The Effect of Covid-19 Pandemic on Information Asymmetry

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Abstract

This paper examines intraday information asymmetry dynamics around the COVID-19 pandemic. We document a surge in informed trading activity following the outbreak, which reverses monotonically after the approval of a vaccine. Our findings are consistent across alternative metrics and placebo analyses. We delve into the mechanisms driving these patterns and find that the pandemic amplifies analysts' forecasting biases and elevates information asymmetry surrounding macroeconomic news announcements. By leveraging internet search activity related to COVID-19 and the Coronavirus Aid, Relief, and Economic Security (CARES) Act, we provide evidence that active retail investors play a pivotal role in these dynamics. Notably, we show that investors' focus on S&P 500-related information precedes an increase in information asymmetry prior to the pandemic, yet this effect reverses following the outbreak. Finally, we find that while the COVID-19 pandemic reduces price efficiency, informed trading plays a crucial role in facilitating price discovery during this period.

JEL Code: D82, G14, G4,

Keywords: Information asymmetry, market efficiency, uncertainty, order flow volatility, forecasting error, retail trader

1. Introduction

Information asymmetry risk is crucial for asset pricing and decision-making in financial markets. As indicated by Barro et al. (2020) and Hassan et al. (2020), the COVID-19 pandemic represents an unprecedented disruption that necessitates a thorough reevaluation of past epidemic experiences and existing theoretical models, as traditional policy remedies may no longer be applicable. Furthermore, the COVID-19 pandemic has imposed substantial disruptions on information collection processes, stemming primarily from the widespread implementation of lockdowns and the enforcement of social distancing measures. Those policies can hinder information collection efforts (Bai and Massa, 2021), potentially exacerbating the issue of information asymmetry. During such challenging times, the composition of sophisticated and unsophisticated traders may shift (Bernhardt and Miao, 2004), further complicating the dynamics of information asymmetry. Consequently, the evolution of information asymmetry during the COVID-19 outbreak remains unclear. This study aims to examine the impact of the pandemic on information asymmetry, identify key drivers of its evolution, and explore its implications for market efficiency.

Among the multifaceted factors influencing information asymmetry, uncertainty stands out as a prominent obstacle to efficient information transmission. In particular, heightened uncertainty can exacerbate behavioral biases among individuals and confer advantages on informed traders, as suggested by research (e.g., Kumar, 2009; Baig, Blau, Butt, & Yasin, 2022). During periods of high uncertainty, the potential losses faced by informed traders may lead to the withdrawal of retail investors and a resultant depletion of market liquidity (Chordia, 2008). Empirical studies have provided robust evidence supporting investors' concerns regarding information asymmetry risks during such uncertain times, and have further indicated that hedge fund analysts possess informational advantages related to political uncertainty (Gao & Huang, 2016; Christensen, Mikhail, Walther, & Wellman, 2017; Bradley et al., 2018).

Moreover, Nagar (2019) documents that economic policy uncertainty leads to wider bid-ask spreads and dampened stock price reactions to earnings surprises, suggesting that investors demand higher compensation for providing liquidity in markets characterized by high uncertainty.

The COVID-19 pandemic is unique and differs from the various types of uncertainty discussed in the literature. Without a precedent, predicting the evolution of the COVID-19 pandemic in terms of its impact and investors' reaction is difficult. Such uncertainty may remain strong even among those informed traders who traditionally hold information advantage. For example, Bai and Massa (2021) report that lockdowns resulting from the COVID-19 pandemic prevent fund managers from collecting soft information and adversely affect their investment performance. Goldstein and Yang (2015) show that traders would reduce their information collection and trade less actively with an increase in the level of uncertainty; this leads to their inability to acquire the necessary information concerning the fundamental value of assets. Furthermore, Beckmann and Czudaj (2017) posit that the revision of professional forecasts become more pronounced with the exacerbation of uncertainty. Because of the lack of reliable economic models to forecast the evolutionary path of the COVID-19 pandemic, investors have been encountering substantial challenges in gathering information on firms' expected future payoffs. According to the aforementioned studies, if professionals have difficulty obtaining and processing information during the COVID-19 pandemic, the information asymmetry risk would be naturally alleviated.

However, if certain professionals maintain access to material information or exhibit superior efficiency in processing such information during the COVID-19 pandemic, the risk of information asymmetry may intensify as these informed traders strategically aim to maximize their profits. Baig et al. (2023) provide evidence that retail trading activity during the pandemic contributed to heightened volatility and price deviations from fundamental value, thereby creating opportunities for informed traders to exploit market inefficiencies. Furthermore, uncertainty associated with the pandemic can exacerbate the divergence of investors' opinions regarding stock valuation (Miller, 1977). This divergence in expectations concerning future stock returns can amplify market price movements away from fundamental value and impose additional costs on arbitrageurs (Shleifer and Vishny, 1997; Baker and Wurgler, 2006). Consequently, the persistence of informed trading activity during the pandemic remains uncertain, and the literature thus far has not reached a consensus on the precise impact of the pandemic on information asymmetry.

To investigate the competing effects of the COVID-19 pandemic on information asymmetry, we follow Chordia (2019) to measure information asymmetry with order flow volatility on the basis of intraday trading. We observe an increase in order flow volatility following the outbreak of COVID-19, implying the worsening of information asymmetry risk. The results are robust to the alternative measure of information asymmetry based on order imbalance. We also investigate the impact of the COVID-19 pandemic by considering changes in the number of new cases in the United States and around the world, and obtain consistent results. Furthermore, we perform a placebo test by replacing the COVID-19 pandemic with influenza epidemics. The findings of the placebo test indicate that the COVID-19 pandemic, instead of other omitted factors, leads to changes in information asymmetry.

We elucidate mechanisms through which information asymmetry increases with the duration of the COVID-19 pandemic. On the basis of the existing literature, we speculate that the increase in information asymmetry risk can result from challenges encountered by professional investors in collecting information during the pandemic and an increase in individuals' behavioral bias (Barber et al., 2008; Goldstein and Yang, 2015; Beckmann and Czudaj 2017; Chen, Kelly, and Wu, 2021; Barardehi et al., 2022). We first examine changes in news surprises on macroeconomic forecasts before and after the crisis. If the COVID-19 outbreak leads to more forecasting surprises, the increase in information asymmetry can be due to the inability in information collection and analysis of professional investors. Following Bernile et al. (2016), we focus on the announcements of the gross domestic product (GDP), nonfarm payroll (NFP), Federal Open Market Committee (FOMC), and producer price index (PPI). The results indicate increases in forecast surprises after the COVID-19 outbreak. Those announcements could reduce information asymmetry before the COVID-19 pandemic, but they impair it after the pandemic.

In response to the COVID-19 outbreak, the US federal government paid US$1,200 and US$600 in April 2020 and December 2020, respectively, to eligible adults under the Coronavirus Aid Relief and Economic Security (CARES) Act. The findings from a survey reveal that approximately 10%–15% of these funds[1] flow into the stock market (Greenwood, Laarits, and Wurgler, 2022). This provides an opportunity to study whether the increased retail investors' involvement is responsible for changes in information asymmetry when the level of uncertainty increases. We observe that the CARES Act increases information asymmetry risk, indicating that uncertainty aggravates individuals' behavioral bias and leads to higher information asymmetry.

To provide additional supporting evidence for retail investors' behavioral bias, we consider the well-documented attention hypothesis. In particular, Da, Engelberg, and Gao (2011) find that online information collection can amplify retail investors' behavioral bias. We focus on Google searches for Standard & Poor's 500 (S&P 500) before and after the start of COVID-19 pandemic. Our empirical results reveal that the Google searches of S&P 500 are positively associated with the information asymmetry level before the COVID-19 pandemic, implying that retail investors overreact to information they received. The behavioral bias

[1] With the income restriction on individuals eligible for the CARES payout, it is fairly safe to consider them as the naïve retail investors.

widens the deviation from the fundamental value of S&P 500. By contrast, we find that retail investors' attention to information on S&P 500 reduces information asymmetry after the COVID-19 outbreak. The threat of infectious diseases does not seem to prevent investors from processing information related to financial markets effectively. This result is in line with Drake, Roulstone, and Thornock (2012) and Brown, Stice, and White (2015) that Internet searches can encourage information processing and reduce the information asymmetry level.

We conduct two additional tests to investigate the impact of COVID-19 on information quality in financial markets. First, to confirm that our results are correlated with disease uncertainty, we use the infectious disease equity market volatility (IDEMV) index developed by Baker, Bloom, Davis, Kost, Sammon, and Viratyosin, (2020). We find that the index can explain part of the deterioration in information asymmetry. Second, if the uncertainty is truly increased by COVID-19, its impact would decrease with an increase in individuals' knowledge on the medical consequences of the infection, its overall impact on the society, and research on vaccines. We examine subsamples based on the severity level of perceptions regarding COVID-19 and estimate to what extent the severity of COVID-19 causes a decline in the level of information asymmetry. We observe that information asymmetry increases at the beginning of the breakout and then peaks when the World Health Organization（WHO）characterized COVID-19 as a pandemic. After the reopening of California, information asymmetry monotonically decreases over time. Moreover, the announcement on the news of vaccines reduces information asymmetry to a level lower than what's observed before COVID-19. This finding supports our main argument that information asymmetry changes with the level of uncertainty related to COVID-19. Moreover, our results indicate that investors can adjust their information collection across time and find effective methods to resolve information bias during periods of high uncertainty.

We also investigate how COVID-19 and changes in information asymmetry affect price efficiency, one of the most crucial functions of financial markets. Studies have argued that order flow can help incorporate information into asset prices (Hasbrouck, 1991; Evans and Lyons, 2002). The participation of informed trading can further accelerate the price discovery process. However, informed traders may believe that the information advantage is long-lived during a high level of uncertainty and thus use various trading strategies to arbitrage (Kaniel and Liu, 2006; Collin-Dufresne and Fos, 2015). Their sophisticated trading strategies can maximize their profits but delay the price discovery process. Thus, the impact of COVID-19 on order flow volatility and price discovery is an empirical question. We find that COVID-19 slows down the price discovery process. However, informed trading helps remove roadblocks to information incorporation.

This study contributes to several strands of research in the literature. First, we provide evidence on the dynamic of information asymmetry from a setting where uncertainty varies due to an external shock. Prior studies have shown that although uncertainty can reduce information quality, some investors can access to private information and increase trading costs (Chung and Chuwonganant, 2014; Nagar, 2019). Because the unprecedented COVID-19 pandemic creates extreme uncertainty that differs from those explored in the existing literature (Barro et al. 2020, Hassan et al., 2020), it poses challenges for investors as most were isolated and worked from home. Bai and Massa (2021) indicate that the lockdown disrupted the channel for obtaining soft information for professional managers in the fund market. Moreover, this paper sheds light on the connection between uncertainty and information asymmetry by analyzing forecasting errors and individuals' behavioral bias. We also explore the role of institutional traders and retail traders on information asymmetry, which is well discussed in the existing literature (Barber et al., 2009; Chen et al., 2020; Barardehi et al., 2022), during an extremely uncertain period.

Second, by employing information theory, we examine the connection between informed trading and price efficiency with high uncertainty. The mechanism through which information is incorporated is particularly crucial during a crisis. Our study is most related to Chen (2021) who discusses the role of sophisticated investors in price discovery based on changes in information efficiency. This paper differs by focusing on an exogenous shock. Moreover, we examine the overall effect of uncertainty, instead of the impact of specific traders, on price efficiency and thus provide empirical evidence for the theoretical framework of Goldstein and Yang (2015).

Third, this study contributes to an emerging stream of the literatCure that focuses on the impact of the COVID-19 pandemic on financial markets (O'Hara and Zhou, 2021; Bai and Massa, 2021; Jones, Zhang, and Zhang, 2022; Chung and Chuwonganant, 2023). Complementing studies on market liquidity, we differentiate information asymmetry risk from aggregate liquidity risk and investigate information asymmetry risk on the basis of intraday trading with order flow. Our findings indicate weak side effect of government policies during COVID-19 in that the CARES Act enabled more retail investors to enter the volatile market and aggravated the level of information asymmetry.

This paper proceeds as follows. Section 2 presents the sample and summary statistics. Section 3 discusses preliminary empirical results and robustness test findings. Section 4 provides the mechanism analysis and Section 5 offers additional test on information asymmetry and price efficiency. Section 6 concludes the paper.

2. Data and sample description

This study includes three data sets for empirical analyses. First, we measure the level of information asymmetry by using the tick data of actively traded S&P 500 exchange-traded funds (SPY), which are obtained from the Trade and Quote database. The sample period spans from January 1, 2019 to July 31, 2021. To prevent potential bias measurements, we exclude any trading days with fewer than 500 trades and trading before 5 AM.

Previous studies have demonstrated the presence of an intraday pattern of informed trading (Madhavan et al. 1992, 1997). To capture intraday informed trading, following Chordia (2018), we calculate 1-minute order flow volatility to proxy for information asymmetry risk. Figure 1 presents the intraday patterns of 1-minute order flow volatility before and after March 11, 2020 when WHO declared the novel coronavirus (COVID-19) outbreak a global pandemic. We find reverse J-shaped curves and a significant upward movement after the COVID-19 pandemic. First, the reverse J shape is consistent with the findings reported by Madhavan et al. (1997) and McInish and Van Ness (2002), indicating that information asymmetry risk peaks at the beginning of the day and then declines over the day. Second, Figure 1 indicates that the COVID-19 pandemic causes an upward shift in the information asymmetry level across the entire trading hours. On the basis of these patterns, we examine and discuss the evolution of information asymmetry risk with the global spread of COVID-19.

<Insert Figure 1 Here>

In addition to the order flow volatility, we also calculate other measurements of market quality in the financial market that can be used as control variables, including return volatility, trading cost, and trading volume. Table 1 provides the summary statistics of those variables before and after the COVID-19 shock based on the declaration day of the global pandemic on March 11, 2020. In brief, we observe that the COVID-19 pandemic leads to changes in market quality. In line with Figure 1, Table 1 indicates that the information asymmetry level significantly increases after the COVID-19 shock. In addition, we observe that return volatility increases from 0.4712 to 0.8645, implying that the market becomes more uncertain due to COVID-19. Although the result of spreads is in line with findings from the perspective of high compensation for liquidity supply, it is not statistically significant.

In contrast to other crises, we observe that trading volume significantly increases after the COVID-19 outbreak. To stimulate economic activity, governments around the world choose to reduce the interest rate and adopt quantitative easing policies. Thus, a large amount of capital inflows to stock markets. A survey conducted by the Charles Schwab Corporation indicates that approximately 15% retail traders enter the stock market after the COVID-19 shock.[2] JMP Securities also observed approximately 10 million new clients in the brokerage industry in 2020.[3] Moreover, the Schwab survey reveals that those new entrants are more optimistic and younger than existing investors.[4] Therefore, we speculate that those new investors can be a mediator of the supposedly negative impact from COVID-19. We discuss the influence in the later section.

To determine the causes of the evolution of information asymmetry, we collect major macroeconomic news releases from Bloomberg. We follow Bernile (2016) to focus on the GDP, NFP, consumer price index (CPI), and FOMC announcements. Finally, we collect the research numbers of topics on S&P 500 from Google Search.

3. Baseline results

3.1 COVID-19 crisis and information asymmetry

This study first examines the relation between COVID-19 and information asymmetry. Specifically, we consider the following regression:

$$IA_{i,t} = \alpha + \beta_1 Covid_t + \Psi Z_{i-1,t} + FE + \varepsilon \tag{1}$$

[2] https://pressroom.aboutschwab.com/press-releases/press-release/2021/The-Rise-of-the-Investor-Generation-15-of-U.S.-Stock-Market-Investors-Got-Their-Start-in-2020-Schwab-Study-Shows/default.aspx

[3] https://www.cnbc.com/2020/12/30/how-the-pandemic-drove-massive-stock-market-gains-and-what-happens-next.html

[4] The survey of Schwab demonstrates that the average age of those new participants (post-COVID investors) in stock markets is 35 years, whereas the average age of those existing participants (pre-COVID investors) is 48 years. Additionally, the questionnaire asks investors about the trend of stock market. Approximately 57% post-COVID investors believe it will be a bull market in 2021, but only 44% pre-COVID investors agree with it.

where $IA_{i,t}$ is information asymmetry in minute *i* on day *t*, which is measured by the order flow volatility in minute *i*. $Covid_t$ denotes the COVID-19 crisis. We have three proxies for the crisis; first, we employ a day dummy (*Lockdown*) to investigate the impact of COVID-19, which equals one if day *t* is on days after WHO announced the COVID-19 outbreak a global pandemic and zero otherwise. Furthermore, we exploit changes in case numbers in the United States (*UIF*) and globally (*WIF*) to proxy for the COVID-19 crisis. *Z* represents a metrics of control variables, including 1-minute price volatility, realized spread, and logarithm trading volume. In addition, according to the J-curve hypothesis and the pattern in Figure 1, we include the hourly fixed effect (*FE*) into our model to remove the impact of the intraday pattern.

The results of Equation (1) shown in Column (1) of Table 2 indicate a positive relationship between *IA* and *Covid*, suggesting that information asymmetry significantly increases after the WHO declared COVID-19 a pandemic. This finding is consistent with the argument of informed trading increase after COVID-19 outbreak (Chung and Chuwonganant, 2023). For the robustness test, we replace the main dependent variable, and Models (2) and (3) indicate that increases in the number of infected cases in the United States and globally cause higher information asymmetry. As shown in Table 2, the COVID-19 outbreak leads to higher information asymmetry risk, which is in accordance with the argument that uncertainty causes severe information asymmetry (Chordia, 2008; Nagar, 2019). The results can be attributed to two possible reasons. First, uncertainty can hamper the information collection ability and delay information processing (Bai and Massa, 2021). The inefficient price discovery creates an arbitrage opportunity and leads to severe information asymmetry risk. Second, the uncertainty induced by the COVID-19 pandemic can amplify retail traders' behavior bias and push asset prices away from fundamental value (Baber et al., 2008; Barardehi et al., 2022). Thus, informed traders can arbitrage from those deviations. We will test those arguments in the later sections.

<Insert Table 2 Here>

The control variables are significantly associated with order flow volatility. Higher price volatility can lead to higher information asymmetry (Table 2). Higher price volatility can represent higher level of divergent opinion or noise trading, and the deviation from fundamental price can attract more informed traders (De Long et al., 1990; Dontoh et al., 2004; Aabo et al., 2017). The finding indicates that COVID-19 can enhance individuals' behavior bias and mediate the impact of the COVID-19 pandemic on information asymmetry risk. Consistent with the literature (Jiang et al., 2012), we find that lower trading cost and higher market liquidity, quantified by spread and trading volume, can reduce the information asymmetry level.

In line with the pattern presented in Figure 1, coefficients for intraday fixed effects indicate that information asymmetry reaches the peak at the beginning of the day and decreases over time. Thus, those coefficients support the reverse J-curve argument.

3.2 Robustness analysis

To prevent the measurement bias of information asymmetry, we perform two robustness analyses by using new measurements of information asymmetry. First, we follow Bernile et al. (2016) to calculate the order imbalance to proxy for information asymmetry. The order imbalance is a well-known proxy for information asymmetry and can prevent the econometric problem in the estimation process. Second, market microstructure noise can dominate our measure of information asymmetry. To alleviate this concern, we re-estimate order flow volatility by the hourly frequency. The low frequency can resolve the concern because our results are obtained from a large sample size.

We begin our analysis by replacing order flow volatility with order imbalance, which is calculated as the difference between the numbers of buy and sell orders and standardized by the sum of buy and sell orders. Then, we regress those independent variables in Model 1 on order imbalance, and Columns (1) and (2) of Table 3 indicate that the COVID-19 crisis increases the new measure for information asymmetry; this finding is in line with our baseline analysis results.

<Insert Table 3 Here>

For a low frequency sample, we re-estimate order flow volatility by a 1-hour interval. Columns (3) and (4) report estimated results for regression on hourly order flow volatility. Coefficients for *Covid* are still significantly positive, indicating that COVID-19 enhances information asymmetry risk in the US stock market.

3.3 Placebo test

To ensure that the results discussed in previous sections are not driven by a spurious measure of COVID-19, we perform a placebo test wherein we examine the impact of influenza in 2019 and 2020. We replicate the aforementioned regression and set up a new dummy variable to determine the impact of influenza. *INFLU* equals one if the day is between October 1, 2019, and April 4, 2020, and zero otherwise, which is based on the disclosure of the US Centers for Disease Control.

This study runs the model for two data sets, including the whole sample and the subsample before COVID-19. No statistical significance of *INFLU* is observed in both the analyses (Table 4), indicating that *Covid* affects information asymmetry. In addition, the results demonstrate that the impact of COVID-19 differs from those of common diseases. Barro et al. (2020) and Hassan et al. (2020) have reported that the COVID-19 pandemic is different from previous diseases and the existing economic model cannot be extended to it. We complement their arguments by focusing on information asymmetry.

<Insert Table 4 Here>

Overall, our results indicate that the COVID-19 pandemic can worsen information asymmetry risk in financial markets irrespective of the measurements of information asymmetry and COVID-19 pandemic employed. Thus, the information asymmetry level increases after the COVID-19 outbreak. We speculate that COVID-19 can hamper information collection and analysis. In addition, the behavior bias of retail traders plays a crucial role in the association between uncertainty induced from the COVID-19 pandemic and information asymmetry.

4. Mechanism analysis

Changes in the information asymmetry level resulting from the COVID-19 crisis involve the interplay of various forces that drive price discovery and market liquidity. In this section, we focus on the emergence of information asymmetry by examining causes for increased informed trading. Drawing on information theory, risk preference, and behavioral bias theory, existing research has emphasized that during the COVID-19 pandemic, fund managers faced challenges due to disruptions in soft information collection and behavioral biases, such as disposition effects (Bai and Massa, 2021; Huber, Huber, and Kirchler, 2021; Wang and Zhang, 2025). Likely, existing literature indicates that the uncertainty emerging from COVID-19 make retail investors destabilize financial markets (Baig et al., 2023). Based on their study, we analyze how uncertainty resulting from COVID-19 impedes information incorporation from the angle of institutions' information collection. We then determine the increase in retail investors' behavior bias during COVID-19 spread by focusing on the role of retail investors, which is thoroughly discussed by Baber et al. (2008) and Barardehi et al. (2022).

4.1 Forecasting surprises

COVID-19 is a new virus that was identified during the end of 2019 and continues to spread until now. To prevent and control the spread of epidemic-prone diseases, a lockdown was imposed in Shanghai in April 2022, which affected supply chain worldwide. In the medical field, treatment for infectious diseases has not yet been developed. Thus, it is difficult to forecast the evolution of COVID-19 and future economic dynamics. We believe that the uncertainty caused by COVID-19 differs from political or financial uncertainty, and this poses a major challenge for analysts to collect information and release precise forecasts. Moreover, this obstacle can increase information asymmetry among analysts and prevent retail investors from exacting information on the future economic condition.

Following Bernile et al. (2016), we analyze whether news surprises regarding the GDP, NFP, CPI, and FOMC increase during the COVID-19 pandemic. We compute news surprises by determining the difference between the mean of the forecasted numbers of institutions and actual numbers. In addition, to make those numbers comparable, we standardize surprises by their standard deviations during our study period.

Table 5 summarizes the statistics for the news surprises of the four macroeconomic news announcements. In Columns (1) and (2), we observe that the mean of news surprises before the Wuhan lockdown is 0.2469, but it increases to 0.6585 after the COVID-19-induced lockdown in Wuhan on January 24, 2020. In addition, we determine that the standard deviation increases after the COVID-19 outbreak. To examine robustness, we calculate those numbers after COVID-19 become officially a pandemic on March 11, 2020, and obtain the same pattern in Columns (3) and (4). The findings indicate that the bias of analysts' forecast for the macroeconomic index increases after the COVID-19 pandemic, thus supporting our first argument regarding difficulty faced by professionals in information collection. In addition, this finding provides complementary evidence for the discussion of Bai and Massa (2021) based on professional participants' forecasting bias.

<Insert Table 5 Here>

We directly examine whether the increased bias in forecasting increases information asymmetry. If COVID-19 reduces professionals' ability to forecast macroeconomic numbers, information asymmetry cannot be resolved before announcements because traders in the market cannot follow those forecast values to react to the forthcoming news. Furthermore, we examine whether news announcements can resolve the uncertainty induced by COVID-19. We extend our model by including the news dummy into our model

$$IA_{i,t} = \alpha + \beta_1 Covid_t + \beta_2 News\,Pr\,e_t + \beta_3 News\,P\,o\,st_t + \beta_4 Covid_t * NewsPre_t$$
$$+ \beta_5 Covid_t * NewsPost_t + \Psi Z_{i-1,t} + FE + \varepsilon \tag{2}$$

where $NewsPre_t$ is a dummy to examine the impact before the macro news releases on the GDP, NFP, CPI, and FOMC; it equals 1 if the *i* minute is in the 30 minutes before the announcement on day *t* and zero otherwise. $NewsPost_t$ is a dummy used to examine the impact before those macro news releases; it equals 1 if the *i* minute is in the 30 minutes after the announcement on day *t* and zero otherwise. The other variables are as described in Equation (1). In this model, we focus on β_4 and β_5. If COVID-19 reduces professionals' information collection ability, we would find a positive value for β_4 (Table 5). In addition, if the uncertainty cannot be alleviated by the news announcement, we will obtain a positive value for β_5.

Column (1) of Table 6 displays negative coefficients for $NewsPre_t$ and $NewsPost_t$, implying that the GDP can resolve information asymmetry regarding news releases before the COVID-19 pandemic. Columns (2) to (4) suggest that information asymmetry decreases before the news on the NFP and FOMC are released prior to the COVID-19 outbreak. Similarly, we find that the news releases on the NFP, CPI, and FOMC can resolve information asymmetry before the disease outbreak. Thus, our empirical results coincide with the previous literature indicating that news releases can resolve uncertainty and reduce divergence in private opinions (Tetlock, 2010; Perez and Tourani-Rad, 2017; Wu and Gau, 2022).

<Insert Table 6 Here>

The main coefficients of our interest are positive in Column (1). β_4 indicates that information asymmetry significantly increases before the news release on GDP after the COVID-19 outbreak. The interaction terms of *Covid* and $NewsPre_t$ are positive in columns (2) and (4), indicating that the forecasting of professional traders on the NFP and FOMC do not reduce information asymmetry, which is in contrast to our finding before COVID-19, and even increase the information asymmetry problem. Thus, the forecasting bias of the forthcoming NFP and FOMC from professional traders in institutions increases information asymmetry. The significantly positive coefficients support our conjecture that the forecast bias in macro news is a crucial channel mediating the impact of the COVID-19 pandemic on information asymmetry.

We determine whether news releases can resolve the uncertainty during the COVID-19 pandemic. Column (1) in Table 6 lists a significantly positive coefficient for the interaction term *Covid* and $NewsPost_.$ The positive number implies that the information asymmetry risk decreases after the GDP is announced after the COVID-19 outbreak. We speculate that the news announcement can cause increased uncertainty in the market. For example, an increase in the GDP can reflect an improvement in the economic condition. However, a fluctuation in COVID-19 cases would result in no usability of the number because the increase in cases can adversely affect labor productivity. However, if some investors depend too much on announcements, the divergent opinion problem can become more severe and lead to a higher information asymmetry level. This finding contradicts those of most previous studies (Tetlock, 2010; Perez and Tourani-Rad, 2017; Wu and Gau, 2022). Our empirical results even extend the suggestion of Nagar (2019) that disclosure cannot resolve the information asymmetry problem during a high level of economic policy uncertainty. Moreover, the difference in the findings of this study and those reported by Nagar (2019) indicates that the uncertainty induced by

COVID-19 differs from the uncertainty discussed in the literature.

4.2 Retail investor

Kumar (2009) suggested that uncertainty increases individual investors' behavior bias; thus, we examine the impact of a pandemic on individual investors' behavior. To determine how individual investors' behavior bias mediates the impact of COVID-19 on the information environment in financial markets, we perform a quasi-natural experiment. The US Federal paid US$1,200 and US$600 in April 2020 and December 2020, respectively. Greenwood et al. (2022) suggested that approximately 10%–15% fund of the CARES Act flows into the stock market. Thus, if active retail traders cause information asymmetry, the information asymmetry would increase after the policy.

To examine the impact of the CARES Act, we revise our model as

$$IA_{i,t} = \alpha + \beta_1 Covid_t + \beta_2 Naive1_t + \beta_3 Naive2_t + +\Psi Z_{i-1,t} + FE + \varepsilon \quad (3)$$

where $Naive1_t$ and $Naive2_t$ are dummies for the CARES Act. $Naive1_t$ equals one if the day *t* is after March 30, 2020, but before December 9, 2020. $Naive2_t$ equals one if the day *t* is after December 9, 2020. The other variables are as described in Equation (1). If our argument is applicable, the impact of the COVID-19 pandemic can be absorbed by the CARES Act; in other words, the magnitude of β_1 will decrease and thus β_2 and β_3 will be significantly positive.

Column (1) in Table 7 indicates that the coefficient of *Naive*1 is significantly positive and the coefficient of *Covid* decreases from 0.0033 to 0.0016. In addition, we determine that β_3 is significantly positive at the 1% level. This finding indicates that individual investors' behavior bias caused by COVID-19 can cause higher information asymmetry. But the second pay does not significantly affect the information asymmetry and we conjecture the impact can coincide with the first pay.

<Insert Table 7 Here>

Da et al. (2011) indicated that the intensity of search on Google can reflect the topic of interest for retail investors. After the COVID-19 outbreak, the increasing numbers of infected cases and deaths attracted people's attention to the disease. The volume of research on the disease reflects individuals' worry. Drawing from recent research which analyzed the impacts of news narrativity and unrelated information on market behavior during the COVID-19 pandemic (Mamaysky, 2023; Xu, Zhang, and Zhao, 2023), it is evident that investors tend to become overly attentive to high-narrativity news topics or macroeconomic news , potentially causing them to neglect other important information. This tendency, as highlighted by the study, results in market inefficiencies. Accordingly, we suppose that attention to COVID-19 can disrupt individuals' attention to financial markets and reduce their information collection ability.

However, we determine the outcome if individuals pay more attention to financial markets. Internet research volume is a well-known proxy for the behavior bias of retail investors (Barber and Odean, 2008; Da et al., 2011). Alternatively, the research volume can reflect individuals' information demand or information collection activity (Drake, Roulstone, and Thornock, 2012; Brown, Stice, and White, 2015). Xu, Xuan and, Zheng (2021) indicated that Google is a vital online information resource for retail traders; they observed that firms' crash risk increased by 19% after Google's withdrawal of their research business from China. The search of firms' stock price crash risk on Google before its withdrawal increased by 19%, suggesting that Internet search facilitates investors' information processing. Accordingly, we cannot conclude how people's attention to financial markets affects information asymmetry during the COVID-19 pandemic. To understand the role of attention in information asymmetry, we replace *Naïve* in model (3) based on the Google research volume on COVID-19 and S&P 500 (*GR*)

$$IA_{i,t} = \alpha + \beta_1 Covid_t + \beta_2 GR_t + \beta_3 Covid_t * GR_t + \Psi Z_{i-1,t} + FE + \varepsilon \tag{4}$$

where $IA_{i,t}$ is information asymmetry in the *i* minute on day *t*, which is measured by order flow volatility in the *i* minute. *Covid* denotes the COVID-19 crisis. We employ a day dummy (*Lockdown*) to investigate the impact of COVID-19, which equals one if the day *t* is after WHO announced COVID-19 pandemic and zero otherwise. GR_t represents research on the COVID-19 pandemic (*GR_Covid-19*) and S&P 500 on Google (*GR_SP500*). The other variables are as described in Equation (1).

Column (2) in Table 7 indicates that the coefficient of $Covid\text{-}19^{*}GR$ is significantly positive, suggesting that more people searched for "COVID-19" on Google during the COVID-19 pandemic, thus increasing information asymmetry risk. This finding implies that with investors paying more attention to the infectious disease, they spend less time on information digestion. Thus, the price discovery process experiences a prominent delay and order flows become more informative. To echo this finding, this study replaces the research volume on COVID-19 with the S&P 500. The coefficient of GR_t in Column (3) of Table 7 is significantly positive, indicating that increasing research volume on S&P 500 before COVID-19 increases information asymmetry. Our result reveals that attention can increase retail investors' behavior bias before COVID-19. However, the coefficient of $Covid_t * GR_t$ in column (3) is negative, indicating that investors' attention to S&P 500-related news can resolve information asymmetry during the COVID-19 outbreak. Thus, Internet research enables retail traders to efficiently collect information and thus reduce information asymmetry.

4.3 Market-wild uncertainty and learning effect

We focus on two additional aspects. First, although the virus causes a high level of uncertainty worldwide, the effect of uncertainty on financial markets remains unclear. The main challenge can be the measurement of disease uncertainty. We employ the IDEMV index developed by Baker et al. (2020). Baker et al. (2020) quantify the contribution of the COVID-19 pandemic to US equity market volatility (EMV) by using two steps. First, they compute the monthly frequency of articles in 11 major US newspapers that include (1) terms associated with the economic problem, (2) terms associated with US equity markets, and (3) terms associated with market volatility and then rescale the frequency to match the mean value of the Chicago Board Options Exchange's volatility index. Second, they recognize the subset of EMV articles that include at least one term related to infectious diseases. For example, they flag those articles that contain epidemic, pandemic, virus, flu, disease, coronavirus, MERS, SARS, Ebola, H5N1, or H1N1. Then, they multiply the frequency of EMV articles that contain one of these terms by using the EMV tracker and obtain the IDEMV value.

We include the IDEMV index into our model (1) to determine whether the effect of COVID-19 discussed in the previous section can be explained by the uncertainty caused by the infectious disease. Column (1) of Table 8 indicates that the coefficient of *Covid-19* decreases to 0.0022 and is still statistically significant. The coefficient of *IDEMV* is also significantly positive. Thus, the decrease in the coefficient of *Covid-19* indicates that the *IDEMV* can explain part of the increase in information asymmetry.

Although a model is not yet available to predict the evolution of the COVID-19 pandemic, researchers can develop useful models to predict the impact of COVID-19 across time based on earlier experiences. In addition, scientists around the world can work to find and develop treatments for COVID-19 after the outbreak, and this can reduce the uncertainty. We extend model (1) to divide the period of the COVID-19 outbreak into four subperiods and revise the model as

$$IA_{i,t} = \alpha + \sum_{j=1}^{4} \beta_j \, Learning\_j_t + \Psi Z_{i-1,t} + FE + \varepsilon \quad (5)$$

where $Learning\_j$ denotes different periods during the COVID-19 crisis. j equals 1 as the day after the lockdown of Wuhan but before WHO declared COVID-19 is a global outbreak of coronavirus . j equals 2 as days after the announcement of WHO but before California's reopening in June 2020. j equals 3 as days after the reopening of California but before the development of the coronavirus vaccine. j equals 4 as days after the drug maker Pfizer announced that its coronavirus vaccine was 95% effective against COVID-19 on November 18, 2020. The other variables are as described in Equation (1). The development of the vaccine can alleviate uncertainty and partially reduce information asymmetry.

Panel B of Figure 1 presents an overall picture of the movements of 1-minute order flow volatility patterns during different periods. We observe that the outbreak induces information risk and causes the risk to peak with the United States facing a major challenge to manage an increasing number of infected cases. However, information asymmetry starts to decline couple months after the first case. Thus, we speculate that people can learn from their experience and develop strategies to overcome the barrier to collection information.

Column (2) in Table 8 indicates that the impact of COVID-19 reaches the peak during the third sample period and becomes negative during the final period, which is consistent with the Panel B of Figure 1. Thus, we observe that the negative effect of Covid-19 on information asymmetry reaches the peak after Covid-19 is characterized pandemic, but begins to decrease after the reopening of California. This monotonic pattern suggests that investors are gradually used to live with the virus and overcome the challenge resulting from the COVID-19 crisis. Thus, the findings indicate that individuals in financial markets can learn from experience and adjust their reaction to the COVID-19 crisis.

<Insert Table 8 Here>

5. Information asymmetry and price efficiency

We observe that the poor information collection ability of institutions and the bias of retail traders contribute to information asymmetry during the pandemic. If this finding is true, we would find that the COVID-19 pandemic affects price efficiency. Thus, we confirm whether the findings reported in the previous sections are robust from the aspect of price efficiency.

Although informed traders can create information asymmetry risk for uninformed traders, private information trading can accelerate information incorporation (Green, 2004; Pasquariello and Vega, 2007). Thus, information asymmetry risk can contribute to price efficiency. Alternatively, in contrast to the positive influence, if information asymmetry is mainly driven by retail traders' behavior bias, the high uncertainty can provide an opportunity for informed traders to strategically arbitrage and would not significantly contribute to price discovery. Thus, we investigate whether informed trading can contribute to price efficiency during the COVID-19 period.

We follow Barnea (1974) and use variance ratios to test whether prices follow a random movement, which suggests that the ratio of long-term to short-term price return variances equals 1. Because we did not identify asymmetry in the gap between actual and efficient prices in buy and sell, we calculate $|1 - VR(n, m)|$, where $VR(n, m)$ represents the ratio of the mid-quote return variance over the m period to the return variance over the n period, and divide it by the length of the period. This study considers intraday measures based on the ratios of (1, 2) and (1, 5) minutes. If the value deviates from 1, the price efficiency becomes poor. Thus, we estimate the following model:

$$PE_{i,t} = \alpha + \beta_1 Covid_t + \beta_2 IA_{i-1,t} + \beta_3 Covid_t * IA_{i-1,t} + \Psi Z_{i-1,t} + FE + \varepsilon \quad (3)$$

where PE is the price efficiency and IA is information asymmetry, which are measured based on 1-minute order flow volatility. *Covid* denotes the COVID-19 crisis. We employ a day dummy to investigate the impact of COVID-19, which equals one if the day is after WHO announced COVID-19 is a pandemic and zero otherwise. Z represents the control variables, including 1-minute price volatility, realized spread, and logarithm trading volume. Additionally, we include the hourly fixed effect into our model to remove the impact of the intraday pattern.

During the COVID-19, Columns (1) and (2) of Table 9 indicates the prices of S&P500 require a longer period to converge to fundamental value, irrespective of whether we use a day dummy or a change in the number of infected cases in the United States, suggesting that the price efficiency is deteriorated during a high level of uncertainty. The decrease in price efficiency also supports our previous evidence that some institutional investors face difficulty in collecting information and retail traders' behavior bias can increase during COVID-19. For the robustness test, we consider different time-intervals for the variance ratio measurement and obtain the same consequences shown in Columns (3) and (4).

<Insert Table 9 Here>

The coefficients for the interaction term of COVID-19 proxies and order flow volatility are significantly negative in Table 9. The results indicate that the level of price efficiency can be enhanced through informed trading during the COVID-19 crisis. From the aspect of information risk, COVID-19 results in higher information risk. However, the increased informed trading can help improve the information incorporation process with a rapid increase in uncertainty.

6. Conclusion

We examine how uncertainty induced by the COVID-19 pandemic affects information asymmetry. This study determines whether uncertainty increases information asymmetry risk by hindering the information collection activities of informed traders, increasing trading cost, or enhancing arbitrage risk because an economic model related to the crisis and information channel is unavailable. We observe that the COVID-19 pandemic enhances information risk, which is measured by intraday order flow volatility and order imbalance.

Uncertainty induces shifts in the trading behavior of both professional and retail investors. To assess the implications of COVID-19, we examine its consequences for analysts' forecasting proficiency and retail traders' behavioral biases. Our results demonstrate that GDP, NFP, FOMC, and PPI news surprises have markedly intensified subsequent to the COVID-19 outbreak. In addition, we show that, prior to the pandemic, the anticipation and release of macroeconomic announcements mitigated information asymmetry. Conversely, following the pandemic, these announcements exacerbated information asymmetry.

Given the potential for increased behavioral biases among retail investors, we conduct an analysis grounded in the provisions of the CARES Act aimed at fostering greater retail trader participation. Our findings indicate that this policy exacerbates information asymmetry. To test the attention hypothesis, we examine Google search volume trends. We observe that as search volume for COVID-19-related information increases, information asymmetry also intensifies. Furthermore, our analysis suggests that retail investors' online searches for S&P 500 data prior to the pandemic tended to exacerbate their behavioral biases. However, during the pandemic, retail investors' online searches for S&P 500 information accelerated the price discovery process and mitigated information asymmetry.

Additionally, we provide support for the learning hypothesis by demonstrating that information asymmetry significantly decreased several months after the pandemic outbreak. Notably, information asymmetry further diminished following Pfizer's announcement of its coronavirus vaccine development, serving as a countermeasure to the uncertainty examined in our study.

Lastly, this study examines the impact of informed trading on price efficiency. Our empirical analysis suggests that the COVID-19 pandemic disrupts price efficiency, yet informed trading can counteract this adverse effect. Our findings further indicate that uncertainty arising from a health crisis tends to exacerbate information asymmetry, as sophisticated investors' forecasting accuracy diminishes and retail investors' behavioral biases intensify. Nonetheless, despite these challenges, the role of informed traders in disseminating information remains crucial in facilitating the price discovery process.

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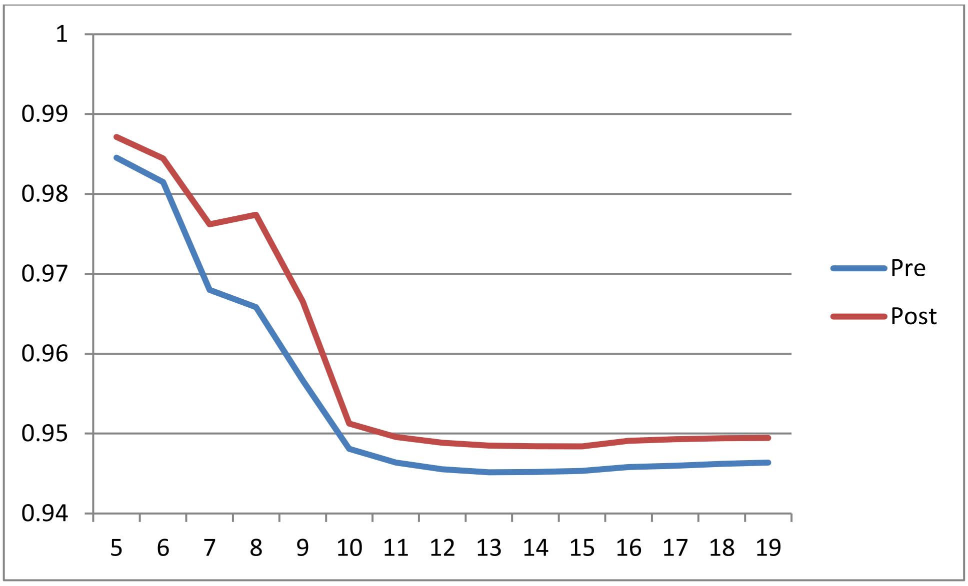
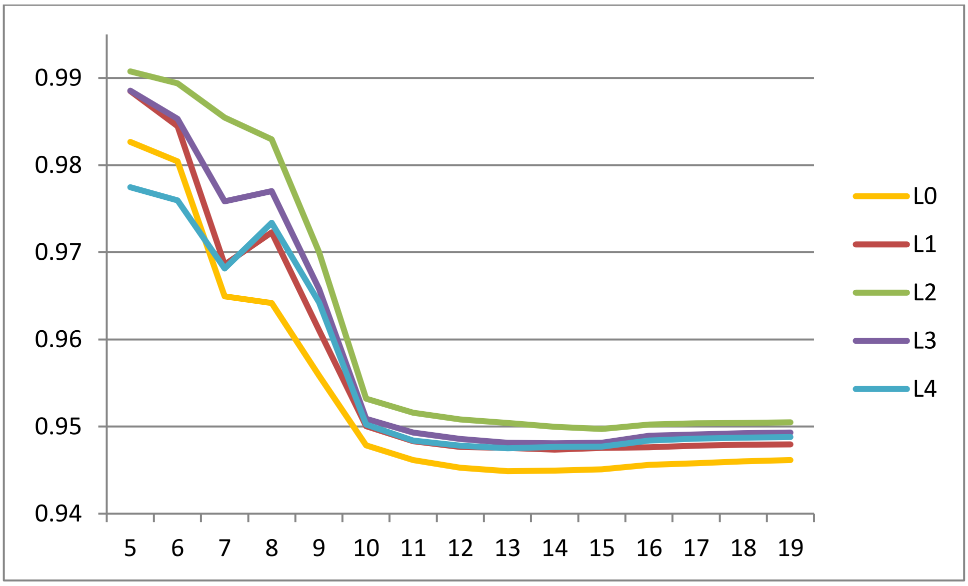


Panel A



Panel B

Figure 1. One-minute Order Flow Volatility

This figure plots 1-minute order flow volatility averaged across our sample period. The horizontal axis denotes trading hours (between 5 a.m. and 8 p.m). In Panel A, we dissect our sample into two periods based on the day on which the California government announced lockdown on March 21. 2020. Thus, the blue (Pre) and red (Post) lines present information asymmetry levels before and after the day of lockdown, respectively. In Panel B, we dissect our sample into five periods based on the day on which China announced lockdown on January 24, 2020; the day on which the WHO announced Covid-19 is a global outbreak of coronavirus on March 11, 2020; the day on which California government announced reopening on June, 8; and when Pfizer announced that its coronavirus vaccine was 95% effective against COVID-19 on November 18, 2020.

Table 1 Summary Statistics

	OIV		Volatility		Realized Spread		Volume	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Mean	0.9528	0.9584	0.4712	0.8645	-0.000016	-0.000017	35824242	42299886
Median	0.9491	0.9518	0.3403	0.6674	-0.000008	-0.000019	26222266	29387291
Maximum	1.0328	1.0054	3.4146	4.7127	0.0017	0.0071	322000000	306000000
Minimum	0.6019	0.7331	0.0189	0.0541	-0.0056	-0.0093	836	5629
Std. Dev.	0.0176	0.0172	0.4034	0.6754	0.0002	0.0003	39767092	47917389
Skewness	-1.1797	0.0360	2.6821	2.0992	-3.9366	-0.3595	2	2
Kurtosis	31.4896	10.8663	13.8810	8.9235	71.8537	106.7864	12	8
Obs.	134456	143275	134456	143275	134456	143275	134456	143275
Difference	0.0056***		0.3933***		0.000001		6475644***	
t-Value	17.66		38.56		0.40		7.99	

Notes: The table reports the summary statistics for dependent and independent variables in our analysis. *OIV* presents order flow volatility and is computed using the standard deviation of 1-minute order flow. *Volatility* presents the standard deviation of 1-minute mid-quote return. *Realized Spread* is calculated as the difference between the traded price and 1-minute delay midpoint, relative to the current midpoint. *Volume* is the sum of total trading volume in minutes. The table reports the mean, median, standard deviation, minimum, maximum, skewness, and kurtosis for each variable. The sample is broken down into two based on the day of the announcement of Covid-19 pandemic as the cutoff. Significant mean differences are observed between samples before (Pre) and after (Post) the lockdown.

Table 2 Baseline Results

	IA_t		
	Lockdown	*UIR*	*WIR*
C	0.9614***	0.9618***	0.9629***
	(174.07)	(174.71)	(175.46)
$Covid\text{-}19_t$	0.0033***	0.0106***	0.008***
	(15.25)	(16.18)	(10.81)
$Volatility_{t,i-1}$	0.0039***	0.0038***	0.0041***
	(14.51)	(14.49)	(15.12)
$Spread_{t,i-1}$	-0.6702***	-0.6004***	-0.5792***
	(-1.92)	(-1.76)	(-1.71)
$Volume_{t,i-1}$	-0.001***	-0.0011***	-0.0011***
	(-3.33)	(-3.41)	(-3.6)
$D5_{t,i}$	0.033***	0.0328***	0.0326***
	(13.27)	(13.19)	(13.15)
$D6_{t,i}$	0.0306***	0.0304***	0.0302***
	(14.38)	(14.3)	(14.25)
$D7_{t,i}$	0.0208***	0.0206***	0.0204***
	(12.13)	(12.03)	(11.94)
$D8_{t,i}$	0.021***	0.0208***	0.0207***
	(15.13)	(15.03)	(14.95)
$D9_{t,i}$	0.0122***	0.0121***	0.012***
	(12.07)	(11.97)	(11.92)
$D10_{t,i}$	0.0017***	0.0016***	0.0016***
	(3.18)	(3.05)	(3.03)
$D11_{t,i}$	0.0000	0.0000	0.0000
	(0.11)	(0.00)	(-0.06)
$D12_{t,i}$	-0.0007***	-0.0008***	-0.0008***
	(-2.03)	(-2.13)	(-2.21)
$D13_{t,i}$	-0.0011***	-0.0011***	-0.0011***
	(-3.34)	(-3.43)	(-3.53)
$D14_{t,i}$	-0.0011***	-0.0011***	-0.0012***
	(-3.72)	(-3.78)	(-3.9)
$D15_{t,i}$	-0.001***	-0.001***	-0.0011***
	(-3.82)	(-3.86)	(-4)
$D16_{t,i}$	-0.0003	-0.0003	-0.0003
	(-1.16)	(-1.16)	(-1.28)
$D17_{t,i}$	-0.0002	-0.0002	-0.0002
	(-0.77)	(-0.77)	(-0.83)
$D18_{t,i}$	-0.0001	-0.0001	-0.0001
	(-0.4)	(-0.4)	(-0.42)

Adj-R^2	56.86%	56.86%	56.61%
Obr.	277,731	277,731	277,731

Notes: The table presents changes in information asymmetry on the day before and after the lockdown of California and changes in the number of infected cases across time. Specifically, we report the results for the following regression:

$$IA_{i,t} = \alpha + \beta_1 Covid_t + \Psi Z_{i-1,t} + FE + \varepsilon$$

where *IA* is information asymmetry in the *i* minute on day *t*, which is measured by order flow volatility in *i* minute. *Covid* denotes the COVID-19 crisis. We employ a day dummy (*Lockdown*) to investigate the impact of COVID-19, which equals one if the day *t* is after WHO announced the COVID-19 outbreak a global pandemic and zero otherwise. Furthermore, we exploit changes in infection numbers in the United States (*UIF*) and all over the world (*WIF*) to proxy for the impact of COVID-19. *Z* represents control variables, including 1-minute price volatility (Volatility), realized spread (Spread), and logarithm trading volume (Volume). Additionally, we include the hourly fixed effect (*FE*) into our model to remove the impact of the intraday pattern. The *t* statistics are calculated using the Newey–West standard errors and are reported in parentheses. ***, ** and * indicate statistical significance at 0.01, 0.05, and 0.1 levels, respectively.

Table 3 Robustness Analysis

	$IA_{t,i}$ *(OIB)*		$IA_{t,I}$ *(OIV_H)*	
	Lockdown	UIR	Lockdown	UIR
C	0.0946***	0.0952***	0.9412***	0.9417***
	(3.6)	(3.63)	(103.12)	(103.07)
$Covid\text{-}19_t$	0.0043***	0.0135***	0.0051***	0.0161***
	(3.79)	(3.8)	(6.9)	(7.03)
$Volatility_{t,i-1}$	0.0039***	0.0038***	0.0041***	0.004***
	(3.09)	(3.05)	(5.71)	(5.53)
$Spread_{t,i-1}$	-26.059***	-25.9724***	1.3115	1.4361
	(-9.72)	(-9.69)	(1.42)	(1.51)
$Volume_{t,i-1}$	-0.0058***	-0.0058***	0.0016***	0.0016***
	(-3.87)	(-3.89)	(2.44)	(2.39)
Intrday Fixed Effect	YES	YES	YES	YES
Adj-R^2	2.54%	2.54%	24.63%	24.64%
Obr.	277,731	277,731	4,986	4,986

Notes: The table presents changes in information asymmetry on the day before and after the lockdown of California and changes in the number of infected cases across time. Specifically, we report results for the following regression:

$$IA_{i,t} = \alpha + \beta_1 Covid_t + \Psi Z_{i-1,t} + FE + \varepsilon$$

where *IA* is information asymmetry, which is measured by order imbalance in 1 minute (*OIB*) and order flow volatility in 1 hour (*OIV_H*). *Covid* denotes the Covid-19 crisis. We employ a day dummy to determine the impact of Covid-19, which equals one if the day is after WHO announced the COVID-19 outbreak a global pandemic and zero otherwise. Furthermore, we exploit changes in infection numbers in the United States (*UIF*) to proxy for the impact of COVID-19. *Z* represents control variables, including 1-minute price volatility (Volatility), realized spread (Spread), and logarithm trading volume (Volume). Additionally, we include the hourly fixed effect (*FE*) into our model to remove the impact of the intraday pattern. The *t* statistics are calculated using the Newey–West standard errors and are reported in parentheses. ***, ** and * stand for statistical significance at 0.01, 0.05 and 0.1 levels, respectively.

Table 4 Placebo Analysis

	$IA_{t,i}$	
	Flu (Whole sample)	Flu (Subsample)
C	1.0174***	0.9795***
	(422.43)	(98.02)
$INFLU_t$	-0.0004	0.0006
	(-1.43)	(1.45)
$Volatility_{t,i-1}$	0.0068***	0.0084***
	(36.52)	(13.43)
$Spread_{t,i-1}$	-0.4262	0.6201
	(-0.79)	(0.98)
$Volume_{t,i-1}$	-0.004***	-0.0021***
	(-29.55)	(-3.79)
Intrday Fixed Effect	YES	YES
Adj-R^2	14.93%	42.17%
Obr.	277,731	112,448

Notes: The table presents changes in information asymmetry on the day before and after the influenza epidemics period defined by the disclosure of the US Centers for Disease Control. and changes in the number of infected cases across time. Specifically, we report results for the following regression:

$$IA_{i,t} = \alpha + \beta_1 INFLU_t + \Psi Z_{i-1,t} + FE + \varepsilon$$

where *IA* is information asymmetry in the *i* minute on day *t*, which is measured by order flow volatility in *i* minute. *INFLU* denotes influenza in 2019 and 2020. *INFLU* equals one if the day *t* is during October 1, 2019, to April 4, 2020, and zero otherwise. *Z* represents the control variables, including 1-minute price volatility (volatility), realized spread (spread), and logarithm trading volume (volume). Additionally, we include the hourly fixed effect (*FE*) into our model to remove the impact of the intraday pattern. Column (2) is based on the whole sample, and Column (3) is based on the sample before January 1, 2020. The *t* statistics are calculated using Newey–West standard errors and are reported in parentheses. ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.1 levels, respectively.

Table 5 News Surprise

	Lockdown(W)=0	*Lockdown(W)*=1	*Lockdown(C)*=0	Lockdown(C)=1
Mean	0.2469	0.6585	0.3164	0.6491
Median	0.0397	0.3821	0.0794	0.3774
Maximum	1.1463	6.2071	1.1463	6.2071
Minimum	0.0000	0.0000	0.0000	0.0000
Std. Dev.	0.3625	1.1639	0.4054	1.2360
Skewness	1.3936	3.6844	1.0757	3.5481
Kurtosis	3.6155	17.2770	2.6764	15.6997
Observations	47	64	55	56
t-value	2.66^{***}		1.91^{*}	

Notes: Lockdown (W) and Lockdown (C) are dummies denoting days after the lockdown in Wuhan and WHO announced the COVID-19 outbreak a global pandemic, respectively. Lockdown (W) = 1 denotes those days after the government announced a lockdown in Wuhan. Lockdown (W) = 0 denotes those days before the government announced a lockdown in Wuhan. Likely, Lockdown (C) = 1 and Lockdown (C) = 0 respectively denote days after and before the announcement of the COVID-19 pandemic.

Table 6 Impact of Macro News Announcements

	$IA_{t,i}$			
	GDP	NFP	FOMC	PPI
C	0.9656***	0.9656***	0.9652***	0.9657***
	(335.54)	(335.54)	(336.41)	(335.79)
$Covid\text{-}19_t$	0.0035***	0.0035***	0.0035***	0.0035***
	(-0.0123)	(-0.0123)	(0.0002)	(-0.0129)
$News\_Pre_t$	-0.0123***	-0.0123***	0.0002	-0.0129***
	(-14.68)	(-14.68)	(0.52)	(-3.48)
$News\_Post_t$	-0.0111***	-0.0111***	-0.0007***	-0.0125***
	(-16.26)	(-16.26)	(-2.22)	(-3.93)
$Covid\text{-}19_t * News\_Pre_t$	0.0106***	0.0106***	0.0004	0.0180***
	(5.66)	(5.66)	(0.93)	(4.85)
$Covid\text{-}19_t * News\_Post_t$	0.0117***	0.0117***	0.0009***	0.0192***
	(8.07)	(8.07)	(2.26)	(6.02)
$Volatility_{t,i-1}$	0.004***	0.004***	0.004***	0.004***
	(37.54)	(37.54)	(37.44)	(37.56)
$Spread_{t,i-1}$	-0.4087***	-0.4087***	-0.4079***	-0.4136***
	(-2.83)	(-2.83)	(-2.83)	(-2.87)
$Volume_{t,i-1}$	-0.0013***	-0.0013***	-0.0013***	-0.0013***
	(-7.96)	(-7.96)	(-7.83)	(-7.99)
Intrday Fixed Effect	YES	YES	YES	YES
Adj-R^2	49%	49%	49%	49%
Obr.	277,731	277,731	277,731	277,731

Notes: The table presents changes in information asymmetry responses to the interaction of the COVID-19 pandemic and macro news announcements. Specifically, we report the results for the following regression:

$$IA_{i,t} = \alpha + \beta_1 Covid_t + \beta_2 \mathrm{News\,Pr}e_t + \beta_3 \mathrm{News\,P}ost_t + \beta_4 Covid_t * \mathrm{News\,Pr}e_t + \beta_5 Covid_t * \mathrm{N}ewsPost_t + \Psi Z_{i-1,t} + FE + \varepsilon$$

where *IA* is information asymmetry in the *i* minute on day *t*, which is measured by order flow volatility in *i* minute. *Covid* denotes the COVID-19 crisis. We employ a day dummy (*Lockdown*) to capture the impact of Covid-19, which equals one if the day *t* is after WHO announced the COVID-19 outbreak a global pandemic and zero otherwise. $News\,\mathrm{Pr}e_{i,t}$ is a dummy to capture the impact before the macro news releases on the GDP, NFP, CPI, and FOMC that equals 1 if the *i* minute is in the 30 minutes before the announcement on day *t*. $NewsPost_{i,t}$ is a dummy used to examine the impact before those macro news releases that equals 1 if the *i* minute is in the 30 minutes after the announcement on day *t*. *Z* represents control variables, including 1-minute price volatility (volatility), realized spread (spread), and logarithm trading volume (volume). Additionally, we include the hourly fixed effect (*FE*) into our model to remove the impact of the intraday pattern. The *t* statistics are calculated using the Newey–West standard errors and are reported in parentheses. ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.1 levels, respectively.

Table 7 Impact of Individual Investors

	$IA_{t,i}$		
	Naïve investor	GR_Covid-19	GR_SP500
C	0.9615***	0.9769***	1.0140***
	(167.33)	(141.07)	(418.89)
$Covid\text{-}19_t$	0.0016***	0.0064***	0.0042***
	(2.53)	(12.08)	(9.64)
$Naive1_t$	0.0021***		
	(3.42)		
$Naive2_t$	0.0005		
	(0.66)		
GR_t		-0.00001	0.0001***
		(-0.57)	(9.46)
$Covid\text{-}19_t{}^{*}\ GR_t$		0.0001*	-0.0001***
		(1.93)	(-4.33)
$Volatility_{t,i\text{-}1}$	0.0041***	0.0006***	0.0048***
	(16)	(3.1)	(23.33)
$Spread_{t,i\text{-}1}$	-0.727***	0.3385	-0.0532
	(-2.09)	(0.97)	(-0.12)
$Volume_{t,i\text{-}1}$	-0.0011***	-0.0018***	-0.0040***
	(-3.26)	(-4.63)	(-29.56)
Intrday Fixed Effect	YES	YES	YES
Adj-R^2	56.90%	79.56%	48.44%
Obs.	277,731	277,731	277,731

Notes: The table presents the role of retail investors in changes in information asymmetry measures. Specifically, we report the results for the following regressions:

$$IA_{i,t} = \alpha + \beta_1 Covid_t + \beta_2 Naive1_t + \beta_3 Naive2_t + \Psi Z_{i-1,t} + FE + \varepsilon$$

$$IA_{i,t} = \alpha + \beta_1 Covid_t + \beta_2 GR_t + \beta_3 Covid_t * GR_t + \Psi Z_{i-1,t} + FE + \varepsilon$$

where *IA* is information asymmetry in the *i* minute on day *t*, which is measured by order flow volatility in *i* minute. *Covid* denotes the COVID-19 crisis. We employ a day dummy (*Lockdown*) to determine the impact of COVID-19, which equals one if the day *t* is after WHO announced the COVID-19 outbreak a global pandemic and zero otherwise. To capture retail traders' activity, this paper builds up the first proxy by employing the program of US government's Coronavirus Aid Relief and Economic Security Act. $Naive1_t$ equals one if the day *t* is after March 30, 2020, but before December 9, 2020. $Naive2_t$ equals one if the day *t* is after December 9, 2020. The second proxy for retail investor activity is the research for topics on the COVID-19pandemic (*GR_Covid-19*) and Standard & Poor's 500 on Google (*GR_SP500*). *Z* represents control variables, including 1-minute price volatility (*volatility*), realized spread (*spread*), and logarithm trading volume (*volume*). Additionally, we include the hourly fixed effect (*FE*) into our model to remove the impact of the intraday pattern. The *t* statistics are calculated using the Newey–West standard errors and reported in parentheses. ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.1 levels, respectively.

Table 8 Uncertainty and Learning Effect

	$IA_{t,i}$	
C	0.9652***	1.0152***
	(167.57)	(415.04)
$Covid\text{-}19_t$	0.0022***	
	(7.11)	
$IDEMV_t$	0.0001***	
	(6.26)	
$Learning1_t$		0.003***
		(7.32)
$Learning2_t$		0.0077***
		(24.83)
$Learning3_t$		0.0042***
		(14.5)
$Learning4_t$		-0.0027***
		(-6.68)
$Volatility_{t,i-1}$	0.0034***	0.0045***
	(13.76)	(23.23)
$Spread_{t,i-1}$	-0.4523	-0.1423
	(-1.34)	(-0.26)
$Volume_{t,i-1}$	-0.0012***	-0.0039***
	(-3.82)	(-28.74)
Intrday Fixed Effect	YES	YES
Adj-R^2	56.89%	44.99%
Obs.	277,731	277,731

Notes: The table presents changes in information asymmetry related to uncertainty caused by an infectious disease and its pattern across different stages of the COVID-19 pandemic. Specifically, we report the results for the following two regressions:

$$IA_{i,t} = \alpha + \beta_1 Covid_t + \beta_2 IDEMV_t + \Psi Z_{i-1,t} + FE + \varepsilon$$

$$IA_{i,t} = \alpha + \sum_{j=1}^{4} \beta_j Learning\_j_t + \Psi Z_{i-1,t} + FE + \varepsilon$$

where $IA_{i,t}$ is information asymmetry in the *i* minute on day *t*, which is measured by order flow volatility in *i* minute. $Covid_t$ denotes the COVID-19 crisis. We employ a day dummy (*Lockdown*) to capture the impact of COVID-19, which equals one if the day *t* is after WHO announced the COVID-19 outbreak a global pandemic and zero otherwise. $IDEMV_t$ denotes the uncertainty raised by the infectious disease index reported by of Baker et al. (2020) on day *t*. $Learning\_j_t$ denotes different periods during the COVID-19 crisis. *j* equals 1 as the day *t* is after lockdown in Wuhan, but before the lockdown in California. *j* equals 2 as day *t* is after lockdown in California but before its reopening in June, 2020. *j* equals 3 as day *t* is after the reopening of California but before the creation of the coronavirus vaccine. *j* equals 4 as day *t* is after the drug maker Pfizer announced its coronavirus vaccine was 95% effective against COVID-19 on November 18, 2020. *Z* represents control variables, including 1-minute price volatility (volatility), realized spread (spread), and logarithm trading volume (volume). Additionally, we include the hourly fixed effect (*FE*) into our model to remove the impact of the intraday pattern. The *t* statistics are calculated using the Newey–West standard errors and are reported in parentheses. ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.1 levels, respectively.

Table 9 Price Efficiency and Information Asymmetry

	$PE_{i,t}$ (Variance Ratio)			
	(1,2)	(1,2)	(1,5)	(1,5)
	Lockdown	*UIR*	*Lockdown*	*UIR*
C	0.3326***	0.3226***	0.1601	0.1637
	(2.26)	(2.19)	(0.77)	(0.78)
$Covid\text{-}19_{t,i-1}$	0.3499***	1.1637***	0.6152***	1.9175***
	(2.04)	(2.16)	(2.33)	(2.27)
$IA_{t,i-1}$	0.0065	0.0143	0.3766*	0.3703***
	(0.05)	(0.1)	(1.95)	(1.92)
$Covid\text{-}19_{t,i-1}{}^{*}IA_{t,i-1}$	-0.3847***	-1.2765***	-0.6615***	-2.0601***
	(-2.14)	(-2.26)	(-2.39)	(-2.34)
$Volatility_{t,i-1}$	-0.0058	-0.0054	-0.0186***	-0.0184***
	(-1.01)	(-0.93)	(-2.41)	(-2.38)
$Spread_{t,i-1}$	-7.5902	-8.0966	11.8235	11.3103
	(-1.03)	(-1.1)	(0.69)	(0.65)
$Volume_{t,i-1}$	-0.0075***	-0.0074***	-0.0114***	-0.0112***
	(-2.23)	(-2.18)	(-2)	(-1.97)
Intrday Fixed Effect	YES	YES	YES	YES
Adj-R^2	5.12%	1.80%	5.13%	1.78%
Obr.	4,653	4,653	4,653	4,653

Notes: The table presents the impact of informed trading on changes in price efficiency on the day before and after the announcement of COVID-19 outbreak a global pandemic and changes in the number of infected cases across time. Specifically, we report the results for the following regression:

$$PE_{i,t} = \alpha + \beta_1 Covid_t + \beta_2 IA_t + \beta_3 Covid_t * IA_t + \Psi Z_{i-1,t} + FE + \varepsilon$$

where *PE* is the price efficiency in *i* minute on day *t*, which is calculated by $|1 - VR(n, m)|$, where $VR(n, m)$ represents the ratio of the mid-quote return variance over the *m* minutes to the return variance over *n* minutes, divided both by the length of the period. This paper considers intraday measures based on ratios of (1, 2), and (1, 5) minutes. $IA_{i,t}$ is information asymmetry in the *i* minute on day *t*, which is measured by order flow volatility in *i* minute. $Covid_t$ denotes the COVID-19 crisis. We employ a day dummy (*Lockdown*) to capture the impact of Covid-19, which equals one if the day *t* is after WHO announced the COVID-19 outbreak a global pandemic and zero otherwise. *Z* represents control variables, including one-minute price volatility (*volatility*), realized spread (*spread*), and logarithm trading volume (*volume*). Additionally, we include the hourly fixed effect (*FE*) into our model to remove the impact of the intraday pattern. The *t* statistics are calculated using the Newey–West standard errors and are reported in parentheses. ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.1 levels, respectively.