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SZCZYGIELSKI, J.J., BRZESZCZYŃSKI, J., CHARTERIS, A. and BWANYA, P.A.

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The COVID-19 storm and the energy sector: The impact and role of uncertainty

1. Jan Jakub Szczygielski

Department of Accounting and Financial Management, Newcastle Business School (NBS), Northumbria University, City Campus East, Newcastle upon Tyne, NE1 8ST, United Kingdom. E-mail: kuba.szczygielski@northumbria.ac.uk
Department of Financial Management, University of Pretoria, Private Bag x20, Hatfield, Pretoria, 0028, South Africa. E-mail: kuba.szczygielski@up.ac.za

2. Janusz Brzeszczyński*

Department of Accounting and Financial Management, Newcastle Business School (NBS), Northumbria University, City Campus East, Newcastle upon Tyne, NE1 8ST, United Kingdom. E-mail: janusz.brzeszczynski@northumbria.ac.uk, Phone: +44 191 243 7491

3. Ailie Charteris

Department of Finance and Tax, University of Cape Town, Rondebosch, 7700, Cape Town, South Africa. E-mail: ailie.charteris@uct.ac.za

4. Princess Rutendo Bwanya

Department of Accounting and Financial Management, Newcastle Business School (NBS), Northumbria University, City Campus East, Newcastle upon Tyne, NE1 8ST, United Kingdom. E-mail: princess.bwanya@northumbria.ac.uk

* Corresponding author.

The COVID-19 storm and the energy sector: The impact and role of uncertainty

Abstract

Prior research has shown that energy sector stock prices are impacted by uncertainty. The coronavirus (COVID-19) pandemic has given rise to widespread health and economic-related uncertainty. In this study, we investigate the impact and the timing of the impact of COVID-19 related uncertainty on returns and volatility for 20 national energy indices and a global energy index using ARCH/GARCH models. We propose a novel 'overall impact of uncertainty' (OIU) measure, explained using a natural phenomenon analogy of the overall impact of a rainstorm, to gauge the magnitude and intensity of the impact of uncertainty on energy sector returns. Drawing from economic psychology, COVID-19 related uncertainty is measured in terms of searches for information relating to COVID-19 as captured by Google search trends. Our results show that the energy sectors of countries further west from the outbreak of the virus in China are impacted to a greater extent by COVID-19 related uncertainty. A similar observation is made for net energy and oil exporters relative to importers. We also find that the impact of uncertainty on most national energy sectors intensified and then weakened as the pandemic evolved. Additional analysis confirms that COVID-19 uncertainty is part of the composite set of factors that drive energy sector returns over the COVID-19 period although its importance has declined over time.

Keywords: COVID-19, pandemic, returns, volatility, uncertainty, energy sector

JEL classification: C22, C58, D53, G12, G01, G14, Q40

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1.Introduction

Storms create panic and uncertainty. The novel coronavirus (COVID-19) storm, which began in 2019 is no different as it has left a trail of destruction with over a million deaths reported so far (World Health Organization (WHO), 2020a) and economies around the world struggling due to the implementation of containment policies such as lockdowns and travel bans. Even as lockdowns ease, travel bans persist, some industries remain closed, while others are operating at less than full capacity due to social distancing or a lack of demand. Notably, COVID-19 has contributed to a palpable fear among investors attributable not only to concerns about health, but also to potential losses in livelihoods and a downturn in global economic activity. In short, uncertainty abounds (Altig et al., 2020; Salisu & Akanni, 2020).

Energy is the lifeblood of the global economy and all economic activities require energy. Previous research has confirmed that slower economic growth reduces the demand for energy, and in turn, reduced energy consumption restrains further economic growth (Mehrara, 2007; Odhiambo, 2009; Ozturk and Acaravci, 2010; Shabaz et al., 2013). The same relationship has also been found for oil demand and economic growth, consistent with the fact that oil remains a driver of the energy sector (Ghosh, 2009; Hanabusa, 2009). The importance of the energy sector in the global economy is readily evident. As of August 2020, six of the eleven largest companies in the world by revenue are in the oil and gas sector (Sinopec Group, China National Petroleum (China), Royal Dutch Shell (United Kingdom, (UK)), Saudi Aramco (Saudi Arabia), BP (UK) and Exxon Mobile (United States, (US)) (Murray and Meyer, 2020).

COVID-19 has heavily impacted stock prices in the energy sector, with this industry amongst the worst affected (Nguyen, 2020; Ramelli and Wagner, 2020). According to Ftiti et al. (2020) and Iyke (2020), the impact on energy stock prices has arisen through two primary channels.[1] Firstly, the energy sector has been impacted *via* the output channel through restrictions on travel, production and worker mobility which have resulted in a reduction in the demand for oil, coal and gas. This effect is exacerbated given that the manufacturing and travel sectors account for close to 60% of total energy demand (International Energy Agency, 2020). In the US, COVID-19 has resulted in reductions in demand for aviation fuel and gas of 50% and 30%, respectively (Gillingham et al., 2020). Similar falls in energy demand have been noted in China and India (Aruga et al., 2020; Norouzi et al., 2020). Additionally, oil

[1] Their arguments draw from the seminal work of Hamilton (1983) who conjectured that the relationship between the oil market and the real economy occurs through several channels such as stock valuation, monetary and fiscal measures, output and uncertainty.

prices have plummeted due to a fall in demand and the Russia-Saudi Arabia price war in March 2020,[2] resulting in a decline of over 80% in the first quarter of the year (Ozili & Arun, 2020; Qin et al., 2020).

Secondly, energy sector prices have been impacted by uncertainty related to the future of the global economy due to infections and deaths arising from COVID-19. The resultant negative sentiment contributes to pessimistic expectations about energy demand, especially oil, prompting capital flows away from energy stocks (see Sadorsky, 2001; Ji & Guo, 2015 for a review of the impact of uncertainty on energy stock returns in previous crises). Gillingham et al. (2020) argue that the long-run effects of COVID-19 on energy demand are highly uncertain as they depend on the time needed to bring the pandemic under control and whether the economic contraction is sustained. If effects are short-lived (with the discovery of a vaccine and low-cost treatment), energy demand will likely return to pre-COVID-19 levels quickly, with continued investment in the energy sector. However, if effects are more prolonged (such as more deaths and larger global macroeconomic contractions), energy demand will fall due to changing consumer behaviour (such as working from home and less travel) resulting in a drop in investment in the energy sector. Such a drop in investment will not only be reflected in oil, gas and other consumable fuels but also in services and equipment related to and used in the extraction of consumable fuels.

The impact of uncertainty on energy sector stocks is not only limited to crisis periods. Bianconi and Yoshino (2014) found that greater uncertainty, as measured by implied volatility indices, was associated with negative returns on oil and gas companies across 24 countries. Zhu et al. (2020) reported that investor sentiment was significantly related to the pricing of securities in the oil and gas sector as it contributes to pricing anomalies. Fazelabdolabadi (2019) discovered that implied crude oil price uncertainty and economic policy uncertainty had a negative impact on Iranian energy sector returns and result in increased volatility. These results are consistent with a broader body of literature that finds uncertainty negatively impacts asset prices and is crucial to investment decisions (Anderson et al., 2009; Bams et al., 2017; Naeem et al., 2020). Nikkinen and Rothovius (2019) disaggregated the sources of uncertainty faced by companies in the energy sector and showed that this can be attributed to uncertainty around crude oil prices and stock markets, as measured by implied volatility indices. In addition, uncertainty, as measured by increases in searches related to crude oil, results in an increase in the weight of the crude oil uncertainty component. Research has also shown that oil prices respond to various types of uncertainty. Aloui et al. (2016) illustrated that higher financial market and economic policy uncertainty has a negative effect on crude oil returns except for periods prior to a financial crisis, where the effect is positive. Antonakakis et al. (2014) also found that oil prices respond negatively to economic policy uncertainty while Zavadska et al. (2020) reported that oil prices

[2] Saudi Arabia flooded the oil market as a result of a disagreement with Russia regarding a proposal to reduce oil supply due to a drop in the oil price resulting from reduced demand because of the spread of the virus. News of increased production caused the oil price to fall by more than 30% on 8 March 2020, which was the largest one day drop since the Gulf War (Ftiti et al., 2020; Iyke, 2020).

exhibited greater volatility as a result of uncertainty during oil-related crises and greater volatility persistence due to uncertainty during financial crises.

Despite the theoretical assertions of the role of uncertainty arising from COVID-19 and prior research demonstrating the impact of uncertainty on the energy sector, little is known about the effects of COVID-19 related uncertainty on energy sector returns and volatility as well as the arising implications for investors. In this study, we examine the impact of COVID-19 related uncertainty on returns and volatility in the energy industry. We identify the COVID-19 period as from 16 December 2019 to 17 July 2020 (at the time of writing). The energy sector is defined as per the MSCI Global Industry Classification Standard (GICS), which includes two industry groupings in the energy sector: energy equipment and services and oil, gas and consumable fuels. Our sample comprises the MSCI World Energy Index and the MSCI national energy sector indices for the 20 largest energy sectors prior to the outbreak of COVID-19 in December 2019. We draw upon economic psychology and use COVID-19 Google search trends data to quantify the impact of COVID-19 related uncertainty on energy sector returns and volatility. Internet searches serve to satisfy investor demand for information prior to investment decisions being made, with increased search intensity representing a response to increased uncertainty faced by economic agents (Da et al., 2011; Dzielinski, 2012, Preis et al., 2013; Castelnuovo & Tran, 2017; Salisu et al., 2020). Therefore, the premise of our analysis is that search frequency provides a direct and unambiguous measure of uncertainty. This measure is also consistent with concurrent work on the impact of COVID-19 related uncertainty on financial markets (such as Ahundjanov et al., 2020; Liu, 2020; Ramelli and Wagner, 2020). In order to investigate the impact of COVID-19 related uncertainty on both returns and volatility simultaneously, we utilize the ARCH/GARCH model framework.

Our study makes several contributions to existing literature on COVID-19 and financial markets. First, we add to the nascent literature on the impact of COVID-19 on financial markets. In particular, we offer a detailed study of the impact of COVID-19 related uncertainty. Research has shown that returns and volatility have been severely affected by the pandemic, both directly and via the uncertainty channel (Al-Awadhi et al., 2020; Ramelli and Wagner, 2020; Zhang et al., 2020 amongst others). Furthermore, our focus is the energy sector, which is of importance to any economy and is especially vulnerable during crises (Gillingham et al., 2020; Iyke, 2020). Second, we introduce a novel measure, which we term the 'overall impact of uncertainty' (OIU), that jointly reflects the impact *and* intensity of COVID-19 related uncertainty on national energy sectors. Third, we make a methodological contribution by applying a factor analytic augmentation to fully account for all common drivers of returns without the need to search for proxies for omitted factors or the need to identify an appropriate market index (Szczygielski, Brümmer & Wolmarans, 2020). The efficacy of this approach is demonstrated by an adequately specified model that approximates the diagonality assumption. This matters particularly in the present context as simplified models relating returns on financial assets to measures of COVID-19 (such as the number of infections, deaths or COVID-19 related uncertainty) may incorrectly quantify the impact of the pandemic (see Szczygielski et al., 2021). Fourth, we examine whether COVID-19 uncertainty is a driving factor in energy sector returns and finally, we shed light on the transmission mechanism between returns and COVID-19 related uncertainty. Our study is of an explorative nature, positioned within the context of the nascent nature of the COVID-19 crisis and related research.

We find that COVID-19 related uncertainty has a significant negative impact on returns in all energy markets and drives heightened volatility in the majority of countries. We also show that geographical proximity and a country's net oil and energy exporter/importer position matter in terms of the effects of COVID-19 uncertainty on the energy sector. Countries further west from the outbreak of the virus in China are more impacted by COVID-19 related uncertainty as are net energy and oil exporters. Furthermore, structural break analysis indicates that the effects of uncertainty on the energy sector initially intensified, consistent with rising uncertainty, and then dissipated. Distinct periods of varying impact identified correspond to major events during the evolution of the pandemic, such as the first deaths in Italy and that country implementing a lockdown for approximately 50 000 people and later, the simultaneously occurring events of US cases hitting 50 000, the suspension of the Olympic Games and the lockdown in China's Hubei province being lifted. Nevertheless, as the pandemic has further evolved, volatility triggering effects have continued to persist.

We demonstrate that the use of a factor analytic augmentation results in an approximation of the diagonality assumption. Specifications that rely upon a global market index (the MSCI World Market Index), a global energy index or a combination of both fail to produce an approximation of the diagonality assumption. This has consequences for the measurement of the impact of COVID-19 uncertainty on returns and the interpretation of overall model results. We also confirm that COVID-19 related uncertainty is part of the composite factor set driving energy sector returns although its role diminishes over time. In addition, our results reveal that our Google search trends based measure reflects market uncertainty over the COVID-19 period is closely correlated with an established measure of market uncertainty namely, the Chicago Board of Exchange Volatility Index (VIX). The analysis also reveals that the primary transmission channel between returns and COVID-19 related uncertainty appears to be through uncertainty, whereas the second is through the oil price. Finally, we show that the energy sector as a global aggregate and in individual countries has performed poorly prior to the COVID-19 crisis and performed even worse during the COVID-19 crisis period. The implication of our findings is that the energy sector is likely to remain vulnerable, and may continue to perform poorly, as long as the COVID-19 crisis persists.

The remainder of this paper is structured as follows: Section 2 provides an overview of nascent research on the impact of COVID-19 on financial markets. Section 3 outlines the data and methodology applied in investigating the impact of COVID-19 related uncertainty on energy sectors. Section 4 presents the main results and the accompanying analysis and, finally, Section 5 concludes the study.

2. Literature Review

Previous research has identified different types of events that have affected stock returns including disasters (Kowalewski & Śpiewanowski, 2020), news (Li, 2018), political events (Shanaev & Ghimire, 2019) and pandemics, such as the SARS outbreak (Chen et al., 2009) and Ebola (Ichev & Marinč, 2018). Several studies have also examined the impact of the COVID-19 pandemic on stock returns and volatility. Ashraf (2020) found that increasing daily case numbers and deaths had a negative impact on stock returns across 64 affected countries. Similarly, Bretscher et al. (2020) reported that firms headquartered in a specific county of the US earned lower returns in the 10-day period post the first reported case in the area compared to returns before the event and compared to firms headquartered in counties without infections, with lower returns occurring in counties where the virus spread more rapidly. Al-Awadhi et al. (2020) observed that the growth in COVID-19 cases and deaths had a negative impact on Chinese stock returns with the effect more pronounced for larger firms. Turning to volatility, Albulescu (2020a) found that the death rate had a greater impact on stock market volatility than the number of new cases. Zhang et al. (2020) showed that both COVID-19 infections and deaths contributed to a rise in systematic risk, with individual stock market reactions linked to the severity of the outbreak in that country. Ali et al. (2020) emphasised that volatility worsened as COVID-19 evolved from an epidemic to a pandemic in the US, UK, Germany and South Korea. This is consistent with the finding of Gormsen and Koijen (2020) that only once COVID-19 had spread to Italy, Iran and South Korea, did the US and German stock markets decline sharply. Gerding et al. (2020) found that stock price reactions to COVID-19 were greater in countries with higher debt-to-GDP ratios, whereas Ru et al. (2020) observed that stock markets reacted faster and more intensely to COVID-19 in countries that were affected by the SARS outbreak in 2003.

A number of studies have documented heterogeneous effects of COVID-19 on returns and volatility across sectors and there is evidence that the energy sector has been particularly impacted. Using a sample of ten countries, Nguyen (2020) documented that national energy sectors experienced the largest negative abnormal returns. Mazur et al. (2020) found that stocks in the crude petroleum and oil services, real estate, hospitality and entertainment sectors in the US experienced substantial losses whereas those in healthcare, food, software, technology and natural gas sectors earned the highest returns. Furthermore, stocks in crude petroleum and oil services, and real estate experienced the highest levels of volatility. Ramelli and Wagner (2020) also found that the energy and consumer services sectors were the hardest hit industries in the US in the early stages of the pandemic. Thorbecke (2020) found the machinery sector (comprising construction, agriculture, specialised and tools) to be the worst performing sector in Japan, while Al-Awadhi et al. (2020) identified the transport sector as the worst impacted by the pandemic while the information technology and medical sectors were the best performers.

Iyke (2020) investigated the reaction of US oil and gas firms to COVID-19 and found that COVID-19 deaths affected returns and volatility for approximately a quarter of firms. However, the effects on returns and volatility differed across firms ranging from positive to negative. Dutta et al. (2020) analysed the impact of COVID-19 on oil prices and the US energy sector. Using an event study methodology, they investigated the effect of: (i) the Chinese government confirming the existence of a novel coronavirus, (ii) WHO announcing COVID-19 as a public health emergency of international concern, and (iii) WHO confirming COVID-19 as a pandemic. The energy sector and oil prices were found to be most influenced by the announcement of COVID-19 as a pandemic. However, the impact on the energy sector was smaller than that on oil prices. Albulescu (2020b) showed that while daily COVID-19 cases had a marginal effect on crude oil prices, infections amplified market volatility which, in turn, affected oil prices. It is evident from the aforementioned literature that firms belonging to the oil and gas sector have been particularly affected by the COVID-19 crisis.

Several studies have considered the impact of COVID-19 related uncertainty on financial markets using Google search trends as a proxy for uncertainty. Baig et al. (2020), Chen et al. (2020), Papadamou et al. (2020) and Szczygielski et al. (2021) showed that Google search terms are positively correlated with implied volatility indices, such as the VIX. Ahundjanov et al. (2020) studied the impact of COVID-19 related uncertainty, measured by Google search queries, on stock market indices in the US, UK, Germany, France, Japan, China and India. They found that an increase in search queries resulted in a decline in the indices of all countries the following day and a week thereafter. Similarly, Liu (2020), Papadamou et al. (2020) and Smales (2021) observed that COVID-19 related Google search trends impacted stock returns negatively in major developed and developing countries. Szczygielski et al. (2021) also reported a negative relationship between Google search trends and returns on regional stock markets, with Asian markets least impacted and Latin American markets most impacted. They also obtained evidence of an increased impact of COVID-19 related uncertainty which dissipated as the crisis evolved except for the Arab and African regions. The results of the study by Costola et al. (2020) revealed that Google search trends in Italy impacted returns on the stock markets of Italy, Germany, France, Spain, UK and US, where the most severe declines occurred at each step of the Italian lock-down process. Smales (2020) confirmed that the energy, financial and information technology sectors were negatively influenced by COVID-19 related search trends, while consumer staples and healthcare industries were positively influenced. At the firm level, the study of Ramelli and Wagner (2020) revealed that greater COVID-19 related uncertainty, as captured by Google search trends, contributed to lower performance for firms with greater leverage and smaller cash holdings, even in the absence of international operations in China. COVID-19 uncertainty has also been found to impact volatility. The study of China by Liu (2020), the analysis of G20 countries by Smales (2021) and the regional study of Szczygielski et al. (2021) showed that COVID-19 related Google search trends contributed to increased volatility, although Liu (2020) found that the impact differs across industries.

From the literature above, it emerges that, without a doubt, various industry sectors and global stock markets have been impacted by COVID-19. We proceed to add to this nascent literature by exploring the role and impact of COVID-19 related uncertainty on the returns and volatility for a global energy aggregate and national energy sectors.

3. Data and Methodology

Our data sample spans the period from 1 January 2015 to 17 July 2020, comprising daily levels for the MSCI World Energy index – the global energy aggregate – and national MSCI Energy indices for the 20 countries with the largest energy sectors by market capitalization in US Dollars as of 30 November 2019. The MSCI Energy indices cover two industries, as per the MSCI GICS (2018) definition. These are the energy equipment and services and oil, gas and consumable fuels industries. In turn, these industries include a total of seven sub-industries. Descriptive statistics for the global aggregate and respective national energy sectors ranked according to market capitalization are reported in Table 1.

Following an analysis of Google search trends data, we identify nine COVID-19 related terms associated with high search volumes over the COVID-19 period worldwide from the beginning of the pandemic. Szczygielski et al. (2021) show that worldwide Google search trends dominate regional trends, except for US trends. Therefore, the use of worldwide Google search trends data to quantify COVID-19 related uncertainty for national markets – as opposed to regional or national trends - is more appropriate. While the beginning of the COVID-19 crisis continues to be debated, we denote it as coinciding with the first documented hospitalisation on 16 December 2019 (Huang et al., 2020). This date is two weeks before the WHO China Country Office was officially informed of pneumonia of an unknown cause, the suspected first COVID-19 case, in Wuhan city (WHO, 2020b). The individual terms that we consider are “coronavirus”, “COVID19”, “COVID 19”, “COVID”, “COVID-19”, “SARS-CoV-2”, “SARS-COV”, “severe acute respiratory syndrome-related coronavirus” and “severe acute respiratory syndrome”. Each of these show rising search volumes shortly after 16 December 2019 (see Figure 1). We construct an overall search term index[3] by combining trends for the terms above. To construct the overall search term index, index values for individual terms are added and the sum is divided by nine. The highest value is adjusted to 100 with remaining values adjusted accordingly relative to this base. Index values are then differenced to obtain $\Delta CV19I_t$.

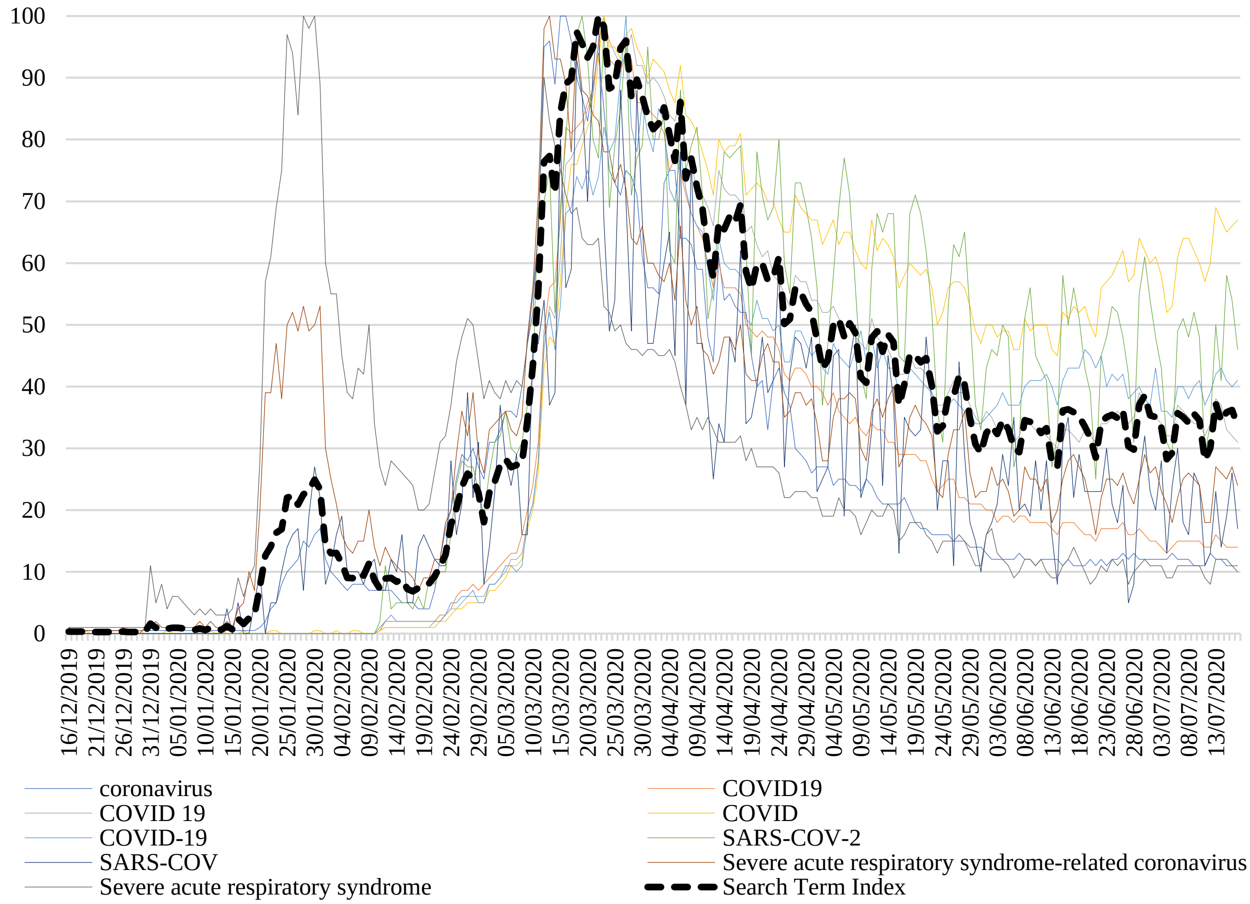
[3] Data obtained from Google search trends is the sum of the scaled total number of searches between 0 to 100 based upon a topic’s proportion to all searches on all topics.

Table 1: Descriptive statistics for returns on MSCI Energy indices

Country	Market Cap (USD BN)	Mean	Median	Maximum	Minimum	Std. dev.	Skewness	Kurtosis	Shapiro-Wilk
0.World	3567.68	-0.0005	-0.0001	0.1567	-0.2123	0.0169	-1.9761	36.1654	0.7952***
1. USA	1135.66	-0.0005	0.0000	0.1502	-0.2270	0.0188	-1.6315	28.8436	0.8182***
2. Russia	353.86	0.0003	0.0002	0.1073	-0.1264	0.0187	-0.2530	9.4274	0.9287***
3. UK	351.08	-0.0004	0.0000	0.2095	-0.1957	0.0195	-0.7228	27.4013	0.8302***
4. China	300.63	-0.0004	0.0000	0.0937	-0.1068	0.0170	-0.0316	6.7977	0.0527***
5. Canada	288.42	-0.0005	0.0000	0.1409	-0.2260	0.0195	-1.9523	33.3068	0.7993***
6. India	222.10	0.0005	0.0000	0.1076	-0.1467	0.0169	-0.5567	13.9279	0.8951***
7. France	139.96	-0.0002	0.0002	0.1403	-0.1690	0.0179	-1.2249	22.2818	0.8505***
8. Brazil	104.98	0.0000	0.0000	0.2184	-0.3456	0.0341	-1.2352	17.1742	0.8849***
9. Norway	71.79	-0.0002	0.0000	0.1176	-0.2417	0.0226	-0.8162	15.5582	0.9185***
10. Italy	67.46	-0.0004	0.0000	0.1287	-0.2207	0.0182	-2.2149	31.6520	0.8436***
11. Australia	66.25	-0.0005	0.0001	0.0931	-0.2343	0.0204	-1.6897	20.9556	0.8749***
12. Thailand	65.62	0.0000	0.0000	0.1264	-0.2913	0.0188	-2.5090	48.3330	0.8115***
13. Colombia	38.46	-0.0003	-0.0002	0.1330	-0.2784	0.0280	-0.8992	14.5001	0.8954***
14. Japan	36.90	-0.0001	0.0000	0.0783	-0.1055	0.0175	0.0476	5.3868	0.9757***
15. Taiwan	29.96	0.0002	0.0000	0.0948	-0.1133	0.0171	-0.1436	7.8146	0.9426***
16. Finland	26.00	0.0011	0.0008	0.1507	-0.1136	0.0208	0.0262	10.1997	0.9080***
17. Spain	24.04	-0.0003	0.0000	0.1462	-0.1522	0.0201	-0.4686	13.5118	0.8837***
18. Korea	23.74	0.0001	0.0000	0.1866	-0.1400	0.0214	0.6601	11.2857	0.9245***
19. Poland	21.29	0.0001	0.0000	0.0617	-0.1004	0.0187	-0.3211	4.8508	0.9811***
20. Austria	18.65	0.0002	0.0000	0.1849	-0.2220	0.0220	-0.9115	21.9478	0.8586***

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

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



This figure plots levels in the combined COVID-19 search term index created from Google search trends volumes for nine COVID-19 related search terms over the period 16 December 2019 to 17 July2020. Levels of search volumes for individual COVID-19 related terms are also plotted.

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

Table 2: Specifications estimated

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

This table lists the specifications fitted in this study. The mean equation is specified in the "mean" row, equation (1). ARCH(p), GARCH(p,q) and IGARCH(p,q) specifications, equations (2a)/(2b)/(2c) respectively, follow after the "ARCH/GARCH" row. $Dum_{0,1}$ is the shift dummy, which takes on a value of 0 during the pre-COVID-19 period, designated as 1 January 2015 to 15 December 2019 and a value of 1 during the COVID-19 period, designated as 16 December 2019 to 17 July 2020.

Table 2 lists all specifications, where $r_{i,t}$ is the return on index *i* at time *t*, $\Delta CV19I_t$ are first differences in the combined COVID-19 worldwide search term index, i.e. our measure of global COVID-19 related uncertainty, and $h_{i,t}$ is the conditional variance. $Dum_{0,1}$ is a shift dummy taking on a value of 0 in the pre-COVID-19, defined as 1 January 2015 to 15 December 2019, and 1 in the COVID-19 period, defined as 16 December 2019 to 17 July 2020. Given that our global and national energy sector return indices comprise sub-industries that are primarily concerned with the manufacturing of oil extraction equipment, the extraction of oil and related fuels, and the processing and distribution of oil and oil related products, we include logarithmic differences in the brent crude US dollar price in equation (1), which we denote as ΔOIL_t. Sadorsky (2001), Oberndorfer (2009), Bianconi and Yoshino (2014), Degiannakis et al. (2018) and Ma et al. (2019) confirm that energy stocks respond to changes in the oil price. Therefore, while the impact of ΔOIL_t is only of a peripheral interest in this study, it is included as a control factor in the mean equation given its importance to the energy sector. The results of the analysis are reported in Sections 4.1 – 4.3.

To address potential underspecification and the omission of relevant factors, a factor analytical derived proxy factor set, $\sum_{k\geq 0}^{k}\beta_{i,k} F_{k,t}$, is incorporated into equation (1). Factors comprising the factor analytic augmentation, accounting for both contemporaneous and lagged relationships, are derived from the residuals of regressions of index returns on $\Delta CV19I_t$ and ΔOIL_t. Szczygielski, Brümmer and Wolmarans (2020) demonstrate that the use of a factor analytic augmentation offers a simplified approach to model specification by removing the need to identify pre-specified factors, reducing incidences of Type II errors and producing an empirical approximation of the diagonality assumption underlying factor models.[4] Importantly, the use of this approach produces more accurate coefficient estimates which are of particular

[4] Szczygielski, Brümmer and Wolmarans (2020) and Szczygielski, Brümmer, Wolmarans and Zaremba (2020) show that a residual market factor may be insufficient to ensure that the residual correlation matrix conforms to an empirical diagonal matrix, implying that a model omits factors with a systematic (common) impact. The inclusion of a factor analytic augmentation is shown to result in a diagonal residual matrix.

interest given that this study aims to quantify the impact of COVID-19 related uncertainty on national energy sectors.[5] An alternative to using a factor analytic augmentation to account for omitted influences and to arrive at an adequate representation of the return generating process would be to combine macroeconomic, residual market and the characteristic-based factors of Fama and French (1993; 2015) and Carhart (1997). However, Szczygielski, Brümmer, Wolmarans and Zaremba (2020) demonstrate that a combination of macroeconomic, residual market and characteristic-based factors yields a poor approximation of the systematic drivers of stock returns quantified by statistically derived factor scores.[6] Notably, Middleton and Satchell (2001) argue that the problem of underspecification can only be avoided if explanatory factors are statistically derived and a sufficiently significant number of factors is arrived at. It is for this reason that we elect to rely upon this approach to ensure an adequately specific return generating process. The efficacy of this approach as well as the validity of the mean specification that incorporates the

[5] The use of regressors derived from the residuals of an auxiliary regression results in standard errors which are too small (and hence the increased possibility of Type I errors) as regressors are measured with sampling error (Pagan, 1984; Murphy & Topel, 1985). Bai and Ng (2006) prove mathematically that as $N \rightarrow \infty$, $T \rightarrow \infty$, and $N^2/T \rightarrow \infty$ (where $i = 1, 2, 3 \ldots N$ is a vector of observed time-series and T is the total number of time-series observations), errors in the estimated factors can be ignored when the factors are used as regressors (Stock & Watson, 2016). With the factors extracted from the indices of the 20 largest energy markets and 1448 daily observations (from 1 January 2015 to 17 July 2020 in most cases), the impact of the sampling error can be considered small. The use of derived regressors without adjusting for sampling error is demonstrated in seminal studies that apply multifactor models, notably those of Burmeister and Wall (1986), Burmeister and McElroy (1988, 1991, 1992) and Wei (1988) and other studies such as Kryzanowski et al. (1997), van Rensburg (1997), van Rensburg (2002), Deetz et al. (2009) and Szczygielski, Brümmer and Wolmarans (2020), where the principal focus is on the elimination of Type II errors due to underspecification. Stock and Watson (2002) also confirm that the omitted variable bias is avoided with the use of a factor analytic specification compared.

A proposed solution to the generated regressor problem is to bootstrap standard errors. However, Hall and Yao (2003) show that when the true innovations are relatively heavy tailed, quasi-maximum likelihood estimator in the ARCH/GARCH framework is particularly difficult to estimate using standard bootstrap parametric procedures. They propose a subsample bootstrap procedure that yields asymptotic confidence sets, however, they also report problems with the coverage accuracy in their confidence sets for the GARCH(1,1) parameters even when the sample size is as large as 1000. In response, Luger (2012) proposes an alternative parametric bootstrap procedure that achieves exact *p*-values with a relatively small number of bootstrap replications. However, the model is computationally intensive. To reduce this complexity, Luger (2012) suggests a simplification, but this increases the probability of a Type I error in small samples. Shimizu (2010) also highlights that the application of standard bootstrapping approaches to GARCH models has limitations. The literature thus reveals that bootstrapping in an ARCH/GARCH framework is fraught with econometric problems.

Accordingly, given the difficulties associated with bootstrapping within the ARCH/GARCH framework, and the preceding discussion which suggests that with the given sample size used the impact of the sampling error can be considered small, we opted for a factor analytic augmentation.

[6] Szczygielski, Brümmer, Wolmarans and Zaremba (2020) investigate the adequacy of macroeconomic, residual market and the characteristic-based factors of Fama and French (1993;2015) and Carhart (1997) in proxying for the systematic drivers of South African stock returns which are quantified using three factor analytically derived score series. The first residual market factor is derived from returns on the JSE All Share Index and the second is derived from returns on the MSCI World Market Index, which is treated as a proxy for global systematic influences. When a combination of all these factor types is considered, the unrestricted factor set approximates 45% of the first factor score series (the most important factor score series approximating 41.2% of shared return variance), over 30% of the second factor score series (approximating 7.2% of shared return variance) and over 40% of the third factor score series (which is the least important approximating under 6% of total shared return variance).

factor analytic augmentation is demonstrated in Section 4.4. For parsimony, only significant proxy factors are retained and/or those required to ensure that residuals are free of serial correlation and heteroscedasticity. Finally, autoregressive terms, $\sum_{\tau\geq 0}^{\tau}\gamma_{i,\tau}\, r_{i,t-\tau}$, of order τ identified from a residual correlogram are included to address remaining residual serial correlation, if required.

Next, we investigate whether the impact of $\Delta CV19I_t$ differs across sub-periods for each series. To identify breakpoints in the relationship between returns and $\Delta CV19I_t$, we use the Bai-Perron test (Bai & Perron, 1998; Carlson et al., 2000). If breakpoints are detected, we re-specify equations (1) and (2a)/(2b)/(2c) as follows, accounting for breakpoints:

Table 3: Specifications estimated with breakpoints

Model	**Specification**	
Mean:	$r_{i,t} = \alpha_i + \sum_{\pi\geq 1}^{\pi}\beta_{i,\pi,\Delta CV19I}\Delta CV19I_t Dum_{0,1,\pi} + \beta_{i,\Delta OIL}\Delta OIL_t + \sum_{k\geq 0}^{k}\beta_{i,k}\, F_{k,t} + \sum_{\tau\geq 0}^{\tau}\gamma_{i,\tau}\, r_{i,t-\tau} + \varepsilon_{i,t}$	(3)
ARCH/GARCH:		
ARCH(p)	$h_{i,t} = \omega_i + \sum_{p\geq 1}^{p}\alpha_i\varepsilon_{i,t-p}^2 + \sum_{\pi\geq 1}^{\pi}\varphi_{i,\pi,\Delta CV19I}\Delta CV19I_t Dum_{0,1,\pi}$	(4a)
GARCH(p,q)	$h_{i,t} = \omega_i + \sum_{p\geq 1}^{p}\alpha_i\varepsilon_{i,t-1}^2 + \sum_{q\geq 1}^{q}\beta_i h_{i,t-q} + \sum_{\pi\geq 1}^{\pi}\varphi_{i,\pi,\Delta CV19I}\Delta CV19I_t Dum_{0,1,\pi}$	(4b)
IGARCH(p,q)	$h_{i,t} = \sum_{p\geq 1}^{p}\alpha_i\varepsilon_{i,t-p}^2 + \sum_{q\geq 1}^{q}\beta_i h_{i,t-q} + \sum_{\pi\geq 1}^{\pi}\varphi_{i,\pi,\Delta CV19I}\Delta CV19I_t Dum_{0,1,\pi}$	(4c)

This table lists the specifications fitted in this study. The mean equation is specified in the "mean" row, equation (2). ARCH(p), GARCH(p,q) and IGARCH(p,q) specifications, equations (4a)/(4b)/(4c) respectively, follow after the "ARCH/GARCH" row. $Dum_{0,1,\pi}$ is the shift dummy, which takes on a value of 0 during the pre-COVID-19 period, designated as 1 January 2015 to 15 December 2019 or 1 during the COVID-19 period, designated as 16 December 2019 to 17 July 2020, for segment π as identified by the Bai-Perron test.

where all coefficients and variables remain as in Table 2, with the exception of $\beta_{i,\Delta CV19I}\Delta CV19I_t Dum_{0,1}$ in equation (1) which is now replaced by $\sum_{\pi\geq 1}^{\pi}\beta_{i,\pi,\Delta CV19I}\Delta CV19I_t Dum_{0,1,\pi}$ in equation (3) and $\varphi_{i,\Delta CV19I}\Delta CV19I_t Dum_{0,1}$ in equations (2a)/(2b)/(2c) is replaced by $\sum_{\pi\geq 1}^{\pi}\varphi_{i,\pi,\Delta CV19I}\Delta CV19I_t Dum_{0,1,\pi}$ in equations (4a)/(4b)/(4c). The shift dummies, $Dum_{0,1,\pi}$, take on a value of 1 or 0 otherwise for segment π between breakpoints from the beginning of the COVID-19 period. The ARCH(p), GARCH(p,q) or IGARCH(p,q) specifications fitted to the conditional variance in the first part of the analysis without structural breaks are retained unless residuals exhibit serial correlation and/or heteroscedasticity after accounting for structural breaks over the COVID-19 period. Equations (1)/(3) and (2a)/(2b)/(2c)/(3a)/(3b)/(3c) are estimated using quasi-maximum likelihood (QML) estimation with Bollerslev-Wooldridge standard errors and covariance to account for potential deviations from normality in the residuals (Fan et al., 2014). The results of the analysis with breakpoints are reported in Section 4.5.

The final part of our study examines the role of COVID-19 related uncertainty as a factor in energy sector returns. We therefore analyse the structure of the return generating process during the pre-COVID-19 and COVID-19 periods and the role of $\Delta CV19I_t$ during the COVID-19 period. First, returns over the pre-COVID-19 and COVID-19 periods are factor analysed to determine whether new factors emerge during the latter period. Extracted factor scores can be interpreted as representations of the composite factors driving national energy sector returns (Szczygielski, Brümmer & Wolmarans, 2020). To determine the number of factors in returns during each period, the minimum average partial (MAP) test is utilised. This test identifies the number of factors that is congruent with the assumption of uncorrelated residuals, $E(\varepsilon_{i,t}, \varepsilon_{j,t})$, underlying linear factor models (Zwick and Velicer, 1986). Given the evolving nature of the COVID-19 crisis, we estimate rolling correlations between the extracted factor scores, which summarise the composite set of energy sector return drivers, and $\Delta CV19I_t$ during the pandemic to gain insight into the dynamic relationship between $\Delta CV19I_t$ and the common energy sector return drivers. The results are reported in Section 4.6.

4. Results

4.1 Model Results

Table 4 reports results for the specifications in Table 2. Of particular interest are the $\beta_{i,\Delta CV19I}$ and $\varphi_{i,\Delta CV19I}$ coefficients which quantify the impact of $\Delta CV19I_t$ on the conditional mean and variance. Panel A of Table 4 shows that $\Delta CV19I_t$ has a statistically significant and negative effect on global energy sector returns with a $\beta_{i,\Delta CV19I}$ of -0.0028, and on all national energy sectors. These results are consistent with the nascent literature on the negative impact of COVID-19 uncertainty on market aggregates (Costola et al., 2020; Liu et al., 2020; Smales, 2021 among others) and mirror prior studies on the sensitivity of this sector to uncertainty (Bianconi & Yoshino, 2014; Fazelabdolabadi, 2019; Nikkinen & Rothovius, 2019).

The impact of COVID-19 related uncertainty, however, varies across countries. Figure 2 illustrates differences in the impact of $\Delta CV19I_t$ on all 20 national energy sectors and across three main regions, namely Australasia, Europe and the Americas. On average, the impact is strongest in the Americas, followed by Europe and weakest in Australasia, with respective average $\beta_{i,\Delta CV19I}$ estimates of -0.0039, -0.0032 and -0.0024. The most impacted national energy sectors are those of Brazil and Canada, with $\beta_{i,\Delta CV19I}$ estimates of -0.0051 and -0.0044, respectively. Conversely, the least impacted national energy sectors are those of Japan and Taiwan with respective $\beta_{i,\Delta CV19I}$ estimates of -0.0010 for both. The pattern of the $\beta_{i,\Delta CV19I}$ parameters across individual markets and regions implies that $\Delta CV19I_t$ has, on average, an increasingly stronger influence on energy sector returns the further west a country is located from the COVID-19 origin (in Wuhan, China). This westly direction is important because the COVID-19 pandemic itself spread geographically from east to west of its origin, first affecting countries in Europe, most notably Italy, Spain and the UK, and then countries in the Americas, most notably the US and Brazil.

Table 4: Model results for energy sectors without breaks

Country	**0.World Energy**	**1. USA**	**2. Russia**	**3. UK**	**4. China**	**5. Canada**	**6. India**	**7. France**
				Panel A: Conditional mean				
Intercept	-0.0002	-0.0003	0.0006*	-0.0001	-0.0003	-0.0003*	0.0006*	-0.0001
$\beta_{i,\Delta CV19I}$	-0.0028***	-0.0029***(12)	-0.0033***(8)	-0.0041***(3)	-0.0023***(18)	-0.0044***(2)	-0.0033***(9)	-0.0024***(17)
$\beta_{i,\Delta OIL}$	0.3639***	0.3907***	0.2778***	0.3334***	0.1321***	0.4158***	0.0552***	0.2894***
Proxy factors	0.0003F_{4t} 0.0051F_{5t}*** 0.008F_{8t}***	-0.0019F_{3t}*** 0.0087F_{5t}*** 0.0004F_{6t}**	0.0082F_{2t}*** 0.0010F_{3t}** 0.0042F_{8t}***	0.0127F_{2t}***	0.0009F_{1t}*** 0.0053F_{2t}*** 0.0035F_{3t}*** 0.0008F_{5t}*** 0.0007F_{7t}** 0.0011F_{8t}**	0.0074F_{2t}*** 0.0095F_{5t}***	0.0035F_{2t}*** 0.018F_{5t}*** -0.0015F_{7t}*** -0.0042F_{8t}***	0.0009F_{4t}***
AR Terms		0.1421r_{t-1} ***	-0.0359r_{t-1}		-0.0728r_{t-1}*** -0.0194r_{t-3} -0.0390r_{t-5}**		0.0361r_{t-1}	-0.0774r_{t-4}*** -0.0798r_{t-10}***
				Panel B: Conditional variance				
ARCH/GARCH	IGARCH(1,1)	GARCH(2,1)	IGARCH(1,1)	IGRACH(2,1)	IGARCH(1,2)	IGARCH(2,1)	IGARCH(2,1)	GARCH(1,1)
ω_i		3.51E-07**						1.60E-06**
α_1	0.0351***	0.0968**	0.0460***	0.1624***	0.0420***	0.1489***	0.0905*	0.0437***
α_2		-0.0673*		-0.1545***		-0.1303***	-0.07784*	
β_1	0.9649***	0.9631***	0.9540***		0.2312	0.9814***	0.9874***	0.9442*
β_2				0.9922***	0.7269***			
β_3								
$\varphi_{i,\Delta CV19I}$	0.129***	0.098***(12)	0.170***(8)	0.0370**(20)	0.094***(14)	0.0384***(19)	0.086**(15)	0.245***(4)
				Panel C: Model diagnostics				
$\bar{R}^2$	0.6588	0.7464	0.4965	0.8641	0.6744	0.8817	0.2698	0.2911
$Q(1)$	0.1512	0.0024	1.2271	1.0586	0.7426	1.1437	0.9735	11.274
$Q(10)$	5.1885	10.354	7.5846	10.120	13.723	5.4682	14.674	11.026
ARCH(1)	1.6587	0.0001	0.1096	0.5703	2.1340	0.3848	0.9357	0.1406
ARCH(10)	1.0259	0.4000	0.7404	1.0454	1.0430	0.6449	1.1284	1.3058
Log-likelihood	4979.651	5026.536	4348.622	5305.923	4749.635	5350.234	4170.967	4297.946

Table 4: Model results for energy sectors without breaks (continued…)

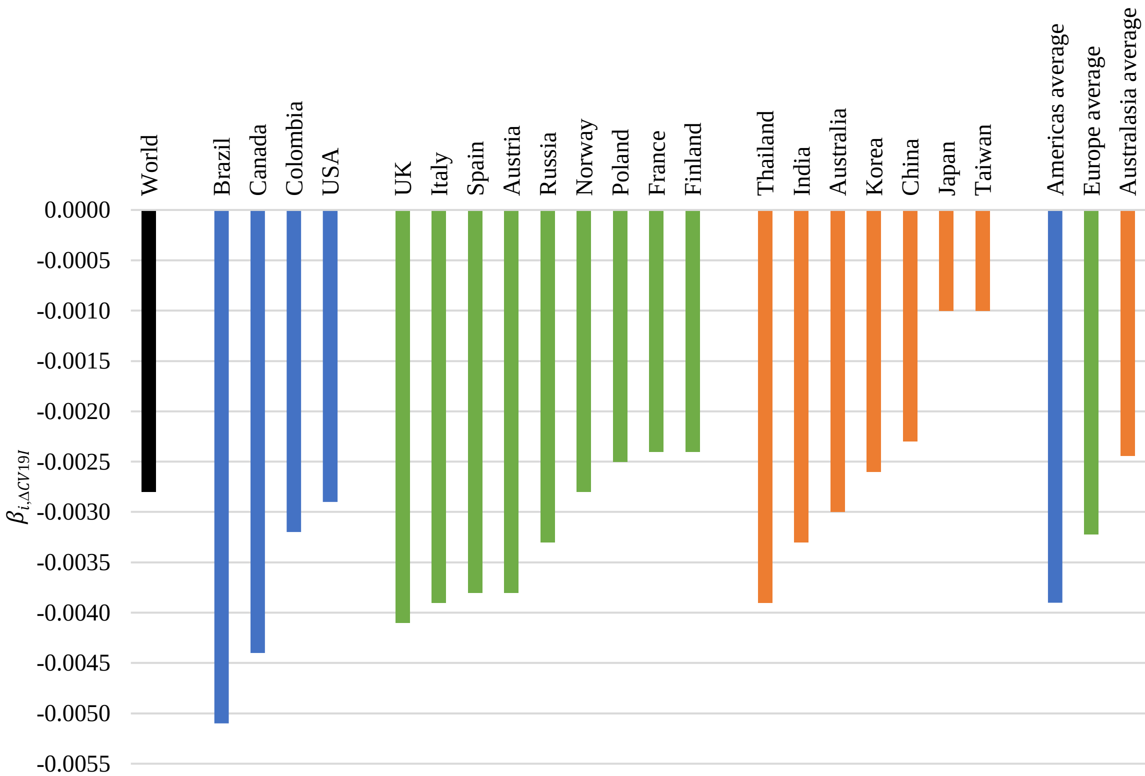
Country	8. Brazil	9. Norway	10. Italy	11. Australia	12. Thailand	13. Colombia	14. Japan	15. Taiwan
Panel A: Conditional mean								
Intercept	0.0005	0.001	-0.0003*	-0.0001	0.0003	0.00004	0.0001	0.0002
$\beta_{i,\Delta CV19I}$	-0.0051***(1)	-0.0028*** (13)	-0.0039***(4)	-0.0030***(11)	-0.0039***(5)	-0.0032***(10)	-0.0010**(19)	-0.0010***(20)
$\beta_{i,\Delta OIL}$	0.4984***	0.4083***	0.3115***	0.1948***	0.1745***	0.5657***	0.0589***	0.1182***
Proxy factors	0.0098F_{2t}***	-0.0026F_{1t}**	0.0130F_{2t}***	0.0059F_{2t}***	0.0050F_{2t}***	0.0026F_{4t}***	0.0006F_{1t}	0.0030F_{2t}***
AR Terms	-0.01294r_{t-1}***	-0.0955r_{t-1}***		-0.0379r_{t-3}**	$-0.0418r_{t-1}$*	-0.0185r_{t-1}	-0.0928r_{t-1}***	-0.1392r_{t-1}***
Panel B: Conditional variance								
ARCH/GARCH	IGARCH(1,1)	IGARCH(1,1)	GARCH(1,1)	IGARCH(1,1)	GARCH(1,1)	IGARCH(1,1)	GARCH(1,1)	GARCH(1,1)
ω_i			4.34E-07*		6.51E-07		2.98E-06*	3.20E-05**
α_1	0.0708**	0.0486**	0.0387***	0.0385***	0.0296***	0.0455***	0.0303***	0.0919**
α_2								
α_3								
β_1	0.9292***	0.9514***	0.9488	0.9615***	0.9644***	0.9545***	0.9525***	0.7483***
β_2								
β_3								
$\varphi_{i,\Delta CV19I}$	0.369***(1)	0.367***(2)	0.048***(18)	0.159***(9)	0.185(6)	0.313***(3)	0.104***(14)	0.095(13)
Panel C: Model diagnostics								
$\bar{R}^2$	0.3940	0.3161	0.847	0.6541	0.5331	0.4019	0.4031	0.2991
$Q(1)$	0.0127	0.8385	0.468	2.1037	0.3094	2.2515	1.1898	0.2038
$Q(10)$	7.9839	9.9225	10.06	12.411	7.7829	8.9213	9.9936	12.937
ARCH(1)	0.2617	0.7249	2.2087	0.0005	0.3578	0.1588	0.2766	0.778
ARCH(10)	0.2430	0.7883	0.4831	0.6736	0.6512	0.9176	0.6417	0.4092
Log-likelihood	3303.201	3232.797	5275.721	4535.573	4458.789	3640.628	4246.733	4136.558

Table 4: Model results for energy sectors without breaks (continued…)

	16. Finland	17. Spain	18. Korea	19. Poland	20. Austria
Panel A: Conditional mean					
Intercept	0.0013***	0.0003	-0.00001	0.0001	0.0002
$\beta_{i,\Delta CV19I}$	-0.0024***(16)	-0.0038***(6)	-0.0026***(14)	-0.0025***(15)	-0.0038***(7)
$\beta_{i,\Delta OIL}$	0.1742***	0.2898***	0.1134***	0.1122***	0.2868***
Proxy factors	0.0075F_{2t}***	0.0136F_{2t}***	0.0048F_{2t}***	0.0071F_{2t}***	0.0013F_{2t}***
	-0.0030F_{7t}***		0.0096F_{8t}***	0.002F_{4t}***	0.0011F_{3t}**
				0.0031F_{8t}***	0.0005F_{4t}*
					0.0015F_{8t}*
AR Terms			-0.0580r_{t-1}***		-0.0653r_{t-1} ***
Panel B: Conditional variance					
ARCH/GARCH	GARCH(1,1)	IGARCH(1,1)	IGARCH(1,1)	IGARCH(1,1)	GARCH(1,2)
ω_i	0.0002**				1.20E-05**
α_1	0.1251**	0.0314***	0.0169***	0.0183***	0.0889***
α_2					
β_1	0.3782*	0.9686***	0.9831***	0.9817***	0.0089
β_2					0.8218***
β_3					
$\varphi_{i,\Delta CV19I}$	0.085(16)	0.081***(17)	0.198**(5)	0.151***(10)	0.177***(7)
Panel C: Model diagnostics					
$\bar{R}^2$	0.2699	0.7958	0.3851	0.2429	0.6114
$Q(1)$	0.3397	0.5218	1.8052	1.0391	2.1796
$Q(10)$	7.4607	6.6898	11.627	6.5428	3.9282
ARCH(1)	0.1645	0.4119	1.9376	0.3287	0.9598
ARCH(10)	0.1807	0.2268	1.2421	1.2894	0.7686
Log-likelihood	3815.63	4953.259	3966.49	3933.347	4333.249

This table reports the impact of changes in COVID-19 related uncertainty on the returns ($\beta_{i,\Delta CV19I}$) and variance ($\varphi_{i\Delta CV19I}$) for the global and national energy sectors. National energy markets are ordered largest to smallest in terms of the market capitalisation. Coefficients of $\Delta CV19I_t$ in the conditional variance equation are scaled by 10 000. Panel A reports estimation results for the conditional mean, which also includes proxy factors derived from national energy sector returns using factor analysis. Panel B reports results for the conditional variance. Values in brackets (…) rank the order of absolute impact according to the magnitude of the absolute $\beta_{i,\Delta CV19I}$ and $\varphi_{i,\Delta CV19I}$ coefficients. Panel C reports model diagnostics, with $Q(1)$ and $Q(10)$ being Ljung-Box tests statistics for joint serial correlation at the 1st and 10th orders. ARCH(1) and ARCH(10) are test statistics for the ARCH LM test for heteroscedasticity. Pre-COVID-19 and COVID-19 periods are defined as 1 January 2015 to 15 December 2019 and 16 December 2019 to 17 July 2020 respectively. The asterisks ***,** and * indicate statistical significance at 1%, 5% and 10% levels of significance, respectively.

Figure 2: Impact of COVID-19 related uncertainty on returns of the world energy sector and national energy sectors and, their regional averages



This figure plots the estimates of COVID-19 related uncertainty on returns of the world energy index and 20 national energy sectors ($\beta_{i,\Delta CV19I}$) grouped by region, and their three regional averages (Australasia, Europe and the Americas).

The results suggest that geographical proximity matters. The closer a region is positioned to the epicentre of the COVID-19 pandemic in China (according to the geographical sequence of locations from east to west) the more investors may have known about the virus or possibly had better information about the likely future development of the pandemic. Such information could have been converted into a resolution of some of the overall uncertainty in the respective markets leading to less severe impacts on stock prices, including the prices of energy stocks. Likewise, the experience that Asian countries have in dealing with pandemics (namely SARS and MERS) may have aided in reducing the impact of uncertainty (Lu et al., 2020; Wang & Enilov, 2020). These patterns largely mirror results reported by Smales (2021) for each of the G20 country stock markets, who found that Asian countries were least impacted, followed by European countries with American countries most impacted.

Why does uncertainty impact the energy sector in particular? The demand for oil, gas and related equipment and services is directly tied to economic conditions. Given that uncertainty relating to the length and depth of economic contractions over the COVID-19 period and measures introduced to curb the spread of the virus, the future profitability of firms in the oil and gas industry is unclear.[7] Hence, it is reasonable to assume that uncertainty should directly affect stock prices in this sector. This is the case given that the commercial activities of these firms - whether production, provision of the manufacturing of equipment or distribution – are dependent directly upon oil. The impact of uncertainty on stock markets, in particular uncertainty related to such events as COVID-19 pandemic, may differ upon whether a given country is a net oil (or more broadly a net energy) exporter or importer. We explore this issue further below in section 4.3.

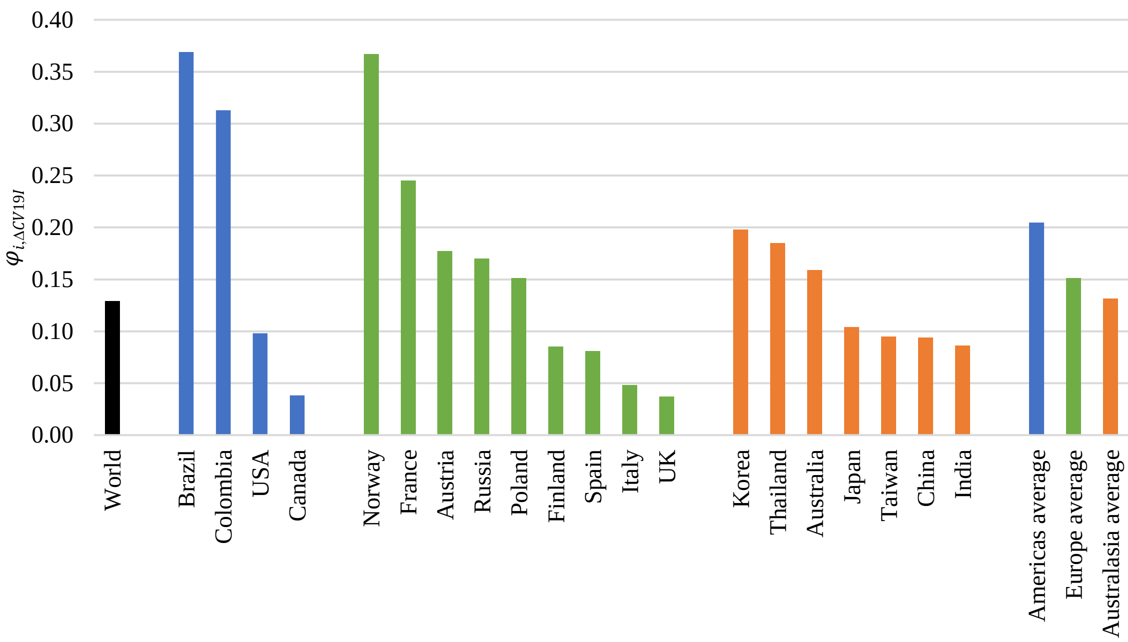
Panel B in Table 4 reports the estimates of $\varphi_{i,\Delta CV19I}$, quantifying the impact of $\Delta CV19I_t$ on the conditional variance. For the world energy index, the impact is positive with $\varphi_{i,\Delta CV19I}$ equal to 0.129. The impact is positive for all national energy sectors and for 17 out of 20 markets it is statistically significant, with the exceptions of Thailand, Taiwan and Finland. Brazil, Norway and Colombia are the most impacted with $\varphi_{i,\Delta CV19I}$ estimates of 0.369, 0.367 and 0.313, respectively. These results constitute evidence that COVID-19 related uncertainty triggers volatility for most national energy sectors. In line with this, Fazelabdolabadi (2019) reported that oil price uncertainty contributed to increased volatility in the Iranian energy sector. Whilst, Liu (2020) found that COVID-19 related uncertainty fuelled greater Chinese stock return volatility. Smales (2021) also reported increased stock market return volatility in response to COVID-19 uncertainty similarly measured using Google search trends for individual markets that comprise the G7 grouping. A limitation of considering individual markets is that these do not reflect a global perspective, in particular with respect to differences across countries in various geographical regions. Our study contributes to the extant literature by providing such a global perspective.

Figure 3 depicts the impact of COVID-19 related uncertainty on conditional variance for all 20 national energy sectors and the three regions. As in the case of returns in the mean equation, the Americas are most impacted, followed by Europe and then Australasia, with average $\varphi_{i,\Delta CV19I}$ estimates of 0.2046, 0.1512 and 0.1316, respectively. Similarly to the pattern for the $\beta_{i,\Delta CV19I}$ estimates, the geographical distance from the origin of the COVID-19 pandemic in China appears to play a role. This can be analogously interpreted from

[7] In addition to the broader macroeconomic effects and transmission channels, there may also exist company-level factors that help explain why uncertainty impacts energy sector firms. For example, many Asian national oil companies are well-funded, with low debt burdens, and are thus well positioned to be able to handle the fall-out from the virus (ERIA, 2020; Parameswaran, 2020) and the consequent impact of uncertainty. Many European oil and gas companies, in contrast, have been forced to tap into financial markets to raise debt financing to weather the COVID-19 storm (Raval & Smith, 2020) which may have contributed to the increased impact of uncertainty. However, on average, they remain well-capitalised and are not highly geared. In comparison, national oil companies in Brazil and Colombia, are highly indebted and the COVID-19 pandemic has exacerbated a number of other problems. Petrobras (Brazil), for example, was forced to halt planned non-core asset sales meant to reduce its debt burden (Slav, 2020; Waine, 2020) while EcoPetrol (Colombia) had its credit rating downgraded (Fitch, 2020). These financial concerns could have fuelled the impact of uncertainty on national energy stocks. The link between the financial position of oil and gas companies globally and the impact of uncertainty is consistent with Ramelli and Wagner (2020) findings that firms with higher debt levels are more impacted by COVID-19 uncertainty.

the perspective of the varying degrees of uncertainty resolution depending upon a region's global location relative to the pandemic's source and potentially the better preparedness of Asian countries for dealing with a pandemic.

Figure 3: Impact of COVID-19 related uncertainty on the volatility of the global energy sector and national energy sectors and regional averages



This figure plots the estimates of COVID-19 related uncertainty on conditional volatility of the world energy index and 20 national energy sectors $\varphi_{i,\Delta CV19I}$, grouped by region, and their three regional averages (Australasia, Europe and the Americas).

4.2. Overall Impact of COVID-19 Uncertainty

Uncertainty is defined as a situation that arises when it is not known *whether* some event will occur in the future or *when* it may occur or, specific to the context of this study, what its *consequences* (i.e. outcomes) will be and/or how *severe* these consequences may be (see Aven & Renn, 2009; Aven et al., 2011). Uncertainty about an event and the seriousness of the consequences associated with this event can be quantified when the outcomes and the associated probabilities of occurrence can be determined and become known to decision-makers (Renn, 2005; Aven, 2007; Aven & Renn, 2009; Aven, 2010; Park & Shapira, 2018). At the wider macroeconomic level, uncertainty has numerous obvious adverse economic effects. At the firm level, it negatively impacts stock prices (returns) due to a lack of knowledge amongst investors or their decreased confidence in understanding the paths of future cash flows (in particular dividends and their growth rates) and discount rates (Gormsen & Koijen, 2020). The negative impact of broadly defined uncertainty on stock returns is also predicted by theoretical models (see Pástor & Veronesi, 2012). At the same time, uncertainty is positively related to stock price volatility. As new information arrives, the market is uncertain about expected profitability. The result is a process of price discovery that leads to upward and downward revisions resulting in volatility as market participants are not sure about the true value of assets following arrivals of new information (Engle, 2004; Nwogugu, 2006; Engle et al., 2008). The results reported in this study indicate that uncertainty has a negative effect on energy stock prices and triggers heightened volatility. However, these two channels of the impact of uncertainty are typically considered separately. We therefore combine both aspects of the influence of uncertainty on stock markets and we propose a two-dimensional measure of uncertainty, which we call the overall impact of uncertainty (OIU). We use it next to further explore the impact of uncertainty on the energy sector.

The effect of COVID-19 related uncertainty is directly gauged in our models by two parameters: $\beta_{i,\Delta CV19I}$, which measures the magnitude of the impact, and $\varphi_{i,\Delta CV19I}$, which can be interpreted as the impact's intensity. Therefore, the overall influence of $\Delta CV19I_t$ is captured by the product of the magnitude and intensity parameters as follows:

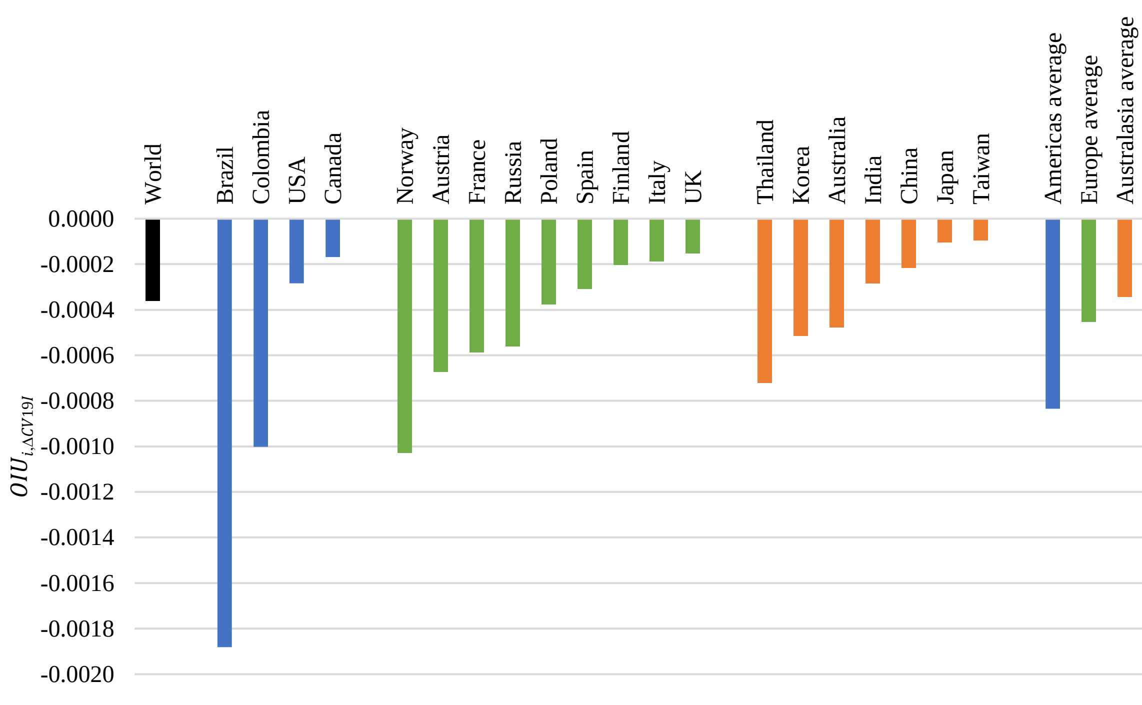
$$OIU_{i,\Delta CV19I} = \beta_{i,\Delta CV19I} \cdot \varphi_{i,\Delta CV19I} \tag{5}$$

The logic behind the overall impact of uncertainty (OIU) measure, $OIU_{i,\Delta CV19I}$, expressed by equation (5) is that it captures the directional strength of the effect of uncertainty, which is amplified by the intensity with which information enters a market. For example, in the case of two countries with the same magnitude of the impact of COVID-19 related uncertainty on returns, as reflected by $\beta_{i,\Delta CV19I}$, the overall impact is tronger for the country with the higher intensity of the impact, $\varphi_{i,\Delta CV19I}$. Likewise, for two countries with the same level of intensity ($\varphi_{i,\Delta CV19I}$), the overall impact is stronger the greater the magnitude ($\beta_{i,\Delta CV19I}$).

The design of the $OIU_{i,\Delta CV19I}$ measure intuitively permits a comparison with natural phenomenon, such as the impact of rainstorms on the environment. Rainstorms can produce different amounts of water, i.e. an analogy for the magnitude component in $OIU_{i,\Delta CV19I}$ represented by $\beta_{i,\Delta CV19I}$. There may also be a varying force of the rain and wind, i.e. the "volatility" of the storm. This means that storms can have different levels of intensity. This is analogous to the intensity component in $OIU_{i,\Delta CV19I}$ represented by $\varphi_{i,\Delta CV19I}$ that can range from low to high. The destruction of the environment caused by a rainstorm is heaviest when it generates a lot of water and, at the same time, the intensity of the storm is high (e.g. it is accompanied by extremely strong winds). This happens when both $\beta_{i,\Delta CV19I}$ and $\varphi_{i,\Delta CV19I}$ are high. Conversely, the impact on the environment is weak when there is only light rain and its intensity is small, i.e. when both $\beta_{i,\Delta CV19I}$ and $\varphi_{i,\Delta CV19I}$ are low. There may also occur other combinations, such as heavy rain but with low intensity and weak winds or light rain but with strong intensity and heavy winds, in which case the overall impact on the environment is likely to be only moderate. The $OIU_{i,\Delta CV19I}$ measure reflects all these possible situations.

Figure 4 shows the overall impact of COVID-19 related uncertainty, $OIU_{i,\Delta CV19I}$, for all 20 markets in our sample and the world energy index together with regional breakdowns. The most heavily impacted country is Brazil in the Americas, while Japan and Taiwan in the Australasian region are least impacted. The overall impact of COVID-19 related uncertainty, $OIU_{i,\Delta CV19I}$, captures more vividly the differences between national energy sectors relative to the global energy market. For instance, in Figure 2, the $\beta_{i,\Delta CV19I}$ for the Brazilian energy sector is about twice as large as the respective $\beta_{i,\Delta CV19I}$ for the global energy sector. In Figure 4, this difference is more than five-fold. Moreover, due to the fact that $OIU_{i,\Delta CV19I}$ directly reflects the intensity of the impact of the COVID-19 related uncertainty, in some markets, where intensity is weak, i.e. the values of $\varphi_{i,\Delta CV19I}$ are small, the overall impact of uncertainty is lower compared to what is implied only by $\beta_{i,\Delta CV19I}$. For example, $OIU_{i,\Delta CV19I}$ for Canada, the UK and Italy diminishes substantially, after intensity is taken into account, to less than one in terms of its ratio with $OIU_{i,\Delta CV19I}$ for the world energy index, while for these three countries the same ratios are much greater than 1 (see Figure 2).

Figure 4: Overall impact of COVID-19 related uncertainty (OIU) on national energy sectors



This figure plots the measure of the overall impact of COVID-19 related uncertainty on the global energy sector and 20 national energy sector indices ($OIU_{i,\Delta CV19I}$) grouped by region, together with three broad regional averages for Australasia, Europe and the Americas. $OIU_{i,\Delta CV19I}$ is calculated as the product of the magnitude of the impact ($\beta_{i,\Delta CV19I}$) and the intensity of the impact ($\varphi_{i,\Delta CV19I}$) of COVID-19 related uncertainty.

4.3. The Role of Oil

In the next step, we turn our attention to the analysis of $\beta_{i,\Delta OIL}$ estimates, which are reported in Panel A of Table 4. The impact of oil price changes, ΔOIL_t, on energy sector returns is significant and positive for the MSCI World Energy index ($\beta_{i,\Delta OIL}$ of 0.3639) and all national energy sectors. Positive $\beta_{i,\Delta OIL}$ estimates indicate that a decrease in the oil price triggers lower returns. This effect is expected given that the crude oil price is an important determinant of revenue for companies involved in the production, exploration and refining of oil and gas. Additionally, the demand for oil is moderately to highly price inelastic (Cooper, 2003; Narayan & Smyth, 2007; Dash et al., 2018) and, thus, increased revenues from higher oil prices are likely to exceed any related reduction in demand. Investments in the oil and gas sector are more probable with higher oil prices, resulting in a greater need for related equipment and services, boosting returns for firms in this sub-sector. This is consistent with the results of prior studies (Sadorsky, 2001; Nandha & Faff, 2008; Elyasiani et al., 2011; Bianconi & Yoshino, 2014) that show that stock prices in the oil and gas sector are positively impacted by changes in the oil price.

The impact of oil price movements can be related to stock prices through the role of oil as a proxy for macroeconomic conditions and the impact of oil prices on economic conditions which, in turn, impact expected cash flows and discount rates (Jones & Kaul, 1996; Arouri et al., 2011). Given the nature of the energy sector, oil prices are of particular importance. The energy sector has been shown to move with oil prices and the macroeconomic environment. For example, Sadorsky (2001) report that Canadian oil and gas stock prices respond positively to oil price movements while increases in interest and exchanges rates have a negative effect. Boyer and Filion (2007) document that Canadian energy stock returns are positively impacted by interest rates and negatively impacted by exchange rate (Canadian Dollar/US Dollar) movements. Sadorsky (2008), Ramos and Veiga (2011) and Bianconi and Yoshino (2014) find that oil price changes have positive effects on oil and gas stock returns, arguing that changes in oil prices, interest rates, and foreign exchange rates are systematic risk factors for firms operating in this sector. Oil prices impact profits and operating costs, interest rates impact investment costs, and foreign exchange rates determine input costs as well as profits (Liu & Kemp, 2019), thus impacting returns on energy stocks. Henriques and Sadorsky (2008) note that rising oil prices impact the discount rate because rising oil prices are often indicative of inflationary pressures which central banks can control by raising interest rates**.** Kang et al. (2017) report hat that oil demand-side shocks have a positive impact on oil and gas stock returns, while policy uncertainty shocks have a negative impact and suggest that the effects of oil shocks on stock returns are amplified by policy uncertainty. Liu and Kemp (2019) suggest that the most useful information for predicting the future performance of the energy industry is mostly reflected by output, income, labour markets, prices, interest, exchange rates, monetary aggregates and stock market behaviour.

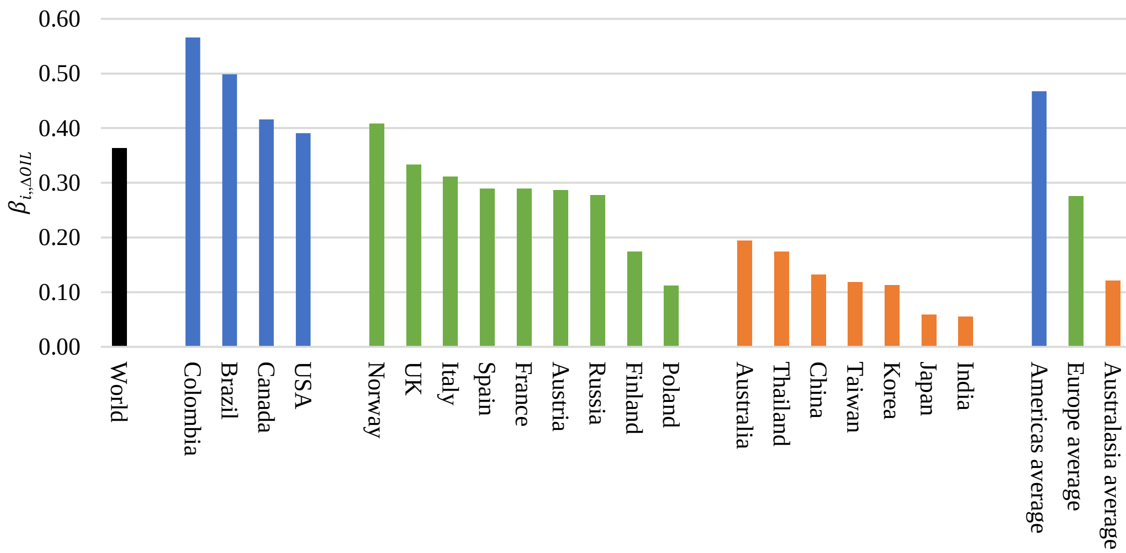
The macroeconomic state impacts oil prices and oil price volatility. Sadorsky (2001) and Hamilton (2003) explore the sources of oil price shocks and find that oil prices are themselves affected by macroeconomic forces suggesting that oil price shocks may not be exogenous as macroeconomic forces affect systematic asset price risk (Gupta, 2016). Ratti and Vespignani (2016) report that the world oil price is positively related to proxies of the macroeconomic state, namely global output (industrial production), inflation and the money supply. Barsky and Kilian (2001) argue that a change in monetary policy regimes was a key factor behind oil price increases of the 1970s. Ratti and Vespignani (2013) report that shocks to the global real money supply have statistically significant effects on real oil prices and global oil production. Belke et al. (2014) find bidirectional causality between global monetary aggregates and oil prices with the view that oil prices serve as an important information variable for the conduct of monetary policy by signalling future movements in macroeconomic variables. Kilian (2010) and Kilian and Murphy (2014) document that the bulk of the 2003-2008 increase in the real price of oil was caused by fluctuations in the global business cycle, driven in large part by unexpected growth in emerging Asia superimposed on strong growth in the OECD grouping. van Robays (2016) explains that during periods of increased macroeconomic uncertainty, oil prices become more sensitive to shocks in oil demand and supply, which implies that oil fundamentals explain a larger part of oil price variability during periods of increased uncertainty. Similarly, Chatziantoniou et al. (2021) suggest that realised oil price volatility movements are attributed to changes in oil market fundamentals and highlight the importance of financial shocks that transmit information, contributing to contributing to a significant variation in oil prices. In other words, macroeconomic uncertainty is associated with higher oil price volatility.

What emerges from the preceding discussion is that the macroeconomic environment impacts the energy sector directly and through the oil price. While we do not reflect macroeconomic factors in equation (1), the impact of the macroeconomic state is reflected by the factor analytic augmentation, $\sum_{k\geq 0}^{k} \beta_{i,k} F_{k,t}$. However, we include ΔOIL_t in this equation, which as suggested by the literature, is impacted by innovations in the macroeconomic environment. Therefore, the impact of oil prices on energy sector returns, as measured by $\beta_{i,\Delta OIL}$, is also related to the macroeconomic fundamentals that impact the oil market. In other words, $\beta_{i,\Delta OIL}$ indirectly reflects that impact of the macroeconomic state. As oil prices move positively with the macroeconomic state, a positive $\beta_{i,\Delta OIL}$ is expected.

The impact of movements in the oil price varies in magnitude across countries. It is highest for Colombia and Brazil with $\beta_{i,\Delta OIL}$ parameters of 0.5657 and 0.4984, respectively, and lowest for India and Japan with $\beta_{i,\Delta OIL}$ coefficients of 0.0552 and 0.0589, respectively. As shown in Figure 5, regional variation in $\beta_{i,\Delta OIL}$ estimates are very similar to patterns observed for other parameters discussed earlier. Energy sectors in the

Americas are most sensitive to changes in oil prices, followed by European energy sectors, with Australasian energy sectors being the least responsive. Averages of the respective $\beta_{i,\Delta OIL}$ estimates are 0.4677, 0.2759 and 0.1210 for the Americas, Europe and Australasia. This means that American energy sectors are, on average, nearly four times more sensitive to oil price movements relative to Australasian ones.[8] There appears also to exist a link with geographical distance (to the west of China) and the impact of oil price changes on energy sector returns consistent with the spread of the virus in a westerly direction. This effect, however, may also be linked to the net oil (energy) import/export position of each country, which we examine further below.

Figure 5: Impact of ΔOIL_t on the global energy sector and national energy sectors with regional averages



This figure plots the estimates of oil price changes on the returns of the world energy index and 20 national energy sectors ($\beta_{i,\Delta OIL}$) grouped by region, and their three regional averages (Australasia, Europe and the Americas).

In order to explain the differences between estimates across national energy sectors, we divide the markets into four groups as follows: (a) net oil exporters (Austria, Brazil, Canada, Colombia, Russia and Norway), (b) net oil importers (China, India, Australia, Thailand, Japan, Taiwan, Korea, UK, France, Italy, Finland, Spain, Poland and US), (c) net energy exporters (Australia, Brazil, Canada, Colombia, Russia, Norway and US) and (d) net energy importers[9] (Austria, Thailand, China, Taiwan, Korea, Japan, India, UK, Italy, Spain, France, Finland and Poland). To do so, we use International Energy Agency (2020) data for all 20 countries.

[8] The low impact on the returns for Chinese oil and gas companies is broadly consistent with the results of Caporale et al. (2015), who found that oil price volatility has no impact on Chinese oil and gas sector returns during periods characterised by demand-side shocks.
[9] The definition of energy encompasses oil, coal and gas (IEA, 2020) and aligns with our sample.

Table 5 presents average values of key parameters from Table 4 and the $OIU_{i,\Delta CV19I}$ measure, which comprehensively capture the effects of COVID-19 uncertainty on the net oil/ energy exporters and importers. A consistent pattern emerges as the net oil exporting countries and net energy exporting countries have higher average values of all three parameters, namely $\beta_{i,\Delta CV19I}$, $\varphi_{i,\Delta CV19I}$ and $OIU_{i,\Delta CV19I}$. For $\beta_{i,\Delta CV19I}$, the difference is 36% and 25% higher, respectively, while for $\varphi_{i,\Delta CV19I}$ and $\beta_{i,\Delta OIL}$, it is roughly twice as large relative to net oil and energy importers. This regularity, depicted in Table 5, means that oil and energy net exporters are more sensitive to COVID-19 related uncertainty. We interpret this finding as attributable to the negative effect of lower energy prices - in particular, lower oil prices - as a consequence of the pandemic, which during national lockdowns impacted energy and oil exporters more severely than energy and oil importers, as evidenced by $\beta_{i,\Delta CV19I}$ averages. While lower energy and oil prices are beneficial for energy and oil importing countries through lower input costs, they adversely impact energy and oil exporting countries by negatively affecting the profitability of energy firms and, more specifically, oil companies in those markets.[10] This interpretation is further supported by results illustrating the impact on risk, which is substantially stronger in the group of energy and oil exporting countries as evidenced by higher $\varphi_{i,\Delta CV19I}$ averages. Moreover, the returns for these markets' energy sectors are also more sensitive to COVID-19 related uncertainty as indicated by, in turn, higher $\beta_{i,\Delta OIL}$ averages.

Table 5: Averages of $\boldsymbol{\beta_{i,\Delta CV19I}}$, $\boldsymbol{\varphi_{i,\Delta CV19I}}$, $\boldsymbol{\beta_{i,\Delta OIL}}$ estimates and the $\boldsymbol{OIU_{i,\Delta CV19I}}$ measure

	Panel A: Averages based on oil trade		**Panel B. Averages based on energy trade**	
	Net Oil Exporters	**Net Oil Importers**	**Net Energy Exporters**	**Net Energy Importers**
$\boldsymbol{\bar{\beta}_{i,\Delta CV19I}}$	-0.0038	-0.0028	-0.0035	-0.0028
$\boldsymbol{\bar{\varphi}_{i,\Delta CV19I}}$	0.2391	0.119	0.2163	0.122
$\boldsymbol{\overline{OIU}_{i,\Delta CV19I}}$	-0.000886	-0.000322	-0.000772	-0.00034
$\boldsymbol{\bar{\beta}_{\Delta OIL,i}}$	0.4088	0.1963	0.3931	0.1884

This table reports the averages of the $\beta_{i,\Delta CV19I}$, $\varphi_{i,\Delta CV19I}$, $\beta_{i,\Delta OIL}$ estimates and the $OIU_{i,\Delta CV19I}$ measure for net oil exporters and importers in Panel A and net energy exporters and importers in Panel B. Net oil exports comprise Austria, Brazil, Canada, Colombia, Russia and Norway and the net oil importers comprise China, India, Australia, Thailand, Japan, Taiwan, Korea, UK, France, Italy, Finland, Spain, Poland and the US. Net energy exporters comprise Australia, Brazil, Canada, Colombia, Russia, Norway and US and the net energy importers comprise Austria, Thailand, China, Taiwan, Korea, Japan, India, UK, Italy, Spain, France, Finland and Poland.

These patterns are concisely captured by our measure of the overall impact of uncertainty, which is more than twice as high in the group of net energy and oil exporting countries as it is evident from $OIU_{i,\Delta CV19I}$ averages. In other words, using the weather metaphor outlined previously, the impact of the rainstorm in terms of its magnitude and intensity is much stronger for markets whose economies are more vulnerable to lower energy prices, and in particular, lower oil prices.

[10] See Szczygielski and Chipeta (2015) for a synthesis of literature on the differential impact of oil prices on national markets.

Finally, we verify the relationships between the parameters capturing COVID-19 related uncertainty, as well as our overall impact of uncertainty measure, and actual exports and imports of oil and energy for countries in our sample. For this purpose, we define $NetOilExpImp_i$ as net oil exports and imports for country i and $NetEnergyExpImp_i$ as the net energy exports and imports for country i. Consequently, we specify the models as shown in Table 6. The respective dummy variables for the net oil exporting countries are defined as $D^{Oil}_{i,\beta_{i,\Delta CV19I}}$, $D^{Oil}_{i,\varphi_{i,\Delta CV19I}}$, $D^{Oil}_{i,OIU_{i,\Delta CV19I}}$ and $D^{Oil}_{i,\beta_{i,\Delta OIL}}$ and those for the net energy exporting countries are defined as $D^{Energy}_{i,\beta_{i,\Delta CV19I}}$, $D^{Energy}_{i,\varphi_{i,\Delta CV19I}}$, $D^{Energy}_{i,OIU_{i,\Delta CV19I}}$ and $D^{Energy}_{i,\beta_{i,\Delta OIL}}$. Dummies take on a value of 1 when a country is a net oil or energy exporter, respectively, and 0 otherwise.

Table 6: Specifications estimated

Panel A: Specification for net oil exporters	
$\beta_{i,\Delta CV19I} = \lambda^{Oil}_{i,\beta_{i,\Delta CV19I}} + \gamma^{Oil}_{i,\beta_{i,\Delta CV19I}} D^{Oil}_{i,\beta_{i,\Delta CV19I}} + \delta^{Oil}_{i,\beta_{i,\Delta CV19I}} NetOilExpImp_i + \varepsilon_i$	(6a)
$\varphi_{i,\Delta CV19I} = \lambda^{Oil}_{i,\varphi_{i,\Delta CV19I}} + \gamma^{Oil}_{i,\varphi_{i,\Delta CV19I}} D^{Oil}_{i,\varphi_{i,\Delta CV19I}} + \delta^{Oil}_{i,\varphi_{i,\Delta CV19I}} NetOilExpImp_i + \varepsilon_i$	(6b)
$OIU_{i,\Delta CV19I} = \lambda^{Oil}_{i,OIU_{i,\Delta CV19I}} + \gamma^{Oil}_{i,OIU_{i,\Delta CV19I}} D^{Oil}_{i,OIU_{i,\Delta CV19I}} + \delta^{Oil}_{i,OIU_{i,\Delta CV19I}} NetOilExpImp_i + \varepsilon_i$	(6c)
$\beta_{i,\Delta OIL} = \lambda^{Oil}_{i,\beta_{i,\Delta OIL}} + \gamma^{Oil}_{i,\beta_{i,\Delta OIL}} D^{Oil}_{i,\beta_{i,\Delta OIL}} + \delta^{Oil}_{i,\beta_{i,\Delta OIL}} NetOilExpImp_i + \varepsilon_i$	(6d)
Panel B: Specifications for net energy exporters	
$\beta_{i,\Delta CV19I} = \lambda^{Energy}_{i,\beta_{i,\Delta CV19I}} + \gamma^{Energy}_{i,\beta_{i,\Delta CV19I}} D^{Energy}_{i,\beta_{i,\Delta CV19I}} + \delta^{Energy}_{i,\beta_{i,\Delta CV19I}} NetOilExpImp_i + \varepsilon_i$	(7a)
$\varphi_{i,\Delta CV19I} = \lambda^{Energy}_{i,\varphi_{i,\Delta CV19I}} + \gamma^{Energy}_{i,\varphi_{i,\Delta CV19I}} D^{Energy}_{i,\varphi_{i,\Delta CV19I}} + \delta^{Energy}_{i,\varphi_{i,\Delta CV19I}} NetOilExpImp_i + \varepsilon_i$	(7b)
$OIU_{i,\Delta CV19I} = \lambda^{Energy}_{i,OIU_{i,\Delta CV19I}} + \gamma^{Energy}_{i,OIU_{i,\Delta CV19I}} D^{Energy}_{i,OIU_{i,\Delta CV19I}} + \delta^{Energy}_{i,OIU_{i,\Delta CV19I}} NetOilExpImp_i + \varepsilon_i$	(7c)
$\beta_{i,\Delta OIL} = \lambda^{Energy}_{i,\beta_{i,\Delta OIL}} + \gamma^{Energy}_{i,\beta_{i,\Delta OIL}} D^{Energy}_{i,\beta_{i,\Delta OIL}} + \delta^{Energy}_{i,\beta_{i,\Delta OIL}} NetOilExpImp_i + \varepsilon_i$	(7d)

This table lists the cross-sectional specifications fitted in this study to assess the impact of net oil trade, equations (6a) – (6d), and net energy trade, equations (7a) – (7d), on the coefficients from the regression results presented in Table 4.

Table 7 reports estimates for coefficients on the dummies in specifications (6a) - (7d). Results show similar effects as in Table 5. Net oil and energy exporters are clearly more sensitive to COVID-19 related uncertainty than the net oil and energy importers. Estimates of all dummy variables are statistically significant with the exception of $\gamma^{Oil}_{i,\beta_{i,\Delta CV19I}}$ and $\gamma^{Energy}_{i,\beta_{i,\Delta CV19I}}$, although for $\gamma^{Oil}_{i,\beta_{i,\Delta CV19I}}$ the estimate is marginally insignificant (with a p-value equal to 0.1374). Results for specifications (6a) - (7d) thus provide confirmatory evidence that COVID-19 uncertainty impacts those national energy sectors more severely for which the drop in energy prices and, in particular, oil prices during the pandemic was more painful, namely those that are net oil and energy exporters.

Table 7: Summarised results for specifications in Table 6

Panel A: Net oil exporters				
Eq.	**(6a)**	**(6b)**	**(6c)**	**(6d)**
Coeff.	$\gamma_{i,\beta_{i,\Delta CV19I}}^{Oil}$	$\gamma_{i,\varphi_{i,\Delta CV19I}}^{Oil}$	$\gamma_{i,OIU_{i,\Delta CV19I}}^{Oil}$	$\gamma_{i,\beta_{i,\Delta OIL}}^{Oil}$
Estimate	-0.000930	0.134621 ***	-0.000651 ***	0.223559 ***
Panel B: Net energy exporters				
Eq.	**(7a)**	**(7b)**	**(7c)**	**(7d)**
Coeff.	$\gamma_{i,\beta_{i,\Delta CV19I}}^{Energy}$	$\gamma_{i,\varphi_{i,\Delta CV19I}}^{Energy}$	$\gamma_{i,OIU_{i,\Delta CV19I}}^{Energy}$	$\gamma_{i,\beta_{i,\Delta OIL}}^{Energy}$
Estimate	-0.000446	0.150361 ***	-0.000551 ***	0.263524 ***

This table reports summarized results from the specifications in Table 6. Coefficients on the dummy variables in equations (6a) – (6d) are presented in Panel A, where the dummy is set to one for net oil exporting markets (Austria, Brazil, Canada, Colombia, Russia and Norway). The coefficients from the dummy variables in equations (7a) to (7d) are presented in Panel B, with the dummies set to one for net energy exporting markets (Australia, Brazil, Canada, Colombia, Russia, Norway and US). Asterisks *** indicate statistical significance at the 1% level of significance.

In summary, "rainstorm events" such as the COVID-19 pandemic appear to have a more severe impact on markets which are net oil and energy exporters, both in terms of magnitude and intensity, relative to those which are net importers of oil and energy.

4.4. Specification Adequacy

The aim of this study is to quantify the impact of the COVID-19 uncertainty, captured by $\Delta CV19I_t$, on energy sectors returns. However, if the diagonality assumption is violated as a result of model underspecification and $\Delta CV19I_t$ is not orthogonal to other COVID-19 related factors, then the coefficient on $\Delta CV19I_t$, $\beta_{i,\Delta CV19I}$, will be biased. We therefore apply the factor analytic augmentation technique expounded by Szczygielski, Brümmer and Wolmarans (2020) to account for the common drivers of national energy sector returns. In this section, we demonstrate the efficacy of this approach and confirm the validity of equation (1). As shown in Table 8, we re-specify equation (1) to exclude the factor analytic augmentation, $\sum_{k\geq 0}^{k} \beta_{i,k} F_{k,t}$ (equation (8)). Thereafter, we include a global market index, (equation (9)), the MSCI World Market Index, $R_{M,t}$, in place of $\sum_{k\geq 0}^{k} \beta_{i,k} F_{k,t}$ (see Clare & Priestley, 1998; Bilson et al., 2001; Brown et al., 2009; Szczygielski & Chipeta, 2015 for a discussion of the role of a global equity index in factor models). We also incorporate the MSCI World Energy Index, $R_{I,t}$, in equation (10) and replace $\sum_{k\geq 0}^{k} \beta_{i,k} F_{k,t}$ with a combination of both $R_{I,t}$ and $R_{M,t}$ in equation (11). All equations are estimated using the ordinary least squares method.

The respective residual correlation matrices are factor analysed using the MAP test to identify the remaining number of common factors, if any. The equality of the pairwise residual correlation matrices for equations (8) to (11) is also tested against that of the unrestricted specification in equation (1) to determine whether

$\sum_{k\geq 0}^{k}\beta_{i,k}\,F_{k,t}$ accounts for information omitted in equations (8) to (11) (Meyers, 1973; McElroy & Burmeister, 1988; van Rensburg, 2000; Szczygielski, Brümmer & Wolmarans, 2020).

Table 8: Alternative conditional mean specifications

Model	Specification	
Restricted	$r_{i,t} = \alpha_i + \beta_{i,\Delta CV19I}\Delta CV19I_t Dum_{0,1} + \beta_{\Delta OIL,i}\Delta OIL_t + \sum_{\tau\geq 0}^{\tau}\gamma_{i,\tau}\, r_{i,t-\tau} + \varepsilon_{i,t}$	(8)
Market	$r_{i,t} = \alpha_i + \beta_{i,\Delta CV19I}\Delta CV19I_t Dum_{0,1} + \beta_{\Delta OIL,i}\Delta OIL_t + \beta_{\Delta M,i}R_{M,t} + \sum_{\tau\geq 0}^{\tau}\gamma_{i,\tau}\, r_{i,t-\tau} + \varepsilon_{i,t}$	(9)
Industry	$r_{i,t} = \alpha_i + \beta_{i,\Delta CV19I}\Delta CV19I_t Dum_{0,1} + \beta_{\Delta OIL,i}\Delta OIL_t + \beta_{\Delta I,i}R_{I,t} + \sum_{\tau\geq 0}^{\tau}\gamma_{i,\tau}\, r_{i,t-\tau} + \varepsilon_{i,t}$	(10)
Combined	$r_{i,t} = \alpha_i + \beta_{i,\Delta CV19I}\Delta CV19I_t Dum_{0,1} + \beta_{\Delta OIL,i}\Delta OIL_t + \beta_{\Delta I,i}R_{I,t} + \beta_{\Delta M,i}R_{M,t} + \sum_{\tau\geq 0}^{\tau}\gamma_{i,\tau}\, r_{i,t-\tau} + \varepsilon_{i,t}$	(11)

This table lists the specifications fitted for comparative purposes. Each mean equation is estimated using least squares with heteroscedasticity and autocorrelation consistent (HAC) standard errors. $Dum_{0,1}$ is the shift dummy, which takes on a value of 0 during the pre-COVID-19 period, designated as 1 January 2015 to 15 December 2019 or 1 during the COVID-19 period, designated as 16 December 2019 to 17 July 2020.

As shown in Table 9, three factors, explaining 47.05% and 38.79% of common variation in the residuals, are extracted from the residuals of equations (8) and (9), respectively. In the latter instance, this result implies that returns on the MSCI World Market Index are an incomplete proxy for omitted influences. In the former instance, the higher communality indicates a higher level of underspecification for the restricted model. The Kaiser-Meyer-Olkin (KMO) index values for the residual correlation matrices in equations (8) and (9) are 0.9326 and 0.8853, respectively. Both values are favourable for factor extraction implying that both specifications fail to account for sources of common variation (see Kaiser, 1974). Two factors explaining 31.36% and 31.29% of common variation, respectively, are extracted from the residuals of equations (10) and (11). The respective KMO index values are 0.8108 and 0.8120, which is lower than those for equations (8) and (9). Although an improvement, the two factors extracted from the residual correlation matrices of both equations and favourable KMO index values point towards a violation of the diagonality assumption indicative of underspecification. In contrast, the pairwise residual correlation matrix derived from equation (1) produces a single factor with a communality of 0.1095 and KMO index value of 0.2752. This result implies that the unrestricted model adequately reflects all common factors driving national energy sectors and suggests that the single factor extracted is likely to be a transient factor that will not invalidate the specification.

Jennrich test statistics are highly significant confirming that the factor analytic augmentation accounts for information relegated to the residuals of equations (8) to (11). Interestingly, χ^2 test statistics decrease as the residual correlation matrix of the unrestricted specification, U_{20}, is compared against that of the restricted model, R_{20}, (χ^2 of 23476.24) and finally to that of equation (11) which incorporates both $R_{M,t}$ and $R_{I,t}$ (χ^2 of 18012.94). Although differences remain significant, this implies that the differences between the residual correlation matrix structures of U_{20} and C_{20} are lower than those between U_{20} and R_{20}. This is expected, given that equation (11) incorporates two proxies for omitted factors whereas none are included in equation (8) (see Sullivan & Feinn, 2012:279 for a discussion of effect size).

Table 9: Summary of residual analysis

Eq.	Factors	Communality	Uniqueness	KMO
(8) Restricted	3	0.4705	0.5295	0.9326
(9) Market	3	0.3879	0.6121	0.8853
(10) Industry	2	0.3136	0.6864	0.8108
(11) Combined	2	0.3129	0.6871	0.8120
(1) Unrestricted	1	0.1095	0.8905	0.2752
Jennrich χ^2 $(U_{20} = R_{20})$		23476.24***		
Jennrich χ^2 $(U_{20} = M_{20})$		21098.35***		
Jennrich χ^2 $(U_{20} = I_{20})$		20953.94***		
Jennrich χ^2 $(U_{20} = C_{20})$		18012.94***		

In this table, communality is the proportion of common variance explained across return series by statistical factors extracted on the basis of the MAP test. Uniqueness is the proportion of variance across return series attributable to the return series themselves and not to systematic factors**.** For the Jennrich test of matrix equality, the asterisk *** indicate statistical significance at the 1% level of significance. The null hypothesis tested is the hypothesis of the equality of two matrices. The χ^2 statistic is the resultant test statistic (with 190 degrees of freedom) for the Jennrich test. U_{20} denotes the residual correlation matrix derived from equation (1) and R_{20}, M_{20}, I_{20} and C_{20} denote the respective residual correlation matrices for equations (8) - (11).

While theoretical diagonality may be a restrictive assumption, the factor analytic augmentation results in an approximation of empirical diagonality.[11] The low communality and KMO index unfavourable to factor analysis of the pairwise residual correlation matrix derived from the unrestricted specification points towards a most likely trivial or transient factor (Szczygielski, Brümmer & Wolmarans, 2020). The factor analytic augmentation offers a simplification as it does not require the identification of the most appropriate market index or other (control) factors that are not of direct interest in this study (see Brown & Brown, 1987 for a discussion of the impact of the composition of a market proxy).

4.5. Structural Breaks

COVID-19 related uncertainty impacted the global energy sector as represented by the MSCI World Energy index, in phases, which is evident from structural breaks on 17 January, 19 February and 25 March 2020 in Table 10. The first segment coincides with an 'incubation period' (Ramelli & Wagner, 2020) during which details of the virus began to emerge. Examples are two deaths in China and the first reported cases in Thailand and Japan. The 17 January breakpoint occurs immediately prior to two notable events on 20 January, namely Chinese confirmation of human-to-human transmission of the virus and WHO issuing the first COVID-19 report. During the second segment, known as the 'outbreak period' (Ramelli & Wagner, 2020) between 17 January to 18 February, the virus spread beyond Asia, with the first of these cases

[11] Admittedly, the diagonality assumption is excessively restrictive and unattainable in practice (Connor & Korajczyk, 1993:1264). However, we argue, that an empirical approximation may be derived. Such an approximation is in the form of a pairwise residual correlation matrix which shows sporadic and insignificant pairwise residual correlation. A KMO index value of 0.2752 in Table 9 suggests this is indeed the case for the unrestricted specification, equation (1).

reported in Italy, Iran and South Korea (Think Global Health, 2020). The 19 February breakpoint occurs prior to Italy placing more than 50 000 people under strict lockdown after the first reported deaths in the country. The third segment, 'the fever period' up until 25 March (Ramelli & Wagner, 2020), coincides with the introduction of travel bans and lockdowns in many countries,[12] WHO's declaration of COVID-19 as a pandemic on 11 March and a dramatic fall in global stock markets. The final structural break on 25 March occurs after three significant events on the previous day: the US reaching 50 000 cases, Japan postponing the Olympics and China lifting the lockdown on Hubei province (Think Global Health, 2020), with the latter event providing an indication of the containment of the virus at the source of origin.

During the incubation period, COVID-19 uncertainty had no impact on global energy sector returns as an aggregate. Following the first break on 17 January, the effect on returns was negative and significant, ($\beta_{i,2,\Delta CV19I}$ of -0.0018), intensifying after the second break in mid-February ($\beta_{i,3,\Delta CV19I}$ of -0.0051), which coincides with the fever period (see Panel A, Table 10). Following the third break in late March, COVID-19 uncertainty no longer appears to impact the global energy sector. This is consistent with the virus appearing to be contained in Hubei province (Think Global Health, 2020) and with the findings of Szczygielski et al. (2021) of a weakening impact of COVID-19 related uncertainty on stock returns after late March across some regions. The dissipating impact of uncertainty on returns can potentially be attributed to the crisis being viewed by economic agents as no longer novel but rather a persistent situation. The onset of the volatility triggering effects of COVID-19 related uncertainty is delayed, occurring only during the 'fever period' post 19 February and persists after the third structural break on 25 March, with $\varphi_{i,3,\Delta CV19I}$ and $\varphi_{i,4,\Delta CV19I}$ statistically significant and equal to 0.1280 and 0.1250, respectively.

The Korean, Thai, Taiwanese and Chinese energy sectors – all located in east Asia – do not experience a time-varying impact of COVID-19 related uncertainty, as evident from an absence of structural breaks in the return-$\Delta CV19I_t$ relationship. For these countries, this finding attests to a stable relationship between $\Delta CV19I_t$ and returns and volatility throughout the study period. As set out in Section 4.1., while all these countries experienced a significant negative impact on returns, only the Chinese and Korean energy sectors experienced a significant increase in volatility associated with COVID-19 related uncertainty. The immediate and sustained impact of COVID-19 related uncertainty on returns in all four east Asian markets is consistent with prior studies which have found that stock returns on these financial markets reacted immediately to the virus with this effect being attributable to the source of the outbreak being in China (Liu et al., 2020; Ru et al., 2020; Szczygielski et al., 2021).

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[12] By 26 March 2020, almost one third of the world's population were living under some form of lockdown (Think Global Health, 2020).

Table 10: Model results for energy sectors with breaks

Country	**World Energy**	**1. USA**	**2. Russia**	**3. UK**	**4. China**	**5. Canada**	**6. India**	**7. France**
				Panel A: Conditional mean				
Breakpoints	17/01/2020 19/02/2020 25/03/2020	05/02/2020 25/03/2020	25/03/2020	02/03/2020 07/04/2020		19/02/2020 26/03/2020	12/03/2020	19/03/2020 05/05/2020
Intercept	-0.0003	-0.0003***	0.0006*	-0.0001		-0.0003***	0.0006*	-0.0001
$\beta_{i,1,\Delta CV19I}$	0.0011	-0.0017***	-0.0034***	-0.0034***		-0.0038***	-0.0022***	-0.0027***
$\beta_{i,2,\Delta CV19I}$	-0.0018***	-0.0045***	-0.0033***	-0.0050***		-0.0045***	-0.0042***	-0.0046***
$\beta_{i,3,\Delta CV19I}$	-0.0051***	-0.0019**	-	-0.0037***		-0.0043***		0.0006
$\beta_{i,4,\Delta CV19I}$	-0.0013	-	-					
$\beta_{i,\Delta OIL}$	0.3645***	0.3910***	0.2771***	0.3300***		0.4154***	0.0559***	0.2891***
Proxy factors	0.0003F_{4t}	-0.0019F_{3t}***	0.0082F_{2t}***	0.0125F_{2t}***		0.0074F_{2t}***	0.0034F_{2t}***	0.0009F_{4t}***
AR Terms		0.1350r_{t-1} ***	0.0352r_{t-1} ***				0.0406r_{t-1}	-0.0741r_{t-4}***
				Panel B: Conditional variance				
ARCH/GARCH	IGARCH(1,1)	GARCH(2,1)	IGARCH(1,1)	IGRACH(2,1)		IGARCH(2,1)	IGARCH(2,1)	GARCH(1,1)
ω_i		6.80E-07**						2.09E-06**
α_1	0.0545***	0.0984***	0.0452***	0.1554***		0.1484***	0.0863***	0.0459***
α_2		-0.0645*		-0.1463***		-0.1322***	-0.0748***	
β_1	0.9649***	0.9515***	0.9548***					
β_2						0.9838***	0.9885***	0.9380***
β_3								
$\varphi_{i,1,\Delta CV19I}$	0.0743	0.0573**	0.1470**	0.0199**		0.0141**	0.0687**	0.2870***
$\varphi_{i,2,\Delta CV19I}$	0.0095	0.0953**	0.1700***	0.0921		0.0518***	0.1190*	0.2180
$\varphi_{i,3,\Delta CV19I}$	0.1280***	0.0075		0.108**		0.0631***		0.1200
$\varphi_{i,4,\Delta CV19I}$	0.1250***							
				Panel C: Model diagnostics				
$\bar{R}^2$	0.6798	0.7531	0.4961	0.8669		0.8818	0.2755	0.3077
$Q(1)$	0.3094	10.023	1.3114	0.6404		1.2139	0.8124	1.4006
$Q(10)$	6.6607	9.8456	7.6880	10.790		5.6614	14.430	11.626
ARCH(1)	0.8154	0.0021	0.1261	0.4786		0.4199	1.1145	0.1504
ARCH(10)	0.6429	0.3728	0.7463	1.1349		0.6749	1.1263	1.2178
Log-likelihood	4983.383	5030.650	4348.765	5313.030		5353.162	4173.918	4301.749

Table 10: Model results for energy sectors with breaks (continued…)

Country	8. Brazil	9. Norway	10. Italy	11. Australia	12. Thailand	13. Colombia	14. Japan	15. Taiwan
Panel A: Conditional mean								
Breakpoints	19/02/2020 25/03/2020	19/02/2020 15/03/2020	20/02/2020 26/03/2020	16/01/2020 21/02/2020 25/03/2020		21/02/2020 25/03/2020	25/03/2020	
Intercept	-0.0004	0.0010	-0.0003*	-0.0001		0.0002	0.0002	
$\beta_{i,1,\Delta CV19I}$	-0.0040***	-0.0012*	-0.0041***	-0.0097**		-0.0026***	-0.0017***	
$\beta_{i,2,\Delta CV19I}$	-0.0079***	-0.0063***	-0.0044***	-0.0013***		-0.0055***	-0.0004	
$\beta_{i,3,\Delta CV19I}$	-0.0045***	0.0001	-0.0030***	-0.0052**		-0.0009		
$\beta_{i,4,\Delta CV19I}$				-0.0020***				
$\beta_{i,\Delta OIL}$	0.4927***	0.4006***	0.3109***	0.1913		0.5539***	0.0594***	
Proxy factors	0.0097F_{2t}***	-0.0026F_{1t}**	0.0127F_{2t}***	0.0058F_{2t}***		0.0026F_{4t}***	0.0006F_{1t}	
AR Terms	-0.0129r_{t-1}***	-0.0960r_{t-1}***		-0.0402r_{t-3}**		-0.0276r_{t-1}	-0.0966r_{t-1}***	
Panel B: Conditional variance								
ARCH/GARCH	IGARCH(1,1)	IGARCH(1,1)	IGARCH(1,1)			IGARCH(1,1)	GARCH(1,1)	
ω_i							4.97E-06	
α_1	0.0765***	0.0516**	0.0372***	0.0389***		0.0386***	0.0370	
α_2								
β_1	0.9235***	0.9484***	0.9628***	0.9610***		0.9614***	0.9317	
β_2								
β_3								
$\varphi_{i,1,\Delta CV19I}$	0.1110	0.0705	0.0015	0.0078		0.0131	0.156	
$\varphi_{i,2,\Delta CV19I}$	0.9390**	0.367**	0.0860	0.0392		0.414***	0.0752**	
$\varphi_{i,3,\Delta CV19I}$	0.2840	0.372**	0.0793***	0.1380**		0.337*		
$\varphi_{i,4,\Delta CV19I}$				0.1440***				
Panel C: Model diagnostics								
$\bar{R}^2$	0.4017	0.3404	0.8470	0.6656		0.4179	0.4047	
$Q(1)$	0.1041	0.5395	0.7943	2.0643		1.6095	1.5789	
$Q(10)$	7.3073	10.386	9.3097	11.707		8.4235	10.393	
ARCH(1)	0.3359	0.6073	2.5224	0.0073		0.4153	0.0395	
ARCH(10)	0.2384	0.5622	0.6163	0.5689		1.2484	0.5946	
Log-likelihood	3309.389	3241.478	5282.053	4543.296		3651.684	4249.103	

Table 10: Model results for energy sectors with breaks (continued…)

Country	**16. Finland**	**17. Spain**	**18. Korea**	**19. Poland**	**20. Austria**
Panel A: Conditional mean					
Breakpoints		17/04/2020		04/02/2020 13/03/2020	19/02/2020 26/03/2020
Intercept		0.0003		0.0001	7.44E-05
$\beta_{i,1,\Delta CV19I}$		-0.0042***		-0.0017	-0.0038***
$\beta_{i,2,\Delta CV19I}$		-0.0026***		-0.0044***	-0.0055***
$\beta_{i,3,\Delta CV19I}$				-0.0018***	0.0031***
$\beta_{i,4,\Delta CV19I}$					
$\beta_{i,\Delta OIL}$		0.2893***		0.0989***	0.3148***
Proxy factors		0.0136F_{2t}***		0.0066F_{2t}*** 0.0023F_{4t}*** 0.0031F_{8t}***	0.0137F_{2t}*** 0.0006F_{3t}*** 0.0010F_{4t}** 0.0020F_{8t}***
AR Terms					-0.0767r_{t-1} **
Panel B: Conditional variance					
ARCH/GARCH				IGARCH(1,1)	GARCH(1,2)
ω_i					1.45E-05***
α_1		0.0288***		0.0097	0.0814***
α_2					
β_1		0.9712		0.9903	-0.0102
β_2					0.8268***
β_3					
$\varphi_{i,1,\Delta CV19I}$		0.0594***		0.105*	-0.0377
$\varphi_{i,2,\Delta CV19I}$		0.1210***		0.0851*	0.5290**
$\varphi_{i,3,\Delta CV19I}$				0.151**	0.0473
$\varphi_{i,4,\Delta CV19I}$					
Panel C: Model diagnostics					
$\bar{R}^2$		0.7960		0.2512	0.6272
$Q(1)$		0.4765		1.6928	0.1697
$Q(10)$		7.4564		7.0085	1.9258
ARCH(1)		0.5822		0.0181	0.2358
ARCH(10)		0.2468		1.5263	0.6723
Log-likelihood		4958.334		3935.025	2754.216

This table reports the impact of changes in COVID-19 related uncertainty on the returns ($\beta_{i,\pi,\Delta CV19I}$) and variance ($\varphi_{i,\pi,\Delta CV19I_t}$) for global and nations energy sectors, taking into account structural breaks. Segments are identified using the Bai-Perron test of L+1 vs L sequentially determined breaks with robust standard errors (HAC) and heterogenous error distributions. Coefficients on $\Delta CV19I_t$ in the conditional variance equation are scaled by 10 000. Energy markets are ordered largest to smallest in terms of market capitalisation in US Dollars. Panel A reports estimation results for the conditional mean, which also includes proxy factors derived from national energy sector returns using factor analysis. Panel B reports results for the conditional variance. Panel C reports model diagnostics, with $Q(1)$ and $Q(10)$ being Ljung-Box tests statistics for joint serial correlation at the 1st and 10th orders. ARCH(1) and ARCH(10) are test statistics for the ARCH LM test for heteroscedasticity. Breakpoint identifies the date on which each structural change occurs during the COVID-19 period. Pre-COVID-19 and COVID-19 periods are defined as 1 January 2015 to 15 December 2019 and 16 December 2019 to 17 July 2020 respectively. Each model is estimated over the primary data period between 1 January 2015 and 17 July 2020 unless residuals show dependence structures in which case differing estimation periods are used. Asterisks ***,** and * indicate statistical significance at 1%, 5% and 10% levels of significance, respectively.

Most national energy sectors experienced two structural breaks with largely similar timings. The first break occurring predominantly in mid-February and the second in late March 2020, as seen for Canada, Brazil and Norway, amongst others. The timing of these structural breaks is largely consistent with the timing of the breaks for the MSCI World Energy index. The first segment for most national energy sectors corresponds with the first two segments identified for the global energy sector capturing the incubation and outbreak phases, with the break coinciding with fever period as the virus spread rapidly around the world. The second break coincides with the implementation of hard lockdowns by many countries to curb the spread of COVID-19. The coefficient estimates show that the negative impact of COVID-19 related uncertainty on energy sector returns was immediate, with $\beta_{i,1,\Delta CV19I}$ estimates (first period coefficients) significant for 18 of the 20 national energy sectors. This effect intensified as the crisis evolved. For example, the $\beta_{i,2,\Delta CV19I}$ (second period) coefficients for Brazil and UK of -0.0079 and -0.0050, respectively, are more negative than the $\beta_{i,1,\Delta CV19I}$ (first period) coefficients of -0.0040 and -0.0050, respectively.

Following the late March structural break, there is evidence that the negative effect of COVID-19 uncertainty on returns dissipates in some national energy sectors. For example, in the US and UK, $\beta_{i,3,\Delta CV19I}$ (third period) coefficients of -0.0018 and -0.0037, respectively, are smaller than the $\beta_{i,2,\Delta CV19I}$ (second period) coefficients of -0.0045 and -0.0050, respectively, although the effect is still significant. The same is true for Canada, Brazil, Italy, Poland and Australia. The dissipating effect of COVID-19 uncertainty on returns is seen more strongly in France, Norway, Colombia and Austria, where the $\beta_{i,3,\Delta CV19I}$ coefficients are not only smaller in magnitude than the $\beta_{i,2,\Delta CV19I}$ coefficients but also insignificant as shown by those in France and Norway, having respective magnitudes of 0.0006 and -0.0046, and 0.0001 and -0.0063, respectively. As with the results in Section 4.1, oil continues to have a significant positive impact on returns on most national energy sectors except for Australia and Austria.

The discovery of an increasing impact of $\Delta CV19I_t$ on energy stock returns is in line with the finding of Dutta et al. (2020) that COVID-19 related announcements in March 2020 had a greater impact on US energy sector returns relative to announcements in January 2020. The immediate response of national energy sectors in Europe and the Americas to COVID-19 related uncertainty differs from studies of broad stock market indices in these countries, which have shown more delayed reactions to COVID-19 (Ru et al., 2020; Gormsen & Koijen, 2020). An immediate response may reflect that energy sectors were already in the doldrums prior to the outbreak - the analysis in Section 4.7 confirms this - and thus further negative news and the uncertainty thereof was rapidly evident. This highlights the importance of this sector to economies and the fear that the virus may have substantial ramifications for countries and, accordingly, the energy sector (Gillingham et al., 2020).

The initial effect of COVID-19 related uncertainty on energy sector return volatility is immediate for eight markets, including the six largest, but delayed in most of the smaller markets, as seen, for example, with the value of $\varphi_{i,1,\Delta CV19I}$ of 0.0573 for the US compared to 0.0015 for Italy. Furthermore, the results in Panel B of Table 10 demonstrate that for most national energy sectors, the impact of $\Delta CV19I$ on volatility intensified during the 'fever period' from mid-February to late March ($\varphi_{i2,\Delta CV19I}$ estimates significant and larger than $\varphi_{i1,\Delta CV19I}$ estimates). Generally, the impact of $\Delta CV19I$ on volatility persisted although there is evidence of a strong waning effect for the US, French and Brazilian energy sectors as reflected by insignificant estimates of $\varphi_{i,3,\Delta CV19I}$ of 0.0075, 0.1200 and 0.2840, respectively, and a weak tapering effect in Colombia, where a $\varphi_{i,3,\Delta CV19I}$ of 0.337 is smaller than a $\varphi_{i,2,\Delta CV19I}$ of 0.414 but still significant. We interpret the limited evidence of a dissipating effect of COVID-19 uncertainty on volatility across national energy sectors as evidence of a long-term uncertainty effect associated with the pandemic in the energy sector. As suggested by Ftiti et al. (2020) and Iyke (2020), this finding can potentially be attributed to continued concerns over COVID-19 deaths and global economic contractions, which will keep the demand for oil and other energy products low (and hence prices low) as well as reduce investment in energy equipment and services.

4.6. Structure of the Return Generating Process and COVID-19 Related Uncertainty as a Factor

We also investigate whether the return generating process differs for the pre-COVID-19 and COVID-19 periods and whether COVID-19 related uncertainty is a distinct factor, or a significant part of the composite factor set, driving returns. We begin by factor analysing the pre-COVID-19 and COVID-19 periods using the MAP test to identify the number of factors during each period. For the pre-COVID-19 period, we analyse two sub-period samples, 1 January 2015 to 15 December 2019 (long) and 1 January 2018 to 15 December 2019 (short). Samples of varying lengths are considered for the pre-COVID-19 period to avoid the extraction of pseudo-factors. Returns between 16 December 2019 to 17 July 2020 are factor analysed for the COVID-19 period. Results are presented in Panel A of Table 11.Three factors are extracted from national energy sector returns for the long and short pre-COVID-19 periods and the COVID-19 period, respectively. However, factors extracted for the COVID-19 period are associated with a higher communality of 0.7050 indicative of a higher amount of shared variance explained relative to communalities of 0.5022 and 0.4701 for the respective long and short pre-COVID-19 periods. A higher communality for the COVID-19 period points towards strengthened dependence between national energy sectors. This is likely to be attributable to the global nature of the COVID-19 crisis and is indicative of associated contagion.

As a further test of this hypothesis, namely that correlations between national energy sector returns have increased during the COVID-19 period, we calculate and report average return correlations (Junior & Franca, 2012; Uddin et al., 2020). The results in Panel B of Table 11 confirm increased dependence between national energy sectors during the COVID-19 period. Mean Spearman (ordinary) correlation coefficients, denoted $\bar{\rho}_S$ ($\bar{\rho}_P$), are 0.345 (0.3417) and 0.3184 (0.3123) for the respective long and short pre-COVID-19 samples. In contrast, during the COVID-19 period, Spearman correlation increases to 0.4862 (0.5895). This provides support for the increased communality associated with the common factors derived from returns over the COVID-19 period.

Table 11: Pre-COVID-19 and COVID-19 factor structures

Panel A: Factor structure summary			
Period	Factors extracted	Communality	KMO
1) Pre-COVID-19 (long)	3	0.5022	0.9416
2) Pre-COVID-19 (short)	3	0.4701	0.9285
COVID-19	3	0.7050	0.9418
Panel B: Dependence structures			
	Spearman ($\bar{\rho}_S$)	Ordinary ($\bar{\rho}_P$)	
1) Pre-COVID-19 (long)	0.3425	0.3417	
2) Pre-COVID-19 (short)	0.3184	0.3123	
COVID-19	0.4862	0.5895	

This table reports the results of factor analysis applied to returns over the pre-COVID-19 and COVID-19 periods. The Pre-COVID-19 sub-periods are defined as 1 January 2015 to 15 December 2019 (long) and 1 January 2018 to 15 December 2019 (short), respectively. The COVID-19 period is defined as 16 December 2019 to 17 July 2020. Panel A reports the factors extracted for each period, associated communalities and KMO index values. KMO index values indicate suitability for factor analysis. 1 January 2015 to 15 December 2019 values of over 0.8 are deemed desirable for factor analysis although values above 0.6 are desirable. Panel B reports average return correlations for the pre-COVID and COVID-19 periods.

Next, we estimate rolling correlations between $\Delta CV19I_t$ and factor scores for the three factors extracted over the COVID-19 period. Rotated factor loadings, reported in Table A1 of the Appendix, for each series are positive, with loadings averaging 0.5399 for $F_{1t,CV19I}$, 0.3636 for $F_{2t,CV19I}$ and 0.4111 for $F_{3t,CV19I}$ (see Szczygielski, Brümmer, Wolmarans & Zaremba, 2020). $F_{1t,CV19I}$ is the most important factor, accounting for 60.15% of shared variance, whereas $F_{2t,CV19I}$ and $F_{3t,CV19I}$ account for 6.15% and 4.20%, respectively. Figure 6 shows that rolling correlations between factor scores for $F_{1t,CV19I}$ and $\Delta CV19I_t$, are initially uncorrelated up until the end of January 2020. Thereafter, Spearman correlations increase (in absolute magnitude) to around (negative) 0.5 in early April 2020 (ordinary correlation between -0.5 and -0.6) before decreasing in magnitude from early May 2020 onwards until correlation is negligible or weakly positive from 1 June 2020 onwards. Given the prominence of this factor in accounting for shared variance, $\Delta CV19I_t$ is indeed a major driver of returns, especially between late March and mid-May 2020 when correlations are highest. Negative correlations indicate that as COVID-19 related uncertainty increases, $F_{1t,CV19I}$ scores decrease. As all series load positively on $F_{1t,CV19I}$, national energy sector returns decrease as $F_{1t,CV19I}$ decreases, with decreases associated with increases in $\Delta CV19I_t$. Rolling correlations for $F_{2t,CV19I}$ present a similar picture (Figure 7). Negative Spearman and ordinary correlation coefficients strengthen from around

16 December 2019, fluctuating around -0.2 for most of the sample period before increasing towards 0 at the end of June 2020. Although weaker relative to correlations for $F_{1t,CV19I}$, these correlations again suggest that $\Delta CV19I_t$ is indeed a part of the composite set of common factors driving returns, although to a lesser extent given the lower importance of this factor. As with $F_{1t,CV19I}$, all return series load positively onto $F_{2t,CV19I}$, implying that as $\Delta CV19I_t$ increases, $F_{2t,CV19I}$ scores decrease, resulting in declining returns.

Figure 6: Rolling correlations for $F_{1t,CV19I}$ and $\Delta CV19I_t$

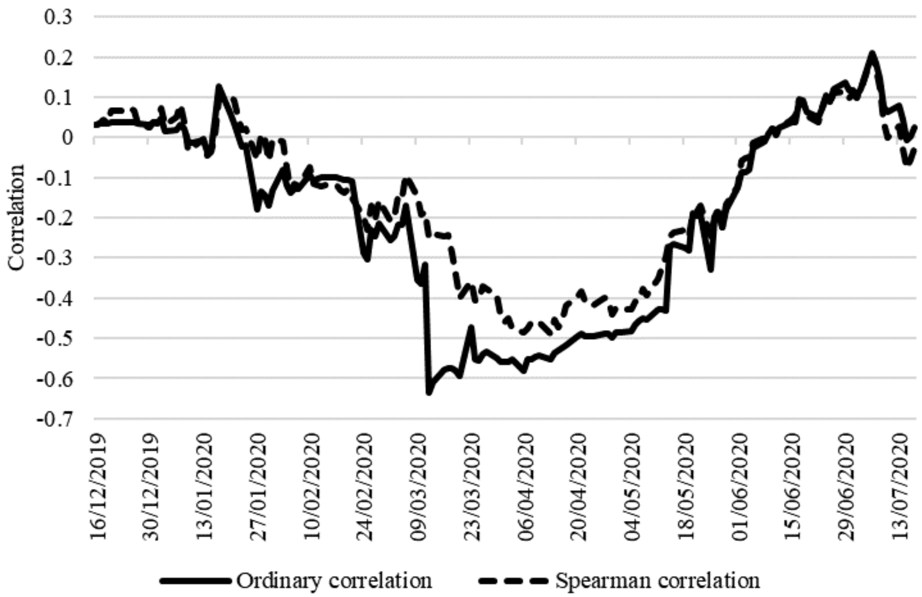


Figure 7: Rolling correlations for $F_{2t,CV19I}$ and $\Delta CV19I_t$

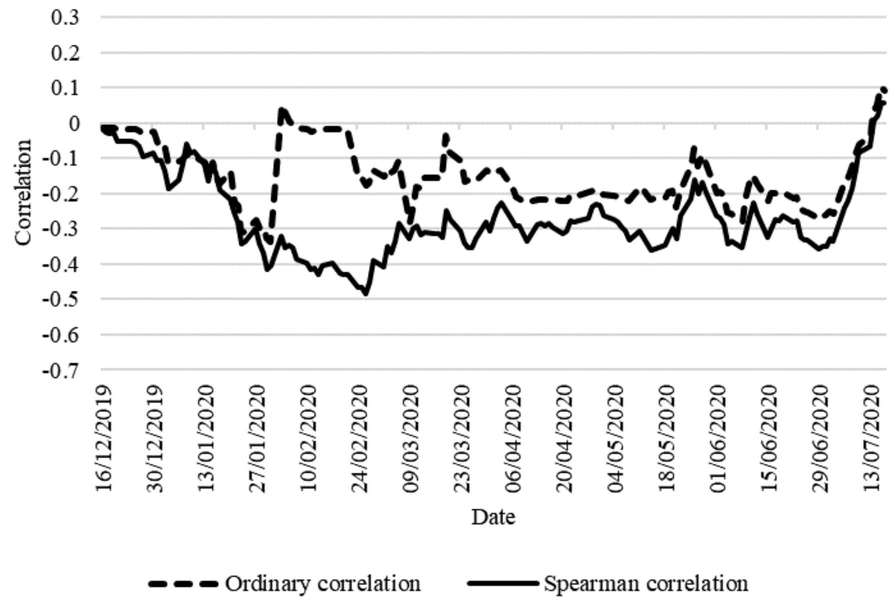
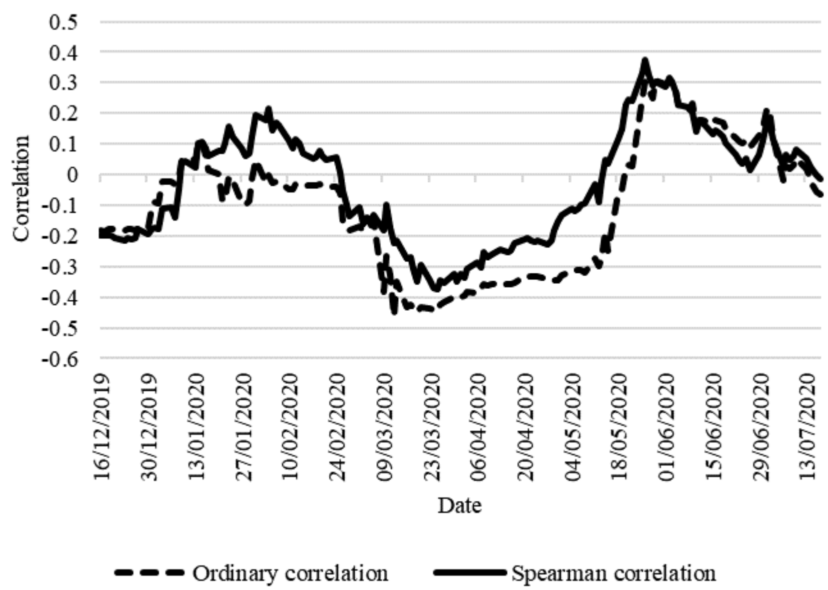


Figure 8: Rolling correlations for $F_{3t,CV19I}$ and $\Delta CV19I_t$



Figures 6 to 8 report rolling ordinary and Spearman correlations between factor scores extracted from returns on national energy sectors. Factor scores are extracted over the period 1 October 2019 to 17 July 2020 with rolling correlations estimated using windows of 45 observations and reported for the period between 16 December 2019 and 17 July 2020 (the COVID-19 period).

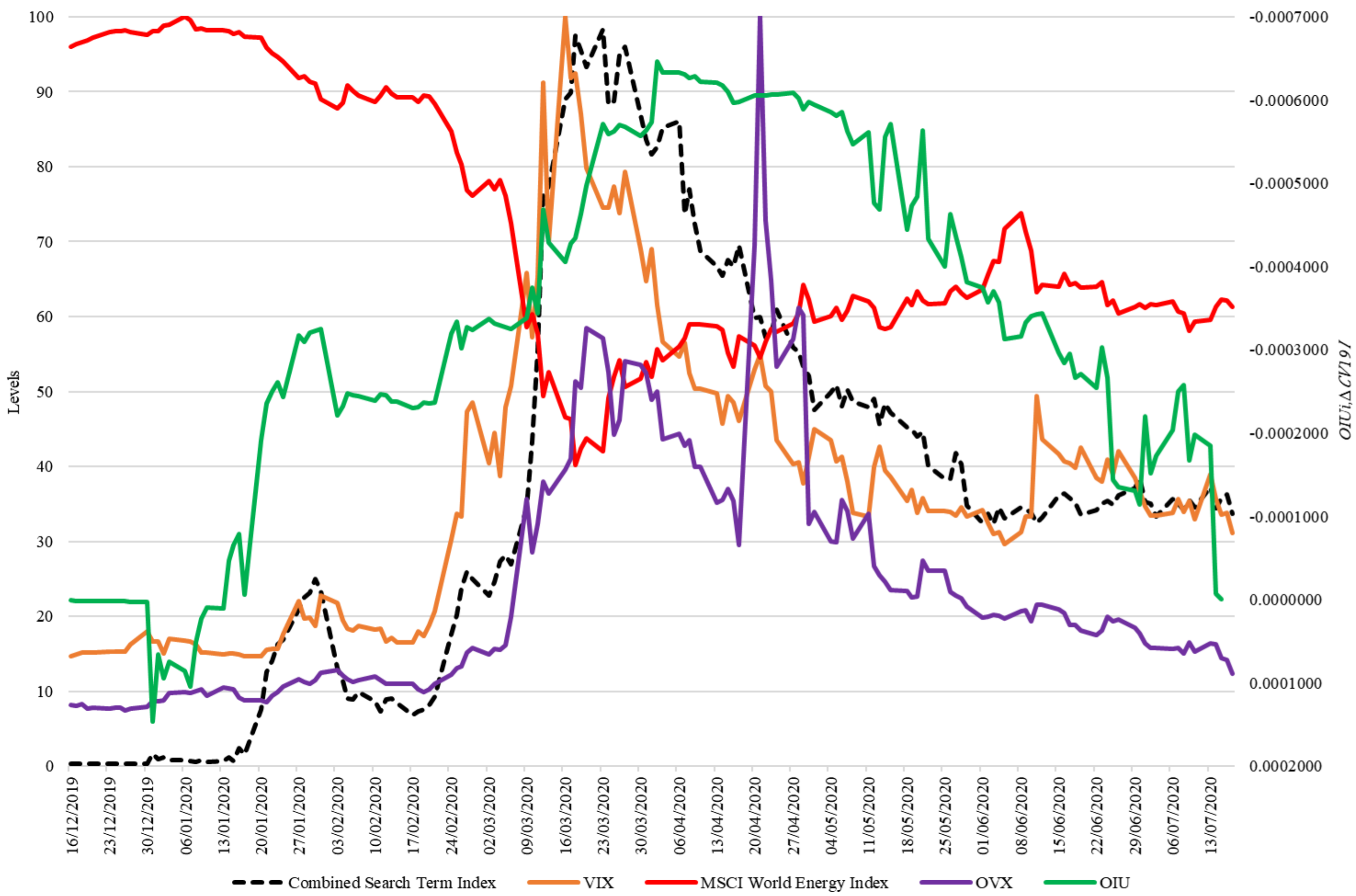
For $F_{3t,CV19I}$, we observe a similar pattern (Figure 8); both Spearman and ordinary correlations become strongly negative towards the end of February 2020, declining to around -0.3 and -0.4, respectively, towards the end of March 2020, before beginning to weaken in mid-May 2020. A short-lived period of heightened positive correlations of over 0.2 occurs for less than a month, between mid-May 2020 and mid-June 2020. Correlations for $F_{3t,CV19I}$ are somewhat ambiguous, given a period of substantial negative correlations, short sporadic periods of (albeit weak) positive correlations and the relative low importance of this factor. Nevertheless, this analysis suggests that $\Delta CV19I_t$ is indeed a major driver of national energy sector returns, mostly during the peak of the COVID-19 crisis. This is evidenced by strong negative correlations with the most important factor, $F_{1t,CV19I}$, for over a period of three months (February 2020 to May 2020) and lower but still negative and notable correlations for most of the sample period with the second most important factor, $F_{2t,CV19I}$.

Our measure of COVID-19 related uncertainty is based upon Google search trends data for COVID-19 related searches. We therefore seek to confirm its suitability as a measure of uncertainty. In order to do so, we require an alternate and established measure of global market uncertainty and risk. Such a measure is the CBOE VIX. The VIX index is considered to be an information repository associated with stock market uncertainty, reflecting information about risk and risk aversion (Bekaert et al., 2013). We choose to use the US version of this index as an established alternative measure of market uncertainty, because it has been shown that US market uncertainty is reflected by global markets, whereas global markets do not impact US market uncertainty (Smales, 2019). Given the composition of the sample that we use, we also consider the crude oil volatility index, the CBOE OVX. Luo and Qin (2017) suggest that this is a forward-looking looking index that reflets information on investor expectations relating to the future of the oil market. Liu et al. (2013) show that the OVX shows significant hikes around economic crisis and major political events linked to potential economic disruptions. Figure 9 plots VIX and OVX levels and our composite COVID-19 search term index juxtaposed against the MSCI World Energy Index, together with a rolling version of the $OIU_{i,\Delta CV19I}$ for the MSCI World Energy Index.

The composite COVID-19 Google search trends index and the VIX move together. Both begin increasing towards the end of February 2020, although the VIX leads the COVID-19 search term index, falling from mid-March 2020 (16 March 2020), a trend that is followed by the COVID-19 search term index approximately a week later. This is an identical finding to that of Szczygielski et al. (2021) who additionally show that the COVID-19 Google search trend index moves together with another internet-based measure of uncertainty, the Twitter-based Market Uncertainty (TMU) index of Renault et al. (2020). Moreover, they demonstrate that both these alternative measures of uncertainty have a similar impact on regional returns and volatility to that of changes in the COVID-19 search term index used in this study. Similarly, the OVX and COVID-19 Google search trend index move together, although not as closely as the VIX suggesting that COVID-19 Google search trends reflect a more general level of market uncertainty. According to Liu et al (2013), specific volatility indices are impacted by their own specific factors in addition to common economic fundamentals. Additionally, increases in the OVX levels occur later than those observed for COVID-19 Google search trends and the VIX.[13] These observations suggest that while the oil market reacted to COVID-19 related uncertainty, the reaction differed from that reflected by the VIX likely as a result of different factors influencing and specific to volatility in the oil market. The juxtaposition of the MSCI World Energy Index demonstrates that this index experiences a decline around the same time when the VIX , OVX and COVID-19 Google search trends index increase and peak and shows a recovery around mid-March 2020 that is aligned with the beginning of a decrease in both uncertainty measures. We conclude that, as Figure 9 illustrates, movements in the COVID-19 Google search trends index levels are led by changes in the VIX levels, suggesting that Google search trends are indeed a proxy for uncertainty, albeit a lagging one and the global energy sector performed negatively under conditions of heightened uncertainty. In contrast, movements in the COVID-19 Google search trends index lead changes in OVX levels and while both move together, they do so to a lesser extent.

[13] The spike in the OVX on 21 April 2020 coincides with US oil prices dipping below zero for the first time in record the day before (Aspinall, 2020).

Figure 9: Plot of COVID-19 Google search trend index, VIX, OVX, OIU and MSCI World Energy Index



This figure plots US VIX, OVX and COVID-19 Google search term index levels and juxtaposes levels of the MSCI World Energy Index for comparative purposes over the COVID-19 period, 16 December 2019 to 17 July 2020. Figure 9 also reports an inverse (right hand side axis) rolling version of the $OIU_{i,\Delta CV19I}$ measure for the global energy sector as represented by the MSCI World Energy Index. To construct t a rolling $OIU_{i,\Delta CV19I}$ measures for this series, the $\beta_{i,\Delta CV19I}$ and $\varphi_{i,\Delta CV19I}$ coefficients are estimated using rolling windows of 45 observations over the period 1 October 2019 - 17 July 2020.

Figure 9 also plots (the inverse of) the $OIU_{i,\Delta CV19I}$ for the MSCI World Energy Index constructed using rolling $\beta_{i,\Delta CV19I}$ and $\varphi_{i,\Delta CV19I}$ coefficients as opposed to point estimates used to report the $OIU_{i,\Delta CV19I}$ measure in Figure 4 for the global and individual national energy sectors. While the usefulness of the $OIU_{i,\Delta CV19I}$ measure primarily arises from its usefulness in comparisons across markets, Figure 9 suggests that this measure captures the initial increase in the impact of $\Delta CV19I_t$ on global energy sector returns and volatility followed by a dissipation of the impact over time towards the end of the sample, consistent with the results in Table 10 in Section 4.5. The $OIU_{i,\Delta CV19I}$ increases in (absolute) magnitude as COVID-19 Google searches intensify and VIX and OVX levels rise but remains negative throughout the period, consistent with the decline in the levels of the MSCI World Energy Index. The overall negative evolution of the rolling $OIU_{i,\Delta CV19I}$ is expected, given the negative impact of $\Delta CV19I_t$ on returns resulting in negative $\beta_{i,\Delta CV19I}$ estimates but positive volatility triggering effects reflected by positive $\varphi_{i,\Delta CV19I}$ estimates in Table 4.

In the final part of our analysis, we provide some preliminary insight as to the transmission mechanism of COVID-19 related uncertainty. We estimate rolling correlations between $\Delta CV19I_t$, ΔOIL_t and changes in the VIX, ΔVIX_t and OVX, ΔOVX_t.

Figure 10: Plot of $\Delta CV19I_t$ and ΔVIX_t correlations

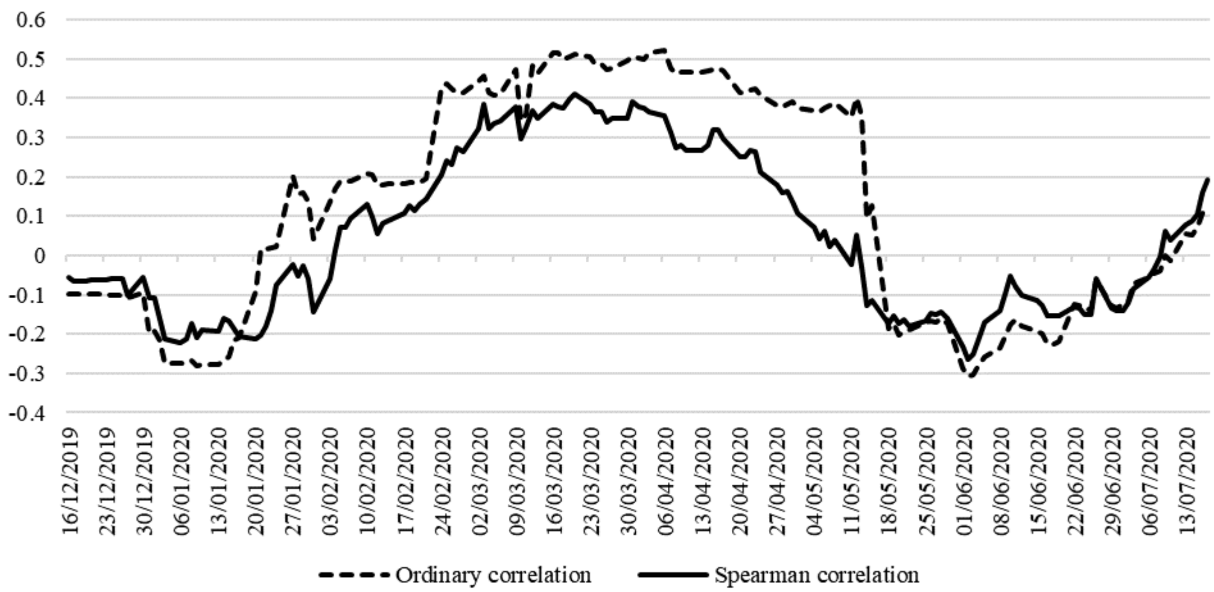


Figure 11: Plot of $\Delta CV19I_t$ and ΔOIL_t correlations

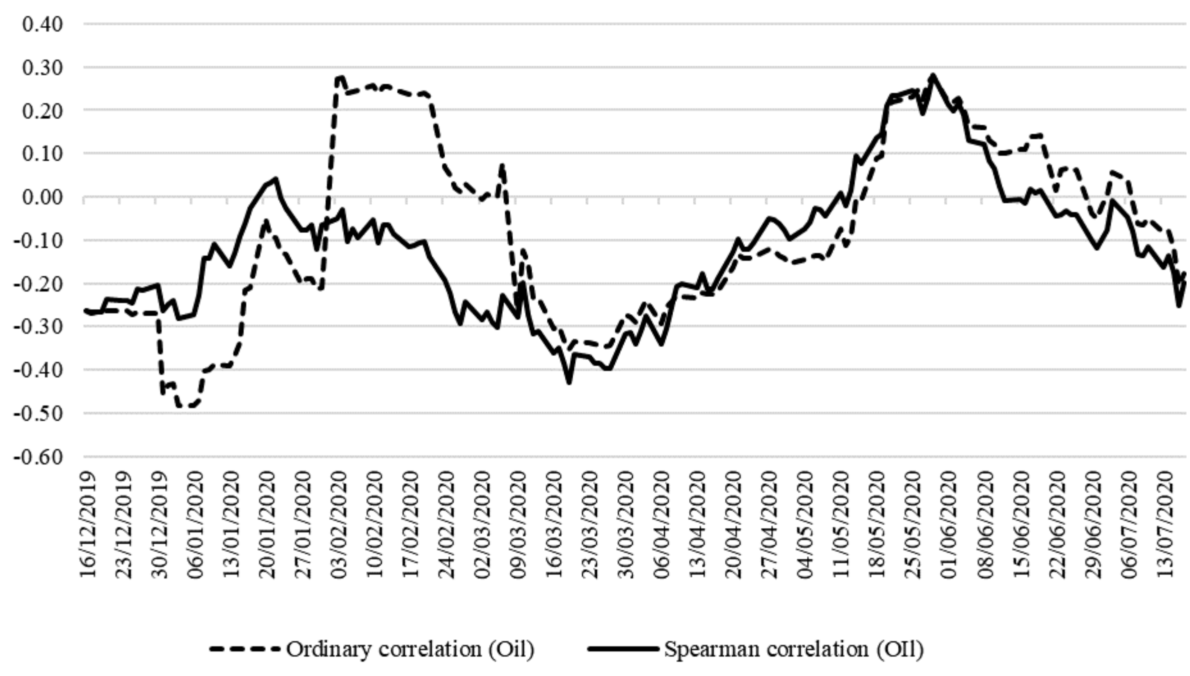
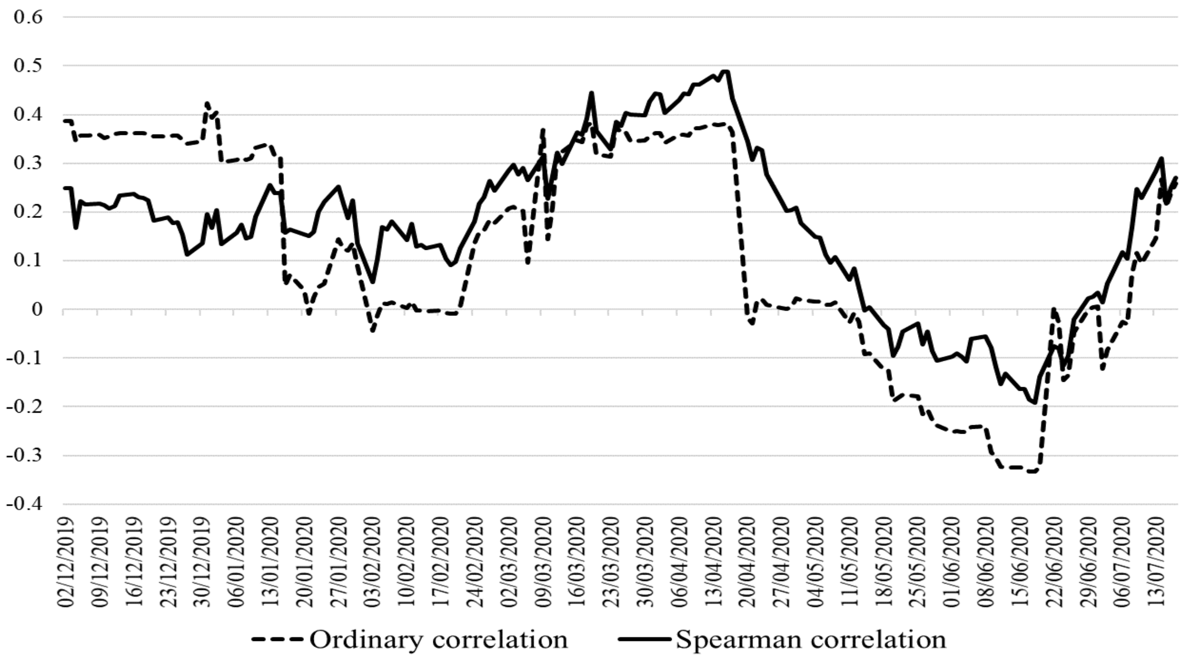


Figure 12: Plot of $\Delta CV19I_t$ and ΔOVX_t correlations



Figures 10, 11 and 12 report ordinary and Spearman rolling correlations between ΔVIX_t, ΔOIL_t, ΔOVX_t and $\Delta CV19I_t$, respectively, over the COVID-19 period, defined as 16 December 2019 - 17 July 2020. Rolling correlations are estimated using rolling windows of 45 observations over the period 1 October 2019 - 17 July 2020.

Figure 10 shows that there is an increase in correlations between ΔVIX_t and $\Delta CV19I_t$ starting in early January 2020 and rising to correlations of over 0.4 (and 0.5 according to ordinary correlation) in mid-March 2020 before declining again in early May 2020. Together with the movements depicted in Figure 9, this pattern points towards $\Delta CV19I_t$ reflecting uncertainty. Imperfect correlations can be expected, because $\Delta CV19I_t$ is not an equivalent of ΔVIX_t and ΔVIX_t is a broader proxy for uncertainty, reflecting both COVID-19 related uncertainty and the indirect effects thereof, such as deteriorating economic conditions and general levels of uncertainty prevailing in the market at the time. In a similar vein, we observe in Figure 11 that the negative correlation between $\Delta CV19I_t$ and ΔOIL_t strengthens between late January 2020 and late March 2020, declining to around -0.4 according to both correlation measures. This implies the existence of an oil transmission channel: oil prices fall as COVID-19 related uncertainty increases. Given that the relationship between oil and national energy sector returns is positive (Table 4), returns will decline because of oil price decreases driven by COVID-19 related uncertainty. Similarly, in Figure 12, we observe that correlations between $\Delta CV19I_t$ and ΔOVX_t strengthen according to both measures of correlation between the beginning of March and the end of April 2020. However, the correlation between $\Delta CV19I_t$ and ΔVIX_t

appears to be more distinct relative to the relationship between $\Delta CV19I_t$ and ΔOVX_t, potentially owing to the specific nature of the oil market. Consequently, we suggest two possible transmission channels. The first is an uncertainty channel whereby returns on national energy sectors react negatively to COVID-19 uncertainty. The second is through the oil price, whereby increases in COVID-19 related uncertainty are associated with declining oil prices, which in turn impact national energy sector returns. We acknowledge that there is a multitude of transmission channels related to COVID-19, i.e. the impact of COVID-19 on interest rates, inflation, output and macroeconomic fundamentals (Apergis & Apergis, 2020; del Rio-Chanona et al. 2020). Some of these channels are likely to be reflected in the relationship between $\Delta CV19I_t$ and the factor scores. In other words, this relationship is a proxy for the relationship between $\Delta CV19I_t$ and a multitude of other factors. We relegate a detailed exposition, study and disentanglement of these relationships and resultant transmission channels to further research.

4.7. Investing during the COVID-19 Period

As the final element of our analysis, we estimate cumulate abnormal returns (CAR) over the pre-COVID-19 and COVID-19 periods for national energy sectors.[14] Results in Table 12 show that in the eleven months prior to the COVID-19 crisis, national energy sectors on average experienced a decline of 17.84%. Only the Australian, Canadian and Indian energy sectors experienced cumulative abnormal gains of 8.67%, 4.50% and 0.54%, respectively. As shown in Panel A of Figure 12, all regions performed poorly with Europe experiencing the lowest CAR (-22.09%) while the Americas (-10.62%) had the smallest negative CAR. Net energy importing countries (-22.81%), on average, performed worse than net energy exporting countries (-9.37%). According to Cunningham (2019) and Egan (2019), the poor performance of the energy sector prior to COVID-19 was largely driven by low oil and gas prices, a trade way between the US and China, as well as greater investor awareness about climate change, which contributed to capital flight away from energy stocks. Therefore, at an aggregate level, the global energy sector was not in a good shape nor did it offer attractive investment opportunities prior to the COVID-19 outbreak.

[14] We control for the impact of systematic factors unrelated to the pandemic by estimating the market model for each country's energy sector for the period from 1 January 2015 to 31 December 2018 according to the equation: $r_t = \alpha_i + \beta_{i,M} r_{M,t} + \varepsilon_t$, where r_{mt} are the daily returns on the MSCI World Index. Abnormal daily returns ($AR_{i,t}$) are then computed for each day in the pre-COVID-19 period and COVID-19 periods as follows: $AR_{i,t} = r_{i,t} - \alpha_i - \beta_{i,M} R_{M,t}$, with the CARs for the two periods calculated as$CAR_{i,t} = \prod_t^T \left(1 + AR_{i,t}\right) - 1$.

Table 12: Cumulative Abnormal Returns for the Pre-COVID-19 and COVID-19 Periods

	Pre-COVID-19 Period	**COVID-19 Period**	**Change in CAR**
0.World	-0.1271	-0.3300	-0.2029▼
1. USA	-0.1188	-0.3457	-0.2269▼
2. Russia	-0.0083	-0.3849	-0.3766▼
3. UK	-0.2274	-0.4341	-0.2067▼
4. China	-0.2193	-0.2475	-0.0282▼
5. Canada	0.0450	-0.2662	-0.3112▼
6. India	0.0054	-0.0615	-0.0669▼
7. France	-0.2143	-0.2961	-0.0818▼
8. Brazil	-0.2538	-0.4665	-0.2127▼
9. Norway	-0.3092	-0.2656	0.0436▲
10. Italy	-0.1964	-0.3353	-0.1389▼
11. Australia	0.0867	-0.3517	-0.4385▼
12. Thailand	-0.1848	-0.3126	-0.1278▼
13. Colombia	-0.0972	-0.4135	-0.3163▼
14. Japan	-0.1934	-0.2983	-0.1049▼
15. Taiwan	-0.3062	-0.1590	0.1472▲
16. Finland	-0.2277	0.0853	0.3140▲
17. Spain	-0.2383	-0.4028	-0.1645▼
18. Korea	-0.3953	-0.3616	0.0338▲
19. Poland	-0.4628	-0.3186	0.1443▼
20. Austria	-0.1040	-0.4596	-0.3557▼
Average	-0.1784	-0.3060	-0.1275▼

This table reports cumulative abnormal returns (CAR) for national energy sectors and the global energy sector over the pre-COVID-19 and the COVID-19 periods. Returns on the global energy sector and national energy sectors are first regressed onto a constant and returns of the MSCI All Country World Index for the period from 1 January 2015 to 31 December 2018 based on the market model. Abnormal returns are then computed as the daily returns for the given country less the constant and country beta multiplied by market return. Finally, CARs are obtained for each period as the product of one plus the daily abnormal return less one. The pre-COVID-19 period is defined as 1 January 2019 - 15 December 2019 and the COVID-19 period is defined as 16 December 2019 - 17 July 2020. The arrows, ▲ and ▼, indicate an increase and decrease respectively in the CAR from the pre-COVID-19 period to the COVID-19 period.

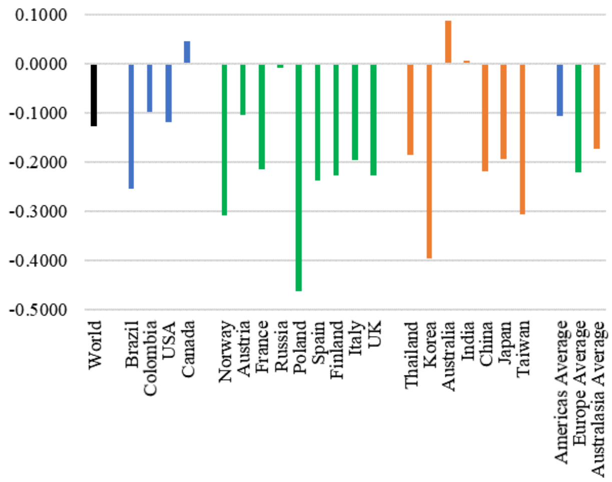
During the COVID-19 crisis, the average CAR for the energy sector was even lower at -30.60%. Worst performers were the Brazilian, Austrian, British, Colombian and Spanish energy sectors with abnormal cumulative negative returns of 46.65%, 45.96%, 43.41%, 41.35% and 40.28%, respectively. Over the COVID-19 period, the further decline of the energy sector can be attributed to compounding events, namely the Saudi Arabian-Russian oil war, lower demand caused by lockdowns and travel bans as well as uncertainty surrounding the impact of COVID-19 on health, livelihoods and economic activity (Ftiti et al., 2020; Iyke, 2020; Ozili & Arun, 2020). Energy sectors in the Americas earned the lowest returns on average (CAR of -37.30%), followed by Europe (CAR of -31.25%), with the Australasia energy sector earning the smallest negative CAR (-25.60%) during the COVID-19 period. The finding that energy sectors in the Americas are the worst performers is in line with the observation that returns on energy sectors in these markets are most impacted (see Section 4.1). As such, the results of the CAR analysis reflect that geographical proximity matters. Energy sectors in countries further west of the COVID-19 outbreak in China experienced greater losses. Moreover, according to Wang and Lee (2020), the greater resilience of energy stocks in the Australasian region may reflect that these countries will be among the quickest to return to their pre-COVID-19 growth trajectories with limited structural changes to their economies. The Economic Research Institute for ASEAN and East Asia (ERIA) (2020) and Parameswaran (2020) attribute the relative strength of the Asian energy sector to well-funded national oil companies, which are in a good position to take advantage of global opportunities in the post-COVID economy.

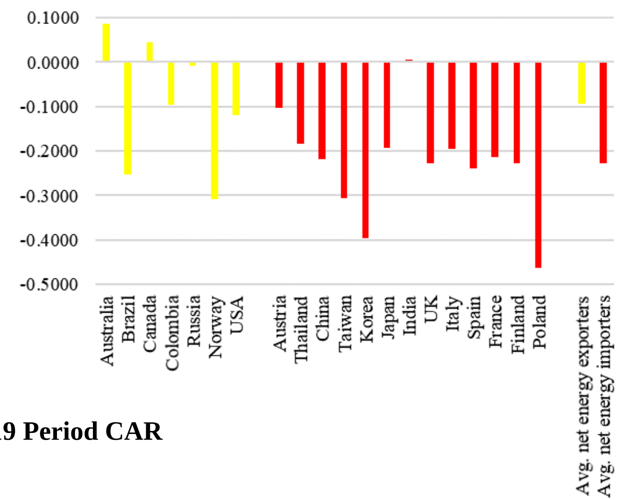
These results also reveal that net energy trade exposure matters. The net energy exporters on average incurred greater losses (-35.63%) since the onset of the pandemic than net energy importers (-27.71%). Moreover, net energy exporters outperformed net energy importers prior to the pandemic and, thus, the change in CAR for these countries is notable as demonstrated in Panel C of Figure 12 (-26.26% compared to -4.90%, on average). Energy demand dropped markedly with the implementation of measures to contain the spread of the virus and hence net exporters were more impacted than net importers. The net energy exporting countries were also found to be most impacted by uncertainty (see Section 4.1).

The story that emerges reveals a poorly performing sector. This effect is aggravated, in part, by uncertainty related to the COVID-19 crisis. This is supported by the results in Section 4.1. Although Figure 1 illustrates that uncertainty, as measured by Google search trends, has tapered as the pandemic evolved, the analysis in Section 4.5 demonstrated that COVID-19 uncertainty still influences returns and return volatility for most national energy sectors although to a lesser extent. The recommendation to investors is that they should be wary of investing in the energy sector stocks in the times of the COVID-19 pandemic as this sector is likely to perform poorly as long as the health and economic crisis, along with the related uncertainty, persist.

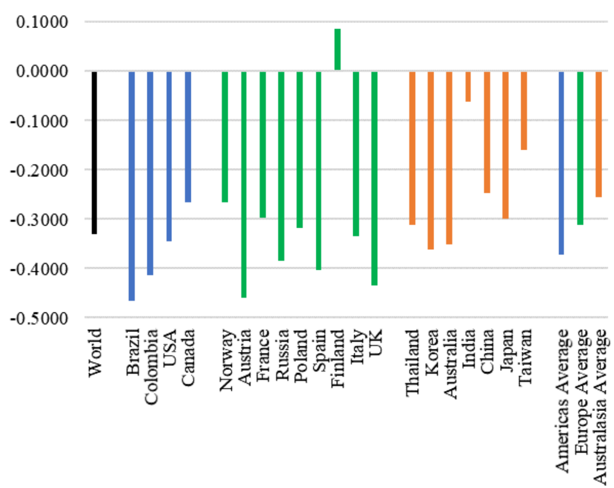
Figure 13: Cumulative Abnormal Returns for the Pre-COVID-19 and COVID-19 Periods

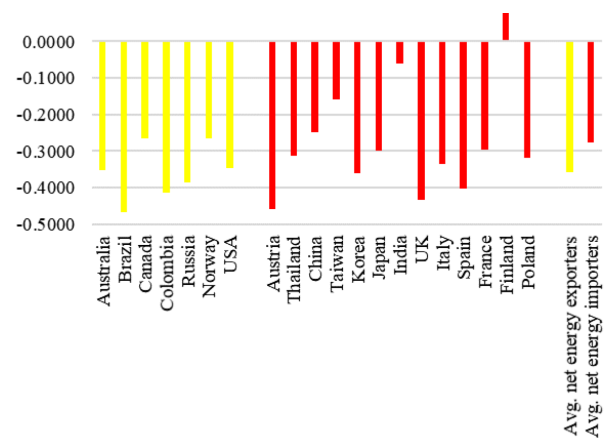
Panel A: Pre-Covid-19 Period CAR



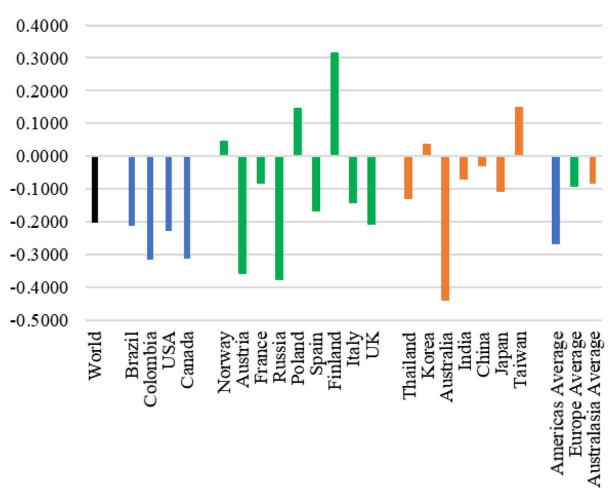


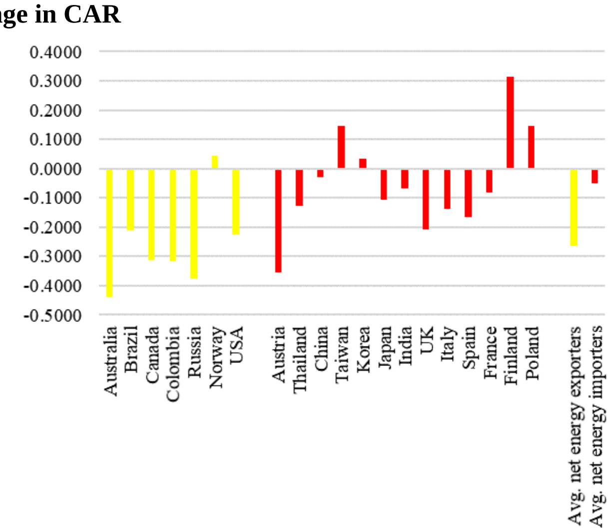
Panel B: COVID-19 Period CAR





Panel C: Change in CAR





These figures plot the cumulative abnormal returns (CAR) presented in Table 12 for national energy sectors and the global energy sector over the pre-COVID-19 and the COVID-19 periods grouped according to region (left side) and energy exporter/ importer (right side).

5. Conclusion

This study extensively investigates the impact of COVID-19 related uncertainty on national energy sectors represented by MSCI energy indices. Uncertainty is measured using Google search trends which quantify searches for information related to the pandemic. We use ARCH/GARCH models but propose a methodological improvement with the use of a factor analytic augmentation constructed using statistically derived factors. This approach yields a more adequate specification relative to the conventional approach of using market indices to proxy for omitted factors. This offers a simplified methodology for the quantification and interpretation of the impact of COVID-19 proxy variables, such as new infections or deaths, within a parsimonious model that does not require the identification and inclusion of appropriate market indices and/or control factors. We also introduce a novel overall measure of uncertainty using an analogy of a rainstorm. This measure reflects both the magnitude – the amount of water - of the impact of $\Delta CV19I_t$ and its intensity – the varying force of rain during a storm.

Our results show that no national energy market is unscathed by COVID-19 uncertainty. $\Delta CV19I_t$ has a negative impact on returns for all national energy markets and is associated with heightened volatility in most. Given uncertainty about the future profitability of firms within the energy sector, it is not surprising that returns respond negatively and volatility increases. Based on our novel measure of the 'overall impact of uncertainty', we find that geographical proximity matters as countries further to the west of the outbreak and early epicentre of the pandemic in Asia are most negatively impacted, such as Brazil and Canada. This suggests that, according to the geographical sequence of locations from east to west, more investors in the former locality may have known about the virus or possibly had better information about the likely future development of the pandemic and associated outcomes. This information may have resulted in the resolution of some of the overall uncertainty in the respective markets leading to a less severe impact on energy stock prices. The transmission mechanism can also be tied to economic conditions and their impact on the demand for oil, gas and related equipment as net oil and energy exporters are found to experience larger declines in returns and greater volatility in response to COVID-19 related uncertainty relative to net oil and energy importers respectively.

We also undertake an analysis of the time-varying impact of $\Delta CV19I_t$. Changes in the relationship between returns and COVID-19 have been identified for 15 markets, with structural breaks coinciding firstly with deaths from the virus in Italy and that country implementing a lockdown for approximately 50 000 people, and secondly, with US cases reaching 50 000, the Olympics being suspended and the lockdown on China's Hubei province being lifted. The general trend that emerges is that COVID-19 related uncertainty has an intensifying effect which then dissipates over time. This reflects the evolution of the pandemic from its beginning in the geographic east and spreading west, with $\Delta CV19I_t$ becoming an increasingly important driver of energy sector returns (see Section 4.6). Notably, China and countries close to China, the epicentre of the COVID-19 pandemic, namely Thailand, Taiwan, and Korea, did not experience a change in the relationship between returns and $\Delta CV19I_t$. This suggests that $\Delta CV19I_t$ has a uniform effect in these markets potentially attributable to a less intense but ongoing response related to experience in dealing with pandemics. Another observation is that numerous national energy markets show heightened volatility from the onset of the COVID-19 pandemic. This can potentially be explained by the national energy sectors already performing poorly prior to the COVID-19 crisis. Consequently, any negative news was rapidly reflected by an already vulnerable sector. Although the dates of structural breaks differ across markets, the pattern is similar to that observed for returns; COVID-19 related uncertainty is associated with increasingly higher levels of volatility which then dissipates.

The application of our newly proposed 'overall impact of uncertainty' measure may be helpful in other future studies. In addition, further research may focus on explaining the reasons for the dissipating effect of $\Delta CV19I_t$ on both returns and volatility. It could be that this dissipation is related to effective containment measures. Alternatively, investors may have become accustomed to a "new normal" and now understand the implications of containment measures and COVID-19 related news and events. Therefore, while $\Delta CV19I_t$ continues to be associated with a negative impact on the national energy sectors and heightened volatility, it no longer continues to have an impact that is as severe as it was during the explosive and initial phase of the pandemic. Another observation that calls for further research is the distinctly low impact of $\Delta CV19I_t$ on east Asian countries – especially on returns – and the lack of structural breaks. It is possible that there are country-specific institutional factors that result in these markets being less severely impacted. It may also be that investors in those markets better understand the nature of a pandemic and the impact of associated containment measures whereas for markets outside of east Asia, there is a surprise factor.

By undertaking this explorative study on the impact of COVID-19 uncertainty on the energy sector, we shed light on the impact of the COVID-19 crisis on a particularly vulnerable sector. What emerges is that the energy sector has not been in a good shape prior to the outbreak of COVID-19. However, the pandemic further contributed to its woes with one such negative contribution attributable to uncertainty surrounding COVID-19.

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