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In search of COVID-19 and stock market behavior

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ABSTRACT

The aim of this paper is two-fold. First, we investigate the nexus between investor attention to COVID-19 and daily returns in 59 countries. We use Google Search Volume Index to account for investor attention. Our empirical findings suggest that the search volume of the pandemic is negatively associated with daily returns. The effect was strong in the week that the World Health Organization declared it as pandemic and among advanced countries. Second, we explore the relationship between search volume and market volatility. The findings suggest that COVID-19 sentiment generated excess volatility in the market. Our findings remain robust with alternative specifications.

1. Introduction

The novel coronavirus (COVID-19) outbreak has shaken the global financial markets drastically (Zhang, Hu, & Ji, 2020). This pitfall is partly due to the lockdown of economic activities and partly due to the investor sentiments. The scope of this paper lies in the latter, i.e., we investigate how the feeds on COVID-19 affects the stock market in 59 countries. Our study is motivated by the existing evidence that people's emotions and anxiety affect investment decisions in the stock market (Kamstra, Kramer, & Levi, 2003; Kaplanski & Levy, 2010). A bad mood may exacerbate pessimism and negative sentiments that can affect the decisions of market participants *-mood sensitivity hypothesis* (Hirshleifer, Jiang, & DiGiovanni, 2020). In our scenario, the new pandemic has forced a large number of people into difficult situations and also affected several aspects of their lives. In fact, even WHO (2020) has recognized that COVID-19 related news could induce stress and anxiety.

We capture investor attention to the pandemic with the help of the Google Search Volume Index (GSVI).[1] The Google web search is extensively used to gather information on both economic and non-economic aspects (Ginsberg et al., 2009; González-Fernández & González-Velasco, 2018). In financial literature, the GSVI is widely employed to predict stock returns and their volatility (Heyman, Lescrauwaet, & Stieperaere, 2019; Kim, Lučivjanská, Molnár, & Villa, 2019; Vlastakis & Markellos, 2012).

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[1] GSVI is used as a measure of investor attention, and investor attention is essentially a means to capture the investor sentiment. Therefore, GSVI can be considered as a measure on investor sentiment as well. Thus, we have used the terms investor attention and investor sentiment interchangeably.

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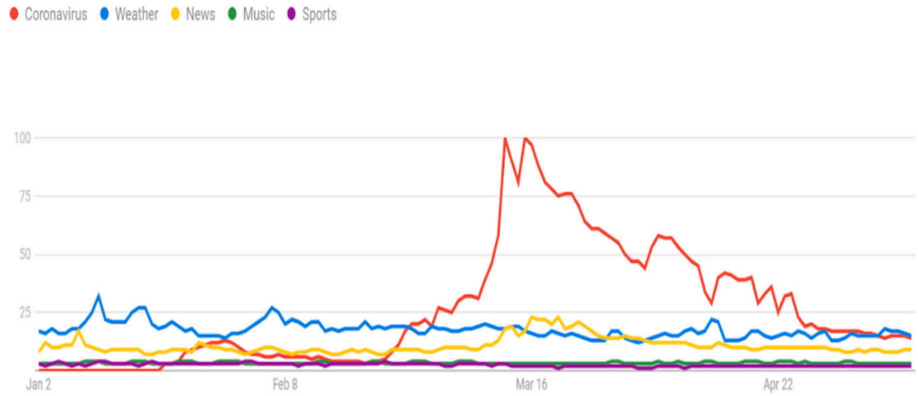

Source: Google trends

Fig. 1. Top searched topics in Google.
Source: Google trends.

In this paper, we use Google search volume on the keyword *covid+coronavirus* as a proxy for investor attention and relate it with stock market behavior.[2] The web search regarding coronavirus became the trending query after the outbreak of the COVID-19, especially in the mid of March when the World Health Organization (WHO) declared it as pandemic (Fig. 1).

This study first investigates whether the pandemic generates a negative sentiment that depresses stock markets all over the world. In other words, we hypothesize that the pandemic affects people's mood and increases their anxiety, which may get reflected in their investment decisions. Recent studies have highlighted that investors' emotion explains the variations in financial markets (Duxbury, Gärling, Gamble, & Klass, 2020; Hirshleifer et al., 2020). Aligned with these studies, we expect to observe a negative correlation between GSVI of COVID-19 and returns. We test this hypothesis using the benchmark indices of several countries and find that a one standard deviation increase in GSVI reduces the daily returns between 0.21 and 0.40%, which is 73%–183% in annualized terms. This finding remains robust with alternative model specifications. Our extended analysis shows that the effect is more pronounced in the first week after WHO declared the COVID-19 as a pandemic and in the set of advanced countries.

The second set of analysis explores the nexus between search volume and stock market volatility. De Long, Shleifer, Summers, and Waldmann (1990) show that the trading decisions based on sentiment lead to more noise trading and excess volatility in the market. Although the empirical findings on long-run survival of behavioral bias are debatable, there is enough evidence that it can induce excess volatility in the short-run (Da, Engelberg, & Gao, 2015; Kogan, Levin, Routledge, Sagi, & Smith, 2009; Kogan, Ross, Wang, & Westerfield, 2006). Following the existing literature, we hypothesize that the pandemic and the resultant sentiment-driven trade would increase volatility in the market. That is, we expect to observe a positive relation between GSVI of COVID-19 and volatility. Our empirical analysis investigates the volatility of the benchmark indices of several countries and find a strong relationship between search volume and market volatility. This finding reveals that COVID-19 sentiments cause excess volatility in the market during the study period.

This study lifts the frontier of existing literature in the following ways. *First*, this study belongs to the literature that examines the economic impact of pandemics (Alfani & Murphy, 2017; De La Fuente, Jacoby, & Lawin, 2019; Kentikelenis, King, McKee, & Stuckler, 2015). We study COVID-19 period that has shattered the economy with a 3% fall in the global GDP which is much worse than during the time of the 2008 crisis (IMF, 2020). *Second*, this paper contributes to the behavioral finance literature that examines the nexus between investor sentiments and stock market (Da et al., 2015; Kamstra et al., 2003; Kaplanski & Levy, 2010). The current study unravels how the COVID-19 sentiment is related to the daily stock market behavior across the world. *Finally*, in accordance with the *mood sensitivity hypothesis*, we present robust evidence for the impact of the pandemic on stock market through investors' sentiments. These findings align with existing studies that argue investor sentiments play a key role in the market (Baker & Wurgler, 2007; Hirshleifer et al., 2020; Stambaugh, Yu, & Yuan, 2012).

The remainder of this paper is organized as follows. Section 2 explains the data and variables used in the study. Section 3 presents our empirical findings. Section 4 concludes the study.

[2] The investors might use google search to keep abreast with the pandemic related news, to gauge the economic circumstances. However, it is also recognized that the negative news would lead to an increase in anxiety and stress. This is also reflected in the message by WHO, wherein the general public is advised to minimize watching, reading or listening to news about COVID-19 to reduce anxiety and distress. Hence, we believe that exposure to pandemic related news, even though individuals intend to assess the economic circumstances, would invariably have an impact on the individuals' mood.

Table 1
Descriptive statistics.

Country	Index	Returns	Volatility	GSVI_Covid		Correlation b/w GSVI_Covid and	
		Mean	Mean	Mean	sd	Returns	Volatility
Argentina	S&P Merval	−0.292	0.023	26.481	27.549	−0.075	0.665
Austria	ATX	−0.448	0.017	22.131	22.534	−0.292	0.819
Australia	S&P/ASX 200	−0.234	0.014	27.675	26.109	−0.040	0.791
Belgium	BEL 20	−0.312	0.013	25.393	24.623	−0.180	0.823
Bulgaria	BSE SOFIX	−0.299	0.010	29.864	29.378	−0.145	0.543
Bahrain	Bahrain All Share	−0.243	0.004	31.395	29.269	−0.124	0.249
Brazil	Bovespa	−0.478	0.022	24.805	27.590	0.016	0.667
Canada	S&P/TSX	−0.176	0.011	31.964	31.635	−0.049	0.853
Switzerland	SMI	−0.129	0.012	24.675	23.453	−0.152	0.883
Chile	S&P CLX IPSA	−0.225	0.015	22.471	23.358	−0.110	0.660
Colombia	COLCAP	−0.461	0.015	27.805	28.470	−0.012	0.501
Cyprus	Cyprus Main Market	−0.464	0.013	26.987	26.306	−0.302	0.656
Czech Republic	PX	−0.304	0.012	27.226	24.460	−0.268	0.837
Germany	DAX	−0.252	0.012	23.000	20.497	−0.233	0.836
Denmark	OMXC20	0.033	0.011	23.313	22.853	−0.274	0.615
Egypt	EGX 30	−0.340	0.010	24.427	28.680	0.043	0.300
Spain	IBEX 35	−0.405	0.013	23.571	24.429	−0.210	0.915
Finland	OMX Helsinki 25	−0.166	0.012	23.988	20.532	−0.293	0.827
France	CAC 40	−0.336	0.012	25.750	25.049	−0.128	0.877
United Kingdom	FTSE All-Share	−0.313	0.013	28.202	27.798	−0.093	0.825
Greece	Athens General Composite	−0.504	0.016	29.152	27.590	−0.079	0.709
Hungary	Budapest SE	−0.329	0.016	29.452	25.708	−0.212	0.801
Indonesia	IDX Composite	−0.346	0.011	19.905	23.473	0.154	0.549
Ireland	ISEQ Overall	−0.321	0.016	30.345	28.714	−0.192	0.868
India	BSE Sensex	−0.223	0.013	27.111	31.734	0.049	0.587
Iceland	ICEX Main	−0.158	0.010	30.878	28.949	−0.097	0.615
Italy	FTSE Italia All Share	−0.355	0.014	27.810	25.631	−0.313	0.719
Jordan	Amman SE General	−0.172	0.003	9.208	13.108	−0.619	0.597
Japan	Nikkei 225	−0.178	0.011	29.506	23.848	0.024	0.542
South Korea	KOSPI	−0.136	0.012	40.354	25.048	−0.061	0.524
Kuwait	FTSE Coast Kuwait 40	−0.348	0.010	28.212	26.270	0.019	0.293
Lebanon	BLOM Stock	−0.404	0.006	25.288	21.866	0.046	−0.137
Sri Lanka	CSE All-Share	−0.617	0.006	9.813	12.675	−0.559	0.696
Morocco	Moroccan All Shares	−0.298	0.007	19.942	22.423	−0.091	0.288
Malta	MSE	−0.188	0.000	24.988	23.590	−0.329	0.176
Mexico	FTSE BIVA Real Time Price	−0.206	0.012	24.552	25.413	−0.004	0.479
Malaysia	KLCI	−0.154	0.007	34.188	30.592	0.023	0.588
Namibia	NSX	−0.352	0.014	34.759	32.494	−0.099	0.729
Nigeria	NSE 30	−0.216	0.008	25.929	29.985	−0.009	0.113
Netherlands	AEX	−0.214	0.012	26.298	23.942	−0.222	0.815
Norway	OSE Benchmark	−0.237	0.014	22.867	21.779	−0.248	0.734
New Zealand	NZX 50	−0.092	0.010	23.360	24.372	0.013	0.614
Oman	MSM 30	−0.147	0.004	29.262	31.391	0.021	0.191
Peru	S&P Lima General	−0.402	0.010	28.214	28.749	−0.140	0.624
Philippines	PSEi Composite	−0.378	0.012	30.512	29.703	−0.036	0.520
Pakistan	Karachi 100	−0.231	0.013	26.000	29.642	0.007	0.485
Poland	WIG20	−0.352	0.014	31.470	28.169	−0.081	0.807
Portugal	PSI 20	−0.249	0.011	23.619	25.930	−0.211	0.843
Qatar	QE General	−0.219	0.007	36.917	35.118	0.050	0.452
Russia	MOEX	−0.184	0.013	24.061	23.925	0.116	0.490
Sweden	OMXS30	−0.166	0.012	27.530	22.715	−0.247	0.699
Singapore	STI Index	−0.239	0.008	40.805	27.525	−0.026	0.622
Thailand	SET	−0.245	0.011	20.595	18.357	−0.016	0.564
Turkey	BIST 100	−0.163	0.012	27.635	24.901	−0.078	0.491
Taiwan	Taiwan Weighted	−0.128	0.008	26.303	20.112	0.022	0.401
Ukraine	PFTS	−0.024	0.000	26.506	26.684	−0.328	0.033
United States	Dow 30	−0.208	0.013	30.663	29.642	−0.053	0.837
South Africa	FTSE/JSE Top 40	−0.127	0.013	28.301	30.028	0.061	0.344

Note: This table provides country-wise descriptive statistics of market returns, volatility, and Google Search Volume Index of keyword *coronavirus* + *covid* (GSVI_Covid). The last two columns report the correlation of GSVI_Covid with market returns and volatility.

Table 2
COVID-19 sentiments and stock returns.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GSVI_Covid	−0.00828***	−0.00873***	−0.0155***	−0.0123**		−0.00256	−0.00704*	−0.00683
	(0.00221)	(0.00234)	(0.00354)	(0.00472)		(0.00361)	(0.00363)	(0.00483)
Past Returns		−5.261**	−7.986***	−8.893**	−1.952	−12.58***	−8.720**	−3.530
		(2.561)	(2.667)	(3.482)	(3.139)	(3.184)	(3.408)	(3.077)
GSVI_Index				−0.0165***		−0.0107***	−0.00889***	−0.00747*
				(0.00426)		(0.00349)	(0.00244)	(0.00377)
D.GSVI_Covid					−0.0747***			
					(0.0149)			
D.GSVI_Index					−0.00858**			
					(0.00400)			
GSVI_Covid* Pandemic declared week						−0.0353***		
						(0.00709)		
Pandemic declared week						−1.216**		
						(0.485)		
GSVI_Covid* Advanced countries							−0.0128***	
							(0.00469)	
Advanced countries							0.568***	
							(0.165)	
D.Stringency Index								−0.0191
								(0.0259)
Constant	−0.0288	−0.0299	−0.897***	−0.598*	−0.931***	−0.770**	−0.877***	−0.867***
	(0.0784)	(0.0828)	(0.219)	(0.346)	(0.308)	(0.342)	(0.330)	(0.293)
Day of the week dummies	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Month dummies	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3552	3552	3552	2644	2065	2644	2644	2021
R-squared	0.005	0.008	0.092	0.099	0.092	0.162	0.100	054

Note: This table presents the relationship between Google Search Volume of COVID-19 (GSVI_Covid) and daily market returns. GSVI_Index is the search volume of market indies. Higher value of Stringency Index indicates higher restrictions. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

2. Data and variables

To investigate the link between investor attention on COVID-19 and stock market behavior, we use the benchmark indices of 59 countries. We obtain the index data from https://www.investing.com/ for the period starting from 1st February to 30th April 2020.[3] Our choice of the starting period, February, is based on the availability of GSVI data on the pandemic across countries. Even though the outbreak has happened even before, it received global attention after the WHO declared it as a Public Health Emergency of International Concern, on January 30.

The GSVI data is obtained from https://trends.google.com/. The GSVI provided by Google Trends, as the name suggests, is an index and not search volume in absolute terms. It is rather a value that is based on the search for a specific topic relative to the total number of searches on Google in the corresponding time interval. This relative value is further normalized such that the value of GSVI ranges between 0 and 100. GSVI value of 100 corresponds to the highest relative volume indicating the peak popularity for the searched term, and 0 indicates the absence of enough data for the searched term. Thus, the use of GSVI allows us to measure interest in a particular topic, among all searches, from a particular geographical location. This is one of the most widely used measures of investor attention (see for instance Da, Engelberg, & Gao, 2011). We use the GSVI of search term *covid+coronavirus* to capture investors' attention to the pandemic.

The index return is calculated as the difference between the log of current and previous day index values. To calculate the daily volatility in the stock market, we construct a measure proposed by Garman and Klass (1980).

$$Vol_{i,t} = 0.511 ln\left(\frac{h_{i,t}}{l_{i,t}}\right) - 0.019\left[ln\left(\frac{c_{i,t}}{o_{i,t}}\right) ln\left(\frac{h_{i,t}l_{i,t}}{o_{i,t}^2}\right) - 2ln\left(\frac{h_{i,t}}{o_{i,t}}\right) ln\left(\frac{l_{i,t}}{o_{i,t}}\right)\right] - 0.383\left[ln\left(\frac{c_{i,t}}{o_{i,t}}\right)\right]^2$$

where $Vol_{i,t}$ is the log volatility of i^{th} firm at time *t*. *h*, *l*, *o*, and *c* are the highest, lowest, opening, and closing price.

Table 1 reports country-wise descriptive statistics of index return, volatility and GSVI of COVID-19. The mean values of the indices are showing a negative sign which implies a global downturn of stock markets. Brazil, Colombia, Greece, Cyprus and Sri Lanka are the most affected countries during our study period whereas Denmark and Ukraine are the least affected countries. The Garman and Klass (1980) measure of volatility suggests that stock markets in Brazil and Argentina experienced higher fluctuations during this period. The last two columns provide a correlation of GSVI of COVID-19 with returns and volatility respectively. It indicates that most of the

[3] Previous studies have used this data source (González-Concepción, Gil-Fariña, & Pestano-Gabino, 2018; Li, Shang, & Wang, 2019; Zhang et al., 2020).

countries register a negative linear relationship between index returns and search volume, especially in Sri Lanka and Jordan. We also observe that many developed countries register a higher correlation between search volume and market volatility.

3. Empirical evidence

3.1. COVID-19 sentiments and returns

We first examine whether the information on the pandemic influences the stock market. If the news on the pandemic creates negative sentiments among market participants, then returns from the stock market should be negatively correlated with the search volume. But if the feeds do not influence the mood or anxiety of the investors, leaving little impact on market sentiments, then there should be no statistically significant relationship between index returns and search volume. To test that, we estimate the following model similar to Kaplanski and Levy (2010).

$$R_{i,t} = \alpha + \beta GVSI\_Covid_{i,t} + Controls + \epsilon_{i,t} \tag{1}$$

where R_{it} is the daily rate of returns on the major indices of country *i* at time *t*. $GSVI\_Covid_{it}$ is the search volume index for the keyword *covid+coronavirus* in the country *i* at time *t*. *Control* is a set of control variables that includes past returns, day of the week dummies, month dummies and GSVI of market indices.[4] The coefficient of *GSVI_Covid* is expected to be negative and significant when the COVID-19 news creates negative sentiments and affects the stock market.

Table 2 reports the estimation results. Column 1 reports the most parsimonious model, i.e., the regression of returns on search volume index. Consistent with the *mood sensitivity hypothesis*, we find the coefficient of search volume is negative and statistically significant at 1% level. More specifically, a one standard deviation increase in search volume is associated with a 0.21% fall in the returns, which is approximately around 73% in annualized terms. This finding indicates that the information on COVID-19, as hypothesized, has generated a negative sentiment in the market and as a consequence, the stock markets have plunged.

Due to non-synchronous trading, market-maker inventory control, transaction costs, and time-varying expected returns, there could be a weak tendency for movements in aggregate stock returns (Fisher, 1966; Kaplanski & Levy, 2010). As a result, our parsimonious model may suffer from the problem of serial correlation (Schwert, 1990a, 1990b). To account for the possible serial correlation, we include the past value of returns into the model. Column 2 reports estimation results after adding the previous day's returns, and the result implies that the inclusion of past returns does not alter our findings.[5]

Further, the stock markets behave unevenly on different days of the week. The famous "weekend effect" or "Monday effect" is an example of the same (Cho, Linton, & Whang, 2007; French, 1980). Hence, we add dummy variables for the day of the week as an additional control measure to capture the effect. In a similar fashion, we include month dummies to alleviate the month-fixed effects, if any. Column 3 reports the estimation results of our model including the day of the week and month dummies. The coefficient estimate is even bigger after controlling for the day of the week and month fixed effects. For instance, an increase of one standard deviation in the search volume is associated with a 0.04% fall in the returns, which is around 183% in annualized terms.[6] Previous studies (Vozlyublennaia, 2014) have identified that returns are correlated with the search volume of the indices (GSVI_Index) as well. To check the consistency of the result, we add GSVI of market indices in our model. GSVI_Index is used to capture the information demand of the assets in the earlier studies (Chronopoulos, Papadimitriou, & Vlastakis, 2018; Vlastakis & Markellos, 2012). Column 4 suggests that the addition of the new control measure does not alter our main findings.[7]

Moreover, this paper carries out three additional exercises. First, we use a change in the search volume index instead of the level variable. Column 5 reports the estimation result and we find the coefficients of both search volume measures of COVID-19 and indices are negative and statistically significant. Second, we attempt to explore the stock market behavior for the week WHO declared COVID-19 as a pandemic. There is a higher chance for the news to affect people's mood in the first few days of the events. Therefore, this analysis allows us to capture the differential effect of the pandemic news on returns through negative market sentiments. To do that, we construct a dummy variable that takes value 1 for the week after WHO declared the pandemic on 11th March 2020. Then we interact the dummy variable with the search volume index of the pandemic. Column 6 reports the estimation result with all other control variables. We find negative and significant coefficients for the interaction term which suggests that the impact of COVID-19 mood on the stock market is relatively severe on the week of pandemic declaration.

In another analysis, we examine the differential effect of search volume in advanced and developing countries. For this purpose, we construct a dummy variable that takes value 1 for those countries that are in the IMF (International Monetary Fund)'s list of advanced countries; zero otherwise. Covid spread was announced as a pandemic across the world, both developed and developing countries.

[4] We acknowledge that there will be lead-lag relationship between the stock returns of different countries due to differing time zones. e.g. the returns in Asia, Europe may influence the U.S. as these markets open before the U.S. We tried to resolve part of this issue by including time (day) dummies into the model. The results are qualitatively similar to our main findings and are not reported due to breveity.

[5] As a further robustness check, we extended the lag of returns up to 7 days, however, the results are qualitatively similar to the above findings; not reported due to brevity.

[6] There is a possibility for day of the week and month effects differ across global markets. Therefore, we include interaction between the time (week and month) dummies and country dummies in the model. The results are qualitatively similar and not reported for breveity.

[7] The search volume of market indices used above are constructed based on the worldwide search; we also constructed a search volume of market indices using searches in the corresponding countries. However, the results are qualitatively similar and not reported due to brevity.

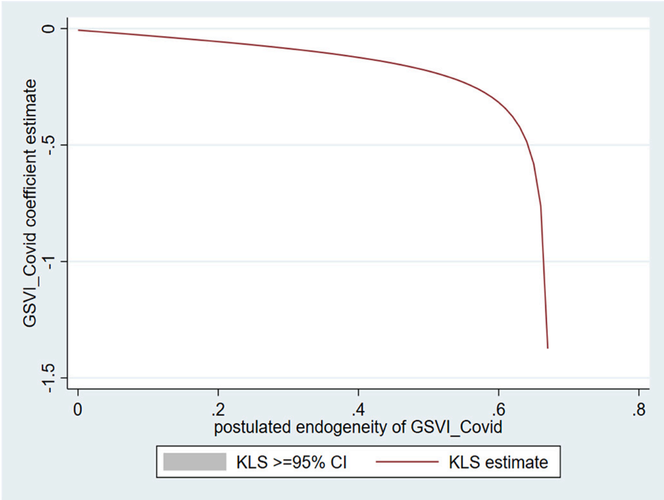

Fig. 2. KLS estimation coefficient of GSVI_Covid for different postulated endogeneity.

Table 3
KLS estimation results.

Variables	ρ =0.01	ρ =0.1	ρ =0.25	ρ =0.5
GSVI_Covid	−0.00919***	−0.0307***	−0.0139***	−0.0187***
	(0.00355)	(0.00429)	(0.00361)	(0.00374)
Past returns	−3.676*	−5.002**	−3.967*	−4.260**
	(2.092)	(2.120)	(2.094)	(2.098)
GSVI_Index	−0.00703**	−0.00299	−0.00614*	−0.00525
	(0.00356)	(0.00362)	(0.00356)	(0.00357)
D.stringencyindex	−0.0171	0.00165	−0.0130	−0.00883
	(0.0172)	(0.0175)	(0.0172)	(0.0173)
Constant	0.766	1.827***	0.999**	1.233***
	(0.467)	(0.486)	(0.469)	(0.472)
Observations	2021	2021	2021	2021

Note: This table presents the relationship between Google Search Volume of COVID-19 (GSVI_Covid) and daily market returns using KLS estimation method. ρ is the correlation between error term and GSVI_Covid. GSVI_Index is the search volume of market indies. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Since the developed countries have better health infrastructure and rank higher in human development indicators, we conjecture that developed countries are better equipped to deal with pandemic. This encourages us to hypothesis that the impact of the pandemic on the anxiety levels of individuals in advanced economies will be lesser and thus, its adverse effect on the stock market will be milder compared to that in the developing economies. Column 7 presents the results with the interaction between dummy variable and search volume.[8] Intrestingly, the result reveals that the negative relationship between search volume and index returns are relatively high among advanced countries.

Finally, to alleviate the effect of macroeconomic environment during the pandemic, we include change in *Government Stringency Index*[9] into the model; Column 8 suggests the results remain qualitatively similar to our main findings. One of the pertinent issues in the above analysis is the endogeneity problem. There may be factors such as internet quality and accessibility that can influence both returns (through information flow) and search volume index. The failure to capture such information leads to endogeneity problem due to omitted variable bias. In other words, there is a possibility for a significant correlation between error terms and GSVI_Covid. To address this issue, we use Kinky Least Squares (KLS) estimation technique (Kiviet, 2020a, 2020b). The advantage of KLS is that it does not rely on instrumental variables, instead it analytically corrects the bias in OLS estimates for the range of postulated endogeneity (correlation between error terms and GSVI_Covid $=\rho$). In addition, KLS confidence intervals are often narrower than those from 2SLS, particularly if instruments are weak. Since we assume that GSVI_Covid is positively correlated with omitted variables, we estimate KLS model for ρs within the range of 0 to +1. Fig. 2 plots the coefficients of GSVI_Covid for different values of ρ. As mentioned above, the confidence interval for the estimates is too narrow. The coefficient of GSVI_Covid is negative for any range of ρs under consideration.

[8] We use a random-effect model rather than a fixed-effect model since our dummy variables for advanced countries are not time-invariant.

[9] Government Stringency Index is obtained from from OxCGRT (Oxford COVID-19 Government Response Tracker). The index is constructed based on nine response indicators including workplace closures, travel bans and school closures, rescaled to a value from 0 to 100 (100 = strictest).

Table 4
COVID-19 sentiments and return volatility.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GSVI_Covid	0.000231***	0.000226***	0.000179***	0.000156***		0.000138***	0.000138***
	(1.90e-05)	(1.84e-05)	(1.47e-05)	(1.83e-05)		(1.73e-05)	(2.41e-05)
Past Returns		−0.0596***	−0.0361***	−0.0327***	−0.0687***	−0.0239***	−0.0321***
		(0.00679)	(0.00652)	(0.00748)	(0.00929)	(0.00665)	(0.00717)
GSVI_Index				0.000127***		0.000113***	0.000117***
				(2.57e-05)		(2.40e-05)	(2.54e-05)
D.GSVI_Covid					6.54e-05**		
					(2.77e-05)		
D.GSVI_Index					2.70e-05**		
					(1.17e-05)		
GSVI_Covid* Pandemic declared week						3.67e-05	
						(5.00e-05)	
Pandemic declared week						0.00616*	
						(0.00356)	
GSVI_Covid* Advanced countries							4.46e-05
							(3.48e-05)
Advanced countries							−0.00274**
							(0.00121)
Constant	0.00542***	0.00541***	0.00475***	0.00141	0.00801***	0.00176	0.00930***
	(0.000675)	(0.000642)	(0.00155)	(0.00151)	(0.00150)	(0.00151)	(0.00194)
Day of the week dummies	No	No	Yes	Yes	Yes	Yes	Yes
Month dummies	No	No	Yes	Yes	Yes	Yes	Yes
Observations	3550	3550	3550	2642	2062	2642	2642
R-squared	0.279	0.304	0.440	0.488	0.366	0.515	0.490

Note: This table presents the relationship between Google Search Volume of COVID-19 (GSVI_Covid) and daily market volatility. GSVI_Index is the search volume of market indies. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

To make our finding more explicit, we report the estimation results in Table 3 for $\rho = 0.01$, 0.1, 0.25 and 0.5. The coefficients of our main variable of interest are negative and significant for all the values of ρs. That is, our main finding remain consistent even after addressing the issue of endogeneity.

3.2. COVID-19 sentiments and return volatility

In the previous subsection, we observe that the COVID-19 created a negative sentiment among market participants which drastically affected the stock market across the globe. Another important element in the interest of investors is the volatility of the market. Previous studies have highlighted that a negative mood of market participants can generate excess volatility in the market (Da et al., 2015). In order to verify that in the context of COVID-19, this subsection investigates whether the COVID-19 attention generates excess volatility in the market. For that purpose, we estimate the following econometric model.[10]

$$Vol_{i,t} = \alpha + \beta GVSI\_Covid_{i,t} + Controls + \epsilon_{i,t} \tag{2}$$

Table 4 reports the estimation result of various specifications of eq. 2 to explore the nexus between search volume and market volatility. Column 1 presents the results for our parsimonious model that tries to explain the volatility in returns solely in terms of search volume. Consistent with our hypothesis, the result suggests that there exists a positive and significant relation between the search volume of COVID-19 and market volatility. This allows us to infer that the pandemic has influenced the emotions of investors and thereby cause excess volatility in the market. Our result is consistent with the literature that argues investor sentiment can explain the volatility in the market (Da et al., 2015).

Theoretical and empirical literature points at the underlying link between the return of a financial asset and its volatility (see, for instance, Baillie & DeGennaro, 1990; Whitelaw, 2000). To control for the impact of returns on volatility, we include past return as a control variable to our parsimonious model. We find, consistent with the *leverage effect*[11] (Bekaert & Wu, 2000; Christie, 1982), that past returns and volatility are negatively related (see Column 2). Interestingly, even after controlling for returns, we find that the relationship between search volume and market volatility is positive and significant. This result further reinforces the validity of our main findings.

Further, in line with our econometric analysis in the previous section, we include the day of the week and month dummies to capture week and month specific effects respectively. Nevertheless, the results in Column 3 indicate that the coefficient of the search volume index continues to be positive and significant. Further, since empirical literature documents strong co-movement among market attention and volatility (Dimpfl & Jank, 2016), we include the GSVI of market indices as well in the model. Column 4 implies

[10] We omitted two observations from South African data since their value of closing price is less than their low price.

[11] Leverage effect refers to the empirically observed tendency of an asset's volatility to be negatively correlated with the asset's returns. It is argued that the negative relation is driven by the fact that a fall in return increases financial leverage and thereby causes an increase in volatility.

Table 5
GARCH(1,1) results.

Country	Constant		GSVI_covid		Constant		ARCH Coefficient		GARCH Coefficient		Observations
Argentina	−0.344	(0.429)	0.0486***	(0.0125)	−0.486	(1.052)	0.0771	(0.0762)	0.524***	(0.113)	57
Austria	−0.426	(0.443)	0.0402***	(0.0155)	1.246**	(0.614)	−0.224***	(0.0512)	−0.0361	(0.175)	62
Australia	0.131	(0.161)	0.0599***	(0.0151)	−1.580	(1.284)	0.932	(0.748)	−0.0117	(0.0448)	62
Belgium	0.220***	(0.0678)	0.0208***	(0.00210)	2.162***	(0.0387)	0.209***	(0.0253)	−0.986***	(0.00312)	62
Bulgaria	−0.143	(0.203)	0.0419	(0.0648)	−4.077	(4.425)	0.715	(0.803)	0.323	(0.204)	59
Brazil	−0.212	(1.192)	0.0354***	(0.0136)	0.396	(1.069)	0.771	(0.764)	0.00718	(0.410)	60
Canada	0.240*	(0.130)	0.0557***	(0.00807)	−1.293*	(0.755)	0.820**	(0.324)	−0.0234	(0.0346)	62
Chile	−0.230	(0.249)	0.0536***	(0.00898)	−0.0980	(0.548)	−0.0755	(0.101)	0.319***	(0.0958)	63
Colombia	−0.289	(0.422)	0.0503***	(0.00898)	−0.612	(0.743)	0.263	(0.281)	0.221	(0.248)	61
Cyprus	−0.261	(0.681)	0.0388***	(0.0126)	−0.0781	(0.969)	−0.212***	(0.0761)	0.142	(0.387)	56
Czech Republic	0.0388	(0.161)	0.0532***	(0.00870)	−0.493	(0.463)	−0.110	(0.113)	0.0615	(0.129)	62
Germany	0.125	(0.141)	0.0593***	(0.0124)	0.344	(0.459)	−0.0833***	(0.0259)	−0.0757	(0.0749)	62
Egypt	−0.145	(0.199)	0.0205**	(0.00833)	−1.284**	(0.634)	0.883*	(0.523)	0.140	(0.153)	62
Finland	−0.161	(0.871)	0.0433***	(0.0136)	0.805	(0.575)	0.0714	(0.150)	−0.422	(0.270)	62
France	−0.157	(0.320)	0.0533***	(0.0121)	−0.278	(0.897)	−0.0719	(0.108)	0.216	(0.393)	62
United Kingdom	−0.233	(0.318)	0.0409***	(0.0129)	−0.0103	(0.777)	0.0266	(0.287)	0.109	(0.250)	62
Greece	−0.265	(0.345)	0.0505***	(0.00893)	−0.411	(0.598)	0.492	(0.358)	0.138	(0.144)	58
Indonesia	−0.479	(1.993)	0.0248*	(0.0139)	1.077	(3.503)	0.474	(1.964)	−0.235	(1.389)	62
Ireland	0.0646	(0.244)	0.0562***	(0.00844)	−1.110*	(0.637)	0.000355	(0.0698)	0.247	(0.161)	62
India	−0.579*	(0.314)	0.0264**	(0.0103)	1.702*	(0.986)	−0.00996	(0.0854)	−0.346	(0.424)	58
Iceland	0.00531	(0.452)	0.0294**	(0.0135)	0.268	(1.001)	0.406*	(0.220)	−0.512*	(0.273)	60
Italy	0.485**	(0.223)	0.0602***	(0.0154)	−0.478	(0.607)	−0.0711	(0.102)	0.0338	(0.126)	62
Jordan	−0.141***	(0.0333)	0.0815***	(0.00458)	−2.770***	(0.214)	−0.575***	(0.202)	0.577***	(0.209)	32
Japan	−0.337	(0.329)	0.0238**	(0.0105)	0.195	(0.706)	0.611*	(0.324)	−0.0874	(0.157)	60
Lebanon	−0.201	(0.408)	−0.0770***	(0.0211)	3.821***	(1.010)	−0.120	(0.0900)	0.152**	(0.0668)	44
Morocco	−0.574**	(0.237)	−0.0212	(0.0171)	−0.131	(0.544)	0.894	(0.575)	0.170	(0.132)	64
Malta	−0.134	(0.487)	0.0376***	(0.0117)	−0.983	(0.732)	−0.0765***	(0.0158)	−0.113	(0.255)	59
Mexico	−0.217	(0.170)	0.0397**	(0.0165)	−2.947***	(0.901)	0.450*	(0.237)	0.480***	(0.151)	64
Malaysia	0.0102	(0.0803)	0.0417***	(0.0104)	−1.976***	(0.685)	0.821*	(0.462)	−0.0183	(0.0246)	64
Namibia	−0.133	(0.266)	0.0387***	(0.00518)	0.210	(0.566)	−0.0366	(0.198)	0.115	(0.213)	61
Nigeria	−0.249**	(0.106)	0.0260*	(0.0141)	−1.460***	(0.466)	0.727***	(0.254)	0.00485	(0.115)	62
Norway	0.0901	(0.266)	0.0505***	(0.00996)	0.186	(0.498)	0.0958	(0.298)	−0.117	(0.0771)	61
New Zealand	−0.0581	(0.267)	0.0461***	(0.0125)	−0.828	(1.171)	0.139	(0.149)	0.246	(0.242)	74
Oman	0.0261	(0.126)	0.0818**	(0.0334)	−8.065***	(2.718)	0.450*	(0.250)	0.428***	(0.118)	64
Peru	−0.305	(0.188)	0.0423***	(0.0126)	−1.077	(1.357)	0.184	(0.241)	0.344*	(0.200)	62
Philippines	−0.161	(0.282)	0.0442***	(0.00760)	−0.0458	(0.423)	−0.00467	(0.0611)	0.116	(0.130)	60
Pakistan	−0.348	(0.330)	0.0231***	(0.00749)	0.503	(1.077)	0.0467	(0.328)	0.243	(0.265)	62
Poland	−0.176	(0.198)	0.0428***	(0.00755)	0.245	(0.484)	0.127*	(0.0651)	−0.242***	(0.0914)	62
Portugal	0.0517	(0.204)	0.0490***	(0.00971)	−0.242	(0.596)	0.198	(0.223)	−0.0739	(0.402)	62
Qatar	−0.174	(1.086)	0.0243***	(0.00632)	−0.843	(5.137)	0.539	(0.497)	0.102	(1.880)	63
Sweden	−0.00209	(0.217)	0.0540***	(0.00908)	−1.372	(0.845)	0.231	(0.158)	0.335***	(0.114)	62
Singapore	−0.333	(0.213)	0.0311***	(0.00981)	−0.507	(0.758)	0.621	(0.394)	−0.171*	(0.0994)	64
Thailand	−0.136	(0.292)	0.0704***	(0.0247)	−0.228	(1.059)	−0.0471	(0.0297)	0.211	(0.200)	62
Turkey	−0.603**	(0.291)	0.0308***	(0.00986)	−0.109	(0.502)	−0.202***	(0.0458)	0.659***	(0.186)	63
Ukraine	−0.0974	(0.0887)	−0.0112	(0.0153)	−0.621	(0.647)	−0.0515	(0.0750)	−0.497*	(0.255)	59
United States	−0.0247	(0.193)	0.0785***	(0.0190)	−3.224*	(1.648)	0.280***	(0.0965)	0.366***	(0.0852)	62

Note: This table presents the results of GARCH-X model that examines the relationship between Google Search Volume of COVID-19 (GSVI_Covid) and daily market volatility. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

that our results are qualitatively similar even after controlling for market attention. Also, using a change in GSVI for COVID-19 and indices instead of their level forms, leaves our results unchanged (see Column 5).

To make our analysis more rigorous, similar to the previous subsection, we conduct additional two tests. First, we take a closer look at the relationship between market volatility and pandemic by examining whether the declaration of COVID-19 as a pandemic has a differential impact. To do that, we plug an interaction term of a dummy variable (that takes value 1 for the week after declaration) and search volume index into our model. Second, we examine the impact of search volume on volatility for advanced countries vis-à-vis developing countries. For this analysis, we interact a dummy variable (that takes value 1 for countries identified as advanced) with search volume index. In Column 6 and 7, the coefficients of the interaction terms suggest that the sentiment-led market volatility is relatively higher in the first week of pandemic declaration and for advanced countries, however, their significance level is weak.

3.3. Robustness test

The previous section examines the relation between pandemic related sentiment and volatility using the panel regression technique. GARCH family models is another technique that is widely used for volatility modelling (for instance, Efimova & Serletis, 2014; Vlastakis & Markellos, 2012; among others). We have conducted a country-wise analysis using the GARCH-X (1,1) model with search volume as an exogenous variable to examine the impact of pandemic related sentiment on return volatility. The results reported in Table 5 suggest that the investor sentiment has led to increased volatility in the stock markets for the majority of the countries examined in our study.

4. Conclusion

The paper explores whether the recent COVID-19 news has any impact on investor sentiment that can affect the stock market behavior. The Google search volume index for the keyword *covid+coronavirus* is used as a proxy for investors' attention to COVID-19. Our first analysis examines the relationship between search volume and stock market returns in 59 countries. We find strong cross-country evidence suggesting that attention to novel coronavirus has created a general negative sentiment among market participants and consequently depressed the stock markets. More specifically, one standard deviation change in the search volume is associated with a negative market returns to the tune of 0.21– 0.40%. We also find that this effect is higher in the week when the World Health Organization declared COVID-19 as a pandemic. Moreover, the inverse relation between search volume and return is more pronounced in advanced countries. Second, we explore the nexus between search volume and stock market volatility. We find that pandemic sentiment has generated excess volatility in the market. Our main findings remain consistent with various specifications.

Though Google trends based sentiment index is accepted and widely used in the empirical literature, it is not free of limitations. One of the major limitations is that it is difficult to segregate positive and negative sentiment. For instance, the present study uses the search term *covid+coronavirus* to capture the pandemic-related sentiment and conjecture that the resultant search volume index represents the negative sentiment generated due to the pandemic. However, not all the sectors are negatively impacted due to the pandemic (the Pharmaceuticals sector, biotechnology sector are a few of the sectors that have gained from the pandemic). It is imperative that a proper distinction is made between positive and negative sentiment. Further, Google Trends provides overall normalized search volumes, this limits the scope of research from examining the differential impact of the pandemic among investors belonging to different demographic categories. These issues will be addressed in future research with the availability of more nuanced information on investor sentiments.

CRediT authorship contribution statement

Radeef Chundakkadan: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing - original draft; Writing - review & editing. **Elizabeth Nedumparambil:** Conceptualization, Formal analysis, Investigation, Methodology, Software, Writing - original draft; Writing - review & editing.

Declaration of Competing Interest

This statement is to certify that all Authors have seen and approved the manuscript being submitted. We warrant that the article is the Authors' original work. We warrant that the article has not received prior publication and is not under consideration for publication elsewhere. On behalf of all Co-Authors, the corresponding Author shall bear full responsibility for the submission.

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