The only certainty is uncertainty: An analysis of the impact of COVID-19 uncertainty on regional stock markets

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Abstract

Uncertainty surrounding COVID-19 is widespread. In this study, we investigate the timing and quantify the impact of COVID-19 related uncertainty on returns and volatility for six regional market aggregates using ARCH/GARCH models. We draw upon the paradigm of economic psychology, defining COVID-19 related uncertainty in terms of searches for information as measured by Google Trends. Our results indicate that Asian markets, although immediately impacted, have been more resilient than others. Latin American markets are found to be the most impacted in terms of both returns and volatility. Apart from Arab and African markets, there is evidence of an increasing impact of COVID-19 related uncertainty which then dissipates as the crisis evolves. We further show that COVID-19 related uncertainty is part of the composite set of factors that drive returns over this period although its importance has declined substantially. Finally, we confirm the empirical relationship between COVID-19 related uncertainty as measured by Google Trends and alternative measures of uncertainty during the COVID-19 period.

Keywords: COVID-19, pandemic, returns, volatility, regions, structural breaks

JEL classification: C22, C58, D53, G12, G01, G14

1.Introduction

While several pandemics and serious disease outbreaks have occurred in the past, such as the Spanish flu (1918), SARS (2003), MERS (2012)[1] and Ebola (2014), the novel coronavirus (COVID-19) outbreak of 2019-2020 ranks amongst the most severe and widespread, with infections recorded in more than 200 countries (World Health Organisation (WHO), 2020). The emergence of COVID-19 has resulted in a global economic crisis coupled with severe stock market declines. Prior studies show that not only are financial markets negatively impacted by diseases and crises in general, but that the intensity and timing of impact differs across countries (Nippani and Washer, 2004; McTier et al., 2013; Bekaert et al., 2014). Ichev and Marinč (2018) report that Ebola outbreaks had a more significant impact on companies that had operations in, or were geographically nearer to, Ebola origins (West Africa). Claessens et al. (2010) documented that during the 2007-2008 financial crisis, countries with closer ties to the United States' (US) financial system or direct exposure to asset-backed securities were the first to be affected.

Research on the differential effects of COVID-19 across countries has identified varying intensities and timing. Liu et al. (2020) observe that Asian financial markets experienced an immediate downturn when the outbreak occurred. The impact on US and European markets was delayed, occurring several days after outbreaks of the virus in South Korea and Italy,[2] and less severe. Similarly, Gormsen and Koijen (2020) show that only once COVID-19 spread to Italy, Iran and South Korea, did US and German stock markets decline sharply. Gunay (2020) reports a structural break in volatility for Chinese stock returns earlier (30th January 2020) than other countries.[3] Ru et al. (2020) find that market reactions to early COVID-19 outbreaks were more immediate and substantial in countries that suffered from SARS in 2003. Gerding et al. (2020) document that stock markets in countries with higher debt-to-gross domestic product ratios were more impacted.

Uncertainty surrounding COVID-19 is widespread, both with respect to the evolution of the disease itself and its economic impact (McKibbin and Fernando, 2020). Moreover, COVID-19 related uncertainty has impacted both returns and volatility in the US (Baig et al., 2020; Bretscher et al., 2020; Ramelli and Wagner, 2020) and internationally (Liu, 2020; Papadamou et al., 2020). However, no study has examined the differential impact of COVID-19 related uncertainty on regional markets around the world and the timing of these effects.

We quantify the differential impact of COVID-19 related uncertainty on returns and variance for six regional market aggregates using the ARCH/GARCH framework and structural change analysis. Drawing from economic psychology, which proposes that individuals respond to uncertainty about specific events by searching more intensively for relevant information (Liemieux and Peterson, 2011;

[1] Severe acute respiratory syndrome and middle east respiratory syndrome respectively.
[2] 19 and 21 February 2020 respectively.
[3] The US, Italy, Spain, Turkey and the United Kingdom.

Dzielinski, 2012; Castelnuovo and Tran, 2017; Bontempi et al., 2019), we measure uncertainty using Google Trends search data for terms related to COVID-19. We contribute to the burgeoning literature on the impact of COVID-19 on financial markets. To the best of our knowledge, this is the first study that investigates the relationship between uncertainty reflected by Google search trends and COVID-19 for regional market aggregates. We find that returns for all regions are negatively impacted by *global* COVID-19 uncertainty and that COVID-19 uncertainty has volatility triggering effects for all regions with the exception of Arab markets. Furthermore, we find that a number of regions show a weakening of the impact of COVID-19 uncertainty as the crisis evolved. We go on to confirm that Google Trends are a proxy for uncertainty which drives returns and triggers volatility.

2. Data and Methodology

Our primary data sample spans 1 January 2019 to 19 June 2020.[4] For regional markets, the MSCI All Country (AC) Asia, AC Europe, Emerging Frontier Markets (EMF) Africa, Emerging Markets (EM) Latin America, North America and Arabian Markets indices are used. Returns are defined as logarithmic differences in index levels. Data is of a daily frequency and is stated according to MSCI's local currency methodology, representing performance unimpacted by foreign exchange rate movements.

Table 1: Descriptive statistics for returns on MSCI indices

Region	**Asia**	**Europe**	**Africa**	**Latin**	**North**	**Arab Markets**
Index	**MSCI AC Asia**	**MSCI AC Europe**	**MSCI EFM Africa**	**MSCI EM Latin America**	**MSCI North America**	**MSCI Arabian Markets**
Mean	0.0002	0.0002	-0.0001	-7.80E-05	0.0006	-0.0003
Median	0.0005	0.0011	0.0004	0.0001	0.0009	0.000000
Maximu	0.0525	0.0761	0.0614	0.0954	0.0911	0.0529
Minimum	-0.0503	-0.1193	-0.0925	-0.1238	-0.1282	-0.1631
Std. dev.	0.0101	0.0137	0.0153	0.0184	0.0176	0.0131
Kurtosis	8.7745	22.6102	13.0918	18.1083	18.1819	67.3530
Skewness	-0.3311	-2.0972	-1.4676	-1.6940	-1.1366	-5.5057
SW	0.9107***	0.7858***	0.8440***	0.7726***	0.7524***	0.6213***

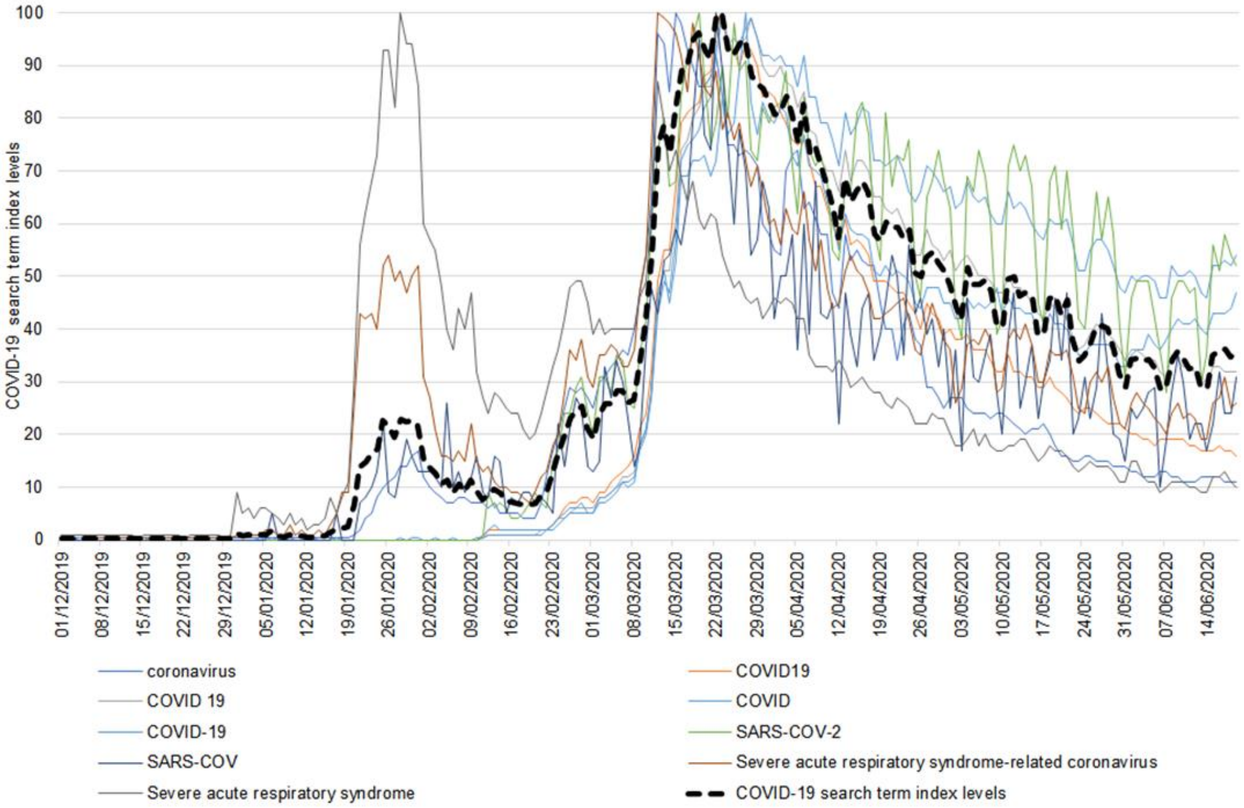
This table reports descriptive statistics for the regional indices in our sample. Returns are defined as logarithmic differences in index levels. *** indicates statistical significance at the 1% level of significance. SW is the Shapiro-Wilk test statistic verifying normality.

Following an analysis of Google Trends, we identify nine COVID-19 related terms associated with high search volumes globally. These are: "coronavirus", "COVID19", "COVID 19", "COVID", "COVID-19", "SARS-CoV-2", "SARS-COV", "severe acute respiratory syndrome-related coronavirus" and "severe acute respiratory syndrome". We construct a search term index[5] by combining search trends for the terms above. Individual index values are added and the sum is divided by nine. The highest value is

[4] 1 December 2019 is chosen as the start of the COVID-19 crisis as this was the day on which the first case was reported (Huang et al., 2020). However, we use a longer sample for estimation purposes.
[5] Data obtained from Google Trends is the sum of the scaled total number of searches between 0 to 100 based upon a topic's proportion to all searches on all topics.

adjusted to 100, with remaining values adjusted accordingly relative to this base. Index values are then differenced (Figure 1A, Appendix).

Figure 1: COVID-19 related searches over time as captured by Google Trends



This figure plots levels in the combined COVID-19 search term index created from Google Trends search volumes for nine COVID-19 related search terms over the period 1 December 2019 to 19 June 2020. Levels of search volumes for individual COVID-19 related terms are also plotted.

We apply the ARCH/GARCH framework to measure the impact of changes in search volumes on both returns and conditional variance, a proxy for risk (Brzeszczyński and Kutan, 2015). We begin with an ARCH(p) model and proceed to estimate an GARCH(p,q) model if the ARCH(p) specification exhibits residual heteroscedasticity. We also consider the IGARCH(p,q) model if ARCH and GARCH parameters sum to unity (Engle and Bollerslev, 1986). Following preliminary specification testing, the following models are proposed:

Table 2: Model specifications

Model	**Specification**	
Mean:	$r_{i,t} = \alpha_i + \beta_{i,\Delta CV19I} \Delta CV19I_t Dum_{0,1} + \beta_{i,IM} R\varepsilon_{IM,t} + \sum_{k\geq 0}^{k} \beta_{i,k} F_{k,t} + \gamma_i r_{i,t-\tau} + \varepsilon_{i,t}$	(1)
ARCH/GARCH:		
ARCH(p)	$h_{i,t} = \omega_i + \sum_{p\geq 1}^{p} \alpha_i \varepsilon_{i,t-p}^2 + \varphi_{i,\Delta CV19I} \Delta CV19I_t Dum_{0,1}$	(2a)
GARCH(p,q)	$h_{i,t} = \omega_i + \sum_{p\geq 1}^{p} \alpha_i \varepsilon_{i,t-1}^2 + \sum_{q\geq 1}^{q} \beta_i h_{i,t-q} + \varphi_{i,\Delta CV19I} \Delta CV19I_t Dum_{0,1}$	(2b)
IGARCH(p,q)	$h_{i,t} = \sum_{p\geq 1}^{p} \alpha_i \varepsilon_{i,t-p}^2 + \sum_{q\geq 1}^{q} \beta_i h_{i,t-q} + \varphi_{i,\Delta CV19I} \Delta CV19I_t Dum_{0,1}$	(2c)

This table lists the specifications fitted in this study. The mean equation, equation (1), is specified in the "mean" row. ARCH(p), GARCH(p,q) and IGARCH(p,q) specifications, equations (2a)/(2b)/(2c) respectively, follow after the "ARCH/GARCH" row.

Table 2 lists all specifications, where $r_{i,t}$ is the return on index *i* at time *t*, $\Delta CV19I_t$ are first differences in the combined COVID-19 search term index – our measure of COVID-19 related uncertainty – and, $h_{i,t}$ is the conditional variance. $Dum_{0,1}$ is a shift dummy denoting pre-COVID-19 and COVID-19 periods, defined as 1 January 2019 to 30 November 2019 and 1 December 2019 to 19 June 2020, respectively. A residual market factor, $R\varepsilon_{IM,t}$, derived from returns on the MSCI AC World Market index, is included to address potential underspecification (Burmeister and McElroy, 1991). Additionally, a factor analytically derived factor set, $\sum_{k\geq 0}^{k} \beta_{i,k} F_{k,t}$, is incorporated into equation (1) to account for influences that may not be reflected by $R\varepsilon_{IM,t}$. Factors comprising the factor analytic augmentation, accounting for both contemporaneous and lagged relationships, are derived from regional return series and are then adjusted for the impact of $\Delta CV19I_t$ and $R\varepsilon_{IM,t}$ (Szczygielski et al., 2020).[6] For parsimony, only significant proxy factors are retained. Finally, autoregressive terms, $r_{i,t-\tau}$, of order τ identified from an analysis of a residual correlogram are included to address remaining autocorrelation if required. To identify periods for which the impact of $\Delta CV19I_t$ differs, breakpoints are identified using the Bai-Perron test (Carlson et al., 2000). If breakpoints are detected, the $\Delta CV19I_t$ variable, together with associated coefficients and shift dummies in equations (1) and (2a)/(2b)/(2c), are replaced with $\sum_{\pi\geq 1}^{\pi} \beta_{i,\pi,\Delta CV19I} \Delta CV19I_t Dum_{0,1,\pi}$ and $\sum_{\pi\geq 1}^{\pi} \varphi_{i,\pi,\Delta CV19I} \Delta CV19I_t Dum_{0,1,\pi}$ respectively, with $Dum_{0,1,\pi}$ taking on a value of one or zero otherwise for segment π between breakpoints. The equations are first estimated using maximum likelihood estimation (MLE). 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).

3. Results

3.1. The impact of COVID-19 related uncertainty on regional markets

Panel A, Table 3 reports coefficients on $\Delta CV19I_t$ in the conditional mean ($\beta_{i,\Delta CV19I}$) and Panel B reports the impact of $\Delta CV19I_t$ on the conditional variance ($\varphi_{i,\Delta CV19I}$).[7] The results in Panel A, Table 3 indicate that returns for all regions are negatively and significantly impacted by $\Delta CV19I_t$. The results in Panel B indicate that coefficients on $\Delta CV19I_t$ in the respective ARCH/GARCH models, $\varphi_{i,\Delta CV19I}$, are positive and statistically significant for five regions. The negative impact of $\Delta CV19I_t$ on returns can be attributed to a combination of lower expected cash flows and heightened risk aversion. The adverse economic effects of COVID-19 uncertainty are likely to be associated with declining expected cash flows to firms (Ramelli & Wagner, 2020). Also, heightened risk aversion attributable to uncertainty surrounding the pandemic means that investors will require a higher risk premium which is reflected in the forward

[6] Szczygielski et al. (2020) show that a residual market factor may be insufficient to ensure residual correlation matrix diagonality, implying that a model omits factors with a systematic (common) impact. The inclusion of a factor analytic augmentation is shown to result in a diagonal residual matrix.

[7] All estimation procedures converge and residuals are free of ARCH effects and serial correlation.

looking discount rate (Andrei & Hasler, 2014; Smales, 2020; Cochrane, 2018). Together, lower expected cash flows and a higher discount rate translate into lower stock prices.[8]

Although returns in North America are negatively impacted ($\beta_{i,\Delta CV19I}$ of -0.003417(3rd)), this region does not show significant volatility triggering effects. However, the results in Panel B, Table 4 paint a different picture suggesting that North American markets experienced delayed volatility triggering effects. Similarly, while returns in Europe are also impacted ($\beta_{i,\Delta CV19I}$ of -0.003459(2nd)), volatility triggering effects are relatively low ($\varphi_{i,\Delta CV19I}$ of 0.1460(4th)). Arab markets do not appear to experience heightened volatility associated with $\Delta CV19I_t$, although returns are impacted ($\beta_{i.\Delta CV19I}$ of -0.00188(5th)). The lack of volatility triggering effects is surprising, given the economic dependency on oil of Arab markets and the consequent uncertainty surrounding their macroeconomic prospects (Ashraf, 2020). However, an analysis of realized variance suggests that Arab markets showed extreme, but short-lived, heightened volatility around 7 to 9 March 2020. These dates coincide with COVID-19 cases surpassing 100 000 and a call by the WHO for more stringent actions to control the spread of COVID-19 (WHO, 2020). While $\varphi_{i,\Delta CV19I}$ may not be significant, forecasted conditional variance captures this volatility spike (Figure 7A, Appendix).

Asian markets are relatively resilient to COVID-19 uncertainty ($\beta_{i,\Delta CV19I}$ of -0.001814(6th) and $\varphi_{i,\Delta CV19I}$ of 0.1300(5th) respectively). This may be attributable to experience that Asian countries have in dealing with pandemics (SARS and MERS outbreaks) (Lu et al., 2020; Wang and Enilov, 2020). While these results differ from those of Liu et al. (2020) and Ru et al. (2020), who report that Asian markets were severely impacted by COVID-19 infection numbers, this finding demonstrates the varying effect of COVID-19 uncertainty relative to infection numbers on stock markets.

Finally, the substantial impact of $\Delta CV19I_t$ on returns and volatility in African and Latin American markets ($\beta_{i,\Delta CV19I}$s of -0.00314(4th) and -0.003625(1st) and, $\varphi_{i,\Delta CV19I}$s of 0.2680(2rd) and 0.5480(1st)) can be attributed to risk aversion in relation to developing markets in times of crisis and spillovers from developed markets (Frank and Hesse, 2009; Bekaert et al., 2014). Both regions comprise two of the larger and more developed stock markets in the world, the Johannesburg Stock Exchange (JSE) (19th) and the Brazilian BM&F Bovespa (20th) (Haqqi, 2020), which are highly integrated with global markets (Babu et al., 2016; Nashier, 2015) and therefore likely to readily reflect global developments (Szczygielski and Chipeta, 2015).[9] In contrast, Arab markets, while comprising developing countries,

[8] We would like to thank an anonymous reviewer for a comment relating to this issue as well as for other comments which helped in improving this paper.

[9] Spearman rank-order correlations for realized volatility over the pre-COVID-19 and COVID-19 periods are compared across respective regions (see Table 2A, Appendix). All regions show stronger and (now always) significant positive correlation over the COVID-19 period. Latin American and African markets are now significantly and positively correlated with North American and Arab markets. Also, African markets are now correlated with Asian markets, which was not true prior to the COVID-19 period. Furthermore, correlation between African and European market volatility doubles. Volatility in Arab markets is now significantly correlated with all regions although correlations become insignificant after adjusting for realized oil variance, which can be viewed as an important factor for this market. If volatility is interpreted as a proxy for information,

have been found to be less integrated globally (Marashdeh & Shrestha, 2010; Alotaibi & Mishra, 2017), which is consistent with our findings in that they are less impacted by COVID-19 related uncertainty. Our results are generally consistent with previous studies on the differential impact of pandemics and crises on different regions (Claessens et al., 2010; Bekaert et al., 2014).

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this suggests that volatility in these markets now reflects spillovers from new sources of information (see Singh, Kumar and Pandey, 2010).

Table 3: Results for specifications without breaks

Region	Asia	Europe	Africa	Latin	North America	Arab markets
Index	**MSCI AC Asia**	**MSCI AC Europe**	**MSCI EFM Africa**	**MSCI EM Latin America**	**MSCI North America**	**MSCI Arabian Markets**
Panel A: Conditional mean (eq.(1))						
$Intercept$	0.0001	0.0003	0.0002	0.0002	0.0004***	-0.0001
$\beta_{i,\Delta CV19I}$	-0.001814***(6th)	-0.003459***(2nd)	-0.00314***(4th)	-0.003625***(1st)	-0.003417***(3rd)	-0.001882***(5th)
β_{iM}	0.5622***	0.9471***	0.6537***	0.9293***	1.1430***	0.4290***
Proxy factors:						
β_{i1}	0.0049***	0.0013**		-0.0012**		0.0021***
β_{i2}	0.0061***	0.00876***	0.0229***			0.0111***
AR Terms						
	-0.2639r_{t-1}***	-0.1128r_{t-1}**		-0.0747r_{t-1}*	-0.1791r_{t-1}*** 0.0136r_{t-4}***	0.1306 r_{t-5}***
Panel B: Conditional variance (eq.(2a)/(2b)/(2c))						
Model	IGARCH(1,1)	GARCH(1,1)	GARCH(1,1)	IGARCH(1,1)	GARCH(1,2)	GARCH(1,2)
ω_i		4.10E-07*	1.11E-06*		3.25E-07***	6.55E-06*
α_i	0.0171**	0.1426***	0.1125***	0.0238**	0.2470***	0.2842*
β_1	0.9829***	0.8376***	0.8640***	0.9762***	0.4637*	0.0120
β_2					0.2618	0.6548***
$\varphi_{i,\Delta CV19I}$	0.1300***(5th)	0.1460***(4th)	0.2680***(2nd)	0.5480**(1st)	0.0599(6th)	0.1720(3rd)
Panel C: Diagnostics						
$\bar{R}^2$	0.6907	0.8491	0.7177	0.6983	0.9404	0.4169
F-statistic	144.5589***	291.9546***	404.4670***	61.7861***	1584.791***	15.5807***
$Q(1)$	0.0013	1.3880	2.6949	0.1089	1.4571	1.1509
$Q(10)$	10.615	9.2321	12.852	11.598	8.5414	11.417
ARCH(1)	1.5753	0.0085	0.7341	0.0227	1.2751	0.0497
ARCH(10)	0.4548	0.5198	0.5901	0.9616	0.6879	1.0301
Log-likelihood	1484.054	1597.812	1378.156	1276.960	5384.058	1320.595

This table reports the impact of changes in COVID-19 related uncertainty on the returns ($\beta_{i,\Delta CV19I}$) and variance ($\varphi_{i\Delta CV19I}$) for regional markets. Coefficients on $\Delta CV19I_t$ in the conditional variance equation are scaled by 100 000. Panel A reports estimation results for the conditional mean, which also includes proxy factors derived from regional returns using factor analysis and adjusted for the impact of $\Delta CV19I_t$ and $R\varepsilon_{IM,t}$. Panel B reports the results for the conditional variance. Values in brackets (…) rank the order of absolute impact according to the magnitude of the $\beta_{i,\Delta CV19I}$ and $\varphi_{i,\Delta CV19I}$ coefficients. Panel C reports model diagnostics, with $Q(1)$ and $Q(10)$ being Ljung-Box tests statistics for joint serial correlation at the 1st and 10th orders. ARCH(1) and ARCH(10) are test statistics for the ARCH LM test for heteroscedasticity. Each model is estimated over the primary data period between 1 January 2019 and 19 June 2020 unless residuals show dependence structures in which case longer estimation periods are used. Pre-COVID-19 and COVID-19 periods are defined as 1 January 2019 to 30 November 2019 and 1 December 2019 to 19 June 2020 respectively. The asterisks ***,** and * indicate statistical significance at 1%, 5% and 10% levels of significance respectively.

As $\Delta CV19I_t$ is constructed from global Google Trends, we also consider value-weighted regional versions by replacing $\Delta CV19I_t$ with $\Delta CV19R_t$[10] in Table 2 as an extension and robustness test.

Table 4: Abridged regional results for specifications without breaks

	Asia	Europe	Africa	Latin America	North America	Arab markets
	MSCI AC Asia	**MSCI AC Europe**	**MSCI EFM Africa**	**MSCI EM Latin America**	**MSCI North America**	**MSCI Arabian**
$\beta_{i,\Delta CV19R}$	-0.00078*** (5^{th})	-0.000910*** (2^{nd})	-0.000789*** (4^{th})	-0.000876*** (3^{rd})	-0.002296*** (1^{st})	0.000158** (6^{th})
$\varphi_{i\Delta CV19R}$	0.0947** (4^{th})	0.1010*** (3^{rd})	0.2970** (2^{nd})	1.0700*** (1^{st})	0.0421(5^{th})	-0.0076 (6^{th})

This table reports the abridged results for the impact of changes in regional COVID-19 related uncertainty as captured by Google Trends on the returns ($\beta_{i,\Delta CV19R}$) and variance ($\varphi_{i\Delta CV19R}$) for regional markets. Coefficients on $\Delta CV19R_t$ in the conditional variance equation are scaled by 100 000. The asterisks, ***,** and * indicate statistical significance at 1%, 5% and 10% levels of significance, respectively. Figure 8A in the appendix presents a comparison of global and regional search term indices. Unabridged results are reported in Table 1A in the appendix.

Results in Table 4 show a similar pattern. Returns for all regions, with the exception of Arab markets[11], are impacted negatively although to a lesser magnitude. For example, coefficients on $\Delta CV19R_t$ for Latin and North America decrease to -0.000876 and -0.002296 respectively. The order of the magnitude of impact is approximately the same across regions although North American and Arab markets are now most and least impacted respectively. We attribute this effect to the dominance of US uncertainty. Specifically, uncertainty experienced by the US dominates the North American market, but also US uncertainty impacts all other regions (Chiang et al., 2015; Dimic et al., 2016; Smales, 2019) and hence with regional measures, US uncertainty is excluded resulting in a reduced impact. Volatility triggering effects associated with $\Delta CV19R_t$ are also lower, with the exception of Latin America where $\Delta CV19R_t$ is now associated with a coefficient of 1.0700 in the conditional variance. The generally greater impact of $\Delta CV19I_t$ on both returns and conditional variance indicates that regional markets likely reflect not only regional uncertainty but also spillovers from the rest of the world (see discussion that follows). Importantly, it appears that global COVID-19 related uncertainty, as opposed to region or country-specific uncertainty, primarily matters most for stock markets and volatility (see Mumtaz and Mussom, 2019).[12] This is broadly consistent with the findings of Costola et al. (2020) that US, German, French,

[10] This measure is constructed by value weighting combined country specific search term indices for each country in each respective region. In constructing regional measures, we include all countries in each region, with the exception of Africa for which we include major constituents only (Egypt, South Africa, Kenya, Mauritius, Morocco, Nigeria and Tunisia) given the unavailability of country level market capitalizations for some minor constituents.

[11] The positive relationship between Arab markets returns and $\Delta CV19R_t$ becomes statistically insignificant and decreases further in absolute magnitude when the conditional variance is re-specified as a GARCH(1,1) process ($\beta_{i,\Delta CV19R}$ of 0.000114) and negative and statistically insignificant when the mean equation is re-estimated using least squares (($\beta_{i,\Delta CV19R}$ of -0.0000343). This suggests that the unexpected positive relationship between returns and the regional measure of COVID-19 uncertainty is not robust for Arab markets and is potentially attributable to the relatively noisier nature of the regional COVID-19 related uncertainty measure for Arab markets (see Figure 8A, Appendix).

[12] Furthermore, using $\Delta CV19R_t$ instead of $\Delta CV19I_t$ while retaining original conditional mean and variance functional forms for comparative purposes generally results in lower log-likelihood values (with the exception of Europe and Arab markets, for which the log-likelihood values increase). For most regions, relying on global Google Trends to capture COVID-19 uncertainty produces a superior model fit (see Panel C, Table 1A; Myung, 2003).

Spanish and UK stock markets respond more to Italian Google search trends than those in their own countries. Smales (2020) also finds that global search trends have a greater impact than regional search trends on the stock markets of the G20 countries. We conclude that, overall, the results of the analysis using $\Delta CV19R_t$ are mostly qualitatively consistent with those for $\Delta CV19I_t$.[13]

Table 5 reports results after accounting for breakpoints. Results in Panel A suggest that the negative impact of $\Delta CV19I_t$ on returns first intensified and then weakened as the COVID-19 crisis evolved, although all regions continued to be significantly impacted. No structural breaks were detected for the African and Arab markets. For North America, Europe, Latin America and Asia, the results in Panel B indicate that the negative impact of $\Delta CV19I_t$ on volatility intensified and then weakened as the crisis evolved. The dates of breakpoints across European, North American and Latin American markets are similar, with all three experiencing breaks in late February[14] and in late March (26 March 2020 for all three). Breakpoints in late February coincide with President Trump's request for $1.25 billion from the US Congress to respond to the COVID-19 crisis (24 February 2020) and the first reported case in Latin America (Brazil) (26 February 2020) (Onali, 2020; Taylor, 2020). Gunay (2020) also identified a structural break in volatility in North America and Europe in late February. The structural break on 26 March 2020 coincides with most European, North American and Latin American countries under lockdown (Taylor, 2020). We also identify a breakpoint for North America in January (20 January 2020)[15] and one for Latin America in mid-May (13 May 2020).

Returns in North America are most impacted ($\beta_{i,3,\Delta CV19I}$ of -0.003697) after late February whereas returns in Europe are most impacted following the end of March 2020 ($\beta_{i,3,\Delta CV19I}$ of -0.003448). For both North America and Europe, the impact of $\Delta CV19I_t$ on volatility is greatest following the February breakpoint ($\varphi_{i,3,\Delta CV19I}$ of 0.2250 and $\varphi_{i,2,\Delta CV19I}$ of 0.9460 respectively) but, the impact of uncertainty on volatility dissipates thereafter (and is insignificant). The delay in impact mirrors the findings of Gormsen and Koijen (2020) and Liu et al. (2020) about the impact of COVID-19 infections on markets outside of Asia and is consistent with Ichev and Marinč's (2018) assertions that geographical proximity matters. It is only when these two regions become centres of the outbreak that volatility (and to a lesser extent returns) is most impacted in these markets. For returns in Latin America, the initial impact is less severe but more than doubles ($\beta_{i,1,\Delta CV19I}$ of -0.002338 to $\beta_{i,2,\Delta CV19I}$ of -0.0054) after the end of

[13] We investigate the direction of causality between regional returns and $\Delta CV19I_t$ to determine whether market declines during the COVID-19 period contribute to COVID-19 related uncertainty or whether COVID-19 related uncertainty contributes to market declines. See Black (1976) and Bouchaud et al. (2001) for a discussion of the leverage effect which is concerned with the asymmetric relationship between volatility and returns. The results in Table 3A of the Appendix show that $\Delta CV19I_t$ overwhelmingly Granger-causes regional market returns, with the exception of Africa for which there appears to be a bi-directional relationship. Although we do not undertake an extensive study of the intertemporal structure of return-$\Delta CV19I_t$ relationships, bi-directionality for this region continues at higher orders of lags although the *F*-statistic for the test of Granger-causality from returns on African markets to $\Delta CV19I_t$ decreases as the number of lags is increased.
[14] 24 February 2020 in Europe and North America and 26 February 2020 for Latin America.
[15] More cases outside of China were documented on 20 January (Japan, South Korea and Thailand), with the first US case reported on 21 January (Taylor, 2020).

February, before declining progressively ($\beta_{i,3,\Delta CV19I}$ of -0.003980 and $\beta_{i,4,\Delta CV19I}$ of -0.002243, respectively). A similar pattern emerges with $\Delta CV19I_t$ triggering heightened volatility after the end of February and further after late March (significant $\varphi_{i,2,\Delta CV19I}$ and $\varphi_{i,3,\Delta CV19I}$ of 0.6190 and 0.7780, respectively) before dissipating after mid-May. The dissipating effect of uncertainty on volatility thus occurs later in Latin American markets than in North American or European markets. The weakening impact of $\Delta CV19I_t$ on volatility can potentially be attributed to the COVID-19 crisis being viewed by economic agents as a no longer novel but persistent situation. The decline in uncertainty reflected in Figure 1 can also mean that a higher risk premium is no longer needed as risk aversion has dissipated or decreased substantially and/or that the decline in expected cash flows due to the pandemic is not as severe as initially predicted by the markets. Alternatively, this decline may be attributable to government responses to the pandemic, such as lockdowns and/or economic stimulus packages. A role for government interventions in reducing uncertainty and volatility is suggested by Kizys et al. (2020) but not by Zaremba et al. (2020). The latter is investigated further in Section 3.2.

For Asia, the effects of $\Delta CV19I_t$ are immediate. The respective parameters ($\beta_{i,1,CV19I}$ of -0.001865 and $\varphi_{i,1,\Delta CV19I}$ of 0.1740) are largest and statistically significant prior to the first breakpoint on 18 May 2020. These findings are in line with those of Liu et al. (2020) and Ru et al. (2020) regarding the timing of the impact of COVID-19 infections on Asian markets. The effects on volatility in Asia dissipate similarly to North America, Europe and Latin America but, consistent with Latin America, this occurs later than in North America and Europe (the timing of the single breakpoint for Asia is similar to that of the final break for Latin America in May 2020). A finding of no structural breaks for African markets implies that the impact of COVID-19 uncertainty is still high. For African markets, this is potentially attributable to the pandemic still being far from its peak (WHO, 2020). For Arab markets, this may reflect a return to persistently lower levels of volatility following a large but short-lived volatility spike in early March 2020.

Table 5: Results for specifications with breaks

Region	Asia	Europe	Africa	Latin America	North America	Arab markets
Index	**MSCI AC Asia**	**MSCI AC Europe**	**MSCI EFM Africa**	**MSCI EM Latin America**	**MSCI North America**	**MSCI Arabian Markets**
Panel A: Conditional mean (eq.(1)) with breaks						
Breakpoints	18/05/2020	24/02/2020, 26/03/2020	No breaks	26/02/2020, 26/03/2020, 13/05/2020	20/01/2020, 24/02/2020, 26/03/2020	No breaks
Intercept	0.0002	0.0003*		0.0003	0.0004***	
$\beta_{i,1,CV19I}$	-0.001865***	-0.003399***		-0.002338***	-0.001972***	
$\beta_{i,2,CV19I}$	-0.001504***	-0.003282***		-0.005448***	-0.003341***	
$\beta_{i,3,CV19I}$		-0.003448***		-0.003980***	-0.003697***	
$\beta_{i,4,CV19I}$				-0.002243***	-0.003258***	
β_{iM}	0.5581***	0.9515***		0.8811***	1.1405***	
Proxy factors:						
β_{i1}	0.0049***	0.0011*		-0.0014**		
β_{i2}	0.0062***	0.0088***				
AR Terms						
	-0.2653r_{t-1}***	-0.1107r_{t-1}**		-0.0970r_{t-1}**	-0.1778r_{t-1}***	
					0.0157r_{t-4}	
					0.0062r_{t-4}	
Panel B: Conditional variance (eq.(2a)/(2b)/(2c)) with breaks						
Model	IGARCH(1,1)	GARCH(1,1)		IGARCH(1,1)	GARCH(1,2)	
ω_i		1.11E-06***			3.50E-07***	
α_i	0.0322***	0.0558*		0.0410***	0.2251***	
β_1	0.9678***	0.8280***		0.9590***	0.4951*	
β_2					0.2322	
$\varphi_{i,1,\Delta CV19I_t}$	0.1740***	0.1650***		0.6000	-0.0288	
$\varphi_{i,2,\Delta CV19I_t}$	-0.1920	0.9460**		0.6190**	0.0728**	
$\varphi_{i,3,\Delta CV19I_t}$		-0.2790		0.7780**	0.2250*	
$\varphi_{i\Delta,4,CV19I_t}$				-0.3750	-0.0519	
Panel C: Diagnostics						
$\bar{R}^2$	0.6909	0.8450		0.710	0.9400	
F-statistic	108.5422***	468.0253***		44.0270***	1054.943***	
$Q(1)$	0.0433	1.6874		0.1303	1.6350	
$Q(10)$	9.2844	9.5584		10.927	8.7518	
ARCH(1)	0.7557	0.6367		0.0232	2.3943	
ARCH(10)	0.3983	0.8531		0.3965	0.6533	
Log-likelihood	1484.948	1610.274		1280.500	5395.083	

This table reports the impact of changes in COVID-19 related uncertainty on the returns ($\beta_{i,\pi,\Delta CV19I}$) and variance ($\varphi_{i,\pi,\Delta CV19I_t}$) for regional markets, taking in account structural breaks. Segments identified using the Bai-Perron test of L+1 vs L sequentially determined breaks with robust standard errors (HAC) and heterogenous error distributions. Coefficients on $\Delta CV19I_t$ in the conditional variance equation are scaled by 100 000. Panel A reports estimation results for the conditional mean, which also includes proxy factors derived from regional returns using factor analysis and adjusted for the impact of $\Delta CV19I_t$ and $R\varepsilon_{IM,t}$. Panel B reports the results for the conditional variance. Panel C reports model diagnostics, with $Q(1)$ and $Q(10)$ being Ljung-Box tests statistics for joint serial correlation at the 1st and 10th orders. ARCH(1) and ARCH(10) are test statistics for the ARCH LM test for heteroscedasticity. Breakpoint identifies the date on which each structural change occurs during the COVID-19 period, where the beginning of the COVID-19 period is taken as 1 December 2019. Each model is estimated over the primary data period between 1 January 2019 and 19 June 2020 unless residuals show dependence structures in which case longer estimation periods are used. Pre-COVID-19 and COVID-19 periods are defined as 1 January 2019 to 30 November 2019 and 1 December 2019 to 19 June 2020 respectively. Asterisks ***,** and * indicate statistical significance at 1%, 5% and 10% levels of significance respectively.

3.2. COVID-19 related uncertainty as a factor

To confirm that $\Delta CV19I_t$ is indeed driving returns, we factor analyse the structure of returns during the pre-COVID-19 and COVID-19 periods.

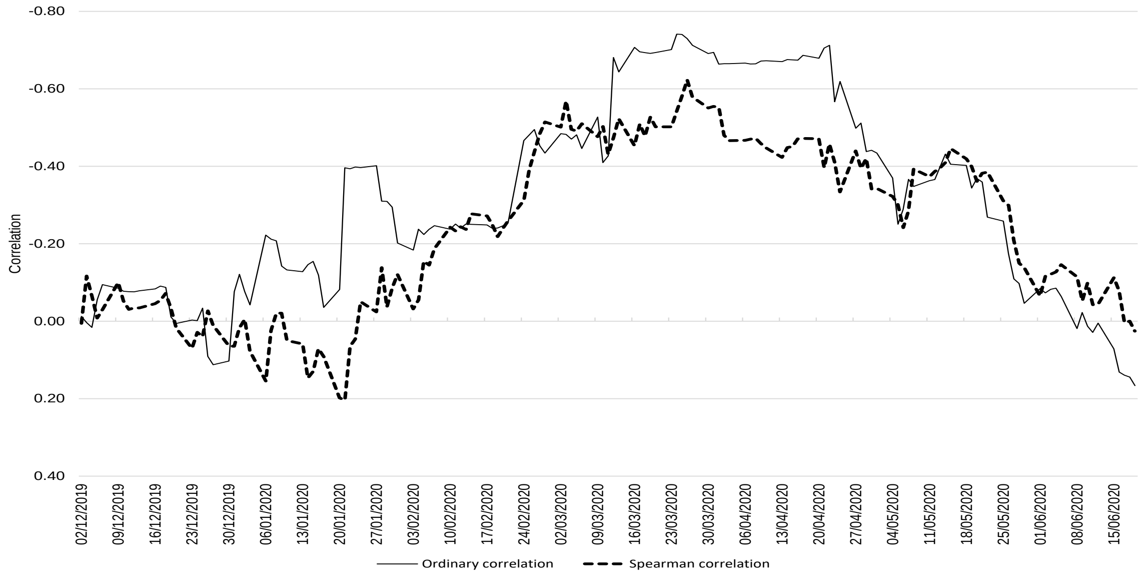
Table 6: Summary of factor analysis

Period	Factors extracted	Mean communality	KMO
Pre-COVID-19	1	0.3834	0.7177
COVID-19	1	0.6505	0.8650

This table reports the results of factor analysis applied to returns over the pre-COVID-19 and COVID-19 periods. Pre-COVID-19 and COVID-19 periods are defined as 1 January 2019 to 30 November 2019 and 1 December 2019 to 19 June 2020 respectively. The number of factors extracted for each period are reported in the second column. Mean communality is the mean proportion of common variance explained by common factors across the return series extracted on the basis of the minimum average partial (MAP) test. KMO is the Kaiser-Meyer-Olkin (KMO) index which indicates suitability for factor analysis; values of over 0.8 are deemed desirable for factor analysis although values above 0.6 are desirable.

For both periods, a single factor is extracted. The higher mean communality for the COVID-19 period suggests that the extracted factor explains a greater proportion of shared variance. The higher KMO statistic also suggests that a greater proportion of shared variance is attributable to underlying factors. Both measures point towards strengthened dependence, likely attributable to the global impact of COVID-19 (Uddin et al., 2020). Spearman correlation between factor scores and $\Delta CV19I_t$ is highly significant with a coefficient of -0.3240 (ordinary $\rho =$ -0.5619). This implies that $\Delta CV19I_t$ is indeed part of a composite factor set driving regional returns over this period. Figure 2 shows that the rolling correlation between factor scores summarising the drivers of returns and $\Delta CV19I_t$ during the COVID-19 pandemic steadily grows in magnitude from early February, peaking between mid-March and late April, and decreasing thereafter. These increases (decreases) correspond to a growing (decreasing) negative impact on returns and higher (lower) periods of volatility attributable to $\Delta CV19I_t$, notably for Europe, Latin America and North America as identified using structural break analysis.

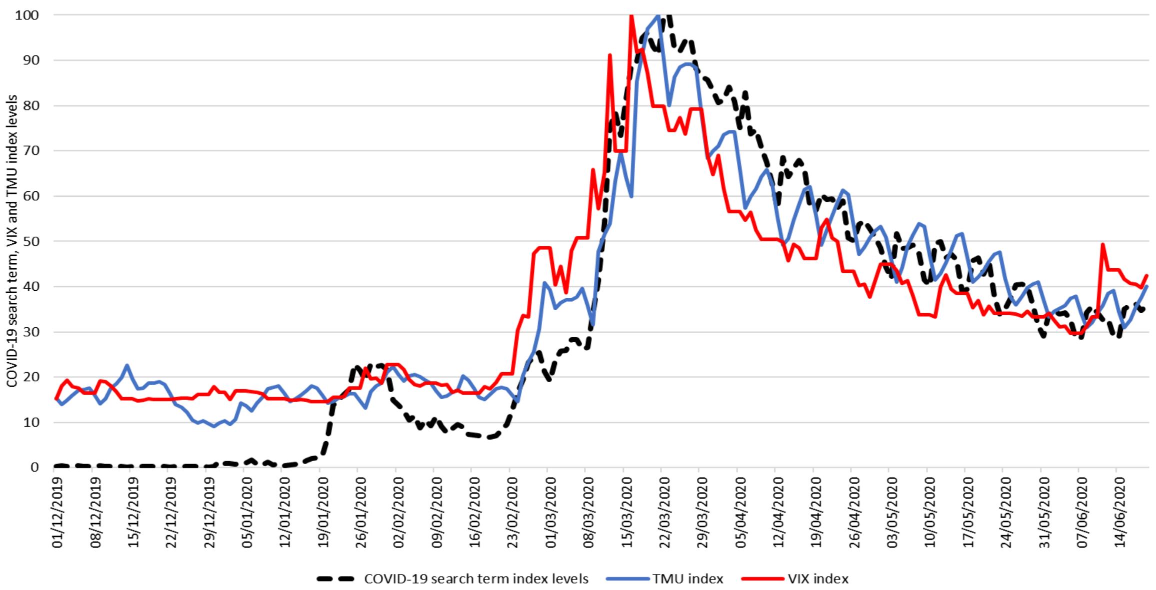
Figure 2: Rolling correlations between $\Delta CV19I_t$ and factor scores



This figure plots rolling ordinary and Spearman's correlations between factors scores and $\Delta CV19I_t$ on an inverted vertical axis. Factor scores are estimated for the period 1 November 2019 and 19 June 2020 and are reported for the COVID-19 period 1 December 2019 and 19 June 2020 using rolling windows of 30 observations.

To confirm that $\Delta CV19I_t$ reflects uncertainty during the pandemic, we compare our measure against two other measures over the COVID-19 period. The first is the CBOE Volatility index (VIX) which we treat as a measure of stock market uncertainty (Bekaert et al., 2013). Although this is the US version of the index, Smales (2019) shows that VIX captures global market uncertainty. Chiang et al. (2015) and Dimic et al. (2016) also utilise the US version of this index as a measure of global uncertainty. The second is the recently developed Twitter-based Market Uncertainty (TMU) index of Renault et al. (2020).

Figure 3: Comparison of COVID-19 search term index, VIX and TMU index in levels



This figure plots levels in the combined COVID-19 search term index created from Google Trends search volumes for nine COVID-19 related search terms over the period 1 December 2019 to 19 June 2020 against levels of the TMU index and the VIX. The TMU index has been exponentially smoothed for illustrative purposes.

Figure 3 shows that COVID-19 search term index levels move closely with the two alternative measures of market uncertainty, although with somewhat of a lag especially between the end of January 2020 and the end of the sample period. Furthermore, changes in both measures become highly correlated with $\Delta CV19I_t$ between the end of January 2020 and end of April 2020, implying that both reflect $\Delta CV19I_t$ during this period (see Figure 9A and10A in the Appendix).

Given that these two measures appear to reflect COVID-19 related uncertainty over the COVID-19 period, we re-estimate the specifications in Table 2, replacing $\Delta CV19I_t$ with ΔVIX_t and ΔTMU_t. Panel A and Panel B of Table 7 show that ΔVIX_t and ΔTMU_t have a similar impact on returns and volatility over the COVID-19 period as $\Delta CV19I_t$. Both measures impact returns negatively across all regions. ΔVIX_t is associated with significant volatility triggering effects across half of the regions, with the exception of European, North American and Arab markets, as in Table 3 for the latter two regions. ΔTMU_t triggers volatility in all regions except Arab markets. Returns on Latin American markets are now second most impacted after North American markets whereas returns on Asian and Arab markets remain least impacted. As in Table 3, North American markets experience the lowest volatility triggering effects in response to both alternative measures although they respond significantly to ΔTMU_t. Conversely, Latin American markets continue to be significantly and highly impacted. Overall, our results are largely consistent with those presented in Table 3, providing support for the role of $\Delta CV19I_t$ as a measure of uncertainty during the COVID-19 period.

Table 7: Abridged results for specifications with alternative measures

	Asia	**Europe**	**Africa**	**Latin America**	**North America**	**Arab markets**
	MSCI AC Asia	**MSCI AC Europe**	**MSCI EFM Africa**	**MSCI EM Latin America**	**MSCI North America**	**MSCI Arabian Markets**
			Panel A: Abridged specifications with ΔVIX_t			
$\beta_{i,\Delta VIX}$	-0.000806***	-0.002420***	-0.002083***	-0.003270***	-0.003911***	-0.000960**
	(6th)	(3rd)	(4th)	(2nd)	(1st)	(5th)
$\varphi_{i,\Delta VIX}$	0.1850**	0.1560	0.3050**	0.7670**	0.0180	0.9810
	(4th)	(5th)	(3rd)	(2nd)	(6th)	(1st)
			Panel B: Abridged specifications with ΔTMU_t			
$\beta_{i,\Delta TMU}$	-0.000920***	-0.002454**	-0.001760***	-0.002774***	-0.002828***	-0.001367***
	(6th)	(3rd)	(4th)	(2nd)	(1st)	(5th)
$\varphi_{i,\Delta TMU}$	0.3400***	0.1850***	0.2300**	0.8630***	0.0489***	0.3000
	(2nd)	(5th)	(4th)	(1st)	(6th)	(3rd)

This table reports the abridged results for the impact of changes in VIX and the TMU index on the returns ($\beta_{i,\Delta VIX}, \beta_{i,\Delta TMU}$) and variance ($\varphi_{i,\Delta VIX}$, $\varphi_{i\Delta TMU}$) for regional markets. Coefficients on ΔVIX_t and ΔTMU_t in the conditional variance equation are scaled by 100 000. Values in brackets (…) rank the order of absolute impact according to the magnitude of coefficients on ΔVIX_t and ΔTMU_t. The asterisks ***,** and * indicate statistical significance at 1%, 5% and 10% levels of significance respectively. Unabridged results are reported in Table 4A and 5A in the appendix.

Given that $\Delta CV19I_t$ shows a dissipating impact on returns and volatility in Table 5 and that Figure 2 suggests that the importance of $\Delta CV19I_t$ diminishes, we set out to determine whether this can be attributed to government responses during the COVID-19 crisis. We first construct a response measure,

$\Delta RESP_t$, using the Oxford COVID-19 Government Response Tracker database[16] and then test model specifications by incorporating $\Delta RESP_t$ in place of $\Delta CV19I_t$ in Table 2 after adjusting returns for the impact of $\Delta CV19I_t$.

Table 8: Abridged results for the impact of government responses

	Asia	Europe	Africa	Latin America	North America	Arab markets
	MSCI AC Asia	**MSCI AC Europe**	**MSCI EFM Africa**	**MSCI EM Latin America**	**MSCI North America**	**MSCI Arabian Markets**
$\beta_{i,\Delta RESP}$	0.000487**	-0.001210***	-0.001282**	-0.003618***	-0.003133***	-0.000449
	(6th)	(4th)	(3rd)	(1st)	(2nd)	(5th)
$\varphi_{i,\Delta RESP}$	0.1070***	0.2360*	0.3120	0.3630**	0.1540	1.9600***
	(6th)	(4th)_	(3rd)	(2nd)	(5th)	(1st)

This table reports the abridged results for the impact of changes in government responses to the COVID-19 crisis on the returns ($\beta_{i,\Delta RESP}$) and variance ($\varphi_{i,\Delta RESP}$) or regional markets. Coefficients for $\Delta RESP_t$ in the conditional variance equation are scaled by 100 000. Values in brackets (…) rank the order of absolute impact according to the magnitude of coefficients on $\Delta RESP_t$. The asterisks ***,** and * indicate statistical significance at 1%, 5% and 10% levels of significance respectively. Unabridged results are reported in Table 6A in the appendix. Regional returns are adjusted for $\Delta CV19I_t$.

Results in Table 8 show that returns for most regions, with the exception of Asia, respond negatively to government responses to the pandemic. While this measure also reflects economic support measures, it may be that containment measures (lockdowns and restrictions) dominate. This would explain a negative relationship. Four regions are significantly and negatively impacted with North America and Arab markets the most and least impacted respectively. Moreover, response measures are associated with significant volatility triggering effects in four regions, namely Asia, Latin America, Europe and Arab markets, which show the greatest response by far. A potential reason for the positive impact is that these measures were implemented around the times and in response to significant COVID-19 related events which also had an adverse impact on stock markets and volatility, and therefore responses are a proxy for the immediate impact of these events.[17] These findings are in line with that of Zaremba et al. (2020) who find that stringent policy responses tend to increase return volatility in international markets. We therefore propose that the lessening importance of $\Delta CV19I_t$ in Table 5 is attributable to a normalisation of economic agents' expectations.

Finally, we present variance forecasts obtained from ARCH/GARCH specifications against realized variance for the COVID-19 period. Plots in Figures 2A to 7A in the Appendix[18] show that our forecasts

[16] We value-weight individual government response indices which reflect the stringency of measures imposed, containment policies implemented and economic support responses by the market capitalization of the three largest markets in each region. The sum of value-weighted response indices is then differenced. The exception of North America, which comprises of two markets. A total of 17 markets are used in the calculation of $\Delta RESP_t$.

[17] Correlation analysis shows that $\Delta RESP_t$ and $\Delta CV19I_t$ are contemporaneously correlated suggesting that responses occurred around the time of heighted COVID-19 related uncertainty (ordinary correlation of 0.2415, Spearman's correlation of 0.1496, statistically significant at 1% level of significance).

[18] We use squared residuals from a least squares regression of the mean without breaks to proxy for realized variance.

approximate the changing volatility dynamics and that the increases (decreases) in variance coincide with increases (decreases) in search volumes (see Figure 1A).

4. Conclusion

Using the ARCH/GARCH framework, we demonstrate that COVID-19 uncertainty has impacted almost all regions in terms of lower returns and increased market volatility. Asian markets appear to be more resilient to COVID-19 related uncertainty, while European, North and Latin American markets experience a weakening of the impact over time. The evidence of a differential impact of COVID-19 across time and regions paves the way for further research into the reasons why such effects exist and as to why they dissipate over time. We confirm that our measure of COVID-19 related uncertainty reflects uncertainty by showing that it moves closely with alternative measures of uncertainty during the COVID-19 period. These measures, namely the VIX and TMU index, have a similar impact on returns and volatility over the COVID-19 period. Our results, together with the analysis of the structure of the return generating process show that COVID-19 uncertainty is part of the factor set driving regional returns although its role has lessened substantially.

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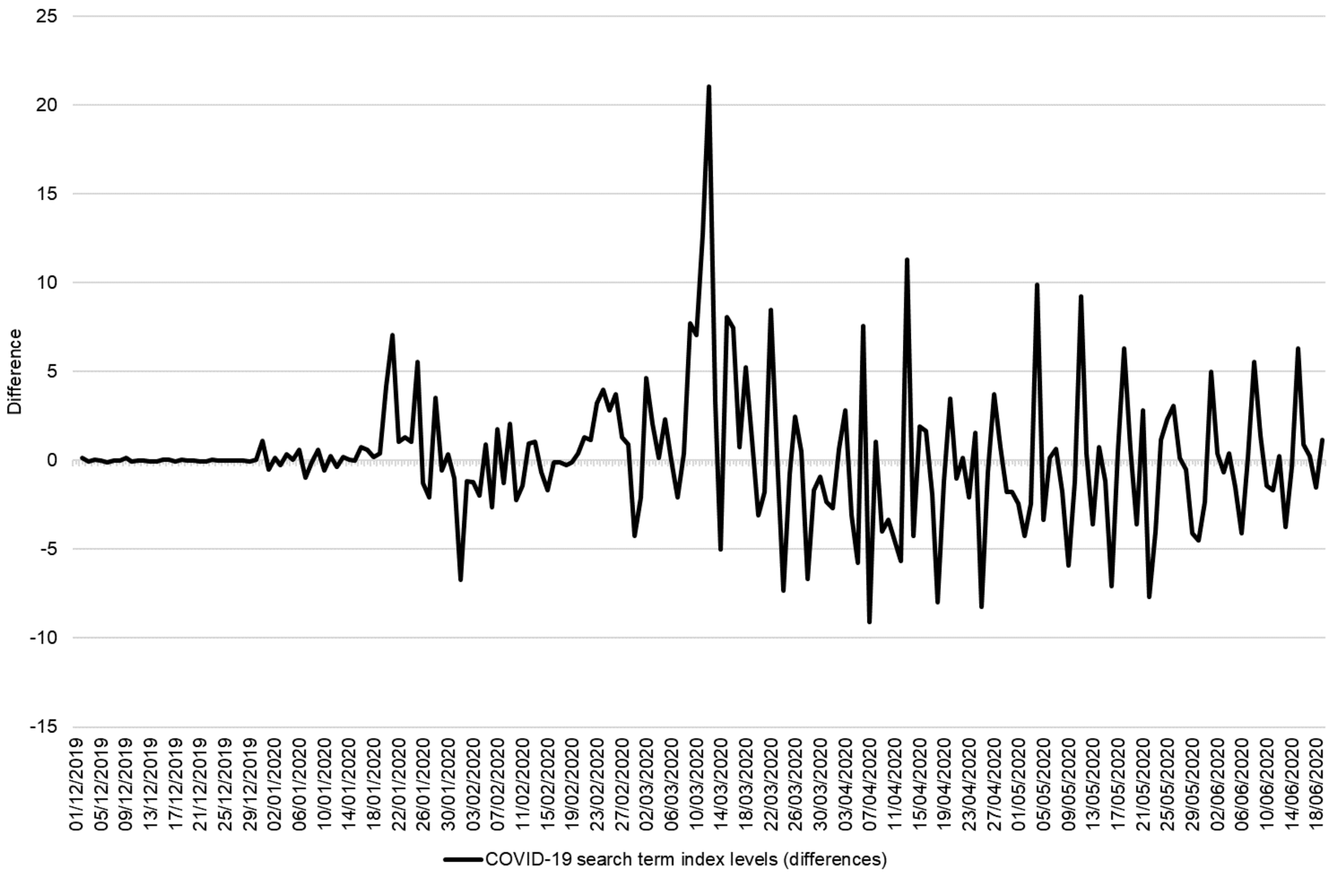
SUPPLEMENTARY APPENDIX

The only certainty is uncertainty: An analysis of the impact of COVID-19 uncertainty on regional stock markets

Figure 1A plots first differences for the combined COVID-19 search term index over the period 1 December 2019 to 19 June 2020. Figures 2A to 7A plot realized variance, as measured by the squared residuals of a least squares regression of the conditional mean for each region (see Table 2) against variance forecasts obtained from ARCH/GARCH specifications fitted to the conditional variance. Figure 8A plots global search volumes against regional search volumes as measured by Google Trends search data. Figure 9A reports rolling correlations between movements in the VIX, ΔVIX_t, which is treated as an alternative measure of uncertainty and the measure of COVID-19 related uncertainty as constructed from Google Trends, designated as $\Delta CV19I_t$. Figure 10A reports rolling correlations between movements in the Twitter-based market uncertainty index, ΔTMU_t, which is treated as an additional alternative measure of uncertainty, and $\Delta CV19I_t$. Table 1A reports unabridged regional results for specifications without breaks using a value-weighted regional measure of COVID-19 related uncertainty constructed from search volumes in countries constituting the respective regions, designated as $\Delta CV19R_t$. Table 2A reports correlations between regional variances during the pre-COVID-19 and COVID-19 periods. Table 3A reports the results of causality tests for $\Delta CV19I_t$ and regional return series. Table 4A reports unabridged results for the relationship between returns and volatility and ΔVIX_t. Table 5A reports unabridged results for the relationship between returns and volatility and ΔTMU_t. Table 6A reports unabridged results for the relationship between COVID-19 related uncertainty, adjusted returns and volatility and, a government response index constructed using data from the Oxford COVID-19 Government Response Tracker database.

Figure 1A: Differences in COVID-19 search term index



This figure plots first differences over the period 1 December 2019 to 19 June 2020 for the combined COVID-19 search term index created from Google Trends search volumes for nine COVID-19 related search terms.

Figure 2A: Forecasted and realized variance plots for Asia

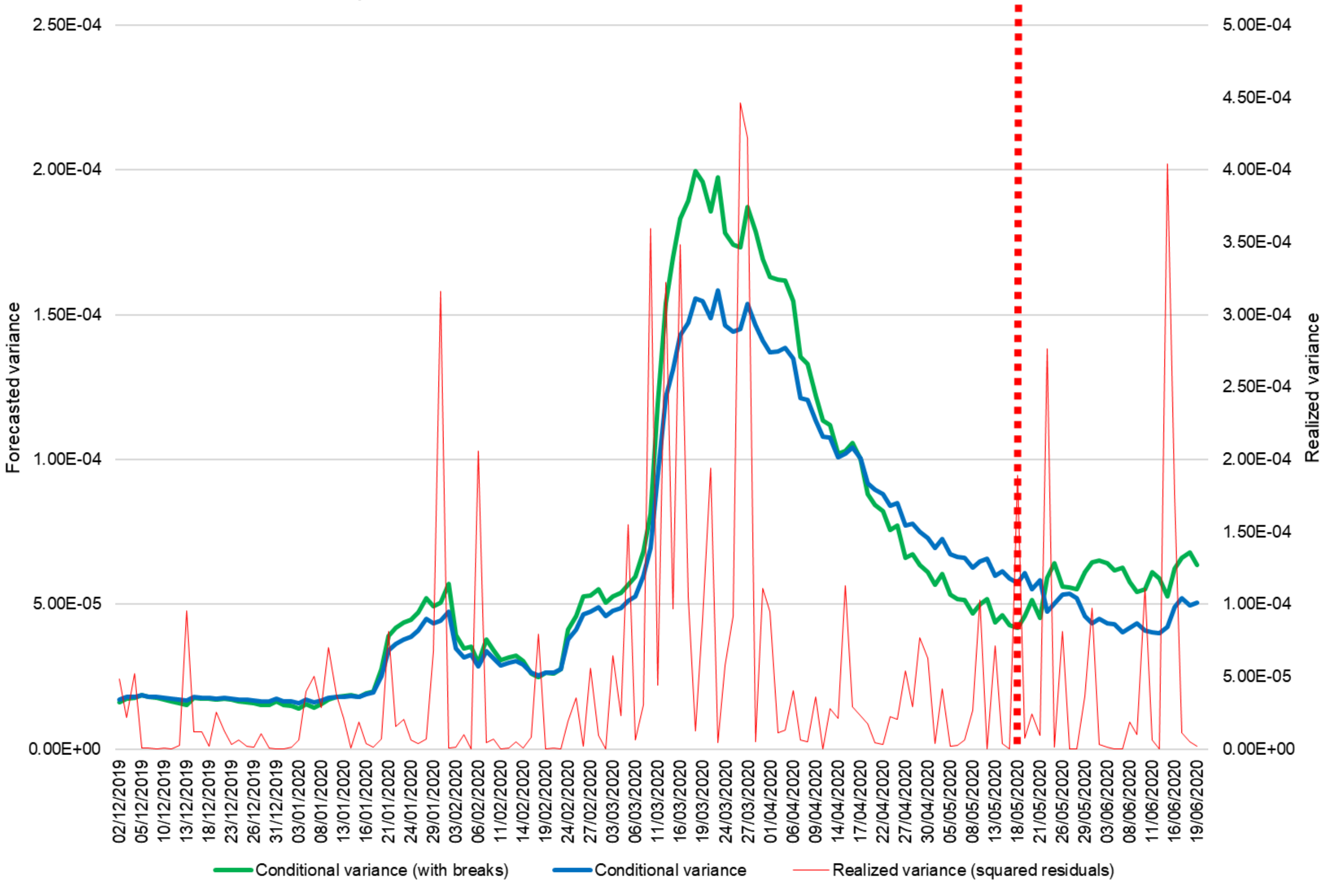


Figure 3A: Forecasted and realized variance plots for Europe

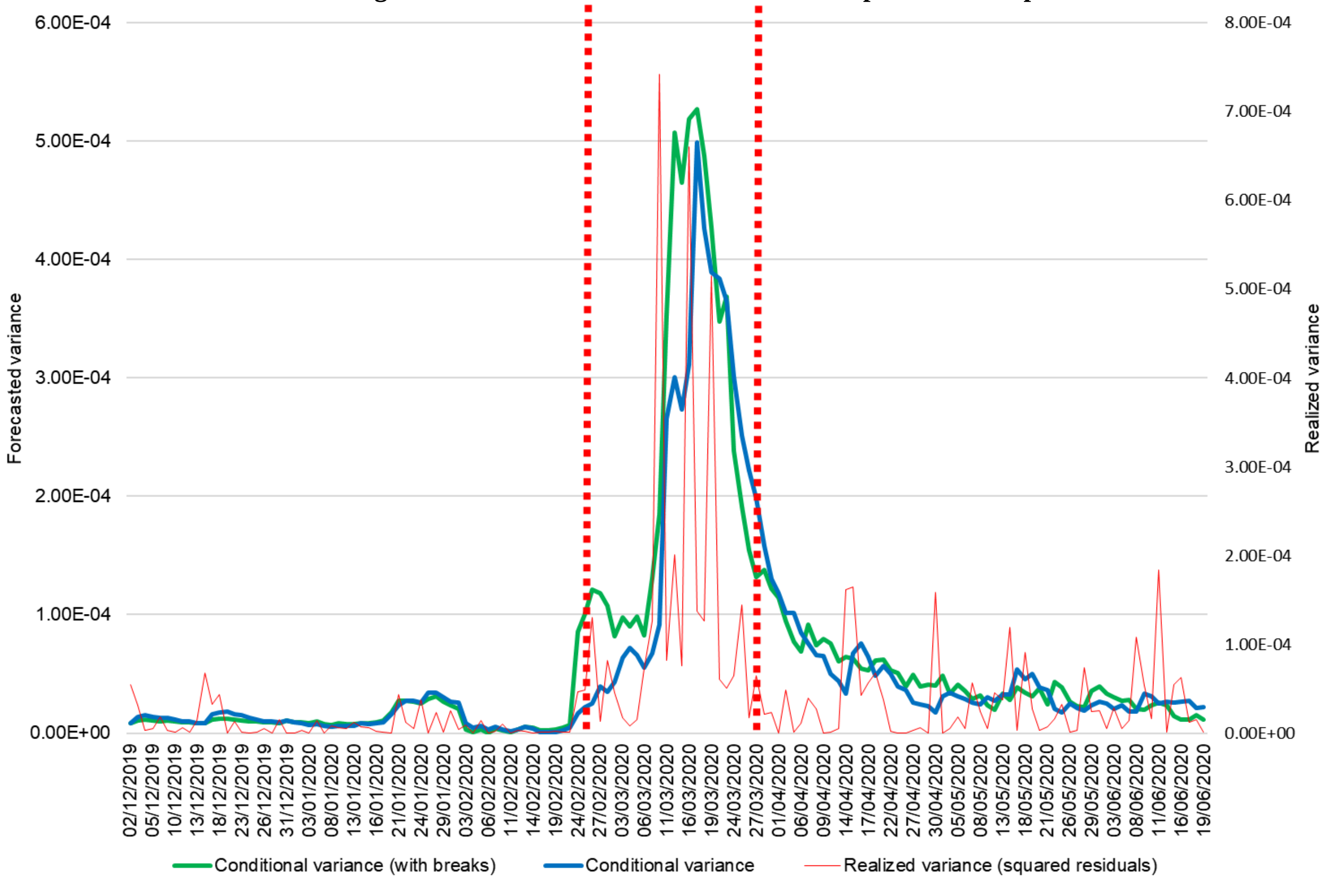


Figure 4A: Forecasted and realized variance plots for Africa

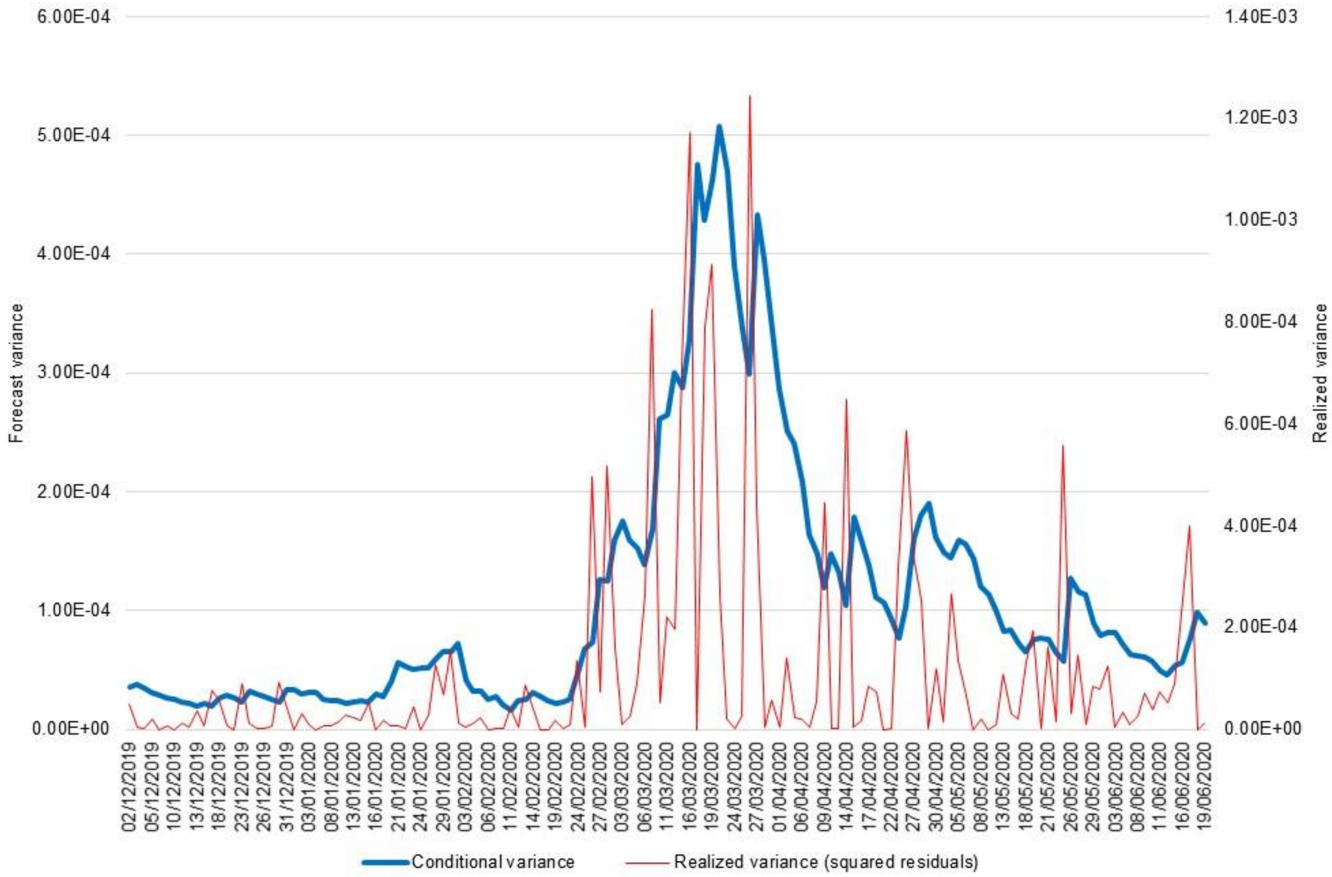


Figure 5A: Forecasted and realized variance plots for Latin America

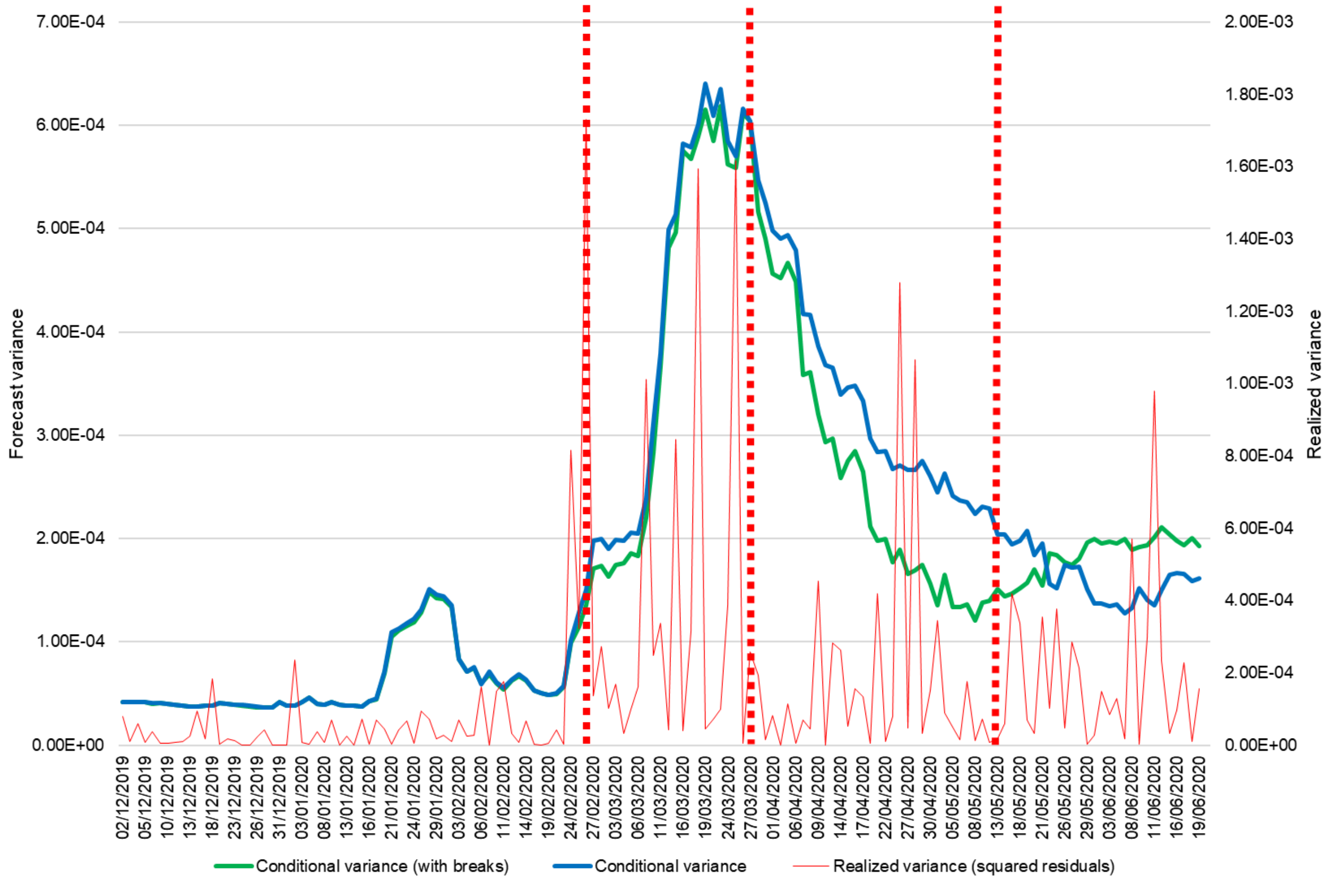


Figure 6A: Forecasted and realized variance plots for North America

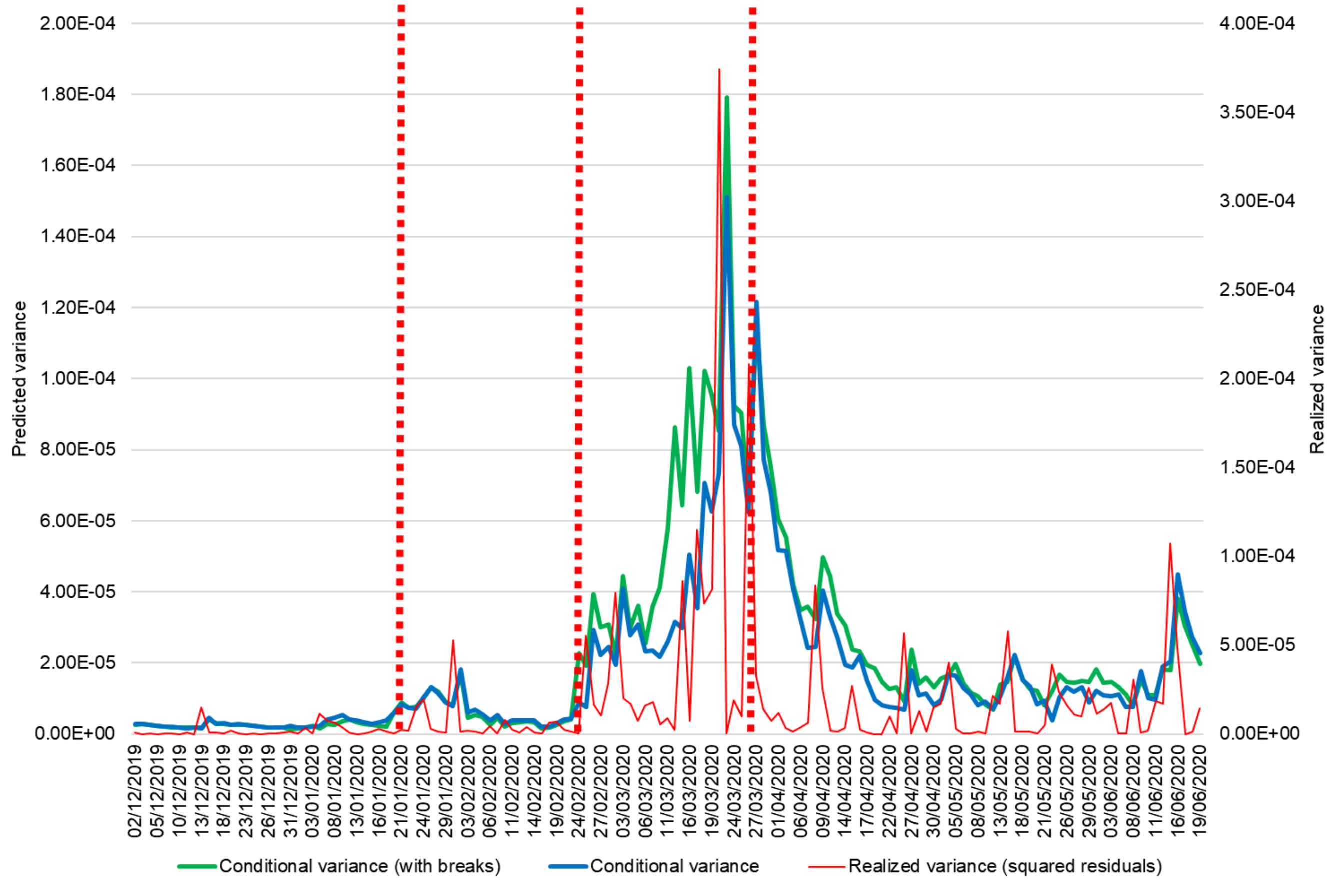
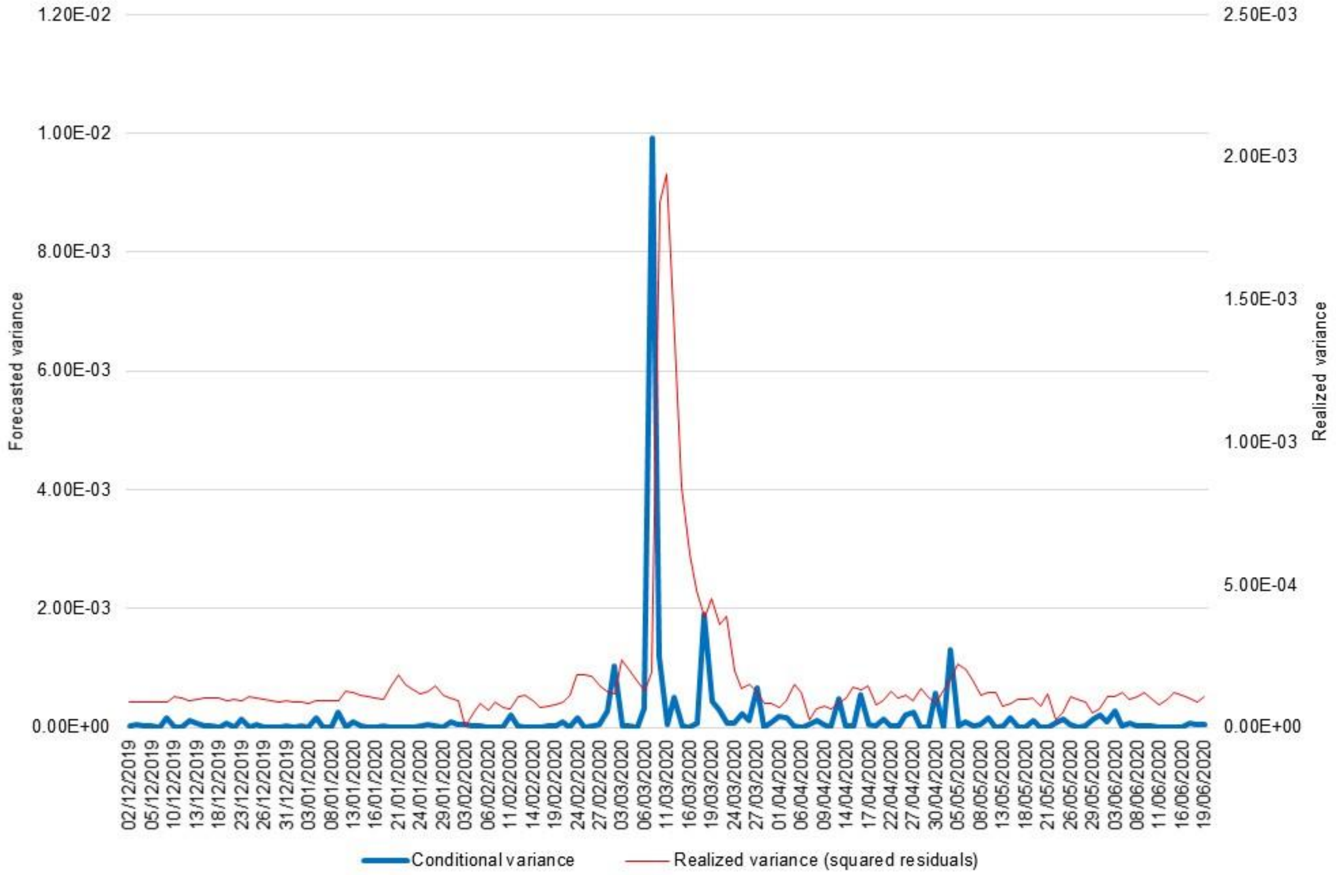
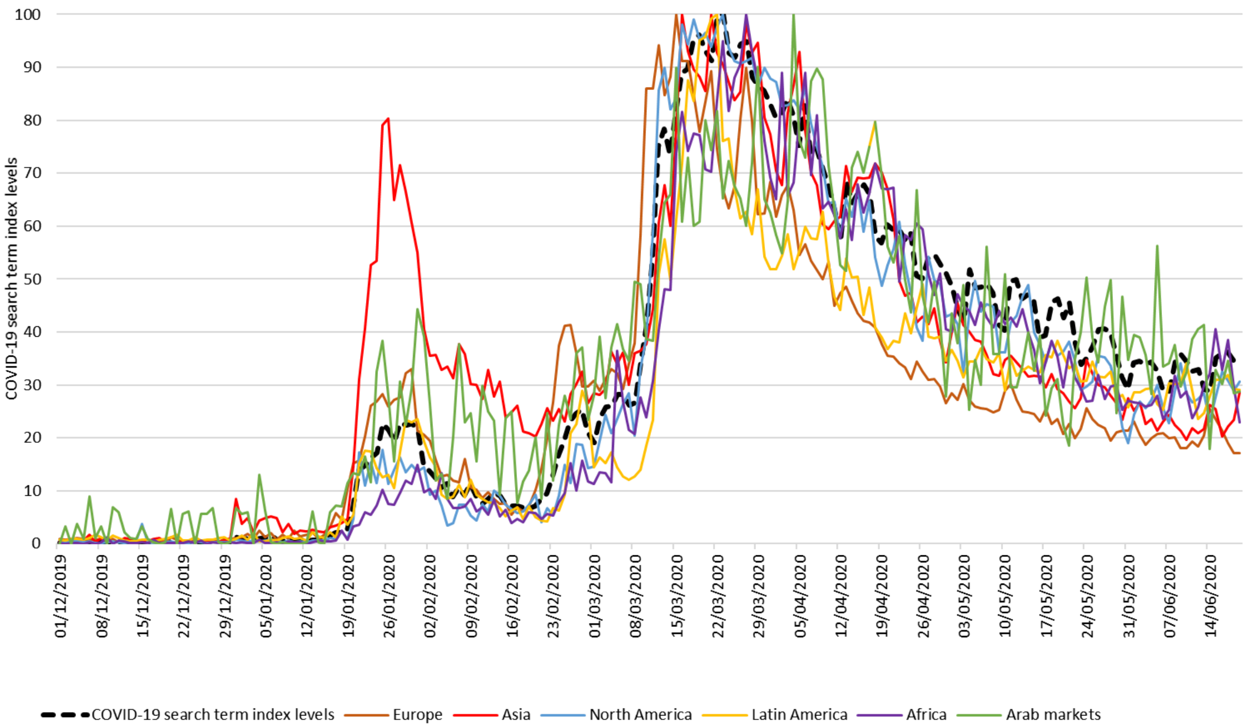


Figure 7A: Forecasted and realized variance plots for Arab markets



Figures 2A to 7A plot realized variance as measured by the squared residuals of a least squares regression of the conditional mean for each region (see Table 2) against variance forecasts obtained from ARCH/GARCH specifications fitted to the conditional variance with breaks where applicable (Asia, Europe, Latin America and North America) and without breaks. Plots are for the COVID-19 period, 1 December 2019 to 19 June 2020. The red dashed vertical lines designate breakpoints for the respective regions.

Figure 8A: Global and regional search term index levels



This figure plots global search volumes (COVID-19 search term index levels) for the terms “coronavirus”, “COVID19”, “COVID 19”, “COVID”, “COVID-19”, “SARS-CoV-2”, “SARS-COV”, “severe acute respiratory syndrome-related coronavirus” and “severe acute respiratory syndrome” and regional search volumes for Europe, Asia, North America, Latin America, Africa and Arab markets.

Table 1A: Regional results for specifications without breaks

Region	Asia	Europe	Africa	Latin America	North America	Arab markets
Index	**MSCI AC Asia**	**MSCI AC Europe**	**MSCI EFM Africa**	**MSCI EM Latin America**	**MSCI North America**	**MSCI Arabian Markets**
Panel A: Conditional mean (eq.(1))						
$Intercept$	0.0001	0.0002	0.0001	0.0002	0.0005***	-0.0002
$\beta_{i,\Delta CV19R}$	-0.00078***(5th)	-0.000910***(2nd)	-0.000789***(4th)	-0.000876**(3rd)	-0.002296***(1st)	0.000158**(6th)
β_{iM}	0.5315***	0.9301***	0.8264***	0.8540***	1.1444***	0.3866***
Proxy factors:						
β_{i1}	0.0048***	0.0011*	0.0244	-0.0011**		0.0024***
β_{i2}	0.0058***	0.0090***				0.0101***
AR Terms	-0.2703r_{t-1}***	-0.0875r_{t-1}		-0.0365r_{t-2}	-0.1786r_{t-1}*** 0.0104r_{t-4}	0.1047r_{t-5}**
Panel B: Conditional variance (eq.(2a)/(2b)/(2c))						
Model	IGARCH(1,1)	GARCH(1,1)	GARCH(1,1)	IGARCH(1,1)	GARCH(1,2)	GARCH(1,2)
ω_i		4.23E-07**	1.23E-06		2.77E-07**	7.89E-06**
α_i	0.0156*	0.1277***	0.0735*	0.0286***	0.2248***	0.3419*
β_1	0.9844***	0.8464***	0.9061***	0.9714***	0.4329	-0.0156
β_2					0.3189	0.6226***
$\varphi_{i,\Delta CV19R}$	0.0947**(4th)	0.1010***(3rd)	0.2970**(2nd)	1.0700*** (1st)	0.0421(5th)	-0.0076(6th)
Panel C: Diagnostics						
$\bar{R}^2$	0.6929	0.8547	0.6973	0.5887	0.9406	0.3918
F-statistic	81.0396***	579.5084***	175.1093***		1783.081***	19.8008***
$Q(1)$	0.0022	1.4930	1.2442	0.1005	1.9576	1.1626
$Q(10)$	9.7900	8.9557	11.048	9.4297	8.9688	12.756
ARCH(1)	0.9062	0.0485	1.7945	0.0041	1.7483	0.0737
ARCH(10)	0.5919	0.5077	0.9050	0.7095	0.7444	1.2232
Log-likelihood	1481.028	1600.327	2286.704	2134.003	5380.017	1322.463

This table reports the impact of changes in COVID-19 related uncertainty on the returns ($\beta_{i,\Delta CV19R}$) and variance ($\varphi_{i\Delta CV19R}$) for regional markets. Coefficients on $\Delta CV19R_t$ in the conditional variance equation are scaled by 100 000. Panel A reports estimation results for the conditional mean, which also includes proxy factors derived from regional returns using factor analysis and adjusted for the impact of $\Delta CV19R_t$ and $R\varepsilon_{IM,t}$. Panel B reports the results for the conditional variance. Values in brackets (…) rank the order of absolute impact according to the magnitude of the $\beta_{i,\Delta CV19R}$ and $\varphi_{i\Delta CV19R}$ coefficients. Panel C reports model diagnostics with $Q(1)$ and $Q(10)$ being Ljung-Box tests statistics for joint serial correlation at the 1st and 10th orders. ARCH(1) and ARCH(10) are test statistics for the ARCH LM test for heteroscedasticity. Each model is estimated over the primary data period between 1 January 2019 and 19 June 2020 unless residuals show dependence structures in which case longer estimation periods are used. Pre-COVID-19 and COVID-19 periods are defined as 1 January 2019 to 30 November 2019 and 1 December 2019 to 19 June 2020 respectively. The asterisks, ***,** and * indicate statistical significance at 1%, 5% and 10% levels of significance respectively.

Table 2A: pre-COVID-19 and COVID-19 period correlations

Panel A: pre-COVID-19 correlations

Region	Asia	Europe	Africa	Latin America	North America	Arab markets	Arab market adjusted
Asia	1.000						
Europe	0.1291**	1					
Africa	-0.0243	0.1732***	1				
Latin America	0.1735***	0.2652***	0.1200*	1			
North America	0.2521***	-0.0033	-0.0243	0.0384	1		
Arab markets	0.0299	0.0374	-0.0468	0.0031	0.0353	1	
Arab markets adjusted	-0.044956	-0.0204	-0.0989	0.0093	0.0159	0.7917***	1

Panel B: COVID-19 correlations

Region	Asia	Europe	Africa	Latin America	North America	Arab markets	Arab market adjusted
Asia	1.0000						
Europe	0.3355***	1.0000					
Africa	0.2419***	0.3480***	1.0000				
Latin America	0.1758**	0.3444***	0.3456***	1.0000			
North America	0.3605***	0.3936***	0.3546***	0.3853***	1.0000		
Arab markets	0.1812**	0.2582***	0.3047***	0.1846**	0.2155***	1.0000	
Arab markets adjusted	0.0380	-0.0183	0.0954	0.0398	0.0166	0.5433***	1.0000

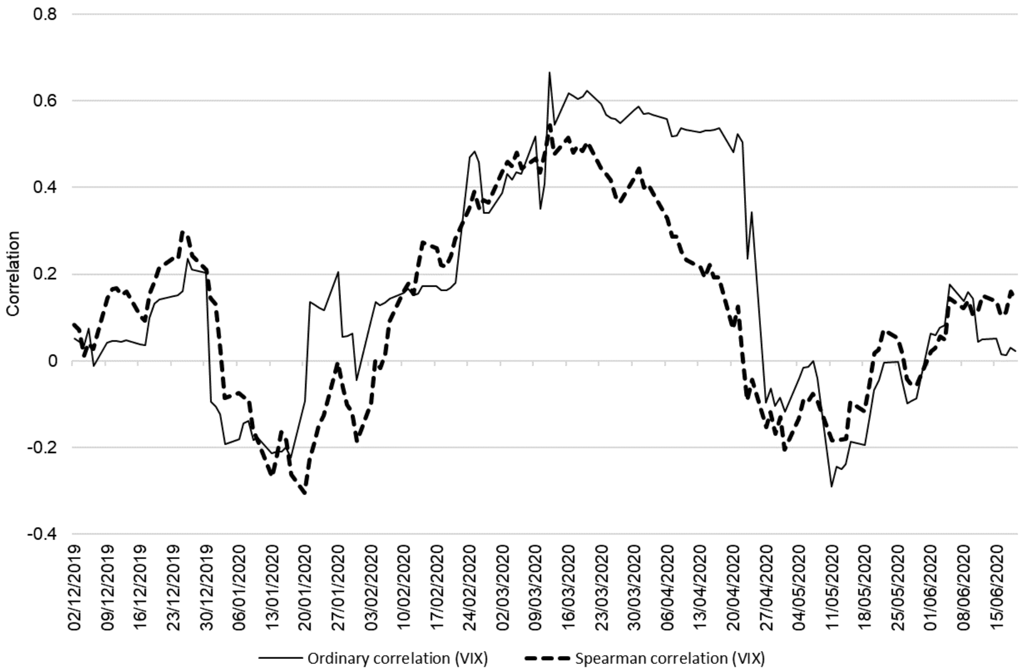
This table reports Spearman's rank-order correlations between regional realized variances derived from the residuals of equation (1) estimated using the least squares methodology. Correlations for the pre-COVID-19 period, 1 January 2019 to 30 November 2019, are reported in Panel A whereas correlations for the COVID-19 period, 1 December 2019 to 19 June 2020, are reported in Panel B. "Arab market adjusted" refers to realized variance for Arab markets adjusted for realized oil variance. The asterisks, ***, ** and *, indicate statistical significance at the respective 1%, 5% and 10% levels of significance.

Table 3A: Causality tests

Panel A: Response of $\Delta CV19I_t$ to returns	
Hypothesis	***F*-statistic**
$r_{Asia,t}$ does not cause $\Delta CV19I_t$	0.7187
$r_{Europe,t}$ does not cause $\Delta CV19I_t$	2.0103
$r_{Africa,t}$ does not cause $\Delta CV19I_t$	4.8311***
$r_{LatAm,t}$ does not cause $\Delta CV19I_t$	0.8360
$r_{NorthAm,t}$ does not cause $\Delta CV19I_t$	0.1928
$r_{Arab,t}$ does not cause $\Delta CV19I_t$	0.1955
Panel A: Response of returns to $\Delta CV19I_t$	
Hypothesis	***F*-statistic**
$\Delta CV19I_t$ does not cause $r_{Asia.t}$	3.9068**
$\Delta CV19I_t$ does not cause $r_{Europe,t}$	4.1713**
$\Delta CV19I_t$ does not cause $r_{Africa,t}$	15.6703***
$\Delta CV19I_t$ does not cause $r_{LatAm,t}$	5.5230***
$\Delta CV19I_t$ does not cause $r_{NorthAm,t}$	7.2902***
$\Delta CV19I_t$ does not cause $r_{Arab,t}$	3.9925**

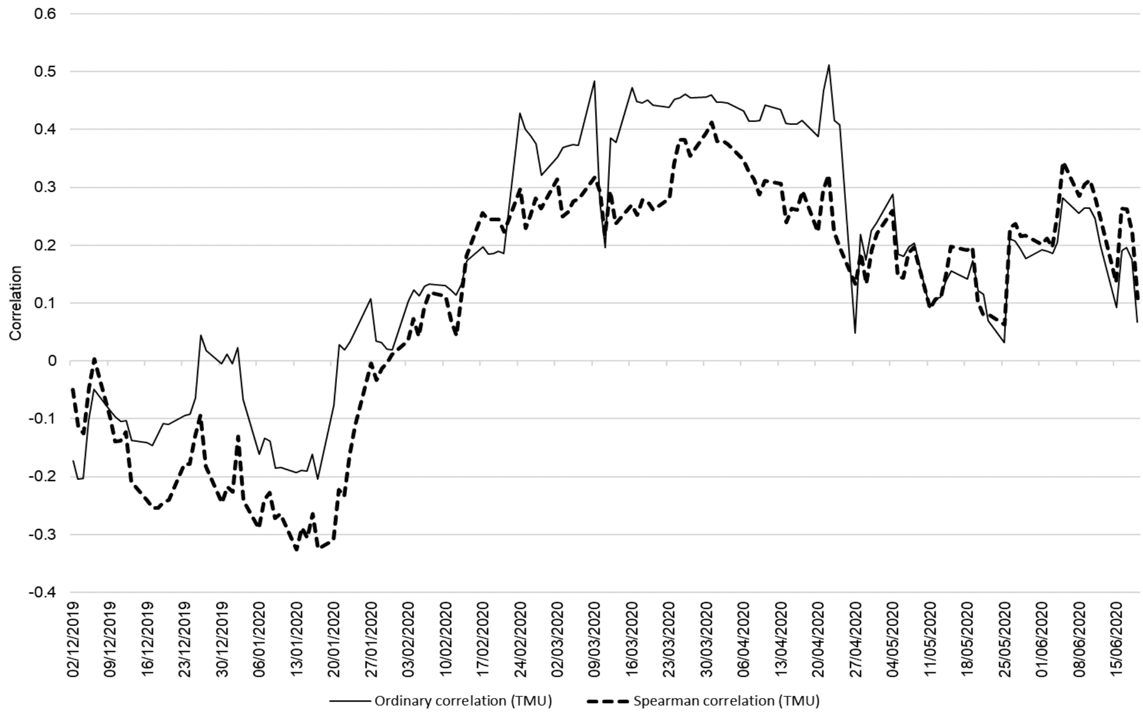
Panel A tests the null hypothesis that regional returns Granger-cause $\Delta CV19I_t$. Panel B tests the null hypothesis that $\Delta CV19I_t$ Granger-causes regional returns. The Granger causality test is conducted with 2 lags. The asterisks ***, ** and *, indicate statistical significance at the respective 1%, 5% and 10% levels of significance.

Figure 9A: Rolling correlations between $\Delta CV19I_t$ and ΔVIX_t



This figure plots rolling ordinary and Spearman's correlations between $\Delta CV19I_t$ and an alternate measure of uncertainty, the VIX, ΔVIX_t. Rolling correlations are estimated using windows of 30 observations over the period 1 October 2019 and 19 June 2020 and reported for the period 1 December 2019 and 19 June 2020 using rolling windows of 30 observations.

Figure 10A: Rolling correlations between $\Delta CV19I_t$ and ΔTMU_t



This figure plots rolling ordinary and Spearman's correlations between $\Delta CV19I_t$ and an alternate measure of uncertainty, the TMU index, ΔTMU_t. Rolling correlations are estimated using windows of 30 observations over the period 1 October 2019 and 19 June 2020 and reported for the period 1 December 2019 and 19 June 2020 using rolling windows of 30 observations.

Table 4A: Results with alternative measures of uncertainty: VIX

Region	Asia	Europe	Africa	Latin America	North America	Arab markets
Index	**MSCI AC Asia**	**MSCI AC Europe**	**MSCI EFM Africa**	**MSCI EM Latin America**	**MSCI North America**	**MSCI Arabian Markets**
Panel A: Conditional mean (eq.(1))						
$Intercept$	0.0001	0.0003	0.0001	0.0001	0.0005***	0.0002
$\beta_{i,\Delta VIX}$	-0.000806***(6th)	-0.002420***(3rd)	-0.002083***(4th)	-0.003270***(2nd)	-0.003911***(1st)	-0.000960**(5th)
β_{iM}	0.6741***	1.0102***	0.9144***	0.9439***	1.1235***	0.3964***
Proxy factors:						
β_{i1}	0.0049***	0.0016**		-0.0011*		0.0024**
β_{i2}	0.0060***	0.0090***				0.0107***
AR Terms	-0.2613r_{t-1}***	-0.12863r_{t-1}**	0.0243***	-0.0846r_{t-2}**	-0.1670r_{t-1}*** 0.0176r_{t-4}*	0.1173r_{t-5}*
Panel B: Conditional variance (eq.(2a)/(2b)/(2c))						
Model	IGARCH(1,1)	GARCH(1,1)	GARCH(1,1)	IGARCH(1,1)	GARCH(1,2)	GARCH(1,2)
ω_i		3.15E-07	1.87E-06*		4.68E-07***	3.04E-06
α_i	0.0143**	0.0937***	0.0763**	0.0215**	0.2808***	0.0503
β_1	0.9857***	0.8849***	0.8897***	0.9785***	0.4918*	0.1680
β_2					0.1832	0.7310***
$\varphi_{i,\Delta VIX}$	0.1850**(4th)	0.1560(5th)	0.3050**(3rd)	0.7670**(2nd)	0.0180 (6th)	0.9810(1st)
Panel C: Diagnostics						
$\bar{R}^2$	0.6906	0.8611	0.6987	0.6866	0.9403	0.4105
F-statistic	96.7864***	252.3178***	186.0212***	88.7367***	2214.858***	12.6638***
$Q(1)$	0.0108	0.7311	0.9284	0.0843	2.4755	2.4805
$Q(10)$	11.043	8.3720	9.1184	10.616	9.5269	12.110
ARCH(1)	1.0659	0.0862	2.0811	0.0751	0.7662	0.0093
ARCH(10)	0.5215	0.4043	0.8983	0.6608	0.5657	1.2484
Log-likelihood	1486.056	1594.075	2287.892	1279.153	5385.874	1326.310

This table reports the impact of changes in the VIX on the returns ($\beta_{i,\Delta VIX}$) and variance ($\varphi_{i,\Delta VIX}$) for regional markets. Coefficients on ΔVIX_t in the conditional variance equation are scaled by 100 000. Panel A reports estimation results for the conditional mean, which also includes proxy factors derived from regional returns using factor analysis and adjusted for the impact of ΔVIX_t and $R\varepsilon_{IM,t}$. Panel B reports the results for the conditional variance. Values in brackets (…) rank the order of absolute impact according to the magnitude of the $\beta_{i,\Delta VIX}$ and $\varphi_{i\Delta VIX}$ coefficients. Panel C reports model diagnostics, with $Q(1)$ and $Q(10)$ being Ljung-Box tests statistics for joint serial correlation at the 1st and 10th orders. ARCH(1) and ARCH(10) are test statistics for the ARCH LM test for heteroscedasticity. Each model is estimated over the primary data period between 1 January 2019 and 19 June 2020 unless residuals show dependence structures in which case longer estimation periods are used. Pre-COVID-19 and COVID-19 periods are defined as 1 January 2019 to 30 November 2019 and 1 December 2019 to 19 June 2020 respectively. The asterisks ***,** and * indicate statistical significance at 1%, 5% and 10% levels of significance respectively.

Table 5A: Results with alternative measures of uncertainty: TMU index

Region	Asia	Europe	Africa	Latin America	North America	Arab markets
Index	**MSCI AC Asia**	**MSCI AC Europe**	**MSCI EFM Africa**	**MSCI EM Latin America**	**MSCI North America**	**MSCI Arabian Markets**
Panel A: Conditional mean (eq.(1))						
$Intercept$	0.0001	0.0005***	0.0002	2.64E-05	0.0005***	-0.0001
$\beta_{i,\Delta TMU}$	-0.000920***(6th)	-0.002454***(3rd)	-0.001760***(4th)	-0.002774***(2nd)	-0.002828***(1st)	-0.001367***(5th)
β_{iM}	0.5605***	0.9055***	0.6905***	1.0050***	1.1530***	0.3535***
Proxy factors:						
β_{i1}	0.0049***	0.0015***		-0.0010**		0.0023***
β_{i2}	0.0062***	0.0091***	0.0227***			0.0105***
AR Terms	-0.2529r_{t-1}***	-0.1149r_{t-1}**		-0.1113r_{t-2}**	-0.1760r_{t-1}*** 0.0128r_{t-4} ***	0.1168r_{t-5}**
Panel B: Conditional variance (eq.(2a)/(2b)/(2c))						
Model	IGARCH(1,1)	GARCH(1,1)	GARCH(1,1)	IGARCH(1,1)	GARCH(1,2)	GARCH(1,2)
ω_i		3.98E-07***	1.86E-06**		4.19E-07	8.69E-06
α_i	0.0203**	0.1071***	0.1462***	0.0185***	0.2269***	0.2208*
β_1	0.9797***	0.8682***	0.8182***	0.9815***	0.6148***	0.0045
β_2					0.1036	0.6580***
$\varphi_{i,\Delta TMU}$	0.3400***(2nd)	0.1850***(5th)	0.2300**(4th)	0.8630***(1st)	0.0489***(6th)	0.3000(3rd)
Panel C: Diagnostics						
$\bar{R}^2$	0.6855	0.8510	0.7160	0.6914	0.9410	0.4425
F-statistic	92.3803***	634.7660***	297.0804***	133.2035***	7977.043***	17.7644***
$Q(1)$	2.E-06	2.3468	2.6816	0.1326	1.8629	1.4478
$Q(10)$	9.5351	11.129	14.917	10.126	8.1822	11.053
ARCH(1)	0.8144	0.0602	0.3618	0.2067	1.0848	0.0593
ARCH(10)	0.5191	0.7449	0.7459	0.9134	0.6612	1.6115
Log-likelihood	1487.703	1597.835	1377.169	1275.420	5381.861	1329.912

This table reports the impact of changes in the TMU index on the returns ($\beta_{i,\Delta TMU}$) and variance ($\varphi_{i\Delta TMU}$) for regional markets. Coefficients on ΔTMU_t in the conditional variance equation are scaled by 100 000. Panel A reports estimation results for the conditional mean, which also includes proxy factors derived from regional returns using factor analysis and adjusted for the impact of ΔTMU_t and $R\varepsilon_{IM,t}$. Panel B reports the results for the conditional variance. Values in brackets (…) rank the order of absolute impact according to the magnitude of the $\beta_{i,TMU}$ and $\varphi_{i\Delta TMU}$ coefficients. Panel C reports model diagnostics, with $Q(1)$ and $Q(10)$ being Ljung-Box tests statistics for joint serial correlation at the 1st and 10th orders. ARCH(1) and ARCH(10) are test statistics for the ARCH LM test for heteroscedasticity. Each model is estimated over the primary data period between 1 January 2019 and 19 June 2020 unless residuals show dependence structures in which case longer estimation periods are used. Pre-COVID-19 and COVID-19 periods are defined as 1 January 2019 to 30 November 2019 and 1 December 2019 to 19 June 2020 respectively. The asterisks ***,** and * indicate statistical significance at 1%, 5% and 10% levels of significance respectively.

Table 6A: Results for specifications measuring the impact of government policy responses on returns adjusted for $\Delta CV19I_t$

Region	Asia	Europe	Africa	Latin America	North America	Arab markets
Index	MSCI AC Asia	MSCI AC Europe	MSCI EFM Africa	MSCI EM Latin America	MSCI North America	MSCI Arabian Markets
Panel A: Conditional mean (eq.(1))						
$Intercept$	-0.0002	-7.86E-05	0.0003	0.0002***	0.0003***	-0.0003
$\beta_{i,\Delta RESP}$	0.000487** (6th)	-0.001210***(4th)	-0.001282**(3rd)	-0.003618***(1st)	-0.003133***(2nd)	-0.000449 (5th)
β_{iM}	0.5363***	0.9507***	0.6537***	0.9700***	1.1499***	0.4140***
Proxy factors:						
β_{i1}	0.0049***	0.0015**		-0.0012*		0.0013***
β_{i2}	0.0062***	0.0088***	0.0231***			0.0138***
AR Terms	-0.2648r_{t-1}***	-0.1306r_{t-1}**		-0.0812r_{t-2}**	-0.1833r_{t-1}*** 0.0105r_{t-4}	0.1258r_{t-5}***
Panel B: Conditional variance (eq.(2a)/(2b)/(2c))						
Model	IGARCH(1,1)	GARCH(1,1)	GARCH(1,1)	IGARCH(1,1)	GARCH(1,2)	GARCH(1,2)
ω_i		9.72E-07**	2.03E-06*		3.68E-07***	3.69E-06***
α_i	0.0329***	0.1755***	0.1498***	0.0288*	0.2536***	0.0337
β_1	0.9671***	0.7551***	0.8048***	0.9712***	0.4874*	0.8506**
β_2					0.2208	0.0216
$\varphi_{i,\Delta RESP}$	0.1070***(6th)	0.2360*(4th)	0.3120(3rd)	0.3630**(2nd)	0.1540(5th)	1.9600***(1st)
Panel C: Diagnostics						
$\bar{R}^2$	0.6365	0.8080	0.6472	0.6210	0.9308	0.3826
F-statistic	130.7343***	253.6120***	163.7673***	66.94091***	1497.823***	61.2471***
$Q(1)$	0.0385	0.8977	2.6261	0.0020	1.5852	2.2115
$Q(10)$	11.874	8.9143	14.147	14.214	7.5598	11.680
ARCH(1)	2.3646	0.0697	0.4373	0.2609	0.9150	0.0672
ARCH(10)	0.5784	0.8122	0.8528	1.0551	0.6100	0.6254
Log-likelihood	1477.965	1591.661	1375.150	1271.097	5374.221	1319.255

This table reports the impact of changes in government responses to COVID-19 on the returns ($\beta_{i,\Delta RESP}$) and variance ($\varphi_{i,\Delta RESP}$) for regional markets. Coefficients on $\Delta RESP_t$ in the conditional variance equation are scaled by 100 000. Panel A reports estimation results for the conditional mean, which also includes proxy factors derived from regional returns using factor analysis and adjusted for the impact of $\Delta RESP_t$ and $R\varepsilon_{IM,t}$. Panel B reports the results for the conditional variance. Values in brackets (…) rank the order of absolute impact according to the magnitude of the $\beta_{i,\Delta RESP}$ and $\varphi_{i,\Delta RESP}$ coefficients. Panel C reports model diagnostics, with $Q(1)$ and $Q(10)$ being Ljung-Box tests statistics for joint serial correlation at the 1st and 10th orders. ARCH(1) and ARCH(10) are test statistics for the ARCH LM test for heteroscedasticity. Each model is estimated over the primary data period between 1 January 2019 and 19 June 2020 unless residuals show dependence structures in which case longer estimation periods are used. Pre-COVID-19 and COVID-19 periods are defined as 1 January 2019 to 30 November 2019 and 1 December 2019 to 19 June 2020 respectively. The response period is defined as 1 January 2020 to 19 June 2020 with the former date coinciding with the start of tracking in the Oxford COVID-19 Government Response Tracker database. The asterisks ***,** and * indicate statistical significance at 1%, 5% and 10% levels of significance respectively.