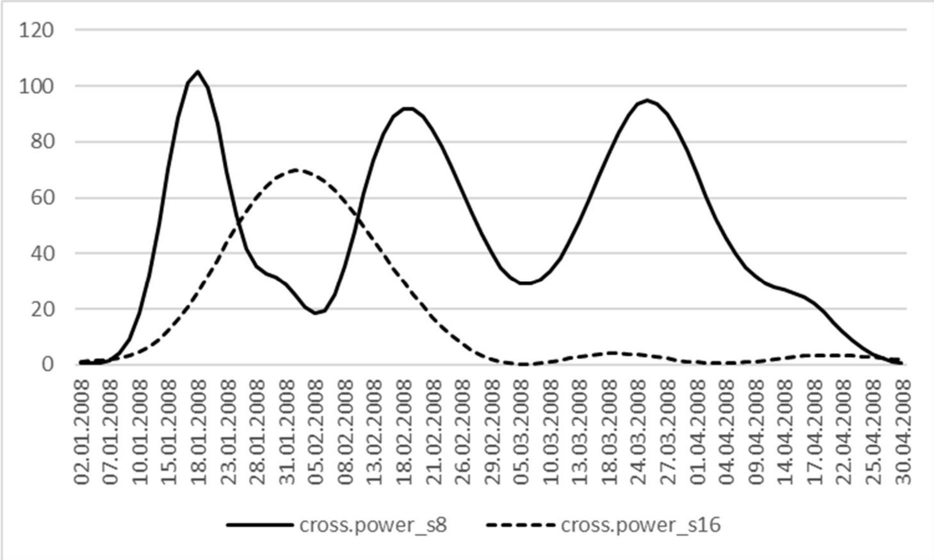


data	DJI	DAX	phae s_16
02.04.2008	1,367	1,813	2,191
03.04.2008	-0,112	0,158	1,830
04.04.2008	0,014	-0,104	1,433
07.04.2008	-0,054	0,586	1,110
08.04.2008	-0,131	0,063	0,891

data	DJI	DAX	phase s_8
23.01.2008	0,974	-2,622	2,364
24.01.2008	1,667	0,390	2,573
25.01.2008	-0,256	2,807	2,844
28.01.2008	0,022	-0,016	-3,126
29.01.2008	1,104	0,557	-2,810

Source: own calculations and elaboration.

Fig. 5. Covariance between January – May 2008 (scales s8 and s16)



Source: own calculations and elaboration.

Figure 4 presents an attempt to combine the parameters in model (5) with the behaviour of rates of return. However, it should be noted at all times that the wavelet analysis results refer to particular scales – they represent the microstructure of the market. In the variance model, the shock was represented by the rates of return from the partner's market. The dates provided in Table 2 refer to (as indicated by Figure 4) to the moments of response (in January, following the decline – s8; in April, prior to the decline – s16). As the aim of studying markets is to predict their responses, it must be agreed that at this stage more detailed research is needed covering the responses of different markets. This would make inference more consistent over different time horizons. In order to assess whether the two shocks under analysis could cause contagion, Figure 5 was drawn up, in which the comovement of the two markets in shown on scales s8 and s16. In neither case is there a rise in the comovement of rates of return at the time of their occurrence. Nor are there moments connected with significant time periods for coherence coefficients above the cone of influence. Both markets are strongly correlated (Table 3). Such a huge growth of variance can be associated with liquidity shocks. Success in recognising them on scales s8 and s16, connected with the medium term time horizon, may imply the occurrence of strategic incidents that changed the behaviour of long-term investors. However, such an inference still requires confirmation provided by more results gained from broader empirical research.

Summary

The statistical significance of most phase breakdowns in econometric models confirms the occurrence of jumps (shocks) in the course of time series, which proves that the methodology used allows their verification. The financial shocks identified have much more significance in terms of assessing insecurity in financial markets than the changes in the expected value of rates of return. A bigger amount of phase breakdowns at the initial stage of a crisis foreruns growing instability in capital markets. Further, it could also be inferred that the strategic incidents which change the fractal structure of the market must be looked for on higher scales (s8 and s16), spanning longer time horizons. If our inference is confirmed by the results of a study involving a bigger number of capital markets, it will be possible to classify the identified jumps and examine the effects of their occurrence.

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