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Contagion among major world markets: a wavelet approach

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Abstract

Purpose – The purpose of this paper is to examine contagion among the major world markets during the last 25 years and propose a new way to analyze contagion with wavelet methods.

Design/methodology/approach – The analysis uses a novel way to study contagion using wavelet methods. The comparison is made between co-movements at different time scales. Co-movement methods of the discrete wavelet transform and the continuous wavelet transform are applied.

Findings – Clear signs of contagion among the major markets are found. Short time scale co-movements increase during the major crisis while long time scale co-movements remain approximately at the same level. In addition, gradually increasing interdependence between markets is found.

Research limitations/implications – Because of the chosen method, the approach is limited to large data sets.

Practical implications – The research has practical implications to portfolio managers etc. who wish to have better view of the dynamics of the international equity markets.

Originality/value – The research uses novel wavelet methods to analyze world equity markets. These methods allow the markets to be analyzed in the whole state space.

Keywords World equity markets, Wavelet correlation, Wavelet coherence, Waves, Waveforms, Transforms

Paper type Research paper

1. Introduction

The debate around a phenomenon called contagion has been active in recent years. Contagion has many definitions and there is widespread disagreement about the correct definition. Forbes and Rigobon (2002) define contagion as an increase of correlation between markets after some crisis. This is a narrow definition that is not universally accepted. Some researchers argue that contagion cannot be defined based on changes in cross-market linkages. Instead, they argue that analysis of contagion should be based on the analysis of shock propagation from one country to another and that only certain types of transmission mechanisms constitute contagion. However, Forbes and Rigobon's definition has been the most popular in recent papers discussing contagion. Their definition is adopted in this study with a slightly different perspective. Contagion is defined as a temporary increase of short time-scale co-movements. Examining the structure of co-movements along the scale dimension this study avoids the heteroscedasticity problem that has plagued contagion research based on correlation coefficients. Using wavelets as a tool, linkages between markets can be studied at different time scales. If the structure of linkages along the scale dimension changes in periods of turmoil, it should be an indication of contagion.

A significant increase of interest in contagion occurred after the 1987 stock market crash. King and Wadhwani (1990) study correlations around the crash, focussing on

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the major stock markets. They find an increase in contagion, evidenced by an increase in stock market correlations, during periods of turmoil. Lee and Kim (1993) add developing countries to the study and also find evidence of contagion. Overall consensus during the 1990s was that contagion exists[1]. Forbes and Rigobon (2002) argue that previous studies found contagion because they did not correct the correlation measure for heteroscedasticity. Using a heteroscedasticity corrected correlation measure, they find that contagion does not exist. Following the guidelines of Forbes and Rigobon, other studies end up with similar conclusions. For example, Collins and Biekpe (2002) study the integration of African countries with the world financial markets and find very little evidence of contagion. Lee *et al.* (2007) find that the South-East Asia tsunami did not trigger contagion in international stock markets (although they find some signs of contagion in foreign exchange markets). Recently the contagion and financial crisis analysis has become more and more specific. For example Zaki *et al.* (2011) analyze the behavior of UAE banks during financial distress and stress out the independence of the banks of these markets for macroeconomic situations. Yang and Chang (2008) analyze the contagion from currency movements to stock prices. Their empirical results show that managers who invest to newly emerging markets need to evaluate the currencies also as part of their investment decisions. Lien and Yang (2009) analyze intraday data for return and volatility spill-over across international copper futures markets. They find similar findings as others have found in the equity markets like increasing integration and prominent contagion. The recent global financial crisis of 2008 has also been analyzed. Bancel and Mittoo (2011) for example examine how financial flexibility affects the firm's ability to survive from the crisis.

Corsetti *et al.* (2005) argue that Forbes and Rigobon's model assumes unrealistic restrictions on the variance of country-specific shocks. Bartram and Wang (2005) note that the bias Forbes and Rigobon document follows directly from the assumptions of their analysis (see also Pesaran and Pick, 2007). Hon *et al.* (2007) correct the bias using a GARCH-model (see also Jokipii and Lucey, 2007). Rodriguez (2007) uses a copula approach to investigate contagion and finds that the dependence structure is different when studying tail dependence compared to overall dependence. The tail dependence exhibits strong changes during the Asian and Mexican crises which is a clear sign of contagion. Taking this recent criticism into account, overall consensus has changed from "no contagion" to "at least some contagion" or in some cases very strong signs of contagion (see e.g. Yang and Bessler, 2008; Dungey *et al.*, 2007).

The interdependencies of markets have also been examined with different perspectives than contagion. Lin *et al.* (1994) study the correlation of the volatility of the New York and Tokyo markets and they notice that one market has a global impact on the returns of the other market. Ramchand and Susmel (1997) examine the relation between correlation and variance using a switching ARCH technique. They find that correlations between the USA and other world markets are on average 2 to 3.5 times higher when the US market is in a high-variance state, as compared to a low-variance regime. This underlines the statement that one has to be very careful in contagion conclusions based purely on correlation. Andersen *et al.* (2001) study volatility and correlation using high-frequency data on individual stocks in the Dow Jones industrial average. They find that correlations move together with volatility, reducing the benefits to portfolio diversification when the market is the most volatile. Longin and Solnik (2001) question this and find that correlation is not related to market volatility *per se* but to the market trend and that correlation between markets increases in bear markets. Ball and Torous (2000) examine correlations across a number of international stock market indices using stochastic correlation from returns data. They find that the estimated correlation structure is dynamically changing over time emphasizing the need for more detailed analysis of correlation structure. Kearney (2000) finds evidence of world equity market volatility being caused predominantly by volatility in the Japanese and US markets, which is subsequently transmitted across European markets. He also finds that low inflation tends to be associated with high stock market volatility. Morana and Belratti (2008) study the co-movements in international stock markets. They form monthly realized moments for stock market returns and find progressive integration of the four stock markets, leading to increasing co-movements in prices, returns, volatilities and correlations. Beaulieu *et al.* (2009) focus their integration analysis to Canada and the USA. Their analysis stresses the importance of integration analysis to portfolio managers who try to diversify their portfolio as much as possible.

Overall the recent consensus emphasizes the increasing integration of world markets (see e.g. Rua and Nunes, 2009) and skepticism for volatility being the driving factor of correlation. For example Amira *et al.* (2011) find evidence using impulse response functions that the past returns and the market direction are the driving factors of correlation. Mun and Brooks (2012) also note that news have a significant role to the level of correlation between market.

Wavelet correlation is achieving increasing popularity in financial time series analysis. Although other approaches for improved co-movement analysis (see e.g. Mendes and Aíube (2011) for copula-based dependence analysis) have been proposed, the wavelets have acquired the most attention. The intelligent compromise between time- and frequency dimensions of wavelet analysis gives researcher a possibility to separate new relationships from financial time series. Long list of wavelet correlation research includes Gallegati and Gallegati (2005) in the study of the industrial production index of the G-7 countries, Kim and In (2005) in the analysis of stock returns and inflation, In and Kim (2006) analyzing stock and the futures markets, In and Brown (2007) comparing international swap markets and Raghavan *et al.* (2010) comparing the Malaysian stock market to leading world markets. All mentioned paper stress out the efficiency of wavelet methods to separate new connections from the analyzed time series that are not easily identified using ordinary methods.

Wavelet dependence methods applied to financial and economic time series have evolved greatly since then. Ranta (2008) integrates GARCH model to wavelet correlation and present rich structure between interactions of international markets at different time scales. Nikkinen *et al.* (2011) apply wavelet correlation to option-implied volatility and end up to similar conclusions of richer structure between interactions than previously thought. Rua (2011) extends recent wavelet methods to forecasting. He joins wavelets and factor-augmented models and shows how the unification of these two methods helps to improve the forecasting power.

In the evolution of wavelet dependence methods, the wavelet correlation of discrete wavelet transform has been recently accompanied by the wavelet coherence of continuous wavelet transform that is quickly gaining popularity in finance and economics. The wavelet coherence estimator was introduced by Grinsted *et al.* (2004), Torrence and Webster (1999) and Torrence and Compo (1998). Rua and Nunes (2009) analyze the co-movements of stock market returns using wavelet coherence. They examine the overall dependence of developed markets at the aggregate level and also separated into different sectors. One of the main conclusions is that in the side of analyzing time-varying properties of the co-movements, it is also of utmost importance to analyze frequency-varying properties of the co-movements. McLoughlin (2010) applies wavelet coherence methods to study the evolution of international consumption risk sharing over time and frequency. He shows how the inclusion of new dimension reveals new information of correlation between output and consumption. Graham and Nikkinen (2011) find a high degree of co-movements of stock returns and volatilities at low frequencies between Finland and rest of the world using wavelet coherence. They also find high levels of co-movement of returns and volatilities across all frequencies between the world equity portfolio and equities in France, Germany, Switzerland and the UK. Graham *et al.* (2012) apply wavelet coherence for thorough analysis of co-movements of emerging markets and find significant differences between markets. These all papers stress out the importance of taking into account the time scale in analysis. Vacha and Barunik (2012) apply wavelet coherence maps to analyze the co-movement of energy commodities. They end up to similar conclusion in energy commodities as others have ended up in equities. The rich structure of interrelations and co-movements need methods that can analyze both the time- and frequency dimensions.

This study addresses the debate around the correlation measure being a biased measure of contagion by studying co-movements at different time scales. In addition to making conclusions about co-movements as a function of time, conclusions as a function of time scale (frequency) are made. If short time-scale co-movements change (increase), while long time-scale co-movements remain approximately the same, this is considered as a sign of contagion. This study is divided into two parts. The first part uses wavelet coherence of the continuous wavelet transform similar to Rua and Nunes (2009). The second study uses the estimator of wavelet correlation calculated with the maximal overlap discrete wavelet transform to analyze and support the findings of the wavelet coherence findings.

2. Wavelet correlation

2.1 Maximal overlap discrete wavelet transform (MODWT)

The MODWT (Percival and Walden, 2000) is similar to the discrete wavelet transform (DWT) in that the high-pass and low-pass filters are applied to the input signal at each level. However, in the MODWT, the output signal is never subsampled (not decimated). Instead, the filters are upsampled at each level.

Suppose we are given a signal $s[n]$ of length N where $N = 2^J$ for some integer J. Let $h_1[n]$ and $g_1[n]$ be the low-pass filter and the high-pass filter defined by an orthogonal wavelet. At the first level of MODWT, the input signal $s[n]$ is convolved with $h_1[n]$ to obtain the approximation coefficients $a_1[n]$, and with $g_1[n]$ to obtain the detail coefficients $d_1[n]$:

$$a_1[n] = h_1[n] \times [n] = \sum_k h_1[n-k]s[k] \tag{1}$$

$$d_1[n] = g_1[n] \times [n] = \sum_k g_1[n-k]s[k] \tag{2}$$

Because no subsampling is performed, $a_1[n]$ and $d_1[n]$ are of length N instead of $N/2$ as in the DWT case. At the next level of the MODWT, $a_1[n]$ is split into two parts using the same scheme, but with modified filters $h_2[n]$ and $g_2[n]$ obtained by dyadically upsampling $h_1[n]$ and $g_1[n]$. This process is continued recursively. For $j=1, 2, \ldots, J_{0-1}$, where $J_0 \leqslant J$, we define:

$$a_{j+1}[n] = h_{j+1}[n] * a_j[n] = \sum_k h_{j+1}[n-k]a_j[k] \tag{3}$$

$$d_{j+1}[n] = g_{j+1}[n] * a_j[n] = \sum_k g_{j+1}[n-k]a_j[k] \tag{4}$$

where $h_{j+1}[n] = U(h_j[n])$ and $g_{j+1}[n] = U(g_j[n])$. Here U is the upsampling operator that inserts a zero between every adjacent pair of elements of time series. The output of the MODWT is then the detail coefficients $d_1[n], d_2[n], d_3[n], \ldots, d_{J_0}[n]$ and the approximation coefficients $a_{J_0}[n]$.

2.2 MODWT estimator for the wavelet correlation

In this section, the estimator for the wavelet correlation is constructed using MODWT. These estimators were introduced in the works of Percival (1995), Whitcher (1998) and Whitcher *et al.* (2000). The estimator for the wavelet cross-correlation is just the estimator of the wavelet correlation with circular shifting of time series. Using a simple rolling window approach, the estimator is used to calculate a time series of correlation values.

The MODWT coefficients indicate the changes at a particular scale. Thus, applying the MODWT to a stochastic time series produces a scale-by-scale decomposition. The basic idea of the wavelet variance is to substitute the notion of variability over certain scales for the global measure of variability estimated by the sample variance (Percival and Walden, 2000). The same applies to the wavelet covariance where the wavelet covariance decomposes the sample covariance into different time scales. In other words, wavelet covariance in a particular time scale indicates the contribution to the covariance between two stochastic variables from that scale. As explained in Gençay *et al.* (2002), the wavelet covariance at scale $\lambda_j \equiv 2^{j-1}$ can be expressed as:

$$\mathrm{cov}_{XY}(\lambda_j) = \frac{1}{\tilde{N}} \sum_{t=L_j-1}^{N-1} d_{j,t}^X d_{j,t}^Y \tag{5}$$

where $d_{j,t}^l$ are the MODWT wavelet coefficients of variables x, y at scale λ_j. $\tilde{N}_j = N - L_j + 1$ is the number of coefficients unaffected by the boundary, and $L_j = (2^j - 1)(L - 1) + 1$ is the length of the scale λ_j wavelet filter.

We can construct a biased estimator of the wavelet covariance by simply including the MODWT wavelet coefficients affected by the boundary and renormalizing. To obtain a full set of MODWT coefficients we need to combine the beginning and end of the data set to calculate coefficients close to the boundaries. Calculation with a data set including these boundary-affected coefficients induces bias to the estimator.

Given that the covariance does not take into account the variation of the univariate time series, it is natural to introduce the concept of wavelet correlation. The wavelet correlation is simply made up of the wavelet covariance for $\{X_t, Y_t\}$ and the wavelet variance for $\{X_t\}$ and $\{Y_t\}$. The MODWT estimator of the wavelet correlation can be expressed as:

$$\rho_{XY}(\lambda_j) \equiv \frac{\mathrm{cov}_{XY}(\lambda_j)}{v_X(\lambda_j)v_Y(\lambda_j)} \tag{6}$$

where $v_l(\lambda_j) \equiv \frac{1}{N}\sum_{t=L_j-1}^{N-1}\left[d_{j,t}^l\right]^2$, $l = X, Y$ is the wavelet variance of stochastic process (Percival, 1995).

Confidence intervals. Calculation of confidence intervals is based on Whitcher *et al.* (1999, 2000). More thorough representation of the derivation of the confidence intervals is presented there. The random interval:

$$\left[\tanh\left\{h[\rho_{XY}(\lambda_j)] - \frac{\Phi^{-1}(1-p)}{\sqrt{N_j - 3}}\right\}, \tanh\left\{h[\rho_{XY}(\lambda_j)] + \frac{\Phi^{-1}(1-p)}{\sqrt{N_j - 3}}\right\}\right] \tag{7}$$

captures the true wavelet correlation and provides an approximate 100 $(1-2p)$ percent confidence interval. Function $h(p) \equiv \tanh^{-1}(\rho)$ defines Fisher's z-transformation and N_j is the number of wavelet coefficients associated with a certain scale and computed via the DWT, not the MODWT. This is because Fisher's z-transformation assumes uncorrelated observations and the DWT is known to approximately decorrelate a wide range of power-law processes. One can assume that the amount of independent data points in the MODWT coefficients is the same as in the DWT coefficients. This assumption is based on the close linkage between the MODWT and the DWT. After all the only difference between them is the lack of subsampling of the MODWT. So we get more realistic confidence intervals using the number of DWT coefficients in the Fisher's z-transformation.

2.3 Wavelet coherence

The second applied method is the wavelet coherence and this is defined according to Grinsted *et al.* (2004). Instead of the discrete wavelet transform, the estimator of dependence is now based on the continuous wavelet transform. A wavelet $\psi(t)$ admissibility condition in continuous time is a function of time that obeys the admissibility condition:

$$C_\psi = \int_0^\infty \frac{|\psi(f)|}{f} df < \infty \tag{8}$$

where $\psi(f)$ is the Fourier transform of $\psi(t)$. The continuous wavelet transform is defined as:

$$W(u,s) = \int_{-\infty}^{\infty} x(t)\psi_{u,s}(t)dt \tag{9}$$

where

$$\psi_{u,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right)$$

is the translated and dilated version of the original wavelet function. The wavelet coherence of two time series is defined as:

$$R_n^2(s) = \frac{|S(s^{-1}W_n^{XY}(s))|^2}{S(s^{-1}|W_n^X(s)|^2) \cdot S(s^{-1}|W_n^Y(s)|^2)} \tag{10}$$

where S is smoothing operator, s is the wavelet scale, $W_n^X(s)$ is the continuous wavelet transform of the time series X, $W_n^Y(s)$ is the continuous wavelet transform of the time series Y and $W_n^{XY}(s) = W_n^X W_n^Y *$ is the cross wavelet transform of the two time series X and Y (Grinsted *et al.*, 2004; Torrence and Webster, 1999). Cohen and Walden (2010) argue that Morse wavelets are usually the best option for wavelet coherence analysis. After quick comparison, this study, however, follows the guidelines of Grinsted *et al.* (2004) and the Morlet wavelet was chosen for the study. It is the best wavelet for feature extraction purposes and it provides good balance between time- and frequency localization. Also for the Morlet wavelet the Fourier period is almost equal to the wavelet scale used. As explained in Torrence and Webster (1999), the smoothing operator is defined to be similar to the wavelet used as shown below:

$$S(W) = S_{scale}(S_{time}(W_n(s))) \tag{11}$$

where $S_{time}(W)|_S = \left(W_n(s) * c_1^{\frac{-t^2}{2s^2}}\right)$ and $S_{scale}(W)|_S = (W_n(s) * c_2 \Pi(0.6s))|_n$. c_1 and c_2 are normalization constants and Π is the rectangle function. The factor of 0.6 is empirically determined and follows Torrence and Compo (1998). The statistical significance levels of the wavelet coherence are determined using Monte Carlo methods with 1,000 samples.

3. Empirical analysis

3.1 Empirical data

The empirical data consists of four major stock indices. Included are DAX 30 (Germany), FTSE 100 (Great Britain), S&P 500 Composite (the USA) and Nikkei 225 (Japan). The sample period starts from January 2, 1984 and ends on January 8, 2009, and includes 6,529 daily closing prices for each index. The estimator of wavelet correlations is calculated from the series using the MODWT. The dependence of the indices is also examined using wavelet coherence analysis. Based on the descriptive analysis of interdependence structure, contagion is tested at different time scales. A test statistic for the difference between correlations before and after an incident is calculated.

3.2 Empirical results

Forbes and Rigobon (2002) argue that using an ordinary comparison of correlation coefficients during periods of turmoil and stability is biased because of the heteroscedasticity present in the data. Their arguments where questioned, for example, by Bartram and Wang (2005) and Corsetti *et al.* (2005). They question the assumptions made on the variance of country-specific noise, however, their questions are yet to be resolved. As previously mentioned, Forbes and Rigobon (2002) define contagion simply as an increase of the correlation coefficient as a result of some financial crisis. With the introduction of multiresolution analysis, these issues can be separated and examined using different time scales. An increase of co-movements at shorter time scales accompanied with unchanging co-movements of longer time scales is assumed to be a signal of contagion. This should be quite a plausible assumption, because co-movement structure is analyzed along the scale dimension.

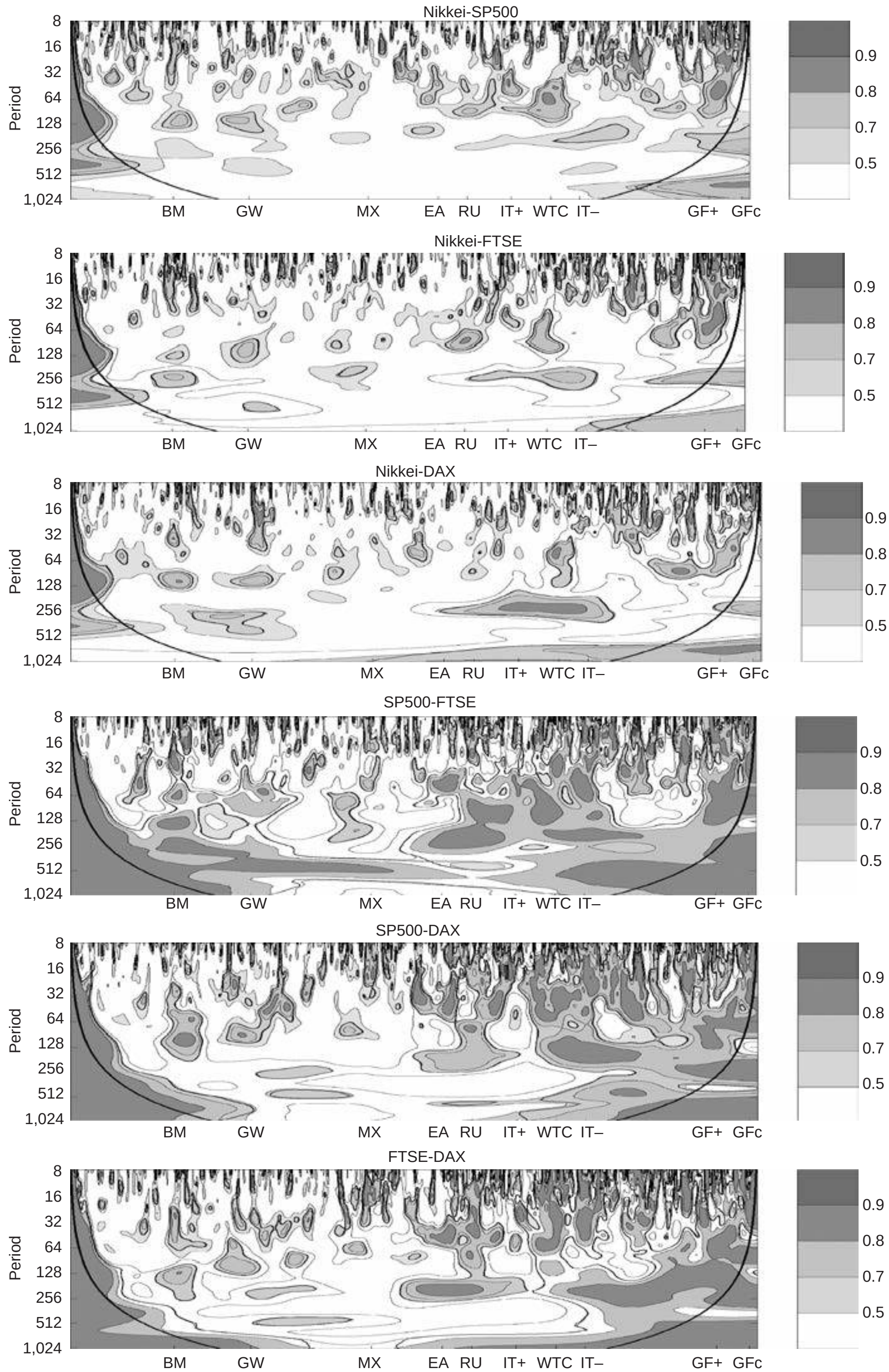
Wavelet coherence maps are used as a descriptive tool to analyze the correlation structure. The coherence maps between markets are in Figure 1. Abbreviations used in the maps are presented in Table I. Maps are calculated using the Morlet wavelet. The Morlet wavelet is suggested for wavelet coherence analysis by Grinsted *et al.* (2004). It is the best wavelet for feature extraction purposes and it provides good balance between time- and frequency localization. Also for the Morlet wavelet the Fourier period is almost equal to the wavelet scale used.

The structure of the figures is as follows. Along the horizontal axis goes the time from January 2, 1984 to January 8, 2009. Along the vertical axis goes the time scale (frequency) from the longest scale (1,024 days) to shortest scale (7 days). The coherence maps present the level of co-movement between markets at different times and different time scales as a two dimensional map. Statistically significant (95 percent) areas in the maps are surrounded with thick black lines. These were calculated using Monte Carlo methods and 1,000 simulated white noise series. Also in the figures is the cone of influence.

These present the boundary where calculated values are affected by the boundary conditions. Because the length of the wavelet filter increases with the scale studied, the number of affected wavelet coherence values is much larger at the longer time scales.

The wavelet coherence figures provide good tools for a descriptive analysis of contagion. We can survey the correlation from point to point along the state space. If we keep as our signal of contagion an increase of short time-scale correlation, the figures give many indications of contagion. The area where short time-scale correlation increases varies between different crises. Sometimes there is an increase of correlation at the seven-day time scale and sometimes the increase is around the two weeks to one month time scale. Also the breakpoint between a changing short time-scale correlation and an approximately constant long time-scale correlation varies around 60 and 150 days. Below is a short list of findings from the wavelet coherence maps:

- There is an overall increase of co-movements during the last 25 years. The increase is slightly weaker with Nikkei but still clearly visible. On the other hand the European indices and SP500 have experienced a very strong increase of co-movement.
- The Black Monday caused clear contagion effects. The increase of short time-scale correlation is strongest with FTSE and SP500 but other indices also show clear contagion effects.
- Around the Gulf war there are also signs of contagion, but the signs are not as clear as with Black Monday.
- Probably the strongest signs of contagion can be seen around the ongoing global financial crisis. Strong interdependencies extend to longer time scales in the figures.
- Around the East-Asian financial crisis and the Russian financial crisis there are some signs of contagion. The signs are, however, quite weak.
- With the gradually increasing co-movements during the last 25 years and the contagion effects of the ongoing financial crisis, markets are very strongly correlated at the moment. The SP500, FTSE and DAX are all highly correlated at every time scale.



Note: See text for explanation

Figure 1.
Wavelet coherence maps of major indices

Previous studies have concentrated mainly on the study of ordinary correlation analysis but wavelet coherence figures show that covariance alone is insufficient to capture the relationships that vary along time scale. When analyzing the "wrong" time scale, signs of contagion could be missed.

A study of short time-scale correlations using the discrete version of the wavelet transform is used to accompany wavelet coherence analysis. A multiresolution analysis with the focus on two short time scales is performed. The first scale represents 2-4-day averages and the second scale represents 16-32-day averages. The time scale of two to four days was chosen as the shortest time scale to avoid the bias of different closing times. The longer time scale was chosen to be 16-32 because it includes one month in its scale making comparison with earlier studies easier. Also the results begin to be uncertain at longer time scales because the rolling window does not have enough data points for the analysis of longer time scales. After experimenting with few different wavelet filters, the Haar filter was utilized in the MODWT. Being the simplest of all wavelet filters, it mostly avoids the boundary problems of filtering. The Haar filter has poor band-pass properties, but is sufficient for the purposes of this study (Percival and Walden, 2000).

Figure 2 presents a rolling wavelet correlation series for these two different time scales. These figures provide support for the findings of the wavelet coherence figures. There are clear signs that short time scale co-movements increased after the 1987 stock market crash, at the beginning of the Gulf War and at the beginning of the global financial crisis of 2008. There is also an increase of co-movements at the end of 1990s. This increase cannot be attributed to one specific crisis so easily. The increase begins around the East Asian crisis and is strongest during the Russian crisis. Also the figures show that during the tranquil periods and bull markets, co-movements tend to decrease. To make the results more robust, the effect of the individual wavelet filter is determined, but the chosen filter does not appear to have any major effect on the results. The calculations with different DWT filters produce very similar results with only small differences.

To test the presence of contagion, a *t*-test is used to evaluate if there is a significant increase in the wavelet correlation coefficients after the major world incidents. By applying the transformation:

$$z = \frac{1}{2}\ln\frac{1+r}{1-r}$$

Table I.
In a chronological order the description of abbreviations used in the text and figures

BM	The Black Monday – the major collapse of US stock market on October 17, 1987
GW	The Gulf War – August 2, 1990, when Saddam Hussein attacked Kuwait
MX	The Mexican peso crisis. The date chosen is December 19, 1994 (Forbes and Rigobon, 2002)
EA	The East Asian financial crisis. The date chosen is July 15, 1997
RU	The Russian financial crisis. The date chosen is August 13, 1998
IT +	The peak of SP500 index during the Dot-Com bubble. The date is March 24, 2000
WTC	The suicide attacks of al-Qaeda upon the United States on September 11, 2001
IT−	The low point (a bear market ends) after the Dot-Com bubble burst. The date is October 2, 2002
GF +	The peak of SP500 during the last bull market before the global financial crisis of 2007-2009
GFc	The crash of global stock markets during the global financial crisis of 2007-2009

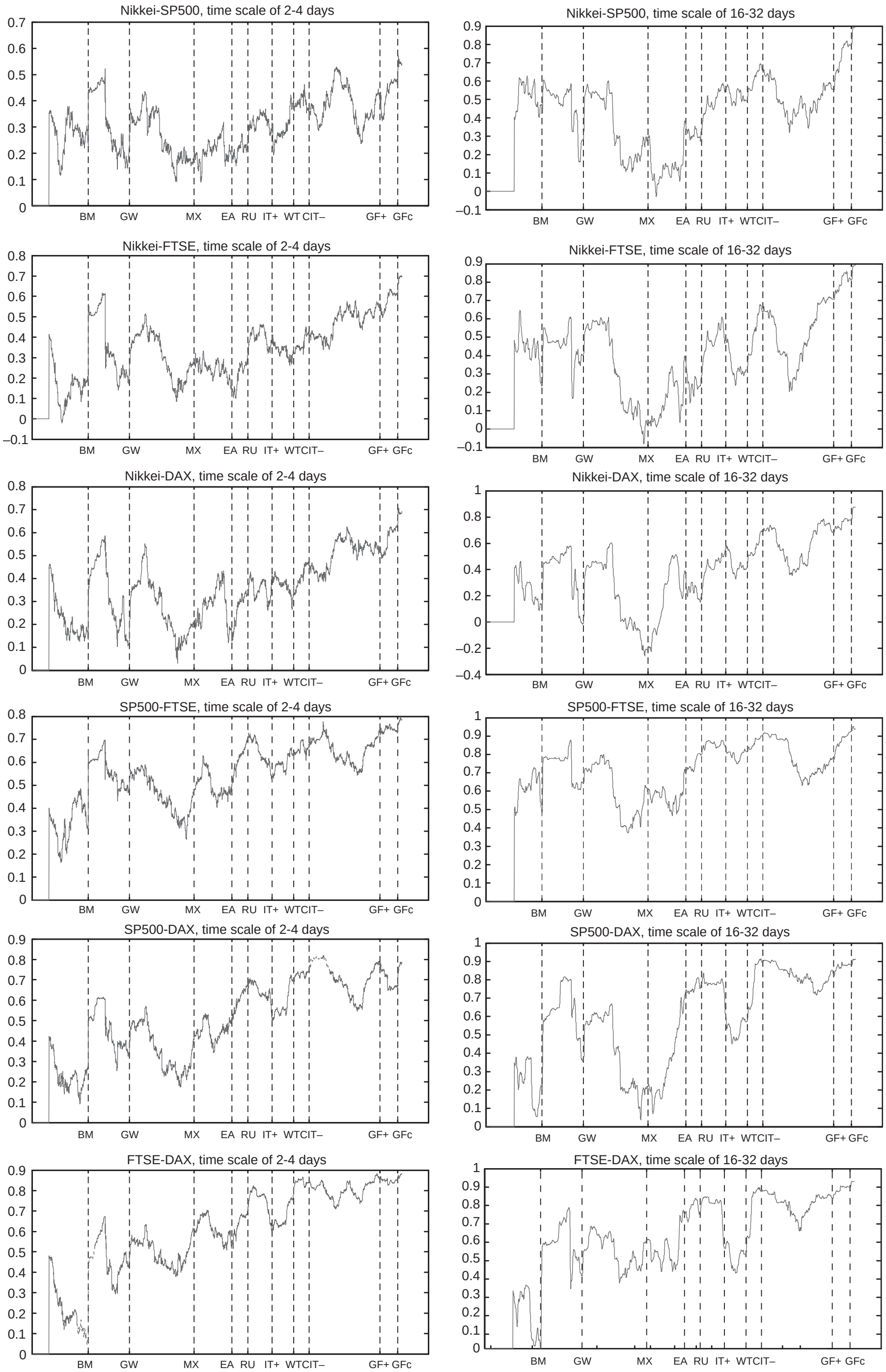


Figure 2.
Rolling wavelet correlations

Notes: On the left side is the time scale of two to four days. On the right side is the time scale of 16-32 days. The width of the rolling window is 200 days to the correlations and calculating the test statistic.

$$t = \frac{z_1 - z_2}{\sqrt{\frac{1}{(n_1-3)} + \frac{1}{(n_2-3)}}} \tag{12}$$

we can compare the equality of correlations. For this examination, the time periods used before and after the incidents have 250 days. This was a compromise, since a shorter time period would not have had enough data points to study longer time scales, while a longer time period would not have isolated different incidents. If p_1 is the correlation coefficient before the incident and p_2 the correlation coefficient after the incident, the test hypotheses are:

$$\begin{aligned} H_0 &: p_1 > p_2 \\ H_1 &: p_1 = p_2 \end{aligned} \tag{13}$$

The results are shown in Table II. There are four different time scales from two to four days to 16-32 days. The smallest scale of one to two days was not used, because different closing times of the markets disturb consistent results in this scale. Time scales longer than 16-32 days could not be studied because the degrees of freedom of the test decrease quickly with the scale. The time scale of 16-32 days was the last scale with reasonably solid results.

The results of the *t*-test support the results of wavelet coherence analysis, since the strength of change in correlations decreases with scale. The results indicate that there have been contagion effects between the major markets at least three times: during the 1987 financial crisis, at the beginning of the Gulf War, and now during the global financial crisis. In these cases there is a significant increase of co-movements between every studied index. The increase is often significant even at the one percent level at the shortest time scale, giving support to the results of wavelet coherence analysis. Also in these cases the strength of correlation change decreases when the time scale increases. This was the main assumption for the indication of contagion. This decrease of significance with increasing scale is also seen in those cases where confident conclusions could not be made and significant correlation changes are absent. These weak indications of contagion are seen with the East Asian crisis and the bursting of the dot-com bubble. These results indicate that contagion does exist and has occasionally been present across all major markets in the last 25 years.

4. Conclusion

This paper studies the presence of contagion between major world markets. Contagion has been a widely studied subject for two decades. Papers after the 1987 stock markets crash provide evidence of contagion between markets (King and Wadhwani, 1990; Lee and Kim, 1993). Somewhat later, many papers examined the presence of contagion in developing markets. There the results were mainly similar and provided evidence of contagion (see e.g. Calvo and Reinhart, 1996). Forbes and Rigobon (2002) end up with a different conclusion since they argue that the heteroscedasticity of the return series causes a bias in the correlation and therefore contagion mostly does not exist. Their conclusions are criticized by Corsetti *et al.* (2005) and Bartram and Wang (2005) as they note that their results are caused by the model assumptions. Today the consensus of contagion research concludes that there is some contagion but exact specifications have not yet been established.

Table II. The results of t-tests comparing equality of correlation coefficients

	2-4 days			4-8 days			8-16 days			16-32 days		
	Correlation before	Correlation after	t-value	Correlation before	Correlation after	t-value	Correlation before	Correlation after	t-value	Correlation before	Correlation after	t-value
October 17, 1987 (BM)												
SP500-Nikkei	0.266	0.507	2.209*	0.377	0.619	1.734*	0.391	0.596	0.978	0.395	0.600	0.615
SP500-FTSE	0.268	0.704	4.631**	0.296	0.773	3.839**	0.289	0.832	3.199*	0.358	0.906	2.537*
SP500-DAX	0.266	0.613	3.403**	0.258	0.603	2.309*	0.128	0.675	2.463*	0.008	0.830	2.646*
Nikkei-FTSE	0.186	0.633	4.312**	0.122	0.680	3.759**	0.044	0.710	3.006**	0.110	0.693	1.663
Nikkei-DAX	0.129	0.602	4.373**	0.117	0.668	3.669**	0.087	0.696	2.755**	0.054	0.719	1.908
FTSE-DAX	0.008	0.677	6.293**	−0.121	0.745	5.758**	−0.271	0.819	5.105**	−0.351	0.874	3.842*
August 2, 1990 (GW)												
SP500-Nikkei	0.161	0.426	2.258*	0.245	0.485	1.487	0.319	0.581	1.188	0.280	0.714	1.360
SP500-FTSE	0.454	0.602	1.591	0.540	0.644	0.860	0.613	0.698	0.532	0.676	0.841	0.904
SP500-DAX	0.347	0.561	2.096*	0.452	0.576	0.898	0.433	0.674	1.268	0.294	0.793	1.743
Nikkei-FTSE	0.172	0.516	3.064*	0.258	0.568	2.022*	0.380	0.591	0.992	0.437	0.734	1.050
Nikkei-DAX	0.103	0.545	3.925*	0.085	0.637	3.550*	0.088	0.766	3.284*	−0.023	0.796	2.492*
FTSE-DAX	0.463	0.620	1.720*	0.476	0.661	1.477	0.525	0.733	1.253	0.557	0.779	0.929
December 19, 1994 (MX)												
SP500-Nikkei	0.224	0.229	0.042	0.374	0.255	−0.703	0.469	0.066	−1.576	0.467	−0.138	−1.446
SP500-FTSE	0.499	0.554	0.584	0.530	0.652	1.003	0.543	0.660	0.654	0.589	0.697	0.416
SP500-DAX	0.420	0.459	0.366	0.429	0.509	0.549	0.260	0.366	0.419	0.092	0.229	0.314
Nikkei-FTSE	0.278	0.231	−0.385	0.282	0.320	0.220	0.188	0.355	0.642	0.117	0.144	0.062
Nikkei-DAX	0.194	0.293	0.811	0.093	0.352	1.463	−0.103	0.451	2.098*	−0.244	0.411	1.538
FTSE-DAX	0.589	0.654	0.814	0.614	0.635	0.180	0.594	0.460	−0.668	0.557	0.318	−0.669
July 15, 1997 (EA)												
SP500-Nikkei	0.156	0.301	1.179	0.226	0.377	0.888	0.298	0.440	0.587	0.314	0.494	0.485
SP500-FTSE	0.566	0.715	1.965*	0.570	0.775	2.042*	0.682	0.833	1.299	0.803	0.884	0.640
SP500-DAX	0.531	0.702	2.155*	0.596	0.770	1.775	0.693	0.847	1.398	0.755	0.873	0.812
Nikkei-FTSE	0.095	0.420	2.713**	0.025	0.436	2.349*	0.072	0.449	1.463	0.182	0.515	0.865
Nikkei-DAX	0.207	0.385	1.510	0.181	0.379	1.150	0.200	0.387	0.735	0.195	0.407	0.524
FTSE-DAX	0.583	0.780	2.929**	0.575	0.799	2.340*	0.633	0.842	1.711	0.751	0.844	0.576

(*continued*)

Table II.

	2-4 days Correlation before	2-4 days Correlation after	2-4 days *t*-value	4-8 days Correlation before	4-8 days Correlation after	4-8 days *t*-value	8-16 days Correlation before	8-16 days Correlation after	8-16 days *t*-value	16-32 days Correlation before	16-32 days Correlation after	16-32 days *t*-value
August 13, 1998 (RU)												
SP500-Nikkei	0.263	0.352	0.758	0.344	0.495	0.979	0.352	0.550	0.893	0.343	0.630	0.862
SP500-FTSE	0.707	0.605	−1.386	0.770	0.716	−0.645	0.808	0.763	−0.420	0.826	0.853	0.200
SP500-DAX	0.672	0.628	−0.594	0.795	0.705	−1.108	0.788	0.762	−0.235	0.789	0.772	−0.093
Nikkei-FTSE	0.345	0.449	0.952	0.351	0.475	0.798	0.358	0.487	0.562	0.339	0.618	0.828
Nikkei-DAX	0.361	0.396	0.309	0.343	0.496	0.990	0.300	0.573	1.223	0.279	0.627	1.006
FTSE-DAX	0.724	0.779	0.980	0.763	0.778	0.202	0.794	0.790	−0.037	0.746	0.848	0.638
March 24, 2000 (IT)												
SP500-Nikkei	0.186	0.407	1.877*	0.387	0.464	0.504	0.496	0.462	−0.160	0.551	0.458	−0.280
SP500-FTSE	0.564	0.655	1.124	0.656	0.772	1.274	0.701	0.830	1.137	0.738	0.896	1.135
SP500-DAX	0.518	0.719	2.565**	0.574	0.805	2.433*	0.529	0.845	2.316*	0.359	0.866	2.108*
Nikkei-FTSE	0.376	0.295	−0.706	0.426	0.285	−0.860	0.386	0.307	−0.320	0.311	0.312	0.003
Nikkei-DAX	0.389	0.346	−0.380	0.485	0.348	−0.887	0.486	0.357	−0.565	0.577	0.298	−0.786
FTSE-DAX	0.631	0.761	1.983*	0.589	0.793	2.149*	0.504	0.827	2.229*	0.361	0.828	1.800
September 11, 2001 (WTC)												
SP500-Nikkei	0.393	0.352	−0.367	0.503	0.439	−0.434	0.518	0.612	0.495	0.625	0.745	0.515
SP500-FTSE	0.654	0.655	0.021	0.788	0.796	0.110	0.821	0.898	1.072	0.884	0.934	0.654
SP500-DAX	0.748	0.741	−0.133	0.854	0.803	−0.882	0.895	0.860	−0.549	0.905	0.925	0.278
Nikkei-FTSE	0.358	0.394	0.325	0.378	0.515	0.909	0.374	0.636	1.278	0.566	0.736	0.675
Nikkei-DAX	0.340	0.458	1.092	0.388	0.624	1.718*	0.446	0.738	1.658	0.552	0.805	1.103
FTSE-DAX	0.815	0.834	0.474	0.855	0.868	0.277	0.864	0.875	0.162	0.881	0.892	0.115
July 15, 2007 (GF)												
SP500-Nikkei	0.398	0.560	1.631*	0.625	0.842	2.634**	0.697	0.925	2.710*	0.686	0.933	1.880
SP500-FTSE	0.750	0.776	0.482	0.864	0.845	−0.381	0.870	0.915	0.806	0.889	0.961	1.216
SP500-DAX	0.710	0.769	1.004	0.808	0.834	0.421	0.841	0.881	0.568	0.886	0.915	0.345
Nikkei-FTSE	0.538	0.701	2.079*	0.660	0.832	2.131*	0.751	0.906	1.899*	0.785	0.908	1.024
Nikkei-DAX	0.531	0.707	2.226*	0.592	0.830	2.695**	0.689	0.893	2.111*	0.711	0.906	1.371
FTSE-DAX	0.856	0.864	0.245	0.850	0.878	0.582	0.864	0.924	1.084	0.887	0.940	0.729

Notes: The correlation coefficients were calculated using 250-day sample periods before and after a significant date. *,**Significant at 95 and 99 percent levels, respectively

This paper extends the contagion literature by adding a time scale dimension to the analysis. Different time scales are analyzed using the continuous wavelet transform-based wavelet coherence and the discrete wavelet transform-based wavelet correlation. As Rua and Nunes (2009) note, much more thorough analysis of interrelations can be achieved using the wavelet methods. This also applies to a study on contagion. The co-movement structure changes that are found with wavelet methods might be missed with ordinary methods, since co-movements in time could change only at certain time scales. The definition of contagion in this study follows Forbes and Rigobon (2002). If there is an increase of co-movement after some crisis point, we have contagion. In this paper contagion is defined to be a change in the short-time scale co-movements while long time-scale co-movements remain the same. Using this definition, clear signs of contagion are found. This is most clearly seen with the 1987 stock market crash, the Gulf War and the 2008-2009 global financial crisis. Some signs of contagion are seen with other crises, both in the wavelet coherence analysis and the wavelet correlation analysis. However, these changes are not as clear. The results also show how the short time-scale correlations decrease at tranquil periods (bull markets) giving support to the conclusions of Longin and Solnik (2001). Also long time-scale correlations indicate an overall increase of interdependence during the studied time period.

The inclusion of a multiresolution analysis, i.e. different time scales, proves to be very important since co-movements change quickly as a function of the time scale. With the inclusion of the time scale dimension, we are able to see how the short time scale interdependencies react to the major incident and at the same time observe the behavior of long time-scale interdependencies. The results indicate that contagion has been a major factor between the markets a few times in the last 25 years. Also the contagion phenomenon is not disappearing since very strong signs of contagion can be seen during the 2008-2009 financial crisis.

Note

1. See Claessens *et al.* (2000) for survey of the contagion literature before the new millennium.

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