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Does non-fundamental news related to COVID-19 matter for stock returns? Evidence from Shanghai stock market

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ABSTRACT

The COVID-19 outbreak generates various types of news that affect economic and financial systems. No studies have assessed the effects of such news on financial markets. This study sheds light on the impact of non-fundamental news related to the COVID-19 pandemic on the liquidity and returns volatility. Because we examined extreme events, we performed quantile regression on daily data from December 31, 2019 to the end of lockdown restrictions in China on April 7, 2020. Results showed that the non-fundamental news, as the number of deaths and cases related to the COVID-19, raised the stock market returns volatility and reduced the level of stock market liquidity, increasing overall risk, whereas fundamental macroeconomic news remained largely immaterial for the stock market. These findings are explained by a knock-on effect because the health system’s inability to manage and treat a high number of COVID-19 patients in intensive care led the country to implement a lockdown and the global economy to largely shut down.

1. Introduction

Human history has experienced numerous outbreaks of potentially lethal diseases during the past two thousand years, and each outbreak has led to severe consequences, especially in terms of deaths (see Appendix Fig. A.1 for more details on the history of pandemics). Over many centuries, the world has significantly progressed in areas, such as health, technology, and economics. For instance, globalization since the end of the 1980s has allowed advances in health knowledge to be shared among countries, which has resulted in rising life expectancies and decreasing mortality rates. Despite the progress, however, outbreaks continue to occur, and COVID-19 has caused record devastation.

In December 2019, 41 patients in the city of Wuhan were identified to be suffering from a mysterious type of pneumonia. All of the patients had been exposed to a large seafood market selling many species of live animals, particularly bats. On January 7, 2020, the Chinese authorities began to suspect a pathogenic zoonotic human coronavirus, with bats being the likely origin or source (Lu et al., 2020; Zhou et al., 2020). On January 10, Chinese authorities concluded that this was a new type of coronavirus, which was later named COVID-19. Similar to the severe acute respiratory syndrome (SARS) and Middle East respiratory syndrome (MERS) coronaviruses, this new virus’s method of transmission is evidently human to human, since some health care practitioners were infected in the Wuhan hospital. Transmission occurs quickly and through respiratory droplets. The primary symptoms of the virus are cough, fever, and shortness of breath after a period believed to range from 2 to 14 days following exposure (Chen et al., 2020). Based on the first 3 months of COVID-19, approximately 80% of the infected patients’ illnesses are mild, and approximately 25% of patients do not present any symptoms. Furthermore, 15%–20% of the infected patients require respiratory support, with 25% of that group requiring ventilators and the rest needing only oxygen support. COVID-19 has a fatality rate of approximately 2%–5% across countries (Johns Hopkins Coronavirus Resource Center), which is lower than the fatality rate for other human coronaviruses (HCoVs). Similar to other HCoVs, the new coronavirus is more dangerous for older patients, especially for those with comorbidities. By April 26, 2020, more than 3,004,892 cases of COVID-19 had been diagnosed with more than 207,262 deaths. More than 100 countries have experienced the disease, with several significant disease clusters in China; the European Union (particularly Italy, France, and Spain); the United Kingdom; and the United States (Fig. A.2 provides more information about the spread of COVID-19).

From an economic standpoint, outbreaks usually lead to abrupt supply shocks that affect several vital economic sectors, including...
production, travel, and trade. This is proving to be particularly true for the COVID-19 crisis because the primary response to the outbreak has been lockdowns in many countries. Lockdown decisions are based on the daily number of deaths and number of newly confirmed cases. Currently, the health systems of many countries are overwhelmed; high numbers of confirmed COVID-19 patients signal a prolonged lockdown. Information about the number of deaths and new cases is likely to affect investors’ beliefs and may damage the economy in general and financial markets specifically. Other information related to COVID-19 may also affect the stock market, such as health news releases about the pandemic’s status.

This study is related to the literature that examines the stock market’s reaction to information or news releases. A subgroup of studies has investigated the effect of macroeconomic announcements on stock markets (Anensen and Bollerslev, 1998; Boyd et al., 2005; Jawadi et al., 2019; Jones et al., 1998; Ozatay et al., 2009). Another strand of the literature investigates the effect of nonfundamental news, such as natural disasters and terrorist attacks, on stock markets (Brounen and Derwall, 2010; Gürtler et al., 2016; Braun et al., 2019; Ammar, 2020).

In this study, we aim to expand the literature related to the impact of fundamental and nonfundamental announcements on stock markets. More specifically, we investigated the effect of new kinds of nonfundamental news related to the COVID-19 pandemic level on stock market volatility, trading activity, and liquidity risk. We tested whether COVID-19 pandemic news, assessed by the number of daily deaths and most recent number of confirmed cases, has impacted the Chinese stock market. Our choice of China as the study’s geographic locale was not arbitrary. We chose China because it was the first country to be grappled with the outbreak and first to end its lockdown. Our study contributes to the literature investigating the impact of COVID-19 on the regulation of Chinese banks (Funke and Tsang, 2020), the current population in Korea (Seong and Lee, 2021), and litigation funding in Australia (Singh, 2021).

Our study contributes to the literature in several ways. First, we extend previous studies on the effect of news on the stock market by exploring the effect of a new type of nonfundamental news related to the health system. Goodell (2020) expressed that there are no studies on the effect of the pandemic on financial markets, thereby making this study the first to examine the effect of COVID-19 pandemic news on the Shanghai stock market. Second, we highlight the necessity of a strong and effective health system, which is critical for lowering the number of infected patients—a measure that is strongly linked to limiting the negative effect of the virus on the financial system. Third, our empirical framework is the first to highlight the effect of health news releases on returns volatility, trading volume, and liquidity risk.

The remainder of the paper is organized as follows: Section 2 presents an overview of the COVID-19 crisis and discusses the related literature; Section 3 presents an empirical analysis; Section 4 discusses our primary empirical results and policy implications; and Section 5 concludes.

2. COVID-19 facts and theoretical background

HCoV was first observed in the 1960s, having emerged from animal coronaviruses that are divided into four subgroups: alpha, beta, delta, and gamma. Only two animal coronavirus subgroups are known to infect humans currently, namely alpha and beta. Most human coronaviruses have been considered inconsequential pathogens for a long time, such as the virus causing the common cold. However, since 2002, two severe pathogens have appeared and led to pandemics. SARS coronavirus (SARS-CoV) occurred in China between 2002 and 2003, and MERS coronavirus (MERS-CoV) occurred in Saudi Arabia from 2012 to 2018. The main symptoms of SARS were fever, cough, dyspnea, and occasionally, watery diarrhea. SARS required mechanical ventilation for approximately 25%–30% of the infected patients with 10% leading to death. A higher mortality rate was observed for older patients alongside those having other pathologies. The transmission of SARS in healthcare settings has been documented. Its virological spread has been identified as through the lower respiratory tract. SARS has been transmitted to more than 20 countries in North and South America, Europe, and Asia, infecting nearly 10,000 people, with a fatality rate of approximately 8%. In comparison, MERS exhibits some differences. Although it is an HCoV, its human-to-human transmission rate is relatively lower than that of SARS with healthcare settings having been significantly less infected. The spreading mechanisms of MERS were strikingly similar to those of SARS; however, MERS spread to 27 countries (Bleibtreu et al., 2019). Although symptoms are similar to SARS, especially severe atypical pneumonia, there are also many different ones, such as prominent gastrointestinal issues and acute kidney failure. Another observed difference is the relatively smaller number of infected patients, approximately 2500 patients. However, the health deterioration of the impacted patients is significant compared to SARS, as 50%–90% of the infected patients required mechanical ventilation, with a global fatality rate of approximately 37%.

COVID-19 has some specificities related to an easy mode of transmission. Its transmission is via close face-to-face social contact, and primarily due to the absence of preventative actions, its transmission is particularly speedy. The severity of this outbreak is evidenced by the identification of a high number of newly infected patients each day. While the mortality rate linked to the virus is alarming, the most concerning problem is whether health systems will become overwhelmed in the wake of rapid transmission. If that occurs, affected patients cannot receive the required care. Furthermore, patients with other urgent medical conditions would be at risk of neglect. Countries with vulnerable health systems are of particular concern because the COVID-19 outbreak requires a developed health system that can receive a high number of patients needing intensive care (e.g., oxygen support, ventilator support, intubation, etc.).

National lockdowns remain the primary responses to deal with transmissions and speed of transmissions throughout and across countries, which lead to high numbers of infected patients. However, lockdowns have had a knock-on effect on economies with financial consequences that should be analyzed. Lockdown decisions are related to pandemic news and are assessed by the number of deaths and/or infected patients per day. A high number of deaths and/or infected patients is a signal that a lockdown will be prolonged, whereas a small number may signal that a lockdown could be eased. Effectively, lockdown adoption and lockdown draw-out decisions are conditioned by specific data about the status of the pandemic. From economic and financial perspectives, lockdowns dramatically slow down economic activity, increase uncertainty, and, consequently, affect conditions in financial markets. As a result, investors are more attentive to health-system information (e.g., the current number of infected patients and/or the current number of deaths) so that they may update predictions, financial positions, and strategies.

The knock-on effects of the COVID-19 outbreak have led to supply shock and dramatic economic and financial consequences. The severity of the crisis is directly related to the fragility of health systems, and it can be highlighted by several points. The limited number of resuscitation beds, lack of respiratory support, high portion of people with comorbidities, and absence of mass screening policies lead to high numbers of infected patients and rising death tolls. Under such conditions, the primary countermeasure is to limit personal contact; implementing this measure includes steps, such as closing schools and universities, halting travel, and locking down specific geographic regions with clusters of COVID-19. Given the exponential increases in infected patients and deaths, these measures have only been tightened, thus resulting in total lockdowns. The fragility of health systems increases in the number of deaths, and the heightened probability of lockdowns will affect financial markets through different mechanisms (Fig. 1 models the relationship between the health system and stock market).

In the literature, the connection between the health sector and financial markets has been investigated, but only unidirectionally from the stock market to the health system. Chen et al. (2012) investigated the impact of stock market movement on incidences of strokes, thus finding evidence of a relationship among the bearish stock market, market
crashes, and a greater incidence of strokes. Related evidence has been recently confirmed by Engelberg and Parsons (2016), thus supporting a strong inverse relationship between the U.S. stock market returns and hospital admissions in California, particularly in hospitalizations for psychological conditions, such as anxiety, panic disorder, and major depression. Cotti et al. (2015) demonstrated an excessive relationship between returns and deteriorating self-reported mental health and risky health behaviors, including increased smoking, excessive drinking, and alcohol-related fatal car crashes. Olafsson (2016) investigated the impact of the 2008 financial crisis on the health of immediate and long-term health of newborns and on their health in the long term. Results indicate that financial distress negatively impacts newborns’ weights, and the impact on their health prolongs. Berliner and Kenworthy (2017) analyzed the consequence of the financial crisis in the health sector, thus leading to the creation of crowdfunding to serve healthcare. More recently, Giulietti et al. (2020) investigated the impact of stock market stress on fatal car crashes in the U.S. They conclude that the immediate emotions triggered by negative stock market performance have an increasing impact on the number of fatal accidents, especially among inexperienced investors.

The studies cited previously investigated the consequences of financial market stress on the health sector (e.g., health financing and mental health). To the best of our knowledge, no studies have investigated the relationship in the reverse direction: the impact of health system stress on the stock market. This study aims to fill this gap through an investigation of whether health system news related to the COVID-19 outbreak (specifically, the number of newly infected patients and the current death totals) affects the stock market. Our study’s goal is to extend the analysis of market returns to examine whether this kind of pandemic affects stock market volatility, trade volume, and liquidity risk.

3. Empirical analysis

3.1. Data and empirical research model

We study the impact of COVID-19 on the Chinese stock market through an investigation of the impact of health news related to the outbreak on the Shanghai stock market. To evaluate the pandemic, we employ daily reports of the number of newly confirmed cases and daily number of deaths related to COVID-19 in China. This data was obtained from the Johns Hopkins Coronavirus Resource Center. In parallel, stock market reaction is analyzed through different dimensions, such as volatility, liquidity, and trading volume. To calculate measures of stock market variables, we collected data about trades from the Bloomberg database information (price and transaction volume) for the SSE50 index, the main stock index of the Shanghai Stock Exchange, representing the capitalization of the top 50 companies. We selected China because it was the first country impacted by COVID-19 and the first country to end the lockdown strategy on April 7, 2020. Our study covers the period from December 31, 2019, the date on which China reported a cluster of cases of pneumonia in Wuhan, until the end of China’s lockdown on April 7, 2020.

In our analysis, the market reaction is measured through returns, volatility, and liquidity. For robustness purposes, we use two measures of volatility. The first is the traditional method recommended by Forsberg and Ghysels (2007), with volatility as the absolute daily returns (vol1). The second measure of volatility (vol2) is the squared returns, which can be interpreted as a conditionally unbiased estimator of the true unobserved conditional variance of the asset over the considered period. Stock market returns are calculated as the absolute log-difference of closing prices: \( \text{return}_t = \log(P_t / P_{t-1}) \times 100 \), where \( P_t \) and \( P_{t-1} \) are the closing prices for the day \( t \) and the day \( t - 1 \), respectively, and \( \text{Vol}_1 = |\text{return}_t| \) and \( \text{Vol}_2 = \text{return}_t^2 \). Regarding market liquidity, we use two proxies. The first is the turnover volume (TV), which is the simplest measure of liquidity obtained using the logarithm of the trading volume in the monetary value. The second proxy is the Hasbrouck ratio (\( \text{Illiq} \)), which is the square root transformation of the Amihud (2002) illiquidity ratio. This Hasbrouck ratio is defined as the ratio of absolute returns to volume. A higher value of the ratio indicates a greater level of illiquidity in the market. Hasbrouck (2009) showed that the square root transformation of the Amihud ratio performs better empirically, capturing the systematic market illiquidity and avoiding extreme values. Therefore, we compute the square roots of daily ratios as a measure of market illiquidity.

\[ TV_t = \ln(\text{volume}_t) = \ln(P_t \times Q_t) \] where \( Q_t \) is the traded volume at day \( t \). (1)
Health news related to the pandemic level of COVID-19 is measured in our study based on two types of information. We employ the daily rate of the increase in infected patients (Δcases) and daily rate of increase in deaths (Δdeaths):

\[
\Delta \text{cases} = \frac{\text{cumulative cases} - \text{cumulative cases}_{-1}}{\text{cumulative cases}_{-1}}
\]

(3)

where \(\text{cumulative cases}\) and \(\text{cumulative cases}_{-1}\) denote the cumulative number of patients for date (t) and date (t – 1), respectively.

\[
\Delta \text{deaths} = \frac{\text{cumulative deaths} - \text{cumulative deaths}_{-1}}{\text{cumulative deaths}_{-1}}
\]

(4)

where \(\text{cumulative deaths}\) and \(\text{cumulative deaths}_{-1}\) denote the cumulative number of deaths for date (t) and date (t – 1), respectively. For Monday, we take the previous calendar day as (t – 1). We also take into account the mean of the daily growth rate during the weekend (Saturday and Sunday) and find similar results. Additionally, we introduce two dummies to control for the weekend effect.

More formally, the effect of COVID-19 on China’s stock market is investigated based on the following models:

\[
\text{Volatility}_t = \alpha_0 + \alpha_1 \text{Volatility}_{t-1} + \alpha_2 \text{Health News}_{t-1} + \sum_{k=1}^{3} \beta_k \text{CTR}_k + \epsilon_t
\]

(5)

\[
\text{Liquidity}_t = \gamma_0 + \gamma_1 \text{Liquidity}_{t-1} + \gamma_2 \text{Health News}_{t-1} + \sum_{k=1}^{3} \rho_k \text{CTR}_k + \nu_t
\]

(6)

where \(\text{Volatility}_t\) is China’s stock returns volatility on trading day (t) measured using \(\text{vol}_t\), and \(\text{Volatility}_{t-1}\), \(\text{Health News}_{t-1}\), \(\text{CTR}_k\), \(\epsilon_t\), and \(\nu_t\) denote the error term at time (t) for both models presented in Eqs. (5) and (6), respectively. Finally, we note that for each model (Eqs. (5) and (6)), four specifications are estimated as we have two proxies for health news and two proxies for our dependent variables (volatility and liquidity). Thus, height specifications are estimated.

3.2. Preliminarily analysis

Before moving on to empirical estimations, it is worth investigating the statistical properties of our data. Table 1 presents the descriptive statistics of our variables. The mean SSE50 returns index is approximately −0.1308%, thus demonstrating the poor performance of the Chinese stock market during the COVID-19 outbreak. The minimum (−8.0392%) and maximum (3.0980%) values emphasize the extreme variability of the returns, with the most significant intensity on the negative side of the distribution. This pattern is confirmed by both proxies of stock market volatility as they exhibit similar behavior. For liquidity, its two proxies show a behavior similar to stock returns volatility. For health news, the variability is more pronounced. The mean growth rate is approximately 47.07% (40.32%) for infected patients (deaths), thus indicating the gravity of the pandemic and the speed of its spread. Health news exhibits a high variability with maximum values 2211.24% (infected patients) and 1688.24% (deaths). For Macro News, we note that there is at least one macroeconomic announcement for 51.6% of the trading days of our study period. Except for returns showing further evidence of left asymmetrical distribution, all other variables are rightly asymmetric. The leptokurtic excess observed for all variables except for \(\text{Liquidity}_t\) confirms the results of Jarque–Bera statistics, thus rejecting the normality of their distribution.

Table 2 confirms linkages among all the variables considered in this study based on the unconditional correlation matrix. We note an increase of our pandemic level measures (Δcases and Δdeaths) is accompanied by an increase in stock price volatility and a decrease in market liquidity. We note positive correlations among our measures of the pandemic level with the volatility of stock returns (\(\text{vol}_t\) and \(\text{vol}_{t-1}\)) and illiquidity ratio (\(\text{Illiq}\)). By contrast, Table 2 shows a negative correlation between the pandemic level and trading volume (TV). These preliminary results demonstrate a potential negative relationship between the Chinese stock market characteristics and health news releases about the increase of the pandemic level.

Two characteristics of Table 1 should be considered in modeling the potential relationships between the variables. First, the variables exhibit high-level tails and particularly high variability, which indicates potential outliers in our data. Therefore, a linear relationship based on ordinary least squares (OLS) does not hold. However, the most appropriate approach in the presence of outliers, including the high tail distribution of the studied variables, is the quantile approach; we use this method to estimate the aforementioned models. This approach, introduced by Koenker and Bassett (1978), is a robust regression approach to investigate quantile properties and can take into account the high-level tail of financial returns.
the distribution. It provides a less-restrictive framework as, for example, the normality of the distribution is not required. Quantile regression parameters provide an estimate of the impact in a specific quantile of the explained variable in response to a one-unit change in the explanatory variable. Therefore, the estimation provides a more detailed description than OLS since the entire distribution of the explained variable can be studied and not only the mean. This analysis is of particular interest as it allows to measure the impact of coronavirus-related reports of new cases and deaths per day on the different quantiles of the distributions of the variables measuring the liquidity and volatility of the Chinese financial market. To control for the robustness of our results, we use the bootstrap quantile regression technique, which allows the limitations of the regressions to be addressed when performed for small sample sizes. By combining bootstrap advantages and quantitative regression, this method provides a robust answer to sample size problems. Hahn (1995) shows that the bootstrap quantile regression approach is robust since the bootstrap distribution obtained by the percentile method weakly converges with the appropriate limit distribution in probability. Moreover, Tarr (2012) examined the robustness of the bootstrap quantile regression method. He demonstrated that this technique is appropriate for a small sample size and distribution with heavy-tailed errors.

### 3.3. Results

Table 3 (Panels A–D) reports the results of the estimation of the first model (Eq. (5)) for both proxies of the SSE50 volatility across all quantiles (q = 10%, q = 50%, and q = 90%). We conduct bootstrap robust quantile regressions to control for the robustness of the p-values. Panels A and C report results that consider the rate of the increase in new cases as a measure of the pandemic level. The coefficient (α2) is positive and significant, which shows a strong positive relationship between the Shanghai stock returns volatility and growth rate of the number of new cases.

### Table 2

Correlation matrix between the studied variables.

|        | VoI    | Vo2    | Illiq  | TV     | Δcases   | Δdeaths  | Macro News |
|--------|--------|--------|--------|--------|----------|----------|------------|
| VoI    | 1.0000 | 0.8949 | 0.9491 | 0.0687 | 0.6767   | 0.6880   | 0.0672     |
| Vo2    | 0.8949 | 1.0000 | 0.7852 | −0.0839| 0.9188   | 0.9244   | 0.1021     |
| Illiq  | 0.9491 | 0.7852 | 1.0000 | −0.0650| 0.5809   | 0.5916   | −0.0865    |
| TV     | 0.0687 | −0.0839| 1.0000 | 0.0000 | −0.2129  | −0.2093  | 0.1702     |
| Δcases | 0.6767 | 0.9188 | 0.5809 | 1.0000 | 0.0000   | 0.9893   | 0.1523     |
| Δdeaths| 0.6880 | 0.5916 | 0.5916 | 0.0000 | 1.0000   | 0.1632   | 1.0000     |
| Macro News | 0.0672 | 0.1021 | −0.0865| 0.1702 | 0.1523   | 0.1632   | 1.0000     |

Note: VoI and Vo2 represent the proxies of the stock market volatility, defined as the absolute daily returns and the squared daily returns, respectively. Illiq and TV denote proxies of liquidity defined based on the Hasbrouck ratio and the logarithm of the turnover volume, respectively. Macro News denotes the macroeconomic news measure.
confirmed COVID-19 cases. This finding is confirmed when we consider the rate of increase in the number of deaths as the second measure of the pandemic level (Panels B and D) and when we control for the robustness of the significance level of p-values with the bootstrap approach. An increase in the number of COVID-19 cases/deaths increases economic uncertainty and the risk level of the market. These results indicate that stock markets react to health news. Specifically, the COVID-19 crisis has had a strong negative impact on financial markets and has led to a change in investors’ beliefs. An increase in the daily number of new cases and/or deaths will make investors revise their expectations and become more pessimistic and uncertain. The explanation behind this effect is that information about the number of confirmed COVID-19 cases and deaths are important indicators about the economic situation. A decrease in the pandemic level may increase the probability of a lockdown ending and may lead to economic recovery. By contrast, an increase in the number of new cases combined with the inability of the health system to manage a high number of patients increases the probability of a lockdown and an economic shutdown. As the financial market reflects investors’ expectations, the stock market volatility will increase in response to a worsening COVID-19 pandemic situation. Quantile regression indicates that the coefficients of our measures of the COVID-19 crisis (\(\alpha_2\)) are significant across all quantiles. However, the amplitude of the volatility reaction is more pronounced at lower quantiles than at upper quantiles. Finally, we highlight an increase in stock returns volatility around macroeconomic announcements and a Monday effect, corresponding to higher volatility compared with other trading days.

The aforementioned results indicate that the information released concerning the worsening of the COVID-19 pandemic level negatively impacts the Shanghai stock market as it leads to an increase in returns volatility. Next, we investigate the relationship between the COVID-19 crisis and liquidity risk. Thus, we regress our second model (Eq. (6)) for the two proxies of liquidity, that is, trading volume in monetary value and the square root transformation of the Amihud (2002) illiquidity ratio. Results reported in Table 4 from Panels A–D indicate a negative relationship between the liquidity of the market and measures of the pandemic level. An increase in the number of COVID-19 cases leads to a decrease in trade volume and an increase in the liquidity risk. This finding can be explained by the rise of uncertainty and asymmetric information around negative news about the pandemic level. These results continue to hold across all quantiles even after controlling for the bootstrap p-values. Table 4 results indicate that the coefficient of the lagged liquidity is significant, thus revealing that the liquidity time series is autocorrelated. The coefficient of the day of the week indicates that Monday is characterized by low transaction volume and liquidity level. Additionally, our results concerning the pandemic news continue to be applicable even after controlling for macroeconomic announcements. Finally, we note that the R-square for all regressions is 35.6%–55.7%.

Our findings highlight the stock market reaction to the new type of nonfundamental news related to the pandemic of COVID-19. Our results show whether the pandemic level negatively impacts the stock market by increasing risk and illiquidity and reducing trading activity. These findings may have some interesting policy implications in terms of price discovery during turmoil periods, such as the outbreak period or in terms of the health policy role in reducing economic and financial damages.

### 4. Discussions and policy implications

Our study produces some interesting findings. We show that the COVID-19 outbreak has negatively impacted the Chinese stock market; we demonstrate that during the pandemic period, the volatility of the

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**Table 4**

Results of the effects of COVID-19 on SSE50 stock liquidity.

| Parameters | q = 10% | P-value | P.Boot |
|------------|---------|---------|--------|
| Coefficients |        |         |        |
| \(\gamma_0\) | 1.9831  | 0.2591  | 0.1539 |
| \(\gamma_1\) | 0.8969  | 0.0000  | 0.0000 |
| \(\gamma_2\) | -0.0120 | 0.0021  | 0.0811 |
| \(\gamma_3\) | 0.0089  | 0.0827  | 0.0767 |
| \(\gamma_4\) | 0.0758  | 0.0842  | 0.0181 |
| \(\gamma_5\) | -0.0417 | 0.3754  | 0.2224 |
| Pseudo R²   | 0.5577  | 0.4895  | 0.3678 |
| \(\gamma_0\) | 1.9791  | 0.2590  | 0.2007 |
| \(\gamma_1\) | 0.8971  | 0.0000  | 0.0000 |
| \(\gamma_2\) | -0.0158 | 0.0020  | 0.0071 |
| \(\gamma_3\) | 0.0089  | 0.0825  | 0.0832 |
| \(\gamma_4\) | 0.0754  | 0.0860  | 0.0190 |
| \(\gamma_5\) | -0.0422 | 0.3696  | 0.2247 |
| Pseudo R²   | 0.5577  | 0.4895  | 0.3678 |
| \(\gamma_0\) | 0.0010  | 0.0118  | 0.0264 |
| \(\gamma_1\) | 0.0214  | 0.8923  | 0.9230 |
| \(\gamma_2\) | -0.0002 | 0.0000  | 0.0000 |
| \(\gamma_3\) | -0.0001 | 0.7757  | 0.8403 |
| \(\gamma_4\) | -0.0002 | 0.7922  | 0.8154 |
| \(\gamma_5\) | -0.0005 | 0.1126  | 0.1391 |
| Pseudo R²   | 0.1365  | 0.1470  | 0.3425 |
| \(\gamma_0\) | 0.0010  | 0.0101  | 0.0074 |
| \(\gamma_1\) | 0.0211  | 0.8873  | 0.9189 |
| \(\gamma_2\) | 0.0003  | 0.0000  | 0.0000 |
| \(\gamma_3\) | 0.0001  | 0.7566  | 0.8042 |
| \(\gamma_4\) | -0.0002 | 0.7542  | 0.6777 |
| \(\gamma_5\) | -0.0006 | 0.0420  | 0.0685 |
| Pseudo R²   | 0.1689  | 0.1823  | 0.3746 |

Note: Coefficients denote the estimated values of the parameters of the equation. P.Boot is the p-value based on the bootstrap technique. In Panel A, we use the trading volume as a proxy for liquidity and the rate of increase in the number of cases as a proxy for the pandemic level. In Panel B, we use the trading volume as a proxy for liquidity and the rate of the increase in the number of deaths as a proxy for the pandemic level. In Panel C, we use the Hasbrouck ratio as a proxy for illiquidity and the rate of the increase in the number of deaths as a proxy for the pandemic level. In Panel D, we use the Hasbrouck ratio as a proxy for illiquidity and the rate of the increase in the number of deaths as a proxy for the pandemic level.
5. Conclusion

This study aimed to shed light on the impact of the COVID-19 outbreak on the Shanghai stock market by investigating the impact of a new type of nonfundamental news related to the pandemic on the stock market. Interestingly, we explore the influence of news concerning the contemporary and dangerous COVID-19 virus on the Chinese stock market. More specifically, we propose novel measures of health news data by relying on the number of new confirmed coronavirus cases and the increase in the death rate of the disease to evaluate the level of the COVID-19 crisis in China. We find that the crisis negatively impacted the Shanghai market by increasing price volatility and reducing the levels of liquidity. These results are explained by a knock-on effect caused by the fragility of the healthcare system. Taking into account the speed of transmission of the coronavirus and the incapacity of the health system to treat a high number of patients in intensive care involving oxygen support, ventilator support, and intubation, the country’s primary response, in this case, China, remains a lockdown. Lockdowns usually lead to a supply shock and harm the economy in general and the financial market specifically.

The COVID-19 outbreak highlights the important role health systems play in terms of the economy. This crisis places the health system at the heart of the economic and political systems of a country and demonstrates that investing in the system is key to economic success (Augier and Yaly, 2013). We suggest that a powerful healthcare system becomes an international goal with a concerted effort toward more positive and lasting future health and economic outcomes. From a theoretical perspective, our study contributes to the literature by analyzing a new type of nonfundamental news and its impact on the financial markets. This study may help highlight the role of this type of information in asset price discovery.

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Declaration of competing interest

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Appendix

Fig. A.1. History of pandemics over the past 2000 years.

Source: Desjardin, J. 2020. The 7 best COVID-19 resources we have discovered so far. Visual Capitalist, 24 March. https://www.visualcapitalist.com/7-best-covid-19-resources/

Fig. A.2. Spread of COVID-19 among countries worldwide.

Source: The World Health Organization, Coronavirus disease 2019 (COVID-19) Situation Report-76.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.econmod.2021.03.003.

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