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Which COVID-19 information really impacts stock markets?

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A B S T R A C T

Information about the COVID-19 pandemic abounds, but which COVID-19 data actually impacts stock prices? We investigate which measures of COVID-19 matter most by applying elastic net regression for measure selection using a sample of the 35 largest stock markets. Out of 24 measures, COVID-19 related Google search trends, the stringency of government responses and media hype prevail during the height of the COVID-19 crisis. These measures proxy for COVID-19 related uncertainty, the economic impact of lockdowns and panic-driven media attention, respectively, summarizing key aspects of COVID-19 that move stock markets. Moreover, geographical proximity to the virus's outbreak and a country's development level also matter in terms of impact.

1. Introduction

The novel coronavirus (COVID-19) has led to unprecedented global health and economic crises. The virus, which originated in 2019 in Wuhan, China, infected over 102 million people and resulted in 2.22 million deaths (as of 1 February 2021) globally (World Health Organization (WHO), 2020). Economies around the world are reeling as a consequence of the implementation of containment policies, such as lockdowns and travel bans, which have restricted economic activity. Global gross domestic product (GDP) contracted by 3.3% in 2020 (International Monetary Fund (IMF), 2021). Governments and central banks have attempted to support economies through stimulus packages, reductions in interest rates, asset purchase programmes and credit guarantees (Capelle-Blancard and Desroziers, 2020).

A burgeoning body of literature has sought to assess how stock markets have been impacted by the COVID-19 pandemic.[1] These studies can be grouped according to measures used to quantify the impact of COVID-19. At a broad level, a distinction can be made between direct and indirect measures (the former referring to measures that directly capture the various facets of COVID-19, while the latter indirectly reflect the impact of COVID-19 along with other influences, such as the outcome of the United States (US) election or Brexit negotiations). Direct measures used in the literature can be further sub-divided. The first group of studies use health-related statistics, such as cases and deaths. Studies report that COVID-19 cases and deaths have a negative impact on stock returns globally

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[1] Several studies have also examined the impact of COVID-19 on other asset markets, such as debt securities (Gupta et al., 2020), cryptocurrencies (Chen, Liu & Zhao, 2020), commodities (Salisu et al., 2020) and derivatives (Hanke et al., 2020).

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(see for example, Al-Awadhi et al., 2020; Ali et al., 2020; Capelle-Blancard and Desroziers, 2020), although the findings are mixed whether cases (Ashraf, 2020a) or deaths (Adekoya and Nti, 2020) have the largest impact.

A second category of direct COVID-19 measures has focused on COVID-19 related attention and market sentiment. Google search trends (GST) for COVID-19 related terms have been used extensively as a proxy for retail investor attention (Da et al., 2011; Smales, 2021a). Furthermore, according to economic psychology, individuals respond to uncertainty about specific events by searching more intensively for relevant information (Dzielinski, 2012; Da et al., 2015; Castelnuovo and Tran, 2017; Bontempi et al., 2019) and, as such, increases/decreases in COVID-19 related Google searches can also be seen as a measure of retail investor uncertainty or fear (Da et al., 2015; Lyócsa et al., 2020; Smales, 2021a; Szczygielski et al., 2021). Studies of the impact of changes in COVID-19 related GST report a negative effect for developed and developing countries stock markets (see for example, Capelle-Blancard and Desroziers, 2020; Costola, Iacopini et al., 2020; Liu, 2020; Papadamou et al., 2020; Smales, 2021a; Szczygielski et al., 2021). The intensity of the impact of COVID-19 related GST has also been found to vary over time and across countries, industries and firms (Ramelli and Wagner, 2020; Smales, 2021b; Szczygielski, Charteris et al., 2022; Szczygielski et al., 2021).

Measures that quantify attention and sentiment related to COVID-19 but with a focus on the media have also been formulated and used. Baker et al. (2020) extend their Equity Market Volatility (EMV) index to include infectious diseases (IDEMV). The EMV, a daily index counting newspaper articles that contain at least one term relating to equity, markets and volatility, is scaled by the number of articles related to infectious diseases. A higher value is indicative of greater COVID-19 related media attention. Ravenpack Analytics has also devised several media attention measures of COVID-19 such as the Media Hype and Media Coverage indices (MHI and MCI respectively), which measure the percentage of all news sources and all news focused on COVID-19, respectively. Consistent with the findings for Google Search Trends - although the debate on whether search trends reflect attention, uncertainty (or both) continues - Capelle-Blancard and Desroziers (2020) document that greater media attention captured by IDEMV negatively impacted stock returns globally. In contrast, Cepoi (2020) finds that media hype had a weak positive effect on stock returns in the US, United Kingdom (UK), France, Germany, Spain and Italy.

A third category of studies investigates the impact of government responses such as lockdowns and stimulus packages on financial markets. Government responses are quantified by the Oxford COVID-19 Stringency Government Response Tracker (GRT).[2] Google and Apple Mobility Trackers (GMT and AMT respectively) have also been used to capture changes in behaviour in response to policies introduced by governments.[3] Physical mobility can be seen as a *de facto* measure of containment compared to the *de jure* GRT (Chen, Igan et al., 2020). Studies document a mixed impact of government responses on global stock market returns with both negative (Szczygielski et al., 2021) and positive (Capelle-Blancard and Desroziers, 2020) effects reported. Research also examines the impact of specific aspects of government responses. Stimulus packages have been found to positively impact stock returns (Ashraf, 2020b; Narayan et al., 2020). Social distancing measures and lockdowns had a negative effect on stock returns (Ashraf, 2020b; Aggarwal et al., 2021). However, evidence of a positive impact of lockdowns on global stock returns has also been reported (Narayan et al., 2020). Capelle-Blancard and Desroziers (2020) report that decreases in mobility, measured by GMT and AMT, are associated with a negative impact on stock returns.

The effects of COVID-19 have also been measured using economic and market uncertainty measures. These include the Chicago Board of Exchange Volatility index (VIX), an indicator of global financial market uncertainty,[4] and economic uncertainty measures such as the Twitter economic and market uncertainty indices (TEU and TMU respectively), business expectation surveys and the Economic Policy Uncertainty (EPU) index of Baker et al. (2016), which comprises newspaper coverage of policy-related uncertainty, the number of Federal tax code provisions due to expire and disagreement among economic forecasters. Although these measures capture overall trends in uncertainty and thus reflect influences aside from the pandemic, they experienced significant 'jumps' during the COVID-19 crisis (Altig et al., 2020; Barrero and Bloom, 2020; Caggiano et al., 2020). Moreover, research shows that VIX and TMU moved closely with COVID-19 related GST during the COVID-19 pandemic, suggesting that search trends reflect market uncertainty (Chen, Liu & Zhao, 2020; Papadamou et al., 2020; Szczygielski et al., 2021). A number of studies examine the impact of COVID-19 on financial markets using these indirect measures and find that VIX and TMU have a negative effect on stock returns globally (Capelle-Blancard and Desroziers, 2020; Salisu and Akanni, 2020; Szczygielski et al., 2021).

Four notable conclusions emerge from the literature: (i) COVID-19 impacted stock returns, (ii) impact has varied across countries, (iii) numerous measures of COVID-19 have been utilised to measure its impact (see Table 1A in Appendix A for a summary of studies) and (iv) it is not clear which of these measure(s) is/are most important.

In this study, we undertake a comprehensive analysis assessing which COVID-19 measures have the greatest impact on global stock markets between January 2020 and July 2021, i.e. a period coinciding with the outbreak of COVID-19 which saw severe downturns in global markets (COVID-19 crisis period) which were followed by a rapid recovery (post-COVID-19 crisis period). To do so, we use a sample of 35 MSCI national market aggregates and the MSCI All Country World Index. We focus exclusively on direct measures as they

[2] The composite GRT is the aggregation of 18 individual indicators (as of time of writing), which are combined into three sub-indices reflective of containment and health measures, economic support and lockdown measures. Each indicator ranges between 0 and 100 and is based upon the level of stringency of the response.

[3] GMT measures the percentage change in the daily trips of users to retailers and recreational facilities, grocers and pharmacies, parks, transit stations, workplaces and residences, from the median number for the corresponding day of the week during the pre-lockdown period (3 January to 6 February 2020). AMT compares the volume of its users' travel searches on its map application for public transport, car and walking to a benchmark value on 13 January 2020.

[4] Although this is the US version of the index, Smales (2019) shows that VIX captures global market uncertainty and has been used by several other authors for this purpose (Chiang et al., 2015; Dimic et al., 2016; Salisu and Akanni, 2020).

capture the unadulterated effects of the COVID-19 health and economic-induced crises. We adopt a novel approach to identify and select COVID-19 measures. Specifically, we use machine learning (ML) algorithms in the form of elastic net regression (Zou and Hastie, 2005) for measure identification and selection. We then relate these measures to statistically derived factors that summarise the return generating process. The selected measures are related to returns on the 35 stock markets that comprise our sample and the global market aggregate using regressions to determine their impact.

Our study makes several contributions to existing literature. First, we conduct a comprehensive review of existing studies on the impact of COVID-19 on financial markets during its outbreak with the aim of identifying a set of direct measures that are most important and encompass other measures during the COVID-19 outbreak and the associated crisis period. In total, we consider (to the authors' knowledge) the most extensive set of COVID-19 measures, i.e. totalling 24 measures. In doing so, we provide clarity as to which measures mattered most for markets and investors, and quantify their impact across markets. By using factor analysis, we are able to summarise the systematic influences that drive global stock markets and are able to determine the proportion of common global market movements that are attributable to the COVID-19 pandemic. Second, we contribute to the increasing application of ML methods in finance such as explaining stock price movements and variables selection (see for example Patel et al., 2015a,b; Chatzis et al., 2018), filtering information from news to evaluate its impact on stock markets (Atkins et al., 2018; Khan et al., 2020) and asset pricing anomalies (Weigand, 2019; Tobek and Hronec, 2020). We add to a growing number of studies using ML methods in various facets of COVID-19 research, such as epidemiological, molecular studies and drug development, medical, socio-economic (Lalmuanawma et al., 2020; Peng and Nagata, 2020;) and financial (Adekoya and Nti, 2020; Baek et al., 2020; Costola, Nofer et al., 2020). Third, we build on the work on financial markets and COVID-19 by considering a broader set of COVID-19 measures that includes COVID-19 related uncertainty, investor sentiment and attention and not only health-related statistics such as deaths or cases (as per Adekoya and Nti, 2020). Fourth, we apply a novel empirical impact measure first proposed by Szczygielski, Brzeszczyński et al. (2022), termed the 'overall impact of uncertainty' (*OIU*). We apply it to quantify the impact and intensity of COVID-19 related uncertainty (as measured by movements in GST; see Section 3.3 for interpretation) on individual stock markets and stock markets grouped according to regions. Finally, we ascribe meaning and interpretation to the most important COVID-19 measures identified over the crisis period. By providing insight into which aspects of COVID-19 matter most to markets and quantifying their impact, our study is of interest to investors and practitioners. By demonstrating an application of ML methods for COVID-19 measure identification and by proposing and outlining a novel empirical impact measure and a method of disentangling the influence of correlated measures, our study is also of interest to researchers and econometricians.

We identify four key measures that summarise the impact of COVID-19 on stock markets during the crisis period. The most important measure, which we interpret as a proxy for uncertainty, comprises COVID-19 related search volumes as measured by Google searches, which we designate as GST_t. The second measure is the stringency of government responses, designated as GSM_t, aimed at reducing the spread of the virus. We view GSM_t as an economic impact factor given its association with reduced economic activity. The third measure is related to the weighted overall government response index, designated as GOR_t. The stringency of government responses and the weighted overall government response indices are highly correlated. We therefore exclude GOR_t and treat GSM_t as a proxy for this measure. The media hype index, MHI_t, is the final measure. This measure is interpreted as an attention measure strongly influenced by panic. GST_t, GSM_t and MHI_t explain between 10% and 20% of shared variance across national markets over the COVID-19 crisis period, depending on whether they are considered individually, jointly, with or without structural breaks. Finally, we repeat the identification process for an approximately equal sample period - a post COVID-19 crisis period - from the end of October 2020 to July 2021. Our results indicate that the behaviour of stock markets in relation to the COVID-19 pandemic has changed with markets no longer responding as severely to measures of the pandemic as during the initial crisis period from January 2020 to the end of October 2020.

The broader implications of our findings for investors, analysts, researchers and econometricians are outlined and discussed in Section 4. We show that some markets – notably those located in Asia – are more resilient to the impact of COVID-19 than others. This knowledge can be used to formulate investment strategies that favour resilient markets and limit exposure to losses and heightened volatility.

The remainder of this study is structured as follows: Section 2 outlines the data and methodology applied in selecting, identifying, interpreting and quantifying the impact of key COVID-19 measures on stock markets. Section 3 presents the results of the COVID-19 measure identification and selection process. The results of the impact of selected measures on stock markets are also presented in this section. Section 4 describes the implications of the findings for investment, analytical and research applications. Section 5 concludes.

2. Data and methodology

2.1. Data

Our primary financial data spans the period from 1 January 2015 to 20 October 2020,[5] comprising daily levels for 35 of the largest MSCI Country Indices by market capitalisation in US dollars as of the end of November 2019.[6] We designate January 2020 to the end of

[5] While the COVID-19 crisis period is defined as 1 January 2020 to October 2020, the period 1 January 2015 to 20 October 2020 is used for the purposes of examining the return generating process and estimating models with ARCH/GARCH errors.

[6] Our sample comprises markets with the largest market capitalisation as of November 2019. We chose November 2019 for sample selection because of the somewhat unclear emergence of COVID-19 in late December 2019. As of December 2019, there was little data quantifying COVID-19 although early reports about aspects of the virus emerged. The return indices used are total return gross indices which include the reinvestment of dividends. These indices reflect price appreciation and dividend yield, which are both important to investors.

October 2020 as the height of the COVID-19 crisis for financial markets, coinciding with the outbreak of the virus which is followed by a severe market downturn and a subsequent recovery (see Fig. 1A in Appendix A).[7] We also include a global market aggregate in the form of the MSCI All Country World Index. Logarithmic returns are obtained by differencing daily index levels. Descriptive statistics for the sample are reported in Table 1.

We set out our COVID-19 measures in Table 2.[8] The sample comprises 24 measures obtained from numerous sources. Given that the series of interest are logarithmic returns for the respective markets in the sample, the COVID-19 measures are differenced in instances where the order of integration is greater than $I(0)$. The COVID-19 measures, descriptive statistics and the results of the Augmented Dickey Fuller (ADF) and Phillips–Perron (PP) unit root tests are reported in Table 2. Each series is stationary following differencing.

We also report upon the correlation structure of the COVID-19 measures. We estimate both ordinary (Pearson) and non-parametric Spearman correlations, given that ordinary correlation coefficients may be unreliable in the presence of non-normality, heteroscedasticity and outliers. The full correlation matrix is reproduced in Table 3A in Appendix A.

2.2. Analysis of the structure of the return generating process

We begin our investigation of the impact of COVID-19 measures on returns by investigating the structure of the return generating process prior to the COVID-19 period, 1 January 2015 to 31 December 2019, and during the COVID-19 crisis period designated as 1 January 2020 to 20 October 2020. The start of the COVID-19 pandemic is based upon events occurring shortly before this date and the availability of data that follows. The first documented COVID-19 hospital admission took place on 16 December 2019 in Wuhan, China (Huang et al., 2020). Numerous measures, such as the number of total cases and data on government containment and economic support measures, are reported from early January or mid-January 2020 as is the case for the number of deaths.

Returns over the pre-COVID-19 and COVID-19 crisis periods are factor analysed to determine the number of factors in the return generating process prior to the COVID-19 outbreak and during the COVID-19 crisis period. To identify the number of latent factors representative of composite common factors driving national stock market returns, the minimum average partial (MAP) test is applied (Szczygielski et al., 2020a). This test identifies the number of factors that most closely result in an approximation of the assumption of uncorrelated residuals, $E(\varepsilon_{i,t}, \varepsilon_{j,t})$, that underlies factor models (Zwick and Velicer, 1986). Once factor scores have been derived, they are subjected to varimax rotation and are then used to select and identify the impact of COVID-19 measures on stock markets.

2.3. Identification and selection of COVID-19 measures

While the preceding analysis yields insight into the structure of the return generating process for the pre-COVID-19 and COVID-19 crisis periods, it also serves another important purpose. It produces factor scores that are a summary of the common forces driving movements across the 35 markets that comprise the sample. By having a representation of these forces, we are able to relate the composite drivers of returns for national stock markets to COVID-19 measures. The methodology that we use to identify COVID-19 measures that impact stock markets draws upon the field of ML. Specifically, we first apply the elastic net estimator to identify and estimate coefficients in a specification relating derived factor scores, $F_{k,t}$, to COVID-19 measure $F_{CV19,t}$:

$$F_{k,t} = \alpha_k + \sum_{k=1}^{m} \beta_{CV19,k} F_{CV19,t-\tau} + \varepsilon_{k,t} \tag{1}$$

$$\beta_{k,CV19}(\text{enet}) = \text{argmin} \left[\begin{array}{c} \frac{1}{2n} \sum_i^n \left(F_{k,t} - \sum_{k=1}^m \beta_{k,CV19} F_{CV19,t-\tau} \right)^2 \\ +\lambda \left(\frac{1-\alpha}{2} \sum_{k=1}^m \beta_{k,CV19}^2 + \alpha \sum_{k=1}^m |\beta_{k,CV19}| \right) \end{array} \right] \tag{2}$$

where λ is the penalty parameter determined by cross-validation, α controls the amount of penalties applied and n is the number of observations in a sample. The elastic net estimator combines a mixture of LASSO (L1 norm, $\sum_{k=1}^m |\beta_{k,CV19}|$) and Ridge (square of L2 norm,$\sum_{k=1}^m \beta_{k,CV19}^2$) penalties, where the L1 norm is a sparsity inducing penalty and L2 norm is a coefficient shrinkage penalty that performs well in the presence of multicollinearity (Zou and Zhang, 2009). We include a time operator, τ, in equation (1) in the form of lagged COVID-19 measures to take into account that some measures may not be known immediately (such as the number of cases) and/or may impact markets with a lag (see discussion relating to preliminary analysis in Section 3.2).[9]

[7] In Section 3.7, we analyse the period between 21 October 2020 and 31 July 2021 and show that the return generating process underlying global markets has changed and that the impact of COVID-19 on markets appears to have waned.

[8] Sources are detailed in Table 2A in Appendix A.

[9] This approach is well-suited to the selection and identification of COVID-19 measures for a number of reasons. The COVID-19 measures considered exhibit high levels of correlation. For example, GOR_t, GER_t and GCR_t are almost perfectly correlated (see Table 3A in Appendix A). Due to multicollinearity, it will be difficult to determine the relative importance of specific measures to obtain stable coefficients and to retain the power of significance tests (Alin, 2010).

Table 1
Descriptive statistics for returns on MSCI All Country World and country indices

Index	Market Cap (USD bn)	Mean	Median	Maximum	Minimum	Std. dev.	Skewness	Kurtosis	Shapiro-Wilk
World	64,623,330	0.0002	0.0005	0.0806	−0.1000	0.0095	−1.5891	26.5588	0.8134***
1. US	28,808,028	0.0004	0.0003	0.0899	−0.1292	0.0117	−1.1265	25.2140	0.8014***
2. China	8,071,533	0.0003	0.0002	0.0584	−0.0661	0.0128	−0.2904	5.4133	0.9726***
3. Japan	4,817,633	0.0002	0.0000	0.0733	−0.0726	0.0112	0.0361	8.8015	0.9326***
4. UK	2,456,466	−0.0002	0.0001	0.0992	−0.1330	0.0124	−1.3165	20.6915	0.8577***
5. France	2,383,072	0.0001	0.0004	0.0812	−0.1403	0.0126	−1.3398	19.4491	0.8781***
6. Canada	1,669,916	0.0000	0.0000	0.1182	−0.1364	0.0127	−1.5260	32.6239	0.7932***
7. Germany	1,642,472	0.0000	0.0004	0.0996	−0.1422	0.0128	−1.0455	18.7842	0.8911***
8. Switzerland	1,474,858	0.0002	0.0004	0.0599	−0.1040	0.0094	−1.0450	15.6798	0.9213***
9. India	1,353,521	0.0001	0.0004	0.0928	−0.1479	0.0125	−1.5323	22.7709	0.8635***
10. Australia	1,089,376	0.0000	0.0002	0.0697	−0.1105	0.0133	−1.1193	14.0422	0.8978***
11. Korea	992,949	0.0002	0.0000	0.1055	−0.0700	0.0132	−0.0996	9.2303	0.9366***
12. Hong Kong	931,809	0.0001	0.0001	0.0535	−0.0715	0.0108	−0.4991	7.4799	0.9465***
13. Taiwan	883,919	0.0003	0.0000	0.0747	−0.0687	0.0113	−0.3517	8.0493	0.9445***
14. Brazil	770,022	−0.0001	0.0003	0.1516	−0.1943	0.0229	−1.0193	14.7586	0.8998***
15. Netherlands	745,075	0.0003	0.0008	0.0697	−0.1121	0.0112	−1.0181	13.6633	0.9160***
16. Russia	584,517	0.0002	0.0000	0.0974	−0.1325	0.0178	−0.5481	10.5548	0.9266***
17. Spain	577,200	−0.0002	0.0000	0.0757	−0.1635	0.0142	−1.9444	25.9133	0.8734***
18. Italy	482,304	−0.0001	0.0001	0.0834	−0.1966	0.0156	−2.1701	27.9465	0.8673***
19. Sweden	456,920	0.0001	0.0002	0.0692	−0.1330	0.0137	−1.3410	16.4428	0.9066***
20. Saudi Arabia	404,885	0.0001	0.0000	0.0836	−0.1721	0.0128	−2.3229	36.1817	0.7902***
21. Thailand	370,781	−0.0001	0.0000	0.0770	−0.1207	0.0118	−1.4372	21.6501	0.8543***
22. South Africa	356,191	−0.0002	0.0000	0.0831	−0.1271	0.0195	−0.6647	7.0594	0.9558***
23. Denmark	336,688	0.0004	0.0002	0.0550	−0.0869	0.0114	−0.4991	7.4540	0.9574***
24. Singapore	296,370	−0.0002	0.0000	0.0705	−0.0778	0.0105	−0.3307	10.4218	0.9217***
25. Belgium	292,243	−0.0002	0.0000	0.0695	−0.1735	0.0134	−1.8577	24.8084	0.8748***
26. Indonesia	291,250	−0.0002	0.0000	0.1548	−0.1022	0.0158	−0.0937	14.0310	0.8948***
27. Malaysia	263,317	−0.0002	0.0000	0.0730	−0.0575	0.0094	−0.2455	9.8986	0.9230***
28. Mexico	237,681	−0.0003	−0.0001	0.0685	−0.1118	0.0156	−0.8599	9.3586	0.9336***
29. Norway	177,487	−0.0001	0.0000	0.0702	−0.1352	0.0151	−0.9380	11.3521	0.9289***
30. Finland	172,694	0.0001	0.0000	0.0672	−0.1175	0.0126	−1.0116	13.7798	0.9218***
31. Philippines	165,397	−0.0002	0.0000	0.0832	−0.1414	0.0132	−1.5205	19.8684	0.8801***
32. UAE	137,466	−0.0003	0.0000	0.0860	−0.1541	0.0128	−1.6365	27.7963	0.7885***
33. Qatar	123,568	−0.0002	0.0000	0.0598	−0.1387	0.0119	−1.3513	19.8220	0.8474***
34. Israel	105,410	−0.0001	0.0002	0.0984	−0.1169	0.0129	−0.9967	16.1453	0.8690***
35. Chile	99,088	−0.0003	−0.0002	0.1045	−0.1674	0.0152	−1.2087	22.9906	0.8592***

Notes: This table reports descriptive statistics for the indices in our primary sample. Returns are defined as logarithmic differences in index levels. *** indicates statistical significance at the 1% level of significance. The Shapiro Wilk test is used to investigate normality. Country indices are ranked according to market capitalisation in billions of US dollars as of 30 November 2019.

The elastic net estimator (equation (2)) draws upon ML, i.e. the computational methods that learn and adapt to new data and identify patterns without human intervention (Bottou, 2014; Alpaydin, 2020). Elastic net, by combining LASSO and Ridge penalties, can automatically perform measure selection while preventing overfitting and the algorithm performs well under multicollinearity (Zou and Hastie, 2005; Zou and Zhang, 2009; Goeman et al., 2018; Liu et al., 2018).

To select COVID-19 measures, an iterative process is followed. Equation (1) is estimated relating each factor score series (see Section 2.3) to the full set of COVID-19 measures. This is then repeated but only retaining those measures for which coefficients are non-zero for λ_{min}, λ_{1SE} and λ_{2SE}, where λ_{1SE} and λ_{2SE} are penalties one and two standard errors from λ_{min}. Measures that are taken forward are those for which coefficients are not shrunk to zero in the final iteration across all penalties.

Once we have selected COVID-19 measures, we set out to establish the amount of explanatory power associated with each identified COVID-19 measure. To do so, we relate each factor score series to each individual COVID-19 measure and then relate each series to all measures jointly by re-estimating equation (1) but replacing $F_{CV19,t}$ with identified COVID-19 measures. Explanatory power is quantified using the adjusted coefficient of determination, $\bar{R}^2$.

A benefit of relating COVID-19 measures to factor scores is that we can determine the *total* amount of shared variance that is explained by the identified COVID-19 measures jointly. Defining the communality associated which each factor score series, c_k, and $\bar{R}^2_{k,CV19}$ as the explanatory power associated with each measure as established by regressing $F_{k,t}$ onto the identified measures, $F_{CV19,t}$, *ShVr* measures the amount of total shared variance attributable to the COVID-19 measures as follows:

$$ShVr = \sum_{k\geq 1}^{k} c_k \bar{R}^2_{k,CV19} \tag{3}$$

Table 2
COVID-19 measures

Symbol	Measure	Diff.	Base measure	Start	Obs.	Mean	Std.	Max.	Min.	ADF	PP
CAS_t	Growth in total cases	FDL	Total cases	01/01/2020	210	0.0677	0.1449	1.2759	0.0000	−8.2434***	−8.2398***
DEA_t	Growth in deaths	FDL	Total deaths	14/01/2020	201	0.0693	0.1477	1.1364	0.0000	−6.8698***	−10.4043***
REC_t	Growth in recoveries	FDL	Total recoveries	24/01/2020	193	0.0712	0.1196	1.0319	0.0072	−3.2010***	−6.4728***
ACT_t	Growth in number of active cases	FDL	Active cases	01/01/2020	209	0.0620	0.0159	1.2937	−0.0785	−7.2745***	−8.0639***
DEC_t	Death curve - Growth in 7 day moving average of reported COVID-19 deaths	FDL	Moving average of daily deaths	13/01/2020	202	0.0404	0.1351	1.0986	−0.1893	−4.5206***	−10.0016***
CAC_t	Case curve - Growth in 7 day moving average of reported COVID-19 cases	FDL	Moving average of daily cases	08/01/2020	205	−0.4051	0.1466	0.9808	−0.7577	−6.8902***	−10.6404***
CFR_t	Changes in case fatality rate	FD	Number of deaths to number of cases, a measure of mortality	14/01/2020	201	0.0001	0.0023	0.0165	−0.0174	−1.8517	−13.9805***
RCI_t	Changes in reported case index	FDL	Deviation of expectations for reported cases in a 14-day window from present reported cases.	04/02/2020	186	−0.0030	0.1971	1.2187	−1.4603	−6.1014***	−18.4379***
RDI_t	Changes in reported death index	FDL	Deviation of expectations for reported deaths in a 14-day window from present reported cases.	05/02/2020	185	−0.0034	0.2580	1.8371	−1.3215	−4.4718***	−34.4848***
GFI_t	Changes in global fear index	FDL	Equal weighted combination of RCI_t and RDI_t	05/02/2020	185	−0.0031	0.1834	1.6635	−1.2511	−4.7766***	−25.4509***
GOR_t	Changes in government responses	FD	Weighted overall government response, combining containment, policy and economic responses and the stringency of responses.	02/01/2020	209	0.4343	1.5609	15.5107	−1.8812	−3.1246**	−12.6964***
GER_t	Changes in government economic support	FD	Weighted government economic support index	26/02/2020	170	0.5554	3.6002	43.7660	−1.7880	−2.5367	−12.2261***
GCR_t	Changes in government containment measures	FD	Weighted government health containment measures	02/01/2020	209	0.4280	1.6117	15.6492	−2.1329	−2.9981**	−12.2199***
GSM_t	Changes in the stringency of measures applied by government in response to COVID-19 outbreak.	FD	Weighed stringency index of government lockdown style measures	02/01/2020	209	0.3917	1.8979	17.9481	−2.7997	−2.9482**	−12.1768***
GST_t	Changes in Google Search Trends related to COVID-19	FD	A composite measure of Google Search Trends for 9 COVID-19 related terms.	17/12/2019	221	0.0823	3.7663	30.6100	−18.870	−10.7529***	−10.9468***
EMV_t	Changes in the EMV index (Seasonally adjusted)	FD	Equity Market Volatility (EMV): Infectious Disease Tracker	17/12/2019	221	0.1250	4.6981	19.0440	−10.7942	−11.1992***	−13.7341***
GMT_t	Changes in Google Mobility Tracker (Seasonally adjusted)	FD	Weighted Google mobility reports for constituent markets	14/01/2020	175	−0.1786	4.5853	18.8655	−17.2502	−4.1096***	−13.0865***
AMT_t	Changes in Google Mobility Tracker (Seasonally adjusted)	FD	Weighted Apple mobility reports for constituent markets	19/02/2020	201	−0.0029	1.9049	5.9281	−7.6528	−2.8769*	−10.1456***
RPI_t	Changes in the Ravenpack Panic Index	FD	Ravenpack Panic Index measuring references to hysteria or panic and coronavirus.	02/01/2020	209	0.0148	0.8845	3.7900	−3.9100	−3.6005***	−28.9717***
MHI_t	Changes in the Ravenpack Media Hype Index	FD	Ravenpack Media Hype Index measuring the percentage of news talking about COVID-19	02/01/2020	209	0.1653	3.4414	19.6800	−11.1100	−3.1019**	−18.7932***
FNI_t	Changes in the Ravenpack Fake News Index	FD	Ravenpack Fake News Index that makes reference to misinformation or fake news alongside COVID-19	02/01/2020	209	0.0028	0.2488	1.0700	−0.7700	−12.0908***	−43.9619***
WSI_t	Changes in the Ravenpack Worldwide Sentiment Index	FD	Ravenpack Worldwide Sentiment Index which measures sentiment across all entities mentioned alongside COVID-19	02/01/2020	209	0.0053	4.7082	28.6300	−24.9500	−8.0672***	−12.7501***
INI_t	Changes in the Ravenpack Infodemic Index	FD	Ravenpack Infodemic Index calculating percentage of all entities (places, companies, etc.) that are linked to COVID-19	02/01/2020	209	0.2440	3.1635	11.9700	−8.9400	−2.9003***	−20.8285***
MCI_t	Changes in the Ravenpack Media Coverage Index	FD	Ravenpack Media Coverage Index calculating percentage of all news topics covering COVID-19	02/01/2020	209	0.3496	2.4899	13.6100	−7.2400	−3.8213***	−17.6395***

Notes: Start is the start date of each respective measure series. Obs. is the number of observations comprising each series. The end date is the end of the COVID-19 crisis period as defined in this study as 20 October 2020. Mean is the series mean. Std. is the standard deviation. Max. is the largest observed value whereas min. is the lowest observed value. ADF and PP are test statistics for the Augmented Dickey-Fuller (ADF) and non-parametric Phillips-Perron (PP) tests applied to confirm the stationarity of the COVID-19 measure series. Both tests are applied assuming an intercept with the number of lags selected using the Akaike Information Criterion (AIC). ***, ** and * indicate statistical significance at the respective 1%, 5% and 10% levels of significance.

2.4. Interpretation of COVID-19 measures

Once we selected and identified COVID-19 measures that are part of the composite factor set driving stock market returns, we set out to interpret and ascribe meaning to them. We do this by relating these measures to some of the direct measures and a few indirect measures. The indirect measures that we introduce are (changes in) the CBOE Volatility index (VIX_t), Twitter-based Market (TMU_t) and Economic Uncertainty (TEU_t) indices (Baker et al., 2021), a newspaper-based Global Economic Policy Uncertainty (NEU_t) index (Baker et al., 2016), the Société Générale Global Sentiment Index (SGS_t), the Credit Suisse Ravenpack Artificial Sentiment Index (AIS_t), the Piraeus Bank Dry Bulk Shipping Index (BDI_t) and Brent Crude Oil prices (OIL_t). Unlike novel COVID-19 measures, such as deaths or infections, these measures comprise more extensive time-series and have better established interpretations.[10] Following preliminary analysis, we apply the iterative selection procedure outlined in Section 2.3 and also report Spearman and ordinary correlation coefficients for measures with the 10 highest correlation coefficients. As measures may be contemporaneously and intertemporally associated with, or may respond to information reflected by, the COVID-19 measures, each measure enters the set contemporaneously and with three lead terms (Canova and De Nicolo, 1995).

2.5. Impact of COVID-19 on stock market returns

The final part of the analysis relates the COVID-19 measures that have been identified as proxies (Section 2.3) for the factor scores to the individual stock markets in our sample:

$$r_{i,t} = \alpha_i + \sum_{k\geq 1}^{k} \beta_{i,CV19} F_{CV19,t} + \varepsilon_{CV19,t} \tag{4}$$

where $r_{i,t}$ is the logarithmic return on stock market i and $F_{CV19,t}$ represents COVID-19 measures identified by following the process summarised by equations (1) and (2). Equation (4) is estimated for each individual COVID-19 measure identified and for all measures jointly. Here we seek to quantify the explanatory power of the COVID-19 measures both individually and jointly. To do so, we consider the adjusted coefficient of determination derived from each regression as a measure of the explanatory power of the COVID-19 measures for each market. Equation (4) is estimated using the least squares methodology over the COVID-19 crisis period.

3. Results and analysis

3.1. Structure of the return generating process

Table 3 presents the results of factor analysis applied to returns over the pre-COVID-19 and COVID-19 crisis periods. Three factors are extracted from returns over the long and short pre-COVID-19 periods, respectively.[11] The results in Panel A of Table 3 indicate that both the long and short pre-COVID-19 periods are characterised by sets of three factors with similar communalities of 0.5310 and 0.5096, respectively. However, four factors are extracted during the COVID-19 crisis period with a communality of 0.7307, which is indicative of a higher amount of shared variance reflected by these factors. The first factor, $F_{1,k}$, is the most important explaining over 56% of total shared variance in returns (Panel B). This is followed by $F_{2,k}$, which explains 9% of shared variance. $F_{3,k}$ and $F_{4,k}$ explain just over 4% and 3% of shared variance, respectively. We attribute the higher overall communality associated with the factors extracted for the COVID-19 crisis period to the global nature of the COVID-19 crisis and view this as indicative of contagion (Uddin et al., 2020).

To confirm whether correlations between markets have increased during the COVID-19 crisis period, we report average return correlations (see Junior and Franca, 2012). Correlations in Panel C of Table 3 confirm increased dependence between national markets during the COVID-19 period. Mean Spearman (ordinary) correlation coefficients, $\bar{\rho}_S$ ($\bar{\rho}_P$), are 0.3614 (0.3946) and 0.3138 (0.3452) for the respective long and short pre-COVID-19 periods. Over the COVID-19 period, Spearman (ordinary) correlations increase to 0.4590 (0.5630). These findings are in line with the increased communality reflected by factors extracted over the COVID-19 period and are indicative of a change in the structure of the return generating process.

3.2. COVID-19 measure selection

Table 4 reports the results of the final iterations of elastic net regressions.[12] Following preliminary analysis and tests of different

[10] For example, the VIX is considered to be a measure of stock market uncertainty (Bekaert et al., 2013; Chiang et al., 2015). The Dry Bulk Shipping Index (BDI) is highly dependent upon fluctuations in dry cargo freight rates which are reliant on shifts in global real activity. Consequently, it may be viewed as a high-frequency indicator of shifts in economic conditions (Yilmazkuday, 2020). We exclude case and death-based measures, namely CAS_t, DEA_t, ACT_t, DEC_t, CAC_t, CFR_t, RCI_t, RDI_t, GFI_t. While these measures are likely to drive government responses, they are unlikely to be associated with a direct interpretation.

[11] The short period spans 1 January 2019 to 31 December 2019. We factor analyse this period as opposed to only the full sample period prior to the COVID-19 crisis for comparative purposes. The short period is of a similar length to the COVID-19 period whereas the long pre-COVID-19 period is five times as long. It is therefore possible that the long pre-COVID-19 period may be characterised by a somewhat different factor structure.

[12] Full results are available in Excel format upon request.

Table 3
Pre-COVID-19 and COVID-19 crisis period factor structures

Panel A: Factor structure summary			
Period	**Factors extracted**	**Communality**	**KMO**
1) Pre-COVID-19 (long)	3	0.5310	0.9660
2) Pre-COVID-19 (short)	3	0.5096	0.9421
3) COVID-19 crisis	4	0.7307	0.9526
Panel B: Proportion of variance explained by each factor over COVID-19 period			
Factor	**Communality**	**Cumulative communality**	
$F_{1,k}$	0.5692	0.5692	
$F_{2,k}$	0.0900	0.6593	
$F_{3,k}$	0.0408	0.7001	
$F_{4,k}$	0.0306	0.7307	
Panel C: Dependence structures			
Period	**Spearman ($\bar{\rho}_S$)**	**Ordinary ($\bar{\rho}_P$)**	
1) Pre-COVID-19 (long)	0.3614	0.3936	
2) Pre-COVID-19 (short)	0.3138	0.3452	
3) COVID-19 crisis	0.4590	0.5630	

Notes: This table reports the results of factor analysis applied to returns over the pre-COVID-19 and COVID-19 crisis periods. The pre-COVID-19 sub-periods are defined as 1 January 2015 to 31 December 2019 (long) and 1 January 2019 to 31 December 2019 (short), respectively. The COVID-19 crisis period is defined as 1 January 2020 to 20 October 2020. Panel A reports the number of factors extracted for each period, associated communalities and KMO index values. KMO index values indicate suitability for factor analysis. Panel B reports the communalities associated with each extracted factor score series and the cumulative community for all four factor score series. Panel C reports average return correlations for the pre-COVID and COVID-19 crisis periods. Spearman and ordinary correlations are reported.

intertemporal structures, COVID-19 measures associated with and based upon the number of cases – death, recoveries, active cases and the total number of cases – enter the measure set contemporaneously and with a single lag to account for delays in reporting. This case-based measure set comprises CAS_t, DEA_t, REC_t, ACT_t, DEC_t, CAC_t, CFR_t, RCI_t, RDI_t and GFI_t.

A single measure with non-zero coefficients is identified for each factor score series. $F_{1,t}$ is related to changes in Google searches, GST_t. $F_{2,t}$ is related to the stringency of government measures applied to control the spread of COVID-19, GSM_t. $F_{3,t}$ is related to changes in the weighted overall government response index, GOR_t. $F_{4,t}$ is related to movements in the media hype index, MHI_t. Given the recency of the COVID-19 crisis, a limitation that arises is that of short data series. The number of data points that we use in the starting iterations because of balanced series lengths is 170. This starting point corresponds to that of the shortest series, namely changes in government economic support, GER_t, which starts on 26 February 2020. We therefore repeat this exercise to confirm the consistency of the results but exclude all measures with fewer than 200 observations. Excluded measures are changes in the reported case index, RCI_t, changes in the reported death index, RDI_t, changes in the global fear index, GFI_t, growth in recoveries, REC_t, changes in the Google Mobility Tracker, GMT_t and GER_t. As with the full factor set, GST_t, GSM_t, GOR_t and MHI_t, are associated with non-zero coefficients for $F_{1,t}$, $F_{2,t}$, $F_{3,t}$ and $F_{4,t}$ across λ_{min}, λ_{1SE} and λ_{2SE}. Given the consistency of these results, GST_t, GSM_t, GOR_t and MHI_t are taken forward to the next stage of the analysis as the first COVID-19 measure set.

Table 5 presents the results of factor score regressions for each COVID-19 measure individually and jointly. In the Std. row, we report regressions of factor scores onto the measures jointly and include a residual market factor derived from returns on the MSCI All Country World Index and standardise the coefficients. The inclusion of a residual market factor addresses potential underspecification that may result in an increased incidence of Type II errors (an erroneous failure to reject the null hypothesis of no relationship) as a result of inflated standard errors (van Rensburg, 2002). Additionally, standardised coefficients permit us to confirm the results in Table 4 which identify a single measure for each factor score series. Measures that are associated with larger standardised coefficients are more important relative to the remaining measures (Fabozzi, 1998; Nimon and Oswald, 2013; Szczygielski et al., 2020b).

In Table 5, GST_t is significantly related to $F_{1,t}$ with an $\bar{R}^2$ of 0.1758 and is the most important measure given its association with $F_{1,t}$. The standardised model confirms this. The coefficient on the residual market factor is larger and significant, although this is expected and implies that there are other (more important) factors that are reflected in $F_{1,t}$ factor scores. A similar observation in relation to the size of the coefficient on GSM_t is also made for $F_{2,t}$ in the standardised model suggesting that this is the most important measure for $F_{2,t}$ with an $\bar{R}^2$ of 0.0780 for GSM_t when considered individually. Interestingly, coefficients on GSM_t and GOR_t are both statistically significant and of a similar magnitude, -0.1587 and -0.1649 respectively. This can be attributed to high levels of correlation between the two (Spearman corr. (ord. corr.)) 0.9064 (0.9396)). Standardised coefficients confirm that GSM_t is the most important measure for

$F_{2,t}$ although not statistically significant, which is a likely result of multicollinearity. Similarly, for $F_{3,t}$, individual coefficients on both GSM_t and GOR_t are somewhat similar, −0.1406 and −0.1831, respectively, and both are significant. The $\bar{R}^2$ for GOR_t individually is 0.0671. The standardised coefficient is −0.2788.[13]

In light of the high correlation between GSM_t and GOR_t and given that GSM_t is also related to $F_{2,t}$ which explains a higher proportion of shared variance (0.0900 *versus* 0.0408 in Panel B of Table 3) and is more readily interpretable,[14] we elect to include GSM_t in our COVID-19 measure set. The interpretation that we use for GSM_t is as per the Oxford Coronavirus Government Response Tracker (Hale et al., 2020), i.e. GSM_t reflects the strictness of policies that restrict people's behaviour and economic activity by implication.The relatively greater importance of this measure suggests that lockdown-style restrictions matter more than a combination of economic, containment and restriction measures. Finally, MHI_t, is significantly related to $F_{4,t}$ with an $\bar{R}^2$ of 0.0983 and has the largest standardised coefficient. Overall, the results in Table 5 confirm that each measure identified using elastic net regression is significantly related to the respective factor score series.[15]

Next, we estimate the amount of total shared variance attributable to the COVID-19 measures, *ShVr* (equation (3)).[16] GST_t is the most important measure over the overall period, explaining 10.065% of total shared variance. GSM_t, GOR_t and MHI_t explain 0.7020%, 0.2738% and 0.3008% of total shared variance, respectively, when considered individually ($\bar{R}^2_{k,CV19}$ derived from univariate regressions). In total, these measures explain 11.28% of shared variance over the COVID-19 crisis period or 11.0093% if GOR_t is excluded from this calculation. When measures are considered jointly – the $\bar{R}^2$s are those for models relating factor scores to all four factors – the total shared variance is similar with *ShVr* equal to 11.37%. This is arguably not a large amount of shared market movement attributable to the COVID-19 measures. This may, however, be somewhat misleading without accounting for structural breaks in the relationship between factor scores and COVID-19 measures. It may be that some measures become more important during certain stages of the COVID-19 crisis. We therefore estimate breakpoint regressions for each factor score series against the single most important measure for that series (Bai and Perron, 1998).

Results indicate that the relationship between $F_{1,t}$ and GST_t is not stable with structural breaks on 13 March 2020 and 30 April 2020 (see Table 4A in Appendix A for results). For the first two segments, GST_t is negatively and significantly related to $F_{1,t}$. From 30 April 2020, the relationship is no longer significant. Interestingly, the relationship between $F_{2,t}$ and GSM_t changes from being negative and statistically significant prior to 23 March 2020 to positive and statistically significant suggesting that market perceptions of lockdown-style restrictions may have changed over time. The relationship between $F_{3,t}$ and GOR_t is initially positive but insignificant whereas it is negative and statistically significant from 13 March 2020 onwards. Given that GOR_t and GSM_t are highly correlated, we re-estimate the breakpoint regression for $F_{3,t}$ replacing GOR_t with GSM_t. The results are similar. Given that GSM_t is related to both $F_{2,t}$ and $F_{3,t}$ (as is GOR_t), but the nature of the relationship differs between both factor score series, we conclude that $F_{2,t}$ and $F_{3,t}$ represent different aspects of COVID-19 related restrictions and, by extension, government responses. The relationship between $F_{4,t}$ and MHI_t shows no breaks. After accounting for breaks and estimating total shared variance (equation (3)) using $\bar{R}^2$ for the individual measures, *ShVr* is 18.88% (18.41% excluding GOR_t) with GST_t accounting for 16.96% of shared variance – still the most important measure. In other words, these measures explain almost a fifth of movements across markets attributable to the COVID-19 pandemic during the crisis period. As a final analysis, we test for breakpoints between each factor score series and all four measures jointly. The respective $\bar{R}^2$s are 0.3250, 0.1691, 0.1656 and 0.3005 for $F_{1,t}$, $F_{2,t}$, $F_{3,t}$ and $F_{4,t}$ (unreported in the text). We again apply equation (3) and find that *ShVr* increases marginally to 21.62% (20.94% excluding GOR_t).

While the results in Table 5 and the subsequent structural break analysis are indicative of the presence of relationships and changes

[13] To determine whether GSM_t encompasses GOR_t, we regress $F_{2,t}$ scores onto GSM_t and the resultant residuals onto GOR_t. This yields an insignificant coefficient on GOR_t and an $\bar{R}^2$ of zero suggesting that GSM_t reflects information in GOR_t. Similarly, given the high correlation between GSM_t, and GOR_t, we also test to determine whether GSM_t encompasses information in $F_{3,t}$. A regression of GOR_t onto the residuals of $F_{3,t}$ after adjusting for GSM_t produces an insignificant coefficient and an $\bar{R}^2$ of zero.

[14] We view GSM_t as measuring a specific aspect of government response to the COVID-19 pandemic: the stringency of government measures applied to contain the pandemic as opposed to measuring an overall government response which comprises economic, containment and the stringency of measures.

[15] We investigate whether there are alternative COVID-19 measures that matter aside from GST_t, GSM_t and MHI_t. We apply an approach that relies upon using factor score series adjusted for GST_t, GSM_t and MHI_t to identify alternative measures without the need to transform either variable of interest – the dependant and independent variables – through orthogonalisation. This approach avoids the limitations associated with orthogonalisation to capture aspects of COVID-19 that impact international markets but are unrelated to the three measures identified (Wurm and Fisicaro, 2014; see Appendix B for a detailed exposition of the methodology and results). We identify two sets of alternative measures by applying the iterative procedure to all measures and to measures with over 200 observations but excluding GST_t, GSM_t and MHI_t. Two measures sets emerge: GMT_t, FNI_t, ACT_{t-1}, AMT_t and ACT_{t-1}, DEC_{t-1} and AMT_t, respectively. The first alternative set explains an additional 2.20% (2.65%) of shared variance whereas the second alternative set explains an additional 1.36% (2.01%) of shared variance when the alternative measures are related to factor scores individually (jointly). After adjusting for structural breaks, total shared variance explained increases to 4.67% and 3.10%, respectively. The conclusion is that most of the impact of COVID-19 over the COVID-19 crisis period on international markets can be summarised by a small number of COVID-19 related measures, namely GST_t, GSM_t and MHI_t.

[16] For example, from Table 3 we know that $F_{1,t}$ accounts for 56.92% of shared variance. From Table 5 we know that GST_t explains 17.58% ($\bar{R}^2_{k,GST_t}$ of 0.1758) of variation in $F_{1,t}$. Multiplying the communality, c_k, associated with $F_{1,k}$ by the amount of variation explained by $\bar{R}^2_{k,GST_t}$ implies that GST_t explains 10.065% of total shared variance.

Table 4
Final iteration results of elastic net regularisation for the COVID-19 crisis period

	***F*₁: 2 iterations**		
	λ_{min}	λ_{1SE}	λ_{2SE}
α_i	−0.0358	−0.0056	−0.0056
CAS_t	0.0000	0	0
CAS_{t-1}	−0.0001	0	0
DEA_t	0.0000	0	0
DEA_{t-1}	1.8807	0	0
REC_t	−0.0001	0	0
REC_{t-1}	−0.2491	0	0
DEC_t	0.0000	0	0
DEC_{t-1}	−1.4487	0	0
CAC_t	−0.0004	0	0
CFR_t	−13.2386	0	0
CFR_{t-1}	−58.5815	0	0
RCI_t	0.0001	0	0
RCI_{t-1}	0.0002	0	0
RDI_t	0.0000	0	0
RDI_{t-1}	1.38E-05	0	0
GFI_t	0.0170	0	0
GCR_t	0.0000	0	0
GST_t	−0.1146	−1.55E-09	−1.55E-09
EMV_t	0.0045	0	0
AMT_t	−6.83E-07	0	0
MHI_t	3.42E-06	0	0
WSI_t	−0.0035	0	0
INI_t	−0.0243	0	0
MCI_t	3.15E-07	0	0
d.f.	19	1	1
L_1	75.5992	5.59E-03	5.59E-03
R^2	0.2643	4.93E-09	4.93E-09

	***F*₂: 5 iterations**		
	λ_{min}	λ_{1SE}	λ_{2SE}
α_i	0.0447	−5.42E-06	−5.42E-06
GCR_t	−0.0146	0	0
GSM_t	−0.0820	−3.14E-09	−3.14E-09
MHI_t	−0.0385	0	0
d.f.	3	1	1
L_1	0.179837	5.43E-06	5.43E-06
R^2	0.10169	3.26E-09	3.26E-09

	***F*₃: 4 iterations**		
	λ_{min}	λ_{1SE}	λ_{2SE}
α_i	−0.0001	−0.0001	−0.0001
GOR_t	−1.71E-09	−1.71E-09	−1.71E-09
MCI_t	0.0000	0.0000	0.0000
d.f.	1	1	1
L_1	0.0001	0.0001	0.0001
R^2	1.34E-09	1.34E-09	1.34E-09

	***F*₄: 4 iterations**		
	λ_{min}	λ_{1SE}	λ_{2SE}
α_i	0.0342	−0.0023	−0.0023
CAS_t	0.0000	0.0000	0.0000
AMT_t	−0.1386	0.0000	0.0000
MHI_t	−0.0818	−1.41E-09	−1.41E-09
MCI_t	−0.0658	0.0000	0.0000
d.f.	3	1	1
L_1	0.3205	0.0023	0.0023
R^2	0.17491	2.82E-09	2.82E-09

Notes: This table reports the results of the final iteration of the elastic-net based selection and identification procedure for the COVID-19 crisis period from 1 January 2020 to 20 October 2020. The procedure is repeated until only measures for which coefficients are non-zero for the λ_{min}, λ_{1SE} and λ_{2SE} penalties remain. *d.f.* is the number of measures with non-zero coefficients and L1 is the sparsity inducing penalty. R^2 is the coefficient of determination for COVID-19 measures with non-zero coefficients.

Table 5
Factor score regressions for COVID-19 crisis period

Factor	α_i	GST_t	GSM_t	GOR_t	MHI_t	R_{Met}	$\bar{R}^2_{k,CV19}$	$ShVr$
$F_{1,t}$	0.0080	−0.1118***					0.1758	0.1001
	0.0229		−0.0585				0.0071	0.0040
	0.0327			−0.0753			0.0085	0.0048
	0.0029				−0.0171		0.0000	0.0000
	0.0368	−0.1109**	0.0026	−0.0669	0.0016		0.1732	0.0986
Std.	0.0368	−0.4199***	0.0049	−0.1024	0.0054	0.5096***	0.4353	
$F_{2,t}$	0.0011	−0.0147					0.0000	0.0000
	0.0622		−0.1587**				0.0780	0.0070
	0.0716			−0.1649**			0.0603	0.0054
	0.0131				−0.0790***		0.0719	0.0065
	0.0309	−0.0093	−0.2664	0.1929	−0.0578***		0.1019	0.0092
Std.	0.0309	−0.0343	−0.4819	0.2870	−0.1902***	0.1163*	0.1114	
$F_{3,t}$	0.0029	−0.0409***					0.0172	0.0007
	0.0550		−0.1406***				0.0579	0.0024
	0.0794*			−0.1831***			0.0671	0.0027
	0.0055				−0.0341		0.0074	0.0003
	0.0819*	−0.0376**	0.0092	−0.1907	0.0017		0.0722	0.0029
Std.	0.0819**	−0.1360**	0.0164	−0.2788***	0.0054	0.6073***	0.4456	
$F_{4,t}$	0.0025	−0.0343					0.0100	0.0003
	0.0329		−0.0838**				0.0158	0.0005
	0.0406			−0.0935***			0.0125	0.0004
	0.0171				−0.1031***		0.0983	0.0030
	0.0081	−0.0293	−0.0980*	0.1140**	−0.1017***		0.0990	0.0030
Std.	0.0081	−0.1017	−0.1674*	0.1602**	−0.3160***	−0.0238	0.0951	

Notes: This table reports the results of regressions of factor scores derived from returns onto the COVID-19 measures over the COVID-19 crisis period (1 January 2020 to 20 October 2020), individually, jointly and jointly with standardised coefficients and a residual market factor incorporated (std. row). Least squares with Newey-West heteroscedasticity and autocorrelation consistent (HAC) standard errors is used for estimation purposes. GST_t are changes in worldwide COVID-19 related Google Search Trends. GSM_t are changes in the stringency of government response measures to control the spread of the COVID-19 virus as measured by the Oxford Coronavirus Government Response Tracker. GOR_t are changes in the overall government response to control the spread of the COVID-19 virus as measured by the Oxford Coronavirus Government Response Tracker. MHI_t are changes in the Ravenpack Media Hype Index. R_{Met} is the residual market factor derived by a regression of the MSCI All Country World index onto the four measures. $ShVr$ is the contribution to total shared variance estimated by applying equation (3). ***, ** and * indicate statistical significance at the respective 1%, 5% and 10% levels of significance.

in relationships between the drivers of international markets over the COVID-19 crisis period as represented by the factor scores and the COVID-19 measures, they do not lend themselves to direct interpretations and analysis at this stage owing to limitations associated with the interpretation of factor scores (Priestley, 1996; Chimanga and Kotze, 2009). Nevertheless, these results confirm that COVID-19 is a driver of global stock markets.

3.3. Interpretation

In this section, we ascribe meaning to the three COVID-19 measures identified. We do this by relating these measures to the remaining measures and a number of indirect measures (Section 2.4).[17] Preliminary analysis yields somewhat conflicting results for elastic net iterative procedure and results are therefore reported for sets comprising all measures and only measures with over 200 observations.

In Panel A of Table 6 (all measures), the only measure that is related to GST_t is AIS_t. In Panel B (measures with over 200 observations) the only measure that is related to GST is VIX_t. In Panel A and Panel B of Table 7 (correlations), uncertainty/volatility-related measures feature prominently (TMU_t, VIX_t, VIX_{t+2} (Spearman)/ VIX_t, TMU_{t+2}, VIX_{t+2}, TMU_t (Ordinary)). Other notable measures are the sentiment-related measures (AIS_{t+2}/AIS_t, WSI_{t+2}), the economic-related measures (BDI_t/BDI_t) and the oil price (OIL_{t+2}/OIL_{t+2}). The positive association, contemporaneous and in leads, with uncertainty/volatility related measures suggests that increasing (decreasing) Google searches are associated with rising (falling) uncertainty. Economic psychology lends support to the nature of such a relationship: individuals respond to uncertainty by searching for information (Dzielinski, 2012; Castelnuovo and Tran, 2017; Bontempi et al., 2019). Notably, Szczygielski et al. (2021) demonstrate that COVID-19 related Google search volumes move (very) closely with VIX_t and TMU_t in levels and that changes in VIX_t and TMU_t have a similar impact on regional returns to that of GST_t. Other studies that suggest that GST are associated with, or predict, uncertainty are those of Choi and Varian (2012), Donadelli and Gerotto (2019) and Bilgin et al. (2019). Furthermore, these studies propose that uncertainty is reflected in, and negatively impacts,

[17] GOR_t and GOC_t are excluded given their almost perfect correlation with one of the measures identified: GSM_t.

Table 6
Final iteration results of elastic net regularisation over the COVID-19 crisis period

Panel A: All measures

	GST_t: 3 iterations				GSM_t: 1 iteration				MHI_t: 1 iteration		
	λ_{min}	λ_{1SE}	λ_{2SE}		λ_{min}	λ_{1SE}	λ_{2SE}		λ_{min}	λ_{1SE}	λ_{2SE}
α_i	−0.1518	0.0570	0.0570	α_i	0.1930	0.2233	0.2623	α_i	0.1168	0.1277	0.1327
RPI_{t+2}	0.5526	0	0	GMT_{t+1}	−0.0699	−0.0448	−0.0158	RPI_t	3.1308	2.3854	2.0665
WSI_{t+2}	−0.0990	0	0	AMT_t	−0.1312	−0.0878	−0.0336	FNI_t	0.7464	0.8171	0.7140
MCI_{t+2}	0.2757	0	0	AMT_{t+1}	−0.2031	−0.1755	−0.1310				
VIX_t	0.0000	0	0	AMT_{t+2}	−0.0850	−0.0704	−0.0416				
VIX_{t+2}	0.0265	0	0	AMT_{t+3}	−0.2477	−0.2007	−0.1382				
TMU_t	0.0033	0	0	MCI_t	0.3210	0.2600	0.1830				
TMU_{t+2}	0.0046	0	0	VIX_t	0.0211	0.0140	0.0054				
AIS_t	−0.0538	−2.73E-10	−2.73E-10	BDI_{t+2}	−0.7913	−0.5231	−0.2004				
BDI_t	−0.8474	0	0								
BDI_{t+3}	−1.2621	0	0								
d.f.	9	1	1	d.f.	8	8	8	d.f.	2	2	2
L_1	3.2767	0.0570	0.0570	L_1	2.0633	1.5995	1.0113	L_1	3.9940	3.3302	2.9132
R^2	0.3686	5.26E-10	5.26E-10	R^2	0.6377	0.6015	0.4488	R^2	0.6832	0.6473	0.6080

Panel B: Measures with over 200 observations

	GST_t: 4 iterations				GSM_t: 4 iterations				MHI_t: 4 iterations		
	λ_{min}	λ_{1SE}	λ_{2SE}		λ_{min}	λ_{1SE}	λ_{2SE}		λ_{min}	λ_{1SE}	λ_{2SE}
α_i	−0.0403	0.0716	0.0716	α_i	0.2441	0.3012	0.3286	α_i	0.0282	0.0596	0.0764
MCI_{t+2}	0.3508	0	0	AMT_t	−0.1338	−0.0510	−0.0125	EVM_{t+1}	0.0430	0.0224	0.0121
VIX_t	0.0240	6.05E-10	6.05E-10	AMT_{t+1}	−0.2246	−0.1652	−0.1323	AMT_{t+2}	−0.1732	−0.1342	−0.1125
VIX_{t+2}	0.0508	0	0	AMT_{t+2}	−0.1116	−0.0625	−0.0357	AMT_{t+3}	−0.0137	−0.0176	−0.0143
AIS_t	−0.0733	0	0	AMT_{t+3}	−0.2329	−0.1500	−0.1107	RPI_t	3.0905	2.5706	2.3322
				MCI_t	0.3080	0.2062	0.1610	FNI_t	0.6757	0.7532	0.7247
				VIX_t	0.0164	0.0080	0.0039	INI_t	0.1257	0.0525	0.0221
				BDI_t	−0.3182	−0.2652	−0.1964	MCI_t	0.1371	0.1280	0.1173
				BDI_{t+2}	−0.7321	−0.3242	−0.1379	AIS_t	−0.0230	−0.0155	−0.0113
								OIL_{t+2}	−0.0366	−0.0306	−0.0261
d.f.	4	1	1	d.f.	8	8	8	d.f.	9	9	9
L_1	0.539249	0.071619	0.071619	L_1	2.3217	1.5334	1.1190	L_1	4.3466	3.7842	3.4490
R^2	0.267324	1.77E-09	1.77E-09	R^2	0.5960	0.5104	0.4054	R^2	0.7558	0.7321	0.7031

Notes: This table reports the results of the final iteration of the elastic-net based selection and identification procedure over the COVID-19 crisis period, 1 January 2020 to 20 October 2020. The procedure is repeated until only measures for which coefficients are non-zero for the λ_{min}, λ_{1SE} and λ_{2SE} penalties remain. *d.f.* is the number of measures with non-zero coefficients and L1 is the sparsity inducing penalty. R^2 is the coefficient of determination for COVID-19 measures with non-zero coefficients. Panel A reports the results for the full measure set. Panel B excludes measures that have fewer than 200 observations.

macroeconomic conditions. This study also suggests that GST_t is negatively associated with economic-related measures, both contemporaneously and in leads. It is negatively associated with BDI_t in Table 7 implying that uncertainty results in short-term downturns in economic activity. GST_t also leads OIL_{t+2} which may be viewed as a proxy for economic policy uncertainty (Hailemariam et al., 2019).

Relatedly, we observed negative contemporaneous and intertemporal association with the sentiment measures, AIS_t (Panel A, Table 6), AIS_{t+2}, (Panel A, Table 7) and AIS_t, AIS_{t+2}, WIS_{t+2} (Panel B, Table 7). We interpret the negative relationship as negative sentiment generated by, and related to, increasing COVID-19 related uncertainty (Da et al., 2015; Bilgin et al., 2019; Chen, Liu & Zhao, 2020). We also acknowledge the positive association of GST_t with a number of news-related measures, notably MCI_{t+1}, RPI_{t+2}, INI_{t+1} and MCI_{t+2}, INI_{t+2} in Panels A and B of Table 7, respectively. News relating to the evolution of, and significant news events relating to, the COVID-19 pandemic are likely to fuel uncertainty resulting in increased searches for information and further reporting. The interpretation that emerges is that GST_t reflects uncertainty around the COVID-19 pandemic and that this uncertainty is associated with fear, negatively impacting the economy, nationally and globally. This implies decreased expected future cash flows and heightened risk aversion with the latter resulting in a higher risk premium reflected in the forward-looking discount rate, leading to a decline in stock market levels (Cochrane, 2018; Smales, 2021a). Consequently, we designate GST_t as an uncertainty factor with an associated impact on sentiment and the economic state.

We turn to the interpretation of the measure of stringency of lockdown-type policies, GSM_t. Across both Panels A and B in Table 6, AMT_t, AMT_{t+1}, AMT_{t+2} and AMT_{t+3} are identified, whereas in Table 7, GSM_t is correlated with AMT_t, AMT_{t+3}, AMT_{t+1}, AMT_{t+2} and GMT_t in Panel A and AMT_{t+1}, AMT_{t+3}, AMT_{t+2}, GMT_{t+1} and AMT_t in Panel B. These relationships may be viewed as arising from, and an indicator of, the *de facto* state of affairs resulting from lockdown-type policies. A reduction in human mobility is expected following the implementation of restrictions to contain COVID-19. The impact of lockdown-style policies on stock markets can be explained by their impact on economic activity. For example, Deb et al. (2020) report that while workplace closures and stay-at-home orders were effective in curbing COVID-19 infections, they were the costliest in impact on retail activity. The easing of such measures was associated with rising economic activity. Eckert and Mikosch (2020) report close co-movement between physical mobility and spending activity in Switzerland during the COVID-19 crisis. Bonaccorsi et al. (2020) report that mobility trends associated with tourism, retail and services experienced a 90% contraction during the Italian lockdown. They document declines in economic activity in Italian municipalities that are related to reduced mobility and find that reduced mobility is associated with lower average individual incomes. Henríquez et al. (2020) assess the effectiveness of public policies in Spain applied to limit the evolution of COVID-19. They report that a stringent confinement policy enforced through fines resulted in a reduction in mobility and economic activity. What emerges is that the imposition of lockdown-style measures and other restrictions stifles economic activity. Reduced mobility reflects the imposition of such measures resulting in decreased economic activity during lockdowns and persistent industrial economic inoperability thereafter (see Baker et al., 2020; Yu et al., 2020). This translates into lower growth forecasts and therefore lower expected cash flows and a higher implied risk premium resulting in declining stock prices.

We also note in Panels A and B of Table 6 that BDI_{t+2} and BDI_t, BDI_{t+2} respectively are related negatively to GSM_t. Similarly, in Panels A and B of Table 7, BDI_{t+1} and BDI_t (BDI_t constituting a high-frequency measure of economic activity) are negatively correlated with GSM_t, respectively. This provides further support for a transmission mechanism of reduced economic activity. Other measures that are associated with GSM_t across both panels in Tables 7 are MCI_t and VIX_t, with this association being contemporaneous. Following from the enormity of the economic, political and social consequences of lockdown-type policies, it is a given that media outlets and news providers report extensively on such developments and that markets will reflect this uncertainty. A positive relationship between GSM_t, MCI_t and VIX_t is expected and may be viewed as the result of the *de jure* state of affairs. In summary, it appears that GSM_t reflects the impact of restrictions on economic activity. Consequently, we designate GSM_t as an economic impact factor.

Finally, we interpret MHI_t. In Panel A of Table 6, this measure is positively related to two news-related measures, RPI_t and FNI_t. In Panel B, news-related measures, namely RPI_t, FNI_t, INI_t, MCI_t dominate, both in number and coefficient magnitude, although other measures are also identified as being related to MHI_t. These other measures are mobility measures, AMT_{t+2}, AMT_{t+3}, an uncertainty measure, EVM_{t+1}, a sentiment measure, AIS_t, and oil prices, OIL_{t+2}. Similarly, Table 7 shows that this measure is highly correlated with news-related measures (RPI_t, FNI_t/RPI_t, INI_t, RPI_{t+1},MCI_t). Other measures that also feature prominently are the mobility measures, GMT_t, AMT_{t+2}, AMT_{t+3}, GMT_{t+1}/GMT_{t+1}, AMT_{t+2}, and the indirect uncertainty measures, TEU_{t+3}, EVM_{t+1}/TMU_t, TEU_{t+3}. The contemporaneous association with other news-related measures is expected. MHI_t is likely to be driven by significant events relating to the COVID-19 pandemic, such as increases in deaths and infections and the implementation of restrictions and lockdowns. These are also likely to be reflected by the panic index, RPI_t, the fake news index, FNI_t, the infodemic index, INI_t, and general media coverage, MCI_t. However, what is of particular interest is the high level of correlation between MHI_t and RPI_t (over 0.6) and FNI_t in Panel A and RPI_t (over 0.8) in Panel B of Table 7, respectively. This suggests that there are influences other than media coverage focusing public attention on COVID-19 (Gozzi et al., 2020). Instead, we argue that fake news, media panic and media hype are inter-related and they re-enforce and fuel each other. Speculation as to the implications of the COVID-19 pandemic is fuelled by panic and fake news (Vasterman, 2005; Nicomedes and Avila, 2020). The result is a media frenzy with financial markets being unable to assess information accurately and quickly, resulting in large market movements (Haroon and Rizvi, 2020).[18] In this spirit, Mamaysky (2020) suggests that the severe decline experienced by the S&P500 between February and March 2020 was accompanied by speculation fuelled by media hype relating to the onset of a severe recession. While economic data was not available at this early stage of the crisis, journalists speculated upon the dire economic consequences for corporate profitability. Investors paid attention to this, revising beliefs about future cash flows downwards. Information therefore played a first-order role in informing market responses. Another possible mechanism driven by media hype and panic is panic selling. Given a perception of a crisis partly fuelled by the media, investors engage in panic selling, resulting in price declines and further rounds of panic selling – a vicious cycle of price declines (Shiller, 1987; Maharani, 2008; Ramelli and Wagner, 2020). It is very likely that panic and hype are associated with uncertainty. This is suggested by positive correlations between MHI_t and TEU_{t+3}, EVM_{t+1} and TMU_t, TEU_{t+3} in Panels A and B in Table 7 respectively. MHI_t is also correlated with OIL_t, another proxy of economic policy uncertainty (Hailemariam et al., 2019). While we recognise that MHI_t likely drives uncertainty, we nevertheless designate MHI_t as an attention factor that not only reflects media coverage but also panic, given its strong correlation with RPI_t. Such panic can be linked to irrationality and fear as opposed to a state of somewhat measured and persistent uncertainty about the COVID-19 pandemic. MHI_t also represents an information 'glut' during the pandemic, one that is inflated by panic and fake news. Given the novelty of the COVID-19 pandemic (during the designated crisis period) and its global nature, investors are also unlikely to understand its full impact but must nevertheless process this higher information quantum.

In summary, we designate our three measures GST_t, GSM_t and MHI_t as measures of uncertainty, economic impact and attention tainted by fear and an extensive novel information quantum, respectively. We view GST_t as a proxy for a *generalised* state of uncertainty around the COVID-19 pandemic. We interpret GSM_t as a proxy for the economic impact of the COVID-19 pandemic arising from restrictions and shutdowns resulting in reduced consumer spending and subdued economic activity. Finally, we designate MHI_t as an attention measure strongly influenced by panic. While impacting uncertainty, it is separate from a generalised state of uncertainty, proxying for the quantum of COVID-19 news which investors must interpret but may have difficulties in interpreting given the global and novel nature of the COVID-19 pandemic. It is driven by and reflects specific COVID-19 events, which are not readily understood or interpreted by markets.

[18] Haroon and Rizvi (2020) attribute this attention to the Ravenpack Panic Index (RPI_t). We, however, find that that media hype MHI_t is a driver of returns. Nevertheless, the results in Table 7 suggest that RPI_t and MHI_t are highly correlated making this interpretation plausible.

Table 7
Largest measure correlations over the COVID-19 crisis period

Panel A: Spearman (ρ_S)						Panel B: Ordinary (ρ_P)					
GST_t		GSM_t		MHI_t		GST_t		GSM_t		MHI_t	
MCI_{t+1}	0.2506***	AMT_t	−0.3314***	RPI_t	0.6242***	VIX_t	0.3586***	MCI_t	0.5183***	RPI_t	0.8251***
OIL_{t+2}	−0.2288***	AMT_{t+3}	−0.2860***	FNI_t	0.3806***	AIS_t	−0.3557***	AMT_{t+1}	−0.4378***	INI_t	0.3830***
TMU_t	0.2202***	AMT_{t+1}	−0.2828***	GMT_t	−0.2448***	TMU_{t+2}	0.3473***	AMT_{t+3}	−0.4087***	RPI_{t+1}	−0.3165***
VIX_t	0.2129***	AMT_{t+2}	−0.2494***	AMT_{t+2}	−0.2356***	MCI_{t+2}	0.3466***	BDI_t	−0.3723***	TMU_t	0.2826***
BDI_t	−0.2018***	GER_{t+3}	0.2481***	AMT_{t+3}	−0.2067***	VIX_{t+2}	0.3402***	AMT_{t+2}	−0.3638***	GMT_{t+1}	−0.2666***
VIX_{t+2}	0.1934***	GER_t	0.2442***	TEU_{t+3}	0.1991***	AIS_{t+2}	−0.2979***	VIX_t	0.3383***	TEU_{t+3}	0.2410***
RPI_{t+2}	0.1797***	BDI_{t+1}	−0.2431***	GER_t	0.1961***	OIL_{t+2}	−0.2936***	GMT_{t+1}	−0.3364***	OIL_{t+2}	−0.2376***
INI_{t+1}	0.1720**	OIL_{t+3}	−0.2302***	GMT_{t+1}	−0.1860**	TMU_t	0.2844***	INI_t	0.3232***	AMT_{t+2}	−0.2207***
AMT_{t+3}	−0.1715**	MCI_t	0.2253***	EVM_{t+1}	0.1839**	BDI_t	−0.2641***	AIS_t	−0.3031***	MCI_t	0.2179***
AIS_{t+2}	−0.1638**	GMT_t	−0.2237***	OIL_{t+2}	−0.1830	WSI_{t+2}	−0.2607***	AMT_t	−0.2803***	BDI_t	−0.2077***

Notes: This table reports Spearman and ordinary correlations in Panel A and Panel B respectively between the measures identified by applying the iterative procedure and direct and indirect measures included in the measure set over the COVID-19 crisis period, 1 January 2020 to 20 October 2020. Direct and indirect measures are considered contemporaneously and with up to three lags. GST_t are changes in worldwide COVID-19 related Google Search Trends. GSM_t are changes in the stringency of government response measures to control the spread of the COVID-19 virus as measured by the Oxford Coronavirus Government Response Tracker. MHI_t are the changes in the Ravenpack Media Hype Index. ***, ** and * indicate statistical significance at the respective 1%, 5% and 10% levels of significance.

3.4. The impact of COVID-19 on international stock returns

We relate returns on MSCI market aggregates to the three COVID-19 measures, GST_t, GSM_t and MHI_t over the COVID-19 crisis period.[19] Panel A to Panel C in Table 8 report the results of least squares regressions for returns against GST_t, GSM_t and MHI_t individually.

GST_t has a statistically significant and negative effect on the MSCI All Country World Index ($\beta_{i,GST}$ of −0.0021) and on all individual market aggregates. Most impacted markets are Italy, Canada and Norway (respective $\beta_{i,GST}$s of −0.0031, −0.0027 and −0.0027). Least impacted markets are those of Malaysia, Taiwan, Qatar and Hong Kong (respective $\beta_{i,GST}$s of −0.0006, −0.0007, −0.0008 and −0.0008). These results are in line with findings in the nascent literature on the negative impact of COVID-19 related uncertainty, quantified by GST, on market indices (Costola, Lacopini et al., 2020; Liu, 2020; Papadamou et al., 2020; Ramelli and Wagner, 2020; Smales, 2021a,b; Szczygielski et al., 2021). They are also consistent with the explanation posited in Section 3.3 that the negative impact of COVID-19 related uncertainty can be attributed to both lower expected cash flows and heightened risk aversion.

GSM_t has a negative and significant effect on the MSCI All Country World Index ($\beta_{i,GSM}$ of −0.0036) and all individual markets except Qatar. Brazil, Indonesia and India ($\beta_{i,GSM}$s of −0.0071, −0.0053 and −0.0049, respectively) are most impacted, whereas Qatar, Japan and Denmark ($\beta_{i,GSM}$s of −0.0006, −0.0009 and −0.0016, respectively) are least impacted. These results point to a negative impact of the stringency of lockdown measures on stock markets. Capelle-Blancard and Desroziers (2020) observed that the stringency index had a positive impact on global stock market returns, whereas Narayan et al. (2020) and Aggarwal et al. (2021) report a mixed impact. We attribute differences in the results of this study to differences in the sample period used. Existing studies use shorter periods with the sample of Capelle-Blancard and Desroziers (2020) and Narayan et al. (2020) ending in April 2020 and Aggarwal et al.'s (2021) in May 2020. Restrictive measures may have initially helped reduce the spread of COVID-19 and, were viewed as positive in nature. However, the long-term economic impact has been negative (König and Winkler, 2021). Such a conclusion is consistent with the evidence of Cross et al. (2020) and Etemad-Sajidi (2020) that countries with severe lockdowns experienced more dramatic declines in economic growth.

MHI_t has a negative impact on individual stock markets with $\beta_{i,MHI}$s statistically significant for 24 countries but not for returns on the MSCI All Country World Index. South Africa, Brazil and India are most impacted ($\beta_{i,MHI}$s of −0.0027, −0.0026 and −0.0026, respectively), while Denmark, Japan, Switzerland and the Netherlands are least impacted ($\beta_{i,MHI}$s of −0.0005, −0.0006, −0.0008 and −0.0008, respectively). Cepoi (2020) finds that media hype had a weak positive effect on the US, UK, French, German, Spanish and Italian stock markets for the period from 3 February to 17 April 2020, although across stock return quantiles the effect was insignificant. However, as with the differing findings observed in this study compared to other research on GSM_t, the longer period used may account for the negative impact of MHI_t across some of the 35 largest stock markets globally.

GST_t explains a greater proportion of the variation in individual stock market returns than GSM_t followed by MHI_t with respective $\bar{R}^2$s averaging 0.1193, 0.0797 and 0.0594. These results are similar to those in Section 3.2, which suggest that GST_t is the most important measure.

Next we group countries with respect to region, namely Asia-Pacific, Middle East and Africa (MEA), Europe and the Americas.[20]

[19] GOR_t is excluded owing to its almost perfect correlation with GSM_t and its relatively lesser importance.

[20] Groupings are in accordance with MSCI Global classifications.

Table 8
Mean specification estimated using least squares over the COVID-19 crisis period

	Panel A: GST_t			Panel B: GSM_t			Panel C: MHI_t			Panel D: GST_t, GSM_t, MHI_t (combined)				
	α_i	$\beta_{i,GST}$	$\bar{R}^2$	α_i	$\beta_{i,GSM}$	$\bar{R}^2$	α_i	$\beta_{i,MHI}$	$\bar{R}^2$	α_i	$\beta_{i,GST}$	$\beta_{i,GSM}$	$\beta_{i,MHI}$	$\bar{R}^2$
World	0.0003	−0.0021***	0.1716	0.0016	−0.0036***	0.1296	0.0003	−0.0013	0.0545	0.0016**	0.0020***	−0.0031***	−0.0006	0.2946
US	0.0005	−0.0022***	0.1247	0.0021*	−0.0043***	0.1126	0.0006	−0.0014	0.0348	0.0021	−0.0021***	−0.0038***	−0.0004	0.2272
China	0.0010	−0.0012***	0.0772	0.0018*	−0.0022**	0.0627	0.0011	−0.0012**	0.0617	0.0017	−0.0011***	−0.0015*	−0.0008**	0.1555
Japan	−4.23E-05	−0.0009***	0.0505	0.0002	−0.0009**	0.0085	−0.0000	−0.0006	0.017	0.0002	−0.0009***	−0.0005	−0.0005	0.0633
UK	−0.0012	−0.0024**	0.1744	−0.0002	−0.0031***	0.0706	−0.0012	−0.0014	0.0415	0.0002	−0.0023***	−0.0024***	−0.0007	0.2425
France	−0.0004	−0.0025***	0.1849	0.0064	−0.0032***	0.0698	−0.0004	−0.0012*	0.0299	0.0007	−0.0024**	−0.0026***	−0.0005	0.2466
Canada	−0.0001	−0.0027**	0.1726	0.0014	−0.0044***	0.1047	5.30E-05	−0.0018	0.0530	0.0014	−0.0026**	−0.0035***	−0.0008	0.2738
Germany	0.0001	−0.0026***	0.1993	0.0011	−0.0030***	0.0628	0.0001	−0.0011*	0.0259	0.0012	−0.0025***	−0.0025***	−0.0004	0.2532
Switzerland	0.0002	−0.0018***	0.2180	0.0006	−0.0014***	0.0255	0.0002	−0.0008	0.0258	0.0006	−0.0018**	−0.0009*	−0.0005	0.2434
India	4.67E-05	−0.0015***	0.0571	0.0019	−0.0049***	0.1667	0.0004	−0.0026***	0.1560	0.0017	−0.0013***	−0.0036***	−0.0018***	0.2763
Australia	−0.0003	−0.0021***	0.1134	0.0014	−0.0048***	0.1360	−0.0002	−0.0015	0.0414	0.0014	−0.0020***	−0.0042***	−0.0005	0.2392
Korea	0.0005	−0.0016***	0.0685	0.0017	−0.0032**	0.0684	0.0007	−0.0017***	0.0625	0.0016	−0.0015***	−0.0023*	−0.0011**	0.1519
Hong Kong	−0.0004	−0.0008***	0.0334	0.0004	−0.0022**	0.0650	−0.0002	−0.0015***	0.095	0.0003	−0.0007***	−0.0014**	−0.0011***	0.1412
Taiwan	0.0007	−0.0007***	0.0269	0.0018**	−0.0030***	0.1174	0.0009	−0.0012***	0.0583	0.0018	−0.0007***	−0.0025***	−0.0006**	0.1497
Brazil	−0.0020	−0.0036**	0.1257	0.0005	−0.0071***	0.1213	−0.0018	−0.0026	0.0501	0.0005	−0.0034***	−0.0060***	−0.0011	0.2413
Netherlands	0.0005	−0.0022***	0.2163	0.0012	−0.0020***	0.0374	0.0005	−0.0008	0.0150	0.0012	−0.0022	−0.0016***	−0.0003	0.2450
Russia	−0.0017	−0.0025***	0.1304	−0.0010	−0.0024**	0.0249	−0.0017	−0.0012**	0.0220	−0.0010	−0.0024***	−0.0016**	−0.0008	0.1547
Spain	−0.0011	−0.0026**	0.1860	7.65E-05	−0.0034**	0.0738	−0.0010	−0.0016**	0.056	5.66 E-05	−0.0025**	−0.0025***	−0.0010	0.2643
Italy	−0.0006	−0.0031**	0.2457	0.0004	−0.0033***	0.0614	−0.0006	−0.0012**	0.0264	0.0005	−0.0030**	−0.0026**	−0.0005	0.2977
Sweden	0.0007	−0.0024***	0.1680	0.0015	−0.0026**	0.0444	0.0007	−0.0015***	0.0460	0.0015	−0.0023***	−0.0017**	−0.0010*	0.2198
Saudi Arabia	−0.0001	−0.0011**	0.0455	0.0008	−0.0027***	0.0698	0.0002	−0.0024***	0.1891	0.0006	−0.0009***	−0.0011*	−0.0021***	0.2332
Thailand	−0.0017	−0.0022***	0.1540	−0.0003	−0.0040***	0.1195	−0.0015	−0.0021***	0.1051	−0.0003	−0.0021***	−0.0029***	−0.0013**	0.2976
South Africa	−0.0009	−0.0022***	0.0846	0.0009	−0.0049***	0.1039	−0.0006	−0.0027**	0.1073	0.0007	−0.0020***	−0.0034***	−0.0019***	0.2228
Denmark	0.0014	−0.0016***	0.1759	0.0019	−0.0016**	0.0377	0.0014	−0.0005	0.0098	0.0020**	−0.0016***	−0.0014***	−0.0001	0.2036
Singapore	−0.0011	−0.0011***	0.0533	2.74 E-05	−0.0032***	0.1111	−0.0009	−0.0018***	0.1243	−8.25E-05	−0.0010***	−0.0021***	−0.0013***	0.2110
Belgium	−0.0010	−0.0025***	0.1538	0.0003	−0.0037***	0.0743	−0.0009	−0.0014***	0.0330	−0.0003	−0.0024**	−0.0030***	−0.0006	0.2213
Indonesia	−0.0014	−0.0010*	0.0142	0.0006	−0.0053***	0.1280	−0.0012	−0.0017***	0.0424	0.0005	−0.0008*	−0.0047***	−0.0006	0.1405
Malaysia	−0.0003	−0.0006**	0.0241	0.0007	−0.0027***	0.1269	−0.0001	−0.0014***	0.1057	0.0006	−0.0005***	−0.0021***	−0.0009***	0.1836
Mexico	−0.0010	−0.0021***	0.0914	0.0003	−0.0038***	0.0736	−0.0009	−0.0011*	0.0182	0.0004	−0.0020***	−0.0034***	−0.0003	0.1550
Norway	−0.0007	−0.0027***	0.1691	2.44 E-05	−0.0024**	0.0292	−0.0006	−0.0017***	0.0486	−2.10E-05	−0.0026**	−0.0013	−0.0012**	0.2134
Finland	0.0007	−0.0021***	0.1718	0.0014	−0.0024***	0.0510	0.0007	−0.0014***	0.0590	0.0014	−0.0020**	−0.0015**	−0.0010*	0.2366
Philippines	−0.0009	−0.0016***	0.0623	0.0008	−0.0044***	0.1260	−0.0007	−0.0016***	0.0547	0.0007	−0.0014***	−0.0038**	−0.0008*	0.1877
UAE	−0.0008	−0.0014*	0.0555	0.0006	−0.0039***	0.1041	−0.0005	−0.0022**	0.1093	0.0005	−0.0013**	−0.0027***	−0.0015***	0.1974
Qatar	−0.0004	−0.0008***	0.0411	−0.0003	−0.0006	0.0001	−0.0003	−0.0011***	0.0567	−0.0003	−0.0008***	−0.0003	−0.0011***	0.0894
Israel	0.0002	−0.0023***	0.1665	0.0012	−0.0028***	0.0563	0.0003	−0.0013	0.0368	0.0012	−0.0022***	−0.0021**	−0.0007	0.2213
Chile	−0.0014	−0.0021***	0.0860	0.0003	−0.0045**	0.0952	−0.0012	−0.0021	0.0659	0.0002	−0.0020***	−0.0035**	−0.0012	0.1906
Average		−0.0019	0.1193		−0.0033	0.0797		−0.0015	0.0594		−0.0017	−0.0025	−0.0009	0.2107

Notes: This table reports the results of regressions of returns onto the three COVID-19 measures individually in Panels A, B and C, respectively, and jointly in Panel D over the COVID-19 crisis period, 1 January 2020 to October 2020. Least squares with Newey-West heteroscedasticity and autocorrelation consistent (HAC) standard errors is used for estimation purposes. GST_t are changes in worldwide COVID-19 related Google Search Trends. GSM_t are changes in the stringency of government response measures to control the spread of the COVID-19 virus as measured by the Oxford Coronavirus Government Response Tracker. MHI_t are changes in the Ravenpack Media Hype Index. $\bar{R}^2_{CV19}$ is the adjusted coefficient of determination associated with a given COVID-19 measure. ***, ** and * indicate statistical significance at the respective 1%, 5% and 10% levels of significance.

Fig. 1 reveals that the impact of GST_t is greatest in the Americas (average $\beta_{i,GST}$ of -0.0025), followed by Europe (average $\beta_{i,GST}$ of -0.0024), MEA (average $\beta_{i,GST}$ of -0.0016) and Asia-Pacific (average $\beta_{i,GST}$ of -0.0014). Uncertainty surrounding the pandemic as measured by GST_t accounts for close to three times the variation in European stock returns (average $\bar{R}^2$ of 0.1886) relative to those in the Asia-Pacific region (0.0666) with the Americas (0.1202) and MEA (0.0786) in between the two extremes. The pattern of the $\beta_{i,GST}$s across individual markets and regions implies that COVID-19 uncertainty has, on average, an increasingly stronger influence on stock markets further west from the outbreak of COVID-19 in Wuhan, China. Szczygielski, Brzeszczyński et al. (2022) suggest that the closer a region is positioned to China, the better information and understanding investors may have had about the COVID-19 pandemic and its evolution, resulting in reduced uncertainty and hence a less severe impact on stock prices. In addition, Lu et al. (2020) and Szczygielski, Brzeszczyński et al. (2022) propose that the experience of countries in the Asia-Pacific region in dealing with the SARS and MERS epidemics may have aided in reducing the effect of uncertainty. Moreover, the COVID-19 pandemic spread geographically from east to west of its origin, first affecting countries in Europe, such as Italy, Spain and the UK, and then countries in the Americas, most notably the US and Brazil. The pattern of the spread of the virus is also consistent with the large explanatory power of GST_t for European stock returns as Europe became the epicentre of the virus after Asia.

Death tolls for the virus were also the highest in the Americas and Europe, which may have translated into a greater impact of uncertainty on these stock markets (Salisu and Akanni, 2020). Findings that geographical proximity to the COVID-19 outbreak matters for the 35 largest stock markets globally with respect to the impact of COVID-19 related uncertainty is consistent with findings obtained for the G20 country stock markets (Smales, 2021a) and the 20 largest national energy sectors (Szczygielski, Brzeszczyński et al., 2022).

In Fig. 1 GSM_t has the greatest impact on the Americas followed by Asia-Pacific, MEA and Europe (average $\beta_{i,GSM}$s of -0.0048, -0.0033, -0.0030 and -0.0027, respectively). In terms of explanatory power, the measure of the stringency of responses can explain a similar proportion of variation in returns for the Americas and Asia-Pacific ($\bar{R}^2$ of 0.1015 and 0.097, respectively) followed by MEA (0.0668) and Europe (0.0532). All countries in the European region in this sample are in developed markets and are less affected by lockdowns than emerging markets because of the greater fraction of employment that can be performed from home and consumer spending playing a smaller role in driving economic growth (Dingel and Neiman, 2020; Strohecker, 2020; Gottlieb et al., 2020a,b). Other regions, in contrast, comprise both developed and/or only developing countries. This observed pattern of impact likely reflects trade ties with and the spillover effects of US economic activity. While Europe exports goods to all regions, intra-regional trade dominates (Our World in Data, 2020). Accordingly, this region is less affected by the curbing of economic activity in other regions of the world. Our measure of stringency is market-weighted and thus the stringency of US lockdowns has the greatest impact on the metric with US government responses among the most stringent globally as quantified by the Oxford COVID-19 Stringency Government Response Tracker. US GDP contributes close to 24% to world GDP and is the most important export destination for 20% of countries around the world (World Economic Forum, 2019). Economic activity in the US impacts all regions of the world (Dées and Saint-Guilhem, 2011; Kose et al., 2017). Hence, the strict lockdowns and travel bans imposed by the US have repercussions for countries globally which is consistent with the documented patterns. Likewise, restrictions imposed in Europe have less impact globally because intra-regional trade dominates.

Coefficients on MHI_t are closer in magnitude across regions: largest for MEA ($\beta_{i,MHI}$ of -0.0019), followed by the Americas ($\beta_{i,MHI}$ of -0.0018), Asia-Pacific ($\beta_{i,MHI}$ of -0.0015) and Europe ($\beta_{i,MHI}$ of -0.0012). Similarly, the $\bar{R}^2$ is also highest for MEA (0.0998) followed by Asia-Pacific (0.0728), the Americas (0.0444) and Europe (0.0347). This pattern can be associated with the level of economic development. Most MEA countries are emerging markets. Stock markets in emerging countries are more affected by media hype and panic relative to stock markets in developed countries. Moreover, the media is seen as having played a critical role in the collapse of tyrannical regimes and the dissemination of sensitive information in the Middle East and South Africa during the last decade (Rezaei and Cohen, 2012; Wasserman, 2020). The role and influence of the media in affecting investor behaviour may be heightened in MEA compared to other regions.

We also regress returns on each market aggregate onto all three measures using least squares regression. GST_t, GSM_t and MHI_t continue to negatively impact stock returns with coefficients similar in magnitude (Panel D, Table 8). GST_t and GSM_t coefficients remain significant for the MSCI All Country World Index and all individual countries (with the exception of the Netherlands for the former and Japan, in addition to Qatar which was found to be insignificant in the individual analysis, for the latter). The impact of MHI_t is slightly weaker in combined regressions, with the coefficient significant for 16 stock markets (compared to 24 when analysed individually) and remains insignificant for the MSCI All Country World Index. As a robustness test, we apply a different econometric methodology by estimating ARCH/GARCH models that incorporate a factor analytic augmentation to account for omitted factors.[21] The signs, magnitude and patterns of the coefficients for regressions of GST_t, GSM_t and MHI_t on stock returns with ARCH/GARCH errors are consistent with findings for the individual and joint least squares estimates (see Table 5A in Appendix A for results).

3.5. The impact of COVID-19 on stock market volatility

Given that GST_t, GSM_t and MHI_t impact returns, we also set out to determine whether these measures are associated with higher

[21] ARCH/GARCH modelling offers an alternative to the use of Newey-West Heteroscedasticity and autocorrelation consistent standard errors to account for serial correlation and volatility dynamics (Andersen et al., 2003; Szczygielski et al., 2020a).

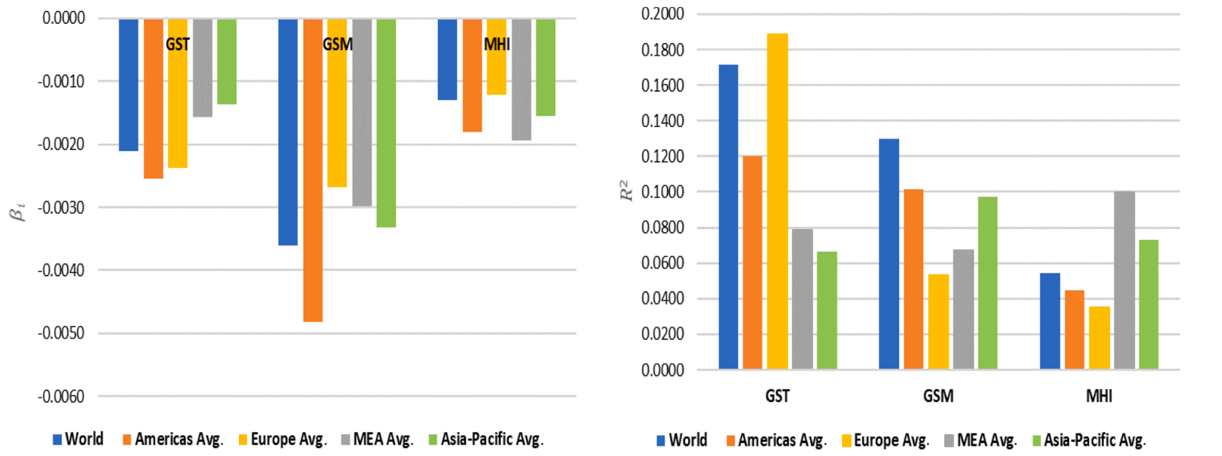

Fig. 1. Impact of GST, GSM and MHI on returns and averages across individual countries grouped according to region during the COVID-19 crisis period

Notes: This figure plots the average estimates of COVID-19 related Google Search Trends ($\beta_{i,GST}$), the government stringency index ($\beta_{i,GSM}$) and the Ravenpack media hype index ($\beta_{i,MHI}$) on returns of the MSCI All Country World index and 35 country indices grouped according to region (the Americas, Europe, Middle East and Africa (MEA) and Asia-Pacific) (left side) and the average $\bar{R}^2$ estimates from these regressions (right side) over the COVID-19 crisis period from 1 January 2020 to 20 October 2020.

volatility. Several studies have examined the effect of COVID-19 on volatility and find that the COVID-19 crisis is associated with higher volatility. Ali et al. (2020) and Zhang et al. (2020) report that increases in cases and deaths contributed to increased market volatility in countries most impacted by COVID-19. In the US, Baek et al. (2020) find that COVID-19 cases and deaths resulted in greater volatility with the effect of the latter being more pronounced. Albulescu (2020) reports a positive relationship between new cases and increases in the fatality ratio on US and global stock market volatility. Increased COVID-19 related uncertainty, quantified by GST, has been shown to be associated with increased volatility for China (Liu, 2020), G20 countries (Smales, 2021a) and various regions (Szczygielski et al., 2021). There is also evidence that volatility triggering effects associated with increased Google searches have intensified as the pandemic spread (Szczygielski et al., 2021; Szczygielski, Brzeszczyński et al., 2022) and that some industries, such as financials and energy, have been more impacted than others, such as consumer staples and health care (Smales, 2021b; Szczygielski, Charteris et al., 2022).

Heightened volatility has also been associated with increased media attention (Bai et al., 2020). Haroon and Rizvi (2020) report that increased measures of panic and hysteria related to the pandemic, reflected by the Ravenpack Panic Index, resulted in increased US and global stock return volatility, whereas greater negative sentiment in the media quantified by the Ravenpack Sentiment Index resulted in heightened US volatility but not global market volatility. In contrast, greater media coverage led to lower volatility for global stock returns but with no impact on US stock returns. Szczygielski et al. (2021) and Zaremba et al. (2020) examine the effect of government responses to the pandemic on market volatility and found that more extensive responses contributed to heightened volatility. It follows that there is ample evidence that various aspects of COVID-19 impact not only returns but also volatility.

To quantify the impact of the COVID-19 measures on volatility, we apply the ARCH/GARCH framework. We control for all common factors by using statistically derived factors in the mean equation adjusted for the three COVID-19 measures. By adopting this approach, residual variance will reflect the components of variance that are associated with the identified COVID-19 measures and not any other COVID-19 measures or influences (Bera et al., 1988; Koutoulas and Kryzanowski, 1994; Szczygielski et al., 2020a). The mean equation is, therefore, specified as:

$$r_{i,t} = \alpha_i + \sum_{k\geq 0}^{k} \beta_{i,k\varepsilon} F_{k\varepsilon,t} + \gamma_i r_{i,t-\tau} + \varepsilon_{i,t} \tag{5}$$

where $\sum_{k\geq 0}^{k}\beta_{i,k}F_{K\varepsilon,t}$ is the set of statistically derived factors from return series, $r_{i,t}$, adjusted for the proportion of shared variance reflected by $\sum_{k\geq 0}^{k}\beta_{CV19,k}F_{CV19,t}$ so that $\varepsilon_{i,t}$ represents returns uncorrelated with any other measures in the broader measure set that we begin with. Statistically derived factors are obtained as before by applying the MAP test and deriving a set of factor scores. We use an extended sample period from 1 January 2015 to 20 October 2020 to reduce biases in maximum likelihood (ML) estimates and the persistence of non-linear dependence associated with small sample sizes (Hwang and Valls Pereira, 2006). We begin with an ARCH(p) model and proceed to estimate an GARCH(p,q) model if the ARCH(p) specification exhibits residual heteroscedasticity or non-linear dependence. If heteroscedasticity or non-linear dependence are present following the application of the GARCH(p,q) specification, we increase the number of ARCH and/or GARCH parameters. We also consider IGARCH(p,q) specifications if ARCH and GARCH parameters are close to unity (Engle and Bollerslev, 1986; Brzeszczyński and Kutan, 2015). The respective ARCH(p), GARCH(p,q) and IGARCH(p,q) conditional variance specifications are as follows:

Table 9
ARCH/GARCH estimates for conditional variance with COVID-19 measures over the COVID-19 crisis period

	Panel A: GST_t						Panel B: GSM_t					
	ω_i	α_1	α_2	β_1	β_2	γ_{GST_t}	ω_i	α_1	α_2	β_1	β_2	γ_{GSM_t}
World	1.03E-07***	0.2277***	-0.1758***	0.9367***		0.2740**	2.15E-07***	0.2741***	-0.1724**	0.8842***		0.1300
US	4.00E-07**	0.1415***	-0.0438	0.8865***		0.4850**	5.23E-07**	0.1801***	-0.0722	0.8746***		0.3470
China	3.24E-06***	0.0477	0.0952**	0.7603***		0.2190*	2.81E-06***	0.0493	0.0762*	0.7887***		0.2520
Japan	7.52E-06***	0.1985***		0.7183***		0.2440	7.87E-06***	0.2089***		0.7050***		0.4780
UK	1.36E-06***	0.1081**		0.6655	0.1859	0.5400	1.11E-06*	0.0997*		0.6697	0.2002	0.3400
France	6.62E-08**	0.2033***	-0.1598***	0.9502***		0.4240***	2.02E-07**	0.2163***	-0.1219**	0.8921***		0.1310
Canada	1.89E-06*	0.1265***		0.8459***		0.4210***	2.25E-06*	0.1317***		0.8361***		0.4670
Germany	1.63E-07*	0.1450***	-0.1055**	0.9501***		0.5200***	4.69E-07***	0.1897***	-0.1008*	0.8858***		0.1540
Switzerland	1.26E-06	0.0899**		0.8710***		0.2910	1.96E-06*	0.0919**		0.8442***		0.3040
India	4.40E-06**	0.0924***		0.8624***		0.5110***	6.09E-06***	0.1127***		0.8255***		0.7140
Australia	1.87E-06**	0.0650***		0.9115***		0.4670***	2.32E-06*	0.0816***		0.8903***		0.5740
Korea	1.42E-06*	0.0375**		0.9388***		0.4500*	2.00E-06	0.0374***		0.9279***		0.5820
Hong Kong	4.45E-07***	0.0838***		0.8967***		0.1460***	5.23E-07***	0.0901***		0.8857***		0.3120
Taiwan	2.97E-06**	0.0628***		0.8862***		0.4190**	5.10E-06**	0.0845***		0.8290***		0.4460
Brazil	6.95E-06	0.0644***		0.9087***		2.3200*	1.08E-05**	0.0816***		0.8781***		1.3800
Netherlands		0.1086***	-0.0888**	0.9802***		0.5140***		0.1219**	-0.0871	0.9652***		0.3260
Russia	2.23E-06*	0.0408***		0.9450***		1.3200**	4.12E-06***	0.0607***		0.9144***		0.9760
Spain	1.40E-07	0.0887**	-0.0710*	0.9786***		0.8400**	7.23E-07*	0.1490**	-0.1115*	0.9475***		0.4210
Italy	2.35E-06***	0.1974***		0.2179*	0.5527***	0.6930	4.34E-06***	0.2379***		0.1974*	0.5009***	0.6340***
Sweden	1.63E-06***	0.3585*	-0.2748	0.8896***		0.3850	2.84E-06***	0.3718*	-0.2537	0.8340***		0.5170
Saudi Arabia	1.69E-06**	0.0307***		0.9568***		1.2800***	4.58E-06***	0.0685**		0.9015***		0.9130**
Thailand	1.13E-06*	0.1234***	-0.0680	0.9287***		0.7750*	1.90E-06**	0.1072***	-0.0272	0.8944***		0.5120
South Africa	1.63E-05*	0.1167***		0.7780***		1.2600	2.45E-05**	0.1305***		0.7099***		1.4800
Denmark	7.85E-06**	0.1086***		0.7826***		0.2300	9.92E-06**	0.0990***		0.7557***		1.0700**
Singapore	1.54E-06***	0.0927***		0.8592***		0.2370	2.41E-06***	0.1168***		0.8073***		0.2990
Belgium	7.03E-06**	0.1745***		0.7078***		0.2510	1.09E-05**	0.2505***		0.5712***		1.0600
Indonesia	5.12E-06**	0.1265***		0.4716*	0.3591	1.0500***	6.67E-06***	0.1438***		0.3772*	0.4191**	3.0600*
Malaysia	7.35E-07**	0.1018***		0.6658	0.2123	0.2970	1.01E-06***	0.1148***		0.7356**	0.1192	0.9670**
Mexico	4.63E-06***	0.1013***		0.8585***		0.6540	6.05E-06***	0.1154***		0.8316***		0.9130
Norway	2.10E-07**	0.0862**	-0.0808**	0.6093*	0.3801	1.3700***	2.27E-06**	0.1320**	-0.0805	0.7163*	0.1938	0.6370
Finland	5.92E-06***	0.2767***		0.6736***		0.2330	8.44E-06***	0.2639***		0.6257***		0.9810***
Philippines	4.36E-06**	0.0891***		0.8644***		0.5140	5.63E-06***	0.1007***		0.8383***		1.2200**
UAE	7.06E-06*	0.0240	0.1740	0.7676***		0.4480	9.37E-06**	0.0303	0.1624	0.7416***		1.3100
Qatar	4.61E-06**	0.0495***		0.9085***		0.6000*	7.97E-06**	0.0639***		0.8607***		0.9690
Israel	2.24E-06	0.0267***		0.9504***		0.6410**	4.54E-06**	0.0368***		0.9153***		0.7270
Chile		0.0596		0.9404***		1.7600***		0.0634***		0.9366***		0.8650
Average						0.6412						0.7352

Table 9
ARCH/GARCH estimates for conditional variance with COVID-19 measures over the COVID-19 crisis period (continued…)

	Panel C: MHI_t						Panel D: GST_t, GSM_t, MHI_t							
	ω_i	α_1	α_2	β_1	β_2	γ_{MHI_t}	ω_i	α_1	α_2	β_1	β_2	γ_{GST_t}	γ_{GSM_t}	γ_{MHI_t}
World	2.58E-07**	0.2987***	-0.1884**	0.8732***		0.0846	1.40E-07**	0.2349***	-0.1816***	0.9299***		0.3690***	0.0224	-0.2880***
US	6.62E-7**	0.2032***	-0.0937	0.8671***		0.0608	3.54E-07**	0.1549***	-0.0735	0.9035***		0.6610***	0.0860	-0.4670***
China	2.30E-06***	0.0458	0.0666*	0.8180***		0.2660	2.13E-06***	0.0459	0.0704**	0.8191***		0.2260*	0.0088	-0.0095
Japan	7.61E-06***	0.2037***		0.7139***		0.4500	7.49E-06***	0.1977***		0.7184***		0.2890	0.2770	-0.0120
UK	1.23E-06*	0.1102***		0.5682	0.2888	0.4000	1.15E-06**	0.1131**		0.6877	0.1680	0.6160	-0.5080	0.0984
France	1.20E-07**	0.2609***	-0.1883***	0.9216***		0.3510***	5.52E-08***	0.1580***	-0.1248***	0.9599		0.5270***	-0.0159	-0.1680
Canada	2.39E-06*	0.1378***		0.8294***		0.3800	1.00E-06***	0.0958***		0.8876***		0.5530*	0.3870	-0.2580
Germany	4.15E-07**	0.1883***	-0.1042*	0.8941***		0.1940	1.51E-07	0.1347***	-0.0970*	0.9525***		0.6660***	0.0692	-0.2670**
Switzerland	1.99E-06*	0.1018**		0.8363***		0.2000	1.44E-06	0.0891**		0.8647***		0.2620	0.1480	0.0402
India	5.61E-06**	0.1029***		0.8396***		1.0400	4.77E-06**	0.0918***		0.8577***		0.6330*	0.2880	0.4380
Australia	1.77E-06*	0.0685***		0.9097***		1.2900**	1.68E-06*	0.0608***		0.9173***		0.6710***	0.1860	0.2870
Korea	2.01E-06*	0.0466***		0.9205***		0.4830	4.37E-06	0.0653**		0.8599***		0.3150	0.5700	-0.1450
Hong Kong	5.38E-07***	0.1011***		0.8774***		0.1870	4.36E-07***	0.0784***		0.9000***		0.2340**	0.2400**	-0.1420
Taiwan	4.62E-06***	0.0817***		0.8411***		0.4540	2.69E-06**	0.0616***		0.8926***		0.4320*	-0.0886	0.0048
Brazil	9.31E-06*	0.0788***		0.8876***		2.0300	6.78E-06	0.0639***		0.9098***		2.4800*	0.1210	-0.8080
Netherlands		0.1275**	-0.1045**	0.9770***		0.5380**		0.1021***	-0.0839**	0.9817***		0.6710***	0.0219	-0.4090***
Russia	3.58E-06***	0.0577***		0.9215***		1.3100	2.09E-06*	0.0392***		0.9473***		1.5600**	0.1770	-0.5580
Spain	3.60E-07***	0.1561**	-0.1323**	0.9685***		0.6560*	9.62E-06***	0.1265***	0.0261	0.6495***		0.2860	0.9940	-0.0625
Italy	4.02E-06***	0.2533***		0.2087*	0.4864***	0.4170	2.75E-06***	0.1965***		0.1986*	0.5632***	0.6840	0.6060	-0.0962
Sweden	2.35E-06***	0.3669*	-0.2553	0.8513**		0.2360	1.74E-06***	0.3664*	-0.2831	0.8870***		0.4670**	0.3350	-0.3780
Saudi Arabia	3.96E-06**	0.0561**		0.9164***		1.4200***	3.19E-06**	0.0480**		0.9290***		0.6200	0.4410	0.7680**
Thailand	5.68E-07*	0.1157***	-0.0652	0.9429***		1.0800***	1.15E-06*	0.1199***	-0.0653	0.9289***		0.9130*	0.1140	-0.3340
South Africa	2.42E-05	0.1396***		0.7043***		1.6600	2.21E-05**	0.1303***		0.7244***		1.0100	0.5750	0.7740
Denmark	8.42E-06**	0.1048***		0.7771***		0.4480	8.93E-06**	0.0943***		0.7750***		0.1670	0.9600**	-0.1590
Singapore	2.22E-06***	0.1210***		0.8121***		0.1350	1.62E-06***	0.0907***		0.8572***		0.2750*	0.1860	-0.1190
Belgium	9.00E-06**	0.2242***		0.6332***		0.4400	1.10E-05**	0.2466***		0.5695***		0.2740	0.9610	0.1260
Indonesia	6.75E-06***	0.1564***		0.4139	0.3770*	0.7740	4.85E-06***	0.1163***		0.4652***	0.3735**	1.5800***	1.9800**	-1.7300*
Malaysia	9.71E-07***	0.1273***		0.5637**	0.2840	0.5800	8.59E-07**	0.1084***		0.7913*	0.0758	0.3510	0.4060	-0.1160
Mexico	5.96E-06***	0.1247***		0.8260***		0.2200	4.40E-06***	0.0978**		0.8630***		0.8830*	0.4980	-1.1600
Norway	1.90E-06*	0.1344**	-0.0844	0.7106*	0.2084	0.9880*	2.25E-07	0.0805**	-0.0649	0.6987*	0.2804	1.5000**	0.0304	-0.4770
Finland	7.23E-06***	0.2886***		0.6398***		0.1800	6.62E-06***	0.2716***		0.6597***		0.2670	1.0100***	-0.2010
Philippines	4.83E-06**	0.1073***		0.8450***		0.6640	4.77E-06**	0.0854***		0.8611***		0.6280	0.8440	-0.2220
UAE	1.02E-05**	0.0508	0.1751*	0.7133***		0.8110	5.73E-06**	0.0225	0.0687	0.8525***		0.5510	0.7770	0.1680
Qatar	6.79E-06**	0.0610***		0.8761***		0.7100**	6.65E-06**	0.0561***		0.8810***		0.6210**	0.6330	0.0740
Israel	3.83E-06***	0.0324***		0.9278***		1.0400***	3.38E-06*	0.0299***		0.9346***		0.2570	0.1260	0.6480
Chile		0.0606***		0.9394***		1.9900***		0.0587***		0.9413***		1.7400***	-0.5860	0.1060
Average						0.6713						0.6733	0.3578	-0.1404

Notes: This table reports the results of ARCH/GARCH models of the conditional variance with COVID-19 measures included over the COVID-19 crisis period, 1 January 2020 to 20 October 2020. Model estimation sample is 1 January 2015 to 20 October 2020. Measures are included individually in Panels A, B and C and jointly in Panel D. GST_t are changes in worldwide COVID-19 related Google Search Trends. GSM_t are changes in the stringency of government responses to control the spread of the COVID-19 virus as measured by the Oxford Coronavirus Government Response Tracker. MHI_t are changes in the Ravenpack Media Hype Index. ***, ** and * indicate statistical significance at the respective 1%, 5% and 10% levels of significance.

$$h_{i,t} = \omega_i + \sum_{p\geq 1}^{p} \alpha_i \varepsilon_{i,t-p}^2 + \sum_{k\geq 0}^{k} \varphi_{i,CV19} F_{CV19,t} Dum_{0,1} \tag{6a}$$

$$h_{i,t} = \omega_i + \sum_{p\geq 1}^{p} \alpha_i \varepsilon_{i,t-1}^2 + \sum_{q\geq 1}^{q} \beta_i h_{i,t-q} + \sum_{k\geq 0}^{k} \varphi_{i,CV19} F_{CV19,t} Dum_{0,1} \tag{6b}$$

$$h_{i,t} = \sum_{p\geq 1}^{p} \alpha_i \varepsilon_{i,t-1}^2 + \sum_{q\geq 1}^{q} \beta_i h_{i,t-q} + \sum_{k\geq 0}^{k} \varphi_{i,CV19} F_{CV19,t} Dum_{0,1} \tag{6c}$$

where $\sum_{k\geq 0}^{k} \varphi_{i,CV19} F_{CV19,t} Dum_{0,1}$ is the set of identified COVID-19 measures and $Dum_{0,1}$ is a shift dummy denoting pre-COVID-19 and COVID-19 crisis periods, defined as 1 January 2015 to 31 December 2019 and 1 January 2020 to 20 October 2020, respectively. The system of equations (5)/(6a)/(6b)/(6c) is estimated for each measure individually and for all identified measures jointly.

Table 9 reports results for ARCH/GARCH estimation. In Panel A, GST_t has a statistically significant and positive effect on MSCI All Country World Index return volatility ($\varphi_{i,GST}$ of 0.2740). The impact is positive for all individual indices and significant for 22 markets. The most impacted markets are Brazil, Chile and Norway ($\varphi_{i,GST}$s of 2.3200, 1.7600 and 1.3700, respectively). The least impacted are Hong Kong, China and Denmark ($\varphi_{i,GST}$s of 0.1460, 0.2190 and 0.2300, respectively). Overall, these results suggest that as investors become more uncertain about the pandemic and search for information, equity prices become more volatile.

In contrast, the stringency of government responses appears to have little impact on volatility. In Panel B, the $\varphi_{i,GSM}$ coefficient is significant and positive for only seven countries implying that in these markets the increased stringency of government responses is associated with heightened volatility. Indonesia is most affected, followed by the Philippines and Denmark ($\varphi_{i,GSM}$s of 3.0600, 1.2200 and 1.0700, respectively). In Panel C, the impact of MHI_t is also limited; only 10 stock markets exhibit significant volatility triggering in response to MHI_t. The most responsive markets are Chile, Australia and Saudi Arabia ($\varphi_{i,MHI}$s of 1.9900, 1.4200 and 1.2900, respectively). This suggests that increased hype and panic in the media surrounding COVID-19 fuels volatility in a limited number of markets, i.e. less so than GST_t.

As a confirmatory step, ARCH/GARCH models are estimated with all three measures jointly (Panel D in Table 9). GST_t is the only measure that shows consistent coefficient magnitudes and direction of impact, with $\varphi_{i,GST}$ statistically significant for 20 of 35 markets and the MSCI All Country World Index ($\varphi_{i,GST}$ of 0.3690). Coefficients on GST_t remain stable when considered individually and jointly with the other measures averaging 0.6412 and 0.6733, respectively. When GSM_t is combined with GST_t and MHI_t, the impact is positive and significant for four markets compared to seven in the individual analysis of GSM_t, with only Indonesia, Denmark and the Philippines retaining their significance. The average $\varphi_{i,GSM}$ estimate is substantially lower compared to when GSM_t is considered individually (0.3578 and 0.7352, respectively) indicating that GSM_t coefficients are not consistent across different specifications. Similarly, coefficients on MHI_t are unstable when this measure is combined with GST_t and GSM_t with coefficients exhibiting different signs in comparison to when examined individually with significance also affected. Average $\varphi_{i,MHI}$s of 0.6713 and -0.1404 for individual and combined analyses, respectively, illustrate this instability with $\varphi_{i,MHI}$ for the MSCI All Country World Index becoming negative and statistically significant ($\varphi_{i,MHI}$ of -0.2880). Only the impact of MHI_t on Saudi Arabia's stock market remains significant from individual market regressions.

A finding that movements in GST_t contribute to increased volatility is similar to that of Liu (2020) for the Chinese stock market and

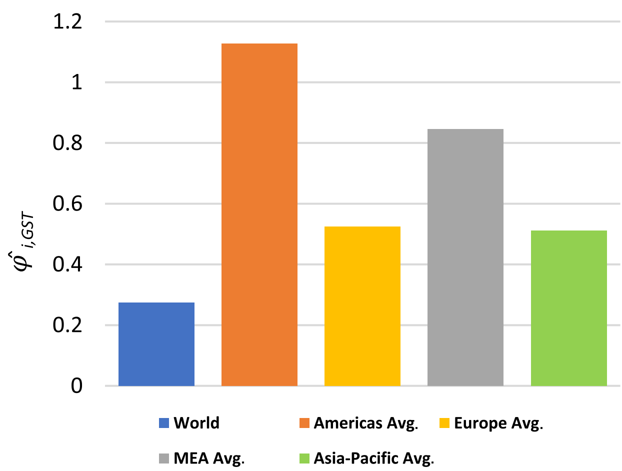

Fig. 2. Average impact of GST on return volatility across individual countries grouped according to region during the COVID-19 crisis period

Notes: This figure plots the average estimates of COVID-19 related Google search trends ($\varphi_{i,GST}$) on the volatility of stock returns of the MSCI All Country World Index and 35 country indices grouped according to region (the Americas, Europe, Middle East and Africa (MEA) and Asia-Pacific).

Smales (2021a) for G20 countries. The association of this measure with increased volatility provides support for the interpretation that this is a measure of market uncertainty. A finding of a limited effect of GSM_t on volatility differs from the results of Zaremba et al. (2020) but it is broadly consistent with Szczygielski et al. (2021) who demonstrated differential effects of government responses across regions. Haroon and Rizvi (2020) report mixed results for the role of the various COVID-19 related media attention metrics on US and global stock market volatility. We find that media hype and panic have a limited effect. The finding of a limited role of MHI_t compared to a widespread and significant role of GST_t on stock return volatility suggests that the transmission mechanism of MHI_t differs from that of GST_t. As reported in Section 3.3, MHI_t is unrelated to measures of market uncertainty. Consequently, we maintain that this is an attention measure.

Given the widespread impact of GST_t on stock return volatility and support in the literature for information searches as a measure of market uncertainty, we undertake a further analysis of the impact of GST_t on markets grouped according to regions. The average impact of GST_t on return volatility across regions is summarised below in Fig. 2. Volatility is most impacted by GST_t in the Americas, followed by MEA, Europe and Asia, with respective average $\varphi_{i,GST}$s of 1.1280, 0.8458, 0.5243 and 0.5115. This pattern is similar to the $\beta_{i,GST}$s but with the positions of MEA and Europe reversed. This positional reversal is consistent with the reduced role of uncertainty among developed countries compared to emerging countries as most markets in Europe fall into the former category.[22] As with the analysis of returns, there is evidence that increased geographical distance from the origin of the COVID-19 pandemic in China gives rise to a greater impact of COVID-19 uncertainty on stock return volatility. This can likewise be attributed to market participants closer to the outbreak having better information and understanding of the pandemic and its evolution, the experience of countries at the epicentre in dealing with past epidemics (Lu et al., 2020; Szczygielski, Brzeszczyński et al., 2022) and the geographic spread of the virus from China in a westerly direction to Europe and America.[23]

3.6. Overall impact of uncertainty

Uncertainty arises when it is not known whether an event will occur, when it will occur and/or what its consequences will be (see Aven and Renn (2009), amongst others). Previous studies have shown that uncertainty affects stock prices (Pastor and Veronesi, 2012; Ko and Lee, 2015) and volatility (Arnold and Vrugt, 2008; Su et al., 2019) with the same being true for uncertainty surrounding the COVID-19 period (see Liu, 2020; Smales, 2021a; Szczygielski et al., 2021; Szczygielski, Brzeszczyński et al., 2022). Uncertainty about future cash flows and discount rates has a negative impact on stock prices (Gormsen and Koijen, 2020). Moreover, when new information arises and investors are uncertain as to how this information impacts the true value of an asset, increased volatility ensues (Szczygielski, Brzeszczyński et al., 2022). The results reported in this study indicate that uncertainty, as reflected by GST_t, has a negative effect on stock prices and triggers heightened volatility. However, the return and volatility channels of the impact of uncertainty are typically considered separately. Following Szczygielski, Brzeszczyński et al. (2022), we therefore combine both aspects of

[22] We conducted an identical analysis for countries grouped according to levels of economic development. The impact of COVID-19 related uncertainty on returns is stronger for developed markets relative to emerging markets (average $\beta_{i,GST}$s of −0.0021 and −0.0016, respectively). This may be linked to greater apprehension about the virus in developed countries by investors who are less accustomed to health or other economic disturbances that are more common in emerging countries. Notably, high-income countries initially accounted for an unequal proportion of global deaths, which was further breeding panic and uncertainty (Salisu and Akanni, 2020). GSM_t had a larger impact on emerging markets relative to developed markets (respective $\beta_{i,GSM}$s of −0.0037 and −0.0029 and $\bar{R}^2$s of 0.0943 and 0.0648) suggesting that investors in these countries may have viewed the curbing of economic activity as more harmful. Similarly to GSM_t, MHI_t has a greater impact on emerging markets (average $\beta_{i,MHI}$ of −0.0018) than developed markets (average $\beta_{i,MHI}$ of −0.0013). In the variance equation, emerging market volatility was found to be more impacted by COVID-19 related uncertainty than developed market volatility with average $\varphi_{i,GST}$s of 0.8673 and 0.4071, respectively. Such results are congruent with the greater susceptibility of emerging markets to fluctuating risk tolerance in general (Froot and O'Connell, 2003; FitzGerald, 2007), especially during times of crises (such as the Global Financial Crisis in 2007/2008) (McCauley, 2013) and to uncertainty surrounding the COVID-19 health and economic crises (Arnold and Mattackal, 2020; Szczygielski et al., 2021). For conciseness, a detailed analysis is excluded from the final version of this paper.

[23] Given that GST_t, GSM_t and MHI_t impact both returns and volatility, we tested whether the effect of these COVID-19 measures on returns could occur through the volatility channel. We thus re-estimated models using the ARCH-in-mean/GARCH-in-mean framework. The results show that the COVID-19 measures impact returns independently of volatility. No coefficients on the COVID-19 measures became insignificant in the presence of volatility in the mean equation. The coefficient on volatility, which captures the risk premium, is significant for only 6 of the 35 countries. This reveals that volatility does not have a significant impact on returns during the COVID-19 crisis period despite theory suggesting that returns should have a positive relationship with risk, modelled by variance (Baillie and DeGennaro, 1990). This finding is consistent with Duttilo et al. (2021), who found the risk premium significant for only six of 16 countries during the COVID-19 crisis period, and studies outside of the COVID-19 crisis period on developed (Baillie and DeGennaro, 1990) and emerging markets (Shin, 2005). We further examined whether GST_t alone masks the impact of volatility on returns given that GST_t represents uncertainty (Section 3.3), while return volatility is also seen an uncertainty measure (Alsalman, 2016). We estimated the ARCH/GARCH-in-mean model for each country with and without GST_t in the mean equation. The results suggest GST_t does not capture the impact of volatility on returns as the risk premium is insignificant for all countries, except India, UAE and Qatar, regardless of whether GST_t is included or not. These results confirm that volatility during the COVID-19 crisis period does not have a positive impact on returns as theory predicts (Baillie and DeGennaro, 1990). It is important to distinguish between volatility, which is as an *ex-post* measure of uncertainty, and VIX_t, which is an *ex-ante* measure of uncertainty (Federal Reserve Economic Data, 2021). The results in Section 3.3 show that GST_t is correlated with VIX_t and can therefore be viewed as an *ex-ante* measure of uncertainty. Our results suggest that *ex-post* (volatility) and *ex-ante* (GST_t) measures of volatility have a differing impact on returns.

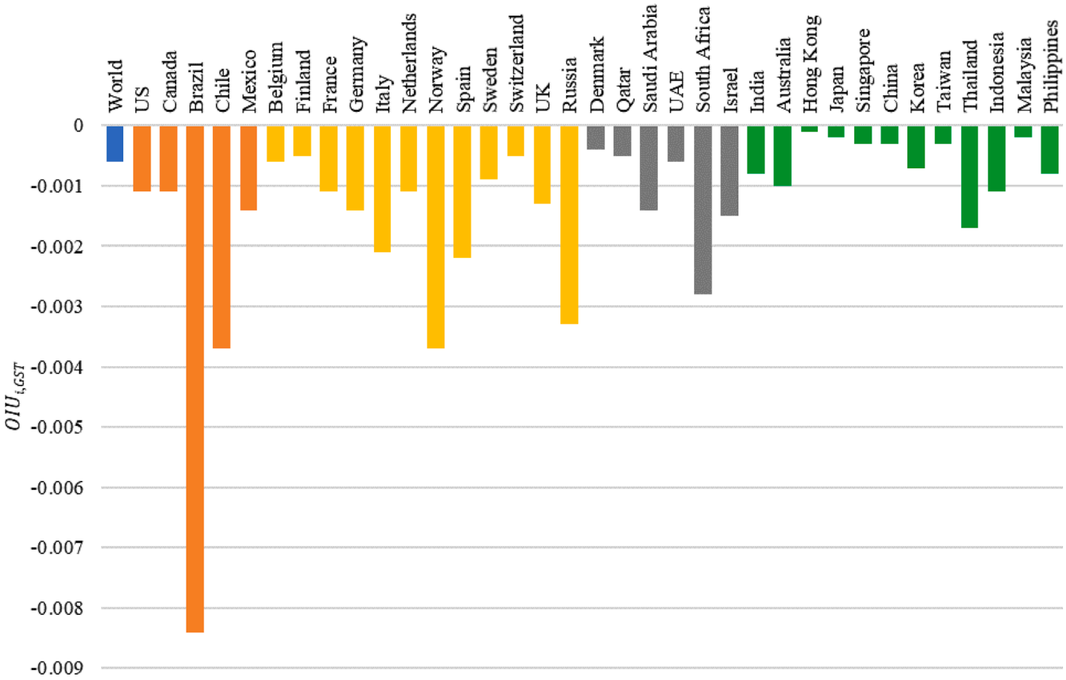

Fig. 3. Overall impact of uncertainty on the world stock market and individual countries over the COVID-19 crisis period
Notes: This figure plots the overall impact of uncertainty ($OIU_{i,GST}$) measure for individual countries and the MSCI All Country World index based on COVID-19 related Google Search Trends on an inverted vertical axis over the COVID-19 crisis period from 1 January 2020 to October 2020. The $\beta_{i,GST}$s and $\varphi_{i,GST}$s used to estimate the OIU measure in equation (7) are derived from equations (4) and (6a)/(6b)/(6c), respectively.

the influence of uncertainty on stock markets in a two-dimensional measure of uncertainty, termed the 'overall impact of uncertainty', $OIU_{i,GST}$, which is calculated as follows:

$$OIU_{i,GST} = \beta_{i,GST} \cdot \varphi_{i,GST} \tag{7}$$

where $\beta_{i,GST}$, the coefficient on GST_t, captures the magnitude of the impact of GST_t on returns and $\varphi_{i,GST}$ gauges the impact's intensity in the form of volatility associated with GST_t. $\beta_{i,GST}$s in equation (7) are derived from equation (4) whereas the values of the $\varphi_{i,GST}$ are derived from equations (6a)/(6b)/(6c). The overall influence of uncertainty is, therefore, quantified as the product of these two parameters.[24]

The results for $OIU_{i,GST}$ are summarised in Fig. 3 (estimates for $OIU_{i,GST}$ are presented in Table 6A in Appendix A). The overall impact of COVID-19 uncertainty on the MSCI All Country World Index is −0.0006. Most impacted markets are Brazil, Norway and Chile with respective $OIU_{i,GST}$s of −0.0084, −0.0037 and −0.0037. Markets showing the lowest overall impact of COVID-19 related uncertainty are Hong Kong, Malaysia and Japan ($OIU_{i,GST}$s of −0.0001, −0.0002 and −0.0002, respectively).

Adjusting for intensity in the manner proposed by the $OIU_{i,GST}$ measure yields a somewhat different perspective. For example, Canada and Norway are the second most impacted markets by COVID-19 related uncertainty in returns ($\beta_{i,GST}$ of −0.0027). However, after adjusting for intensity, the $OIU_{i,GST}$ for Norway is much higher than that of Canada (−0.0037 and −0.0011, respectively) due to the much higher intensity of impact for Norway compared to Canada ($\varphi_{i,GST}$s of 1.370 and 0.421, respectively). Likewise while COVID-19 related uncertainty has only a limited impact on the returns for Singapore and Saudi Arabia ($\beta_{i,GST}$ of −0.0011), the much

[24] Szczygielski, Brzeszczyński et al. (2022) designed this measure to capture the directional strength of the effect of uncertainty, which is adjusted by the intensity with which information enters a market. For example, in the case of two countries with the same magnitude of the impact of COVID-19 related uncertainty on returns ($\beta_{i,GST}$), the overall impact is stronger for the country with the higher intensity of the impact ($\varphi_{i,GST}$). Likewise, for two countries with the same level of intensity ($\varphi_{i,GST}$), the overall impact is stronger the greater the magnitude ($\beta_{i,GST}$). Szczygielski, Brzeszczyński et al. (2022) argue that the design of the $OIU_{i,GST}$ measure allows for a comparison with natural phenomenon such as the impact of rainstorms on the environment. Rainstorms can produce different amounts of water, i.e. an analogy for the magnitude component in $OIU_{i,GST}$ represented by $\beta_{i,GST}$, and there may also be a varying force of the rain and wind, i.e. the 'volatility' of the storm. This means that storms can have different levels of intensity. The impact of a rainstorm on the environment, therefore, depends on the product of parameters $\beta_{i,GST}$ and $\varphi_{i,GST}$ and the $OIU_{i,GST}$ measure directly quantifies this effect. The reason why we consider GST_t in the calculation of this measure and not the remaining two measures is because GSM_t and MHI_t have an impact on returns but, as it is evident in Table 9, not on the variance. GST_t is shown to have a persistent and stable impact on conditional variance.

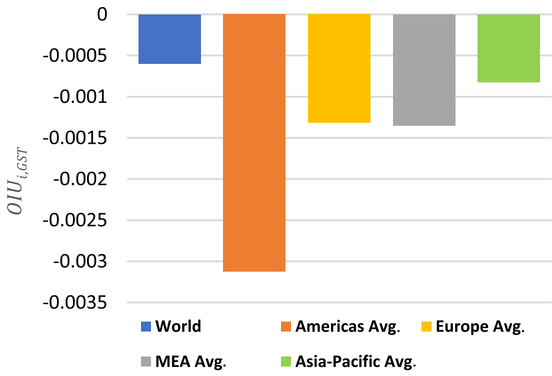

Fig. 4. Overall impact of uncertainty on the world stock market and averages across individual countries grouped according to region over the COVID-19 crisis period

Notes: This figure plots the average estimates of the overall impact of COVID-19 related Google Search Trends ($OIU_{i,GST}$) on markets (the product of the impact on returns ($\beta_{i,GST}$) and volatility ($\varphi_{i,GST}$)) of the MSCI All Country World index and 35 country indices grouped according to region over the COVID-19 crisis period from 1 January 2020 to 20 October 2020.

higher intensity for Saudi Arabia ($\varphi_{i,GST}$ of 1.280 compared to 0.237) contributes to a much greater overall impact of uncertainty on the country's stock market ($OIU_{i,GST}$ of −0.0014) compared to that of Singapore ($OIU_{i,GST}$ of −0.0003). This is an important finding as it demonstrates that considering the $\beta_{i,GST}$ or $\varphi_{i,GST}$ coefficients individually does not fully capture the impact of uncertainty.

Next, we group countries according to region with respect to the $OIU_{i,GST}$ measure. Fig. 4 illustrates that the average impact of COVID-19 related uncertainty on stock markets is strongest for the Americas followed by MEA and Europe (approximately equivalent) with the Asia-Pacific region least impacted (respective average $OIU_{i,GST}$s of −0.0031, −0.0014, −0.0013 and −0.0008).

Average $\beta_{i,GST}$s for the Americas and Europe are very similar (−0.0025 and −0.0024, respectively) although average $OIU_{i,GST}$s for these regions differ substantially (−0.0031 and −0.0013, respectively). This effect is due to the much larger intensity parameter $\varphi_{i,GST}$ for the Americas compared to Europe (averages of 1.1280 and 0.5243, respectively). A similar picture emerges from the analysis of the MEA and Asia-Pacific regions with similar average values of the magnitude of the impact ($\beta_{i,GST}$s of −0.0016 and −0.0014, respectively) while $OIU_{i,GST}$ averages are −0.0014 and −0.0008, implying that the overall impact of uncertainty was much lower in the Asia-Pacific region because of substantially lower intensity (respective average $\varphi_{i,GST}$s of 0.8458 and 0.5115). Regional results again confirm that geographical proximity matters in terms of the overall impact of COVID-19 uncertainty on financial markets. Countries further west from the origin of the COVID-19 pandemic in Wuhan in China are more impacted. Szczygielski, Brzeszczyński et al. (2022) attribute this finding to market participants closer to the outbreak having more information about this pandemic (see Sections 3.4 and 3.5). Lu et al. (2020), Szczygielski et al. (2021) and Szczygielski, Brzeszczyński et al. (2022) also highlight the greater experience of countries at the epicentre in dealing with past epidemics, which may have contributed to resolving uncertainty. Finally, the virus was also transmitted geographically from China in a westerly direction to Europe and America heightening uncertainty as it spread. This is seen in Fig. 4.

3.7. Changing stock market behaviour and COVID-19 measures

We now turn to the question of whether stock markets experienced a fundamental change following the COVID-19 crisis period. Our analysis is motivated by a recognition, and suggestions from the literature, that the impact of the COVID-19 pandemic may be characterised by distinct periods (Capelle-Blancard and Desroziers, 2020; Ramelli and Wagner, 2020) and waves (Ahmad et al., 2021) with measures, such as restrictions, having a differential impact over time (Aggarwal et al., 2021; Narayan et al., 2020) and changes in the empirical return-COVID-19 measure relationship (Szczygielski, Brzeszczyński et al. (2022)). Notably, Bradley and Stumper (2021) suggest that the period from late October 2020 onwards is distinct from the height of the crisis. They observe that this period has been characterised by news of vaccines, which has led to anticipations of recovery, with the hardest hit industrial sectors partially recovering while those that thrived during the pandemic continuing to do so.

We also observed that not only had markets returned to levels last seen at the start of the COVID-19 pandemic, but also that MSCI All Country World Index levels increased by approximately 24% by the end of July 2021 (see Fig. 1A in Appendix A) suggesting that markets were no longer as adversely impacted by the pandemic. Additionally, the period following the end of October 2020 coincides with a largely uninterrupted increase in MSCI All Country World Index levels. A potential explanation is that economic agents' expectations normalised as the pandemic evolved implying that the effect of COVID-19 related uncertainty and other measures of COVID-19 began exhibiting a weaker effect on global stock markets as government rescue packages restored investor confidence and as investors began to view the pandemic as a persistent state and formulated expectations, adapted to restrictions and began better understanding COVID-19 information, i.e. a 'new normal' (see Szczygielski et al., 2021; Seven and Yılmaz, 2021). Consequently, we analyse an approximately similar period using additional 9 months of data from the end of October 2020 to the end of July 2021.

We begin by investigating whether the structure of the return generating process resembles the pre-COVID-19 period (see Section

2.2, Section 3.1, Table 3). Factor analysis yields somewhat ambiguous results. In contrast to the initial COVID-19 crisis period, which is characterised by four factors, five factors are now extracted (see Table 7A in Appendix A). This is a larger number of factors than that which characterises the return generating process over the pre-COVID-19 period. However, the communality associated with these factors is 0.5678, which is more comparable to that for the three factors extracted for the pre-COVID-19 period (0.5310/0.5096 for the long/short pre-COVID-19 periods) than that for the COVID-19 period (0.7307). Similarly, average correlations ($\bar{\rho}_S = 0.3320$, $\bar{\rho}_P = 0.3613$) (Panel C, Table 7A in Appendix A) are closely comparable to those for the pre-COVID-19 period. Yarovaya et al. (2021) illustrate the mean-reverting tendencies of major equity markets after the COVID-19 shock suggesting that the shock experienced by markets has dissipated. Our results imply that interdependence between markets has weakened and returned to pre-COVID-19 levels, pointing towards an abatement of contagion associated with the pandemic period.

We also relate an extended measure set to the five extracted factor score series to determine whether the three measures identified previously, GST_t, GSM_t and MHI_t, continue to form part of the factor set driving returns. Results of the iterative selection procedure and factor regressions indicate that the first factor score series, $F_{1,t}$, which is also the most important in accounting for common market movements, is not significantly related to any measures (see Table 8A in Appendix A). However, $F_{2,t}$, $F_{3,t}$, $F_{4,t}$ and $F_{5,t}$ are significantly related to measures that are related to COVID-19 cases. These are the growth in total COVID-19 cases, CAS_{t-1}, changes in the case fatality rate, CFR_t, the growth in the 7-day moving average of reported COVID-19 deaths, DEC_t, and the growth in deviations of expectations over a 14-day window from present reported cases, RDI_t, respectively. When considered individually (jointly), these measures account for 0.46% (0.39%) of total shared variance (*ShVr*), which contrasts with the approximate 11.00% explained by GST_t, GSM_t and MHI_t between the start and height of the COVID-19 pandemic between January 2020 and October 2020 individually and jointly.[25]

These findings suggest that as the COVID-19 pandemic evolved, uncertainty abated as investors gained a greater understanding of the pandemic, business and employees adapted to restrictions, governments eased restrictions and media-fuelled panic and attention lessened as investors became accustomed to a flow of news relating to COVID-19, resulting in the three measures, GST_t, GSM_t and MHI_t no longer dominating. That a 'new normal' emerged is suggested by the change in the structure of the return generating process. Such a change implies that there may be new COVID-19 measures with limited time series – such as the number of vaccines administered or uncertainty relating to specific variants of COVID-19 – that may play a role. Finally, the emergence of case related measures that matter suggests that investors now focus on these measures to monitor the evolution of the COVID-19 pandemic.

4. Implications and discussion

We find that not all regions and markets are equally impacted with the effect of COVID-19 appearing to grow the further west a market is located. This is particularly noticeable for GST_t, returns and volatility are least impacted in the Asia-Pacific region while the Americas are most impacted. A suggested reason for this is that the closer a region is positioned to China, the better the information and understanding that investors have about the COVID-19 pandemic and its evolution given prior occurrences of similar crises in this region (Lu et al., 2020; Szczygielski et al., 2021; Szczygielski, Charteris et al., 2022). This is supported by a finding that during the extended post-crisis sample period after October 2020, COVID-19 related uncertainty no longer plays such a dominant role in driving returns. This suggests that a resolution of uncertainty and an understanding of the pandemic in countries closer to the outbreak of the pandemic may mitigate the impact of COVID-19. These findings are likely to be of interest to analysts and researchers by providing insight into how the COVID-19 pandemic evolved.

While Asia-Pacific is not the region that is least impacted by GSM_t and MHI_t, it is least impacted by the measure that matters most. GST_t by itself explains between 10% and almost 17% of shared market variance whereas the remainder explain between under 1% and just under 5% depending upon how shared market variance is measured (see Section 3.2). Given that GST_t is the measure that matters most, a recommendation to investors is to invest in countries in the Asia-Pacific region if they wish to minimise potential losses and avoid heightened volatility. Our analysis (in Section 3.6) based upon the *OIU* measure suggests that investors could limit their losses *and* exposure to volatility by investing in certain Asia-Pacific markets (notably in Hong Kong, Japan and China), while avoiding markets that simultaneously suffered extensive losses and exhibit high levels of volatility (i.e. Brazil, Chile, Norway and Russia) during the height of the COVID-19 crisis.

The proposed *OIU* measure which we expound and apply in this study jointly reflects the impact and intensity of COVID-19 related uncertainty on stock returns. This contrasts with standard approaches of quantifying the impact of uncertainty on returns and volatility separately. We show in Section 3.6 that when we compare the impact of COVID-19 related uncertainty by taking into consideration the intensity of information arrival as measured by $\varphi_{i,GST}$, then the overall impact of uncertainty will differ from that suggested by the $\beta_{i,GST}$ coefficients alone. By applying this measure, we distinctly show that Asian-Pacific markets are least impacted. While we use this measure to quantify the impact of uncertainty, it can be adapted to consider other measures that are context specific. This new measure presents an empirical approach that can be applied by analysts and researchers to gain an alternative and more holistic perspective into the impact of information flows on financial markets.

We demonstrate how elastic net regression can be used to tame the 'COVID-19 information zoo' (borrowing the terminology of Feng et al., 2020) by selecting only three measures out of an extensive set of 24 measures that appear to capture most of the market movements and summarise the impact of COVID-19 on international stock markets during the height of the COVID-19 pandemic.

[25] Structural break analysis does not reveal any changes in the empirical relationship between factor scores derived from returns over the post-crisis period and the identified COVID-19 measures.

Similarly to Feng et al. (2020), who apply regularised regression to establish the asset pricing contribution of over 150 factors (in a cross-sectional context), we use elastic net regression to sort COVID-19 information. Pernagallo and Torrisi (2020) argue that investors have a limited computational capacity, yet they must deal with large information flows, leading to potential departures from market efficiency if information flows become too large and too costly to process. The volume of information flows is compounded by ease of access facilitated by the internet and the growing prominence of social media (Agarwal et al., 2019). Consequently, investors must be selective in processing information (Peng and Xiong, 2006; Smales, 2021b). News agencies, governments and other institutions have tried to calm citizens by providing as much information as possible, especially considering that the nature of the COVID-19 crisis far exceeds the knowledge scope of most ordinary citizens (Chen, Huang & Li, 2020; Starosta et al., 2020). Our application of ML in the form of elastic net regression not only permits us to determine which COVID-19 information matters but also demonstrates how information complexity faced by investors can be reduced. Feature selection by ML can indicate to which information specifically the markets respond to and reduce information processing costs.

Relatedly, the use of factor analysis to represent composite common return drivers and to identify measures that matter most permits us to assign relative importance to the measures identified. This is because factor analysis indicates which factors account for the most shared variance (Section 3.1). We are therefore able to precisely quantify the contribution for each identified measure. Such an approach may aid investors in contextualising the relevance of specific factors that may matter for portfolio analysis and stock selection. It is hence not only a matter of statistical significance, but also a matter of relative importance in accounting for portfolio movements, which our approach captures by quantifying the proportion of explained shared variance by a given measure. This application of factor analysis may be of interest in an investment management context.

An important question addressed in this study relates to the nature of Google search trends. In the introduction, we outline literature that suggests that Google searches may represent uncertainty or investor attention (Da et al., 2011; Smales, 2021a; Castelnuovo and Tran, 2017; Bontempi et al., 2019; Szczygielski et al., 2021). The interpretation in Section 3.2 suggests that Google searches represent an uncertainty factor. However, we argue that the nature of Google searches as an uncertainty measure differs from that of other existing and established measures of market uncertainty, such as the VIX, which can be seen as reflecting *general* information about risk and risk aversion (Bekaert et al., 2013). In line with this reasoning, Google search trends, given their specific nature, reflect risk and risk aversion to a *specific* event. By using Google search trends, econometricians and financial analysts will be able to isolate and analyse the effects of uncertainty associated with specific events, offering an opportunity for a more focused and granular analysis.

We add to the literature on the evolution of the COVID-19 pandemic, and not only its impact, in Section 3.7. We extend our sample by a roughly equivalent period to the COVID-19 crisis period. We show that the structure of the return generating process has changed and that market interdependence again approximates that of the pre-COVID-19 period. However, the number of factors that drive returns during the post-COVID-19 crisis period (the extended period) is greater than that during the pre-COVID-19 period. This, together with the observation relating to interdependence, suggests that a 'new normal' has emerged. COVID-19 related uncertainty and media fuelled-panic and attention no longer have such a severe impact on international stock markets. This finding suggests that uncertainty, which dominated the COVID-19 measure set, has been resolved (potentially by government rescue packages and investors having a better understanding of the pandemic). Investors now appear to monitor case-based measures of COVID-19. There may also be other emerging measures that are relevant but did not exist at the genesis of the COVID-19 crisis. The key finding is that the response of markets to the COVID-19 pandemic has evolved.

5. Conclusion

The COVID-19 pandemic has taken the world by storm. While the literature has employed various measures to quantify the impact of COVID-19 on financial markets – notable examples being cases and deaths, various indicators of government responses, uncertainty and media attention – the question of which mattered most remained open. By focusing on direct measures that capture the unadulterated effects of COVID-19 on financial markets, we sought to identify those that had the greatest impact during the height of the COVID-19 crisis. We used elastic net regression for measures selection and we identified Google search trends, GST_t, the stringency of government responses, GSM_t, and media hype, MHI_t. These measures were shown to be related to statistical factor scores representative of the systematic influences driving the 35 stock markets in our sample, explaining between 10% and 20% of global market movements. While other indicators also impact stock markets, their influence is weaker. We also considered the impact of these COVID-19 measures on market volatility. Only GST_t is associated with volatility triggering effects. This suggests that media related measures, such as MHI_t, reflect a different transmission mechanism. The results indicate that not all regions and markets were equally impacted and that the effect of the pandemic grew from the geographic east to the west as COVID-19 spread during the crisis period. Our interpretation of these three measures in Section 3.3 suggests that stock markets responded to: (i) a general state of uncertainty driven by COVID-19, (ii) an adverse impact on economic activity attributable to lockdown-style policies and (iii) attention combined with bouts of panic related to the evolution of the COVID-19 pandemic.

By undertaking this study, we shed light onto the COVID-19 measures that had the greatest impact on global stock markets during the COVID-19 crisis and provide clarity as to which of them mattered most for investors. We present an overview of how the pandemic spread from its origin in China to other markets and indicate which countries are most resilient, i.e. a finding that may be of interest to investors and portfolio managers. For econometricians and other researchers, we demonstrate the application of a ML technique for identifying the most important COVID-19 measures that matter for international stock markets. In doing so, we show how this approach can be applied to reduce information complexity and yield a limited set of information proxies that matter. The application of the *OIU* measure may also be helpful in future studies that investigate the impact of COVID-19 and stock returns. In line with the literature, we find that the response of international markets to COVID-19 has evolved. Much of the impact of uncertainty and media-fuelled panic has abated and government attempts to control the spread of COVID-19 virus no longer appear to adversely impact stock markets in the post-crisis period. We view this as the emergence of a 'new normal'. Detailed reasons for the emergence of this 'new normal' for international markets pose an avenue for further detailed research. Another area for future research may include an investigation of whether over the longer-term other and more relevant COVID-19 measures emerged, such as vaccination information or COVID-19 variant specific information.

CRediT authorship contribution statement

Jan Jakub Szczygielski: Conceptualization, Methodology, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration. **Ailie Charteris:** Formal analysis, Data curation, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Princess Rutendo Bwanya:** Investigation, Data curation, Writing – original draft, Writing – review & editing. **Janusz Brzeszczyński:** Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.intfin.2022.101592.

References

Adekoya, A.F., Nti, I.K., 2020. The COVID-19 outbreak and effects on major stock market indices across the globe: A machine learning approach. Indian J. Sci. Technol. 13 (35), 3695–3706.

Agarwal, S., Kumar, S., Goel, U., 2019. Stock market response to information diffusion through internet sources: A literature review. Int. J. Inf. Manage. 45, 118–131.

Aggarwal, S., Nawn, S., Dugar, A., 2021. What caused global stock market meltdown during the COVID pandemic–Lockdown stringency or investor panic? Finance Res. Lett. 38, 101827.

Ahmad, W., Kutan, A.M., Chahal, R.J.K., Kattumuri, R., 2021. COVID-19 outbreak and firm-level dynamics in the USA, UK, Europe, and Japan. Int. Rev. Financial Anal., 101888

Al-Awadhi, A.M., Al-Saifi, K., Al-Awadhi, A., Alhamadi, S., 2020. Death and contagious infectious diseases: Impact of the COVID-19 virus on stock market returns. J. Behav. Exp. Finance 100326.

Albulescu, C., 2020. Coronavirus and financial volatility: 40 days of fasting and fear. Working Paper No. 3550630. Politehnica University of Timisoara, Romania. Available at: https://ssrn.com/abstract=3550630.

Ali, M., Alam, N., Rizvi, S.A.R., 2020. Coronavirus (COVID-19) - An epidemic or pandemic for financial markets. J. Behav. Exp. Finance 100341.

Alin, A., 2010. Multicollinearity. Wiley Interdiscip. Rev. Comput. Stat. 2 (3), 370–374.

Alpaydin, E., 2020. Introduction to Machine Learning, 4th ed. MIT Press, Massachusetts.

Altig, D., Baker, S., Barrero, J.M., Bloom, N., Bunn, P., Chen, S., Mizen, P., 2020. Economic uncertainty before and during the COVID-19 pandemic. J. Publ. Econ. 191, 104274.

Andersen, T.G., Bollerslev, T., Diebold, F.X., Labys, P., 2003. Modeling and forecasting realized volatility. Econometrica 71 (2), 579–625.

Arnold, I.J., Vrugt, E.B., 2008. Fundamental uncertainty and stock market volatility. Appl. Financ. Econ. 18 (17), 1425–1440.

Arnold, T., Mattackal, L.P., 2020. Emerging market resurgence carries relapse risk. Reuters. Available at: https://www.reuters.com/article/us-investment-summit-emerging/emerging-market-resurgence-carries-relapse-risk-idUSKBN28D2NF.

Ashraf, B.N., 2020a. Stock markets' reaction to COVID-19: Cases or fatalities? Res. Int. Bus. Finance 54, 101249.

Ashraf, B.N., 2020b. Economic impact of government interventions during the COVID-19 pandemic: International evidence from financial markets. J. Behav. Exp. Finance 27, 100371.

Atkins, A., Niranjan, M., Gerding, E., 2018. Financial news predicts stock market volatility better than close price. J. Financ. Data Sci. 4 (2), 120–137.

Aven, T., Renn, O., 2009. On risk defined as an event where the outcome is uncertain. J. Risk Res. 12 (1), 1–11.

Baek, S., Mohanty, S.K., Glambosky, M., 2020. COVID-19 and stock market volatility: An industry level analysis. Finance Res. Lett. 101748.

Baillie, R.T., DeGennaro, R.P., 1990. Stock returns and volatility. J. Financ. Quantit. Anal. 25 (2), 203–214.

Baker, S.R., Bloom, N., Davis, S.J., 2016. Measuring economic policy uncertainty. Q. J. Econ. 131 (4), 1593–1636.

Baker, S.R., Bloom, N., Davis, S.J., Kost, K., Sammon, M., Viratyosin, T., 2020. The unprecedented stock market reaction to COVID-19. Rev. Asset Pricing Stud. 10 (4), 742–758.

Baker, S.R., Bloom, N., Davis, S., Renault, T., 2021. Twitter-based uncertainty indices. Available at: https://www.policyuncertainty.com/twitter_uncert.html.

Bai, J., Perron, P., 1998. Estimating and testing linear models with multiple structural changes. Econometrica 66 (1), 47–78.

Bai, L., Wei, Y., Wei, G., Li, X., Zhang, S., 2020. Infectious disease pandemic and permanent volatility of international stock markets: A long-term perspective. Finance Res. Lett. 101709.

Barrero, J.M., & Bloom, N. (2020). Economic uncertainty and the recovery. Working paper. Federal Reserve Bank of Kansas City. Available at: https://nbloom.people.stanford.edu/sites/g/files/sbiybj4746/f/jh_final.pdf.

Bekaert, G., Hoerova, M., Duca, M.L., 2013. Risk, uncertainty and monetary policy. J. Monet. Econ. 60 (7), 771–788.

Bera, A., Bubnys, E., Park, H., 1988. Conditional heteroscedasticity in the market model and efficient estimates of betas. Financ. Rev. 23 (2), 201–214.

Bilgin, M.H., Demir, E., Gozgor, G., Karabulut, G., Kaya, H., 2019. A novel index of macroeconomic uncertainty for Turkey based on Google-Trends. Econ. Lett. 184, 108601.

Bonaccorsi, G., Pierri, F., Cinelli, M., Flori, A., Galeazzi, A., Porcelli, F., Pammolli, F., 2020. Economic and social consequences of human mobility restrictions under COVID-19. Proc. Natl. Acad. Sci. 117 (27), 15530–15535.

Bontempi, M.E., Frigeri, M., Golinelli, R., Squadrani, M., 2019. Uncertainty, perception and the internet. Working Paper No. 1134. Quaderni Working Paper, Department of Economics. University of Bologna, Italy. Available at: https://www.econstor.eu/bitstream/10419/213531/1/167922378X.pdf.

Bottou, L., 2014. From machine learning to machine reasoning. Mach. Learn. 94 (2), 133–149.
Bradley, C., Stumper, P., 2021. The impact of COVID-19 on stock markets, one year in. Our Insights. McKinsey & Company. Available at: https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/the-impact-of-covid-19-on-capital-markets-one-year-in.
Brzeszczyński, J., Kutan, A.M., 2015. Public information arrival and investor reaction during a period of institutional change: An episode of early years of a newly independent central bank. J. Comparat. Econ. 43 (3), 727–753.
Caggiano, G., Castelnuovo, E., Kima, R., 2020. The global effects of Covid-19-induced uncertainty. Econ. Lett. 194, 109392.
Canova, F., De Nicolo, G., 1995. Stock returns and real activity: A structural approach. Eur. Econ. Rev. 39 (5), 981–1015.
Capelle-Blancard, G., Desroziers, A., 2020. The stock market is not the economy? Insights from the COVID-19 crisis. COVID Econ. Vetted Real-Time Papers 28, 29–69.
Castelnuovo, E., Tran, T.D., 2017. Google it up! A google trends-based uncertainty index for the United States and Australia. Econ. Lett. 161, 149–153.
Cepoi, C.O., 2020. Asymmetric dependence between stock market returns and news during COVID19 financial turmoil. Financ. Res. Lett. 101658.
Chatzis, S.P., Siakoulis, V., Petropoulos, A., Stavroulakis, E., Vlachogiannakis, N., 2018. Forecasting stock market crisis events using deep and statistical machine learning techniques. Expert Syst. Appl. 112, 353–371.
Chen, S., Igan, D., Pierri, N., & Presbitero, A.F. (2020). Tracking the economic impact of COVID-19 and mitigation policies in Europe and the United States. Working paper no. WP/20/125. International Monetary Fund (IMF). Available at: https://www.imf.org/en/Publications/WP/Issues/2020/07/10/Tracking-the-Economic-Impact-of-COVID-19-and-Mitigation-Policies-in-Europe-and-the-United-49553.
Chen, H., Huang, X., Li, Z., 2020. A content analysis of Chinese news coverage on COVID-19 and tourism. Curr. Issues Tourism. 1763269.
Chen, C., Liu, L., Zhao, N., 2020. Fear sentiment, uncertainty, and bitcoin price dynamics: The case of COVID-19. Emerg. Markets Financ. Trade 56 (10), 2298–2309.
Chiang, T.C., Li, J., Yang, S.Y., 2015. Dynamic stock–bond return correlations and financial market uncertainty. Rev. Quant. Financ. Acc. 45 (1), 59–88.
Chimanga, A., Kotze, D., 2009. A multivariate analysis of factors affecting stock returns on the JSE. African Financ. J. 11 (2), 80–96.
Choi, H., Varian, H., 2012. Predicting the present with Google Trends. Economic Record 88 (1), 2–9.
Cochrane, J. (2018). Stock gyrations. (blog post). Available at: https://johnhcochrane.blogspot.com/2018/02/stock-gyrations.html.
Costola, M., Iacopini, M., Santagiustina, C., 2020. Public concern and the financial markets during the COVID-19 outbreak. Working Paper No. 3591193. Ca' Foscari University of Venice, Italy. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3591193.
Costola, M., Nofer, M., Hinz, O., Pelizzon, L., 2020. Machine learning sentiment analysis, Covid-19 news and stock market reactions. SAFE Working paper no. 288. Leibniz Institute for Financial Research, Goethe University Frankfurt, Germany. Available at: https://www.econstor.eu/bitstream/10419/224131/1/173177205X.pdf.
Cross, M., Ng, S.K., Scuffham, P., 2020. Trading health for wealth: The effect of COVID-19 response stringency. Int. J. Environ. Res. Public Health 17 (23), 8725.
Da, Z., Engelberg, J., Gao, P., 2011. In search of attention. J. Finance 66, 1461–1499.
Da, Z., Engelberg, J., Gao, P., 2015. The sum of all FEARS investor sentiment and asset prices. Rev. Financ. Stud. 28, 1–32.
Deb, P., Furceri, D., Ostry, J.D., Tawk, N., 2020. The economic effects of Covid-19 containment measures. Working paper no. WP/20/158. International Monetary Fund (IMF). Available at: www.imf.org/en/Publications/WP/Issues/2020/08/07/The-Economic-Effects-of-COVID-19-Containment-Measures-49571.
Dées, S., Saint-Guilhem, A., 2011. The role of the United States in the global economy and its evolution over time. Empiric. Econ. 41 (3), 573–591.
Dimic, N., Kiviaho, J., Piljak, V., Äijö, J., 2016. Impact of financial market uncertainty and macroeconomic factors on stock–bond correlation in emerging markets. Res. Int. Bus. Finance 36, 41–51.
Dingel, J.I., Neiman, B., 2020. How many jobs can be done at home? Journal of Public Economics 189, 104235.
Donadelli, M., Gerotto, L., 2019. Non-macro-based Google searches, uncertainty, and real economic activity. Res. Int. Bus. Financ. 48, 111–142.
Duttilo, P., Gattone, S.A., Di Battista, T., 2021. Volatility modeling: an overview of equity markets in the euro area during COVID-19 Pandemic. Mathematics 9 (11), 1212.
Dzielinski, M., 2012. Measuring economic uncertainty and its impact on the stock market. Finance Res. Lett. 9 (3), 167–175.
Eckert, F., Mikosch, H., 2020. Mobility and sales activity during the Corona crisis: Daily indicators for Switzerland. Swiss J. Econ. Statist. 156 (1), 1–10.
Engle, R.F., Bollerslev, T., 1986. Modelling the persistence of conditional variances. Econometric Rev. 5 (1), 1–50.
Etemad-Sajidi, R., 2020. The relationship between the stringency of COVID lockdown measures and GDP. EHL Insights. Available at: https://hospitalityinsights.ehl.edu/stringency-covid-lockdown-gdp.
Fabozzi, F.J., 1998. Factor-based approach to equity portfolio management. In: Fabozzi, F.J. (Ed.), Active Equity Portfolio Management, Frank J. Fabozzi Associates, New Hope, pp. 71-90.
Federal Reserve Economic Data (FRED), 2021. Measuring uncertainty and volatility with FRED data. The FRED Blog. Available at: https://fredblog.stlouisfed.org/2021/06/measuring-uncertainty-and-volatility-with-fred-data/.
Feng, G., Giglio, S., Xiu, D., 2020. Taming the factor zoo: A test of new factors. J. Finance 75 (3), 1327–1370.
Froot, K.A., O'Connell, P.G., 2003. The risk tolerance of international investors. Working paper no. w10157. National Bureau of Economic Research (NBER). Available at: https://ideas.repec.org/cgi-bin/get_doc.pl?urn=RePEc%3Anbr%3Anberwo%3A10157&url=http%3A%2F%2Fwww.nber.org%2Fpapers%2Fw10157.pdf.
FitzGerald, V., 2007. International risk tolerance, capital market failure and capital flows to emerging markets. In: Mavrotas, G., Shorrocks, A. (Eds.), Advancing Development: Core Themes in Global Economics. Palgrave Macmillan: London, 299-318.
Goeman, J., Meijer, R., Chaturvedi, N., 2018. L1 and L2 penalized regression models. Vignette R Package Penalized. Available at: https://mran.microsoft.com/snapshot/2016-05-19/web/packages/penalized/vignettes/penalized.pdf.
Gormsen, N.J., Koijen, R.S., 2020. Coronavirus: Impact on stock prices and growth expectations. Rev. Asset Pricing Stud. 10 (4), 574–597.
Gottlieb, C., Grobovšek, T., Poschke, M., Imbert, C., Panizza, U., 2020a. How do lockdowns affect economic activity in developing countries? Economics Observatory. Available at: https://www.economicsobservatory.com/how-do-lockdowns-affect-economic-activity-developing-countries.
Gottlieb, C., Grobovsek, J., Poschke, M., Saltiel, F., 2020b. Lockdown accounting. Discussion Papers no. 13397, Institute of Labour Economics (IZA). Available at: https://ideas.repec.org/cgi-bin/get_doc.pl?urn=RePEc%3Aiza%3Aizadps%3Adp13397&url=https%3A%2F%2Fdocs.iza.org%2Fdp13397.pdf.
Gozzi, N., Tizzani, M., Starnini, M., Ciulla, F., Paolotti, D., Panisson, A., Perra, N., 2020. Collective response to media coverage of the COVID-19 pandemic on Reddit and Wikipedia: Mixed-methods analysis. J. Med. Internet Res. 22 (10), e21597.
Gupta, R., Subramaniam, S., Bouri, E., Ji, Q., 2020. Infectious disease-related uncertainty and the safe-haven characteristic of US treasury securities. Int. Rev. Econ. Finance 71, 289–298.
Hailemariam, A., Smyth, R., Zhang, X., 2019. Oil prices and economic policy uncertainty: Evidence from a nonparametric panel data model. Energy Econ. 83, 40–51.
Hale, T., Webster, S. Petherick, A., Phillips, T., Kira, B., 2020. Oxford COVID-19 government response tracker. Blavatnik School of Government, University of Oxford. Available at: https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker.
Hanke, M., Kosolapova, M., Weissensteiner, A., 2020. COVID-19 and market expectations: Evidence from option-implied densities. Working paper. Available at: https://ssrn.com/abstract=3616625.
Haroon, O., Rizvi, S.A.R., 2020. COVID-19: Media coverage and financial markets behaviour – a sectoral inquiry. J. Behav. Exp. Financ. 27, 100343.
Henríquez, J., Gonzalo-Almorox, E., Garcia-Goñi, M., Paolucci, F., 2020. The first months of the COVID-19 pandemic in Spain. Health Pol. Technol. 9 (4), 560–574.
Huang, C., Wang, Y., Li, X., Ren, L., Zhao, J., Hu, Y., Cao, B., 2020. Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. The Lancet 395 (10223), 497–506.
Hwang, S., Valls Pereira, P.L., 2006. Small sample properties of GARCH estimates and persistence. Eur. J. Finance 12 (6–7), 473–494.
International Monetary Fund (IMF). (2021). Real GDP growth. Annual percent change. Available at: https://www.imf.org/external/datamapper/NGDP_RPCH@WEO/OEMDC/ADVEC/WEOWORLD.
Junior, L.S., Franca, I.D.P., 2012. Correlation of financial markets in times of crisis. Physica A 391 (1–2), 187–208.
Khan, W., Ghazanfar, M.A., Azam, M.A., Karami, A., Alyoubi, K.H., Alfakeeh, A.S., 2020. Stock market prediction using machine learning classifiers and social media news. J. Ambient Intell. Humanized Computing 01839.

Ko, J.H., Lee, C.M., 2015. International economic policy uncertainty and stock prices: Wavelet approach. Econ. Lett. 134, 118–122.
König, M., Winkler, A., 2021. COVID-19: Lockdowns, fatality rates and GDP growth. Intereconomics 56 (1), 32–39.
Kose, A., Lakatos, C., Ohnsorge, F.L., Stocker, M., 2017. The global role of the US economy: Linkages, policies and spillovers. Policy Research Working Paper no. 7962. World Bank. Available at: https://openknowledge.worldbank.org/handle/10986/26021.
Koutoulas, G., Kryzanowski, L., 1994. Integration or segmentation of the Canadian stock market: Evidence based on the APT. Can. J. Econ. 329–351.
Lalmuanawma, S., Hussain, J., Chhakchhuak, L., 2020. Applications of machine learning and artificial intelligence for Covid-19 (SARS-CoV-2) pandemic: A review. Chaos, Solitons Fractals 139, 110059.
Liu, K., 2020. The effects of COVID-19 on Chinese stock markets: An EGARCH approach. Working Paper No. 3612461. University of Sydney, Australia. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3612461.
Liu, J., Liang, G., Siegmund, K.D., Lewinger, J.P., 2018. Data integration by multi-tuning parameter elastic net regression. BMC Bioinf. 19 (1), 1–9.
Lu, N., Cheng, K.W., Qamar, N., Huang, K.C., Johnson, J.A., 2020. Weathering COVID-19 storm: Successful control measures of five Asian countries. Am. J. Infect. Control 48 (7), 851–852.
Lyócsa, Š., Baumöhl, E., Výrost, T., Molnár, P., 2020. Fear of the coronavirus and the stock markets. Finance Res. Lett. 36, 101735.
Maharani, A., 2008. Panic selling. Working paper. Available at: http://ssrn.com/abstract=1301842.
Mamaysky, H., 2020. Financial markets and news about the Coronavirus. Available at: https://ssrn.com/abstract=3565597.
McCauley, R.N., 2013. Risk-on/risk-off, capital flows, leverage and safe assets. J. Financ. Perspect. 1 (2), 1–10.
Narayan, P.K., Phan, D.H.B., Liu, G., 2020. COVID-19 lockdowns, stimulus packages, travel bans, and stock returns. Finance Res. Lett. 101732.
Nicomedes, C.J.C., Avila, R.M.A., 2020. An analysis on the panic during COVID-19 pandemic through an online form. J. Affect. Disord. 276, 14–22.
Nimon, K.F., Oswald, F.L., 2013. Understanding the results of multiple linear regression: Beyond standardized regression coefficients. Org. Res. Methods 16 (4), 650–674.
Our World in Data, 2020. Western European exports by region of destination. Available at: https://ourworldindata.org/grapher/exports-from-western-europe-to-other-regions.
Papadamou, S., Fassas, A., Kenourgios, D., Dimitriou, D., 2020. Direct and indirect effects of COVID-19 pandemic on implied stock market volatility: Evidence from panel data analysis. MPRA Paper No. 100020. University of Thessaly, Greece. Available at: https://mpra.ub.uni-muenchen.de/id/eprint/100020.
Pastor, L., Veronesi, P., 2012. Uncertainty about government policy and stock prices. J. Finance 67 (4), 1219–1264.
Patel, J., Shah, S., Thakkar, P., Kotecha, K., 2015a. Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques. Expert Syst. Appl. 42 (1), 259–268.
Patel, J., Shah, S., Thakkar, P., Kotecha, K., 2015b. Predicting stock market index using fusion of machine learning techniques. Expert Syst. Appl. 42 (4), 2162–2172.
Peng, Y., Nagata, M.H., 2020. An empirical overview of nonlinearity and overfitting in machine learning using COVID-19 data. Chaos Solitons Fractals 139, 110055.
Peng, L., Xiong, W., 2006. Investor attention, overconfidence and category learning. J. Financ. Econ. 80, 563–602.
Pernagallo, G., Torrisi, B., 2020. A theory of information overload applied to perfectly efficient financial markets. Rev. Behav. Finance 1940–5979.
Priestley, R., 1996. The arbitrage pricing theory, macroeconomic and financial factors, and expectations generating processes. J. Bank. Finance 20 (5), 869–890.
Ramelli, S., Wagner, A.F., 2020. Feverish stock price reactions to COVID-19. Discussion Paper No. DP14511. Centre for Economic Policy Research (CEPR). Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3550274.
Rezaei, F., Cohen, R.A., 2012. The role of social media in the recent political shifts in the Middle East and North Africa. J. Humanities Soc. Sci. 4 (6), 1–10.
Salisu, A.A., Akanni, L., 2020. Constructing a global fear index for the COVID-19 pandemic. Emerg. Markets Financ. Trade 56 (10), 2310–2331.
Salisu, A.A., Akanni, L., Raheem, I., 2020. The COVID-19 global fear index and the predictability of commodity price returns. J. Behav. Exp. Finance 27, 100383.
Seven, Ü., Yılmaz, F., 2021. World equity markets and COVID-19: Immediate response and recovery prospects. Res. Int. Business Finance 56, 101349.
Shiller, R.J., 1987. Investor behavior in the October 1987 stock market crash: Survey evidence. Working paper no. w2446, National Bureau of Economic Research (NBER). Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=227115.
Shin, J., 2005. Stock returns and volatility in emerging stock markets. Int. J. Bus. Econom. 4 (1), 31–43.
Smales, L.A., 2019. How does policy uncertainty influence financial market uncertainty across the G7? Working Paper No. 3427659. University of Western Australia, Australia. Available at: https://papers.ssrn.com/sol3/Papers.cfm?abstract_id=3427659.
Smales, L.A., 2021a. Investor attention and global market returns during the COVID-19 crisis. Int. Rev. Financ. Anal. 73, 101616.
Smales, L.A., 2021b. Investor attention and the response of US stock sectors to the COVID-19 crisis. Rev. Behav. Finance 13 (1), 1940–5979.
Strohecker, K. (2020 April 24). The cost of lockdowns in emerging markets. Reuters. Available at: http://www.reuters.com/article/us-health-coronavirus-emerging-lockdowns-idUSKCN2261RM.
Starosta, K., Onete, C.B., Grosu, R., Plesea, D., 2020. COVID-19 mass media infodemic in six European countries. Advance. https://doi.org/10.31124/advance.13333697.v1.
Su, Z., Fang, T., Yin, L., 2019. Understanding stock market volatility: What is the role of US uncertainty? The North American Journal of Economics and Finance 48, 582–590.
Szczygielski, J.J., Brzeszczyński, J., Charteris, A., Bwanya, P., 2022. The COVID-19 storm and the energy sector: The impact and role of uncertainty. *Energy Econ.* 109, 105258 https://doi.org/10.1016/j.eneco.2021.105258.
Szczygielski, J.J., Brümmer, L.M., Wolmarans, H.P., 2020a. Underspecification of the empirical return-factor model and a factor analytic augmentation as a solution to factor omission. Stud. Econ. Economet. 44 (2), 133–165.
Szczygielski, J.J., Brümmer, L., Wolmarans, H.P., 2020b. An augmented macroeconomic linear factor model of South African industrial sector returns. J. Risk Finance 21 (5), 517–541.
Szczygielski, J.J., Bwanya, P., Charteris, A., Brzeszczyński, J., 2021. The only certainty is uncertainty: An analysis of the impact of COVID-19 uncertainty on regional stock markets. Finance Res. Lett. 101945.
Szczygielski, J.J., Charteris, A., Bwanya, P., Brzeszczyński, J., 2022. The impact and role of COVID-19 uncertainty: A global industry analysis. Int. Rev. Financ. Anal. 80, 101837.
Tobek, O., Hronec, M., 2020. Does it pay to follow anomalies research? Machine learning approach with international evidence. J. Financ. Markets 100588.
van Rensburg, P., 2002. Market segmentation on the Johannesburg stock exchange II. Stud. Econ. Econometr. 26 (1), 83–99.
Uddin, G.S., Yahya, M., Goswami, G.G., Ahmed, A., Lucey, B.M., 2020. Stock market contagion of COVID-19 in emerging economies. Working Paper No. 3573333. Linkoping University, Sweden. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3573333.
Vasterman, P.L., 2005. Media-hype: Self-reinforcing news waves, journalistic standards and the construction of social problems. Eur. J. Commun. 20 (4), 508–530.
Wasserman, H., 2020. The state of South African media: A space to contest democracy. Publizistik 65 (3), 451–465.
Weigand, A., 2019. Machine learning in empirical asset pricing. Fin. Markets. Portfolio Mgmt. 33 (1), 93–104.
World Economic Forum (2019). The $86 trillion world economy – in one chart. Available at: https://www.weforum.org/agenda/2019/09/fifteen-countries-represent-three-quarters-total-gdp/.
World Health Organisation (WHO) (2020). WHO COVID-19 Dashboard 1st February 2021. Retrieved February 2, from: https://covid19.who.int.
Wurm, L.H., Fisicaro, S.A., 2014. What residualizing predictors in regression analyses does (and what it does not do). J. Mem. Lang. 72, 37–48.
Yarovaya, L., Matkovsky, R., Jalan, A., 2021. The COVID-19 black swan crisis: Reaction and recovery of various financial markets. Research in International Business and Finance, p. 101521.
Yilmazkuday, H. (2020). Coronavirus disease 2019 and the global economy. Working paper. Available at: https://papers.ssrn.com/sol3/Papers.cfm?abstract_id=3554381.
Yu, K.D.S., Aviso, K.B., Santos, J.R., Tan, R.R., 2020. The economic impact of lockdowns: A persistent inoperability input-output approach. Economies 8 (4), 109.

Zaremba, A., Kizys, R., Aharon, D.Y., Demir, E., 2020. Infected markets: Novel coronavirus, government interventions, and stock return volatility around the globe. Finance Res. Lett. 101597.
Zhang, D., Hu, M., Ji, Q., 2020. Financial markets under the global pandemic of COVID-19. Finance Res. Lett. 101528.
Zou, H., Hastie, T., 2005. Regularization and variable selection via the elastic net. J. Roy. Statist. Soc.: Series B (Statist. Methodol.) 67 (2), 301–320.
Zou, H., Zhang, H.H., 2009. On the adaptive elastic-net with a diverging number of parameters. Ann. Stat. 37 (4), 1733–1751.
Zwick, W.R., Velicer, W.F., 1986. Comparison of five rules for determining the number of components to retain. Psychol. Bull. 99 (3), 432–442.