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Spatial financial contagion during the COVID-19 outbreak: Local correlation approach

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ABSTRACT

The purpose of this paper is to examine the effect of spatial proximity on financial contagion during the COVID-19 outbreak. We use the daily stock index series of Asian, American, and European countries from January 1, 2014 to January 30, 2021. Two groups of countries are considered: the first includes China and geographically close countries, namely Taiwan, Hong Kong, Singapore, India, Australia, Indonesia, Malaysia, South Korea, Singapore, Vietnam and Russia. The second group includes countries that are geographically distant from China: the United States, Brazil, Mexico, Argentina, Italy, France and Germany. Using local correlation measurement and polynomial regressions, we show that the spatial contagion effect exists between China and geographically distant countries. However, this effect is absent for geographically close countries (Taiwan, Vietnam and Hong Kong).

These findings have strong implications for investors and present guidance for regulators and policymakers in understanding the true impact of the COVID-19 on financial markets.

1. Introduction

The World Health Organization declared the outbreak of COVID-19 as a global pandemic on March 11, 2020. It was first announced in December 2019 in China (in the city of Wuhan) and has since shaken the global financial markets. Following the announcement of this pandemic, the literature on the financial and economic effects of COVID-19 has been increasingly developed ever since (Devpura & Narayan, 2020; Mensi et al., 2020; Qiu et al., 2020; Salisu, 2020; Sharif et al., 2020; Akhtaruzzaman, Abdel-Qader, et al., 2021).

Several studies focus on the effects of COVID-19 on financial markets and financial assets such as gold, oil price exposure, and exchange rate prediction. For instance, Akhtaruzzaman et al. (2020) investigate the role of gold as a safe-haven asset during two phases of the COVID-19 outbreak using the intraday data and dynamic conditional correlations (DCCs) approaches. The authors find that gold is a safe-haven asset for the stock markets of the U.S., Japan and China. The authors also show that gold has lost this property for these markets during the second phase. In the same vein, Mensi et al. (2020) study the impact of the COVID-19 outbreak on the multifractality of gold and oil prices. Using Asymmetric Multifractal Detrended Fluctuation Analysis (A-MF-DFA), the authors find evidence of asymmetric multifractality and show that the efficiency of gold and oil markets is sensitive to COVID-19, highlighting the investor sentiment effect. Furthermore, Salisu, Vo, and Lawal (2020) examine the role of gold in hedging against the risks associated with crude oil prices. The authors use the asymmetric VARMA-GARCH model and find that gold is a significant safe-haven asset against oil price

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risks.

The literature on the impact of COVID-19 on the oil price exposure effect has been growing at a fast pace. Akhtaruzzaman, Boubaker, and Sensoy (2021) investigate the oil price risk exposure of financial and non-financial industries during the COVID-19 outbreak. The authors conclude that the COVID-19 outbreak mitigates the oil price risk exposure for both financial and non-financial industries. Devpura and Narayan (2020) investigate the evolution of hourly oil price volatility. Using different measures of oil price volatility, they show an increase in volatility after the onset of COVID-19. In the same vein, Salisu, Vo, and Lawal (2020) examine the response of oil and stocks to crisis using the panel Vector Autoregressive (pVAR) model. Using daily U.S. data and the wavelet-based Granger causality tests, Sharif et al. (2020) investigate the connectedness between the oil price volatility shock, the spread of the COVID-19 outbreak, the stock market, and both economic policy uncertainty and geopolitical risk. The authors find that the impact of COVID-19 on geopolitical risk is higher than on the U.S. economic policy uncertainty.

Moreover, several researchers focus on the effect of COVID-19 on the exchange rate prediction. Folger-Laronde et al. (2020), for instance, focus on the differences and the relationship between the financial returns of exchange-traded funds (ETFs) and their Eco-fund ratings during the COVID-19 outbreak. They find that the high sustainability performance levels of ETFs do not protect investments from financial loss during crises. He and Harris (2020) examine the effect of the COVID-19 outbreak on developments in corporate social responsibility (CSR) and marketing. Qiu et al. (2020) study the evolution of stock prices following the adoption of CSR activity during crisis. Using the event study methodology and the difference-in-difference approach, their results show that during COVID-19, CSR engagement has increased stock returns. Just and Echaust (2020) study the structural breaks in stock returns and focus on volatility expectations, illiquidity and correlation expectations during the COVID-19 outbreak. Using the two-regime Markov switching model, they detect a structural break between stock market returns and stock market indicators. The authors also find that stock market illiquidity does not affect stock market returns and is not related to COVID-19. Another study by Belaid et al. (2021) focuses on the consequences of the COVID-19 crisis on the interdependencies between advanced and emerging economies. The authors use daily market index data from 22 markets and show an increase in interdependence between emerging and advanced economies. The results also show an increase in the transmission of uncertainty between financial markets during the COVID-19 pandemic.

Due to such crises and shocks, the contagion phenomenon has become one of the most considered topics in finance (Rigobon, 2002; Kuusk & Paas, 2010). Several studies have defined the concept of contagion. As such, according to Eichengreen et al. (1996), contagion is the “significant increase in the probability of a crisis in one country, conditional on the occurrence of a crisis in another country”. Forbes and Rigobon (2002) present contagion as “a significant increase in cross-market linkages following a shock to an individual country (or group of countries)”. For their side, Bradley et al. (2004) and Fabrizio (2014) show that spatial contagion between two financial markets X and Y exists when there is a high dependence between X and Y.

Several studies have examined financial contagion (Eichengreen et al., 1996; Forbes & Rigobon, 2002; Dungey & Fry, 2009; Kenourgios et al., 2013; Kenourgios & Dimitriou, 2015; El Ghini & Saidi, 2015; Zorgati et al., 2019; Akhtaruzzaman et al., 2020). Indeed, Kenourgios et al. (2013) investigate financial contagion as a mechanism of asymmetric propagation in equity and change markets. They use an asymmetric generalized dynamic conditional correlation (AG-DCC) model and find that conditional correlations between stock markets increase significantly during a crisis period, supporting the presence of financial contagion. Kenourgios (2014) studies contagion during the subprime and euro zone crises. They apply conditional correlation dynamics for the two periods of crisis and non-crisis. Subsequently, Kenourgios and Dimitriou (2015) investigate the contagion effects of the subprime crisis by testing different channels of financial contagion via regions and sectors of the real economy. Using the dynamic conditional correlation approach, Akhtaruzzaman and Shamsuddin (2016) investigate contagion through financial and non-financial firms using 49 countries. The authors show that financial contagion is linked positively to the level of development of stock markets and the intensity of bilateral trade. Recently, Zorgati et al. (2019) investigate the existence of the financial contagion phenomenon in the context of the subprime crisis based on the copulas approach. They prove the existence of contagion effect between the U.S. and all other American countries as well as the Australian, Indian, Malaysian, Indonesian, Singaporean, and Chinese ones. Moreover, Akhtaruzzaman et al. (2020) find that Chinese and U.S. companies have transmitted more spillovers than they received during the global financial crisis.

Regarding the COVID-19 crisis, Akhtaruzzaman et al. (2020) show a significant increase in conditional correlations between different stock returns. Okorie and Lin (2020) show significant fractal contagion effects of COVID-19 on the stock markets' return and volatility using Detrended Moving Cross-Correlation Analysis (DMCA) and Detrended Cross-Correlation Analysis (DCCA) techniques.

Network approaches are also applied to study the financial contagion effect. Gai and Kapadia (2010) investigate how the impact of contagion is affected by overall and idiosyncratic shocks, changes in network structure, and asset market liquidity. The authors find that the financial system is robust but fragile. Using the Maximum Entropy method, Paltalidis et al. (2015) study systemic risk and the spread of financial contagion within the euro area banking system. Recently, Chakrabarti et al. (2021) investigate the interconnections of stock markets and the contagion effect during the COVID-19 outbreak. They show the existence of contagion in the global stock markets due to the COVID-19 pandemic. The network theory increases the understanding of structural changes and their interconnections between stock markets. Guo et al. (2021), investigate the tail risk contagion during the COVID-19 outbreak. They use the FARM-Selection approach and the time-varying financial network model. The authors show that the COVID-19 outbreak negatively influences the international financial system. Indeed, it increases tail risk spillovers for the international financial market. Moreover, using 19 international financial markets (including China, Singapore, Hong Kong, Japan, Taiwan, France, Germany, Brazil, and the U.S.), they find that COVID-19 influences the tail risk contagion in the local network system.

We draw on the work of Bradley and Taqqu (2004, 2005b) by studying spatial financial contagion during the COVID-19 outbreak. We consider Asian, American, and European countries over the period from January 1, 2014 to January 30, 2021. This paper extends the work of Kenourgios et al. (2013), who focused on financial contagion during the Asian crisis and used an asymmetric generalized dynamic conditional correlation (AG-DCC) model. Furthermore, it differs from Zorgati and Lakhal (2020) who investigate financial spatial contagion and compare findings by applying adjusted and local correlation approaches in the subprime crisis context. The purpose of this paper is to investigate the effect of spatial proximity on financial contagion during the COVID-19 outbreak using the local correlation approach.

The contribution of this paper is twofold: first, to the best of our knowledge, there are no studies that investigate the spatial aspect on financial contagion using the local correlation approach during the period of the COVID-19 pandemic. Indeed, the local correlation approach is a non-parametric dependence measure. It differs from other approaches such as those of cointegration, copulas, GARCH, simple and adjusted correlation. Indeed, it does not require the specification of stability and crisis periods. Moreover, the spatial aspect is rarely studied in the literature.

Second, we investigate the effect of spatial proximity on financial contagion by applying non-linear forms of dependence. If X denotes the return of market X, the contagion exists when there is more dependence in the lowest quantile of the distribution X than there is in the median of this distribution using the local correlation approach.

The data we consider covers the period from January 1, 2014 to January 30, 2021. We consider those countries in the same region as China. Two groups of countries are used: the first includes China and a number of geographically close countries, namely Taiwan, Vietnam, Hong Kong, Singapore, Japan, India, Indonesia, Australia, Malaysia, South Korea, Singapore and Russia. The second group comprises geographically distant countries from China: the United States, Brazil, Mexico, Argentina, Italy, France and Germany.

We focus on the geographic links between markets during the COVID-19 pandemic. For more robust results, we use local correlations and polynomial regressions. Our findings show that the spatial contagion effect exists between China and geographically distant countries, while it is absent for geographically close countries (Taiwan, Vietnam and Hong Kong).

The remainder of this paper is organized as follows: Section 2 presents the econometric methodology. Section 3 describes the collected data and relative descriptive statistics. Section 4 presents the results and discussion. Section 5 concludes the paper.

2. Econometric methodology

Numerous methods have been used to test the existence of the spatial contagion. Using a simple correlation approach, Calvo and Reinhart (1996), Forbes and Rigobon (2001), Corsetti et al. (2005), Forbes and Rigobon (2002) and Chiang et al. (2007) show that this measurement of contagion is biased due to the problems of heteroscedasticity, endogenous variables and omitted variables. Forbes and Rigobon (2001) use the adjusted correlation approach to correct this bias. However, the adjusted correlation power is weak due to the short period of crisis, making it difficult to detect contagion. Recently, attention has been paid to modelling the tail of the distribution of financial markets. Bjerve and Doksum (1993) recommend the local correlation approach as a non-parametric measure to overcome issues related to the simple and adjusted correlation approaches. This method is used for data which are not jointly Gaussian.

Bradley and Taqqu (2004) and Zorgati and Lakhal (2020) also use the local correlation approach. This method uses nonlinear forms of dependence and provides a better understanding on the degree of dependence between financial markets. Local correlation is a good and robust measure of dependence that allows for conclusions about the existence of spatial contagion between markets. This measure is different from other approaches such as cointegration, copulas, simple and adjusted correlation. It does not require the specification of stability and crisis periods. This method overcomes the difficulties of correlation breakdown tests, specifically when data are hand-collected.

Although Stove et al. (2014) find that the local correlation approach may better reveal an asymmetry in multivariate financial distributions rather than contagion, Bradley and Taqqu (2004, 2005a, 2005b), Inci et al. (2011) and Zorgati and Lakhal. (2020) show that local correlation is a local measure of dependence suitable for measuring financial contagion. It is a non-parametric measure used to handle nonlinear forms of dependency. Inci et al. (2011) compare international contagion patterns of different markets for a period of more than 20 years. Furthermore, Zorgati and Lakhal (2020) also use a long time frame to study spatial contagion between the markets during the subprime crisis.

Let $X = (x_t, t = 1, 2, \ldots n)$ and $Y = (y_t, t = 1, 2, \ldots n)$ the returns in two different financial markets. The local correlation approach is a dependence measure based on localizing a first order regression relation. Indeed, in a regression of Y on X, the parameters of regression and the residual variance may depend on X. This method allows for extending the links between correlation, regression slopes and the variance.

Following Bradley and Taqqu (2004), the linear regression model is presented as follows:

$$Y = \alpha + \beta(X)X + \sigma(X)\varepsilon = m(X) + \sigma(X)\varepsilon \tag{1}$$

With: $\varepsilon \to N(0, 1)$, α is the vertical intercept, $\beta(X) = m'(X)$is the slope of the regression function, $\sigma^2(X)$, is the residual variance and $m(x) = E(Y/X = x)$.

Bradley and Taqqu (2004) define the local correlation approach as follows: X and Y are two random variables and have finite variance. The local correlation between X and Y.at $X = x$ is given by

$$\rho(X) = \sigma_X\beta(X) / \left[\sigma_X^2\beta^2(X) + \sigma^2(X)\right]^{1/2} \tag{2}$$

With: σ_X the standard deviation of X.

And $\sigma_X^2 = \mathrm{var}(Y/X = x)$ the non-parametric residual variance.

To test the spatial contagion effect, Bradley and Taqqu (2004) investigate the contagion between markets using local correlation estimators.

Indeed, there is a spatial contagion from market X to Y if:

$$\rho(x_L) > \rho(x_M) \tag{3}$$

With $x_L = F_X^{-1}(0.025)$ the lowest quantile of the distribution $F_X(x) = P(X \prec x)$ of X and $x_M = F_X^{-1}(0.5)$ the.median of this distribution.

The choice of the 2.5% quantile depends on the notion of crisis. It can be reached when the data is heavily concentrated around the median. Although contagion may exist in this case, it may be irrelevant. We then need to study the data and the losses incurred at this quantile. Indeed, we use heavy-tailed distributions and losses may be significant.

The spatial contagion effect exists when there is more dependence in the lowest quantile of the distribution X than in the median of this distribution using the local correlation approach. Nadaraya (1964) presents two non-parametric regression methods for the estimation: the kernel regression and the polynomial local regression. Using the first method, the author finds that its estimators lack robustness. Therefore, he suggests the use of the local polynomial regression method.

In this study, we follow the estimation procedure of Bradley and Taqqu (2005a) based on local polynomial regression.

Our analysis procedure can be summarized in three steps:

Step 1. Consists of applying a local quadratic regression in order to infer$\beta(x_0)$. We use an optimal bandwidth for that regression.

The solution of the local polynomial regression problem is given by:

$$\widehat{\beta}\left(x_0\right) = x_0\Big)\left(x_0\right)\left(x_0\right)^T W_h\left(x_0\right) X_P\left(x_0\right)\Big)^{-1} X_P\left(x_0\right)^T W_h\left(x_0\right) y \tag{4}$$

We obtain the estimator of $\beta(x_0)$and deduce $\widehat{\beta}(x_M)$and$\widehat{\beta}(x_L)$.

Step 2. Consists of applying a local linear regression on the squared residuals to estimate $\sigma^2(x_0)$. In this case, we use another optimal bandwidth appropriate to the second regression.

We determine the estimator of residual variance at x_0 using theses equations (Bradley and Taqqu (2005a):

- If $\widehat{m}$ is biased,

$$\widehat{\sigma}^2\left(x_0\right) = \frac{e_1^T x_0\Big)\left(x_0\right)\left(x_0\right)^T W_{h_2}\left(x_0\right)\left(X_{p_2}\left(x_0\right)\right)^{-1} X_{p_2}\left(x_0\right)^T W_{h_2}\left(x_0\right)\widehat{r}^2}{1 + e_1^T x_0\Big)\left(x_0\right)\left(x_0\right)^T W_{h_2}\left(x_0\right)\left(X_{p_2}\left(x_0\right)\right)^{-1} X_{p_2}\left(x_0\right)^T W_{h_2}\left(x_0\right)\Delta} \tag{5}$$

- And if$\widehat{m}$is unbiased,

$$\widehat{\sigma}^2 = \frac{H_{p_2,h_2}\widehat{r}^2}{1 + H_{p_2,h_2}\Delta} \tag{6}$$

We obtain the residual variance estimator in this point and then deduce $\widehat{\sigma}^2(x_L)$and$\widehat{\sigma}^2(x_M)$.

Step 3. Consists of calculating the estimator of the local correlation $\widehat{\rho}(x_0)$and concluding whether or not the spatial contagion is present.

$\widehat{\rho}(x_0)$ is calculated as follows:

$$\widehat{\rho}^2(x_0) = \frac{s(X)\widehat{\beta}(x_0)}{\sqrt{s_X^2\widehat{\beta}^2(x_0) + \widehat{\sigma}^2(x_0)}} \tag{7}$$

Where $s_X^2 = \frac{1}{n-1}\sum_{i=1}^n (X_i - \overline{X}^2\Big)$ is the variance estimator$\sigma_X^2$and $\widehat{\beta}(x_0)$is the result of the quadratic local regression.

We then compute the Z-statistic, calculated as follows:

$$Z = \frac{\widehat{\rho}(x_L) - \widehat{\rho}(x_M)}{\sqrt{\widehat{\sigma}^2_{\widehat{\rho}(x_L)} + \widehat{\sigma}^2_{\widehat{\rho}(x_M)}}} \tag{8}$$

We use $\widehat{\rho}(x_0) = \frac{s(X)\widehat{\beta}(x_0)}{\sqrt{s_X^2\widehat{\beta}^2(x_0) + \widehat{\sigma}^2(x_0)}}$ and $\widehat{\sigma}^2_{\widehat{\rho}(x_0)} = \widehat{\sigma}_{\widehat{\beta}}^2(x_0)\frac{S_X^2}{\widehat{\sigma}^2_{(x_0)}}[1 - \widehat{\rho}^2(x_0)]^3$ to calculate $\widehat{\rho}(x)$ and $\widehat{\sigma}^2_{\widehat{\rho}(x)}$.

If $Z \succ z_{1-\alpha}$, we conclude that there is spatial contagion between the designed markets.

We adopt the spatial contagion test to draw a conclusion about the spatial contagion existence between China and different markets during the COVID-19 outbreak.

According to Bradley and Taqqu (2004), the test of spatial contagion is as follows:

$$H_0: \rho(x_L) \leq \rho(x_M)(nospatialcontagion)$$
$$H_1: \rho(x_L) \succ \rho(x_M)(spatialcontagion)$$

3. Data and descriptive statistics

3.1. Data description

We consider the daily series of stock indexes of Asian, American, and European countries.[1] Narayan (2015) documents that daily data is better than monthly data when the goal is to gain as much information as possible from the data. As are investigating the COVID-19 outbreak of 2019, the sampled period lasts from January 1, 2014 to January 30, 2021. We consider the first date of the pre-COVID-19 period as the January 1, 2014.

Using the adjusted and unadjusted correlation approaches, our sample covers both the pre-COVID-19 (1 January 2014–30 December 2019) and during COVID-19 (31 December 2019–30 January 2021) periods.[2]

Two groups of countries are considered: the first includes China (SSE), the country from which the COVID-19 outbreak originated, and geographically close countries: Taiwan (TWII), Malaysia (KLSE), Hong Kong (Hangseng HIS), Australia (AORD), Singapore (STI), Indonesia (JKSE), India (BSESN), South Korea (KS11), Vietnam (VNM), Japan (Nikkei225), and Russia (RTSI). The second group includes countries that are geographically distant from China: the United States (SP500), Brazil (BVSP), Mexico (MXX), Argentina (Merv), Italy (FTSEMIB), France (CAC40) and Germany (GDAXI).[3] All these countries were affected by the COVID-19 outbreak.

We calculate the daily returns from the return index.

$$r_t = 100^*(\log P_t - \log P_{t-1})\ t = 1, 2, 3, \ldots T$$

Where r_t is the daily returns and P_t is the price of the index at time t. We use local currency returns in our study.[4]

3.2. Descriptive statistics

Table 1 illustrates the characteristics of stock returns indexes for the various markets during the whole period. Table 1 shows that the mean of stock returns indexes is close to zero for all stock indices while being positive for all countries with the exception of Mexico, Vietnam, Singapore, Russia, Japan and Malaysia. The mean varies between −0.0135 (Russia) and 0.1328 (Taiwan). Table 1 also shows that the value of skewness is negative and far from zero for all stock returns indexes. Hence, the return distribution has a long tail on the left. In addition, the value of kurtosis is more than 3, indicating the non-normality of return series and the occurrence of extreme values. The distribution of index returns is then leptokurtic. The Jarque-Bera test supports this result as it shows that none of the return indexes is normally distributed. Finally, the Box-Pierce-Ljung portmanteau test of order 15 shows that most index returns are uncorrelated. These results support the use of the local correlation approach.

4. Results and discussion

We first begin our analysis by the use of an unadjusted correlation measure. We show the changes between the market correlations during the pre-COVID-19 and the COVID-19 periods and make a conclusion about the existence of contagion. Based on the studies of Forbes and Rigobon (2001), a contagion effect exists when this coefficient increases significantly during the crisis.

Table 2 reports the results of unadjusted correlation coefficient during pre-COVID-19 and COVID-19 periods and the t-statistics tests. We show that the correlation coefficient increases during the COVID-19 period for all markets studied and conclude on the existence of contagion for all markets. For instance, the correlation between the Chinese market and the Brazilian market is 0.1039 during the pre-COVID-19 period and 0.3128 during the COVID-19 period.

We then present in Table 3 the results associated with the adjusted correlation coefficient. We rely on the work of Forbes and Rigobon (2002) and Collins and Biekpe (2002) to test the existence of contagion. We show that the adjustment of heteroskedasticity significantly impacts on the results of the contagion tests and show the absence of contagion for all studied markets. Our results are consistent with those of Forbes and Rigobon (2002), who show the existence of interconnection between markets instead of pure contagion.

The results associated with the simple and adjusted correlation approaches are inconclusive and have certain limitations. Indeed, they are not sufficiently robust to conclude on the existence of contagion. Moreover, these approaches present short-term relationships between the stock markets and do not take into account the direction of causality between them.

Regarding the local correlation test, the first step was to infer$\beta(x_0)$ by making a quadratic local regression. We first determine the optimal bandwidth related to this regression. Table 4 presents the optimal bandwidth *h1* for China with different markets. We find that

[1] We choose countries that are affected by COVID-19 and for which data were available from January 2014, taking into consideration the spatial proximity of China. We consider that the countries in the same region with China are neighbours.

[2] The date 31 December 2019 is when the first case of COVID-19 was reported to the World Health Organization by China (2020).

[3] We note that the data are obtained from the website: http://fr.finance.yahoo.com/and that the empirical treatment is ensured from using the software R.

[4] Mink (2015) argues that the use of local currency returns is than common currency returns (e.g., USD). Furthermore, Akhtaruzzaman and Shamsuddin (2016) find the same results for financial contagion when they use local and common currency returns.

Table 1
Statistics summary.

Market	U.S	Brazil	Mexico	Argentina	Italy	France	Germany
n.obs	1828	1828	1828	1828	1828	1828	1828
Min	−12.76	−15.99	−6.638	−6.519	−18.54	−13.098	−13.054
Max	8.968	13.022	4.180	6.1726	8.549	8.0560	10.414
Mean	0.034	0.0438	−0.0076	0.0232	0.0009	0.0082	0.0164
Variance	1.249	2.8224	0.9269	0.7799	2.3428	1.538	1.6289
Stdev	1.1179	1.6800	0.9627	0.8831	1.5306	1.2401	1.2762
Skewness	−1.079	−1.063	−0.594	−0.8442	−1.738	−1.193	−0.7728
Kurtosis	23.567	15.150	5.299	8.4035	19.292	12.7608	11.747
J.B	39265***	16412***	2069.5***	5153.2***	26941***	11818***	9845.5***
Q(15)	399.56***	120.51***	74.354***	51.385***	52.057***	73.977***	69.308***
Market	Taiwan	Hong Kong	Japan	Singapore	India	Indonesia	Malaysia
n.obs	1828	1828	1828	1828	1828	1828	1828
Min	−47.692	−6.018	−14.343	−13.25	−14.10	−6.805	−5.4047
Max	9.7732	4.924	13.234	13.246	8.5948	4.653	6.626
Mean	0.1328	0.0034	−0.0006	−0.009	0.0352	0.0103	−0.0086
Variance	7.3254	1.278	2.5550	3.487	1.1797	0.9173	0.4358
Stdev	2.7065	1.1307	1.5984	1.8673	1.0861	0.9577	0.66021
Skewness	−3.5899	−0.394	−0.5656	−0.593	−1.691	−0.63381	−0.4144
Kurtosis	59.898	2.768	12.352	8.960	27.057	5.3536	12.8742
J. B	255087***	582.11***	15064.6***	5730.7***	52124***	2123.9***	11671***
Q(15)	21.869	26.334***	53.2141***	31.157	121.45***	28.324	44.936***
Market	South Korea	Vietnam	Russia	Australia	China		
n.obs	1828	1828	1828	1828	1828		
Min	−8.766	−11.326	−7.637	−10.009	−8.872		
Max	8.2512	7.8296	5.8946	6.354	6.3693		
Mean	0.0084	−0.0093	−0.0135	0.0083	0.0264		
Variance	0.8903	2.1348	0.7585	0.9867	2.0471		
Stdev	0.9435	1.46112	0.8709	0.9933	1.4307		
Skewness	−0.313	−0.6569	−0.7214	−1.3603	−1.143		
Kurtosis	13.668	5.9902	10.9605	15.146	7.7076		
J. B	13128***	2638.7***	8570.7***	16604***	4533.8***		
Q(15)	83.862***	31.372	48.89***	135.06***	86.275***		

Notes.
J.B: The Jarque–Bera test, used to check the normality of the return distribution.
Q(15): The Box–Pierce–Ljung statistic for autocorrelation, which is distributed as a $\chi 2$ with 15 degrees of freedom.
, and * represent significance at 5%, and 1% levels, respectively.

for the group of countries geographically close to China, bandwidth *h1* is between 0.2150 (China/Australia) and 1.1586 (China/Taiwan), while for American and European countries, *h1* is between 0.4572 (China/Argentina) and 1.0181 (China/France).

Bandwidth *h1* is only related to this quadratic local regression. We next apply another linear local regression using bandwidth *h2* (Table 2). This step is important for the estimation of $\beta(x_0)$and $\sigma^2(x_0)$.

Following the identification of the bandwidth *h1*, we estimate$\beta(x_0)$and deduce$\widehat{\beta}(x_L)$and$\widehat{\beta}(x_M)$, where $x_M = F_X^{-1}(0.5)$ is the median of the distribution and $x_L = F_X^{-1}(0.025)$ is the lowest quantile of this distribution. Table 5 presents the estimators$\widehat{\beta}(x_L)$and $\widehat{\beta}(x_M)$for the two groups of countries during the whole period of study. We show that $\widehat{\beta}(x_L)$is greater than$\widehat{\beta}(x_M)$and is negative for China and Hong Kong (−0.0201) and for China and Malaysia (−0.0021). Moreover, the slope $\widehat{\beta}(x_M)$is negative for all studied markets and therefore there is a negative relationship between the Chinese stock indexes returns and the other index returns.

The next step in this study is to infer $\sigma^2(x_0)$. The estimation procedure of $\sigma^2(x_0)$ is identical to the one used in the first step. We make a local linear regression on the squared residuals to infer the residual variance $\sigma^2(x_0)$. We follow Ruppert et al. (1997) by using the asymptotically optimal bandwidth estimate which is suitable for this regression.

The polynomial (*p* = *1*) in this step is different from the one found in the quadratic regression (*p* = *2*). Moreover, the bandwidth *h2* differs from *h1*. The value of *h2* is given in Table 2 and is between 0.2004 (China/India) and 1.1279 (China/Taiwan) for the group of countries which are close to China and between 0.3854 (China/India) and 0.8099 (China/France) for the other group. Table 6 presents the estimation of residual variance for China and other countries associated with points x_L and x_M. We find that $\widehat{\sigma}^2(x_L)$is higher than$\widehat{\sigma}^2(x_M)$. We use these estimators to compute the estimator of local correlation.

In the last step, we determine$\widehat{\rho}(x_0)$and draw a conclusion.regarding the presence of spatial contagion for China and the two groups of countries during the COVID-19 period. Table 7 reports the local correlations estimators associated with the x_L and x_M points ($\widehat{\rho}(x_L)$ and$\widehat{\rho}(x_M)$ for China with different markets. We note first that$\widehat{\rho}(x_L)$and$\widehat{\rho}(x_M)$have the same sign as$\widehat{\beta}(x_L)$and$\widehat{\beta}(x_M)$. We then conclude

Table 2
Unadjusted correlation during pre-COVID-19 and COVID-19 periods.

Markets	Pre-covid19	Covid-19	t-student	Contagion?
	P	ρ		
China/USA	0.1459	0.2874	5.98262***	yes
China/Brazil	0.1039	0.31287	8.7360***	yes
China/Mexico	0.1377	0.2633	5.322***	yes
China/Italy	0.1089	0.2692	6.7598***	yes
China/France	0.1696	0.3575	7.8868***	yes
China/Germany	0.163	0.3541	8.0164***	yes
China/Argentina	0.0694	0.3049	9.789***	yes
China/Hong Kong	0.5212	0.6298	4.6110***	yes
China/Taiwan	0.3065	0.4956	7.93550***	yes
China/Japan	0.091	0.183	3.91264***	yes
China/Russia	0.0768	0.2823	8.59691***	yes
China/India	0.1882	0.4372	10.3192***	yes
China/Indonesia	0.1720	0.3604	7.9071***	yes
China/Malaysia	0.1686	0.4820	12.772***	yes
China/South Korea	0.2799	0.5047	9.3670***	yes
China/Vietnam	0.1497	0.3791	9.5492***	yes
China/Singapore	0.3218	0.5193	8.2750***	yes
China/Australia	0.2235	0.4003	7.4355***	yes

Notes.
t-student's critical values are (2.326), (1.645) and (1.282) at the 1%, 5% and 10% levels respectively.
*** and ** denote statistical significance at the 1% and 5% levels, respectively.
ρ : The unadjusted correlation coefficient.

$$\rho_{(x_t,y_t)} = \frac{\mathrm{cov}(x_t, y_t)}{\sigma_{x_t}\sigma_{y_t}}.$$

$$t = (\rho_1^* - \rho_2^*)\sqrt{\frac{n_1 + n_2 - 4}{1 - (\rho_1^* - \rho_2^*)^2}} \rightarrow t(0.05, n1 + n2 - 4)$$

Table 3
Adjusted correlation during pre-COVID-19 and COVID-19 periods.

Markets	Pre-covid19	Covid-19	t-student	Contagion?
	ρ_{adjusted}	ρ_{adjusted}		
China/USA	0.4773	0.2579	−9.6042	No
China/Brazil	0.4609	0.1625	−13.3524	No
China/Mexico	0.3686	0.1981	−7.3899	No
China/Italy	0.3673	0.1529	−9.3746	No
China/France	0.5031	0.2531	−11.0272	No
China/Germany	0.4954	0.2414	−11.2157	No
China/Argentina	0.3607	0.0837	−12.3119	No
China/Hong Kong	0.7172	0.6127	−4.4875	No
China/Taiwan	0.6301	0.4104	−9.6147	No
China/Japan	0.2214	0.1135	−4.6352	No
China/Russia	0.3548	0.1501	−8.93	No
China/India	0.5276	0.3158	−9.2556	No
China/Indonesia	0.4816	0.2410	−10.586	No
China/Malaysia	0.652	0.2587	−18.2695	No
China/South Korea	0.6328	0.4393	−8.4232	No
China/Vietnam	0.4979	0.2075	−12.961	No
China/Singapore	0.695	0.4754	−9.6134	No
China/Australia	0.598	0.3654	−10.2141	No

Notes.
ρ_{adjusted}:The adjusted correlation coefficient.

$$\rho_{adjusted} = \frac{\rho}{\sqrt{1 + \delta(1 - (\rho)^2)}}.$$

$\delta = \frac{v^c(x_t)}{v^t(x_t)} - 1$, where c and t indicate the crisis and stability periods, respectively.
t-student's critical values are (2.326), (1.645) and (1.282) at the 1%, 5% and 10% levels respectively.
*** and ** denote statistical significance at the 1% and 5% levels respectively.

$$t = (\rho_1^* - \rho_2^*)\sqrt{\frac{n_1 + n_2 - 4}{1 - (\rho_1^* - \rho_2^*)^2}} \rightarrow t(0.05, n1 + n2 - 4).$$

Table 4
Optimal bandwidths for China and different markets (total period).

Markets	*Bandwidth: h1*	*Bandwidth: h2*
China/U.S	0.5845	0.3870
China/Brazil	0.9782	0.4205
China/Mexico	0.6625	0.3854
China/Italy	0.6474	0.4308
China/France	1.0181	0.8099
China/Germany	0.7120	0.6583
China/Argentina	0.4572	0.3928
China/Hong Kong	0.3681	0.5293
China/Taiwan	1.1586	1.1279
China/Japan	1.1457	0.5871
China/Russia	0.2762	0.2391
China/India	0.3630	0.2004
China/Indonesia	0.4058	0.3420
China/Malaysia	0.3147	0.2172
China/South Korea	0.3010	0.4189
China/Vietnam	0.6611	0.7310
China/Singapore	0.2575	0.3864
China/Australia	0.2150	0.3120

Notes.
$h1$: The optimal bandwidth related to the local quadratic regression, which the polynomial ($p = 2$).
$h2$: The optimal bandwidth related to the second regression (local linear regression), which the polynomial ($p = 1$).
The determination of bandwidth $h1$ and $h2$ is crucial for the estimation of $\beta(x_0)$and $\sigma^2(x_0)$.

Table 5
Estimation of $\beta(x_0)$ for China and different markets (total period).

Markets	$\widehat{\beta}(x_L)$	$\widehat{\beta}(x_M)$
China/U.S	0.0596	−0.7241
China/Brazil	0.0432	−0.3600
China/Mexico	0.0210	−0.5445
China/Italy	0.0503	−0.5590
China/France	0.0511	−0.6691
China/Germany	0.0433	−0.6953
China/Argentina	0.0679	−1.2735
China/Hong Kong	−0.0201	−1.8415
China/Taiwan	0.0720	−0.2811
China/Japan	0.0258	−0.2471
China/Russia	0.1332	−1.0631
China/India	0.0828	−0.8117
China/Indonesia	0.0835	−0.8747
China/Malaysia	−0.0021	−0.5301
China/South Korea	0.0838	−1.0414
China/Vietnam	0.0124	−0.6285
China/Singapore	−0.0164	−0.2571
China/Australia	0.0536	−0.8291

Notes.
$\beta(X) = m'(X)$: The slope of the regression function.
Using local polynomial regression we estimate$\beta(x_0)$and deduce$\widehat{\beta}(x_L)$and.$\widehat{\beta}(x_M)$
$x_L = F_X^{-1}(0.025)$: The lowest quantile of the distribution $F_X(x) = P(X \prec x)$ of X.
$x_M = F_X^{-1}(0.5)$: The median of this distribution.

that spatial contagion exists between all European and American countries and China during the COVID-19 outbreak (China and the U.S., China and Brazil, China and Mexico, China and France, and China and Germany). Indeed, the Z-statistics for countries that are distant from China are higher than the critical values of the test statistic[5] ($z_{1-\alpha}$). Our results also reveal the non-existence of spatial contagion between China and most of countries geographically close to China (China and Vietnam, China and Hong Kong, China and Singapore, China and Taiwan). These findings suggest that China's spatial proximity is not a very important factor in financial contagion. In fact, there is no financial contagion between China and countries geographically close to it. On the other hand, there is financial contagion between European and American developed countries (France, Italy, Germany, the U.S., and Canada) and China.

[5] The critical values of the test statistic are 1.65, and 2.33 for 5%, and 1% significance levels, respectively.

Table 6
Estimation of residual variance $\sigma^2(x_L)$ / $\sigma^2(x_M)$ for China and other countries (total period).

Markets	$\hat{\sigma}^2(x_L)$	$\hat{\sigma}^2(x_M)$
China/U.S	1.805	1.6421
China/Brazil	1.824	1.5520
China/Mexico	1.8287	1.7081
China/Italy	1.721	1.3533
China/France	1.7419	1.6247
China/Germany	1.7105	1.6148
China/Argentina	1.5666	1.4170
China/Hong Kong	1.1738	0.9412
China/Taiwan	1.917	1.6440
China/japan	1.253	1.1725
China/Russia	1.4480	1.2895
China/India	1.855	1.3216
China/Indonesia	1.7343	1.355
China/Malaysia	1.5833	1.4273
China/South Korea	1.7291	1.6388
China/Vietnam	1.8243	1.6983
China/Singapore	1.6872	1.2706
China/Australia	1.5348	1.4769

Notes.
$\sigma_X^2 = \mathrm{var}(Y/X = x)$: The non-parametric residual variance.
We make a local linear regression on the squared residual to infer the residual variance $\sigma^2(x_0)$ and deduce $\hat{\sigma}^2(x_L)$and $\hat{\sigma}^2(x_M)$.
$x_L = F_X^{-1}(0.025)$: The lowest quantile of the distribution $F_X(x) = P(X \prec x)$ of X.
$x_M = F_X^{-1}(0.5)$: The median of this distribution.
$\hat{\sigma}^2(x_L)$and $\hat{\sigma}^2(x_M)$are used to compute the estimator of local correlation.

Contagion between China and other countries can be explained by economic factors such as the net capital flows and trade intensity (Akhtaruzzaman & Shamsuddin, 2016; Frankel & Rose, 1998).

For the sensitivity checks, we study the spatial contagion for a different study period from 2010 to 2020. The results remain unchanged throughout the study except for Germany; we find the absence of spatial financial contagion during the COVID-19 outbreak. We conclude on the importance of the study period.

These results differ from those obtained by Zorgati and Lakhal (2020), who show the importance of spatial proximity during the subprime crisis.

Our results support the fact that the COVID-19 outbreak affects stock markets around the world. This pandemic has put the world economy at risk and has quickly spread in the European, American and Asian markets. The COVID-19 has affected the economic and social conditions in Asia. It has also affected the banking sector and weakened the trade flows.

According to Liu et al. (2020), the consequences of the COVID-19 outbreak are important and directly affect stock markets around the world. It increases uncertainties and the fear of stock market investors around the world. Besides, it creates pessimistic feelings on future returns. The authors study the short-term impact of COVID-19 in 21 stock market indexes (Korea, Singapore, Japan, the U.S., Germany, Italy) over the period from February 21, 2019 to March 18, 2020. They find that COVID-19 outbreak have a negative impact on stock market indexes for all studied countries and that the Asian markets respond more quickly to the pandemic. This result is different from ours. This is explained by the short period from January 20, 2020 to March 18, 2020 investigated that we extend in this study.

5. Conclusion

The purpose of this paper is to investigate the effect of spatial proximity on financial contagion during the COVID-19 outbreak using the local correlation approach. We consider the daily stock index series of Asian, American, and European countries over the period of January 1, 2014 to January 30, 2021. As for countries that are geographically close to China (Taiwan, Vietnam, Singapore and Hong Kong), we show the non-existence of spatial contagion as these countries mitigate the spread of the COVID-19. Indeed, following the epidemic in 2003 (severe acute respiratory syndrome (SARS)), they have been on alert and acting rapidly on epidemics arising from China. As for countries that are geographically distant for China, we prove the presence of spatial contagion and the continual spread of COVID-19.

Our results are consistent with those of Okorie and Lin (2020) who show the existence of significant but short-lived contagion effect on the stock markets (the U.S., Italy, France, and so on) during the COVID-19 pandemic. Furthermore, our findings are consistent with Zorgati and Lakhal (2020), who find the presence of spatial contagion between China and the U.S. during the subprime crisis.

These results have strong implications for investors, who want to diversify their portfolios internationally and hedge benefits so that portfolio managers predict and minimize market risk. Although holding an internationally diversified portfolio offers little

Table 7
Results of spatial contagion test for China and other countries.

Markets	$\widehat{\rho}(x_L)$	$\widehat{\rho}(x_M)$	$\widehat{\sigma}^2_{\widehat{\rho}(x_M)}$	$\widehat{\sigma}^2_{\widehat{\rho}(x_L)}$	Z	Spatial contagion
China/U.S	0.0474	−0.5177	0.0318	0.0082	2.8255***	Yes
China/Brazil	0.0509	−0.4159	0.0680	0.0071	1.7033**	Yes
China/Mexico	0.01437	−0.3587	0.0236	0.0085	2.0822**	Yes
China/Italy	0.05613	−0.5760	0.0631	0.0154	2.2561***	Yes
China/France	0.0450	−0.5292	0.0406	0.0092	2.5730***	Yes
China/Germany	0.0404	−0.5560	0.0438	0.0114	2.5384***	Yes
China/Argentina	0.0458	−0.6710	0.0223	0.00362	4.4522***	Yes
China/Hong Kong	−0.0209	−0.2991	0.0391	0.0143	1.2038	No
China/Taiwan	0.1337	−0.4942	0.1709	0.0278	1.4086	No
China/Japan	0.0387	−0.2010	0.0457	0.1680	0.5185	No
China/Russia	0.0919	−0.6274	0.0227	0.00511	4.3132***	Yes
China/India	0.0631	−0.5921	0.0290	0.00751	3.4290***	Yes
China/Indonesia	0.0561	−0.5676	0.0572	0.0148	2.3243***	Yes
China/Malaysia	−0.0010	−0.2702	0.0294	0.01058	1.3463	No
China/South Korea	0.0575	−0.5924	0.0527	0.0110	2.5749***	Yes
China/Vietnam	0.0129	−0.5595	0.1268	0.0350	1.4230	No
China/Singapore	−0.0225	−0.3778	0.2106	0.0333	0.71943	No
China/Australia	0.0412	−0.5734	0.0668	0.0177	2.1142**	Yes

Notes.
$\widehat{\rho}$: The local correlation estimator.

$$\widehat{\rho}(x_0) = \frac{s(X)\widehat{\beta}(x_0)}{\sqrt{s_X^2\widehat{\beta}^2(x_0) + \widehat{\sigma}^2(x_0)}}$$

$x_L = F_X^{-1}(0.025)$: The lowest quantile of the distribution $F_X(x) = P(X \prec x)$ of X.
$x_M = F_X^{-1}(0.5)$: The median of this distribution.

$$\widehat{\sigma}^2_{\widehat{\rho}(x_0)} = \widehat{\sigma}_{\widehat{\beta}}^2(x_0)\frac{S_X^2}{\widehat{\sigma}^2_{(x_0)}}[1-\widehat{\rho}^2(x_0)]^3$$

Where.$s_X^2 = \frac{1}{n-1}\sum_{i=1}^{n}(X_i - \overline{X}^2\Big)$

The Z-statistic is calculated as follow.$Z = \frac{\widehat{\rho}(x_L) - \widehat{\rho}(x_M)}{\sqrt{\widehat{\sigma}^2_{\widehat{\rho}(x_L)} + \widehat{\sigma}^2_{\widehat{\rho}(x_M)}}}$

If$Z \succ z_{1-\alpha}$, we conclude that there is spatial contagion between the designed markets.
The critical values of the test statistic are 1.65, and 2.33 for 5%, and 1% significance levels, respectively.
, and * represent significance at the 5%, and 1% levels, respectively.

protection against sharp declines in a market, the long-term gains from international diversification remain economically attractive. In addition, these findings have implications for policymakers, to make informed decisions about financial stability measures and decisions for different sectors of the economy.

One limitation of this paper is that it did not take into consideration the African region. It would be interesting to examine the existence and intensity of financial contagion during the COVID-19 epidemic for Asian, American, European and African markets.

CRediT authorship contribution statement

Imen Zorgati: Conceptualization, Methodology, Software, Validation, Writing – original draft, Writing – review & editing. **Riadh Garfatta:** Conceptualization, Data curation, Writing – review & editing.

Declaration of competing interest

Imen Zorgati and Riadh Garfatta declare that there is no conflict of interest.

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