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Heterogeneous responses of stock markets to covid related news and sentiments: Evidence from the 1st year of pandemic

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ABSTRACT

In this paper, we study the impact of news and sentiments related to covid-19 on United Kingdom (UK)’s stock returns from February 4, 2020 to December 7, 2020. Our results show that covid-19 daily cases exert a significant negative effect on stock returns whereas covid-19 daily deaths have a significant positive impact. These findings hold when covid-related news and sentiments indices are controlled with the 2nd wave data, and when the US policies and equity market volatilities from infectious diseases are used as controls. The magnitude of the effect of covid cases and deaths indicates that the pandemic is not very harmful to the UK stock market.

1. Introduction

Financial markets across the globe observed severe downturns due to covid-19 (Ding et al., 2021; Cox et al., 2020). For example, when the pandemic first hit, the decline in the United States (US) and United Kingdom (UK) stock markets was comparable to the global financial crisis (GFC) of 2007–09, black Monday of 1987 and even the great depression period of 1929–30. The French stock market lost 44 percent of stock valuation within three and half months of the pandemic (Thorbecke, 2022). Interestingly, the stock markets could not regain what it lost in first few months of covid through the whole of 2020, even though unprecedented policy actions were taken to calm the market.

In a study with the G7 countries stock markets, Izzeldin et al. (2021) find that the UK stock market was hardly affected from covid. They also find that the UK stock market saw the highest heterogeneity in terms of business sectors’ response as oppose to the G7 counterparts, which might be due to ambiguity in the governments’ initial response. In a report from the OECD and Office of National Statistics (ONS), the UK real GDP decline was the highest within G7 countries in 2020 (around 11%), while the UK suffered the highest excess mortality rate and the longest and stringent responses were in effect compared to the other G7 counterparts. Fig. 1 (in the appendix) depicts covid cases and deaths during 2020 in G7 countries, where it is seen that UK observed the highest cumulative deaths and the 2nd highest cumulative cases after the US in the initial phase of covid. Earlier literature investigates G7 stock markets during covid; for example, Cox et al., 2020; Rehman et al. (2021), Thorbecke (2022), Izzeldin et al. (2021), to name a few. However, a

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1 G7 countries constitutes 40 percent of the global output.

2 https://www.ons.gov.uk/economy/grossdomesticproductgdp/articles/internationalcomparisonsofgdpduringthecoronaviruscovid19pandemic/2021-02-01.

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separate study on the impact of covid-19 related news and sentiments on the UK stock market is missing and thus such a study is needed considering the economic importance of the UK at the global level. This is also due to the fact that fluctuations in the stock market during covid is due to sentiments rather than the substance (Cox et al., 2020). Also, overall, these issues make UK a unique case to study whether covid-related news and sentiments had an impact on the stock market volatility during the 1st year of pandemic. We are more interested in investigating how stock markets react to the covid news and sentiments during March-April of 2020, when the infection rates and covid mortality rates were rising fast in UK.

Prior literature highlights the effects of infectious diseases, such as SARS, MERS, Ebola on financial markets (Del Giudice and Paltrinieri, 2017; Chen et al., 2007). Infectious diseases cause stock markets to overreact and lead to negative abnormal returns. Like previous outbreaks, covid has negative impacts on the market in general (Harjoto et al., 2021a). To stop the impact, governments around the world reacted with different policies. For example, Cox et al. (2020) document that federal reserve policy actions led to a V shape pattern in US stock market during March-April 2020. Deev and Příhal (2022) studied how policy actions calmed 28 stock markets of 23 countries. They find that US macroprudential policies have calmed international stock markets, specifically that of other developed markets. Thus, US policies have positive spillovers to the other developed markets. Kizys et al. (2021) find that government measures alleviate herding behavior during covid-19. Ortmans and Tripler (2021) studied how sovereign bond spreads respond to covid before and after the ECB declaration of 12th March, 2020. They used yield differentials between the bond issued by the governments of individual EU countries and Germany with respect to 10-year benchmark rates. They find that the bond spreads rose to 3.05 percentage points in response to 10 new confirmed cases per million people before March 9, however such impact went to zero after 12th march ECB’s announcements. This can be indicated as the success of the policy initiative in the financial market to stop harmful effect of covid. Thorbecke (2022) finds that investors were benefitted (with higher stock returns) from the rise in covid cases in French market given higher cases might trigger expansionary monetary policy. While, banks are not harmed from increase in the covid cases. The author also finds that the appreciation in the euro and then fall in oil prices harmed investors. Rahman and Al Mamun (2021) find that governments’ response somehow calmed the market but could not restore investors’ confidence completely. Baker et al. (2020) suggest that restrictive measures by the government functioned as the accelerator of stock market volatility during the covid-19 than any other previous pandemics. UK government came up with lockdown in 16th March, stimulus package in 17th March and Travel bans in 25th March of 2020 (Bannigidadmath et al., 2022). In response to the government policy, stock market in the UK should have behaved differently before and after UK governments’ policy actions.

Covid 19 has been identified as black swan event. The pandemic created fear in the people’s mind (Lyócsa et al., 2020; Mamaysky, 2020), disrupted global economic activity mainly through lockdowns, social distancing measures, travel bans and caused unprecedented declines in the major financial markets around the world. Due to stress in financial markets, people rush to safe haven assets. For example, people move to euro assets when they anticipate US monetary authority would reduce interest rates more than the ECB (Martin and Szalay, 2020). The Pound sterling also experienced a positive move against USD given UKs’ vaccine program optimism. While, gold held its safe haven properties against high stock volatility and negative real returns in the covid crisis (Drake, 2022). Gold was a safe haven during December 2019 to March 2020, however, such properties are lost during the March 2020–April 2020 period due to increases in hedging cost (Akhtaruzzaman et al., 2021). Oil prices slumped due to the fall in demand in the transportation sector which caused disinflationary pressure in Europe (Thorbecke, 2022). US China Trade war disrupted supply chains and harmed firms participating in the global value chains (Shih, 2020). These factors might have caused covid news and sentiments to exert a negative impact on stock markets. A discussion of the extent literature dealing with the impact of covid on the financial markets of other developed and emerging countries can be found in Table 10 (in the appendix).

We contribute to the literature in a number of ways. First, this study contributes to the emerging literature on covid-19 and financial markets (Al-Awadhi et al., 2020, Al-Awadhi & Alhamadi, S., 2020; Mazur et al., 2020; Ashraf et al., 2020a,b; Cepoi, 2020; Sergi et al., 2021; Goodell and Goutte, 2020; Narayan et al., 2020; Zhang et al., 2020, Baker et al., 2020, Alfaro et al., 2020, Ding et al., 2021, Ramelli and Wagner, 2020, Sergi et al., 2021, Harjoto and Rossi, 2021, among others). This pandemic is surely not the last one. Even after two years of pandemic, the relevant impacts still have important implications for the policymakers, professionals, and the investors. As Goodell (2020) suggests, this area is very important in research in coming days. Second, we contribute the literature of how news and media exert a role in financial markets during the pandemic (Tetlock, 2007; Fang and Peress, 2009). We used both macroeconomic and covid related news and sentiments as two different sets of control variables in our estimation. This might add a different comparable dimension between fundamentals and media driven security pricing. This is also important because the market consists of both rational and noise traders (Chatjuthamard et al., 2021). Third, the impact of news is time varying, our analysis considers multiple sub-periods in the estimation to reveal heterogenous and time-varying response of the stock market to covid news and sentiments. That contributes to the literature. Finally, our results have important implications for the developed stock markets.

Our paper has similarity with respect to some controls used in the regression with the work of Capelle-Blancard and Desroziers (2020). They used a panel model on 74 countries data. We applied ordinary least square (OLS) regression on time series data of UK. We might have improved outcomes from the Capelle-Blancard and Desroziers (2020) because they used a panel data set that did not separate out developed and developing countries. Thus, they could not find why coefficients differ across countries. Though they control for some country-specific characteristics, lack of accounting for institutional factors across the countries might be the reason for absence of cross-country differences in the results. Calomiris and Mamaysky (2019) studied developed and developing countries separately for accounting various institutional differences across the countries. Harjoto et al. (2021a) suggest that the impact of covid

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[3] https://www.theguardian.com/business/2021/feb/19/pound-covid-vaccine-optimism-sterling-dollar-euro.
between developed and the emerging countries will vary because of institutional differences between them (North, 1991). We do not consider emerging markets in our analysis because they present distinct characteristics as compared to the developed markets. Ramelli and Wagner (2020) divided timespan into three period in which covid-19 had an impact on the stock market: Incubation (January 2 – January 17), Outbreak (January 20- February 21), and Fever (February 24- March 20). Capelle-Blancard and Desroziers (2020) used another period that is rebound (March 23- April 30). These timespans are based on the series of events during initial months of covid outbreak (Ramelli and Wagner, 2020). In this study, we follow both papers, and use the period such as Fever (February 24- March 20), Rebound (March 23- April 30). We do not include incubation and outbreak in our analysis because we may not find significant impact in both periods considering low daily cases and no deaths within such periods. In addition, we further use a 2nd wave period (September 1-December 7) to see the robustness of our results.

Our paper is organized as follows. Section 2 reviews the literature. Section 3 presents the methods and data. Section 4 exposes our results, and robustness cheks are provided in Section 5. Section 6 concludes the article.

2. Literature review

Assuming that investors are rational, the efficient market hypothesis (EMH) suggests that all the available information is already included in stock prices and future returns are not predictable on the basis of past information/news (Fama, 1970). However, any overreaction or underreaction does not fall within the realm of explanation of the EMH. Behavioral economists assume irrational investor’s sentiments might have led to excess volatility in the markets. Early finance theory had no role for investor sentiment. The recent literature has established that sentiment can predict stock returns (Baker and Wurgler, 2006). Different news stories might have increased or decreased investors’ sentiment, which translates into excess market volatility.

The extant literature suggests that news can predict stock returns (Tetlock, 2007, 2014; Tetlock et al., 2008; Garcia, 2013). Sinha (2016) documents that weekly news stories predict 13-week stock returns. Given the expected negative impact of covid on the stock market, we have our first hypothesis as follows:

**H1.** Covid news and sentiments should have negative and significant impacts on the stock returns.

Nepp et al. (2022) find that the effects of media coverage on the pandemic on the stock market performance is equal or often larger than the effect of the actual pandemic. This is because news coverage may make investors more emotional and led them to do irrational things. Stock markets overreact to good news, while underreact to bad news (Frank and Sanati (2018); Heston and Sinha, 2017). Chan (2003) suggests that stocks with news have momentum while stocks with no news do not have momentum. According to Jegadeesh and Titman (1993), stocks with previously good performance over a 3 to 12-month period, also observe high returns in equivalent future periods, and the same things happens for bad performance, implying bad performance is followed by bad performance. In short, good brings good and bad brings bad. This particular phenomenon is known as the momentum effect in finance. This momentum challenges the so called EMH and supports investors underreaction hypothesis (UH). As per the EMH, the new information reflects in price immediately and completely. If there is a subsequent upward trend for good news and a downward trend for negative news even after the news date, it means underreaction takes place. Behavioral finance suggests that underreaction results in different biases of investors (Barberis et al., 1998; Daniel et al., 1998). When people underreact, they tend not to adjust or process new information initially, which is known as conservatism (Edwards, 1968). Over the time, they update themselves and incorporate new information completely. Thus, there will be a delayed response as well as a momentum effect in stock prices (positive association between past and the future returns). While, with respect to the overreaction hypothesis, investors initially overreact, but subsequently settle down and the significance of the event diminishes in later periods. For the overreaction hypothesis, there will be systematic price reversals, implying extreme movements in the price which is followed by extreme adjustment in the opposite direction (De Bondt and Thaler, 1985, 1987). Hong and Stein (1999) proposed a unified model for both underreaction and overreaction, where economic agents are either news watchers or momentum traders. In their model, news watchers react to information slowly, thus underreaction takes place, which is utilized by momentum traders to bring efficiency. Based on above discussion, we have developed our second hypothesis as follows:

**H2.** Markets should behave to covid news differently in March,2020 than the market in April,2020. There will be overreaction in March, which will vanish in April. Sign and significance will change (reverse) between March and April. While, the underreaction suggests that lagged values of independent variables are significant in the market. According to underreaction hypothesis, the sign and the significance between March and April will remain same.

3. Econometric method and data

In recent covid-19 and stock market related studies, regression and event study methods are largely used. To examine the effects of covid-19 registered cases and deaths on UK stock returns, we prefer to adopt classical OLS regression for our time series data over the cointegration, and event study method for a number of factors. First, OLS regression is suitable to capture short run effect among multiple stationary I(0) series, and our timespan of data is eleven months which is short term in nature. Thus, we took first difference of data series which do not pass our test of stationarity, and there is no question of losing long term information as the data timespan is short and we use OLS regression. Second, event study methodology does not perform well when there is market inefficiency, multiple events coexist which make assessing the effect of particular event difficult. We used heteroscedasticity and autocorrelation (HAC) consistent standard error in the estimation of the parameter. In line with Ross (1976) and Chen et al. (1986), the econometric model
specified in this study is as follows:

\[
RS_t = \alpha_t + \beta_{Covid_t} + \sum_{i=1}^{n} \beta_i X_{it} + \varepsilon_t
\]  

(1)

where \(RS_t\) is stock returns, \(Covid_t\) is daily covid-19 cases and deaths respectively, \(X_{it}\) is explanatory control variables (macroeconomic variables and covid related news and sentiment indices), and \(\varepsilon_t\) is error term.

Considering global market integration (Solnik, 1974) and to remove misspecification error, we further added world stock index returns (RSW) in eq. (1). We also lagged the independent variables by one period to examine the slow response of the market. Slow response supports the underreaction hypothesis, which suggests investors adjust slowly to new information.

\[
RS_t = \alpha_t + \beta_{Covid_{t-1}} + \beta_{RSW_{t-1}} + \sum_{i=2}^{n} \beta_i X_{it-1} + \varepsilon_t
\]  

(2)

UK registered its first case in January 31, 2020 and no deaths since March, 2020, thus our sample starts from 4th of February. Covid-19 data are available for each day, but stock returns are not available for weekends and national holidays. Thus, we filtered non-trading day variables data. Daily cases and deaths consider off-trading days numbers, when trading starts after holiday or off-trading day. Our dataset consists of 215 observations over the period from February 4, 2020 to December 7, 2020.

We use well-established control variables from the asset pricing literature pertaining to covid 19 (both macroeconomic and covid related news) as follows.

**Economic policy uncertainty**: In general, economic policy uncertainty (EPU) is detrimental to the economy and financial markets. During covid, economic policy uncertainty has increased tremendously. See for example, Al-Thaqeb et al. (2020) for the impact of EPU during covid. Economic policy uncertainty is found to be a predictor of stock returns both in-sample and out-of-sample, however this predictability is dependent on the country or sector (Phan et al., 2018). Brogaard and Detzel (2015), Arouri, et al. (2016) and Christou et al. (2017) find that economic uncertainty exerts a negative effect on stock returns. We use the widely employed Baker et al. (2016) newspaper based EPU index for daily economic uncertainty in our analysis.

**Lockdown/Stimulus/Government response**: Moser and Yared (2020) studied optimal lockdown policy where the government can reduce the impact of pandemic at the cost of lowering economic output. Credible rules increase the efficiency of lockdown policy by limiting the government ability to lock down in the future. However, such social distancing measures adopted by the governments was also found to be contributing to the stabilization of growth rate in the new covid-19 cases around the globe and in the US, which also led the governments in US and Europe to relax the restrictions from May 15, 2020 to revive the economic activity (Albulescu, 2020). Government announcement on the social distancing reduces stock returns while income support related announcement increases stock returns for 77 countries (Ashraf, 2020b). We used government stringency response index\(^4\) by Hale et al. (2020a,b) as the proxy of government response in our model.

**Hope for Covid-19 vaccine**: The hope for vaccine or positive news on covid-19 vaccine may affect stock market positively. Rouatbi et al. (2021) study the impact of covid-19 vaccination on stock markets of 66 countries. They find that vaccination reduces stock market volatility. Capelle-Blancard and Desroziers (2020) used Google search-based index to see its impact on the stock returns. We use Google trend search of the term “covid-19 vaccine” as the proxy of hope for vaccine in our model.

**Option implied volatility**: Option implied volatility represents forward-looking uncertainty in the stock market. We use VSTOXX (implied volatility index in Europe) as a measure of investor sentiment. Investor sentiment have significant effects on stock returns (Baker and Wurgler, 2006; Yang and Zhou, 2015). The sentiment also triggers herding behavior among UK mutual fund managers (Hudson et al., 2020). Herding behavior is seen at the beginning of the crisis and disappears when the crisis goes away, while implied volatility plays a key role in exhibiting irrational behavior (Bekiros et al., 2017). Using the consumer confidence index as proxy for sentiment, Schemeling (2009) find that countries with less market integrity and culture of overreaction show more sensitivity to the sentiment. Hudson and Green (2015) find that UK investors sentiment affects most during a crisis time and US based sentiment indicators also have an impact on UK returns.

**Oil Price**: Oil prices fell significantly in response to covid-19. Using hourly oil price data, Devpura and Narayan (2020) find that covid-19 cases and deaths increases oil volatility between 8% and 22% respectively. Oil price risk has a strong impact on stock returns (Basher and Sadorsky, 2006). Narayan and Gupta (2015) find that oil prices predict US stock returns over a century data, while energy prices are not robust predictor of stock returns (Kim et al., 2019). We used crude brent oil price in US dollars from Energy Information Administration (EIA) and then converted it into pound by applying bilateral exchange rate because brent is standard for two-third of oil price in the world and more related to the UK.

**Exchange rate uncertainty**: Exchange rates affects stock returns negatively through capital mobility\(^5\) (Frankel, 1983; Liang et al., 2015; Kamal and Haque, 2016). Exchange rate volatility affects stock return volatility (Kasman et al., 2011). Baum et al. (2001) find that the permanent component of the exchange rate uncertainty exerts a greater variation on the firm’s profit growth relative to the temporary component. During covid-19, exchange rate uncertainty increased significantly. We used GARCH (1,1) model (Bollerslev, 2013).

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\(^4\) This is a composite index of different criteria such as school closure, Workplace closure, public events cancellation, restriction on gatherings, stay at home, close of public transport, international travel control, other fiscal and monetary measures, and health measures (See Hale et al., 2020a).

\(^5\) See, Caporale et al. (2015) for exchange rate uncertainty and international portfolio flows.
to generate exchange rate uncertainty from exchange rate returns (see Fig. 2 for the graph of exchange rate uncertainty). The mean and variance equation is as follows:

\[ r_e = \alpha + \epsilon_t \]  

Mean eqn.  

(3)

We also tried to compute exchange rate uncertainty keeping covid-19 cases daily growth as the dependent variable in the mean equation, however this did not bring any improved result. Benzid and Chebbi (2020) estimated exchange rate uncertainty using covid-19 as dependent variable in the mean equation applying GARCH (1, 1).
\[ \sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \] Variance eqn. (4)

The graph presents GARCH (1,1) real exchange rate uncertainty. Data is from excelrates.com.

Liability: Financial frictions increase during the crisis period, such as GFC 2007–09, which amplifies the effect of economic uncertainty on investment (Arellano et al., 2019; Gilchrist et al., 2014). Stock illiquidity can be a proxy of financial friction during the crisis period of covid-19. Ben-Rephael (2017) find that during extreme uncertainty period mutual fund managers reduce illiquid asset in their portfolio. This selling-off of illiquid stocks takes place in response to the initial deterioration of market conditions. Amihud (2002) provided a popular measure of illiquidity in the financial market, which is widely used in the literature. We used this measure to examine how market liquidity affects the stock returns. It is calculated as the ratio of absolute daily stock returns divided by the dollar volume.

Media coverage/attention/media sentiment: Media affects stock prices through investors reaction, sentiments and attention. The role of media is well highlighted in the literature (Tetlock, 2007; Fang and Peress, 2009). Media news, whether it is true or false, can have important impact on the stock prices. News on covid-19 creates panic and affects stock returns (Haroon and Rizvi, 2020; Cepoi, 2020). We used media coverage indices related to covid (false news, infodemic, media coverage, media hype, panic and sentiment indices) from RAVENPACK database as additional set of control variables (we define these variables as set 2 variables).

4. Empirical analysis

Table 1 presents the definition and sources of the data of the variable for both set 1 and set 2 variables. RS is stock returns, CASES is covid daily cases, DEATHS is covid daily deaths, RSW is MSCI world equity index returns, UKEPU is UK economic policy uncertainty, GOOGLE is google search based index on covid vaccine, GRSI is government response stringency index, VSTOXX is implied volatility, OIL is oil, REUNC is GARCH based exchange rate uncertainty, ILLIQ is illiquidity, USEPU is united states economic policy uncertainty, DEMV is stock market volatility tracker from infectious disease in US. FAKENEWS, INFODEMIC, PANIC, MEDIACOVERAGE, MEDIAHYPE, SENTIMENT are media coverage indices on covid. Table 2 reports that the first differenced series for the variables are stationary or I(0) variables. Table 3 reports the summary statistics of the variables used in this study. The mean RS is −0.0005, which suggests that during the sample period investors receive on average negative daily return. The distribution of stock returns is not normally distributed-which is supported by its fat tail and left-skewed feature, which is normal to high frequency equity returns (Narayan et al., 2020). The 5720 mean value of changes in covid-19 cases indicates that the daily covid-19 registered cases increase by 5720 daily on average. While the 229 mean value of the changes in covid-19 deaths indicates that on average daily 229 people die from covid-19. All other variables from variable set 1 and 2 are non-normally distributed and have positive excess kurtosis. Table 4 presents the correlation matrix. It can be seen that stock returns have positive correlation CASES and DEATHS. While, covid related sentiment index (SENTIMENT) has negative correlations with FAKENEWS, MEDIACOVERAGE, MEDIAHYPE, PANIC indices. Table 5 reports the main regression results (eq. (1)) for stock returns and daily growth in registered cases of covid-19 in UK which we estimate using OLS regression. Model 1–4 show baseline models results (without control variables) for different samples-full sample, fever, rebound, and 2nd wave. We take the 2nd wave as a robustness test, which is discussed in the robustness section later. As shown in model 1–4, in Table 5, CASES variable enters negatively and significant in the full sample at the 1% significance level. For models 5–8, CASES remain negative and significant at the 1% significance level with the macroeconomic variables used as controls. Our first hypothesis is verified. The negative effect of covid cases confirms the findings of Ashraf (2020a) and Al-Awadhi et al. (2020). Among control variables, GRSI enters significant and negative in the full-sample and rebound stage respectively. This suggests that government responses help stock markets to correction. Our result contradicts those of Narayan et al. (2020), who find a positive impact for government responses on stock returns. VSTOXX is negative and significant in fever, rebound stages, it suggests the investors are uncertain on the economic and financial market development during March and April. OIL exerts a positive impact on the stock returns of UK in full sample and fever stage. Liquidity is significant and positive in the full sample.

Table 6 reports regression result (eq. (1)) for stock returns and DEATHS from covid-19 in UK. As shown in Table 6, DEATHS enter positive and significant in the full sample and rebound stage only both without and with controls. We cannot verify our first hypothesis with respect to covid related deaths news. The positive impact may be due to an overreaction, which may be induced by the governments actions/policies/stimulus packages. Investors might have been benefitted from the rise in deaths and possible expansionary monetary policies (Thorpbecke, 2022). It is also may be due to the fact that investors overreact to the good news, such as declaration of government stimulus packages. This is consistent with the findings of Ashraf (2020a) and Heston and Sinha (2017). The coefficients for the controls display similar sign and significance as Table 5.

Table 7 presents results for eq. (1) when we control set 2 variables (covid related news and sentiment indices). CASES is negative and significant in full sample and rebound stages. DEATHS is positive and significant in full sample, fever, rebound stages. This finding is important because it differs with the outcome of Table 6, where we find positive and significant result for DEATHS in full sample and rebound stages. Thus, when we use covid related news indices as controls, the outcome is intensified as opposed to the macroeconomic news controls. In Table 7, with respect to the controls, it is found that FAKENEWS, and SENTIMENT affect stock returns positively and significantly in fever stage only. Thus, in early stage of pandemic, fake news become important. While, MEDIACOVERAGE reduces stock returns in fever stage. While INFODEMIC affects stock returns significantly in the full sample, but negatively. The result for FAKENEWS is contrast to Cepoi (2020) who find negative effects for covid related fake news on the stock returns. In the initial stage of pandemic, FAKENEWS manipulated the market by increasing share prices. However, MEDIACOVERAGE and INFODEMIC exert a negative effect on the stock market. So, there is role of media coverage on market correction and in preventing manipulation of market from fake news.
Table 2
Unit root test results. (i) Variables: Set 1, (ii) Variables: set 2 Unit root test results of set 2 variables are available on request. For brevity, we do not present this.

This table presents unit root tests results. Stock market returns (RS) is calculated as log daily change of FTSE100 stock index. CASES is daily cases of covid-19 registered cases in UK. DEATHS is daily cases of covid-19 deaths in UK. RSW is MSCI world equity indices returns. UKEPU is newspaper-based uncertainty index taken form Baker et al. (2016), available in policyuncertainty.com. Google search result on covid-19 vaccine updates is taken from google trend. VSTOXX is implied volatility index, taken from Investing.com. GRSI is government response stringency index. Oil price is taken from EIA in USD and then converted into Pound by multiplying with GBP/USD exchange rate. Exchange rate return (Re) is calculated using log difference of bilateral exchange rate of GBP/USD taken from excelrates.com. Then GARCH (1, 1) is applied on exchange rate return to measure exchange rate uncertainty. Illiq is Amihud (2002) illiquidity measure. USEPU and IDEMV is US economic policy uncertainty and equity market volatility tracker from infectious disease of US, both taken from policyuncertainty.com. Set 2 variables are taken from coronavirus.ravenpack.com.

UNIT ROOT TEST TABLE (PP)

| With Constant & Trend | RS    | CASES | DEATHS | RSW   | UKEPU | GOOGLE | GRSI  | VSTOXX | OIL   | REUNC | ILLIQ | USEPU | IDEMV |
|-----------------------|-------|-------|--------|-------|-------|--------|-------|--------|-------|-------|-------|-------|-------|
| At Level              |       |       |        |       |       |        |       |        |       |       |       |       |       |
| With Constant & Trend | t-Statistic | -15.37 | -2.30  | -10.79 | -17.15 | -5.12  | -9.89 | -1.83  | -2.85 | -1.92 | -3.11 | -14.99 | -5.18  | -6.28 |
| Prob.                 | 0.00  | 0.42  | 0.00   | 0.00  | 0.00  | 0.00   | 0.69  | 0.18   | 0.64  | 0.10  | 0.00  | 0.00  | 0.00  |
|                       | ***   | no    | ***    | ***   | ***   | ***    | no    | no     | no    | *     | ***   | ***   | ***   |
| At First Difference   |       |       |        |       |       |        |       |        |       |       |       |       |       |
| With Constant & Trend | t-Statistic | -80.54 | -21.78 | -64.45 | -156.39 | -37.43 | -70.99 | -12.92 | -14.37 | -13.81 | -11.97 | -64.06 | -35.15 | -36.70 |
| Prob.                 | 0.00  | 0.00  | 0.00   | 0.00  | 0.00  | 0.00   | 0.00  | 0.00   | 0.00  | 0.00  | 0.00  | 0.00  | 0.00  |
|                       | ***   | ***   | ***    | ***   | ***   | ***    | ***   | ***    | ***   | ***   | ***   | ***   | ***   |

UNIT ROOT TEST TABLE (ADF)

| With Constant & Trend | RS    | CASES | DEATHS | RSW   | UKEPU | GOOGLE | GRSI  | VSTOXX | OIL   | REUNC | ILLIQ | USEPU | IDEMV |
|-----------------------|-------|-------|--------|-------|-------|--------|-------|--------|-------|-------|-------|-------|-------|
| At Level              |       |       |        |       |       |        |       |        |       |       |       |       |       |
| With Constant & Trend | t-Statistic | -15.39 | -1.60  | -2.50  | -8.56  | -2.48  | -9.72  | -1.52  | -2.61  | -1.84  | -3.08  | -14.82 | -3.42  | -6.42 |
| Prob.                 | 0.00  | 0.78  | 0.32   | 0.00  | 0.34  | 0.00   | 0.82   | 0.27   | 0.68   | 0.11   | 0.00   | 0.05   | 0.00  |
|                       | ***   | no    | no     | ***   | no    | ***    | no     | no     | no     | ***   | no     | ***   | ***   |
| At First Difference   |       |       |        |       |       |        |       |        |       |       |       |       |       |
| With Constant & Trend | t-Statistic | -11.25 | -4.37  | -13.58 | -9.30  | -13.28 | -10.04 | -12.63 | -14.30 | -13.79 | -12.05 | -9.96  | -14.82 | -11.54 |
| Prob.                 | 0.00  | 0.00  | 0.00   | 0.00  | 0.00  | 0.00   | 0.00   | 0.00   | 0.00   | 0.00   | 0.00   | 0.00   | 0.00  |
|                       | ***   | ***   | ***    | ***   | ***   | ***    | ***    | ***    | ***    | ***    | ***    | ***    | ***   |

Notes: *** indicates 1% significance level, ** indicates 5% significance level and * indicates 10% significance level. Null hypotheses is that there is unit root in the series. ADF and PP test of unit root conducted. Test statistic are reported. Lag length is chosen by SIC.
Table 3
Descriptive statistics results, (i) variables: set 1, (ii) variables: set 2.
This table reports summary statistics of main variables used in the regression model. Stock market returns (RS) is calculated as log daily change of FTSE100 stock index. CASES is daily cases of covid-19 registered cases in UK. DEATHS is daily cases of covid-19 deaths in UK. RSW is MSCI world equity indices returns. UKEPU is newspaper-based uncertainty index taken form Baker et al. (2016), available in policyuncertainty.com. Google search result on covid-19 vaccine updates is taken from google trend. VSTOXX is implied volatility index, taken from Investing.com. GRSI is government response stringency index. Oil price is taken from EIA in USD and then converted into Pound by multiplying with GBP/USD exchange rate. Exchange rate return (Re) is calculated using log difference of bilateral exchange rate of GBP/USD taken from excelrates.com. Then GARCH (1, 1) is applied on exchange rate return to measure exchange rate uncertainty. Illiq is Amihud (2002) illiquidity measure. USEPU and IDEMV is US economic policy uncertainty and equity market volatility tracker from infectious disease of US, both taken from policyuncertainty.com. Set 2 variables are taken from coronavirus.ravenpack.com.

| RS   | CASES | DEATHS | RSW   | UKEPU | GOOGLE | GRSI | VSTOXX | OIL   | REUNC | ILLIQ | USEPU | IDEMV |
|------|-------|--------|-------|-------|--------|------|--------|-------|-------|-------|-------|-------|
| Mean | −0.0005 | 5720   | 229   | 0.0005 | 533.09 | 13.13 | 60.99  | 31.11 | 30.36 | 0.0000426 | 0.000000000000002 | 309.63 | 21.84 |
| Std. Dev. | 0.019 | 7639   | 375   | 0.01 | 237.05 | 18.53 | 21.16  | 12.66 | 7.59 | 0.0000277 | 0.000000000000001 | 142.31 | 13.05 |
| Skewness | −0.95 | 1.49 | 6.78 | −1.25 | 0.46 | 1.94 | −1.67 | 1.89 | −0.73 | 3.12 | 1.30 | 0.68 | 1.08 |
| Kurtosis | 9.74 | 3.99 | 73.74 | 1.31 | 2.72 | 7.56 | 4.25 | 7.58 | 3.48 | 12.91 | 5.24 | 3.20 | 4.24 |
| Jarque-Bera | 438 | 89.11 | 65.65 | 77.54 | 316.24 | 116.24 | 315.42 | 21.14 | 1225.99 | 105.49 | 16.95 | 55.65 |
| Probability (JB) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Observations | 215 | 215 | 215 | 215 | 215 | 215 | 215 | 215 | 215 | 215 | 215 | 215 |

| FAKENEWS | INFODEMIC | MEDIACOVERAGE | MEDIAHYPE | PANIC | SENTIMENT |
|----------|------------|---------------|-----------|-------|-----------|
| Mean     | 1.02       | 55.86         | 65.65     | 44.55 | 4.75      | −5.98   |
| Std. Dev. | 0.72     | 13.90         | 12.37     | 13.03 | 2.15      | 18.25   |
| Skewness | 1.99      | −1.91         | −1.70     | −1.08 | 1.42      | −0.16   |
| Kurtosis | 8.63      | 5.55          | 5.47      | 4.24  | 6.63      | 2.34    |
| Jarque-Bera | 428.31 | 189.93        | 158.92    | 56.10 | 190.65    | 4.81    |
| Probability | 0.00 | 0.00          | 0.00      | 0.00  | 0.00      | 0.09    |
| Observations | 216 | 216          | 216       | 216   | 216       | 216     |
Table 4
Correlation matrix, (i) control variables: set 1, (ii) control variables: set 2.
This table presents correlation matrix. Stock market returns (RS) is calculated as log daily change of FTSE100 stock index. CASES is daily cases of covid-19 registered cases in UK. DEATHS is daily cases of covid-19 deaths in UK. RSW is MSCI world equity indices returns. UKEPU is newspaper-based uncertainty index taken form Baker et al. (2016), available in policyuncertainty.com. Google search result on covid-19 vaccine updates is taken from google trend. VSTOXX is implied volatility index, taken from Investing.com. GRSI is government response stringency index. Oil price is taken from EIA in USD and then converted into Pound by multiplying with GBP/USD exchange rate. Exchange rate return (Re) is calculated using log difference of bilateral exchange rate of GBP/USD taken from excelrates.com. Then GARCH (1, 1) is applied on exchange rate return to measure exchange rate uncertainty. Illiq is Amihud (2002) illiquidity measure. USEPU and IDEMV is US economic policy uncertainty and equity market volatility tracker from infectious disease of US, both taken from policyuncertainty.com. Set 2 variables are taken from coronavirus.ravenpack.com.

|       | RS   | CASES | DEATHS | RSW   | UKEPU | GOOGLE | GRSI | VSTOXX | OIL   | REUNC | ILLIQ | USEPU | IDEMV |
|-------|------|-------|--------|-------|-------|--------|------|--------|-------|-------|-------|-------|-------|
| RS    | 1    | 0.07  | 0.13   | 0.81  | 0.15  | -0.002 | 0.23 | -0.17  | -0.03 | 0.08  | -0.16 | 0.16  |
| CASES |      | 1     | 0.21   | 0.05  | -0.15 | 0.23   | 0.26 | 0.08   | -0.49 | -0.22 | -0.14 | -0.11 |
| DEATHS|      |       | 1      | 0.12  | 0.38  | -0.08  | 0.25 | 0.86   | 0.009 | 0.38  | 0.05  | 0.33  |
| RSW   |      |       |        | 1     | 0.17  | -0.08  | 0.62 | 0.43   | 0.76  | 0.15  | 0.005 | 0.175 |
| UKEPU |      |       |        |       | 1     | 0.16   | 0.14 | 0.22   | 0.31  | 0.08  | 0.06  | 0.01  |
| GOOGLE|      |       |        |       |       | 1      | 1    | 0.01   | -0.64 | 0.76  | 0.32  | 0.22  |
| VSTOXX|      |       |        |       |       |        | 1    | 1      |       | -0.49 | -0.23 |       |
| OIL   |      |       |        |       |       |        |      |        | 1     |       | 0.46  | 0.15  |
| REUNC |      |       |        |       |       |        |      |        |       | -0.64 | 0.46  |       |
| ILLIQ |      |       |        |       |       |        |      |        |       |       | 0.64  |       |
| USEPU |      |       |        |       |       |        |      |        |       |       |       | 1     |
| IDEMV |      |       |        |       |       |        |      |        |       |       |       |       |

|       | FAKE NEWS | INFODEMIC | MEDIACOVERAGE | MEDIAHYPE | PANIC | SENTIMENT |
|-------|-----------|------------|---------------|-----------|-------|-----------|
| FAKE NEWS | 1         |            |               |           |       |           |
| INFODEMIC  |           | 0.28       |               |           |       |           |
| MEDIACOVERAGE | 0.39       | 0.92       |               |           |       |           |
| MEDIAHYPE    | 0.38       | 0.89       | 0.96          |           |       |           |
| PANIC         | 0.39       | 0.35       | 0.54          | 0.60      |       |           |
| SENTIMENT     | -0.10      | 0.02       | -0.12         | -0.23     | -0.27 | 1         |
Table 5
UK Stock index returns in response to the COVID-19 pandemic registered cases.

This Table shows how UK stock returns react to the COVID-19 CASES. The table reports the OLS regression results. The dependent variable is stock returns in all model and is measured as the daily log change of FTSE 100 stock index of UK. The regression model is specified as for equation (1): $R_{St} = \alpha_t + \beta_0 Covid_t + \sum_{i=1}^{n} \beta_i X_{it} + \epsilon_t$. In this table, we used daily growth of COVID-19 cases. In panel A, we test model without controls, in panel B we test with controls. In columns (2)–(4) and (6)–(8) the sample is divided in sub-periods: Fever period is Feb. 24-March 20; Rebound is March 23-April 30; 2nd wave period is September 1-December 7. Full sample is February 4 to December 7, 2020. Stock market returns (RS) is calculated as log daily change of FTSE100 stock index. CASES is daily cases of COVID-19 registered cases in UK. DEATHS is daily cases of COVID-19 deaths in UK. RSW is MSCI world equity indices returns. UKEPU is newspaper-based uncertainty index taken from Baker et al. (2016), available in policyuncertainty.com. Google search result on COVID-19 vaccine updates is taken from google trend. VSTOXX is implied volatility index, taken from Investing.com. GRSI is government response stringency index. Oil price is taken from EIA in USD and then converted into Pound by multiplying with GBP/USD exchange rate. Exchange rate return (Re) is calculated using log difference of bilateral exchange rate of GBP/USD taken from excelrates.com. Then GARCH (1, 1) is applied on exchange rate return to measure exchange rate uncertainty. Illiq is Amihud (2002) illiquidity measure. D refers to first difference. HAC standard errors are used to compute t statistics. *** indicates 1% significance level, ** indicates 5% significance level and * indicates 10% significance level.

|                | Panel A                      | Panel B                      |
|----------------|------------------------------|------------------------------|
|                | 1               | 2               | 3               | 4               | 5               | 6               | 7               | 8               |
| Full sample    | 0.0004          | 0.018            | 0.006           | 0.001           | 0.006           | 0.018           | 0.006           | 0.001           |
| Fever          | 0.000132        | -0.00000132      | -0.00000938     | -0.000000983**  | -0.00000945***  | -0.00000263***  | -0.00000199***  | -0.000000857***  |
| Rebound        | 0.0000483       | 0.0000575       | -0.00000350     | 0.0000743       | 0.0000402**     | 0.00000083**    | 0.000000945***  | 0.0000000945***  |
| 2nd wave       | 0.001145***     | -0.001145**     | -0.001532***    | -0.000596       | -0.00437***     | -0.00412***     | -0.004532***    | -0.005139***    |
| D(CASES)       | 0.001728*       | 0.005045**      | -0.001501       | 0.0011719       | 0.001258        | 0.002287       | 0.006620        | -0.0004076*     |
| D(UKEPU)       | 0.001583*       | 0.002005       | 0.005135        | 0.002842***     | 0.001258        | 0.002287       | 0.006620        | -0.0004076*     |
| D(GRSl)        | 0.074580        | 0.090354        | 0.239726        | 0.0566          | 0.62            | 0.86           | 0.64            | 0.72            |
| LOG(REUNC)     | 0.000132        | 0.00012         | -0.0000075      | 0.000000983**   | 0.00000945***   | -0.00000263***  | -0.00000199***  | -0.000000857***  |
| LOG(ILLIQ)     | 0.0001258       | 0.00613         | 0.1532          | 0.004532***     | 0.0001258       | 0.002287       | 0.006620        | -0.0004076*     |
| Constant       | -0.0004         | -0.018          | 0.006           | 0.001           | 0.006           | 0.018          | 0.006           | 0.001           |
| R square       | 0.008           | 0.014           | 0.06            | 0.03            | 0.62            | 0.86           | 0.64            | 0.72            |
| Period         | Feb4-Dec7       | Feb24-Mar20     | Mar23-Apr30     | Sep1-Dec7       | Feb4-Dec7       | Feb24-Mar20     | Mar23-Apr30     | Sep1-Dec7       |
| # of Obs       | 215             | 20              | 27              | 70              | 214             | 20              | 27              | 70              |
Table 6
UK Stock index returns in response to the COVID-19 pandemic deaths.
This Table shows how UK stock returns react to the covid-19 DEATHS. The table reports the OLS regression results. The dependent variable is stock returns in all model and is measured as the daily log change of FTSE 100 stock index of UK. The regression model is equation (1) specified as: $r_t = \alpha + \beta_0 \text{Covid}_{i,t} + \sum_{n=1}^{\infty} \beta_n X_n + \epsilon_t$. In this table, we used daily covid-19 deaths. In panel A, we test model without controls, in panel B we test with controls. In columns (2)–(4) and (6)–(8) the sample is divided in sub-periods: Fever period is Feb. 24-Mar. 20; Rebound is March 23- April 30, 2nd wave (September 1-December 7). Full sample is February 04 -December 07. Covid-19 DEATHS is calculated as daily growth in registered deaths in UK. Stock market returns (RS) is calculated as log daily change of FTSE100 stock index. CASES is daily cases of covid-19 registered cases in UK. DEATHS is daily cases of covid-19 deaths in UK. RSW is MSCI world equity indices returns. UKEPU is newspaper-based uncertainty index taken form Baker et al. (2016), available in policyuncertainty.com. Google search result on covid-19 vaccine updates is taken from google trend. VSTOXX is implied volatility index, taken from Investing.com. GRSI is government response stringency index. Oil price is taken from EIA in USD and then converted into Pound by multiplying with GBP/USD exchange rate. Exchange rate return (Re) is calculated using log difference of bilateral exchange rate of GBP/USD taken from excelrates.com. Then GARCH (1, 1) is applied on exchange rate return to measure exchange rate uncertainty. Log (Illiq) is Amihud (2002) illiquidity measure in log form. D refers to first difference. HAC standard errors are used to compute t statistics. *** indicates 1% significance level, ** indicates 5% significance level and * indicates 10% significance level.

|                | Panel A |                | Panel B |
|----------------|---------|----------------|---------|
|                |         | Fever          | Rebound | 2nd wave |
|                |         | Full sample    |         |         |
| D(DEATHS)      | 0.00000731*** | -0.00276     | 0.0000687*** | -0.0000143 |
| D(UKEPU)       | -0.00000246 | 0.000133      | -0.0000446*  | 0.00000196  |
| D(GOOGLE)      | 0.0000537 | 0.000817      | 0.0000697   | 0.0000860  |
| D(GRSI)        | -0.0011161*** | -0.005777 | -0.001325*** | -0.00066  |
| D(VSTOXX)      | -0.0044328*** | -0.005125** | -0.004811*** | -0.005071*** |
| D(OIL)         | 0.001634*  | 0.005160***   | 0.000331    | 0.001867   |
| LOG(REUNC)     | 0.001269   | 0.0000438     | 0.000050    | -0.003946* |
| LOG(Illiq)     | 0.001552** | 0.007454      | 0.004221    | 0.002448*** |
| Constant       | -0.0052   | -0.017203**   | 0.005       | 0.013      |
| R square       | 0.02     | 0.01          | 0.05       | 0.02       |
| Period         | Feb4-Dec7 | Feb24-Mar20  | Mar23-Apr30 | Sept1-Dec7 |
| # of Obs       | 215     | 20            | 27         | 70         |
Table 7
UK Stock index returns in response to the COVID-19 media news.
This table shows how UK stock returns react to the covid-19 pandemic related media news and sentiments. The table reports the OLS regression results. The dependent variable is stock returns in all model and is measured as the daily log change of FTSE 100 stock index of UK. The regression model is based on equation (1) specified as: \( R_{St} = \alpha + \beta_0 \text{Covid}_t + \sum_{i=1}^{n} \beta_i X_{it} + \epsilon_t \). In panel A, we test model with daily growth of covid-19 CASES, in panel B we test with daily growth of covid 19 DEATHS. In columns (2)–(4) and (6)–(8) the sample is divided in sub-periods: Fever period is Feb. 24-Mar. 20; Rebound is March 23- April 30; 2nd wave period is September 1- December 7. Full sample is February 4 to December 7. CASES is calculated as daily registered cases in UK. DEATHS is daily death from the COVID-19. D refers to first difference. HAC standard errors are used to compute t statistics. *** indicates 1% significance level, ** indicates 5% significance level and * indicates 10% significance level. FAKENEWS, INFODEMIC, MEDIA COVERAGE, MEDIAHYPE, PANIC AND SENTIMENT INDEX is from coronavirus.Ravenpack.com.

| Panel A |       |       |       |       | Panel B |       |       |       |
|---------|-------|-------|-------|-------|---------|-------|-------|-------|
|         | 1     | 2     | 3     | 4     |         | 5     | 6     | 7     |
|         | Full sample | Fever | Rebound | 2nd wave | Full sample | Fever | Rebound | 2nd wave |
| D(CASES) | -0.000000104** | -0.00000259 | -0.0000154* | -0.00000734* |         |       |       |       |
| D(DEATHS) | -0.0017 | 0.0335*** | -0.01042 | -0.0000431 | 0.00000786*** | 0.000313*** | 0.00000659*** | 0.000237** |
| D(FAKENEWS) | -0.0006* | 0.004 | -0.00062 | -0.0000749 | -0.001529 | 0.033** | -0.0070 | 0.000893 |
| D(INFODEMIC) | -0.00059 | 0.00602* | -0.0021 | 0.00058 | -0.000800** | 0.0052 | -0.00285 | -0.00057 |
| D(MEDIA COVERAGE) | -0.00059 | 0.00602* | -0.0021 | 0.00058 | -0.000800** | 0.0052 | -0.00285 | -0.00057 |
| D(MEDIAHYPE) | -0.00062 | -0.0014 | 0.00058 | 0.00000550 | -0.0000556 | -0.0060* | 0.00218 | 0.000663 |
| D(PANIC) | -0.000114 | 0.006339 | -0.003485 | -0.001353 | -0.0000758 | 0.00633 | -0.0028 | -0.0014 |
| D(SENTIMENT) | 0.000105 | 0.003323* | -0.001 | 0.00243 | 0.000115 | 0.00332 | -0.0011 | 0.00021 |
| Constant | -0.0002 | 0.0141 | 0.007 | 0.0015 | -0.00027 | -0.0142* | 0.005 | 0.0013 |
| R square | 0.04 | 0.43 | 0.25 | 0.13 | 0.06 | 0.45 | 0.20 | 0.15 |
| Period | Feb4-Dec7 | Feb24-Mar20 | Mar23-Apr30 | Sept1-Dec7 | Feb4-Dec7 | Feb24-Mar20 | Mar23-Apr30 | Sept1-Dec7 |
| # of Obs | 215 | 20 | 27 | 70 | 215 | 20 | 27 | 70 |
Table 8
UK Stock index returns in response to the COVID-19 pandemic cases and deaths lagged effects.
This Table shows how UK stock returns react to the covid-19 pandemic cases and deaths lagged effects. The table reports the OLS regression results. The dependent variable is stock returns in all model and is measured as the daily log change of FTSE 100 stock index of UK. The regression model is equation (2) specified as: 

\[ R_s = \alpha_t + \beta_0 \text{Covid}_{t-1} + \beta_1 \text{Covid}_{i,t-1} + \sum_{i=2}^{n} \beta_i X_{it-1} + \epsilon_t. \]

In panel A, we test model covid CASES, in panel B we test with DEATHS. In columns (2)–(4) and (6)–(8) the sample is divided in sub-periods: Fever period is Feb. 24-Mar. 20; Rebound is March 23- April 30, 2nd wave (September 1-December 7). Full sample is February 04-December 07. Covid-19 CASES is calculated as daily growth in registered cases in UK Covid-19 DEATHS is calculated as daily growth in registered deaths in UK. Stock market returns (RS) is calculated as log daily change of FTSE100 stock index. CASES is daily cases of covid-19 registered cases in UK. DEATHS is daily cases of covid-19 deaths in UK. RSW is MSCI world equity indices returns. UKEPU is newspaper-based uncertainty index taken form Baker et al. (2016), available in policyuncertainty.com. Google search result on covid-19 vaccine updates is taken from google trend. VSTOXX is implied volatility index, taken from investing.com. GRSI is government response stringency index. Oil price is taken from EIA in USD and then converted into Pound by multiplying with GBP/USD exchange rate. Exchange rate return (Re) is calculated using log difference of bilateral exchange rate of GBP/USD taken from excelrates.com. Then GARCH (1, 1) is applied on exchange rate return to measure exchange rate uncertainty. Log (Illiq) is Amihud (2002) illiquidity measure in log form. D refers to first difference. HAC standard errors are used to compute t statistics. *** indicates 1% significance level, ** indicates 5% significance level and * indicates 10% significance level.

|                  | 1                  | 2                  | 3                  | 4                  | 5                  | 6                  | 7                  | 8                  |
|------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
|                  | Full sample        | Fever              | Rebound            | 2nd wave           | Full sample        | Fever              | Rebound            | 2nd wave           |
| **D(CASES)** t-1 | -0.00000113***     | -0.000195          | -0.0000293         | -0.00000856**      | -0.0000229         | 0.00085            | -0.0000133***     | -0.0000154         |
| **D(DEATHS)** t-1| -0.0341            | -0.8057*           | 0.0793             | 0.112414           | -0.0215            | -0.8849           | 0.1098             | 0.185388           |
| **D(UKEPU)** t-1 | -0.0000194**       | 0.00053988         | 0.0000272          | -0.00000996        | -0.0000194**       | 0.000422**        | -0.0000385         | -0.0000108*        |
| **D(GOOGLE)** t-1| -0.0000617         | 0.00149            | -0.000128          | 0.0000256          | -0.0000565         | 0.000379          | -0.0000985         | 0.0000148          |
| **D(GRSI)** t-1  | 0.0015**           | 0.001794           | 0.000223***        | -0.000539          | 0.001494**         | 0.001419          | 0.0002398**        | -0.0000611         |
| **D(VSTOXX)** t-1| -0.0000279         | -0.001424          | 0.000834           | 0.00000163         | -0.0000561         | -0.00026          | 0.000086           | 0.0000116          |
| **D(OIL)** t-1   | 0.001266           | 0.0412**           | 0.002093           | -0.0014-701        | 0.001237           | 0.0116***         | 0.002582           | -0.001311          |
| **LOG(REUNC)** t-1| -0.000317          | -0.03143           | -0.003053          | -0.003325          | -0.000260          | -0.0394           | -0.008441          | -0.002168          |
| **LOG(Illiq)** t-1| 0.00064            | 0.000754           | 0.010990           | -0.000272          | 0.000526           | 0.001343          | 0.0119             | 0.0000496          |
| **Constant**     | 0.017              | -0.31618           | 0.342868           | -0.04229           | 0.0144             | -0.3792           | 0.3245             | -0.038255          |
| **R square**     | 0.09               | 0.56               | 0.43               | 0.09               | 0.08               | 0.49              | 0.52               | 0.08               |
| **Period**       | Feb4-Dec7          | Feb24-Mar20        | Mar23-Apr30        | Sept1-Dec7         | Feb4-Dec7          | Feb24-Mar20        | Mar23-Apr30        | Sept1-Dec7         |
| **# of Obs**     | 215                | 20                 | 27                 | 70                 | 214                | 20                 | 27                 | 70                 |
Effect of US EPU and IDEMV tracker on UK stock returns (Full Sample).
This Table shows how UK stock returns react to the US EPU and infectious disease EMV tracker. The table reports the OLS regression results. The dependent variable is stock returns in all model and is measured as the daily log change of FTSE 100 stock index of UK. Model 1 and 3 include covid-19 CASES and DEATHS and using USEPU and IDEMV index as control variable and model 2 and 4 includes interaction term. Full sample is February 04-December 07. Covid-19 cases is calculated as daily registered cases in UK, notation as CASES. Covid-19 deaths is measured as daily deaths from covid-19 in UK, notation as DEATHS. USEPU is US economic policy uncertainty, taken from policyuncertainty.com. IDEMV is infectious disease Equity Market Volatility Tracker, taken from policyuncertainty.com. D is first difference. HAC standard errors are used to compute t statistics. *** indicates 1% significance level, ** indicates 5% significance level and * indicates 10% significance level.

### Table 9

|                | 1 Full sample | 2 Full sample | 3 Full sample | 4 Full sample |
|----------------|---------------|---------------|---------------|---------------|
| D(CASES)       | -0.0000011**  | -0.00000105*  |               |               |
| D(DEATHS)      |               |               |               |               |
| D(USEPU)       | 0.00000747    | 0.00000814    | 0.00000744*** | 0.00000607*** |
| D(IDEMV)       | -0.00000698   | -0.00000667   | -0.000349     | -0.0000449    |
| D(CASES) * D(USEPU) | 0.00000000010 | 0.00000000816 |               |               |
| D(CASES) * D(IDEMV) |               |               |               |               |
| D(DEATHS) * D(USEPU) | 0.000000000016 | 0.00000000876 |               |               |
| D(DEATHS) * D(IDEMV) |               |               |               |               |
| Constant       | -0.0004       | -0.0004       | -0.0005       | -0.0006       |
| Adjusted R square | 0.01          | 0.01          | 0.22          | 0.02          |
| Period         | Feb4-Dec7     | Feb4-Dec7     | Feb4-Dec7     | Feb4-Dec7     |
| # of Obs       | 215           | 215           | 215           | 215           |

In Table 8, we present the results of eq. (2). In Table 8, we show the lagged effects of covid news and sentiments, as well as we included lagged effects of RSW. We find that CASES are significant and negative in full sample, but interestingly, DEATHS become negative and significant in the rebound stage. This contrasts to our earlier results in Tables 6 and 7, where DEATHS was positive and significant in rebound stage. Thus, our second hypothesis is partially verified. Lagged effects of USEPU is significant and positive in full sample in both panel A and panel B. GRSI is positive and significant in full sample and rebound stage in both Panel A and Panel B, which also contrasts our earlier findings that GRSI is negative and significant.

Due to brevity, we do not present the results for lagged effects based on equation (2), when we used set 2 variables (covid related news sentiments indices) as the controls. We find that CASES and DEATHS are negative and significant in full sample and the rebound stage respectively. INFODEMIC and the PANIC index is significant in the rebound stage. With respect to the lagged effects, we find some slow response in the rebound stage. This signifies underreaction and verifies our hypothesis 2.

5. Robustness

We conduct robustness tests in two ways. First, we examined the 2nd wave data to see whether our 1st wave results hold. During the 2nd wave, there is a significant rise in the cases and deaths from covid. From Table 5, we find that CASES coefficients are negative and significant in 2nd wave in both Panel A and Panel B, which shows that the results are robust. As per Table 6, DEATHS coefficients become insignificant in 2nd wave after being significant and positive in the rebound stage. This suggest that investors are not fearful on the 2nd wave deaths news. Table 7 show that negative effects for CASES and positive effects for DEATHS hold in 2nd wave. Table 8 also supports that negative effects for CASES holds in 2nd wave.

Second, we examined the effect of US economic policy uncertainty and infectious disease Equity Market Volatility Tracker (IDEMV) on the UK stock returns. This is important because US policy has international spillovers and the FED policy affects other developed markets (Harjoto et al., 2021b). Table 9 reports the results of effects of US EPU and IDEMV index on UK stock returns. We also use interaction terms (CASES and USEPU and CASES and IDEMV) in model 2 and (DEATHS and USEPU and DEATHS and IDEMV) in model 4 in Table 9. It can be observed from Table 9 that CASES are negative and significant both without and with interaction terms. While, DEATHS is positive and significant without and with interaction terms. Our results are robust for both CASES and DEATHS controlling global uncertainties. Interestingly, interaction terms are not significant in model 2 and model 4. This indicates that response of investors to the covid-19 does not depend on the foreign EPU and infectious disease equity market volatility index in the full sample.

6. Conclusion

This paper attempts to investigate the relationship between covid-19 and UK stock returns from February 4 to December 7, 2020. To this end, we divided our timespan into: (i) Fever (February 24-March 20), (ii) Rebound (March 23- April 30), (iii) 2nd wave (September 1- December 7), and (iv) Full sample (February 04- December 7). Using OLS regressions, we find negative and significant effects of covid-19 registered cases on stock returns. However, the coefficient of covid-19 deaths’ growth exerts a significant and positive effect on stock returns in the rebound stage mainly. Overall, the size of the effect of the growth of covid-19 cases and deaths

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7 However, this results are available on request.
suggests that the impact is very small and investors are not very wary on the pandemic effect. This may be due to the success of the government’s response to the pandemic in the UK. Among the control variables, the government stringency response exerts a negative impact on the stock returns, which may calm any overreaction due to the covid related deaths in the rebound stage. Investors tend to benefit from the rise in deaths and, subsequently, to expansionary monetary policies. Thus, in this case, policymakers should follow the stock market development in response to expansionary monetary policies.

Data availability statement

Data are available upon request from authors.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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APPENDIX

| Study                  | Countries          | Data                                           | Method             | Results                                                                                                                                 |
|------------------------|--------------------|------------------------------------------------|--------------------|----------------------------------------------------------------------------------------------------------------------------------------|
| Mazur et al. (2020)    | US                 | March 2020 for S&P 1500 firms                  | Event study        | Natural gas, food, and software stocks earn high positive returns while petroleum, hospitality earn a negative return. Firms respond differently to covid-19 revenue shocks such as remuneration cut, cash bonuses or salary increases. |
| Topcu and Gulal (2020) | Emerging Countries | March 10 – April 30, 2020                      | Panel regression   | The effect of covid-19 on Asian emerging stock markets is higher than that of European (continued on next page) |

Fig. 1. Cumulative Covid cases and Deaths in G7 countries (7 days rolling average).
Source: https://ourworldindata.org/ .

Table 10

Literatures on the covid-19 and stock returns
| Study                                      | Countries                                      | Data                          | Method                        | Results                                                                                                                                                                                                 |
|--------------------------------------------|------------------------------------------------|-------------------------------|-------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Sharif et al. (2020)                       | US                                            | January 21st to March 30, 2020| Wavelet analysis              | Covid-19 exerts higher effect on geopolitical risk than on the US economic uncertainty. The perception on the covid-19 effect is different between the short and the long run.                                      |
| Ashraf (2020a)                             | 64 countries                                   | January 22, 2020 to April 17, 2020| Panel data regression and event study | When there is an increase in confirmed cases, stock market returns decreased, while stock returns responded more proactively to the growth in confirmed cases than the growth of deaths. Another key finding is that negative stock returns response occurs early days of confirmed cases and again during 40–60 days of first case. |
| Capelle-Blancard and Desroziers (2020)     | 74 countries                                   | January to April 2020         | Panel regression model        | Initially stock market ignored the pandemic (until February 21), but stock market reacted sharply to the covid-19 when infection and cases surge (February 23-March 20). This health crisis lost investors’ concern once central bank intervened (March 23- April 30) across the world. Lockdown, low policy rates, credit facilities reduced the stock market’s sensitivity to the covid-19 impact. |
| Ramelli and Wagner (2020)                  | US                                            | Russell 3000 constituents     | OLS regression               | Firms having trade with China underperformed in initial stages of pandemic later they revert when Chinese economy started to open. Cash and leverage affect the stock returns in feverish period of pandemic. Real effects from the health crises are amplified through the financial channel. |
| Albulescu (2020)                           | US                                            | March 11 and May 15, 2020     | OLS regression and RLS approach | The new infection in the global level and the US level increase the US financial market volatility as proxied by S&P implied volatility index.                                                                 |
| Ashraf (2020b)                             | 77 countries                                   | January 22 to April 17, 2020  | Panel OLS                    | Government social distancing related announcements reduce stock market returns, while such government response also reduces covid-19 spread or new cases. However, income support related announcement increases stock market returns.  |
| Haroon and Rizvi Ali et al. (2020)         | Benchmark indices for world and US             | January 1, 2020 till 30 April 2020 | Regression                   | News of covid-19 created panic and which increased equity market volatility. Earlier stage China suffered but in later stage of pandemic the global financial market volatility largely increased. Even safer assets became volatile as the pandemic reaches US. |
| Narayan et al. (2020)                      | G7 countries                                   | April 16, 2020–July 1, 2019  | Regression                   | With time series data, it is found that government measures (lockdown, travel bans, stimuli packages) exert a positive effect on G7 stock returns.                                                                 |
| Bai, Wei, Wei Li, and Zhang (2020)          | US, China, UK and Japan                        | January 2005 to April 2020   | GARCH-MIDAS model            | Using Equity Market Volatility Tracker (IDEMV), they find that pandemic increases volatility of international financial markets in different time, where immediate government response is a key factor. |
| Al-Awadhi et al. (2020)                    | China                                          | January 10 to March 16, 2020  | Panel regression             | Covid-19 new cases and new deaths affect stock returns negatively.                                                                                                                                 |
| He et al. (2020)                            | China                                         | June 1, 2019–16 March 2020   | t-tests and nonparametric Mann-Whitney tests | Covid-19 impact stock markets negatively in the short run.                                                                                                                                 |
| Mazumder (2020)                            | US                                            | January 02 –May 30.           | Regression model and event study | Increase in Social trust increases stock returns. Federal reserve announcement on March 23, 2020 benefitted firms in low trust estates more than the firms in high trust estates. |
| Zaremba et al. (2020)                      | 67 countries                                   | January 1- April 3            | Panel regression             |                                                                                                                                                                                                            |
Table 10 (continued)

| Study                                | Countries | Data                  | Method       | Results                                                                 |
|--------------------------------------|-----------|-----------------------|--------------|-------------------------------------------------------------------------|
| Brueckner and Vespignani (2020)      | Australia | May 2019 to May 2020  | VAR model    | Government intervention increases stock market volatility.         |
| Rahman et al. (2021)                 | Australia | January–April 2020    | Event study  | Covid-19 increases stock returns.                                    |
|                                      |           |                       |              | Small, less profitable and value stocks suffer most.                  |

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