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COVID-19 and Stock Market Behaviors: Evidence from Countries in Asia, Europe, North America and South Africa

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Abstract

This study explores the impact of COVID-19 on the stock market from 22nd January 2020 to 19th July 2021. We select 12 worst-hit and representative countries from 4 continents worldwide including China, Japan, Russia, India, United Kingdom, Germany, France, Italy, Spain, United States, Canada and South Africa. By using panel data model, we find both the new confirmed case and total vaccinations have negative effect on the stock index returns. The government interventions positively affect the stock market. Central banks are better to apply moderate numbers of financial tools since countries response at median level gain higher returns than countries response at low level and high level. The Coronavirus Panic Index and the Coronavirus Media Coverage Index show significant positive effect on stock returns.

Keywords: COVID-19, stock market, vaccine, monetary policy, investor sentiment

1. Introduction

COVID-19 is not merely a global health event harming people's health, but also an economic recession inducing a decline in economic growth worldwide. Governments has placed strict restrictions including mandatory business closures, voluntary social distancing, and international travel bans, which leads to an abrupt decline in global trade and commerce, tourism, production and transportation sectors, coupled with the fall in commodity prices and the outflows of large foreign capital, and the shortage in labor markets.

There have been some researchers studying about the impact of COVID-19 on world economy and financial market. Some of them concentrate on the stock market reactions to the coronavirus-related variables like cumulative or new confirmed cases/deaths, like Burdekin and Samuel (2021), Bahrini and Filfilan (2020), Gao et al. (2021), Anh and Gan (2021). Some focus on the presence of volatility clustering (Mishra & Mishra, 2020), volatility spillovers (Yousfi et al., 2021; Malik et al., 2021**)** effect in the stock market. The rising volatility due to the pandemic can be confirmed by Bora and Basistha (2021), Insaidoo et al. (2021), Kusumahadi and Permana (2021), Haldar and Sethi (2021). There are also researchers who identify the occurrence of structural changes. (Kusumahadi & Permana, 2021; Buszko et al., 2021)

Wu and Hui (2021), Abe (2021) and Yoon (2021) conduct their research in the Asian markets like China, Japan and Korea. Developing markets are studied by researchers like Shipalana and O'Riordan (2020) who centered on Africa, and Pires et al. (2021) who presents evidences from Brazil. Researchers like Zeren and Hizarci (2020), Naeem et al. (2021) investigate the impact of COVID-19 in a global perspective rather than a single market. Event study is a common method used to study the abnormal returns (ARs) during pandemic. (Alam et al., 2020; Orhun, 2021) Researchers like Singh et al. (2020), Liu et al. (2020), Chowdhury et al. (2021) and Wu et al. (2021) also conduct further panel data regression to explain the causes.

We contribute to the existing literature in two aspects. First, we study the impact of COVID-19 vaccinations on the stock market which has not been explored by many previous researchers due to the data limit. Few literatures have investigated about the impact of coronavirus vaccines except for Rouatbi et al. (2021) who concentrate on the impact on stock market volatility, Chan et al. (2021) who focus on the different phases of human clinical trials, Vierlboeck and Nilchiani (2021) who only study the pharmaceutical companies. Second, the actions of the central banks during COVID-19 have not been studied well enough. Rakshit and Neog (2021) mention the importance for the central bank to stabilize the stock market and boost investors' confidence. Actually, the central banks have applied multidimensional financial tools in face of COVID-19 such as asset purchasing, regulatory easing, liquidity provision and credit support, but many researchers only take rate cuts into considerations.

We select 12 worst-hit and representative countries worldwide covering Asia, Europe, North America and South Africa, including China, Japan, Russia, India, United Kingdom, Germany, France, Italy, Spain, United States, Canada and South Africa. By using daily data from January 22nd, 2020 to July 19th, 2021, we conduct panel data model and find that the stock index returns are negatively affected by the total vaccinations per hundred of population, which is consistent with Acharya et al. (2021). Although the development of vaccine minimize infection and lowers the risks of the pandemic, the welfare cost arising from labor choice with exposure to a health shock and the permanent loss in consumption diminish the value of the vaccine.

Besides, Countries with median response level gain higher returns than countries with low response level and high response level, so it is better for central banks to apply moderate numbers of financial tools. Moreover, the media-related index has positive impact on the stock returns, which supports Mishra and Mishra (2020) and Garcia (2013).

The remainder of this paper is organized as follows. Section 2 presents the literature review and proposes the hypothesis. Section 3 describes the data and variables utilized in this paper. Section 4 introduces the methodology. Section 5 analyze the empirical findings and Section 6 concludes the remarks.

2. Literature Review and Hypothesis

Most previous literature concentrate on the impact of rising cases and deaths in COVID-19 pandemic on the economy and stock market in a single country or a global market. Besides, the role of the investor sentiment and media coverage have also been investigated. (Burdekin & Samuel, 2021; Bahrini & Filfilan, 2020; Donnell et al., 2021; Chowdhury et al., 2021; Wu et al., 2021; Alam et al., 2020; Singh et al., 2020; Liu et al., 2020; Mishra & Mishra, 2020; Haldar & Sethi, 2021; Cox et al., 2020; Sobia et al., 2021)

In the background that many countries have made breakthrough in vaccine against coronavirus, and the government have urged people to get vaccinated, the effect of vaccine on the stock market should also be taken into consideration. As far as we know, few literatures have explored about the COVID-19 vaccine due to the time limit and data access. Researchers like Rouatbi et al. (2021) find COVID-19 vaccination help reduce the stock market volatility. Acharya et al. (2021) shows the stock market have negative response to the vaccine progress indicator. Chan et al. (2021) find that global stock markets react positively when different phases of human clinical trials on COVID-19 vaccines begin. In this paper, we try to add to the literature about the impact of the total vaccinations against coronavirus on the stock market returns.

Besides, researchers such as Grasselli (2021), Clarida et al. (2021), Chow and Ho (2021) study the monetary policies in response to COVID-19 but they mainly focus on explaining and analyzing the measures taken by central banks. What distinguish us from them is we summarize the measures into several categories and construct a novel index to reflect the whole response level of central banks based on the financial tools used during the pandemic. Although the specific measures taken by each central bank depend on the economic situations in countries, there exists common use of the multidimensional set of tools such as rate cuts and asset purchases.

Therefore, we mainly focus on the impact of vaccinations and the role of central banks during the pandemic, and propose the following two hypothesis in this paper.

Hypothesis 1: The stock market reactions change significantly at different response level in monetary policies.

The various response level reflects the different extent of strong will and the ability of central banks to handle risks and boost the economy, which would directly impact the stock market. Chow and Ho (2021) indicate that the timely monetary and fiscal responses ensure credit support to firms and individuals facing financial difficulties, which help reduce debt obligations and lower funding costs. Fiscal support also protects jobs and support businesses, especially with targeted measures for specific sectors most hit by the pandemic. Since both individuals and firms are impacted, the stock market would also be affected when central banks provide fiscal and monetary support.

Besides, higher level response indicates more active measures taken by central banks, which could possibly suggest faster recovery speed from the pandemic. But the reactions in the stock market also relies on how investors process these policies. Investors may regard the change of the response level as a negative or positive signal from central banks and expect darker or brighter future prospect of economy. This will be eventually reflected in their investment behaviors and stock market could be impacted negatively or positively.

In summary, the monetary support from central banks directly affects the stock market at individual and firm level. Various response level in monetary policies could indicate different signals and prospect of future economy. The overall effect on the stock market also needs to consider how investors process these signals from central banks. We assume the stock market reactions change at different response level in monetary policies.

Hypothesis 2: The increasing vaccinations per hundred of population would significantly impact the stock market returns.

Vaccines have long been proved to provide beyond sole medical protection for society. Earlier researchers like Heaton and Lucas (1999) indicate that vaccinations improve the public health conditions and increase the life expectancy. The improvement will increase households' wills to smooth consumption over time and save a larger proportion of their income, which could possibly be used to invest in stock market. The development of vaccine helps slow the pace of the spread of a virus and minimize the risks of infection, so any breakthrough and advance in research and distribution process would stimulate the global economy and the stock markets.

However, it is also possible that vaccine could have a negative effect on the stock markets. Their model indicates that the sensitivity of the stock market to vaccine progress indicator is essentially determined by the expected rate of loss of wealth during a pandemic. The labor is restricted under central planning during the pandemic, which makes the value of vaccine or cure lower at the central planners' solutions such as social lockdown (labor withdrawal), than at the private optimal labor choice. The magnitude of the health shocks thus be endogenized via labor choice, resulting in the diminished value of vaccine. Besides, Kozlowski et al. (2020) suggest that learning effects lead to long-term scarring after the pandemic. The vaccine may not bring the consumption to the pre-pandemic levels due to the increase in updated probability of future pandemics. So, the loss in consumption also lessens the value of vaccine.

Therefore, based on the above discussion on positive and negative influences of the vaccine, we assume the stock market would be impacted by the increasing vaccinations but the overall effect is not certain.

In the next section, we will discuss about the details of the variables and data sources.

3. Data and Variables

In this study, we have selected 12 countries worldwide covering four continents including Asia, Europe, North America and Africa. These countries are China, Japan, Russia, India, United Kingdom, Germany, France, Italy, Spain, United States, Canada and South Africa. They also represent the major stock markets in global markets. Table 1 lists the stock market indices selected from these countries. The data spanned the date range of 22nd January 2020–19th July 2021.

The daily data on closing stock market indices come from the web database of finance.yahoo.com, markets.businessinsider.com and wsj.com. The daily new confirmed COVID-19 cases per million of population (*CNC*), total vaccinations against COVID-19 per hundred of population (*VACCINE*), the stringency index (*STRINGENCY*), are compiled from the website ourworldindata.org. The daily Coronavirus Sentiment Index (*CSI*), Coronavirus Media Coverage Index (*CMCI*), and Coronavirus Panic Index (*CPI*), are obtained from the website coronavirus.ravenpack.com.

The daily Brent crude oil prices (*OIL*) and gold prices (*GOLD*) have been compiled from markets.businessinsider.com. The daily domestic exchange rates against USD (*EXC*) are from federalreserve.gov and Bank of Russia. The TED Spread are sourced from the Federal Reserve Economic Database (*FRED*). We construct the Monetary policy Response Index (MPRI) based on the collected information from English et al. (2021). And we use dummy variables to indicate the response level of monetary response from central banks, which we will discuss in Section 4.4. Table 2 gives the description and sources of these variables.

4. Methodology

We calculate the stock returns by using the following equation:

$$R_t = lnP_t - lnP_{t-1} \tag{1}$$

where R_t is the stock return at day *t*, P_t and P_{t-1} represent the closing price of the stock index at day *t* and the previous day's closing price at day $t - 1$ respectively, while *ln* symbolizes the natural log.

To investigate the impact of the COVID-19 outbreak on stock market returns in selected countries, we apply a panel data regression. The panel data model captures the heterogeneity involved both in cross-section units and time dimensions, and reduces estimation bias and multicollinearity. We use pooled ordinary least squares (OLS), motivated by other studies that examined the effects of COVID-19 on financial markets like Ashraf (2020), Khan et al. (2020), Wu et al. (2021), Rouatbi et al. (2021), Kizys et al. (2021) and Papadamou et al. (2021).

We specify the following panel data model. The only difference among equation (2) to (4) is we alter the number of the dummy variables which indicating the response level of monetary policies. Besides, the commonly used variables from equation (2) to (4) is COVID-related variables, Government response and Media coverage index. We also control for global risk factors.

$$R_{it} = a_0 + a_1 Case_{i,t} + a_2 Vaccine_{i,t} + a_3 GovReponse_{i,t} + a_4 Media_{i,t} + a_5 LPR_{i,t} + \sum_{k=1}^{k} \varphi_k \boldsymbol{X}_{i,t}^{k} + \mu_{it} \quad (2)$$

$$R_{it} = \beta_0 + \beta_1 Case_{i,t} + \beta_2 Vaccine_{i,t} + \beta_3 GovReponse_{i,t} + \beta_4 Media_{i,t} + \beta_5 MPR_{i,t} + \beta_6 HPR_{i,t} + \sum_{k=1}^{k} \varphi_k \boldsymbol{X}_{i,t}^{k} + \mu_{it} \quad (3)$$

$$R_{it} = \gamma_0 + \gamma_1 Case_{i,t} + \gamma_2 Vaccine_{i,t} + \gamma_3 GovReponse_{i,t} + \gamma_4 Media_{i,t} + \gamma_5 LPR_{i,t} + \gamma_6 HPR_{i,t} + \sum_{k=1}^{k} \varphi_k \boldsymbol{X}_{i,t}^{k} + \mu_{it} \quad (4)$$

R_{it} represents the stock market return in country *i* in day *t*, a_0 is constant term and μ_{it} is error term. The following section gives detailed description of these variables.

4.1 COVID-Related Variables

$Case_{i,t}$ represents the natural logarithm of the new confirmed coronavirus cases per million of population (*lnnc*) in country *i* at day *t*. $Vaccine_{i,t}$ represents the natural logarithm of the total vaccinations against COVID-19 per hundred of population (*lntv*) in country *i* at day *t*.

4.2 Government Response

$GovResponse_{i,t}$ denotes the natural logarithm of the daily stringency index (*lnstr*) from the Oxford COVID-19 Government Response Tracker (OxCGRT). Researchers like Alaoui et al. (2021), Burdekin and Samuel (2021) use the stringency index as an indicator of the government policy response to the COVID-19 pandemic. The data can be downloaded from the website ourworldindata.org.

4.3 Media Coverage and Sentiment

$Media_{i,t}$ represents one of the following three media coverage related variables to measure the news effect during the coronavirus, which are the Coronavirus Sentiment Index (*CSI)*, Coronavirus Media Coverage Index (*CMCI)*, Coronavirus Panic Index (CPI). They are suggested by recent studies like Haldar and Sethi (2021), Rogone et al. (2020), Haroon and Rizvi (2020a), Subrhamanyam (2019), Ding et al. (2019) as a proxy for the news effect of COVID-19. The data can be downloaded from the RavenPack's website.

4.3.1 The Coronavirus Panic Index (*CPI*)

The Coronavirus Panic Index measures the level of news chatter that makes reference to panic or hysteria alongside the Coronavirus. Values range between 0 and 100 where a value of 8.00 indicates that 8 percent of all news globally is talking about panic related terms and COVID-19. In this paper, we use the natural logarithm of the Coronavirus Panic Index (*lnpanic*).

4.3.2 The Coronavirus Sentiment Index (*CSI*)

The Coronavirus Sentiment Index measures the level of sentiment across all entities mentioned in the news alongside the Coronavirus. The index ranges between -100 and 100 where a value of 100 is the most positive sentiment, -100 is the most negative, and 0 is neutral.

Since CSI has negative values, we have following transformation:

$$lnsent_{i,t} = \ln\left(CSI_{i,t} + 100\right) \quad (5)$$

And we use *lnsent* in this paper.

4.3.3 The Coronavirus Media Coverage Index (*CMCI*)

The Coronavirus Media Coverage Index calculates the percentage of all news sources covering the topic of the novel Coronavirus. Values range between 0 and 100 where a value of 60.00 means that 60 percent of all sampled news providers are currently covering stories about COVID-19. In this paper, we use the natural logarithm of the Coronavirus Media Coverage Index (*lnmedia*).

4.4 Central Banks and Monetary Policy

4.4.1 Monetary Policy Response

In equation (2) to (4), *LPR, MPR* and *HPR* are dummy variables which reflects the response level of central banks to the COVID-19. To identify the response level, we should first analyze the monetary policy tools adopted by central banks in face of the pandemic.

The COVID-19 shock brought a global sudden stop of economic activity, a problem which had never been faced before. In response, central banks took quick and aggressive actions by deploying multiple tools to overcome the overlapping challenges. According to English et al. (2021), these tools can be roughly classified into four categories, which are rate cuts and forward guidance, asset purchases, liquidity provision and credit support as well as regulatory easing. Table 3 summarizes these tools taken by central banks and provides detailed analysis of the measures and functions.

In Table 4, we evaluate whether these measures have been used by central banks in our selected countries, and "Y" means Yes while "N" means no. We construct a novel index *MPRI* (Monetary Policy Response Index) to measure the extent to which the central banks in different countries try to support financial markets and save the economy from the pandemic. In Table 2, if there is "Y" in column, which indicates that the central bank has used this tool, then we add the value of *MPRI* by 1. If there is "N" in column, which indicates that central bank has not taken the action in this aspect, then we add the value of *MPRI* by 0. Therefore, *MPRI* rages between 0 and 12 where a value of 5 means that the central bank in this country has deployed 5 financial tools to support the economy and the functioning of financial markets in order to fight the pandemic and generate a recovery.

Table 5 summarize the *MPRI* for selected 12 countries. If the *MPRI* is less than 5, which means the central bank has used less than 5 financial tools, this country would be regarded as low-level of response to the COVID-19, such as China and South Africa. If the *MPRI* is between 5 and 7 (5 and 7 included), this country would be regarded as median-level of response to the COVID-19, such as Russia, U.S. and Canada. If the central bank has used more than 7 financial tools, this country response at a high level to the COVID-19, such as Japan, India, Germany, France, Italy, Spain and UK.

4.4.2 Dummy Variables

We use the dummy variable *LPR* which takes the value of one if the central bank in this country has been classified as low-level of response, and zero otherwise. The dummy variable *MPR* equals one if the central bank in this country has been classified as median-level of response, and zero otherwise. The dummy variable *HPR* equals one if the central bank in this country acted as high-level of response, and zero otherwise.

In equation (2), we only include the dummy variable *LPR.*

We first test whether there exist significant differences in the impact on the stock returns between countries using less than 5 tools and countries using no less than 5 tools. If α_5 is significant, this means low-level of response from central banks exert different impact on stock returns when compared to higher level of response.

In equation (3), we include the dummy variables *MPR* and *HPR.*

We further test whether the differences in the impact on stock returns is significant between countries response at low-level and countries response at median-level, which is reflected by coefficient β_5, and whether the difference is significant between countries response at low-level and countries response at high-level, which is reflected by coefficient β_6.

In equation (4), we include the dummy variables *LPR* and *HPR.*

Since in equation (2) we have already examine the difference between low-level response and no less than low-level response, and in equation (3) we examine low-level response and median-level response, as well as low-level response and high-level response. The only left question is whether countries response at median-level exert significant differences in the impact on stock market when compared to countries response at high-level. Therefore, we use the dummy variables *LPR* and *HPR* in equation (4), and coefficient γ_6 could reflect the difference between median-and high-level response.

4.5 Control Variables

$\boldsymbol{X}_{i,t}^{k}$ is a vector of variables which control for global market systematic risks. We use the natural logarithm of the Brent oil price (*lnoil*) reflect the supply-side shocks, and we take the natural logarithm of the exchange rates against U.S. Dollars (*lnexc*) to reflect demand-side shocks. These control variables are suggested by Mishra and Mishra (2020), Donnell et al. (2021), Alaoui et al. (2021), Uddin et al. (2021).

Donnell et al. (2021) also suggests the natural logarithm of the TED Spread (*lnted*) as control variable to measure liquidity risk, and the natural logarithm of the gold price (*lngold*) to measure safe-haven asset demand.

5. Empirical Results

5.1 Summary Statistics

Table 6 summarize the descriptive statistics of variables we used in this paper. It reveals that the mean returns during the study period are positive, at 0.03%, with standard deviations of 0.91%. The minimum and maximum return are -4.07% and 4.63% respectively. The average level is 3.945 for the natural logarithm of the new confirmed cases per million of population (*lnnc*), and this figure is 2.498 for the natural logarithm of the total vaccinations against COVID-19 per hundred of population (*lntv*). The natural logarithm of the stringency index (*lnstr*) has a mean of 4.148 and standard deviations of 0.233.

For three chosen media-related variables, the natural logarithm of the Coronavirus Panic Index (*lnpanic*) fluctuates from -0.431 to 3.527 over the study period and has the highest standard deviations of 0.654, while the natural logarithm of the Coronavirus Media Coverage Index (*lnmedia*) has the least standard deviations of 0.149. This indicates that these media-related variables reflect different aspect of the investor sentiment since the outbreak of COVID-19.

For control variables, the Brent oil price (*lnoil*) is more volatile than the gold price (*lngold*), with standard deviations of 0.094 and 0.033 respectively, showing the supply and demand movements in oil and gold markets. And the wide standard deviations of TED spread (*lnted*) reveal the liquidity risks during the pandemic.

Table 7 displays the pairwise correlation coefficients between all the variables used in our paper. It can be seen that the new confirmed cases (*lnnc*), the stringency index (*lnstr*), the Coronavirus Media Coverage Index (*lnmedia*), the gold price (*lngold*) are highly correlated with the stock returns, thus providing preliminary evidence that these variables play an important role in the global equity markets during the pandemic. Moreover, the correlation coefficients between the three media-related variables are highly positive, especially the correlations between the Coronavirus Panic Index (*lnpanic*) and the Coronavirus Media Coverage Index (*lnmedia*), so we run our regressions by using only one of these three variables each time.

5.1.1 Monetary Policy Response

In Table 8, we can see that the coefficient of *LPR* is significantly negative regardless of the media-related variables used. Specifically, the stock index returns would be reduced by 0.25%, 0.20% and 0.30%, at 5%, 10% and 1% significance level for *lnpanic*, *lnsent* and *lnmedia* used respectively.

This reveals that if we only group the countries into two categories, which are low-level response (less than 5 financial tools used) and more than low-level response, the former would have significantly negative impact on the stock index returns when compared to the latter.

Our results in Table 8 prove that there exist significant differences between low-level and more than low-level monetary response, so the classification between them is meaningful. Central banks should use more financial tools in order to boost the stock market when facing the COVID-19 pandemic.

To further explore this question, we add median-level and high-level response. The median-level response indicates the central banks deploy no less than 5 financial tools but no more than 7 financial tools, and the high-level response indicates the central banks deploy more than 7 financial tools.

Table 9 reports the estimations results for equation (3) which includes two dummy variables *MPR* and *HPR*. *MPR* takes the value of one if countries response at median-level and zero otherwise. *HPR* takes the value of one if countries response at high-level and zero otherwise.

We can see that the coefficients for two dummy variables are all significantly positive, which means the differences between low-level and median-level, low-level and high-level are significant. When compared to countries response at low level, the stock index returns in countries response at median level would be lifted up by 0.38%, 0.29% and 0.36%, at 1%, 5% and 1% significance level for the Coronavirus Panic Index (*lnpanic*), the Coronavirus Sentiment Index (*lnsent*) and the Coronavirus Media Coverage Index (*lnmedia*) used respectively. These numbers are 0.23%, 0.18% and 0.27%, at 5%, 10% and 1% significance level for countries response at high level.

Another thing worth to mention is that the coefficient of *MPR* is larger than that of *HPR*. This suggest that when compared to low-level response, median-level response has larger positive impact on stock index returns than high-level response does. Therefore, it may be better for central banks to stimulate the stock market by applying moderate numbers of financial tools since low-level response would worsen the stock returns and high-level response does not achieve better effect than median-level response does.

So far, we know that the differences between the impact of low-level response and median-level response, low-level response and high-level response are significant on the stock market. Naturally we will raise another question that whether there exist significant differences between median-level and high-level response regarding the impact on the stock market.

Table 10 reports the regression results for equation (4) which includes two dummy variables *LPR* and *HPR*. *LPR* takes the value of one if countries response at low level and zero otherwise. HPR takes the value of one if countries response at high level and zero otherwise.

The coefficients for two dummy variables are all significantly negative, indicating that the differences between low-level and median-level, median-level and high-level are significant. The coefficient of *LPR* in equation (4) has the same value as the coefficient of *MPR* in equation (3) except for their opposite signs, and the former is negative while the latter is positive. When compared to countries response at median level, the stock index returns in countries response at high level would be reduced by 0.15%, 0.11% and 0.09%, at 5%, 10% and 5% significance level for *lnpanic*, *lnsent* and *lnmedia* used respectively.

Thus, the results for equation (4) confirm the differences between low-level and median-level, median-level and high-level response regarding the impact on the stock market. Besides, both negative coefficients reveal that median-level response is the most appropriate measure which should be taken by central banks in face of the threat brought by COVID-19, consistent with our prior conclusions.

Overall, Table 8-10 confirm the hypothesis 1 that the stock market reactions change significantly at different response level in monetary policies.

The results show that our classification according to the monetary response level from central banks are effective and significant. The various response level from central banks would have different impact on the stock market.

If we group the countries into two categories, which are low-level response and more than low-level response, we can find that the stock index returns would be smaller in the countries response at low level compared to countries response at more than low level.

If we further group countries into three categories, low-, median- and high-level response, we can find that there exist significant differences between low- and median-, low- and high-, median-and high-level response regarding the impact on the stock market.

Countries response at median and high level would gain higher stock returns than countries response at low level, and of the three categories, median-level response is the most appropriate since the difference between low- and median-level is larger than that between low- and high-level response, which can also be testified by the significantly negative difference between median- and high-level response regarding the impact on the stock market.

Previous researcher like Uddin et al. (2021) and Mishra and Mishra (2020) only consider the monetary policy rates. Uddin et al. (2021) find that central banks across the world have reduced their policy rate to increase the money supply and boost consumer confidence during the COVID-19 pandemic. Their findings indicate that increasing (lowering) the policy rate will increase (lower) the market variance.

Mishra and Mishra (2020) study Asian countries and find that the changes in central bank policy rate have positive effects on stock market's abnormal returns. However, such observation is not statistically significant.

Our paper considers the more detailed measures applied by central banks, including rate cuts, sovereign debt, liquidity provision and regular easing, and we classify the response level and prove that this classification is effective and meaningful for policy makers.

5.1.2 Vaccinations

The significantly negative coefficients of *lntv* in Table 8-10 show that the total vaccinations have a negative effect on the stock market returns.

Specifically, in Table 8 when we only classify the selected countries into two groups, which are low-level response and more than low-level response, the total vaccinations against COVID-19 per hundred of population decrease the stock index returns by 0.06%, 0.05% and 0.06% for *lnpanic*, *lnsent* and *lnmedia* respectively, all at 10% significance level. These numbers change into 0.07%, 0.06% and 0.07%, all at 5% significance level, in both Table 9 and 10. So, after we classify the countries into 3 groups, low-, median-and high-level response from the central banks, the coefficient of *lntv* become larger and the significance level increase.

Our results confirm the Hypothesis 2 that the increasing vaccinations per hundred of population would significantly impact the stock market returns.

The significant negative effect is also consistent with Acharya et al. (2021). They observe negative responses of stock market to vaccine progress indicator. They use a general equilibrium model to show the mechanism that makes the vaccine more or less valuable. In their model, the sensitivity of stock returns to vaccine progress is determined by the expected rate of loss of wealth during the pandemic, which pins down the economy-wide welfare gain attributable to a cure. According to their estimate, the value of the vaccine or cure, which means ending the pandemic is worth 5-15% of total wealth.

The driver of the value is related to labor choice and loss in consumption.

The magnitude of the health shocks is endogenized via labor choice in their model. Under the pandemic, people need to mitigate the economic exposure to a health shock. But the individual optimal labor choice is not the same as the labor choice by a central planner. The value of the vaccine, or cure is estimated to be 12%-19% lower under central planning such as the socially lockdown which restricts the labor. Therefore, the labor choice under the pandemic reduces the value of vaccine.

Another source of welfare cost is the permanent loss in consumption. The pandemic could destroy forever a part of the economy's stock of wealth. The learning effects lead to long-term scarring after the pandemic (Kozlowski et al., 2020). The consumption may not revert to the pre-pandemic level. The possibility that the vaccine and the pandemic effectively lasting forever leads to extreme savings for people and little utility flow from consumption. Thus, the long-term scarring also reduces the value of vaccine.

Thus, the restricted labor and permanent loss in consumption lessen the value of the vaccine, which determines the sensitivity of the stock market returns to vaccinations. The negative response detected by us is in line with Acharya et al. (2021).

5.1.3 Media-Related Index

We use three media-related variables to gauge investor sentiment, which are the Coronavirus Panic Index (*lnpanic*), the Coronavirus Sentiment Index (*lnsent*) and the Coronavirus Media Coverage Index (*lnmedia*).

The regression results with different media-related variables are listed in Column 1-3 in Table 8-10. We can find that only the coefficients of *lnpanic* and *lnmedia* are significantly positive, while the coefficient of *lnsent* is insignificant no matter which group specification we use according to the response level from central banks.

The differences among three indicators can be seen from the previous Table 7. The correlation between *lnpanic* and *lnmedia* is 0.528, which is highly significant, while the correlation between *lnpanic* and *lnsent*, *lnmedia* and *lnsent* is -0.276 and -0.169 respectively, which is relatively lower. Besides, both *lnpanic* and *lnmedia* are related to the media news, which calculate the percentage of the daily news reference to the chosen keywords, so *lnpanic* and *lnmedia* are similar in some way. The index *lnsent* is more complicated than the other two indexes by considering the RavenPack's Event Sentiment Score (ESS) of all detected news events. Therefore, the three media-related variables measure different aspect of investor sentiment.

The Coronavirus Panic Index (*lnpanic*) and the Coronavirus Media Coverage Index (*lnmedia*) increase the stock index returns by 0.08% and 0.45%, at 5% and 1% significance level respectively in Table 8. These numbers change into 0.11% and 0.40%, both at 1% significance level, in Table 9 and Table 10. So, after we classify the countries into 3 groups, which are low-, median-and high-level response from the central banks, the coefficient of *lnpanic* become larger and the significance level increase, and the coefficient of *lnmedia* decrease slightly.

Our results suggest that the more news that mentions the coronavirus, or co-mention the panic and coronavirus, the higher the stock index returns. The media-related variables have positive impact on stock market.

This is consistent with Mishra and Mishra (2020) who find a significant positive effect of the fear index on abnormal returns. They think that the investors might not be that much pessimistic in their analysis of stock return predictions in Asia during the COVID period. And our results also support Garcia (2013) who uses the news contents from the New York Times and they find the news contents helps predict stock returns particularly during recessions. However, our findings contradict Haldar and Sethi (2021) who find that countries with greater media coverage experience significant decline in returns.

5.1.4 New Confirmed Cases

We then look at the commonly used COVID-related variables, the new confirmed coronavirus cases per million of population.

The coefficient of *lnnc* is significantly negative regardless of the chosen media-related index. This suggests that the COVID-19 has a negative impact on the stock market returns. The new confirmed cases of the coronavirus reduce the stock index returns by 0.03% for either Coronavirus Panic Index (*lnpanic*) or the Coronavirus Media Coverage Index (*lnmedia*) used, but at 5% and 1% significance level respectively. This number is 0.02% for the Coronavirus Sentiment Index (*lnsent*), but the significance level changes from 10% in Table 8 to 5% in Table 9 and 10. This suggests that the significance level would increase after we switch into a more specified classification of selected countries according to the response level from central banks.

Our results are consistent with Burdekin and Samuel (2021) who finds that the increased cases exserts the overall effect of worsening the relative stock market performance, and the negative effect also supports Uddin et al. (2021), Chowdhury et al. (2021) and Donnell et al. (2021).

5.1.5 Stringency Index

The Stringency Index, which synthesizes nonpharmaceutical government interventions, is insignificant overall in Table 8 when we only have two groups, countries which response at low level and more than low level. However, the coefficient become significant in Table 9 and 10 after we have more specified groups for countries which response at low level, median level and high level.

In Table 9 and 10, the Stringency Index significantly increase the stock index returns by 0.24%, 0.23% and 0.18%, at 5%, 5% and 10% significance level for *lnpanic*, *lnsent* and *lnmedia* used respectively. This suggest that the stock market is positively affected by the government interventions such as school and workplace closures, stay at home restrictions and travel bans.

Our results partly support Burdekin and Samuel (2021) since their findings are quite mixed. They find the Stringency Index is significant overall with the expected positive effect only for Africa. And it is significant overall for East Asia with a negative sign. In Eastern and Southern Europe as well as Latin America, stringency is significant with the expected positive sign in June and insignificant for other months. South Asia and Middle East also has a significant positive effect of stringency in June.

5.1.6 Control Variables

For control variables, we use the natural logarithm of the Brent oil price (*lnoil*), the exchange rates against U.S. Dollars (*lnexc*), the TED Spread (*lnted*) and the gold price (*lngold*). Table 8-10 indicates that the coefficients of the control variables are all significantly positive except for the exchange rates.

The significantly positive coefficient of the Brent oil price support Donnell et al. (2021) who state that under current situations of COVID-19, the oil prices may instead act as a gauge of economic activity and of global political tensions, thus explaining the positive association observed with stock indexes. And this relationship has also been addressed by Kilian and Park (2009) who reveal that the resilience of stock markets in the presence of increasing oil prices can be explained by strong global demand for industrial commodities, which can more widely be representative of increasing economic activity. As such, any indication of increasing economic activity during COVID-19 was a positive signal to financial markets. Our findings contradict Mishra and Mishra (2020) who detect negative effect of oil price in Asian economies.

The coefficient of the gold price is significantly positive, which partly support Donnell et al. (2021) since they only observe a significant result for the UK and the U.S. indices. For China, Italy and Spain, they find no significant relationship between the gold price and stock markets in the current pandemic.

The TED spread shows a significantly positive relations with stock returns, which also partly support Donnell et al. (2021) since they find the TED spread were only significant in influencing the Chinese SSE 180 index. We find the exchange rate negatively influencing the stock index returns, consistent with Mishra and Mishra (2020).

6. Conclusions

In this paper, we use panel data model to explore the impact of COVID-19 on the stock market from 22nd January 2020 to 19th July 2021. We select 12 countries worldwide including China, Japan, Russia, India, United Kingdom, Germany, France, Italy, Spain, United States, Canada and South Africa, covering four continents including Asia, Europe, North America and Africa. We use the COVID-related variables like new confirmed cases and the total vaccinations, the stringency index reflecting government response, monetary policy from central banks and media-related indexes reflecting investor sentiment. We also control for global risks like the oil price, exchange rates, TED spread and the gold price.

Our results are summarized below.

First, we confirm the Hypothesis 1 that the stock market reactions change significantly at different response level in monetary policies. Through our comparation and analysis, we find countries with median-level response would gain higher stock returns than countries with low-and high-level response. In face of the COVID-19, it is better for central banks to apply moderate numbers of financial tools.

Second, we confirm the Hypothesis 2 that the increasing vaccinations per hundred of population would significantly impact the stock market returns. The negative effect supports Acharya et al. (2020) who highlight that the observed market response to vaccine progress is essentially determined by the expected rate of loss of wealth during the pandemic. The driver of this value is related to the labor choice with exposure to a health shock and permanent loss in consumption. The restricted labor under central planning and long-term scarring effect in consumption lessen the value of ending pandemic.

Third, for investor sentiment, we choose three media-related indexes, which are the Coronavirus Panic Index, the Coronavirus Sentiment Index and the Coronavirus Media Coverage Index. We can find that only the Coronavirus Panic Index and the Coronavirus Media Coverage Index show significantly positive effect, which is consistent with Mishra and Mishra (2020) and Garcia (2013).

Moreover, for the government response, the stock market is positively affected by the stringency index, proving the effectiveness of the government interventions such as school and workplace closures, stay at home restrictions and travel bans. The new confirmed cases per million of population negatively affect the stock returns, which is consistent with Uddin et al. (2021), Chowdhury et al. (2021) and Donnell et al. (2021). The global factors such as the oil price, TED spread and the gold price exhibit positive effect, while the exchange rate shows a negative correlation with stock returns.

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Appendix

Table 1. List of Selected Countries and Stock Market Indices

Country	Stock Market Index	Abbreviation
China	Shanghai Composite Index	SSEC

Japan	Nikkei 225 Index	NI225
Russia	MOEX Russia	MOEX
India	Nifty 50 Index	Nifty50
UK	FTSE 100 Index	FTSE100
Germany	Deutscher Aktienindex	GDAXI
France	CAC 40	CAC 40
Italy	FTSE MIB	FTSEMIB
Spain	IBEX 35	IBEX 35
USA	Dow Jones Industrial Average Index	DJIA
Canada	S&P/TSX Composite	GSPTSE
South Africa	JSE FTSE ALL SHARE INDEX	JALSH

Table 1 lists the stock market indices from the selected countries. The data covers from 22rd January 2020 to 19th July 2021 and can be downloaded from the website of Yahoo Finance.

Table 2. List of the Independent Variables, Definition and Sources

Independent Variables	Definition	Sources
Variable related to COVID-19		
CNC	The new confirmed coronavirus cases per million of population	https://ourworldindata.org/
VACCINE	Total vaccinations against COVID-19 per hundred of population	https://ourworldindata.org/
Variables related to government response		
STRINGENCY	The stringency index	https://ourworldindata.org/
Variables related to monetary policy		
MPRI	The Monetary Policy Response Index	Authors constructed the index based on https://voxeu.org/article/monetary-policy-and-central-banking-covid-era-new-ebook
Variables related to media coverage		
CSI	The Coronavirus Sentiment Index	https://coronavirus.ravenpack. com
CMCI	The Coronavirus Media Coverage Index	
CPI	The Coronavirus Panic Index	
Control variables		
OIL	Brent crude oil prices	https://markets.businessinsider.com/
GOLD	Gold prices	https://markets.businessinsider.com/
EXC	Daily exchange rates of each country against the U.S. dollar	https://www.federalreserve.gov/ and Bank of Russia
TED	The difference between the three-month Treasury bill and the three-month LIBOR based in U.S. dollars.	Federal Reserve Economic Database (*FRED*)

Table 2 lists the independent variables, their definition and sources. The data covers from 22rd January 2020 to 19th July 2021. Independent variables are collected from various sources, which include the online website of macrotrends, ourworldindata.org, RavenPack's website, Yahoo Finance and Investing.com, and Federal Reserve Economic Database.

Table 3. Monetary policies adopted by central banks since COVID-19

Measures		Functions
Rate cuts and forward guidance		Ease strains in markets as well as support aggregate demand and help economies to rebound.
Asset purchases		Address widespread dysfunction in key financial markets and provide additional support for aggregate demand.
Liquidity provision and credit support	Such as lending to financial firms, purchases of corporate securities, direct lending to nonfinancial firms, and Funding-for-Lending type programs to support bank lending	Often done in conjunction with governments to support the provision of credit to businesses to ensure that viable firms could survive the crisis and would be able to ramp up production and support employment once the crisis ebbed.
Regulatory easing	Such as reductions in the countercyclical capital buffer (CCyB) and other reductions in requirements for liquidity and capital buffers.	Ensure banks would not amplify the contraction in credit and liquidity to meet regulatory standards.

Sources: English, B., Forbes, K., & Ubide, Á. (2021). *Monetary policy and central banking in the COVID era: A new eBook.*

Table 4. Monetary policies in each selected country

Central bank	Rate cuts and forward			Asset purchases		Liquidity provision and credit support					Regulatory easing	
	Rate cuts	Negative rates	Forward guidance	Sovereign Debt [1]	Other assets	Liquidity provision	Use of f/x swap lines	F/x operations	Direct lending	Programs to encourage bank lending [2]	CCyB [3]	Capital requirements
China	Y	N	N	N	N	Y	N	N [4]	N	Y	N [5]	N
Japan	N	Y [6]	Y [7]	Y	Y	Y	Y	N	N	Y	N [5]	Y
India	Y	N	Y	Y [8]	Y	Y	N	Y	N	Y	N [5]	Y
Russia	Y	N	N	N	N	Y	N	Y	N	Y	N [5]	Y
United Kingdom	Y	N	Y	Y [8]	Y	Y	Y	N	N	Y	Y	Y
Euro Area	N	Y [6]	Y	Y	Y	Y	Y	N	N	Y	N	Y
United States	Y	N	Y	Y	Y	Y	N	N	Y	N	N [5]	Y
Canada	Y	N	Y	Y	Y	Y	N	N	N	N	N [5]	Y
South Africa	Y	N	N [9]	Y	N	Y	N	N	N	N	N [5]	Y

Sources: English, B., Forbes, K., & Ubide, Á. (2021). *Monetary policy and central banking in the COVID era: A new eBook.*

Notes: [1] Central governments only. State or regional governments are included in the "Other assets" column. [2] Includes funding for lending programs as well as other steps to reduce lending costs, including targeted reductions in reserve requirements. [3] CCyB means countercyclical capital buffer. [4] The PBOC took steps to "advance RMB exchange rate formation mechanism reform". [5] The CCyB was zero prior to the pandemic. [6] The policy rates in the Euro area and Japan were already negative. They were not reduced further. [7] The Bank of Japan already had strong forward guidance in place prior to the pandemic, and it did not change that guidance. [8] In addition to securities purchases, temporary funding was provided to the government through Ways and Means arrangements. In the case of India, Ways and Means advances were also provided to state governments. [9] The South African Reserve Bank regularly reports model results that provide a policy path for the next year. Table 5 Classification of different level of monetary policy response

Table 5.

Central banks	*MPRI*	Classification
China	3	Low-level of response
South Africa	4	
Russia	5	Median-level of response
United States	6	
Canada	7	
Japan	8	High-level of response
India	8	
Germany	8	
France	8	
Italy	8	
Spain	8	
United Kingdom	9	

Table 6. Summary statistics

Variable	*Mean*	*Median*	*S.d.*	*Min*	*Max*	*Observations*
return (%)	0.030	0.070	0.910	-4.070	4.630	1373
lnnc	3.945	4.514	2.473	-5.809	7.604	1391
lntv	2.498	2.918	1.867	-4.605	4.801	1391
lnstr	4.148	4.227	0.233	3.219	4.477	1391
lnpanic	1.160	1.058	0.654	-0.431	3.527	1391
lnsent	4.449	4.499	0.244	1.883	4.879	1391
lnmedia	4.061	4.068	0.149	3.308	4.456	1391
lnexc	1.367	0.218	1.763	0	4.715	1391
lnoil	4.197	4.205	0.094	3.914	4.337	1391
lngold	7.497	7.494	0.033	7.429	7.575	1391
lnted	-2.046	-1.966	0.267	-2.813	-1.661	1391

This table presents descriptive statistics on the variables used in our primary analysis. *lnnc* represents the natural logarithm of the new confirmed coronavirus cases per million of population. $lntv$ represents the natural logarithm of the total vaccinations against COVID-19 per hundred of population. *lnstr* represents the natural logarithm of the stringency index. *lnpanic* is the natural logarithm of the Coronavirus Panic Index. *lnsent* is calculated as following equation: $lnsent_{i,t} = ln\,(CSI_{i,t} + 100)$, where CSI stands for The Coronavirus Sentiment Index. *lnmedia* represents the natural logarithm of the Coronavirus Media Coverage Index. *lnoil, lnexc, lnted* and *lngold* denotes the natural logarithm of the Brent oil price, the exchange rates against U.S. Dollars, the TED Spread and the gold price respectively.

Table 7. Pairwise correlation coefficients between major variables

	return	*lnnc*	*lntv*	*lnstr*	*lnpanic*	*lnsent*	*lnmedia*	*lnexc*	*lnoil*	*lngold*	*lnted*
return	1										
lnnc	0.0652	1									
lntv	-0.0283	-0.0548	1								
lnstr	0.102	0.281	0.0528	1							
lnpanic	0.000900	-0.0497	-0.269	0.258	1						
lnsent	0.00760	0.148	0.120	-0.131	-0.276	1					
lnmedia	0.0665	0.101	-0.330	0.688	0.528	-0.169	1				
lnexc	0.00950	-0.239	-0.341	-0.131	-0.00870	-0.110	-0.0287	1			
lnoil	0.00620	0.160	0.657	-0.138	-0.395	0.253	-0.438	0.00330	1		
lngold	0.0786	0.281	0.0158	0.356	-0.0391	0.306	0.249	0.00800	0.181	1	
lnted	-0.00570	-0.179	-0.426	0.0502	0.331	-0.372	0.235	-0.00730	-0.698	-0.586	1

This table denotes the correlation matrix for the different variables used in our primary analysis. *lnnc* represents the natural logarithm of the new confirmed coronavirus cases per million of population. $lntv$ represents the natural logarithm of the total vaccinations against COVID-19 per hundred of population. *lnstr* represents the natural logarithm of the stringency index. *lnpanic* is the natural logarithm of the Coronavirus Panic Index. *lnsent* is calculated as following equation: $lnsent_{i,t} = ln\,(CSI_{i,t} + 100)$, where CSI stands for the Coronavirus Sentiment Index. *lnmedia* represents the natural logarithm of the Coronavirus Media Coverage Index. *lnoil, lnexc, lnted* and *lngold* denotes the natural logarithm of the Brent oil price, the exchange rates against U.S. Dollars, the TED Spread and the gold price respectively.

Table 8. Estimation results for panel data model

	(1)	(2)	(3)
lnnc	-0.0003**	-0.0002*	-0.0003***
	(0.0001)	(0.0001)	(0.0001)
lntv	-0.0006*	-0.0005*	-0.0006*
	(0.0003)	(0.0003)	(0.0003)
lnstr	0.0014	0.0017	0.0011
	(0.0009)	(0.0010)	(0.0011)
lnpanic	0.0008**		
	(0.0003)		
lnsent		0.0003	
		(0.0008)	
lnmedia			0.0045***
			(0.0010)
LPR	-0.0025**	-0.0020*	-0.0030***
	(0.0010)	(0.0010)	(0.0009)
lnexc	-0.0004**	-0.0003*	-0.0004**
	(0.0001)	(0.0001)	(0.0001)
lnoil	0.0214***	0.0191***	0.0223***
	(0.0047)	(0.0042)	(0.0042)
lngold	0.0264***	0.0234***	0.0252***
	(0.0049)	(0.0047)	(0.0045)
lnted	0.0062***	0.0063***	0.0062***

	(0.0007)	(0.0007)	(0.0007)
constant	-0.2780***	-0.2475***	-0.2881***
	(0.0425)	(0.0368)	(0.0321)
R^2	0.0230	0.0202	0.0239
Adjusted R^2	0.0166	0.0137	0.0175
F-value	65.7450***	37.5408***	36.2301***

This table displays the results for equation (2):

$$R_{it} = a_0 + a_1 Case_{i,t} + a_2 Vaccine_{i,t} + a_3 GovReponse_{i,t} + a_4 Media_{i,t} + a_5 LPR_{i,t} + \sum_{k=1}^{k} \varphi_k \boldsymbol{X}_{i,t}^{k} + \mu_{it}$$

$Case_{i,t}$ denotes the natural logarithm of the new confirmed coronavirus cases per million of population (*lnnc*). $Vaccine_{i,t}$ denotes the natural logarithm of the total vaccinations against COVID-19 per hundred of population ($lntv$). $GovReponse_{i,t}$ denotes the natural logarithm of the stringency index (*lnstr*). $Media_{i,t}$ denotes the media-related variables and Column 1-3 reports the results for using the Coronavirus Panic Index (*lnpanic*), the Coronavirus Sentiment Index (*lnsent*) and the Coronavirus Media Coverage Index (*lnmedia*) respectively. $LPR_{i,t}$ is a dummy variable which equals one if the central bank in the selected countries response to the COVID-19 at a low level and zero otherwise. We use the natural logarithm of the Brent oil price (*lnoil*), the exchange rates against U.S. Dollars (*lnexc*), the TED Spread (*lnted*) and the gold price (*lngold*) to control for the global systematic risks. Robust standard errors are reported in parentheses, and the asterisks *, ** and *** indicates statistical significance at 10%, 5% and 1% level respectively.

Table 9. Estimation results for panel data model

	(1)	(2)	(3)
lnnc	-0.0003**	-0.0002**	-0.0003***
	(0.0001)	(0.0001)	(0.0001)
lntv	-0.0007**	-0.0006**	-0.0007**
	(0.0003)	(0.0003)	(0.0003)
lnstr	0.0024**	0.0023**	0.0018*
	(0.0009)	(0.0010)	(0.0009)
lnpanic	0.0011***		
	(0.0003)		
lnsent		0.0000	
		(0.0008)	
lnmedia			0.0040***
			(0.0010)
MPR	0.0038***	0.0029**	0.0036***
	(0.0011)	(0.0010)	(0.0009)
HPR	0.0023**	0.0018*	0.0027***
	(0.0010)	(0.0009)	(0.0008)
lnexc	-0.0004**	-0.0003*	-0.0003**
	(0.0001)	(0.0001)	(0.0001)
lnoil	0.0245***	0.0209***	0.0234***
	(0.0041)	(0.0037)	(0.0037)
lngold	0.0278***	0.0238***	0.0253***
	(0.0041)	(0.0042)	(0.0043)
lnted	0.0063***	0.0064***	0.0063***

	(0.0007)	(0.0007)	(0.0007)
constant	-0.3083***	-0.2616***	-0.2978***
	(0.0266)	(0.0267)	(0.0269)
R^2	0.0272	0.0226	0.0256
Adjusted R^2	0.0200	0.0154	0.0184
F-value	69.1719***	69.6692***	41.4447***

This table displays the results for equation (3):

$$R_{it} = \beta_0 + \beta_1 Case_{i,t} + \beta_2 Vaccine_{i,t} + \beta_3 GovReponse_{i,t} + \beta_4 Media_{i,t} + \beta_5 MPR_{i,t} + \beta_6 HPR_{i,t} + \sum_{k=1}^{k} \varphi_k \boldsymbol{X}_{i,t}^{k} + \mu_{it}$$

$Case_{i,t}$ denotes the natural logarithm of the new confirmed coronavirus cases per million of population (*lnnc*). $Vaccine_{i,t}$ denotes the natural logarithm of the total vaccinations against COVID-19 per hundred of population ($lntv$). $GovReponse_{i,t}$ denotes the natural logarithm of the stringency index (*lnstr*). $Media_{i,t}$ denotes the media-related variables and Column 1-3 reports the results for using the Coronavirus Panic Index (*lnpanic*), the Coronavirus Sentiment Index (*lnsent*) and the Coronavirus Media Coverage Index (*lnmedia*) respectively. $MPR_{i,t}$ is a dummy variable which equals one if the central bank in the selected countries response to the COVID-19 at a median level and zero otherwise. $HPR_{i,t}$ is a dummy variable which equals one if the central bank in the selected countries response to the COVID-19 at a high level and zero otherwise. We use the natural logarithm of the Brent oil price (*lnoil*), the exchange rates against U.S. Dollars (*lnexc*), the TED Spread (*lnted*) and the gold price (*lngold*) to control for the global systematic risks. Robust standard errors are reported in parentheses, and the asterisks *, ** and *** indicates statistical significance at 10%, 5% and 1% level respectively.

Table 10. Estimation results for panel data model

	(1)	(2)	(3)
lnnc	-0.0003**	-0.0002**	-0.0003***
	(0.0001)	(0.0001)	(0.0001)
lntv	-0.0007**	-0.0006**	-0.0007**
	(0.0003)	(0.0003)	(0.0003)
lnstr	0.0024**	0.0023**	0.0018*
	(0.0009)	(0.0010)	(0.0009)
lnpanic	0.0011***		
	(0.0003)		
lnsent		0.0000	
		(0.0008)	
lnmedia			0.0040***
			(0.0010)
LPR	-0.0038***	-0.0029**	-0.0036***
	(0.0011)	(0.0010)	(0.0009)
HPR	-0.0015**	-0.0011*	-0.0009**
	(0.0005)	(0.0005)	(0.0004)
lnexc	-0.0004**	-0.0003*	-0.0003**
	(0.0001)	(0.0001)	(0.0001)
lnoil	0.0245***	0.0209***	0.0234***
	(0.0041)	(0.0037)	(0.0037)
lngold	0.0278***	0.0238***	0.0253***

	(0.0041)	(0.0042)	(0.0043)
lnted	0.0063***	0.0064***	0.0063***
	(0.0007)	(0.0007)	(0.0007)
constant	-0.3045***	-0.2587***	-0.2942***
	(0.0268)	(0.0272)	(0.0273)
R^2	0.0272	0.0226	0.0256
Adjusted R^2	0.0200	0.0154	0.0184
F-value	69.1718***	69.6692***	41.4447***

This table displays the results for equation (4):

$$R_{it} = \gamma_0 + \gamma_1 Case_{i,t} + \gamma_2 Vaccine_{i,t} + \gamma_3 GovReponse_{i,t} + \gamma_4 Media_{i,t} + \gamma_5 LPR_{i,t} + \gamma_6 HPR_{i,t} + \sum_{k=1}^{k} \varphi_k \boldsymbol{X}_{i,t}^{k} + \mu_{it}$$

$Case_{i,t}$ denotes the natural logarithm of the new confirmed coronavirus cases per million of population (*lnnc*). $Vaccine_{i,t}$ denotes the natural logarithm of the total vaccinations against COVID-19 per hundred of population ($lntv$). $GovReponse_{i,t}$ denotes the natural logarithm of the stringency index (*lnstr*). $Media_{i,t}$ denotes the media-related variables and Column 1-3 reports the results for using the Coronavirus Panic Index (*lnpanic*), the Coronavirus Sentiment Index (*lnsent*) and the Coronavirus Media Coverage Index (*lnmedia*) respectively. $LPR_{i,t}$ is a dummy variable which equals one if the central bank in the selected countries response to the COVID-19 at a low level and zero otherwise. $HPR_{i,t}$ is a dummy variable which equals one if the central bank in the selected countries response to the COVID-19 at a high level and zero otherwise. We use the natural logarithm of the Brent oil price (*lnoil*), the exchange rates against U.S. Dollars (*lnexc*), the TED Spread (*lnted*) and the gold price (*lngold*) to control for the global systematic risks. Robust standard errors are reported in parentheses, and the asterisks *, ** and *** indicates statistical significance at 10%, 5% and 1% level respectively.