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The sum of all SCARES COVID-19 sentiment and asset return

Md. Tanvir Hasan
Department of Finance, University of Dhaka, Nilkhet Road, Dhaka 1000, Bangladesh

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In this study, I constitute a search based COVID-19 sentiment index using Google search volume. I develop an alternative Scared COVID-19 Attitude Revealed by Eager Search (SCARES) index using the household search volume i.e. “coronavirus pandemic”, “coronavirus epidemic”, and “coronavirus outbreak” of United States (US) during the COVID-19 pandemic. Using daily data from May 1, 2020 to July 30, 2021, I find that SCARES index negatively explains stock market return and subsequent return reversals, implying that households’ increased pandemic sentiment negatively affects equity market return. Furthermore, decile regressions on characteristics-sorted portfolio returns show that SCARES index predicts the return reversals of firms that are small, less profitable, and with low investment. I also report that COVID-19 search shocks of households do not significantly predict any of the Fama-French five-factors except SMB (small-minus-big). Moreover, I use two state Markov switching model and find that structural breaks associated with pandemic phases make SCARES positively related to indices i.e. twitter based uncertainty, volatility index, economic policy uncertainty, and business condition in high volatility regime. Finally, sub-period analysis reports that, in stock market context, people start to react slowly and become relatively less responsive to the COVID-19 search keywords. The findings of this paper can assist key stakeholders in the market to carefully analyze the asset return pattern during pandemic regimes.

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1. Introduction

As of July 26, 2021, novel coronavirus, initially identified in Wuhan city in China in December 2019, takes around 4.22 million lives and infects about 197.89 million people (World Health Organization, 2021). Such unpredictable shocks not only make the world face a new normal but also initiate unwanted transformation in the globalization era. This unprecedented event has officially been declared by World Health Organization (WHO) as a global pandemic on March 11, 2020. Consequently, countries around the world come up with a range of shut down measures e.g. travel limits, business shut down, educational institutions closure, lockdowns, reduced public events, and socializing. These uncertain events along with government restrictions put unparalleled pressures on country’s economy and stock market and that is further warranted by the 31.32% drop of S&P500 on March 23, 2020 accompanied by frequent breach of circuit breaker (e.g. Just & Echaust, 2020; Hong et al., 2021). Moreover, not only COVID-19 makes investors act against the rational risk-return or alpha optimizing strategy, it also forces investors to liquidate their savings of stock market in the face of uncertain futures (e.g. Okorie & Lin, 2021). Consequently, this brings about a sharp fall in the capital market. Furthermore, according to International Monetary Fund (IMF), COVID-19 shrinks the Gross Domestic Product (GDP) of US by 8.2%. Thus, it is important to investigate the extent to which COVID-19 affects the stock market return.

Information play vital role in return predictability and capturing fluctuation of capital market. People reveal their interest to a particular aspect of economy and market by searching for the information they intend to capitalize on. Given this context, prior studies explore the importance of information on corporate actions (e.g. Hirshleifer & Shumway, 2003; Bushee et al., 2010) or on stock market reaction (e.g. Chan, 2003). Earlier evidence attributes the market fluctuations to different phases of sentiment shocks of investors (e.g. Baker & Wurgler, 2006; Ding et al., 2019; Duan et al., 2021) and to different measures of sentiment i.e. news sentiment (e.g. Tetlock, 2007; Garcia, 2013), social media (e.g. Chen et al., 2014), corporate disclosures (e.g. Jiang et al., 2019), sports events (e.g. Edmans et al., 2007) and others are widely examined in early studies. Along with these measures, investigation of sentiment and perception of people through Google search volume gain popularity in recent times (e.g. Da et al., 2015; Arora et al., 2019). In COVID-19 context, studies also delve into the exploration of internet search (e.g. Salisu & Vo, 2020; Baig et al., 2021; John & Li, 2021) and media news (e.g. Duan et al., 2021), justifying the fact that people express...
their real time perception, feelings, and sentiment through internet search and news media. Such insights of people through news media and internet search to some extent play crucial role in predicting stock market return and associated volatility shocks. Thus, the analysis of the impact of sentiment on asset returns using direct search shock requires further exploration. Consequently, I aim to investigate the magnitude to which households’ COVID-19 sentiment perception measured by Google search based SCARES index (i) affects the stock market return, (ii) predicts the firm characteristics-sorted portfolio returns, (iii) influences factor returns i.e. Fama-French five-factor (FFS) and Momentum factor (MOM), and (iv) is related to infectious diseases equity market volatility, twitter based uncertainty, business circumstance, news based economic policy uncertainty, volatility index, and Amihud’s (2009) liquidity measure in regime switching context.

In this paper, I utilize Google search volume index (SVI) of Google Trends (GT)1 to develop SCARES index. Google is the largest search engines with 86% of the overall market shares. As part of Google’s massive exploration, GT analyzes the search popularity of any term across such different dimensions as countries, regions, categories, frequencies, and search subcategories. More specifically, search for any term in GT represents the term’s interest over time.

Search index values of the GT range from 0 to 100 with maximum search popularity is denoted by 100. Index number denotes the significance of the terms across countries and regions. For instance, index value 50 indicates mediocre significance while 0 represents the absence of enough data to generate index value. Fig. 1 represents the SVI of “community spread”, “coronavirus epidemic”, “coronavirus outbreak”, and “coronavirus pandemic”.

This pictorial depiction claims some intuitive interpretation. During 2020, people were so much panicked and anxious about coronavirus and such situation gives unique spikes in those search terms. After first COVID-19 case detection on January 23, 20212 in US people started to panic about coronavirus. This, consequently, initiates peaks of the SVI of these search terms in the first and second quarter of 2020 followed by sharp declines in the later part of the year. Such decline may be attributable to the fact that households’ interest, anxiety, and uncertainty about the terms go down with time. Subsequently, SVI becomes random and volatile because of the time varying demand of these search terms particularly in the policy formulation and research context.

My research makes several contributions to the strand of COVID-19 literatures. First, I develop SCARES index using backward rolling regressions of the key COVID-19 search terms of GT. To the best of my knowledge, this is the first paper that develops a composite COVID-19 sentiment, the SCARES index, related to coronavirus using internet search. Earlier studies primarily focus on daily COVID-19 cases and/or deaths as the mainstream proxies to measure the severity of pandemic (e.g. Just & Echaust, 2020; Okorie & Lin, 2021; Ozkan, 2021). I use objective analysis to measure the COVID-19 fatalities in addition to externally supplied secondary source. Closest paper that matches to my analysis is that of John and Li (2021) who also utilize Google search index and construct five sentiment indices i.e. COVID sentiment, market sentiment, lockdown sentiment, banking sentiment, and government relief effort sentiment. However, unlike John and Li (2021), I compress the search terms specifically in COVID-19 dimensions and use rolling regression to choose the important search terms as objectively as possible. Likewise, my study is also related to that of Smales (2021) who utilizes Google search volume to measure COVID-19 investor attention. Author concludes that the increase in COVID-19 related Google search has negative impact on stock market. However, Smales (2021) considers only “coronavirus” keyword search term as measure of search based investor attention. Unlike Smales (2021), I develop SCARES COVID-19 sentiment by objectively selecting keywords from a broader set of COVID-19 related search terms. Second, prior evidence, among other aspects, primarily focus on the impact of COVID-19 on market return (e.g. Liu et al., 2020; Narayan & Phan, 2020; Baker et al., 2020; Duan et al., 2021) and volatility (e.g. Cheng, 2020; Adekoya et al., 2021) context. Unlike these studies, my paper shifts the gear and investigates the impact of COVID-19 sentiment on decile decomposition of firm characteristics-sorted portfolio returns. Third, I make the first attempt to analyze the COVID-19 sentiment on factor returns. Prior studies analyze the impact of pandemic on firm level performance (e.g. Shen et al., 2020) and industry and commodity market (e.g. Aloui et al., 2020; Ahmed & Sarkodie, 2021; Yakubu & Sarkodie, 2021; Kanno, 2021). In a different aspect, I investigate the impact of COVID-19 sentiment on factor returns i.e. FF5 and MOM. Fourth, I integrate other event responsive feedback indices i.e. twitter based uncertainty, business condition, volatility index, infectious diseases equity market volatility, liquidity, and economic policy uncertainty with SCARES index and conduct regime switching investigation of the link between SCARES index and broad set of above mentioned indices.

Rest of the paper is organized as follows. Section 2 discusses the literature review. Section 3 presents data and methodology. Section 4 outlines the results and discussion. Section 5 discusses conclusion.

2. Literature review

Recent COVID-19 literatures investigate the influence of coronavirus pandemic on stock market return. In this regard, Ashraf (2020) examines the fatalities of COVID-19 across 64 countries and concludes that market reacts negatively to the increase in COVID-19 confirmed cases. Taking similar proxies in panel data context, Al-Awadhi et al. (2020) find that increase in COVID-19 confirmed cases and deaths has significant negative association with stock returns. Schell et al. (2020) also find that COVID-19 significantly negatively influences stock market in a 30-day window. Also, Baig et al. (2021) conclude that spike of COVID-19 confirmed cases and deaths contributes to the corresponding increase in illiquidity and volatility. In addition, authors argue that government restrictions and waning sentiment lead to hamper the liquidity and stability of the market. Similarly, applying Markov switching approach, Just and Echaust (2020) report that COVID-19 crisis has significant association with return, volatility, and implied correlation. However, in contrast to Baig et al. (2021), authors find no significant relationship between returns and liquidity. Shehazad et al. (2020) employ Asymmetric Power GARCH model and conclude that COVID-19 yields harmful effect on US and Japan’s stock market. Similarly, Alfaro et al. (2020) examine the reaction of market to unanticipated fluctuations of COVID-19 infection rates and report that unexpected doubling of anticipated infections leads to a decline in US market value by around 4–11% in aggregate terms. Pinheiro-Chousa et al. (2022) analyze the stock market reaction of two US biopharmaceutical companies before and during COVID-19 regimes. Authors consider technological market index, market volatility, and investor sentiment and find an asymmetric impact of market volatility and sentiment on the returns of both companies. Harjoto, Rossi, Lee et al. (2021) analyze the impact of COVID-19 on both emerging and developed countries. Findings reveal that COVID-19 exerts adverse effect on stock returns, volatility, and trading volume. Emerging countries are more responsive to both cases and deaths, whereas developed countries react more only to COVID cases. Similarly, Aharon and Siev (2021) explore the extent to which government intervention to face COVID-19 plays role in capital market in MSCI emerging market economies. Authors reveal that restrictions negatively affect the market return especially when
closures are enforced. Likewise, Baker et al. (2020) compare COVID-19 with previous pandemics and attribute the severe, widespread, and lengthier COVID-19 response relative to Spanish Flu and influenza to government restrictions, business closures, or social distancing. Authors use news textual analysis and document that COVID-19 initiates the highest shocks of stock market compared to other infectious diseases. Feng et al. (2021) explore the impact of COVID-19 on US service industry by using FFS model. Authors document that “…Mkt-Rf factor is always significant, representing the portfolio’s risk premium. The HML factor of business service becomes significant after the epidemic…” (p. 2862).

Use of GT is also rationalized in prior studies. For example, Arora et al. (2019) argue that approximately 80% US internet users search for health and health policy related issues and such search was explored in various infectious diseases regimes i.e. Lyme disease, influenza, syphilis, HIV, and Zika virus. Similarly, López-Cabarcos et al. (2020) utilize GT and consider “coronavirus” SVI a measure of COVID-19 Google attention. Authors follow SVI methods of Da et al. (2011) and report that Google attention on coronavirus exerts significant negative impact on eSports exchange traded fund (ESPO) returns. Considering media news, O’Donnell et al. (2021) find that even after controlling for investor sentiment, growth of COVID-19 severity significantly affects stock market of Spain, Italy, the United Kingdom, and the United States. Salisu and Vo (2020) investigate the relevance of health-news trend in predicting stock returns. Authors use top-20 infected countries and results suggest that health-news index embedded model better predicts stock returns than the benchmark average return model does. Ramelli and Wagner (2020) analyze the cross-sectional stock price response to COVID-19 shocks. Authors find that incubation and outbreak periods generate lower cumulative returns. By employing detrended moving cross-correlation analysis and detrended cross-correlation analysis techniques, Okorie and Lin (2021) conclude that fractal contagion effect of COVID-19 is eminent in stock market and that impact disappears in middle and long run.

By summarizing prior empirical studies related to the impact of COVID-19 on asset returns, I assume that household COVID-19 sentiment has significant negative impact on asset returns. Furthermore, such negative impact of COVID-19 sentiment on asset returns initiates return reversals in subsequent periods. Additionally, it is expected that COVID-19 sentiment has more pronounced effect on sentiment sensitive assets than on sentiment resistant assets. Specifically, stocks that are small, less profitable, or have low investment are mostly affected by COVID-19 sentiment. I also assume that asset return response to COVID-19 sentiment is volatility regime dependent.

3. Data and methodology

Since I investigate the impact of SCARES index that is, to investigate the impact of COVID-19 sentiment on market return, primary focus, thus, lies on the construction of SCARES index.

3.1. The SCARES index

Construction of SCARES index comprises of selection of relevant COVID-19 sentiment related keywords. In this aspect, at first I use COVID-19 jargons and buzzwords that are explored during the pandemic phase. I use the terms reported in The New York Times and Cable News Network (CNN) to make sure the selection is as objective as possible. Moreover, I also utilize COVID-19 outbreak glossaries available in Kaiser Family Foundation (KFF). In addition, I consider top search terms related to coronavirus provided by GT. Terms that do not represent the coronavirus related keywords are removed. For example, searching for the SVI of term “infection” in GT provides a wide array of top search terms i.e. “infection”, “urinary tract infection”, “sexually transmitted infection”. To be more specific
and to exclude irrelevant SVI, I include “coronavirus/ COVID-19” in search terms to make sure that the SVI denotes relevant data series. For example, in GT, I search for the SVI of “coronavirus infection” as opposed to “infection”, I avoid the duplication among sources and exclude too much technical words related to COVID-19 for two reasons. First, households search for the top COVID-19 buzzwords that are widely used and closely related to wider perceptions. Mass people usually ignore the COVID-19 technical terms and leave it for the scientific innovation purpose. Second, technically complex COVID-19 terms less likely to capture households’ attitudes towards coronavirus. As such, this may bias the significance of the results. These procedures generate 68 COVID-19 related search terms. Daily SVI of these search terms from January 23, 2020 to July 30, 2021 are obtained. I separately download daily data in every 90-day window since GT provides daily data for up to 90 days. To make the data comparable, I standardize the terms following Baker and Wurgler (2006). Furthermore, the dataset is winsorized at 5% level as in Da et al. (2015) to adjust for the potential outliers.

As part of SCARES index construction, I download SVI of 68 COVID-19 related search terms from GT from January 23, 2020 to July 30, 2021. As discussed, GT allows the customization of search terms across regions and countries. Since in this paper I investigate the impact of COVID-19 sentiment on stock returns in US context, I, therefore, confine my search to US. Selected search terms are standardized and winsorized to make the comparison apparent. This leads to the generation of adjusted SVI or ASVI. As mentioned, I run backward rolling regression between ASVI and contemporaneous market return to identify more relevant search terms out of 68 search index. I run regression every three months to estimate the return-SVI linkage. Note that, pandemic attitude resembles negativity of households. Specifically, whatever terms households search for they do it out of anxiety or uncertainty, ceteris paribus. Hence, it rationalizes the expectation of those keywords with negative relation between SVI and market return. I focus on the search terms that have negative impact on returns over the sample period. Consequently, formal SCARES index on day \( t \) is represented by Eq. (1),

\[
\text{SCARES}_t = \sum_{i=1}^{25} \phi_i'(\text{ASVI}_t),
\]

where \( \phi_i'(\text{ASVI}_t) \) denotes the average for the search terms with \( t \)-statistics rank of \( i \) over the sample period from January 23, 2020 to the most contemporary three months. In this case \( t \)-values are ranked in ascending order from smallest to largest. One of the problems of unadjusted ordinary least squares (OLS) \( t \)-values is the spurious relations associated with persistent coefficient predictors (e.g. Ferson et al., 2003). Furthermore, small sample bias also initiates less reliable \( t \)-values (e.g. Stambaugh, 1999). Also, the extent to which autoregressive disturbance is related to lagged predictors may generate spurious estimators of the lagged predictors. As a result, use of ordinary \( t \)-values makes the estimation more prone to bias. To address these issues, I use heteroskedasticity and autocorrelation consistent Newey-West \( t \)-values.

I run 340 regressions in total to estimate the parameters and select the search series in three month rolling window. Use of backward rolling regression is not uncommon and it less subjectively selects the items with more relevance. Kogan et al. (2009) utilize rolling regression approach to figure out pertinent 10-ks words and Da et al. (2015) use the same approach to develop Financial and Economic Attitudes Revealed by Search (FEARS) index to measure market level household sentiment. In this study, for example, to get the SCARES index for months February 1, 2021 to April 30, 2021, I run rolling regression of each of the 68 search terms on contemporaneous market return from January 23, 2020 to January 31, 2021. I rank the \( t \)-values of the regression from smallest to largest in which the parameter estimates with the most negative \( t \)-values are ranked first. I choose twenty five most negative COVID-19 related search terms to determine the SCARES index for the period February 1, 2021 to April 30, 2021. In this period window, SCARES index for any particular day is the simple average of the ASVI of the selected search terms. For the regression, I match daily data with stock market information. Specifically, people search for COVID-19 terms irrespective of the market trading days. So, I remove non-trading day
search terms to synchronize the series. Similar omission of non-trading days is done by Kamaludin et al. (2021). Choice of twenty five search terms is based on their relative magnitude of importance to influence market return. For robustness purpose, I also select the top ten search series with the most negative $t$-values. Since I run three month backward rolling regression, data availability is required for at least prior three months. Therefore, I cover the data period from May 1, 2020 to July 30, 2021. Table 1 reports the top twenty five search terms that are used in the first rolling window and in the entire sample. Panel A reports the terms selected from the rolling regression in the first three months. In that case, terms that have the largest negative link with market return include “SARS” ($t$-value $=-14.58$), “community spread” ($t$-value $=-2.84$), and “coronavirus epidemic” ($t$-value $=-2.79$). Panel B represents the top twenty five search terms that have inverse association with market return over entire sample period. Seemingly, “coronavirus outbreak” ($t$-value $=-2.36$), “coronavirus infection” ($t$-value $=-1.88$), and “community spread” ($t$-value $=-1.78$) are the three search terms with the lowest $t$-values.

3.2. Other variables

I investigate the impact of COVID-19 sentiment on stock market and conduct the empirical test based on the aggregate market level. To measure the impact of the SCARES index on market return, I use eight control variables. I also use these variables to conduct the Markov switching model. Daily S&P500 index data are obtained from Yahoo! Finance. Both NYSE and DJIA are also considered part of additional analysis. Dollar volume data are taken from stooq.pl.

In this study, I use daily newspaper-based Infectious Disease Equity Market Volatility (EMVID) index developed by Baker et al. (2020). The EMVID index comprises of 3000 US newspaper articles that include one of the terms related to (i) “E” (“economic”, “economy”, “financial”); (ii) “M” (“stock market”, “equity”, “equities”, “Standard and Poors”); (iii) “V” (“volatility”, “volatile”, “uncertain”, “uncertainty”, “risk”, “risky”); and (iv) “ID” (“epidemic”, “pandemic”, “virus”, “flu”, “disease”, “coronavirus”, “MERS”, “SARS”, “Ebola”, “H5N1”, “H1N1”). Baker et al. (2020) provide a detailed explanation about the composition methodology of the EMVID and the impact of outbreaks on the stock market reaction and volatility.

People use social media to express their perceptions, emotions, and thoughts related to contemporary events. Thus, in this study, I utilize the Twitter-based Economic Uncertainty (TEU) index developed by Baker et al. (2021). This twitter based index constitutes the households’ sentiment related to uncertainty and economy. Uncertainty related keywords are “uncertain”, “uncertainty”, “uncertainties”, or “uncertainty” and economy related keywords include “economic”, “economical”, “economically”, “economics”, “economies”, “economist”, “economists”, or “economy”. Out of four tweet indices, I use TEU-USA, which mainly focuses on the users of US. I incorporate this index as one of the control variables given its importance on the context that people’s attitude toward the economy and market during COVID-19 phase may to some extent be captured by their twitter posts.

Aruoba et al. (2009) construct a real time high frequency measure of business condition (ADS index henceforth) by taking dynamic factor model into consideration. Federal Reserve Bank of Philadelphia provides a clear interpretation of the framework of ADS index. Value of the index is continuously updated based on the availability of such seasonally adjusted fundamental indicators as initial jobless claims in weekly frequency; payroll employment, industrial production, real personal income less transfer payments, and real manufacturing and trade sales in monthly frequency; and finally quarterly real Gross Domestic Product (GDP). Business condition is treated as above (below) average when ADS index value is progressively more positive (negative). In this study, following Da et al. (2015), I use ADS index to control for the economic condition.

To make the COVID-19 sentiment-market return prediction more economic policy uncertainty responsive, I utilize news based Economic Policy Uncertainty (EPU) index of Baker et al. (2013). This index is formulated based on NewsBank Access World News database, which comprises of rich source of newspaper across the world. The index construction mainly focuses on the number and frequency of news articles that cite at least one of the terms related to first set of category i.e. “economic” or “economy”, second set of category i.e. “uncertain” or “uncertainty” and finally, third set of category that includes terms “legislation”, “deficit”, “regulation”, “congress”, “federal reserve”, and “white house”. Considering the relevance and effectiveness of news based EPU to capture the potential news based policy related uncertainty, I consider this index one of the control variables.

I also capitalize the information content of Chicago Board Options Exchange (CBOE) market volatility index (VIX). Daily VIX data are obtained from CBOE webpage. Volatility index is one of the widely accepted and globally recognized measure of volatility and this index measure is often referred to as “investor fear gauge” among the researchers, academics, and practitioners. The VIX is estimated based on the real time call-put option quotes of the S&P500 index and estimates the 30-day expected volatility of stock market. Previous papers not only use VIX as a measure of volatility but also as a barometer of investor sentiment. Whaley (2000), for instance, attributes the spikes of VIX in October 1987 and in 1998 to the Black Monday and Long Term Capital Management (LTCM) crisis. Da et al. (2015) examine the linkage between VIX and FEARS index. Baker and Wurgler (2007) treat this index as alternative measure of investor sentiment. Similarly, Ding et al. (2021) postulate a VIX based trading strategy because of this index’s representation of investor sentiment and volatility measure. On the other hand, Chow et al. (2021) develop an alternative model-free generalized volatility index (GVIX) and document that GVIX is a special case of VIX and that spread between GVIX and VIX is mean reverting. In this study, I use VIX as one of the control variables given the importance of VIX as proxy of uncertainty and volatility.

To control the impact of liquidity, I consider widely recognized and popular measure of illiquidity (ILLIQ) of Amihud (2002). This approach of daily illiquidity is measured as the ratio of absolute stock returns to daily dollar volume of the trade. This version of liquidity measures the cost per dollar-volume proxies as mentioned in Fong et al. (2017) and Just and Echaust (2020). Amihud (2002) denotes liquidity as an elusive concept and it is less likely to be accommodated in a single proxy. For the purpose of the study, I estimate daily ILLIQ using Eq. (2),

$$\text{ILLIQ}_d = \frac{|R_d|}{\text{VOLD}_d},$$

(2)

where $R_d$ is the daily log return and $\text{VOLD}_d$ represents the daily dollar volume. Liquidity is one of the important aspects of stock market and recent COVID-19 pandemic affects overall market liquidity of stock market. This pattern may be attributable to the fact that market becomes more illiquid when the stock market is volatile (e.g. Będowska-Sójka & Echaust, 2020). Since coronavirus pandemic initiates uncertainty and volatility in the stock market, it is more persuasive to control for the impact of illiquidity to estimate the predictability of SCARES index in explaining market return. Finally, I also control daily COVID-19 confirmed cases and deaths of US from 4 See https://finance.yahoo.com/
5 See https://stooq.pl/
May 1, 2020 to July 30, 2021. People usually treat these two statistics as measures of severity of pandemic period. Prior COVID-19 literatures use these statistics to investigate the impact of COVID-19 (e.g. Just & Echaut, 2020; Ahmed & Sarkodie, 2021; Ashraf, 2021). Data are collected from WHO and similar to that of other non-market data series, I remove non-trading days’ COVID cases and deaths to match with market data.

3.3. The models

3.3.1. SCARES and asset returns

It is expected that households’ fear associated with COVID-19 usually exerts negative shocks to stock market followed by return reversal. Such reversal is supported by Tang and Zhu (2017) and Cheng et al. (2019). I investigate this pattern by applying Eq. (3) following the approach of Anand et al. (2021),

\[ R_{mt} = \alpha_0 + \beta_1 R_{m,t-1} + \beta_2 \text{SCARES}_{t-1} + \sum_{q} \gamma_q \text{Control}_t^q + \epsilon_t, \]  

(3)

where \( R_{mt} \) denotes the market return on day \( t \). Control variables are EMVID index, TEU index, ADS index of Aruoba et al. (2009), EPU, VIX, new daily COVID-19 cases and deaths, and Amihud’s ILLIQ measure. In Eq. (3), \( k \) ranges from 1 to 3 and \( n \) ranges from 1 to 5. Prior to running the regression, I check for unit root of the variables using augmented Dickey–Fuller (ADF) tests. In an unreported analysis, results confirm that variables are I (0).

3.3.2. SCARES and characteristics-sorted decile distributions

Next, I analyze the extent to which SCARES index affects the decile returns of size, book-to-market (B/M) ratio, operating profit (OP), and investment (INV) sorted portfolios. Portfolio sorts daily data are obtained from Kenneth French data library\(^7\) from May 1, 2020 to July 30, 2021. I run separate regression on every decile after considering the control variables. For example, for decile 1, I run regression by taking decile return as dependent variable and SCARES as independent variable. In addition, to investigate the impact of SCARES on sentiment embedded decile returns, I run regressions on sentiment sensitive and sentiment resistant portfolios by taking the spread of the average returns of three sentiment sensitive and sentiment resistant portfolios as dependent variable and SCARES as independent variable. For instance, in size-sorted portfolio, average of bottom three decile return is subtracted from that of top three decile returns to obtain the spread since small firms are more sentiment sensitive (e.g. Baker & Wurgler, 2006; Ding et al., 2019). Similar sentiment sensitive firms comprise of those that are less profitable, distressed (high B/M ratio), or have low investment (e.g. Jiang et al., 2019).

3.3.3. SCARES and factor model for asset returns

Next, I investigate the impact of SCARES on MOM and FF5 factor returns. In finance, capital asset pricing model (CAPM) plays crucial role in predicting asset returns. Fama and French (1993) modify the CAPM model by including size and book-to-market beta factors and that is known as Fama-French three-factor model. Fama and French (2016) add two new factors, which consist of profitability (RMW) and investment (CMW) factor. I also consider MOM factor, which is the average return differentials of two high performing and low performing portfolios based on prior returns. Daily factor return data are obtained from Kenneth French’s data library. Horvath and Wang (2021) examine the impact of crises on FF5 beta factors. Using rolling beta, authors conclude that all five factors of FF5 decrease 18 months prior to COVID-19 pandemic. In contrast to Horvath and Wang (2021), I investigate the impact of SCARES on factor models by applying Eq. (4),

\[ R_{id} = \beta_0 + \beta_1 \text{SCARES}_d + \epsilon_{id}, \]  

(4)

where \( R_{id} \) is the factor return on day \( d \), SCARES is the COVID-19 sentiment, and \( \epsilon_{id} \) is the stochastic residual. I investigate the predictive power of SCARES index in explaining FF5 and MOM factor return. Indeed, it is expected that these equilibrium factor returns respond to the stochastic COVID-19 sentiment shocks of the households. Specifically, investors react differently in aggregate term depending on the idiosyncratic risk factors of the asset returns.

3.3.4. Markov switching model

Markov switching model has become one of the popular and widely used approaches to analyze the regime dependent stochastic shocks. First application of regime switching approach stretched back to Hamilton (1989) who examines the long term economic trend by considering expansion and contraction. In financial modeling, it has become one of the popular methods because of this model’s utilities in capturing sudden shocks that persist after variation in several periods (e.g. Ang & Timmermann, 2012; Ahmed & Sarkodie, 2021). I apply following model to study the regime switching impact,

\[ y_t = \beta_0 + \beta_1 x_t + \beta_2 \theta_t + \epsilon_t, \quad \epsilon_t \sim i.i.d(0, 1), \]  

(5)

where \( y_t \) is the dependent variable, which consists of S&P500, EMVID, TEU, ADS, EPU, VIX, and ILLIQ in different market sets, \( x_t \) is SCARES index, \( \theta_t \) denotes the regimes; either 1 or 2 at time \( t \), and \( \epsilon_t \) is the stochastic error term. In Eq. (5), I conjecture that transition probabilities of the exogenous variables define the corresponding switch between regimes from state m to state n and this formulation is denoted by

\[ P_{m,n} = P(y_t = n| y_{t-1} = m), \quad m = 1, 2, \quad n = 1, 2. \]  

(6)

Regime transition probabilities depend on the extent to which regime transition probabilities are achieved.

4. Results and discussion

This section focuses on the analysis of the impact of SCARES index on stock market. I first discuss the effect of SCARES on S&P500 followed by the analysis related to the response of NYSE and DJIA to COVID-19 sentiment. Next, I examine the results of decile distributions, factor returns, and regime switching model of SCARES index.

4.1. Descriptive statistics

Table 2 reports the descriptive statistics in Panel A and correlation matrix of the variables under consideration in Panel B. Statistical parameters include mean, standard deviation, minimum, and maximum values. High standard deviations of all variables suggest that during the sample period COVID-19 sentiment sensitive response of households is relatively less stable. Fig. 2 displays the trend of variables over the sample period. Panel A of Table 2 shows that average daily returns of S&P500 index during the sample period is 0.13% with standard deviation of 1.06%. As depicted in Fig. 2, market return hits the minimum of 6.08% in the second quarter of 2020 followed by two other shocks in third quarter and at the end of year 2020. One important point that can be derived from Fig. 2 is that all variables experience negative shock between second and third quarter of 2020. Average EMVID index is 19.05 with minimum and maximum values of 0.99 and 79.59 respectively, inferring that a highly volatile pattern as represented by jigsaw shape in Fig. 2. SCARES index is positively related with VIX with a correlation coefficient of 0.17. This is not surprising because the extent to which

\[ \text{See } \text{https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html} \]
people start searching for COVID-19 terms e.g. “SARS” “Social distancing”, “Coronavirus deaths” and so on increases people’s fear and makes them more risk averse. Indeed, increase in SCARES coincides with the increase in VIX as shown in Fig. 2. Both EPU and TEU move together with average values of 235.76 and 196.03 respectively. That co-movement suggests that household’s response to economic uncertainty in both news based and twitter platforms during coronavirus pandemic substitutes each other. Amihud’s illiquidity measure (ILLIQ) also demonstrates large variations, which coincide with the associated fall (rise) of S&P500 return (VIX). Furthermore, increase in SCARES is positively related to ILLIQ. All of these suggest that when people are highly uncertain (as represented by high VIX and SCARES values) about the future market movement, they become more risk averse and are less likely to involve in trading (e.g. Just & Echaust, 2020; Będowska-Sójka & Echaust, 2020).

4.2. SCARES index and market return

Table 3 reports the results of the regression analysis followed by Table 4, which considers NYSE and DJIA to investigate the SCARES index impact. Table 3 summarizes the results of multivariate regressions. From Model 1 to Model 9, I include the control variables separately and in Model 10, I run a kitchen-sink regression by incorporating all control variables. It is apparent that SCARES has marginally (at 10% level) significant negative impact on S&P500 index return on day \( t-1 \), suggesting a negative association between market return and COVID-19 sentiment. Such negative association is also found by Smales (2021). Specifically, this result implies that when people become more anxious and search for terms like “SARS”, “community spread”, “coronavirus epidemic” and so on, market goes down in the following day. These findings remain consistent even after controlling for contemporaneous EMVID in Model 2, TEU in Model 3, EPU in Model 5, new confirmed cases in Model 7, new deaths in Model 8, and Amihud’s illiquidity measure (ILLIQ) in Model 9. In terms of magnitude of coefficients, SCARES index exerts more negative impact when new deaths are controlled for. This is not unusual in the sense that people, during this pandemic phase, are very concerned about the level of death tolls. Inverse association between SCARES and S&P500 is not surprising since, as mentioned earlier, the construction of SCARES index is related to the relative importance of COVID-19 related search terms by the households. Consequently, the apparent significant relationship of SCARES and market return is attributable to the fact that COVID-19 sentiment and market return are negatively linked. The significance of association, however, becomes weak when all of the control variables are considered in Model 10 and ADS and VIX are controlled for in Model 4 and 6 respectively. Note that, the effect of day \( t-1 \) SCARES on market return is momentary. In subsequent days, day \( t \) shocks of SCARES converge since market initiates a price reversal, which is notable from Table 3. Ensuing days’ impact of SCARES on market return becomes positive and insignificant.

Table 4 shows the estimates of regression result using NYSE or DJIA return as dependent variable. Apparently, in none of the cases SCARES index has significant impact on market return. However, the effect of SCARES on both NYSE and DJIA is negative, albeit insignificant, on day \( t \) and reverses in longer horizons in magnitude of day \( t \) to \( t+5 \). Note that, SCARES has significant impact on S&P500, whereas the impact is insignificant for both NYSE and DJIA. Prior evidence also find that the severity of COVID-19 is more pronounced for S&P500 stocks (e.g. Chebbi et al., 2021). These findings are attributable to the fact that S&P500 comprises of stocks of all sectors and is representative to the economic and financial circumstances while DJIA is less comprehensive and consists of only 30 blue-chip stocks. These blue-chip stocks are expected to be more resilient to the pandemic shocks and have more stable performance (e.g. Nurhayati et al., 2021). Similar pattern is observed for the stocks that are listed on NYSE. Furthermore, DJIA excludes transportation sector, which is most hit by the lockdown procedure. Overall, from the result it is apparent that the impact of SCARES on market return is temporary and becomes insignificant after day \( t \). Moreover, SCARES captures the return movements of more representative S&P500 index than those of NYSE and DJIA.

4.3. SCARES and decile decomposition

In this section I discuss the impact of SCARES on decile decomposition return. Table 5 reports the decile regression coefficients of SCARES index and results are shown in column 3–12. Table 5 confirms that sentiment inference is evident for size, profitability, and investment sorted portfolios in lag of three days. Decile coefficients of small firms (decile 1 and 2) are significant at 10% level and suggest that increase in SCARES is associated with corresponding decrease in returns of small firms. Moreover, positive response in lag two implies that return is mean reverting irrespective of pandemic shocks. Evidently, similar pattern is observed for profitability-sorted portfolio regressions in which only coefficient of decile return spread, \( D_i - D_j \), regression is significantly negatively (positively) related to SCARES in lag of three (two) days.

Explanation of this finding is twofold. First, according to sentiment literature, less profitable firms are harder to arbitrage and hence are speculative (e.g. Baker & Wurgler, 2007; Berger & Turtle, 2012). Moreover, during pandemic phases noise traders become more risk averse and are less likely to speculate. Second, when crisis fear spikes, people liquidate their profitable stocks to deal with future uncertainty.
Correspondingly, more profitable firms underperform as documented by positive coefficient of OP-sorted portfolio in two days lag. Similar sign flipping coefficients of OP sorts as in for size-sorts also signify the mean reverting feature of asset returns. If we zoom in the coefficients of B/M and INV sorts, it is apparent that no notable significant association with SCARES index is evident. Note that, SCARES exerts marginally significant positive impact on decile 3 B/M-sorted portfolio. Decile spread regression coefficient of INV-sorts implies that firms with low investment are more affected by the COVID-19 sentiment. As shown, SCARES stimulates moderately significant impact on INV-sorts and the impact is marginally significant at 10% level. Not only crisis period stimulates fear but it also opens a window of investment.

Fig. 2. Graphical depiction. Figure demonstrates the pictorial depiction of SCARES index, infectious diseases equity market volatility (EMVID) index, twitter based uncertainty (TEU) index, macro fundamental and business circumstance index (ADS) of Aruoba et al. (2009), news based economic policy uncertainty (EPU), volatility index (VIX), return of S&P 500, and Amihud’s liquidity measure (ILLIQ).
opportunity since market predictability and volatility increase in unfavorable times (e.g., Cujean & Hasler, 2017; Hong et al., 2018; Hong et al., 2021). These findings that firms with low investment underperform those with high investment in three days lag during COVID-19 pandemic are attributable to investors’ less willingness to hold stocks of the firms that have limited investment in long lived assets. Findings that low investment firms are the more sentiment sensitive are consistent with those of Jiang et al. (2019).

Overall, SCARES insets significant impact on small and less profitable firms and that effect is sign-flipping as represented by return reversals in lag two and three. In other words, price reversal occurs for size and profitability-sorted portfolios but not for investment-sorted portfolio. Moreover, SCARES does not create notable significant impact on B/M-sorts but marginally significant impact on investment-sorts. This implies that investment and book-to-market-sorted portfolios are becoming more resistant to pandemic shocks.

4.4. Factor returns

Table 6 demonstrates the regression analysis result of the impact of SCARES on factor asset returns. Apparently, none of the factors of FF5 is significantly affected by SCARES index except for the SMB factor. As shown, increase in SCARES is associated with corresponding decrease in SMB factor in lag three. Whereas the response is positive in lag two. It is evident that, in lag of three days, impact of SCARES on SMB is more pronounced both in terms of significance level and coefficient estimates.

Negative response of SMB factor to SCARES shocks in lag three suggests that small firms are more sensitive to COVID-19 outbreaks. This result is consistent with those of Baker and Wurgler (2006), Shen et al. (2020), and Harjoto et al. (2021). Moreover, decile regression outputs of Table 5 in which three-day lag SCARES produces significant impact on small firms further supports this finding. Meanwhile, large firms are less affected by COVID-19 as
Table 5
Decile regressions of sorts.

| Size     | D1  | D2  | D3  | D4  | D5  | D6  | D7  | D8  | D9  | D10 | D1−D5 |
|----------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-------|
| SCARES<sub>i,1</sub> | -0.006 | -0.096 | 0.042 | 0.005 | 0.036 | -0.031 | -0.040 | -0.100 | -0.090 | -0.183 | -0.110 |
| SCARES<sub>i,2</sub> | 0.453 | 0.497** | 0.292 | 0.314 | 0.287 | 0.283 | 0.330 | 0.140 | 0.100 | -0.145 | 0.545** |
| SCARES<sub>i,3</sub> | -0.512* | -0.558* | -0.371 | -0.352 | -0.328 | -0.210 | -0.283 | -0.071 | -0.017 | -0.135 | -0.763*** |
| SCARES<sub>i,4</sub> | 0.24 | 0.341 | 0.268 | 0.223 | 0.154 | 0.151 | 0.260 | 0.160 | 0.246 | 0.340 | 0.246 |
| SCARES<sub>i,5</sub> | -0.117 | -0.139 | -0.022 | -0.015 | 0.063 | 0.072 | 0.097 | 0.074 | 0.065 | 0.088 | -0.285 |
| SCARES<sub>i,6</sub> | (0.54) | (0.65) | (0.10) | (0.07) | (0.29) | (0.31) | (0.47) | (0.34) | (0.81) | (0.56) | (1.30) |

Controls

| R²(%) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Note: Table reports the decile regression coefficients of SCARES index and decile returns of size, book-to-market (B/M) ratio, operating profit (OP), and investment (INV) sorted portfolios. Portfolios are formulated based on Kenneth French data library. i and j represent the sentiment sensitive and sentiment resistant portfolios respectively. Dependent variable is the respective decile return. Independent variables are five day lags SCARES index, infectious diseases equity market volatility (EMVID) index, twitter based uncertainty (TEU) index, macro fundamental and business circuitry index (ADS) of Aruoba et al. (2009), news based economic policy uncertainty (EPU), volatility index (VIX), new daily COVID-19 cases and deaths, and Amihud’s liquidity measure (ILLIQ). Numbers in the parenthesis are the respective heteroskedasticity and autocorrelation consistent Newey-West t-values. *, **, and *** denote the significance level of 10%, 5%, and 1% respectively.

denoted by the positive insignificant coefficient of decile 10 regression. Similarly, mean reverting asset return is evident by day two positive return. This finding is also supported by the negative (positive) coefficient of decile 10 (decile 1) regression as demonstrated in Table 5. Impact of SCARES on MOM factor is rather instant. Apparently, the magnitude to which people explore their COVID-19 sentiment initiates negative impact on MOM factor at 10% level. The results suggest that spread of high performing and low performing portfolios responds negatively to the associated increase in SCARES in lag one. Further inference lies on the fact that prior period’s high performing portfolios underperform relative to low performing portfolios during COVID-19 outbreak. Insignificant association between SCARES and RMV, HML, CMA, and MktRF factor implies that these factor returns become more resilient to COVID-19 sentiment shocks.

4.5. SCARES and Markov switching

Table 7 summarizes the result of Markov switching model. Two regimes are split in low (Regime 1) and high (Regime 2) volatility regimes as in Ahmed and Sarkodie (2021). I investigate the impact of SCARES index on S&P500, EMVID, TEU, ADS, EPU, VIX, and ILLIQ in different regimes. One important point from Table 7 is that variables’ durations across regimes are persistent as denoted by \( \pi_{m,n} \), ranging from 0.60 to 0.99 with TEU being the most persistent. Panel A reports the result of SCARES and S&P500. As shown,
SCARES has insignificant negative impact on S&P500 in both regimes. In Panel B, SCARES produces significant effect on EMVID in low volatility regimes when one standard deviation increase in SCARES leads to 4.47 (= 0.43 x 10.48) unit increase of EMVID in low volatility regime and 2.90 unit increase in high volatility regime. Opposite pattern is found for ADS in Panel D. Apparently, one standard deviation increase in SCARES in low volatility regime decreases ADS by 0.65 unit and by 0.38 unit in high volatility regime. Findings are significant at 5% level in Regime 2 since p-value < 0.05.

Announcement of efficacy of COVID-19 vaccine trials, approval of Remdesivir as first COVID-19 drug, introduction of Health, Economic Assistance, Liability Protection, and Schools (HEALS) Act explain inverse association of ADS with SCARES index in Regime 2. Reduction of uncertainty and unawareness related to economy and pandemic over time also suggests the reverse movement with SCARES. In contrast, TEU (Panel C), EPU (Panel E), and VIX (Panel F) have positive association with SCARES in both regimes. However, EPU has significant positive relationship with SCARES in both regimes, whereas VIX and TEU are significantly positively related to SCARES in high volatility regime. These results of positive relations in high volatility regime may be attributable among other facts to spikes of deaths and confirmed cases, reversal of ease of restrictions, loss of health insurance coverage, and postponement of Hydroxychloroquine by WHO. Specifically, the extent to which people are uncertain about stochastic pandemic shocks leads to positive coefficient of TEU, EPU, and VIX in high volatility regimes. For instance, one standard deviation increase in SCARES index leads to 18.75 unit increase of TEU in high volatility regime. This suggests that twitter based sentiment spikes in line with SCARES and EPU in high volatility regime when pandemic is exploded in China (e.g. Baker et al., 2021). ILLIQ in Panel G has no significant relationship with SCARES and this result is consistent with that of Just and Ehaust (2020). Transition probabilities of 65% and 60% respectively in P11 and P22 imply that ILLIQ is relatively less persistent than other variables under consideration.
4.6. Further analysis

4.6.1. Sub-period analysis

This section provides additional analysis, which covers sub-period analysis and the impact of SCARES index on market return considering top ten search terms. I apply Zivot and Andrews (1992) approach to detect the structural breakpoint, which is also observed to choose sub-periods. In Zivot-Andrews test, breakpoints are estimated rather than fixed. Analysis reveals that first breakpoint occurs on May 8, 2020.8 This fact is also evident in Fig. 2 in which it is obvious that SCARES index shows certain break in the third quarter of 2020. Thus, I divide the full sample into two sub-periods; sub-period one is from May 8, 2020 to September 30, 2020 and sub-period two is from October 8, 2020 to July 30, 2021.

Table 8 reports the sub-period regression results. Compared to sub-period two, the impact of SCARES in sub-period one is more evident as demonstrated by negative effect in lag one. Such noteworthy impact of SCARES in sub-period one is attributable to the fact that this period is accompanied by such notable events as new record infection rates, loss of health insurance, unemployment shocks, fall of real GDP, and stimulus relief packages. Note that, in sub-sample one, lagged SCARES does not exert significant impact on market return when EPU and VIX are controlled for in Model 5 and Model 6 respectively. Apparently, the impact of SCARES on market return in sub-period two is less pronounced, albeit negative, as evident by insignificant coefficients. Several rescue packages such as purchase of treasury and mortgage-backed securities, reduced federal fund rate, lending to securities fund through Primary Dealer Credit Facility (PDCF), Money Market Mutual Fund Liquidity Facility (MMLF), vaccine approvals, and repurchase operation by Fed assist the market to operate smoothly and make the market more resistant to COVID-19 shocks. It is also obvious by the insignificant response of market return to SCARES shocks and by late lag response of market return to COVID-19 sentiment.

4.6.2. Alternative SCARES index

Structuring of SCARES index entails a number of choices, which are reflected by the alternative construction premise. Initially, I consider top twenty five search terms whose resultant ASVI, is most inversely related to market return in backward rolling regression context (e.g. Da et al., 2015). Consequently, taking as many objectively selected variables as possible assists me not only to identify the prevailing variation but also to minimize the idiosyncratic shocks. Table 9 reports the result of alternative top ten search term induced SCARES index. In this case, I construct alternative SCARES by considering the ASVI, of most negatively related top ten search terms with the S&P500 return. Findings denote that SCARES has negative impact on market return in lag one, albeit the result is insignificant when compared to that of Table 3. This suggests that top twenty five search terms capture more common COVID-19 sentiment. Minor change is evident in terms of VIX, EPU, ILIQ, and TEU in Model 10 compared to that of Table 3 when alternative SCARES is considered.

4.7. Endogeneity and reverse causality

One point that needs further explanation is that the inclusion of new proxies addresses the endogeneity issues associated with search shocks. For example, macro events may induce search spikes by households and that may raise the argument in favor of fact that sentiment is endogenous to macro and pandemic events. Consequently, controlling for news index and lag return in each specification assists the SCARES to capture sentiment related to particular event.

Another point is the reverse causality, which infers that sentiment is caused by some exogenous events. It is unlikely to predict that COVID-19 sentiment is associated with the lower market return.

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8 Minimum t-statistic of -4.683 occurs at the data point on May 8, 2020.
Because of the mean reverting pattern of asset returns, it is more likely to predict the returns. As such, high SCARES with corresponding low and subsequent high market return mitigates the concerns associated with reverse causality. It is unlikely that investors, expecting lower market return next day, would stop searching for terms like “coronavirus” or “coronavirus epidemic” today. Subsequently, mean reverting asset return following SCARES shocks supports the sentiment models.

5. Conclusion

In this study, I develop an alternative Scared COVID-19 Attitude Revealed by Eager Search (SCARES) index by combining household search volume i.e. “coronavirus pandemic”, “coronavirus epidemic”, and “coronavirus outbreak”. The data period of the study covers from May 1, 2020 to July 30, 2021 when COVID-19 has seen its relative peaks and bottoms. During this time frame, COVID-19 pandemic initiated turbulence in both financial sectors and stock market. I investigate the impact of internet search embedded COVID-19 SCARES index on different aspects of asset returns i.e. market return, factor return, and characteristics-sorted portfolio returns. I demonstrate that SCARES index has predictive power in explaining stock market return. Specifically, higher SCARES index is associated with lower stock market return in lag one. These results imply that higher households’ COVID-19 sentiment revealed by internet search initiates lower market return in the following day. Furthermore, return reversal is evident but in insignificant magnitude. Such findings are consistent with those of empirical evidence of sentiment inference (e.g. Baker & Wurgler, 2006).

I also report that impact of COVID-19 sentiment is more pronounced for the stocks that are harder to arbitrage. In particular, small, less profitable, and low investment firms demonstrate negative performance on third day after people become sentimental about COVID-19. This finding suggests that small, less profitable, and low investment firms are more speculative and higher households’ COVID sentiment leads to lower subsequent returns for such stocks. However, positive response in lag two suggests that asset return is mean reverting and this pattern is more in line with the temporary sentiment shocks.

I also explore the effect of SCARES index factor models of asset returns. Analysis reveals that SCARES is negatively related to SMB factor of F5 and of MOM. These findings imply that small firms are more sensitive to COVID-19 outbreaks. Results of the regime switching Markov regression report that twitter based sentiment, economic policy uncertainty, and VIX are positively related to SCARES index in high and low volatility period, whereas SCARES has no significant impact on S&P500 and illiquidity in either regimes. Further analysis infers that government intervention and support make the market more resistant to COVID-19 sentiments in later periods relative to earlier shocks.

Findings of the paper contribute to the existing literature by investigating whether objectively constructed COVID-19 sentiment using GT affects asset returns. Unlike prior studies, further analyses are conducted by utilizing several event responsive feedback indices. The contributions of this study have several practical implications to the government, policy makers, regulators, academics, and market participants. My findings have implications to policymakers and regulators who can learn about the short run market dynamics
during crisis period and can formulate policies in comparable shocks. In addition, government might develop premise about households’ response to pandemic shocks and take corrective actions in future to boost up the confidence of investors in similar crisis period such as COVID-19 regime. The results of the study have implications to market participants who can get an idea about asset price response to COVID-19 sentiment shocks and accordingly can take optimal asset allocation decisions. Academics might get insights about the implications that composite SCARES index has on multifactor asset return models.

My study, however, has some limitations that need to be discussed so that future research endeavor can address these issues. First, I develop SCARES index using internet search volume of US households only. Further research can explore the impact of SCARES index by taking other developed and developing countries. Second, I consider FF5 and MOM as multifactor asset return models. Future research can supplement the existing literature by considering other multifactor asset pricing models. Furthermore, COVID-19 SCARES index can be aligned with other market and survey based sentiment indexes to analyze sentiment’s impact on other aspects such as return volatility, liquidity, government intervention, or vaccination.

I develop an alternative high frequency measure of pandemic sentiment that is not derived from the market given information. I use internet search data to develop SCARES index, which has the potential advantage of being as objective as possible. Overall, the results of the study reveal that COVID-19 pandemic crisis exerts substantial impact on asset returns.

Declaration of Competing Interest

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

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