Explaining stock markets' performance during the COVID-19 crisis: Could Google searches be a significant behavioral indicator?

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Summary
The purpose of this study is to examine the impact of the pandemic on the performance of stock markets, focusing on the behavioral influence of the fear due to COVID-19. Using a data set of 10 developed countries during the period December 31, 2019, to September 30, 2020, we examine the impact of COVID-19 on the performance of the stock markets. We incorporate the impact of the COVID-19 pandemic using the following variables: (a) the number of new COVID-19 cases, which was widely used as the main explanatory variable for market performance in early financial studies, and (b) a Google Search index, which collects the number of Google searches related to COVID-19 and incorporates the health risk and the fear of COVID-19 (the higher the number of searches for Covid terms, the higher the index value, and the higher the fear index). We employ our input into an EGARCH(1,1,1) model, and the findings show that the Google Search index enables us to draw statistically significant information regarding the impact of the COVID-19 fear on the performance of the stock markets. On the other hand, the variable of the number of new COVID-19 cases does not have any statistically significant influence on the performance of the stock markets. Google searches could be a useful tool for supporters of behavioral finance, scholars, and practitioners.

1 | INTRODUCTION

On 31 December, 2019, the World Health Organization (WHO) country office in the People’s Republic of China was informed by the Wuhan Municipal Health Commission of a cluster of cases of “viral pneumonia” in Wuhan. On 9 January, 2020, the WHO informed that the cause of these cases of pneumonia was a novel coronavirus. The novel coronavirus was not contained, and on 30 January the Director-General declared the novel coronavirus outbreak a Public Health Emergency of International Concern. On 11 February, the disease was named COVID-19, and a month later, on 11 March, COVID-19 was declared a pandemic.

COVID-19 has had a significant impact on people’s lives in 2020 and this stress period has drawn the attention of scholars in many fields of study, from epidemiologists to social scientists and financial economists. Since the beginning of this health crisis, and as of 25 October, 2020, more than 42 million cases and more than 1.15 million deaths have been reported worldwide according to the European Centre for Disease Prevention and Control (ECDC). COVID-19 is considered the most severe health crisis of the last few decades.

The health risk affected the economies and financial markets worldwide. When a pandemic breaks out, lockdown and social distance measures are imposed, and these government policies lead to a slowdown in economic activity. In such an environment, consumption declines, profits for many sectors/industries fall (e.g., tourism, sports, travels, restaurants), and the prospects for the profitability of the companies are negative (Vasileiou, 2021a). Taking into consideration that increased health risk leads to increased risk aversion (Decker & Schmitz, 2016), there are behavioral factors that could explain the market performance during pandemics.
The importance of behavioral factors in predicting the performance of the stock prices has been highlighted in financial literature. Seminal papers argue that "... most people ‘overreact’ to unexpected and dramatic news events" (De Bondt & Thaler, 1985) and that risk aversion varies through time (Rabin & Thaler, 2001). During the COVID-19 pandemic, many stock markets worldwide documented periods of sharp price decline, approximately up to the end of March 2020, and since then a growth period has followed, especially after the stimulus packages were announced around the world (Vasileiou et al., 2021). Was the COVID-19 pandemic a reason for overreaction? What was the impact of the fear of COVID-19 on the performance of the stock markets?

To answer these questions, it is crucial that we quantify this fear, and the main objective of this study is to present some ideas regarding how we can measure the health risk and the fear of COVID-19, as well as its impact on the financial markets. In our analysis, we try to quantify the impact and the health/fear risk of COVID-19 using (i) data on the daily reported new COVID-19 cases (announcement effect), which have been widely used in similar studies (Al-Awadhi et al., 2020; Albulescu, 2020; Ashraf, 2020), and (ii) an index based on Google searches that are related to the COVID-19 disease. The Google index can be used as a leading indicator on the impact of COVID-19 (O’Leary & Storey, 2020) and as a means to quantify the COVID-19-health risk and introduce a behavioral factor (Vasileiou, 2021a).

We examine our assumptions using a wide sample of 10 developed stock markets according to the MSCI classification,3 for the period December 31, 2019–September 30, 2020. Table 1 presents the countries and the stock indices of our sample.

In order to quantify the fear of COVID-19, we use two measures. First, we draw information on the new COVID-19 cases per day from the ECDC.4 A high number of new COVID-19 cases means increased health risk and risk aversion. Second, we employ a code that draws information from Google regarding internet searches and indexes them from 0 to 100. The higher the index is, the greater the fear of COVID-19 and the risk aversion is (and vice versa). We employ an exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model in order to examine if fear of COVID-19 significantly influences the performance of the stock markets, and which variable better quantifies the COVID-19 fear. The empirical evidence confirms (a) our assumptions that Google searches could be a significant tool to enable us to quantify behavioral variables, such as the health risk in our case, and (b) the health risk negatively influences the performance of the stock markets.

The rest of the paper goes as following: Section 2 presents the literature review and the theoretical framework, Section 3 shows the preliminary statistical analysis, Section 4 provides the econometric analysis, and Section 5 concludes the study and suggests some ideas for further research.

### TABLE 1

| Country   | Index          |
|-----------|----------------|
| Australia | S&P/ASX 200    |
| Canada    | S&P/TSX        |
| France    | CAC 40         |
| Germany   | DAX            |
| Italy     | FTSE MIB       |
| Japan     | TOPIX          |
| Singapore | Straits Times Index (STI) |
| Spain     | IBEX           |
| UK        | FTSE           |
| USA       | S&P 500        |

The data sample of our study for the period December 31, 2019–September 30, 2020

COVID-19 is not the first pandemic in human history, and there are empirical studies which show that, when a pandemic breaks out, economic activity and investments decrease (Garrett, 2008; Keogh-Brown et al., 2010), and consumption declines (Haacker, 2004). Thus, the theory suggests that the impact of the pandemic on economies will be negative, and this should lead to the decline of the financial markets.

The early empirical studies on the impact of COVID-19 on financial markets confirm previous findings in the literature and show the statistically significant negative relationship between the markets’ performance and the number of COVID-19 cases and/or deaths (Al-Awadhi et al., 2020; Ashraf, 2020; Vasileiou, 2021b). Ashraf (2020) showed that the number of new COVID-19 cases reflects more accurately the fear of COVID-19 than the number of new COVID-19 deaths; therefore, we use the former, as it is the more appropriate explanatory variable. However, after mid-March most indices present a rapid growth even though COVID-19 cases and deaths significantly increase worldwide. Thus, some other factors have played a crucial role in this seemingly “abnormal” growth performance of the financial markets during the post mid-March pandemic period. Which factor(s) could explain this abnormality?

Decker and Schmitz (2016) showed that health risk is positively associated with risk aversion. Investors are a part of society. Thus, when a new virus spreads, we assume that health risk, COVID-19 fear, and risk aversion increase and, consequently, the stock market prices decline (and vice versa). Internet and social media-based sources, such as Google and Twitter, are used in financial studies in order to produce indices that could be helpful in predicting future market performance (Chen et al., 2020; Shen et al., 2019).

Twitter is considered more appropriate when more expertise is needed; for example, for special issues, such as predictions for Bitcoin performance (Shen et al., 2019). However, on COVID-19 issues, anyone can be informed by several internet sources via official authorities, such as WHO, ECDC, and so on, because in most of the cases it does not require expertise in order to gather information on COVID-19 new cases, symptoms, and so on. In our study, we want to quantify COVID-19 fear, thus a Google Search index may be more appropriate for our purpose because most people search Google to get the latest information.
news on COVID-19, which is a systemic health risk (Vasileiou, 2021b). The higher the number of Google searches is that include COVID-19 terms, the higher the fear of COVID-19 is.

Increased interest in COVID-19 issues has been the driving force behind the publication of a growing body of research on the impact of COVID-19 on the economy and on stock markets. A number of these studies show that fear of coronavirus significantly influences the performance of a stock market, although different approaches are used in order to quantify/measure this fear (e.g., Albulescu, 2020; Fetzer et al., 2020; Lyócsa & Molnár, 2020; Lyócsa et al., 2020; Vasileiou, 2021a). Thus, we test whether the announcement of new COVID-19 cases (announcement effect) and Google searches captured the fear surrounding COVID-19.

### 3 | DATA, VARIABLES, AND DESCRIPTIVE STATISTICS

The main objective of this study is to examine how we can measure fear during an extreme health crisis, such as the ongoing COVID-19 pandemic, and the impact of this fear on the performance of the financial markets. For this reason, we include a wide sample of the main indices of developed countries, using the number of new COVID-19 cases and internet-based indices as explanatory variables.

From the Eikon database, we collect the stock market indices per day during the period December 31, 2019–September 30, 2020, and we estimate the daily returns per day using the formula

$$R_t = \frac{\text{Index}_t}{\text{Index}_{t-1}} - 1$$

where $R_t$ is the daily return on day $t$, and $\text{Index}_t$ and $\text{Index}_{t-1}$ are the index prices on day $t$ and on day $t - 1$, respectively.

We draw information on the new COVID-19 cases per day for each country from the ECDC. Figure 1 shows the relationship between each index's performance and the domestic number of new cases per million of population for each country in our sample. In our study, we do not use the raw number of new cases per day because, in most countries, the number of tests is lower during the nonworking days (i.e., weekends). Consequently, the seasonality in the number of cases per day is great. We take into account the day of the week and the impact of holidays on market performance.
### TABLE 2 Descriptive statistics

|                | Australia |             | Canada |             |
|----------------|-----------|-------------|--------|-------------|
|                | S&P ASX_200 d% | Δ7dMANC | Δ7dMAG | S&P/TSX d% | Δ7dMANC | Δ7dMAG |
| Mean           | –0.051%  | 0.004      | 0.042  | –0.002%    | 0.209    | 0.105  |
| Median         | 0.097%   | 0.000      | –0.126 | 0.193%     | 0.000    | –0.063 |
| Maximum        | 7.001%   | 3.186      | 7.571  | 11.957%    | 7.603    | 11.946 |
| Minimum        | –9.700%  | –3.140     | –6.040 | –12.345%   | –8.829   | –3.983 |
| SD             | 2.089%   | 0.849      | 1.804  | 2.360%     | 1.641    | 1.984  |
| Skewness       | –0.781   | 0.292      | 0.884  | –0.772     | 0.495    | 2.976  |
| Kurtosis       | 7.264    | 7.845      | 7.386  | 13.986     | 11.155   | 17.076 |
| Jarque–Bera    | 164.1363*| 188.5757*  | 177.9773* | 969.2893* | 528.6063* | 1,839.331* |
| ADF            | –18.5675*| –3.803396* | –5.28285* | –18.27808* | –4.559291* | –4.127* |

|                | France |             | Germany |             |
|----------------|--------|-------------|---------|-------------|
|                | CAC40 d% | Δ7dMANC | Δ7dMAG | DAX d% | Δ7dMANC | Δ7dMAG |
| Mean           | –0.089% | 0.922     | 0.042  | 0.001%   | 0.121    | 0.044  |
| Median         | –0.020% | 0.051     | 0.000  | –0.024%  | 0.000    | –0.030 |
| Maximum        | 8.390%  | 23.731    | 8.951  | 10.976%  | 14.054   | 8.193  |
| Minimum        | –12.277%| –11.320   | –8.480 | –12.239% | –15.155  | –5.489 |
| SD             | 2.199%  | 3.716     | 1.947  | 2.267%   | 2.123    | 2.000  |
| Skewness       | –0.998  | 1.769     | 0.466  | –0.541   | 0.205    | 1.010  |
| Kurtosis       | 9.200   | 12.505    | 11.661 | 10.023   | 28.143   | 7.704  |
| Jarque–Bera    | 339.4077*| 818.5641* | 607.0227* | 399.7082* | 4,979.708* | 207.4276* |
| ADF            | –13.99196*| –2.933404**| –8.70959* | –13.79703* | –4.837513* | –5.318804* |

|                | Italy |             | Japan |             |
|----------------|-------|-------------|-------|-------------|
|                | FTSE MIB d% | Δ7dMANC | Δ7dMAG | TOPIX d% | Δ7dMANC | Δ7dMAG |
| Mean           | –0.112% | 0.152     | 0.069  | –0.116%   | 0.021226 | 0.044232 |
| Median         | 0.045%  | 0.000      | –0.041 | 0.058%    | 0.003378 | –0.002857 |
| Maximum        | 9.054%  | 21.859    | 10.819 | 9.054%    | 2.550612 | 13.39286 |
| Minimum        | –10.875%| –8.151    | –6.611 | –10.875%  | –1.870449| –14.23429 |
| SD             | 2.018%  | 2.589     | 2.208  | 2.085%    | 0.427767 | 2.413172 |
| Skewness       | –0.746  | 3.533     | 1.922  | –0.721    | 1.007579 | 0.022337 |
| Kurtosis       | 9.162   | 31.422    | 11.771 | 8.800     | 15.10559 | 15.85671 |
| Jarque–Bera    | 318.2057*| 6754.628* | 726.0274* | 257.5005* | 1,079.345* | 1,191.516* |
| ADF            | –14.56539*| –3.375692**| –3.778139* | –13.84225* | –6.32737* | –6.931371* |

|                | Singapore |             | Spain |             |
|----------------|-----------|-------------|-------|-------------|
|                | STI d% | Δ7dMANC | Δ7dMAG | IBEX d% | Δ7dMANC | Δ7dMAG |
| Mean           | –0.126% | 0.014819  | 0.063557 | –0.157% | 1.205198 | 0.047894 |
| Median         | –0.101% | 0.000     | 0.0   | –0.083%   | 0.088264 | –0.045714 |
| Maximum        | 6.072%  | 37.85343  | 6.061429 | 7.818%  | 28.68583 | 13.3  |
| Minimum        | –7.353% | –21.31409 | –6.014286 | –14.059% | –28.03755 | –5.871429 |
| SD             | 1.607%  | 5.93638   | 2.086678 | 2.257%  | 5.828084 | 2.110536 |
| Skewness       | –0.353  | 1.412489  | –0.063903 | –1.271  | 0.331492 | 3.30105 |
| Kurtosis       | 7.930   | 14.0612   | 4.327563 | 11.324  | 9.862525 | 21.34227 |
| Jarque–Bera    | 198.4498*| 1.037215* | 14.23007* | 605.9963* | 378.2899* | 3.040212* |
| ADF            | –15.27387*| –5.022306* | –4.294836* | –8.085259* | –4.335938* | –4.540663* |
TABLE 2 (Continued)

|          | UK            |          | USA            |          |
|----------|---------------|----------|----------------|----------|
|          | FTSE d%       | Δ7dMANC  | Δ7dMAG         | S&P 500 d% | Δ7dMANC  | Δ7dMAG  |
| Mean     | −0.112%       | 0.483192 | 0.081602       | 0.051%    | 0.680724 | 0.057256 |
| Median   | 0.045%        | 0.002143 | −0.099286      | 0.285%    | 0.001085 | −0.097143 |
| Maximum  | 9.054%        | 12.78161 | 10.14571       | 9.383%    | 16.57424 | 10.45857 |
| Minimum  | −10.875%      | −11.9178 | −5.692857      | −11.984%  | −11.71154 | −4.628571 |
| SD       | 2.018%        | 2.437084 | 1.847099       | 2.439%    | 4.18782  | 1.933136 |
| Skewness | −0.746        | 1.272647 | 1.947687       | −0.472    | 0.860962 | 1.989366 |
| Kurtosis | 9.162         | 12.55664 | 12.75079       | 9.036     | 6.576676 | 11.96403 |
| Jarque–Bera | 318.2057* | 770.2367* | 872.8276* | 293.9552* | 123.4348* | 757.4495* |
| ADF      | −14.56539*    | −7.473526** | −2.954081*       | −20.13494* | −3.695958** | −4.303896* |

Note: d% indicates the daily returns of the respective index. *, ** indicate statistical significance at the 1% and 5% confidence level, respectively. ADF, Augmented Dickey–Fuller; Δ7dMANC, first difference of the moving average of new cases per million of population of the last 7 days; Δ7dMAG, first differences of the 7-day moving average of the Google index values.

tests leads to a seasonality in the number of new cases. When fewer tests are performed, a lower number of new COVID-19 cases will be reported, and this leads to seasonality issues that are easily observed in Figure 1.

In order to avoid seasonality issues, we do not use the raw data of the reported number of new cases. Rather, we use the moving average of new cases per million of population of the last 7 days (7dMANC). In this way, we (a) remove the weekly seasonality and (b) obviate the need for several adjustments regarding the way we should handle data recorded on nonworking days. Moreover, the preliminary analysis of the data showed that the time series of the 7dMANC suffers from stationarity issues. Therefore, we use the first differences of the 7dMANC (Δ7dMANC), which allows us not only to resolve the stationarity issue but also to show what happens when the number of new COVID-19 cases increases from day to day.

Regarding Google searches, we employ a code in which we index the Google searches from 0 to 100. At least one of the terms “coronavirus cases,” “COVID,” or “coronavirus symptoms” are included in a search. We handle the Google index data set in a similar way to how we handled the variable of new COVID-19 cases in order to remove the seasonality and stationarity issues from the raw data set of Google index. Thus, we use the first differences of the 7-day moving average of the Google index values (Δ7dMAG).6

Table 2 presents the descriptive statistics of (i) the daily returns per index, (ii) Δ7dMANC, and (iii) the Δ7dMAG. The descriptive statistics show that:

- The time series do not follow the normal distributions. The Jarque–Bera test is statistically significant at the 1% confidence level (c.l.) in all the time series examined.
- The time series do not have a unit root. Augmented Dickey–Fuller tests are statistically significant at the 5% c.l. in the DAX and FTSE case, and at the 1% c.l. for the rest of the indices.

Moreover, the autocorrelation and the partial autocorrelation of the absolute daily returns are presented in Figure 2. The plots and the statistics show that there are autocorrelation issues, which is an indication for volatility clustering; thus, GARCH family models are more appropriate than the ordinary least-squares for the time series examined.7

4 | ECONOMETRIC ANALYSIS

In Section 3, we presented the descriptive statistics of the variables we use in our study. In this section, we present the econometric analysis of these data. The ordinary least-squares approach is not appropriate for our data set due to nonnormality and volatility clustering issues. Thus, we examined several GARCH family models (simple GARCH, integrated GARCH, threshold GARCH, EGARCH) in order to select the most appropriate for our study. The Akaike and Schwarz criteria show that the most appropriate GARCH model for our data set is the asymmetric EGARCH model. We apply the following formulas.

Mean equation:

$$R_t = c + a_1 \times \Delta 7dMANC_{t-1} + a_2 \times \Delta 7dMAG_t + \epsilon_t$$  (2)

where Δ7dMANCt −1 is the first difference of the 7-day moving average of new cases per million of population of the previous day, Δ7dMAGt is the first difference of the 7-day moving average of Google index on the day examined, εt is the error term (εt ~ N(0, σ_t)), a1 is the coefficient of the Δ7dMANCt −1, and a2 is the coefficient of the Δ7dMAGt.8

Variance equation:

$$\log(\sigma_t^2) = \omega + \beta_1 \log(\sigma_{t-1}^2) + \beta_2 \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \gamma \frac{\epsilon_{t-1}}{\sigma_{t-1}}$$  (3)

$$\log(\sigma_t^2) = \omega + \beta_1 \log(\sigma_{t-1}^2) + \beta_2 \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \gamma \frac{\epsilon_{t-1}}{\sigma_{t-1}}$$  (3)
where $\sigma^2_t$ satisfies the nonnegativity because of the log. If $\gamma < 0$ (and statistically significant), it is evidence of the leverage effect, and terms $\beta_1$ and $\beta_2$ are the respective coefficients of the GARCH and ARCH coefficients. The results are reported in Table 3.

The empirical findings show that the increased number of new COVID-19 cases does not have a significant influence on the performance of the markets. These findings are consistent with previous studies, which suggest that the reported number of new cases could be a significant explanatory performance indicator of the market during the early stages of the pandemic, but when a longer period is examined the announcement effect does not affect the performance of the markets (Vasileiou, 2021a).

Unlike new cases, the Google index provides significant information regarding market performance during the pandemic. When Google searches regarding the coronavirus increase, this is an indication of increased fear, and it leads to market decline. Our findings support the theory that increased health fear leads to market decline (Decker & Schmitz, 2016; Smith et al., 2005; Vasileiou, 2021a). The only indices that do not present negative and statistically significant coefficients are the TOPIX and the STI, which are the stock indices of Japan and Singapore, respectively. The time frame within which the spread of COVID-19 unfolded in Asian countries and the way that these countries responded to the COVID-19 crisis may account for the differences in results. Concerning the variance equation, the

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**FIGURE 2** Correlation and partial autocorrelation on absolute returns of the examined indices: The volatility clustering issue. AC, autocorrelation; PAC, partial autocorrelation; Q-Stat, quantile statistics; Prob, probability.
### TABLE 3 Econometric analysis

|                        | S&P ASX 200 | S&P/TSX | CAC 40 | DAX 30 | FTSE MIB | TOPIX | STI | IBEX | FTSE | S&P 500 |
|------------------------|------------|---------|--------|--------|----------|-------|-----|------|------|---------|
| **Mean equation**      |            |         |        |        |          |       |     |      |      |         |
| $c$                    | 0.000122   | 0.001522** | -0.000714 | 6.85 x 10^{-6} | -0.001247 | -0.001402 | -0.001589** | -0.001110 | -0.001194 | 0.001411 |
| (0.0009)               | (0.0006)   | (0.0010) | (0.0012) | (0.0010) | (0.0010) | (0.0006) | (0.0008) | (0.0010) | (0.0008) |
| $\alpha_1$             | 0.000984   | -4.50 x 10^{-5} | 1.33 x 10^{-6} | 0.000334 | -0.000261 | 0.000719 | -9.33 x 10^{-5} | -0.000178 | 0.000301 | 0.000126 |
| (0.0013)               | (5.43 x 10^{-5}) | (8.98 x 10^{-5}) | (0.0007) | (0.0006) | (0.0033) | (0.0001) | (0.0002) | (0.0006) | (0.0002) |
| $\alpha_2$             | -0.001965** | -0.002271* | -0.003087* | -0.003466* | -0.002343* | 0.000045 | -0.000793 | -0.004062* | -0.001668* | -0.002597* |
| (0.0008)               | (0.0006)   | (0.001) | (0.0005) | (0.0004) | (0.0006) | (0.0004) | (0.0006) | (0.0004) | (0.0003) |

| **Variance equation**  |            |         |        |        |          |       |     |      |      |         |
| $\omega$               | -0.512058** | -0.691096* | -0.532896* | -0.356599* | -0.536498* | -0.444848** | -0.678148** | -0.665805* | -0.592255* | -1.103322* |
| (0.2026)               | (0.1979)   | (0.1491) | (0.1129) | (0.1807) | (0.1749) | (0.3055) | (0.2118) | (0.2024) | (0.2706) |
| $\beta_1$              | 0.224783** | 0.395063* | 0.193110** | 0.125607** | 0.195502** | 0.139135 | 0.375877* | 0.237959** | 0.237435* | 0.604446* |
| (0.1067)               | (0.1085)   | (0.0810) | (0.0501) | (0.0967) | (0.0919) | (0.1029) | (0.0961) | (0.0990) | (0.1232) |
| $\gamma$               | -0.162958* | -0.208508* | -0.171658* | -0.194499* | -0.191068* | -0.187568* | -0.130271* | -0.153326* | -0.114126* | -0.038728 |
| (0.0529)               | (0.0615)   | (0.0400) | (0.0349) | (0.0426) | (0.0351) | (0.0585) | (0.0612) | (0.0671) |
| $\beta_2$              | 0.959930* | 0.956631* | 0.951505* | 0.96635* | 0.952644* | 0.957602* | 0.955033* | 0.938941* | 0.949820* | 0.921664* |
| (0.0184)               | (0.0179)   | (0.0139) | (0.0113) | (0.0183) | (0.0172) | (0.0293) | (0.0207) | (0.0193) | (0.0288) |

| **Q-statistics and ARCH LM tests** | Q1 | Q2 | LM1 | LM2 |
|-------------------------------------|----|----|-----|-----|
| $Q_1$                               | 3.6470 | 4.9663 | 7.31 x 10^{-5} | 0.763321 |
| (0.056)                             | (0.938) | (0.973) | (0.894) | (0.894) |
| $Q_2$                               | 0.0060 | 0.2240 | 0.002910 | 0.673321 |
| (0.938)                             | (0.973) | (0.894) | (0.894) | (0.894) |
| $LM1$                               | 0.0012 | 0.470742 | 0.470218 | 0.632623 |
| (0.0012)                            | (0.894) | (0.894) | (0.894) | (0.894) |
| $LM2$                               | 0.1930 | 0.2312 | 0.112012 | 0.105114 |
| (0.0012)                            | (0.894) | (0.894) | (0.894) | (0.894) |

Note: *,** indicate the statistical significance at the 1% and the 5% confidence level, respectively. Standard errors are presented in parentheses and $P$-values are presented in brackets. ARCH LM, autoregressive conditional heteroscedasticity Lagrange multiplier; Q, quantile.
leverage effect is present in most cases, and \( \gamma \) is negative \((\gamma < 0)\) and statistically significant in the stock markets of our sample examined, apart from FTSE and S&P 500, which is an indication of the leverage effect. The Q-statistics and the F-statistics of the Lagrange multiplier tests confirm the econometric validity of the models and verify that the empirical models do not suffer from autocorrelation and ARCH effects.

5 | CONCLUDING REMARKS

The empirical findings show that the health risk influences the performance of the markets not only because of the negative economic consequences (economic slowdown, reduced consumption, etc.), but also because of behavioral factors, such as risk aversion and fear. This paper provides empirical evidence that, in the current period, Google searches can serve as a useful tool for scholars who wish to assess the role of fear of COVID-19 as a factor in market performance. Such an approach allows us to provide an analysis of market performance during stress periods within a behavioral framework. Moreover, this paper provides empirical evidence that the number of new cases, which was initially assumed as the driver of stock market performance, does not have a statistically significant influence when a longer period of the COVID-19 outbreak is examined.

However, further analysis is required to produce indices that could better incorporate fear associated with COVID-19; for example, in Japan and Singapore, the most popular terms are in their native language. Hence, the fact that in our study we used international terms may account for the lack of statistically significant findings in our results concerning the influence of the Google index on market performance.10

Moreover, the Google Trends tool could be useful to behavioral finance supporters and practitioners who pay significant attention to herding behavior (Clement & Tse, 2005; Demirer & Kutan, 2006; Trueman, 1994). In particular, an internet-based tool, such as the Google Trends index and Twitter, could contribute to more accurate models based on herding behavior because such an index incorporates the investors’ fears/expectations. However, further research should be done on how we can refine the selection of the keyword list that we use in our search index. Moreover, evaluation of new information using textual analysis could also contribute to more accurate economic models (Boudoukh et al., 2013; Loughran & McDonald, 2015, 2020).

Additionally, the impact of COVID-19 could be a real experimental case for the impact of inflation on financial markets. Empirical studies present controversial findings regarding the inflation–market performance relationship (Boudoukh & Richardson, 1993; Fama & Schwert, 1977). During the COVID-19 pandemic, some scholars suggested that a reason for the rapid growth in the financial markets despite the increased number of COVID-19 cases and deaths is linked to the stimulus packages that were given by governments11(Vasileiou, 2021b). However, other scholars warn that certain nonconventional policy interventions12 may cause long-term problems (Zhang et al., 2020). Therefore, beyond the behavioral factors, the impact of stimulus packages on investors’ prospects should be examined. The stimulus packages may promote inflation, and the COVID-19 period will provide empirical evidence on the relationship between inflation and market performance.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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ENDNOTES

1 The source of this paragraph’s timeline is the WHO official webpage https://www.who.int/news/item/29-06-2020-covidtimeline
2 https://www.ecdc.europa.eu/en/covid-19
3 https://www.msci.com/market-classification
4 https://www.ecdc.europa.eu/en/geographical-distribution-2019-ncov-cases
5 We should mention that the announcement of new cases is subject to a 1 day lag because the number of new cases announced on any given day refers to the number of positive COVID tests recorded on the previous day. If we use the raw data of the announcement, the following issue emerges: for example, for Mondays, which number should we use as the number of new cases? The reported number of Sunday or the sum of the reported numbers of Friday, Saturday, and Sunday?
6 We do not present the figures on market performance and Google indices in order to avoid repeating an analysis that is similar to the one we presented on the variable of new COVID-19 cases. However, these data are available upon request for anyone who is interested.
7 Similar conclusions were reached when we run the procedure for the squared daily returns. These data are available upon request.
8 We have previously mentioned that new cases are reported with a 1 day lag; that is why the difference of new cases has subscript \( t - 1 \) and the difference of Google index has subscript \( t \).
9 Asian countries were the first countries in which COVID-19 spread and the first countries that effectively responded to the health crisis.
10 For example, in Japan the Google Trends searches appeared in Japanese https://trends.google.com/trends/yis/2020/JP/ (searches for 2020) and https://trends.google.com/trends/?geo=JP (recent trends).
11 https://abcnews.go.com/Business/futures-us-financial-markets-spike-overnight-hit-limit/story?id=69765921, https://www.dw.com/en/coronavirus-what-aid-packages-have-governments-agreed/a-52908669
12 https://www.marketwatch.com/story/fed-saying-aggressive-action-is-needed-starts-unlimited-qe-2020-03-23

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