



The contagion effects of the COVID-19 pandemic: Evidence from gold and cryptocurrencies

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ARTICLE INFO

Keywords:
COVID-19
Coronavirus
Contagion
Stock market
Sentiment,

ABSTRACT

At the beginning of the 2020 global COVID-2019 pandemic, Chinese financial markets acted as the epicentre of both physical and financial contagion. Our results indicate that a number of characteristics expected during a “flight to safety” were present during the period analysed. The volatility relationship between the main Chinese stock markets and Bitcoin evolved significantly during this period of enormous financial stress. We provide a number of observations as to why this situation occurred. Such dynamic correlations during periods of stress present further evidence to cautiously support the validity of the development of this new financial product within mainstream portfolio design through the diversification benefits provided.

1. Introduction

The escalation of the 2020 COVID-19 pandemic represented a global example of the fragility of the world in which we live and as to how vulnerable we are as a society to exceptional risks. However, such financial implications did not proceed without forewarning. In previous pandemics, such as the outbreak of 2003, [Bhuyan et al. \(2010\)](#) found that the stock market returns of the infected countries exhibited a significant increase in the cointegrated relationship and dynamic comovements, when compared to the pre-SARS period. While considering both the physical and psychological re-estimation of financial markets as to how global finance will return to normality in the aftermath the current global pandemic, our understanding of the interactions between financial assets must be scrutinised, particularly due to the ever-expanding side-effects of technological development of both the exchange, the speed of information flow ([Corbet et al., 2018a; 2020a](#)), the role of algorithmic trading ([Jarrow and Protter, 2012; Kirilenko et al., 2017](#)), and in more recent times, as to how digital currencies can act as not only a store of value during periods of market turmoil, but also as a source of portfolio diversification. [Gil-Alana et al. \(2020\)](#) identified a potential role for cryptocurrencies in investor portfolios as a significant diversification option for investors, with particular emphasis on Bitcoin and Ethereum. While [Omane-Adjepong and Alagidede \(2019\)](#) identified that any probable diversification benefits within cryptocurrencies are most likely to be found within intra-week to intra-monthly time horizons for specific market pairs, while the level of inter-market connectedness and volatility inter-linkages are identified as being sensitive to both liquidity and volatility. [Liu \(2019\)](#) further identified portfolio benefits from the inclusion of cryptocurrency. When specifically investigating the market relationships between cryptocurrency and other traditional

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<https://doi.org/10.1016/j.frl.2020.101554>

Received 30 March 2020; Accepted 19 April 2020

Available online 14 May 2020

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Table 1
Key dates in the Chinese COVID-2019 outbreak.

Date	Event
December 31, 2019	Cases of pneumonia detected in Wuhan, China, are first reported to the WHO. During this reported period, the virus is unknown. The cases occur between December 12, and December 29, according to Wuhan Municipal Health.
January 1, 2020	Chinese health authorities close the Huanan Seafood Wholesale Market after it is discovered that wild animals sold there may be the source of the virus.
January 5, 2020	China announces that the unknown pneumonia cases in Wuhan are not SARS or MERS
January 7, 2020	Chinese authorities confirm that they have identified the virus as a novel coronavirus, initially named 2019-nCoV by the WHO.
January 11, 2020	The Wuhan Municipal Health Commission announces the first death caused by the coronavirus. A 61-year-old man, exposed to the virus at the seafood market, died on January 9, after respiratory failure caused by severe pneumonia.
January 13, 2020	First cross-border transmission as Thai authorities report a case of infection caused by the coronavirus. The infected individual is a Chinese national who had arrived from Wuhan.
January 30, 2020	WHO declares 2019-nCoV to be a “Public Health Emergency of International Concern”
February 11, 2020	WHO announces a new name for the virus, COVID-19
March 11, 2020	WHO declares COVID-19 to be a Pandemic

Note: The above table consists of the key events relating to the Chinese epicentre COVID-2019 outbreak. The dates represent dummy variables in the associated GARCH and DCC-GARCH estimations.

financial variables, [Bouri et al. \(2017\)](#) found that Bitcoin is a poor hedge and is suitable for diversification purposes only, a result that was echoed when considering the S&P500 exchange ([Tiwari et al., 2019](#)) and for each of the Eurostoxx 50, the Nikkei 225 and the CSI 300 ([Feng et al., 2018](#)). More recently, [Conlon and McGee \(2020\)](#) suggests that Bitcoin was neither a safe haven nor a hedge against the extreme bear market in the S&P500 occasioned by the COVID-19 pandemic.

2. Data and methodology

We specifically investigate the contagion effects associated with the onset of the COVID-2019 pandemic between Chinese stock markets, identified as the epicentre of the first registered cases as outlined in the timetable presented in [Table 1](#). We utilise these events to generate dummy variables through which we analyse the contagion effects centred in the price volatility of both the Shanghai and Shenzhen Stock Exchanges. [Ramelli and Wagner \(2020\)](#) identified that the COVID-19 pandemic had morphed into an economic crisis amplified through financial channels through a whipsaw pattern as corporate investors became increasingly worried about the accumulation of corporate debt and the substantial liquidity shortage that had manifested. Through the inclusion of these Chinese financial markets, denoted as the epicentre of the COVID-2019 pandemic, the Dow Jones Industrial Average as a measure of international financial performance ([Ekinci et al., 2019](#)), West Texas Intermediate oil and gold as international flight to safety assets ([Akyildirim et al., 2020](#)) and Bitcoin, which has presented evidence of inverse correlations with some international stock exchanges, thereby providing strong diversification benefits ([Akhtaruzzaman et al., 2019](#); [Akyildirim et al., 2019a](#)). In this study, we use hourly, and for robustness, daily returns to analyse the dynamic correlations between this range of financial assets. Our hourly returns are calculated as:

$$r_{t,h} = (\ln r_{t,h} - \ln r_{t,h-1}) \times 100 \quad (1)$$

where $r_{t,h}$ is the return for hour h on trading day t . Time periods with no trading activity are determined to be best represented by the last traded price. Hourly data from 11 March 2019 to 10 March 2020 (5701 observations), are used¹ denoted as both pre- and post-COVID-2019 pandemic (4580 and 1122 observations respectively) is denoted to be before or after 31 December 2019. Data is sourced through Thomson Reuters Eikon. Evidence of sharp declines are evident in the period thereafter through exceptionally changes evident in the minima, skewness and kurtosis of these short-term returns. The summary statistics for each variable are presented in [Table 2](#), with evidence of the associated share price behaviour and volatility presented in [Fig. 1](#). Times are adjusted to Greenwich Mean Time to allow for comparability across the selected geographical regions. For the purpose of exchange comparison out-of-session, daily returns are used to measure dynamic correlations (similarly to the methods used by [Akyildirim et al. \(2019b\)](#); [Katsiampa et al. \(2019a,b\)](#)).

The changing correlations between these financial assets are presented in [Table 3](#). Comparing the periods both before and after the COVID-2019 pandemic, we observe some strong changes in dynamic behaviour. There is evidence of elevated correlations between the selected Chinese exchanges, increasing from +0.889 to +0.967 as market conditions began to deteriorate. Particularly sharp increased correlation is also evident between Chinese markets and WTI (increasing sharply from +0.091 to +0.485), while the correlation between Chinese markets and gold, which was negative prior to the COVID-19 outbreak, grew to +0.335 and +0.347 respectively with the Shanghai and Shenzhen stock exchanges. However, with regards to the interactions between Chinese stock

¹ The time period also allows us to disaggregate the effects of the COVID-19 pandemic from the generalised equity market rout that was occasioned by the widespread arrival of the virus to the USA and European countries (on 27 February 2020 new cases outside China exceeded those within China for the first time, on 30 January 2020 the World Health Organization recognized the disease as a “Public Health Emergency of International Concern” and on 11 March 2020 declared it a Pandemic) and the “oil price war” which began on 9–10 March. Similar techniques were used by [Corbet et al. \(2020b\)](#).

Table 2
Summary statistics of selected financial market variables.

	Shanghai	Shenzhen	DJIA	WTI	Gold	Bitcoin
<i>Total Period Analysed</i> (5701 observations)						
Mean	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001
Std Dev	0.0023	0.0028	0.0023	0.0047	0.0018	0.0092
Minimum	-0.0718	-0.0750	-0.0615	-0.0666	-0.0225	-0.0886
Maximum	0.0252	0.0304	0.0295	0.0724	0.0175	0.0865
Variance	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001
Skewness	-5.9042	-3.4336	-4.3918	-0.0317	-0.6658	-0.2070
Kurtosis	196.9949	113.1889	140.2742	35.0332	17.6908	8.9373
<i>Before Coronavirus</i> (4580 observations)						
Mean	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001
Std Dev	0.0020	0.0025	0.0016	0.0039	0.0016	0.0097
Minimum	-0.0337	-0.0371	-0.0189	-0.0410	-0.0225	-0.0886
Maximum	0.0252	0.0304	0.0175	0.0337	0.0138	0.0865
Variance	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001
Skewness	-0.5488	-0.2841	-1.0825	-0.5360	-0.4233	-0.2010
Kurtosis	41.2553	33.4127	34.5759	10.4541	16.9029	8.3757
<i>After Coronavirus</i> (1122 observations)						
Mean	0.0000	0.0001	-0.0001	-0.0002	0.0000	0.0002
Std Dev	0.0031	0.0037	0.0040	0.0072	0.0022	0.0067
Minimum	-0.0718	-0.0750	-0.0615	-0.0666	-0.0209	-0.0530
Maximum	0.0129	0.0248	0.0295	0.0724	0.0175	0.0428
Variance	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000
Skewness	-11.6273	-6.9313	-3.8890	0.3583	-0.9857	-0.1866
Kurtosis	271.3470	151.0273	72.4226	28.6361	14.7752	7.6318

Note: Hourly data is presented to the period 11 March 2019 and 10 March 2020, where the period denoted as both pre- and post-COVID-2019 pandemic is denoted to be before and after 31 December 2019.

markets and digital currencies, we observe sharp, short-term, dynamic correlations between Bitcoin and Chinese stock markets in the period after the identification of the COVID-19 pandemic. To specifically To analyse the dynamic correlations between the corporate entities exposed to reputational exposure due to naming similarity from the COVID-2019 pandemic, we employ a standard GARCH (1,1) methodology of [Bollerslev \(1986\)](#) and extract dynamic conditional correlations (of [Engle, 2002](#)) that takes the form:

$$r_t = \alpha_t + \sum_{j=1}^t \sigma r_{t-j} + \sum_{j=1}^t \eta b_{t-j} + \sum_{j=1}^t \gamma w_{t-j} + u_t \quad (2)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (3)$$

where r_t , e_t and h_t are the returns of the investigated lagged corporate returns, international exchanges (Shanghai SE, Shenzhen SE and DJIA) and hedging alternatives (WTI, gold and BTC) at time t respectively. α , η and γ represent the effects of lagged returns of each selected variable on the returns of the company's hourly price volatility. The variance equation includes the long-term average volatility α_0 . Similar methodological structures were utilised by [Corbet et al. \(2015\)](#) and [Corbet et al. \(2020c\)](#). We explore the dynamic co-movements via the dynamic conditional correlations of [Engle \(2002\)](#). The GARCH (1,1) specification requires that in the conditional variance equation, parameters α_0 , α_1 and β should be positive for a non-negativity condition and the sum of α_1 and β should be less than one to secure the covariance stationarity of the conditional variance. Moreover, the sum of the coefficients α_1 and β must be less than or equal to unity for stability to hold. The GARCH (1,1) methodology used in this study has the following form:

$$R_t = a_0 + \sum_{j=1}^n b_j R_{t-j} + b_2 DJIA_t + b_3 WTI_t + b_4 G_t + b_5 BTC_t + D_t + \varepsilon_t \quad (4)$$

$$\varepsilon_t | \Omega_t \sim i. i. d. \quad N(0, h_t) \quad (5)$$

$$h_t = \omega + \alpha_1 h_{t-1} + \beta_1 u_{t-1}^2 + \sum_{i=1}^{10} D_{COVID} \quad (6)$$

R_{t-j} represents the lagged value of the selected Chinese stock exchanges, the first being the Shanghai Stock Exchange, the second being the Shenzhen Stock Exchange. j represents the number of hourly periods before R_t is observed. $b_2 DJIA_t$ represents the interactions between the selected Chinese stock exchange and the DJIA, representing the influence of international effects. $b_3 WTI_t$, $b_4 G_t$ and $b_5 BTC_t$ represent the relationship between the selected companies and the returns of WTI, gold and Bitcoin respectively. D_t and $\sum_{i=1}^t D_v$ are included in both the mean and variance equations to provide estimates of the corporate pricing and volatility estimates relating directly to the COVID-2019 pandemic. [Bollerslev \(1986\)](#) argued for restrictions on the parameters for positivity, $\omega > 0$, $\alpha \geq 0$ and $\beta \geq 0$, and the wide-sense stationarity condition, $\alpha + \beta < 1$. While the GARCH (1,1) process is uniquely stationary if $E[\log(\beta + \alpha \varepsilon_t^2)] < 0$, [Bollerslev \(1986\)](#) also proved that if the fourth order moment exists, then the model can handle leptokurtosis.

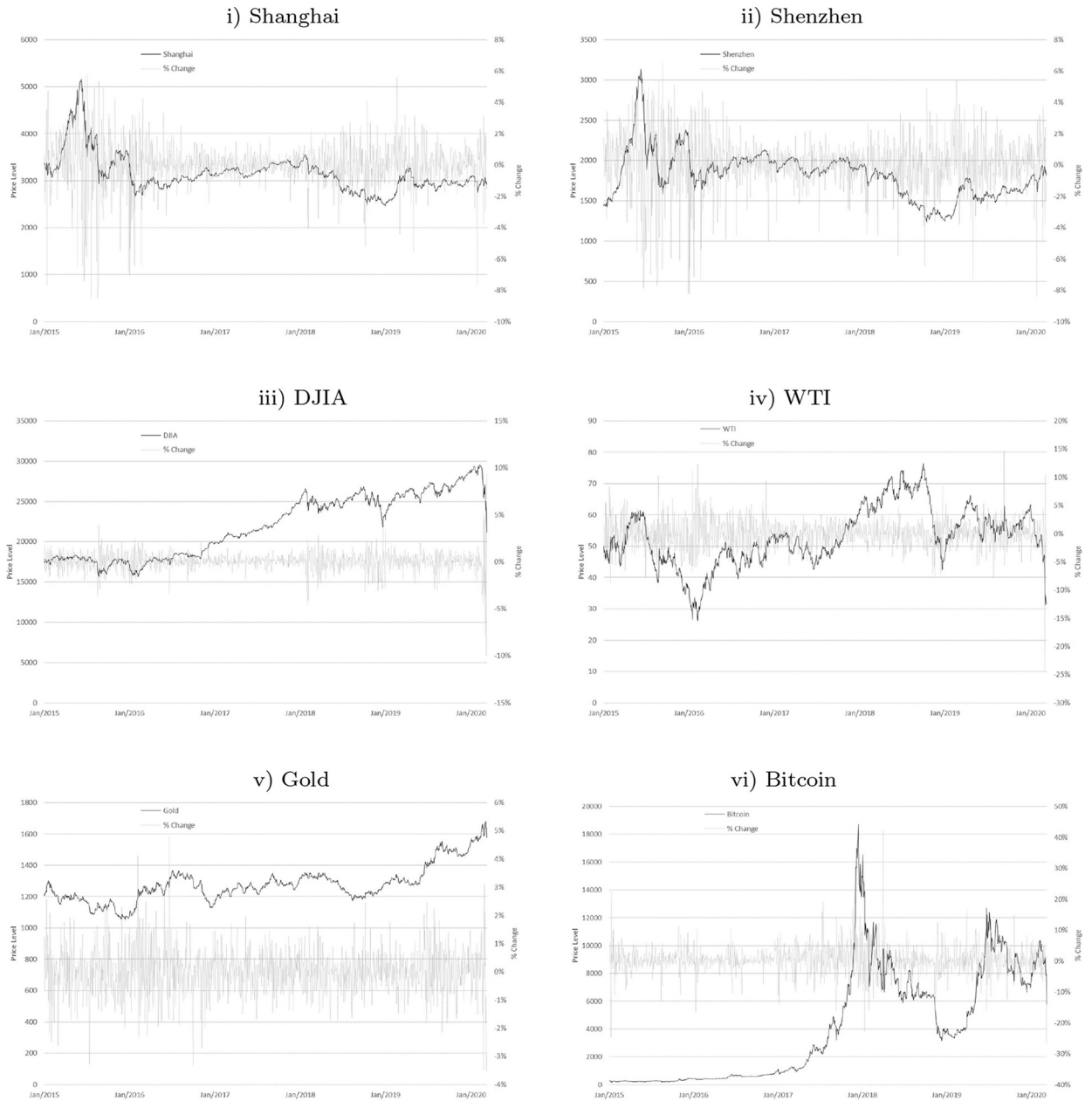


Fig. 1. Price and volatility performance of the selected traditional financial assets *Note:* The above figure represents the estimated price and volatility behaviour of the selected Chinese stock exchange and the selected traditional financial assets.

Bonferroni adjusted results are presented in this analysis. To cater the multiple hypothesis problem, we adjust the significance level using the Bonferroni correction, which leads to a significance level of 0.1%. The generalised Bonferroni method adjusts the significance level such that hypothesis $H_{0(i)}$, $i = 1, \dots, s$, is deemed rejected if and only if:

$$\hat{p}_{(i)} \leq \alpha_{(i)} \equiv k \cdot \alpha / s.$$

This procedure has the advantage of being robust to the dependence structure of the hypothesis tests.

3. Empirical results

In Table 4 we observe the results of the estimated GARCH methodology which was also presented as separated by the starting date of the Chinese outbreak of COVID-19. While some strong relationships between markets are identified when analysing the full sample of data, a number of interesting observations arise when considering the periods both before and after the start of the

Table 3

Correlations between traditional financial markets, both before and after the COVID-2019 outbreak.

	Shanghai	Shenzhen	DJIA	WTI	Gold	Bitcoin
<i>Before COVID-2019</i>						
Shanghai	1.0000					
Shenzhen	0.8894	1.0000				
DJIA	0.1652	0.1454	1.0000			
WTI	0.0911	0.0802	0.3023	1.0000		
Gold	-0.0091	-0.0141	-0.1805	0.0136	1.0000	
Bitcoin	0.0188	0.0209	0.0361	-0.0071	0.0392	1.0000
<i>After COVID-2019</i>						
Shanghai	1.0000					
Shenzhen	0.9670	1.0000				
DJIA	0.2439	0.2630	1.0000			
WTI	0.4849	0.4880	0.6012	1.0000		
Gold	0.3350	0.3473	-0.1168	0.0143	1.0000	
Bitcoin	0.3436	0.3857	0.4299	0.2792	0.4688	1.0000

Note: In the above table, the changing correlations between the identified companies susceptible to the 'corona' naming shock and these financial assets. The date indicating the start of the pandemic is that of 31 December 2019, when cases of pneumonia detected in Wuhan, China, are first reported to the WHO.

Table 4

GARCH methodology estimates.

	Shanghai			Shenzhen		
	Before	After	Total	Before	After	Total
L1	-0.0090 (0.0129)	-0.0207 (0.0199)	-0.0658*** (0.0233)	-0.0121 (0.0272)	-0.0755 (0.0461)	-0.0755* (0.0461)
L2	-0.0090 (0.0119)	-0.0321* (0.0181)	-0.0468*** (0.0145)	0.0041 (0.0188)	-0.0169 (0.0376)	-0.0169 (0.0376)
DJIA	0.0435* (0.0247)	0.1141*** (0.0226)	0.1198*** (0.0304)	0.1789*** (0.0550)	0.1598*** (0.0618)	0.1598*** (0.0618)
WTI	0.0059 (0.0081)	0.0195 (0.0115)	0.0427*** (0.0133)	0.0115 (0.0191)	0.1102 (0.0290)	0.1102 (0.0290)
Gold	0.0179 (0.0253)	0.0354 (0.0245)	0.0110 (0.0407)	0.0170 (0.0644)	0.0238 (0.0689)	0.0238 (0.0689)
Bitcoin	0.0028 (0.0044)	-0.0011 (0.0045)	-0.0029 (0.0072)	0.0080 (0.0133)	0.0170 (0.0108)	0.0170 (0.0108)
COVID-19 Mean			0.0000*** (0.0000)			0.0000*** (0.0000)
COVID-19 Volatility			0.0044*** (0.0001)			0.0018*** (0.0003)
Constant	0.0001* (0.0001)	0.0002* (0.0001)	0.0001*** (0.0000)	0.0001*** (0.0000)	0.0001*** (0.0000)	0.0001*** (0.0000)
ARCH	0.4294 (0.0602)	0.4382 (0.0662)	0.4424 (0.0446)	0.4022 (0.0506)	0.0251 (0.0153)	0.0126*** (0.0153)
GARCH	0.5314 (0.0510)	0.5161 (0.2057)	0.5548 (0.0291)	0.5156 (0.0467)	0.9632 (0.0158)	0.9824*** (0.0158)
Log-likelihood	2,432.8	1,740.0	2,557.7	1,815.4	1,278.7	2,389.7
$\chi^2(10)$	4325.19	4325.19	7,542.1	220.2	456.4	420.3
Prob > χ^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note: The presented analysis was conducted using hourly data between the period 11 March 2019 and 10 March 2020 (5701 observations), where the period denoted as both pre- and post-COVID-2019 pandemic (4580 and 1122 observations respectively) is denoted to be before and after 31 December 2019. ****, ***, ** and * indicates statistical significance at the 0.1%, 1%, 5% and 10% levels respectively.

pandemic. Considering both the Shanghai and Shenzhen Stock Exchanges, COVID-19 is found to have a strong, significant positive impact on the volatility of each exchange. There is evidence of quite a sheltered interaction between Chinese and US financial markets, +0.119 and +0.160 for Shanghai and Shenzhen respectively. Similarly, there is quite a subdued positive interrelationship between WTI and Chinese stock markets, albeit it strongly significant. It is very interesting to note that neither gold nor cryptocurrencies, as measured through the price dynamics of Bitcoin, are found to have a significant relationship with Chinese stock markets. However, when analysing this same relationship using high-frequency data as presented in Fig. 2, we notice a peculiar interaction between Chinese stocks indices at the point of the onset of the COVID-19 outbreak. There is evidence of sharp elevations in dynamic correlations between these markets. Despite the elevation in dynamic correlations, the Chinese markets themselves held up remarkably well in the face of the domestic phase of the pandemic. A partial explanation might arise from the findings in Albuлесcu (2020) which finds that the spread of COVID-19 geographically is closely related to the degree of financial instability.

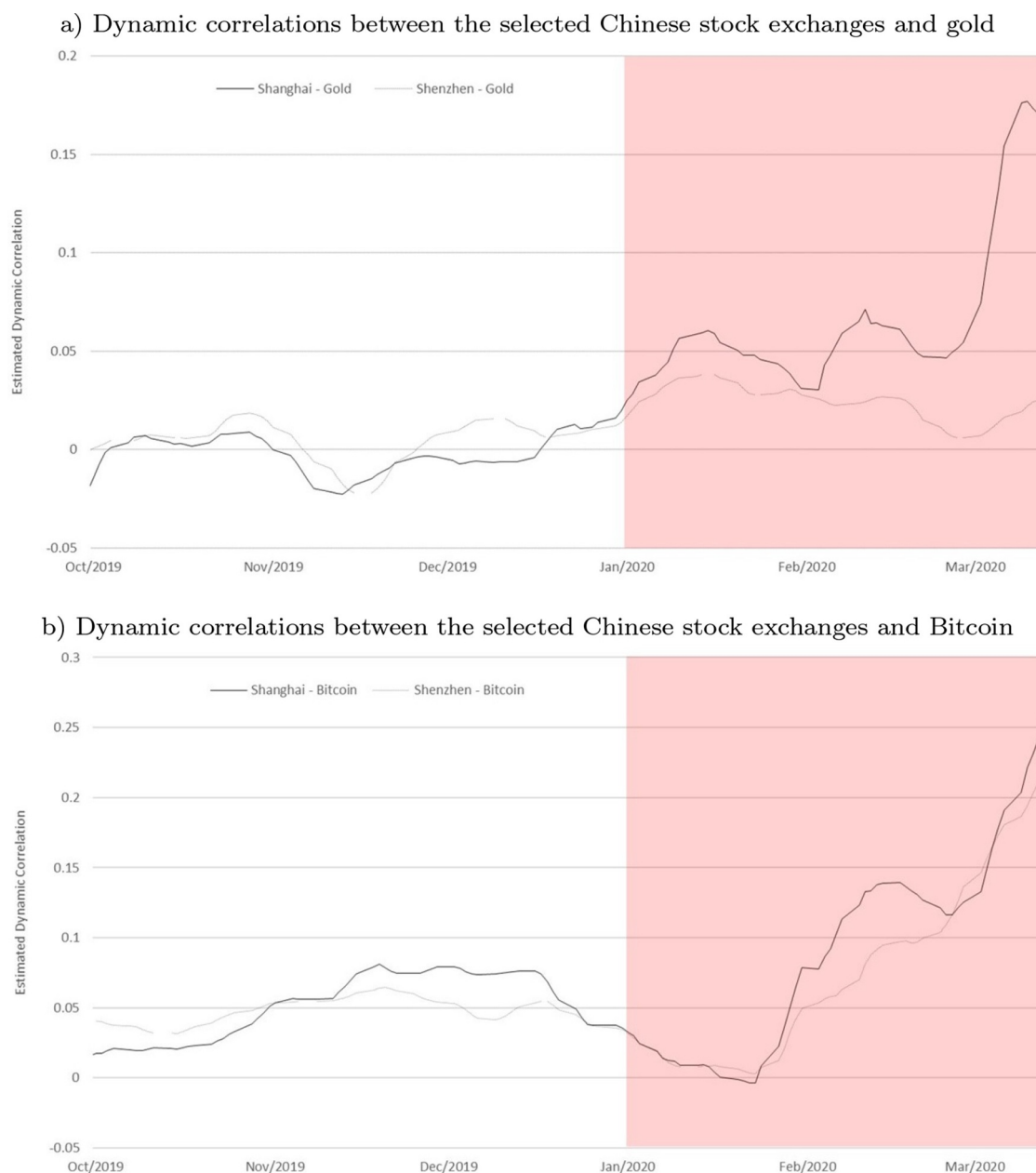


Fig. 2. Dynamic correlations between denoted company and the Shanghai & Shenzhen Stock Exchanges *Note:* The above figure represents the estimated dynamic correlations between the selected traditional financial assets and the Chinese stock exchange.

Similarly (Caporale et al., 2020) shows profound non-linear and phase transition behaviour in cryptocurrencies. Bitcoin is also exceptionally volatile. In the January-February period it showed a significant rise, led it is argued by fundamentals including position forming before an expected May forking event,² much but not all of which was erased as the global spread of the virus manifested. The two Chinese indices showed resilience over this period, as there was a sharp drop quickly erased as the Wuhan situation peaked as the perception of the Chinese government taking control was widespread. Gold prices also rose over this period, the early March period excepted but then showing a massive spiking as global travel restrictions and supply chain disruptions impacted supply.

² See for example <https://asiatimes.com/2020/03/bitcoins-2020-rally-organic-not-manipulated/>

4. Concluding comments

Cryptocurrencies have emerged as a new financial instrument. Their novelty, both in terms of time and their nature, makes it as yet unclear what their final status will be as a potential diversifier or otherwise. The evidence here, and in papers such as Conlon and McGee (2020) indicates that in times of serious financial and economic disruption these assets do not act as hedges, or safe havens, but perhaps rather as amplifiers of contagion. The behaviour of gold relative to cryptocurrencies in the Chinese markets reinforces results in papers by Corbet et al. (2018b) and Corbet et al. (2019).

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