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Constructing a positive sentiment index for COVID-19: Evidence from G20 stock markets

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ABSTRACT

The present study investigates the degree of market responses through the scope of investors' sentiment during the COVID-19 pandemic across G20 markets by constructing a novel positive search volume index for COVID-19 ($COVID19^{+}$). Our key findings, obtained using a Panel-GARCH model, indicate that an increased $COVID19^{+}$ index suggests that investors decrease their COVID-19 related crisis sentiment by escalating their Google searches for positively associated COVID-19 related keywords. Specifically, we explore the predictive power of the newly constructed index on stock returns and volatility. According to our findings, investor sentiment positively (negatively) predicts the stock return (volatility) during the COVID-19. This is the first study assessing global sentiment by proposing a novel proxy and its impacts on the G20 equity market.

1. Introduction

The COVID-19 pandemic is a textbook case of an exogenous shock to the functioning of the global economy, raising the question of its economic and financial impacts. An exogenous shock in investor sentiment can lead to a chain of events, and it might show up first in investor beliefs, which could be extracted from different sources, such as from surveys or Google search queries. These beliefs might then translate to observable patterns of securities trades, which are recorded (Baker & Wurgler, 2007). Especially during periods of great uncertainty, the effect of investor sentiment and particularly overconfidence is more pronounced than fundamentals (Daniel, Hirshleifer, & Subrahmanyam, 2005; Baker & Wurgler, 2007).

In order to assess the adverse impact of COVID-19 on the global economy, economists started to examine various channels. This resulted in a vast amount of literature in a short period of time examining the negative impact of the pandemic on various facets of the economic environment, such as stock markets (Lyócsa, Baumöhl, Výrost, & Molnár, 2020; Szczygielski, Brzeszczyński, Charteris, & Bwanya, 2021; Delis, Savva, & Theodossiou, 2021; Apostolakis, Floros, Gkillas, & Wohar, 2021; Izzeldin, Muradoğlu, Pappas, & Sivaprasad, 2021), the energy sector (Szczygielski, Brzeszczyński, et al., 2021; Zhang, Chen, & Shao, 2021), tourism sector (Sigala, 2020; Škare, Soriano, & Porada-Rochoń, 2021), firm performance (Didier, Huneeus, Larrain, & Schmukler, 2021; Shen, Fu, Pan, Yu, & Chen, 2020), cryptocurrencies (Jiang, Wu, Tian, & Nie, 2021; Khelifa, Guesmi, & Urom, 2021; Sarkodie, Ahmed, & Owusu, 2021) etc.

Following already known in the relevant literature methodologies to assess investors' negative (crisis) sentiment (Da, Engelberg, & Gao, 2015; Irresberger, Mühlnickel, & Weiß, 2015), Salisu and Akanni (2020), Chen, Liu, and Zhao (2020), and Subramaniam and Chakraborty (2021) constructed a COVID-19 fear index to capture investors' fear (negative) sentiment during the COVID-19 pandemic and to measure its impact either on stock markets or on Bitcoin price dynamics.

However, the announcements in mid-November 2020 on the successful development of several vaccines may have partly reversed this negative impact of COVID-19 on financial markets. With the vaccines from AstraZeneca, Pfizer-BioNTech, Moderna, and Johnson & Johnson now being widely distributed, a natural question that arises is whether an initially undoubtedly adverse phenomenon (i.e., the COVID-19 pandemic) can result in a more boosted investor confidence which in turn increases stock price returns and diminishes stock price volatility.

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Furthermore, heading towards an immunity through vaccines lowers the risks of unexpected and uncontrolled pandemic growth, which in turn decreases the potential fatalities. The results should provide less economic uncertainty, a lower likelihood of unexpected policies, and—in the end—greater stock price stability (Rouatbi, Demir, Kizys, & Zaremba, 2021). Therefore, the core notion driving this study is to construct and then explore whether the vaccine-related positive sentiment, as manifested by the Google search volume data, affects stock market returns and volatility from major economies.

In order to construct our positive search volume index for COVID-19 (COVID19^{+}), we employ vaccine-related Google search volume data as a direct measure of investors' positive sentiment. Specifically, we create a list of 24 vaccine-related search terms, which exert the most positive tone/sentiment, with our identification assumption being that these 24 keywords are able to capture investors' positive sentiment stemming from the declining uncertainty due to the initialization and the availability of the vaccination programs. In line with the analysis of Subramaniam and Chakraborty (2021), we also construct a negative search volume index for COVID-19 (COVID19^{-}). The rationale behind this tactic is that the COVID-19 still exists as an adverse phenomenon, and thus negative investor sentiment stemming from it may continue to exert a negative response to stock markets.

The novelty of our research design can be summarized as follows. First, to the best of our knowledge, despite the rapidly growing academic literature on the negative implications of COVID-19, this is the first analysis that introduces a positive sentiment index as a direct measure of stock market price returns. Apart from the novelty itself, other reasons we construct and consider the impact of positive sentiment are the following: First, because a lower negative sentiment does not necessitate higher positive sentiment, given the dispersion of investor opinions (Hong & Stein, 2007). Second, because positive sentiment may be more important than negative sentiment in substantiating the market impact of noise traders (Yu and Yuan, 2011; Gao, Ren, & Zhang, 2020). More importantly, apart from addressing stock returns, as the previous literature does, our study also emphasizes the effects of investor sentiment on the stock market volatility during the pandemic.

Furthermore, our study showcases that our novel positive sentiment index (COVID19^{+}) and the negative sentiment index (COVID19^{-}) of Subramaniam and Chakraborty (2021) follow distinct trajectories when associated with stock market returns and volatility during the COVID-19 pandemic, constituting a significant addition to the relevant literature. Specifically, our results show that a higher COVID19^{+} (COVID19^{-}) index decreases (increases) the so-called investors' crisis sentiment, foreshadowing higher (lower) stock returns in G20 stock markets during the COVID-19 era. We also find that a higher COVID19^{+} (COVID19^{-}) dampens (accentuates) stock market volatility. In addition, although the majority of past studies focus on a single country or specific market, this research approaches a larger scale of countries (G20 economies). Ultimately, this analysis further enlarges the vast growing academic literature on how sentiment affects various facets of economic activity (see, among others, Da et al., 2015; Fu, Wu, Liu, & Chen, 2020; Anastasiou & Katsafados, 2020; Anastasiou and Drakos, 2021a; Anastasiou & Drakos, 2021b; Anastasiou, Ballis, & Drakos, 2021; Anastasiou & Drakos, 2021a; Anastasiou, Kapopoulos, & Zekente, 2021; Anastasiou & Drakos, 2021b; Anastasiou, Kallandranis, & Drakos, 2022).

The remainder of the paper is structured as follows. Section 2 provides a brief discussion on the previous literature review. Section 3 describes the dataset, and the construction of the variables, while Section 4 demonstrates the econometric models and the empirical methodology used in the analysis. Section 5 discusses the empirical findings. Finally, Section 6 concludes.

2. Literature review

Early papers focused mainly on financial volatility (Albulescu, 2021; Bakas & Triantafyllou, 2020; Zaremba, Kizys, Aharon, & Demir, 2020) and stock market returns (Ashraf, 2020; Cakici & Zaremba, 2021; Yong & Laing, 2021; Zhang, Hu, & Ji, 2020). In the early days of the pandemic, Ortmann, Pelster, and Wengerek (2020), using transaction-level trading data, showed that investors increased their trading activities, both at the extensive and the intensive margin. Furthermore, Shahzad, Naeem, Peng, and Bouri (2021) provide formal evidence regarding the asymmetric impact of good and bad volatilities in China during the COVID-19 period, while Sharif, Aloui, and Yarovaya (2020), in their analysis, examined the relationship among oil prices, the stock market, geopolitical risk, economic policy uncertainty and the COVID-19 pandemic in the US.

Furthermore, in their study, Yarovaya, Brzeszczynski, Goodell, Lucey, and Lau (2020) review the mechanism for information transmission of the pandemic to financial markets, helping researchers to conduct further analyses on the issue at hand, while Goodell (2020) delivers an agenda for future research on the financial aspects of the COVID-19 pandemic.

In their study, Barberis, Shleifer, and Vishny (1998) identified investor sentiment as the process through which investors tend to formulate their beliefs. The findings of Yu and Yuan (2011) showcase that sentiment traders undermine an otherwise positive mean-variance tradeoff during high-sentiment periods. Chau, Deesomsak, and Koutmos (2016) assessed the role of investor sentiment on trading behavior, with their analysis resulting informal evidence of sentiment-induced buying and selling in the US stock market. Frijns, Verschoor, and Zwinkels (2017) found in their study that stock return comovements are mainly driven by investor sentiment.

Google search data offer the possibility to uncover an individual's sentiments. Thus, using search volume data through proxies is of great importance in economics and finance. Ginsberg et al. (2009) were among the first to introduce Google search data in an empirical study, coincidentally dealing with another health-related issue (influenza epidemics). In the area of finance and economics, Da, Engelberg, and Gao (2011) introduced in their study the utilization of search volume data as a metric for investors' attention, while Bank, Larch, and Peter (2011) show that Google search volume serves as an intuitive proxy for overall firm recognition and manages to capture the stock market's attention. Additionally, in their research paper, Preis, Moat, and Stanley (2013) scrutinized whether Google search data can help in the formulation of investment strategies and portfolio diversification, while Bijl, Kringhaug, Molnár, and Sandvik (2016) investigated whether data from Google Trends can be used to forecast stock returns. Finally, Anastasiou and Drakos (2021b) conducted a nowcasting exercise using the Google search intensity for the term «Drachma» and showed that higher search intensity leads to more deposits withdrawals,

In a more related to this study's strand of the literature, Aguilar, Ghirelli, Pacce, and Urtasun (2021), through the construction of a new newspaper-based sentiment indicator, showed that compared to the Economic Sentiment Indicator of the European Commission, this new index performs better into nowcasting the Spanish GDP. Brodeur, Clark, Fleche, and Powdthavee (2021) utilized Google data to test if an association between COVID-19 lockdowns and well-being changes exists. Meanwhile, Lyócsa et al. (2020) determined that fear of COVID-19 as manifested by Google search volume data represents a significant way of forecasting stock price variation during the pandemic. Similarly, Costola, Iacopini, and Santagiustina (2020) and Smales (2021) show that the search query volume of significant markets is connected to a faster flow of information into financial markets during the pandemic. Huynh, Foglia, Nasir, and Angelini (2021) propose a novel approach to assess feverish international sentiments, along with their impacts on the equity market. Huang and Luk (2020) constructed a new monthly index of Economic Policy Uncertainty for China in 2000–2018 based on Chinese newspapers that foreshadow declines in equity price, employment and output. Finally, Lucey, Vigne, Wang, and Yarovaya (2021) constructed a novel cryptocurrency uncertainty index based on news coverage capturing two types of uncertainty, that of the price of cryptocurrency and uncertainty of cryptocurrency policy, while Lucey, Vigne, Yarovaya, and Wang (2021) developed a new index of cryptocurrency environmental attention based on news coverage, that captures the extent to which environmental sustainability concerns are discussed.

3. Data and variables

The dataset consists of daily returns spanning from January 1, 2020, to May 16, 2021,[1] for the G20 stock market indices, using the Thomson Reuters database. The resulting panel generates a sample of 10,040 observations. Our main independent variables proxy the positive/negative related Google search queries regarding COVID-19 on the stock market returns behavior of the G20 economies.[2]

In particular, we retrieve data from the Google Trends database that permits accessing internet search volume data on a monthly frequency. Given the daily nature of our dataset, we have developed an R-based programming code that allows us to extract daily data from the Google Trends database for this analysis. To construct the COVID19^{+} index, we have utilized keywords with a “positive” tone. This positive tone is highly correlated with keywords related to COVID-19 vaccines. Regarding the COVID19^{-} index, following the analysis of Subramaniam and Chakraborty (2021), we proceed to construct it by utilizing search terms related “negatively” to the coronavirus pandemic.

Any given Google search term is called Google Search Volume Index (GSVI henceforward), and according to its definition, the GSVI reads as follows:

$$\text{GSVI} = \frac{\text{number of queries for each keyword}}{\text{total Google search queries}} \tag{1}$$

As stated in McLaren and Shanbhoge’s (2011) analysis, the core importance of employing internet search volume data for capturing public sentiment is comprehending how individuals actively seek information on their topics of interest. In addition, Dimpfl and Jank (2016) supported that Google search queries qualify as a good proxy for retail investors’ attention to the stock market, while Gao et al. (2020) supported that Google searches not only reflect the attitudes of market participants, but they also reveal information on time.

Consistent with Baker and Wurgler (2006) and Da et al. (2015), we also adopt the idea that sentiment (proxied by the COVID19^{+} and COVID19^{-} indices) mirrors investors’ beliefs about the future trajectory of stock prices that cannot be justified by the already existing set of financial information accessible to market participants.

Fig. 1 offers a graphical representation of the daily Google search volumes provided by the Google Trends Database.

As stated earlier, for the construction of the COVID19^{-} index, we utilize the Google search terms proxying a “negative” tone (sentiment), firstly proposed by Subramaniam and Chakraborty (2021). Table 1 displays the 80 search terms utilized.

To determine and construct the novel COVID19^{+} index, we scrutinized search terms associated with the COVID-19 pandemic but with positive content. Our identification assumption relies on the idea that COVID-19 vaccine-related keywords signify a positive investor sentiment since the introduction and the roll-out of COVID-19 vaccination programs are signaling a normalization of the economic activity, therefore boosting economic confidence and agents’ expectations.

A Google search is a revealed attention measure (Da et al., 2011). Consequently, if someone repeatedly searches the terms “COVID-19 vaccine” or “Vaccination rate” in Google, then she is undeniably paying attention to this search term. Hence, Google searches constitute a direct and explicit measure of agents’ Internet search behavior/attention. Moreover, Internet search-based sentiment metrics can reveal more personal information than other sentiment proxies, such as the economic sentiment or consumer confidence indicator (Da et al., 2015). Thus, we created a list of 24 vaccine-related search terms, which exert the most positive tone. These 24 GSVIs capture investors’ positive sentiment stemming from the declining uncertainty due to the initialization and the roll out of the vaccination programs. Table 2 displays the search terms used to construct the COVID19^{+} index.

The daily changes for each search term are computed as follows:

$$\Delta GSVI_{j,t} = ln\left(GSVI_{j,t}\right) - ln\left(GSVI_{j,t-1}\right) \tag{2}$$

where j denotes each search term (GSVI) and t the time.

Then, we deseasonalized each series to eliminate any seasonal pattern in it. As a final step, we construct the COVID19^{+} and COVID19^{-} indices for each search term j and period t, with two alternative methods. First, we take the average of the 24 and 80 $\Delta GSVIs$ accordingly, and we define the COVID19^{+sa} index as the first proxy for positive sentiment and COVID19^{-sa} as the first proxy for negative sentiment. The indices read as follows:

$$COVID19_t^{+sa} = \frac{1}{24}\sum_{j=1}^{24} \Delta AGSVI_{j,t} \tag{3}$$

$$COVID19_t^{-sa} = \frac{1}{80}\sum_{j=1}^{80} \Delta AGSVI_{j,t} \tag{4}$$

where j denotes each search term (GSVI), t the time and $\Delta AGSVI_{j,\,t}$ is the adjusted deseasonalized daily change in each search term.

As a second measure capturing the positive and negative sentiment of Google searches during the COVID-19 pandemic, we employ the COVID19^{+pc} and COVID19^{-pc} indices, utilizing the common factor between the 24 and 80 GSVIs mentioned above accordingly, obtained after a Principal Component Analysis (PCA). Such an approach is also in line with the studies of Anastasiou and Drakos (2021a) and Subramaniam and Chakraborty (2021).

The implementation of the PCA method has numerous merits. First, it can aggregate the information of the different GSVIs into a sole composite indicator. Also, PCA copes with multicollinearity concerns when more than a few highly correlated variables (Wooldridge, 2010). A supplementary benefit stemming from the PCA method is that it produces the weights of each variable as a byproduct. Therefore, it is not required to pre-assign the weights for each variable (Wooldridge, 2010), signifying that the new indices we construct can explain as much of the variance in the set of the different GSVI variables as possible.

The correlation based on the Pearson correlation coefficient between the two positive and the two negative indices is relatively high, reaching around 0.83, and statistically significant at the 1% level of significance. This high correlation is reasonable as each pair of indices contains the same Google search queries, while the only difference is the construction methodology. However, the fact that each pair exerts a significant but not absolute correlation suggests using each index as an alternative to the other, which allows us to investigate the robustness of our novel index. With respect to the Pearson correlation coefficient between the positive and the negative index, we find a significantly low correlation (0.25) and statistically significant only at the 10% of significance. The latter indicates that each pair of positive-negative indices can be used in the same regression without incurring any multicollinearity concerns. Additionally, such a low correlation denotes that the two indices (positive-negative) are almost orthogonal, and therefore capture different sets of information, which they bring into the model.

Figs. 2 and 3 depict the trajectory between COVID19^{-} and

[1] We define the starting point of the COVID-19 pandemic on December 31, 2019, in accordance with the timeline that World Health Organization (WHO) has provided regarding the outbreak of the virus.

[2] The G20 economies, a big group of major developed countries and emerging markets, accounts for approximately 85% of Gross World Product, as well as approximately 80% of the world trading (Zhang, Zhuang, Lu, & Wang, 2020). Therefore, a financial turbulence in G20 represents large changes in global economics and choosing G20 being the research object is very suitable.

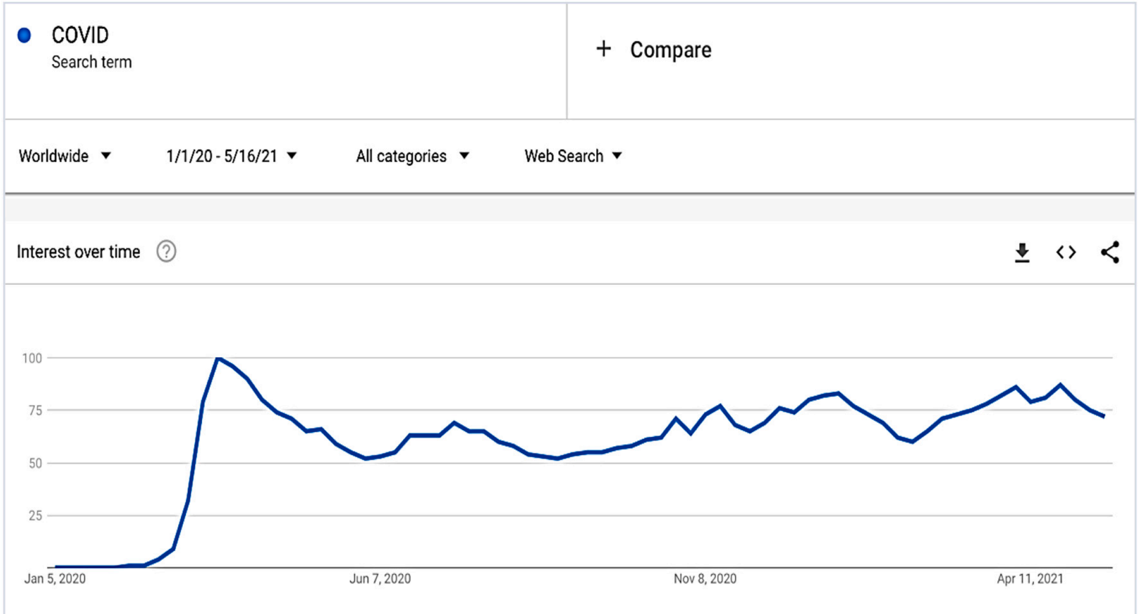

Fig. 1. Graphical representation of the daily Google search volumes provided by the Google Trends Database.
Source: Google Trends.

Table 1
Search terms used for the construction of COVID19^{-} index.

COVID	Contagious	Person to person transmission
Corona	Infectious	Screening
Coronavirus	Flatten the curve	Herd immunity
Virus	Respirator	Forehead thermometer
COVID-19	Ventilator	Fatality rate
Pandemic	Flu	Acute respiratory distress syndrome
Quarantine	Spanish flu	COVID breakout
Pneumonia	Sars	COVID symptoms
Who	Mers	Shortness of breath
Social distancing	Asymptomatic	Can you get corona virus more than once
Lockdown	Vaccine	What are the symptoms of corona virus
Disease outbreak	Clinical trial	Corona virus airborne
Fomite	Containment area	Can you get corona more than once
Community spread	Hydroxycholoroquine	Is corona virus getting better
Contact tracing	Incubation period	What are the symptoms of corona virus
Mortality	Novel coronavirus	How is corona virus transmitted
Morbidity	Physical distancing	What percentage of people die from corona virus
Mortality rate	Social distancing	How long after corona virus are you contagious
Unemployment	Shutdown	How long does it take to get results from the corona virus test
Hand sanitizer	Face mask	Early signs of corona virus
COVID death	Work from home	Economic chaos
Sore throat	Remdesevir	Economic uncertainty
Ppe kit	Ards	Respiratory droplets
Recession	Crisis	Communicable disease
Fever	Loss of taste	Antibodies
Hand wash	Loss of smell	Plasma therapy
Viral load	Wfh	

Notes: This table presents the eighty search terms for the construction of the COVID19^{-} index as proposed by Subramaniam and Chakraborty (2021).

Table 2
Search terms used for the construction of COVID19^{+} index.

Astrazeneca COVID-19	Moderna COVID-19	Pfizer
Astrazeneca COVID	Moderna COVID	Vaccination centre
Astrazeneca vaccine	Moderna vaccine	Vaccination certificate
Astrazeneca	Moderna	Vaccination rate
Johnson and Johnson COVID-19	Pfizer	Vaccination location
Johnson and Johnson COVID	Pfizer COVID-19	Vaccination center
Johnson and Johnson vaccine	Pfizer COVID	COVID vaccination certificate
Johnson and Johnson	Pfizer vaccine	COVID-19 vaccination certificate

Notes: This table presents the twenty-four search terms for the construction of the COVID19^{+} index.

COVID19^{+} for the period under examination as the average for the G20 countries, respectively. In particular, from Fig. 2, we clearly observe that both COVID19^{-} indices (either with the simple average or with the PCA method) had a steep upward trend in the first half of 2020 when the COVID-19 pandemic broke out. Since then, although there have been some periods of resurgence, they have remained stable over time. Fig. 3 shows that albeit COVID19^{+} indices exhibited high volatility during the pandemic outbreak, they started to abruptly increase when the first COVID-19 vaccines were released in the market.

At this point, it should be noted that Subramaniam and Chakraborty (2021) constructed their corresponding COVID19^{-} index only with the PCA method. Thus, our study further contributes to the literature by re-constructing this index with an alternative methodology (i.e., averaging all the search terms under scrutiny).

We estimate two specifications of our empirical model, one in which only the two sentiment proxies are included and another one in which we incorporate a group of control variables. The rationale of our analysis, as previously stated, is that the COVID-19 still exists as an adverse phenomenon, and thus negative investor sentiment stemming from it may continue to exert a negative response to stock markets. Therefore, aiming at reducing any possible unobserved heterogeneity levels, we choose to include additional determinants apart from the two under examination variables. The control variables are listed below:

(i) The economic policy uncertainty index based on newspaper coverage frequency (*EPUI*) of Baker, Bloom, and Davis (2016),

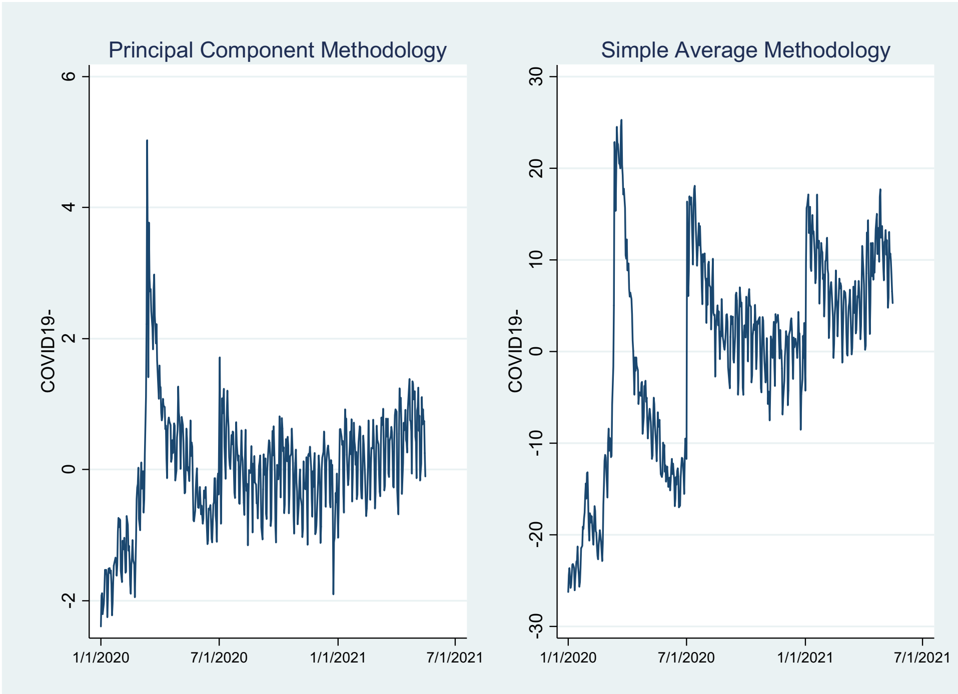

Fig. 2. Graphical representation of the daily COVID19^{-} index (Average across G20).
Source: Google Trends, Own estimates.
Notes: This Figure shows the daily COVID19^{-} index as average across the G20 markets. Specifically, the left (right) panel depicts the COVID19^{-} index constructed with the PCA (simple average) method. For their construction we employed the Google search keywords reported in Table 1, and which were firstly proposed by Subramaniam and Chakraborty (2021).

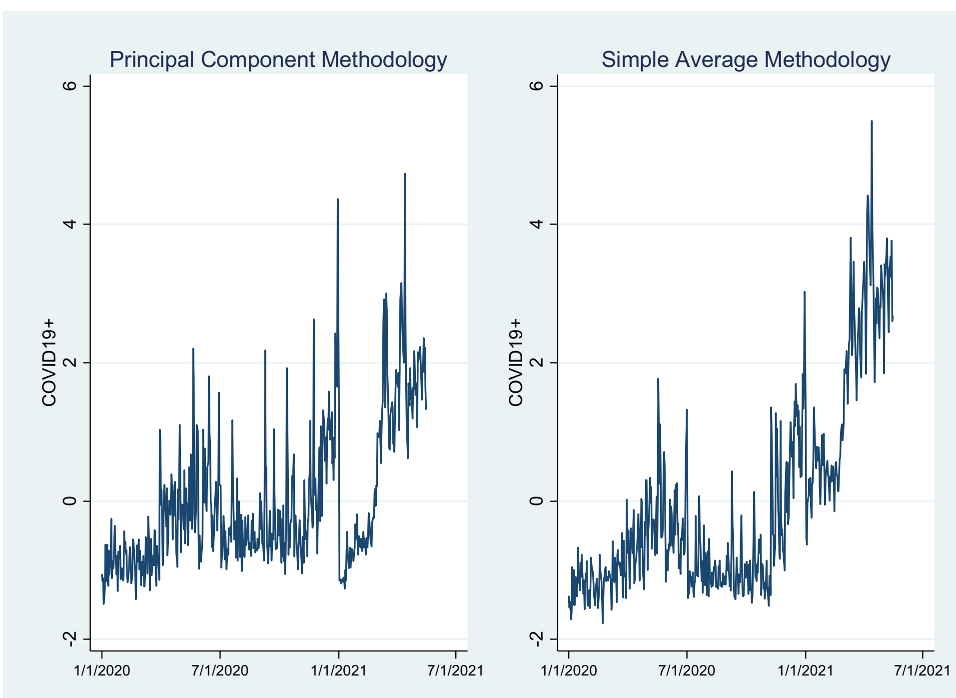

Fig. 3. Graphical representation of the daily COVID19^{+} index (Average across G20).

capturing the general level of economic uncertainty. As supported by, among others, Antonakakis, Chatziantoniou, and Filis (2013), Kang and Ratti (2013) and Chen, Jiang, and Tong (2017), a rise in the economic policy uncertainty dampens stock market returns.

(ii) The CBOE implied volatility index (*VIX*) which proxies the uncertainty in the equity markets (source: Tomson Reuters). The CBOE VIX measures market expectations of stock return volatility over the next 30 calendar days and is calculated from S&P 500 stock index options (Whaley, 2009). VIX has also been denoted as an 'investor fear gauge' (Whaley, 2000) since high levels of VIX concurred with periods of financial market turmoil.

(iii) The Morgan Stanley Capital International Index (*MSCI*), which following prior literature (see among others, Abugri, 2008; Chau, Deesomsak, & Wang, 2014; Bouri, 2015; Al-Khazali, Bouri, Roubaud, & Zoubi, 2017) proxies for the global market portfolio performance (source: Tomson Reuters).

The summary statistics of our data are presented in Tables 3 and 4. Specifically, Table 3 provides the by-country information regarding the main descriptive statistics of the stock prices utilized in this study. Table 4 provides the main descriptive statistics for all the under-examination variables (i.e., dependent variable, main explanatory variables, and other controls).

The descriptive statistics demonstrated in Table 3 show that the mean value is higher than the median in most cases. Additionally, Brazil, Argentina, South Africa, and Mexico experienced the most volatility, while the EU, South Korea, Turkey, and Russia experienced the least as per the standard deviation. Twelve out of twenty indices were negatively skewed. In addition, almost all indices had kurtosis lower than 3. All indices present low skewness and kurtosis values, indicating that extreme changes do not tend to occur frequently. Finally, we perform the Im, Pesaran, and Shin's (1997) panel unit root test to examine whether our variables are stationary. Unit-root test results support that the initial data are stationary only after differencing them. To this end, we transform all the variables into percentage changes using the following formula: $\left(\frac{X_t - X_{t-1}}{X_{t-1}}\right) \times 100$. Thus, we efficiently mitigate any non-stationarity concerns (see Table 4).

4. Econometric methodology

This paper draws on Cermeño and Grier's (2006) approach that extends traditional GARCH models to a panel context. As with panel data models for estimating conditional means, Panel-GARCH models entail potential efficiency gains in estimating the conditional variance and covariance processes by incorporating relevant information about heterogeneity across economies and their interdependence.

For a cross-section of N countries and T time periods (days), the conditional mean equation for stock price return (STOCKS_RET_{it}) can be expressed as a dynamic panel with fixed effects as follows:

$$\begin{aligned}\text{STOCKS\_RET}_{it} = {} & \mu_i + \alpha \times \text{STOCKS\_RET}_{i,t-1} + \lambda_1 \times COVID19^{+}_{t-1} \\ & + \lambda_2 \times COVID19^{-}_{t-1} + \varepsilon_{it}, i = 1, \ldots, N; t = 1, \ldots, T\end{aligned} \tag{5}$$

Respectively, when we control for additional determinants that might well affect the stock price return (described above in Section 3.1), then the conditional mean equation for stock price return (STOCKS_RET_{it}) reads as follows:

$$\begin{aligned}\text{STOCKS\_RET}_{it} = {} & \mu_i + \alpha \times \text{STOCKS\_RET}_{i,t-1} + \lambda_1 \times COVID19^{+}_{t-1} \\ & + \lambda_2 \times COVID19^{-}_{t-1} + \sum_{i=1}^{q=3} \theta_i \times controls_{t-1} + \varepsilon_{it},\end{aligned} \tag{6}$$

where μ_i captures possible country-specific effects, $COVID19_{t-1}{}^{+}$ and $COVID19_{t-1}{}^{-}$ are our main explanatory variables, $\sum_{i=1}^{3} \theta_i \times controls_{t-1} = \theta_1 \times EPUI_{t-1} + \theta_2 \times VIX_{t-1} + \theta_3 \times MSCI_{t-1}$ and $\varepsilon_{i,\,t}$ is a well-behaved error term with a zero mean and normal distribution along with the following conditional moments:

$$E\left[\varepsilon_{it}\varepsilon_{js}\right] = 0 \; for \; i \neq j \; and \; t \neq s \tag{7}$$

$$E\left[\varepsilon_{it}\varepsilon_{js}\right] = 0 \; for \; i = j \; and \; t \neq s \tag{8}$$

$$E\left[\varepsilon_{it}\varepsilon_{js}\right] = \sigma^2_{ij,t} \; for \; i \neq j \; and \; t = s \tag{9}$$

$$E\left[\varepsilon_{it}\varepsilon_{js}\right] = \sigma^2_{i,t} \; for \; i = j \; and \; t = s \tag{10}$$

The first condition assumes no non-contemporaneous cross-sectional correlation, and the second condition assumes no autocorrelation. The third and fourth assumptions define the general conditions of the conditional variance-covariance process.

Letting φ_i be the country-specific effects in the conditional variance, then the conditional variance processes of stock return are assumed to follow a GARCH(1,1) process[3]:

$$\sigma^2_{i,t} = \varphi_i + \gamma\sigma^2_{i,t-1} + \delta\varepsilon^2_{i,t-1}\lambda_1 \times COVID19^{+}_{t-1} + \lambda_2 \times COVID19^{-}_{t-1}, i = 1, \ldots, N \tag{11}$$

Because the disturbance term ε_{it} is conditional heteroskedastic and cross-sectionally correlated, the least-squares estimator is no longer efficient even though it is still consistent. We resolve this problem by adopting Cermeño and Grier's (2006) maximum-likelihood (ML) method. Thus, each Panel-GARCH model is estimated via maximization of the volatility component of the log-likelihood function using numerical methods. The Log-likelihood function of the complete fixed-effects panel model is formulated as follows:

$$L = -\frac{1}{2}NTln(2\pi) - \frac{1}{2}\sum_{t=1}^{T} ln|\Omega_t| - \frac{1}{2}\sum_{t=1}^{T}\left[(y_t - \mu - Z_t\theta)' \times \Omega_t(y_t - \mu - Z_t\theta)\right] \tag{12}$$

At this point, it must be mentioned that each model was estimated twice, once for each methodology employed for the construction for each index (that is, simple average and PCA). In addition, the reason we consider a dynamic specification, where in each model we include the lagged dependent variable in the right-hand side of each equation, is twofold. First, because we want to remove any potential serial correlation, and second to capture the possible persistence that stock returns might exhibit.

In Panel-GARCH regression models, it is essential to assess the poolability of our data initially. If the data are poolable, then country-specific effects do not exist, and a single intercept instead of different intercepts for different countries is warranted. We test for individual effects in the conditional mean equation using the Least-Squares Dummy Variable estimation method with a heteroskedasticity and autocorrelation consistent covariance matrix. The Wald test statistic for testing the null hypothesis H_0: $\theta_1 = \theta_2 = \ldots = \theta_{20}$ was not found to be statistically significant since it was found to be less than 1.50 to each specification. Thus, we employ a common intercept for all countries.

5. Empirical results

As stated earlier, our main objective is to provide a new explanation for market response through the scope of investors' sentiment during the COVID-19 pandemic across G20 markets. Before we embark on a detailed discussion of our main findings, we deem it appropriate to graphically inspect the relationship between the under-scrutiny indices and stock prices. To this end, we graphically present the lowess smoother[4] between the daily stock prices and $COVID19^{-}$ ($COVID19^{+}$) index as shown in Figs. 4 and 5, respectively. As we observe in Fig. 4[5] (Fig. 5), there is a negative (positive) association between stock prices and the $COVID19^{-}$ ($COVID19^{+}$) index, which confirms our prior beliefs. This distinct association between each sentiment indicator and stock prices becomes even more apparent with the $COVID19^{+}$ index (Fig. 5),

[3] Alternative ARCH/GARCH specifications were estimated. However, the preferred specification was the GARCH(1,1) since it found to have the lowest AIC and SBIC scores. In addition, in the finance literature, the GARCH(1,1) consists of the most popular ARCH specification (Hwang & Valls Pereira, 2006).

[4] The Lowess smoother fitted at a given point is derived by locally averaging the data in a neighborhood of that point. A polynomial is fitted to the data (red line) using (iterative) weighted least squares, with the weights computed according to a 'tri-cube' weight function (Cleveland, 1979).

[5] The right panel of Fig. 4, which depicts the lowess smoother with the $COVID19^{sa}$ index, shows that there might be a quadratic relationship between stock returns and the $COVID19^{sa}$ index. However, the inclusion of quadratic terms in the regression models turned out to be statistically insignificant across all model specifications.

Table 3
Stock prices descriptive statistics by country.

	Mean	Median	Minimum	Maximum	Standard Deviation	Skewness	Kurtosis	Observations
US - SPX Index	3416.1	3373.9	2237.4	4232.6	434.6	−0.2	2.6	345
UK - UKX Index	6404.4	6340.2	4993.9	7674.6	567.5	0.4	2.7	346
Saudi Arabia - SASEIDX Index	8179.3	8244.8	5959.7	10,531.2	1018.6	0.1	2.5	343
Turkey - XU100 Index	1228.9	1188.0	842.5	1570.4	191.6	0.2	2.1	344
Brazil - IBOV Index	103,787.0	104,309.7	63,569.6	125,076.6	14,503.0	−0.7	2.6	339
Germany - DAX Index	12,911.2	13,103.4	8441.7	15,459.8	1449.7	−0.7	3.5	347
France - CAC Index	5301.5	5334.9	3754.8	6386.0	613.0	−0.1	2.1	350
Italy - FTSEMIB Index	21,013.4	20,808.8	14,894.4	25,477.6	2602.2	−0.2	2.0	348
South Korea - KOSPI Index	329.6	312.1	199.3	437.3	63.7	0.3	1.9	339
South Africa - TOP40 Index	52,416.6	51,669.2	34,239.3	63,187.5	6057.0	−0.2	3.1	343
Mexico - MEXBOL Index	41,119.5	40,404.6	32,964.2	49,867.2	4550.3	0.2	1.7	343
Russia - MOEX RX Equity	3039.3	3021.3	2112.6	3694.8	341.1	0.0	2.3	342
India - SENSEX	12,079.7	11,908.5	7610.3	15,314.7	1973.4	0.0	2.0	341
Australia - AS51 Index	6300.8	6298.8	4546.0	7172.8	594.6	−0.5	2.4	347
Indonesia - JCI Index	5493.9	5462.7	3937.6	6435.2	625.6	−0.2	1.7	331
Japan - NKY Index	24,398.2	23,474.9	16,552.8	30,467.8	3468.7	0.1	2.1	358
Canada - SPTSX Index	16,707.3	16,656.1	11,228.5	19,472.7	1651.0	−0.6	3.2	345
China - SHCOMP Index	4612.2	4720.8	3530.3	5807.7	561.2	−0.1	1.9	329
Argentina - MERVAL Index	44,328.5	46,483.7	22,087.1	55,427.3	7258.7	−1.0	3.5	332
EU – ESTX PR Index	376.3	369.4	261.5	446.9	41.1	−0.4	2.6	351

Notes: This Table displays the descriptive statistics for stock prices by country. The data covers the period January 1, 2020, to May 16, 2021. Data obtained from Thomson Reuters.

Table 4
Main descriptive statistics, unit root and normality tests for all the under-examination variables.

	Mean	Median	Minimum	Maximum	Standard Deviation	Skewness	Kurtosis	Jarque-Bera test	IPS unit root test	Observations
STOCKS_RET	0.05	0.1	−16.9	13.9	1.7	−0.5	15.6	0.000	0.000	5385
MSCI	0.06	0.1	−9.9	8.7	1.5	−0.5	14.8	0.000	0.000	5720
VIX	−0.02	−1.2	−23.4	61.6	9.2	2.4	14.5	0.000	0.000	5700
EPUI	0.08	−0.01	−0.8	3.2	0.4	1.9	11.1	0.000	0.000	10,020
$COVID19^{+pc}$	0.0	−0.4	−1.5	4.7	1.0	1.3	4.3	0.000	0.000	10,040
$COVID19^{+sa}$	0.0	−0.6	−1.8	5.5	1.5	1.2	3.6	0.000	0.000	10,040
$COVID19^{-pc}$	0.0	0.0	−2.4	5.0	0.9	0.6	5.8	0.000	0.000	10,040
$COVID19^{-sa}$	0.0	1.9	−26.2	25.3	11.1	−0.4	2.6	0.000	0.000	10,040

Notes: This Table displays the descriptive statistics for the main variables used in the Panel-GARCH models. The variables are expressed in percentage changes. The data covers the period January 1, 2020, to May 16, 2021. The null hypothesis of the IPS unit root test is the presence of unit root. For the Jarque-Bera test the null hypothesis is that the disturbance term has a normal distribution. For both tests probability values are reported.

thus enhancing our choice for its construction.

Table 5 reports the main estimations for each panel model specification, using the estimation techniques discussed in section 3.2. Our analysis begins with the results of columns (1)–(2) and (5)–(6), which report the results including only the $COVID19^{-}$ index with the PCA and the simple average methodology, respectively. With respect to the results stemming from the mean equation, we find that the $COVID19^{-}$ index carries a negative and significant sign, as expected. This result is also in line with Subramaniam and Chakraborty (2021) since they also supported that an increase in the $COVID19^{-}$ index negatively affects stock market returns. In other words, an increased $COVID19^{-}$ index suggests that investors increase their crisis sentiment[6] (or fear) by intensifying their Google searches for COVID-19 related keywords with a negative tone. This increased fear leads them to sell-off stocks from their portfolios, therefore causing a decline in stock returns.

Columns (3)–(4) and (7)–(8) in Table 5 report the estimation results after the incorporation of the $COVID19^{+}$ index either with the PCA or with the simple average methodology. We find that the $COVID19^{+}$ index carries a positive sign, significant at all conventional levels across specifications. Thus, a higher $COVID19^{+}$ index decreases investors' crisis sentiment, which in turn increases stock returns. Our results suggest that a higher internet search intensity of vaccine-related keywords on the previous day, proxying for positive investor sentiment during the COVID-19 era, foreshadows a higher stock return in the G20 stock markets. The fact that investors continuously search vaccine-related keywords related to the COVID-19 infectious disease indicates that they have "better" expectations regarding the future path of the pandemic since they expect a rebound of the economic activity, thus leading them to buy stocks.

Furthermore, when we turn our attention to the results from the variance equation, we find some additional interesting results. We uncover opposite signs for $COVID19^{+}$ and $COVID19^{-}$ indices related to their impact on G20 stock market volatility, with their estimated coefficients being again statistically significant at the 1% level of significance. In some more detail, our findings suggest that a higher positive (negative) sentiment in the previous day, proxied by the $COVID19^{+}$ ($COVID19^{-}$) index, dampens (accentuates) stock market volatility in the G20 countries. Therefore, the $COVID19^{+}$ index not only increases average stock returns but also decreases their volatility. These findings are in line with prior research, also supporting that market sentiment proxied by Google search queries has a significant impact on stock market volatility indeed, and that Google attention measures are particularly informative for the future realized volatility (see among others, Hamid & Heiden, 2015; Dimpfl & Jank, 2016; Audrino, Sigrist, & Ballinari, 2020).

Finally, we find that the vast majority of the estimated coefficients of

[6] In a recent study, Anastasiou and Drakos (2021a) argued that a higher crisis sentiment proxied by Google searches with a negative meaning, increases the price crash risk of the cryptocurrencies. Accordingly, Anastasiou and Drakos (2021a) supported that bank deposit flows are negatively correlated with depositors' crisis sentiment.

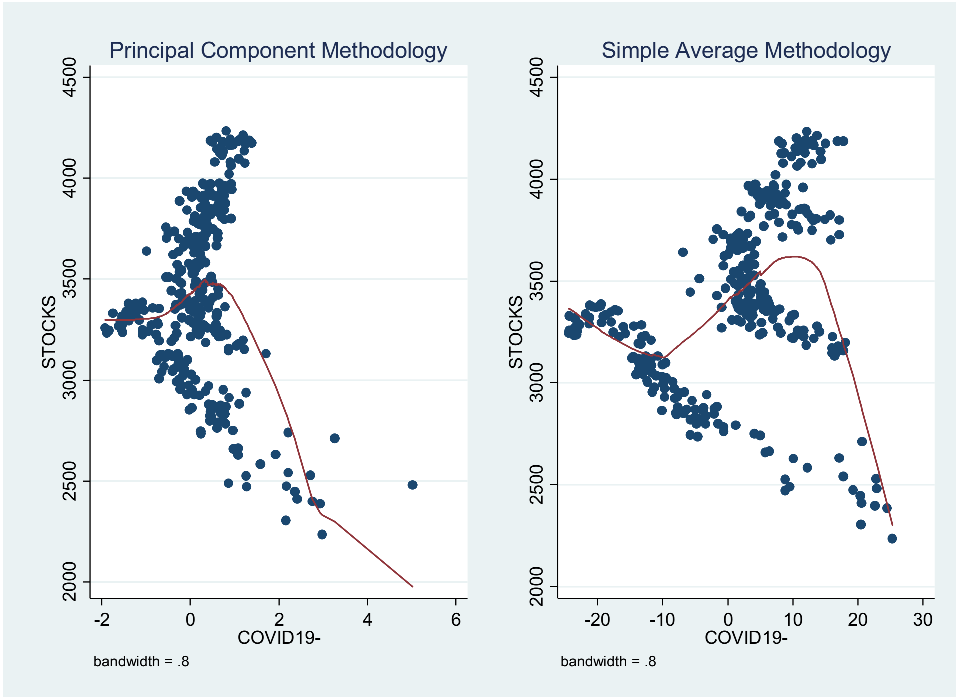

Fig. 4. Graphical representation of the lowess smoother between daily stock prices and COVID19^{-} index (Average across G20).

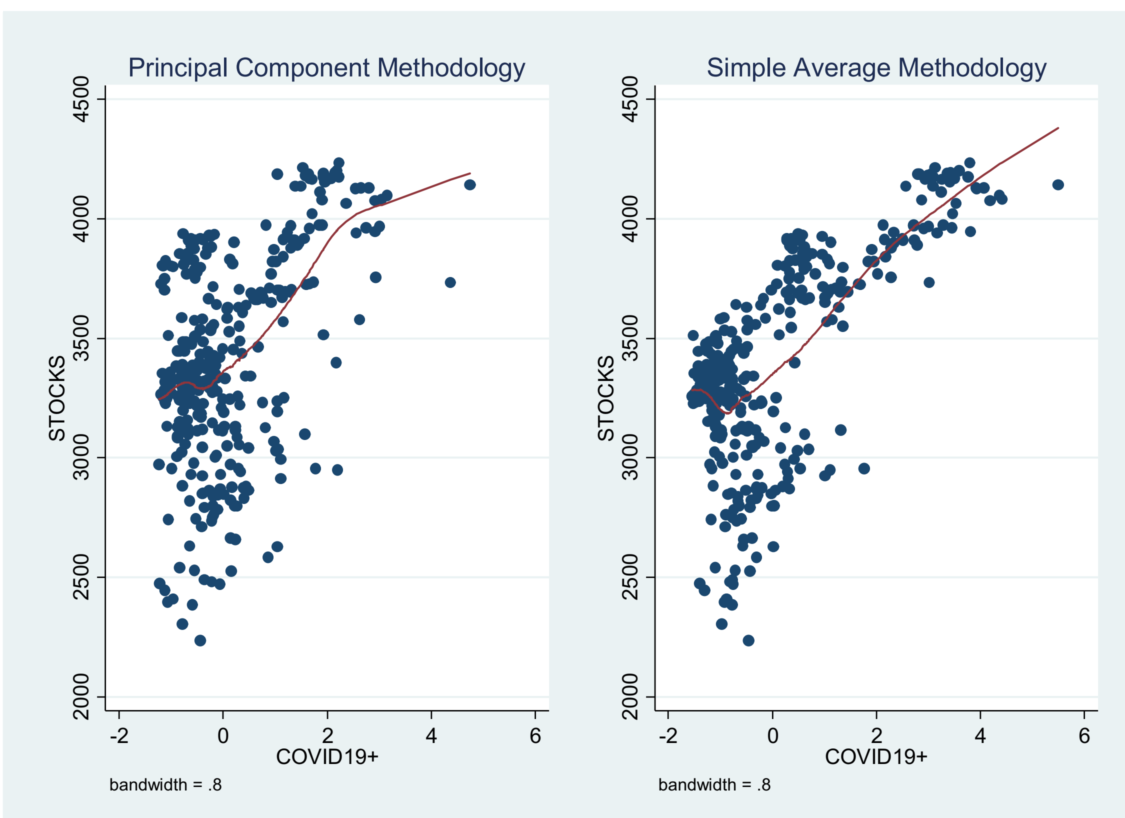

Fig. 5. Graphical representation of the lowess smoother between daily stock prices and COVID19^{+} index (Average across G20).

Table 5
Estimation results of Panel-GARCH models.

Variables	Principal component methodology				Simple average methodology			
Dependent variable: STOCKS_RET(t)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Mean equation							
STOCKS_RET(t-1)	0.040	−0.096***	−0.008	−0.105***	0.048	−0.227***	0.0002	−0.151***
	[0.028]	[0.029]	[0.023]	[0.028]	[0.033]	[0.059]	[0.026]	[0.040]
COVID19^{+}(t-1)	–	–	**0.080*****	**0.084*****	–	–	**0.098*****	**0.086*****
			[0.018]	**[0.017]**			**[0.015]**	**[0.014]**
COVID19^{-}(t-1)	**−0.058****	**−0.003**	**−0.086*****	**−0.073*****	**−0.0001**	**−0.002****	**−0.009*****	**−0.008*****
	[0.026]	**[0.024]**	**[0.028]**	**[0.027]**	**[0.001]**	**[0.001]**	**[0.002]**	**[0.002]**
EPUI(t-1)	–	−0.155***	–	−0.177***	–	−0.192***	–	−0.183***
		[0.047]		[0.045]		[0.049]		[0.047]
VIX(t-1)	–	−0.021***	–	−0.024***	–	−0.017**	–	−0.023***
		[0.005]		[0.004]		[0.007]		[0.005]
MSCI(t-1)	–	0.155***	–	0.121***	–	0.341***	–	0.183***
		[0.041]		[0.040]		[0.071]		[0.057]
Constant	−0.010	−0.007	−0.012	−0.001	−0.022	0.030	−0.036	−0.019
	[0.022]	[0.020]	[0.021]	[0.020]	[0.026]	[0.024]	[0.024]	[0.022]
	Variance equation							
COVID19^{+}(t-1)	–	–	**−1.186*****	**−1.212*****	–	–	**−0.430*****	**−1.258*****
			[0.266]	**[0.188]**			**[0.035]**	**[0.212]**
COVID19^{-}(t-1)	**0.607*****	**2.592*****	**1.302*****	**1.424*****	**0.772*****	**0.757*****	**0.031*****	**0.065*****
	[0.046]	**[0.235]**	**[0.193]**	**[0.215]**	**[0.052]**	**[0.059]**	**[0.004]**	**[0.016]**
ARCH(t-1)	0.112***	0.223***	0.179***	0.199***	0.247***	0.427***	0.169***	0.293***
	[0.030]	[0.027]	[0.028]	[0.027]	[0.041]	[0.071]	[0.028]	[0.047]
GARCH(t-1)	−0.218***	0.540***	0.507***	0.488***	0.662***	0.480***	−0.043	0.407***
	[0.077]	[0.026]	[0.045]	[0.038]	[0.045]	[0.039]	[0.055]	[0.034]
Constant	0.685***	−3.669***	−1.704***	−1.986***	−14.547***	−13.816***	0.635***	−1.209***
	[0.129]	[0.386]	[0.526]	[0.492]	[1.088]	[1.267]	[0.108]	[0.412]
Observations	3934	3866	3934	3866	3934	3866	3934	3866
Prob>chi2	0.029	0.000	0.000	0.000	0.276	0.000	0.000	0.000

Notes: This Table reports the estimates from the Panel-GARCH model described in Section 2.2 by considering eqs. (5 & 6) (conditional mean equation), and (11) (conditional variance equation). All the parameters were estimated simultaneously by maximum likelihood. Asterisks *, **, *** denote statistical significance at the 10, 5 and 1% level, respectively. Numbers in brackets denote robust standard errors. All variables are expressed in percentage changes. The data covers the period January 1, 2020, to May 16, 2021.

the ARCH/GARCH terms in the conditional variance equation range from 0.6 to 0.8 in each specification, meaning that a moderately persistent GARCH process captures the G20 stock return volatility.

5.1. Robustness tests

5.1.1. Constructing a common index

As a robustness test, we construct an alternative index (NETP) which we define as the difference between COVID19^{+} and COVID19^{-} indices. Given that we define the NETP as the difference between positive and negative sentiment (and not the other way around), by construction, it is expected that higher values would suggest more positive sentiment. Fig. 6 demonstrates the lowess smoother between daily stock prices and the NETP index (as an average across G20). We observe that these two variables exhibit a prominent positive association, therefore preliminary supporting our choice for its construction. Based on this, we reach a tentative conclusion that a significant phenomenon may be present. However, a formal answer can only be given once more through a proper econometric framework.

Turning to the estimation results from the Panel-GARCH model, columns (1)–(2) and (3)–(4) in Table 6, report the estimation results after incorporating in our model the NETP index, either with the PCA or with the simple average methodology. Our findings for the mean equation indicate that the NETP index carries a statistically significant positive sign. To put it in layman's terms, a higher NETP index indicates an increase in the positive investor sentiment, which increases stock returns.

Our findings suggest that a higher internet search intensity on the previous day, denoted by the NETP index, foreshadows a higher stock return in G20 stock markets during the COVID-19 era. Moving on now to the results from the variance equation, we find opposite signs for the NETP index related to their impact on G20 stock market volatility, with their estimated coefficients being statistically significant at the 1% level of significance.

In some more detail, our findings suggest that a higher positive sentiment in the previous day, proxied by the NETP index, foresees a lower stock market volatility in the G20 countries. Finally, concerning the estimated ARCH/GARCH terms in the conditional variance equation, we find that they range from 0.6 to 0.8 in each specification, meaning that moderately persistent GARCH processes capture the G20 stock return volatility. Overall, these results suggest that investors have become more willing to look through the near-term challenges of the pandemic.

5.2. Forecasting power of sentiment

In this subsection, we compare the forecasting power of the proposed sentimental shocks. To this end, we follow the prior work of Anastasiou and Drakos (2021a), and we split the data into a training sample and a testing sample, performing an out of sample forecast for 1, 2, 5 and 30 days ahead. Then, we compare the forecasting errors between three alternative specifications, namely a complete model with both COVID19^{+} and COVID19^{-} indices, as well as the controls; a restricted model containing only the negative sentiment (COVID19^{-} index) along with the controls; and a third model which explains the stock price returns only by the control variable (benchmark model). The results presented in Table 7 show the forecasting accuracy measures we used, i.e., the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE), the mathematical notations of which read as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Actual - Forecast)^2} \tag{13}$$

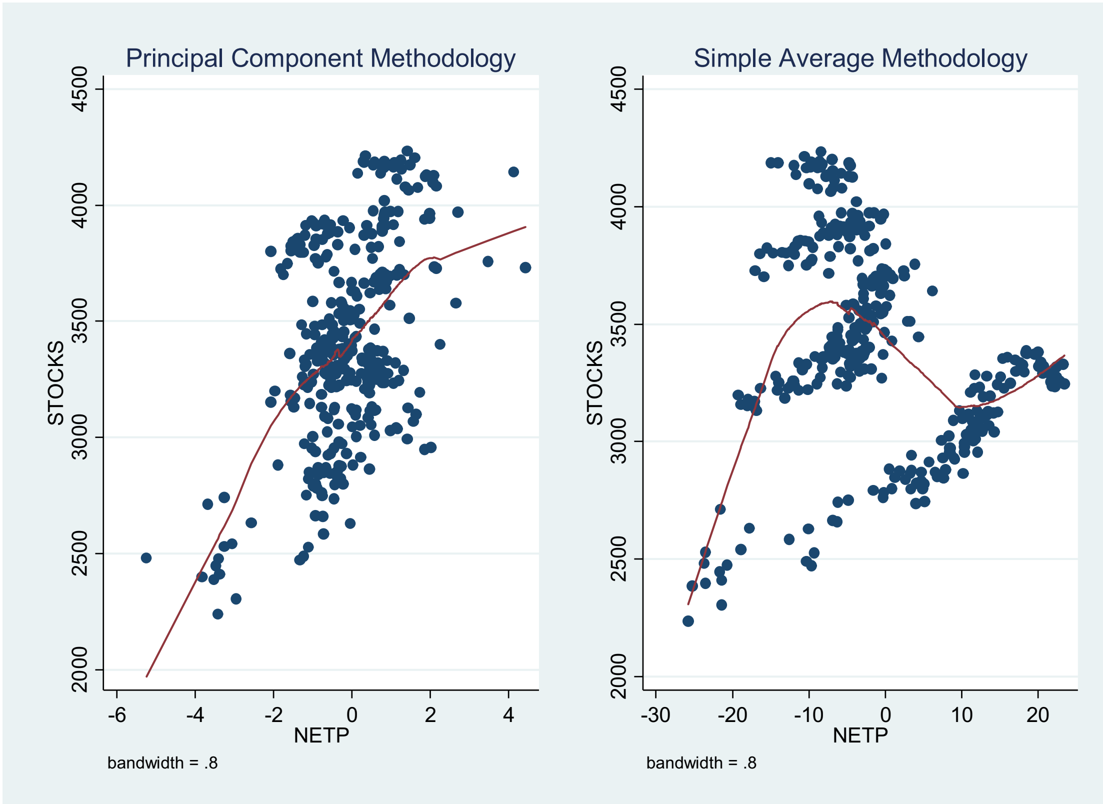

Fig. 6. Graphical representation of the lowess smoother between daily stock prices and NETP index (Average across G20).

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|Actual - Forecast| \tag{14}$$

Panel A of Table 7 presents the results with the indices constructed with the Simple Average methodology, while Panel B reports the corresponding results when the indices are constructed with the PCA methodology. We find that the model with the highest RMSE and MAE values is the one that does not incorporate any sentiment variable (benchmark model), while the model incorporating only the negative sentiment (COVID19^{-}) has the second-highest RMSE and MAE values. Although the inclusion of the COVID19^{-} index slightly improves our model's forecasting accuracy, the inclusion of the COVID19^{+} sentiment indicator further enhances its predictive ability. Overall, our findings suggest that the model incorporating our novel positive sentiment index (COVID19^{+}) has the lowest forecast errors (both in terms of RMSE and MAE) than the other two models. Thus, not only is the COVID19^{+} index statistically and economically significant in explaining stock price returns in G20 countries, but it also increases the model's short-term forecasting accuracy.

These results are in line with some past empirical literature supporting that those models in the financial literature that take into account the role of sentiment, in addition to some other (more fundamental) factors, have better forecasting ability (e.g., Anastasiou & Drakos, 2021a; Coqueret, 2020; Granziera & Kozicki, 2015; Ling, Ooi, & Le, 2015; Sun, Najand, & Shen, 2016).

6. Conclusions

Our study contributes to the literature by quantifying and then investigating the impact of the positive sentiment stemming from the COVID-19 pandemic on stock market returns and volatility for the G20 countries. According to our empirical findings, we document that the COVID19^{-} index carries a negative and significant sign, being in line with the results in the analysis of Subramaniam and Chakraborty (2021), meaning essentially that an increased COVID19^{-} index suggests that investors increase their crisis sentiment by escalating their Google searches for negatively associated COVID-19 related keywords. Furthermore, our results show that the COVID19^{+} index carries a positive sign, meaning that a higher COVID19^{+} index decreases the so-called investors' crisis sentiment, foreshadowing a higher (lower) stock return (volatility) in G20 markets.

In addition, the NETP index was found to carry a positive (negative) sign, indicating that a higher internet search intensity on the previous day, as denoted by the NETP index, foreshadows a higher (lower) stock return (volatility) in G20 stock markets during the COVID-19 era. Finally, from our short-term forecasting exercise, we concluded that incorporating our novel positive sentiment increases the forecasting accuracy of the model, thus better predicting future stock price returns.

Future research directions could include exploring the association between the COVID19^{+} index and different aspects of the economic activity, paying special attention to its interconnection with bank deposit flows, long-term government bond yields, and mutual funds. Finally, such a sentiment indicator could be explored on how it is correlated with different economic uncertainty measures.

Disclaimer

The views and opinions expressed in this paper are those of the authors and do not reflect those of their respective institutions.

Credit authorship contribution statement

Dimitris Anastasiou: Formal Analysis, Conceptualization, Writing, Review & Editing, Data curation, Software. Antonis Ballis: Formal Analysis, Conceptualization, Writing, Review & Editing, Data curation, Software, Data curation. Konstantinos Drakos: Formal analysis, Writing

Table 6
Estimation results of Panel-GARCH models with NETP index.

Variables	Principal component methodology		Simple average methodology	
Dependent variable: STOCKS_RET(t)	(1)	(2)	(3)	(4)
	Mean equation			
STOCKS_RET(t-1)	−0.009 [0.023]	−0.107*** [0.028]	0.044 [0.032]	−0.227*** [0.058]
NETP(t-1)	**0.081*** [0.017]**	**0.083*** [0.017]**	**0.002 [0.001]**	**0.003* [0.001]**
EPUI(t-1)	–	−0.177*** [0.045]	–	−0.188*** [0.049]
VIX(t-1)	–	−0.024*** [0.004]	–	−0.017** [0.007]
MSCI(t-1)	–	0.117*** [0.040]	–	0.343*** [0.071]
Constant	−0.013 [0.020]	0.001 [0.019]	−0.021 [0.025]	0.029 [0.024]
	Variance equation			
NETP(t-1)	**−1.293*** [0.182]**	**−1.377*** [0.184]**	**−0.752*** [0.060]**	**−0.735*** [0.080]**
ARCH(t-1)	0.179*** [0.028]	0.200*** [0.028]	0.245*** [0.041]	0.425*** [0.071]
GARCH(t-1)	0.512*** [0.039]	0.489*** [0.037]	0.662*** [0.045]	0.480*** [0.038]
Constant	−1.784*** [0.495]	−2.043*** [0.515]	−14.728*** [1.299]	−13.978*** [1.802]
Observations	3934	3866	3934	3866
Prob>chi2	0.000	0.000	0.133	0.000

Notes: This Table reports the estimates from the Panel-GARCH model described in Section 2.2 by considering eqs. (5 & 6) (conditional mean equation), and (11) (conditional variance equation). All the parameters were estimated simultaneously by maximum likelihood. Asterisks *, **, *** denote statistical significance at the 10, 5 and 1% level, respectively. Numbers in brackets denote robust standard errors. All variables are expressed in percentage changes. The data covers the period January 1, 2020, to May 16, 2021.

Table 7
Predictive Power of Sentiment on Stock returns.

Panel A: Results with Simple Average Methodology						
	Forecast including both positive and negative sentiment (COVID19$^+$, COVID19$^-$)		Forecast with only negative sentiment (COVID19$^-$)		Forecast without sentiment	
Time Horizon	RMSE	MAE	RMSE	MAE	RMSE	MAE
1 day	1.316	0.979	1.392	1.079	1.398	1.087
2 days	1.263	0.943	1.285	0.986	1.288	0.991
5 days	1.140	0.742	1.277	0.932	1.287	0.945
30 days	0.565	0.452	0.681	0.554	0.682	0.554
Panel B: Results with Principal Component Methodology						
	Forecast including both positive and negative sentiment (COVID19$^+$, COVID19$^-$)		Forecast with only negative sentiment (COVID19$^-$)		Forecast without sentiment	
Time Horizon	RMSE	MAE	RMSE	MAE	RMSE	MAE
1 day	1.355	1.026	1.407	1.096	1.398	1.087
2 days	1.273	0.962	1.293	0.997	1.288	0.991
5 days	1.210	0.833	1.303	0.961	1.287	0.945
30 days	0.638	0.511	0.700	0.572	0.682	0.554

Notes: This Table provides the forecasting comparisons based on the root-mean squared error (RMSE) and mean absolute error (MAE) criteria.

& editing, Project administration, Supervision.

Source: Google Trends, Own estimates.

Notes: This Figure shows the daily COVID19$^+$ index as average across the G20 markets. Specifically, the left (right) panel depicts the COVID19$^+$ index constructed with the PCA (simple average) method. For their construction we employed the Google search keywords reported in Table 2.

Source: Google Trends, Thomson Reuters, Own estimates.

Notes: This Figure shows the lowess smoother between the daily stock prices and the COVID19$^-$ index as average across G20. Specifically, the left (right) panel depicts the lowess smoother with the COVID19$^-$ index being constructed with the PCA (simple average) method.

Source: Google Trends, Thomson Reuters, Own estimates.

Notes: This Figure shows the lowess smoother between the daily stock prices and the COVID19$^+$ index as average across G20. Specifically, the left (right) panel depicts the lowess smoother with the COVID19$^+$ index being constructed with the PCA (simple average) method.

Source: Bloomberg, Google Trends, Thomson Reuters, Own estimates.

Notes: This Figure shows the lowess smoother between the daily stock prices and the NETP index as average across G20. Specifically, the left (right) panel depicts the lowess smoother with the NETP index being constructed with the COVID19$^+$ and COVID19$^-$ indexes with the PCA (simple average) method.

Declaration of Competing Interest

No conflict of interest exits in the submission of this manuscript, and this manuscript is approved by all authors for publication.

Data availability

Data will be made available on request.

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