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Chinese jigsaw: Solving the equity market response to the COVID-19 crisis: Do alternative asset provide effective hedging performance?

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\textbf{ABSTRACT}

Against COVID-19 risks, this paper examines the hedging performance of alternative assets including some financial assets and commodities futures for the Chinese stock market in a multi-scale setting. Dynamic conditional correlations and optimal hedge ratios of the Shanghai stock exchange with Bitcoin, Dow Jones Industrial Average, Gold, WTI, Bonds and VIX returns are estimated before and during the pandemic crisis. In the short-term, the use of wavelet decomposition shows that Bitcoin provides the best hedge to the Shanghai stock market. In the long-term, commodities dominate. Whereas WTI offers the highest hedging effectiveness, Gold ranks second by a slight margin. These results allow investors to choose the highest returns and protecting tail risk during the current sanitary crisis. Our findings suggest particularly more pronounced economic benefit of diversification including alternative financial assets while commodities futures serve as good hedge assets especially during unpredictable crisis like the current sanitary crisis relating to the covid-19.

1. Introduction

The Covid-19 pandemic hit the world economy, without anyone knowing, at light-speed, leading to partial unemployment and factories’ shut down around the globe, leaving policymakers, businessmen, doctors, and citizens alike in disarray. The origin of the virus itself is not known with certainty, although most theories attach it to zoonotic transfer to the human species (Andersen et al., 2020). As a proteiform disease, Covid-19 is drowning the macro-financial environment into a recession that it is too early to foreshadow.

Nowadays, we are experiencing a new kind of sanitary crisis that leads to a worldwide economic and financial downturn. However, the cause of this recession was unpredictable. The COVID-19 (Coronavirus) surprised all actors around the world. The appearance of this health pandemic caused panic and turmoil at both social (humanity) and financial levels around the world. The COVID-19 has been qualified by the general secretary of the UN, Antonio Guterres, Tuesday, March 31, 2000, as the worst crisis humanity has faced since the Second World War. The U.N. chief suggests that “the combination of a threatening disease for everyone and an economic impact leading to an unprecedented recession in the recent past.”

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Due to the Covid-19 pandemic, stock markets (such as the NYSE) briefly halted from trading in March 2020 and have not recovered yet from the crash that ensued. Economic uncertainty has increased. The global activity is freezing as a consequence of the population lockdowns imposed by governments around the world. Such desperate measures taken to contain the spread of the Coronavirus are already having a severe impact on the global economy, and this has been projected to continue. Macroeconomic (e.g., industrial production) and financial indices took a severe blow since mid-March 2020.

The financial contagion of the Covid-19 across worldwide stock markets originated from China. Specifically, restrictions in China and other countries reduced manufacturing activities and exports from China and adversely impacted other countries that interact with China, especially oil exporters. In China, industrial production dropped by about 13.5%. Retail sales declined by 21%, car and restaurant sales fell by 92% and 95%, respectively, while some sectors such as transportation and tourism almost collapsed (McKee and Stuckler, 2020). Falling demand for crude oil from China had a direct impact on the global energy market through a significant reduction in the price of crude oil. Additionally, the confrontation between key players in the oil market, including Russia and Saudi Arabia as a consequence of falling demand for crude oil, resulted in the most massive oil price crash in decades.

With a focus on the Shanghai Composite stock exchange as the primary financial "hub," this paper aims to provide an in-depth investigation of the economic and financial consequences of the new pandemic crisis. We propose some issues to neutralize or, at least, reduce the impact of this crisis on the economic and financial sphere at a time when governments are giving more attention to the social side at the expense of economic growth.

In this paper, we try to solve the financial contagion "jigsaw" puzzle stemming from the Shanghai stock exchange. Regarding the origin of Covid-19, most researchers do not believe in the conspiracy theory that the virus originated in a lab in Wuhan, China. As Andersen et al. (2020) put it, "we do not believe that any type of laboratory-based scenario is plausible." Do optimal diversification and safe-haven assets like Gold and other alternative assets as best hedge assets provide good solution to smooth or cancel the worst financial consequences of this unpredictable crisis? This is an important issue to deal with in this study which, we believe, according to our knowledge, to be the first providing a good response to this question.

In recent days characterized by a new breed of a health crisis, a.k.a. the COVID-19, a large number of studies have been conducted to examine the reaction of stock markets to the new pandemic. Among others, we may cite Goodell (2020), who highlights the enormous economic and social impact of COVID-19. Zhang et al. (2020) map the unprecedented level of risk, causing investors to suffer significant losses during the COVID-19 crisis. Ji et al. (2020) evaluate the safe-haven role of assets in the current COVID-19 pandemic.

Furthermore, Ashraf (2020) finds that stock markets responded negatively to the growth in COVID-19 confirmed cases. That is, stock market returns declined as the number of confirmed cases increased. Using detrended moving and cross-correlation techniques, Okorie and Lin (2020) provide pieces of evidence for the COVID-19 fractal contagion effect on the stock markets. Previous studies by Abid et al. (2019) document that contagion effect may be more likely shown during crisis periods, which is the case here with the Covid pandemic, rather than tranquil periods.

The empirical findings in Akhtaruzzaman et al. (2020a,b) show strong evidence of contagion effects between China, Japan, and the G7 markets. Gagnon et al. (2020) conclude that an unrecorded decrease follows the COVID-19 crisis in interest rates. In such a context, commodities-based diversification can be more useful for investors. Zaremba et al. (2020) document that non-pharmaceutical interventions significantly increased equity market volatility.

More interesting is the study of Corbet et al. (2020a, b) which shows that over the COVID-19 period, Chinese financial markets are determined to be the epicenter of physical and financial contagion. Several financial assets may offer new opportunities for diversification, such as the DJIA, World oil prices, Gold, and Bitcoin, Bonds and VIX among others. Furthermore, Goodell and Goutte (2020) apply wavelet methods to daily data of COVID-19 world deaths and Bitcoin prices. They find that levels of COVID-19 caused a rise in Bitcoin prices.

Previous studies—such as Basher and Sadorsky (2016); Abid et al. (2020a, b) – further documented that, in a period of crisis, oil prices and Gold may offer abundant opportunities to hedge against risk. These studies also show strong evidence of the economic benefit of diversification during the crisis period. During Covid-19, various alternative assets, like Gold, commodities, oil, and cryptocurrencies, provide best diversification benefits and or hedging effectiveness (Conlon and McGee, 2020; Adekoya et al., 2021; Goodell and Goutte, 2021a,b; Khelifa et al., 2021; Yousaf et al., 2021, among others). Among other, cryptocurrencies is considered as a good diversifier in Covid period (Goodell and Goutte, 2021a,b; Khelifa et al., 2021). In another hand, precious metals provide important hedging effectiveness against risks. Particularly, Salisu et al. (2021) shows that Gold has a high hedging effect against oil price risk during the covid-19.

This paper studies the hedging performance of financial assets and commodities futures for the Shanghai stock market in a multi-scale setting against COVID-19 turmoil. It completes the paper by Sharif et al. (2020), who also examine the connectedness between the recent spread of COVID-19, oil price volatility shock, the stock market, geopolitical risk, and economic policy uncertainty in the U. S. from a wavelet-based approach.

Significant co-movements between the Shanghai stock index (SSEC) and financial assets (Bitcoin, DJIA, Bonds and VIX) over the COVID-19 crisis period are observed. In the realm of commodities, the empirical results document as well as the dependency between the Shanghai stock index, on the one hand, Gold and WTI on the other hand. WTI provides more opportunities for hedging against risk, as it presents the highest hedging effectiveness ratio.

Moreover, our results show that the dependence between the Chinese stock market and commodities is lower than that with financial variables. Perhaps, the COVID-19 epidemic will have a smaller short-term effect on commodities. Other than that, we depict a recessionary macroeconomic outlook in the years to come, based on this preliminary data inspection and the identification of frequent spikes on stock markets against the pandemic background.
The remainder of this paper is organized as follows. Section 2 provides the methodology and model specification. Section 3 describes the data. Section 4 contains the main results and their discussion. Finally, section 5 concludes the study.

2. Methodology

To study the relationship between the Chinese stock market, commodities, and financial variables on several time-scales, we resort to the wavelet technique. The use of this technique has several salient features. The most important is the ability to decompose the data into several time-scales.1 Let the returns of our variables be a time-series function $f(t)$, under wavelet transform, which can be decomposed as follows:

$$f(t) = \sum_{j,k} s_{j,k} \psi_{j,k}(t) + \sum_{d_{j,k}} d_{j,k} \psi_{j,k}(t) + \ldots + \sum_{d_{1,k}} d_{1,k} \psi_{1,k}(t). \ (j,k \in \mathbb{Z})$$

where $J$ represents the number of multi-resolution levels. In our study, we take $J = 5^2$. $k$ describes the ranges from 1 to the number of coefficients at each level. $\psi_{j,k}(t)$ and $\psi_{j,k}(t)$ illustrate the approximating wavelet functions, while the coefficients $s_{j,k}$, $d_{j,k}$, $\ldots$ $d_{1,k}$ are the wavelet transform coefficients.

We use the Discrete Wavelet Transform (DWT) and, in particular, its developments regarding the Maximum Overlap (MODWT), which allows a multi-resolution analysis (MRA) into segments of time-domain named “scales” or frequency “bands.” The shortest scale which allows a multi-resolution analysis (MRA) into segments of time-domain named “scales” or frequency “bands.”

We make use of its developments such as Wavelet Coherence (WTC) and the cross-wavelet phase angle, which allow us to analyze the relative phase in time-frequency space, then the phase-differences between components. The WTC enables us to detect unexpected significant variations that can occur in co-movements of the time series under observation in the domain of time-frequency. Torrence and Webster (1998) stated that the wavelet coherence could be clarified by two-time sequence $a(t)$ and $b(t)$ as:

$$W²(p,q) = \left| \frac{M^{-1}N_{ab}(p,q)}{M^{-1}|N_a(p,q)| M^{-1}|N_b(p,q)|} \right|^2$$

where, M is the smoothing function. $W²(p,q)$ shows the range of squared wavelet coherence coefficient, which must be between 0 and 1. When it is very close to zero (unity), it indicates the independence (high dependence).

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Another family of wavelets is used in our study, such as the Continuous Wavelet Transform (CWT).3 We make use of its developments such as Wavelet Coherence (WTC) and the cross-wavelet phase angle, which allow us to analyze the relative phase in time-frequency space, then the phase-differences between components. The WTC enables us to detect unexpected significant variations that can occur in co-movements of the time series under observation in the domain of time-frequency. Torrence and Webster (1998) stated that the wavelet coherence could be clarified by two-time sequence $a(t)$ and $b(t)$ as:

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To learn more about the advantages of using this technique, see In and Kim (2006).

2 $J$ should describe the maximum integer such that $2^J$ has a value less than the number of observations.

3 Even the DWT is very used in economic research, the CWT is also, due to their advantages related to data decomposition of many variables at the same time, see Grinsted et al. (2004).

4 Note that the make use of Monte Carlo method is in the order to examine the hypothetical allocation of wavelet coherence.

5 For more information, see Kroner and Sultan (1993).
To proceed with the separation of the effects across time-scales and frequency bands, we use the MODWT based wavelet covariance analysis. First, we make use the multi-resolution analysis (MRA) of the MODWT based upon the Daubechies (1992) least asymmetric (L.A.) wavelet filter LA (8), with order J = 5, to decompose our series into five different frequency components (D1, . . . , D5) and a smoothed part (S5). Note that our choice of a filter length L = 8 responds to a reasonable strategy. In previous empirical studies, the smallest L gives consistent results. Our setting provides the most accurate time-alignment between wavelet coefficients at various scales and the original time-series.

Table A1 presents the summary statistics for daily returns before and during the COVID-19 period. The returns for the different variables (SSEC and the alternative assets) were close to zero in both periods. Moreover, the average value of all returns was positive before the pandemic (except for VIX) and negative during the pandemic for SSEC, DJIA, WTI, and Bonds. Standard deviations were higher during COVID-19 period in every case, indicating an increase in volatility and relatively high risk. Globally, these returns presented negative asymmetry for both periods. All the returns showed an excess of Kurtosis that increased in the crisis period (except for Gold and VIX). The normality of the unconditional distribution was rejected for all series in the two subperiods. Finally, the results from the ARCH-LM test suggest strong evidence of autoregressive conditional heteroskedasticity (ARCH) effects in most returns for the two subperiods.

Table A2 reports the Pearson correlations between daily returns for the two subperiods, before and during COVID-19 epidemics. During the pandemic period, we observe an increase in the correlation coefficients between SSEC and the different alternative assets, except for SSEC-Bonds pair, which can be explained by the “flight-to-quality” phenomenon between stocks to bonds during previous crises (see Baur and Lucey, 2009). For Bitcoin and Gold, the correlation was negative before the pandemic and positive during the crisis period. For VIX, the correlation is always negative, even in times of turbulence.

4. Empirical results

The purpose of our study is to analyze the connectedness, the lead-lag interplay, and hedging between the Chinese stock market with Bitcoin, DJIA, Gold, WTI, Bonds and VIX using both time frequency-based approach and GJR-DCC-GARCH model.

4.1. Wavelet approach

Firstly, we make use the multi-resolution analysis (MRA) of the MODWT based upon the Daubechies’ (1992) least asymmetric (L.A.) wavelet filter LA (8), with order J = 5, to decompose our series into five different frequency components (D1, . . . , D5) and a smoothed part (S5). Note that our choice of a filter length L = 8 responds to a reasonable strategy. In previous empirical studies, the smallest L gives consistent results. Our setting provides the most accurate time-alignment between wavelet coefficients at various scales and the original time-series.

To proceed with the separation of the effects across time-scales and frequency bands, we use the MODWT based wavelet covariance analysis (Fig. A2) between the Chinese stock market (SSEC), Bitcoin, DJIA, Gold, WTI, Bonds and VIX (per pair of variables) for the two subperiods, before and during COVID-19 epidemic. Each Figure reports the results during the non-crisis period (solid lines) and crisis period (dashed lines).

Fig. A2 shows how the selected variables are associated with one another from calm period to crisis period. We observe that the...
wavelet covariance increase during the COVID-19 spread, indicating a strong association between our series of returns during this epidemic. These results suggest an increased possibility of contagion effect between SSEC and alternative assets.

Notice that in the calm period, there was a weak dependence between SSEC, Bitcoin, DJIA, Gold, WTI, Bonds and VIX, with covariance in all times scales closes to zero. Whereas in the crisis period, the wavelet covariance fluctuates with positive values over the wavelet scales for Bitcoin, DJIA, Gold and WTI, suggesting, thus, the existence of positive association (positive dependence).

On the other hand, there was a negative association between SSEC and VIX, where the wavelet covariance is negative over the frequency scales, implying that an increase in VIX prices is associated with a depreciation of SSEC price (lose money) over the investment horizons, considering that it is an indicator of uncertainty in Chinese financial markets.

For bonds, the wavelet covariance is positive over the high frequencies and negative over the middle and low frequencies (D3, D4 and D5), through the crisis period. This reveals the existence of “flight-to-quality” phenomenon during the COVID-19 period, especially in middle and low frequencies, where there is a positive dependence between SSEC and Bonds in D1 and D2 and negative dependence in D3, D4 and D5. This is good news for investors since it implies that Bonds are considered as an asset class for Chinese stock market in the COVID-19 period.

Therefore, an interpretation of the wavelet correlation is necessary to examine the extent of association across scales (Fig. A3). We standardize the covariance, dividing by the variance of each series, in order to identify the existence of interdependence and financial contagion between each couple of variables.

By distinguishing between the different subperiods (before and during the COVID-19 epidemic), the wavelet correlation evidences show a significant increase of correlation during the COVID-19 spread, which indicates the existence of financial contagion during the crisis period especially between SSEC, Bitcoin, DJIA, Gold and WTI. These contagion effects are scale dependent, in the sense that they do not display their effects uniformly across scales. There was a weak correlation in the short-run (high frequencies) and a strong one in the long-run (low frequencies). This reveals that during the COVID-19 crisis, these cross-market linkages have become stronger mostly at low frequency scales.

In contrast, the analysis of the SSEC-Bonds and SSEC-VIX estimated wavelet correlation shows a significant decrease in wavelet correlation respectively at low and high frequency scales, suggesting, thus, a de-contagion effect (weakening linkages) for SSEC-Bonds and SSEC-VIX on these scales.

It is important to note that for Gold, the wavelet correlation is negative in normal period, indicating negative dependence between SSEC and Gold. Whereas in crisis period, it is positive over the wavelet scales, which implies that gold price has been influenced by the known disruptions in the Shanghai stock markets.

Taken together, the results from the wavelet analysis show globally that with the onset of the COVID-19 crisis, financial contagion effects are more identified between SSEC, Bitcoin, DJIA, Gold and WTI. Notice, however, that these connectedness change across scales and then there is an impact of investment scales on these markets.

To better examine these interdependences across investment horizons, we perform the dynamic conditional correlation of low and high frequency separately for each pair (Fig. A4), combining between wavelets and multivariate GJR-DCC-GARCH approach. This type of combination allows us to examine the conditional correlations and optimal hedge ratios over short and long-run investment horizons.

Fig. A4 shows that Shanghai stock returns are positively correlated with Bitcoin, DJIA, WTI and Bonds and negatively with Gold and VIX throughout the full sample period (before and during the crisis). For Gold, a particular important interaction with SSEC was observed at the beginning of the COVID-19 epidemic. Especially, a high correlation with positive values between Gold and SSEC was recorded during March-2020, while it was weak and strictly negative before the pandemic. In addition, this interaction did not last very long, as the correlation between this pair of variables rapidly decreased to reach negative values in May 2020.

Furthermore, for Bitcoin, DJIA, WTI and Gold, upwards trends are shown following the covid-19 spread while for Bonds and VIX this correlation has been trending downwards, recording values lower than calm period. This result indicates that Bitcoin, DJIA, WTI and Gold have a very important role in transmission of financial recession (contagion effect) for Shanghai stock market during the COVID-19 period than Bonds and VIX, which identifies the results found in Fig. A3. The interaction effects recorded in these markets can be explained by the travel restrictions in the world and the disruptions of production and supply chain which have affected firms and industries because of total confinement known in the COVID-19 period.

Likewise, when analyzing this same relationship using low and high-frequency data, we notice a peculiar interaction between SSEC and the six selected assets at the point of the onset of the COVID-19 outbreak. Interestingly, both short and long-run correlation estimates fluctuate around the correlation series of raw returns. However, the long-run correlations present higher values with fewer variations than do the short-run correlations. In the long-run, the SSEC-VIX dynamic conditional correlation shows less pronounced variability compared to the rest of variables, which was negative during the COVID-19 period. This indicates immense economic benefits for Shanghai stock market gained from optimal diversification with VIX in this pandemic period.

To detect the leader of interactions revealed in previous Figures, Fig. A5 shows the pair-wise wavelet coherence of the Shanghai stock market with the six selected assets. Firstly, this Figure shows very significant co-movements (warmer colors) between SSEC and financial assets (Bitcoin, DJIA, Bonds and VIX) over the sampled period, especially in the long-run (low frequencies) and huge islands of colder color (blue) are shown between SSEC and commodities (Gold and WTI), indicating the existence of weak connectedness between these two markets.

For SSEC-Bitcoin, SSEC-DJIA and SSEC-Bonds wavelet coherence, the arrows are mostly turned to the right, indicating that they move in the same direction (in-phase) over the sample period, whereas for SSEC-VIX, they turn to the left (antiphase) over the sample period and over scales, because when uncertainty increases, SSEC price decreases.

Notice that SSEC is leading Bitcoin, DJIA and VIX just during COVID-19 pandemic, which means that they seem to react to the bad...
news coming from China in January-2020 more than the other variables, whose first death by the coronavirus was recorded on January 11 by the Chinese health authorities. Knowing that the sharp decrease in the Chinese stock exchange because of the COVID-19 has strikingly reduced the financial performance worldwide and increased the uncertainty in financial markets.

Therefore, we might infer that COVID-19 epidemic is expected to have a lower effect on the co-movements between the Chinese stock market and commodities, given that the connectedness between SSEC and commodities is lower than that with financial variables. This result provides important economic implication. In fact, the low connectedness between the Chinese stock market and commodity assets implies that these latter may act as better hedge assets to the SSEC. Notice that our results show, particularly, a better hedging effectiveness during the crisis period.

4.2. Hedging

For more deep analysis, and to better verify how to hedge against variations in the Shanghai stock market with Bitcoin, DJIA, Gold, WTI, Bonds and VIX during the COVID-19 turmoil, we calculate their optimal hedge ratios through this pandemic period (Fig. A6). These ratios are determined from the GJR-DCC-GARCH model estimates, considering a long position in the Chinese stock market and a short position in Bitcoin, DJIA, Gold, WTI, Bonds and VIX.

According to these results, we observe that these ratios are positive for Bitcoin, DJIA, Gold, WTI and Bonds and negative for VIX, this occurs because the SSEC-VIX pairs are negatively correlated. These results confirm our previous findings suggesting economic benefits of diversification (negative interdependence between SSEC and VIX) and hedging effectiveness capacity for the other alternative assets (commodities).

Comparing the results over the two subperiods (before and during the COVID-19 epidemic), the ratios known small increase at the beginning of the crisis, which means that there is an increase in hedging costs because of the pandemic. This explained that health authorities have no information on this novel virus, which is spreading the world. It is important to note that this increase did not last long, where the ratios recognized a decrease in April-2020.

Furthermore, the long-run hedge ratios present the highest values with fewer variations than do the short-run ratios.

To identify the best performing variable for the Chinese markets offering the best hedging effectiveness, Table A3 presents the descriptive statistics of the hedge ratios and hedging effectiveness index (HE). A higher value of HE indicates higher hedging effectiveness.
For raw series, VIX provides the highest hedging effectiveness in calm period and Bitcoin the lowest one. It is because the Bitcoin has long been considered as an asset more volatile and less liquid to transact than other traditional financial assets (see Smales, 2019). Notice that the average value of the hedge ratios between SSEC returns and VIX is 5.89 cents, which indicates that a 1-Yuan long position in the Shanghai stock market can be hedged for 6 cents in the China volatility index. In crisis period, VIX preserves its place as the best hedging asset for Shanghai stock market, whereas Bitcoin provides the second highest hedging, this can be explained because the levels of COVID-19 cause a rise in Bitcoin prices. These results corroborate those from the study conducted by Goodell and Goutte (2021a,b).

After decomposing the series into frequency bands, the short-run level shows that VIX still the best hedging asset just in calm
period, while during COVID-19 pandemic he lost his place, where Bitcoin becomes the best hedging asset thanks to its prices which are on the rise during the COVID-19 period. Then, diversification with Bitcoin can be more efficient in the short runs. This latter result confirms of course that from Omame-Adjepong and Alagidede (2019).

In contrast, for the long-term investment horizons, commodities provide the best hedging effectiveness during the crisis period. WTI offers the first highest value of HE followed by Gold, but with a very slight difference. Knowing that before the COVID-19 spread, VIX and Bonds provide the first and the second highest hedging, respectively.

Taken together, our results indicate that in raw series and in short-run series, financial assets provide the best hedging effectiveness for the Shanghai stock market during the pandemic period of COVID-19. Whereas, in the long-run investment horizons, commodities
offer abundant opportunities to hedge against risk during this epidemic period. These are important findings for investors and decision makers. In fact, our findings provide important economic implications. In the short-term, it is possible to hedge equity market by financial assets. However, in the long term, it is better to rely on commodities to hedge for the equity market. Also an optimal diversification of investment between stocks and other alternative financial assets (Bonds, VIX) provides a good protection against unpredictable risk induced by an unpredictable crisis such as the recent one relating to the Covid-19.

4.3. Robustness checks

In Table A4, we identify the causal relationship between selected variables for the different subperiods (before and during COVID-19 pandemic) by resorting to the wavelet-based Granger Causality tests. This robustness check is implemented for raw, short-run and long-run series. Table A4 shows that causalities during COVID-19 crisis are more significant than before the pandemic, especially for

Fig. A4. Dynamic conditional correlation.
Note: The raw series show the correlation estimates using returns without decomposition. Short and long-run series show the correlation estimates obtained through the decomposed series of D1 and D5, respectively. The colored part presents the correlation estimates during the COVID-19 period.
Before the crisis, we observe a causal relationship from DJIA to SSEC for the three levels which is coherent with Fig. A5 where the DJIA is leading the SSEC before COVID-19 spread. In the same period, the most important causalities are found for SSEC-Bonds and SSEC-VIX, where the causalities are bidirectional in the short term.

During the COVID-19 period, the causalities are more attractive in the long-run investment horizons, where the strong SSEC

Fig. A5. Wavelet coherence plots by pair-wise estimates.
Note: The thick black contour designates the 5% significance level estimate from the Monte Carlo simulations using the phase randomized surrogate series.
bidirectional causalities are found with the DJIA and Gold. Furthermore, causal relationship is shown from SSEC to Bitcoin, from Bonds to SSEC and from SSEC to VIX. These results confirm the stability of those from the wavelet coherence analysis reported in Fig. A5, where SSEC is leading Bitcoin and VIX, while Bond is leading SSEC during the COVID-19 crisis.

The causalities between SSEC and WTI are very weak and non-significant for the different levels, since the co-movements recorded between them are very weak (Fig. A5). This confirms our previous findings relating to the hedging effectiveness (Table A3), where WTI offers the first highest value of HE in the long-term.

5. Conclusion

Given the level of integration of the global financial system, the eminent risk of financial contagion becomes prevalent during the COVID-19 sanitary crisis. Economies currently at different growth paths are faced with unique macroeconomic conditions that determine the stability and resilience of their respective financial systems. Different policy responses adopted by different economies in

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Fig. A6. Optimal hedge ratios.
Note: The raw series show the hedge ratios using returns without decomposition. Short and long-run series show the hedge ratios obtained though the decomposed series of D1 and D5, respectively. The colored part presents the hedge ratios during the COVID-19 period.
combating the pandemic will, to a large extent, determine the severity, duration, and management of both the health and consequent crisis with spillover effects expected (Battiston et al., 2012).

This paper examines the role of alternative assets, which allow investors to hedge their investment in China against COVID-19 financial risks. We provide substantial evidence of significant co-movements between the Chinese stock exchange (SSEC) and financial assets (Bitcoin, DJIA, Bonds and VIX) over the Covid-19 crisis period. Besides, the empirical results document the dependency between the Shanghai stock index (SSEC) and commodities (Gold and WTI).

Our results show, moreover, that the COVID-19 epidemic is expected to have a lower short-term effect on the commodity prices, given that the dependence between the Chinese stock market and commodities is less than that with financial variables. We also find that VIX has immense economic benefits (optimal diversification) for Shanghai stock market in this pandemic period and commodities have hedging effectiveness capacity, especially in the long-term. WTI provides more opportunities for hedging against risk. The sharp decrease in oil prices over the recent period offers investors the opportunity to purchase energy at low costs.

For the long-term investment horizons (high scales), the hedging effectiveness is highest for SSEC/commodities. In the short-term (low scales), it is highest for SSEC/Bitcoin. These findings have important implications for investors desiring to hedge their investment in the Shanghai stock market during this pandemic period.

### Table A1
Summary statistics for daily returns.

|                          | Before COVID-19 pandemic | During COVID-19 pandemic |
|--------------------------|--------------------------|-------------------------|
|                          | Mean | Std.Dev. | Skew. | Kurt. | Shapiro.Wilk | ARCH-LM (10) |
| SSEC                    | 0.0009 | 0.0110 | −0.1824 | 5.4236 | 0.9280*** | 22.961*** |
| Bitcoin                 | 0.0023 | 0.0471 | 0.3588 | 7.1893 | 0.8676*** | 14.133* |
| DJIA                    | 0.0008 | 0.0077 | −0.6603 | 3.3407 | 0.9387*** | 37.166*** |
| Gold                    | 0.0005 | 0.0107 | 0.3265 | 7.9937 | 0.8460*** | 49.013*** |
| WTI                     | 0.0011 | 0.0209 | 0.5287 | 7.2066 | 0.9232*** | 6.105 |
| Bonds                   | 0.00002 | 0.0060 | −0.2439 | 1.4679 | 0.9813*** | 9.811 |
| VIX                     | −0.0014 | 0.0536 | 1.1074 | 5.5757 | 0.9012*** | 25.164** |

Note: SSEC stands for Shanghai Composite Stock Exchange, DJIA for Dow Jones Industrial Average, WTI for West Texas Intermediate (crude oil) and VIX for Volatility Index. *, **, and *** denote rejection of the null hypothesis at the 10 %, 5 %, and 1 % levels of significance, respectively.

### Table A2
Pearson correlations between daily returns.

|                          | Before COVID-19 pandemic | During COVID-19 pandemic |
|--------------------------|--------------------------|-------------------------|
|                          | SSEC | Bitcoin | DJIA | Gold | WTI | Bonds | VIX |
| SSEC                     | 1
| Bitcoin                  | −0.014 | 1
| DJIA                     | 0.163*** | −0.114* | 1
| Gold                     | −0.149** | 0.049 | −0.233*** | 1
| WTI                      | 0.0150** | −0.207 | 0.029*** | −0.068 | 1
| Bonds                    | 0.0258*** | 0.0075 | 0.0071 | −0.002 | −0.001 | 1
| VIX                      | −0.247*** | 0.0192*** | −0.589*** | 0.0236*** | −0.163*** | −0.048 | 1

Note: SSEC stands for Shanghai Composite Stock Exchange, DJIA for Dow Jones Industrial Average, WTI for West Texas Intermediate (crude oil) and VIX for Volatility Index. *, **, and *** denote rejection of the null hypothesis at the 10 %, 5 %, and 1 % levels of significance, respectively.
Table A3
Hedge ratio summary statistics and hedging effectiveness (HE).

|                        | Before COVID-19 pandemic | During COVID-19 pandemic |
|------------------------|--------------------------|-------------------------|
|                        | Mean         | Minimum  | Maximum  | HE          | Mean         | Minimum  | Maximum  | HE          |
| Raw series             |              |          |          |             |              |          |          |             |
| Bitcoin                | 0.0015       | 0.0007   | 0.0033   | 0.00006     | 0.0075       | 0.0036    | 0.0159   | 0.0071     |
| DJIA                   | 0.0271       | 0.0079   | 0.0577   | 0.0347      | 0.0179       | 0.0028    | 0.0501   | 0.0055     |
| Gold                   | -0.1121      | -0.1736  | -0.0668  | 0.0025      | 0.0237       | 0.0116    | 0.0695   | 0.0039     |
| WTI                    | 0.00936      | 0.0537   | 0.0739   | 0.0245      | 0.0077       | 0.0072    | 0.0289   | 0.0059     |
| Bonds                  | 0.04871      | 0.03249  | 0.0715   | 0.00702     | 0.0096       | 0.0046    | 0.0204   | 0.0010     |
| VIX                    | -0.0589      | -0.1036  | -0.0151  | 0.00761     | -0.0520      | -0.1071   | -0.0212  | 0.00883    |
| Short-run series       |              |          |          |             |              |          |          |             |
| Bitcoin                | -0.0104      | -0.2838  | 0.0291   | 0.0269      | 0.0105       | -0.0241   | 0.0471   | 0.0190     |
| DJIA                   | -0.0087      | -1.3879  | 12.518   | 0.0095      | 0.0782       | -0.4870   | 0.0549   | 0.0071     |
| Gold                   | -0.081       | -0.4786  | 0.0492   | 0.00725     | 0.0205       | -0.2676   | 0.1308   | 0.0076     |
| WTI                    | 0.00616      | -0.4891  | 0.0516   | 0.00705     | 0.00837      | -0.0411   | 0.0515   | 0.01483    |
| Bonds                  | 0.04158      | -0.5837  | 1.896    | 0.00106     | 0.02540      | -0.2481   | 0.09321  | 0.00775    |
| VIX                    | -0.0300      | -0.3343  | 0.0252   | 0.00745     | -0.0434      | -0.1577   | 0.0103   | 0.0119     |
| Long-run series        |              |          |          |             |              |          |          |             |
| Bitcoin                | 0.01345      | 0.1677   | 0.0456   | 0.03107     | 0.00622      | -0.4666   | 0.0438   | 0.05369    |
| DJIA                   | 0.0517       | -3.0223  | 34.216   | 0.04816     | 0.02032      | -0.6708   | 0.0937   | 0.05528    |
| Gold                   | -0.1157      | -4.8646  | 0.227    | 0.03816     | 0.01002      | -0.0776   | 0.3485   | 0.07148    |
| WTI                    | 0.04573      | -0.5761  | 0.2721   | 0.04672     | 0.01034      | -0.1117   | 0.02646  | 0.01483    |
| Bonds                  | 0.08049      | -2.9585  | 40.953   | 0.05137     | 0.02165      | -3.8224   | 0.21394  | 0.06161    |
| VIX                    | -0.0837      | -0.5566  | 0.06983  | 0.06202     | -0.0939      | -0.2667   | 0.00473  | 0.06028    |

Note: DJIA stands for Dow Jones Industrial Average, WTI for West Texas Intermediate (crude oil) and VIX for Volatility Index.

Table A4
Wavelet-based Granger causality test.

| Causal relationship | Before COVID-19 pandemic | During COVID-19 pandemic |
|---------------------|--------------------------|-------------------------|
|                     | Raw series | Short-run series | Long-run series | Raw series | Short-run series | Long-run series |
| SSEC → Bitcoin      | 0.186      | 0.362           | 1.711           | 0.817      | 0.175           | 2.47*          |
| Bitcoin → SSEC      | 0.356      | 0.860           | 0.791           | 0.551      | 0.284           | 0.164          |
| SSEC → DJIA         | 0.134      | 1.664           | 0.412           | 0.580      | 4.718**         | 7.978***       |
| DJIA → SSEC         | 7.603***   | 5.374***        | 8.320***        | 2.532*     | 0.548           | 2.392*         |
| SSEC → Gold         | 0.108      | 2.947*          | 0.164           | 1.067      | 1.573           | 7.860***       |
| Gold → SSEC         | 0.327      | 0.496           | 10.136***       | 1.142      | 1.616           | 5.508***       |
| SSEC → WTI          | 1.425      | 0.482           | 0.997           | 0.067      | 0.015           | 0.136          |
| WTI → SSEC          | 1.880      | 1.152           | 2.355*          | 0.439      | 0.991           | 0.284          |
| SSEC → Bonds        | 1.018      | 5.526***        | 0.156           | 2.497*     | 0.886           | 1.184          |
| Bonds → SSEC        | 1.295      | 2.945*          | 1.961           | 0.887      | 2.557*          | 6.502***       |
| SSEC → VIX          | 0.006      | 6.665***        | 1.481           | 2.116      | 4.784**         | 4.734**        |
| VIX → SSEC          | 4.278**    | 6.661***        | 5.567           | 5.587***   | 0.580           | 0.065          |

Note: SSEC stands for Shanghai Composite Stock Exchange, DJIA for Dow Jones Industrial Average, WTI for West Texas Intermediate (crude oil) and VIX for Volatility Index. *, **, and *** denote rejection of the null hypothesis at the 10 %, 5 %, and 1 % levels of significance, respectively.

CRediT authorship contribution statement

Salma Tarchella: Conceptualization, Methodology, Software, Data curation, Writing- Original draft preparation. Abderrazak Dhaoui: Writing- Original draft preparation, Visualization, Investigation, Supervision, Validation, Writing- Reviewing and Editing, Revision.

Appendix A
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