Are American and European equity markets in phase? — Frequency aspects of return and volatility spillovers

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(This version: June 2, 2016)

Abstract

We consider three equity markets, represented by stock indices DJIA (USA), FTSE 100 (UK), and EURO STOXX 50 (euro area). Connecting these three markets together via vector autoregressive processes in index returns (or volatilities), we construct "propagation values" to measure, on a daily basis, the relative importance of a market as a volatility creator within the network, where volatility is due to either a return shock (case ret2vol) or a volatility shock (case vol2vol) in a market. A cross-wavelet analysis can reveal the joint frequency structure of pairs of the propagation value series, in particular whether or not two series tend to move in the same direction at a given frequency. This approach can replicate certain findings of traditional business cycle research, and it has the advantage of using readily available stock market data.

Our findings are: (i) Frequency properties of ret2vol and vol2vol propagation values are by and large similar, namely such that the European markets are in phase, while the US market is not in phase with either European market; (ii) the band of relevant frequencies has become narrower in ret2vol propagation values from year 2000 onwards, but not in vol2vol propagation values; (iii) the financial crisis of 2007/08 and the European debt crisis since the end of 2009 have left prominent traces in vol2vol, but not ret2vol, propagation values. This provides new insight into the time-dependent interplay of equity markets.

1 Introduction

Efforts to understand cyclical behavior of economic time series go back to as early as the 19th century, with researchers aiming to forecast the future of economies. Juglar (1862) was among the first to identify economic cycles and their synchronicity in 1862. He proposed 7–11 year cycles of fixed capital investments which were more or less synchronous for France, the UK and the US. Beginning with the 20th century, several other cycles have been identified: (i) the Kitchin (1923) cycles with 3–5 years of periodicity arising from fluctuations of inventories, (ii) the Kuznets (1930) swings of 15–25 years associated with infrastructure investments and (iii) the Kondratieff (1935) "Long Waves" of 40–60 years along with smaller cycles of 3–4 and 7–10 years.

Cyclical behavior of stock markets have also been widely documented, among the patterns found are included but not limited to: (i) the "Halloween effect" also known as "Sell in May and Go Away", which refers to returns during winter (November–April) exceeding that of during

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summer (May–October), see e.g. Bouman and Jacobsen (2002), Dichtl and Drobetz (2014), (ii) the "January effect" that leads to abnormally large returns on stocks in most January months, see e.g. Gu (2003), Haug and Hirschey (2006), and (iii) the four-year US-Presidential Election Cycle that implies US stock prices are tracking US-Presidential Elections, see e.g. Wong and McAleer (2009), Booth and Booth (2003).

The question addressed in the present study is: Using readily available daily stock market data, can we find cycles similar to those exposed in business cycle literature? The present study is thus an effort to investigate frequency aspects with respect to information transmission, focusing on a network consisting of three Western asset markets, each represented by a stock index: Dow Jones Industrial Average (USA), FTSE 100 (UK) and EURO STOXX 50 (proxy for euro area). To that end, departing from the Diebold and Yilmaz (2009, 2012, 2014) connectedness framework, and extensions detailed in Schmidbauer et al. (2013, 2016), we undertake the following steps:

- Construct a measure, which we call "propagation value", of the relative importance of an asset market as a news propagator within the network considered. "News" in a market on a given day means either a shock to the return of the corresponding stock index or a volatility shock, and "propagation" means that this shock creates volatility across the network. With respect to return-to-volatility (ret2vol) and volatility-to-volatility (vol2vol) spillovers, each market has its own propagation value, updated on a daily basis. A shock in an important market (that is, with a relatively high propagation value) will create more network volatility than a shock in a less important market (which has a relatively low propagation value).

- For pairs of the three asset markets under consideration, identify jointly significant and powerful periods (or frequencies) in their propagation value series, using cross-wavelet analysis. "Powerful" means that this period will be selected with high priority when reconstructing a propagation value series on the basis of wavelets; it is thus a substantial constituent of both propagation value series involved. Statistical significance is assessed by comparison with simulated white noise.

- Investigate whether, at a given powerful period, the propagation value series of two markets are in phase or out of phase at a given point in time. If they are in phase, their propagation values will tend to move, at a certain pace determined by the period, together from trough to peak (for example). If they are out of phase, one market will become more important in the sense explained above, again at the pace determined by the period, at the expense of the other market's importance as a news spreader.

- Similarly, investigate which of two propagation value series is leading at a given powerful period and a given point in time. The leading one will be the first to increase (or decrease) in importance at a certain pace, and the other one will follow suit.

This paper is organized as follows. Section 2 describes the data on which the study is based. The methodology to obtain a market's series of daily propagation values, and concepts of cross-wavelet analysis, as far as relevant, are expounded in Section 3. Empirical results of our study are presented in Section 4, followed by a discussion in Section 5. — All computations were carried out with scripts written in R (2016); wavelet computations and plots are accomplished with R package *WaveletComp* (Rösch and Schmidbauer, 2014).

2 Data

The present study requires daily opening, high, low, and closing quotations of three Western equity market indices: Dow Jones Industrial Average (New York Stock Exchange, in the following called dji), FTSE 100 (London Stock Exchange, ftse) and EURO STOXX 50 (proxy for Euro Area equity markets, sx5e). Data from March 1998 through May 2016 constitute the empirical basis for the construction of daily "propagation values", which are then subjected to cross-wavelet analysis. The methodology is briefly outlined in the following.

3 Methodology

3.1 Daily propagation values

The markets (more specifically, stock market indices) in our study can be seen as nodes in a weighted network, with weights representing volatility spillovers between them. Volatility creation in the network can be due to either a return shock in one of the markets or a volatility shock. Accordingly, two different types of spillovers are addressed in this study: return-to-volatility spillovers (case ret2vol), and volatility-to-volatility spillovers (case vol2vol). Following Diebold and Yilmaz (2009, 2012, 2014), vector autoregressive (VAR) models fitted to daily simple stock index returns (case ret2vol; using closing quotations) and (range-based) volatilities (case vol2vol) are used to derive the forecast error variance for each market index in the network, and to decompose this variance with respect to its origin: Which share of market volatility is due to shocks in which other market? — These shares are arranged in the so-called spillover matrix which has an interpretation as network adjacency matrix.

Building on and extending this framework, Schmidbauer et al. (2013) developed the concept of a market's "propagation value" measuring that market's relative importance as a volatility creator across the network of markets. In case of ret2vol, it renders the value of a return shock from that market as seed for future uncertainty in *returns*, while in case of vol2vol, it gauges the value of a volatility shock as seed for future uncertainty in *volatility* across the network; cf. Schmidbauer et al. (2016). This concept is in the spirit of eigenvector centrality of nodes in social networks (Bonacich, 1987).

Propagation vales (cases ret2vol and vol2vol) are updated on a daily basis using rolling VAR models for the past 100 days.

3.2 Cross-wavelet analysis

With the time series of daily propagation values (in either case, ret2vol and vol2vol) at hand, the concepts of cross-wavelet analysis provide appropriate tools for (i) comparing the frequency content of the series for pairs of the three markets, (ii) drawing conclusions about the series synchronicity at certain periods and across certain ranges of time. We use the functionality of R package *WaveletComp* (Rösch and Schmidbauer, 2014), and adopt the Morlet wavelet which is a continuous wavelet transform, a band-pass filter, and complex-valued, therefore is highly redundant and information-preserving with any careful selection of time and frequency parameters. It provides information on both amplitude and phase, and a method to reconstruct the original series.

The cross-wavelet transform of two time series decomposes the Fourier co- and quadrature-spectra in the time-frequency (time-period) domain simultaneously. Its modulus has the interpretation as cross-wavelet power and lends itself to an assessment of the similarity of the two series' wavelet power (resp. energy) with respect to any periodic component and how it evolves with time. A "heat map" is the usual way to visualize the cross-wavelet power spectrum. Power averages illustrate the prominence of certain periodic components across time.

The statistical significance of the patterns emerging is assessed by comparison with simulated white noise. In addition, package reconstruction tools support the identification of "powerful", i.e. substantial periodic constituents of the series.

Furthermore, the cross-wavelet transform carries information about the series' synchronicity in terms of the local phase advance of any periodic component of one series with respect to the correspondent component of the other series. This so-called phase difference equals the difference of individual local phase displacements (relative to a localized origin) when converted into an angle in the intervall $[-\pi, \pi]$. An absolute value less (larger) than $\pi/2$ indicates that the two series move in phase (anti-phase) at the respective period, while the sign of the phase difference shows which is the leading series in this relationship. Figure 1 (in the style of a diagram by Aguiar-Conraria and Soares (2011)) illustrates the range of possible phase differences and their interpretation. Information on phase differences at certain periods can be retrieved and analyzed separately.

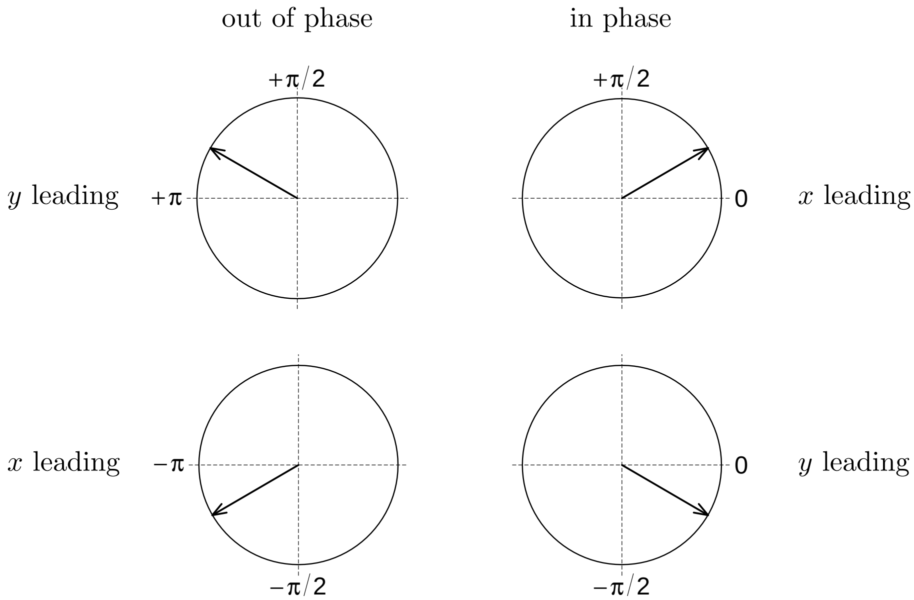

Figure 1: Phase differences and their interpretation

4 Empirical results

In the first step of our study, three-dimensional time series of daily propagation values — one for each stock index under consideration, namely dji, ftse, and sx5e — were obtained, the result of which is shown in terms of stacked plots in Figures 2 and 3.

For a given day, the propagation values reflect the relative importance of asset markets as network volatility creators. Many characteristics of the series can be related to economic and geopolitical events. However, the plots reveal that patterns differ with respect to whether volatility creation is due to a return shock (case ret2vol) or volatility shock (case vol2vol). For example: The most distinct peak of dji propagation value series in the ret2vol case coincides with the March 2000 crash of the "dot-com bubble",[1] whereas in the vol2vol case dji propagation

[1] "...The technology-heavy Nasdaq reached its pinnacle of 5,048.62 on March 10, [2000]. Then the Internet bubble burst and the index plummeted nearly 40 percent, dropping below 3,000 in December [2000] in its worst

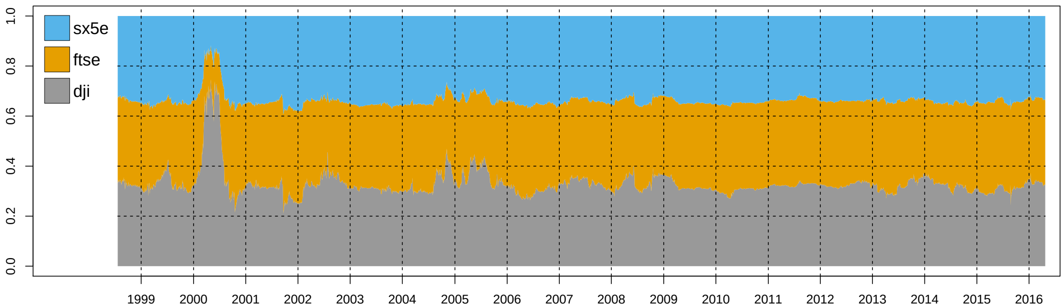

Figure 2: Daily propagation values, case ret2vol

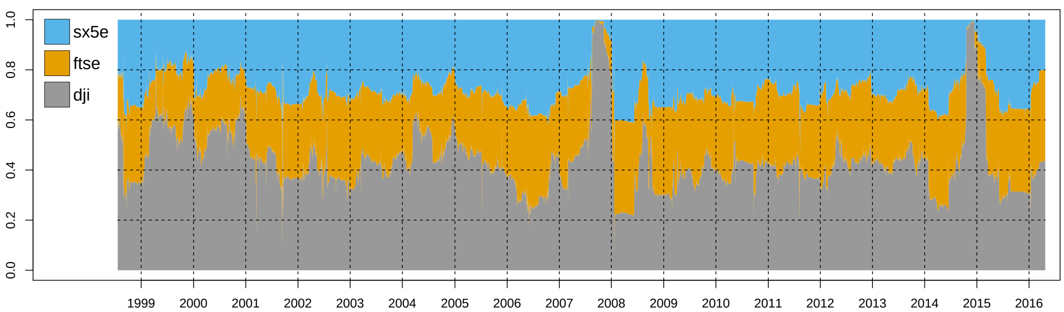

Figure 3: Daily propagation values, case vol2vol

values rocketed high in timely coincidence with the onset of the US "subprime mortgage crisis" in August 2007[2], and with refueled global growth concerns in October 2014[3].

From an overall perspective, we observe that, from about 2001 onwards, each ret2vol series fluctuates around 1/3, with less pronounced bulges and spikes: For the creation of volatility in the network, it does not really matter where a return shock is coming from. The course of vol2vol series, however, indicates that it does matter from where a volatility shock originates.

In the second step of our study, the three pairs of propagation value series in each case, ret2vol and vol2vol, are subjected to cross-wavelet transformation. Figures 4 and 5 show "heat maps" of the cross-wavelet power spectra obtained. The power spectrum gives information on the relative power of a wavelet component at a certain period length (the vertical axis) and at a certain location in time (the horizontal axis). The period ranges from 32 to approximately 1500 days; about 260 days represent a year. The so-called cone of influence excludes (shaded) areas of edge effects. The white contour lines delineate the time/period domain of joint significance at the 5% level with respect to deviations from the null hypothesis of white noise. The arrows within the significant area indicate the phase difference, at a given time and period, between a pair of propagation value series, according to the scheme in Figure 1.

The power spectrum plots of Figure 4 for the ret2vol case reveal that the range of significant frequencies has become narrower from year 2000 through 2016. For example, a period of 256 (corresponding to approximately one year) was persistantly significant until 2005, but only sporadically after 2005. These plots also show that the power of the cross-wavelet transforms has diminished; this is in line with the smoother character of the propagation value series (Figure 2).

annual loss", The New York Times, 2012-03-13.

[2] "CSI: credit crunch. Central banks have played a starring role.", The Economist, 2007-10-18; available online at http://www.economist.com/node/9972489. Retrieved 2016-06-01.

[3] "This is not another financial crisis", CNN Money, 2014-10-15; available online at http://money.cnn.com/2014/10/15/investing/stocks-plunge-not-like-2008/. Retrieved 2015-09-18.

As compared to ret2vol, the joint frequency content of vol2vol propagation values has remained more or less constant over the same period, marked by elevated power only recently; see Figure 5.

Both sets of heat maps give the first rough impression that, with respect to network volatility creation, dji and sx5e (ftse) are out of phase (arrows pointing to the left), while sx5e and ftse are in phase (arrows pointing to the right).

For further investigation of the joint cyclical behavior of the propagation value series, it is useful to identify those periods which are powerful across time. Figures 6 and 7 display the average cross-wavelet power, taken over the entire time interval 1998–2016, by period. In both cases, ret2vol and vol2vol, we can identify essentially three local peaks, at periods 260, 600, and 1040. — This pattern is robust with respect to the time interval over which the power is averaged.

A finer analysis of phase differences for these periods sheds light on the synchronicity of each pair of propagation value series. The time series of phase differences are plotted in Figures 8 and 9. Significant (insignificant) parts are represented by solid (dashed, respectively) lines. The relation of the two series involved (which one is leading; are they in phase or out of phase) can be classified in accordance with Figure 1.

The results in the ret2vol case can be described as follows (mentioning a stock index name in the following means that we speak of its propagation value series):

- period 260: The pair dji and ftse is out of phase (except in insignificant short time intervals), and so is the pair dji and sx5e. The pair ftse and sx5e is mostly in phase. There is no persistent significance at period 260. The leading index is alternating, but highly pronounced from 2005 onwards only.
- period 600: Except for the two time intervals 1998–2000 and 2007–2008, the following can be observed:
  - The pair dji and ftse is out of phase, with dji leading.
  - The pair dji and sx5e is out of phase, with sx5e leading.
  - The pair ftse and sx5e is in phase, with sx5e leading.
- period 1040:
  - The pair dji and ftse is out of phase, with ftse leading until 2007; dji has been leading from 2008 onwards.
  - The pair dji and sx5e is out of phase, with dji leading until 2007; sx5e has been leading from 2008 onwards.
  - The pair ftse and sx5e is in phase, with ftse leading until 2007; sx5e has been leading from 2008 onwards.

The vol2vol case reveals different patterns with respect to leading and lagging behavior:

- period 260: The pair dji and ftse is mostly out of phase, and so is the pair dji and ftse, except in 2000 and 2010–2012 respectively. The pair ftse and sx5e is mostly in phase, with the same time intervals excluded. There is no persistent significance at period 260. The leading index is alternating frequently.
- period 600: Except for the two time intervals 2006–2010 and 2014–2016, the following can be observed:
  - The pair dji and ftse is out of phase, with ftse leading.

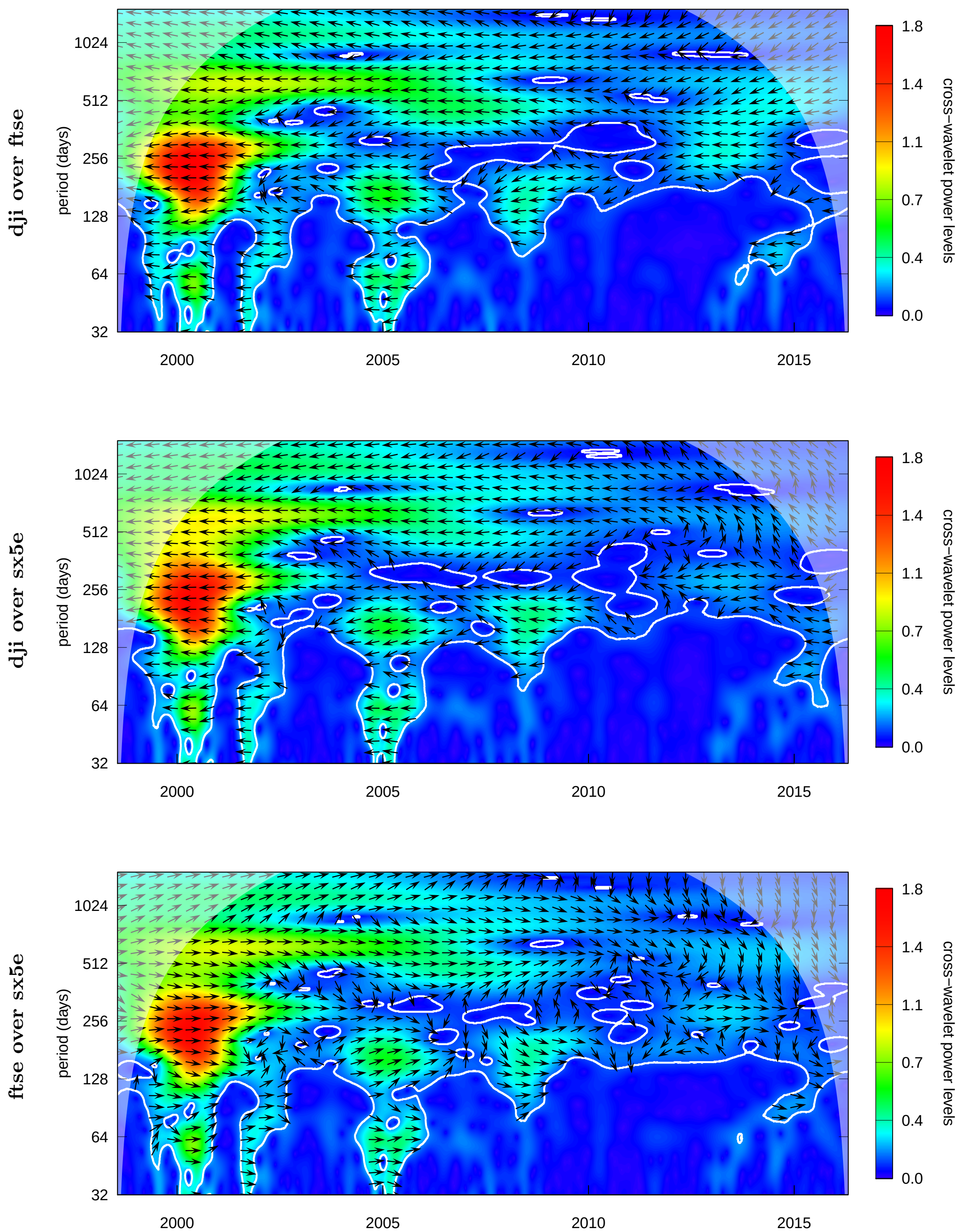

Figure 4: Cross-wavelet power spectra, case ret2vol

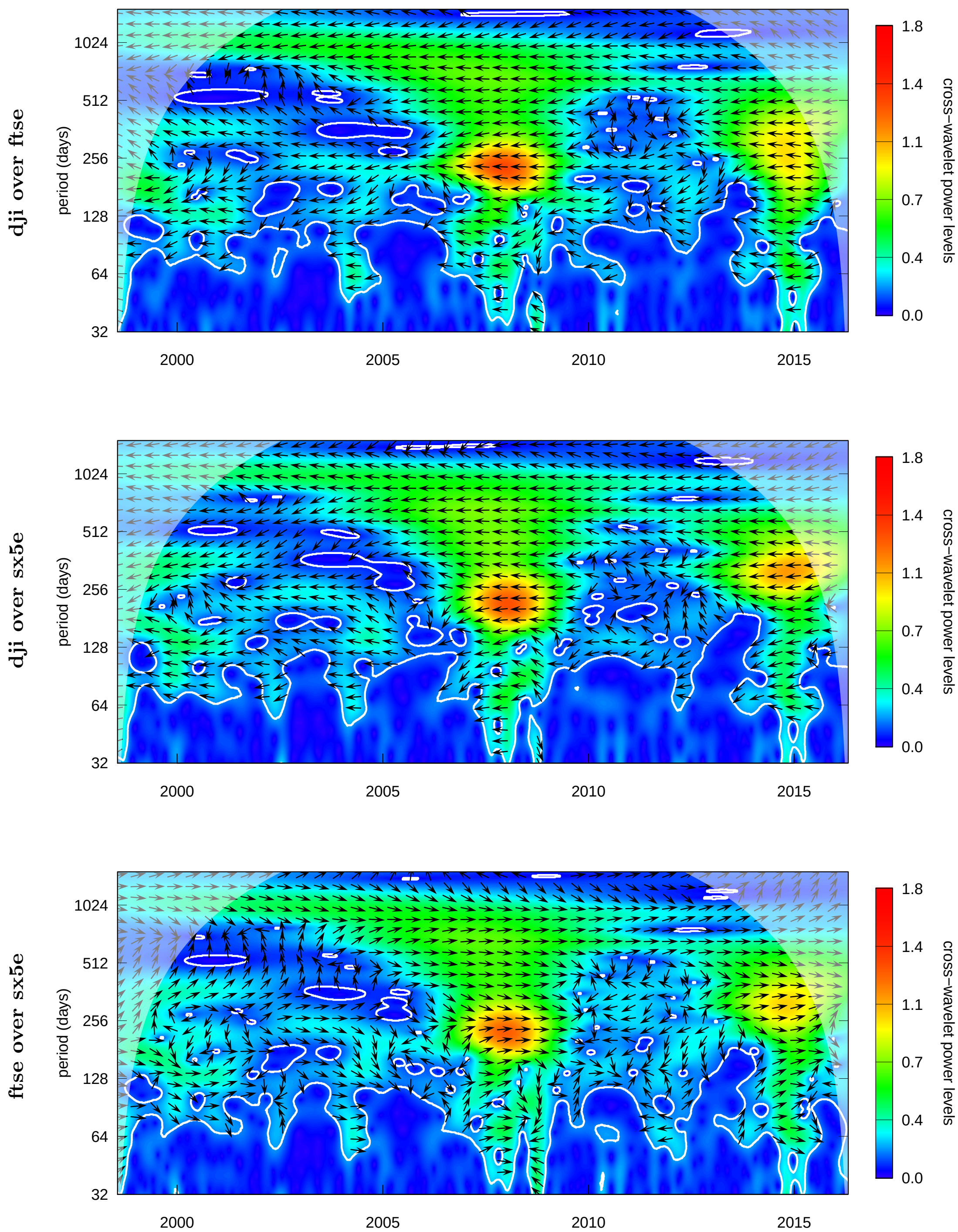

Figure 5: Cross-wavelet power spectra, case vol2vol

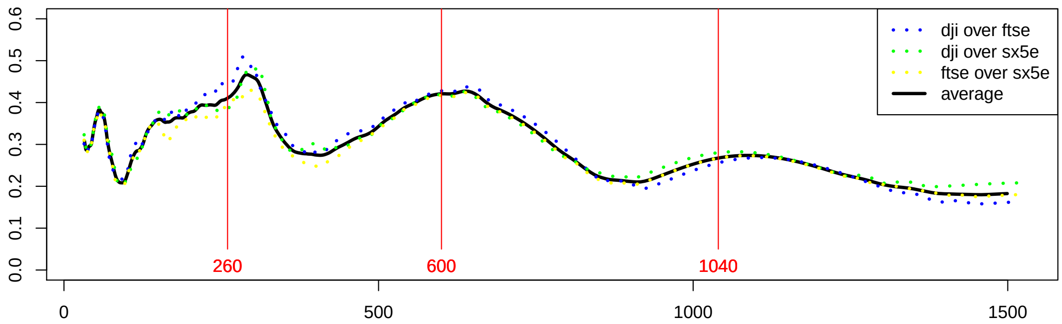

Figure 6: Average power of cross-wavelet transform, case ret2vol

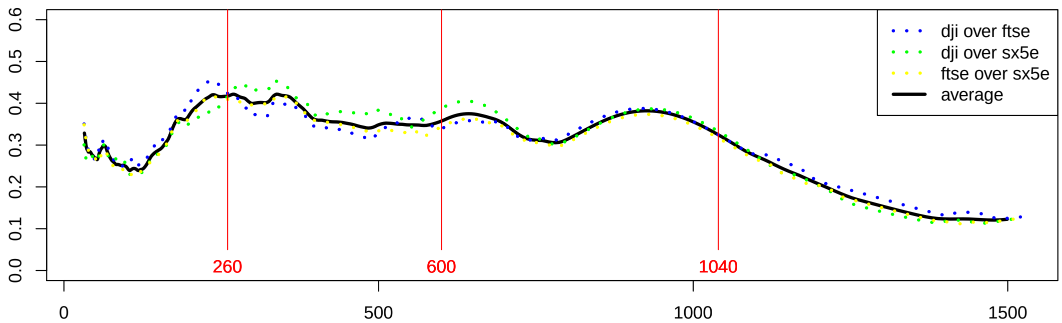

Figure 7: Average power of cross-wavelet transform, case vol2vol

  - The pair dji and sx5e is out of phase, with dji leading.
  - The pair ftse and sx5e is in phase, with ftse leading (excepting the time interval 2001-2002).

- period 1040:
  - The pair dji and ftse is out of phase, with dji leading until 2011; ftse has been leading from 2012 onwards.
  - The pair dji and sx5e is out of phase, with sx5e leading until 2011; dji has been leading from 2012 onwards.
  - The pair ftse and sx5e is in phase, with sx5e leading until 2011; ftse has been leading from 2012 onwards.

5 Discussion

Concerning network volatility creation, the European markets are in phase, while the US market is not in phase with either European market considered in this study. In this respect, frequency properties of ret2vol and vol2vol propagation values are by and large similar.

Our findings further suggest that the band of relevant power of frequency information which could contribute to our understanding of the shock propagation potentials of the markets in our study (USA, UK, euro area) has become narrower in ret2vol propagation values from year 2000 onwards, whereas vol2vol series, more or less, span a constant frequency band over the same period. The diminishing range of frequencies may have an explanation in terms of the strength of information exchange, which has become much higher than could be measured by the concept

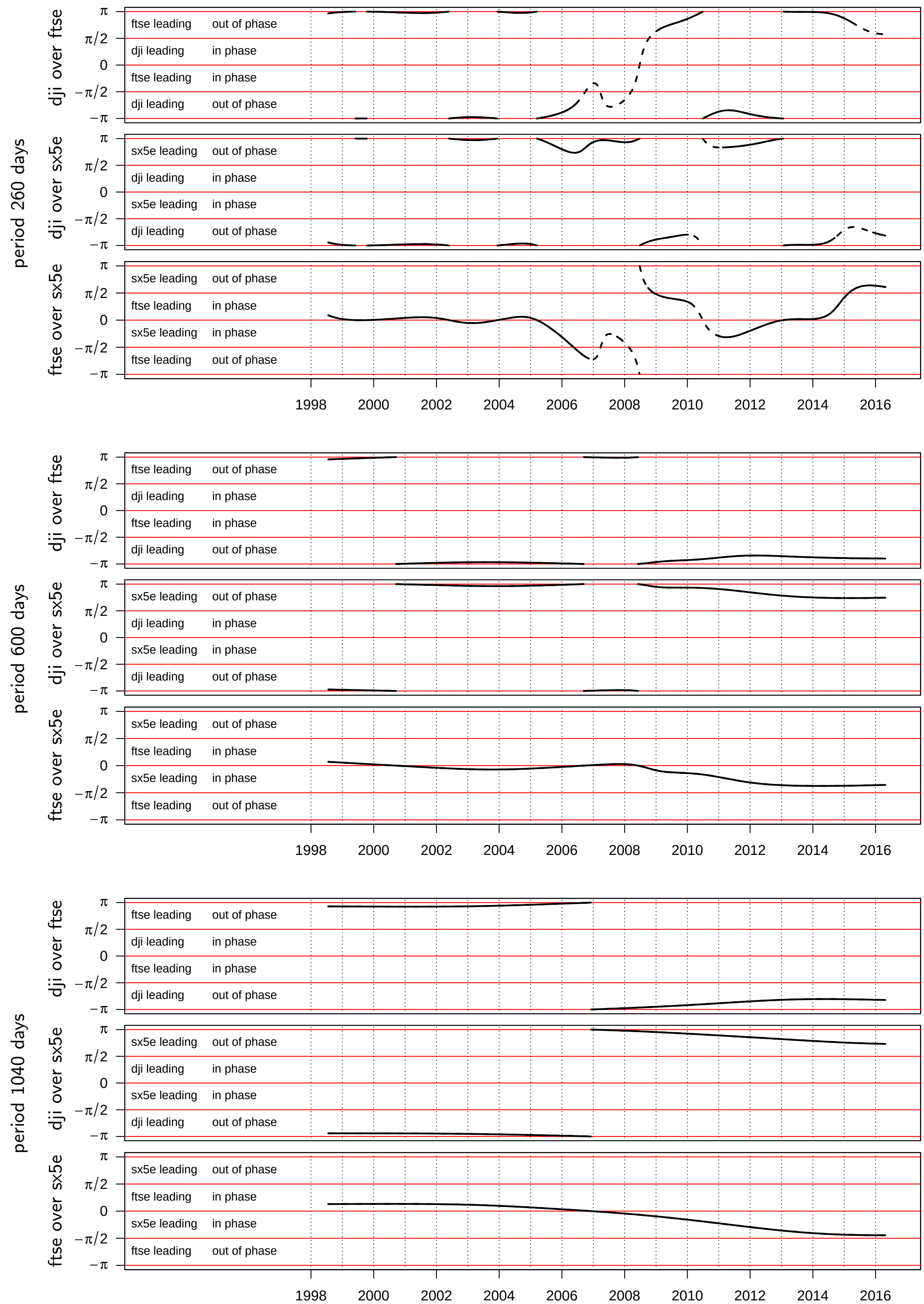

Figure 8: Phase differences, selected periods, case ret2vol

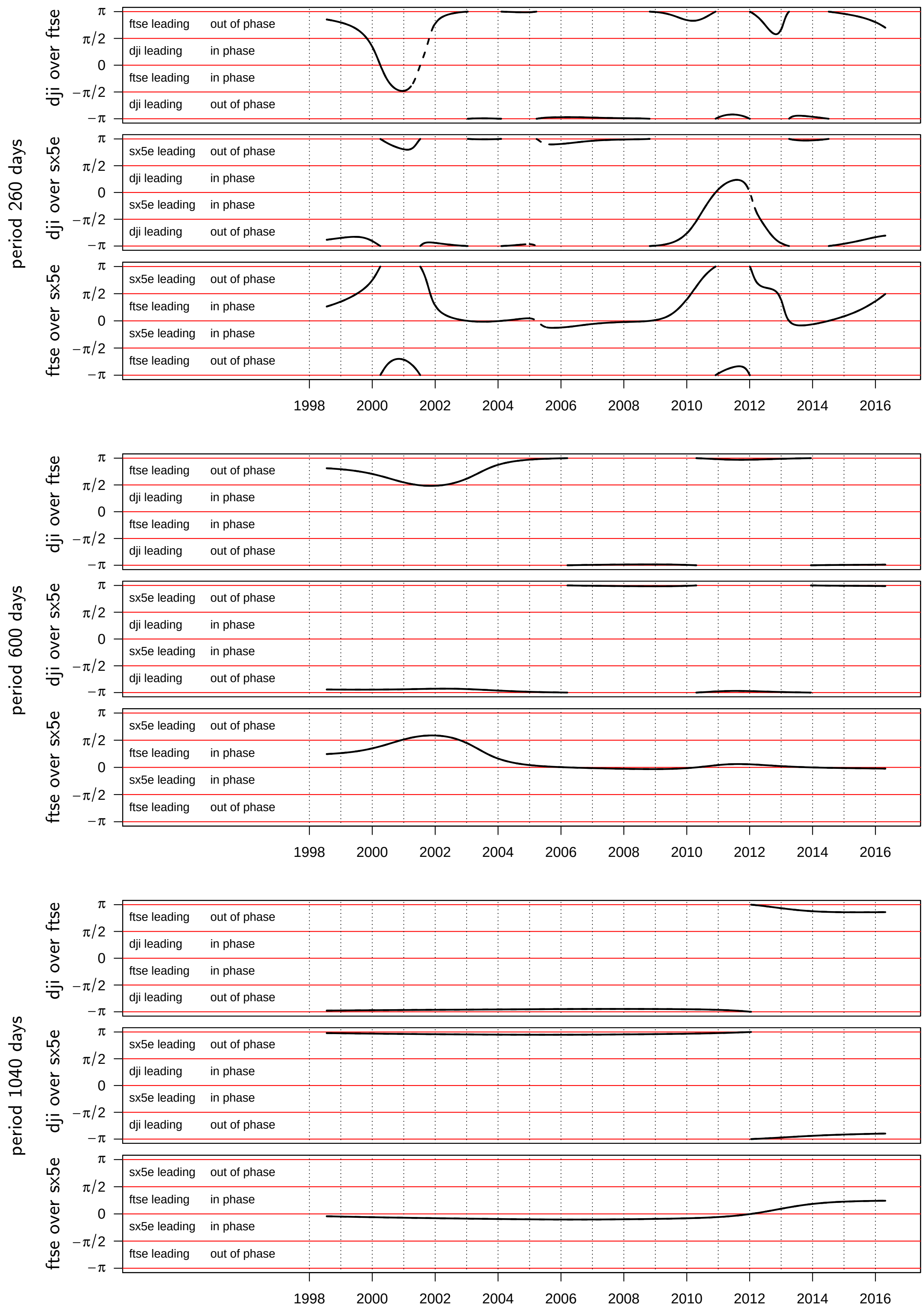

Figure 9: Phase differences, selected periods, case vol2vol

of daily ret2vol spillovers. Information flows easily today. The observation of decreasing holding times of stocks is an argument in the same vein.[4] Two decades ago, the frequency structure of information transmission was richer and more telltale for investors to wait for similar patterns to occur repeatedly, while they rather tend to act immediately today and are less inclined to bet on frequency. White noise became more important, and the frequency structure of information transmission too unpredictable to build one's portfolio on, especially in the ret2vol case. In this respect, the availability of a larger frequency band in the vol2vol case could help investors respond to a richer set of frequency dynamics and allow hedging their portfolios.

Another interesting empirical finding, in line with relevant literature, is the joint powerful cyclicality at periods 260, 600 and 1040 days, respectively. Among these, 260-day period corresponds to the average number of trading days in a year. Similarly, the 1040-day period reflects a 4-year period for the stock markets under scrutiny. These periods correspond to cycles as in the "January effect" and the "four-year US-Presidential Election Cycle" or the "Kitchin Cycle", respectively.

The financial crisis of 2007/08 and the European debt crisis since the end of 2009 have left prominent traces in vol2vol, but not ret2vol, propagation values. This provides new insight into the time-dependent interplay of equity markets.

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[4] The average holding period of stocks has dropped secularly in all markets studied over our analysis period. Haldane (2010) reports that the mean duration for the US equity holdings has dropped from around 7 years (in 1940) to around 7 months (in 2007), for the UK market, the similar trend is observed with average holding period of stocks around 5 years (in mid-1960s) to 7.5 months (in 2007). Furthermore, at the international level this trend is also confirmed for the major equity markets, for the Shanghai stock index, the mean duration is closer to 6 months. Decreasing transaction costs as well as advances in High-Frequency-Trading (HFT) tehnology, which allows transactions in milli- or micro-seconds, are believed to have impact on the decreasing average holding periods (see Haldane (2010)).

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