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Fear of COVID-19 Effect on Stock Markets: A Proposal for an Algorithmic Trading System Based on Fear

Jessica Paule-Vianez *, Carmen Orden-Cruz, Raúl Gómez-Martínez and Sandra Escamilla-Solano

Business Economics Department, Rey Juan Carlos University, 28933 Madrid, Spain
* Correspondence: jessica.paule@urjc.es; Tel.: +34-91-488-84039

Abstract: This study analyzes the fear of COVID-19 effect on European stock market returns. For this purpose, the search volumes (SV) collected by Google Trends (GT) and Wikipedia were used as proxies of fear of COVID-19. In a sample from 13 European stock markets, fear of COVID-19 was found to be associated with negative European stock returns. Our research employed this observation to propose an algorithmic trading system based on fear of COVID-19. Back-testing results show the possibility of extraordinary returns based on this system. These findings have important implications for political authorities, the mass media, and investors.

Keywords: COVID-19; fear; stock returns; Google Trends; algorithmic trading system

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1. Introduction

The coronavirus outbreak, which was officially declared a pandemic on 11 March 2020, by the World Health Organization (WHO), led to significant changes around the world [1], causing difficulties to the world's economies in a similar way to the Great Depression of 1929 [2]. Governments worldwide faced severe challenges, including a deep economic recession, an increase in unemployment, the collapse of international trade, and an increase in fiscal deficits [3].

The latest estimates of pandemic costs are high. The IMF calculated a cost of $12.5 trillion through until 2024 [4]. The increasing number of infections not only gave rise to countermeasures by governments but also caused a severe fall in the stock markets, with February and March 2020 recording the most dramatic crashes. The authors of [5] showed a positive correlation existed between the stress on a country's financial system and the severity of the pandemic a country experienced, resulting in a significant increase in cross-border spillover effects.

COVID-19 fear represents a fear of the unknown. This fear caused considerable anxiety around the world. Hence, it affected the economy and financial markets [6]. According to [7], the fear associated with the deaths caused a more rapid increase in panic than the spread of the virus. Investors' fear sentiment is a transmission channel of the COVID-19 effect in the stock markets [8].

Thus, it is appropriate to analyze the impact that fear of COVID-19 may have on stock market returns. Previous studies investigated this issue [9,10], but few focused on Europe [11]. Hence, more research is necessary, especially since Europe is one of the continents that suffered most from the economic and social ravages of the pandemic [12].

The research's first objective was to analyze COVID-19 fear's impact on European stock returns. Therefore, this study used search volumes of the coronavirus topic collected by GT [11,13–15] and Wikipedia to measure fear of COVID-19. Using these proxies is justified because when people feel fear, they tend to search for more information regarding the events that generate this feeling [16].

Using a sample of 13 countries and applying a panel data approach from 2 January to 17 September 2020, it was found that the fear of COVID-19, measured by GT, had a significant negative impact on European stock returns. The results are robust when lags were included in the explanatory variables, confirming its predictive capacity.

The second objective was to propose a trading strategy to evaluate the ability to obtain extraordinary benefits by incorporating a fear index. Previous studies approached the predictive power of the fear of COVID-19 on stock market returns [17] and volatility [9], but, to our knowledge, no one has presented a tool for investors to take advantage of its predictive capacity. Our study used the predictive power of GT during the COVID-19 pandemic to design a trading system based on algorithms. The results showed the possibility of obtaining extraordinary profits in the European stock markets using an algorithmic trading system based on COVID-19 fear.

This study contributes to the literature in four ways: (1) We provide more evidence of the impact of exogenous events and the ability of internet search volumes to measure the impact of fear on financial markets; (2) we contribute to the studies on the impact of COVID-19 on financial markets by utilizing GT and Wikipedia as indicators of fear of COVID-19; (3) we evidence the negative impact of fear of COVID-19 on European stock returns; (4) we show how fear of COVID-19 has predictive power on future stock market returns; (5) finally, we present an innovation for the financial trading business with the first proposal of an algorithmic trading system based on fear of COVID-19 that shows good performance.

After Section 1 Introduction, Section 2 presents the theoretical framework. Section 3 describes the data. Section 4 explains the methodology. Section 5 shows and discusses the results. Finally, Section 6 presents the conclusions.

2. Theoretical Framework

The coronavirus pandemic was the first major global threat to life and livelihood since the Spanish Flu in 1918 [18] and still represents a worrying event for both society and the population [19]. This "black swan" phenomenon is engendering an intellectual paradigm shift in policy [20], economics [21], business [22], and society [23]. In particular, COVID-19 has exposed the fragility of the financial system [24]. However, regulatory and institutional reforms instituted over the past decade due to the global financial crisis made it more resilient [24]. One of the most remarkable effects was the volatility and negative returns of financial asset prices [8,25].

One of the determining factors considered in all related studies is the risk generated by COVID-19 and the uncertainty created. While investors care about the variance of a risky asset's payoff, they care much more about the ambiguity of events over which the variance occurs. In this sense, a broad literature distinguishes between these concepts where the investors deviate from rationality when faced with uncertainty [26].

The high risk and uncertainty associated with COVID-19 generated an important public concern that led to fear regardless of place [27]. Considering fear as a behavior resulting from an explosion of general concern about a problem [28], such as COVID-19, one of the best proxies for measuring it is the stock markets. The previous literature evidenced that fear can bring overreactions or underreactions among investors [29].

Recent behavioral finance literature has examined the impact of negative sentiment induced by COVID-19 on stock market performance. For example, Bansal [30] showed how emotions and biases generated by COVID-19 affected financial institutions and markets. In addition, Mann et al. [31] studied the people's anxiety the day after the historical stock market crash due to the pandemic declaration. They showed that factors such as location, age, awareness, self-esteem, openness to experience, vulnerability to illness, and group membership are determining factors in anxiety levels when people face financial difficulties. Moreover, Zaremba et al. [32] analyzed the government policies to slow the impact of the pandemic on stock market volatility, showing that non-pharmaceutical measures significantly boosted stock market volatility. They found that the effect was not dependent on the role of the coronavirus pandemic itself and that the result was robust to many considerations. In [33], the authors studied the possible relationship between the level of freedom in a country and stock performance in response to COVID-19 announcements and found that the adverse effects of COVID-19 on stock markets were lower in the countries with higher freedom. In [34], the authors examine the response of emerging stock markets to the uncertainty of epidemics and pandemics, demonstrating that they were more vulnerable than developed market stocks. In [35], the authors show a persistent link between US returns, uncertainty, and the COVID-19 pandemic during the first and second waves of the outbreak. The authors of [36] demonstrated that European non-financial firms suffered a significant loss in their valuations, falling, in extreme cases, to 60% of their intrinsic value.

The COVID-19 threat was an unexpected shock that led people to search for more information about the pandemic. As an infectious disease is spreading, humans show more interest in the latest information and significant incidents, searching for disease-related words on the Internet [16]. Generally, high-power events, such as the COVID-19 pandemic, result in an intense focus by the media, causing fear [37] and consequences beyond the initial event. There is broad evidence in the literature on the relationship between financial markets and the media [38]. The so-called "bad news principle" (in investment decision-making, only negative news matters) was defended in [39,40], although other authors point out that investment decisions can be affected by positive news [41].

Technology and the simplicity of access to the Internet permit the accessibility of a vast amount of news. Web search traffic has been used to track several social phenomena [42]. Mass online behavior is now considered to represent trends in people's thinking [43]. In finance, studies have employed online sources as proxies to describe the behavior of the financial markets [44]. Different indicators are used, such as web search traffic on Yahoo [45], activity on Twitter [46], GT [44], and Wikipedia [47].

Regarding GT, its explanatory power was tested in a stress scenario for the impact of fear of COVID-19 on stock returns. The authors in [11] examined the dynamic of fear in Italy, the first European country to experience an outbreak of COVID-19, and the public concern in Italy was found to be an indication of the concerns in other countries. They documented that GT data for Italy better explained the stock index returns of other countries to their country-based indicators. Similarly, the authors in [13] concluded different negative impacts depending on the stock China index sector. In [14], the authors showed how greater attention, measured by Google Search Volumes (GSV), towards COVID-19 negatively influenced US stock returns. The authors in [15] found that an increased GT synthetic index for COVID-19 had a direct effect on volatility and an indirect effect on stock returns, with effects being stronger in European markets than in the rest of the world.

However, Wikipedia has not attracted as much attention as GT as a proxy to measure investors' fear, with the literature providing some evidence prior to the pandemic. The authors in [48] showed how Wikipedia records have an inverse model of a "sour smile" for the bull market and a "merry frown" for the bear market in stock prices. In addition, in [49], the authors used Wikipedia records as a proxy for smart investors' attention.

Furthermore, another relevant question is whether fear of COVID-19, as it is able to explain stock market returns, can also predict future returns. There is literature that explored the predictive character of different online sources such as stock micro-blog sentiments [50], Twitter activity [51], GT [52,53], and search volumes in Wikipedia [54]. Of these, GT is considered to be one of the best measures due to its explanatory power, especially during unfavorable events [55,56].

Related to the metadata of Wikipedia articles, in finance, the authors in [57] found that fluctuations in Wikipedia page views provided information for investors to make decisions. Using the S&P 500 Index, the authors in [58] evaluated traditional stock technical indicators combined with online data sources (such as Google and Wikipedia), showing that including online data sources makes it possible to improve stock price predictability.

The pandemic provided an opportune moment for reassessing the predictive power of metrics based on online sources and for testing them in a stressful scenario. Using GSV, the authors in [17] demonstrate the predictive power GT for stock returns through health-news searches adjusted for macro-economic factors and financial news. In [9], the authors employed GSV activity as an indicator of panic, selecting terms specific to the coronavirus crisis and phrases related to non-pharmaceutical intervention policies to fight physical contagion. Their results confirmed that the fear created by COVID-19 was a good predictor of stock market movements. In the case of Wikipedia, to our knowledge, there are no studies that use Wikipedia search volumes (WSV) based on COVID-19 to predict stock market performance.

Based on the above, the first hypothesis of this study is the following:

H1. *Fear of COVID-19 can be used to predict European stock returns.*

The evidence shows the predictive power of internet search volumes, which has led several researchers to design trading strategies based on these metrics. To our knowledge, there is limited literature that considers GT and/or Wikipedia data. In [54], the authors proposed trading strategies to anticipate stock market decision-making based on the data that internet users create when searching for information online using Google and Wikipedia. They showed that search levels around politics and business were successful in anticipating the subsequent movements of the stock markets. Specifically, they showed how these searches predicted subsequent falls in these markets. In [53], the authors found that high GSV related to listed companies leads to negative returns when examining a trading system based on selling stocks with high search volumes on Google versus buying stocks with low search volumes on Google. They demonstrated how it was possible to obtain positive returns with these strategies without considering transaction costs. In [59], the authors proposed implementing an algorithmic trading system based on GSV regarding various financial terms, revealing that the level of Google searches is a good metric to measure the mood of global investors. In [60], the authors presented a highly profitable algorithmic trading system based on Wikipedia and GSV to trade Bitcoin. The authors in [61] found that a simple trading strategy informed by Wikipedia views of digital currencies offered significant returns, in terms of returns on investment, compared to baseline strategies.

According to this literature, the second hypothesis to be tested is the following:

H2. *An algorithmic trading system based on GT and Wikipedia can be profitable.*

Based on the gaps found, this study attempted to contribute to the existing literature by evaluating the explanatory and predictive power of fear of COVID-19 using both GT and Wikipedia. In addition, this study proposes to use the fear of COVID-19 in the creation of an algorithmic trading system. To the best of our knowledge, this is the first study that proposes a trading system based on fear of COVID-19 using internet search levels as proxies for the fear.

This hypothesis was considered valid if the net return and, therefore, the ROI of the back tests performed was positive, the profit factor (the ratio between wins and losses) was greater than one, and the percentage of winning sessions was greater than 50%.

3. Data

To analyze the influence of fear generated by COVID-19 on the return of European stock markets, a sample of daily data was taken from 2 January to 17 September 2020.

In this study, we proposed two indicators as proxies of internet users' behaviors to measure fear. On the one hand, internet search data from GT (https://trends.google.com/trends/) (accessed on 30 September 2021) ($Fear_1$) were selected in line with [62,63]. GT offers a free query index between 0 and 100 that describes search volume and allows for data to be sorted by categories such as activity, geographic location, and others. The "search by the topic" was chosen in our study, and the topic "coronavirus" was selected. This topic choice allowed for several synonyms, translations from different languages, and spelling errors to be included in the study [64].

In addition, search data from Wikipedia (https://pageviews.toolforge.org/) (accessed on 30 September 2020) ($Fear_2$) were also selected. The predictive models based on Wikipedia searches were explored by [57,65]. WSVs are available at Pageviews Analysis, and each dataset shows the search volume that users had realized in one day worldwide. Similarly, the topic included was "coronavirus", but with Wikipedia, it was not possible to obtain the data by country, unlike GT.

To evaluate the impact of fear of COVID-19 on European stock market returns, this study included countries belonging to the European Union with a population of more than 10 million inhabitants. We selected the most active stock markets with a representative index. The motivation for considering the stock market indices of the most inhabited countries resides in the fact that our analysis was based on how much of the population was conditioned by fear of contagion. Thus, for the countries that met these requirements and whose stock market information was contained in Investing (https://es.investing.com/) (accessed on 30 September 2020), the prices of their major stock indices were used. The selected countries and stock indices are shown in Table 1.

Table 1. Countries and stock indices of the study.

Country	Stock Index
Belgium	BEL 20
France	CAC 40
Germany	DAX 30
Greece	Athens General Composite
Italy	FTSE MIB
Netherlands	AEX
Poland	WIG 20
Portugal	PSI 20
Romania	BET
Spain	IBEX 35
Sweden	OMX S30
Turkey	BIST 100
United Kingdom	FTSE 100

To measure stock returns, we selected two variables of stock index returns to obtain greater soundness in the results. The first measure used was the rate of change of the closing price of a stock index over two consecutive days.

$$\mathbf{R_{1it}} = \frac{\mathbf{P_{it}} - \mathbf{P_{i,t-1}}}{\mathbf{P_{i,t-1}}} \tag{1}$$

where R_{1it} represents the return of the stock index i on day t using Equation (1) for the return, and P_{it} represents the closing price of the index on day t.

The second measure of stock returns was the logarithm of the ratio of the closing prices over two consecutive days.

$$R_{2it} = \log\left(\frac{P_{it}}{P_{i,t-1}}\right) \tag{2}$$

where R_{2it} represents the return of index i on day t using Equation (2) for the return.

Although, a priori, the use of one metric or another may be equivalent, by using the two ways of calculating profitability, we avoided non-linear effects and increased the robustness of the results.

We also considered control variables related to the COVID-19 impact on stock market returns. The control variables used were gold returns [66,67], the rate of change of the Volatility Index (VIX) [8,68], and the rate of change of Trading Volume (TV) [32].

The descriptive statistics of the variables are shown in Table 2. Attending to stock return measures, the results revealed that during the study period, the average daily return was negative, with the minimum return being found in the Italian market on 12 March 2020, with a price decline of −16.924%. Analyzing fear of COVID-19, it was registered that the maximum values were between 11 and 18 March in GT, while the highest WSV was on 27 January. Focusing on the control variables, the results showed that gold maintained a positive return during the analyzed period, recording its maximum return of 5.77% on 23 March. In the case of the VIX, it achieved its maximum rate of change of 47.950% on 11 June 2020, while the maximum and minimum rate of change of TV were found in the Romanian market on 24 February and 18 August 2020, respectively.

Table 2. Descriptive statistics of the target study variables.

Variable	Mean	Median	Minimum	Maximum	S.D.	C.V
R_1	−0.00087	0.00038	−0.16924	0.10976	0.02148	24.633
R_2	−0.00048	0.00017	−0.08052	0.04523	0.00948	19.701
$Fear_1$	15.770	10.000	0.00000	100.00	17.491	1.1091
$Fear_2$	1.235×10^5	28,731	807.00	9.826×10^5	1.849×10^5	1.4975
Gold	0.00130	0.00150	−0.04680	0.05770	0.01427	10.952
VIX	0.00764	−0.01100	−0.23370	0.47950	0.10498	13.734
TV	0.06996	−0.00483	−0.91481	9.8198	0.50676	7.2440

The correlations between the different target study variables are shown in Table 3. It shows how the proposed return measures were negatively correlated with fear of COVID-19 (with both $Fear_1$ and $Fear_2$), the VIX index, and TV; meanwhile, they were positively correlated with gold returns. Regarding the representative measures of fear of COVID-19, it shows how, as one would hope, both measures were positively correlated with each other. In addition, these measures were negatively correlated with gold returns and TV, but positively with the VIX index.

Table 3. Bivariate correlations of the target study variables.

Variable	R_1	R_2	$Fear_1$	$Fear_2$	Gold	VIX	TV
R_1	1.0000	0.9994	−0.1608	−0.1493	0.1804	−0.5147	−0.0734
R_2		1.0000	−0.1750	−0.1576	0.1810	−0.5204	−0.0760
$Fear_1$			1.0000	0.4548	−0.1165	0.0934	−0.0083
$Fear_2$				1.0000	−0.0579	0.2054	0.0070
Gold					1.0000	−0.0479	0.0059
VIX						1.0000	0.1381
TV							1.0000

Note: Critical value at 5% (two-tailed) = 0.0400.

4. Methodology

Before defining the appropriate methodology and establishing the models to study the proposed hypotheses, it was necessary to analyze the variables to be studied. Thus, firstly, the stationarity of the variables was examined with the augmented Dickey–Fuller test [69].

The results when applying the augmented Dickey–Fuller test, assuming constant and trend, showed how all target study variables were stationary except for the variables referring to fear of COVID-19: $Fear_1$ and $Fear_2$. Hence, following [70], we discarded the application of the cointegration analysis. However, to resolve the spurious regression problem derived from the use of non-stationary variables, we incorporate the difference to the variables $Fear_1$ and $Fear_2$ to eliminate the problem of unit root [71].

With all stationary variables, we proposed to apply a panel data approach. This approach is more appropriate for our study than a time series analysis or cross-sectional analysis [72].

To determine which model was most appropriate, the application of the Hausman test [73] was essential. This test allowed us to evaluate whether the determinants of the panel data model were more reliable based on the fixed effects model or the random effects model. The results of the Hausman test determined that the random effects model was more appropriate (see Tables 4 and 5).

Table 4. Influence of fear of COVID-19 on European stock returns (Equations (3) and (4)).

Variable	R_{1i}				R_{1i}			
	Coef.	S.D.	z	*p* Value	Coef.	S.D.	z	*p* Value
Const	−0.00039	0.00037	−1.057	0.291	−0.00036	0.00038	−0.945	0.345
$d.Fear_{1t}$	−0.00070	7.42×10^{-5}	−9.477	0.000 ***				
$d.Fear_{2t}$					−0.00017	0.00044	−0.372	0.710
$Gold_t$	0.20292	0.02569	7.900	0.0002 ***	0.23496	0.02593	9.060	0.000 ***
VIX_t	−0.09860	0.00354	−27.89	0.000 ***	−0.10357	0.00356	−29.06	0.000 ***
TV_t	0.00056	0.00073	0.768	0.442	−0.00019	0.00074	−0.252	0.801
Durbin Watson test	2.21464				2.14170			
Hausman test	0.55286 (0.968)				0.44024 (0.979)			
Obs.	2405				2405			

Note: *** indicate the significance at 1% level.

Table 5. Influence of fear of COVID-19 on European stock market returns (Equations (5) and (6)).

Variable	R_{2i}				R_{2i}			
	Coef.	S.D.	z	*p* Value	Coef.	S.D.	z	*p* Value
Const	−0.00026	0.00016	−1.622	0.105	−0.00025	0.00017	−1.490	0.136
$d.Fear_{1t}$	−0.00032	3.26×10^{-5}	−9.717	0.000 ***				
$d.Fear_{2t}$					-7.95×10^{-5}	0.00020	−0.408	0.683
$Gold_t$	0.08951	0.01128	7.937	0.000 ***	0.10393	0.01140	9.120	0.000 ***
VIX_t	−0.04396	0.00155	−28.33	0.000 ***	−0.04620	0.00157	−29.50	0.000 ***
TV_t	0.00022	0.00032	0.68	0.495	−0.00012	0.00032	−0.362	0.717
Durbin Watson Test	2.21466				2.13938			
Hausman test	0.57083 (0.966)				0.49329 (0.974)			
Obs.	2405				2405			

Note: *** indicate the significance at 1%, level.

Hence, the panel data models proposed to study the impact of fear of COVID-19 on European stock returns were the following:

$$\mathbf{R_{1it}} = \boldsymbol{\alpha} + \boldsymbol{\beta_1}\mathbf{d.Fear_{1it}} + \boldsymbol{\beta_2}\mathbf{Gold_{it}} + \boldsymbol{\beta_3}\mathbf{VIX_{it}} + \boldsymbol{\beta_4}\mathbf{TV_{it}} + \mathbf{w_i} + \boldsymbol{\varepsilon_{it}},\ \ \mathbf{t = 1, 2, \ldots, T} \quad (3)$$

$$\mathbf{R_{1it}} = \boldsymbol{\alpha} + \boldsymbol{\beta_1}\mathbf{d.Fear_{2it}} + \boldsymbol{\beta_2}\mathbf{Gold_{it}} + \boldsymbol{\beta_3}\mathbf{VIX_{it}} + \boldsymbol{\beta_4}\mathbf{TV_{it}} + \mathbf{w_i} + \boldsymbol{\varepsilon_{it}},\ \ \mathbf{t = 1, 2, \ldots, T} \quad (4)$$

$$\mathbf{R_{2it}} = \boldsymbol{\alpha} + \boldsymbol{\beta_1}\mathbf{d.Fear_{1it}} + \boldsymbol{\beta_2}\mathbf{Gold_{it}} + \boldsymbol{\beta_3}\mathbf{VIX_{it}} + \boldsymbol{\beta_4}\mathbf{TV_{it}} + \mathbf{w_i} + \boldsymbol{\varepsilon_{it}},\ \ \mathbf{t = 1, 2, \ldots, T} \quad (5)$$

$$\mathbf{R_{2it}} = \boldsymbol{\alpha} + \boldsymbol{\beta_1}\mathbf{d.Fear_{2it}} + \boldsymbol{\beta_2}\mathbf{Gold_{it}} + \boldsymbol{\beta_3}\mathbf{VIX_{it}} + \boldsymbol{\beta_4}\mathbf{TV_{it}} + \mathbf{w_i} + \boldsymbol{\varepsilon_{it}},\ \ \mathbf{t = 1, 2, \ldots, T} \quad (6)$$

where R_{1it} and R_{2it} are the dependent variable, α is the constant term, β_k is the regression coefficient of every explanatory variable k, w_i is a random variable of the individual effects, and ε_{it} is the error term.

Based on the results from these proposed models, a trading system created with algorithms is proposed to evaluate the possibility of obtaining extraordinary returns based on the fear of COVID-19. Further details of the system are shown in the following section.

5. Results

According to the proposed models, Table 4 presents the results when evaluating the impact of fear of COVID-19 ($d.Fear_{1t}$ and $d.Fear_{2t}$) on European stock market returns, taking into consideration the rate of change of the market price (R_{1t}). Fear of COVID-19, measured by GT, had a significant negative impact on European stock indices' returns, with more than 99.9% confidence. Considering the control variables, the returns for gold had a significant positive impact on the European market's returns and the variation of the VIX index had a significant negative impact. However, no significant influence of TV was found.

If we look at the fear of COVID-19 measured by Wikipedia searches (d.$Fear_{2t}$), although the coefficient of this variable had a negative value, it cannot be said that the coefficient had a value different from 0. A possible reason for this observation can be found in the limitation of Wikipedia's search level extraction. As explained in the data section, it was not possible to obtain the level of searches for the coronavirus topic by country. The platform only provides details at the global level. Thus, while fear of COVID-19, may differ between countries, the limitations of the global measure using Wikipedia may not accurately reflect the fear of COVID-19 present in the population of a specific country.

Looking at the results for the models presented around the second measure of the return proposed, R_{2t} (Table 5), similar results were observed to those included in Table 4. In both cases, the models meet the uncorrelated and homoscedasticity of the residuals, and they show how fear of COVID-19 measured by GSV had a negative and significant impact on European stock market returns. Similarly, taking the variable based on WSVs, it was again not found to have a substantial influence on stock market returns.

Based on the results of these proposed models and d.$Fear_{2t}$ for European stock market returns, is clear that rising fear due to the COVID-19 pandemic caused reductions in European stock market returns. These results were in line with those reported in [11,13–15].

The specification of the variables was modified to check the robustness of the analysis, considering the lagged variables to validate the findings. In particular, we analyzed the effects of the explanatory variables at time $t - 1$ on stock market returns at time t. Therefore, this specification not only tested the robustness of our results but also allowed for the assessment of the predictive ability of fear of COVID-19 on next-day stock market returns.

Table 6 presents the results by including a lag to the explanatory variables of the proposed models. It can be observed that even after inserting a lag, fear of COVID-19 continued to present a significant inverse relationship with stock market return, with more than 99.9% confidence when we took GT as a reference. In contrast, considering WSVs, no significant influence was evidenced. Similarly, the variables of gold returns and the variation of the VIX index continued to maintain the relationship found in the previous models. Therefore, these results show how fear of COVID-19 not only had an explanatory power regarding European stock market returns, but it also had a predictive capacity, which means H1 can be accepted. The validation of this research hypothesis confirms the conclusions in [9,17] regarding the predictive power of this metric.

This study proposes going one step further. After demonstrating that fear of COVID-19 explains and predicts part of the European stock market performance, we analyzed the possibility of obtaining extraordinary profits by participating in these markets using the fear of COVID-19. We ruled out the consideration of using WSVs due to the lack of significance shown with stock returns. Thus, the first model proposed was considered using GSV (Equation (3)) with the lag of explanatory variables, whose impact on the stock market return was found to be significant. The proposed system design used an algorithmic trading system to take investment decisions using the following equation:

$$R_{1it} = -0.000847037 - 0.000756169 \cdot \mathrm{d.Fear}_{(1it-1)} + 0.0905054 \cdot \mathrm{Gold}_{(it-1)} - 0.0150954 \cdot \mathrm{VIX}_{(it-1)}. \quad (7)$$

Considering the previous equation, we designed an algorithmic trading system that operated in the following manner:

- If the result of the equation was positive, the system opens a long position in the future of the index at the opening;
- If the result of the equation was negative, the system opens a short position in the future of the index;
- At the end of the market session, the positions that were open were closed.

Table 6. Predictive capacity of the fear of COVID-19 regarding European stock returns.

Variable	R_{1t}		R_{1t}		R_{2t}		R_{2t}	
	Coef.	z (p Value)	Coef.	z (p Value)	Coef.	z (p Value)	Coef.	z (p Value)
Const	−0.0009	−2.01 ** (0.044)	−0.0008	−1.84 * (0.066)	−0.0005	−2.52 ** (0.012)	−0.0005	−2.34 ** (0.019)
$d.Fear_{1t-1}$	−0.0008	−8.69 *** (0.000)			−0.0003	−8.75 *** (0.000)		
$d.Fear_{2t-1}$			−0.0004	−0.75 (0.452)			−0.0002	−0.71 (0.477)
$Gold_{t-1}$	0.0901	2.96 *** (0.003)	0.1247	4.07 *** (0.000)	0.0390	2.90*** (0.004)	0.0544	4.02 *** (0.000)
VIX_{t-1}	−0.0154	−3.68 *** (0.000)	−0.0207	−4.93 *** (0.000)	−0.0069	−3.72 (0.000)	−0.0092	−4.97 *** (0.000)
TV_{t-1}	0.0005	0.58 (0.564)	−0.0003	−0.3 (0.719)	0.0003	0.67 (0.502)	−0.0001	−0.27 (0.785)
Durbin Watson test	2.31524		2.22535		2.31838		2.22512	
Hausman test	0.4119 (0.982)		0.3318 (0.988)		0.4487 (0.978)		0.3868 (0.98355)	
Obs.	2392		2392		2392		2392	

Note: ***, **, and * indicate the significance at 1%, 5%, and 10% levels, respectively.

We ran a back test using the Trading Motion platform (https://www.tradingmotion.com/) (accessed on 30 September 2021). Since 2002, Trading Motion has offered automated trading systems from different designers to investors through more than 20 brokers all over the world. Considering the European market, this platform allows trading with the indices: CAC 40, AEX, DAX 30, FTSE MIB, and IBEX 35. Therefore, the results were analyzed. Figure 1 shows the P&L (profit and loses) graphs following the determined operation.

It was found for all indices that the trading systems outperformed the market during the study time and were lucrative during the phase of the pandemic that coincided with the massive lockdowns. However, it was observed that the return to normality resulted in poorer performance of the system.

Therefore, the next step was to optimize the system. To avoid over-optimization, we only considered two parameters: to close positions if a profit of 1% was achieved and that the system only operated if the equation gave a result greater than 0.25%. The profit and loss charts of the optimized systems are available in Figure 2.

It can be observed that utilizing the optimized trading system resulted in better performance during the confinement time of the pandemic that coincided with massive lockdowns and when closures were relaxed (see Table 7). The five optimized systems offered a positive return, both gross and net (brokerage and slippage commissions were estimated). The profit factor (total profits divided by total losses) was greater than 1, and the ratio of winning sessions was greater than 50%, i.e., minimum thresholds for considering that the systems were profitable. Therefore, as can be seen in Table 7, there was a positive annualized return on investment (ROI) in all cases. It was calculated by dividing net profit and loss by capital positions suggested by brokers.

Therefore, these findings mean H2 can be accepted, i.e., it was demonstrated that it is possible to run a profitable algorithmic trading system based on fear of COVID-19. Net P&L and gross P&L were positive and the annual ROI (which was calculated as net P&L divided by suggested capital, the result of which was annualized) was strong (8.03% to 65.52%). Moreover, the profit factor (the ratio between profit and loss) was greater than one for all back tests, and the success rate (the ratio between win sessions and all sessions in the market) was greater than 50%. Considering these results, the market requires a minimum level of capital to activate the system (required capital) although brokers suggest depositing a larger amount of cash (suggested capital) to prevent a sudden draw from shutting down the system. The rest of the back-test statistics support the conclusions obtained and are sufficiently self-explanatory.

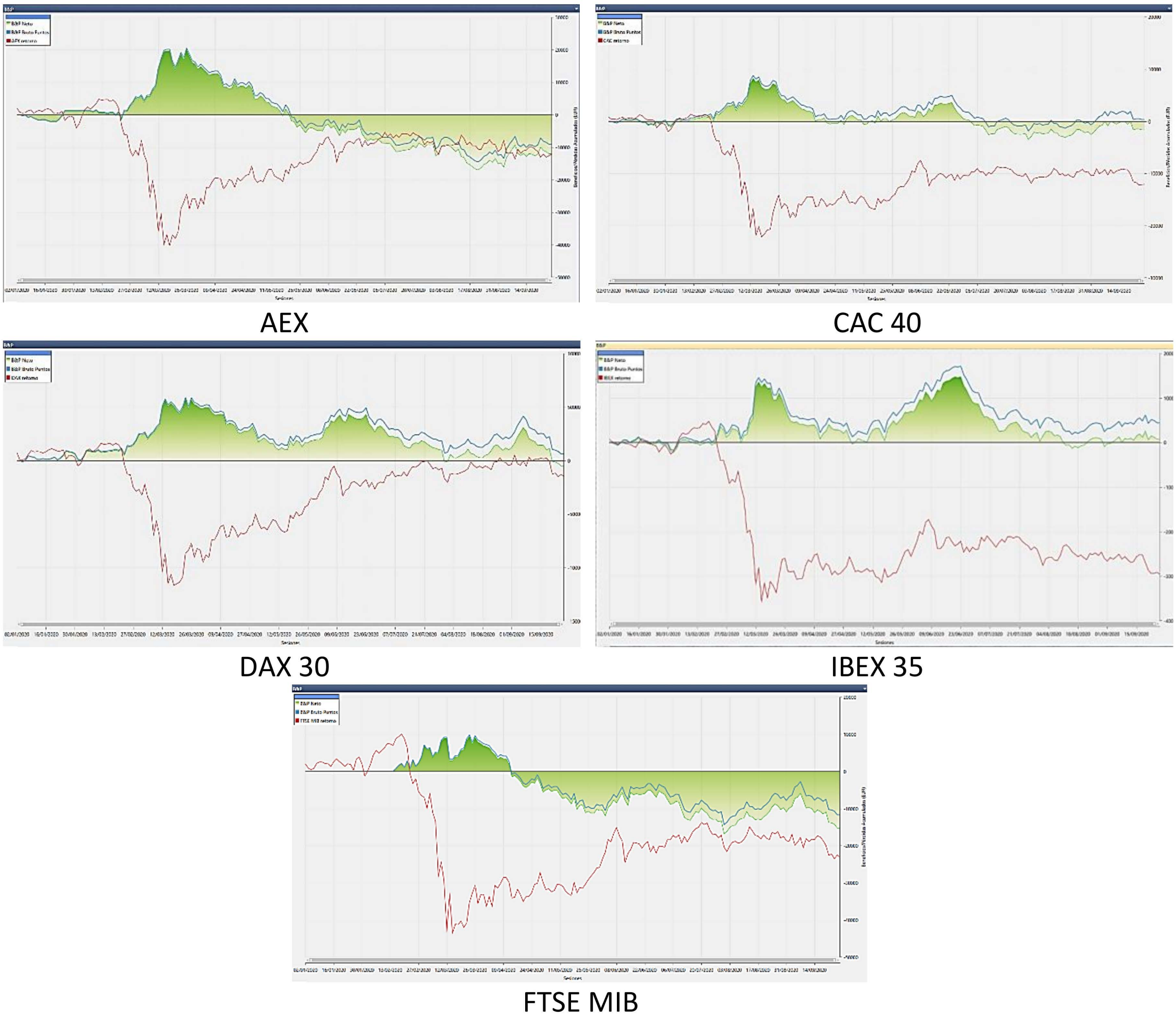

Figure 1. Algorithmic trading system P&L for stock market indices.

Table 7. Performance of the optimized trading systems.

Indicator	AEX	CAC 40	DAX 30	IBEX 35	FTSE MIB
Net P&L	2957.63 €	1322.56 €	49,566.16 €	6140.00 €	4327.10 €
Gross P&L	3740.00 €	1830.00 €	52,837.50 €	7040.00 €	5220.00 €
Profit factor	1.13	1.13	2.04	1.47	1.19
Sharpe ratio	0.55	0.54	2.97	1.49	0.83
Annual ROI	8.03%	8.97%	58.92%	33.32%	11.74%
Analyzed sessions	181	190	189	190	181
Sessions in market	47	46	58	45	53
Success rate	57.45%	63.04%	65.52%	62.22%	56.60%
30 days volatility	135.45%	60.22%	30.52%	74.90%	98.95%
1 year volatility	0.00%	0.00%	0.00%	0.00%	0.00%
5 years volatility	0.00%	0.00%	0.00%	0.00%	0.00%
Suggested capital	50,000.00 €	20,000.00 €	115,000.00 €	25,000.00 €	50,000.00 €
Required capital	3600.00 €	2000.00 €	13,800.00 €	2700.00 €	2800.00 €

These results are consistent with those of other authors who used this technique, such as [53,54,59,60]. This is evidence for the opportunity of using fear of COVID-19 to construct algorithmic trading systems.

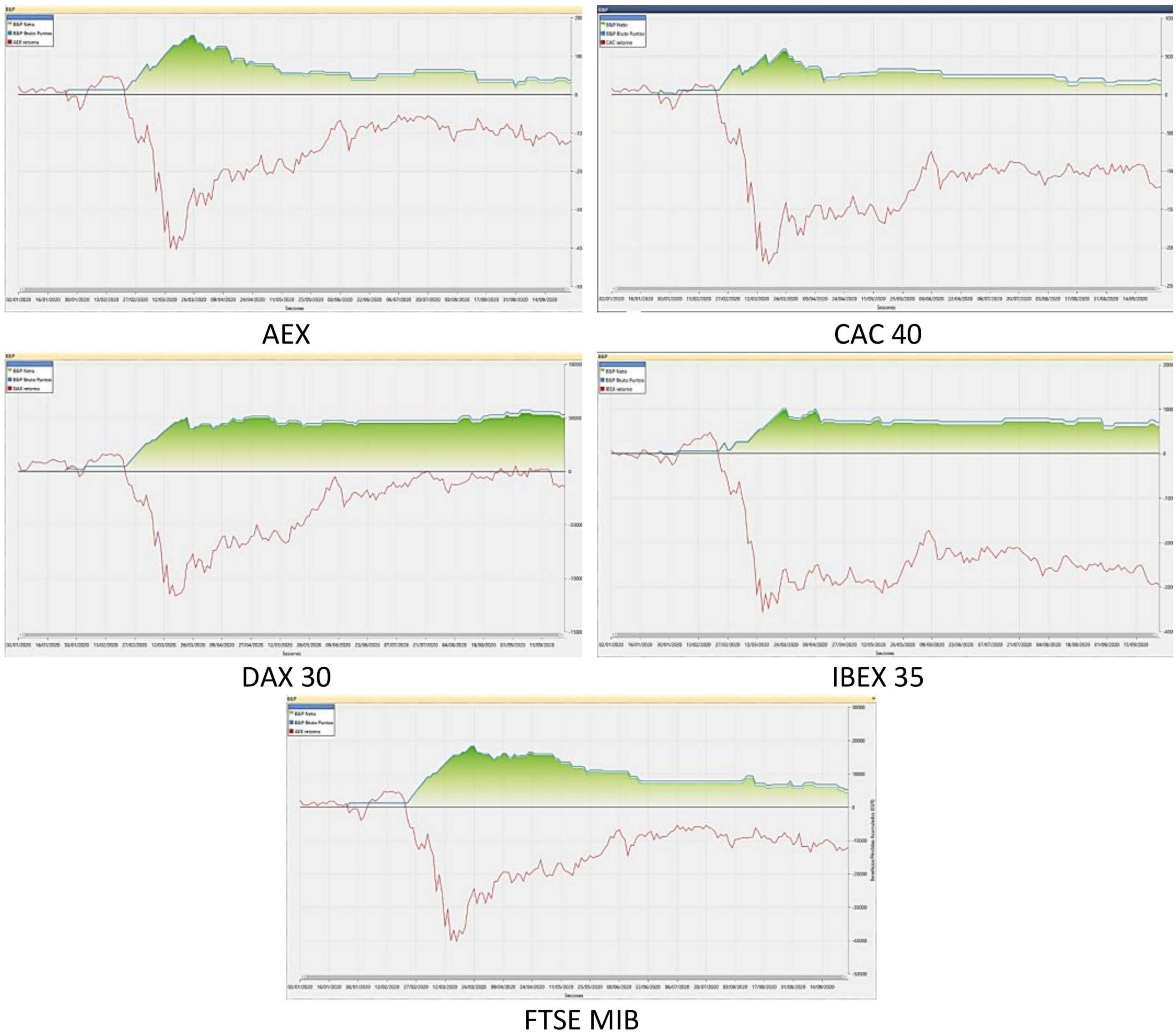

Figure 2. Optimized algorithmic trading system profit and loss for stock market indices.

6. Conclusions

In this research, we evaluated the effect that fear of COVID-19 had on European stock market returns. In accordance with the previous literature that found that anxious populations tend to search for information regarding events that are the source of the anxiety, we considered search volumes registered on Google and Wikipedia for coronavirus as good proxies of fear of COVID-19.

Applying panel data analysis on a sample of 13 European countries from 2 January to 17 September 2020, we showed that fear of COVID-19, measured by GT, had a significant negative impact on European stock returns. Using WSVs as a proxy for COVID-19 fear was not found to have a significant impact. Therefore, it was confirmed that rises in fear generated by the COVID-19 pandemic caused reductions in European stock returns, adding more evidence to the previous literature. In addition, the results were robust to the inclusion of a lag in the explanatory variables, demonstrating the predictive capacity of the proposed models.

Finally, there are few studies that assess using algorithmic trading systems, especially in stress scenarios such as COVID-19. This study developed profitable algorithmic trading systems based on fear of COVID-19 according to the predictors previously identified in the panel data models. It showed how these systems offered gross and net positive returns, a positive profit factor, and more than 50% winning trading sessions. We consider it remarkable that our study was not only limited to identifying significant variables, but also exploited them in a real and profitable use case.

Our findings have several important implications. On the one hand, the fact that fear of COVID-19 had a significant negative impact on European stock markets demonstrates the importance of good management of fear by the authorities and the media. This points to the importance of striking the right equilibrium between the needed concern from a public health perspective and the possible panic, which has a negative impact on the economy and, especially, the stock markets. On the other hand, we show the possibility of obtaining extraordinary profits with an algorithmic trading system based on fear of COVID-19. The trading system is useful to investors as it provides the possibility of obtaining positive returns in the face of financial instability due to a public health crisis.

Finally, this study points to the need for further research to provide a deeper understanding of the role of fear and its impact on stock markets. Considering the fear factor as a predictor in the development of trading strategies may be an important theoretical advance.

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