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FINANCIAL CONTAGION DURING THE COVID-19 PANDEMIC: A WAVELET-COPULA-GARCH APPROACH

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Financial Contagion During the Covid-19 Pandemic: A Wavelet-Copula-GARCH Approach

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Abstract

In this study we examine the impact of the Covid-19 pandemic on stock market contagion. Empirical analysis is conducted on six major stock markets using a novel wavelet-copula-GARCH procedure to account for both the time and frequency domain of stock market correlation. We find evidence of contagion in the stock markets under consideration during the Covid-19 pandemic.

Keywords: Stock Market Contagion; Covid-19 Pandemic; Wavelet decomposition; Copula- GARCH models.
JEL classification: C35, F37, G10, G15

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1. Introduction

The escalation of the Covid-19 pandemic in 2020 represents a major challenge for financial markets. As the contagion spread from the city of Wuhan in China's Hubei province to become a global pandemic, stock prices volatility reached levels unseen since the Great Financial Crisis in 2007-2008. In finance it is well known that such extreme values do not occur in isolation, but financial shocks experienced in one market are often transferred to another.

In the literature a large body of empirical works distinguish between two forms of contagion (see for example, Wolf, 1999; Forbes and Rigobon, 2000; Pritsker, 2001; Dornbusch, 2000). The first form is referred to as "interdependence" between economic systems and emphasizes on spillovers that result from the interaction among markets. In this case, the transmission mechanism of shocks is caused by interdependence across countries in relation to their real and financial linkages. The second form of contagion relates to cross-market linkages generated by shocks on financial markets that are not linked to observed changes in macroeconomic fundamentals but are mainly the result of the investors' behaviour. This form of contagion is sometime referred to as "shift" contagion or "pure" contagion. In the literature, theoretical models explaining this form of contagion are based on multiple equilibria, endogenous-liquidity shocks affecting portfolio allocation, investor psychology, and capital market liquidity. For example, Masson (1998) presents a multiple equilibria model where a crisis in one country can act as sun-spot for another. In this model the shift from a good to a bad equilibrium is not driven by real linkages among economic systems but by investor expectations. In the same vein, Hernández and Valdés (2001) propose a model where a crisis in one country causes a liquidity shock to market participants and induce investors to portfolio rebalances. Realigning the weightings of portfolio assets causes a sell-off of certain asset classes, which in turn lower asset prices in countries not affected by the initial crisis. In behavioural finance theoretical models relate contagion to investors' herding behaviour. In these models, investment decisions by market participants are influenced by the investment choices of others. For example, Bikhchandani and Sharma (2000) study the social learning effects of actions taken by agents who act sequentially. The authors argue that when decisions are sequential the earliest actions may have disproportionate effect on the choices of the following agents and herd behaviour may arise.

In the literature, evidence of contagion due to financial or real economy shocks has been documented in several empirical works. Some of the most influential studies are those by Kaminsky and Reinhart (2000); Allen and Gale (2000); Bae *et al*., (2003); Bekaert *et al*., (2005). Consensus literature agrees, however, that pandemic-related developments rarely cause stock market contagion. For example, Baker *et al*. (2020) looking back to 1900 found no evidence of cross market linkages in relation to infectious-disease outbreak. Remarkably, the authors found that the Spanish Flu, which infected an estimated 500 million people worldwide between 1918-1920 and claimed approximately 50 million victims, had only a limited impact on the financial markets. In striking contrast, the Covid-19 outbreak is having a massive impact on the real economy driving many countries into recession. Unlike other pandemic-related developments the Covid-19 outbreak has triggered a massive spike in uncertainty in the financial markets. For example, in the U.S. stock markets volatility levels in the first quarter of 2020 surpassed those last seen in October 1987 and December 2008 and, before that, in late 1929 and the early 1930s (see Baker *et al*., 2020).

Partially motivated by these observations, the present study looks for fresh insights into the extent to which stock markets have been affected by the Covid-19 crisis, asking whether the apparent market transmission is actually the effect of contagion or interdependence. Following the seminal paper by Forbes and Rigobon (2002) we investigate if correlations between different equity markets increased significantly during the pick of the Covid-19 outbreak. The authors argue that to be classified as contagion correlation between stock markets should increase during the crisis episode. In absence of a surge in cross-market linkages, volatility spillover would better be classified as market interdependence.

In this paper we propose a novel methodology that combines the benefits of wavelet series expansions with copula estimation. We name it "wavelet-copula-GARCH" procedure, in short "WC-GARCH". The procedure can easily be carried out in two steps. The first stage involves using wavelet analysis to decompose the series of stock market returns into components associated with different scale resolution. In the second step, the decomposed series of stock market returns are used as input variables to estimate the transmission mechanisms of shocks using copula functions. Since modelling dependence by copula is sensitive to marginal model assumptions to allow for heteroskedasticity, autocorrelation and volatility asymmetry we follow Jondeau and Rockinger (2006) and estimate the marginal distributions using a GARCH-type model.

The main innovation of the suggested procedure is the combination of wavelet analysis with copula models. Wavelet analysis is a filtering method closely related to time series and frequency domain methods that transforms the original data into different frequency components with a resolution matched to its scale. Unlike time series and spectral analysis, which only provide information on time-domain and frequency domain respectively, wavelet decomposes the stock market return series with respect to both time and frequency domains simultaneously. This allows us to investigate if financial markets respond differently in dissimilar time scales. For example, two stock markets may be highly correlated in the long run, but not in the short run. Analysing separately different frequency components of the series enables us to examine the stock markets over different time intervals (i.e., short, medium, and long term) and allows us to assess how the evolution of market connectedness has evolved over time, thus capturing the possible changes in the relationship. To analyse the strength of the comovements between stock markets over different time interval we estimate a copula-GARCH-type model. Conditional copulas are extremely useful in financial applications because copula functions allow separation of the marginal distributions from the dependence structure that is entirely represented by the copula function. This separation enables researchers to construct multivariate distribution functions, starting from given marginal distributions that avoid the common assumption of normality for either marginal distributions or their joint distribution function (Bartram *et al*., 2007). Moreover, copulas are invariant to strictly increasing transformations of the random variables, while asymptotic tail dependence is an important property of them.

Stock market contagion has important consequences for financial stability as well as portfolio management since they affect optimal asset allocation, risk measurement, and asset pricing. However, standard time-domain techniques can have problems in identifying contagion from other forms of shock transmission because of the inability of these methodologies of combining information from both the time-domain and the frequency-domain. The modelling issues related to the analysis of comovements between financial markets are well documented by the variety of econometric procedures used in empirical studies to investigate financial contagion. They include testing for changes in correlation coefficients (King and Wadhwani, 1990; Lee and Kim, 1993), ARCH and GARCH models (Billio and Caporin, 2010), estimating cointegration models (e.g. Chiang *et al.*, 2007; Gallo and Otranto, 2008; Voronkova, 2004; Yang *et al*., 2003), limited dependent variable models (Eichengreen *et al*., 1996; Kaminsky and Reinhart, 2000), nonlinear models (Gallo and Otranto, 2008), and factor models (Corsetti *et al*., 2005). In this paper we argue that most of these models can only describe the average behaviour of the correlation patterns, since standard time series models do not allow for more than two time scales: the short run and the long run. According to theoretical models shocks transmission due contagion should be rapid and should die out fast due to arbitrage opportunities in different markets. However, how fast is fast? This is a fundamental question in practical applications. In this respect, by applying a j-level multi-resolution decomposition of the stochastic processes the suggested procedure provides a complete reconstruction of the signal partitioned into a set of j frequency components. Each component corresponds to a particular range of frequencies. For example, the low-frequency part can be associated to what the literature has defined “interdependence”, and the high-frequency part can reflect “pure” contagion. Available literature confirms the effectiveness of adopting wavelet analysis to take into account the difference between short and long term investors (see, for example, Yazgan and Özkan, 2015; Yogo, 2008; Gallegati, 2012, Ranta, 2013; Conlon, et al. 2018).

The present study contributes to the literature in several ways. First, analysing daily returns for six large stock markets in the USA, Canada, UK, Honk Hong, China, and Japan evidence of significantly increasing dependence among stock markets was found since the start of the Covid-19 outbreak. Our results reveal evidence of contagion in line with the Forbes and Rigobon's (2002) definition: a significant increase in linkages among stock markets after a shock to one country as measured by the degree to which asset prices move together across markets relative to this comovement in tranquil times.

Second, evidence of contagion among stock markets constitutes an unprecedented event since, according to the literature (see Baker *et al,* 2020; Nippani and Washer, 2004 among others), no previous infectious disease outbreak has impacted the stock market as forcefully as the Covid-19 pandemic. Most empirical studies agree that previous pandemics greatly affected stock market volatility but had only mild impact in term of stock market contagion. The proposed methodological approach is the third contribution of the paper. In this work we present a novel wavelet-copula GARCH procedure that has not previously used in the literature. The combination of wavelet decomposition and GARCH-copula models allow us to analyse the evolution of the correlation in the time-frequency space. Consequently, the paper provides a fresh characterization of short term and long term dependencies between stock market returns.

The remainder of this study is organized as follows. Section 2 describes market contagion from a theoretical perspective. Section 3 presents the WC-GARCH model, whereas in Section 4 the estimation results are reported. Finally, Section 5 contains some concluding remarks.

2. Theoretical Considerations

Financial contagion as a result of global event that originates from a country and spreads to other countries or regions has long been an object of interest to economists.

Consensus literature agrees that there are two main channels for propagation of contagion: physical exposure and asymmetric information. Contagion through physical exposure occurs when after a negative shock in one market investors rebalance their portfolios and sell assets in other markets. Therefore, a shock in one market causes instability in other markets, regardless the underlying fundamentals (see Kyle and Xiong, 2001). Contagion may also result from asymmetric information in financial markets. King and Wadhwani (1990) argue that traders in international financial markets face "signal extraction problems". Traders from one country have only imperfect information about the situation in other countries. Therefore, agents extract further information from observable stock price movements, reflecting other traders' behaviour. However, imperfect information cause confusion between price movement related to idiosyncratic shocks in a foreign country with price movements that also reveals changes in information about their home country. As a result, asymmetric information can trigger excessive price spillovers across borders, including stock market crashes.

In the literature contagion has been empirically identified through the propagation of extreme negative returns and the related increase in market correlation with respect to normal times. A large body of research suggests that international financial market contagion has occurred in various economic and financial crises. For example, King and Wadhwani (1990) find evidence of an increase in stock returns' correlation in 1987 crash (see also Bekaert et *al*., 2005). Similarly, Calvo and Reinhart (1996) report evidence of contagion during the Mexican Crisis, and Baig and Goldfajn (1999) reach similar conclusions investigating the stock market correlation during the East Asian Crisis. Hon *et al*. (2004) find evidence of contagion between the Nasdaq and the other stock markets after the dotcom bubble collapse in the United States. In the wake of the subprime market crisis that originated in the U.S. in 2005, several papers have assessed the existence of contagion in financial markets. For example, Park and Shin (2020) investigated the foreign banks' exposure during the crisis and found that emerging market economies were more exposed to banks in the crisis-affected countries, suffered more capital outflows during the global financial crisis. Evidence of contagion was also found in developed economies in Dungey and Gajurel (2015) (see also Zhang *et al*., 2020). Mohti *et al*. (2019) investigate the impact of the U.S. subprime on the Eurozone debt crisis (see also Bashir *et al*., 2016).

Although recent research has greatly improved our understanding of contagion, little attention has been devoted to the impact of infectious disease outbreaks on stock markets. Most empirical works related to the impact of epidemics focus on disease-associated economic costs as a result of morbidity and mortality. For example, Siu and Wong (2004) provide evidence of the economic impact of the SARS epidemic in China, Hong Kong, and Taiwan. Coming to financial markets there is remarkably little literature on the subject. Notably, most of the available evidence finds negligible impact of infectious diseases such as the SARS, EBOLA, Swine Flu or ZIKA on stock markets.[1] For example, Nippani and Washer (2004) examine the effect of SARS outbreak on financial markets and find no evidence of contagious of stock markets in Canada, Hong Kong, Indonesia, the Philippines, Singapore, and Thailand. Similarly, Koo and Fu (2003) argue that despite the serious emotional distress caused by the SARS outbreak, the disease had limited impact in the affected regions (see also Siu and Wong, 2004; Chen *et al*., 2007, 2009; Baker *et al*., 2012; Wang et al., 2013; Del Giudice and Paltrinieri, 2017; Chen *et al*., 2018; Ichev and Marinč, 2018). Macciocchi *et al*. (2016) investigate the effect of Zika virus outbreak in several affected countries and conclude that the impact on the virus on stock markets was only marginal.

Few studies have investigated the impact of the Covid-19 pandemic and financial market volatility. Attempts to understand the effect of Covid-19 on market volatility include a study by Baker *et al*. (2020), that identifies the current pandemic as having the greatest impact on stock market volatility in the history of pandemics. In a similar vein, Zaremba *et al*. (2020) examine the impact of government policy measures on stock market volatility (see also Goodell, 2020). The authors suggest that stock market volatility increased more in countries where governments took strict policy actions to curb the spread of disease such as information campaigns and cancellation of public events. Further, Zhang *et*

[1] In the recent history the World Health Organization (WHO) declared a global emergency due to the rapid spreading of infection diseases sixth times. Past examples include the outbreak of swine flu in 2009, Ebola that mainly spread Democratic Republic of Congo in 2014, the Zika virus in 2016 and SARS. By assessing the risk of spread and severity of Covid-19 outside China WHO declared this virus as a pandemic on March 11, 2020.

al. (2020) find significant increases in volatility for US stock markets in response to reports of Covid-19 cases and deaths in multiple countries.

3. The WC-GARCH Procedure

The proposed WC-GARCH can easily be carried out in two steps. In the first step a discrete wavelet transform (DWT) is applied to the stock market indexes in order decompose the series into high-frequency and low-frequency components. In the second step, the obtained filtered series are used as input variables to analyse correlations among stock markets using copula-GARCH-GJR (1,1) model. The two-step procedure to estimate the correlation in the time-frequency domain is described below in more details.

Step 1: *The Wavelet Series Expansion*

The first step for implementing the WC-GARCH procedure involves applying the wavelet series expansion to the stock market return series.

Wavelet is a technique that decomposes a time series into different short waves that start at a given point in time and end at a given later point in time. In other words, the wavelet approach is a non-parametric method that involves using small wave functions to approximate fluctuations time series to extract information from a sequence of numerical measurements (signals). Broadly speaking, the wavelet decomposition methodology involves applying recursively a succession of low-pass and high-pass filters to the precious metal and stock market series. This process allows separating the high frequency components of the series from the low frequency components (for more details see, for example, Benhmad, 2013). Mathematically, the decomposition of the series in different components can be obtained using wavelet transform which is based on two filters. These are respectively called “mother wavelet” and “father wavelet”. The former is useful to capture the detailed (high frequency) parts of the signal whereas the latter gives information on the smooth (low-frequency) part of the signal. The “father wavelet” (or scaling function) integrates to 1 and is given by

$$\int \phi(t)dt = 1,$$

whereas the mother wavelet integrates to zero and is given by

$$\int \psi(t)dt = 0.$$

Since the use of wavelets is a well-established methodology, in this section we only introduce the concepts and definitions useful for our purposes. For an excellent review of the theory and use of wavelets, see Percival and Walden (2000); Gençay *et al*. (2002).

Let the $f(t) \in L^2(\mathbb{R})$ be a function (for $t = 1, \dots, T$) the time dimensions can be expressed as a linear combination of a wavelet function

$$f(t) = \sum_k s_{j,k}\phi_{j,k}(t) + \sum_k d_{j,k}\,\psi_{j,k}(t) + \sum_k d_{i-1,k}\,\psi_{j-1,k}(t) + \cdots + \sum_k d_{1,k}\psi_{j-1,k}(t), \tag{1}$$

where the orthogonal basis functions $\phi_{j,k}$ and $\psi_{j,k}$ are defined as

$$\phi_{j,k} = 2^{-j/2}\phi\left(\frac{t-2^jk}{2^j}\right),$$
$$\psi_{j,k} = 2^{-j/2}\psi\left(\frac{t-2^jk}{2^j}\right).$$

In Eq. (1) the representation j is the number of multi-resolution components or scales, and $s_{j,k}$ are the smooth coefficients, and $d_{j,k}$ are called the detailed coefficients. They are approximated by the following integrals

$$s_{j,k} = \int f(t)\phi_{j,k}(t)dt, \tag{2}$$
$$d_{j,k} = \int f(t)\psi_{j,k}(t)dt \qquad \text{for } j = 1,2, \dots J. \tag{3}$$

The wavelet functions $\phi_{j,k}(t)$ and $\psi_{j,k}(t)$ are scaled and translated version of ϕ and ψ. The smooth coefficient 2^j control the amplitude of the wavelet window so the wavelet function is stretched or compressed to obtain frequency information. Since the scale factor is an exponential function when j gets larger so does 2^j and the functions $\phi_{j,k}(t)$ and $\psi_{j,k}(t)$ become more spread out and shorter. Therefore, a wider window gives information on the low frequency movements, whereas as narrower windows we get information on the high-frequency movements.

As shown by shown by Bruce and Donoho (1996) if the wavelet coefficients can be approximated by the integral in Eq. (2) and Eq. (3) then a multi-resolution representation in Eq. (1) can be simplified

$$F(t) = S_J + D_J + D_{J-1} + \cdots + D_j + \cdots + D_1\,, \quad j = 1, \dots, J \tag{4}$$

where D_j is the j-th level wavelet and S_J represents the aggregated sum of variations at each detail of the scale.

In Eq. (1) and Eq. (4) the father wavelet reconstructs the smooth and low-frequency parts of a signal, whereas the mother wavelet function describes the detailed and high-frequency parts of a signal. Therefore, the expression in Eq. (4) provides a complete reconstruction of the time series partitioned into a set of j frequency components so that each component corresponds to a particular range of frequencies.

In Eq. (1) and Eq. (4) the father wavelet reconstructs the smooth and low-frequency parts of a signal, whereas the mother wavelet function describes the detailed and high-frequency parts of a signal. In empirical applications to financial data, the father wavelet can be interpreted as the trend (smooth component) which is longest time-scale component of the series, and mother wavelets can be interpreted as the cyclical components around the trend. Therefore, the expression in Eq. (4) provides a complete reconstruction of the signal partitioned into a set of j frequency components so that each component corresponds to a particular range of frequencies. The low-frequency part can detect what in the literature has been referred to as "interdependence", whereas the high-frequency part may reflect "pure" contagion. A similar interpretation was suggested in Gallegati (2012), see also Huang *et al*. (2015).

In the literature several variations of wavelet transform in Eq. (4) have been proposed (see for example Cohen, 1992). In this paper we consider the Maximal Overlap Discrete Wavelet Transform (MODWT). The MODWT has the advantage that the estimated wavelet and scaling coefficients are translation invariant to circularly shifting in the sense that they do not change if the series are shifted in a circular fashion and the smooth coefficients are associated with zero phase filters (for details see Percival and Walden, 2000; Gencay, 2002).

Step 2: *WC-GARCH Model*

The second step of the suggested procedure involves using the filtered series obtained from the j-level multi-resolution decomposition to estimate the copula functions in the time-frequency framework. This second stage requires: *a*) estimating the marginal distributions of the decomposed stock market series, *b*) specifying the copula function, and *c*) estimating the copula.

a) *Marginal Distributions*

The copula estimation procedure used in this paper heavily relies on the results of the Sklar theorem (see Sklar, 1959). According to Sklar's theorem, a two-dimensional joint distribution function G with continuous marginals F_X and F_Y has a unique copula representation so that

$$G(x, y) = C\left(F_x(x), F_y(y)\right),$$

and for a joint distribution function, the marginal distributions and the dependence structure described by a copula can be separated.

Let $\{D_{j,A}\}$ and $\{D_{j,B}\}$ be the stochastic processes denoting the j decomposed signal obtained from the wavelet transform in Eq. (4) for the stock market returns $\{R_A\}$ and $\{R_B\}$, respectively. Note that to simplify the notation, wherever possible the t subscription is omitted at no detriment of the analysis.

Let their conditional cumulative distribution functions (CDFs) be $F_{D_{j,A}}(R_A; \theta_A)$ and $F_{D_{j,B}}(R_B; \theta_B)$. The conditional copula function is defined as $C(u_t, v_t)$ where frequency component $u = F_{D_{j,A}}(R_A; \theta_A)$ and $v = F_{D_{j,B}}(R_B; \theta_B)$ are continuous variables in (0,1).

Using the Skar's theorem, for a given D_j in Eq. (4), the bivariate joint conditional CDF of $\{R_A\}$ and $\{R_B\}$ can be written as

$$G(R_A, R_B) = C\left(F_{D_{j,A}}(R_A, \theta_A), F_{D_{j,B}}(R_B, \theta_B); \pi\right) \tag{5}$$

where π is a parameter vector for the copula, θ_A, θ_B are parameter vectors for each marginal distribution, and $\theta - (\pi', \theta_A', \theta_p')$ is a parameter vector for the joint distribution. The expression in Eq. (5) decomposes the joint distributions into marginal distributions, $F_{D_{j,A}}$, $F_{D_{j,B}}$, and a copula, *C*, representing the dependence structure among the frequency component for the stock market indexes under consideration. Therefore, the expression in Eq. (5) allows us to model marginal distributions and dependence structure separately. However, to make the expression in Eq. (5) operational, the estimation of the marginal distributions is required. To obtain the marginal distributions of D_j in Eq. (4) the GARCH-GJR (1,1) model suggested by Glosten *et al*. (1993) can be used. Specifically, the model for the margins can be expressed as

$$D_{j,t} = \mu + \varepsilon_t, \tag{6}$$

$$\varepsilon_t = Z_t \sqrt{h_t}, \tag{7}$$

$$h_t^2 = \delta + \alpha \varepsilon_t^2 + \gamma \varepsilon_{t-1}^2 M_{t-1} + \beta\, h_{t-1}^2 \tag{8}$$

$$Z_t \sim GHD(\lambda, \chi)$$

where Z_t is a generalized hyperbolic distribution with shape parameters λ and χ. Eq. (6) decomposes the returns into a constant, μ, and an innovation process, ε_t. The expression in Eq. (7) defines this residual as a product of conditional volatility and innovation. Eq. (8) describes the dynamics of conditional volatility which is explained by the coefficients α, β and γ. The parameters measure the size effect and persistence of the shocks on volatility, respectively. The impact of the shocks on the conditional volatility is determined the sign of the parameter γ of the dummy variable, *M*, such that $M_t = 1$ if $\varepsilon_t < 0$ (bad news) and $M_t = 1$ otherwise. Note that the WC-GARCH procedure is a general method which can be readily extended to any GARCH-type model. Therefore, we suggest the investigator of experimenting with several types of GARCH specifications and selecting the model that better describes the data at hand.

b) *Copula Function*

The marginal GARCH-GJR(1,1)-GHD parameter estimates in Eq. (6) provides estimated values of the conditional cumulate distribution function for each frequency component D_j. Therefore, the bivariate copula function with dependence parameter θ is expressed by the following function

$$c(u_t, v_t) = \left(max\{u_t^{\theta} + v_t^{\theta} - 1{,}0\}\right)^{\frac{1}{\theta}}, \tag{8}$$

where $\theta \geq 1$. Note that if $\theta \to 0$, then $\{R_{\mathrm{A}}\}$ and $\{R_B\}$ are independent in D_j, whereas they are perfectly dependent in $\theta \to \infty$. Expression in Eq. (8) is the Clayton copula, among different pair-copula families, Clayton's is preferred for financial data since it allows for more asymmetric tail dependence in the negative tail than in the positive (for more details see, among others, Nikoloulopoulos *et al*., 2012).

c) *Estimation Method*

Under the assumption that all condition CDFs are differentiable, from the Sklar's theorem the joint density function of $D_{j,A}$ and $D_{j,B}$ can be expressed as

$$G(D_{j,A}, D_{j,B}) = \frac{\partial G(D_{j,A}, D_{j,B})}{\partial D_{j,A} \partial D_{j,A}} = C\left(F_{D_{j,A}}(R_A, \theta_A), F_{D_{j,B}}(R_B, \theta_B)\right) \times f_{D_{j,A}}(R_A, \theta_A) \times f_{D_{j,B}}(R_B, \theta_B), \tag{9}$$

where $c(u_t, v_t)$ is the conditional copula density function in Eq. (8). Thus, for each time scale D_j in Eq. (4), the bivariate conditional density function of $\{R_A\}$ and $\{R_B\}$ is represented by the product of the copula density and the two conditional marginal densities $f_{D_{j,A}}(R_A, \theta_A)$ and $f_{D_{j,B}}(R_B, \theta_B)$. From Eq. (9) the log-likelihood function, $log(\theta)$, can be obtained as

$$\log\left(G(D_{j,A}, D_{j,B})\right) = log\left(c(u_t, v_t)\right) + log\left(f_{D_{j,A}}(R_A, \theta_A)\right) + log\left(f_{D_{j,B}}(R_B, \theta_B)\right). \tag{10}$$

To estimate Eq. (10) we use the inference for the margin method suggested in Joe (1997) that involves estimating the parameters of each univariate model via maximum likelihood first, and next the marginal CDF are applied to the standardized residuals.

4. Data and Estimation Results

The data considered in this study are daily closing equity market price indices for six markets. In particular, we consider the S&P500 Composite Index (S&P 500) for the United States, the S&P TSX Composite Index, (S&P/TSX) for Canada, the FTSE 100 Price Index (FTSE100) for the UK, the Nikkei 225 Stock Average Index (N225) for Japan, the Hang Seng index (HIS) for Hong Kong and the Shanghai Share Index (SSE) for China. The HIS index enables us to investigate stock market contagion between Mainland China's markets and Honk Kong. Similarly, the S&P/TSX Composite Index is considered to investigate spill over effects in the North American region

The sample covers the period from January 1st, 2014 to August 8th, 2020. Stock returns are calculated as the difference between the logarithm of the price index. Further, the missing data arising from holidays and special events are bypassed by assuming them to equal the average of the recorded previous price and the next one. Note that that in this application the U.S. stock market is used as a numeraire for the correlations. Therefore, below we consider the level of comovements between the S&P500 and the other stock markets listed above.

4.1. Multiscale Analysis of Correlation

In this section we present the results of estimating the WC-GARCH model. However, as a preliminary investigation, we take advantage of the time-scale decomposition property of the wavelet to calculate the multiscale correlation between the S&P500 and other stock markets. To investigate this issue we follow Fernandez-Macho (2018) and use the time-localized multiple regression model to estimate time varying correlation between precious metals and stock markets. The method allows to calculate the set of multiscale correlations along time and across different scales by estimating a series of windowed wavelet coefficients. Therefore, the wavelet correlation coefficient $\rho_{A,B}(\lambda_J)$ provides a standardized measure of the relationship between the two processes on a scale-by-scale basis and, as with the usual correlation coefficient between two random variables, we assume that $|\rho_{A,B}(\lambda_J)| \leq 1$.

In Figure 1-5, the correlation patterns between the S&P500 and the other stock market indexes are presented in a time-frequency domain on a scale by scale basis. For ease of interpretation, the left-hand horizontal axis is transformed to show the number of days in which the scale moves from low to high wavelengths. The heat maps indicate the increasing strength of the correlation among the stock markets indexes as they move from blue (lowest correlation) to red (highest correlation).

Since related empirical works have shown that a moderate-length filter of length eight is adequate to deal with the characteristic features of financial data (see Gençay *et al*., 2001), we use the Daubechies compactly supported least asymmetric (LA) wavelet filter (Daubechies, 1992). Then, using the wavelet coefficients we estimate the wavelet-unbiased pairwise correlation coefficients. For the choice of ϕ and ψ in Eq. (1) the doublet wavelet function with length 8 is used for this study.

For the multi-resolution level j, this study sets $j = 6$, thus the highest frequency component D_1 represents short-term variations due to shocks occurring at up a time scale of $2^2 = 4$ days, and the next highest component D_2 accounts for variations at a time scale of $2^3 = 8$ days, near the working days of a week. Similarly, D_3 and D_4 components represent the mid-term variations at time scale of $2^4 = 16$ and $2^5 = 32$ days, respectively. Finally, D_5 and D_6 components represent the long-term variations at time scale of $2^6 = 64$ and $2^7 = 128$ days. S_6 is the residual of original signal after subtracting D_1, D_2, D_3, D_4, D_5 and D_6.

Before giving an interpretation on the results of the correlation analysis, one issue that still has to be resolved is the following: For how many days should the increase in correlation between two stock markets last in order to be classified "pure" contagion? This gives us a definition of "interdependence" in turn. Theoretical literature offers only limited help on this matter. According to the market efficiency hypothesis (EMH) stock market prices should reflect all the information made available to market participants at any given time (see Fama, 1970). The EMH therefore implies that the transmission of shocks due to contagion in international financial markets should not exist in the long run. Based on these considerations several papers suggest that the transmission of shocks due to contagion in international financial markets should be very fast and should die out quickly. For example, Gallegati (2012) suggests that to be classified as "pure" contagion the increase of correlation should generally not exceed one week (see also Dewandaru *et al*., 2016). However, in this paper we argue that the Covid-19 pandemic caused a spike in uncertainty unseen in previous crises (see Baker, 2020). In the light of these arguments, we suggest that the definition of "pure" contagion adopted in the related empirical studies should be taken more liberally. For this reason, we assume that the first five wavelet scales provide a realistic measure of contagion, as these scales are associated to changes of up 64 days in correlation shifts. Accordingly, in this paper "pure" contagion is measured by wavelet coefficients $D_1,\ldots, D_5$, whereas "interdependence" is measured by the D_6 scale and the trend, S_6.

From Figures 1-5, there is clear evidence of long-run interdependence between the U.S. stock market and the other markets before the start of the Covid-19 pandemic in December 2019. To be specific, starting with the correlation between the U.S. stock market and the U.K. market, Figure 1 indicates no sign of comovements for the first 8-16 days, but correlation increases in the time scale D_6 between January 2014 and June 2017. Similarly, in Figure 2, it appears that the U.S. and Japan stock markets have stronger long-term comovements since, once again, we see the red colour in the D_6 time scale. As for the correlation between the U.S. and China, weak correlation can be seen for the time scale D_3 and below, as highlighted in Figure 3.

Signs of fundamental-based contagion between the U.S. and Hong Kong stock markets can also be observed in Figure 4, where shock events in the S&P 500 directly diffused to HIS. The correlation between the stock markets in U.S. and Canada, shown in Figure 5, indicates persistent comovements between these financial markets since Canada has close commercial and financial ties to the US economy.

Overall, results in Figure 1-5 suggest that before the Covid-19 pandemic started, the transmission mechanism of shocks was related to normal dependence between markets, due to trade links and geographical position. Therefore, the type of transmission mechanism of shocks that characterised the period before the health crisis began seems better be described as "interdependence" (see Forbes and Rigobon, 2002).

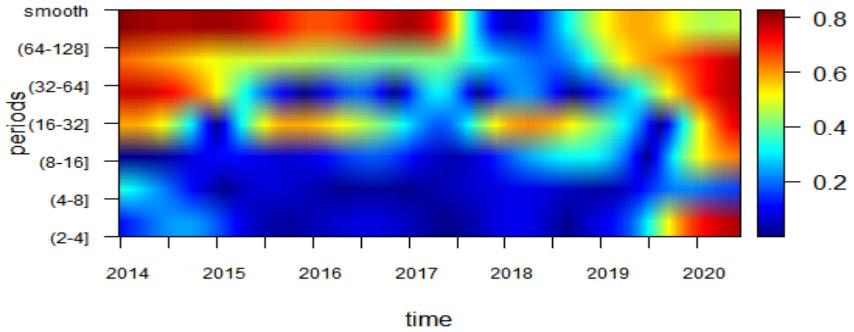

Figure 1: Wavelet multiple correlation between S&P500 and FT100 stock markets returns.

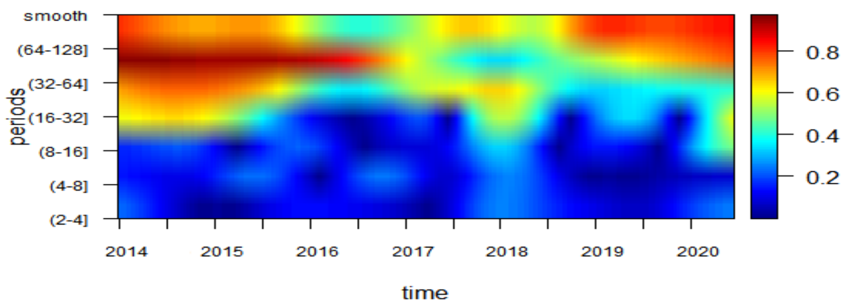

Figure 2: Wavelet multiple correlation between S&P500 and N225 stock markets returns.

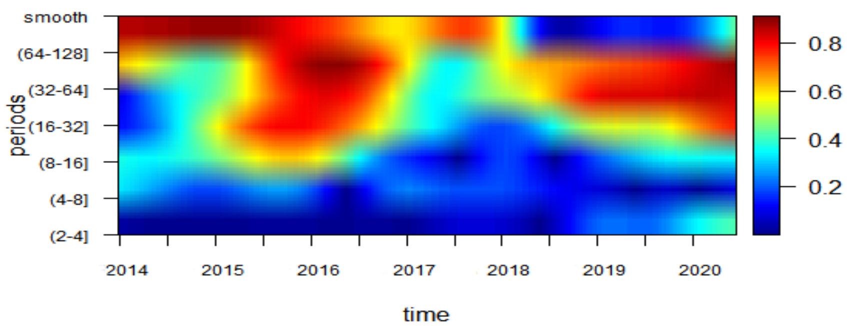

Figure 3: Wavelet multiple correlation between S&P500 and HIS stock markets returns.

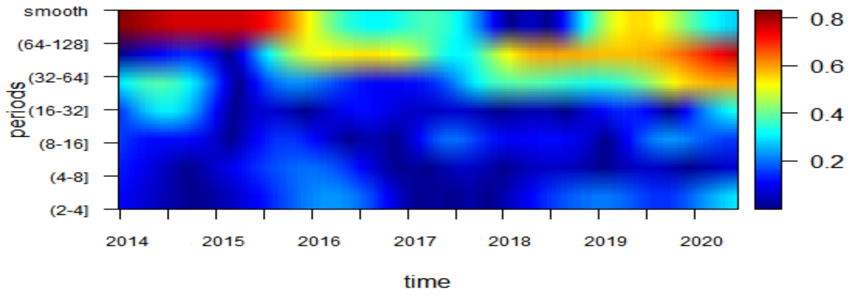

Figure 4: Wavelet multiple correlation between S&P500 and SSE stock markets returns.

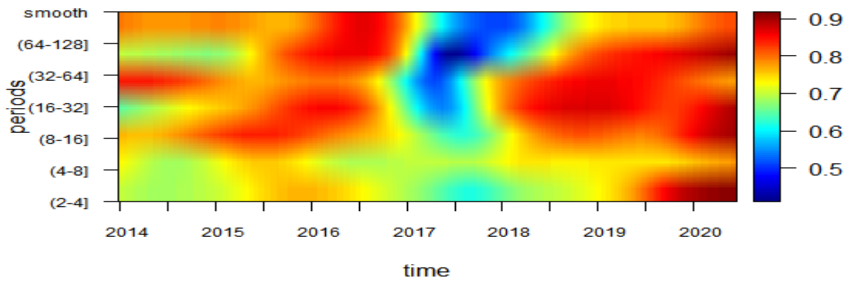

Figure 5: Wavelet multiple correlation between S&P500 and S&P/TSX stock markets returns.

Once the impact of Covid-19 pandemic was felt worldwide, financial assets were immediately repriced. Panic spilled over all the major financial markets as indicated by the wavelet power of pairwise analysis analysed at lower scale brackets. Put differently, the comovements (either positive or negative) seem to have been stronger during the Covid-19 pandemic in most of the series under consideration. Specifically, with the notable exception of Japan, the financial markets under consideration showed significant dominant signs of comovement at periods of high frequency up to 64 days in length. In the case of the correlation UK and Canada, the market contagion appears to be even stronger, as indicated by the red colour in Figures 1 and 5.

The results of the wavelet analysis Figure 1-5 section show a degree of comovement between the U.S. and other financial markets. This suggests that a parametric analysis may reveal more insights on the contagion effects during the Covid-19 outbreak.

4.2. WC-GARCH Procedure Estimation Results

Once the filtered series were extracted in the second step of our analysis, appropriate univariate GARCH models were estimated for the six stochastic processes under consideration. Comparing a number of GARCH-type models, we concluded that the specification that best fitted the data under consideration was a GJR-GARCH model with a GHD distribution for the innovation terms. In order to investigate the effect of the Covid-19 pandemic the sample under consideration was split in two subperiods: the first with $T = 1465$ including data from January 2nd, 2014 to November 29th, 2019, and the second subperiod including a sample of $T = 172$ including observations from December, 2nd 2019 to August 8th, 2020.

The WC-GARCH procedure suggested in Section 3 involves estimating a total of $(6 \times D_j) = 36$ GARCH-GJR (1,1) models for each subperiod. This gives the staggering total of 72 models to be estimated. To save space, the estimation results are not reported here, but they are available upon request. However, to give an idea of the magnitude of the estimated coefficients for the conditional variance equations, the estimation results for the marginal distributions for the six stock market under consideration in the two subperiods are reported in Table 1A-B.

Table 1A and Table 1B present the parameter estimates GARCH-GJR (1,1) for models estimated for the period before and during the Covid-19 outbreak, respectively. From Table 1A-B it appears that stock market indexes are highly persistent since the magnitude of the estimated parameters β is relatively high for all the estimated series. In Table 1A-B it also appears that bad news impact stock market volatility, since all the estimated γ are significantly different from zero. Furthermore, the diagnostic tests included at the bottom of Table 1A-B reject the null hypothesis of autocorrelation up to the 10th lag order.

Finally, from Table 1B it appears that the all the estimated β coefficients are greater in magnitude than those in Table 1A, indicating that the Covid-19 outbreak increased persistence in the stock markets. On the other side, the estimated coefficients for α and γ in Table 1B, in average, do not vary much with respect to those in Table 1A.

Table 1A. Estimation single equation models for the stick market indexes under consider before the Covid-19 outbreak.

	GSPTSE	GSPC	FTSE100	HIS	SSE	N225
α	0.145**	0.343**	0.324*	0.107*	0.077*	0.201*
	(0.044)	(0.167)	(0.002)	(0.049)	(0.003)	(0.011)
β	0.839*	0.652*	0.674**	0.881*	0.907*	0.791**
	(0.016)	(0.109)	(0.241)	(0.203)	(0.310)	(0.360)
γ	-0.708*	-.325**	-0.258**	-0.526*	0.301**	-0.685*
	(0.154)	(0.112)	(0.159)	(0.017)	(0.171)	(0.291)
ARCH Lag (10)	2.624	5.161	4.599	3.233	3.923	3.452
	[0.417]	[0.195]	[0.257]	[0.396]	[0.403]	[0.368]

Note: The table reports the estimation results of the GARCH-GJR(1,1) for the stock market under consideration. Squared brackets indicate the *p*-values, standard errors are reported below the estimated coefficients. Note that *), **) and ***) indicate significance at 1%, 5% and 10%, respectively. The tests for autocorrelation for the estimated models are also reported.

Table 1B (Continue). Estimation single equation models for the stick market indexes under consider after the Covid-19 outbreak started.

	GSPTSE	GSPC	FTSE100	HIS	SSE	N225
α	0.084**	0.034**	0.203*	0.062*	0.076*	0.191*
	(0.033)	(0.156)	(0.013)	(0.360)	(0.008)	(0.020)
β	0.902*	0.905*	0.705*	0.917*	0.920*	0.814**
	(0.005)	(0.098)	(0.011)	(0.214)	(0.321)	(0.371)
γ	0.636*	-0.397*	-0.330**	-0.598*	0.228**	-0.757**
	(0.143)	(0.101)	(0.148)	(0.028)	(0.182)	(0.301)
ARCH Lag (10)	2.364	4.649	4.144	2.913	3.534	3.110
	[0.432]	[0.235]	[0.327]	[0.476]	[0.354]	[0.308]

Note: The table reports the estimation results of the GARCH-GJR(1,1) for the stock market under consideration. Squared brackets indicate the p-values, standard errors are reported below the estimated coefficients. Note that *), **) and ***) indicate significance at 1%, 5% and 10%, respectively. The tests for autocorrelation for the estimated models are also reported.

Table 2A-2B present the results of the pairwise correlation in the time-frequency domain between the S&P500 and the other stock market returns obtained using the suggested WC-GARCH procedure.

Table 2A. WC-GARCH-GJR(1,1) estimation results before the Covid-19 outbreak**.**

	D_1	D_2	D_3	D_4	D_5	D_6
FTSE100	0.433	0.476	0.513	0.570	0.818	0.769
N225	0.056	0.114	0.178	0.359	0.456	0.782
SSE	0.062	0.067	0.041	-0.187	0.269	0.414
HIS	0.144	0.186	-0.331	-0.407	0.431	0.584
S&P TSX	0.596	0.674	0.563	0.631	0.762	0.863

Note: The table reports the WC-GARCH results which give the estimated correlations between the SP500 and the other stock market indexes by frequency. The oscillation periods are 2-4, 4-8, 8-16 days, 6-32, 32-64 days and 64-128 days defined as D_1, D_2, D_3, D_4, D_5 and D_6, respectively between the U.S. and the other stock markets under consideration.

Table 2B. WC-GARCH-GJR(1,1) estimation results during Covid-19 crisis.

	D_1	D_2	D_3	D_4	D_5	D_6
FTSE100	0.582	0.617	0.652	0.768	0.832	0.856
N225	0.172	0.148	0.209	0.226	0.212	0.219
SSE	0.271	0.228	0.370	0.352	0.417	0.433
HIS	0.191	0.216	0.257	0.242	0.245	0.237
S&P TSX	0.645	0.724	0.746	0.758	0.824	0.876

Note: The table reports the WC-GARCH results which give the estimated correlations between the SP500 and the other stock market indexes by frequency. The oscillation periods are 2-4, 4-8, 8-16 days, 6-32, 32-64 days and 64-128 days defined as D_1, D_2, D_3, D_4, D_5 and D_6, respectively between the U.S. and the other stock markets under consideration.

In Table 2A, the pairwise dynamic correlations for the pre-Covid-19 period are reported. From Table 2A it appears that the correlations substantially increase when the timescale increases. In this regard, from columns two, three and four it seems that the tail dependence is relatively weak in the short-run (time scales D_1, D_2 and D_3) and increases by each decomposition in the pre-crisis period. These results are in agreement with the finding in Figure 1-5. For time scale D_4, in column five, it appears that the correlations are higher for all the markets. In particular, the stock returns can be divided into closely correlated markets (Canada and the U.K.) with correlation coefficients around 0.6 and 0.57, respectively. Moderately correlated markets (Japan and Hong Kong) with correlation coefficients 0.36 and 0.41, respectively and mildly correlated markets for those markets whose correlation was less than 0.2, as in China for example.

From time scales D_5 and D_6, the differences in stock market interdependencies begin to show and are relatively high in D6. The U.K. and Canada have the highest correlation with the U.S., since the correlation is higher than 0.75 in these markets for the longest time brackets. Looking now at the remaining stock markets, also in this case the correlation increases with the time scale. For example, the correlation between the U.S. and Japan's was approximately 0.5 in D_5 and increases to approximately 0.8 in D_6, whereas Hong Kong's correlation between approximately 0.4 and 0.6. China's correlation varied substantially and was eventually slightly lower than Japan's, at approximately 0.4 in D_6. Overall, the results in Table 2A are in line with the definition of fundamental-based contagion where spillovers result from the normal interdependence among market economies.

The picture dramatically changes in Table 2B where tail dependency increases in the frequency scale D_1 and D_2 for all the stock market under consideration, thus suggesting the existence of "pure" contagion even according the strict criteria of contagion adopted by Gallegati (2012) and Dewandaru *et al*. (2015). Looking at scales D_3 and D_4 there is still evidence of volatility spillovers after a shock for up to 32 days for all stock markets, but HIS. Looking at the longest frequency scales, the picture changes, as for most pair-wise stock market indexes the estimated correlation coefficients are smaller or approximately the same. Taken together, these results suggest that the Covid-19 pandemic was a source of contagion not linked to observed changes in macroeconomic fundamentals but is mainly the result of the behaviour of investors or other financial agents.

5. Conclusion

In this study we propose a novel procedure to investigate the occurrence of cross market linkages during the Covid-19 pandemic. The main novelty of our model lies in combining wavelet analysis with copula estimation. In other words, the decomposed series obtained from the wavelet spectrum analysis are used to estimate a copula-GARCH model. An interesting feature of the WC-GARCH procedure is its ability of unveiling relationships between stock market returns in the time-frequency domain, allowing a simultaneous assessment of the relationship between markets at different frequencies and the evolution of these links over time. In this respect, the procedure provides an alternative representation of the correlation structure of stock market returns on a scale-by-scale basis.

To investigate cross-market linkages we distinguish between regular "interdependence" and "pure" contagion and associate changes in correlation between stock market returns at higher frequencies with contagion, that is a form of dependence that does not exist in tranquil periods but only occurs during periods of turmoil. On the other hand, changes at lower frequencies are associated with interdependence that relates to spillovers of shocks resulting from the normal dependence between markets and refers to the dependence that exists in all states of the world due to trade links and geographical position. The estimation results reveal evidence of long-run "interdependence" between the markets under consideration before the start of the Covid-19 pandemic in December 2019. However, strong evidence of "pure" contagion between stock markets was detected as the health crisis began.

Our results have important consequences since they show that despite the policy measures that have been put in place after the financial crisis of 2007-2008 still something still has to done to mitigate the impact of shocks on financial markets. The Covid-19 pandemic is the first health crisis that has the potential of triggering the devastating effects seen during the global financial crisis, which was arguably the first truly major global crisis since the Great Depression of 1929-32. The sub-prime financial crisis had its origin in the United States in a relatively small segment of the lending market but it rapidly spread across virtually all countries in the world. In this respect, if lessons have to be learned from past experience, evidence of long and short run cross-market linkages constitutes a wake-up call highlighting the need of policy measures to mitigate contagion.

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