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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, Baumühl, Výrost, & Molnár, 2020; Szczygielski, Brzeszczyński, Charteris, & Bwanya, 2021; Delis, Savva, & Theodossiou, 2021; Apostolakis, Floros, Gkillas, & Wohar, 2021; Izzeldin, Muradoglu, Pappas, & Sivaprasad, 2021), the energy sector (Szczygielski, Brzeszczyński, et al., 2021; Zhang, Chen, & Shao, 2021), tourism sector (Sigala, 2020; Skare, Soriano, & Porada-Rochot, 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, Mühlneckel, & Weiβ, 2015), Salsisu 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, & Zaremma, 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+ 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 & 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 Wengrek (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 Bijn, 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, Lyosca 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 Santagostina (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. Huyh, 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, 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.

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:

\[
\text{GSVI} = \frac{\text{number of queries for each keyword}}{\text{total Google search queries}}
\]

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, Dimpf 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).

\[\Delta \text{GSVI}_{jt} = \ln(\text{GSVI}_{jt}) - \ln(\text{GSVI}_{j,t-1})\]  

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

Then, we deseasonalize 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 GSVIs accordingly, and we define the COVID19+ index as the first proxy for positive sentiment and COVID19- as the first proxy for negative sentiment. The indices read as follows:

\[\text{COVID19}^{+e(w)} = \frac{1}{24} \sum_{j=1}^{24} \Delta \text{GSVI}_{jt}\]  

\[\text{COVID19}^{-e(w)} = \frac{1}{80} \sum_{j=1}^{80} \Delta \text{GSVI}_{jt}\]

where \(j\) denotes each search term (GSVI), \(t\) the time and \(\Delta \text{GSVI}_{jt}\) 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+ and COVID19- 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

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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, Zhang, 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.
COVID-19 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),

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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                 |
| COVID-19       | Respirator       | Forehead thermometer          |
| Pandemic       | Ventilator       | Fatality rate                 |
| Quarantine     | Flu              | Acute respiratory distress syndrome |
| Pneumonia      | Sars             | COVID breakout                |
| Who            | Mers             | COVID symptoms                |
| Social distancing | Asymptomatic   | Can you get coronavirus more than once |
| Lockdown       | Vaccine          | What are the symptoms of coronavirus |
| Disease outbreak | Clinical trial | Can you get coronavirus more than once |
| Fomite         | Containment area |                               |
| Community spread | Hydroxychloroquine |                               |
| Contact tracing | Incubation period |                               |
| Mortality      | Novel coronavirus|                               |
| Morbidity      | Physical distancing |                               |
| Mortality rate | Social distancing |                               |
| Unemployment   | Shutdown         |                               |
| Hand sanitizer | Face mask        |                               |
| COVID death    | Work from home   |                               |
| Sore throat    | Remdesivir       | Early signs of coronavirus     |
| Ppe kit        | Ards             | Economic chaos                |
| Recession      | Crisis           | Economic uncertainty          |
| Fever          | Loss of taste    | Respiratory droplets          |
| Hand wash      | Loss of smell    | Communicable disease          |
| Viral load     | Wfh              | Plasmal therapy               |

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

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.

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

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

| AstraZeneca COVID-19 | Moderna COVID-19 | Pfizer COVID-19 |
|----------------------|------------------|-----------------|
| AstraZeneca vaccine  | Moderna vaccine  | Moderna vaccine  |
| AstraZeneca          | Moderna          | Pfizer          |
| Johnson and Johnson  | COVID-19         | COVID-19 vaccine certificate |
| Johnson and Johnson  | COVID vaccine    | Johnson and Johnson |
| Johnson and Johnson  | COVID-19 vaccine | Pfizer COVID-19 |
| Johnson and Johnson  | Pfizer vaccine   | Johnson and Johnson |
| Johnson and Johnson  | COVID-19 vaccination certificate | Johnson and Johnson |

Notes: This table presents the twenty-four search terms for the construction of the COVID19+ index.
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, ...
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 all model specifications.

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_RETt) can be expressed as a dynamic panel with fixed effects as follows:

\[
\text{STOCKS}_{\text{RET}}_t = \mu + \alpha \times \text{STOCKS}_{\text{RET}}_{t-1} + \lambda_i \times \text{COVID19}_{t-1} + \epsilon_{it}, \quad i = 1, \ldots, N; \quad t = 1, \ldots, T
\]  

(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-S_RETt) reads as follows:

\[
\text{STOCKS}_{\text{RET}}_t = \mu + \alpha \times \text{STOCKS}_{\text{RET}}_{t-1} + \lambda_i \times \text{COVID19}_{t-1} + \sum_{s=1}^{S} \theta_s \times \text{controls}_{s,t-1} + \epsilon_{it},
\]  

(6)

where \(\mu_i\) captures possible country-specific effects, \(\text{COVID19}_{t-1}\) and \(\text{COVID19}_{t-1}\) are our main explanatory variables, \(\sum_{s=1}^{S} \theta_s \times \text{controls}_{s,t-1} = \theta_1 \times \text{EPUI}_{t-1} + \theta_2 \times \text{VIX}_{t-1} + \theta_3 \times \text{MSCI}_{t-1}\) and \(\epsilon_{it}\) is a well-behaved error term with a zero mean and normal distribution along with the following conditional moments:

\[
\mathbb{E}[\epsilon_{it}] = 0 \text{ for } i \neq j \text{ and } t \neq s
\]  

(7)

\[
\mathbb{E}[\epsilon_{it}] = 0 \text{ for } i = j \text{ and } t \neq s
\]  

(8)

\[
\mathbb{E}[\epsilon_{it}] = \sigma_{it}^2 \text{ for } i \neq j \text{ and } t = s
\]  

(9)

\[
\mathbb{E}[\epsilon_{it}] = \sigma_{jt}^2 \text{ for } i = j \text{ and } t = s
\]  

(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 \(\phi_i\) 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:

\[
\sigma_{it}^2 = \phi_i + \alpha \epsilon_{i,t-1}^2 + \delta_i \times \text{COVID19}_{t-1} + \lambda_i \times \text{COVID19}_{t-1}, \quad i = 1, \ldots, N
\]  

(11)

Because the disturbance term \(\epsilon_{it}\) is conditional heteroskedastic and across-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:

\[
L = -\frac{1}{2} NT \ln(2\pi) - \frac{1}{2} \sum_{t=1}^{T} \ln|\Omega_t| - \frac{1}{2} \sum_{t=1}^{T} \left[ (y_t - \mu - \mathbf{Z}_t \theta)^\prime \Omega_t (y_t - \mu - \mathbf{Z}_t \theta) \right]
\]  

(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 \(H_0: \theta_1 = \theta_2 = \ldots = \theta_S = 0\) 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 lowest smothering’ between the daily stock prices and COVID19’ (COVID19’) index as shown in Figs. 4 and 5, respectively. As we observe in Fig. 4, (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 & Valli 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’ index, shows that there might be a quadratic relationship between stock returns and the COVID19’ index. However, the inclusion of quadratic terms in the regression models turned out to be statistically insignificant across all model specifications.
Thomson Reuters. The 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 bank deposit flows are negatively correlated with de-risk 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 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.

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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).
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 lowest 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 conclusions 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, foreshadows 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:

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (Actual - Forecast)^2}
\]
MAE = \frac{1}{n} \sum_{t=1}^{n} |Actual - Forecast|  \quad (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 |
|--------------------|----------------------------------|---------------------------|
|                    | (1)                              | (2)                       | (3) | (4) |
| STOCKS_RET(t)      |                                  |                           |     |     |
| STOXS_RET(t-1)     | $-0.009$                         | $-0.107^{***}$            | $0.044$ | $-0.227^{***}$ |
|                   | [0.023]                          | [0.028]                   | [0.032] | [0.058] |
| NETP(t-1)          | $0.081^{***}$                    | $0.083^{***}$             | $0.002$ | $0.003^{*}$  |
|                   | [0.017]                          | [0.017]                   | [0.001] | [0.001]   |
| EPU(t-1)           | $-0.177^{***}$                   | $-0.188^{***}$            |       |     |
|                   | [0.045]                          | [0.049]                   |       |     |
| VIX(t-1)           | $-0.024^{***}$                   | $-0.017^{***}$            |       |     |
|                   | [0.004]                          | [0.007]                   |       |     |
| MSCI(t-1)          | $0.117^{***}$                    | $0.343^{***}$             |       |     |
|                   | [0.020]                          | [0.021]                   |       |     |
| Constant           | $-0.013$                         | $0.001$                   | $-0.021$ | $0.029$  |
|                   | [0.020]                          | [0.019]                   | [0.025] | [0.024]   |

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

| Time Horizon | Forecast including both positive and negative sentiment (COVID19, COVID19) | Forecast with only negative sentiment (COVID19) | Forecast without sentiment |
|--------------|--------------------------------------------------------------------------|-----------------------------------------------|---------------------------|
|              | 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

| Time Horizon | Forecast including both positive and negative sentiment (COVID19, COVID19) | Forecast with only negative sentiment (COVID19) | Forecast without sentiment |
|--------------|--------------------------------------------------------------------------|-----------------------------------------------|---------------------------|
|              | 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 across average 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 lowest smoother between the daily stock prices and the COVID19 index as average across G20. Specifically, the left (right) panel depicts the lowest 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 lowest smoother between the daily stock prices and the COVID19 index as average across G20. Specifically, the left (right) panel depicts the lowest 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 lowest smoother between the daily stock prices and the NETP index as average across G20. Specifically, the left (right) panel depicts the lowest 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 for publication by all authors.

Data availability

Data will be made available on request.

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