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THE TIME DEPENDENCE AND INTERCONNECTEDNESS OF DEVELOPED STOCK MARKETS

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Abstract. This study examines the interconnectedness in developed stock markets by focusing on the time dependence of their multi-vocal relationships. Conceptually, we discuss the differences between financial contagion, interconnectedness and dominance in order to highlight the argument that stock markets are functionally connected. For capturing the shifts in markets' correlation patterns over time, and their frequencies, we employ a methodology in the framework of Wavelet Local Multiple Correlation (WLMC). We have involved in the analysis three developed stock markets, on a long-time span from 2005-2024. Our findings suggest that the correlation pattern displays significant variations over time at different frequencies.

1. Introduction

During the last decades, the political, economic and financial openness, as well as rapid technological advances, significantly contributed to an increased level of financial integration between financial markets worldwide. Even if globalization brings numerous advantages for various stakeholders, in terms of international diversification and capitalisation, it also enhances the risk transmission within the global financial system, or the so-called phenomenon of financial contagion.

In the study of financial contagion, various scholars have found that developed financial markets are the main drivers of risk spread since they are highly interconnected with global economies through trading and financial ties. Based on the specific literature, developed markets are considered the leading markets for risk spread due to their central role in the global financial system. They hold the largest financial institutions and stock markets, so any shock at the level of interest rates or stock prices would further impact the global capital flows and asset prices.

Developed markets are large in terms of size and liquidity, hence they attract significant capital flows from investors worldwide. Since they are a major source of global capital, the investors from these economies make considerable investments in emerging markets. As a result, any sign of financial instability or economic downturn might determine investors to pull out their capital from emerging or riskier economies, further leading to contagion. In this way, developed markets became a great influence for global risk sentiment, their volatility being

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considered a proxy for global risk. A significant example in this sense is the 2007-2010 global financial crisis, when the shock transferred from the US market to other financial markets worldwide.

Moreover, developed markets are the main drivers of risk spread due to their level of global interconnectedness. These markets are strongly interconnected with other economies through trade, investments and financial markets. Developed markets like the US, the UK and Japan serve as "hubs" for global finance and banking; consequently, any disruption in these markets could quickly spread beyond borders.

Being highly integrated, the interdependence mechanisms in developed markets is significantly different compared to emerging markets. The interconnectedness mechanisms in developed stock markets are driven by various factors such as, cross-border investments, global economic and financial dependencies (that imply, for instance, cross-border capital flows, interconnected banking systems, monetary policies, currency exchange rates, global financial regulation and policy coordination), technological investments, and financial investments. Thus, these mechanisms create a network of financial dependences, making impossible for developed stock markets to operate in isolation. Therefore, the interconnectedness amplifies risk spread and any positive/negative event in one developed market will inevitably impact the others.

In this regard, Liu (2013) found that the correlations of an emerging market with other markets are driven by economic integration, while financial integration, industrial structure and industrial capacity are the correlation drivers of a developed market with other markets. Dai et al. (2023) found that developed financial markets display increased connectivity and that these economies are the risk senders in the "spillover networks". Henceforth, we consider that the first wave of transmission, especially in turmoil periods, is from developed to other developed financial markets. In consequence, understanding the interconnectedness in-between developed markets is instrumental for the analysis of risk transmission.

However, despite the impressive amount of empirical evidence produced by this literature to support the interconnectedness of the developed financial markets, it frequently fails to account for the time dependence of their multi-vocal relationships. Furthermore, the literature mainly focuses on financial markets such as, the oil market, the currency market, bond market, and so on, but less on the stock markets. Thus, by analysing only the developed stock markets, this study brings significant contributions to the literature by narrowing the perspective and mitigating the sampling bias of the findings.

At the conceptual level, the literature upon interrelationships between stock markets does not clearly make a distinction between the concepts of financial contagion, interconnectedness and dominance. We consider that such a distinction is instrumental for a better understanding of spillover effects in-between stock markets. Forbes (2012) and Bricco and Xu (2019) highlighted the difference between contagion and interconnectedness. There is a wide literature where contagion is considered as extreme co-movements between financial markets, especially in turmoil periods (Corsetti et al. 2001; Forbes and Rigobon 2002; Pericoli and Sbracia 2003; Dungey and Tambakis 2005). For instance, Forbes and Rigobon (2002) defined contagion as a "significant increase in cross-market linkages after a shock to one country (or group of countries)".

Based on Forbes (2012), interconnectedness is a distinct concept that is related to contagion, as it refers to the correlations or financial linkages among financial institutions' market prices worldwide. Bricco and Xu (2019), based on Forbes (2012), argued that interconnectedness "manifests as financial linkages or correlations along the market prices of financial institutions", while contagion represents the effects of such linkages from the "interconnectedness magnitude or shocks" upon economies. According to Armijo et al. (2014) and Centeno et al. (2015), the factors that impact the interconnectedness between economies are the imports and exports, the economy scale given by the GDP, and the international currency status.

Our study's main contribution to the literature consists in proposing an analysis of the interrelations among stock markets by introducing the dominance feature of interconnectedness. While interconnectedness means that markets move and evolve together in both directions, dominance occurs in one single direction, from market A to market B. In other words, the cause for a change in market B, is given by a change in market A. Therefore, we consider that dominance refers to a functional connection (i.e. a temporal dependence) between markets, where causality is well determined. Functional connectivity might occur due to portfolio substitutions, return volatility, and so on. The asymmetric nature of the "dominance" concept is critical for the conceptual grounds considered here. Precisely this distinctive feature of the functional connections is at the core of the proposed analysis. However, we assume that such a feature is not fixed once for all. Instead, it has a time-varying nature, and two markets can shift their leading roles over different periods and circumstances. Hence, from a methodological point of view, a depiction of markets' interrelation should reflect the underlying associated dynamics and provide some explanations for the changes that happen at their level.

The main argument considered here can be summarized as follows: large flows of economic resources interlink the markets acting as dominant international financial hubs. These markets are formed by time-heterogenous investors who implement sophisticated "active"/ "passive" trading strategies under different time horizons. By building geographically diversified portfolios, these investors contribute to the manifestation of the "single price law" (i.e. the tendency of returns and risks to be close on integrated markets) (or, at least, a weak form of such "law"). Nonetheless, since for a particular trading horizon, the relative importance of investors acting under such horizon may vary from market to market, there is no "single price" but rather a full spectrum of "short/long-run" returns evolving close to each other. Hence, the perturbation occurring at the level of one market can be translated over the others in specific ways for different trading frequencies. The most important consequence that can be derived from such an argument is the possible existence of non-uniform interconnectedness patterns for different relevant trading horizons. In addition, these patterns can exhibit a time-varying nature due to a large variety of factors (such as endogenous and exogenous shocks, changes in the risk profiles of investors, the portfolio structures selection dynamic mechanisms, and so on).

Our research is grounded on this conceptual framework. It contributes to the literature by: 1) proposing an analysis of stock markets' interrelations by accounting for the dominance feature of interconnectedness; 2) developing a methodology able to capture the shifts in markets' correlation patterns over time and different frequencies; and 3) applying such a methodology for three major developed markets.

The paper is structured as follows: The next section includes a literature review on the subject of interconnectedness. The third section describes the research methodology and the data. The fourth section reports the results, comments, and some robustness checks. Section five concludes and delivers specific policy implications.

2. Literature Review

The risk transmission between financial markets has been extensively studied in the literature, especially in the context of the global crisis of 2007-2010, the European debt crisis of 2010-2012, the pandemic crisis, the 2022 Ukrainian war, and the energy crisis in 2023. BenMim and BenSaida (2019) found that financial markets are interconnected, especially in turmoil periods. Martinez-Jaramillo et al. (2019) considered that interconnections at the level of financial markets could either absorb shocks, further leading to increased robustness, or propagate shocks, resulting in increased fragility. Consequently, the risk propagation significantly increases in periods of uncertainty, exposing the global financial system stability to additional risks.

The interdependency between financial markets was analysed by various scholars who brought significant theoretical and empirical contributions to the literature. According to Pretorious (2002) and Phylaktis and Ravazzolo (2002), financial markets are interconnected based on economic linkages associated to market co-movements. Zeti (2014) argued that the interconnectedness of financial markets is due to financial connections at the global level as they represent the highest source for risk spread. Flavin et al. (2002) showed that the interrelationships between financial markets are also influenced by the geographical location, such that the markets situated in geographical proximity are strongly interconnected.

Abuzayed et al. (2021) revealed that, due to such interrelationships, the increased risk in one market becomes systemic and triggers negative chain reactions upon other financial markets worldwide. In this sense, as Wu et al. (2019) also argued, the study of interconnectedness at the level of financial markets is instrumental for various stakeholders to design accurate policies to mitigate the spread of systemic risk, to build portfolio diversification and asset allocation strategies, and to properly perform risk assessment analyses. Since the first "wave" of risk transmission happens at the level of developed markets, we focus on the interconnectedness of these markets. The interconnectedness at the level of developed markets was investigated by Raddant and Kenett (2021) and Cevik et al. (2024), who found that developed markets are interconnected, the dependences between markets are volatile, the heterogeneity among stocks is not to be neglected, and that the transmission mechanism is not stable as it is influenced by changes in volatility. For this purpose, Raddant and Kenett (2021) involved a GARCH approach to measure the level of interconnectedness and found that the materials, energy and financial sectors are the key factors in connecting markets.

Silva et al. (2023) applied a Vector Autoregressive Model (VAR) and learned that the interconnectedness in the global financial system massively impacts the exporting economies. Bouri et al. (2021) used a TVP-VAR connectedness approach upon five assets and revealed that until the early 2020, the dynamic connectedness between the assets was moderate, while after the COVID-19 shock, the connectedness spikes significantly increased. Moreover, Lang et al. (2024) employed a Global Common Volatility (COVOL) risk measure and conditional and aggregated connectedness approaches on the developed international stock, crude oil and gold markets in the US, Europe and China. They found considerably increased levels of connectedness in periods of financial turmoil and that the main risk senders are the European and the US stock markets.

By applying a different methodology, namely a battery of Wavelet Coherence tools and the Granger Causality test, Younis et al. (2023) have also studied the interrelationships between developed financial markets, such as stock, commodity and oil. For the pandemic crisis period, they discovered strong co-movements between the market volatility index, commodities and S&P 500 stock prices.

Cui and Maghyereh (2023) analysed the time-frequency connectedness and dependence upon the global oil markets. Their results showed that the connectedness level between international oil markets is frequency-dependent and time-dependent; in other words, it varies based on the investment timing horizons. For that reason, we consider time-frequency connectedness as an instrumental aspect in portfolio diversification and risk management. In fact, diversification strategies should not be implemented merely inter-asset, or on asset classes, but must be designed by taking into account time-frequency connectedness. This process could be called "scale time diversification". Significant findings in this regard, which are in line with our results, were provided by Kantardzic et al. (2004), Chen and Szeto (2012), Barkhagen et al. (2023), and Attig and Sy (2023).

3. Methodology and international data

3.1. **Methodology.** In this paper, we employ an analytical framework based on the "Wavelet Local Multiple Correlation" (WLMC) (Fernández-Macho 2018). This approach is an extension of Fernández-Macho (2012), and it is based on the concept of "Wavelet Local Multiple Regression" (see Mann et al. 2009; Fernández-Macho 2018).

A recent stream of literature uses this approach to study the time-scale co-movement of various markets: oil, gold, wheat, and copper (Bouri et al. 2023); the sectors on the Johannesburg Stock Exchange (Nyakurukwa and Seetharam 2023); the cryptocurrency markets (Phiri and Anyikwa 2024); oil and petroleum markets (Polanco-Martínez et al. 2018) or green bonds and energy prices (Kartal et al. 2024). Nevertheless, this literature is less focused on markets acting as key pillars of the international financial system, and which are highly integrated under the impact of financial globalization and international capital movements.

As Polanco-Martínez et al. (2020, 2) explain: "The wavelet correlation via the wavelet transform (WT) can be seen as an "improved version" of the combination of Fourier transform and partial and sliding correlations in different periods". Its various advantages include the capacity to deal with the non-stationarity of the involved time series and its ability to capture different types of multiscale processes. Indeed, the WLMC technique can examine the implied time-varying correlation structure in a multivariate context.

Since the proposed study aims to capture the evolutive patterns of inter-market associations, this technique fits well in the case of a complex network of financial market returns. For such a network, the Data Generative Processes (DGPs) might imply non-Gaussian distributions (with "fat tails" effects), non-linear evolutions, the presence of "structural breaks", "long-term" memory, exogenous or endogenous shocks persistence, the lack of time-scale invariance, volatility clustering, the "information leverage" (the asymmetric response to "good"/ "bad" news) or other features that make the standard approaches unsuitable for producing a robust analysis. In addition, highly relevant to our research is this approach's essential capacity to reveal the dominance that might occur in the dynamic interconnectedness of multivariate series.

In details, if η is a set of multivariate time series (formed by financial markets' returns, of dimension n observed at times $t = 1, \dots, T$), for some $\eta_i \in \eta$ a local regression at a fixed $s \in [1, \dots, T]$ can be used to minimize the weighted sum of squared errors such as:

$$S_s = \sum_t \phi(t-s)\left[f_s(\eta_{(-i,t)}) - \eta_{i,t}\right]^2 \tag{1}$$

Here $\phi(\eta)$ is a given moving average weight function that depends on the time lag between observations η_t and η_s. Meanwhile, $f_s(\eta_{(-i)})$ is a local function of $\{\eta \setminus \eta_i\}$ around s. By letting s move along time, the corresponding local coefficients of determination are given by:

$$R_s^2 = 1 - \frac{\mathrm{RwSS}_s}{\mathrm{TwSS}_s}, \quad s = 1, 2, \dots, T \tag{2}$$

RwSS_s, TwSS_s are the residual and total weighted sum of squares respectively.

As a further step, the wavelet local multiple correlation is defined and estimated. Therefore, let $W_{jt} = (w_{1jt}, \dots, w_{njt})$ be the wavelet coefficients for scale $\lambda_j, j = 1, \dots, J$ (with J indicating the maximum level of the wavelet transform decomposition) obtained by applying the MODWT to each time series $\eta_i \in \eta$. The wavelet local multiple correlation coefficients $\phi_{\eta,s}(\lambda_j)$ can be estimated as the square roots of the regression determination coefficients for that linear combination of variables w_{ij} (where such coefficients of determination are maxima) as:

$$\tilde{\phi}_{X,s}(\lambda_j) = \sqrt{R_{js}^2} \tag{3}$$

Since the R^2 coefficient in the regression of a z_i on the rest of variables in the system is equivalent to the square correlation between the observed and the fitted values $\hat{z}_i$ obtained from such regression, it is possible to express the consistent sample estimator of the WLMC according to Fernández-Macho (2018) as:

$$\phi_{X,s}(\lambda_j) = \mathrm{Corr}\left(\Theta(t-s)^{1/2} w_{ij}, \Theta(t-s)^{1/2} \hat{w}_{ij}\right) \tag{4}$$

In relation (4), w_{ij} is chosen so that its local regression on the set of regressors $w_{kj}, k \neq i$ the corresponding coefficient of determination. $\hat{w}_{ij}$ denotes the corresponding vector of fitted values.

Practical details of the WLMC implementation imply solving at least the following issues:

- The selection of an appropriate weight (window) function;
- The choice of the wavelet filter for MODWT estimation;
- To clarify which variable maximizes the multiple correlation for each wavelet scale.

While several frequently used solutions are available for the first issue (such as "Bartlett's triangular window" or "Wendland's truncated power window"), we consider a Gaussian window due to its desirable properties. In the case of such a window, its Fourier transform is also Gaussian, has near-compact support in the frequency domain, and its spectral window is always positive (for this argument, see Fernández-Macho 2018; Polanco-Martínez 2020). For the second issue, we consider the adequacy of a longer wavelet filter, such as "Daubechies LA(8)" one.

However, a potential objection to these two solutions is: if the DGPs for market returns exhibit the characteristics mentioned earlier, how effectively can the chosen window function and wavelet filter capture them? We will investigate this issue by using different specifications and testing the reliability of their results. For the last issue, the relationships among the components of the dynamical system formed by markets' return are unknown. Therefore, we let the implementation automatically choose the variable that maximises the multiple correlations at each wavelet level. We adopt this approach for all the specifications to avoid distorting results by implying ad hoc assumptions about the functional properties of the markets' network. In addition, there are no solid conceptual arguments to claim on ex-ante basis that a particular market dominates the others for the considered timespan or that the translation of systemic shocks occurs in a single direction.

We follow the WLMC application from the R package (Polanco-Martínez 2023b) and R package "wavemulcor" (Fernández-Macho 2022).

3.2. **International Data.** Daily log returns that cover a period between 2005-01-01 and 2024-05-30 are collected from publicly available data at "Yahoo Finance" (https://finance.yahoo.com/) with the help of the R package "yfR" (Perlin 2023) for three main international financial markets, namely S&P 500 index (S&P), DAX Performance Index (DAX) and, respectively, FTSE 100 index (FTSE).

The data are previously synchronised by removing the non-available data. Therefore, we end with 4744 daily observations as input data.

The selection of these markets is motivated by their critical role as major financial hubs in the current international financial system. Indeed, the considered markets attract an essential fraction of the global capital flows (based on their market capitalization, these markets are among the first ten stock exchanges in the world). In addition, since the financial assets traded on these markets are frequently included in the structures of geographically diversified portfolios, it is plausible to argue that, due to the importance of portfolio substitution effects occurring for these assets, the markets display a high degree of functional integration. Meanwhile, all three markets are characterized by high liquidity, efficient trading mechanisms, and a significant degree of sophistication. For that reason, their returns and risk-generative mechanisms reveal an important similarity. Overall, they can serve as a relevant example of the intricate dynamics of interlinked markets. In other words, the existence of such functional integration (i.e., markets' co-dependence in prices and returns mechanisms due to portfolio substitution effects) leads us to expect that there are (potentially time-varying and nonlinear) functional interlinkages between their trajectories.

Table 1 reports the basic statistics for the return series and applies a unit root test. These statistics show that all the logarithmic returns data follow a left-skewed and leptokurtic distribution with fatter tails. They also show that the data are stationary with a possible structural break in both linear trend and intercept. It is interesting to note that the break data occurred during the financial and real crisis of 2007-2010 for all the markets. Since the structural breaks reflect changes in the main features of the data' DGPs (such as the mean, variance, trend, or autocorrelation) and are a sign of functional instability of markets' "true law" during the analysis period, their presence should be taken into account. For instance, as shown in Figure 1, if the STARS (Sequential T-test Analysis of Regime Shifts) algorithm proposed by Rodionov (2004) is applied, several periods during which there are regime shifts can be identified at the level of the considered markets. Such periods occur (among others) in August and November

2007, February, July, August, September, and October 2008, January and March 2009, April and July 2010, March and October 2011, December 2015, February 2018, March and April 2020, or March and September 2022. These periods can be associated with various endogenous and exogenous-to-market shocks, like the 2007-2010 crisis, the post-2010 recovery period, the 2018 increased volatility of markets, the pandemic crisis, or the short-lived bear market from 2022. During these periods, the regime shifts occurring in individual markets will impact their reciprocal dynamics and can determine changes in the directionality and strength of their bi-univocal influences. However, it should be noted that the algorithm is designed to detect abrupt shifts (Rodionov 2004, 4). Therefore, it cannot properly reflect cases when transitions from one regime to another occur more gradually.

TABLE 1. Basic statistics for the considered time series

Statistics	**FTSE 100**	**DAX**	**S&P 500**
Minimum	-0.115	-0.131	-0.128
Maximum	0.094	0.108	0.110
Mean	0.000	0.000	0.000
Standard deviation	0.011	0.013	0.012
Skewness	-0.386	-0.181	-0.536
'Excess' Kurtosis	10.372	8.350	13.044
Zivot & Andrews (1992) unit root test	-71.185	-69.475	-78.577
(break dates)	(2009-03-03)	(2009-03-06)	(2009-03-09)

Notes: Following the recommendation from Wright and Herrington (2011), empirical (bootstrapped) standard errors are computed for Skewness and Kurtosis (with the number of bootstrap replicates being equal to 1000). Nonetheless, there are no significant differences from the computations that involve parametric standard errors. The Zivot and Andrews (1992) unit root test allows a break at an unknown point in either the intercept, the linear trend, or in both. Here the last case is considered. The 1%, 5%, and 10% critical values of this test are -5.57, -5.08, and -4.82, respectively. The null hypothesis is that the series has a unit root with structural break against the alternative hypothesis that they are stationary with break.

Furthermore, Table 2 applies the Brock-Dechert-Scheinkman (BDS) test (Brock et al. 1996) for the independent and identically distributed (i.i.d.) individual series. This test rejects the null hypothesis for all three markets that the corresponding DGP is an i.i.d. process. Of course, as the case of a pure AR process with constant (or at least stationary time varying) autoregressive coefficients illustrates, the rejection of the i.i.d. hypothesis (for instance, caused by the rejection of its "independent" part) does not automatically imply the presence of nonlinearity in the dynamic of the time series. However, a more detailed investigation of some possible nonlinear behaviour is required in this case.

Therefore, Table 3 reports the results of various more formal linearity tests. These tests provide a heterogeneous picture. For instance, they all reject the null of linearity for the S&P 500. Meanwhile, the Teräesvirta and the White neural network tests do not reject the null hypothesis of 'linearity in mean' for the DAX market. However, the Keenan and Tsay tests reject the null that the corresponding DGP for this market is an AR process. In addition, according to McLeod-Li and Likelihood ratio tests, such DGP does not appear to be an ARIMA process or a threshold autoregressive one. For the FTSE 100 market, there is some (weak) evidence that its DGP follows an AR process (or, at least, displays some "linearity in mean").

Overall, the reported tests support the existence of a mixed behaviour in the considered dataset that combines linear and nonlinear dynamics for markets' returns. Therefore, any estimation method aiming to detect their interconnectivity should be able to properly reflect nonlinear evolutions and their consequences for the stability of the estimates. As Polanco-Martínez (2023a) argues, the WLMC method is an adequate approach, being able to analyse nonlinear and chaotic dynamical systems with multiple components.

FIGURE 1. The Regime Shift Index (RSI) based on STARS (Sequential T-test Analysis of Regime Shifts) algorithm.

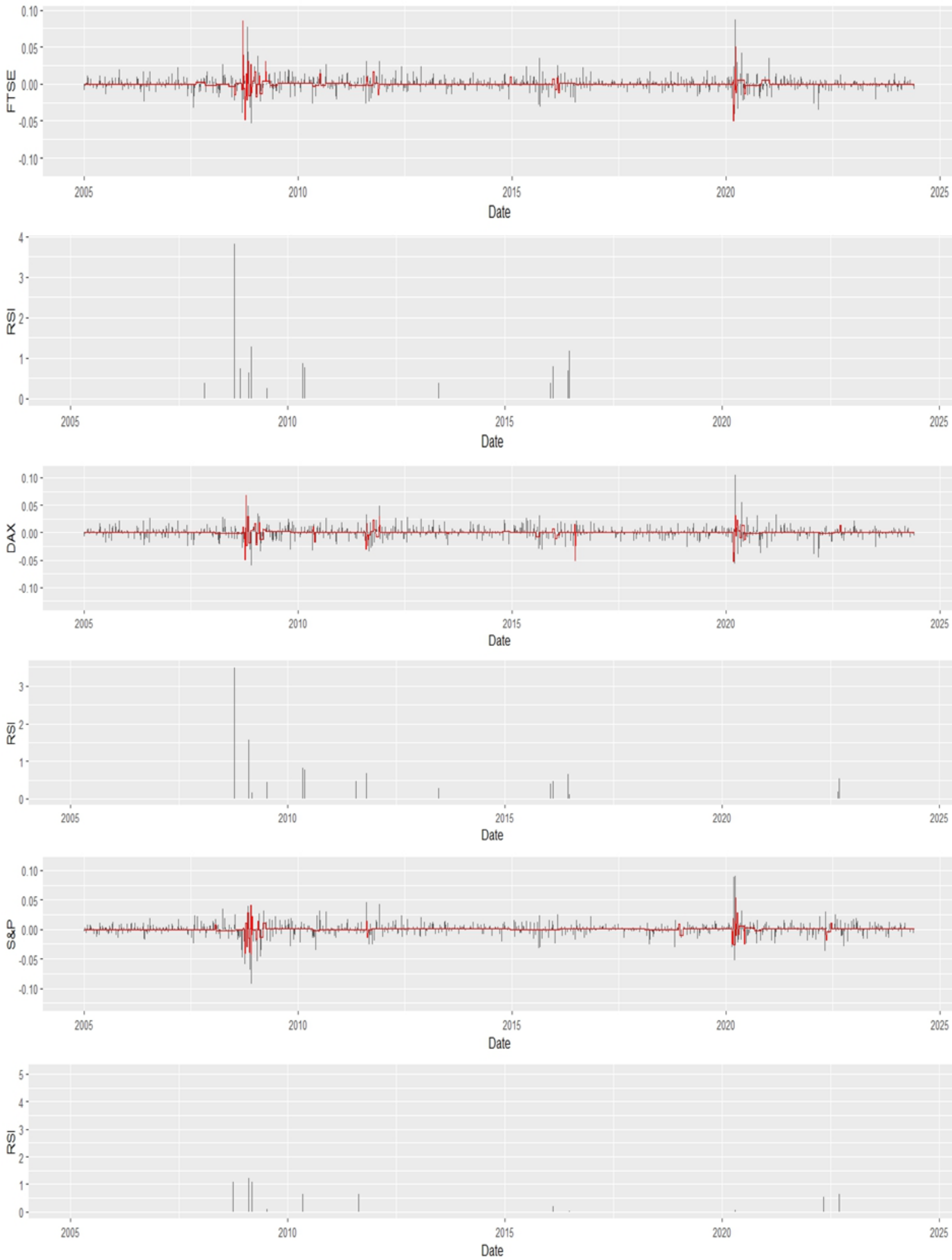


TABLE 2. The BDS test for the considered time series

ε	**Embedding dimension (m)**	**BDS test statistic**	**p-value**
S&P 500			
0.006	2	15.916	0.000
	3	24.625	0.000
	4	32.924	0.000
0.012	2	16.735	0.000
	3	24.553	0.000
	4	30.063	0.000
0.018	2	17.940	0.000
	3	24.683	0.000
	4	28.250	0.000
0.025	2	19.951	0.000
	3	25.922	0.000
	4	28.674	0.000
DAX			
0.007	2	11.803	0.000
	3	17.333	0.000
	4	23.541	0.000
0.013	2	11.553	0.000
	3	16.900	0.000
	4	21.369	0.000
0.020	2	12.217	0.000
	3	17.399	0.000
	4	20.894	0.000
0.026	2	12.067	0.000
	3	17.483	0.000
	4	20.750	0.000
FTSE 100			
0.006	2	16.147	0.000
	3	22.404	0.000
	4	27.568	0.000
0.011	2	16.965	0.000
	3	22.476	0.000
	4	26.764	0.000
0.017	2	17.357	0.000
	3	22.181	0.000
	4	25.514	0.000
0.023	2	18.052	0.000
	3	22.378	0.000
	4	25.244	0.000

Notes: The table reports the results of the Brock–Dechert–Scheinkman (BDS) test for univariate time series (Brock et al. 1996). The null hypothesis is that the DGP is independent and identically distributed (i.i.d.). The alternative hypothesis is not specified. The embedding dimensions of 2, 3, and 4 are considered. For ε, the values defined by `seq(0.5*sd(x), 2*sd(x), length = 4)` are used. The test is implemented in the R package `fNonlinear` (Wuertz et al., 2024).

Finally, to capture the relationships occurring over time and different frequencies between pairs of individual markets, Figure 2 performs a "Wavelet Coherence" analysis (Torrence and Webster 1999; Grinsted et al. 2004). In this analysis, regions in time-frequency space where

Table 3. Various linearity tests

Tests	**S&P 500**	**DAX**	**FTSE 100**
Teräsvirta's neural network test	$\chi^2 = 66.619$ (p-value = 0.000)	$\chi^2 = 3.602$ (p-value = 0.165)	$\chi^2 = 20.032$ (p-value = 0.000)
White neural network test	$\chi^2 = 37.901$ (p-value = 0.000)	$\chi^2 = 2.564$ (p-value = 0.278)	$\chi^2 = 7.084$ (p-value = 0.029)
Keenan's one-degree test for nonlinearity	F-Stat = 32.089 (p-value = 0.000)	F-Stat = 13.807 (p-value = 0.000)	F-Stat = 3.332 (p-value = 0.068)
McLeod-Li test	Maximum p-value = 0.000	Maximum p-value = 0.000	Maximum p-value = 0.000
Tsay's Test for nonlinearity	F-Stat = 6.798 (p-value = 0.000)	F-Stat = 3.326 (p-value = 0.000)	F-Stat = 3.756 (p-value = 0.000)
Likelihood ratio test for threshold nonlinearity	$\chi^2 = 122.720$ (p-value = 0.000)	$\chi^2 = 101.869$ (p-value = 0.000)	$\chi^2 = 168.608$ (p-value = 0.000)

Notes: This table reports the Teräsvirta's neural network test (Teräsvirta et al. 1993; Teräsvirta 1996), White neural network test (White 1989), Keenan's one-degree test for nonlinearity (Keenan 1985), McLeod-Li test (McLeod and Li 1983), Tsay's test (Tsay 1986), and the Likelihood ratio test for threshold nonlinearity (Chan 1990). The null hypothesis for the Teräsvirta and White test is "linearity in mean." For Keenan and Tsay tests, this hypothesis is "The time series follows some AR process," while for McLeod-Li test it is "The time series follows some ARIMA process." For the Likelihood ratio test, the null is "The time series follows some TAR process." The tests are implemented in the R package `nonlinearTseries` (Garcia 2024).

the series co-vary are located by the wavelet coherence. According to the results, the significant regions are highly extensive. Hence, it is improbable that the existence of "in-phase" relationships highlighted here is accidentally occurring. For the first part of the analysis period, between 2005 and 2015, the oscillations manifested in FTSE 100 are transferred over DAX and S&P 500 on wavelengths varying from 16–1024 trading days. However, this influence gradually faded away after 2015. DAX is influencing the S&P 500 until 2020 over low frequencies. After 2022, the influence is preserved mainly over the medium frequencies between 16 and 64 trading days. Nevertheless, as Figure 2 illustrates, the Wavelet Coherence analysis does not provide robust results regarding the selection of a "mother function". With the shift from a Morlet mother function to a DOG one, some critical changes in the results configuration occur. Such changes are more prominent for medium and low frequencies (up to fifteen trading years). Over such frequencies, except for the DAX / S&P 500 pair, there is a decorrelation between the markets (although the correlations manifest themselves over medium and higher frequencies). Therefore, we further focus on the WLMC approach to capture more robustly the heterogeneous correlations among markets over different scales and periods.

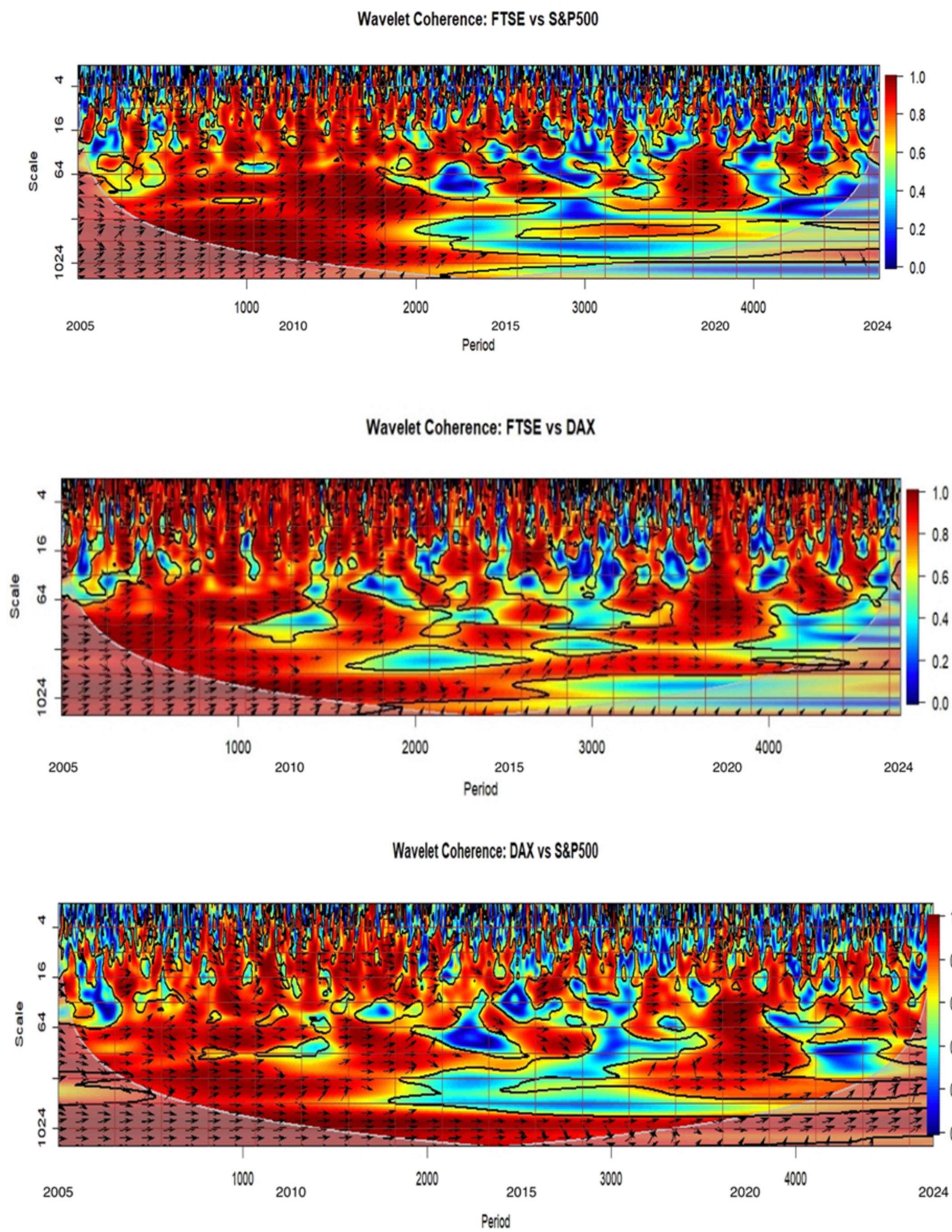
4. Results and Comments

4.1. **Main results.** Figure 3 reports the results for the considered markets. The markets' system has a high correlation (ranging from 0.65 to 0.99) for almost the entire length of the time series. Nevertheless, this correlation is only partially homogenous. There are at least two spans (post-2010 and during 2018) when the correlation coefficients take lower values. At the same time, the highest levels of correlation coefficients occur especially for 'medium' (from one to two conventional trading years) and, respectively, "low" (two to four trading years) frequencies, while higher frequencies are characterised by correlation coefficients that are somehow lower.

However, analysing the dynamic wavelet correlations does not allow clear discrimination of the dominant time series, i.e., the series acting as system driver. To tackle this issue, Figure 2

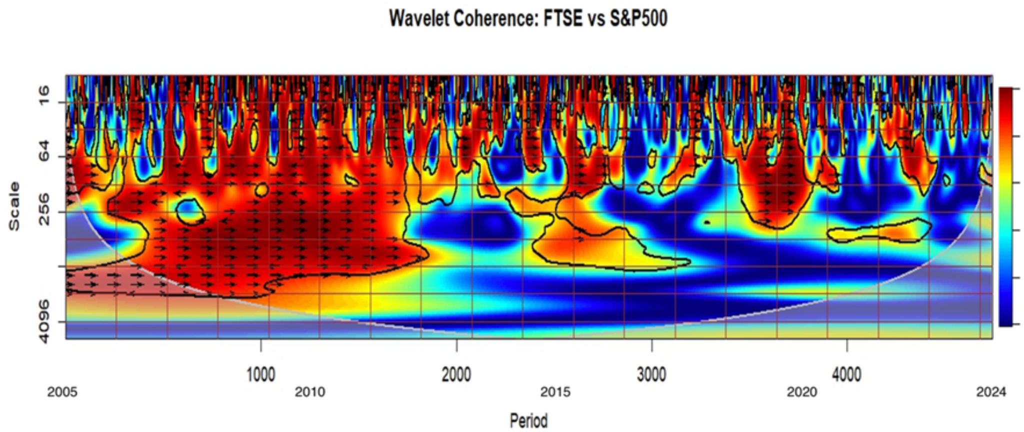
FIGURE 2. Wavelet Coherence analysis for the pairs of markets

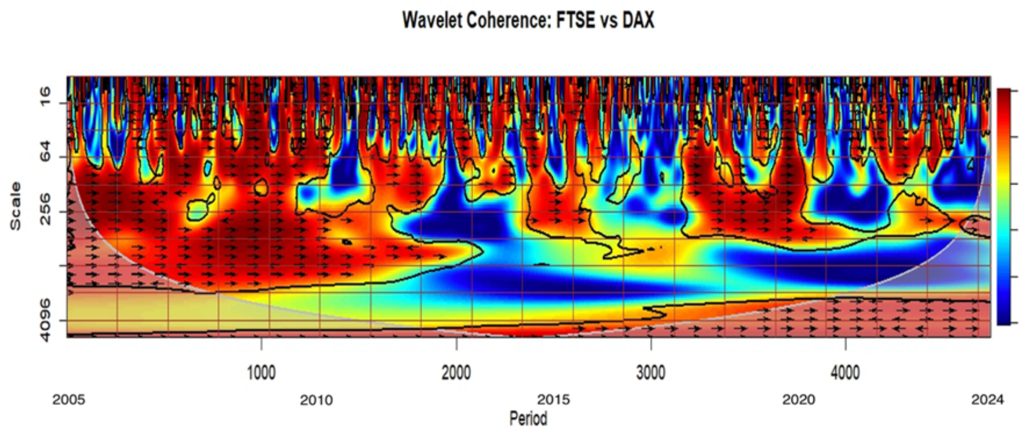
(A) Mother wavelet function: Morlet

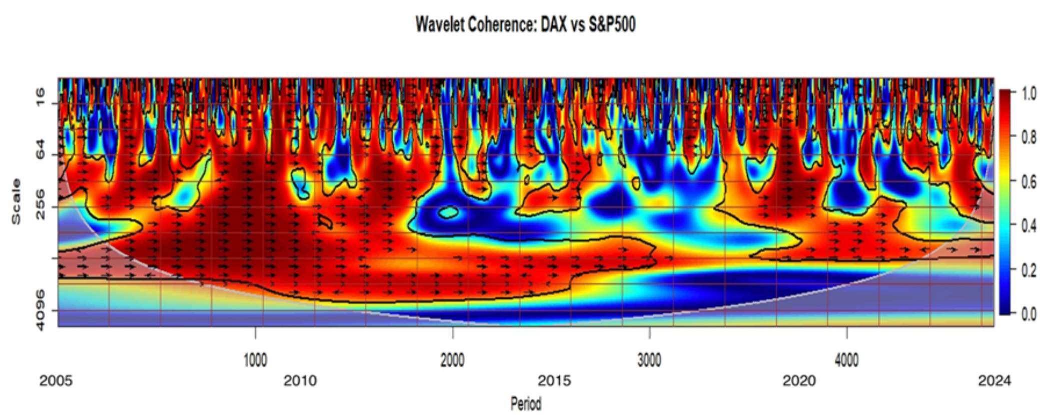


Notes: The figure displays the results of a wavelet coherence analysis (Grinsted et al. 2004) for each pair of markets. The significance level is 95%. A regular χ^2 test is used as a significance test. The number of Monte Carlo randomizations is equal to 10. The 5% significance level against red noise is shown as a thick contour. The estimations follow the implementation from the R package `biwavelet` (Gouhier et al. 2024).

(B) Mother wavelet function: Derivative of a Gaussian (DOG)





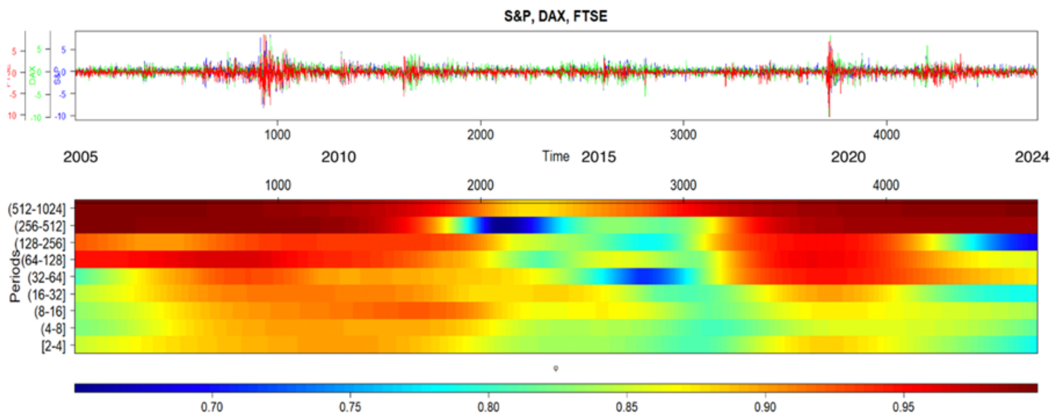


Notes: The figure displays the results of a wavelet coherence analysis (Grinsted et al. 2004) for each pair of markets. The significance level is 95%. A regular χ^2 test is used as a significance test. The number of Monte Carlo randomizations is equal to 10. The 5% significance level against red noise is shown as a thick contour. The estimations follow the implementation from the R package `biwavelet` (Gouhier et al. 2024).

shows the ("dominant") variable(s) that maximize the multiple correlation through time and scale.

Figure 4 shows that for the shortest and medium wavelet scales (from two to thirty-two days), the system is dominated mainly by DAX and, to a lesser extent, by the FTSE 100. However, for higher scales (from two to four trading years), the FTSE 100's dominance surpasses that of the other two European markets. Nonetheless, the FTSE 100 will only maintain such dominance over high scales until 2019. After this period, it is substituted by the one exercised by the S&P 500 until the end of the analysis period (while during this interval, DAX remains dominant for scales between one and two trading years).

Figure 3. The heat map of the wavelet correlation coefficients



Notes: The figure displays the heat map of the wavelet correlation coefficients statistically significant (95% confidence interval). Time and scales are in days. The Daubechies wavelet of length $L = 8$ (least asymmetric family) is used to derive the results.

4.2. **Robustness check.**

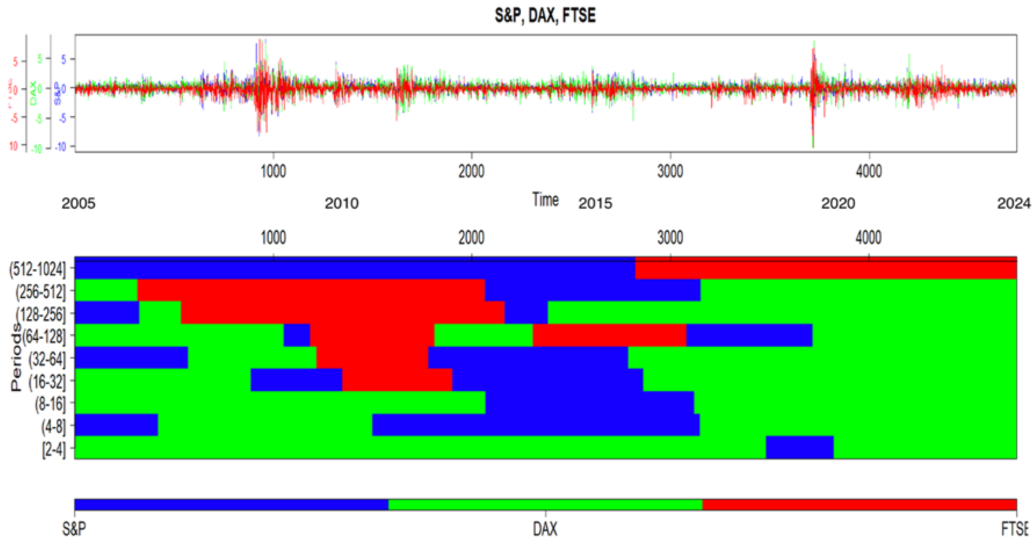
4.2.1. *Different specifications for window functions.* This section aims to verify the robustness of our results if different specifications for window functions are combined with the selection of various wavelet filters. Namely, we consider the following combinations: 1) a Daubechies wavelet of length L=16 with a Wendland's truncated power window; 2) a Daubechies wavelet of length L=4 with Bartlett's triangular window and respectively, 3) a 'Best Localized 'class of wavelet transform filters of length L=4 with a uniform window. Such choices are frequently used in literature and have the potential to provide sound alternatives to the approach based on "Daubechies LA(8)" with the Gaussian window.

The results are reported in Figure 5. Although the markets' network profile shares several similarities with the previously reported results (especially for high and medium frequencies), it also shows some notable changes. First, the correlations seem to lose statistical significance or completely vanish for higher scales (between two and four conventional trading years). This outcome is evident when Wendland's truncated power or uniform types of windows are used.

Second, even for high frequencies, the FTSE 100 appears critically relevant than previously highlighted (prominent for periods between six and nine months).

Third, these additional results indicate the sensitivity of the findings concerning the length of wavelet transform filters. As mentioned, longer wavelet filters are more suitable for reflecting the data structure. Meanwhile, using symmetric/asymmetric coefficients with minimal phase nonlinearity leads to some changes in the results. This is not necessarily a surprise as our data

Figure 4. Dominant variables in time-frequency

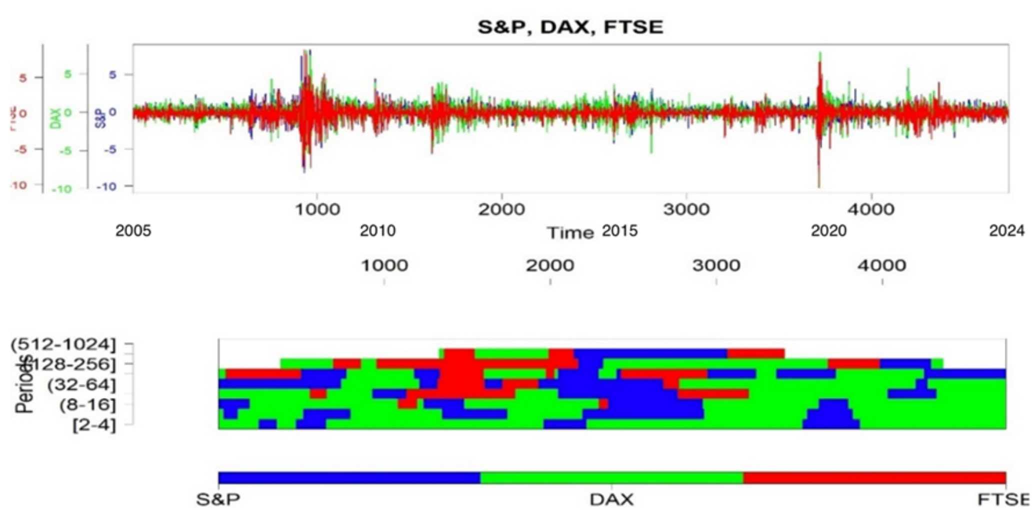


Notes: Same specifications as for Figure 1. No specific return series is a priori defined to maximize the multiple correlation for each wavelet scale. Instead, the procedure itself selects such a variable. The implicit argument is that, while these major developed markets are expected to be correlated among them, the structure of their causality is not necessarily known on an ex-ante basis.

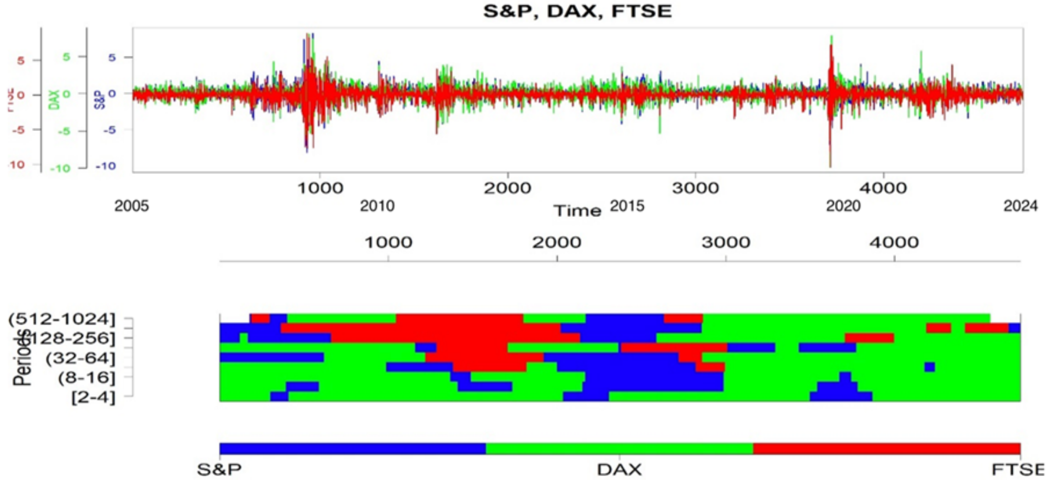
has not been initially denoised, and the stability of the results can be affected by the filters' capacity to deal with noise and various types of non-linear dynamics. However, the primary outcome remains the same: regardless of the specifications, this approach indicates noticeable shifts in market correlation patterns over different periods and frequencies.

Figure 5. Different specifications for the identification of dominant variables

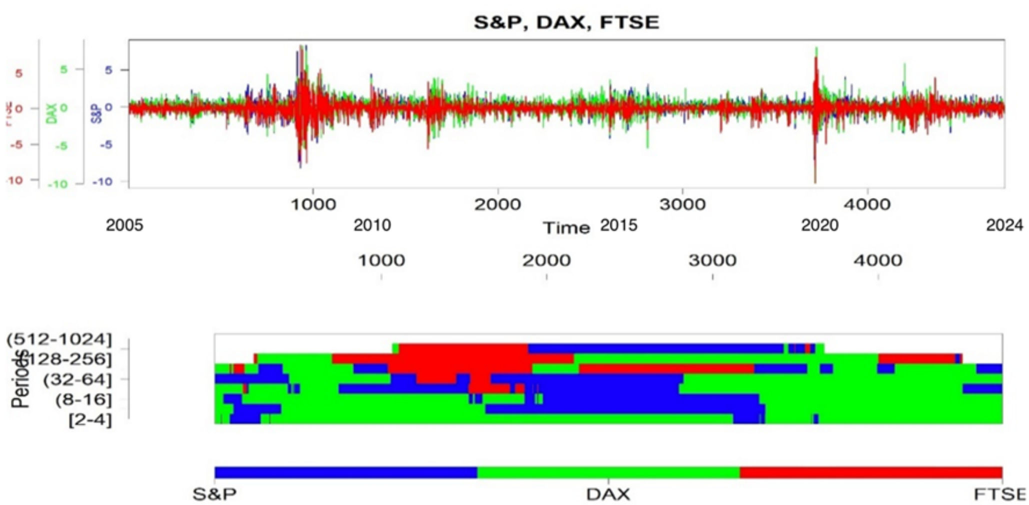
(a) Daubechies wavelet of length $L = 16$ and Wendland's truncated power window



(b) Daubechies wavelet of length $L = 4$ and Bartlett's triangular window



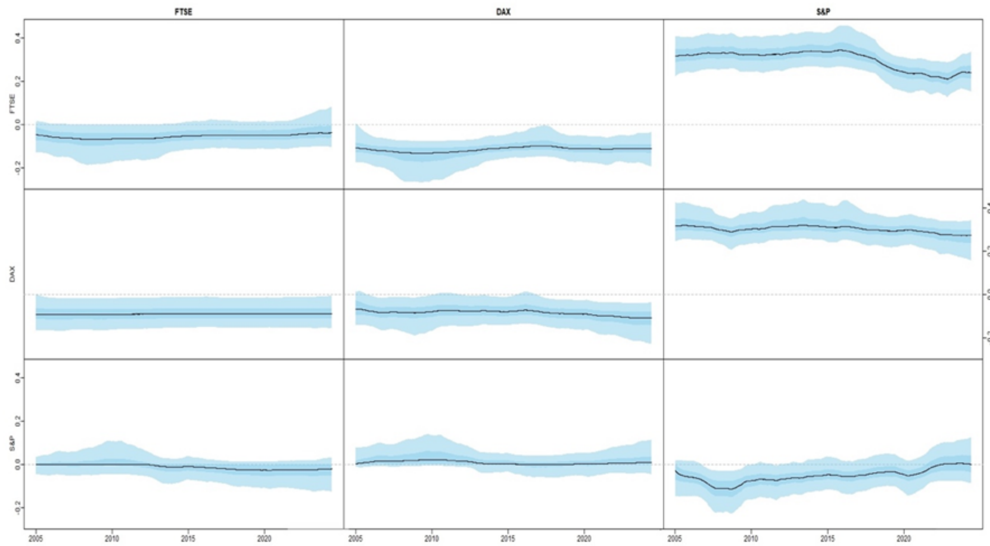
(c) "Best Localized" class of wavelet transform filters of length $L = 4$ and uniform window



4.2.2. *A TVP-VAR approach.* Another robustness check may concern an alternative approach that can capture the dynamic interlinkages in the dataset structure. A Time-Varying Parameter Vector Autoregressive TVP-VAR represents such an alternative model. In implementing it, we involve the shrinkage procedure proposed by Knaus et al. (2021). This procedure seeks to avoid the risk of overfitting in TVP models by considering appropriate global-local shrinkage priors, which pull time-varying parameters towards static ones. Consequently, a fully Bayesian estimation framework is considered to estimate the implied time-varying parameters.

Figure 6 displays the shapes of the time-varying parameters. Several insights can be highlighted here. First the impact exercised by the FTSE 100 on the other two markets appears to be almost stable during the entire analysis period. Meanwhile, the effect associated with the S&P 500 displays an evident time-varying pattern while, for the DAX, the effects appear to vary to a limited extent over time. Second, the effects translated from the S&P 500 displayed (as can be intuitively expected) a higher degree of variability during the 2007-2010 financial and real turmoil and during the post-2020 period. Third, the estimated influence exercised by the DAX market appears to be relatively quickly absorbed by the other two markets. Such behaviour might explain the noticed WLMC analysis outcome, according to which this market's dominance is relevant mainly under short and medium horizons. Fourth, as illustrated by the estimated impact of the lagged values on the current ones, markets' dynamics display a time-varying nature. This is more pronounced for the S&P 500 and, to a lesser extent, for the other two markets.

Figure 6. A TVP-VAR model for the considered markets (full sample; entire period)



Notes: The procedure samples from the joint posterior distribution of the parameters of a TVP-VAR-SV model with shrinkage as described in Cadonna et al. (2020) and it is implemented in the R package "shrinkTVPVAR" (Knaus 2024). One lag is considered. A "Triple Gamma" prior is used for the parameters (see Cadonna et al. 2020 for the main features and advantages of this prior type). The number of MCMC iterations is 100000 and the number of the number of iterations discarded as burn-in is equal with 75000. Meanwhile, the degree of thinning is equal to 1.

5. Comments

Several comments can be drawn from our findings.

First, it should be accounted for that "correlation is not the same thing as causality". Therefore, it is plausible to argue that the interpretation of markets' interconnectedness in a functional sense may ignore the action of hidden factors (such as the financial globalisation forces) that drive the evolutions between the pairs of individual markets. However, in the case of markets displaying a high degree of integration, arguments can be found to support such an interpretation (such as the existence of "portfolio substitution" effects). Investors building geographically diversified portfolios (under different trading horizons) act as interconnectedness agents and ensure the translation of individual market dynamics over others.

Broadly, it is unsurprising that the considered markets were functionally connected during the analysed period. Nevertheless, the results show that the correlation pattern displays an evolutive structure over time and at different frequencies. Of course, we do not analyse the factors leading to the observed changes here. Yet, it can be noticed that a certain "decoupling" occurs (especially over lower scales) after periods of significant turbulence (such as the 2008-2010 financial and real crisis, the 2018 increased volatility period or post-2020 events), with the effects associated with pandemic crisis, energy crisis or significant geopolitical instability and risks.

Second, in our ex-post analysis, we do not explicitly consider the role played by investors' expectations. Indeed, the ensuing reasoning can be advanced. Suppose the investors from an individual market formulate pessimistic expectations about future returns and risks. In that case, they can adjust the structure of their portfolios by including assets from markets that are expected to produce better results in terms of specific return-to-risk ratios. Such a portfolio's structural adjustment will contribute to shifts in the demand and supply in the involved markets. It can impact the performances associated with holding and trading assets from these.

Nonetheless, the mechanisms through which the expectations are formulated are sensitive to the nature and quality of available information. Such quality is only sometimes uniform if investors collect information from different markets. Thus, imperfect and asymmetric distributed information can inhibit market's interconnectedness. Third, more explanations are required to clarify in detail the mechanisms leading to the substitutions of the dominant role played by individual markets over low/high scales. While the arbitrage operations of international investors (which are characterised by different trading horizon preferences) might play an important role, such an argument remains too general. This may represent a future research direction.

Fourth, our dataset is limited (even if it includes a period during which various endogenous and exogenous-to-the-market shocks occurred). Therefore, an extended analysis might provide more insights into the evolving relationships emerging in a financially globalised system.

Fifth, at an empirical level, more efforts should be made to clarify results' sensitivity to the specification of methodology's key parameters. One of the essential issues is explaining the lack of robustness of markets' interconnectedness at higher scales. In the context of accelerated dynamic of markets, increased role of the short-run trade, fast movements of international capitals and the direct and indirect effects of more frequent financial turmoil periods, it is less plausible to find long-run functional stability. Consequently, more research is required to highlight the detailed mechanisms influencing on lower frequencies the stability of the involved DGPs. Accordingly, a possible future research direction is linked to the search for identifying the features of different window functions or wavelet filters more suitable for analytical purposes and which better account for data properties. Notably, it might be interesting to explain why using a symmetrical filter leads to results that are different on lower frequencies than those provided by more asymmetric filters.

Sixth, while our results indicate that the DAX and S&P 500 markets are shifting the role of the network drivers, the FTSE 100 market appears to play a less prominent role (except for the highest and average frequencies). Nevertheless, this holds true especially during the post-Brexit period, regardless of the settings used. Thus, another possible investigation point concerns the changes in the role played by FTSE 100 in the architecture of the international financial system. In addition, the short- and medium-run impact of the S&P 500 needs to be better explained. In particular, it can be argued that due to its more extensive coverage, the S&P 500 can better capture the dynamics of the United States economy as a whole compared with the narrow DAX index, which includes a smaller number of high liquidity companies. For that reason, the extent to which the 'fundamentals' influence these two indexes differs (as is the evolution of the United States and Eurozone macroeconomic conditions).

Seventh, the time and frequency heterogeneity of the results requires an in-depth analysis and a theoretical explanation. Indeed, investors in highly developed financial markets can employ sophisticated trading strategies (such as the "buying the dip" type) to grasp the benefits of "time arbitrage" opportunities. Thus, they will seek to exploit the differences between various investment horizons to obtain abnormal returns. The outcome of such strategies will potentially consist of regime shifts occurring whenever the trading horizons gaps in returns significantly change. However, such changes rarely appear in all markets simultaneously. Therefore, "time arbitrage" opportunities exist inside the same and cross-international financial markets. Such opportunities can explain the coupling / decoupling evolutions highlighted by our results across different scales. Nevertheless, a search for other possible determinants should be considered.

6. Conclusions

Past financial crises taught us that developed financial markets are subject to cross-border interconnections and interdependences. There is an extensive body of literature addressing the interconnectedness on various assets markets, however not precisely on stock markets. Consequently, this study examines the interconnectedness between developed stock markets, by focusing on the time dependence of developed financial markets' multi-vocal relationships. For this purpose, we have employed a Wavelet Local Multiple Correlation (WLMC) approach and included the log returns for three developed leading financial markets, namely S&P 500 index, DAX Performance Index and FTSE 100 index, for a large timespan covering the period between 2005-01-01 and 2024-05-30. The key contribution to the literature is given by the identification of the correlation pattern which captures significant variations over time at different frequencies, increased volatility being captured/proven/revealed in turmoil periods.

Therefore, understanding the interconnectedness of developed financial markets is instrumental for various stakeholders (i.e., investors, policymakers, and financial institutions), to navigate the complexities of the international financial system and to mitigate potential risks.

For investors, the interconnectedness between stock markets implies that events in one market can have a significant impact on investments in other markets. Moreover, understanding and balancing time-dependencies and interconnectedness in developed stock markets are instrumental in taking informed investment decisions in the area of portfolio diversification and risk management. Even though the existing literature mainly focuses on diversification based on the assets' classes and geographic location, we consider time-diversification at least as important. By accounting the time-frequency and risk co-movements, investors should rebalance their long-term and short-term diversification strategies, when building their asset portfolios, for mitigating risks and for increasing their returns. In this sense, investors should develop sophisticated risk management strategies that account for the dynamics of interconnected markets over time. Also, they should build potential scenarios by considering the timing of their trades and the potential impact of market interdependencies on their investment portfolios.

Market regulators and policymakers must consider the implications of interconnectedness when formulating policies and regulations. They need to ensure that regulatory frameworks are robust enough to address cross-border risks and to promote market stability. For policymakers, our results might have a bearing on prudential regulation and supervision. Central banks and governments should consider the time-frequency correlations for accurately adapting their monetary and fiscal policies with the aim of enhancing financial stability and avoiding market disruptions. However, there are economies where the market surveillance attributions are allocated to market regulatory authorities. In view of the fact that correlations between stock markets vary over different time frequencies and scales, regulatory authorities should perform dynamic risk assessment processes to predict periods of increased risk. Similarly, they should implement early warning systems by identifying shifts in correlations that might precede market disruptions. Based on our findings, we consider that adaptive and flexible policies should be implemented by enhancing coordination with international counterparts. Also, developing mechanisms for crisis management and information sharing should be designed and implemented, as well as proactive measures and stabilization efforts for mitigating crises.

Financial institutions, such as banks and investment firms, are also affected by interconnected stock markets. They may face increased risks from cross-border exposures and market volatility. As a result, they may need to adapt their risk management practices and capital planning according to the interconnected nature of the markets. Based on our results, we consider that financial institutions should perform robust stress testing and scenario analysis to assess the impact of interdependencies over different time horizons. At the same time, we consider that financial institutions should also need to adapt their liquidity and capital management practices to account for the time-varying nature of market interconnections.

Overall, the interconnectedness of global developed financial markets displays both complex opportunities and challenges for stakeholders. Hence, an effective risk management is required for global financial system stability which could be improved by implementing international cooperation strategies, robust regulatory frameworks, and proactive risk management strategies.

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