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Market reaction, COVID-19 pandemic and return distribution
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**A B S T R A C T**

The Coronavirus (COVID-19) pandemic is disrupting the world. Employing an event study, we find cross-country evidence that stock markets all significantly react to COVID-19, but with different speeds, strengths and directions. Moreover, reactions to COVID-19 also vary across quantile levels of return distributions in any given country, by using an augmented quantile auto-regression approach. US (Indian) markets generally show overreaction (underreaction), while stock markets in Australia, Germany, Japan and UK overreact to the pandemic when quantile returns are below the median.

**1. Introduction**

The outbreak of coronavirus (COVID-19) has heavily impacted millions of lives and considerably influenced the financial markets from all perspectives (Pan et al., 2021; Iqbal and Bilal, 2021; Zhang et al., 2021). Beyond the direct tragedies of death and disease, the pandemic has had dramatic effects on investors’ decision making and market reactions to information on the COVID-19 pandemic. Moreover, different groups of investors in different countries hold differing biases on the precision and predictive accuracy of pandemic information, which may lead to overreaction or underreaction (Jiang and Zhu, 2017; Borgards et al., 2021). This paper investigates the international evidence of relations between market reaction and COVID-19 and further detects the persistence of market returns at different parts on the return distributions through the use of quantile autoregressive (QAR) models.

An increasing number of studies documents the market reactions to COVID-19, such as those on the US and European markets (Xu, 2021), on Asian markets (Sun et al., 2021; Nguyen and Dinh, 2021), on Australian market (Naidu and Ranjeeni, 2021) and also on cross-country stock markets (Heyden and Hayden, 2021). Although similar event study methods are used, different indicators of COVID-19 have been adopted to identify the event day, including the announcements of the first case, the announcements of the first death or even the announcements of the first related policy. However, these indicators give a fixed day of the event, which might reduce the power of their findings to predict the future impact of the developing COVID-19. We, therefore, set the peak of the new case of COVID-19 during our sample period\textsuperscript{1} as the event day in our study. Our results can help to explain two types of investors’ uncertainty during the decision making process: whether the COVID-19 in a specific country indeed reaches its peak and how the corresponding market reacts to this peak.

The market is hypothesized to positively react to the real peak of COVID-19 if it is efficient. Suggested by the cumulative abnormal returns (CAR), we find that all cross-country markets (Australia, China, Germany, India, Japan, the UK and US) significantly react...
to COVID-19 when a relative long event window ([−30, 30] days) is used. However, the speed, strength and direction of the market reaction across countries are not consistent. For example, only Chinese stock market show significant positive CAR to COVID-19 since the second day of the peak, but it turns to be a negatively significant CAR when the event window lengthens. This suggests that in China there is a very sufficient way in reporting the new case of COVID-19, but the market is less efficient as there are noise traders overreacting to the pandemic information. In contrast, in the US, the market reaction captured by CAR is not significant until the longest event window is considered, indicating a relative long process in decision making.

Moreover, such market reactions are characterized by nonlinear shifts reflecting the relationship between investor beliefs on the connection between COVID-19 and returns. Existing literature attempts to investigate the market reactions to COVID-19 without considering the market status or return distributions. Baur and Schulze (2003) quantile regression framework is commonly used to examine linear and nonlinear linkages between contagion and its determinants. Then, in next step, we aim to enrich this emerging literature by studying investor overreaction and underreaction to the pandemic at different points along the return distribution using a pandemic-related quantile auto-regression model. We thoroughly compare different market behaviors during pandemic period. Empirically, reaction to the pandemics is sensitive to the quantiles used for analysis and varies by country. Stock returns are found to significantly interact with developing pandemics in all regions except China. In particular, US (Indian) markets generally show overreaction (underreaction), while stock markets in Australia, Germany, the UK and Japan overreact to the pandemic when quantile returns are below the median, but this shifts to underreaction to varying degrees.

The remainder of this paper proceeds as follows. Section 2 presents our data and methodological approach. Section 3 shows empirical results. Finally, Section 4 concludes.

2. Data and methodology

We collect stock market returns (national indices) from Datastream and obtain worldwide data on coronavirus from WHO. Since countries vary with the breakout of the pandemics, each country has a different start in our dataset, but all end at December 17, 2020. We present summary statistics of the stock markets and new cases confirmed by country in Table 1. Due to the observed differences in the data across the world, we standardize returns and normalize the number of new cases confirmed to eliminate the impact of variation in the population base.

The event study method has long been used to analyze market reactions to some specific events (Hou and Li, 2020). To examine the cross-country market reactions to COVID-19, an approach followed by Heyden and Heyden (2021) has been also been adopted in this paper, but with different event windows ([−2, 2], [−5, 5], [−10, 10], [−15, 15] and [−30, 30] days). Considering the different quantile levels of return distribution, we use the quantile regression model to fit the dependent variables, estimating conditional quantiles of returns. More precisely, we estimate the first-order conditional quantile autoregressive model (QAR(1)) in Eq. (1):

\[ Q_i(R_t|\Omega_{t-1}) = a_i + \beta_i R_{t-1} \]

where \( R_t \) denotes the return of stock on day \( t \), \( Q_i(R_t|\Omega_{t}) \) is the return of the stock on the \( \tau \)-th quantile and \( \Omega_t \) is the information set publicly available to the market participants at the end of period \( t - 1 \). \( \beta_i \)'s are interpreted as the specific parameters of the \( i \)-th quantile in the auto-regression, which is our main focus.

We extend the preliminary model to a more concrete model in a pandemic scenario, where investor sentiment can be separated into two parts (one caused by the persistence of the market and the other an interactive variable on the spread of COVID-19) (Mezghani et al., 2021). Thus, this variable can have an interactive effect on lagged return, which precisely estimates how the pandemic affects investor behavior across countries, as shown in Eq. (2):

\[ Q_i(R_t|\Omega_{t-1}) = a_i + \beta_i R_{t-1} + \gamma_t R_{t-1} C_{t-1} \]

where the interactive variable \( C_{t-1} \) is equal to the logarithm of new cases confirmed at the end of period \( t \). This “modified model” provides insight into the persistence of returns during the pandemics according to the distribution of returns.

3. Empirical results

We first employ an event study to test the market reaction to COVID-19, as suggested by Heyden and Heyden (2021). Fig. 1 shows our main CAR results and Table 2 reports SCARs and corresponding p-values over 5 different time frames, i.e. 2, 5, 10, 15 and 30 days before and after the event.

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2 This method was first introduced by Koenker and Xiao (2006) to capture the systematic influences of conditioning variables in the stock market, and subsequently adopted by Baur et al. (2012) to examine stock market return autocorrelation. Chen et al. (2020a) thereby use quantile regression to understand how stock market returns link to other financial sectors.

3 Coronavirus disease (COVID-19): www.who.int/emergencies/diseases/novel-coronavirus-2019.

4 In unreported tables, portmanteau tests are implemented to analyze return autocorrelation across countries and Escanciano–Lobato statistics for each country are reported to confirm the absence of auto-correlations in the returns.

5 To test whether the CAR is equal to 0, we adopt a standardized statistics, SCAR, as established by Kakotsis and Sarantis (2006) to test its significance level, where \( SCAR_i = (\bar{CAR}_i / \sqrt{VAR(CAR_i)}) \).
All countries have a drastic change in CARs, indicating significant reactions to the COVID-19 pandemic. The reactions of CARs to the peak of COVID-19 in Australia, China, Germany, Japan and the UK show an upward trend while those in India and the US show a downward trend, UK also fluctuates in the short term. More specific, as illustrated in Table 2, although all stock markets significantly react to COVID-19 with the longest \([-30,30]\) window, the speeds, strengths and directions vary across countries. Most significantly, Chinese market most quickly reacts to COVID-19 with 2-days while the US has no reactions until 30 days are passed.

Considering the developing Fintech and data analytic technologies, Chen et al. (2022) it can be reasonably hypothesized the market should be very efficient and positively react to the real peak of COVID-19 in any efficient market. Suggested by the cumulative abnormal returns (CAR), we find that all cross-country markets (Australia, China, Germany, India, Japan, the UK and US) significantly react to COVID-19 when a relative long event window \((-30,30)\) days is used. However, the speed, strength and direction of the market reaction across countries are not consistent. For example, only Chinese stock market show significant positive CAR to COVID-19 since the second day of the peak, but it turns to be a negatively significant CAR when the event window lengthens. This suggests that in China there is a very sufficient way in reporting the new case of COVID-19, but the market is less efficient in other countries.

### Table 1

A description of the statistics.

| Country | AU | CN | DE | IN | JP | UK | US |
|---------|----|----|----|----|----|----|----|
| Stock index | A551 | SSEC | GDAXI | SENSEX | N225 | FTSE | DJI |
| Start date | 2020-02-03 | 2020-01-06 | 2020-02-03 | 2020-03-02 | 2020-01-06 | 2020-02-03 | 2020-02-03 |
| End date | 2020-12-17 | 2020-12-17 | 2020-12-17 | 2020-12-17 | 2020-12-17 | 2020-12-17 | 2020-12-17 |
| Number of observations | 246.00 | 233.00 | 245.00 | 240.00 | 233.00 | 245.00 | 234.00 |

### Table 2

Test of CARs using SCAR from Kaketsis and Sarantis (2006).

| Event window | AU | CN | DE | IN | JP | UK | US |
|--------------|----|----|----|----|----|----|----|
| \([-2,2]\)  | 0.3445 | 4.0634*** | 0.1673 | -0.6896 | -0.6702 | 0.3104 | -1.0817 |
|             | (0.7310) | (0.0001) | (0.8674) | (0.4916) | (0.5038) | (0.7567) | (0.2813) |
| \([-5,5]\)  | 0.0178 | 0.9287*** | 1.1803 | -1.5938 | -1.7967* | 3.2826*** | -0.2453 |
|             | (0.9858) | (0.0000) | (0.2399) | (0.1133) | (0.0746) | (0.0013) | (0.8066) |
| \([-10,10]\) | 1.3448 | -0.3614** | 1.2081 | -0.4795 | -1.1923 | 5.8622*** | 1.6359 |
|             | (0.1809) | (0.0196) | (0.2291) | (0.6324) | (0.2352) | (0.0000) | (0.1041) |
| \([-15,15]\) | 2.5185** | -1.1878 | 2.5424** | 2.4217** | 1.7142* | 4.9929*** | 0.0226 |
|             | (0.0129) | (0.2369) | (0.0121) | (0.0167) | (0.0887) | (0.0000) | (0.9820) |
| \([-30,30]\) | 2.0116** | -0.7689*** | 7.1555*** | 3.2240*** | 8.4014*** | 3.0581*** | -3.0831*** |
|             | (0.0462) | (0.0000) | (0.0000) | (0.0016) | (0.0000) | (0.0027) | (0.0025) |

This table reports the significance tests of CARs across countries. To test whether the CAR is equal to 0, we adopt a standardized statistics, SCAR, as established by Kaketsis and Sarantis (2006) to test its significance level, where \(SCAR = (\overline{CAR} / \sqrt{Var(CAR)})\). P-values are shown in brackets.

***Indicate that the null hypothesis that the estimates are equal to zero is to rejected at 99% level.
**Indicate that the null hypothesis that the estimates are equal to zero is to rejected at 95% level.
*Indicate that the null hypothesis that the estimates are equal to zero is to rejected at 90% level.
efficient as there are noise traders overreacting to the pandemic information. In contrast, in the US, the market reaction captured by CAR is not significant until the longest event window is considered, indicating a relative long process in decision making.

In second stage, we estimate the results of the preliminary model and modified model of median quantile regression in Table 3 to compare the two models. In general, when $\tau$ equals 0.5, the $p$-value of $\beta_{\tau=0.5}$ tends to be smaller in the modified model than the preliminary model, except for China. The results for China have a better $p$-value in the preliminary model, suggesting that China may not support the hypothesis of our modified model. This result is interesting because China has relatively well controlled the spread of the pandemics and the economy and society of China have long returned to a normal status.

Moreover, Australia, Germany, India and Japan have relatively low $p$-values of $\gamma_{\tau=0.5}$, which may suggest that the effect of new cases confirmed is comparably significant in our model ($p$-value < 0.1), while the effect is not so significant in the UK and US when $\tau$ equals 0.5.

Since the modified model can better explain beliefs in global stock markets during pandemics, we form the quantile regression from $\tau = 0.1, 0.2 \ldots 0.9$ to estimate the corresponding parameters. We present the results in Tables 4 and 5.

\footnote{In another unreported table, we perform a Wald test to investigate the hypothesis on whether the slope coefficients are significantly non-identical when the quantiles are chosen differently as described in Koenker and Bassett (1982). The differences are not statistically significant, especially at the median quantile across most regions.}

\textbf{Fig. 1.} The estimated $\beta_{\tau=0.5}$ (left) and $\gamma_{\tau=0.5}$ (right) using returns across countries.

(a) CAR in AU (b) CAR in CN (c) CAR in DE
(d) CAR in IN (e) CAR in JP (f) CAR in UK
(g) CAR in US
The modified model of each country. In contrast, the value of COVID-19 in each country is set to be the event day, while in quantile regressions the number of new cases of COVID-19 is directly used.

This table further reports the estimates of the quantile regression from Table 3, which represents the persistence of returns during different market conditions (Chevapatrakul and Mascia, 2019), are

The preliminary model

\begin{table}[h]
\centering
\begin{tabular}{lcccccccc}
\hline
 & AU & CN & DE & IN & JP & UK & US \\
\hline
coefficient of $a_{t=0.5}$ & 0.16 & 0.07 & -0.01 & 0.35 & -0.01 & 0.06 & 0.35 \\
std error of $a_{t=0.5}$ & 0.10 & 0.17 & 0.12 & 0.11 & 0.11 & 0.12 & 0.11 \\
t statistic of $a_{t=0.5}$ & 1.50 & 0.42 & -0.11 & 3.21 & -0.09 & 0.45 & 3.20 \\
P-value of $a_{t=0.5}$ & 0.14 & 0.68 & 0.92 & 0.00 & 0.93 & 0.65 & 0.00 \\
coefficient of $\beta_{t=0.5}$ & -0.25 & -0.07 & -0.06 & -0.10 & -0.01 & -0.10 & -0.42 \\
std error of $\beta_{t=0.5}$ & 0.05 & 0.08 & 0.05 & 0.05 & 0.06 & 0.06 & 0.05 \\
t statistic of $\beta_{t=0.5}$ & -4.82 & -0.88 & -1.09 & -2.10 & -0.23 & -1.67 & -9.00 \\
P-value of $\beta_{t=0.5}$ & 0.00 & 0.38 & 0.28 & 0.04 & 0.82 & 0.10 & 0.00 \\
\hline
\end{tabular}
\end{table}

This table reports the median quantile regression of the two models. The top eight lines are: coefficients, standard errors, $t$-statistics and $p$-values of $a_{t=0.5}$ and $\beta_{t=0.5}$, respectively, estimated in the preliminary model for each country, and the next 12 line are the corresponding results for $\tau_{t=0.5}$ in the modified model of each country. In contrast, the value of $\beta_{t=0.5}$ is lower in the modified model than in the preliminary model, except for China, which incompletely reverses in the table.

Table 4

The nonnegative $\tau$ effect of the pandemics (in US, China and India).

\begin{table}[h]
\centering
\begin{tabular}{lcccccccc}
\hline
Quantile & US & & & & & & & \\
\hline
 & US & CN & IN & US & CN & IN \\
\hline
0.1 & -2.04*** & -0.37 & -0.01 & -2.66*** & 0.48* & 0.05 & -2.21*** & 0.76*** & 0.12*** \\
 & 0.45 & 0.32 & 0.02 & 0.28 & 0.27 & 0.04 & 0.34 & 0.17 & 0.01 \\
0.2 & -0.79*** & -0.37*** & -0.02 & -1.5*** & 0.06 & 0 & -1.03*** & 0.54*** & 0.12*** \\
 & 0.16 & 0.09 & 0.01 & 0.2 & 0.22 & 0.03 & 0.21 & 0.12 & 0.01 \\
0.3 & -0.4*** & -0.35*** & -0.02 & -0.92*** & -0.12 & -0.01 & -0.28*** & 0.17** & 0.04 \\
 & 0.13 & 0.11 & 0.01 & 0.17 & 0.25 & 0.03 & 0.14 & 0.24 & 0.06 \\
0.4 & 0 & -0.33*** & 0.01 & -0.34*** & 0.05 & 0.02 & 0.01 & 0.17 & 0.04 \\
 & 0.12 & 0.13 & 0.01 & 0.16 & 0.18 & 0.02 & 0.13 & 0.21 & 0.06 \\
0.5 & 0.32*** & -0.35** & 0.01 & 0.02 & 0 & 0.01 & 0.36** & 0.17 & 0.05 \\
 & 0.11 & 0.15 & 0.01 & 0.17 & 0.19 & 0.02 & 0.11 & 0.17 & 0.03 \\
0.6 & 0.63** & -0.34** & 0 & 0.38** & -0.09 & 0 & 0.59*** & 0.13 & 0.04 \\
 & 0.11 & 0.16 & 0.01 & 0.18 & 0.22 & 0.03 & 0.11 & 0.16 & 0.03 \\
0.7 & 0.86*** & -0.31 & 0.01 & 1.03*** & -0.24 & -0.04 & 0.91*** & 0.17 & 0.06** \\
 & 0.12 & 0.17 & 0.01 & 0.19 & 0.29 & 0.05 & 0.11 & 0.13 & 0.03 \\
0.8 & 1.28*** & -0.18 & 0.02 & 1.85*** & -0.23*** & -0.03* & 1.19*** & 0.22* & 0.06*** \\
 & 0.13 & 0.12 & 0.03 & 0.22 & 0.1 & 0.02 & 0.11 & 0.12 & 0.02 \\
0.9 & 2.04*** & -0.29 & 0.01 & 2.59*** & -0.17*** & -0.03** & 1.86*** & -0.08 & 0.02 \\
 & 0.25 & 0.18 & 0.04 & 0.22 & 0.09 & 0.01 & 0.21 & 0.18 & 0.03 \\
Mean & 0.21 & -0.32 & 0 & 0.05 & -0.03 & 0 & 0.16 & 0.25 & 0.06 \\
 & 0.18 & 0.16 & 0.02 & 0.2 & 0.2 & 0.03 & 0.16 & 0.17 & 0.03 \\
\hline
\end{tabular}
\end{table}

This table further reports the estimates of the quantile regression from $\tau = 0.1, 0.2 \cdots 0.9$ of the modified model. Three countries, US, China and India, of which the $\tau_{t=0.5}$ are nonnegative as shown in Table 3.

*Indicate that the null hypothesis that the estimates are equal to zero is to rejected at 99% level.

**Indicate that the null hypothesis that the estimates are equal to zero is to rejected at 95% level.

***Indicate that the null hypothesis that the estimates are equal to zero is to rejected at 90% level.

The pandemics exert a zero (in China and US) or even a positive effect (in India). More specifically, the coefficients of $\beta_t$ in the US and China, which represents the persistence of returns during different market conditions (Chevapatrakul and Mascia, 2019), are

7 These results are opposite to the negative reactions of China, India and US to COVID-19. It should be notified that in first part of empirical tests the peak of COVID-19 in each country is set to be the event day, while in quantile regressions the number of new cases of COVID-19 is directly used.
more significant than the coefficients of $\gamma_r$, which denotes the panic caused by the pandemics. Stock markets in the US and China show low significance when returns are located above the median. However, they become predictable below the median, especially at the 0.2 and 0.3 quantile, and the negative coefficients of $\beta_r$ are $-0.37$ and $-0.37$, respectively, around the median of the US stock market. The negative return dependence indicates that, during the pandemics, tumbling stock prices in the US market cause investors to overreact and “rush for the exits”, thereby causing prices to fall further. This is typical of overreaction in prices in an inefficient market (Lehmann, 1990). Our results can explain why the US stock market has experienced several meltdowns during the pandemics.

For India, the results show a significant positive belief in purchasing stocks at both the quantiles of low return and high return, when the quantile equals 0.1, 0.2, 0.3, 0.7 and 0.8. Most interestingly, both the perspective of persistence ($\beta_r$) and panic ($\gamma_r$) are consistently positive during the pandemics. This abnormal phenomenon may be attributable to the large number of unicorns going public, which has caused the Sensex Index of India to reach record highs. Thus, although upward persistence of returns is very strong in the Indian stock market, we find a relatively significant drop in $\beta_r$ and $\gamma_r$. Thus, the underreaction of Indian investors is notable and indicates caution regarding the climb of the stock market and an unwillingness to hold more stocks when returns are high.

However, the magnitude of mean $\gamma_r$ in Table 5 reflects a negative impact of the pandemics on stock markets in Australia, Germany, the UK and Japan. These four countries share the similarity that when the quantile return is below the median, there is a significant overreaction where investors prefer to sell stocks when returns are relatively low. The pandemic breakout aggravates this phenomenon, where the magnitude of the interactive variable $\gamma_r$ is significantly below zero. However, the picture is entirely different in the detailed changes of $\gamma_r$. With recovery of the stock market, the influence of the pandemics becomes smaller in Europe. This can be interpreted as that an underreaction to the increase in returns and the boost to the economy can mitigate the panic stemming from the pandemics, which lowers the negative impact from $\gamma_r$ significantly. However, this pattern is not evident around the Pacific Rim. Rather, an uncertain effect on the stock market is found.

The pattern of return dependence is shown in Fig. 2, where the black solid line portrays the estimate of $\beta_r$ and $\gamma_r$ at $r = 0.05$, 0.06, ... to 0.95, while the dotted black lines form 95% point-wise confidence bands around quantile regression estimates (solid black line). The red lines show OLS regression results along with their 95% confidence interval. The effect of investor behavior is not fixed over the distribution of returns. Therefore, the estimated quantile $\beta_r$ and $\gamma_r$ in Germany, the UK and US present statistically negative return autocorrelation at the left tail. In contrast, the corresponding estimation for India is entirely inverse and shows a relatively positive return autocorrelation at the left tail. Moreover, note the statistically negative return autocorrelation in Australia, Japan and China, visible at the right tail of the return distribution. However, evidence for the quantile not at the tail is not significant in most figures, where the red and black dotted lines suggest the absence of return persistence in all countries when the analysis is performed at the means.

### Table 5

| Quantile | AU | DE | GB | JP |
|----------|----|----|----|----|
| a_r | $-0.21^{**}$ | $-0.16$ | $-0.12$ | $0.09^*$ |
| b_r | $0.33$ | $0.06$ | $0.18$ | $0.15$ |
| $\gamma_r$ | $-0.25$ | $0.16$ | $-0.07$ | $-0.14$ |
| 0.1 | $-0.225^{***}$ | $-0.15$ | $-0.09$ | $-0.16^{***}$ |
| 0.2 | $-0.14$ | $0.11$ | $0.04$ | $0.14$ |
| $\beta_r$ | $0.4$ | $0.36$ | $0.22$ | $0.15$ |
| 0.3 | $-0.09$ | $-0.10$ | $-0.04$ | $-0.05$ |
| 0.4 | $-0.09$ | $-0.10$ | $-0.06$ | $-0.06$ |
| 0.5 | $-0.09$ | $-0.06$ | $-0.03$ | $-0.04$ |
| 0.6 | $-0.09$ | $-0.04$ | $-0.04$ | $-0.05$ |
| 0.7 | $-0.09$ | $-0.06$ | $-0.03$ | $-0.03$ |
| 0.8 | $-0.09$ | $-0.09$ | $-0.03$ | $-0.03$ |
| 0.9 | $-0.09$ | $-0.10$ | $-0.06$ | $-0.03$ |
| Mean | $-0.09$ | $-0.10$ | $-0.06$ | $-0.05$ |

This table further reports the estimates of the quantile regression from $r = 0.1,0.2 \cdots 0.9$ of the modified model. Four countries, Australia, Germany, UK and Japan, of which the $\gamma_{r0.03}$ are negative as shown in Table 3.

*Indicate that the null hypothesis that the estimates are equal to zero is to rejected at 99% level.

**Indicate that the null hypothesis that the estimates are equal to zero is to rejected at 95% level.

***Indicate that the null hypothesis that the estimates are equal to zero is to rejected at 90% level.
Fig. 2. Stock reactions of CAR to COVID-19 across countries.
4. Conclusion

This paper investigates the cross-country market reactions to the COVID-19 pandemic and its impacts on stock movements. In particular, we initially explore the structure of market behavior in Australia, China, Germany, India, Japan, the UK and US using an event study and then run a augmented quantile auto-regression model to thoroughly compare market reactions to different quantiles of return distributions. Our results contribute to the literature from two perspectives. First, stock returns are found to be more significantly interacted with developing pandemics in all regions except China. Second, market reaction to the pandemics is sensitive to the quantiles used in the analysis and varies across the study countries.

CRediT authorship contribution statement

Chenglu Jin: Conceptualization, Supervision, Writing, Funding acquisition. Xingyu Lu: Writing – review & editing. Yihan Zhang: Original, Visualization, Software, Investigation.

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