Fear of the coronavirus and the stock markets

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ABSTRACT

Since the outbreak of the COVID-19 pandemic, stock markets around the world have experienced unprecedented declines amid high uncertainty. In this paper, we use Google search volume activity as a gauge of panic and fear. The chosen search terms are specific to the coronavirus crisis and correspond to phrases related to nonpharmaceutical intervention policies to fight physical contagion. We show that during this period, fear of the coronavirus – manifested as excess search volume – represents a timely and valuable data source for forecasting stock price variation around the world.

1. Introduction

The outbreak of the coronavirus (also referred to as COVID-19) has heavily impacted society (Dowd et al., 2020) and decimated the economy. Stock markets around the world have witnessed unprecedented declines. On March 23, 2020, the U.S. benchmark stock market index S&P 500 lost as much as 35% of its value relative to its recent historical maximum achieved on February 19, 2020. In historic fashion, within days, the magnitude of this decline became comparable to the financial crisis of October 2008, Black Monday in 1987, and the start of the Great Depression in October-November 1929. Such evaporation of wealth has costly social and economic consequences, such as decreased consumption and even the reassessment of individual retirement plans (Helppie McFall, 2011).

Research about the impact of the coronavirus pandemic on financial markets has naturally followed. Okorie and Lin (2020) find that financial contagion occurs during the coronavirus crisis, and Akhtaruzzaman et al. (2020) also highlights that financial firms contributed to the contagion more than nonfinancial firms. The results of Baumöhl et al. (2020) indicate that the systemic risk among banks around the world and the density of the spillover network have never been as high – not even during the 2008 financial crisis – as they have been during the COVID-19 pandemic. Corbet et al. (2020a) document that the coronavirus pandemic particularly negatively affected companies with names related to coronavirus, even though these companies were unrelated to the virus. During the COVID-19 crisis, gold acted as a safe haven (Ji et al., 2020), while results for Bitcoin are less conclusive: Goodell and Goutte (2020) suggest that Bitcoin acted as safe haven, while Conlon and McGee (2020), Conlon et al. (2020) and Corbet et al. (2020b) conclude the opposite. Ashraf (2020) find that stock markets responded negatively to the growth in confirmed cases of COVID-19. Further topics for research are suggested in Goodell (2020).

With a sample of the largest 10 stock markets (United States (US), United Kingdom (UK), Japan (JP), France (FR), India (IN),

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Canada (CA), Germany (DE), Switzerland (CH), South Korea (KR) and Australia (AU)), covering approximately 80% of global market capitalization, we show In this paper that during the 'orona crash', stock markets around the world reacted to fear of the coronavirus. To measure fear, we rely on internet searches of corona-related terms. Recently, Bento et al. (2020) showed that the response of the general public to news about local COVID-19 cases is to search for more information on the internet. Internet searches have been shown to be useful in many applications, e.g., tracking influenza-like epidemics in a population (Ginsberg et al., 2009).

The idea of using sentiment or fear to explain stock market volatility is certainly not new; several recent studies have used news, VIX, Twitter posts and other proxies to measure investors' sentiment and fear about the future (e.g., Whaley, 2000; Zhang et al., 2011; Huerta et al., 2011; Smales, 2014; 2017). However, our study is the first to address the predictive power of Google searches on stock market volatility during the COVID-19 pandemic. Our results show that high Google search volumes for COVID-19 predict high stock market volatility in all markets in our sample.

The conclusion that COVID-19 increases stock market volatility accords with Sharif et al. (2020), Zaremba et al. (2020) and Zhang et al. (2020). However, our work complements theirs, as Sharif et al. (2020) measure COVID-19 by the number of the infected cases of COVID-19 in the US, Zaremba et al. (2020) utilized government nonpharmaceutical interventions aimed at curbing the spread of COVID-19 and Zhang et al. (2020) is based on global coronavirus infections obtained from the John Hopkins Coronavirus Resource Center.

The rest of the paper is organized as follows. Section 2 presents the data and describes the construction of the variables. Section 3 presents the methods and results. Section 4 concludes.

2. Data and variables

Data on price variation are retrieved from the Oxford-Man Institute's Realized Library[1]. We use data from the following ten indices: the S&P 500 (US), FTSE 100 (UK), NIKKEI 225 (JP), CAC 40 (FR), NIFTY 50 (IN), S&P/TSX Composite (CA), DAX (DE), SMI (CH), KOSPI (KR), and All Ordinaries (AU). The Google Trends are retrieved using a program package in R (Massicotte, Eddelbuettel). Data are available upon request.

Thus, to capture fear of the coronavirus, we use only data from Google Trends, i.e., a search volume index ($SVI_{t,j}$), where index j denotes a specific search term. The idea proposed by Preis et al. (2013) is that prior to trading, investors search for information; therefore, such data lead future trends, particularly declines in the financial market. We retrieve daily individual search volume indices that are normalized to the range from 0 to 100 for the following 19 English words: 'corona', 'World Health Organization', 'virus', 'COVID-19', 'SARS', 'MERS', 'epidemic', 'pandemic', 'symptom', 'infected', 'spread', 'outbreak', 'social distancing', 'restriction', 'quarantine', 'suspend', 'travel', 'lockdown', and 'postpone'. These terms are related to the coronavirus crisis and are thus unlikely to have been predictive of market uncertainty in the past. We aggregate search intensity across these terms by taking the average across all individual indices for each day t. The first principal component was also highly correlated with the average we used; therefore, we opted for the simpler average. The result is the average search volume index, $ASVI_t$.

As an alternative to Google searches, we considered using data on nonpharmaceutical interventions (NPIs) implemented by governments around the world. We specifically considered data on interventions in these four categories: social distancing, movement restrictions, public health measures, and social/economic measures. (All of the categories included several pandemic-related policy responses[2]). The challenge posed by NPIs is that not only does the public tend to be informed about such measures in advance, but also such measures are publicly discussed before they are agreed upon. Consequently, NPIs cannot be properly synchronized with market data. Using Google searches is free of such issues. To capture the attention of the public to NPIs and the spread of the coronavirus, we use search terms that are derived from the names of various NPIs.

To study how changing patterns in search activity are related to market uncertainty, we follow the work of Da et al. (2011) and calculate the *abnormal search volume activity*:

$$ASVA_t = \ln\left(\frac{ASVI_t}{median\{ASVI_{t-1}, ..., ASVI_{t-5}\}}\right) \tag{1}$$

The $ASVI_t$ is generally considered as a measure of attention (Da et al., 2011), and attention can have various causes. In the case of COVID-19, it could be fear, curiosity, or search for some practical information, e.g., how to create a face mask. Our interpretation is that at the outbreak of COVID-19, given that the speed, extent and the negative consequences of the pandemic on society were largely unanticipated, the sudden increase in the interest, as captured by $ASVA_t$, primarily represents fear of this pandemic. On the other hand, in later stages of COVID-19, once people were familiar with it, people searched for information for various other reasons, and therefore, in general, $ASVA_t$ represents attention rather than fear.

As the speed, extent and the consequences of the coronavirus crisis were largely unanticipated, we interpret the $ASVA_t$ as a gauge of panic and fear. The higher the value of $ASVA_t$ is, the larger the increase in the interest of the population in coronavirus-related

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[1] http://realized.oxford-man.ox.ac.uk/data/download

[2] For example, (1) social distancing includes schools closures, public services closures, lockdowns, and limits on public gatherings; (2) movement restrictions include visa restrictions, travel restrictions, international flight suspensions, border closures, domestic travel restrictions, border checks, and additional health/document requirements upon arrival; (3) public health measures include health screenings in airports and border crossings, introducing quarantine policies, awareness campaigns, and strengthening the public health system; (4) social/economic measures include health screenings in airports and border crossings, introducing quarantine policies, awareness campaigns, and strengthening the public health system.

Table 1
Descriptive statistics.

	US	UK	JP	FR	IN	CA	DE	CH	KR	AU
Panel A: Logarithm of realized variance										
Mean	5.90	5.96	5.86	5.99	5.90	5.24	6.21	5.81	6.11	5.50
SD	1.96	1.57	1.54	1.70	2.01	2.13	1.68	1.59	1.28	1.80
Median	5.68	5.75	6.06	5.87	5.45	4.91	6.09	5.49	5.91	5.61
$\rho(1)$	0.89	0.84	0.70	0.86	0.80	0.90	0.82	0.88	0.70	0.88
$\rho(10)$	0.59	0.61	0.51	0.56	0.56	0.63	0.55	0.57	0.41	0.60
Panel B: Local abnormal search volume intensity										
Mean	0.03	0.03	0.01	0.03	0.05	0.03	0.02	0.06	0.02	0.04
SD	0.22	0.22	0.20	0.23	0.21	0.28	0.25	0.33	0.32	0.27
Median	-0.01	-0.01	0.03	0.00	0.01	-0.04	0.00	-0.03	0.02	-0.04
$\rho(1)$	0.82	0.70	0.32	0.31	0.70	0.76	0.39	0.29	0.23	0.64
$\rho(10)$	0.09	0.08	-0.04	0.18	-0.07	-0.04	0.27	0.05	-0.06	0.10
Panel C: Global abnormal search volume intensity										
Mean	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.04	0.04
SD	0.19	0.20	0.21	0.19	0.21	0.19	0.19	0.19	0.20	0.19
Median	-0.01	-0.02	0.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02
$\rho(1)$	0.55	0.54	0.64	0.60	0.63	0.53	0.62	0.64	0.64	0.57
$\rho(10)$	-0.03	0.00	0.12	0.06	0.16	-0.01	0.08	0.06	0.13	0.01

Notes: $\rho(.)$ *is the autocorrelation coefficient at the given order.*

events, fear and panic; consequently, we hypothesize larger market uncertainty. The same underlying idea has been used by Zhang et al. (2011), who argued that emotional outbursts of any kind posted on Twitter can give a prediction of how the stock market will do the following day. Panel B of Table 1 shows the key statistics of $ASVA_t$ across 10 developed markets. The shocks in search activity show signs of short-term persistence that is much smaller than the persistence of market uncertainty (see Panel A of Table 1).

To measure market uncertainty, we resort to the daily variance of market returns (realized variance) calculated from high-frequency data. The higher the realized variance is, the higher the market uncertainty. Specifically, we model the annualized daily variance as follows: $RV_t = 252 \times (j_t^2 + \sum_{i=1}^{M} r_{i,t}^2)$, where $r_{t,i} = 100\% \times (lnP_{t,i} - lnP_{t,i-1})$ is the ith intraday continuous return and $P_{t,i}$ is the value of a stock market index on day t at intraday time $i = 1, 2, ..., M$. The term $j_t = 100 \times (lnP_{t,1} - lnP_{t-1,M})$ is the return between the closing value of the index on day $t - 1$ and the opening value on day t. The overnight price variation is added because the closing and opening values of the market index often differ. For the intraday component, we use the common 5-minute calendar sampling scheme to sample index values $P_{t,i}$. A standard assumption for the data generating process of P_t is $d \log(P_t) = \mu_t dt + \sigma_t dW_t$, where μ_t is the drift parameter, σ_t is the instantaneous volatility, and W_t is standard Brownian motion. The integrated variance over a time span [t-Δt,t], $IV_t = \int_{t-\Delta t}^{t} \sigma_s^2 ds$, is not directly observable, but Andersen et al. (2001) show that the integrated variance can be approximated from the sum of the squared intraday returns, which are observable from past intraday returns.

3. Methodology and results

We visualize market development and search intensity for the largest market index, the S&P 500. The upper panel of Fig. 1 shows the value (P_t, left y-axis) and realized variance (RV_t, right y-axis) of the S&P 500 index over our sample period from December 2, 2019 to April 30, 2020. We observe that during the onset of the corona crash, the value of the market declined, while uncertainty in the market increased to extreme levels. Fig. 1 also shows the average daily realized variance over 20 years prior to our sample window; the average daily realized variance reached a modest value of 278.53 (red-line). The average over our sample for the U.S. market is much higher at 1776.98.

The lower panel in Fig. 1 plots the average search intensity in the U.S. ($ASVI_t^{US}$) over time and the corresponding abnormal search volume activity ($ASVA_t^{US}$). Fig. 1 shows that the period of extreme market uncertainty coincides with a period of higher attention of investors to corona events. During trading days from March $12 - 16$, 2020, when market variance reached its highest values, $SVI_{t,j}$ was 100 for 11 of 19 terms ('corona', 'virus', 'SARS', 'MERS', 'epidemic', 'infected', 'outbreak', 'restriction', 'suspend', 'travel', 'postpone') on March 12th and reached 100 for two additional terms, namely, 'spread' and 'quarantine', on March 16th. Market uncertainty remained high during this period, as did the $ASVI_t^{US}$ and $ASVA_t^{US}$. The concurrence of high realized variance with $ASVI_t^{US}$ and $ASVA_t^{US}$ suggests that investors were in a state of high uncertainty.

We created $ASVI_t^{global}$ and the corresponding $ASVA_t^{global}$ variables to reflect search intensity in countries other than that of the given market. For example, to calculate $ASVI_t^{global}$ for the U.S., we took the average of $ASVI_t$ across the nine other developed economies in our sample. The $ASVI_t^{local}$ (searches specific to a given country) and $ASVI_t^{global}$ are highly correlated – the Pearson's correlation of 0.77 for South Korea is the lowest. Additionally, the $ASVA_t^{local}$ and $ASVA_t^{global}$ also show strong correlations, with the 0.40 for India being the lowest correlation. These results indicate that the fear was a global phenomenon. Moreover, as developed markets are open to foreign investors, it follows that global search interest might also influence local markets. The above observations are formalized in three models that are estimated using a sample of 10 large developed markets around the world.
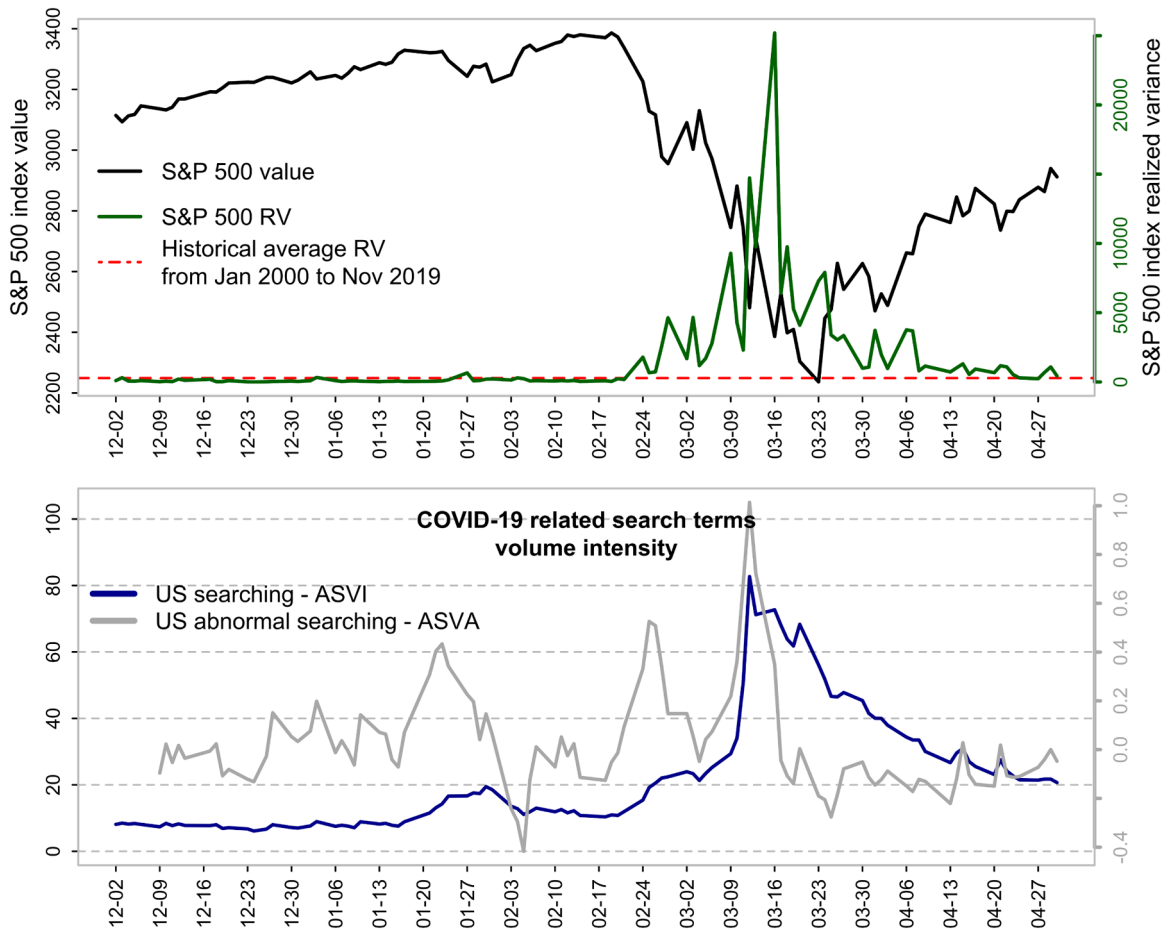
Fig. 1. Market uncertainty and search volume intensity.

First, as a benchmark model, we use a simplified version of the heterogeneous autoregressive (HAR) model of Corsi (2009) (estimated via ordinary least squares (OLS)):

$$lnRV_{t+1} = \beta_0 + \beta_1 lnRV_t + \beta_2 lnRV_t^W + u_t \tag{2}$$

The RV_t^W is the weekly volatility component, calculated as $4^{-1}\sum_{s=t-1}^{t-4} RV_s$, i.e., the daily and weekly components do not overlap. The original HAR model of Corsi (2009) also includes a monthly volatility component, but our conclusions are not influenced if the monthly component (which is not significant) is included. We use the simplified version, as we are also using a shorter sample period. We use the log-log specification to address the positive skew of the variances, while the estimated β_1 and β_2 coefficients can be interpreted as the % change in the RV_{t+1} given a 1% change in RV_t, i.e., the elasticity. Panel A of Table 1 shows statistics of the log of the realized variance across 10 markets. The autocorrelation of the volatility at the 10th lag is still considerable: thus, unconditional volatility is highly persistent, even during our sample period of the corona market crash.

The results from the benchmark model are reported in Table 2. Panel A reveals that the behavior of the variance is very similar across countries – variance is highly persistent, and the variance from the previous day and week provides considerable information about the variance on the subsequent day. A 1% increase in variance on the previous day accounts for at least a 0.298% (India) or even up to a 0.588% (US) increase in realized variance on the next day. For several markets, weekly components are even stronger drivers of market uncertainty. Additionally, the benchmark models already appear to be reasonably well specified; i.e., no serial dependence (see the empirical likelihood (EL) test) with almost always homoscedastic (see White's test) residuals.

Second, we add local abnormal search volume activity:

$$lnRV_{t+1} = \beta_0 + \beta_1 lnRV_t + \beta_2 lnRV_t^W + \beta_3 ASVA_t^{local} + u_t \tag{3}$$

The results reported in Panel B (Table 2) show that the abnormal search volume activity improves the predictability of market uncertainty on the subsequent day. The $ASVA_t$ is positive for all markets and significant for all markets except South Korea, thus suggesting that when search activity related to corona information increased, price variation in stock markets increased the following day. When abnormal search volume activity increases 2 standard deviations (SDs) (see Panel B in Table 1) above the average, the market's realized variance effect almost doubles (RV_t, particularly for the U.S., Japan, India and Germany).

Table 2

Realized variance model with search volume intensity.

	US	UK	JP	FR	IN	CA	DE	CH	KR	AU
Panel A: Benchmark model										
Intercept	-0.257	-0.111	-0.592	-0.165	0.086	-0.166	-0.032	-0.103	0.567^b	-0.116
daily variance – $\ln RV_t$	0.588^c	0.447^c	0.395^c	0.473^c	0.298^b	0.532^c	0.421^c	0.515^c	0.306^c	0.481^c
weekly variance – $\ln RV_t^W$	0.353^c	0.485^c	0.608^c	0.467^c	0.627^c	0.400^c	0.504^c	0.410^c	0.537^c	0.449^c
R^2	0.824	0.766	0.657	0.787	0.761	0.842	0.740	0.803	0.596	0.811
adj. R^2	0.821	0.761	0.648	0.782	0.755	0.839	0.734	0.798	0.587	0.807
EL test	0.877	0.655	0.621	0.729	0.861	0.632	0.769	0.663	0.925	0.854
White's test	0.470	0.331	0.038	0.567	0.600	0.362	0.448	0.657	0.472	0.138
Panel B: Search volume intensity model – local searching										
Intercept	-0.171	-0.110	-0.837	-0.114	0.146	-0.103	0.069	-0.202	0.598b	-0.102
daily variance – $\ln RV_t$	0.462^c	0.410^c	0.299^c	0.405^c	0.235^a	0.458^c	0.343^c	0.432^c	0.276^c	0.395^c
weekly variance – $\ln RV_t^W$	0.475^c	0.523^c	0.751^c	0.533^c	0.677^c	0.469^c	0.573^c	0.512^c	0.565^c	0.542^c
Local abnormal searching – $ASVA_t^{local}$	1.274^c	0.817^b	1.440^c	0.652^b	1.179^b	0.818^b	1.066^c	0.827^c	0.213	0.779^c
R^2	0.844	0.779	0.689	0.793	0.777	0.853	0.763	0.829	0.598	0.824
adj. R^2	0.838	0.772	0.678	0.787	0.768	0.848	0.755	0.823	0.584	0.818
EL test	0.710	0.841	0.187	0.724	0.878	0.534	0.850	0.004	0.863	0.937
White's test	0.585	0.301	0.041	0.342	0.877	0.534	0.716	0.179	0.202	0.032
Panel C: Search volume intensity model – global searching										
Intercept	-0.263	-0.116	-0.725	-0.135	-0.142	-0.194	-0.061	-0.034	0.486^b	-0.213
daily variance – $\ln RV_t$	0.476^c	0.376^c	0.312^c	0.331^c	0.168^b	0.473^c	0.346^c	0.414^c	0.209^b	0.339^c
weekly variance – $\ln RV_t^W$	0.473^c	0.559^c	0.713^c	0.614^c	0.796^c	0.464^c	0.586^c	0.508^c	0.651^c	0.618^c
Global abnormal searching – $ASVA_t^{global}$	1.284^c	0.968^b	1.417^c	1.439^c	1.821^b	1.083^c	1.254^c	1.263^b	1.225^a	1.814^c
R^2	0.839	0.780	0.695	0.809	0.793	0.851	0.759	0.823	0.628	0.845
adj. R^2	0.833	0.772	0.683	0.803	0.785	0.846	0.750	0.817	0.615	0.839
EL test	0.936	0.893	0.717	0.853	0.918	0.490	0.854	0.014	0.818	0.965
White's test	0.495	0.364	0.001	0.226	0.488	0.266	0.116	0.263	0.014	0.020
Number of observations	93	93	84	94	81	91	91	89	92	93

Notes: The superscripts a, b, and c denote statistical significance at the 10%, 5%, and 1% levels, using a random block length bootstrapping scheme with 1000 replications, as in Patton et al. (2009). The EL's test is the p-value of the test of no serial correlation in the residuals of Escanciano and Lobato (2009), and White's test is a nonparametric unweighted bootstrap test of no heteroscedasticity in residuals (Cribari-Neto and Zarkos, 1999).

Third, we add the global abnormal search volume activity:

$$lnRV_{t+1} = \beta_0 + \beta_1 lnRV_t + \beta_2 lnRV_t^W + \beta_3 ASVA_t^{global} + u_t \tag{4}$$

The results reported in Panel C (Table 2) show a similar picture with even larger coefficients for several markets, thereby suggesting not only that the fear is global but also that the economies are highly interconnected. Therefore, these results confirm our previous observation that local and global searches for coronavirus are very similar and, therefore, have the potential to affect markets similarly. In South Korea, global Google searches work much better than local Google searches. The likely reason is that Google is not the most popular search engine in South Korea.

4. Post-fear period

Ashraf (2020) showed that the negative market reaction was strong during the early stages of the COVID-19 pandemic. Stock markets around the world quickly responded to the pandemic, but this response may vary over time depending on the stage of the outbreak. Furthermore, Bento et al. (2020) shows that most interest in COVID-19 was found during the first weeks after the first positive cases were confirmed.

If our results are driven by the period from February and March, i.e., during the initial onset of the COVID-19 pandemic, it strengthens our interpretation that fear drove market movements. We therefore estimated our regressions over the period from April 1, 2020, to July, 31, 2020.[3]

During the post-fear period, $ASVA_t$ reaches less extreme values. Given that the general public already knew about the COVID-19 at that time, this finding is expected. Consequently, for the April to July period, the results are also very different. Regression coefficients loaded at $ASVA_t$ are not positive and significant as before, but are often insignificant and, in some cases, are even negative. The negative coefficient suggests that as the COVID-19 pandemic progressed and the general public increased its awareness about COVID-19 and/or pandemic-related policy responses, market volatility decreased. The fit of these models also decreased dramatically. It therefore appears that for this period, the abnormal interest of the general population in COVID-19 is not a market-moving factor. We therefore interpret our results from the December to May period as being a manifestation of fear, not of mere attention or curiosity.

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[3] Detailed tabulated results, descriptive statistics and regression results, are part of the electronic supplementary material.

5. Concluding remarks

During the outbreak of the COVID-19 pandemic, markets around the world lost an extreme amount value in a short period, strongly negatively affecting societies. We show that at least part of this turbulence was driven by short-term investors' sentiment – that is, fear created by the coronavirus. The level of this fear is measured by Google searches, and this fear has a significant predictive power for future stock market uncertainty.

The observation that Google searches for coronavirus are correlated with price variation is perhaps unsurprising. The research linking stock markets' movements to investors' attention and sentiment has become quite extensive over the last few years (e.g., Hamid and Heiden, 2015; Bijl et al., 2016; Dimpfl and Jank, 2016; Kim et al., 2019; Audrino et al., 2020). However, our results show that Google searches for coronavirus are not simply correlated: these searches predict variance in the future for every country we considered. This result can be utilized in risk management models. During uncertain, unprecedented periods, Google searches present a valuable data source that might improve assessment of market risks. The term 'coronavirus' will probably be the most-searched term in the history of Google Trends.

CRediT authorship contribution statement

Štefan Lyócsa: Conceptualization, Methodology, Software, Data curation, Formal analysis, Writing - original draft, Writing - review & editing, Visualization, Project administration. **Eduard Baumöhl:** Conceptualization, Methodology, Data curation, Investigation, Writing - original draft, Writing - review & editing. **Tomáš Výrost:** Methodology, Software, Validation, Writing - review & editing, Formal analysis. **Peter Molnár:** Conceptualization, Methodology, Validation, Funding acquisition, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they do not have any financial or nonfinancial conflict of interests.

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2020.101735.

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