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COVID-19, volatility dynamics, and sentiment trading

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\textbf{A B S T R A C T}

In this paper, we study how different categories of crucial COVID-19 information influence price dynamics in stock and option markets during the period from 01/21/20 to 01/31/21. We present a theoretical model in which the behavioral traders make perceptual errors based on the intensity of sentiment arising from different types of news. In addition to the magnitude and direction of the news and its payoff relevance to security prices, other factors such as fear, emotion, and social media can influence the sentiment level. Using Google search data, we construct novel proxies for the sentiment levels induced by five categories of news, COVID, Market, Lockdown, Banking, and Government relief efforts. If the relative presence of behavioral traders in the stock market exceeds that in the option market, different predictions obtain for the effect of sentiment indices on jump volatility of the VIX index, the S&P 500 index, and the S&P 500 Banks index. We find that the jump component in the VIX index is increasing significantly with COVID index, Market index, Lockdown index, and Banking index. However, only COVID index and Market index increase the jump component of realized volatility of the stock indices (S&P 500 index and S&P 500 Banks index). The Government relief efforts index decreases this jump component. Banking and Lockdown index reduce jump volatility in the S&P 500 index and S&P 500 Banks index, but only with a delay of 5 days. These results are consistent with the predictions of our model.

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I. Introduction

In January 2020, a novel coronavirus named COVID-19 (so named by World Health Organization (WHO) in March 2020) began to impact US financial markets in unprecedented ways. The COVID-19 pandemic led to stock market plunges and volatility spikes in the US equity market and has spurred tremendous turbulence in the global financial markets. In the US, the COVID-19 led to 574,957 deaths as of April 18, 2021. Basu (2020) finds that COVID-19’s infection-fatality rate is ten times larger than common seasonal flu. COVID-19 has introduced tremendous amount of health risk into people’s daily life. On March 16, 2020, the White House announced a program “15 Days to Slow the Spread,” a nationwide effort to slow the spread of COVID-19 through the implementation of social distancing at all levels of society. Since then, numerous businesses have been permanently shut down or filed for bankruptcy protection. Undoubtedly, the COVID-19 pandemic has brought attention and fear among investors, and consequently created a tremendous amount of volatility in the US equity and option markets.

In financial markets, market fear usually reveals itself in the form of the level and movement of market volatility measures. One commonly used market fear indicator would be the Chicago Board Options Exchange (CBOE) VIX index. It is viewed as “fear gauge” or “fear index” among market participants\textsuperscript{1}. The VIX index is a model-free implied volatility index. It is constructed using out-of-money put and call S&P 500 index options prices. During the COVID-19 pandemic period, the VIX index spiked (S&P 500 plunges) right after three triggering major events. The first event is when number of COVID-19 cases spike in Italy signaling an outbreak of the pandemic on February 21, 2020. The second event is

\textsuperscript{1} See Whaley (2000) on the construction of VIX index and its role as the market “fear gauge”.

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when the President of the US banned travel from Europe and WHO declared COVID-19 as a global pandemic on March 11, 2020. The third event is when the President of US declared a national emergency on Friday, March 13, 2020. The next trading day, the VIX spiked to the highest level in history on Monday, March 16, 2020. In addition to the market attention brought by the COVID-19 pandemic, it has also caused tremendous amount of turbulence both in the level of stock market prices and in the level and movement of market volatility.

In this paper, our goal is to study how different categories of crucial COVID-19 information affects price dynamics in stock and option markets during the period from 01/21/20 to 01/31/21. As mentioned above, the overall volatility in both stock and option markets were very high from late-February to mid-April 2020. We want to examine the details of how different categories of COVID information affects the price dynamics in the stock market, the option market, and if there are important differences between them. We posit that the process of new information affecting security prices is more complex than that of directly mapping the value relevance of the incremental information. Especially during times of great stress, we argue that different categories of information commands different levels of attention from the traders eliciting different intensity of response. In other words, take the example of two pieces of new information about the COVID economy. There is information that death levels have crossed 100,000. Another piece of information is that New York is implementing a lockdown. In both cases, it is a complex process to convert the effect of these news items to their correct payoff relevance to specific securities or the stock market index. An important ingredient of the impact of these pieces of news is the attention paid to the news by the traders and the intensity of their response. In this paper, we will call this ingredient as the sentiment level generated by the specific type of news.

We also construct an equilibrium model of two types of traders who trade based on the information shocks in the economy. The behavioral traders make perceptual errors regarding the future expected prices, and their errors are distributed with a mean equal to the sentiment intensity. The sophisticated traders who coexist in the same economy are not susceptible to the perceptual errors; however, the equilibrium prices and its dynamics are affected by the errors and security holdings of the behavioral traders. In our model, we argue that the role of sentiment will be different for different categories of news. We also assume that the relative fraction of behavioral traders is larger in the stock market than in the option market. Based on these assumptions, we derive several implications of the sentiment intensity for five different categories of news for the volatility dynamics in stock and option markets.

Our paper makes several contributions. The focus of our study is to understand how different types of information influences the price dynamics during a period of great stress. One of our insights is that the intensity of sentiment, over and above the magnitude and direction of different news events can be important to moving prices. In addition, the extent of jump discontinuity in the volatility measures in the stock and option markets will be influenced differentially by the different sentiment indices. Based on the previous literature, we assume a lesser role for behavioral traders in the option market. Our contributions here are twofold: we model the equilibrium price dynamics in the stock and option markets resulting from the trades of behavioral traders (who are influenced by sentiment and make perceptual errors about future prices) and sophisticated traders who do not. Secondly, we generate predictions relating the sentiment levels of different categories of news to jump components of volatility measures in the stock and option markets. Our novel empirical strategy is to work directly with our sentiment indices rather than measures of news intensity. An important part of this strategy would be to carefully construct indices of sentiment related to different categories of news.

Another important contribution of our paper is to construct a proxy for the time-varying sentiment intensity of different categories of news based on the relevant Google search data. We identify five important high-impact categories of news, namely, COVID news, market news, lockdown news, banking news, and government relief efforts news. We recognize that each category of news will have a positive or negative impact on economic factors that map into changes in security prices. The categories of news may differ in the complexity of this mapping. More importantly, in addition to the importance of the news and its direction of impact on security prices, other factors such as fear, emotion, and political affinity may contribute to the sentiment intensity resulting from the news. Our empirical strategy is to construct a time-varying sentiment index for each one of the five categories of news based on Google search data.

The details of the constructing the proxy for the sentiment index is described in Appendix B. The overall strategy is to identify a small dictionary of the most popular search items that epitomize the central forces in that category of information shocks. For example, the dictionary for market news contains the words “dow”, “stock”, and “market”. The dictionary for lockdown news contains the words “lockdown”, “cde”, “trump”, “stay”, “home”, and “government”. The first three information categories, COVID, Market, and Lockdown, contain a large component of bad news for the economy and security prices for the period January 21, 2020 to June 8, 2020. On the other hand, government relief efforts news, when legislatively successful, represents good news for the economy and security prices. Banking news also had a positive component arising from the role of banks in the relief efforts as well as the role of central bank in easing the monetary policy to bail out the economy. We will argue that this could make the role of banking news complex in its mapping to the value relevance of securities. Given our additional assumption regarding the prominent presence of behavioral traders in the stock market (as opposed to the option market), we derive predictions for the impact of our different sentiment indices on the jump volatility in the VIX index differently from that in S&P 500 index and S&P 500 Banks index.

The underlying methodologies to construct the VIX index, the S&P 500 index realized volatility and the S&P 500 Banks index realized volatility are model-free measures of the market index volatility. The VIX index is constructed based on historical daily option prices using a near-term option contract and a next-term option contract. It is interpolated to measure the future 30-day volatility of the underlying market index. On the other hand, the S&P 500 index and S&P 500 Banks index realized volatility is a volatility measure based on historical high-frequency (5-minute) index price and returns. The realized volatility is determined by equity market participants, whereas the VIX index is determined by the sophisticated trades of index option market participants.

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2 Specifically, we decompose various market volatility measures into continuous components and discontinuous components. The discontinuous component is termed the jump component. The discontinuous jump component is caused by news about exogenous shocks to the economy, which leads to changes in the intensity of sentiment regarding that incremental news. Our empirical strategy is to construct five Google search sentiment indices and to examine the effect of these indices on the jump component of the various measures of volatility.

3 In this paper, we explore both the risk neutral probability space (option based) volatility jumps and the physical probability space (historical data based) volatility jumps. The VIX index jumps are measured by the jump tail component in the VIX index as in Martin (2001), Du and Kapadia (2012), and Chow et al. (2018a, 2018b). The physical-probability space volatility is measured by realized volatility. Andersen and Bollerslev (1998) and Andersen et al. (2001) demonstrate that the realized volatility possesses desirable properties, such as model-free and
We predict that COVID index, Market index and Lockdown index will increase the jump component of the VIX index, and that the Government relief effort index will reduce the jump component of the VIX index. Another prediction of our model is that COVID index and Market index will increase the jump component of the realized volatility of S&P 500 index and S&P 500 Banks index. On the other hand, Government relief efforts index will reduce the jump component of the realized volatility of S&P 500 index and S&P 500 Banks index. Banking index and Lockdown index are complex and therefore are predicted to have no contemporaneous effect on the jump component of the realized volatility of S&P 500 index and S&P 500 Banks index. However, we also predict that Banking index and Lockdown index when lagged by a certain number of days, will have a negative contribution to the jump component of the realized volatility of S&P 500 index and S&P 500 Banks index.

Now we provide an overview of our empirical results. We find that the jump component of the VIX index increases significantly with the COVID sentiment index, Market sentiment index, Lockdown sentiment index, and Banking sentiment index. On the other hand, the jump component of the realized volatility of the S&P 500 index increases significantly only with COVID sentiment index and Market sentiment index and decreases significantly with Government relief efforts sentiment index. We find similar evidence for the S&P 500 Banks index, although the relationship with COVID sentiment index is not significant. These empirical findings are mostly consistent with our hypothesized theoretical predictions (See Hypotheses 1 and 2).

We argue that the banking news and the lockdown news are complex, and the behavioral traders find it difficult to extract the value-relevant information from it. However, such news can be the source of big changes in the related sentiment indices. It is possible that the behavioral traders either underestimate the importance of such news (e.g., in the case of banking news) or overreact to it (e.g., in the case lockdown news). However, the behavioral traders learn from the price dynamics and settle down to a balanced reaction to the news in matter of a few days. In those days, the incremental contribution of both the sentiment indices is to reduce the jump component of the realized volatility of S&P 500 index and S&P 500 Banks. Our evidence is consistent with such a relationship that we predicted in Hypothesis 3.

This paper is organized as follows: Section II describes the related literature in two parts. The first part discusses the literature on how sentiment is an important intermediate channel in incorporating news shocks into stock and option prices. In the second part, we discuss how our paper fits into the recent literature on the impact of COVID-19 on the financial market. Section III contains a theoretical model of an economy where both sophisticated and behavioral traders respond to an exogenous shock related to the COVID–19 pandemic. Section IV presents our formulation of hypotheses. Section V contains an overview of some important events and data on the COVID–19 pandemic and the market volatility dynamics during the period from January 21, 2020 to January 31, 2021. Section VI contains our main empirical results along with a brief discussion of estimation of volatility jumps and the construction of our five sentiment indices. Section VII concludes.

II. Related literature

II. A. Price dynamics and sentiment

In our framework, the equilibrium market prices arise from the trading of behavioral traders and sophisticated traders. The behavioral traders make perceptual errors regarding their future prices and determine their optimal holdings accordingly. Beyond the news, the degree of sentiment created by different types of news has an important role in our study. Our theoretical predictions are also based on higher prominence of behavioral traders in the stock market compared to the option market. The importance of sentiment in the price dynamics and the higher prominence of behavioral traders in the stock market have been noted in the existing literature.

Based on estimates from a dynamic asset pricing model, Cox et al. (2020) argue that the high volatility in the stock market during COVID-19 period (February 2020 to July 2020) was driven by shifts in sentiment or risk aversion. They also state that sentiment, rather than the actual implementation of government relief efforts, explains the market volatility as of July 31, 2020. We agree with such a perspective and use direct measures of sentiment arising from five different categories of news to study how they influence measures of market volatility in the stock and option markets.

Lemmon and Ni (2014) find that trades in index options are motivated by hedging demand of sophisticated investors. However, individual stock option and the underlying stock trading are motivated by the hedging demand of individual investors and they are heavily influenced by market sentiment. Our assumption of a higher prominence of behavioral traders in the stock market (compared to the option market) is also consistent with the results of Lemmon and Ni (2014).

Although there are several measures of sentiment that has been proposed in the literature (See, e.g., Baker and Wurgler (2006)), we believe that the sentiment index that we have constructed is superior along two dimensions. Firstly, we construct a proxy that corresponds to the attention and the strength of response elicited by a particular category of news. Secondly, our sentiment indices vary with the news based on Google search volume on a daily basis4. Da et al. (2011) use daily Google search volume to construct an investor attention index and find that it captures investor attention in a more timely fashion. Similarly, Da et al. (2015) use Google daily search volume to construct an investor sentiment index and find that this investor sentiment index predicts short-term reversal. More recently, Azevedo and Elkhayat (2020) find that investor sentiment measure constructed based on Google search volume outperforms the predictability of other proxies5.

II. B. Recent Literature on COVID-19

This section summarizes the recent literature on the effect of the COVID–19 pandemic on financial markets both in the US and internationally. Baker et al. (2020) and Pagano et al. (2020) find that during COVID–19 pandemic, government lockdowns and social distancing practice have a significant effect on the stock market. Baker et al. (2020) also show that the U.S. stock market reacted more forcefully to COVID–19 than to previous pandemics, in-

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4 The details of the construction of our five sentiment indices corresponding to five categories of news are given in Appendix B.

5 Garcia (2013) and Shapiro and Wilson (2021) use textual analysis of print media and newswire to construct a sentiment index to capture the tone of an article in print and on newswire. Those measures are constructed based on word dictionaries that are quite arbitrary and prone to errors. Specifically, Garcia (2013) finds that the sentiment measure’s predictability of stock returns is only concentrated in recessions. Moreover, our indices are available on a daily basis and reflect the information shocks in a more timely fashion.
cluding the Spanish Flu. Pagano et al. (2020) show that security markets price the effect of social distancing; the firms that are more resilient to social distancing outperform firms with lower resilience during the COVID-19 outbreak. Our paper constructs sentiment proxies for broader categories of news namely, COVID, Market, Lockdown, Banking, and Government relief efforts. We also study the price dynamics in the stock and option markets to five different sentiment indices.

Alfaro et al. (2020) and Bretschfer et al. (2020) have shown that COVID-19 had a large impact on the stock market during the early pandemic outbreak. Alfaro et al. (2020) find that unexpected changes in the trajectory of COVID-19 infections predict US stock returns. Bretschfer et al. (2020) show that firms belonging to labor-intensive industries and those located in counties with large mobility declines have worse stock performance during the early COVID-19 outbreak.

Several papers discuss the underreaction in the US financial markets in the early stages of the pandemic. Cheng (2020) documents that the VIX futures prices underreacted compared to the VIX index in March 2020. Consistent with the lack of response of the option-implied measures, Jackwerth (2020); Hanke et al. (2020) and Ampudia et al. (2020) find late or declining response of option-implied densities to COVID-19. On the contrary, Breugem et al. (2020) find that the US equity implied skewness and CDS spread of less pandemic-resilient economic sectors increased ahead of the market index.

Regarding the banking sector, Li et al. (2020) study bank’s liquidity demand and finds that banks faced the largest increase in liquidity demands during March 2020, which is the onset of the COVID-19 pandemic. Acharya et al. (2021) find that stock prices of banks with large ex-ante exposures to undrawn credit lines as well as large ex-post gross drawdowns decline more than those without.

As to international evidence, Guo et al. (2021) show COVID-19 epidemic increases the number of contagion channels in the international financial system, Zhang et al. (2020) find that global stock markets linkages display different patterns before and after the pandemic announcement. Ramelli and Wagner (2020) find that at the beginning of the pandemic internationally oriented firms underperformed. As the virus spread to Europe and the United States, corporate debt and cash holdings emerged as important value drivers.

III. A Model of behavioral traders and sophisticated traders

Following Samuelson (1958) and De Long et al. (1990), we present a simple one-period (two date) theoretical model of an asset market in which behavioral investors and sophisticated investors trade. During periods of severe stress in the capital market, different elements of news that comes out also maps into different levels of sentiment based on economic and non-economic factors.

We model the behavioral traders as being susceptible to making perceptual errors correlated with the degree of market sentiment that is associated with different types of news. We also assume that there is a larger presence of behavioral traders in the stock market and prominent presence of sophisticated traders in the option market. We derive the equilibrium prices and implications for the effect of five different categories of news and sentiment intensity on the volatility dynamics in the stock market and option market. We construct measures of sentiment levels directly from Google search data and use it to test our empirical predictions.

In our model, there are two types of agents: sophisticated investors (denoted s) who have rational expectations and behavioral traders (denoted b). We assume that agents of a given type are identical. We denote by $\theta_s, \theta_b \in (0, 1)$, the measure of behavioral traders and $(1 - \theta_s)$ as the measure of sophisticated traders in our model. Both types of agents choose their portfolios at time $t$ to maximize their perceived expected utility given their own beliefs about the ex-ante mean of the distribution of the price of $\mu$ at time $(t + 1)$. The price of $\mu$ at time $t$ is $p_t$. The economy contains two assets that pay identical dividends. One of the assets, the safe asset $s$, pays a fixed real dividend $r$. The other asset, the risky asset $\mu$, always pays the same fixed real dividend $d$. We also assume that the supply of the risky asset at time $t$ is exogenously specified to be $\psi$.

We assume that different types of news shocks arise at different points in time related to the COVID-19 pandemic that can affect the state of the economy and security prices. Different types of news give rise to different levels of market sentiment denoted by $k_t$ in period $t$. We assume that $k_t$ is uniformly distributed on the interval $[-h, +h]$. $k_t$ depends not only on the magnitude and direction of the news. It also depends on the attention paid to it by the market participants and their response to the news in which non-economic factors such as fear and emotion may have an important role. The realized value of $k_t$ can be large or small, positive or negative.

In our model $k_t$ plays an important role in the volatility dynamics in the stock market and the option market. The representative behavioral traders make perceptual errors about $p_{t+1}$ that is a function of the realized value of $k_t$. The behavioral trader in period $t$ misperceives the expected price of the risky asset as $p_{t+1} + \epsilon_t$. $\epsilon_t$ is normally distributed with a mean $k_t$ and variance $\sigma^2_t$. This assumption implies that when $k_t$ is positive, $P(\epsilon_t \geq 0)$ is higher than $P(\epsilon_t < 0)$. Similarly, when $k_t$ is negative, $P(\epsilon_t < 0)$ is higher than $P(\epsilon_t \geq 0)$. The nature of the correlation between $k_t$ and $\epsilon_t$ makes the behavioral traders be sentiment traders. When the economy-wide shock $k_t$ is positive, they tend to make positive errors with a higher likelihood. When the economy-wide shock $k_t$ is negative, they tend to make negative errors with a higher likelihood. When the shock $k_t$ is positive, the price $p_{t+1}$ moves in the positive direction, and since the sign of $\epsilon_t$ is also positive with a high likelihood, we can characterize the misperceptions of the behavioral trader to be an overreaction to the exogenous shock $k_t$. Whereas the sophisticated traders can accurately incorporate the news into $p_{t+1}$, the behavioral traders can only do so with an error $\epsilon_t$.

Each agent’s utility is a constant absolute risk aversion function of wealth at time $(t + 1)$:

$$U = -e^{-\gamma \theta_s \omega}$$

(1)

where $\gamma$ is the coefficient of absolute risk aversion. With normally distributed returns to holding a unit of the risky asset, maximizing the expected value of (1) is equivalent to maximizing:

$$\hat{\omega} - \gamma \sigma^2_\omega$$

(2)

where $\hat{\omega}$ is the expected final wealth, and $\sigma^2_\omega$ is the one-period-ahead variance of wealth. The sophisticated trader and behavioral trader choose their holdings $\lambda^2_\omega$ and $\lambda^2_b$ of the risky asset $\mu$ to maximize their expected utility. The sophisticated investor chooses her holding $\lambda^2_\omega$ of the risky asset $\mu$ to maximize:

$$E[U] = U_c + \lambda^2_\omega[d + p_{t+1} - (1 + r)p_t] - \gamma (\lambda^2_b \epsilon_t + \sigma^2_{\epsilon_{t+1}})$$

(3)

where $U_c$ is a function of first-period labor income, and $\sigma^2_{\epsilon_{t+1}} = E[(\epsilon_{t+1} - p_{t+1})^2]$ is the one-period variance of $p_{t+1}$. Similarly, the

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6 We are implicitly assuming that behavioral traders know how to factor the effect of future price volatility into their calculations of values. This assumption is made for simplicity. Similar result can be shown using a more complicated model that parameterizes behavioral traders’ beliefs by their expectations of future prices, not by their miscalculations of future returns. The thrust of the results would be the same. See De Long et al. (1990) who make a similar assumption in a similar setting.
behavioral trader chooses her holding $\lambda_i^b$ of the risky asset $\mu$ to maximize:

$$E[U^b] = c_0 + \lambda_i^b \left[d + px_{t+1} - (1 + r)p_t\right] - \gamma(\lambda_i^b)^2(\sigma_{p_{t+1}}^2) + \lambda_i^b(\varepsilon_t)$$

(4)

The maximal holding of the sophisticated trader can be shown to be:

$$\lambda_i^b = \frac{d + px_{t+1} - (1 + r)p_t}{2\gamma(\sigma_{p_{t+1}}^2)}$$

(5)

Similarly, the maximal holding of the behavioral trader can be shown to be:

$$\lambda_i^b = \frac{d + px_{t+1} - (1 + r)p_t}{2\gamma(\sigma_{p_{t+1}}^2)} + \frac{\varepsilon_t}{\theta}$$

(6)

Our model shows that behavioral traders would optimally hold a different amount $\lambda_i^b$ of the risky asset $\mu$ given the error $\varepsilon_t$ that they make in the expected price $p_{t+1}$ (which in turn, depends on the sentiment level $k_t$ that results from the exogenous news shock). In other words, the behavioral traders believe that the expected price of $\mu$ at $(t + 1)$ is $(px_{t+1} + \varepsilon_t)$. When $k_t$ is positive, $\varepsilon_t$ is positive on average and $\lambda_i^b$ is, on average, larger than $\lambda_i^s$.

Now we can examine the influence of the behavioral traders on the current equilibrium price $p_t$. If the behavioral traders were not present in the economy, the price $p_t$ would satisfy $\theta(\lambda_i^r + \lambda_i^b) = \psi$, equivalently, $\lambda_i^r = \psi / \theta$, where $\psi$ is the supply of the risky asset. In this case, the equilibrium price would be:

$$p_t^r = \frac{d + px_{t+1} - 2\gamma(\sigma_{p_{t+1}}^2)\psi}{1 + r}$$

(7)

In the presence of behavioral traders, the market equilibrium price can be derived:

$$d + px_{t+1} - 2\gamma(\sigma_{p_{t+1}}^2)\psi + \frac{\theta\psi}{\theta} = \psi$$

$$p_t^b = \frac{d + px_{t+1} - 2\gamma(\sigma_{p_{t+1}}^2)\psi + \theta\psi}{1 + r}$$

(9)

(10)

By comparing Eqs. (7) and (10), we can see $p_t^b$ is on average higher than $p_t^r$ when $k_t$ is positive. Again, by comparing Eqs. (7) and (10), we can see that $p_t^b$ is on average lower than $p_t^r$ when $k_t$ is negative. In other words, the overreaction of the behavioral traders creates an imbalance in the total excess demand such that the current equilibrium prices overreact to the sentiment shocks, $k_t$. The resulting volatility of $px_{t+1}$ can be derived to be:

$$\sigma_{p_{t+1}}^2 = \frac{d + px_{t+1} - (1 + r)p_t}{2\gamma\psi} + \frac{\theta\varepsilon_t}{2\gamma\psi}$$

(11)

Eqs. (10) and (11) specify the equilibrium price $p_t^b$ at time $t$ and the price dynamics through the volatility of $px_{t+1}$, in terms of $k_t$, the nature of the sentiment shocks and, $\varepsilon_t$, the perceptual errors made by the behavioral traders as well as $\theta$, the participation level of the behavioral traders in the relevant market. We derive our empirical predictions relating the volatility dynamics in the stock market and the option market based on Eqs. (10) and (11). Our empirical test of these hypotheses will use empirical proxies of the relevant factors, $\theta$, $k_t$, and $\varepsilon_t$. We provide some details of our characterization of $\theta$, $k_t$, and $\varepsilon_t$.

In our model, we envisage the following steps through which news shocks move prices: First, news belonging to different types of COVID information is released. Different types of news may contain different degrees of incremental information. Agents in the economy pay different levels of attention to the news items and respond with varying intensity to the news depending on not only its importance to economic factors but also based on non-economic factors such as fear, emotion, and excitement. They are also influenced by the reaction of social media in their networks. This process results in $k_t$ that stands for the sentiment level resulting from the news shock. We model $k_t$ as directly influencing the direction and magnitude of the perceptual errors $\varepsilon_t$, made by the behavioral traders, $\varepsilon_t$ is a function of $k_t$, since $\varepsilon_t$ is normally distributed with a mean $k_t$ and variance $\sigma^2_t$. Other than through this assumption, we do not model the process by which $k_t$ the sentiment level is generated by the news nor the process by which the behavioral traders make their perceptual errors as a function of $k_t$. However, we construct empirical proxies for sentiment levels $k_t$ directly and use them in our empirical test. Using Google search data, we construct empirical measures of sentiment levels corresponding to different types of COVID-related information shocks during the COVID-19 period from January 21, 2020 to June 8, 2020.

The changes in the sentiment levels $k_t$ can result from different types of new information that is related to COVID. It may be medical information, the impact of COVID on the economy, banking, or capital markets, or information about the legislative success of the government relief efforts. It can also be new information related to the degree to which the economy would be shut down. We believe that such COVID-related information shocks, whether they are directly or indirectly related to economic forces, will affect the security prices (stocks and options). As discussed above, we have chosen to model different types of news leading to different levels of sentiment $k_t$, which in turn would affect prices in the stock and option market. Rather than working with measures of news content and its direction, we will work directly with indices of $k_t$ corresponding to five categories of news and therefore five categories of sentiment indexes.

One of the contributions of our paper is to directly construct a proxy for $k_t$ based on Google search information related to the five different categories of news shocks. Recall that the perceptual errors made by the behavioral traders is directly related to the sentiment intensity $k_t$ corresponding to different categories of COVID information. In addition, the degree of presence of the behavioral traders, $\theta$, would affect the price dynamics in stock and option market. Motivated by the prior literature, (See, e.g., Lemmon and Ni (2014)), we will assume that $\theta$ is lower in the options market.7 The behavioral traders will overreact to high sentiment COVID news as argued above in Section III. For certain categories of news shocks with a low $k_t$ value, the trading response of behavioral traders will be delayed.

Our empirical strategy is to construct five sentiment indexes based on five categories of news related to COVID: (1) COVID index, based on a database of search items that contain health and medical information that are typically expected to have an extremely negative effect on security prices, (2) Market index, based on a dictionary of search items that contain typically negative news on security prices and market reactions (especially during March 2020), (3) Lockdown index, based on a dictionary of search

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7 Lemmon and Ni (2014) finds that trades in index options are motivated by hedging demand of sophisticated investors. However, individual stock option and the underlying stock trading are motivated by the hedging demand of individual investors and they are heavily influenced by market sentiment.
items that contain typically negative news related to economic downturn and consequent market declines, (4) Government relief efforts index, based on a dictionary of search items that contain positive or neutral news reflecting ups and downs in the progress of the legislative success of relief efforts, and (5) Banking index, based on a dictionary of search items regarding the effectiveness of central bank initiatives and bank policies to remedy the effect of the pandemic on the economy. For details of the construction of the five indices, see Appendix B. See the Appendix C for the five dictionaries of words used.

The different categories of news shocks will produce a corresponding sentiment shock $k_t$ that, in turn, will lead to misperceptions on the part of the behavioral traders. Recall our assumption that the participation of the behavioral traders is higher in the stock market. On the other hand, the participation of the sophisticated traders is comparatively higher in the option markets. We also assume that the sophisticated traders are better able to map the payoff relevance of the different types of news and related indices into security prices. Based on the characterization of the equilibrium price changes in Eqs. (10) and (11), we hypothesize the effect of our five sentiment indices on discontinuous jumps in (1) the VIX index (computed from portfolios of S&P 500 index option prices), (2) the volatility of the S&P 500 index, and (3) the volatility of S&P 500 Banks index.

In formulating our hypothesis on the discontinuous jumps in the different volatility measures, we consider (1) the degree of participation of the behavioral traders, and (2) the nature of the sentiment shocks. The first three categories of sentiment shocks affect the price dynamics significantly leading to higher jump volatility. Monetary policy efforts (as reflected in banking news) could also move market prices. However, government relief efforts that go through changing vicissitudes in the legislature may not have any immediate effect on jump volatility. As a matter of fact, successful government relief efforts can play a role in mitigating the negative effects of COVID news, market news, and lockdown news. As a result, a higher sentiment level about government relief efforts can reduce jumps in the VIX index.

**Hypothesis 1. COVID index, Market index, and Lockdown index will increase the jump component of the VIX index. Government relief effort index will reduce the jump component of the VIX index.**

We also explore how the dynamics of prices in the stock market will be affected by the sentiment shocks that accompany the five different categories of news during the COVID period. The dynamics of prices in the stock market will be influenced by the relatively higher participation of behavioral traders including individual traders. Compared to the sophisticated traders, the behavioral traders are less accurate in incorporating the payoff implications of the different categories of news. In some cases, they are only able to learn about the price implications of certain types of news with a delay. We examine the price dynamics in the stock market based on the jumps in the realized volatility of the S&P 500 index and S&P 500 Banks index. We hypothesize that the behavioral traders do realize the importance of COVID index, Market index and Government relief efforts index. As discussed before, the first two news categories are dominated by bad news and serve to amplify the jumps in the stock market volatility. Government relief efforts, on the other hand, provides an offsetting factor that has a mitigating effect on the jumps in the realized stock market volatility. The reaction of the behavioral traders to the sentiment indices corresponding to banking news and lockdown news also differs from that of the sophisticated traders. The response of the behavioral traders to these variables are muted compared to that of the sophisticated traders. Sometimes, the behavioral traders either underreact or overreact to the lockdown news and banking news for a few days before they calibrate a balanced response. We hypothesize that an appropriate and significant response to such news may happen with a delay.

**Hypothesis 2. COVID index and Market index will increase the jump component of the realized volatility of S&P 500 index and S&P 500 Banks index. Government relief efforts index reduces the jump component of the realized volatility of S&P 500 index and S&P 500 Banks index. Banking index and Lockdown index are complex and therefore have no contemporaneous effect on the jump component of the realized volatility of S&P 500 index and S&P 500 Banks index.**

**Hypothesis 3. In addition to the predictions in Hypothesis 2, we predict that Banking index and Lockdown index when lagged by a certain number of days, will have a significant negative contribution to the jump component of the realized volatility of S&P 500 index and S&P 500 Banks index.**

V. COVID-19 pandemic

In this section, we present the summary statistics of the COVID-19 pandemic. Death rate data comes from cases confirmation by state authorities. Daily S&P 500 index level data comes from Yahoo.com. VIX data is obtained through Chicago Board Options Exchange (CBOE) website. Major events data comes from Department of Defense website.

The summary statistics of US COVID-19 pandemic, S&P 500 and CBOE VIX index data during the data period January 21, 2020 to June 8, 2020 are reported in Table 1 Panel A and that during the data period January 21, 2020 to January 31, 2021 are reported in Table 1 Panel B.

From Table 1, the cumulative confirmed cases figure grows from 1 case on January 21, 2020 to 1,934,828 cases on June 8, 2020 and 24,384,746 cases on January 31, 2021. Given the population base in 2019 of 328.2 million, about 0.59% of the whole US population has been officially confirmed to have contracted the COVID-19 and that percentage has gone up to 7.43% as of January 31, 2021. Multiple studies around the world has estimated that around 50% of the people who contracted the COVID-19 aren’t aware they have the virus. This means that about 14.86% of the whole US population is estimated to carry the COVID-19 as of January 31, 2021.

The daily new confirmed COVID-19 cases continuous growth rate is 10.63% (11.22% for geometric growth rate). Daily new COVID-19 deaths continuous growth rate is 15.12% (16.23% for geometric growth rate). Both daily new cases growth rate and new death growth rate are high, indicating that that the COVID-19 pandemic is still growing at an alarming speed as of June 8, 2020. These growth rates fall significantly if we extend the sample period to January 31, 2021 as can be seen from Panel B of Table 1.

Further, during the data period from January 21, 2020 to June 8, 2020, S&P 500 index, S&P 500 Banks index and CBOE VIX index
Table 1
Summary Statistics for US COVID-19 Pandemic, S&P 500 index, S&P 500 Banks index, and CBOE VIX index

Table 1 presents the summary statistics for COVID-19 pandemic related statistics along with S&P 500 index, S&P 500 Banks index and CBOE VIX data. Data sample period is from January 21, 2020 to June 8, 2020. Panel A reports COVID-19 cases, deaths and recovered data is obtained from the state authorities. Both the continuous daily growth rate and geometric daily growth rate\(^2\) are estimated using the sample period from March 2, 2020 to June 8, 2020. Panel B reports the Pearson correlation coefficient of the US COVID-19 pandemic statistic, S&P 500 index, S&P 500 Banks index, and CBOE VIX index. The figures in Panel B are reported in percentages.

Panel A: Data Period from January 21, 2020 to June 8, 2020

|                  | Confirmed New Cases | Confirmed Cumulative Cases | New Deaths | Cumulative Deaths | New Recovered | Cumulative Recovered | S&P 500 Index | S&P 500 Banks Index | CBOE VIX Index |
|------------------|---------------------|----------------------------|------------|------------------|---------------|----------------------|---------------|---------------------|----------------|
| Minimum          | 0                   | 1                          | 0          | 0                | 0             | 0                    | 2,237         | 192.4               | 12.85          |
| 25th Quantile    | 2                   | 14                         | 0          | 0                | 0             | 0                    | 6             | 6                   | 225.7          |
| Median           | 19,662              | 160,686                    | 821        | 2,985            | 1,217         | 5,506                | 2,930         | 244.4               | 33.04          |
| Mean             | 19,947              | 559,526                    | 1,071      | 29,432           | 7,974         | 125,328              | 2,942         | 272.6               | 35.33          |
| Standard Deviation | 24,491.35          | 666,123.6                  | 1,324.53   | 38,108.6         | 17,204.49     | 220,824.30           | 223.82        | 58.86               | 14.77          |
| 75th Quantile    | 27,535              | 1,172,921                  | 1,858      | 62,593           | 9,046         | 188,068              | 3,226         | 351.5               | 43.35          |
| Max              | 118,189             | 1,934,828                  | 6,932      | 103,902          | 95,847        | 773,480              | 2,286         | 368.6               | 82.69          |
| Continuous Daily Growth Rate (March 2 to June 8) | 10.63% | 15.12% | 8.15% | 14.14% | 13.56% | 16.47% | 0.07% | -0.12% | -0.37% |
| Geometric Daily Growth Rate (March 2 to June 8) | 11.22% | 16.32% | 8.49% | 15.19% | 17.90% | 17.90% | 0.07% | -0.12% | -0.37% |

Panel B: Data Period from January 21, 2020 to January 31, 2021

|                  | Confirmed New Cases | Confirmed Cumulative Cases | New Deaths | Cumulative Deaths | New Recovered | Cumulative Recovered | S&P 500 Index | S&P 500 Banks Index | CBOE VIX Index |
|------------------|---------------------|----------------------------|------------|------------------|---------------|----------------------|---------------|---------------------|----------------|
| Minimum          | 0                   | 1                          | 0          | 0                | 0             | 0                    | 2,237         | 192.4               | 12.85          |
| 25th Quantile    | 2                   | 14                         | 0          | 0                | 0             | 0                    | 6             | 6                   | 225.7          |
| Median           | 24,222              | 854,522                    | 812.8      | 43,578           | 6,221         | 85,454               | 3,044         | 241.9               | 22.94          |
| Mean             | 21,146              | 6,095,715                  | 1,589.9    | 143,607          | 62,306        | 3,728,249            | 3,257         | 270.8               | 29.69          |
| Standard Deviation | 24,491.35          | 666,123.6                  | 1,324.53   | 38,108.6         | 17,204.49     | 220,824.30           | 223.82        | 26.10               | 14.77          |
| 75th Quantile    | 132,005             | 8,520,034                  | 2,124.5    | 213,364          | 88,052        | 5,844,859            | 3,486         | 303.1               | 33.05          |
| Max              | 806,182             | 24,384,746                 | 8,911      | 413,371          | 610,706       | 16,199,572           | 3,855         | 368.6               | 82.69          |
| Continuous Daily Growth Rate (March 2 to January 31) | 3.55% | 3.59% | 2.72% | 4.80% | 6.60% | 6.21% | 0.08 | -0.01% | -0.00 |
| Geometric Daily Growth Rate (March 2 to January 31) | -3.62% | 5.75% | 2.76% | 4.92% | 4.71% | 6.41% | 0.08 | -0.01% | -0.00 |

Correlation Coefficient (%)

|                  | S&P 500 Index | S&P 500 Banks Index | CBOE VIX Index |
|------------------|---------------|---------------------|----------------|
| S&P 500 Index    | 56.59         | 80.25               | -24.50         |
| S&P 500 Banks Index | 25.74 | 35.73               | -33.29         |
| CBOE VIX Index   | -24.50        | -33.29              | -15.97         |

are volatile with standard deviation of 223.82, 58.86, and 14.77, respectively. The CBOE VIX index reached 82.67 on March 16, 2020. This is highest VIX index level in CBOE VIX history, 1.81 percentage points higher than the second highest record of the CBOE VIX index (80.86) on November 20, 2008.

To visualize the trend of the alarming data series, we plot the COVID-19 pandemic data, S&P 500 index level and CBOE VIX index in the following Fig. 1.

In the above Fig. 1, Panel A plots the S&P 500 index level and the VIX index with major global and domestic events in vertical dashed lines. We observe that the VIX index and the S&P 500 index exhibit the reverse trend. This is not surprising given the correlation coefficient between the VIX index and S&P 500 index is -93.77% reported in Panel B of Table 1. The WHO announcements are plotted as in dashed green vertical lines and the US government- actions are plotted as the blue dashed vertical lines. It can be observed that the VIX spikes (S&P 500 plunges) after three major events. The first event is when cases spike in Italy and signaling an outbreak of COVID-19 on February 21, 2020. Followed by the President of US banned travel from Europe and WHO declared COVID-19 as a global pandemic on March 11, 2020. Followed by the President of US declared a national emergency on Friday, March 13, 2020. The VIX spiked to the highest level in history the next trading day on Monday, March 16, 2020.

Panel B plots the S&P 500 index level and the VIX index during the updated data period from January 21, 2020 to January 31, 2021. Similar to Panel A, Major global and domestic events in vertical dashed lines. The WHO announcements are plotted as in dashed lines.
Panel A: Data Period from January 21, 2020 to June 8, 2020

Panel B: Data Period from January 21, 2020 to January 31, 2021

Fig. 1. COVID-19 Pandemic and Major Events
Plot of COVID-19 pandemic cases, major events and stock market reaction from January 21, 2020 to June 8, 2020. This figure compares the S&P 500 index daily level (in black solid line on the left vertical axis) and CBOE VIX daily value (in red solid line on the right vertical axis). Some major COVID-19 related events are also plotted. WHO announcements and declarations are represented in dashed green vertical line and US governmental actions are plotted in blue dashed vertical line.

green vertical lines and the US governmental actions are plotted as the blue dashed vertical lines. It can be observed that in the second half of 2020 and January 2021, the S&P 500 index spikes and the VIX index stabilizes due to the combining impact of the US General election (Election Day and Inauguration Day) and the positive COVID vaccine information (U.S. Food and Drug Administration issues Emergency Use Authorization for Pfizer and Moderna COVID-19 vaccines).

VI. Empirical results

VI. A. Volatility jumps

VI. A.1. Jump component in the VIX index

Following Martin (2011); Du and Kapadia (2012), and Chow et al. (2021), we use the VIXJ estimation methodology (See details in Appendix A) to extract the jump component in the VIX index during the COVID-19 pandemic period. We plot this jump tail component in VIX index along with the VIX index as a comparison in Fig. 2.

Because of the third moment is negative in our sample, the estimated VIXJ is negative. We take the absolute value of the VIXJ and plot it in comparison with the VIX index. In Fig. 2, the absolute value of VIXJ is plotted in red solid line with the magnitude on the right vertical axis. The VIX index is plotted in black solid line with the magnitude on the left vertical axis. We observe that the VIXJ spikes before the VIX index reached the highest level in history (specifically, on Monday, March 16, 2020). This seems to indicate that VIXJ leads the VIX movement, especially when the market is volatile.

VI. A.2. Jump component in the S&P 500 index and S&P 500 banks index

We follow Andersen and Bollerslev (1998) and Andersen et al. (2001) to estimate the realized volatility of S&P 500 index. Specifically, we estimate the realized volatility for the S&P 500 index and S&P 500 Banks index by summing the 78 intraday five-minute squared log returns covering the normal trading hours from 9:30 am to 4:00 pm along with the close-to-open overnight return.

We decompose the realized volatility for both S&P 500 index and S&P 500 banks index into a continuous variation (CV) component and a jump variation component (JV). The continuous variation (CV) component is estimated by threshold bi-power variation (TPBV) as in equation (A.7) in Appendix A. We plot the daily S&P 500 index realized volatility and the daily S&P 500 banks index realized volatility and their respective estimated jump variation (JV) component and continuous variation (CV) component in the following Fig. 3.

In both Panel A and Panel B of Fig. 3, we observe the JV component (red solid line) captures the daily S&P 500 index and S&P 500 Banks index realized volatility spikes, especially in mid-March, when the market becomes extremely volatile. On the contrary, the CV component (green solid line) is rather smooth, especially for the S&P 500 index and S&P 500 Banks index realized volatility in Panel A. These trends confirm the notion that CV captures the continuous smooth variation of the total realized volatility.
VI. A.3. Summary statistics of volatility jumps

We report the summary statistics for the jumps estimated in the previous sections in the following Table 2. VIXJ (column (1)) magnitude varies from 0.002 to 8.6 with a standard deviation of 1.3. This indicates that VIXJ is a significant component of VIX, especially when the VIX level is high. Recall that the VIXJ is negative due to the sign of skewness, indicating that the VIX index significantly underestimate the market risk-neutral volatility during volatile market conditions. In columns (2) and (3), both the jumps in S&P 500 index and S&P 500 Banks index realized volatility are smaller in magnitude (reported in basis point), S&P 500 Banks index realized volatility jumps in column (3) is relatively more volatile with standard deviation of 14.239, as opposed to 13.329 in column (2).

VI. B. Google search sentiment indices

We construct the five Google sentiment indices as in Appendix B. As a result, we obtain five daily sentiment indices based on Google Search volume data in Google Trends database. We plot the daily variations of Google search COVID sentiment index (COVID), Google search market sentiment index (Market), Google search lockdown sentiment index (Lockdown), Google search banking sentiment index (Banking), and Google search gov-
Table 2 presents the summary statistics for the estimated jumps in the VIX index jumps, S&P 500 realized volatility jumps, and S&P 500 banks realized volatility jumps. Column (1) contains the summary statistics for the jump-tail component (VIXJ) within the VIX index. Due to the negative sign of the VIXJ, the numbers are based on the absolute value of the VIXJ. Columns (2) is the daily S&P 500 index jump variation component (JV). Columns (3) is the daily S&P 500 banks index jump variation component (JVB). All estimates in Columns (2) and (3) are reported in basis point. Data sample period is from January 21, 2020 to June 8, 2020.

|          | VIXJ | JV  | JVB  |
|----------|------|-----|------|
| Minimum  | 0.002| 0.000| 0.000|
| 25\(^{th}\) Quantile | 0.438| 0.139| 0.359|
| Median   | 1.382| 0.792| 3.147|
| Mean     | 1.536| 5.008| 14.239|
| Standard Deviation | 1.300| 13.329| 34.864|
| 75\(^{th}\) Quantile | 2.082| 3.559| 13.038|
| Max      | 8.600| 87.426| 267.088|

Fig. 4. Google Search Sentiment indices for COVID, Market, Lockdown, Banking, and Government Relief Efforts

Figure of daily google search sentiment indices for COVID, market, lockdown, banking, and government relief efforts from time period January 21, 2020 to June 8, 2020. Google search COVID sentiment index is plotted in solid black line, Google search market sentiment index is plotted in solid green line, Google search lockdown sentiment index is plotted in solid pink line, Google search banking sentiment index is plotted in solid blue line, Google search government relief efforts sentiment index is plotted in solid yellow line.

From Fig. 4, we can see that both the Market sentiment index (green), the COVID sentiment index (black) and the Lockdown sentiment index (pink) spike in mid- to late-March, whereas the Banking sentiment index (blue) and the Government relief sentiment index (yellow) spike in mid- to late-April. This indicates that the unexpected COVID, lockdown, market fluctuation news in mid-March draws the tremendous amount of public attention during the same time period. The public attention subsequently switched to unemployment and government relief packages (through banking and government relief efforts related Google search items) in US in late April.

VI. C. Relationship between volatility jumps and sentiment indices

In this section, we explore the relationship between the VIX index jumps (VIXJ), S&P 500 index realized volatility jumps (JV), S&P 500 Banks index realized volatility jumps (JVB) and the five Google search sentiment indices. We standardize all eight variables by subtracting their means and dividing by their standard deviations. Further, due to the high correlation among the five Google search sentiment indices, we orthogonalize them. We end up with three standardized market volatility jump variables, namely VIXJ\(^s\), JV\(^s\) and JVB\(^s\), along with five standardized and orthogonalized Google sentiment jump variables, namely, COVID\(^s\), Market\(^s\), Lockdown\(^s\), Banking\(^s\), and Govt. Relief\(^s\).

Following Bekkert and Hoerova (2014), we have added several macroeconomic control variables in our regression to control for the macroeconomic conditions during the data period. The three macroeconomic control variables are the logarithm of the dividend yield, denoted by log(DY); the credit spread—the difference between Moody’s BAA and AAA bond yield indices, denoted by CS; and the term spread—the difference between the 10-year and the 3-month Treasury yields, denoted by TS.

We present the Pearson correlation coefficients among these eight variables along with the three control variables in the following correlation matrix in Table 3.

In Table 3, all five Google search sentiment index variables are uncorrelated with each other. This is not surprising because these Google search sentiment index variables has been orthogonalized and therefore they are uncorrelated with each other. The standardized VIX jump (VIXJ\(^s\)) is correlated with S&P 500 index realized volatility jump (JV\(^s\)) and S&P 500 Banks index realized volatility jump (JVB\(^s\)) with correlation coefficients of 45.27% and 43.46%, respectively. S&P 500 index realized volatility jump (JV\(^s\)) and S&P 500 Banks index realized volatility jump (JVB\(^s\)) are highly correlated with each other with a correlation coefficient of 92.51%. The correlation coefficients of the three volatility jump variables are considered low except for the that between JV\(^s\) and JVB\(^s\). This is not surprising because the banking sector is a part of the overall market (proxied by the S&P 500 index). This indicates that the three volatility jump variables behave different and is consistent with our theoretical predictions in Section IV. Furthermore, the Google search sentiment index, Govt. Relief\(^s\), is negatively correlated with S&P 500 index realized volatility jump (JV\(^s\)) and S&P 500 Banks index realized volatility jump (JVB\(^s\)), with correlation coefficients of -24.03% and -21.79%, respectively. The three control variables have a low correlation with our eight main variables.
Table 3
Correlation Matrix of Volatility Jumps and Google Search Sentiment Indices
This table presents the correlation matrix of the standardized VIX index jumps (VIXJ), S&P 500 index realized volatility jumps (JV), and the five orthogonalized Google search indices (COVID, Market, Lockdown, Banking, and Govt. Relief) along with three macroeconomic control variables. The three macroeconomic control variables are log(DY) (the logarithm of the dividend yield), CS (the credit spread-the difference between Moody’s BAA and AAA bond yield indices), and TS (the term spread-the difference between the 10-year and the 3-month Treasury yields). All variables are expressed in annualized percentages. The correlation coefficient is statistically significant at the 1%, 5%, and 10% levels, respectively. * indicates 1% significance, ** indicates 5% significance, and *** indicates 10% significance. Adj. R² is the adjusted coefficient of determination. Data sample period is from January 21, 2020 to June 8, 2020.

|       | VIXJ | JV | JVB | COVID | Market | Lockdown | Banking | Govt. Relief | Log(DY) | CS | TS |
|-------|------|----|-----|-------|--------|----------|---------|--------------|---------|----|----|
| VIXJ  |      |    |     |       |        |          |         |              |         |    |    |
| JV    | 0.27 | 0.21|      |       |        |          |         |              |         |    |    |
| JVB   | 0.47 | 0.66|      |       |        |          |         |              |         |    |    |
| COVID | 0.47 | 0.66|      |       |        |          |         |              |         |    |    |
| Market| 0.47 | 0.66|      |       |        |          |         |              |         |    |    |
| Lockdown| 0.29 | 0.16|      |       |        |          |         |              |         |    |    |
| Banking| 0.08 | -0.08|     |       |        |          |         |              |         |    |    |
| t-statistic | -0.71 | -0.21 |      |       |        |          |         |              |         |    |    |
| Govt. Relief | -0.11 | -0.13 |      |       |        |          |         |              |         |    |    |
| t-statistic | -1.36 | -1.98 |      |       |        |          |         |              |         |    |    |
| t-statistic | -0.99 | -3.16 |      |       |        |          |         |              |         |    |    |
| Log(DY) | 0.56 | -0.34 |      |       |        |          |         |              |         |    |    |
| t-statistic | -0.85 | -0.40 |      |       |        |          |         |              |         |    |    |
| NW t-statistic | 0.11 | -0.87 |      |       |        |          |         |              |         |    |    |
| Lockdown | 0.67 | -0.23 |      |       |        |          |         |              |         |    |    |
| Banking | 0.07 | 0.44 |      |       |        |          |         |              |         |    |    |
| t-statistic | 0.32 |      |      |       |        |          |         |              |         |    |    |
| t-statistic | 0.34 |      |      |       |        |          |         |              |         |    |    |
| t-statistic | 0.60 |      |      |       |        |          |         |              |         |    |    |
| t-statistic | 0.77 |      |      |       |        |          |         |              |         |    |    |
| t-statistic | 0.19 |      |      |       |        |          |         |              |         |    |    |
| t-statistic | 0.97 |      |      |       |        |          |         |              |         |    |    |
| t-statistic | 1.03 |      |      |       |        |          |         |              |         |    |    |
| t-statistic | 1.64 |      |      |       |        |          |         |              |         |    |    |
| Adj. R² | 0.04 |      |      |       |        |          |         |              |         |    |    |

We next conduct regression analysis on the relationship between volatility jumps and contemporaneous Google search sentiment indices. In Table 4 regression specification (1), four out of five Google search sentiment index variables, namely COVID, Market, Lockdown, and Banking, are statistically significant (except Govt. Relief) with New-West (1987) heteroskedasticity and autocorrelation corrected (HAC) t-statistic of 3.37, 5.65, 3.03, and 1.71, respectively. Whereas in regression specification (2) only the COVID and Market and Govt. Relief strongly statistically significant with Newey-West (1987) HAC t-statistic of 2.44, 3.62, and -3.16, respectively.

The jump component in the VIX index is increasing in the COVID index, Market index, Lockdown index, and Banking index. These results are consistent with Hypothesis 1. The COVID news, the market news, and lockdown news give rise to largely negative sentiment during the COVID-19 period and were reflected in the corresponding indices. These contributed significantly to jump volatility in the option market where the trading was sophisti-
Table 5

The Effect of Lagged Banking Index on Volatility Jumps in the VIX index, S&P 500 index and S&P 500 Banks index.

This table presents the regression analysis of the VIX index (VIXt), S&P 500 index realized volatility jumps (JVt), and S&P 500 Banks index realized volatility jumps (JVBt), the contemporaneous orthogonalized Google search indices (COVIDt−, Markett−, Lockdownt−, Govt. Relieft−), and the orthogonalized lagged Google search banking index (Bankingt−). The three macroeconomic control variables are log(DY) (the logarithm of the dividend yield), CS (the credit spread—the difference between Moody’s BAA and AAA bond yield indices), and TS (the term spread—the difference between the 10-year and the 3-month Treasury yields). All variables are expressed in annualized percentages. Column (1) is using the Google search indices (COVIDt−, Markett−, Lockdownt−, Govt. Relieft−) to explain the jumps in the VIX index (VIXt). Column (2) is using the Google search indices (COVIDt−, Markett−, Lockdownt−, Govt. Relieft−) to explain the jumps in S&P 500 index realized volatility jumps (JVt), and Column (3) is using the Google search indices (COVIDt−, Markett−, Lockdownt−, Govt. Relieft−) to explain the jumps in S&P 500 Banks index realized volatility jumps (JVBt). All variables have been standardized by subtracting its mean and dividing its standard deviation. Regression t-statistics are reported in brackets (round bracket). NW t-statistics: Newey-West (1987) t-statistics are reported in parentheses (square bracket). ** indicates 1% significance, *** indicates 5% significance, and * indicates 10% significance. Adj. R² is the adjusted coefficient of determination. Data sample period is from January 21, 2020 to June 8, 2020.

|                | (1) VIXt | (2) JVt | (3) JVBt |
|----------------|----------|---------|----------|
| COVIDt−        | 0.37     | 0.24    | 0.09     |
| t-statistic    | (4.02***)| (2.16**)| (0.71)   |
| NW t-statistic | [5.20**+]| [2.38**]| [0.68]   |
| Markett−       | 0.53     | 0.70    | 0.64     |
| t-statistic    | (8.70***)| (8.28**)| (7.99***)|
| NW t-statistic | [4.36**+]| [3.65**]| [3.33**+]|
| Lockdownt−     | 0.36     | 0.20    | 0.18     |
| t-statistic    | (4.40***)| (1.98*) | (1.64)   |
| NW t-statistic | [3.47**+]| [1.32]  | [0.86]   |
| Bankingt−      | 0.10     | -0.16   | -0.25    |
| t-statistic    | (1.05)   | [-1.35] | [-1.95]  |
| NW t-statistic | [1.03]   | [-2.79**]| [-3.09**]|**
| Govt. Relieft− | 0.01     | -0.21   | -0.26    |
| t-statistic    | (0.12)   | [-1.83*]| [-2.06]  |
| NW t-statistic | [0.12]   | [-2.53**]| [-2.86**]|***
| Log(DY)        | -0.06    | -0.33   | -0.67    |
| t-statistic    | (-0.08)  | [-0.37] | [-0.70]  |
| NW t-statistic | [-0.06]  | [-0.69] | [-1.19]  |
| CS             | -0.11    | 0.69    | 1.23     |
| t-statistic    | (-0.26)  | [1.28]  | [2.12**]|***
| NW t-statistic | [-0.31]  | [1.35]  | [1.86*]  |
| TS             | 0.47     | -0.95   | -0.94    |
| t-statistic    | (1.15)   | [-1.89*]| [-1.74]  |
| NW t-statistic | [1.72*]  | [-1.09] | [-0.86]  |
| Adj. R²        | 63.64%   | 45.99%  | 37.81%   |

Weaker. The involvement of banks and the central bank also seem to have contributed to jump volatility in the option market.

Now we turn to the jump components in S&P 500 index and S&P 500 banks index realized volatility. Here we find the jump components in S&P 500 index and S&P 500 banks index realized volatility increase in the COVID index and the Market index. High level of public attention and resulting panic gives rise to high values for COVID index and Market index, which in turn contributed to jump volatility. On the other hand, government relief efforts news provided a calming influence. Government relief efforts are usually targeted at relatively lower income families, individuals, and small businesses. The jump volatility was decreasing significantly in the Government relief efforts index. These findings are as predicted in Hypothesis 2.

VI. D. Learning from banking news and lockdown news?

In this section, we explore whether the behavioral traders learn from the price dynamics. In other words, our results in Table 4 indicate that while the Banking sentiment index contributes to jumps in the VIX index (in the option market), it is not considered by the equity traders in the stock market. A natural question is whether the behavioral traders learn about it gradually and incorporate it into their trading strategies with a delay.

We answer the above question by examining whether the lagged values of the Banking sentiment index have a significant effect in the jump volatility in the stock market. We explored lags of one day, two days, three days, four days, and five days. We find that the Banking index with a lag of 5 days has significant explanatory power in reducing the jump volatility. The results are displayed in Table 5.

In Table 5 regressions (2) and (3), the 5-day lagged Banking index significantly reduces the jump components of JV (the realized volatility jumps of the S&P 500 index) and JVB (the realized volatility jumps of the S&P 500 Banks index) with the Newey-West (1987) HAC t-statistic of -2.79 and -3.09, respectively. The negative sign of the coefficient is consistent with Hypothesis 3. Successful monetary policy initiatives could provide positive news for the economy. Nevertheless, banking information is complex and difficult to map into the price relevance of securities. The behavioral traders may have to learn from the price dynamics before they can formulate effective and balanced trading strategies. This was behind our prediction of a negative sign for the delayed contribution of the Banking index in the jump component of the realized volatility of the S&P 500 index and the S&P 500 Banks index.

The analysis of the lockdown news is similar to that of the banking news. The results are displayed in Table 6.

In regressions (2) and (3) of Table 6, the 5-day lagged Lockdown index significantly reduces the jump components of JV (the realized volatility jumps of the S&P 500 index) and JVB (the realized volatility jumps of the banking index) with the Newey-West (1987) HAC t-statistic of -1.73 and -2.71, respectively. Our results in Table 4 showed that the Lockdown index significantly increased the jump component in the VIX index, but it had no significant effect on the stock market volatility jumps. This is consistent with the sophisticated investors recognizing the negative impact of lockdowns on the economy and market prices. However, the behavioral traders learn the volatility patterns with a delay. The
Table 6
The Effect of Lagged Lockdown Index on Volatility Jumps in the VIX index, S&P 500 index and S&P 500 Banks index
This table presents the regression analysis of the VIX index (VIX\(i\)), S&P 500 index realized volatility jumps (J\(V^i\)), S&P 500 Banks index realized volatility jumps (J\(V^B\)), the contemporaneous orthogonalized Google search indices (COVID\(i\), Market\(i\), Banking\(i\), Govt. Relief\(i\)), and the orthogonalized lagged Google search banking index (Lockdown\(i\), Lockdown\(B\)). The three macroeconomic control variables are log(DY) (the logarithm of the dividend yield), CS (the credit spread-the difference between Moody’s BAA and AAA bond yield indices), and TS (the term spread-the difference between the 10-year and the 3-month Treasury yields). All variables are expressed in annualized percentages. Column (1) is using the Google search indices (COVID\(i\), Market\(i\), Lockdown\(i\), Banking\(i\), Govt. Relief\(i\)) to explain the jumps in the VIX index (VIX\(i\)). Column (2) is using the Google search indices (COVID\(i\), Market\(i\), Lockdown\(i\), Banking\(i\), Govt. Relief\(i\)) to explain the jumps in S&P 500 index realized volatility jumps (J\(V^i\)), and Column (3) is using the Google search indices (COVID\(i\), Market\(i\), Lockdown\(i\), Banking\(i\), Govt. Relief\(i\)) to explain the jumps in S&P 500 Banks index realized volatility jumps (J\(V^B\)). All variables have been standardized by subtracting its mean and dividing its standard deviation. Regression t-statistics are reported in brackets (round bracket). Newey-West (1987) t-statistics are reported in parentheses (square bracket). */***/ indicates 1% significance, ** indicates 5% significance, and * indicates 10% significance. Adj. \(R^2\) is the adjusted coefficient of determination. Data sample period is from January 21, 2020 to June 8, 2020.

|                  | (1) VIX\(i\) | (2) J\(V^i\) | (3) J\(V^B\) |
|------------------|---------------|---------------|---------------|
| COVID\(i\)      | 0.37          | 0.34          | 0.17          |
| t-statistic     | (-4.02***     | (3.02***      | (1.40         |
| NW t-statistic  | [5.15***       | [2.63***      | [0.98         |
| Market\(i\)     | 0.47          | 0.66          | 0.58          |
| t-statistic     | (6.43***      | (7.43***      | (5.97***      |
| NW t-statistic  | [6.35***       | [7.32***      | [3.26***      |
| Lockdown\(i\)   | 0.02          | -0.14         | -0.21         |
| t-statistic     | (0.19)        | (-1.43)       | (-1.91)*      |
| NW t-statistic  | [0.19]        | [-1.73*       | [-2.71**      |
| Banking\(i\)    | 0.20          | -0.06         | 0.00          |
| t-statistic     | (2.18**)      | (-0.57)       | (0.01)        |
| NW t-statistic  | [1.54]        | [-1.01]       | [0.02]        |
| Govt. Relief\(i\) | -0.07        | -0.16         | -0.24         |
| t-statistic     | (-0.80)       | (-1.36)       | (-1.92)       |
| NW t-statistic  | [-0.64]       | [-2.73***     | [-3.77***     |
| Log(DY)         | 0.47          | -0.01         | 0.13          |
| t-statistic     | (0.63)        | (0.01)        | (0.13)        |
| NW t-statistic  | [0.51]        | [-0.02]       | [0.21]        |
| CS               | -0.26         | 0.34          | 0.56          |
| t-statistic     | (-0.68)       | (0.74)        | (1.12)        |
| NW t-statistic  | [-0.61]       | [0.75]        | [1.64]        |
| TS               | 1.29          | -0.49         | -0.03         |
| t-statistic     | (2.69**)      | (-0.84)       | (-0.05)       |
| NW t-statistic  | [2.41**]      | [-0.54]       | [-0.03]       |
| Adj. \(R^2\)    | 64.34%        | 48.76%        | 39.47%        |

The learning process reduces the impact of the Lockdown index leading to a negative effect on the volatility jumps in the stock market.

VII. Conclusion

The COVID-19 pandemic is a global health crisis, that has brought tremendous amount of fear in market participants and turbulence in financial markets. This paper examines how COVID news and resulting sentiment fluctuations affect volatility jumps in the stock and option markets. We construct five Google search sentiment indices. They are COVID sentiment index (COVID), Market sentiment index (Market), Lockdown sentiment index (Lockdown), Banking sentiment index (Banking), and Government relief efforts sentiment index (Govt. Relief). Based on a theoretical model of the trading strategies of behavioral traders and sophisticated traders, we derive several predictions for the effect of different sentiment indices on measures of volatility jumps in the stock and option markets. We specifically examine the jump tail component in the CBOE VIX index and jump component in the S&P 500 index realized volatility and S&P 500 Banks index realized volatility.

We find that the jump component in the VIX index is increasing significantly with COVID index, Market index, Lockdown index, and Banking index. However, only COVID index and Market index increase the jump component in S&P 500 index and S&P 500 Banks index realized volatility (although the COVID result is weaker for the S&P 500 Banks index). However, the Government relief efforts index decreases the jump volatility in S&P 500 index and S&P 500 Banks index. Banking index and Lockdown index reduce jump volatility of S&P 500 index and S&P 500 Banks index after a delay of 5 days. Our evidence can be interpreted as the equity traders learning about the importance of bank information and lock down information with a lag of five days. An explanation could be that they are able to correct the excessive weight they placed on COVID news and redistribute it towards bank news and lockdown news with some experiential learning. These results are consistent with the predictions of our model.

This paper provides insights as to how various COVID related information gets into prices given the dynamics of sophisticated option trading and perhaps more sentiment-based stock trading. In the presence of unprecedented market volatility, what explains large movements of in market sentiment and resulting volatility jumps? Our results provide a better understanding of the interaction between investor sentiment and market volatility jumps. Further research can expand the purview of this study to a global setting examining the spillover effect of market volatility and investor sentiment among various affected countries.

Declaration of Competing Interest

No.
Appendix A. Volatility Jumps Estimation

In Appendix A, we explain our estimation methodology to estimate the jump component in the option-based risk-neutral jump tail component in the VIX index, the jump component in the S&P 500 index realized volatility and the jump component in the S&P 500 Banks index realized volatility. Section A1 contains the estimation of the jump tail component in the VIX index, the daily S&P 500 index option data is obtained from Ivolatility.com. Section A2 contains the estimation of S&P 500 index and S&P 500 Banks index realized volatility jumps, we use the high-frequency (5-minute) intraday S&P 500 index data and S&P 500 Banks index (Ticker: BIX) data, respectively. The high-frequency S&P 500 index and S&P 500 Banks index data comes from Options Price Reporting Authority (OPRA).

A1. Jump Tail Risk in the VIX Index

In 2003, the Chicago Board Options Exchange (CBOE) has introduced the VIX index. As an indicator of market fear, the VIX index measures the 30-day forward-looking market volatility. It is constructed using a series of out-of-the-money put and call option contracts on the underlying S&P 500 index\(^{13}\). Investors trade out-of-the-money option under great amount of economic uncertainty, and their trades have a direct impact on the VIX index level.

Carr and Wu (2009), Martin (2011), Du and Kapadia (2012), Chow et al. (2021), and Chow et al. (2020) have shown that there is a jump tail component embedded within the VIX index. Martin (2011), Du and Kapadia (2012), Chow et al. (2021), and Chow et al. (2020) further demonstrated the methodology to extract the risk-neutral jump tail component in the VIX index.

Under no-arbitrage condition, asset prices are semi-martingales. Assume stock prices follow the Geometric Brownian Motion (GBM),

\[
\frac{dS_t}{S_t} = \mu dt + \sigma dZ_t, \quad \text{and} \quad \{d[\ln(S_t)]\} = \left(\mu - \frac{1}{2}\sigma^2\right)dt + \sigma dZ_t \tag{A.1}
\]

where \(Z_t\) is a Wiener process or Brownian motion, \(\mu\) is a fixed drift, and \(\sigma\) is a constant volatility. It can be shown that The VIX index takes the following formulation:

\[
VIX^2 = E(V) = \frac{2}{T} \int (S_T - \left(F_0 - \left(K_0 \right) - 1 \right) - \ln \left( \frac{K_0}{S_0} \right) + e^{\gamma T} \left[ \int_0^T C_T(K)dK + \int_0^T P_T(K)dK \right] \equiv \mu_T \tag{A.2}
\]

where \(C_T(K)\) and \(P_T(K)\) denote the European call and put options with an exercise price of \(K\) and expired date at \(T\), respectively. \(S_0\) is the current asset value under no-arbitrage condition that determined from ATM Put-Call parity, \(S_0 = C_T(K_S) - P_T(K_S) + K_S e^{-\gamma T}\), and the forward prices is \(F_0 = E(S_T) = S_0 e^{\gamma T}\). \(K_0\) is the first strike price \(y\) below the forward price \(F_0\).

Martin (2011), Du and Kapadia (2012), and Chow et al. (2021) demonstrated that the jump tail component in the VIX index (VIXJ) can be estimated using the following approach:

\[
VIXJ = VIX - \frac{1}{\sqrt{T}} V_T - (\mu_T)^2 \tag{A.3}
\]

where

\[
\mu_T = \ln \left( \frac{K_0}{S_0} \right) + \left( \frac{F_0}{K_0} - 1 \right) - e^{\gamma T} \left[ \int_0^T C_T(K)dK + \int_0^T P_T(K)dK \right] \tag{A.4}
\]

and

\[
V_T = \ln^2 \left( \frac{K_0}{S_0} \right) + 2\ln \left( \frac{K_0}{S_0} \right) \left( \frac{F_0}{K_0} - 1 \right) + 2e^{\gamma T} \left[ \int_0^T \frac{1 - \ln(\frac{S_t}{K_t})}{K_T} C_T(K)dK + \int_0^T \frac{1 + \ln(\frac{S_t}{K_t})}{K_T} P_T(K)dK \right] \tag{A.5}
\]

The VIXJ estimate using the above formulation captures the jump induced high moments (tail) component in the VIX index itself. Du and Kapadia (2012) and Chow et al. (2021) have shown that, this jump tail component in the VIX index is strongly related to the 2008–2009 financial crisis, during which VIX spiked to 80.86 in November 2008.

A2. Jumps in S&P 500 Index and S&P 500 Banks Index Realized Volatility

Continuing previous assumption on underlying price follows GBM, assume time interval \([\tau - 1, \tau]\) is split into \(n\) equally spaced increments (each interval length equals \(1/n\)),

\[
RV_t = \sum_{j=1}^{n} r_j^2 = \sum_{j=1}^{n} \frac{1}{n} \left( \frac{Q[V_{\tau - 1, \tau}]_{X,R} - Q[V_{\tau - 1, \tau}]_{X,L}}{X} \right)^2, \quad \text{for} \quad n \rightarrow \infty \tag{A.6}
\]

where \(RV_t\) denotes the estimated realized volatility in day \(t\), \(r_j\) denotes the log return \(\log(S_j/S_{j-1})\) for the \(j\)th time interval during in day \(t\). Andersen and Bollerslev (1998) and Andersen et al. (2001) show that as the number of high-frequency increment \(n\) goes to infinity, the realized volatility estimator, \(\sum_{j=1}^{n} r_j^2\), converges in probability to the quadratic variation\(^{14}\) of the time interval \([\tau - 1, \tau]\).

We follow Andersen and Bollerslev (1998) and Andersen et al. (2001) to estimate the realized volatility of S&P 500 index and S&P 500 Banks index. Specifically, we estimate the realized volatility for the S&P 500 index and S&P 500 Banks index by summing the 78 intraday five-minute squared log returns covering the normal trading hours from 9:30 am to 4:00 pm along with the close-to-open overnight return.

We use Corsi et al. (2010) threshold bi-power variation (TPBV) estimation methodology to estimate jumps in realized volatility. Corsi et al. (2010) proposes the TBPV as a combination of bi-power variation and threshold estimation. They show that the TBPV provides

\(^{13}\) See also Demeterfi et al. (1999).

\(^{14}\) For any semimartingale \(X\), the quadratic variation process \(\langle Q[V_{\tau - 1, \tau}]_{X,R} - Q[V_{\tau - 1, \tau}]_{X,L} \rangle = X^2 - 2t/XdX\).
more accurate estimates in estimating jumps in the realized volatility than bipower variation \citep{Barndorff-Nielsen2004, Barndorff-Nielsen2006}.

Continuing with the previous realized volatility assumptions that time interval \([t − 1, t]\) is split into \(n\) equally spaced increments (each interval length equals \(1/n\)). TBPV estimator for day \(t\) with interval length of \(1/n\) can be formulated as follows:

\[
\text{TBPV}_t = \sum_{j=1}^{n} \left| r_{t-j} \right| \frac{1}{2} \left( I_{\left\lfloor r_{t-j} \leq v_j \right\rfloor} - I_{\left\lfloor r_{t-j} < v_j \right\rfloor} \right)
\]

where \(v_j = 0.7979\), \(v_j\) is a strictly positive random threshold function, \(v_j : [t − 1, t] \rightarrow \mathbb{R}^\dagger\), and \(I_{()}\) is the indicator function.

We decompose the realized volatility for both S&P 500 index and S&P 500 Banks index into a continuous variation (CV) component and a jump variation component (JV). The continuous variation (CV) component is estimated by TBPV as in equation (A.7).

Appendix B. Construction of the five sentiment indices

In Appendix B, we introduce the construction of Google search sentiment indices based on daily Google search volume data in US during the sample period from January 21, 2020 to June 8, 2020. They are COVID sentiment index, Market sentiment index, Banking sentiment index, Lockdown sentiment index, and Government relief efforts sentiment index. These five Google search sentiment indices serve as proxies for the attention induced by COVID news, market news, lockdown news, banking news, and government relief efforts during the COVID-19 pandemic.

We use Google search volume data available on GoogleTrends.com to construct Google search sentiment indices. GoogleTrends provides trending daily search data on Google.com, which comprises over 75 percent of the search engine market share\textsuperscript{15}. Da et al. (2011), Da et al. (2015) and Azevedo and Elkhayat (2020) have shown that Google search activity timely reflects investor sentiment and impacts stock market return significantly and outperforms the predictability power of other proxies for investor sentiment. Consistent with the literature the search items on Google.com and GoogleTrends data capture the public attention and market sentiment, especially during the COVID-19 pandemic.

We start by text mining the daily trending Google search items in all US cities from March 22, 2020 to April 21, 2020. Only the most popular search item by each city in each US state is recorded. In total, we have 4778 top city-wide search keywords with total frequency of 236514 times across 12212 cities in 51 US states. We plot the word cloud in this text database in the following figure.

Word cloud figure of the search keywords on Google.com. The word cloud is generated by text mining the daily search items in US cities from March 22, 2020 to April 21, 2020. The various colors represent the frequency of appearances in the text database.

In the above figure, the various colors in the word cloud represents the different frequencies of appearances. In our textual analysis database, the word that appeared the most frequently among the trending Google search key words during our sample period is “coronavirus”; it appeared 55559 times (as the daily top-city search keyword) in our textual analysis dataset\textsuperscript{16}. This is not surprising since the coronavirus causes tremendous amount of attention among the public during the COVID-19 period. The second most searched word is “cases”, followed by “update”, “map”, and “news”. The vast majority of search keyword during the COVID-19 pandemic period is health news-related searches.

We next extract the top 210 search keywords of our textual analysis database, and filter out unrelated search items, such as words “how”, “county”, “the”, etc. We keep the rest and classify them into five categories, namely, COVID news related searches, market news related searches, lockdown news related searches, banking news related searches, and government relief efforts news related searches. The top 210 searched keywords and classification details can be found in Appendix C.

We then use the COVID, market, lockdown, banking, and government relief efforts related search keywords to construct Google search sentiment indices through GoogleTrends database. GoogleTrends analyzes the popularity of search queries in Google search engine and scale the popularity for a given time to a maximum of 100. We download the Google search popularity historical trend for each search keyword in the five categories from GoogleTrends database from January 21, 2020 to June 8, 2020.

Finally, we construct Google search sentiment indices by taking the average of the Google search popularity historical trend for all searched keywords within each of the five search categories (COVID, market, lockdown, banking, and government relief efforts).

\textsuperscript{15} https://www.searchenginejournal.com/seo-101/meet-search-engines/#close

\textsuperscript{16} The data is available on Google Trends Datastore. https://googlesearch.trends.github.io/data/
Appendix C. Top 210 Search Keywords on Google.com

The following table reports the top 210 search keywords on Google.com. Data comes from daily search items in US cities from March 22, 2020 to April 21, 2020. Only the most popular search item by each city in each US state is recorded. In total, we have 4778 top city-wide search keywords with total frequency of 236514 times across 12212 cities in 51 states in the US. This data is available on Google Trends Datastore. The different colors represent the different news factors reflected in Google search volume.

| Searched Keywords | Frequency | Searched Keywords | Frequency | Five News Factor Related Search Items |
|-------------------|-----------|-------------------|-----------|---------------------------------------|
| coronavirus       | 55559     | COVID             | Yes       |                                       |
| cases             | 6960      |                   | Yes       |                                       |
| update            | 3905      |                   | Yes       |                                       |
| map               | 3619      |                   |           |                                       |
| news              | 3148      |                   |           |                                       |
| usa               | 3084      |                   |           |                                       |
| corona            | 3029      |                   | Yes       |                                       |
| stimulus          | 2948      |                   |           |                                       |
| virus             | 2774      |                   | Yes       |                                       |
| how               | 2754      |                   |           |                                       |
| county            | 2297      |                   |           |                                       |
| state             | 2279      |                   |           |                                       |
| the               | 2241      |                   |           |                                       |
| deaths            | 2107      |                   | Yes       |                                       |
| many              | 1968      |                   |           |                                       |
| new               | 1873      |                   |           |                                       |
| Hopkins           | 1725      |                   | Yes       |                                       |
| symptoms          | 1696      |                   | Yes       |                                       |
| check             | 1228      |                   |           |                                       |
| covid             | 1143      |                   | Yes       |                                       |
| numbers           | 1112      |                   | Yes       |                                       |
| york              | 1107      |                   |           |                                       |
| john              | 1105      |                   |           |                                       |
| death             | 1057      |                   | Yes       |                                       |
| google            | 1050      |                   |           |                                       |
| irs               | 1050      |                   |           |                                       |
| Dow               | 969       |                   | Yes       |                                       |
| Cdc               | 967       |                   | Yes       |                                       |
| unemployment      | 928       |                   |           | Yes                                   |
| World             | 927       |                   |           |                                       |
| From              | 923       |                   |           |                                       |
| China             | 883       |                   |           |                                       |
| Dakota            | 847       |                   |           |                                       |
| Trump             | 820       |                   |           |                                       |
| For               | 814       |                   | Yes       |                                       |
| What              | 789       |                   |           |                                       |
| Population        | 779       |                   |           |                                       |
| You               | 768       |                   |           |                                       |
| Worldometer       | 765       |                   | Yes       |                                       |
| Today             | 765       |                   |           |                                       |
| South             | 764       |                   |           |                                       |
| 2020              | 757       |                   |           |                                       |
| Home              | 748       |                   | Yes       |                                       |

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georgia 383
cuomo 383
utah 381
order 379
country 376
market 368
washington 363
start 362
bank 362
number 360
portal 358
near 351
oklahoma 345
vermont 344
are 342
lockdown 342
with 340
deposit 338
korea 334
california 333
day 332
wisconsin 331
walmart 330
india 325
payment 322
colorado 321
amazon 319
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test 252
mask 251
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statistics 246
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signs 242
fauci 242
hydroxychloroquine 236
end 236
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| Keywords               | Number of Occurrences |
|------------------------|------------------------|
| cure                   | 228                    |
| confirmed              | 228                    |
| irs.gov/coronavirus    | 228                    |
| act                    | 227                    |
| current                | 227                    |
| rate                   | 226                    |
| translate              | 225                    |
| exotic                 | 224                    |
| missouri               | 224                    |
| city                   | 222                    |
| russia                 | 219                    |
| place                  | 217                    |
| shelter                | 216                    |
| wuhan                  | 216                    |
| usps                   | 211                    |
| flu                    | 210                    |
| kentucky               | 209                    |
| depot                  | 208                    |
| target                 | 208                    |
| charles                | 205                    |
| fargo                  | 204                    |
| surfaces               | 198                    |
| texas                  | 198                    |
| gmail                  | 197                    |
| illinois               | 193                    |
| response               | 189                    |
| doodle                 | 188                    |
| msn                    | 187                    |
| business               | 186                    |
| las                    | 182                    |
| mail                   | 181                    |
| ibuprofen              | 178                    |
| smithfield             | 177                    |
| block/coronavirus      | 176                    |
| zoom                   | 176                    |
| nevada                 | 175                    |
| vegas                  | 174                    |
| zip                    | 174                    |
| youtube                | 173                    |
| **Number of Keywords Used** | **24**    | **3** | **6** | **4** | **7** |
