The impact and role of COVID-19 uncertainty: a global industry analysis.

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A global industry analysis

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Abstract

The novel 2019 Coronavirus (COVID-19) has led to substantial uncertainty that permeates every aspect of life and business. In this study, we undertake a comprehensive analysis of the impact and role of COVID-19 related uncertainty on global industry returns and volatility using the ARCH/GARCH class of models. We use a comprehensive sample of 68 global industries and measure COVID-19 related uncertainty using Google Trends search data. The results indicate that COVID-19 related uncertainty negatively impacts the returns on all industries and generally leads to higher volatility. We interpret these findings as uncertainty related to the future financial performance of firms and also to emerging opportunities for some industries. Certain industries, however, are more resilient than others and increased uncertainty is not only necessarily associated with industries which experienced the largest negative returns. We also find that new factors emerged in the return generating process during the COVID-19 period. We subsequently show that despite an uncertain climate, some industries have performed well, yielding positive cumulative abnormal returns that at times, are greater than those during the pre-COVID-19 period. The implications of our findings for investors are discussed.

Keywords: COVID-19, pandemic, returns, volatility, industries

JEL classification: C22, C58, G12, D53

1. Introduction

In late 2019 and into 2020, the world witnessed the spread of a viral disease, which infected over seven million people globally and resulted in more than 400,000 deaths (as of 12 June 2020) (WHO, 2020). The novel coronavirus, or COVID-19, originated in Wuhan, China in December 2019 and was declared a pandemic on 11 March 2020 by the World Health Organisation (WHO). Notably, this pandemic has caused unprecedented economic and financial disruptions (Gormsen & Koijen, 2020). In March 2020, financial markets experienced one of the most dramatic crashes in history; the S&P 500 Index declined by 9.51% and 11.98% on 12 and 16 March 2020 respectively, representing the largest daily declines since Black Monday on 19 October 1987 on which it declined by 20.4% (Imbert, 2020; Wells, 2020). Likewise, the FTSE 100 fell by 8.50% and 9.30% on 9 and 12 March 2020 respectively (Tew, 2020) and the Australian ASX 200 experienced its largest ever daily loss of 9.7% on 16 March 2020 (Hutchens & Chalmers, 2020). The Dow Jones Index declined by 23.2% in the first quarter of 2020, Germany's Dax Index was down 38% and Japan's Nikkei Index fell 29% (Coy, 2020). Emerging markets were no less affected (Wasserman, 2020). These significant declines are partially attributable to the COVID-19 pandemic and the actions that national governments were forced to take to curb the spread of the virus, namely strict social distancing measures, quarantines and lockdowns (Ashraf, 2020a; Ozili & Arun, 2020). As such, consumer demand for products and services has declined sharply, and production and service supply chains have stalled (De Vito & Gomez, 2020). The current global climate at the time of writing is characterised by lockdowns, remote working, furlough schemes, travel bans, sporting event cancellations, prohibitions of public gatherings and limitations on using public spaces.

The effects of COVID-19 differ from those of other global crises, such as the 2008/9 financial crisis, owing to the fact that COVID-19 is truly a global pandemic, interest rates are at historical lows, global financial markets are highly interconnected and there are spillover effects throughout supply chains (Ozili & Arun, 2020). Consequently, the impact of the COVID-19 pandemic is more severe than previous pandemics, such as the Spanish Flu in 1918 and Ebola in 2014 (Fernandes, 2020; Baker et al., 2020).

In this study, we add to the burgeoning literature on the impact of COVID-19 on financial markets by investigating the impact of a specific aspect of the pandemic, namely that of COVID-19 related uncertainty. The COVID-19 pandemic has resulted in a surge in uncertainty (Altig et al., 2020; Caggiano, Castelnuovo & Kima, 2020). Currently, there is no known cure or vaccine, and conditions are highly variable as there is no clear timeline as to when social distancing will be relaxed and when full economic operations will resume. The possibility of further waves of infections and additional business closures adds to the climate of uncertainty. Moreover, the absence of a comparable historical event means that market participants have little clarity about the effects of the pandemic on output, demand, employment and earnings both in the short and long term (Bretscher, Hsu & Tamoni, 2020; Sharif, Aloui & Yarovaya, 2020). The timing of economic recovery is unclear, with initial suggestions of a "v-shaped" recovery rapidly fading.

Several studies show that uncertainty influences both economic activity and asset prices (Bloom, 2009; Pastor & Veronesi, 2012, 2013; Bianchi, Kung & Tirskikh, 2018). With regards to asset prices, uncertainty shocks give rise to changes in beliefs about probability distributions and can affect the mean, standard deviation, skewness or kurtosis thereof (Kozeniauskas, Orlik & Veldkamp, 2018). Zhang (2006) finds that greater information uncertainty about the impact of news on stock prices led to higher expected stock returns following good news but lower expected stock returns following bad news. Ozoguz (2009) observes a negative relationship between the level of uncertainty and asset valuations although this relationship showed substantial variation across firm-level characteristics and the state of the economy.

Baig et al. (2020), Bretscher et al. (2020) and Ramelli and Wagner (2020) study the impact of COVID-19 related uncertainty on stock markets in the United States (US), Papadamou et al. (2020), Costola, Iacopini and Santagiustina (2020) and Smales (2021) on developed markets, Ahundjanov, Akhundjanov and Okhunjanov (2020), Capelle-Blancard and Desroziers (2020) and Lyócsa et al. (2020) on developed and emerging markets, Szczygielski et al. (2021a) on regional indices and Liu (2020) on Chinese markets. The results indicate that uncertainty had a negative impact on stock returns and triggered heightened volatility. Our study builds on this existing literature related to

COVID-19 uncertainty, with a specific focus on the impact on global industries. Analysing industries is important as several studies have already shown that the effects of the pandemic are heterogenous across sectors (Fernandes, 2020; Ramelli & Wagner, 2020) and hence the impact of uncertainty may also differ. For example, the global hospitality and travel industries are faced with reductions in activity of over 90%. In contrast, COVID-19 related volatility across global stock markets has resulted in investors seeking safe haven investments, such as real estate, suggesting that this sector may benefit (Barker, 2020). Constable (2020) reports that during the peak of the COVID-19 pandemic, many investors sought out exchange traded funds holding precious metals, possibly indicating that industries such as mining may be more resilient to the COVID-19 pandemic, given expectations of high future cashflows. Elder and Dempsey (2020) report that investors began switching to risker assets such as travel and leisure stocks in response to the easing of restrictions, with Germany and Spain lifting travel restrictions. This implies that these investors previously disinvested from these sectors as the COVID-19 crisis intensified. Baek, Mohanty and Glambosky (2020) find that changes in systematic risk differed across industries over the COVID-19 period. Similarly, Choi (2020) documents a differential impact of economic policy uncertainty across US industries during the COVID-19 period. Smales (2020) also reports that that the effect of COVID-19 related uncertainty varied across industries in the US, with the energy sector (consumer staples/ health care) most (least) impacted. Based on Chinese industries, Liu (2020) finds the energy sector to be among the most affected. Szczygielski et al. (2021b) confirm the substantial impact of COVID-19 related uncertainty on the 20 largest energy sectors globally.

We frame our investigation within the paradigm of economic psychology, which proposes that economic agents respond to uncertainty about specific events by searching and intensifying searches for information (Dzielinski, 2012; Liemieux & Peterson, 2011; Castelnuovo & Tran, 2017; Bontempi, Golinelli & Squadrani, 2019). Given Google's position as a leading search engine (Yu et al., 2019), we use Google Trends data to identify search terms closely related to the COVID-19 crisis and construct a composite search term index which acts as a proxy for COVID-19 related uncertainty.

The impact of COVID-19 uncertainty on 68 global industries is explored utilising the ARCH/GARCH class of models, permitting the quantification of COVID-19 related uncertainty on both industry returns and volatility. To arrive at adequately specified models relating industry returns to COVID-19 related uncertainty, we apply a factor analytic augmentation to control for unspecified and omitted variables following Szczygielski, Brümmer and Wolmarans (2020a; 2020b). We then investigate the dynamic structure of the return generating process using factor analysis to determine whether new factors emerge during the COVID-19 period, designated as 1 December 2019 to 22 May 2020, and whether these are associated with COVID-19 related uncertainty. Finally, we estimate cumulative abnormal returns after adjusting for systematic risk for the pre-COVID-19 period, from 1 January 2019 to 30 November 2019, and the COVID-19 period to determine whether, despite high levels of uncertainty, investors can still seek profitable industries to invest in.

Results show that COVID-19 related uncertainty has a negative and significant impact on industry returns and a positive and significant impact on return volatility (see Section 4.2). However, some industries appear to be more resilient than others and certain industries do not exhibit significantly higher volatility. Industries that are least impacted are those that are related to necessities and substitutes (in the time of COVID-19) such as food and staples retailing, household products and telecommunications industries. In contrast, industries that are most impacted are energy equipment and services, consumer finance and airlines. Other industries that stand out in terms of impact are distributors and thrift and mortgage finance. An analysis of the dynamic structure of the return generating process reveals that new factors emerge during the COVID-19 period that we hypothesise are related to the COVID-19 pandemic. A number of these are found to be somewhat correlated with our constructed measure of COVID-19 related uncertainty, suggesting that COVID-19 related uncertainty, while a determinant of returns and volatility, is not a separate factor or major driving force (see Section 4.4). Finally, we show that certain industries have yielded positive cumulative abnormal returns during the COVID-19 period that are, at times, greater than those prior to the COVID-19 crisis (see Section 4.5). This is despite a highly uncertain environment. The recommendation is that investors, when making investment decisions, should rather be concerned with the fundamentals of specific industries related to the nature of the business that is carried out by that industry.

This study contributes to existing literature on the impact of COVID-19 on financial markets in several ways. Firstly, studies of the impact of COVID-19 on stock returns and/or volatility on various industries have predominantly focused on the US stock market. Our study has a global focus, which we argue is appropriate given the global nature of the COVID-19 crisis. Specifically, our analysis focuses on global industries and identifies within-industry differences in terms of the impact of COVID-19 related uncertainty on returns and volatility. This is important as prior research has shown the increased role of global industry factors in the pricing of global equities compared to country-specific risk factors due to the increased integration of capital markets (Baca, Garbe & Weiss, 2000; Cavaglia, Brightman & Aked, 2000; Eiling et al., 2012). Additionally, analysing only aggregated indices may miss important relationships as sectors are heterogenous (Westerlund & Narayan, 2015; Bannigidadmath & Narayan, 2016; Baig et al., 2020). Our results are relevant to investors and portfolio managers in better understanding not only the economic consequences of COVID-19, but also in diversifying their portfolios with regards to industrial sectors that are more resilient during a pandemic. This can serve to inform possible trading strategies, which investors may base on the information about how individual industries reacted to the COVID-19 pandemic.

Secondly, we contribute to the literature on the role of uncertainty in general and particularly COVID-19 uncertainty. Recent studies investigate other aspects of stock market responses to COVID-19 including growth expectations as measured by dividends (Gormsen & Koijen, 2020), responses to COVID-19 cases and deaths (Adekoy & Nti, 2020; Alfaro et al., 2020; Al-Awadhi et al., 2020; Ali, Alam & Rizvi, 2020; Ashraf, 2020b; Capelle-Blancard & Desroziers, 2020; Salisu & Akanni, 2020), asset price spirals (Caballero & Simsek, 2020), the impact of government responses to the pandemic (Aggarwal, Nawn & Dugar, 2021; Ashraf, 2020a; Narayan, Phan & Liu, 2020; Ozili & Arun, 2020; Zaremba et al., 2020), contagion (Uddin et al., 2020) as well as investor behaviour such as herding (Dhall & Singh, 2020; Espinosa-Méndez & Arias, 2021; Kizys, Tzouvanas & Donadelli, 2021; Ukpong, Tan & Yarovaya, 2021).[1]

Some recent studies have also investigated the impact of COVID-19 related uncertainty on stock markets, quantified using Google search trends (such as Baig et al., 2020; Ramelli & Wagner, 2020; Capelle-Blancard and Desroziers, 2020; Szczygielski et al., 2021a), but, with the exception of Liu (2020), Smales (2020) and Szczygielski et al. (2021b), these studies focus on the impact at the country-level, with less known about the differential impact of COVID-19 uncertainty on industries, especially global industries. Similarly to these studies, we use Google search data as a measure of retail investor interest in the COVID-19 pandemic. However, consistent with Szczygielski et al. (2021a,b), we use a much broader measure than used in other studies (such as Ramelli & Wagner, 2020 and Smales, 2020) as we identify eight COVID-19 related terms and formulate a single COVID-19 related search term index that combines these terms. We therefore also extend the work on using Google Trends search data (such as that of Yu et al., 2019) as a measure of uncertainty. Thirdly, our contribution is also methodological. We utilise the comprehensive factor analytic approach of Szczygielski et al. (2020a; 2020b), which simplifies the estimation and specification of models by reducing the complexity required to address potential underspecification. It also reduces coefficient bias, incidences of Type II errors and produces an approximation of the diagonal matrix for the residuals.

The remainder of this paper is organised as follows. Section 2 summarises the literature on the impact of pandemics on financial markets, including some of the research on COVID-19. Section 3 provides an overview of the data and methodology. Section 4 discusses the empirical results and Section 5 concludes.

2. Literature review

Prior studies examine the impact of pandemics on stock markets at an aggregate and industry level. Nippani and Washer (2004) find that the SARS outbreak in 2003 had a

[1] The impact of COVID-19 on other asset classes has also been investigated for cryptocurrencies (Chen, Liu and Zhou, 2020), commodities (Salisu, Akanni & Raheem, 2020), debt securities (Gupta et al., 2020) and derivatives (Hanke, Kosolapova, & Weissensteiner, 2020).

significant impact on the Chinese and Vietnamese stock markets but no impact on the Canadian, Hong Kongese, Indonesian, Filipino, Singaporean and Thai stock markets. At a sector level, Chen et al. (2009) report that SARS had a negative impact on the Taiwanese tourism, wholesale and retail sectors, with findings for the tourism sector consistent with those of Chen, Jang and Kim (2007) who find that stocks in this sector declined by approximately 29% in the month following the outbreak. In contrast, the biotechnology sector was positively impacted. Wang et al. (2013) also find that the SARS virus, along with other contagious diseases (H1N1, Dengue Fever and Enterovirus 71) in Taiwan, resulted in positive abnormal returns for biotechnology stocks. Funck and Gutierrez (2018) consider the impact of Ebola on the US stock market, finding that negative Ebola-related news had a negative impact on airline, cruise ship, and restaurant stocks in the short-term. The pharmaceuticals industry experienced positive returns on negative Ebola news days, potentially attributable to media reports that pharmaceutical firms were developing a cure. Goodwell (2020) suggests that the banking sector is especially vulnerable in times of economic downturns because of the increased likelihood of nonperforming loans. Lagoarde-Segot and Leoni (2013) develop a model showing that the likelihood of a collapse of the banking industry in a developing country increases as the prevalence of large pandemics such as AIDS and malaria increases. Bartram and Bodnar (2009) document that during the peak of the 2008/9 global recession, financial sector stocks were much more negatively impacted in comparison to non-financial sector stocks, falling by 63.9% compared to 38.3%. More recently, Ru, Yang and Zou (2020) examine stock market reactions to early COVID-19 outbreaks and found that there were more immediate and substantial market reactions in countries that suffered from SARS in 2003.

Other recent studies report negative stock market reactions, increased systematic risk and increased market volatility in response to COVID-19 infections and deaths (Adekoya and Nti, 2020; Albulescu, 2020; Al-Awadhi et al., 2020; Ashraf, 2020b; Bai et al., 2020; Cepoi, 2020; Haroon & Rizvi, 2020; Salisu et al., 2020; Sharif, Aloui and Yarovaya, 2020; Wang & Enilov, 2020; Zhang, Hi & Ji, 2020). Al-Awadhi et al. (2020) report a negative association between the growth in COVID-19 cases and deaths and returns on Chinese stock markets. Their results show that the information technology and medicine manufacturing industries performed better than the aggregate market. In contrast, the beverage producer, air transportation, water transportation, and highway transportation sectors performed worse. Similarly, Haroon and Rizvi (2020) find that panic induced by COVID-19 related news was positively and significantly associated with volatility in the transportation, automobiles and components, energy and travel and leisure industries. Mazur, Dang and Vega (2020) investigate the reaction of the S&P 1500 index to the spread of COVID-19 and US government interventions in March 2020. They find the healthcare, food, software, technology and natural gas sectors earned the highest returns during this period, at times yielding monthly returns of over 20%. In contrast, the crude petroleum, real estate, hospitality and entertainment sectors experienced a substantial decrease in market capitalisation, with the crude petroleum stocks experiencing especially high levels of volatility.

Ramelli and Wagner (2020) examine the reactions of internationally oriented US firms to the COVID-19 crisis over three time periods: incubation (2 January to 17 January 2020), outbreak (20 January to 21 February 2020) and fever (24 February to 20 March 2020). The telecommunication services and food staples retailing sectors performed well with risk-adjusted returns of approximately 18% and 8%, respectively for the sample period. The energy and consumer services sectors were among the biggest losers with risk-adjusted returns of approximately -39% and -38% respectively. During the initial incubation period, the healthcare industry performed relatively well but not thereafter. In contrast, the utilities industry yielded positive returns across all periods, appearing unimpacted owing to their domestic nature and relatively inelastic demand. Dhall and Singh (2020) and Ukpong, Tan and Yarovaya (2021) observe differential herding behaviour by investors across sectors in India from 2015 to June 2020 and the US from 1990 to August 2020 respectively, with both studies including the COVID-19 pandemic.

With respect to uncertainty surrounding the COVID-19 pandemic, Ramelli and Wagner (2020) analyse the importance of trade (Chinese-orientated stocks) and levels of leverage on the effect of COVID-19 uncertainty, as captured by Google Trends search data, on the value of US firms. Greater uncertainty surrounding the pandemic resulted in lower performance for firms with greater leverage and smaller cash holdings, even if they did not have international operations. Baig et al. (2020) also use Google Trends search data to capture uncertainty related to COVID-19. The results of their study suggest that the uncertainty associated with increases in infections and deaths led to greater implied market volatility and lower liquidity among US stocks. Smales (2021) utilises Google Trends data as a measure of investor attention and finds that investor attention negatively influenced stock returns in the G7 and G20 countries and volatility (only examined in the G7 countries) during the pandemic. Lyócsa et al. (2020) employ Google Trends data specific to the coronavirus crisis as a gauge of panic and fear and find that increased panic and fear resulted in heightened volatility in 10 developed and developing stock markets. Similarly, Papadamou et al. (2020) find that increased uncertainty had a direct impact on implied volatility and an indirect effect on stock returns across 13 major stock markets. Bretscher et al. (2020) study the effect of uncertainty surrounding COVID-19 on US firm performance and found that firms headquartered in a specific county earned lower returns in the 10-day period post the first reported case in the area compared to the firm's returns before the event and, compared to firms headquartered in other counties.

Liu (2020) examines the effect of COVID-19 uncertainty on China's stock market at the aggregate and sectoral levels, using Google Trends data to capture uncertainty. Overall, greater uncertainty contributed to a decline in market returns and an increase in volatility. At the sector level, greater uncertainty resulted in higher volatility across most industries, although the impact on returns varied. Notably, energy and information technology were most impacted while consumer staples, healthcare and utilities were least impacted. Similarly, Smales (2020) finds that while heightened COVID-19 uncertainty was associated with negative stock returns overall in the US, the energy sector was most impacted while consumer staples, healthcare and information technology were least impacted. Szczygielski et al. (2021b), in a study of the 20 largest energy sectors, also found that COVID-19 related uncertainty, quantified by Google Trends data, had a significant negative impact on energy sector returns and drove heightened volatility in the energy sectors of most countries investigated.

What emerges from the literature is that pandemics impact financial markets, but this impact differs across industries. Certain industries benefit whereas others are adversely impacted. Directly relevant to this study, the literature implies that COVID-19 related uncertainty has a heterogeneous impact on individual firm performance, industries and financial markets in general. However, owing to the novelty of COVID-19, there is no comprehensive analysis of the impact of COVID-19 on industries at the global level, especially that of COVID-19 related uncertainty. This is the gap that we aim to fill in the analysis that follows.

3. Data and methodology

3.1. Data

The data comprises 68 industries closely following MSCI's Global Industry Classification Standard (GCIS), representing 11 global industrial groupings, namely, energy, materials, industrials, consumer discretionary, consumer staples, health care, financials, information technology, communication services, utilities and real estate. Data are daily and stated according to MSCI's local currency methodology for most industrial sectors, representing the performance of an industry unimpacted by foreign exchange rate movements. Our primary sample spans the period 1 January 2019 to 22 May 2020 and returns are defined as logarithmic differences in index levels.[2] Within this sample, the pre-COVID-19 period is designated as 1 January 2019 to 30 November 2019 and the COVID-19 period is designated as 1 December 2019 to 22 May 2020. While the start of the COVID-19 crisis is debated, we chose 1 December 2019 as this was the day on which the first index case was reported (Huang et al*.,* 2020; Qi et al., 2020; Wu et al., 2020).

Descriptive statistics for industry returns, included in Table A1 of the Appendix, show that the null hypothesis of normality is rejected for all the series, with all industry returns leptokurtic and negatively skewed except for the diversified consumer services and household products industries, which are leptokurtic but positively skewed. To gain preliminary insight into the performance of industries prior to and during the COVID-19 period we apply several tests to compare means, medians and variances between the periods. The results are reported in Table A2 of the Appendix. According to the *t*- and

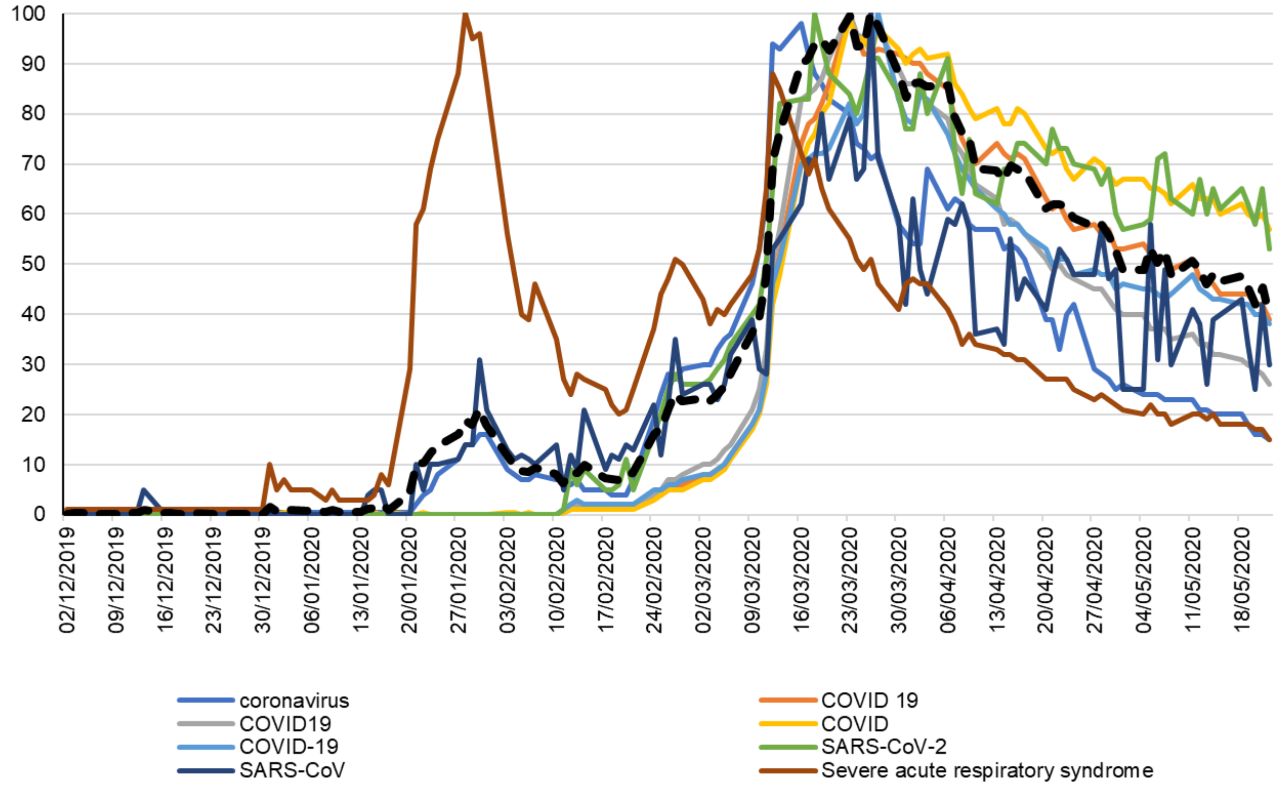
[2] Every attempt was made to obtain indices in levels stated according to MSCI's local currency methodology; however, not all of these series were available at the time of writing. The sectors that are in US Dollars are the diversified consumer services, internet and direct marketing retail, health care equipment and supplies, diversified financial services, mortgage real estate investment trusts (REITs), IT services and interactive media and services.

Welch *t*-tests, differences in the means are only significant for the construction materials, aerospace and defence, building products, airlines, marine transportation, transportation infrastructure, banking and insurance industries. However, mean returns are always lower (except for the internet and direct marketing and biotechnology industries) and almost always negative for the COVID-19 period. Tests of the equality of medians, based on the chi-squared and Kruskal-Wallis tests, indicate that the medians of several industries are significantly lower in the COVID-19 period compared to the pre-COVID period (i.e. construction materials, aerospace and defence, industrial conglomerates, air freight and logistics, etc). For the remaining industries the medians are generally lower for the COVID-19 period, but not overwhelmingly negative. In contrast, the Brown-Forsythe test for the equality of variances is rejected for every sector implying that industrial sector returns experienced higher volatility during the COVID-19 period.

To measure COVID-19 related uncertainty, Google Trends search data is used. We interpret increases (decreases) in search intensity/volumes as increases (decreases) in COVID-19 related uncertainty, as economic agents increase (decrease) their search for information in response to uncertainty (Dzielinski, 2012; Castelnuovo & Tran, 2017; Bontempi et al., 2019). Following an analysis of Google Trends, we identify eight COVID-19 terms associated with high search volumes worldwide within our primary sample period.[3] The terms that we select are “coronavirus, COVID19, COVID 19, COVID, COVID-19, SARS-CoV-2, SARS-CoV” and “severe acute respiratory syndrome”. Next, we formulate a single COVID-19 related search term index that combines Google Trends data for the above search terms. To do so, the individual index values are added together, and the sum is divided by eight. The highest value is adjusted to 100 with the remaining values adjusted accordingly relative to this base value. Index values are then differenced. Figure 1 plots COVID-19 related interest over time as captured by the Google Trends search terms, including the composite search index.

[3] Google outlines data from Google Trends as 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.

Figure 1. COVID-19 related interest 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 eight COVID-19 related search terms, “coronavirus, COVID19, COVID 19, COVID, COVID-19, SARS-CoV-2, SARS-CoV” and “severe acute respiratory syndrome”, over the period 1 December 2019 to 22 May 2020. Levels of search volumes for individual COVID-19 related terms are also plotted.

3.2. Methodology

As we seek to quantify the impact of COVID-19 related uncertainty on *both* (a) returns (the mean) and (b) the conditional variance, with the latter treated as a proxy for risk, we apply the ARCH/GARCH model framework (Brzeszczyński & Kutan, 2015). We begin with an ARCH(1) model and proceed to estimate an GARCH(1,1) model if the residuals of an ARCH(1) specification exhibit heteroscedasticity. We also consider the IGARCH(1,1) model if the ARCH and GARCH parameters sum to unity or are close to unity (Engle & Bollerslev,1986).

Table 1: Model specifications

Model	Specification	
Mean:	$r_{i,t} = \alpha_i + \beta_{iCV19I}\Delta CV19I_t Dum_{0,1} + \sum_{k\leq 7}^{k} \beta_{ik} F_{k,t} + \gamma_i r_{i,t-\tau} + \varepsilon_{i,t}$	(1)
ARCH/GARCH:		
ARCH(1)	$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \varphi_{i\Delta CV19I}\Delta CV19I_t Dum_{0,1}$	(2a)
GARCH(1,1)	$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + \varphi_{i\Delta CV19I}\Delta CV19I_t Dum_{0,1}$	(2b)
IGARCH(1,1)	$h_{i,t} = \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + \varphi_{i\Delta CV19I}\Delta CV19I_t Dum_{0,1}$	(2c)

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

Table 1 lists all specifications, where $r_{i,t}$ is the return on index *i* at time *t*, $\Delta CV19I_t$ are the first differences in the combined COVID-19 search index and $h_{i,t}$ is the conditional variance. We incorporate a shift dummy in both the mean and conditional variance equations ($Dum_{0,1}$) to delineate the pre-COVID-19 and COVID-19 periods (Al Rjoub, 2011), taking on a value of 0 for the former period. Of particular importance are the coefficients on the COVID-19 search term index, β_{iCV19I}, in the mean, and $\varphi_{i\Delta CV19I}$, in the conditional variance quantifying the impact of COVID-19 related uncertainty. If β_{iCV19I} and φ_{iCV19I} are not statistically significant then an industry is unimpacted by COVID-19 related uncertainty and can be considered as being resilient to this aspect of COVID-19. Alternatively, if β_{iCV19I} is negative and statistically significant and/or $\varphi_{i\Delta CV19I}$ is positive and statistically significant, then an industry is adversely impacted by COVID-19 related uncertainty.

Preliminary estimations suggest that a restricted version of equation (1) incorporating only $\Delta CV19I_t$ may be underspecified. We therefore follow the approach of Szczygielski et al. (2020a, 2020b) of using a factor analytic augmentation to resolve underspecification and to control for any other relevant factors. In the first step, returns on index *i* are regressed on $\Delta CV19I_t$ in univariate regressions. Next, the residuals are factor analysed. To identify the number of factors, we first applied the minimum average partial (MAP) test, which identifies the number of factors that results in a residual matrix that most closely resembles an identity matrix – an assumption that underlies linear factor models (Zwick & Velicer, 1986). This yielded a total of 13 factors. However, as we are interested in summarising the most important influences and a parsimonious model, we then applied the Kaiser-Guttman rule, which yielded six factors which we chose as our factor solution. Factors were then subjected to a varimax rotation (Guttman, 1954; Kaiser, 1960; Zwick & Velicer, 1986). Factor scores can be interpreted as composite representations of common influences driving returns and comprise an orthogonal analytically derived factor set, reflected by $\sum_{k\leq 7}^{k} \beta_{ik} F_{kt}$ in equation (1), proxying for omitted influences. As the interpretation of factor scores is not of direct interest and for the purposes of parsimony, only significant proxy factors are retained. Szczygielski et al. (2020a, 2020b) show that this approach results in an approximation of the diagonality assumption that underlies factor models, reduces coefficient bias and also reduces incidences of Type II errors. Importantly, this approach allows for the impact of specific variables to be investigated without the need to specify and estimate complex specifications incorporating multiple pre-specified factors. In addition, Szczygielski et al. (2020a, 2020b) show that a factor analytic augmentation is more effective at accounting for omitted influences than the use of market indices or residual market factors (see Meyers, 1973; Burmeister & McElroy, 1991). Finally, autoregressive terms, $r_{i,t-\tau}$, of order τ identified from an analysis of a residual correlogram for each industry are included to address remaining autocorrelation, if required.

Equations (1) and (2a)/(2b)/2c) are first estimated using maximum likelihood estimation (MLE) and re-estimated using quasi-maximum likelihood (QML) estimation with Bollerslev-Wooldridge standard errors and covariance if the standardised residuals are shown to be non-normal (Fan, Qi & Xiu, 2014).

4. Results and analysis

4.1. Model overview

The results of the impact of COVID-19 related uncertainty on industry returns and variance are reported in Tables 2 and 3, together with regression diagnostics.[4] Figures 2 and 3 visually summarise the impact of COVID-19 related uncertainty on returns and

[4] Maximum likelihood estimators converge for all models estimated indicating that the loglikelihood function is maximised in each instance, implying asymptotic efficiency and consistency.

variance respectively. The adjusted coefficients of determination, $\bar{R}^2$s, range between 0.3752 for diversified consumer services and 0.984 for the media and entertainment industry, averaging approximately 0.80. Such high $\bar{R}^2$s are expected given that the factor analytic augmentation in equation (1), $\sum_{k\leq 7}^{k} \beta_{ik} F_{k,t}$, consists of factors derived from the return series comprising the sample, adjusted for COVID-19 related uncertainty. Both the $Q(1)$ and $Q(10)$ statistics point towards the absence of joint serial correlation in the residuals and first and 10th order ARCH Lagrange multiplier tests do not indicate the presence of ARCH effects. An (unreported) examination of the autocorrelation functions for both linear and non-linear residual dependence confirms the absence of linear and non-linear dependence.

Table 2: Impact of COVID-19-related uncertainty on industrial sector returns

Parameter	α_i	β_{iCV19I}	β_{i1}	β_{i2}	β_{i3}	β_{i4}	β_{i5}	β_{i6}	γ_i
Panel A: Energy									
1.Energy Equipment & Services	-0.0014	-0.0055***	0.0133***	0.0052***	0.0090***	-	0.0075***		
2.Oil, Gas & Consumable Fuels	0.00003	-0.0035***	0.0073***	0.0058***	0.0063***	0.0016***	0.0038***		0.0871**
Panel B: Materials									
3.Chemicals	0.0001	-0.0035***	0.0098***	0.0058***	0.0040***	0.0010***			-0.0636**
4.Construction Materials	0.0002	-0.003***	0.009***				0.002***	0.005***	
5.Containers & Packaging	0.0005	-0.0040***	0.0083***	0.0108***	0.0065***	0.0043***	0.0032***		
6.Metals & Mining	0.0004	-0.0030***	0.0076***	0.0046***	0.0034***		0.0016***		0.0640*
7.Paper & Forest Products	0.0015**	-0.0030***	0.0100***	0.0022***	0.0028***		0.0035***	0.0020***	
Panel C: Capital Goods									
8.Aerospace & Defence	0.0003	-0.0035***	0.0116***	0.0106***	0.0069***	0.0061***			
9.Building Products	0.0007***	-0.0028***	0.0099***	0.0052***		0.0008**			
10.Construction & Engineering	0.00007	-0.0031***	0.0094***	0.0054***					
11.Electrical Equipment	0.0007***	-0.0035***	0.0113***	0.0053***	0.0053***		0.0033***		
12.Industrial Conglomerates	-0.00005	-0.0031***	0.0090***	0.0061***	0.0059***		0.0035***		
13.Machinery	0.0004*	-0.0031***	0.0115***	0.0046***	0.0051***				
14.Trading Companies & Distributors	0.0004**	-0.0025***	0.0096***	0.0033***	0.0033***			-0.0014***	
Panel D: Commercial & Professional Services									
15.Commercial Services & Supplies	0.0009***	-0.0025***	0.0051***	0.0085***	0.0038***			0.0008***	
16.Professional Services	0.0012***	-0.0020***		0.0073***	0.0047***	-0.0016***		-0.0013***	0.1165***
Panel E: Transportation									
17.Air Freight & Logistics	0.0002	-0.0025***	0.0084***	0.0052***	0.0076***		0.0034***		-0.0773**
18.Airlines	-0.0008**	-0.0040***	0.0122***	0.0035***		0.0034***			
19.Marine	-0.0001	-0.0021***	0.0100***	0.0013**	0.0037***	-0.0037***	0.0016***		
20.Road & Rail	-0.0002	-0.0028***	0.0086***	0.0064***	0.0043***				-0.1424***
21.Transportation Infrastructure	0.0001	-0.0034***	0.0069***	0.0033***				0.0041***	
Panel F: Automobiles & Components									
22.Auto Components	-0.0003	-0.0031***	0.0128***		0.0031***				
23.Automobiles	0.00003	-0.0033***	0.0115***	0.0029***	0.0032***		-0.0009***		
Panel G: Consumer Durables & Apparel									
24.Household Durables	0.0007**	-0.0029***	0.0101***	0.0052***	0.0022***		-0.0026***		
25.Leisure Products	0.0005	-0.0024***	0.0081***	0.0032***	0.0030***	-0.0019***		-0.0028***	
26.Textiles, Apparel & Luxury Goods	0.0008**	-0.0033***	0.0092***	0.0066***	0.0061***		0.0028***		
Panel H: Consumer Services									
27.Hotels, Restaurants & Leisure	0.0007**	-0.0037***	0.0090***	0.0072***	0.0071***	0.0058***		0.0021***	0.0814
28.Diversified Consumer Services	0.0021**	-0.0024***	0.0089***	0.0057***				0.0028**	-0.1332**

Table 2 (continued…)

Panel I: Retailing									
29.Distributors	-0.0003	-0.0035***	0.0134***	0.0063***		0.0052***			
30.Internet & Direct Marketing Retail	0.0018***	-0.0030***	0.0049***		0.0121***				
31.Multiline Retail	0.0004	-0.0021***	0.0054***	0.0043***	0.0033***				
32.Specialty Retail	0.0002***	-0.0037***	0.0108***	0.0086***	0.0065***	0.0062***			
Panel J: Food & Staples Retailing									
33.Food & Staples Retailing	0.0006**	-0.0013***		0.0057***	0.0044***		0.0023***		
Panel K: Food, Beverages & Tobacco									
34.Beverages	0.0001	-0.0027***	0.0037***	0.0103***	0.0049***	0.0013***	0.0011***		
35.Food Products	0.0007***	-0.0021***	0.0026***	0.0079***	0.0027***		0.0013***		
36.Tobacco	-0.0003	-0.0026***	0.0037***	0.0079***	0.0036***		0.0024***		
Panel L: Household & Personal Products									
37.Household Products	0.0010***	-0.0019***		0.0099***	0.0039***		0.0012***		
38.Personal Products	-0.00001	-0.0022***		0.0063***	0.0029***				0.2082***
Panel M: Health Care Equipment & Services									
39.Health Care Equipment & Supplies	0.0009***	-0.0027***	0.0052***	0.0095***	0.0068***	0.0016***			-0.0681**
40.Health Care Providers & Services	0.0007	-0.0035***	0.0072***	0.0099***	0.0077***	0.0045***			
41.Health Care Technology	0.0021***	-0.0030***	0.0030***	0.0071***	0.0080***				
Panel N: Pharmaceuticals, Biotechnology & Life Sciences									
42.Biotechnology	0.0010**	-0.0022***		0.0083***	0.0076***			0.0034***	0.0972***
43.Pharmaceuticals	0.0005**	-0.0023***	0.0025***	0.0080***	0.0047***			0.0023***	0.1306***
44.Life Sciences Tools & Services	0.0019***	-0.0027***	0.0054***	0.0081***	0.0073***		0.0029***		
Panel O: Banks									
45.Banks	-0.0001	-0.0027***	0.0096***	0.0051***	0.0049***	0.0041***	0.0024***		0.0699***
46.Thrifts & Mortgage Finance	-0.0002	-0.0020**	0.0110***		-0.0029***	0.0027**		0.0095***	-0.0995**
Panel P: Diversified Financials									
47.Diversified Financial Services	0.0002	-0.0030***	0.0085***	0.0073***	0.0062***	0.0033***	0.0030***		
48.Consumer Finance	-0.00004	-0.0051***	0.0155***	0.0114***	0.0099***	0.0128***	0.0029***	0.0024***	
49.Capital Markets	0.0006**	-0.0030***	0.0077***	0.0077***	0.0069***			0.0030***	
50.Mortgage Real Estate Investment	-0.00005	-0.0025***	0.0059***	0.0047***		0.0034***		0.0021***	
Panel Q: Insurance									
51.Insurance	0.0002	-0.0035***	0.0093***	0.0067***	0.0044***	0.0028***			
Panel R: Software & Services									
52.IT Services	0.0013***	-0.0035***	0.0076***	0.0101***	0.0098***	0.0049***			
53.Software	0.0015***	-0.0030***	0.0049***	0.0095***	0.0125***	0.0017***	0.0016***		

Table 2 (continued…)

Panel S: Technology								
54.Communications Equipment	0.0005	-0.0032***	0.0062***	0.0092***	0.0100***		0.0045***	
55.Technology Hardware	0.0014***	-0.0029***	0.0077***	0.0066***	0.0100***			
56.Electronic Equipment., Instruments & Components	0.0011***	-0.0027***	0.0098***	0.0031***	0.0042***			
Panel T: Semiconductors & Semiconductor Equipment								
57.Semiconductors & Semiconductor	0.0033**	-0.0034***	0.0109***	0.0047***	0.0111***	0.0028***		
Panel U: Telecommunication Services								
58.Diversified Telecommunication Services	0.00006	-0.0019***	0.0035***	0.0076***	0.0034***			
59.Wireless Telecommunication Services	0.0003	-0.0019***	0.0062***	0.0027***	0.0013***			0.0018***
Panel V: Media								
60.Media & Entertainment	0.0011***	-0.0027***	0.0042***	0.0054***	0.0122***	0.0013***		
61.Interactive Media & Services	0.0011***	-0.0028***	0.0032***	0.0050***	0.0148***			
Panel W: Utilities								
62.Electric Utilities	0.0005***	-0.0028***	0.0032***	0.0125***	0.0024***	0.0017***		
63.Gas Utilities	-0.0001	-0.0021***	0.0048***	0.0050***				0.0025***
64.Multi-Utilities	0.0004***	-0.0027***	0.0038***	0.0135***	0.0028***	0.0016***		
65.Water Utilities	0.0008***	-0.0021***	0.0026***	0.0125***	0.0021***			
66.Independent Power & Energy Traders	-0.0001	-0.0029***	0.0066***	0.0050***				0.0028***
Panel X: Real Estate								
67.Real Estate Investment Trusts	0.0003	-0.0033***	0.0060***	0.0119***	0.0040***	0.0049***		0.0018***
68.Real Estate Management & Development	0.00004	-0.0019***	0.0079***			-0.0019***		0.0041***

This table reports the results of regressions of returns on industrial sectors on $\Delta CV19I_t$, the measure of COVID-19 related uncertainty used in this study. The sensitivity of returns is to this factor is captured by $\beta_{iCV19I}\Delta$ in the third column. The beta coefficients, β_{i1} to $\beta_{i6,}$ are coefficients on factors drawn from the factor analytic augmentation which comprises factors that are orthogonal to $\Delta CV19I_t$. γ_i is the coefficient on an autoregressive terms of order τ. The asterisks, ***, ** and *, indicate statistical significance at the respective 1%, 5% and 10% levels of significance.

Table 3: Impact of COVID-19-related uncertainty on industrial sector return variance

Parameters	ω_i	α_i	β_{i1}	φ_{iCV19I}	$\bar{R}^2$	*Q(1)*	Q(10)	ARCH(1)	ARCH(10)
Panel A: Energy									
1.Energy Equipment & Services	-	0.0353***	0.9647***	3.26E-05	0.6637	0.0723	7.5286	0.2550	0.2752
2.Oil, Gas & Consumable Fuels	-	0.0561***	0.9439***	1.87E-05***	0.7097	1.1072	12.998	0.0216	0.1364
Panel B: Materials									
3.Chemicals	-	0.0489***	0.9511***	1.21E-06***	0.9033	0.2176	15.508	0.1638	0.2827
4.Construction Materials	-	0.0326**	0.9674***	3.03E-06***	0.8112	1.3270	12.978	0.0568	0.4849
5.Containers & Packaging	1.88E-06***	0.0394*	0.9142***	2.25E-06**	0.8646	1.4106	13.169	0.0270	0.3679
6.Metals & Mining	7.89E-07*	0.0595***	0.9208***	4.28E-06***	0.6974	2.3642	5.9645	0.3533	0.9431
7.Paper & Forest Products		0.1024*	0.8976***	2.01E-06**	0.7167	0.0542	6.2741	2.4742	0.4528
Panel C: Capital Goods									
8.Aerospace & Defence	7.27E-06***	0.1828***	0.7162***	2.24E-06	0.8248	0.2008	6.5356	0.7337	0.4932
9.Building Products	2.53E-06**	0.1302***	0.7850***	1.24E-06*	0.8287	0.1127	8.8825	0.1471	0.6483
10.Construction & Engineering	9.10E-07	0.0650**	0.9007***	2.35E-06	0.8112	1.3270	12.978	0.0568	0.4850
11.Electrical Equipment	-	0.0196**	0.9804***	4.64E-07**	0.9560	0.0099	9.6335	0.1403	0.5389
12.Industrial Conglomerates	2.00E-05***	0.5087***		1.15E-06	0.8688	0.7019	10.585	1.4786	0.5279
13.Machinery	4.71E-07**	0.0620**	0.9093***	1.28E-06***	0.9014	1.4177	10.907	1.3412	0.9721
14.Trading Companies & Distributors	1.37E-06*	0.0846**	0.8374***	2.42E-07	0.8940	0.2930	5.6227	0.0202	0.9048
Panel D: Commercial & Professional Services									
15.Commercial Services & Supplies	7.33E-07*	0.1025***	0.8599***	1.01E-06	0.8688	0.8261	6.0793	0.4283	0.9052
16.Professional Services	-	0.0567***	0.9433***	5.26E-06***	0.5824	0.1947	14.032	0.9024	0.6307
Panel E: Transportation									
17.Air Freight & Logistics	4.75E-05***	0.3041**		2.92E-06	0.7510	0.6247	4.4227	0.0900	0.5716
18.Airlines	-	0.0450***	0.9550***	8.30E-06***	0.7449	0.0162	5.3088	0.7428	0.7156
19.Marine	-	0.0507*	0.9493***	3.39E-06**	0.6743	0.6468	11.491	0.0016	0.6979
20.Road & Rail	-	0.1390***	0.8610***	2.78E-06***	0.7717	0.3280	4.1125	0.7966	0.7144
21.Transportation Infrastructure	3.30E-07***	0.0318*	0.9420***	2.41E-06***	0.8113	0.0660	3.8750	0.9635	0.6379
Panel F: Automobiles & Components									
22.Auto Components	-	0.0411***	0.9589***	1.88E-06**	0.8916	3.E-05	10.591	0.0740	0.2567
23.Automobiles	1.34E-06	0.1081*	0.8449***	5.35E-07	0.8876	2.5288	9.7917	1.1335	0.8176
Panel G: Consumer Durables & Apparel									
24.Household Durables	2.25E-05***	0.2497**		5.68E-07	0.8620	0.6037	8.8908	0.3249	0.7631
25.Leisure Products	6.13E-05***	0.1333**		6.21E-06***	0.6380	0.4375	7.7224	0.0095	0.5209
26.Textiles, Apparel & Luxury Goods	2.37E-06***	0.0541*	0.8938***	1.68E-06***	0.8134	0.3876	11.146	0.2896	1.1348
Panel H: Consumer Services									
27.Hotels, Restaurants & Leisure	-	0.0827***	0.9173***	2.47E-06*	0.8870	1.0666	8.8982	0.1262	0.5839
28.Diversified Consumer Services	1.66E-05	0.0528*	0.8823***	5.32E-06	0.3752	0.3147	6.9397	0.4010	0.9369

Table 3 (continued…)

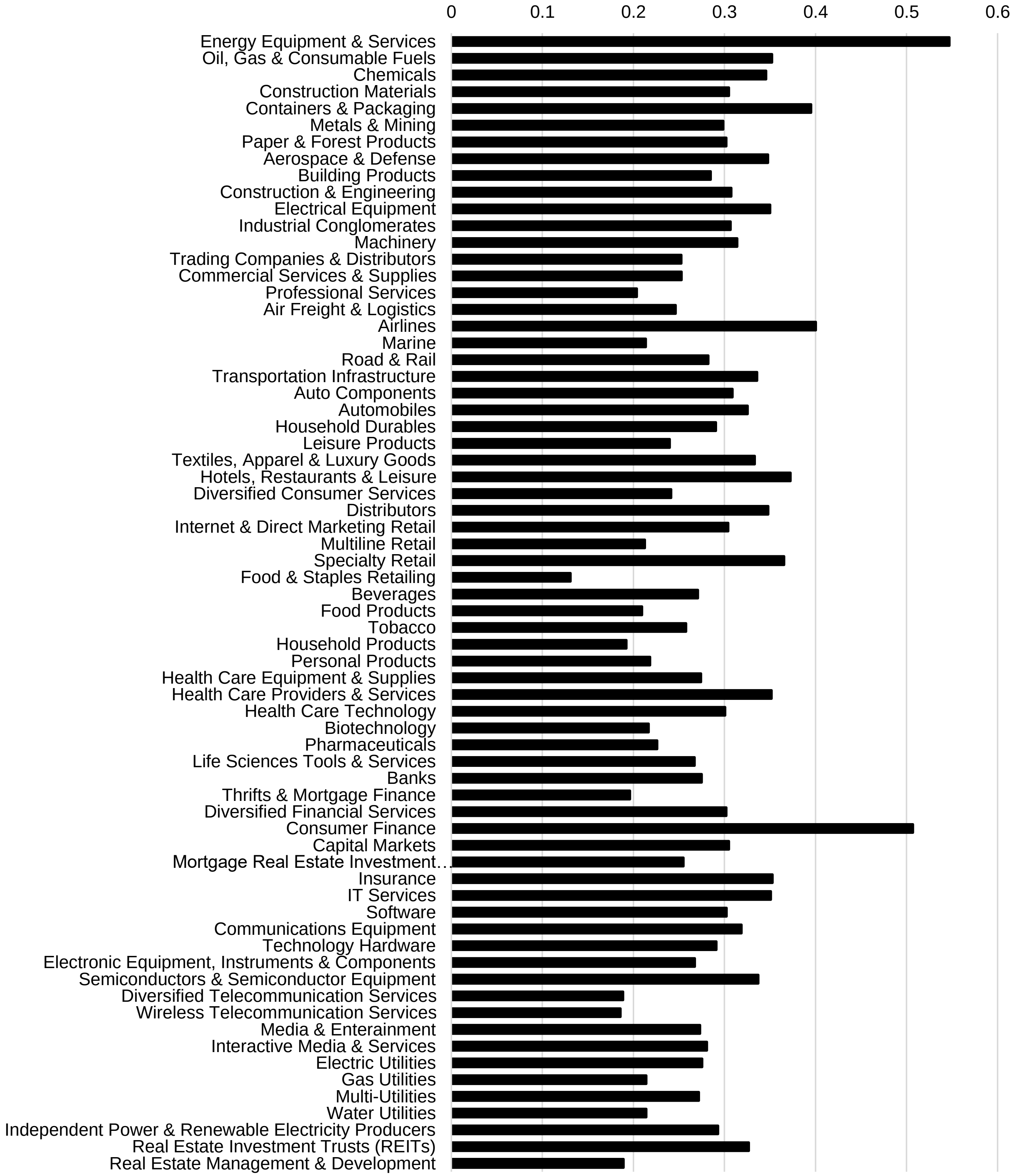
Panel I: Retailing									
29.Distributors	-	0.0336*	0.9664***	1.56E-05***	0.6705	0.0376	7.3862	0.1576	0.1111
30.Internet & Direct Marketing Retail	1.92E-05***	0.5478***	0.3330***	4.94E-07	0.6818	0.0393	7.0453	0.7738	0.7165
31.Multiline Retail	5.48E-06**	0.2656**	0.6711***	1.13E-06	0.6044	1.1129	10.592	0.6964	0.2498
32.Specialty Retail	-	0.0816***	0.9184***	3.18E-06***	0.8555	2.0218	9.1395	0.1967	0.4487
Panel J: Food & Staples Retailing									
33.Food & Staples Retailing	-	0.0436***	0.9564***	2.58E-06**	0.7107	0.0215	8.8233	0.1060	0.9762
Panel K: Food, Beverages & Tobacco									
34.Beverages	-	0.1574**	0.8426***	9.18E-07*	0.8590	2.1446	14.573	0.2217	0.3799
35.Food Products	2.44E-06	0.2278**	0.6648***	1.36E-07	0.7457	0.0027	7.8330	0.7710	0.7011
36.Tobacco	-	0.0363***	0.9637***	2.04E-06**	0.5911	0.1516	1.3334	0.2258	0.3487
Panel L: Household & Personal Products									
37.Household Products	-	0.1001***	0.8999***	4.54E-07	0.7917	0.0011	9.6237	0.2716	0.9538
38.Personal Products	4.66E-06**	0.1604***	0.7621***	1.52E-06	0.5273	0.8905	9.1132	0.5059	0.5758
39.Health Care Equipment & Supplies	-	0.0948***	0.9052***	1.44E-06*	0.8236	0.1038	11.535	1.5911	0.5529
Panel M: Health Care Equipment & Services									
40.Health Care Providers & Services	6.39E-05**	0.2653***	0.2614	7.77E-06	0.6867	0.9300	12.502	0.3207	0.8574
41.Health Care Technology	7.77E-05***	0.1715		2.23E-06	0.5815	0.5524	6.3846	0.1131	0.3441
Panel N: Pharmaceuticals, Biotechnology & Life Sciences									
42.Biotechnology	-	0.0191***	0.9809***	1.36E-06**	0.7302	0.3312	5.1675	0.1108	0.7493
43.Pharmaceuticals	1.75E-06**	0.1458***	0.7758***	9.45E-07*	0.8150	0.1784	9.0612	0.1139	0.1139
44.Life Sciences Tools & Services	4.19E-05***	0.4288***		2.99E-06	0.7255	0.9670	10.120	0.2061	0.3601
Panel O: Banks									
45.Banks	2.71E-06**	0.3663**	0.5242***	1.61E-07	0.8905	2.0010	13.519	0.9721	1.3779
46.Thrifts & Mortgage Finance	-	0.0386***	0.9614***	1.46E-05	0.4093	0.1702	8.6127	2.2556	0.5732
Panel P: Diversified Financials									
47.Diversified Financial Services	5.78E-07	0.1263**	0.8480***	4.69E-07	0.9166	0.1143	3.3052	1.6160	1.1240
48.Consumer Finance	6.57E-06***	0.5597***	0.2974***	1.76E-06	0.9553	0.2638	11.026	0.0125	0.7508
49.Capital Markets	-	0.0923*	0.9077***	3.92E-06***	0.8780	2.1746	11.437	0.0030	0.7251
50.Mortgage Real Estate Investment	3.89E-06*	0.2224***	0.7732***	5.67E-06	0.4130	0.2909	11.928	1.5312	1.3438
Panel Q: Insurance									
51.Insurance	-	0.0209*	0.9791***	9.59E-07**	0.9234	0.8009	8.8919	1.6622	1.4642
Panel R: Software & Services									
52.IT Services	7.84E-06*	0.2585***	0.5096***	1.20E-06	0.9099	0.1793	11.036	0.4677	0.6339
53.Software	7.38E-06	0.1611**	0.6729***	1.94E-06	0.8858	0.4731	12.090	0.5656	0.3722

Table 3 (continued…)

Panel S: Technology									
54.Communications Equipment	6.62E-05***	0.3252*		4.77E-06	0.7579	0.1153	5.8203	0.1747	0.4604
55.Technology Hardware	3.53E-05***	0.0942		5.42E-07	0.8603	0.0122	3.3297	0.0657	1.4497
56.Electronic Equipment Instruments & Components	1.10E-05***	0.3687**	0.2234	1.28E-07	0.8502	0.2498	10.300	0.1624	1.3805
Panel T: Semiconductors & Semiconductor Equipment									
57.Semiconductors & Semiconductor		0.0585***	0.9415***	3.27E-06***	0.7694	0.7379	3.9234	0.5030	0.6195
Panel U: Telecommunication Services									
58.Diversified Telecommunication	2.42E-05***	0.2547***		3.45E-08	0.7656	0.0248	11.276	0.0011	0.7302
59.Wireless Telecommunication	2.64E-05***	0.2605**		5.30E-07	0.6328	2.0385	9.2187	0.1310	0.3520
Panel V: Media									
60.Media & Entertainment	-	0.0599***	0.9401***	2.75E-07***	0.9840	0.1535	9.1540	1.4139	0.7945
61.Interactive Media & Services	-	0.0643**	0.9357***	1.52E-06***	0.9330	0.0274	4.9917	0.9916	0.7298
Panel W: Utilities									
62.Electric Utilities	3.09E-07	0.0837**	0.8816***	4.66E-07	0.9504	0.3968	2.5523	0.1632	1.3841
63.Gas Utilities	1.42E-06*	0.1556***	0.7822***	1.12E-06*	0.7142	0.0887	9.9844	0.0121	0.2015
64.Multi-Utilities	2.72E-07***	0.0282*	0.9442***	8.74E-07**	0.9474	0.0768	5.8687	0.0030	1.0902
65.Water Utilities	1.87E-06	0.1021**	0.8330***	1.24E-06	0.8659	0.2645	8.9985	0.0348	1.2973
66.Independent Power & Energy Traders	-	0.0312*	0.9688***	2.12E-06***	0.7425	0.0965	8.8825	1.3601	0.8004
Panel X: Real Estate									
67.Real Estate Investment Trusts	-	0.0190**	0.9810***	1.70E-06*	0.8856	0.4397	8.0647	0.4583	0.8286
68.Real Estate Management & Development	3.55E-06*	0.1270**	0.7690***	1.51E-06	0.7072	0.1650	3.9229	0.0002	0.6641

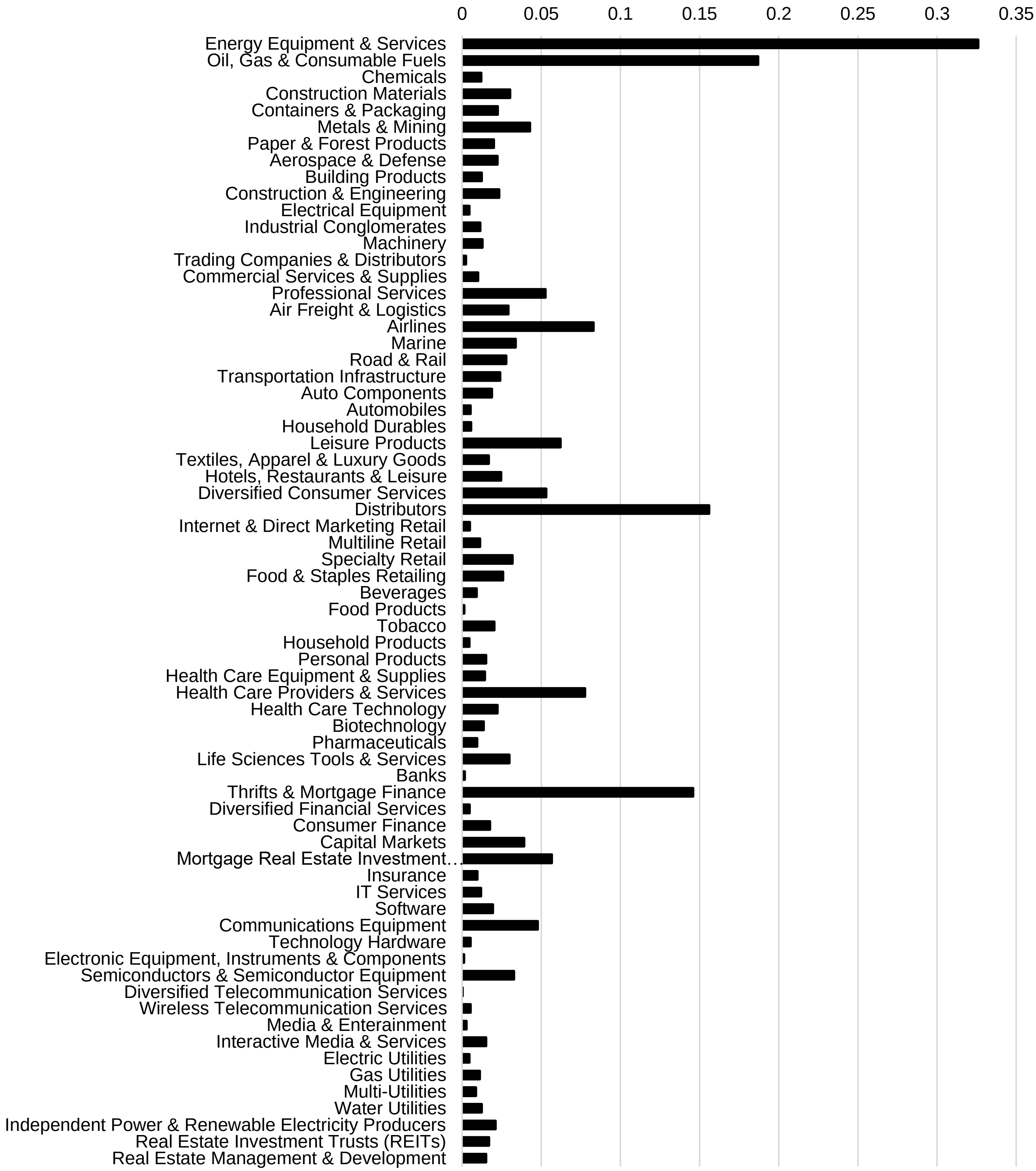
This table reports the results of the ARCH/GARCH model estimation, with three specifications used, namely the ARCH(1), GARCH(1,1) and IGARCH(1,1) specifications. The second and third columns report the ARCH and GARCH coefficients, α_i and β_{i1}. The coefficient $\varphi_{i\Delta CV19I}$ on $\Delta CV19I_t$, the measure of COVID-19 related uncertainty, is reported in the fifth column. Model diagnostics are reported in columns 6 – 10. Q(1) and Q(10) are Ljung-Box test 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 ARCH effects at the 1st and 10th orders .The asterisks, ***, ** and *, indicate statistical significance at the respective 1%, 5% and 10% levels of significance.

Figure 2: Summary of the impact of COVID-19 related uncertainty on industrial sector returns



This figure reports the magnitudes of the coefficients on $\Delta CV19I_t$, β_{iCV19I}, from equation (1). Each β_{iCV19I} is scaled by 100 for ease of comparison.

Figure 3: Summary of the impact of COVID-19 related uncertainty on industrial sector variance



This figure reports the magnitude of the coefficients on $\Delta CV19I_t$, φ_{iCV19I}, from equation (1). Each φ_{iCV19I} is scaled by 10 000 for ease of comparison.

4.2. The impact of COVID-19 related uncertainty

The first striking result in Table 2 is that the β_{iCV19I} coefficients for all industries are consistently negative and almost all statistically significant at the 1% level (except for the thrifts & mortgage finance industry, which is significant at the 5% level). As we have controlled for other factors using a factor analytic augmentation, we interpret this finding as strong evidence that COVID-19 related uncertainty, reflected by Google Trends search data, is associated with negative returns across all sectors. This decline in stock prices due to COVID-19 uncertainty suggests that COVID-19 uncertainty results in a decrease in expected future cashflows of firms and/or an increase in risk aversion which contributes to a higher risk premium in the forward-looking discount rate (Andrei & Hasler, 2014; Smales, 2021; Cochrane, 2018).

The industries most impacted by COVID-19 related uncertainty are energy, equipment and services (β_{iCV19I} of -0.0055) followed by consumer finance, airlines, and containers and packaging (β_{iCV19I}s -0.0051, -0.0040 and -0.0040 respectively). This finding is not surprising, as energy stocks around the world suffered heavily as a consequence of a substantial decrease in the demand for oil as the global economy began entering lockdown from February 2020 onwards and, as overall business activity was drastically restricted in most countries, leading to a plunge in the oil price itself. This was further exacerbated by the Russia-Saudi Arabia oil price war in March 2020 (Szczygielski et al., 2021b). In addition, the airline industry was, naturally, seriously affected by the global travel restrictions, which is also reflected by a β_{iCV19I} estimate of -0.0040 (see Figure 1).

The industry least impacted by COVID-19 related uncertainty was food and staples retailing (β_{iCV19I} of -0.0013). This is followed by the diversified telecommunication, wireless telecommunication, real estate management and development and household products (β_{iCV19I} at the -0.0019 level) industries. These are followed by the professional services, and thrifts and mortgage finance (β_{iCV19I}s of -0.0020) industries. The next five industries are marine (transport), multiline retail, food products, gas utilities and water utilities (β_{iCV19I}s of - 0.0021). Companies in these industries were, to a large degree, resilient to the uncertainty surrounding the COVID-19 pandemic because of the nature of their business activity, predominantly serving households trapped in the lockdown and, as such, lost little of their business or, in some cases, even increased their sales (e.g. supermarkets selling food or telecommunication and technology companies, which offer products such as teleconferencing systems, etc.) although increased revenues have often been partially offset by higher operation costs during the initial weeks of the COVID-19 pandemic. Utilities, which operate in regulated industries were also impacted less by the uncertainty around the pandemic, most likely due to inelastic demand.

Table 3 presents results for the conditional variance equations, (2a)/(2b)/(2c). Similarly, to the pattern of estimates in Table 2, these results are consistent; all the parameters φ_{iCV19I} are positive and mostly significant (often at the 1% level). This finding means that volatility had a tendency to increase along with rising uncertainty related to COVID-19 resulting in investors searching for more information. Notably, these results – the widespread significance of the coefficient on $\Delta CV19I_t$ in the conditional variance equations - also provides further support for the role of Google Trends search data as a measure of uncertainty.

The overall picture becomes more interesting when individual industries are inspected more closely. The effects in variance are strongest in the case of the same industries as those that are most impacted in the mean equations (i.e. energy, equipment & services, consistent with the findings of Szczygielski et al. (2021b) for the energy sector) and in related industries (i.e. oil, gas & consumable fuels) and, also in some of those which were least affected (e.g. thrifts & mortgage finance) as well as in other sectors (such as distributors) (see Figure 3). This mixed set of results implies that increased uncertainty is not necessarily associated only with industries which suffered most in terms of negative returns, but also with other industries. We interpret these findings as uncertainty relating to emerging opportunities for numerous industries as a result of the pandemic. This also implies that with respect to COVID-19 associated risk, as perceived by the markets, industries in certain sectors may not be able to take advantage of new business opportunities. Industries that experience opportunities would be those such as distributors, food and staples retailing and diversified telecommunications industries which benefit from lockdowns and remote working. Further evidence to this effect is provided by industries for which the effects in variance are the weakest. These are food, beverages and tobacco, technology, telecommunication services and utilities. Each of these industries can be viewed as producing either necessities (i.e. food) or substitute goods within the context of lockdown (i.e. telecommunication services) and, being characterised by inelastic demand for their products (i.e. tobacco, utilities); hence less affected by COVID-19 related uncertainty.

Overall, the results in Table 3 provide evidence of volatility triggering effects caused by the uncertainty related to the COVID-19 outbreak. The differences documented across individual industries capture either uncertainty relating to the future (financial) performance of firms or uncertainty about how well some of the companies can exploit the opportunities that they may have as a result of the increased new business following the COVID-19 outbreak and the lockdowns.

Liu (2020) observed the negative impact of uncertainty on the returns for all sectors except utilities, consumer staples and healthcare where the effect was insignificant or, in the case of the information technology sector, significantly positive. While we find that uncertainty negatively impacts returns across all industries, utilities and consumer staples were also among the least affected reflecting the inelastic demand for the goods and services provided by firms in these industries globally. Smales (2020) also finds consumer staples among the least impacted US industries. While both Liu (2020) and Smales (2020) identify the healthcare sector as among the least impacted in their country-level analyses, the effect on this industry differs with the global-level analysis in this study, where the impact is significant. This reflects that globally firms in this industry face uncertainty in terms of coping with the impact of the virus on their operations and the impact of the reduction in demand for elective surgeries.

Smales (2020) documented that the energy sector in the US was most impacted by COVID-19 related uncertainty, with Liu (2020) also finding that this sector was amongst the most impacted in China. The study of the energy sector of Szczygielski et al. (2021b) confirmed the substantial negative impact of COVID-19 related uncertainty, quantified by Google search data, on the 20 largest national energy sectors. Our finding that uncertainty has the greatest impact on returns and volatility in the energy, equipment and services and oil, gas and consumable fuels industrial sectors industries, among others, mirrors prior studies and indicates that these industries have been hardest hit by the pandemic worldwide and the uncertainty of future economic recovery.

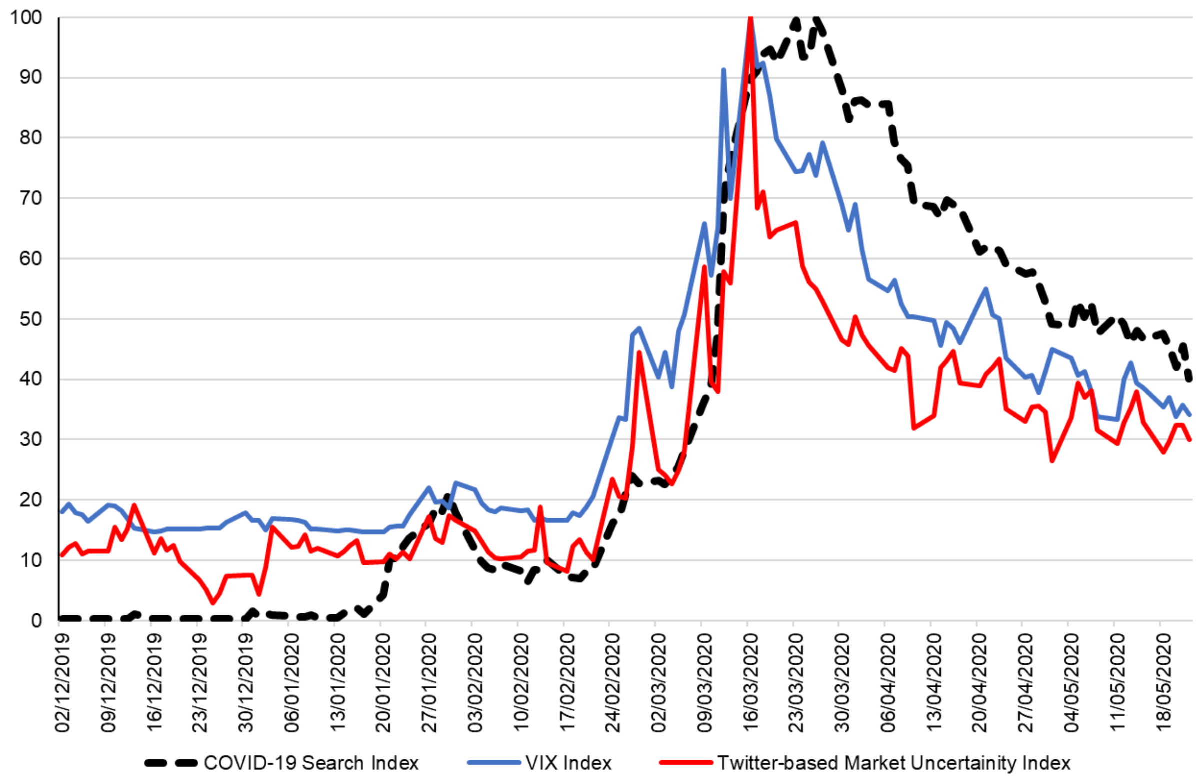
With respect to the telecommunications sector, Liu (2020) found that it was the most impacted sector in China by COVID-19 related uncertainty, but this sector was identified to be among the least impacted industries at a global level in this study. Telecommunications have grown in importance during this period and the sector is well-positioned to be able to respond to changing business and leisure activities; hence the Chinese results are surprising. This may be attributable to the fact that Chinese telecommunications companies have been severely impacted in their ability to roll out 5G as a consequence of the virus. These results thus confirm that in the formation of international portfolios, industry-level influences are important.

At an aggregate level, our findings that COVID-19 related uncertainty, quantified using Google search trends, has a significant negative impact on returns and triggers heightened volatility are consistent with results in nascent literature on the impact of COVID-19 related Google search trends on stock returns (Ahundjanov et al., 2020; Costola et al., 2020a; Liu, 2020; Papadamou et al., 2020; Ramelli and Wagner, 2020; Smales, 2020, 2021; Szczygielski et al. 2021a,b).

4.3. Google Trends search data as a measure of uncertainty during COVID-19

In this section, we juxtapose our COVID-19 related uncertainty index constructed from the eight Google search terms relating to COVID-19 in Section 3.1 against two existing measures of market uncertainty in Figure 2 over the COVID-19 period. This first is the Chicago Board Options Exchange (CBOE) S&P 500 Volatility Index (VIX), a measure of stock market uncertainty (Bekaert et al., 2013). Although we use the US version of this index, Chiang et al. (2015), Dimic et al. (2016) and Smales (2019), show that the VIX reflects global market uncertainty. The second is the recently developed Twitter-based Market Uncertainty (TMU) Index of Renault et al. (2020).

Figure 2. Comparison of COVID-19 search term index, VIX and TMU index levels



This figure plots the levels of the composite COVID-19 search Index, the VIX and the TMU index over the COVID-19 period, defined as 1 December 2019 to 22 May 2020.

Figure 2 shows that the COVID-19 search index moves closely with the two alternative measures of market uncertainty over the COVID-19 sample period. However, the VIX leads both the indices until mid-March. Thereafter, the TMU index leads both the VIX and the COVID-19 search index with the COVID-19 search index somewhat lagging both alternate uncertainty measures. The Google-based COVID-19 index increases sharply, similarly to the VIX and TMU indices, around significant COVID-19 related events which occurred in the first half of March 2020, albeit with a delay relative to the alternate uncertainty measures. These events are the surpassing of 100 000 COVID-19 cases globally (7 March 2020), COVID-19 being declared a pandemic by the WHO (11 March

2020) and Europe becoming the epicentre of the pandemic with more cases and deaths combined than the rest of the world aside from China (13 March 2020).

Given the apparent co-movement between the composite Google search index and levels of the VIX and TMU index, we re-estimate the equations in Table 1 replacing $\Delta CV19I_t$ with changes in the VIX and changes in the TMU index, denoted as ΔVIX_t and ΔTMU_t respectively. We do this for a single industry within each industrial grouping (i.e. a single industry for Energy (Panel A), Materials (Panel B), Capital Goods (Panel C), etc. each in Tables 2 and 3), totalling 24 sectors. In terms of statistical significance and direction of impact, the results are consistent across measures for the conditional mean; $\Delta CV19I_t$, ΔVIX_t and ΔTMU_t have a consistently negative and statistically significant impact on returns. The mean values of the β_{iCV19I} and β_{iVIX} coefficients for these sectors are -0.0029 and -0.0030, respectively, and are therefore comparable in magnitude (see Panel A of Table A4 in the Appendix). This is not the case for the mean of the β_{iTMU} coefficients, which is -0.0019 (see Panel B of Table A4 in the Appendix). The results for the conditional variance when ΔVIX_t is used as a measure of uncertainty are also somewhat comparable. The mean values of the φ_{iCV19I} and φ_{iVIX} coefficients, 3.40E-06 and 3.20E-06, respectively, are comparable in magnitude. Significance (or the lack thereof) is consistent for 18 out of 24 sectors, the exceptions being the energy equipment and services, construction and engineering, road and rail, leisure products and household sectors (see Panel A of Table A5). For example, while $\Delta CV19I_t$ has no significant impact on the conditional variance of the energy equipment and services sector, ΔVIX_t exhibits a significant impact. For some sectors for which ΔVIX_t positively and significantly impacts conditional variance consistent with the significance for $\Delta CV19I_t$, the φ_{iCV19I} and φ_{iVIX} coefficients are comparable. For example, for the containers and packaging sector, the φ_{iCV19I} and φ_{iVIX} coefficients are 2.25E-06 and 2.28E-06, respectively. A similar observation – of comparable coefficient magnitudes in the conditional variance – can be made for the auto components, food and staples retailing, and the media and entertainment sectors.

In contrast to ΔVIX_t, there is less consistency for ΔTMU_t. The respective mean values for the φ_{iCV19I} and φ_{iVIX} coefficients of 3.40E-06 and 2.3E-06 differ noticeably. For ΔTMU_t, 12 of the 24 sectors exhibit consistently statistically significant (insignificant) φ_{iTMU} coefficients. Sectors for which $\Delta CV19I_t$ and ΔTMU_t are consistently statistically significant are the containers and packaging, road and rail, auto components, internet and direct marketing retail, food and staples retailing, pharmaceuticals, mortgage real estate investment, insurance, technology hardware, diversified telecommunication, the media and entertainment sectors and real estate investment trusts. However, the direction of impact is inconsistent for the diversified consumer services sector, for which the φ_{iTMU} is statistically significant (as is the case for φ_{iCV19I}) but negative (as is not the case for φ_{iCV19I}, which is positive). Other sectors that now exhibit negative although statistically insignificant φ_{iTMU} coefficients are technology hardware and diversified telecommunications. Of the φ_{iTMU} coefficients that are significant and consistent in direction of impact, the φ_{iTMU} coefficient for the roads and rail sector of 2.41E-06 is comparable to the φ_{iCV19I} coefficient for this sector of 2.78E-06. For the remaining sectors, significant coefficients diverge noticeably in magnitude.

Our comparison of the three uncertainty measures yields somewhat mixed results. While the results for the ΔVIX_t are somewhat (although not perfectly) comparable in terms of the consistency of estimate significance, overall (mean) β_{iTMU} and φ_{iVIX} coefficient magnitudes and for some individual industries, the results for ΔTMU_t show less consistency. The trends in Figure 2 suggest that all three measures reflect rising uncertainty over the COVID-19 period. However, the VIX and TMU index appear to respond earlier than the Google-based COVID-19 search trends index, especially after the beginning of March 2020. This potentially explains differences in results. Following the differences in the intertemporal co-movement observed in Figure 2, it may be that the three uncertainty measures considered are not contemporaneously interchangeable but may yield more comparable results if entered into specifications with lags. Additionally, if measures of uncertainty are viewed as proxies for information, there is no guarantee (or requirement) that such measures are interchangeable and reflect the same information. Both the VIX and TMU indices are more general measures of market uncertainty whereas our COVID-19 search index is specific to COVID-19. Therefore, it can be argued that both former measures not only reflect uncertainty around the COVID-19 pandemic but also reflect uncertainty around other events that will impact returns and variance.

Szczygielski et al. (2021b) provide some empirical evidence that the VIX, the CBOE oil volatility index (OVX) and a Google-based measure of COVID-19 uncertainty are not interchangeable. The authors estimate rolling contemporaneous correlations between changes in a composite COVID-19 search term index, changes in VIX levels and levels of the OVX. Rolling correlations between changes in the COVID-19 search index and the VIX are positive, ranging between 0.3 and 0.5 during the early stages of the crisis between the end of February 2020 and the end of April 2020. Correlations between changes in the COVID-19 search index and the OVX range between 0.2 and 0.5 between the end of February 2020 and early May 2020. In short, correlations are far from perfect. This may be due to differences in the indices themselves (i.e. in the nature of information reflected) and/or their intertemporal structure. Furthermore, in another study, Szczygielski et al. (2021a) also observe differences between the impact of VIX and TMU compared to a Google Trends search index on returns and volatility of regional indices during the COVID-19 period, with the differences more pronounced for volatility than returns. Chen et al. (2020) find that there is bi-directional intertemporal Granger causality between the VIX and a Google Trends-based COVID-19 search index. Similarly, Papadamou et al. (2020) illustrate that increased searches related to COVID-19 have a positive impact on the VIX, while both Chen et al. (2020) and Papadamou et al. (2020) illustrate that the VIX and Google Trends search index are related, they are not perfect substitutes. Outside of COVID-19 research, Castelnuovo and Tran (2017) also find imperfect correlations between a Google search index and other traditional uncertainty measures. For example, the correlation between their Google search index measure and the CBOE S&P 100 volatility index (VXO) is 0.54. In summary, there is no basis for an expectation that the results should be the same or closely comparable as the uncertainty measures are not directly comparable or perfect substitutes.

We also recognise the heterogeneity of the sectors considered. This heterogeneity implies that there may be variation in how sectors respond to uncertainty specific to the COVID-19 pandemic (reflected by the Google-based COVID-19 search index) and uncertainty that is of a more general nature (reflected by the VIX and TMU indices), making comparisons difficult. The analysis in Section 4.5. suggests that this may be the case. For example, while the internet and direct marketing retail sector experienced negative cumulative returns prior to the COVID-19 pandemic, returns were positive over the COVID-19 pandemic. In contrast, the insurance sector offered moderate positive returns prior to the COVID-19 pandemic but negative returns during the COVID-19 pandemic. In short, we conclude that while the results are mixed, there is some similarly between results when the $\Delta CV19I_t$ with ΔVIX_t are compared.[5] However, we also recognise that the interchangeability of uncertainty measures and the comparability of information in such measures is a topic that warrants further detailed investigation in itself.

4.4. COVID-19 related uncertainty as a factor in returns

Given the widespread impact of COVID-19 related uncertainty, $\Delta CV19I_t$, on both returns and variance, we investigate whether this uncertainty can be viewed as a major factor driving global industry returns. We do this by investigating the dynamic structure of the

[5] Another potential explanation is the methodology applied. We applied the factor analytic augmentation outlined in Section 3.2 but generated augmentation factors from residuals of regressions of returns onto ΔVIX_t and ΔTMU_t respectively for all 68 industry return series. For residuals generated from regressions of returns onto ΔVIX_t, seven statistical factors were extracted. This contrasts with the six factors extracted from the residuals of regressions of returns onto $\Delta CV19I_t$. This suggests that the structure of the ΔVIX_t regression residuals differs from that of $\Delta CV19I_t$ regression residuals and suggests differing informational content. For ΔTMU_t, six statistical factors were extracted which correlation analysis showed are highly but nevertheless imperfectly correlated with factors extracted from the residuals of $\Delta CV19I_t$. To account for these differences, we ensured through the selection of statistical factors that the $\bar{R}^2$ for ΔVIX_t ARCH/GARCH regressions is comparable to that of $\Delta CV19I_t$ (Table 2) thereby capturing a similar proportion of systematic variation. For ΔTMU_t, we retained the factor analytic structures by retaining the same number and the same statistical factors, given the high level of factor analytic factors, as for $\Delta CV19I_t$ ARCH/GARCH regressions. This approach produced similar $\bar{R}^2$s. By obtaining comparable $\bar{R}^2$s, we aim to ensure the equivalence of the informational content reflected in the conditional mean regressions for $\Delta CV19I_t$, ΔVIX_t and ΔTMU_t. Similarly, conditional variance structures identified from the regressions for $\Delta CV19I_t$ in Table 2 were retained for both ΔVIX_t and ΔTMU_t for comparative purposes. It is however possible that the conditional variance structures will differ with this being the case especially if ΔVIX_t and ΔTMU_t reflect somewhat different information from information reflected in $\Delta CV19I_t$ and therefore require a re-specification of the conditional variance structures. That conditional variance structures may differ (and may now be mis-specified) is suggested by the negative φ_{iVIX} and φ_{iTMU} coefficients for the technology hardware and water utilities sectors in Table A5 (also see Koutoulas & Kryzanowski, 1994; Szczygielski et al., 2020a).

underlying return generating process by analysing the factor structure of returns during the pre-COVID-19 and COVID-19 periods. As we are interested in the most comprehensive representation of the return generating process, the number of factors is now identified using the MAP test, with factor scores undergoing varimax rotation to aide interpretability (see Section 3.2.). By following this approach, we test for the potential emergence of new factors in the COVID-19 period that are not present during the pre-COVID-19 period. Although such factors may be transient, they may nevertheless be indicative of COVID-19 related influences that emerge during the COVID-19 period, including the potential role of COVID-19 related uncertainty as an important or separate factor (see Meyers, 1973). Furthermore, correlation analysis is then undertaken for factors extracted from the returns during the COVID-19 period to establish whether any of these factors are correlated with the measure of COVID-19 related uncertainty used in this study (see Szczygielski et al., 2020). The results of the factor and correlation analysis are reported in Table 4 and Table 5 respectively.

Table 4: Summary of factor analysis

Panel A: Full Period Analysis			
Period	**Factors extracted**	**Mean Communality**	**KMO**
Pre-COVID-19	7	0.6336	0.9575
COVID-19	13	0.9192	0.9530

This table reports the results of factor analysis applied to returns over the pre-COVID-19 period (01/01/2019 – 30/11/2019) and the COVID-19 period (01/12/2019 – 22/05/2020). The number of factors extracted for each period are reported in column 2. Mean communality is the mean proportion of common variance explained by common factors across the return series extracted on the basis of the MAP test. KMO is the Kaiser-Meyer-Olkin (KMO) index which indicates suitability for factor analysis; values of over 0.8 are deemed desirable.

The results in Table 4 suggest that there are an additional five factors, totalling 13, that emerge during the COVID-19 period, explaining almost 92% of common variance in returns. This is in contrast to the seven factors that drive returns during the pre-COVID-19 period, explaining 63.4% of common variance. For the correlations, in Table 5, we report non-parametric Spearman correlations (ρ_s) between the factor scores and the COVID-19 uncertainty variable, eigenvalues, the proportion explained by individual factor score series and the cumulative proportion of common variation explained by all 13 factors (Hughes, 1984).

Table 5: Correlation between factor scores and $\Delta CV19I_t$ and proportion explained

Factor:	ρ_s	Eigenvalue	Proportion	Cumulative Proportion
F_{1CV19_t}	-0.0030	51.4323	0.7564	0.7564
F_{2CV19_t}	-0.1918**	4.3494	0.0640	0.8203
F_{3CV19_t}	-0.3320***	1.7856	0.0263	0.8466
F_{4CV19_t}	-0.0094	1.3366	0.0197	0.8662
F_{5V19_t}	0.2298***	1.1263	0.0166	0.8828
F_{6CV19_t}	-0.0437	0.8276	0.0122	0.8950
F_{7CV19_t}	0.0992	0.7142	0.0105	0.9055
F_{8CV19_t}	0.0397	0.5698	0.0084	0.9138
F_{9CV19_t}	-0.0496	0.4819	0.0071	0.9209
F_{10CV19_t}	-0.1257	0.4288	0.0063	0.9272
F_{11CV19_t}	0.0993	0.3790	0.0056	0.9328
F_{12V19_t}	-0.1237	0.3653	0.0054	0.9382
F_{13CV19_t}	-0.0489	0.3531	0.0052	0.9434

This table reports Spearman's correlation coefficients (ρ_s) between the factor scores derived from returns over the COVID-19 period (01/12/2019 – 22/05/2020) and $\Delta CV19I_t$ and the proportion of common variation explained by each of the 13 derived factors. The correlation coefficients are reported in the second column, the eigenvalues for the *k*th factor in the third column and the contribution of each factor to explaining common variation in the fourth column. The cumulative proportion, shown in Table 5 is the total proportion of variance explained up to the *k*th extracted factor. The asterisks, ***, ** and *, indicate statistical significance at the respective 1%, 5% and 10% levels of significance.

The correlation coefficients indicate that $\Delta CV19I_t$ is significantly and negatively correlated with two factors, F_{2CV19_t} and F_{3CV19_t}, and positively and significantly correlated with another factor**,** F_{5V19_t}, with respective correlation coefficients of -0.1918, -0.3320 and 0.2298. This implies that COVID-19 related uncertainty is indeed a driver of global industry returns during the COVID-19 period. However, COVID-19 related uncertainty is not the most important factor or a separate factor in itself. That is, the first factor, F_{1CV19_t}, accounts for almost 76% of variation in returns attributable to common influences and, notably, is uncorrelated with $\Delta CV19I_t$. In contrast, F_{2CV19_t} , F_{3CV19_t} and F_{5V19_t} account for 6.40%, 2.63% and 1.66% of common variation in returns respectively, totalling 10.69%. However, it is important to note that while these three factors account for over 10% of common variation in returns, they are not perfectly (and are arguably weakly) correlated with $\Delta CV19I_t$, implying that the total proportion of common variation explained by this factor is far lower. Multiplying the correlation coefficients reported in the second column by the proportion of common variation explained by each factor results in a sum of 0.0172.

Overall, these results suggest that while COVID-19 uncertainty impacts global industry returns, it is not a major factor, or a separate factor in itself. Furthermore, the emergence of five additional factors, relative to the pre-COVID-19 period, implies that there are other drivers of global industry returns. These may be related to the extraordinary fiscal and monetary measures implemented and restrictive lockdowns that would not otherwise have taken place as well as other aspects of the COVID-19 crisis (see Hale et al*.,* 2020). We consign the interpretation of these emergent factors for further research.

4.5. Investing during the COVID-19 period

Given that COVID-19 related uncertainty has a negative impact on industry returns but that the analysis in Section 4.4. suggests that COVID-19 related uncertainty is not a major factor in driving returns, a natural question that arises is whether investors can profit from investing in specific industries during the COVID-19 crisis given the prevalent levels of uncertainty. To answer this question, we proceed by estimating cumulative abnormal returns (CAR) for the pre-COVID-19 and COVID-19 periods. We control for the impact of systematic factors unrelated to the pandemic by estimating a market model relating returns on each industry in our sample to returns on the MSCI All Country World Index, for the period 1 January 2015 to 31 December 2018.[6] Abnormal daily returns for each industry are then estimated by subtracting the industry alpha and the industry beta mulitplied by the daily market return.[7] CARs for the pre-COVID-19 and COVID-19 periods are then calculated over both periods[8]. The results are reported in Table A3 of the Appendix.

Industries that experienced the largest negative CARs over the COVID-19 period include airlines (-47.23%), thrift and mortgage finance (-36.90%), energy equipment and services (-35.55%), mortgage real estate investment trusts (-35.13%), aerospace and defense (-33.29%), consumer finance (-30.81%), banks (-24.98%), oil, gas and consumable fuels (-21.59%), transportation infrastructure (-21.51%) and distributors (-20.32%). The

[6] $r_t = \alpha + \beta r_{mt} + \varepsilon_t$, where r_{mt} are the daily returns on the market index.
[7] $ar_t = r_t - \alpha - \beta r_{mt}$ for each day in the pre-COVID-19 period and COVID-19 periods. ar_t is the daily abnormal return.
[8] $CAR = \prod_t^T (1 + ar_t) - 1$, where CAR is the cumulative abnormal return.

majority of these industries are those that were found to be the most affected by uncertainty in both the mean and variance, notably energy equipment and services, airlines and consumer finance, and only in the variance (e.g. thrift & mortgage finance; distributors). In contrast, industries with the highest abnormal returns include health care technology (39.76%), internet and direct marketing retailing (22.55%), software (21.61%) and biotechnology (21.32%). These industries were moderately affected by COVID-19 related uncertainty in both the mean and the variance (see Section 3.2 for an overview).

These results are broadly consistent with the findings for US and Chinese industries during COVID-19 based on the studies of Al-Awadhi et al. (2020), Mazur et al. (2020) and Ramelli and Wagner (2020). In particular, the health care industry performed well at a global level as did software and telecommunications. The food staples industry, which Mazur et al. (2020) found to be positively impacted by the pandemic, while positive at a global level, was not amongst the industries with the largest CARs over the period. On the downside, Mazur et al. (2020) found the entertainment and hospitality sectors to be amongst the most negatively impacted by COVID-19. At a global level, these industries likewise performed poorly but this was not as negative as that of the energy equipment and services and oil, gas and consumable fuels, aerospace and defence and airlines industries. Ramelli and Wagner (2020) similarly found that energy companies were amongst the worst performing sectors in the US, while Al-Awadhi et al. (2020) also found stock returns of the air transportation sector to be among the worst in China during the COVID-19 outbreak. While the longer time period examined in this study may explain some of the differences in findings, these differences also reveal that the impact of COVID-19 on industries globally is not the same as within country effects.

During prior pandemics, biotechnology stocks were found to increase substantially in value (Chen et al., 2009, Wang et al., 2013) and this is consistent with the findings documented for COVID-19 in this study. Similarly, the tourism sector, which was severely impacted by the SARS-virus (Chen et al., 2007; Chen et al., 2009) was also negatively affected by COVID-19 but not to the same extent as other industries. This demonstrates the global impact of COVID-19 compared to prior infectious diseases as companies whose operations are internationally-diversified (such as airlines & oil) are affected to a much greater extent.

While COVID-19 uncertainty has a negative impact on global industry returns, investors should not be discouraged. The analysis of CARs suggests that there are still profitable industries (e.g. health care technology, internet & direct marketing retailing, software & biotechnology) that have yielded positive returns which even at times exceed those prior to the COVID-19 period in 2019. The recommendation is that investors, when making investment decisions, should rather be concerned with the fundamentals of specific industries related to the nature of the business that is carried out by that industry. Moreover, the results discussed in this section can also directly serve to inform possible trading strategies, which investors may design based on the information about how individual industries behaved during the COVID-19 pandemic. For example, natural types of strategies in this case are momentum and contrarian strategies (e.g. it is likely that investors will be buying stocks from the industries which suffered most, which means the adoption of contrarian trading rules). Other possibilities are 'long-short' strategies where investors simultaneously buy and sell stocks from different sectors characterised by different levels of resilience for instance, they may buy the most resilient stocks (e.g. from utilities or technology sectors etc.) and at the same time sell the most sensitive stocks (e.g. from energy sector etc.).

These considerations, as well as the knowledge about the performance of all 68 sectors, which we report in this study, open a new avenue for future research regarding the design, construction and implementation of trading strategies together with an evaluation of their performance in the periods after the COVID-19 crisis.

5. Conclusion

In this paper we provided an extensive analysis of the global impact of COVID-19 related uncertainty on industry returns and volatility for a sample of 68 industries. Our results indicate that COVID-19 related uncertainty, as measured by an aggregate index of Google search volumes, has a consistently negative impact on industry returns and a positive impact on return volatility (Section 4.2). Industries that are least impacted are those that are related to the provision of goods and services that can be considered as necessities and substitutes (in the time of COVID-19). Notable examples are the food and staples retailing, household products, and telecommunications industries. Industries that are most adversely impacted are the energy, consumer finance and airlines industries potentially reflecting the adverse impact of COVID-19 on global economic growth and confidence and, the impact of associated lockdowns and restrictions.

We find that changes in COVID-19 related uncertainty translate into increased volatility for a substantial number of industries. As with returns, industries that are most impacted are energy related industries, namely the energy equipment and services, oil, gas and consumable fuels industries and, also the airline industry. Other industries that stand out are distributors, health care providers and services and thrifts and mortgage finance. In the latter case, this most likely reflects uncertainty about the future, with potential property buyers holding back on committing to the repayment of long-term loans. For the remainder, this can potentially be explained by the uncertain nature of the opportunities faced by these industries.

We undertake a limited comparison of alternative measures of uncertainty by comparing our measure of COVID-19 related uncertainty against two alternative measure, the VIX and a Twitter-based Market Uncertainty index. While our results are mixed, they suggest some similarities between our COVID-19 related uncertainty measure and the VIX but not the TMU. Consequently, we recommend the study of the interchangeability of uncertainty measures and the comparability of information in such measures as a topic for further detailed research. We also undertake an investigation of the structure of the return generating process. Additional factors, summarised by statistical factor scores representative of the common drivers of returns, emerge during the COVID-19 period. Three of these factors are significantly correlated with $\Delta CV19I_t$, our aggregate of COVID-19 related search terms. While correlations are significant, they are far from perfect implying that COVID-19 related uncertainty is a component of the return generating process during the COVID-19 period, albeit not a major one. We propose that the newly emergent factors are related to other aspects of COVID-19, such as stimulus packages and restrictions and other associated negative or positive news, and, that COVID-19 related uncertainty is only a part of the story. The precise identity and interpretation of these emergent factors is a suggested avenue for further research.

Finally, we find that there are still opportunities for investors to invest profitably as a number of industries have shown positive risk-adjusted returns and these exceed those prior to the COVID-19 crisis. Notable examples are the metals and mining, internet and direct marketing retail, health care technology and biotechnology sectors. We therefore recommend that investors should focus on industry fundamentals and the nature of the business activities of the constituents thereof. Overall, our results suggest that although uncertainty abounds, opportunities still exist. For investors, portfolio and risk managers, our results provide insights into the impact of COVID-19 related uncertainty, while contextualising its importance and showing that opportunities for investing and diversification persist. These results also provide an indication of possible trading strategies, with examples being contrarian or momentum 'long-short' type strategies. For researchers, these results shed light on an important aspect of the COVID-19 pandemic on financial markets, with research on the economic and financial impact of this pandemic still in its infancy.

References

Adekoya, A.F., & Nti, I.K. (2020). The COVID-19 outbreak and effects on major stock market indices across the globe: A machine learning approach. *Indian Journal of Science and Technology*, *13*(35), 3695-3706.

Aggarwal, S., Nawn, S., & Dugar, A. (2021). What caused global stock market meltdown during the COVID pandemic–Lockdown stringency or investor panic? *Finance Research Letters*, *38*, 101827.

Ahundjanov, B.B., Akhundjanov, S.B., & Okhunjanov, B.B. (2020). Information search and financial markets under COVID-19. *Entropy*, *22*(791), 1-18.

Al Rjoub, S. A. (2011). Business cycles, financial crises, and stock volatility in Jordan Stock Exchange. *International Journal of Economic Perspectives*, *5*(1), 89-95.

Al-Awadhi, A. M., Al-Saifi, K., Al-Awadhi, A., & Alhamadi, S. (2020). Death and contagious infectious diseases: Impact of the COVID-19 virus on stock market returns. *Journal of Behavioral and Experimental Finance*. doi https://doi.org/10.1016/j.jbef.2020.100326

Albulescu, C. (2020). *Coronavirus and Oil Price Crash*. Politehnica University of Timisoara Working Paper No. 3553452. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3553452

Alfaro, L., Chari, A., Greenland, A. N., & Schott, P. K. (2020). *Aggregate and Firm-Level Stock Returns During Pandemics, in Real Time* (No. w26950). National Bureau of Economic Research.

Ali, M., Alam, N., & Rizvi, S.A.R. (2020). Coronavirus (COVID-19) - An epidemic or pandemic for financial markets. *Journal of Behavioral and Experimental Finance*, 100341.

Andrei, D., & Hasler, M. (2014). Investor attention and stock market volatility. *The Review of Financial Studies*, *28* (1), 33–72.

Ashraf, B. N. (2020a). Economic impact of government interventions during the COVID-19 pandemic: International evidence from financial markets. *Journal of Behavioral and Experimental Finance*, *27*, 100371.

Ashraf, B. N. (2020b). Stock markets' reaction to COVID-19: Cases or fatalities? *Research in International Business and Finance*, *54,* 101249.

Baca, S. P., Garbe, B. L., & Weiss, R. A. (2000). The rise of sector effects in major equity markets. *Financial Analysts Journal*, *56*(5), 34-40.

Baek, S., Mohanty, S.K., & Glambosky, M. (2020). COVID-19 and stock market volatility: An industry level analysis. *Finance Research Letters*, 101748.

Bai, L., Wei, Y., Wei, G., Li, X., & Zhang, S. (2020). Infectious disease pandemic and permanent volatility of international stock markets: A long-term perspective. *Finance Research Letters*, 101709.

Baig, A., Butt, H. A., Haroon, O., & Rizvi, S. A. R. (2020). *Deaths, panic, lockdowns and US equity markets: The case of COVID-19 pandemic*. Texas Tech University Working Paper No. 3584947. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3584947

Baker, S. R., & Fradkin, A. (2017). The impact of unemployment insurance on job search: Evidence from Google search data. *Review of Economics and Statistics*, *99*(5), 756-768.

Baker, S. R., Bloom, N., Davis, S. J., Kost, K. J., Sammon, M. C., & Viratyosin, T. (2020). *The Unprecedented Stock Market Impact of COVID-19* (No. w26945). National Bureau of Economic Research.

Bannigidadmath, D. & Narayan, P. K. (2016). Stock return predictability and determinants of predictability and profits. *Emerging Markets Review*, *26*, 153-173.

Barker, G. (2020, March 10). Coronavirus: how it could affect the UK housing market. *Forbes*, Retrieved from https://www.forbes.com/sites/garybarker/2020/03/10/coronavirus-how-it-could-affect-the-housing-market/#728198d8564c

Bartram, S. M., & Bodnar, G. M. (2009). No place to hide: The global crisis in equity markets in 2008/2009. *Journal of international Money and Finance*, *28*(8), 1246-1292.

Bekaert, G., Hoerova, M., & Duca, M. L. (2013). Risk, uncertainty and monetary policy. *Journal of Monetary Economics*, *60*(7), 771–788.

Bianchi, F., Kung, H., & Tirskikh, M. (2018). *The Origins and Effects of Macroeconomic Uncertainty* (No. w25386). National Bureau of Economic Research.

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, *77*(3), 623-685.

Boguth, O., & Kuehn, L. A. (2013). Consumption volatility risk. *The Journal of Finance*, *68*(6), 2589-2615.

Bontempi, M. E., Frigeri, M., Golinelli, R., & Squadrani, M. (2019). *Uncertainty, Perception and the Internet.* University of Bologna Working Paper No. 1134. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3469503

Bretscher, L., Hsu, A., & Tamoni, A. (2020). *The Supply Channel of Uncertainty Shocks and the Cross-Section of Returns: Evidence From the COVID-19 Crisis*. Georgia Tech Scheller College of Business Research Paper No. 3588418. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3588418.

Brzeszczyński, J., & Kutan, A. M. (2015). Public information arrival and investor reaction during a period of institutional change: An episode of early years of a newly independent central bank. *Journal of Comparative Economics*, *43*(3), 727-753.

Burmeister, E., & McElroy, M. B. (1991). The residual market factor, the APT, and mean-variance efficiency. *Review of Quantitative Finance and Accounting*, *1*(1), 27-49.

Caballero, R. J., & Simsek, A. (2020). *A Model of Asset Price Spirals and Aggregate Demand Amplification of a" Covid-19" Shock* (No. w27044). National Bureau of Economic Research.

Caggiano, G., Castelnuovo, E., & Kima, R. (2020). The global effects of Covid-19-induced uncertainty. *Economics Letters*, 194, 109392

Capelle-Blancard, G., & Desroziers, A. (2020). The stock market is not the economy? Insights from the COVID-19 crisis. *COVID Economics Vetted and Real-Time Papers*, 28, 29-69.

Castelnuovo, E., & Tran, T. D. (2017). Google it up! a google trends-based uncertainty index for the United States and Australia. *Economics Letters*, *161*, 149-153.

Cavaglia, S., Brightman, C., & Aked, M. (2000). The increasing importance of industry factors. *Financial Analysts Journal*, *56*(5), 41-54.

Cepoi, C.O. (2020). Asymmetric dependence between stock market returns and news during COVID19 financial turmoil. *Finance Research Letters*, 101658.

Chen, C., Chen, C., Tang, W., & Huang, B. 2009. The positive and negative impacts of the SARS outbreak: a case of the Taiwan industries. *Journal of Developing Areas*, *43*(1), 281-293.

Chen, C., Liu, L., & Zhao, N. (2020). Fear sentiment, uncertainty, and bitcoin price dynamics: The case of COVID-19. *Emerging Markets Finance and Trade*, *56*(10), 2298-2309.

Chen, M. H., Jang, S. S., & Kim, W. G. (2007). The impact of the SARS outbreak on Taiwanese hotel stock performance: An event-study approach. *International Journal of Hospitality Management*, *26*(1), 200-212.

Chiang, T. C., Li, J., & Yang, S. Y. (2015). Dynamic stock–bond return correlations and financial market uncertainty. *Review of Quantitative Finance and Accounting*, *45*(1), 59–88.

Choi, S. Y. (2020). Industry volatility and economic uncertainty due to the COVID-19 pandemic: Evidence from wavelet coherence analysis. *Finance research letters*, *37*, 101783.

Cochrane, J. (2018). Stock gyrations. (blog post). Available at: https://johnhcochrane.blogspot.com/2018/02/stock-gyrations.html.

Constable, S. (2020, April 8). Covid-19 panic sparks record-breaking gold buying binge during first quarter. *Forbes*, Retrieved from https://www.forbes.com/sites/simonconstable/2020/04/08/covid-19-panic-sparks-record-breaking-gold-buying-binge-during-first-quarter/#387ea0463bd9

Costola, M., Iacopini, M., & Santagiustina, C. (2020a). Public concern and the financial markets during the COVID-19 outbreak. Working Paper No. 3591193. Ca' Foscari University of Venice, Italy. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3591193.

Coy, P. (2020, March 19). The Great Coronavirus Crash of 2020 Is Different. *Bloomberg Businessweek*, Retrieved from https://www.bloomberg.com/news/articles/2020-03-19/the-great-coronavirus-crash-of-2020-is-different

De Vito, A., & Gómez, J. P. (2020). Estimating the COVID-19 cash crunch: Global evidence and policy. *Journal of Accounting and Public Policy*,*39*(106741), 1-14.

Dimic, N., Kiviaho, J., Piljak, V., & Äijö, J. (2016). Impact of financial market uncertainty and macroeconomic factors on stock–bond correlation in emerging markets. *Research in International Business and Finance*, *36*, 41–51.

Dhall, R., & Singh, B. (2020). The COVID-19 pandemic and herding behaviour: Evidence from India. *Millennial Asia*, 11(3), 366-390.

Dzielinski, M. (2012). Measuring economic uncertainty and its impact on the stock market. *Finance Research Letters*, *9*(3), 167-175.

Eiling, E., Gerard, B., Hillion, P., & de Roon, F. A. (2012). International portfolio diversification: Currency, industry and country effects revisited. *Journal of International Money and Finance*, *31*(5), 1249-1278.

Elder, B. & Dempsey, H. (2020, May 26). Global stocks push higher on easing virus nerves. *The Financial Times*, Retrieved from https://www.ft.com/content/af1a9670-cec7-41df-8444-e2015859d3e1

Engle, R. F., & Bollerslev, T. (1986). Modelling the persistence of conditional variances. *Econometric Reviews*, *5*(1), 1-50.

Espinosa-Méndez, C., & Arias, J. (2021). COVID-19 effect on herding behaviour in European capital markets. *Finance Research Letters*, *38*, 101787.

Fan, J., Qi, L., & Xiu, D. (2014). Quasi-maximum likelihood estimation of GARCH models with heavy-tailed likelihoods. *Journal of Business and Economic Statistics*, *32*(2), 178-191.

Fernandes, N. (2020). *Economic Effects of Coronavirus Outbreak (COVID-19) on The World Economy*. University of Navarra, European Corporate Governance Institute Working Paper No. 3557504. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3557504

Funck, M., & Gutierrez, J. A. (2018). Has Ebola Infected the Market: A Contagious Reaction to a (Media) Health Care Crisis?. *Journal of Business Strategies*. Available at SSRN: https://ssrn.com/abstract=2786001

Goodell, J. W. (2020). COVID-19 and finance: Agendas for future research. *Finance Research Letters*. doi https://doi.org/10.1016/j.frl.2020.101512

Gormsen, N. J., & Koijen, R. S. (2020). *Coronavirus: Impact on Stock Prices and Growth Expectations.* University of Chicago, Becker Friedman Institute for Economics Working Paper No. 2020-22.Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3555917

Gupta, R., Subramaniam, S., Bouri, E., & Ji, Q. (2020). Infectious disease-related uncertainty and the safe-haven characteristic of US treasury securities. *International Review of Economics & Finance*, *71*, 289-298.

Guttman, L. (1954). Some necessary conditions for common-factor analysis. *Psychometrika*, *19*(2), 149-161.

Hale, T., Angrist, N., Kira, B., Petherick, A., Phillips, T., & Webster, S. (2020). *Variation in Government Responses to COVID-19.* Blavatnik School of Government Working Paper No.31. Available at: https://www.bsg.ox.ac.uk/sites/default/files/2020-05/BSG-WP-2020-032-v6.0.pdf

Hanke, M., Kosolapova, M., & Weissensteiner, A. (2020). COVID-19 and market expectations: Evidence from option-implied densities. Working paper. Available at: https://ssrn.com/abstract=3616625.

Haroon, O., & Rizvi, S. A. R. (2020). COVID-19: Media coverage and financial markets behaviour - A sectoral inquiry. *Journal of Behavioral and Experimental Finance*, *27*, 100343.

Huang, C., Wang, Y., Li, X., Ren, L., Zhao, J., Hu, Y., ... & Cheng, Z. (2020). Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. *The Lancet*, *395*(10223), 497-506.

Hughes, P. J. (1984). A test of the arbitrage pricing theory using Canadian security returns. *Canadian Journal of Administrative Sciences/Revue Canadienne des Sciences de l'Administration*, *1*(2), 195-214.

Hutchens, G. & Chalmers, S. (2020, March 16). Coronavirus fears see Australian market slump to start new week. *ABC News*, Retrieved from https://www.abc.net.au/news/2020-03-16/coronavirus-fears-see-australian-market-slump-to-start-new-week/12058904

Imbert, F. (2020, June 10). Stocks suffer their worst day since March, with the Dow plunging more than 1,800 points. *CNBC*, Retrieved from https://www.cnbc.com/2020/06/10/stock-market-futures-open-to-close-news.html

Kaiser, H. F. (1960). The application of electronic computers to factor analysis. *Educational and Psychological Measurement*, *20*(1), 141-151.

Kizys, R., Tzouvanas, P., & Donadelli, M. (2021). From COVID-19 herd immunity to investor herding in international stock markets: The role of government and regulatory restrictions. *International Review of Financial Analysis*, *74*, 101663.

Kozeniauskas, N., Orlik, A., & Veldkamp, L. (2018). What are uncertainty shocks?. *Journal of Monetary Economics*, *100*, 1-15.

Koutoulas, G., & Kryzanowski, L. (1994). Integration or segmentation of the Canadian stock market: Evidence based on the APT. *Canadian Journal of Economics*, 329-351.

Lagoarde-Segot, T., & Leoni, P. L. (2013). Pandemics of the poor and banking stability. *Journal of Banking & Finance*, *37*(11), 4574-4583.

Liemieux, J., & Peterson, R. (2011). Purchase deadline as a moderator of the effects of price uncertainty on search behavior. *Journal of Economic Psychology*, *32*(1), 33-44.

Liu, K. (2020). *The Effects of COVID-19 on Chinese Stock Markets: An EGARCH Approach.* The University of Sidney Working Paper No. 3612461. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3612461

Lyócsa, Š., Baumöhl, E., Výrost, T., & Molnár, P. (2020). Fear of the coronavirus and the stock markets. *Finance Research Letters*, *36*, 101735.

Mazur, M., Dang, M., & Vega, M. (2020). *COVID-19 and March 2020 Stock Market Crash. Evidence from S&P1500. Evidence from S&P1500.* Catholic University of Lille Working Paper No. 3586603. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3586603

Meyers, S. L. (1973). A re-examination of market and industry factors in stock price behavior. *The Journal of Finance*, *28*(3), 695-705.

Narayan, P. K., Phan, D. H. B., & Liu, G. (2020). COVID-19 lockdowns, stimulus packages, travel bans, and stock returns. *Finance Research Letters*, 101732.

Nippani, S., & Washer, K. M. (2004). SARS: a non-event for affected countries' stock markets?. *Applied Financial Economics*, *14*(15), 1105-1110.

Ozili, P. K., & Arun, T. (2020). Spillover of COVID-19: impact on the Global Economy. *Available at SSRN 3562570*.

Ozoguz, A. (2009). Good times or bad times? Investors' uncertainty and stock returns. *The Review of Financial Studies*, *22*(11), 4377-4422.

Papadamou, S., Fassas, A., Kenourgios, D., & Dimitriou, D. (2020). *Direct and Indirect Effects of COVID-19 Pandemic on Implied Stock Market Volatility: Evidence from Panel Data Analysis.* University of Thessaly MPRA Paper No. 100020. Available at: https://mpra.ub.uni-muenchen.de/id/eprint/100020

Pastor, L., & Veronesi, P. (2012). Uncertainty about government policy and stock prices. *Journal of Finance*, *67*(4), 1219-1264.

Pastor, L., & Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of Financial Economics*, *110*(3), 520-545.

Perlin, M. S., Caldeira, J. F., Santos, A. A., & Pontuschka, M. (2017). Can we predict the financial markets based on Google's search queries?. *Journal of Forecasting*, *36*(4), 454-467.

Preis, T., Moat, H. S., & Stanley, H. E. (2013). Quantifying trading behavior in financial markets using Google Trends. *Scientific Reports*, *3*, 1684.

Qi, H., Xiao, S., Shi, R., Ward, M. P., Chen, Y., Tu, W., ... & Zhang, Z. (2020). COVID-19 transmission in Mainland China is associated with temperature and humidity: a time-series analysis. *Science of the Total Environment*, *728*, 138778.

Ramelli, S., & Wagner, A. F. (2020). *Feverish Stock Price Reactions to COVID-19.* Centre for Economic Policy Research Discussion Paper No. DP14511. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3550274

Renault, T., Baker, S.R., Bloom, N., & Davis, S. (2020). Twitter-based uncertainty indices. Available at: https://www.policyuncertainty.com/twitter_uncert.html.

Ru, H., Yang, E., & Zou, K. (2020). What do we learn from SARS-CoV-1 to SARS-CoV-2: Evidence from global stock markets. *Available at SSRN*, *3569330*.

Salisu, A. A., & Akanni, L. (2020). Constructing a global fear index for the COVID-19 pandemic. *Emerging Markets Finance and Trade*, *56*(10), 2310-2331.

Salisu, A. A., Akanni, L., & Raheem, I. (2020). The COVID-19 global fear index and the predictability of commodity price returns. *Journal of Behavioral and Experimental Finance*, *27*, 100383.

Salisu, A. A., Sikiru, A. A., & Vo, X. V. (2020). Pandemics and the emerging stock markets. *Borsa Istanbul Review*, *20*(S1), S40-S48.

Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *International Review of Financial Analysis*, *70*, 101496.

Smales, L. A. (2019). How does policy uncertainty influence financial market uncertainty across the G7? University of Western Australia, Working Paper No. 3427659. Available at: https://papers.ssrn.com/sol3/Papers.cfm?abstract_id=3427659.

Smales, L. A. (2020). Investor attention and the response of US stock sectors to the COVID-19 crisis. Working Paper No. 3625487. University of Western Australia, Australia. Available at: https://papers.ssrn.com/sol3/Papers.cfm?abstract_id=3625487.

Smales, L.A. (2021). Investor attention and global market returns during the COVID-19 crisis. *International Review of Financial Analysis*, 73, 101616.

Szczygielski, J.J., Brümmer, L.M. & Wolmarans, H. (2020a). Underspecification of the empirical return-factor model and a factor analytic augmentation as a solution to factor omission. *Studies in Economics and Econometrics, 44*(2), 133-165.

Szczygielski, J.J., Brümmer, L.M. & Wolmarans, H. (2020b). An augmented macroeconomic linear factor model of South African industrial sector returns. *Journal of Risk Finance, 21*(5), 517-541.

Szczygielski, J. J., Brümmer, L. M., Wolmarans, H. P., & Zaremba, A. (2020). Are macroeconomic factors adequate proxies for systematic influences in stock returns? A South African perspective. *Investment Analysts Journal*, *49*(1), 34-52.

Szczygielski, J.J., Bwanya, P., Charteris, A., & Brzeszczyński, J. (2021a). The only certainty is uncertainty: An analysis of the impact of COVID-19 uncertainty on regional stock markets. *Finance Research Letters*, 101945.

Szczygielski, J. J., Brzeszczyński, J., Charteris, A., & Bwanya, P. (2021b). The COVID-19 storm and the energy sector: The impact and role of uncertainty. *Energy Economics*, 105258.

Tew, I. (2020, March 12). FTSE on track for biggest fall in 30 years after 9% drop. *The Financial Times,* Retrieved from https://www.ftadviser.com/investments/2020/03/12/ftse-on-track-for-biggest-fall-in-30-years-after-9-drop/

Uddin, G. S., Yahya, M., Goswami, G. G., Ahmed, A., & Lucey, B. M. (2020). Stock market contagion of COVID-19 in emerging economies. Working Paper No. 3573333. Linkoping University, Sweden. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3573333.

Ukpong, I., Tan, H., & Yarovaya, L. (2021). Determinants of industry herding in the US stock market. *Finance Research Letters*, 101953.

Wang, W., & Enilov, M. (2020). The global impact of COVID-19 on financial markets. Working Paper No. 3588021. University of Bradford, England. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3588021.

Wang, Y. H., Yang, F. J., & Chen, L. J. (2013). An investor's perspective on infectious diseases and their influence on market behaviour. *Journal of Business Economics and Management*, 14(Sup.1), 112-127.

Wasserman, H. (2020, March 17). SA shares just suffered another big crash – here's where history says the JSE could be in a year. *Business Insider,* Retrieved from https://www.businessinsider.co.za/jse-crashes-2020-3.

Wu, Y. C., Chen, C. S., & Chan, Y. J. (2020). The outbreak of COVID-19: An overview. *Journal of the Chinese medical association*, *83*(3), 217.

Wells, P. (2020, March 12). S&P 500 suffers its quickest fall into bear market on record. *The Financial Times*, Retrieved from https://www.ft.com/content/d895a54c-64a4-11ea-a6cd-df28cc3c6a68

Westerlund, J., & Narayan, P. (2015). Testing for predictability in conditionally heteroskedastic stock returns. *Journal of Financial Econometrics*, *13*(2), 342-375.

World Health Organisation, (2020). *Coronavirus Disease (COVID-19) Situation Report – 143.* Retrieved June 12, from https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200611-covid-19-sitrep-143.pdf?sfvrsn=2adbe568_4

Yu, L., Zhao, Y., Tang, L., & Yang, Z. (2019). Online big data-driven oil consumption forecasting with Google trends. *International Journal of Forecasting*, *35*(1), 213-223.

Zaremba, A., Kizys, R., Aharon, D. Y., & Demir, E. (2020). Infected markets: Novel coronavirus, government interventions, and stock return volatility around the globe. *Finance Research Letters*, 101597.

Zhang, X. F. (2006). Information uncertainty and stock returns. *Journal of Finance*, *61*(1), 105-137.

Zhang, D., Hu, M., & Ji, Q. (2020 in press). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*.

Zwick, W. R., & Velicer, W. F. (1986). Comparison of five rules for determining the number of components to retain. *Psychological Bulletin*, *99*(3), 432-442.