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

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**A R T I C L E I N F O**

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**A B S T R A C T**

Uncertainty surrounding COVID-19 is widespread. We investigate the timing and quantify the impact of COVID-19 related uncertainty on returns and volatility for regional market aggregates using ARCH/GARCH models. Drawing upon economic psychology, COVID-19 related uncertainty is measured by searches for information as reflected by Google search trends. Asian markets are more resilient than others. Latin American markets are most impacted in terms of returns and volatility. For most regions, there is evidence of an increasing impact of COVID-19 related uncertainty which dissipates as the crisis evolves. We confirm that Google search trends capture uncertainty by comparing this measure against alternative uncertainty measures.

1. Introduction

While several pandemics and serious disease outbreaks have occurred in the past, such as the Spanish flu (in 1918), SARS (2003), MERS (2012)\textsuperscript{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 (in West Africa). Claessens et al. (2010) document that during the 2007-2008 financial crisis, countries with closer ties to the United States’ (US) financial system or with 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 timings. Liu et al. (2020) observe that Asian financial markets experienced an immediate downturn when the outbreak occurred. The impact on US and most
European markets was delayed, occurring several days after outbreaks of the virus in South Korea and Italy, and was 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 (30 January 2020) than in other countries. 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; Bretschers 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 upon economic psychology, which proposes that individuals respond to uncertainty about specific events by searching more intensively for relevant information (Liemieux and Peterson, 2011; Dzieleni, 2012; Castelnuevo and Tran, 2017; Bontempi et al., 2019), we measure uncertainty using Google search trends 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 confirm that Google search trends are a proxy for uncertainty which drives returns and triggers volatility.

2. Data and Methodology

Our primary data sample spans the period between 1 January 2019 and 19 June 2020. 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 values. Returns are defined as logarithmic differences in index values. 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 reports descriptive statistics for return series.

Following an analysis of Google search 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 by combining search trends for the terms above. Individual index values are added and the sum is divided by nine. The highest value is adjusted to 100, with remaining values adjusted accordingly relative to this base. Index values are then differenced (Fig. 1A in the Appendix).

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 (Brzeszczynski and Kutan, 2015). We begin with an ARCH(p) model and proceed to estimate a GARCH(p,q) model if the ARCH(p) specification exhibits residual heteroscedasticity. We also consider the IGARCH(p,q) model if the sum of the ARCH and GARCH parameters is unity or close to unity (Engle and Bollerslev, 1986).

Table 1  
Descriptive statistics for returns on MSCI indices

| Region   | 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 |
| 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 |
| Maximum  | 0.0529 | 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*** |

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

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2 19 and 21 February 2020, respectively.
3 The US, Italy, Spain, Turkey and the United Kingdom.
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 search 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.
Table 2

| Model        | Specification                                                                 |
|--------------|-------------------------------------------------------------------------------|
| Mean:        | \( r_{i,t} = \alpha_i + \hat{\beta}_0 \Delta CV_{19} | D_{i,t} + \hat{\beta}_1 D_{IM,t} + \sum_{k=0}^{p} \hat{\beta}_k F_{k,t} + \gamma_{i,t-1} + \epsilon_{i,t} \) (1) |
| ARCH(p)      | \( h_{i,t} = \alpha_0 + \sum_{j=1}^{p} \alpha_j r_{i,t-j}^2 + \psi_{\Delta CV_{19}} | D_{i,t} + \epsilon_{i,t} \) (2a) |
| GARCH(p,q)   | \( h_{i,t} = \alpha_0 + \sum_{j=1}^{p} \alpha_j r_{i,t-j}^2 + \psi_{\epsilon_{i,t}} + \psi_{\Delta CV_{19}} | D_{i,t} + \epsilon_{i,t} \) (2b) |
| IGARCH(p,q)  | \( h_{i,t} = \sum_{j=1}^{p} \alpha_j r_{i,t-j}^2 + \sum_{k=1}^{q} \phi_k h_{i,t-k} + \psi_{\Delta CV_{19}} | D_{i,t} + \epsilon_{i,t} \) (2c) |

Table 2 lists all specifications, where \( r_{i,t} \) is the return on index \( i \) at time \( t \), \( \Delta CV_{19} \) 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. \( D_{i,t} \) is a shift dummy denoting the 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, \( R_{i,t}^{IM} \), 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, \( \sum_{k=1}^{\pi} \phi_k F_{k,t} \), is incorporated into equation (1) to account for influences that may not be reflected by \( R_{i,t}^{IM} \). 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 \( \Delta CV_{19} \) and \( R_{i,t}^{IM} \) (Szczygielski et al., 2020). For parsimony, only significant proxy factors are retained. Finally, autoregressive terms, \( r_{i,t-\tau} \), of order \( \tau \) identified from an analysis of a residual correlogram are included to address remaining autocorrelation if required. To identify periods for which the impact of \( \Delta CV_{19} \) differs, breakpoints are identified using the Bai-Perron test (Carlson et al., 2000). If breakpoints are detected, the \( \Delta CV_{19} \) variable, together with associated coefficients and shift dummies in equations (1) and (2a)/(2b)/(2c), is replaced with \( \sum_{k=1}^{\pi} \phi_k \Delta CV_{19} + D_{i,t} \) and \( \sum_{k=1}^{\pi} \phi_k \Delta CV_{19} + D_{i,t} \), respectively, with \( D_{i,t} \) taking on a value of one or zero otherwise for segment \( \pi \) between breakpoints. Equations are first estimated using maximum likelihood estimation. If residuals are non-normal, they are re-estimated using quasi-maximum likelihood estimation with Bollerslev-Wooldridge standard errors and covariance (Fan et al., 2014).

Footnote: Szczygielski et al. (2020) show that a residual market factor may be insufficient to approximate 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.
3. Results

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

Panel A, Table 3 reports coefficients on $\Delta CV19_t$ in the conditional mean ($\beta_{\Delta CV19_t}$) and Panel B reports the impact of $\Delta CV19_t$ on the conditional variance ($\varphi_{\Delta CV19_t}$). The results in Panel A, Table 3 indicate that returns for all regions are negatively and significantly impacted by $\Delta CV19_t$. The results in Panel B indicate that coefficients on $\Delta CV19_t$ in the respective ARCH/GARCH models, $\varphi_{\Delta CV19_t}$, are positive and statistically significant for five regions. The negative impact of $\Delta CV19_t$ 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 and Wagner, 2020). In addition, heightened risk aversion attributable to uncertainty surrounding the pandemic means that investors will require a higher risk premium which is reflected in the forward looking discount rate (Andrei and Hasler, 2014; Cochrane, 2018; Smales, 2021). Together, lower expected cash flows and a higher discount rate translate into lower stock prices.8

Although returns in North America are negatively impacted ($\beta_{\Delta CV19_t}$ of -0.003417 (3rd)), this region does not show significant volatility triggering effects. However, the results in Panel B, Table 5 present a different picture suggesting that North American markets experienced delayed volatility triggering effects. Similarly, while returns in Europe are also impacted ($\beta_{\Delta CV19_t}$ of -0.003459 (2nd)), volatility triggering effects are relatively low ($\varphi_{\Delta CV19_t}$ of 0.1460 (4th)). Arab markets do not appear to experience heightened volatility associated with $\Delta CV19_t$, although returns are impacted ($\beta_{\Delta CV19_t}$ of -0.00188 (5th)). The lack of volatility triggering effects is surprising, given the economic dependence on oil of Arab markets and the consequent uncertainty surrounding their macroeconomic prospects (Ashraf, 2020). However, an analysis of realised 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 $\varphi_{\Delta CV19_t}$ may not be significant, forecasted conditional variance captures this volatility spike (Fig. 7A in the Appendix).

Asian markets are relatively resilient to COVID-19 uncertainty ($\beta_{\Delta CV19_t}$ of -0.001814 (6th) and $\varphi_{\Delta CV19_t}$ 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 $\Delta CV19_t$ on returns and volatility in African and Latin American markets ($\beta_{\Delta CV19_t}$ parameters of -0.003114 (4th) and -0.003625 (1st) and $\varphi_{\Delta CV19_t}$ parameters of 0.2680 (2nd) and 0.5480 (1st), respectively) can be attributed to risk aversion in relation to developing markets in times of crisis and spillovers from developed markets (Frank and Hesse, 2009; Bekera 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 (Nashier, 2015; Babu et al., 2016) and therefore more likely to readily reflect global developments (Szczygielaki and Chipeta, 2015). In contrast, Arab markets, while comprising developing countries, have been found to be less globally integrated (Marashdeh and Shrestha, 2010; Atoiba and Mishra, 2017), which is consistent with our findings that they are less impacted by COVID-19 related uncertainty. Our results are generally in line with previous studies on the differential impact of pandemics and crises on different regions (Claessens et al., 2010; Bekera et al., 2014).

As $\Delta CV19_t$ is constructed from global Google search trends, we also consider value-weighted regional versions by replacing $\Delta CV19_t$ with $\Delta CV19_R$ in the equations in Table 2 as an extension and robustness test. Results in Table 4 show a similar pattern. Returns for all regions, with the exception of Arab markets, are impacted negatively although to a lesser magnitude. For example, coefficients on $\Delta CV19_R$ 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
Table 3
Results for specifications without breaks

| Region          | Index   | Asia MSCI AC Asia | Europe MSCI AC Europe | Africa MSCI EFM Africa | Latin America MSCI EM Latin America | North America MSCI North America | Arab markets MSCI Arabian Markets |
|-----------------|---------|-------------------|-----------------------|------------------------|--------------------------------------|---------------------------------|----------------------------------|
| Panel A: Conditional mean (eq.(1)) | Intercept | 0.0001            | -0.001814***          | -0.00314***            | -0.003625***                        | -0.003417***                    | -0.001882***                     |
|                 | \( \beta_{i} \) | \( \Delta CV19I \) | \( \Delta CV19I \) | \( \Delta CV19I \) | \( \Delta CV19I \) | \( \Delta CV19I \) | \( \Delta CV19I \) |
| \( \beta_{i} \) | 0.5622*** | 0.9471***         | 0.6337***             | 0.9293***              | 1.1430***                           | 0.4290***                      | -0.0001                         |
| Proxy factors: | \( \beta_{i} \) | 0.0049***         | 0.0013**              | -0.0012**              | 0.0021***                           | 0.0111***                      | 0.0021***                       |
| \( \beta_{i} \) | 0.0061*** | 0.00876***        | 0.0229***             | -0.0747***             | -0.1791***                         | 0.0136***                      | 0.1306***                       |
| AR terms        | -0.2639*** | -0.1128r_{t - 1}  | -0.0012**             | -0.0012**              | 0.0021***                           | 0.0111***                      | 0.0021***                       |
| Panel B: Conditional variance (eq.(2a)/(2b)/(2c)) | \( \omega_{i} \) | IGARCH(1,1)        | GARCH(1,1)             | IGARCH(1,1)             | IGARCH(1,1)                         | GARCH(1,1)                     | GARCH(1,1)                      |
| \( \omega_{i} \) | 4.10E-07* | 1.11E-06*         | 3.25E-07***           | 6.55E-06*              | 3.25E-07***                         | 6.55E-06*                      | 3.25E-07***                     |
| \( \alpha_{i} \) | 0.0171** | 0.1426***         | 0.2470***             | 0.2842*                | 0.2470***                           | 0.2842*                        | 0.2470***                       |
| \( \beta_{1} \) | 0.9829*** | 0.8376***        | 0.9762***             | 0.4637*                | 0.9762***                           | 0.4637*                        | 0.9762***                       |
| \( \beta_{2} \) | 0.2618 | 0.6548***       | 0.5480**              | 0.0599                 | 0.2618                             | 0.5480**                       | 0.2618                          |
| \( \phi_{i} \) | 0.1300*** | 0.1460***       | 0.5840**              | 0.1720                 | 0.1300***                           | 0.5840**                       | 0.1720                          |
| \( \phi_{i} \) | (5th) | (5th)            | (5th)                 | (5th)                 | (5th)                               | (5th)                          | (5th)                           |
| \( \phi_{i} \) | (6th) | (6th)            | (6th)                 | (6th)                 | (6th)                               | (6th)                          | (6th)                           |
| Panel C: Diagnostics | \( R^2 \) | 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***                     | 15.5807***                     |
| \( Q(1) \) | 0.0013 | 1.3880            | 2.6949                | 0.1089                 | 1.4571                             | 1.1509                         | 1.1509                          |
| \( Q(10) \) | 10.615 | 9.2321            | 12.852                | 11.598                 | 8.5414                             | 11.417                         | 11.417                          |
| ARCH(1) | 1.5753 | 0.6085            | 0.7341                | 0.0227                 | 0.2751                             | 0.0497                         | 0.2751                          |
| ARCH(10) | 0.4548 | 0.5198            | 0.5901                | 0.9616                 | 0.6879                             | 1.0301                         | 1.0301                          |
| Log-likelihood | 1484.054 | 1597.812       | 1378.156              | 1276.960               | 5384.058                           | 1320.595                       | 1320.595                       |

Note: This table reports the impact of changes in COVID-19 related uncertainty on the returns (\( \beta_{i} \Delta CV19I \)) and variance (\( \phi_{i} \Delta CV19I \)) for regional markets. Coefficients on \( \Delta CV19I \) 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 \( \Delta CV19I \) and \( R_{IM,t} \). Panel B reports 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 \( \phi_{i} \Delta CV19I \) coefficients. Panel C reports model diagnostics, with \( Q(1) \) and \( Q(10) \) being Ljung-Box tests statistics for joint residual 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.
attribute this effect to the dominance of US uncertainty. Specifically, uncertainty experienced by the US dominates North American markets and also 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 attribute this effect to the dominance of US uncertainty. Specifically, uncertainty experienced by the US dominates North American returns (J.J. Szczygielski et al., 2020).

This is broadly consistent with the findings of Costola et al. (2020) that US, German, French, Spanish and the United Kingdom stock markets responded more to Italian Google search trends than those for their own countries. Smales (2021) also finds that global search trends had a greater impact than regional search trends on the G20 stock markets. We conclude that, overall, the results of the analysis using ΔCV19R are mostly qualitatively consistent with those for ΔCV19I.13

Table 4 reports results after accounting for breakpoints. Results in Panel A suggest that the negative impact of ΔCV19I, 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 African and Arab markets. For North America, Europe, Latin America and Asia, the results in Panel B indicate that the negative impact of ΔCV19I, 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 202014 and in late March 2020 (26 March 2020 for all three). Breakpoints in late February 2020 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 2020. The structural break on 26 March 2020 coincides with most European, North American and Latin American countries having imposed lockdowns and restrictions and the US becoming the country most impacted by the pandemic (Taylor, 2020). We also identify a breakpoint for North America in January 2020 (20 January 2020)15 and one for Latin America in mid-May 2020 (13 May 2020).

Returns in North America are most impacted (β_{1,3,ΔCV19I} of -0.003697) after late February 2020 whereas returns in Europe are most impacted following the end of March 2020 (β_{1,3,ΔCV19I} of -0.003448). For both North America and Europe, the impact of ΔCV19I, on volatility is greatest following the February 2020 breakpoint (φ_{1,3,ΔCV19I} of 0.2250 and φ_{1,4,ΔCV19I} 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) on the effect of COVID-19 infections on markets outside of Asia and is consistent with Ichev and Marinć’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 (β_{1,1,ΔCV19I} of -0.002338 to β_{1,2,ΔCV19I} of -0.0054) after the end of February 2020 before declining progressively (β_{3,3,ΔCV19I} of -0.003980 and β_{4,4,ΔCV19I} of -0.002243, respectively). A similar pattern emerges with ΔCV19I, triggering heightened volatility after the end of February 2020 and further after late March 2020 (significant φ_{1,3,ΔCV19I} and φ_{3,3,ΔCV19I} of 0.6190 and 0.7780, 2020).

12 Furthermore, using ΔCV19R, instead of ΔCV19I, 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 search trends to capture COVID-19 uncertainty produces a superior model fit (see Panel C, Table 1A).

13 We investigate the direction of causality between regional returns and ΔCV19I, 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 ΔCV19I, 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 the relationships between returns and ΔCV19I, 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 ΔCV19I, 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 2020 (Japan, South Korea and Thailand), with the first US case reported on 21 January 2020 (Taylor, 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, 20/01/2020 | No breaks | 26/02/2020, 24/02/2020, 13/05/2020, 26/03/2020 |
| Intercept  | 0.0002 | 0.0003* | 0.0004*** | 0.0003 | 0.0004*** | 0.0004*** |
| $\beta_{1,ACCV19}$ | -0.001865*** | -0.003399*** | -0.002383*** | -0.001972*** | -0.003341*** | -0.003697*** |
| $\beta_{2,ACCV19}$ | -0.001504*** | -0.003282*** | -0.005488*** | -0.003980*** | -0.003697*** | -0.003258*** |
| $\beta_{\Delta}$ | 0.5581*** | 0.9515*** | 0.8811*** | 1.1405*** | 1.1405*** | 0.1778*** |
| Proxy factors: | | | | | | |
| $\beta_2$ | 0.0049*** | 0.0011* | -0.0014** | 0.0157 | 0.0062 | 0.0062 |
| $\beta_2$ | 0.0062*** | 0.0088*** | 0.0079** | 0.0079 | 0.0079 | 0.0079 |
| AR terms | -0.2653n_{t-1}*** | -0.1107n_{t-1}** | -0.0970n_{t-1}** | -0.0970n_{t-1}** | -0.0970n_{t-1}** | -0.0970n_{t-1}** |
| **Panel B: Conditional variance (eq.(2a)/(2b)/(2c)) with breaks** |
| Model | IGARCH(1,1) | GARCH(1,1) | IGARCH(1,1) | GARCH(1,2) |
| $\omega$ | 1.11E-06*** | 3.50E-07*** | 0.0062 | 0.0062 |
| $\alpha_1$ | 0.0322*** | 0.0558* | 0.0410*** | 0.2251*** |
| $\beta_2$ | 0.9678*** | 0.8280*** | 0.9590*** | 0.4951* |
| $\phi_{1,ACCV19}$ | 0.1740*** | 0.1650*** | 0.6000 | 0.0288 |
| $\phi_{2,ACCV19}$ | -0.1920 | 0.9460* | 0.6190** | 0.0728** |
| $\phi_{4,ACCV19}$ | -0.2790 | 0.7780* | 0.2250* | 0.0728** |
| $\phi_{4,ACCV19}$ | -0.3750 | -0.0519 | -0.0519 | -0.0519 |
| **Panel C: Diagnostics** |
| $R^2$ | 0.6909 | 0.8450 | 0.710 | 0.9400 |
| F-statistic | 108.5422*** | 468.0253*** | -44.0270*** | 1054.943*** |
| Q(1) | 0.0433 | 1.6874 | 1.1303 | 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 |
| Model diagnostics | | | | |

Note: This table reports the impact of changes in COVID-19 related uncertainty on the returns ($\rho_{1,ACCV19}$) and variance ($\phi_{1,ACCV19}$) for regional markets, taking into account structural breaks. Segments are identified using the Bai-Perron test of L-1 sequentially determined breaks with robust standard errors (HAC) and heterogenous error distributions. Coefficients on $\Delta CV_{19}$, 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 $\Delta CV_{19}$ and $R_{RM,t}$. 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 residual 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.

The table indicates that the impact of changes in COVID-19 related uncertainty on volatility is more pronounced in Latin American markets than in North American or European markets. The weakening impact of $\Delta CV_{19}$ 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 Fig. 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 - the role of government interventions - is investigated further in Section 3.2.

For Asia, the effects of $\Delta CV_{19}$ are immediate. The respective parameters ($\rho_{1,1,ACCV19}$ of -0.001865 and $\phi_{1,1,ACCV19}$ 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.

3.2. COVID-19 related uncertainty as a factor

To confirm that $\Delta CV_{19}$ is indeed driving returns, we factor analyse the structure of returns during the pre-COVID-19 and COVID-19 periods. 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 Kaiser-Meyer-Olkin (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 $\Delta CV_{19}$ is highly significant with a coefficient of -0.3240 (ordinary $\rho$ = -0.5619). This implies that $\Delta CV_{19}$ is indeed part of a composite factor set driving regional returns over this period. Fig. 2 shows that the rolling correlation between factor scores summarising the drivers of returns and $\Delta CV_{19}$ during the COVID-19 pandemic grows steadily in magnitude from early February 2020, peaking between mid-March 2020 and late April 2020, and decreases thereafter. These increases (decreases) correspond to a growing (decreasing) negative impact on returns and higher (lower) periods of volatility attributable to $\Delta CV_{19}$, notably for Europe, Latin America and North America as identified using structural break analysis.

To confirm that $\Delta CV_{19}$ reflects uncertainty during the pandemic, we compare our measure against two other measures over the COVID-19 period. The first is the Chicago Board Options Exchange (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 the VIX captures

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

Notes: 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 acceptable.

Fig. 2. Rolling correlations between $\Delta CV_{19}$ and factor scores.

Note: This figure plots rolling ordinary and Spearman’s correlations between factors scores and $\Delta CV_{19}$ 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.
in both measures become highly correlated with although with somewhat of a lag especially between the end of January 2020 and the end of the sample period. Furthermore, changes in market uncertainty. The second is the recently developed Twitter-based Market Uncertainty (TMU) index of Renault et al. (2020).

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. Choi et al. (2020) and He et al. (2020) also utilise the US version of this index as a measure of global uncertainty. Chiang et al. (2015) and Dimic et al. (2016) also utilise the US version of this index as a measure of global uncertainty.

Table 7
Abridged results for specifications with alternative measures

| Region         | Asia MSCI AC Asia | Europe MSCI AC Europe | Africa MSCI EFM Africa | Latin America MSCI EM Latin America | North America MSCI North America | Arab markets MSCI Arabian Markets |
|----------------|-------------------|-----------------------|------------------------|-------------------------------------|----------------------------------|----------------------------------|
| Panel A:       |                   |                       |                        |                                     |                                  |                                  |
| Specifications |                   |                       |                        |                                     |                                  |                                  |
|                |                   |                       |                        |                                     |                                  |                                  |
| β_{ΔVIX}       | -0.000806***      | -0.002420***          | -0.002083***           | -0.003270***                       | -0.003911***                     | -0.000960**                     |
| φ_{ΔVIX}       | 0.1850**          | 0.1560                | 0.3050**               | 0.7520**                           | 0.0180                           | 0.9810                          |
|                 | (6th)             | (3rd)                 | (4th)                  | (2nd)                               | (6th)                           | (1st)                           |
| Panel B:       |                   |                       |                        |                                     |                                  |                                  |
| Specifications |                   |                       |                        |                                     |                                  |                                  |
|                |                   |                       |                        |                                     |                                  |                                  |
| β_{ΔTMU}       | -0.000920***      | -0.002454***          | -0.001760***           | -0.002774***                       | -0.002828***                     | -0.001367***                     |
| φ_{ΔTMU}       | 0.3400***         | 0.1850***             | 0.2300**               | 0.8630***                          | 0.0489***                       | 0.3000                          |
|                 | (6th)             | (3rd)                 | (4th)                  | (1st)                               | (6th)                           | (3rd)                           |

Notes: This table reports the abridged results for the impact of changes in VIX and the TMU index on the returns (β_{ΔVIX}, β_{ΔTMU}) and variance (φ_{ΔVIX}, φ_{ΔTMU}) for regional markets. Coefficients on ΔVIX, and ΔTMU, 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, and ΔTMU. The asterisks *** , ** and * indicate statistical significance at 1%, 5% and 10% levels of significance, respectively. Unabridged results are reported in Tables 4A and 5A in the Appendix.

Fig. 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 market uncertainty.

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 ΔCV19i with ΔVIX, and ΔTMU. Panel A and Panel B of Table 7 show that ΔVIX, and ΔTMU, have a similar impact on returns and volatility over the COVID-19 period to that of ΔCV19i. Both measures impact returns negatively across all regions. ΔVIX, 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, triggers volatility in all regions except Arab markets. Returns on Latin American markets are now second most impacted after North America, 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. 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...
ΔCV19t, as a measure of uncertainty during the COVID-19 period.

Given that ΔCV19t shows a dissipating impact on returns and volatility in Table 5 and that Fig. 2 suggests that the importance of ΔCV19t diminishes, we set out to determine whether this effect can be attributed to government responses during the COVID-19 crisis. We first construct a response measure, ΔRESP, using the Oxford COVID-19 Government Response Tracker database and then test model specifications by incorporating ΔRESP in place of ΔCV19t in Table 2 after adjusting returns for the impact of ΔCV19t.

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 American 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 time of, 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 those 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 ΔCV19t in Table 5 is attributable to a normalisation of economic agents’ expectations.

Finally, we present variance forecasts obtained from ARCH/GARCH specifications against realised variance for the COVID-19 period. Plots in Figs. 2A to 7A in the Appendix show that our forecasts approximate changing volatility dynamics and that the increases (decreases) in variance coincide with increases (decreases) in search volumes (see Fig. 1A in the Appendix).

4. Conclusion

Using the ARCH/GARCH framework, we demonstrate that COVID-19 uncertainty has impacted almost all global regions, resulting in lower returns and increased 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 of COVID-19 related uncertainty over time. The evidence of the differential impact of COVID-19 across time and regions paves the way for further research into the reasons why such effects exist and 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 diminished substantially.

CRediT authorship contribution statement

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

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 capitalisation of the three largest markets in each region. The sum of value-weighted response indices is then differenced. The exception is North America, which comprises two markets. A total of 17 markets are used in the calculation of ΔRESP.

17 Correlation analysis shows that ΔRESPt and ΔCV19t are contemporaneously correlated suggesting that responses occurred around the time of heightened 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 realised variance.
Supplementary materials

Supplementary material associated with this article can be found in the online version at doi:10.1016/j.frl.2021.101945.

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