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# Which COVID-19 information really impacts stock markets?

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# Which COVID-19 information really impacts stock markets?

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# Which COVID-19 information really impacts stock markets?


**Abstract**

Information about COVID-19 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. 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.



**Keywords:** COVID-19, pandemic, returns, global stock markets, elastic net regression, machine learning

**JEL classification:** C22, C38, C58, D53, G01, G12

## 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 result of the implementation of containment policies such as lockdowns and travel bans which have restricted economic activity. The International Monetary Fund (IMF) predicts that global gross domestic product (GDP) will have contracted by 4.4% in 2020 (Amaro, 2020). Governments and central banks have attempted to support economies through stimulus packages, reductions in interest rates, asset purchase programmes and credit guarantees (Capelle-Blancard & 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 (see for example, Al-Awadhi et al., 2020; Ali et al., 2020; Capelle-Blancard & Desroziers, 2020), although the findings are mixed on whether cases (Ashraf, 2020a) or deaths (Adekoya & 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 for COVID-19 related terms have been used extensively as a proxy for retail investor attention (Da et al., 2011; Smales, 2021). Furthermore, according to economic psychology, individuals respond to uncertainty about specific events by searching more intensively for relevant information (Dzielinski,

[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 et al., 2020), commodities (Salisu, Akanni & Raheem, 2020), and derivatives (Hanke et al., 2020).

2012; Da et al., 2015; Castelnuovo & 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, 2021; Szczygielski, Bwanya et al., 2021). Studies of the impact of changes in COVID-19 related Google Search Trends report a negative impact for developed and developing country stock markets (see for example, Ahundjanov et al., 2020; Capelle-Blancard & Desroziers, 2020; Costola et al., 2020a; Liu, 2020; Papadamou et al., 2020; Smales, 2021; Szczygielski, Bwanya et al., 2021). The intensity of the impact of COVID-19 related Google Search Trends has also been found to vary over time and across countries, industries and firms (Ramelli & Wagner, 2020; Smales, 2020; Szczygielski, Charteris et al., 2020; Szczygielski, Bwanya 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 have 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)

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

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, Bwanya et al., 2021) and positive (Capelle-Blancard & 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). In contrast, social distancing measures and lockdowns have 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). In relation to mobility, 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), a measure 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 & Bloom, 2020; Caggiano et al., 2020). Moreover, research shows that VIX and TMU have moved closely with COVID-19 related Google Search Trends during the COVID-19 pandemic, suggesting that search trends reflect market uncertainty (Chen, Liu et al., 2020; Papadamou et al., 2020; Baig et al., 2021; Szczygielski, Bwanya et al., 2021). A number of studies examine the impact of COVID-19 on financial markets using these indirect measures and find that VIX

[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 volume 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 & Akanni, 2020).

and TMU have a negative effect on stock returns globally (Capelle-Blancard & Desroziers, 2020; Salisu & Akanni, 2020; Szczygielski, Bwanya et al., 2021).

Three notable conclusions emerge from the literature: (i) COVID-19 has impacted stock returns, (ii) impact has varied across countries, (iii) numerous measures of COVID-19 have been utilised to measure its impact (see Table A1 in the Appendix for a summary of studies) and (iv) it is not clear which of these measures 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. 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 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 algorithms in the form of elastic net regression (Zou & Hastie, 2005) for measure identification and selection. We then relate these measures to statistically derived factors that summarise the return generating process over the COVID-19 period which we define as 1 January 2020 to 20 October 2020. Finally, the selected measures are related to returns on the 35 stock markets that comprise our sample and the global market 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 with the aim of identifying a set of direct measures that are most important and encompass other measures. In total, we consider (to the authors' knowledge) the most extensive set of COVID-19 measures that are directly related to the crisis, totalling 24 measures. In doing so, we provide clarity as to which measures matter 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 variable 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., 2020; Khan et al., 2020) and asset pricing anomalies (such as Weigand, 2019; Tobek & Hronec, 2020). We also 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 & Nagata, 2020; Raza, 2020) and financial (Adekoya & Nti, 2020; Baek et al., 2020; Costola et al., 2020b). 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 & Nti, 2020). Fourth, we apply and propose empirical-analytical innovations. The first is a novel empirical impact measure first proposed by Szczygielski, Brzeszczyński et al. (2021), which we term the 'overall impact of uncertainty' (OIU). This measure jointly reflects the impact and intensity of COVID-19 related measure(s) on stock markets. We apply this measure to quantify the impact of COVID-19 related uncertainty (as measured by movements in Google Search Trends; Section 3.3 for interpretation) on individual stock markets and stock markets grouped according to region and economic development. The second is a methodological improvement that permits the disentanglement of the impact of correlated variables without the need to transform either variable of interest – the dependant or independent variables – through orthogonalisation (Wurm & Fisicaro, 2014). Finally, we ascribe meaning and interpretation to the most important COVID-19 measures identified in this study. 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.

Following an analysis of the structure of the return generating process using factor analysis, we extract four statistical factors from stock returns for the COVID-19 period and relate these to the COVID-19 measures using elastic net regression. Using this approach, we identify four key measures that summarize the impact of COVID-19 on stock markers. The first and most important factor is associated with COVID-19 related search volumes as measured by Google Search Trends, which we designate as $GST_t$ in our analysis. We interpret this as an uncertainty factor that is also associated with sentiment and economic uncertainty. The second factor is related to the stringency of government responses, which we designate as $GSM_t$ in our analysis, 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 factor is related to the weighted overall government response index, designated as $GOR_t$ in the analysis. 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 fourth factor is related to the media hype index, $MHI_t$. 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 period, depending on whether they are considered individually, jointly, with or without structural breaks.

We confirm the widespread negative impact of COVID-19 related uncertainty on stock market returns and find that $GST_t$ is also widely associated with heightened volatility in most markets. Geographical proximity and a country's level of development matter in terms of the effects of COVID-19 uncertainty on stock markets. Countries further west from the outbreak of the virus in China are more impacted by COVID-19 related uncertainty as are developed countries. Government stringency measures and media hype also have a significant negative effect on stock markets, with emerging markets being more impacted. In contrast, both measures have a limited impact on stock market volatility. We conclude that most of the impact of COVID-19 on international markets can be summarised by a small number of key COVID-19 related measures.

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 is also analysed in this section and it is shown that key measures selected dominate the remaining COVID-19 measures. Section 4 concludes the study.

## 2. Data and Methodology

### 2.1. Data

Our financial data spans the period from 1 January 2015 to 20 October 2020, comprising daily levels for 35 of the largest MSCI Country indices by market capitalization in US Dollars as of the end of November 2019.[5] 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, together with descriptive statistics.[6] The measure sample comprises 24 measures obtained from numerous sources. Given that the series of interest are logarithmic returns on the respective markets in the sample, we difference the COVID-19 measures 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 shown to be 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 A3 in the Appendix.

[5] Our sample comprises markets with the largest market capitalization as of November 2019 although we define the COVID-19 period as 1 January 2020 to 20 October 2020. We chose 19 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.
[6] Sources are detailed in Table A2 in the Appendix.

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

| Index | Market Cap | Mean | Median | Maximum | Minimum | Std. dev. | Skewness | Kurtosis | Shapiro-Wilk |
|---|---|---|---|---|---|---|---|---|---|
| World | 64623330 | 0.0002 | 0.0005 | 0.0806 | -0.1000 | 0.0095 | -1.5891 | 26.5588 | 0.8134*** |
| 1. US | 28808028 | 0.0004 | 0.0003 | 0.0899 | -0.1292 | 0.0117 | -1.1265 | 25.2140 | 0.8014*** |
| 2. China | 8071533 | 0.0003 | 0.0002 | 0.0584 | -0.0661 | 0.0128 | -0.2904 | 5.4133 | 0.9726*** |
| 3. Japan | 4817633 | 0.0002 | 0.0000 | 0.0733 | -0.0726 | 0.0112 | 0.0361 | 8.8015 | 0.9326*** |
| 4. UK | 2456466 | -0.0002 | 0.0001 | 0.0992 | -0.1330 | 0.0124 | -1.3165 | 20.6915 | 0.8577*** |
| 5. France | 2383072 | 0.0001 | 0.0004 | 0.0812 | -0.1403 | 0.0126 | -1.3398 | 19.4491 | 0.8781*** |
| 6. Canada | 1669916 | 0.0000 | 0.0000 | 0.1182 | -0.1364 | 0.0127 | -1.5260 | 32.6239 | 0.7932*** |
| 7. Germany | 1642472 | 0.0000 | 0.0004 | 0.0996 | -0.1422 | 0.0128 | -1.0455 | 18.7842 | 0.8911*** |
| 8. Switzerland | 1474858 | 0.0002 | 0.0004 | 0.0599 | -0.1040 | 0.0094 | -1.0450 | 15.6798 | 0.9213*** |
| 9. India | 1353521 | 0.0001 | 0.0004 | 0.0928 | -0.1479 | 0.0125 | -1.5323 | 22.7709 | 0.8635*** |
| 10. Australia | 1089376 | 0.0000 | 0.0002 | 0.0697 | -0.1105 | 0.0133 | -1.1193 | 14.0422 | 0.8978*** |
| 11. Korea | 992949 | 0.0002 | 0.0000 | 0.1055 | -0.0700 | 0.0132 | -0.0996 | 9.2303 | 0.9366*** |
| 12. Hong Kong | 931809 | 0.0001 | 0.0001 | 0.0535 | -0.0715 | 0.0108 | -0.4991 | 7.4799 | 0.9465*** |
| 13. Taiwan | 883919 | 0.0003 | 0.0000 | 0.0747 | -0.0687 | 0.0113 | -0.3517 | 8.0493 | 0.9445*** |
| 14. Brazil | 770022 | -0.0001 | 0.0003 | 0.1516 | -0.1943 | 0.0229 | -1.0193 | 14.7586 | 0.8998*** |
| 15. Netherlands | 745075 | 0.0003 | 0.0008 | 0.0697 | -0.1121 | 0.0112 | -1.0181 | 13.6633 | 0.9160*** |
| 16. Russia | 584517 | 0.0002 | 0.0000 | 0.0974 | -0.1325 | 0.0178 | -0.5481 | 10.5548 | 0.9266*** |
| 17. Spain | 577200 | -0.0002 | 0.0000 | 0.0757 | -0.1635 | 0.0142 | -1.9444 | 25.9133 | 0.8734*** |
| 18. Italy | 482304 | -0.0001 | 0.0001 | 0.0834 | -0.1966 | 0.0156 | -2.1701 | 27.9465 | 0.8673*** |
| 19. Sweden | 456920 | 0.0001 | 0.0002 | 0.0692 | -0.1330 | 0.0137 | -1.3410 | 16.4428 | 0.9066*** |
| 20. Saudi Arabia | 404885 | 0.0001 | 0.0000 | 0.0836 | -0.1721 | 0.0128 | -2.3229 | 36.1817 | 0.7902*** |
| 21. Thailand | 370781 | -0.0001 | 0.0000 | 0.0770 | -0.1207 | 0.0118 | -1.4372 | 21.6501 | 0.8543*** |
| 22. South Africa | 356191 | -0.0002 | 0.0000 | 0.0831 | -0.1271 | 0.0195 | -0.6647 | 7.0594 | 0.9558*** |
| 23. Denmark | 336688 | 0.0004 | 0.0002 | 0.0550 | -0.0869 | 0.0114 | -0.4991 | 7.4540 | 0.9574*** |
| 24. Singapore | 296370 | -0.0002 | 0.0000 | 0.0705 | -0.0778 | 0.0105 | -0.3307 | 10.4218 | 0.9217*** |
| 25. Belgium | 292243 | -0.0002 | 0.0000 | 0.0695 | -0.1735 | 0.0134 | -1.8577 | 24.8084 | 0.8748*** |
| 26. Indonesia | 291250 | -0.0002 | 0.0000 | 0.1548 | -0.1022 | 0.0158 | -0.0937 | 14.0310 | 0.8948*** |
| 27. Malaysia | 263317 | -0.0002 | 0.0000 | 0.0730 | -0.0575 | 0.0094 | -0.2455 | 9.8986 | 0.9230*** |
| 28. Mexico | 237681 | -0.0003 | -0.0001 | 0.0685 | -0.1118 | 0.0156 | -0.8599 | 9.3586 | 0.9336*** |
| 29. Norway | 177487 | -0.0001 | 0.0000 | 0.0702 | -0.1352 | 0.0151 | -0.9380 | 11.3521 | 0.9289*** |
| 30. Finland | 172694 | 0.0001 | 0.0000 | 0.0672 | -0.1175 | 0.0126 | -1.0116 | 13.7798 | 0.9218*** |
| 31. Philippines | 165397 | -0.0002 | 0.0000 | 0.0832 | -0.1414 | 0.0132 | -1.5205 | 19.8684 | 0.8801*** |
| 32. UAE | 137466 | -0.0003 | 0.0000 | 0.0860 | -0.1541 | 0.0128 | -1.6365 | 27.7963 | 0.7885*** |
| 33. Qatar | 123568 | -0.0002 | 0.0000 | 0.0598 | -0.1387 | 0.0119 | -1.3513 | 19.8220 | 0.8474*** |
| 34. Israel | 105410 | -0.0001 | 0.0002 | 0.0984 | -0.1169 | 0.0129 | -0.9967 | 16.1453 | 0.8690*** |
| 35. Chile | 99088 | -0.0003 | -0.0002 | 0.1045 | -0.1674 | 0.0152 | -1.2087 | 22.9906 | 0.8592*** |

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

**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: 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. 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 the number of lags selected using the Akaike Information Criterion (AIC). Asterisks, ***; ** and *, indicate statistical significance at the respective 1%, 5% and 10% levels of significance.

### 2.2.1. 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 period which we designate 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 this date. The first documented COVID-19 hospital admission took place on 16 December 2019 in Wuhan, China and by 2 January 2020, 41 patients in Wuhan were confirmed to have the novel coronavirus (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 as is the case for the number of deaths.

Returns over the pre-COVID-19 and COVID-19 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 period. Extracted factor scores may be viewed as representations of composite *common* factors driving national aggregate returns (Szczygielski, Brümmer & Wolmarans, 2020a). To identify the number of latent factors in national stock market returns, the minimum average partial (MAP) test is applied. This test identifies the number of factors that most closely result in an approximation of the assumption of uncorrelated residuals, $E\left(\varepsilon_{i,t}, \varepsilon_{j,t}\right)$, that underlies factor models (Zwick & Velicer, 1986). Once factor scores have been derived, these factor scores are subjected to varimax rotation and are then used to selected and identify the impact of COVID-19 measures on stock markets in the next step.

### 2.2.2. Identification and selection of COVID-19

While the preceding analysis yields insight into the structure of the return generating process for the pre-COVID-19 and COVID-19 periods, it also serves another important purpose. It produces factors 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 machine learning. 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 $i$, $F_{CV19,t}$:

$$F_{k,t} = \alpha_i + \sum_{k\geq 0}^{k} \beta_{CV19,k}\, F_{CV19,t} + \varepsilon_{k,t} \quad (1)$$

$$\beta_k(\text{enet}) = \arg\min\left[\frac{1}{2n}\sum_i^n\left(F_{k,t} - \alpha_k \sum_{k\geq 1}^{k} \beta_{k,CV19}\, F_{CV19,t}\right)^2 + \lambda\left(\frac{1-\alpha}{2}\sum_{k=1}^{k}\beta_{k,CV19}^2 + \alpha\sum_{k=1}^{k}\left|\beta_{k,CV19}\right|\right)\right] \quad (2)$$

where $\lambda$ is the penalty parameter determined by cross-validation and $\alpha$ controls the amount of penalties applied. The elastic net estimator combines a mixture of LASSO (L1 norm, $\lambda\sum_{k\geq 1}^{k}\left|\beta_{k,CV19}\right|$) and Ridge (square of L2 norm, $\sum_{k\geq 1}^{k}\beta_{k,CV19}^2$) 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 & Zhang, 2009).

We believe that this approach is well-suited to the selection and identification of COVID-19 measures that move stock markets 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 A3 in the Appendix). Due to multicollinearity, it will be difficult to determine the relative importance of specific measures. Furthermore, with multicollinearity present, coefficients will be sensitive to small changes in model specification and the precision of the estimates will be reduced alongside a reduction in the power of significance tests (Alin, 2010). We could use factor analytic or principal component techniques to extract common factors from highly correlated COVID-19 measure series. A limitation of this approach is that the extracted series will have little economic meaning and the question of the relative importance of each measure will not be addressed (Priestley, 1996; Szczygielski et al., 2020). An alternative is to average individual measures to obtain a single metric. For example, Salisu and Akanni (2020) averaged COVID-19 cases and deaths (the deviation in expectations of cases and deaths over a 14-day period relative to current values). Although they ascribe economic meaning to the constructed metric – calling it a "fear" index – this approach does not allow the relative importance of *individual* measures to be examined.

The elastic net estimator outlined above (equation (2)) draws upon machine learning; 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 & Hastie, 2005; Zou & Zhang, 2009; Goeman et al., 2018; Kirpich et al., 2018; Liu et al., 2018). We are therefore able to identify the most important COVID-19 measures by relating factor scores to COVID-19 measures while accounting for multicollinearity and attaining a degree of confidence that the measures selected should remain relevant out-of-sample.

To select COVID-19 measures, an iterative process is followed. Equation (1) is estimated relating each factor score series (Section 2.2.1) to the full set of COVID-19 measures. This is then repeated but only retaining those measures for which coefficients are non-zero for $\lambda_{min}$, $\lambda_{1SE}$ and $\lambda_{2SE}$, where $\lambda_{1SE}$ and $\lambda_{2SE}$ are penalties one and two standard errors from $\lambda_{min}$. 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 factor score 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 the factor scores is that we can determine the *total* amount of shared variance that is that is explained by the identified COVID-19 measure 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:

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

### 2.2.3. Interpretation of COVID-19 measures

Once we have 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 these COVID-19 measures. 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 (Renault et al., 2020), 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. 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. Following preliminary analysis, we apply the iterative selection procedure outlined in Section 2.2.2. 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 & De Nicolo, 1995).

### 2.2.4. 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 2.2.2.) for the factor scores to the individual stock markets in our sample, jointly and individually:

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

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 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 periods. Three factors are extracted from returns for the long and short pre-COVID-19 periods respectively.[7] Nevertheless, 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 period with a communality of 0.7307, which is indicative of a higher amount of shared variance reflected by these factors. Panel B shows that the first factor, $F_{1,k}$, is the most important, explaining over 56% of total shared variance in returns. This is followed by $F_{2,k}$, which explains 9.00% 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 COVID-19 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 period, we report average return correlations (see Junior & 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 the factors extracted over the COVID-19 period and are indicative of a change in the structure of the return generating process.

[7] 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.

Table 3: Pre-COVID-19 and COVID-19 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 |
| COVID-19 | 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 | | |
|---|---|---|
| | **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 |
| COVID-19 | 0.4590 | 0.5630 |

***Notes:*** This table reports the results of factor analysis applied to returns over the pre-COVID-19 and COVID-19 periods. The pre-COVID-19 sub-periods are defined as 1 January 2015 to 31 December 2019 (full) and 1 January 2019 to 31 December 2019 (short) respectively. The COVID-19 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 extract factor score series and the cumulative communality for all four factor score series. Panel C reports average return correlations for the pre-COVID and COVID-19 periods. Spearman and ordinary correlations are reported.

### 3.2. COVID-19 measure selection

Next, we relate factor scores to the full set of COVID-19 measures with the aim of determining which measures have a systematic impact on stock markets as opposed to identifying measures that impact a subset of markets. Also, by establishing the relative importance of each factor in accounting for shared variance in Panel B of Table 3, we are able to gain an understanding of the importance of COVID-19 measures by establishing which factor score series are associated with specific COVID-19 measures. Table 4 reports the results of the final iterations of elastic net regressions.[8] Following preliminary analysis and tests of different 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 of the factor score series. $F_{1,t}$ is related to changes in Google Search Trends, $GST_t$, following two iterations. $F_{2,t}$ is related to the stringency of government measures applied to control the spread of COVID-19, $GSM_t$, following five iterations. $F_{3,t}$ is related to changes

[8] Full results are available in Excel format from the authors upon request.

in the weighted overall government response index, $GOR_t$, after four iterations. $F_{4,t}$ is related to movements in the media hype index, $MHI_t$, following four iterations. Given the recency of the COVID-19 crisis, a limitation that arises is that of short data series. The number of datapoints 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 COVID-19 measures with fewer than 200 observations. The 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 $\lambda_{min}$, $\lambda_{1SE}$ and $\lambda_{2SE}$. 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 4: Final iteration results of elastic net regularization**

| | $F_1$: 2 iterations | | | | $F_2$: 5 iterations | | | | $F_3$: 4 iterations | | | | $F_4$: 4 iterations | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\lambda_{min}$, | $\lambda_{1SE}$ | $\lambda_{2SE}$ | | $\lambda_{min}$, | $\lambda_{1SE}$ | $\lambda_{2SE}$ | | $\lambda_{min}$ | $\lambda_{1SE}$ | $\lambda_{2SE}$ | | $\lambda_{min}$ | $\lambda_{1SE}$ | $\lambda_{2SE}$ |
| $\alpha_i$ | -0.0358 | -0.0056 | -0.0056 | $\alpha_i$ | 0.0447 | -5.42E-06 | -5.42E-06 | $\alpha_i$ | -0.0001 | -0.0001 | -0.0001 | $\alpha_i$ | 0.0342 | -0.0023 | -0.0023 |
| $CAS_t$ | 0.0000 | 0 | 0 | $GCR_t$ | -0.0146 | 0 | 0 | $GOR_t$ | -1.71E-09 | -1.71E-09 | -1.71E-09 | $CAS_t$ | 0.0000 | 0.0000 | 0.0000 |
| $CAS_{t-1}$ | -0.0001 | 0 | 0 | $GSM_t$ | -0.0820 | -3.14E-09 | -3.14E-09 | $MCI_t$ | 0.0000 | 0.0000 | 0.0000 | $AMT_t$ | -0.1386 | 0.0000 | 0.0000 |
| $DEA_t$ | 0.0000 | 0 | 0 | $MHI_t$ | -0.0385 | 0 | 0 | | | | | $MHI_t$ | -0.0818 | -1.41E-09 | -1.41E-09 |
| $DEA_{t-1}$ | 1.8807 | 0 | 0 | | | | | | | | | $MCI_t$ | -0.0658 | 0.0000 | 0.0000 |
| $REC_t$ | -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 | d.f. | 3 | 1 | 1 | d.f. | 1 | 1 | 1 | d.f. | 3 | 1 | 1 |
| $L_1$ | 75.5992 | 5.59E-03 | 5.59E-03 | $L_1$ | 0.179837 | 5.43E-06 | 5.43E-06 | $L_1$ | 0.0001 | 0.0001 | 0.0001 | $L_1$ | 0.3205 | 0.0023 | 0.0023 |
| $R^2$ | 0.2643 | 4.93E-09 | 4.93E-09 | $R^2$ | 0.10169 | 3.26E-09 | 3.26E-09 | $R^2$ | 1.34E-09 | 1.34E-09 | 1.34E-09 | $R^2$ | 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. The procedure is repeated until only measures for which coefficients are non-zero for the $\lambda_{min}$, $\lambda_{1SE}$ and $\lambda_{2SE}$ penalties remain. *d.f.* is the number of measures with non-zero coefficients and L1 norm is the sparsity inducing penalty. $R^2$ is the coefficient of determination for COVID-19 measures with non-zero coefficients.

Table 5 presents the results of regressions of factor scores onto 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, the use of standardised coefficients permits 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 can now be interpreted as being more important relative to the remaining measures (Fabozzi, 1998; Nimon & Oswald, 2013; Szczygielski, Brümmer, & Wolmarans, 2020b).

**Table 5: Factor score regressions**

| **Factor** | $\alpha_i$ | $GST_t$ | $GSM_t$ | $GOR_t$ | $MHI_t$ | $R_{M\varepsilon t}$ | $\bar{R}^2_{k,CV19}$ | $ShVr$ |
|---|---|---|---|---|---|---|---|---|
| | 0.0080 | -0.1118*** | | | | | 0.1758 | 0.1001 |
| | 0.0229 | | -0.0585 | | | | 0.0071 | 0.0040 |
| $F_{1,t}$ | 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 | |
| | 0.0011 | -0.0147 | | | | | 0.0000 | 0.0000 |
| | 0.0622 | | -0.1587** | | | | 0.0780 | 0.0070 |
| $F_{2,t}$ | 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 | |
| | 0.0029 | -0.0409*** | | | | | 0.0172 | 0.0007 |
| | 0.0550 | | -0.1406*** | | | | 0.0579 | 0.0024 |
| $F_{3,t}$ | 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 | |
| | 0.0025 | -0.0343 | | | | | 0.0100 | 0.0003 |
| | 0.0329 | | -0.0838** | | | | 0.0158 | 0.0005 |
| $F_{4,t}$ | 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, individually, jointly and jointly with standardized coefficients and a residual market factor incorporated (std row). Least squares with Newey-West heteroscedasticity and autocorrelation consistent (HAC) standard errors 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. $R_{M\varepsilon t}$ 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). The asterisks, ***, ** and *, indicate statistical significance at the respective 1%, 5% and 10% levels of significance.

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, with a standardised coefficient of -0.4199 for $GST_t$. 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 the factor scores of $F_{1,t}$. A similar observation in relation to the size of the coefficient on $GSM_t$ is also made for $F_{2,t}$ in the standardized 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 indidivually. 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 it is not statistically significant, a likely result of multicollinearity. 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, 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. Given the high correlation between $GSM_t$ and $GOR_t$, we again test to determine whether $GSM_t$ also 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. In light of the high correlation between that $GSM_t$ 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[9], 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 (2020); $GSM_t$ 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

[9] 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.

in Table 5 confirm that each measure selected and identified using elastic net regression is significantly related to the respective factor score series.

**Table 6: Factor score regressions with breakpoints**

| | Breakpoint | Measure | | | $\bar{R}^2_{k,CV19_t}$ | $ShVr$ |
|---|---|---|---|---|---|---|
| | | $GST_{t,1}$ | $GST_{t,2}$ | $GST_{t,3}$ | | |
| $F_{1,t}$ | 12/03/2020<br>30/04/2020<br>(51/35/124) | -0.0497*** | -0.2121*** | 0.0869 | 0.2980 | 0.1696 |
| | | $GSM_{t,1}$ | $GSM_{t,2}$ | | | |
| $F_{2,t}$ | 23/03/2020<br>(58/151) | -0.18930** | 0.2430*** | | 0.1274 | 0.0115 |
| | | $GOR_{t,1}$ | $GOR_{t,2}$ | | | |
| $F_{3,t}$ | 13/03/2020<br>(52/157) | 0.1224 | -0.2670*** | | 0.1150 | 0.0047 |
| $F_{4,t}$ | No breaks for $MHI_t$ | | | | | |

***Notes:*** This table reports the results of regressions of factor scores derived from returns onto the COVID-19 measures individually with breakpoints. Least squares with Newey-West heteroscedasticity and autocorrelation consistent (HAC) standard errors are used for estimation purposes. Values in brackets (…) indicate the number of observations that comprise each breakpoint segment. Segments are identified using the Bai-Perron test of L+1 versus L sequentially determined breaks with robust standard errors (HAC) and heterogenous error distributions. $GSM_t$ are changes in the stringency of measures applied by governments 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 the changes in the Ravenpack Media Hype Index. $ShVr$ is the contribution to total shared variance estimated by applying equation (3). The asterisks, ***, ** and *, indicate statistical significance at the respective 1%, 5% and 10% levels of significance.

Next, we estimate the amount of total shared variance attributable to the COVID-19 measures, $ShVr$, by following the methodology set out in equation (3). 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% ($\bar{R}^2_{k,GST_t}$= 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. Similarly, we find that $GSM_t$, $GOR_t$ and $MHI_t$ explain 0.7020%, 0.2738% and 0.3008% of total shared total variance respectively when the COVID-19 measures are considered individually ($\bar{R}^2_{k,CV19}$ derived from univariate regressions).

In total, these measures explain a total of 11.28% of shared variance over the COVID-19 period or 11.0093% if $GOR_t$ is excluded from this calculation (equation (3)). $GST_t$ is the most important measure over the overall period. When measures are considered jointly – the $\bar{R}^2$s used 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 the factor scores and the

COVID-19 measures. It may be that some measures become more important during certain stages of the COVID-19 crisis. We therefore go onto estimate breakpoint regressions for each factor score series against the single most important measure for that series (Bai & Peron, 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. 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 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 $GST_t$. Interestingly, the results are similar. A breakpoint also occurs on 13 March 2020 and the relationship is positive and statistically insignificant during the first segment and negative and significant during the second segment. Both coefficients for the regression of $F_{3,t}$ onto $GSM_t$ with breakpoints are of somewhat similar magnitudes, 0.0743 and -0.2183, respectively. The $\bar{R}^2$ is also similar, 0.1029 (not reported in Table 6). 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. As a final test, 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-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 Table 6 are indicative of the presence of relationships and changes in relationships between the drivers of international markets over the COVID-19 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 & 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 that we identify in the preceding discussion. We do this by relating these measures to the remaining measures and a number of indirect measures (Section 2.2.3).[10] Preliminary analysis yields somewhat conflicting results for the iterative procedure relying upon elastic net and results are therefore reported for sets comprising all measures and only measures with over 200 observations.

In Panel A of Table 7 (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 8 (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.

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

**Table 7: Final iteration results of elastic net regularisation**

**Panel A: All measures**

| | $GST_t$: 3 iterations | | | | $GSM_t$: 1 iterations | | | | $MHI_t$: 1 iterations | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\lambda_{min}$, | $\lambda_{1SE}$ | $\lambda_{2SE}$ | | $\lambda_{min}$, | $\lambda_{1SE}$ | $\lambda_{2SE}$ | | $\lambda_{min}$ | $\lambda_{1SE}$ | $\lambda_{2SE}$ |
| $\alpha_i$ | -0.1518 | 0.0570 | 0.0570 | $\alpha_i$ | 0.1930 | 0.2233 | 0.2623 | $\alpha_i$ | 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- | -2.73E- | $BDI_{t+2}$ | -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 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\lambda_{min}$, | $\lambda_{1SE}$ | $\lambda_{2SE}$ | | $\lambda_{min}$, | $\lambda_{1SE}$ | $\lambda_{2SE}$ | | $\lambda_{min}$ | $\lambda_{1SE}$ | $\lambda_{2SE}$ |
| $\alpha_i$ | -0.0403 | 0.0716 | 0.0716 | $\alpha_i$ | 0.2441 | 0.3012 | 0.3286 | $\alpha_i$ | 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. The procedure is repeated until only measures for which coefficients are non-zero for the $\lambda_{min}$, $\lambda_{1SE}$ and $\lambda_{2SE}$ penalties remain. *d.f.* is the number of measures with non-zero coefficients and L1 norm 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. The measure set in Panel B excludes measures that have fewer than 200 observations.

**Table 8: Largest measure correlations**

| Panel A: Spearman ($\rho_S$) | | | | | | Panel B: Ordinary ($\rho_P$) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $GST_t$ | | $GSM_t$ | | $MHI_t$ | | $GST_t$ | | $GSM_t$ | | $MHI_t$ | |
| $MCI_{t+1}$ | 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. Direct and indirect measures are considered contemporaneously and with up to three lags. $GSM_t$ 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 the changes in the Ravenpack Media Hype Index. The asterisks, ***, ** and *, indicate statistical significance at the respective 1%, 5% and 10% levels of significance.

Economic psychology lends support to the nature of such a relationship; individuals respond to uncertainty by searching for information (Liemieux & Peterson, 2011; Dzielinski, 2012; Castelnuovo & Tran, 2017; Bontempi et al., 2019). Notably, Szczygielski, Bwanya 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 Google search trends 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, 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 8 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 7), $AIS_{t+2}$, (Panel A, Table 8) and $AIS_t$, $AIS_{t+2}$, $WIS_{t+2}$ (Panel B, Table 8). 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). Finally, 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 8 respectively. It is expected that $GST_t$ will be positively related to news-based measures. 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, national and global. This implies decreased expected future cash-flows and heighted 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 (Andrei & Hasler, 2014; Smales, 2021; Cochrane, 2018). Consequently, we designate $GST_t$ as an uncertainty factor with an associated impact on sentiment and the economic state.

We now turn to the interpretation of the measure of stringency of lockdown-type policies, $GSM_t$. Across both Panels A and B, Table 7, $AMT_t$, $AMT_{t+1}$, $AMT_{t+2}$ and $AMT_{t+3}$ are identified whereas in Table 8, $GSM_t$ 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 as 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 that physical mobility and spending activity in Switzerland moved closely together during the COVID-19 crisis. Bonaccoris 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. Their results show that a stringent confinement policy enforced through fines resulted in a reduction in mobility and economic activity. What emerges is that an imposition of lockdown-style measures and other restrictions stifles economic activity. Reduced mobility reflects the imposition of such measures resulting in reduced 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 7 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 8, $BDI_{t+1}$ and $BDI_t$ ($BDI_t$ being our 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. Given 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. Therefore, 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 $GSM_t$

impacts market returns through an 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 7, 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 the magnitude of coefficients, 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 8 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 likely to also 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 8 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, 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 & 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 & Rizvi, 2020).[11] 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

[11] 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 8 suggest that $RPI_t$ and $MHI_t$ are highly correlated making this interpretation plausible.

market responses (Mamaysky, 2020). Another possible mechanism driven by media hype and panic is that of 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 of course 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 8 respectively. $MHI_t$ is also correlated with $OIL_t$, another proxy of economic policy uncertainty (Hailemariam et al., 2019). While we recognize 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 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.

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

We now relate returns on the MSCI market aggregates to the three COVID-19 measures, $GST_t$, $GSM_t$ and $MHI_t$.[12] Panel A to Panel C in Table 9 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 are Italy, Canada and Norway (respective $\beta_{i,GST}$s of -0.0031, -0.0027 and -0.0027, respectively). 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 nascent literature on the negative impact of COVID-19 related uncertainty, quantified by Google Search Trends, on market indices (Ahundjanov et al., 2020; Costola et al., 2020a; Liu, 2020; Papadamou et al., 2020; Ramelli and Wagner, 2020; Smales, 2020, 2021; Szczygielski, Bwanya et al., 2021). These results 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. Overall, 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 Nayaran et al. (2020) and Aggarwal et al. (2020) 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 Nayaran et al. (2020) ending in April 2020 and Aggarwal et al.'s (2020) in May 2020. This study uses a longer period, ending in the second half of October 2020. Restrictive measures may have initially helped reduce the spread of COVID-19 and therefore were viewed as positive in nature. However, the long-term economic impact has been negative (König & Winkler, 2021). Such a conclusion is also consistent with evidence of Cross et al. (2020) and

[12] $GOR_t$ is excluded owing to its almost perfect correlation with $GSM_t$ and its relative lesser importance.

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 the $\beta_{i,MHI}$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 stock markets of the US, UK, France, Germany, Spain and Italy for the period 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.

In terms of magnitude of the impact of the three measures of COVID-19, on average, the effect of $GSM_t$ is highest, followed by $GST_t$ and $MHI_t$. $GST_t$ explains a greater proportion of the variation in individual stock market returns than $GSM_t$, followed by $MHI_t$ with the 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.

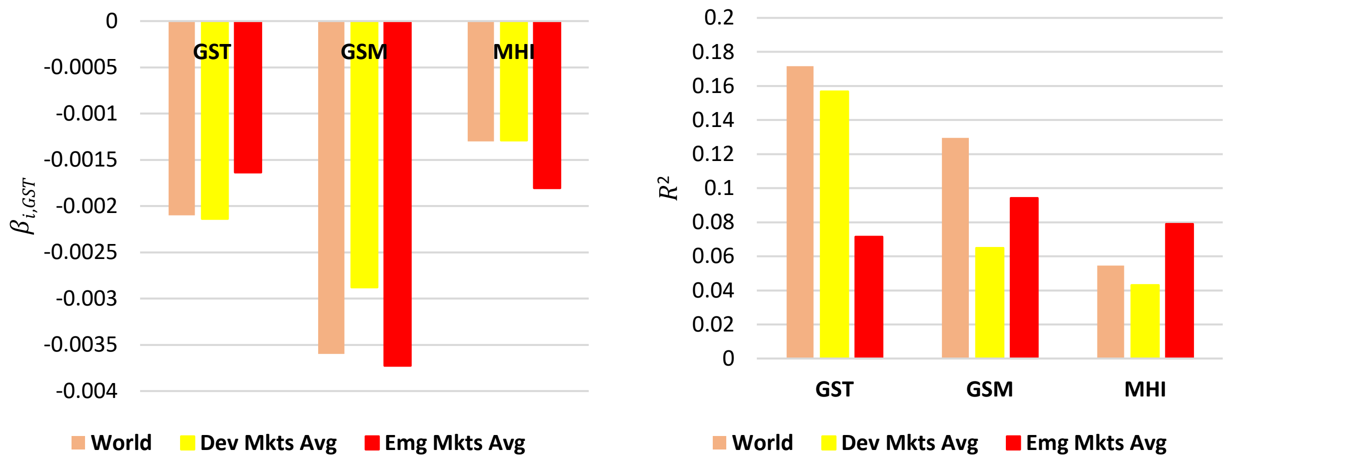
**Table 9: Mean specification estimated using least squares**

| | Panel A: $GST_t$ | | | Panel B: $GSM_t$ | | | Panel C: $MHI_t$ | | | Panel D: $GST_t$, $GSM_t$, $MHI_t$ (combined) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\alpha_i$ | $\beta_{i,GST}$ | $\bar{R}^2$ | $\alpha_i$ | $\beta_{i,GSM}$ | $\bar{R}^2$ | $\alpha_i$ | $\beta_{i,MHI}$ | $\bar{R}^2$ | $\alpha_i$ | $\beta_{i,GST}$ | $\beta_{i,GSM}$ | $\beta_{i,MHI}$ | $\bar{R}^2$ |
| 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 Panel A, B and C respectively and jointly in Panel D. Least squares with Newey-West heteroscedasticity and autocorrelation consistent (HAC) standard errors are used for estimation purposes. $GST_t$ are changes in worldwide COVID-19 related Google searches. $GSM_t$ 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. $\bar{R}^2_{CV19}$ is the adjusted coefficient of determination associated with a given COVID-19 measure. The asterisks, ***, ** and *, indicate statistical significance at the respective 1%, 5% and 10% levels of significance.

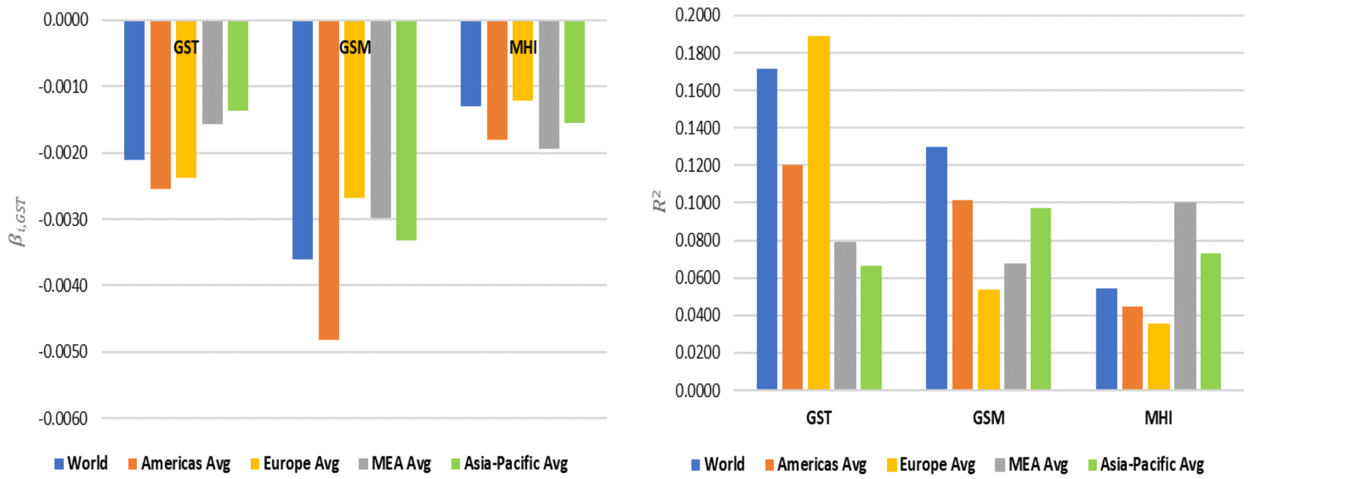
Next, we group countries according to level of development, designating these as developed and emerging, and according to region, namely Asia-Pacific, Middle East and Africa (MEA), Europe and the Americas.[13] In Figure 1, the (average) impact of COVID-19 related uncertainty is stronger for developed compared to emerging markets (average $\beta_{i,GST}$s of -0.0021 and -0.0016, respectively). $\bar{R}^2$ values confirm a greater role of uncertainty in developed markets; the average $\bar{R}^2$ for developed countries is almost double that of emerging countries (0.1567 compared to 0.0715).

**Figure 1: Impact of GST, GSM and MHI on returns of the world stock market and averages across individual countries grouped according to level of development**




**Notes:** These figures plot 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 the level of development (developed and emerging) (left side) and the average $\bar{R}^2$ estimates from the regressions (right side).

**Figure 2: Impact of GST, GSM and MHI on returns of the world stock market and averages across individual countries grouped according to region**




***Notes:*** These figures plot 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).

[13] These groupings are in accordance with MSCI Global classifications.

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, such as historic epidemics in Asia or economic recessions and crises in Brazil or South Africa which may be considered amongst the most influential emerging markets. Relatedly, developed countries outside of Asia, such as Italy, Spain, UK, Canada and US, were initially most affected by the spread of the virus. Only later did emerging countries such as South Africa, Brazil and India become epicentres. Notably, high-income countries initially accounted for an unequal proportion of global deaths related to the virus further breeding panic and uncertainty (Salisu & Akanni, 2020). For example, as of 30 April 2020, the UK, Spain, Italy, US and France accounted for 71% of global COVID-19 deaths compared to only 7% in Brazil, Russia, India, Mexico and Iran. However, as of 20 October 2020 (the last day of our sample) these five developed countries accounted for 33% of total deaths compared to 37% for the five emerging markets (Our World in Data, 2020a).

The opposite pattern is evident for $GSM_t$, which has 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). Thus, government measures have a more negative impact on emerging market stocks. The discussion in Section 3.3 on the interpretation of these measures implies that government measures stifle economic activity with economic activity being performed from home being far lower than in developed countries (Gottlieb, Grobovsek, Poschke, Imbert & Panizza, 2020).[14]

[14] Dingle and Neiman (2020) estimate that 40% of total employment can be conducted from home in the most advanced economies compared to only 10% in the poorest countries while Gottlieb, Grobovsek, Poschke and Saltiel (2020) predict that only 35% of urban employment can be conducted from home in emerging markets compared to 50% in advanced economies.

It then follows that investors may view the curbing of economic activity as more harmful in emerging market firms. In these markets, the fraction of employment that can be performed from home is far lower than in developed countries (Gottlieb, Grobovsek, Poschke, Imbert & Panizza, 2020).[15] Accordingly, lockdowns in these countries are likely to have a far more harmful impact on employment and, by extension economic output and activity, than in developed countries. Allied to this, home environments in many developing countries may not be as amenable to the health benefits of staying at home in comparison to developed countries, thus reducing the success of lockdowns in these countries (Gottlieb, Grobovsek, Poschke, Imbert & Panizza, 2020) which may further hamper firms and drive prices downwards. Lockdowns also choke consumer spending which plays a key role in emerging markets in driving economic growth (Strohecker, 2020). The implementation of economic stimulus packages by governments are meant to be viewed as an antidote to lockdowns to support economic recovery. However, when small in magnitude and/or viewed by market participants as unlikely to be effective, this may exacerbate the effects of lockdowns on stock markets. These fiscal and monetary measures have been far smaller in emerging markets compared to developed markets, thus potentially aggravating the effects of lockdowns on these economies. In addition, prior studies have shown that the multiplier effect of fiscal stimulus packages in emerging economies could be half the size of developed economies or even zero thus limiting their benefits in emerging economies (Steel & Harris, 2020). The weaker institutional capacity of developing countries may also inhibit the effectiveness of stimulus packages meaning that restrictions have a more severe impact in these countries (Gottlieb, Grobovsek, Poschke, Imbert & Panizza, 2020).

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) as illustrated in Figure 1. The average $\bar{R}^2$ of 0.0791 for emerging markets and 0.0431 for developed markets reflects this pattern. As suggested by the analysis in Section 3.3, $MHI_t$ quantifies media attention associated with panic. Within the stock market context, this can potentially be linked to panic selling - rapid increases in sales orders which push down stock prices (Maharani, 2008). This contributes to a vicious cycle where investors see a rapidly falling price as a sign to sell which further contributes

[15] Dingle and Neiman (2020) estimate that 40% of total employment can be conducted from home in the most advanced economies compared to only 10% in the poorest countries while Gottlieb, Grobovsek, Poschke and Saltiel (2020) predict that only 35% of urban employment can be conducted from home in emerging markets compared to 50% in advanced economies.

to a price decline and motivates more investors to sell. This type of selling often arises due to noise rather than fundamentals and is common in market crashes (Shiller, 1987; Maharani, 2008). Ramelli and Wagner (2020) confirm panic selling in stock markets during the COVID-19 induced market crash in March 2020. The media gave considerable attention to the spread of COVID-19 and to the fall of stock prices globally. Theil (2014) argues that the media tends to focus on bad news and worst-case scenarios in times of crisis. This negative media attention likely fuelled investor panic causing more investors to sell, especially in emerging markets where market crashes followed those in developed markets chronologically. Theil (2014) also confirms that the predominant focus of media reports on short-term market movements conveys more noise than fundamental information. Emerging market investors have been found to be prone to noise trading (Morck et al., 2000; Bagchi, 2006; Charteris et al., 2014; Salisu, Sikiru & Vo, 2020) which is consistent with the stronger role of media hype and panic on stock market returns in emerging markets.

The results in Figure 2 reveal that, on average, 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. (2021) 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), Wang and Enilov (2020) and Szczygielski, Brzeszczyński et al. (2021) propose that the experience of countries in the Asia-Pacific region in dealing with 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 this became the epicentre of the virus after Asia. Death tolls for the virus have also been highest in the Americas and Europe, which may have given rise to a greater impact of uncertainty on these stock markets (Salisu & Akanni, 2020). Findings that geographical proximity to the outbreak of the COVID-19 pandemic matters for the 35 largest stock markets globally with respect to the impact of COVID-19 related uncertainty is consistent with the findings obtained for the G20 country stock markets (Smales, 2021) and the 20 largest national energy sectors (Szczygielski, Brzeszczyński et al., 2021).

In Figure 2, $GSM_t$ has the greatest impact on the Americas followed by Asia-Pacific, MEA and Europe (average $\beta_{i,GSM}$ estimates 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 developed markets, and thus, as with the analysis based upon the level of development, such markets are less affected by lockdowns than emerging markets for the reasons outlined (the fraction of employment that can be performed from home is higher, consumer spending plays a smaller role in driving economic growth, etc.). Other regions, in contrast, consist of both developed and developing countries. This pattern of impact is likely to reflect 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, 2020b). Accordingly, the 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 the 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, & Saint-Guilhem, 2011; Kose et al., 2017). Hence, the strict lockdowns and travel bans imposed by the US has repercussions for countries globally which is consistent with the patterns documented. 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 is broadly consistent with the finding of the analysis of the influence of economic development as most MEA countries are emerging markets (in contrast to Europe where all countries in the sample are developed markets) where the stock markets of these countries are more affected by media hype and panic than developed country stock markets. Moreover, the media is seen to have played a critical role in the collapse of tyrannical regimes and the dissemination of sensitive information (Rezaei & Cohen, 2012) in the Middle East and South Africa (Wasserman, 2020) during the last decade. As such, the role and influence of the media in influencing investor behaviour may be heightened in MEA compared to other regions.

We also regress returns on each market aggregate onto all three measures using a least squares regression. As shown in Panel D of Table 9, $GST_t$, $GSM_t$ and $MHI_t$ continue to negatively impact stock returns, with the coefficients similar in magnitude. The $GST_t$ 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 the combined regressions, with the coefficient only significant for 16 stock markets (compared to 24 when this COVID-19 measure was analysed individually) and remains insignificant for the MSCI All Country World Index. The patterns observed across countries with similar levels of development and regions are also consistent. 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. ARCH/GARCH modelling offers an alternative to the use of Newey-West HAC standard errors to account for serial correlation and volatility dynamics (Andersen et al., 2003; Szczygielski, Brümmer, & Wolmarans, 2020a). 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 A4 in the Appendix 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 heightened volatility. Several studies have examined the effect of COVID-19 on volatility and find that the COVID-19 crisis has translated into heightened 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 Google Search Trends, has been shown to be associated with increased volatility for China (Liu, 2020), the G20 countries (Smales, 2021) and various regions (Szczygielski, Bwanya et al., 2021). There is also evidence that volatility triggering effects associated with increased Google searches has intensified as the pandemic spread (Szczygielski, Brzeszczyński et al., 2021; Szczygielski, Bwanya et al., 2021) and that some industries, such as financials and energy, have been more impacted than others such as consumer staples and health care (Smales, 2020; Szczygielski, Charteris et al., 2020).

Heightened volatility has also been associated with increased media attention measured using the IDEMV index (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 world volatility (conditional variance). In contrast, greater media coverage led to lower volatility for global stock returns but with no impact on US stock returns. Szczygielski, Bwanya 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. In summary, 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 factors common to the markets in our sample by using statistically derived factors in the mean equation adjusted for the three COVID-19 measures. By taking 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 & Kryzanowski, 1994; Szczygielski, Brümmer & Wolmarans, 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 the return series, $r_{i,t}$, adjusted for the portion of shared variance reflected by $\sum_{k\geq 0}^{k} \beta_{CV19,k} F_{CV19,t}$ so that $\varepsilon_{i,t}^{*}$ represents that portion of returns that is 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, 1 January 2015 and ending 20 October 2020 to reduce biases in maximum likelihood (ML) estimates and the persistence of non-linear dependence associated with small sample sizes (Hwang & 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 GRACH($p$,$q$) 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 & Bollerslev, 1986; Brzeszczyński and Kutan, 2015). The respective ARCH($p$), GARCH($p$,$q$) and IGARCH($p$,$q$) conditional variance specifications are as follows:

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

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

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

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 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. Equations are estimated using ML estimation. If residuals are non-normal, they are re-estimated using quasi-maximum likelihood (QML) estimation with Bollerslev-Wooldridge standard errors and covariance (Fan et al., 2014).

Table 10 reports the results for the ARCH/GARCH specifications. 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 stock markets are those of Brazil, Chile and Norway ($\varphi_{i,GST}$s of 2.3200, 1.7600 and 1.3700, respectively). The least impacted stock markets are those of Hong Kong, China and Denmark (respective $\varphi_{i,GST}$s of 0.1460, 0.2190 and 0.2300). Overall, these results suggest that as investors become more uncertain about the pandemic and search for more 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 response measures is associated with heightened volatility. Indonesia is most affected, followed by the Philippines and Denmark ($\varphi_{i,GSM}$ estimates 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 significantly heightened volatility in response to $MHI_t$. The most responsive markets are those of Chile, Australia and Saudi Arabia (respective $\varphi_{i,MHI}$s of 1.9900, 1.4200 and 1.2900). This suggests that increased hype and panic in the media surrounding COVID-19 fuels volatility in a limited number of markets – less so than $GST_t$.

**Table 10: ARCH/GARCH estimates for conditional variance with COVID-19 measures**

| | Panel A: $GST_t$ | | | | | | Panel B: $GSM_t$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\omega_i$ | $\alpha_1$ | $\alpha_2$ | $\beta_1$ | $\beta_2$ | $\gamma_{GST_t}$ | $\omega_i$ | $\alpha_1$ | $\alpha_2$ | $\beta_1$ | $\beta_2$ | $\gamma_{GSM_t}$ |
| 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 10: ARCH/GARCH estimates for conditional variance with COVID-19 measures (continued…)**

| | Panel C: $MHI_t$ | | | | | | Panel D: $GST_t, GSM_t, MHI_t$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\omega_i$ | $\alpha_1$ | $\alpha_2$ | $\beta_1$ | $\beta_2$ | $\gamma_{MHI_t}$ | $\omega_i$ | $\alpha_1$ | $\alpha_2$ | $\beta_1$ | $\beta_2$ | $\gamma_{GST_t}$ | $\gamma_{GSM_t}$ | $\gamma_{MHI_t}$ |
| 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. Measures are included individually in Panel A, B and C and jointly in Panel D. $GST_t$ are changes in worldwide COVID-19 related Google searches. $GSM_t$ 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 the changes in the Ravenpack Media Hype Index. $\bar{R}^2_{CV19}$ is the adjusted coefficient of determination associated with a given COVID-19 measure. The asterisks, ***, ** and *, indicate statistical significance at the respective 1%, 5% and 10% levels of significance.

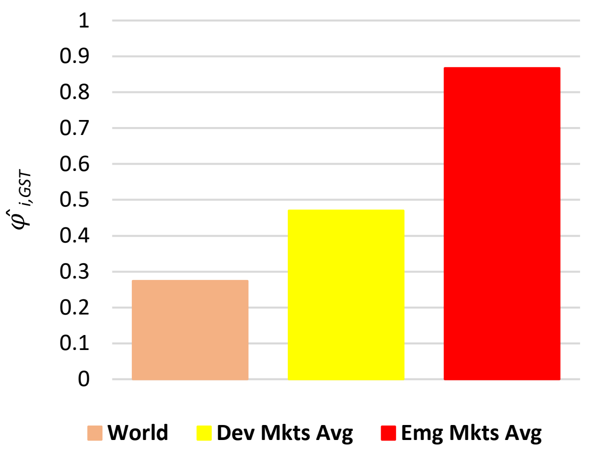
As a confirmatory step, ARCH/GARCH models are estimated with all three measures jointly. The results are reported in Panel D. $GST_t$ is the only measure that shows consistency in terms of coefficient magnitudes and direction of impact, with $\varphi_{i,GST}$ statistically significant for 20 of the 35 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 COVID-19 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 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). This suggests 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 the individual country regressions.

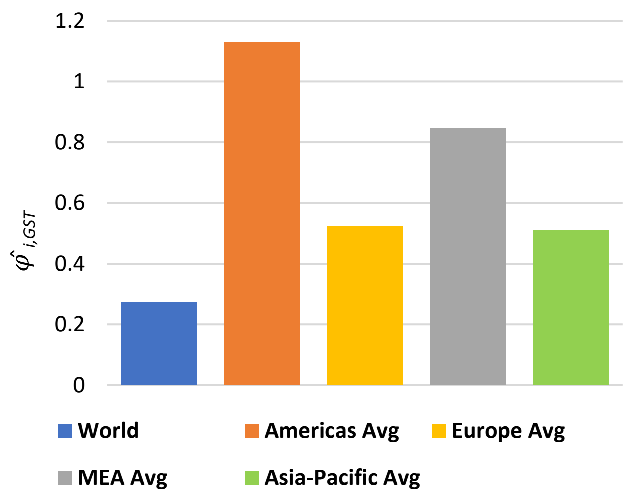
A finding that movements in $GST_t$ contribute to increased volatility is similar to the results of Liu (2020) for the Chinese stock market and Smales (2021) for G20 countries. Importantly, the widespread association of this measure with heightened volatility in this study provides support for the interpretation that this is a measure of market uncertainty. The limited effect of the stringency of government response measures on volatility differs from the findings of Zaremba et al. (2020) but is broadly consistent with Szczygielski, Bwanya et al. (2021) who demonstrated differential effects of government responses across regions. In particular, Szczygielski, Bwanya et al. (2021) found that volatility in North America and Africa was unaffected by government responses and that government responses to the pandemic had a small (but statistically significant) effect in Asia, compared to Europe, South America and Arab markets (all statistically significant). Haroon and Rizvy (2020) report mixed results for the role of the various COVID-19 related media attention metrics on US and world 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 shown in 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 development (developed and emerging) and regions. Figure 3 indicates that emerging market volatility is more impacted by COVID-19 related uncertainty than developed market volatility, with average $\varphi_{i,GST}$s of 0.8673 and 0.4071, respectively. This finding differs from the impact of $GST_t$ on stock returns seen in Section 3.4, where developed country stock markets are more impacted. However, these results are congruent with the greater susceptibility of emerging markets to fluctuating risk tolerance in general (Froot & McConnell, 2003; FitzGerald, 2006), 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 & Mattackal, 2020; Szczygielski, Bwanya et al. 2021).

Volatility is most impacted by $GST_t$ in the Americas, followed by MEA, Europe and Asia, with respective average $\varphi_{i,GST}$ estimates of 1.1280, 0.8458, 0.5243 and 0.5115. This pattern is similar to the $\beta_{i,GST}$ estimates but with the positions of MEA and Europe reversed. This reversal in positions between the MEA and Europe regions is consistent with the reduced role of uncertainty found among developed countries compared to emerging countries, as most markets in Europe fall into the former category. As with the returns analysis, there is evidence that increased geographical distance from the origin of the COVID-19 pandemic in Wuhan, 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 about and understanding of the pandemic and its evolution (Szczygielski, Brzeszczyński et al., 2021), the experience of countries at the epicentre in dealing with past epidemics (Lu et al., 2020; Wang & Enilov, 2020; Szczygielski Brzeszczyński et al., 2021) and the geographic spread of the virus from China in a westerly direction to Europe and America.

**Figure 3: Impact of GST on volatility of world stock returns and averages across individual countries grouped according to level of development and region**




***Notes:*** These figures plot 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 level of development (developed and emerging) (left side) and region (right side).

### 3.6. Overall impact of uncertainty

According to Aven and Renn (2009), uncertainty arises when it is not known whether an event will occur, when it will occur, and/or what its consequences will be. Several studies have shown that uncertainty affects stock prices (Pastor & Veronesi, 2012; Ko & Lee, 2015) and volatility (Arnold & Frugt, 2008; Su et al., 2019), with the same true for uncertainty surrounding the COVID-19 period influencing stock markets (such as Liu, 2020; Smales, 2021; Szczygielski, Brzeszczyński et al., 2021; Szczygielski, Bwanya et al., 2021). Uncertainty about future cash flows and discount rates has a negative impact on stock prices (Gormsen & Koijen, 2020). Moreover, when new information arises and investors are uncertain as to how this information impacts the true value of the asset, this will contribute to increased volatility (Szczygielski Brzeszczyński et al., 2021). 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. (2021), we therefore combine both aspects of the influence of uncertainty on stock markets by presenting a two-dimensional measure of uncertainty, termed the overall impact of uncertainty, $OIU_{i,GST}$, which is calculated as follows:

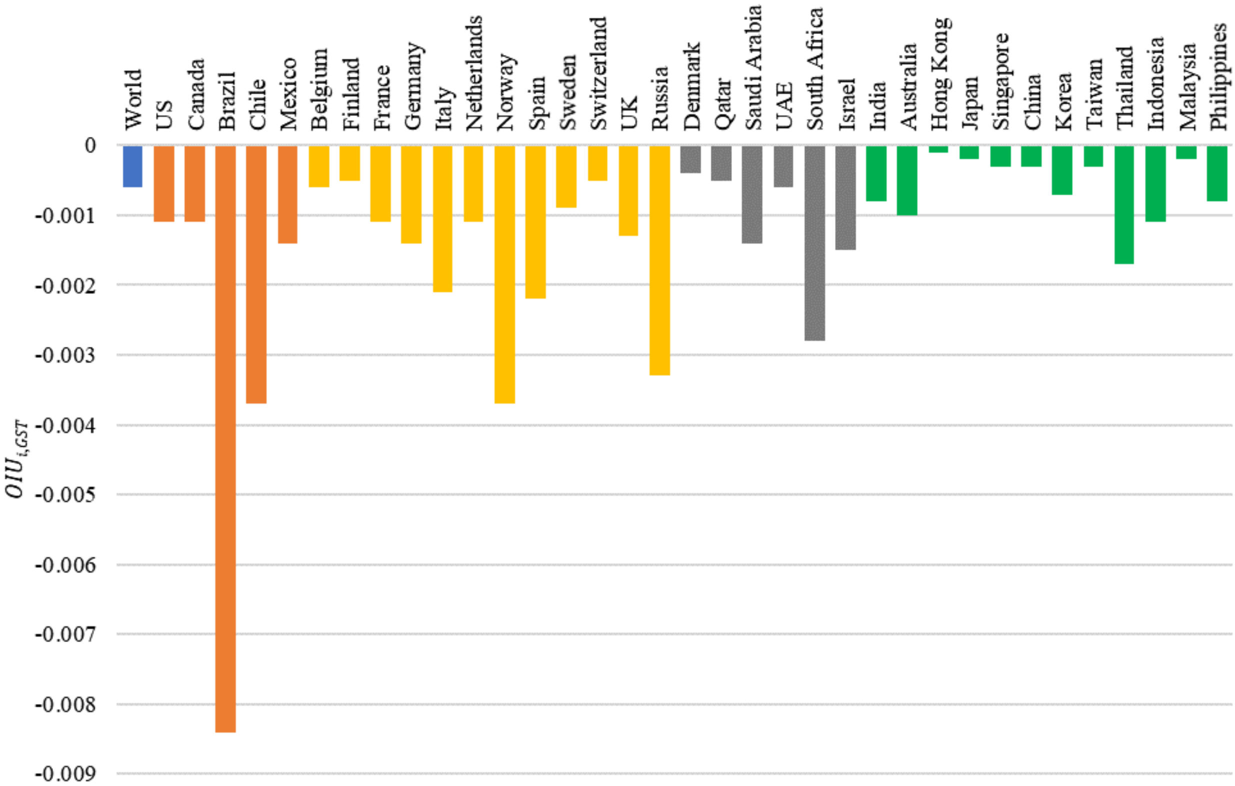
$$OIU_{i,GST} = \beta_{i,GST} \cdot \varphi_{i,GST} \tag{7}$$

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 $GST_t$. The $\beta_{i,GST}$s in equation (7) are derived from equation (4) whereas 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.

According to Szczygielski, Brzeszczyński et al. (2021), the intuition behind this measure is that it captures the directional strength of the effect of uncertainty, which is additionally 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. (2021) argue that the design of the $OIU_{i,GST}$ measure also 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. This is analogous to the intensity component in $OIU_{i,GST}$ represented by $\varphi_{i,GST}$. 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 that 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 evident in Table 10, not the variance. There is therefore no widespread associated intensity component. Importantly, $GST_t$ is shown to have a persistent and stable impact on conditional variance.

The results for $OIU_{i,GST}$ are summarised in Figure 4 (estimates for $OIU_{i,GST}$ are presented in Table A4 in the Appendix). 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).

**Figure 4: Overall impact of uncertainty on the world stock market and individual countries**

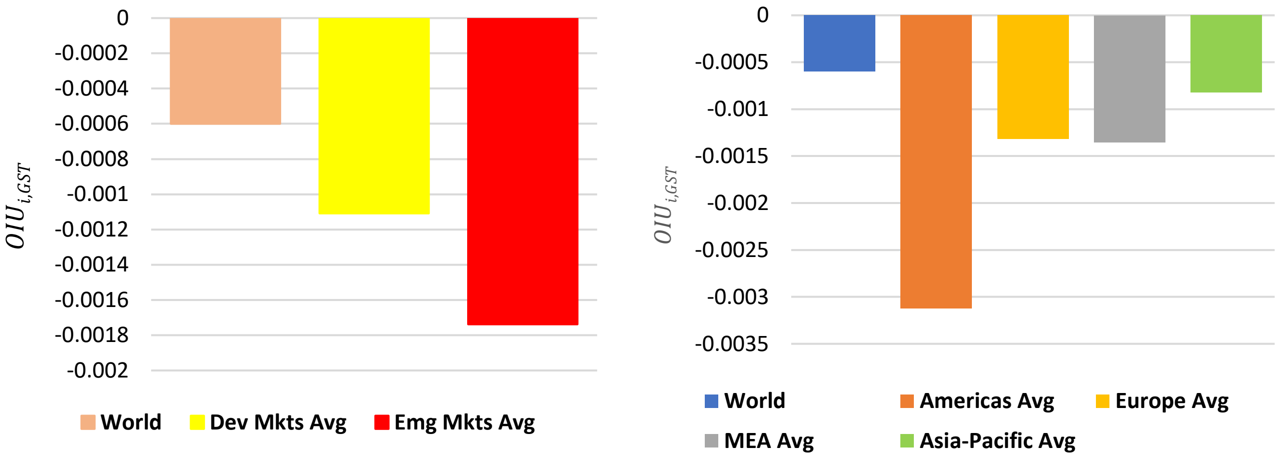



***Notes:*** This figure plots the overall of uncertainty ($OIU_{i,GST}$) measure for individual countries and the MSCI All Country World Index based upon COVID-19 related Google Search Trends on an inverted vertical axis. The $\beta_{i,GST}$s and $\varphi_{i,GST}$s used to estimate the OIU measure in equation (7) are derived from equations (4) and (6a)/(6b)/(6c) respectively.

Next, we again group countries according to level of development (developed and emerging) and region, as with the returns and volatility analyses but now according to the $OIU_{i,GST}$ measure. Figure 5 shows that the average impact of COVID-19 related uncertainty is stronger for emerging compared to developed markets (respective average $OIU_{i,GST}$s of -0.0017 and -0.0011). This pattern is consistent with the volatility results, with the intensity of the impact of uncertainty almost twice as strong in emerging markets relative to developed markets (average $\varphi_{i,GST}$s of 0.8673 and 0.4701, respectively). This contrasts with the magnitude of uncertainty which was larger for developed than emerging countries (respective average $\beta_{i,GST}$s of -0.0021 and -0.0016). Thus, the intensity amplifies the effect of the magnitude of the impact of COVID-19 uncertainty on stock markets, with emerging markets being more impacted overall. This pattern is also seen when examining individual countries. For example, Canada and Norway are the second most impacted by COVID-19 related uncertainty in returns ($\beta_{i,GST}$s of -0.0027) but after adjusting for the 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 in Norway ($\varphi_{i,GST}$s of 1.370 and 0.421, respectively). Likewise while COVID-19 related uncertainty has only a limited impact on the returns of Singapore and Saudi Arabia ($\beta_{i,GST}$s of -0.0011), the much 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 quantify the impact of uncertainty.

Our finding that the full impact of COVID-19 uncertainty is greater on emerging compared to developed markets is consistent with evidence, as noted in Section 3.5, that emerging markets are more prone to fluctuating risk tolerance arising from uncertainty (Froot & McConnell, 2003; FitzGerald, 2006), which is exacerbated during times of crisis (McCauley, 2013). Similarly, other studies that have examined the impact of COVID-19 uncertainty on returns and/or volatility individually have also shown emerging markets to be more affected than developed countries (such as Chahuán-Jiménez et al., 2021 and Szczygielski, Bwanya et al., 2021).

**Figure 5: Overall impact of uncertainty on the world stock market and averages across individual countries grouped according to level of development and region**




***Notes:*** These figures plot 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 level of development (developed and emerging) (left side) and region (right side).

Figure 5 further 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). The 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 the $OIU_{i,GST}$ averages are -0.0014 and -0.0008, implying that the overall uncertainty impact 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). Hence, as seen with the comparison across developed and emerging markets, the intensity parameter ($\varphi_{i,GST}$) amplifies the $OIU_{i,GST}$ measure of overall uncertainty. Regional results again confirm that geographical proximity matters in terms of the overall impact of COVID-19 uncertainty on financial markets. The stock markets of countries further west from the origin of the COVID-19 pandemic in Wuhan, China are more impacted. As noted in Sections 3.4 and 3.5, Szczygielski, Brzeszczyński et al. (2021) attribute this finding to market participants closer to the outbreak having more information about this pandemic. Lu et al. (2020), Wang and Enilov (2020), Szczygielski, Brzeszczyński et al. (2021) and Szczygielski, Bwanya et al. (2021) also highlight the greater experience of countries at the epicentre in dealing with past epidemics which may have further resolved uncertainty. Finally, the virus also spread geographically from China in a westerly direction to Europe and America heightening uncertainty as it spread. This is seen in Figure 5 above.

### 3.7. Other COVID-19 measures

In this section, we investigate whether there could be other COVID-19 measures that matter aside from those identified in Section 3.2. We re-estimate equation (1) applying elastic net estimators for the purposes of measure selection. However, instead of using $F_{k,t}$, the original factor score series, as our dependant series, we use the residuals of the regressions of $F_{k,t}$ onto the three COVID-19 measures jointly, which we define as $F_{K\varepsilon,t}$. Our measure set now excludes $GST_t$, $GSM_t$ and $MHI_t$ and we repeat the measure selection exercise twice, first with all measures and then with all measures with over 200 observations and the original measures excluded in both cases. For brevity, we relegate the results of the final iterations to Table A5 of the Appendix. By using factor score series that are orthogonal to influences reflected in $GST_t$, $GSM_t$ and $MHI_t$, we identify measures that capture aspects of COVID-19 that impact international markets but are unrelated to these measures.

When all measures are considered – including those with under 200 observations - changes in the Google Mobility Tracker data, $GMT_t$, changes in levels of the Ravenpack Fake News Index, $FNI_t$, the (lagged) growth in the number of active cases, $ACT_{t-1}$, and changes in the Apple Mobility Tracker data, $AMT_t$, are associated with $F_{1\varepsilon,t}$, $F_{2\varepsilon,t}$, $F_{3\varepsilon,t}$ and $F_{4\varepsilon,t}$ respectively. When measures with over 200 measures are considered, the (lagged) growth in the number of active cases, $ACT_{t-1}$, the lagged growth in the 7-day moving average of reported COVID-19 deaths, $DEC_{t-1}$ and changes in Apple Mobility Tracker data, $AMT_t$, are related to $F_{1\varepsilon,t}$, $F_{3\varepsilon,t}$ and $F_{4\varepsilon,t}$ respectively. Coefficients on all COVID-19 measures are zero for $F_{2\varepsilon,t}$ across penalties indicating no measure is related to $F_{2\varepsilon,t}$. We designate these as alternative measures, $F_{CV19A,t}$.

Next, we regress each alternative measure, $F_{CV19A,t}$, onto the respective orthogonalised factor score series, $F_{K\varepsilon,t}$. Here we face a limitation. If we were to use the original factor series, $F_{K,t}$, and treat the resultant $\bar{R}^2$s as indicators of each alternative COVID-19 measure's ability to proxy for shared variance, then the amount of shared variance seemingly reflected by each COVID-19 measure will be misleading. This is because the alternative measures would also reflect that portion of shared variance which arises due correlation with the COVID-19 measures identified in Section 3.2. As the $F_{K\varepsilon,t}$s are adjusted for $GST_t$, $GSM_t$ and $MHI_t$, the resultant $\bar{R}^2$s reflect the amount of shared variance that is reflected by each alternative measure but is *unrelated* to $GST_t$, $GSM_t$ and $MHI_t$. In this case, we cannot claim that the resultant $\bar{R}^2$s are representative of explanatory power for $F_{K,t}$ as we are not using the original factor scores in our regressions onto the alternative measures.

We therefore propose an adjustment to the $\bar{R}^2$s from regressions of $F_{CV19A,t}$ onto $F_{K\varepsilon,t}$. We begin by relating the original factor scores to the orthogonalised factor scores, with the resultant $\bar{R}^2$ designated as $\bar{R}^2_{K\varepsilon}$. The $\bar{R}^2_{K\varepsilon}$s represent the remaining proportion of shared variance reflected by $F_{K\varepsilon,t}$ following the orthogonalisation of $F_{K,t}$ against the original COVID-19 measure set:

$$F_{K,t} = \alpha_i + \beta_{K\varepsilon} F_{K\varepsilon,t} + \varepsilon_{k,t} \qquad (8)$$

and

$$F_{K,t} = \alpha_i + \beta_{K,GST'} GST_t + \beta_{K,GSM} GSM_t + \beta_{K,MHI} MHI_t + \pi_{k,t} \qquad (9)$$

where the residuals of equation (9), $\pi_{k,t}$, are now $F_{K\varepsilon,t}$ in equation (8). Next, we regress each $F_{CV19A,t}$ against the respective $F_{K\varepsilon,t}$ that it is found to be associated with following after applying the iterative procedure:

$$F_{K\varepsilon,t} = \alpha_i + \beta_{K\varepsilon,CV19A} F_{CV19A,t} + \varepsilon_{k\varepsilon,t}$$

(10)

The resultant $\bar{R}^2$s, denoted as $\bar{R}^2_{CV19A,\varepsilon}$s, represent the proportion of explanatory power associated with an alternative measure that is *not* attributable to correlation with the original measures, $GST_t$, $GSM_t$ and $MHI_t$, because $F_{K\varepsilon,t}$ is orthogonal to these measures. However, the communality reflected by $\bar{R}^2_{CV19A,\varepsilon}$ for each measure associated with $F_{K\varepsilon,t}$

will be overstated. This is because the $F_{K\varepsilon,t}s$ are adjusted for $GST_t$, $GSM_t$ and $MHI_t$ and do not reflect the same amount of shared variance as $F_{K,t}$, such that in terms of shared variance reflected, $F_{K,t}> F_{K\varepsilon,t}$. It therefore follows that for a regression of $F_{K,t}$ onto the alternative measures, the $\bar{R}^2_{CV19A}$ must be less than $\bar{R}^2_{CV19A,\varepsilon}$ because $F_{K,t}> F_{K\varepsilon,t}$ in terms of total shared variance.

Consequently, the next step is to adjust the $\bar{R}^2_{CV19A,\varepsilon}$ to reflect the unrelated proportion of shared variance that would be explained if an alternative measure was regressed against an unorthogonalised factor score series, $F_{K,t}$. The reason why we need to make this adjustment is because if we regress $F_{K,t}$ – the unadjusted factor score series – onto our alternative measures, the resultant $\bar{R}^2_{CV19A}$ will reflect the portion of shared variance that is also attributable to correlation between $F_{CV19A,t}$ and $GST_t$, $GSM_t$ and $MHI_t$ and therefore the $\bar{R}^2$ will be overstated. We thus adjust $\bar{R}^2_{CV19A,\varepsilon}$ derived from equation (10) by the proportion of remaining shared variance reflected by $F_{K\varepsilon,t}$, $\bar{R}^2_{\varepsilon}$ as determined by equation (8):

$$OSV = \bar{R}^2_{CV19A,\varepsilon}\bar{R}^2_{K\varepsilon} \qquad (11)$$

where $OSV$ is the "orthogonal shared variance" – the amount of total shared variance explained by an alternative measure that is uncorrelated with the original measure set. In summary, this approach allows us to attribute orthogonal explanatory power without the need to transform the explanatory variables through orthogonalization (see Wurm & Fisicaro, 2014).[16]

We begin by estimating equation (8) and estimate $\bar{R}^2_{K\varepsilon}$s of 0.8100, 0.8803, 0.9096 and 0.8831 for $F_{1\varepsilon,t}$, $F_{2\varepsilon,t}$, $F_{3\varepsilon,t}$ and $F_{4\varepsilon,t}$ respectively. Next, each $F_{K\varepsilon,t}$ series is regressed onto each associated measure and then onto all measures jointly for both alternative measure sets. Both the $\bar{R}^2_{CV19A,\varepsilon}$ and $OSV$ measures for each respective alternative measure are lower than that for the measures reported in Table 5. For example, the $\bar{R}^2$ for the regression of $F_{1,t}$ onto $GST_t$ is 0.1758. For regressions for the corresponding orthogonalised factor score series, $F_{1\varepsilon,t}$ and the related measures, $GMT_t$ and $AMT_t$ , the $\bar{R}^2_{CV19A,\varepsilon}$ and $OSV$ measures in Panels A and B in Table 11 are 0.0449 and 0.0364, and 0.0279 and 0.0226, respectively. We expect this to be the case, given that the alternative measures are "secondary" measures – measures that are relevant but were not selected in the first instance.

[16] See Wurm and Fisicaro (2014) for a discussion of orthogonalisation (and its pitfalls) to account for correlation between explanatory variables.

**Table 11: Orthogonalized factor score regressions onto alternative COVID-19 measures**

**Panel A: First alternative measure set**

| **Factor** | $\alpha_i$ | $GMT_t$ | $FNI_t$ | $ACT_{t-1}$ | $AMT_t$ | $\bar{R}^2_{CV19A,\varepsilon}$ | $OSV$ |
|---|---|---|---|---|---|---|---|
| $F_{1\varepsilon,t}$ | -0.0200 | -0.0473** | | | | 0.0449 | 0.0364 |
| | -0.0519 | -0.0488** | -0.2413 | 1.2170 | 0.0690 | 0.0497 | 0.0403 |
| $F_{2\varepsilon,t}$ | 0.0015 | | -0.5248 | | | 0.0128 | 0.0113 |
| | -0.0012 | 0.0042 | -0.4714 | 0.3395 | 0.0398 | 0.0000 | 0.0000 |
| $F_{3\varepsilon,t}$ | -0.0480 | | | 0.7725** | | 0.0084 | 0.0076 |
| | -0.1543** | 0.0380 | 0.4833* | 4.5369** | 0.0279 | 0.0367 | 0.0334 |
| $F_{4\varepsilon,t}$ | -0.0022 | | | | -0.1370** | 0.0559 | 0.0494 |
| | 0.1213 | -0.0190 | -0.3035 | -4.3433 | -0.1829** | 0.0818 | 0.0722 |

**Panel B: Second alternative measure set**

| **Factor** | $\alpha_i$ | $ACT_{t-1}$ | - | $DEC_{t-1}$ | $AMT_t$ | $\bar{R}^2_{CV19A,\varepsilon}$ | $OSV$ |
|---|---|---|---|---|---|---|---|
| $F_{1\varepsilon,t}$ | -0.0701 | 1.0951*** | | | | 0.0279 | 0.0226 |
| | -0.0535 | 1.6084*** | | -1.0080** | 0.0214 | 0.0387 | 0.0313 |
| $F_{2\varepsilon,t}$ | - | - | | | | - | - |
| | 0.0157 | -0.8423*** | | 0.7282*** | 0.0332 | 0.0043 | 0.0038 |
| $F_{3\varepsilon,t}$ | -0.0514 | | | 1.2183*** | | 0.0204 | 0.0186 |
| | -0.0691 | 0.3830 | | 1.0853*** | 0.0267 | 0.0147 | 0.0134 |
| $F_{4\varepsilon,t}$ | -0.0022 | | | | -0.1369** | 0.0559 | 0.0494 |
| | 0.0226 | -0.6236 | | 0.3198 | -0.1424** | 0.0526 | 0.0465 |

***Notes:*** This table reports the results of regressions of orthogonalized factor scores onto the COVID-19 measures individually with breakpoints. Least squares with Newey-West heteroscedasticity and autocorrelation consistent (HAC) standard errors are used for estimation purposes. $GMT_t$ are changes in the Google Mobility Tracker. $FNI_t$ are changes in the Ravenpack Fake News Index. $ACT_{t-1}$ are changes in the number of active cases. $AMT_t$ are changes in Apple Mobility Tracker data. $DEC_{t-1}$ is the growth in 7 day moving average of reported COVID-19 deaths. $F_{K\varepsilon.t}$ are factor scores that are orthogonal to the three COIVD-19 measures identified in Section 3.2. $\bar{R}^2_{CV19A.\varepsilon}$ is the adjusted coefficient of determination for each alternative measure regressed against the orthogonal factor score series. $OSV$ is the orthogonal shared variance, which is the coefficient of determination for each alternative measure adjusted by the amount of shared variance reflected by each $F_{K\varepsilon.t}$ as a fraction of the original factor score series. The asterisks, ***, ** and *, indicate statistical significance at the respective 1%, 5% and 10% levels of significance.

Next, the respective $OSV$ measures are then multiplied by the communalities associated with each $F_{K,t}$ by applying equation (3). Following the methodology outlined above, 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 over and above the original measure set when the alternative measures are related to factor scores individually (jointly). After adjusting for structural breaks in $ACT_{t-1}$ and $AMT_t$ in the respective alternative sets, total shared variance explained increases marginally to 2.68% and 1.72% when calculated considering measures individually. When the $F_{K\varepsilon,t}$s are related to the first and second set of alternative measures jointly with adjustments for structural breaks, the total shared variance explained increases to 4.67% and 3.10% respectively.

What emerges from these results and those presented in Section 3.2. is that there is a set of key COVID-19 measures that move international markets, these being $GST_t$ and $MHI_t$ and two highly correlated (and related measures), $GSM_t$ and $GOR_t$. Depending upon how total shared variance is determined – whether measures are considered individually, jointly, with or without structural breaks – these measures explain between just over 10% and 20% of shared variance across national markets. Then, there are other measures that are far less important. These alternative measures explain, at most, just over 4.6% of shared variance. The conclusion that that follows is that most of the impact of COVID-19 on international markets can be summarised by small number of COVID-19 related measures.

## 4. 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 measures of government responses, uncertainty and media attention – the question of which measures matter most has remained open. By focusing on direct measures that capture the unadulterated effects of COVID-19 on financial markets, we sought to identify measures that matter most for investors. We used elastic net regression for measure selection, selecting three measures, namely 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 measures also impact stock markets, their influence is weaker. We extend the analysis to consider the impact of these COVID-19 measures on market volatility. Only $GST_t$ is associated with volatility triggering effects. Notably, this suggests that media related measures, such as $MHI_t$, reflect a different transmission mechanism. In other words, attention which impacts markets through different transmission channels. 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. None of bode well for financial markets.

Not all regions and markets are equally impacted. When markets are grouped according to economic development, $GST_t$ impacts developed market returns the most whereas lockdown-style policies (reflected by $GSM_t$) and media hype matter more for emerging markets. We propose that the heightened impact of $GST_t$ for developed markets arises because investors in these markets are less accustomed to health or other economic disturbances that are more common in emerging countries. In contrast, emerging markets are more sensitive to $GSM_t$ owing to the key role played by consumer spending in driving growth in these countries and an environment that is less amenable to remote work arrangements. As for $MHI_t$, we argue that investors in emerging markets are more prone to noise trading, resulting in media hype and panic impacting emerging markets to a greater extent. We also note that the impact of the COVID-19 measures appears to grow the further west from the epicentre of the COVID-19 outbreak in China. 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 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 (Szczygielski et al., 2020b; Lu et al., 2020;  Szczygielski et al.; 2021; Wang and Enilov, 2020). While Asia is not the region that is least impacted by $GSM_t$ and $MHI_t$, it is the least impacted by the measure that matters most. $GST_t$ by explains between over 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 developing and Asian-Pacific markets are least impacted by $GST_t$, and given that this is the measure that matters most, a recommendation to investors is that investors invest in developing countries in the Asia-Pacific region if they wish to minimise potentially losses and avoid heightened volatility.

We demonstrate the applicability of elastic net regression which allows us to select just three measures out of an extensive set of 24 measures that appear to capture most of market movements and summarise the impact of COVID-19 on international stock markets. Although there are numerous measures of COVID-19 that have been used in investigating the impact of COVID-19 on financial markets, there is no agreement on which matter most. Elastic net regression, aside from identifying and selecting COVID-19 measures, also permits us to address the inevitable problem of multicollinearity that arises. We also apply an empirical impact measure first proposed by Szczygielski, Brzeszczyński et al. (2021), termed the 'overall impact of uncertainty' (OIU). This measure jointly reflects the impact and intensity of COVID-19 related measure(s) on stock returns. This measure combines both aspects of the influence of uncertainty on stock markets by presenting a two-dimensional measure of uncertainty, contrasting with standard approaches of quantifying the impact of uncertainty on returns and volatility separately. Notably, the OIU measure quantifies both the magnitude and intensity of the impact of uncertainty simultaneously. By applying this measure, we distinctly show that developed and Asian-Pacific markets (Section 3.6) are least impacted overall. This finding differs from previous findings that consider the impact of the individual measures (see discussion above). Importantly, if investors are concerned about the impact of uncertainty (as quantified by $GST_t$) on both returns and volatility, they should invest in developed Asian-Pacific markets. The OIU measure therefore offers a somewhat different perspective. Finally, we propose a procedure that allows us to disentangle the influence of correlated variables without the need to orthogonalise the variables of interest. This procedure relies upon orthogonalising the dependant series (Section 3.7) against variables that we wish to exclude and then regressing the orthogonalised dependant series against the variables of interest. This is followed by an adjustment to the resultant coefficient of determination to reflect the uncorrelated explanatory power for the unorthogonalised series. A criticism aimed at the use of orthogonalised explanatory series is that the original interpretation no longer applies (Wurm & Fisicaro, 2014). Our approach permits us to establish the explanatory power associated with a variable that is not due to correlation with specific variables. We apply this approach to show that while there are other measure of COVID-19 that matter for financial markets, namely $GMT_t$, $FNI_{t,}$ $ACT_{t-1}$, $AMT_t$ and $DEC_{t-1}$ their ability to approximate the drivers of international stock market returns over the COVID-19 period is limited and inferior to that of $GST_t$, $GSM_t$ and $MHI_t$.

By undertaking this study, we shed light onto the COVID-19 measures that have the greatest impact on global stock markets and provide clarity as to which measures matter most for investors and practitioners. For econometricians and researchers, we demonstrate the application of a machine learning techniques for identifying the most import COVID-19 for international stock markets. The application of the OIU measure may also be helpful in future studies that investigate the impact and COVID-19 and stock returns. From an econometric-focused point of view, the procedure outlined in Section 3.7. offers an improved method for disentangling the impact of correlated explanatory factors. Areas for further research include an analysis of the out-of-sample performance of the COVID-19 measures identified in this study and an investigation of whether over the longer-term, other and more relevant COVID-19 measures may emerge. In this vein, we propose a more extensive study of the stability of the relationships between international stock markets and new and existing measures of the COVID-19 pandemic.

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