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Capturing the timing of crisis evolution: A machine learning and directional wavelet coherence approach to isolating event-specific uncertainty using Google searches with an application to COVID-19

Jan Jakub Szczygielski [a,b], Ailie Charteris [c,*], Lidia Obojska [d], Janusz Brzeszczyński [e,f]

[a] Department of Finance, Kozminski University, ul. Jagiellońska 57/59, 03-301, Warsaw, Poland
[b] Department of Financial Management, University of Pretoria, Private Bag x20, Hatfield, Pretoria, 0028, South Africa
[c] Department of Finance and Tax, University of Cape Town, Rondebosch, 7700, Cape Town, South Africa
[d] Department of Quantitative Methods & Information Technology, Kozminski University, ul. Jagiellońska 57/59, 03-301, Warsaw, Poland
[e] Department of Accounting and Finance, Business School, Edinburgh Napier University (ENU), 219 Colinton Road, Edinburgh, EH14 1DJ, Scotland, United Kingdom
[f] Department of Capital Market and Investments, Faculty of Economics and Sociology, University of Łódź, ul. POW 3/5, 90-225, Łódź, Poland

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ABSTRACT

The phases of a crisis are critical to understanding its evolution. We construct an economic agent-determined machine learning-based Google search index that associates search terms with uncertainty to isolate COVID-19-related uncertainty from overall uncertainty. Subsequently, we apply directional wavelet analysis that discriminates between positive and negative associations to study the evolving impact of the COVID-19 pandemic on financial market uncertainty and financial markets. Our approach permits us to delineate crisis phases with high precision according to information type. The analysis that follows suggests that policy responses impacted uncertainty and that the novelty of the COVID-19 outbreak had a significant impact on global stock markets. Regression analysis, wavelet entropy and partial wavelet coherence confirm the informational content of our uncertainty index. The approach presented in this study is applied to the COVID-19 crisis but is generalisable beyond the pandemic and can assist in decision-making during times of economic and financial market turmoil and should be of interest to policymakers, researchers and econometricians.

1. Introduction

As crises evolve, intensifying and waning, their effect on financial markets and the broader economy varies. Distinct phases of a crisis can be identified by a strengthening and weakening impact arising from related events and the implementation of certain policies. For example, the Lehman Brothers bankruptcy, the freezing and unfreezing of credit markets, and quantitative easing changed the course of the impact of the Global Financial Crisis (GFC) on financial markets (Dooley and Hutchison, 2009; Corbet et al., 2019). Policymakers need to understand phases, their timing and drivers in order to ascertain appropriate fiscal, monetary and other policy responses with the aim of limiting the deleterious impact of a crisis (Jana et al., 2022; Lai, 2022). Market participants also seek knowledge and insight into the distinct phases of a crisis to be able to hedge downside risk throughout its evolution. Traditionally, the identification of crisis phases has relied on the timing of pre-selected major events, the introduction of policies or by analysing stock price movements (see Dimitriou et al., 2013; Ramelli and Wagner, 2020; Akhtaruzzaman et al., 2021). More recently, Lai (2022) proposed the use of stock options, which reflect investors' risk preferences and beliefs, to identify phases with an application to the GFC and COVID-19.

The COVID-19 pandemic represented a crisis of an unparalleled scale that had severe repercussions which significantly impacted financial markets. Governments and health authorities faced tough choices regarding policy measures as well as the timing of their implementation and withdrawal. The Oxford COVID-19 Government Response Tracker (OxCGRT)[1] shows that the timing of policy decisions was very similar across countries during the early stages of the crisis but varied substantially when restrictions were being relaxed (Hale et al., 2021). Inevitably, many of these actions did not have the desired outcome or

* Corresponding author.
E-mail addresses: jszczygielski@kozminski.edu.pl, kuba.szczygielski@up.ac.za (J.J. Szczygielski), ailie.charteris@uct.ac.za (A. Charteris), lobojska@kozminski.edu.pl (L. Obojska), j.brzeszczynski@napier.ac.uk (J. Brzeszczyński).

[1] OxCGRT reports a comprehensive dataset of cross-national, longitudinal measures of government responses from 1 January 2020.

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were incorrectly timed, implemented prematurely or relaxed belatedly.[2] A *detailed* understanding of the phases of a crisis and the impact of various measures and actions in propagating or suppressing phases is, therefore, crucial in such situations. An example of a policy dilemma during the COVID-19 crisis was the timing of school closures and their re-opening. Balancing the potential benefits with drawbacks of such actions involves explicit trade-offs for governments (Viner et al., 2021). According to Gurdasani et al. (2021), incorrect policy regarding the re-opening of schools may have led to increases in virus transmission, but with more infectious and possibly more virulent variants, resulting in further restrictions. Moreover, an analysis of the OxCGRT database suggests that some countries may have simply been observing the decisions of their neighbours and/or global responses and reacted accordingly (Hale et al., 2021). This points towards decision-making processes that were partially spontaneous or driven by intuition or even by 'herding behaviour' across different countries and not by detailed analysis of the evolving situation. Jana et al. (2022) confirm that timing mattered for policymakers during COVID-19 with their analysis of the first three months of the pandemic revealing a brief window to implement measures to mitigate the impact of the financial market crash.

Crises are characterised by heightened uncertainty which spills over to stock markets (Karanasos et al., 2022). During a crisis, events and policy measures enacted by governments and central banks can either amplify uncertainty or contribute to its resolution. Knowledge of how such uncertainty contributes to the strengthening and weakening impact on financial markets is important for policymakers as it influences policy formulation and aids in the development of appropriate investment strategies to navigate crisis periods. The dilemmas around responses to crises constitute an important example of the need to identify and understand uncertainty-driven phases in financial markets.

With the onset of the COVID-19 pandemic, widespread uncertainty was driven by health concerns and the impact of lockdowns and border closures on livelihoods and economies (Altig et al., 2020). As the pandemic evolved, uncertainty levels varied with news around key events such as infection milestones, the development and mass rollout of vaccines, and the emergence of new variants (Paul et al., 2021). Uncertainty also fluctuated with the easing and subsequent reimplementation of restrictions, the impact of lockdowns on global supply chains, economies and business conditions, and concerns over the long-term consequences of contracting the virus (Dietrich et al., 2022). Karanasos et al. (2022) illustrate how uncertainty heightened the impact of macroeconomic and financial policies on stock markets during the COVID-19 crisis (as per the GFC).

In this study we isolate and measure COVID-19-related uncertainty using a real-time daily proxy, enabling us to examine the progression of the pandemic within an uncertainty framework. Furthermore, we analyse its impact on global stock market volatility, demonstrating how uncertainty tied to a specific topic or event can be discerned from general stock market uncertainty.

Our study makes several contributions. First, we add to the literature on the construction and application of uncertainty indices based on internet searches. Google searches can be viewed as a measure of uncertainty or fear as economic agents search more intensively for information when faced with greater uncertainty (see Liemieux and Peterson, 2011; Donadelli, 2015). An advantage of using Google searches is that they can be used to isolate and quantify fears around a *specific* topic because they reflect economic agents' views (Niesert et al., 2020; Szczygielski, Charteris & Obojska, 2023). Broad and general proxies such as the Chicago Board of Exchange volatility index (VIX) and Twitter-based market and economic uncertainty indices (TMU and TEU, respectively) of Baker et al. (2021) reflect uncertainty (or sentiment and attention, depending upon the proxy used) around a plethora of other concurrent topics and events, making it difficult to gauge the impact of COVID-19 uncertainty - topic-specific uncertainty - in isolation. Consequently, an easily accessible measure of topic-specific uncertainty that is available without delay, which we develop and apply, is a source of useful information. Our index and approach to constructing it can provide researchers, econometricians, policymakers, investors and market analysts, with timely insight into events and policy decisions that reduce or increase uncertainty.

Second, our index is economic agent-determined, encompassing neutral, objectively selected keywords that Google reports as searched for by economic agents. This differs from existing Google search-based indices where terms selected by researchers may be biased and lack investor relevance (Da et al., 2015; Chen et al., 2020).

Our third contribution is methodological. We use elastic net regression to select relevant search terms for inclusion in the index. Elastic net can automatically perform search term selection while preventing overfitting and accounting for multicollinearity. By following this approach, we identify and isolate terms that reflect COVID-19-related uncertainty and are related to components of general stock market uncertainty as reflected by an established overall stock market uncertainty measure, the VIX. Examples of existing studies that utilise elastic net for variable selection and machine learning techniques for information extraction and text mining are those of Jiang et al. (2018), Topuz et al. (2018), Guo et al. (2020) and Baradaran Rezaei et al. (2022). Our analysis demonstrates the usefulness of machine learning for developing (relative) high-frequency internet search-based indices which are becoming increasingly popular in finance applications and research. We therefore contribute to developing a systematic approach to shaping the narrative of internet search-based indices and measuring the impact thereof.

Fourth, our study presents a novel way of identifying crisis phases by focusing on changing informational contribution to uncertainty. We propose that during times of heightened uncertainty driven by new information, coherence between event-specific crisis-related uncertainty and overall uncertainty will grow as event-specific crisis-related uncertainty increasingly contributes to overall uncertainty. This interpretation is confirmed using Wavelet Shannon Time-Energy Entropy. This approach differs from the traditional approach of delineating phases based on events/policy announcements or stock returns (see Dimitriou et al., 2013; Ramelli and Wagner, 2020) and is related to the work of Lai (2022) who utilises investor risk preferences and beliefs reflected in stock options to identify crisis phases reflected by stock markets. We utilise this approach to improve our understanding of uncertainty surrounding the COVID-19 crisis. To implement our approach, we refine wavelet coherence to directly discriminate between positive and negative associations. We designate this refinement as directional wavelet coherence and apply it to extract localised correlation coefficients to infer phases. Directional wavelet coherence offers a more precise application of wavelet coherence.

Finally, our sample covers the period from December 2019 to March 2022 which encompasses numerous significant information events (outbreak, aftermath and evolution, vaccine development, mass immunisation, COVID-19 variants, etc.) that have not been considered jointly by earlier studies (to the best of our knowledge). Aside from modelling the evolution of the pandemic, we also investigate which policy responses and measures in the OxCGRT database contributed to increasing or decreasing uncertainty. This enables us to provide suggestions on how to prepare for upcoming crises. Dimitriou et al. (2013) identified key phases of the impact of the GFC on stock markets to better understand the evolution of the crisis and its effects. In contrast, the identification of phases of the COVID-19 crisis has been limited to the first few months (see, for example, Capelle-Blancard and Desroziers, 2020; Ramelli and Wagner, 2020). We therefore contribute to the literature by using a longer time period to identify the phases of the COVID-19 pandemic and to study its evolution. Moreover, our contribution lies in identifying

[2] See examples reported in the popular press, such as the Scientific American magazine, by Lewis (2021) and Taylor (2021).

phases through the lens of uncertainty which has not been done in prior studies of the pandemic-induced crisis or the GFC.

Our analysis suggests that the evolution of the COVID-19 crisis is characterised by five clear phases; the initial outbreak, government interventions of various forms, an accustomisation to the situation, the prospect and rollout of vaccinations and the emergence of new variants. While our study focuses on the COVID-19 crisis, our approach can be used to analyse the evolution of crises in general on an ongoing and timely basis, unlike traditional econometric approaches (see Appendix B). This is because we isolate event-specific information and apply directional wavelet coherence that permits more precise analysis and the identification of the timing of changes in relationships. The subsequent analysis suggests that the novel and unique nature of the pandemic, marked by the outbreak and the implementation of unprecedented restrictions, significantly contributed to uncertainty and triggered stock market volatility experienced during the initial stages of the crisis. Over time, expectations gradually returned to normal, and markets started to revert to their inherent state, as other events began to exert an influence. Interventions and policy measures were instrumental in both increasing and reducing uncertainty. Specifically, economic support measures and information campaigns reduced uncertainty. While several interventions considered are COVID-19 specific, economic support measures and information campaigns are viable responses to any future crisis. As our approach allows us to model the evolution of a crisis at a high frequency, it can be used to assess the effectiveness of crisis-specific responses as they are implemented. We find that Google searches are more reflective of interventions relative to overall stock market uncertainty, suggesting that this is a useful proxy for studying the impact of public policy. A number of implications follow directly from the results that provide insight into the evolution of the COVID-19 pandemic, and from the methodology applied which combines machine learning, Google searches and directional wavelet coherence. This will be of interest to policymakers, analysts and researchers.

This study proceeds as follows; Section 2 reviews literature on the COVID-19 crisis and Section 3 outlines the data and methodology. In Section 4, we apply our uncertainty index to designate phases of the COVID-19 crisis and demonstrate how this index can be applied to analyse the impact of COVID-19-related uncertainty on global markets. We report on the impact of response measures, on either reducing or increasing uncertainty and discuss the implications of our findings. The robustness of our index is also tested and confirmed. Section 5 outlines implications and Section 6 concludes.

2. Literature review

As with other crises, stock markets were not immune to the COVID-19 pandemic. Increased cases and fatalities negatively affected stock returns and triggered increased volatility (Al-Awadhi et al., 2020; Baek et al., 2020). Stock market responses to government-imposed restrictions were mixed, depending upon geographical location and the nature of the response (Capelle-Blancard and Desroziers, 2020; Szczygielski et al., 2021). Karamti and Belhassine (2022) assessed how COVID-19 deaths and related fear impacted G7 stock markets over a longer period relative to prior studies, permitting a comparison of findings across the first and second waves of the pandemic (see also Yousfi et al., 2021). They found that deaths and fear impacted returns over short investment horizons through both waves. The long-term impact of deaths was more muted during the second wave although fear continued to exert an impact. Vaccinations during the later stages of the pandemic positively impacted returns and reduced volatility in developed markets (Khalfaoui et al., 2021; Rouatbi et al., 2021). These studies focused on evolving time-series COVID-19-related metrics such as the number of COVID-19 deaths, the stringency of government lockdowns and number of vaccines administered.

Other research examined key events linked to the pandemic that may have impacted returns and/or volatility. Ahmad et al. (2021) utilised the Bai-Perron test to identify structural breaks in stock returns in the United States (US), United Kingdom (UK), China and Italy and mapped these against COVID-19 milestones. Related studies evaluated the impact of key milestones on stock markets by preselecting announcements and events. For example, Corbet et al. (2020) specified key dates related to the Chinese COVID-19 outbreak between December 2019 and March 2020. Al-Awadhi et al. (2020) considered early milestones in the pandemic, between the end of December 2019 (pneumonia cases in Wuhan reported to the World Health Organisation (WHO)) and the beginning of March 2020 (number of new cases in China fell to less than 100 per day) (see also Orhun, 2021). Harjoto et al. (2021a) and Scherf et al. (2022) extend the sample period to April 2020, incorporating lockdown announcements, travel bans, economic stimulus packages and central bank interventions.

Milestones related to vaccination trials and rollouts have also been investigated. Bakry et al. (2022) found that the announcement that the Pfizer-BioNTech vaccine is 90% effective (9 November 2020) resulted in heightened return volatility across both emerging and developed countries while the announcement of the first vaccine being administered (8 December 2020) had no impact on volatility. Chan et al. (2022) reported that the commencement of the final phase of COVID-19 vaccine clinical trials had a significant positive impact on global stock returns (see also Badiani et al., 2020).

Further research analysed the impact on returns over phases of the pandemic rather than around individual events or milestones. Ramelli and Wagner (2020) identified three phases; 'incubation', commencing with reports of pneumonia cases to the WHO, 'outbreak', commencing with the WHO issuing its first situation report and the final phase 'fever', commencing with Italy's strict lockdown. Capelle-Blancard and Desroziers (2020) proposed a fourth phase, 'rebound', commencing with the announcement of support for large businesses by the US Federal Reserve and Treasury. Jana et al. (2022) observed that the pandemic had a time-varying impact on the US stock market during the early months with local fears impacting the stock market more intensely than global fears as the pandemic evolved.

The impact of COVID-19-related uncertainty on markets has also been analysed, with uncertainty quantified using metrics such as the VIX, Economic Policy Uncertainty (EPU), TMU and TEU, business expectation surveys and COVID-19-related Google search trends (GST). Capelle-Blancard and Desroziers (2020) assess the impact of the VIX and Google searches (using the terms 'COVID-19' and 'coronavirus') on 74 markets during the pandemic. Their results show that heightened uncertainty due to COVID-19 negatively impacted returns from January to April 2020. The effect was most negative during the 'fever' period but became positive during the 'rebound' phase. Szczygielski et al. (2021) examine the impact of COVID-19-related uncertainty on regional market returns and volatility during the early stages of the pandemic. Their findings reveal that Latin America and Africa were most impacted, while Asia was least impacted, which they attributed to Asia's prior experience in managing pandemics. Except for Africa and Arab markets, Szczygielski et al. (2021) report a time-varying impact of COVID-19 on all regions, whereby the initial impact intensified and subsequently dissipated. Smales (2021) confirms the negative impact of COVID-19 uncertainty on returns and increased volatility across major stock markets (see also Salisu and Akanni, 2020). Szczygielski et al. (2022), however, show that the effects of COVID-19 uncertainty on stock returns and volatility are heterogeneous across global industries, with some industries more impacted than others. They attribute the observed differential impact across industries to either uncertainty tied to the future financial performance of companies that comprise these industries or uncertainty regarding their ability to leverage potential opportunities arising from increased new business following the COVID-19 outbreak. Liu et al. (2021) document a significant spike in spillovers from Baker et al.'s (2020) Infectious Diseases Equity Market Volatility (IDEMV) index to renewable energy stocks during the pandemic. Using a broader measure of uncertainty, the TMU index, Chatterjee and French (2022) find the effect of the TMU index on stock returns to be significant and negative only during the COVID-19 period and not before the pandemic. Their results also show that TMU contributes to heightened volatility during the pandemic. Beyond stock markets, Dou et al. (2022) find that spillovers from EPU to the carbon futures market intensified during COVID-19 whereas Lu and Zeng (2023) find that transmission from the VIX to the agricultural futures market weakened after the outbreak of the pandemic.

A number of observations follow from the discussion above. Most studies prespecify COVID-19 events that are deemed important and are assumed to delineate phases as opposed to deriving them from the data. The identity of milestones is therefore subjectively imposed. Existing research focuses on examining returns and volatility around critical points and there is limited consideration of the evolution of the pandemic's influence on stock markets especially after April 2020. Milestones such as the emergence of new variants, concerns about the efficacy of vaccines and the reimposition of stringent lockdowns and travel bans have not been examined. Notably, COVID-19-related uncertainty, reflective of events that impact informational content, had a substantial impact on returns and volatility. Nevertheless, studies that investigate the evolving impact of COVID-19-related uncertainty and its resolution are limited.

3. Data and methodology

3.1. Data

Our sample spans the period from 1 December 2019 to 31 March 2022 and comprises two series, namely the VIX and MSCI All Country World Index (ACWI). We use the VIX to isolate COVID-19-related uncertainty components and to identify phases of the COVID-19 crisis. We then use the MSCI ACWI to compare COVID-19-related and overall uncertainty spillovers to global market volatility and to undertake further empirical testing of our index. First differences in the VIX are used to represent changing overall uncertainty, designated as ΔVIX_t, and market returns, $r_{W,t}$, are derived from logarithmic differences in daily MSCI ACWI levels. Global financial market volatility is approximated using squared returns:

$$V_{W,t} = r_{W,t}^2 \tag{1}$$

where $V_{W,t}$ is the realised volatility for the MSCI ACWI at time t. The use of realised volatility offers a method of constructing volatility series that does not require explicit model specification such as an ARCH/GARCH model and/or other parametric models that are complex and restrictive and permits volatility to be modelled directly using standard time series techniques (Lobato and Savin, 1998; Golosnoy et al., 2015). Descriptive statistics for returns on the MSCI ACWI and differences in the VIX over the COVID-19 period are summarised in Table 1.

Table 1
Descriptive statistics for returns on the MSCI ACWI and VIX over the COVID-19 period

Index	$r_{W,t}$	ΔVIX_t
Mean	0.0004	0.0158
Median	0.0010	−0.2056
Maximum	0.0806	30.0641
Minimum	−0.1000	−21.3327
Std. dev.	0.0127	3.3260
Kurtosis	19.6415	25.1823
Skewness	−1.4433	2.3019
SW	0.8176***	0.7688***
ADF	−6.2256***	−7.7232***
PP	−27.2097***	−31.8170***

Notes: SW is the Shapiro-Wilk test statistic verifying normality. ADF and PP are the Augmented Dickey-Fuller and Phillips-Perron test statistics respectively, with the null hypothesis positing that each series has a unit root. Both tests are conducted assuming only an intercept. *** indicates statistical significance at the 1% level of significance.

3.2. Isolating event-specific information: An economic agent-determined uncertainty index

3.2.1. Theoretical development

Risk can be viewed as 'known unknowns', whereby the outcome is unknown but the probability distribution governing the outcome is known. Contrastingly, uncertainty refers to 'unknown unknowns', whereby both the outcome and probability distribution are unknown (Knight, 1921). Theoretical models of the impact of uncertainty in asset pricing, supported by empirical evidence, propose that when economic agents are unsure of the correct probability law governing market returns, they demand a higher premium (Epstein and Wang, 2004; Bali et al., 2017). Uncertainty is a latent variable and cannot be measured perfectly (Jurado et al., 2015). Common proxies used to quantify uncertainty are market-based and include implied volatility indices (such as the VIX) and realised volatility (Cascaldi-Garcia et al., 2021). Other categories of uncertainty measures include news-based approaches that count the frequency of words linked to political and economic uncertainty in the press (such as the EPU index of Baker et al., 2016), econometric-based approaches which utilise stochastic volatility estimates from macroeconomic structural models (such as Jurado et al., 2015) and survey-based measures which capture the dispersion of various market players' views (see Altig et al., 2020). Each approach has comparative advantages. Market-based measures are available daily, with the VIX reflecting market participants' views of overall market conditions that contribute to future volatility. Survey-based measures, available less frequently (usually quarterly), provide precision in measuring uncertainty related to a particular sector or group of market participants (Cascaldi-Garcia et al., 2021).

Google is the dominant internet search engine, accounting for more than 85% of queries worldwide as of 2021 (Statista, 2021). Given its dominance in facilitating internet searches, Google searches may be viewed as representative of the population's general search behaviour. Studies that utilise Google searches as a proxy for investor uncertainty draw on economic psychology suggesting that economic agents respond to heightened uncertainty by increasing their search for information (Liemieux and Peterson, 2011; Donadelli, 2015; Castelnuovo and Tran, 2017). Bontempi et al. (2019) argue that if uncertainty can be reduced by increasing knowledge, then the intensity of searches for more knowledge using information-gathering tools is a reasonable measure of the level of uncertainty, which can be quantified using GST. Consequently, Google searches may be seen as a reflection of uncertainty surrounding a specific topic or event. Importantly, a keyword search-based approach to quantifying event-specific uncertainty is more likely to approximate the latent stochastic process underlying uncertainty suggested by Jurado et al. (2015) relative to other uncertainty measures as it varies directly with uncertainty on that topic.

A GST-based uncertainty index offers several advantages over other keyword-based indices and general uncertainty measures. First, data is available at a daily frequency. Second, it reflects retail investor uncertainty as opposed to institutional investor uncertainty (as with the VIX and some survey-based measures). Retail investors constitute an increasingly important investor segment (Aharon and Qadan, 2020) and have been shown to trade on fundamental information rather than speculation (Kelly and Tetlock, 2013). Third, searches reflect concerns about real events (Manela and Moreira, 2017; Larsen, 2021). Fourth, as economic agents searching for specific keywords also search for related keywords, Google searches can capture changing nomenclature. Fifth, a GST-based uncertainty index can be seen as a 'catch-all' proxy for significant aspects of the event as uncertainty – and searches – will be driven by news and related events. Uncertainty, given its encompassing nature, can assist in understanding investor behaviour and consequently the evolving impact of a crisis on financial markets (Cascaldi-Garcia et al., 2021).

To identify keywords that approximate event-specific uncertainty components using GST, we treat the VIX as a measure of overall uncertainty. The VIX spikes during periods of market turmoil and VIX movements are inversely related to contemporaneous stock returns and positively to volatility, reflecting conditions and data that inform economic agents' behaviour. Although the VIX is based upon S&P500 option prices, it is widely accepted and used as a benchmark for global stock market uncertainty given the strong influence of the US market on other markets (Wang, 2019; Smales, 2022). Furthermore, while there are other indices that are considered to be global uncertainty measures, such as the EPU, TEU and TMU indices, the VIX is derived directly from stock market data and therefore constitutes a well-known and closer approximation of stock market uncertainty (Dzielinski, 2012; Bekaert and Hoerova, 2014; Choi and Furceri, 2019; Wang et al., 2020). It is for these reasons that we elect to use the VIX as our proxy for overall stock market uncertainty.

The VIX has been widely used to study uncertainty during crisis periods (Altig et al., 2020; Batten et al., 2022). Uncertainty is associated with declining expected cash flows to firms as a result of ambiguity about aggregate demand and supply conditions translating into declining stock prices (Bouri et al., 2020; Ramelli and Wagner, 2020). Increased risk aversion during times of heightened uncertainty means that investors will require a higher risk premium which is reflected in the forward-looking discount rate (Andrei and Hasler, 2015).

Stock price volatility responds positively to uncertainty. 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 the arrival of new data (Engle, 2004; Nwogugu, 2006). While the VIX is forward-looking in terms of volatility expectations, it reacts to market movements contemporaneously as do GST which reflect current searches. As economic agents respond to uncertainty by searching for information around a specific issue or topic, it follows that there should be similarity between GST and the VIX as a measure of uncertainty even if the underlying conceptual paradigms differ. As uncertainty increases, economic agents search for information more intensively, reflected by increased Google searches. As uncertainty increases, stock markets respond negatively and levels of the VIX increase. Both the VIX and GST measure a variable that is not directly observable nor forecastable from the perspective of economic agents (Jurado et al., 2015). Given this suggested similarity in reflecting uncertainty, uncertainty components aggregated in the VIX should be identifiable by relating topic-specific proxies to the VIX (see Larsen, 2021; Szczygielski et al., 2023b). Google permits the use of keywords that are related to a specific topic or issue and should therefore proxy for *specific* uncertainty components.

3.2.2. Index construction methodology

The process followed to formulate our COVID-19 uncertainty index is illustrated in Fig. 1. The first step to isolating COVID-19-related uncertainty components requires us to define the search term set. We follow a fully economic agent-determined approach as we do not specify or preselect COVID-19-related search terms and therefore maintain neutrality in the choice of search terms. This contrasts with the more traditional approach (see for example Baker et al., 2016; Castelnuovo and Tran, 2017; Smales, 2021; Szczygielski et al., 2021) to constructing keyword-based indices which explicitly specifies terms that comprise these indices and therefore does not guarantee the true relevance or neutrality of search terms used.[3] We initially analyse the (global) Google 'Year in Search' pages for 2020 and 2021 which list the most popular searches in a given year according to category. Here, we identify any COVID-19-related search terms, which we define as first-level searches. Data is obtained for each of these search terms for the COVID-19 period, as defined in Section 3.1. Thereafter, we obtain data for the top 25 queries related to each first-level COVID-19 search term. 'Related queries,' as defined by Google, are those that have also been searched for by users exploring first level queries. We designate these keywords as second-level searches.

We observe search terms related to second-level searches but do not obtain data for these terms. Depending upon the sample window considered, third-level searches reflect the evolution of the COVID-19 pandemic. For example, during 2020, one of the 25 second-level search terms related to the first level search term 'coronavirus update' is 'coronavirus vaccine update.' Amongst related and rising searches which reflect searches associated with the keyword 'coronavirus vaccine update', we find third-level keywords such as 'vaccine news', 'corona vaccine' and 'coronavirus vaccine news update.' In 2021, we find 'delta variant' amongst related and rising queries. This suggests that searches associated with 'coronavirus vaccine update' are also associated with novel and emerging aspects of the pandemic, namely the Delta variant which was detected in late 2020 (named as such on 31 May 2021). GST thus reflect changing nomenclature as economic agents that searched for first- and second-level keywords also searched for keywords that are reflective of the evolution of the pandemic. The presence of such associations suggests that first- and second-level keywords *broadly* reflect uncertainty experienced by economic agents throughout the sample period. The first- and second-level keywords are listed in Table A1 of Appendix A and include non-English terms. This follows from our keyword search set being fully determined by economic agents and we reflect search terms faithfully. Google data is daily, but weekend observations are excluded for consistency with financial data, and each index is scaled to 100 for the highest value.

In the second step, we select Google search terms that approximate COVID-19-related uncertainty components reflected in the VIX. We apply the elastic net estimator to relate ΔVIX_t to differenced COVID-19 economic agent-determined Google search terms, $\Delta TERM_{k,t}$, iteratively as follows:

$$\Delta VIX_t = \alpha_V + \sum_{k=1}^{m} \beta_{\Delta TERM,k} \Delta TERM_{k,t} + \varepsilon_{V,t} \tag{2}$$

$$\beta_{\Delta TERM,k}(\text{enet}) = argmin \left[\begin{array}{c} \dfrac{1}{2n} \sum_{t=1}^{n} \left(\Delta VIX_t - \sum_{k=1}^{m} \beta_{\Delta TERM,k} \Delta TERM_{k,t} \right)^2 + \\ \lambda \left(\dfrac{1-\alpha}{2} \sum_{k=1}^{m} \beta_{\Delta TERM,k}^2 + \alpha \sum_{k=1}^{m} \left| \beta_{\Delta TERM,k} \right| \right) \end{array} \right] \tag{3}$$

where λ is the penalty parameter determined by cross-validation and α controls the penalties applied. The elastic net estimator combines a mixture of LASSO (L1 norm, $\sum_{k=1}^{m} |\beta_{\Delta TERM,k}|$) and Ridge (L2 norm,

[3] Google searches have been used to quantify investor sentiment. For example, Da et al. (2015) create a sentiment index that relies upon several dictionaries that place words into different categories such as 'positive', 'negative', 'weak' and 'strong.' Their index requires the subjective specification of keywords risking the exclusion of relevant terms and imposes a narrative through the choice of terms (see also Bontempi et al., 2019; Brochado, 2020). Szczygielski et al. (2023b) show that uncertainty and sentiment in stock markets are distinct. As our focus is on uncertainty, this supports our approach which does not distinguish between keywords with positive or negative narratives, as would be the case when measuring sentiment (Da et al., 2015; Brochado, 2020).

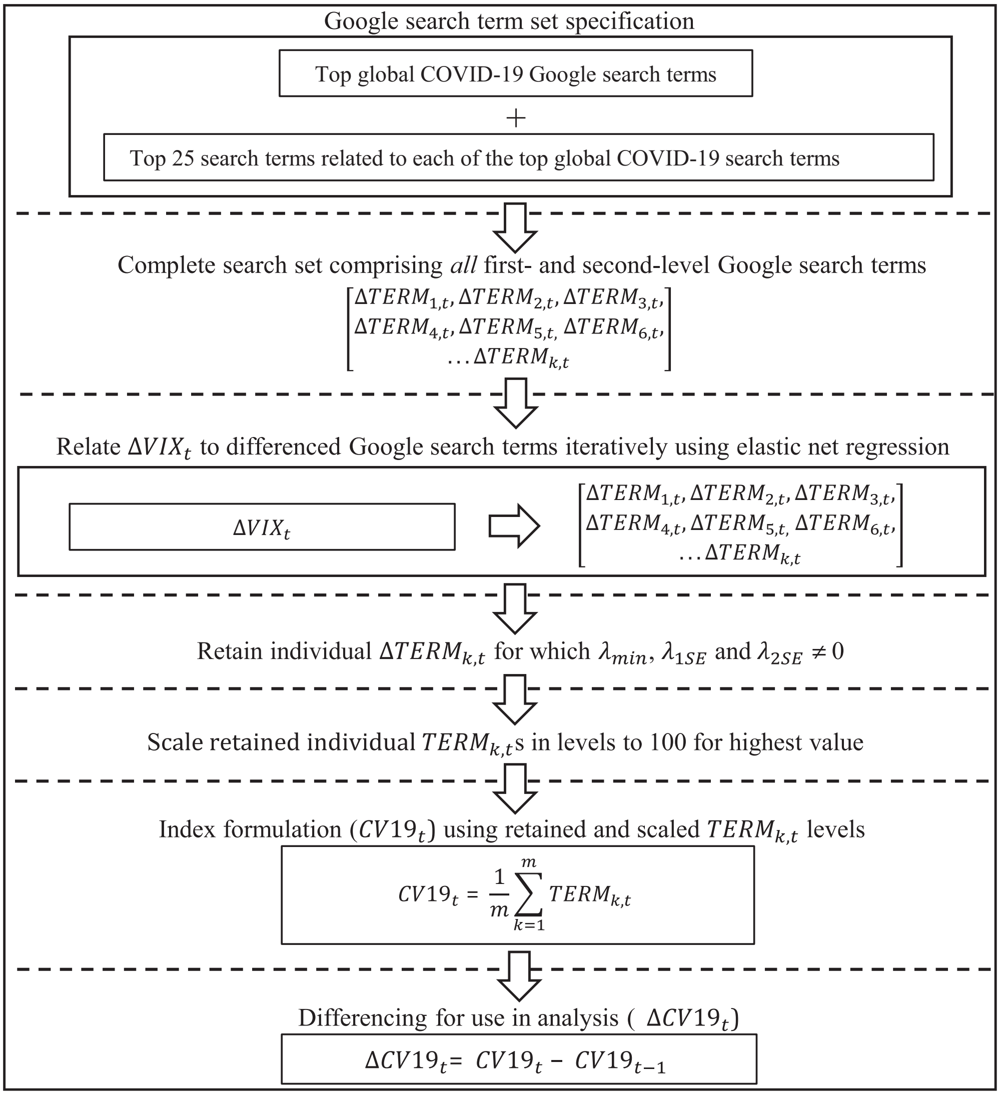


Fig. 1. Economic agent-determined GST-based index methodology summary

$\sum_{k=1}^{m}\beta^2_{\Delta TERM,k}$) penalties, where the L1 norm is a sparsity inducing penalty and L2 norm is a coefficient shrinkage penalty that performs well in the presence of multicollinearity (Zou and Zhang, 2009). Eq. (2) is re-estimated and only those keywords for which coefficients are non-zero for λ_{min}, λ_{1SE} and λ_{2SE}, where λ_{1SE} and λ_{2SE} are penalties one and two standard errors from λ_{min}, are retained. Keywords taken forward to formulate the COVID-19 uncertainty index are those for which coefficients are not shrunk to zero in the final iteration across all penalties.

The elastic net estimator (Eq. (3)) draws upon machine learning. It makes use of k-fold cross-validation, whereby data is partitioned into k sets and each set is individually used as a test set for model validation while remaining sets are used for feature selection (model building) (Jung, 2018; Zhang et al., 2019).[4] By combining LASSO and Ridge penalties and making use of k-fold cross-validation, elastic net will perform proxy keyword selection while mitigating overfitting and performing favourably under multicollinearity (Zou and Hastie, 2005; Zou and Zhang, 2009; Liu et al., 2018). COVID-19-related search terms exhibit high levels of correlation complicating the assignment of relative importance to specific search terms and therefore an application of a technique that performs favourably in the presence of multicollinearity is advantageous.[5]

The index, $CV19_t$, is formulated by adjusting the highest value to 100 and all other values relative to the highest value in each series in levels and then obtaining an average of all m terms in levels:

[4] We use five folds ($k = 5$) for k-fold cross-validation given that our sample comprises 609 observations between 1 December 2019 and 31 March 2022.

[5] We could use the least squares model for the identification of relevant search terms. However, in the presence of multicollinearity, coefficients will be sensitive to small changes in model specification and the precision of estimates will be reduced alongside a reduction in the power of significance tests. Furthermore, the least squares methodology has a propensity towards overfitting, which is increased by the presence of correlated explanatory variables (Mansour, 2020).

$$CV19_t = \frac{1}{m}\sum_{k=1}^{m} TERM_{k,t} \tag{4}$$

where $TERM_{k,t}$ are the retained terms in levels ($\Delta TERM_{k,t}$ for which λ_{min}, λ_{1SE} and $\lambda_{2SE} \neq 0$). $CV19_t$ is then differenced to obtain $\Delta CV19_t$, in line with the convention used for financial time series analysis.

3.3. Directional wavelet coherence and interpretation

The approach to phase identification is based upon wavelet coherence which we use to examine the evolution of the COVID-19 crisis on a day-to-day basis. As results are presented diagrammatically, we can attribute an interpretation to specific events that drive coherence between two variables. Wavelet coherence, understood as *localised* squared correlation, provides information about the co-movement between two series, $x_1(t)$ and $x_2(t)$, in the frequency domain transformed to periods that can be interpreted as different time or, alternatively, investment horizons. Frequency represents energy and can be interpreted as a measure of contribution. This means that high-frequency components (short horizons) contribute the most to the relationship and low-frequency components (long horizons) contribute less. Accordingly, frequency not only conveys information about investment horizons but *indirectly* also indicates the strength of contribution (energy) to the relationship. By following this approach, we can identify relationships, evaluate their strength and persistence, and localise them over time, allowing for a better understanding of the interdependence between two series (see Bouri et al., 2020; Mensi et al., 2021).

We use the Morlet wavelet as a mother wavelet (Aguiar-Conraria and Soares, 2011).[6] Wavelet squared coherence between $x_1(t)$ and $x_2(t)$ is defined as:

$$r^2_{x1,x2} = \frac{\left|S\left(WPS_{x1,x2}\right)(\tau,s)\right|^2}{S(|WPS_{x1}(\tau,s)|)S(|WPS_{x2}(\tau,s)|)} \tag{5}$$

where

$$WPS_{x1,x2}(\tau,s) = WPS_{x1}(\tau,s)WPS^*_{x2}(\tau,s) \tag{6a}$$

$$WPS_{xn}(\tau,s) = \left|W_{xn,\phi}(\tau,s)\right|^2 = \left|\int_{-\infty}^{\infty} x_t \frac{1}{\sqrt{|s|}}\phi^*\left(\frac{t-\tau}{s}\right)dt\right|^2 \tag{6b}$$

where $r^2_{x1,x2}$ represents wavelet squared coherence between $x_1(t)$ and $x_2(t)$, $WPS_{x1,x2}(\tau,s)$ is the cross-wavelet power spectrum (covariance) of $x_1(t)$ and $x_2(t)$, S is a smoothing operator, ϕ is a wavelet function (a mother wavelet), * denotes complex conjugation applied during wavelet transformation from the time to frequency domain, τ denotes a time-lag and s is the scaling parameter. Wavelet coherence takes on values between 0 and 1 with one indicating maximum coherence and zero a lack thereof.

As we have a frequency dimension, we also obtain information about the direction of association between $x_1(t)$ and $x_2(t)$ represented by phase-angles as follows:

$$\theta_{x1,x2}(\tau,s) = tan^{-1}\frac{Im\left(WPS_{x1,x2}(\tau,s)\right)}{Re\left(WPS_{x1,x2}(\tau,s)\right)} \tag{7}$$

where Im and Re denote the imaginary and real parts of $WPS_{x1,x2}(\tau,s)$ estimated for $x_1(t)$ and $x_2(t)$ at location τ and scale s. In general, phase-angles are represented by arrows on spectrograms. If $\theta_{x1,x2}(s,\tau) \in \left(-\frac{\pi}{2},\frac{\pi}{2}\right)$, $x_1(t)$ and $x_2(t)$ are in-phase, meaning they are positively correlated, otherwise, $x_1(t)$ and $x_2(t)$ are out-of-phase, i.e., they are negatively correlated. In this study, we codified positive correlations in red and negative ones in green as follows:

$$A_{x1,x2}\left(\theta_{x1,x2}(s,\tau)\right) = \begin{cases} r^2_{x1,x2} : \theta_{x1,x2}(s,\tau) \in \left(-\frac{\pi}{2},\frac{\pi}{2}\right) \\ -r^2_{x1,x2} : \theta_{x1,x2}(s,\tau) \in \left(-\pi,-\frac{\pi}{2}\right) \cup \left(\frac{\pi}{2},\pi\right) \end{cases} \tag{8}$$

Coherence by definition takes on only positive values and that is why after encoding phase-angles we now refer to positive/negative associations (or directional coherence) with colours indicative of the direction of associations. We term our approach directional wavelet coherence and apply it to analyse the evolving relationship between $\Delta CV19_t$ and ΔVIX_t and to infer phases.

To confirm a contribution-based interpretation of the associations between COVID-19-related and overall uncertainty, we draw upon the concept of Wavelet Shannon Time Energy Entropy (WSTEE). Shannon entropy can be viewed as a classic measure of uncertainty (Shannon, 1948; Schuster and Just, 2006) and, as our study is concerned with uncertainty, its use is arguably appropriate. Shannon entropy can be defined as:

$$H = -\sum_i p_i ln(p_i) : \sum_i p_i = 1 \tag{9}$$

where H indicates Shannon entropy and p_i is a probability distribution estimated within time. In probability theory, entropy quantifies the average flow of information per unit of time. Therefore, entropy represents a loss of information, i.e. the growth of uncertainty within a system observed by an outsider. WSTEE quantifies the expectation of information and related to it, uncertainty, weighted by energy distribution across horizons (Yang and Wang, 2015). A comparison of entropy curves for two series enables an analysis of uncertainty content in both series and indicates the level of contribution of a given measure of uncertainty to the other. The evolution of wavelet Shannon energy entropy (which represents a 'boundary' entropy) can be stated as follows:

$$WSTEE = -\sum_i p_i ln(p_i); p_i = \frac{D_i(t)^2}{\sum_i D_i(t)^2}; \sum_i p_i = 1; \tag{10}$$

where $D_i(t)^2$ denotes energy at scale i and time t, and $\sum_i D_i(t)^2$ is the total energy (at all scales) at time t calculated using squared power spectrum wavelet coefficients. When the association between $\Delta CV19_t$ and ΔVIX_t is positive, COVID-19-related uncertainty increasingly contributes to overall uncertainty. When association becomes negative, COVID-19-related uncertainty contributes less to overall uncertainty over a horizon. When $\Delta CV19_t$ and ΔVIX_t entropies increase (decrease) *simultaneously,* this corresponds to positive association between ΔVIX_t and $\Delta CV19_t$. If $\Delta CV19_t$ entropy increases (decreases) and ΔVIX_t entropy decreases (increases), negative association between ΔVIX_t and $\Delta CV19_t$ will be observed. Negative association in this context does not suggest that our index no longer reflects pandemic-related uncertainty, but that it contributes less to overall uncertainty (Sulthan and Jayakumar, 2016). As long as $\Delta CV19_t$ energy entropy is above zero, COVID-19-related uncertainty contributes to overall uncertainty, although the level of contribution will vary.

4. Uncertainty and crisis evolution

4.1. Crisis evolution and phase identification using directional wavelet coherence

The iterative procedure (Section 3.2.2.) identified seven Google

[6] We utilise wavelet coherence, a method rooted in the continuous wavelet transform, with the Morlet wavelet adopted as the default mother wavelet. To analyse the hypothetical distribution of wavelet coherence, we employ the Monte Carlo transform, using 300 surrogate data sets in the significance calculation. Significance is reported at the 10% level which is often used in finance studies (see Baker and Wurgler, 2006; Bai et al., 2023).

search terms with non-zero coefficients across penalties related to the VIX (see Table A2 in Appendix A for final iteration results).[7] The R^2 values for the final iteration of Eq. (2) remain above zero across penalties indicating that the constituent terms approximate stock market uncertainty components (R^2 of 0.316 at the minimum penalty level (λ_{min}) and 0.2776 and 0.2314 for λ_{1SE} and λ_{2SE}, respectively). These terms were used to formulate $CV19_t$ (Eq. (4)). Ordinary and Spearman correlations for $\Delta CV19_t$ and ΔVIX_t are 0.5565 and 0.1834, respectively.

Fig. 2, which plots the spectrogram of $\Delta CV19_t$ against ΔVIX_t, reveals two important findings. The first is the confirmation of the relationship between overall uncertainty (ΔVIX_t) and COVID-19-related uncertainty ($\Delta CV19_t$) as indicated by significant associations across horizons (see Table A4 in Appendix A). The second is that this approach permits us to determine *how* economic agents perceived specific events during the evolution of the COVID-19 pandemic indicated by whether COVID-19-related uncertainty contributed to overall uncertainty (positive, red) or whether its contribution declined (negative, green). Over the long horizon, association between $\Delta CV19_t$ and ΔVIX_t persists throughout the sample period and is overwhelmingly positive (upper part of Fig. 2). Over short horizons, there are periods during which there is an alternating association between COVID-19-related uncertainty and overall uncertainty although association is mostly positive. Taken together, this explains the overall positive relationship between $\Delta CV19_t$ and ΔVIX_t indicated by correlation coefficients and shows that although localised association may vary, the overall relationship is positive, as expected.

The period between December 2019 and April 2020 is dominated by mostly positive association between $\Delta CV19_t$ and ΔVIX_t, representing a persistent positive relationship with long-term stock market uncertainty (area A and significant short- and medium-run association and highly persistent association beyond the 32-day horizon). Pervasive positive association that extends into all horizons implies that COVID-19-related uncertainty is a major and persistent contributor to overall uncertainty. This period coincides with rising concerns around increasing COVID-19 cases, growing fatalities and a WHO emergency meeting (in January 2020). Notably, this period includes COVID-19 officially being declared a pandemic by the WHO (11 March 2020), which corresponds to a sharp increase in Google searches for information on COVID-19 (Jun et al., 2021). Around the middle of March 2020 and onwards, the G7 and numerous other countries implemented lockdowns and travel bans. To et al. (2021) view the implementation of government non-pharmaceutical interventions as generating higher than usual volatility and having a long-lasting impact that induced distrust of government actions and contributed to rising uncertainty amongst investors and the general public. The shock of the COVID-19 outbreak, coupled with the implementation of unprecedented response measures and the anticipation of severe economic consequences, resulted in elevated levels of uncertainty for economic agents. This was exacerbated by the substantial amount of information they had to process during the outbreak (Haroon and Rizvi, 2020; Ramelli and Wagner, 2020; Harjoto et al., 2021b; see Section 4.3). Association patterns reflecting a severe response in Fig. 2 suggest that our index captures this. Furthermore, fiscal and macroprudential policy responses over the period January to April 2020 exacerbated uncertainty across most financial markets due to their unexpected nature (see Deev and Plíhal, 2022). Alternative measures of uncertainty, such as the TEU and sales uncertainty indices peaked in April 2020 (Altig et al., 2020). Consequently, we designate this first phase as a ‘shock’ phase. During this phase, economic agents were confronted with unprecedented restrictions on economic activity due to the onset of a global pandemic. This compelled them to comprehend the potential consequences, resulting in a severe shock.

Between May and the end of October 2020, short-run positive association gives way to negative association in the medium run and then in the short run (around July 2020), suggesting the emergence of a new normal (area B). While multiple events reflecting the evolution of the pandemic occurred during this period, such as the highest number of infections recorded on a single day (7 June 2020), the surpassing of 10 million cases and 500,000 recorded deaths, the contribution of COVID-19-related uncertainty to overall uncertainty begins declining (Whiting and Wood, 2021). This is suggested by the alternating direction of association between $\Delta CV19_t$ and ΔVIX_t over the short horizon. Significant association is now mostly limited to the short horizon of under four days, implying that although $\Delta CV19_t$ contributes to overall uncertainty, the contribution is not as persistent. Additionally, government support packages and central bank interventions aimed at supporting individuals and economic recovery, introduced between March and April 2020 in numerous countries, resulted in positive stock market responses (Capelle-Blancard and Desroziers, 2020; Siddik, 2020). Although these measures likely contributed to increased uncertainty initially (Deev and Plíhal, 2022), they contributed to lowering uncertainty following the outbreak period (see Seven & Yılmaz, 2021). We designate this phase as the ‘emergence’ phase because of a more muted contribution of $\Delta CV19_t$ to overall uncertainty. Economic agents exhibit less uncertainty during this period suggesting that a process of accustomisation began and expectations normalised, with COVID-19 uncertainty falling in response to the prior introduction of restrictions and extension of economic support measures (see Section 4.3.).

The next phase is the ‘transition phase’ between November 2020 and May 2021 (area C). This period is characterised by a mostly positive association between $\Delta CV19_t$ and ΔVIX_t in the medium run, and in the short run between November 2020 and January 2021. This phase saw the emergence of COVID-19 variants, namely the Alpha, Beta (both December 2020), Gamma (January 2021) and Delta variants (named as such in May 2021) (Centers for Disease Control and Prevention (CDC), 2022), arguably novel aspects suggesting that the COVID-19 virus was evolving, and also coincided with the beginning of vaccination programmes. In November 2020, short-run association is positive implying that COVID-19-related uncertainty again began contributing to overall uncertainty. Significant and protracted co-movement that extends into the medium term (December 2020 and approximately January to May 2021, middle area C) suggests that medium-run positive correlation is driven by the emergence of COVID-19 variants. However, between January and April 2021, numerous COVID-19 vaccines were being tested with many entering Phase 3 trials. Global markets responded positively to the beginning of vaccine trials and subsequent rollouts have been shown to reduce global market volatility. This potentially explains negative co-movement over the short run between the beginning of 2021 and May 2021, suggesting that the contribution of COVID-19-related uncertainty to overall uncertainty declined. Rouatbi et al. (2021) and Chan et al. (2022) document that the prospect of mass vaccinations, which were now foreseeable, contributed to falling COVID-19-related uncertainty by foretelling economic and social benefits such as recovering economic activity and reduced restrictions. We propose that during this phase, uncertainty was simultaneously driven by COVID-19 variants (positive association extending into the medium term) while the *prospect* of mass vaccination rollouts reduced short-term uncertainty temporarily (Baek and Lee, 2022).

[7] As the final iteration identifies search terms that have non-zero coefficients across penalties (see Section 3.2.2) but does not directly indicate statistical significance, we estimate ordinary (ρ_O) and Spearman (ρ_S) correlations between ΔVIX_t and the individual COVID-19-related search terms that comprise our index. Results confirm that the individual search terms identified are significantly correlated with ΔVIX_t, except for a single term, ‘coronavirus usa’, for which ρ_S is statistically insignificant but ρ_O is significant (see Table A3 in Appendix A).

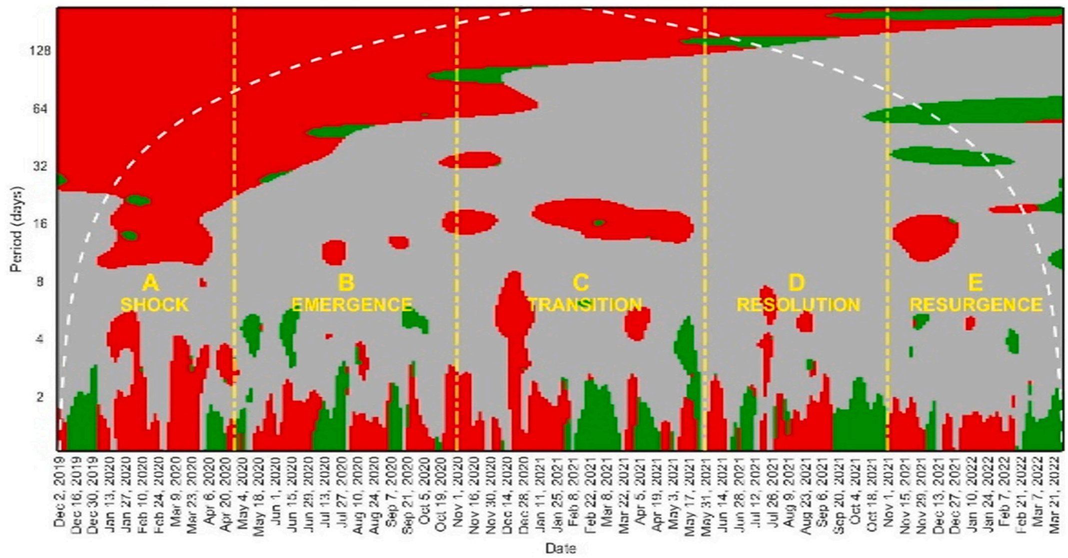


Fig. 2. Spectrogram for $\Delta CV19_t$ and ΔVIX_t.

Notes: Fig. 2 presents a spectrogram for $\Delta CV19_t$ and ΔVIX_t in three dimensions: date on the horizontal axis, frequency domain on the vertical axis expressed in the number of days (periods), indicative of investment horizon, and wavelet coherence values (in colours). Regions in red reflect a positive association between $\Delta CV19_t$ and ΔVIX_t. Regions in green reflect negative association. Coloured regions report associations for $\Delta CV19_t$ and ΔVIX_t at the 10% significance level. The white dashed line indicates the 5% significance level for edge effects occurring in associated data. A greater number of days indicates a longer investment horizon and more persistent associations. However, associations occurring over shorter horizons are more impactful. Periods of between 1 and 4 days are defined as the short run, periods of 5 to 32 days are defined as the medium run and periods greater than 33 days are designated as the long run. [For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.]

The 'resolution' phase coincides with the global rollout of mass COVID-19 vaccination programmes, lasting from the end of May/beginning of June until October 2021 (area D). This period is characterised by limited positive medium-run association between July and September 2021 and negative association between COVID-19-related uncertainty and overall uncertainty over the short run, notably in October 2021. By the end of May 2021, only 10.9% of the global population was fully or partially vaccinated, but by the end of October 2021, this percentage stood at 50% (Ritchie et al., 2022). Yousaf et al. (2023) demonstrate that the availability of vaccines contributed to a resolution of uncertainty, implying that economic agents viewed vaccines as having the potential to bring the pandemic to an end although the effect was fairly short-lived. Both Baek and Lee (2022) and Gächter et al. (2022) also show that the number of vaccinations contributed to a reduction in US stock market uncertainty (measured by the VIX) consistent with the 'restarting' of the economy. However, this calming effect dissipated rapidly. Baek and Lee (2022) similarly find that the vaccination effect was limited to short-term frequency horizons as observed in Fig. 2. While some short-lived medium-run positive association (July 2021) is present during the resolution phase, the presence of short-run negative association, pointing to a lower contribution of COVID-19-related uncertainty to overall uncertainty, is indicative of a degree of uncertainty resolution towards the end of this phase.

The 'resurgence' phase is denoted from November 2021 until the end of the sample (area E). This period is characterised by mostly positive association between $\Delta CV19_t$ and ΔVIX_t in the medium term in November/December 2021 and short run between January and February 2022. The significant event that we believe to be driving COVID-19-related uncertainty, responsible for both positive short- and medium-run association at the beginning of this phase, is the emergence of the Omicron variant in November 2021. This variant exhibited higher transmissibility, evasion against acquired immunity, breakthrough infection in vaccinated individuals, and rapidly accumulated a high number of mutations relative to previous variants. Owing to its high transmissibility, the Omicron variant became the dominant strain in several countries (Khandia et al., 2022). It is likely that these (arguably novel) characteristics contributed to stock market declines and concerns about interrupted global economic recovery driven by an increased number of new confirmed cases and rising global inflation. Furthermore, this variant resulted in the rising possibility of new restrictions and the subsequent implementation thereof in some countries (Meyer, 2021). The potential return of more severe restrictions and the characteristics of the Omicron variant are potential drivers of increasing COVID-19-related uncertainty observed during the resurgence period, notably at the start of this phase.

Fig. 3 indicates that COVID-19 uncertainty ($\Delta CV19_t$, red line) contributed to overall uncertainty (ΔVIX_t, blue line) during all phases although the level of contribution varied. At no point does entropy decline to zero (see Fig. A1 in the Appendix for normalised entropy that takes on values between $[0, 1]$). This confirms our contribution-based interpretation of COVID-19 uncertainty driving overall uncertainty.[8]

4.2. Policy responses and stock market uncertainty

Our analysis suggests that a number of events contributed to rising and falling uncertainty as the COVID-19 pandemic evolved, with the implementation of policy responses featuring prominently, consistent

[8] As confirmation of the validity of our interpretation of Fig. 2, we plot 20-day rolling ordinary (ρ_O) and Spearman (ρ_S) correlations for $\Delta CV19_t$ and ΔVIX_t (see Fig. A2 in Appendix A). Correlation patterns approximate coherence observed in Fig. 2. The highest and most persistent positive correlations, corresponding to the coherence patterns in Fig. 2, are observed during the shock phase (area A) followed by the early stages of the transition period (area C). The emergence period is characterised by alternating positive and negative correlations of a relatively lower magnitude, corresponding to positive and negative short-run coherence in Fig. 2. Towards the end of the transition phase, correlations decline and become negative. This coincides with declining levels of alternating positive and negative short-run coherence.

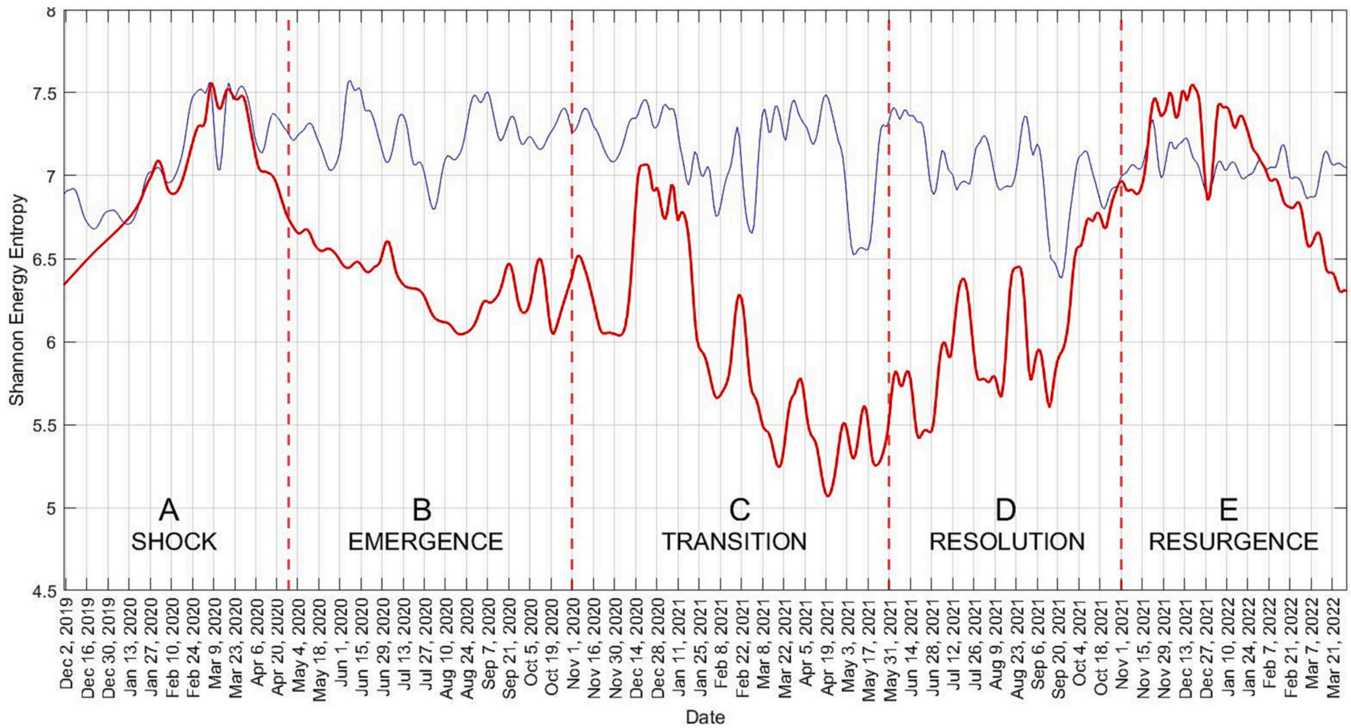


Fig. 3. $\Delta CV19_t$ and ΔVIX_t entropies.
Notes: Fig. 3 presents Wavelet Shannon Time-Energy Entropy for $\Delta CV19_t$ (red line) and ΔVIX_t (blue line). Dates are stated on the horizontal axis whereas the vertical axis reflects energy entropy levels. Vertical dashed lines delineate phases. If $\Delta CV19_t$ and ΔVIX_t entropies increase (decrease) simultaneously, then COVID-19-related uncertainty contributes positively to overall uncertainty. If $\Delta CV19_t$ entropy increases (decreases) and ΔVIX_t entropy decreases (increases) simultaneously, COVID-19-related uncertainty contributes less to ΔVIX_t. [For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.]

with prior studies. Sharif et al. (2020) show that US geopolitical risk and EPU were impacted by government policies during the pandemic. Non-pharmaceutical responses, such as information campaigns, public event cancellations and work and school place closures, resulted in heightened stock market volatility although the impact varied across developed and emerging markets (Zaremba et al., 2020; Bakry et al., 2022). Szczygielski et al. (2021) found that overall government interventions triggered negative returns and increased volatility for most regions apart from Asia. COVID-19 vaccinations contributed to reducing uncertainty and positively led sectoral equity indices (Yousaf et al., 2023). Baek and Lee (2022) find that vaccinations reduced VIX levels. Gächter et al. (2022) illustrate that a positive shock to COVID-19 vaccinations resulted in lower unemployment and stock market uncertainty and increased economic growth. In contrast, Yousfi et al. (2021) show that COVID-19 cases and deaths continued to contribute to heightened stock market uncertainty during the second wave, as observed during the first wave, despite the relaxation of quarantine restrictions.

We apply the Granger causality test to confirm whether policy responses, COVID-19-related deaths and total cases drove $\Delta CV19_t$ and ΔVIX_t. To perform this analysis, we construct indices for every measure in the OxCGRT database by value weighting indices for each measure using market capitalisations for the 35 largest stock markets as of November 2019. To determine the overall direction of responses to innovations in each measure, we examine cumulative response functions for $\Delta CV19_t$ and ΔVIX_t (see Figs. A3 and A4 in Appendix A). The cumulative impulse response function illustrates the accumulation of a shock's impact on $\Delta CV19_t$ and ΔVIX_t over time, rather than just its impact at a specific moment in time.

Table 2 indicates that overall government responses, the stringency of government responses, health and containment, and economic support measures drove both $\Delta CV19_t$ and ΔVIX_t. There is consistency between broad policy responses driving both indices, except for overall government responses. In this case, there is causality at three lags for ΔVIX_t whereas for $\Delta CV19_t$, the null hypothesis of no causality is rejected across all lags. $\Delta CV19_t$ and ΔVIX_t respond positively initially to the former three (see Panels A, B, and C in Fig. A3 and A4 in Appendix A), whereas the response to innovations in economic support measures is negative for both (see Panel R in Figs. A3 and A4 in Appendix A). This means that government responses and health and containment measures contributed to heightened uncertainty whereas economic support measures contributed to reducing uncertainty.

Interestingly, $\Delta CV19_t$ appears to respond to a broader set of measures. For example, contact tracing and facial coverage (both health), stay at home requirements (containment) and debt relief (economic support) drive $\Delta CV19_t$ but not ΔVIX_t. When accumulated impulse responses are significant, they are positive, notably for the accumulated response of $\Delta CV19_t$ to the implementation of testing policies and facial coverage (see Panels D and F in Fig. A3 in Appendix A). Google searches tend to be more reflective of retail investor searches, as institutional investors typically rely on professional information services (e.g.

Table 2
Causality tests

Policy response/measure	Panel A: $\Delta CV19_t$ 1 lag	3 lags	5 lags	Panel B: ΔVIX_t 1 lag	3 lags	5 lags
Government response	19.6573***	13.2881***	9.7112***	0.3109	2.3793*	1.6934
Stringency of response	10.5639***	8.7755***	4.6199***	0.0363	4.8695***	3.2602***
Health and containment	8.9386***	7.6904***	5.059***	0.035	3.9911***	2.7031**
Health						
Testing policy	0.0291	2.8147**	4.249***	1.8686	0.5283	1.139
Contact tracing	0.2456	2.5833*	2.9934**	0.765	1.0014	1.2012
Facial coverage	0.1223	6.4877***	4.6563***	0.3602	2.6561	2.4125**
Vaccination policy	0.0023	0.0265	0.1342	0.0297	0.4025	0.7209
Protection of the elderly	0.2584	0.2748	0.7399	0.0576	0.0293	0.1183
Containment						
Schools closing	0.0069	5.5782***	42.4686***	2.8564*	4.8979***	13.0867***
Workplace closing	2.5413	2.4603*	1.8618*	2.4716	0.9655	1.032
Public event cancellations	0.025	3.3871**	1.7742	1.7068	6.2297***	4.3291***
Restrictions on gatherings	0.0514	0.3292	4.2443***	0.261	1.31	2.8931**
Public transport closures	0.3026	1.2698	1.195	0.5449	1.3431	0.771
Stay at home requirements	11.2574***	9.906***	4.5537***	0.0704	1.1123	1.339
Movement restrictions	3.631*	1.6045	0.6292	0.0286	0.7806	0.6912
International travel restrictions	0.0347	1.0451	0.5026	0.3306	0.5658	0.401
Public information campaigns	20.2434***	30.6907***	23.102***	0.7091	2.353*	3.2001***
Economic support	32.5117***	16.8192***	12.2429***	6.9601***	5.2166***	3.6088***
Income support	29.9496***	15.2458***	12.2134***	11.0961***	6.8719***	4.5811***
Debt relief	14.7280***	8.0111***	4.8946***	1.4539	1.9391	1.4771
Cases	0.0129	0.0029	0.0025	0.4543	0.2239	0.2341
Deaths	1.5241	0.3458	0.2998	0.0021	1.0906	1.8995*

Notes: The Granger causality test, testing the null hypothesis of policy responses, cases and deaths having no effect on $\Delta CV19_t$ and ΔVIX_t, is conducted at 1, 3 and 5 lags with causality assumed to run from policy responses and direct measures of COVID-19, namely death and cases, to $\Delta CV19_t$ and ΔVIX_t. Panels A and B report the results of the Granger causality test for $\Delta CV19_t$ and ΔVIX_t respectively. Policy responses, deaths and cases are constructed by value weighting data from the Oxford COVID-19 Government Response Tracker (OxCGRT) for the 35 largest stock markets in terms of market capitalisation as of November 2019. Data is available from 1 January 2020. Government response, stringency of responses, health and containment, cases and deaths (in **bold**) are broad categories of indicators. Health, Containment and Economic Support (in ***bold*** and *italicised*) by themselves are sub-categories. ***, ** and *, indicate statistical significance at the respective 1%, 5% and 10% levels of significance.

Bloomberg) (Dimpfl and Jank, 2016; Smales, 2021). Also, retail investors, as individuals, are likely to be more acutely impacted by a number of measures, such as stay at home requirements, workplace closures and facial coverage, which will be reflected by Google searches. Furthermore, Google searches may also capture other information not reflected by the VIX, such as sentiment and/or attention (Dergiades et al., 2015). It may also be the case that institutional investors adapted quicker and with greater ease than retail investors, given greater access to financial resources that the former may have had. Retail investors, on the other hand, continued to face various restrictions on a daily basis, explaining the rejection of the null hypothesis of no causality for $\Delta CV19_t$ for a greater number of measures. Therefore, while the ΔVIX_t predominantly reflects uncertainty faced by institutional investors, $\Delta CV19_t$ isolates components of the ΔVIX_t while also reflecting uncertainty faced by individual investors which potentially explains the broader causality observed (Dzielinski, 2012).

Vaccination policy and cases do not Granger cause $\Delta CV19_t$ and ΔVIX_t while deaths only drive ΔVIX_t when the Granger causality test is conducted with five lags. Nevertheless, this does not mean that these measures were inconsequential. Instead, it suggests that these measures might have been significant during specific phases of the crisis, and stock markets might have ceased to react to changes in these measures as a 'new normal' took shape and the pandemic progressed. In other words, their impact would have been localised in time (Bradley and Stumpner, 2021; Seven and Yılmaz, 2021; Yousaf et al., 2023). For example, Szczygielski et al. (2023a) report that from the end of October 2020, case-based measures (infections, deaths) began driving stock markets although their overall impact was very limited. Prior to this, global markets were extensively impacted by COVID-19-related uncertainty, the stringency of government responses and media hype. Spectrograms in Baek and Lee (2022) illustrate that while the number of vaccinations contributed to a reduction in the VIX, this effect was isolated to an approximately 20-week period (early January to May 2021). This is also consistent with the findings of Yousaf et al. (2023) that the effects were relatively short-lived (see Section 4.1). Possible factors contributing to this include supply shortages and delays in vaccine orders, as well as the limited efficacy of vaccines against emerging variants. It may also be that other related information mattered. For example, Bakry et al. (2022) report that the Pfizer vaccine announcement resulted in increased volatility for emerging and developed markets but the administration of the first Pfizer vaccine had no impact on volatility. Relatedly, our sample considers the impact of COVID-19 over a period that is longer than two years meaning that the dynamic between a policy response and stock market uncertainty may have changed and may have been short-lived to begin with. These considerations offer possible reasons why vaccination policies do not Granger cause $\Delta CV19_t$ and ΔVIX_t but nevertheless seemingly contributed to uncertainty resolution during the resolution phase (Section 4.1).

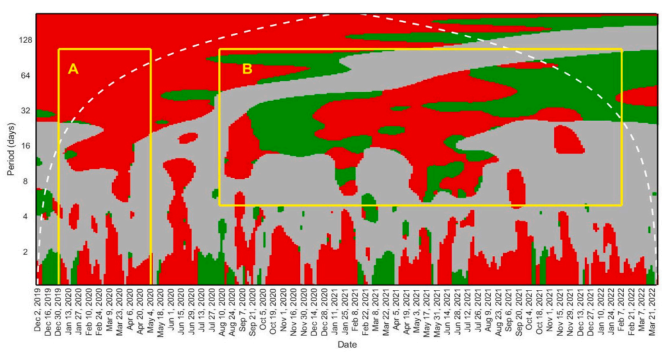
As a final test, we regress $\Delta CV19_t$ and ΔVIX_t onto the contemporaneous, lagged (three lags) and combined (contemporaneous and lagged) differences in index values for the four major categories of responses, and report explanatory power as measured by the $\overline{R}^2$ (see Table A6 in Appendix A for results). All measures have explanatory power for both $\Delta CV19_t$ and ΔVIX_t. Only economic support measures lack contemporaneous explanatory power but have significant intertemporal explanatory power. Measures have higher explanatory power for $\Delta CV19_t$, suggesting that this measure is more responsive to government responses and policy decisions. For example, the $\overline{R}^2$ for the regression relating $\Delta CV19_t$ to overall government responses is 0.1406 whereas for ΔVIX_t, it is 0.0552 when considering contemporaneous and intertemporal terms. This generally holds across response measures and across intertemporal structures, with explanatory power approximately double for $\Delta CV19_t$ relative to that for ΔVIX_t across measures. This supports the argument that $\Delta CV19_t$ also reflects retail investor uncertainty and is therefore driven by a broader set of policy responses than ΔVIX_t. We conclude that both $\Delta CV19_t$ and ΔVIX_t respond to policy interventions – and a plethora of other COVID-19-related news, announcements and events not directly considered here – and that $\Delta CV19_t$ reflects retail investor uncertainty in addition to ΔVIX_t components by design.

4.3. Spillovers to global markets and informational content

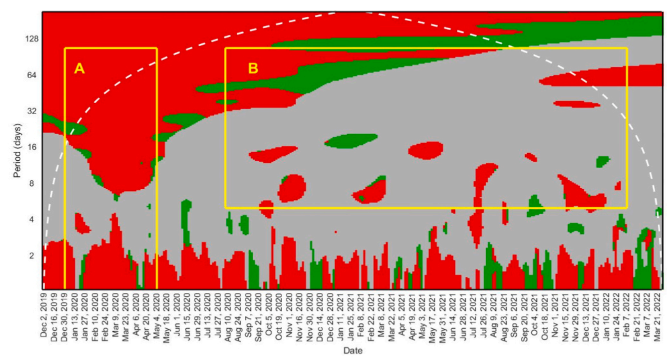
We investigate shared information reflected by $\Delta CV19_t$ and ΔVIX_t by modelling COVID-19-related uncertainty spillovers to global volatility using our index. In Fig. 4, we plot associations between realised variance, $V_{W,t}$, for the MSCI ACWI and ΔVIX_t (Panel A), followed by associations between $V_{W,t}$ and $\Delta CV19_t$ (Panel B). The impact of $\Delta CV19_t$ is isolated by applying partial wavelet coherence to model ΔVIX_t spillovers after controlling for $\Delta CV19_t$ (Panel C):

$$r^2_{x1,x2,z} = \frac{\left|\gamma_{x1,x2}(s,\tau) - \gamma_{x1,z}(s,\tau)\gamma_{z,x2}(s,\tau)^*\right|^2}{\left(1 - r^2_{x1,z}(s,\tau)\right)\left(1 - r^2_{x2,z}(s,\tau)\right)} \tag{11}$$

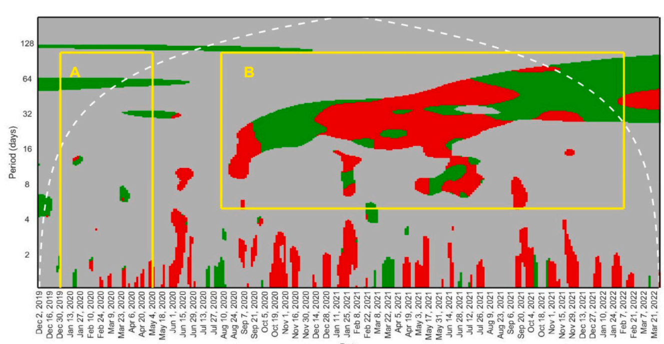
where $r^2_{x1,x2}$ now represents partial wavelet squared coherence between $x_1(t)$ and $x_2(t)$, $\gamma_{x1,x2}(s,\tau)$ is complex wavelet coherence between $x_1(t)$



A: Realised global market variance and ΔVIX_t



B: Realised global market variance and $\Delta CV19_t$



C: Realised global market variance and ΔVIX_t after controlling for $\Delta CV19_t$

Fig. 4. Spectrograms for realised global market variance, $V_{W,t}$

Notes: Fig. 4 reports spectrograms for $V_{W,t}$ and ΔVIX_t (Panel A), $V_{W,t}$ and $\Delta CV19_t$ (Panel B), and $V_{W,t}$ and ΔVIX_t after controlling for the influence of COVID-19-related uncertainty measured using GST, $\Delta CV19_t$ (Panel C), with time on the horizontal axis, the frequency domain on the vertical axis expressed in the number of days (periods) and wavelet coherence values (in colours). $V_{W,t}$ represents the realised variance for the MSCI ACWI, calculated by squaring returns. Red (green) regions are indicative of positive (negative) associations. Coloured regions report associations significant at the 10% significance level. The white dashed line indicates the 5% significance level for edge effects. Higher horizons (periods) indicate a longer investment horizon and more persistent uncertainty spillovers. A greater number of days indicates a longer investment horizon and more persistent associations. Values of (approximately) between 1 and 4 days are defined as the short run, 5 to 32 days are defined as the medium run and values greater than 33 days are designated as the long run. [For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.]

Table 3
Regression results and stability tests.

Panel A: Regression results		
α	$\beta_{\Delta CV19_t}$	$\overline{R}^2$
0.0150	0.8326***	0.3086
Panel B: Quandt-Andrews breakpoint test		
Maximum LR F-statistic (04/08/2020)	Exponential LR F-statistic	Average LR F-statistic
4.7994	0.2957	0.4616
Panel C: Bai-Perron test of m+1 versus m sequentially determined breaks		
Break test	F-statistic	Scaled F-statistic
0 vs. 1	1.3591	2.7182

Notes: In Panel A, least squares with Newey-West heteroscedasticity and serial correlation consistent (HAC) standard errors are used. Panel B reports the results of the Quandt–Andrews breakpoint test for one or more unknown structural breakpoints. Panel C reports the results of the Bai-Perron test with heterogeneous error distributions across breaks with 5% trimming and a 10% level of significance. ***, ** and * indicate statistical significance at the respective 1%, 5% and 10% levels of significance.

and $x_2(t)$ and $x_1(t)$ now becomes $V_{W,t}$, $x_2(t)$ is ΔVIX_t and z(t) is $\Delta CV19_t$ and * denotes complex conjugation applied during wavelet transformation from the time to frequency domain. If $\Delta CV19_t$ reflects uncertainty components that are also reflected in ΔVIX_t, and these components impact realised volatility, directional coherence between ΔVIX_t and $V_{W,t}$ should decrease in areas where COVID-19 uncertainty contributes substantially to overall uncertainty. Remaining directional coherence will be the result of (other) information not captured by $\Delta CV19_t$.

In Panels A and B of Fig. 4, medium- and long-term association patterns are highly similar following the declaration of COVID-19 as a pandemic in March 2020 (area A in both). In Panel C, this association dissipates after accounting for $\Delta CV19_t$ (area A). It thus appears that much of the uncertainty spillovers reflected by ΔVIX_t during the shock phase of the pandemic are attributable to uncertainty around COVID-19. The outbreak of the COVID-19 pandemic and subsequent response measures sparked expectations of a serious economic fallout (i.e., a severe recession), fuelled by media hype, fake news, and speculation about adverse effects (Vasterman, 2005; Nicomedes and Avila, 2020). Also, early in the crisis when economic data was limited, predictions about a severe impact on corporate profitability led investors to anticipate lower future cash flows (Mamaysky, 2020). The information overload and the unprecedented nature of the situation together with the implementation of restrictions impacting economic activity posed a significant challenge for economic agents, resulting in substantial stock market responses as illustrated in Panel A (area A) (Zaremba et al., 2020; Bakry et al., 2022; Szczygielski et al., 2023a).

Patterns differ significantly in Panels A and B of Fig. 4 from August 2020 (area B); while medium-run association is relatively continuous in Panel A, it is far more sporadic in Panel B, suggesting that COVID-19-related uncertainty spillovers to global markets became far more intermittent and less persistent relative to those originating from other sources. This suggests that the impact of COVID-19 on financial markets began dissipating. Bradley and Stumpner (2021) suggest that vaccine news fuelled recovery expectations, with struggling sectors partially bouncing back and thriving sectors maintaining their momentum. Baek and Lee (2022) and Yousaf et al. (2023) report that vaccinations initially had a positive influence on the US economy and stock market attributable to a reduction in the level of aggregate uncertainty. Furthermore, from the end of October 2020 onwards, there was a consistent upward trend in the MSCI ACWI, potentially due to normalised expectations amongst economic agents as the pandemic evolved. This normalisation was facilitated by government rescue packages restoring investor confidence and reducing uncertainty with investors adjusting to a 'new normal' (Seven and Yılmaz, 2021; Yousaf et al., 2023). Relatedly, economic agents no longer had to process such a large quantum of information as was the case following the designation of COVID-19 as a pandemic and the implementation of unprecedented responses (Szczygielski et al., 2023a). The impact of the shock on markets diminished, as major equity markets began reverting to their natural state following the COVID-19 shock (Yarovaya et al., 2022).

Nevertheless, COVID-19-related uncertainty still contributed to medium- and long-run uncertainty, as evident from Panel C, although to a much lower extent. We note significant short-term positive association in both Panels A and B throughout the sample period implying that uncertainty continued to be a source of global market volatility in the short run, even if medium-run association became sporadic from August 2020 onwards (Panel B, area B). This is confirmed in Panel C after adjusting for $\Delta CV19_t$. Less frequent short-run uncertainty spillovers evident after adjusting for $\Delta CV19_t$ suggest short-run spillovers were driven by $\Delta CV19_t$ although markets became less reactive and more rational in relation to COVID-19. Other sources of uncertainty (such as the outcome of US elections in November 2020 and Brexit negotiations) began playing a role in driving market volatility as suggested by medium-run spillovers in Panel C (area B). These, however, are less pervasive than those in Panel A (unadjusted) confirming that COVID-19-related uncertainty still contributed somewhat to medium-run spillovers.

4.4. *Google searches as a measure of uncertainty: Further evidence*

Wavelet analysis presents a decomposition of the relationship between $\Delta CV19_t$ and ΔVIX_t over horizons. However, our index is an aggregate of all horizons and therefore the overall relationship will differ from that suggested by localised correlations. To confirm *overall* stability, ΔVIX_t is regressed onto $\Delta CV19_t$ and the Quandt-Andrews unknown breakpoint (see Andrews and Ploberger, 1994) and Bai and Perron (2003) tests are applied to test for structural changes in the relationship.

Panel A of Table 3 reports a positive coefficient for $\beta_{\Delta CV19_t}$, confirming that $\Delta CV19_t$ moves together with ΔVIX_t throughout the sample period.[9] This result indicates that positive association dominates despite limited localised negative short-run associations in Fig. 2 (see Table A4

[9] The approximative power of $\Delta CV19_t$ for ΔVIX_t is validated by utilising the robust adjusted coefficient of determination, $\overline{R}_w^2$, proposed by Renaud and Victoria-Feser (2010). The $\overline{R}_w^2$ accounts for outliers and deviations from normality in the dependent variable and is derived using robust least squares (MM-estimation).

Table 4
Results for specifications without breaks

Index	$\Delta CV19_t$	ΔVIX_t
Panel A: Conditional mean		
α_W	0.0004***	0.0005***
$\beta_{W,\Delta UN}$	−0.0026***	−0.0028***
$\beta_{W,k}$	0.0067***	0.0061***
r_{t-1}	−0.0363***	−0.0154***
Panel B: Conditional variance		
Model	GARCH(1,1)	GARCH(1,1)
ω_W	5.89E-07***	5.88E-07***
α_1	0.1585***	0.1482***
β_1	0.8107***	0.8081***
$\varphi_{W,\Delta UN}$	0.1160*	0.0736***
Panel C: Diagnostics		
$\overline{R}^2$	0.7896 (0.2732)	0.8274 (0.5594)
$Q(1)$	1.3141	0.3007
$Q(10)$	6.3809	8.7965
ARCH(1)	2.1834	2.1267
ARCH(10)	1.1071	8.1054
Log-likelihood	7969.439	8149.769

Notes: This table reports the results of the impact of both uncertainty measures, $\Delta CV19_t$ and ΔVIX_t, on the returns and variance for the MSCI ACWI. Coefficients on each uncertainty measure in the conditional variance equation are scaled by 100,000. Panel A reports estimation results for the conditional mean, which also includes a proxy factor derived from regional returns using factor analysis and adjusted for the impact of each uncertainty measure. Panel B reports the results for the conditional variance. Panel C reports model diagnostics, with $Q(1)$ and $Q(10)$ being Ljung-Box tests statistics for joint serial correlation at the 1st and 10th orders respectively. ARCH(1) and ARCH(10) are test statistics for the ARCH LM test for heteroscedasticity at the 1st and 10th lags respectively. The $\overline{R}^2$ value in brackets ( ) reports the 'true' explanatory power for $\Delta CV19_t$ and ΔVIX_t obtained by regressing returns onto these uncertainty proxies over the crisis period using least squares while excluding proxy and lags adjusting for serial correlation. This can be viewed as the explanatory power attributable solely to $\Delta CV19_t$ or ΔVIX_t. Each model is estimated over the period 1 January 2015 to 31 March 2022. This extended estimation sample is used to account for dependence structures in the residuals, with the COVID-19 period defined as 1 December 2019 to 31 March 2022. The equations above are first estimated using maximum likelihood estimation. If residuals are non-normal, they are re-estimated using quasi-maximum likelihood estimation with Huber-White standard errors and covariance. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels of significance, respectively.

in Appendix A for disaggregated correlations). This does not preclude transient relationships in terms of alternating direction, which we observe in Fig. 2, notably over the short run. Nor does it preclude certain horizons dominating other horizons, resulting in an overall positive relationship. Results in Panels B and C indicate no structural breaks. Consequently, $\Delta CV19_t$ approximates COVID-19 uncertainty components reflected by ΔVIX_t throughout the sample period – although its contribution to overall uncertainty varies at different points in time (Fig. 2). The latter is to be expected as a crisis evolves.

As an alternative test to confirm, measure and compare the impact of both ΔVIX_t and $\Delta CV19_t$ on global market volatility, we apply GARCH (1,1) modelling:

$$r_{W,t} = \alpha_W + \beta_{W,\Delta UN}\Delta UN_t Dum_{0,1} + \beta_{W,k}F_{k,t} + \gamma_W r_{W,t-\tau} + \varepsilon_{W,t} \tag{12}$$

$$h_{W,t} = \omega_W + \sum_{i=1}^{p}\alpha_W\varepsilon^2_{W,t-i} + \sum_{j=1}^{q}\beta_W h_{W,t-j} + \varphi_{W,\Delta UN}\Delta UN_t Dum_{0,1} \tag{13}$$

where $Dum_{0,1}$ is a shift dummy denoting the pre-COVID-19 (1 January 2015 to 30 November 2019) and COVID-19 periods (1 December 2019 to 31 March 2022). An extended sample is used to reduce biases in maximum likelihood estimates. $F_{k,t}$, an analytically derived factor from regional MSCI market aggregates adjusted for either uncertainty measure, is included to account for omitted influences (see Van Rensburg, 2000).

In Panel A of Table 4, both $\Delta CV19_t$ and ΔVIX_t have a significant negative impact on returns, as evident from negative $\beta_{W,\Delta UN}$ coefficients. Uncertainty translates into declining expected cash flows to firms and heightened risk aversion associated with a higher risk premium (Pástor and Veronesi, 2012). Both ΔVIX_t and $\Delta CV19_t$ trigger heightened volatility, as indicated by positive $\varphi_{W,\Delta UN}$ coefficients in Panel B. The ('true')[10] adjusted coefficient of determination, $\overline{R}^2$, is smaller for the regression of returns onto $\Delta CV19_t$ ($\overline{R}^2$ of 0.2732) relative to that for ΔVIX_t (0.5594). This is to be expected if $\Delta CV19_t$ approximates components of overall uncertainty. This is further confirmed by lower (in absolute terms) standardised coefficients for $\Delta CV19_t$ than ΔVIX_t ($\beta_{W,\Delta CV19}$ and $\varphi_{W,\Delta CV19}$ of −0.4577 and 0.0752, respectively and $\beta_{W,\Delta VIX}$ and $\varphi_{W,\Delta VIX}$ of −0.7333 and 0.0856, respectively). This analysis confirms the (overall) direction of the relationship between $\Delta CV19_t$ and volatility and provides support for the proposition that a GST-based index can be used

[10] The $\overline{R}^2$ value in brackets ( ) reports the 'true' explanatory power for $\Delta CV19_t$ and ΔVIX_t which may be interpreted as the explanatory power of each uncertainty measure over the crisis that is not confounded by proxy factors and adjustments for serial correlation. See note appended to Table 4 for further details.

to reflect event-specific uncertainty spillovers to stock markets.[11]

Finally, as one of the objectives of this study is to demonstrate that Google searches can be used to isolate event-specific uncertainty (see Section 3.2.1), we compare the adequacy of our index against four alternative keyword-based proxies for uncertainty; the newspaper-based IDEMV ($\Delta IDEMV_t$) of Baker et al. (2020), the newspaper-based US Equity Market Volatility Index (ΔEMV_t) of Baker et al. (2019), and the TEU and TMU indices of Baker et al. (2021).[12] Results indicate there is a statistically significant relationship between both ΔTMU_t and ΔTEU_t and ΔVIX_t although the strength of the relationship as indicated by standardised coefficients is weaker than that between ΔVIX_t and $\Delta CV19_t$ (see Panel A of Table A5 in Appendix A). While $\Delta CV19_t$ approximates 30% of ΔVIX_t, ΔTMU_t and ΔTEU_t approximate 12% and 5%, respectively. We expect this to be the case, given that $\Delta CV19_t$ is constructed specifically to approximate COVID-19-related uncertainty components whereas ΔTMU_t and ΔTEU_t are general keyword-based uncertainty proxies. Surprisingly, there is no significant relationship between ΔVIX_t, $\Delta IDEMV_t$ and ΔEMV_t.[13] Next, we examine the ability of $\Delta CV19_t$ to approximate these indices (see Panel B of Table A5 in Appendix A). The relationship between both ΔTMU_t and ΔTEU_t and $\Delta CV19_t$ is positive and significant, with $\Delta CV19_t$ approximating over 2% and 4% of movements in these indices, respectively. There is no relationship between $\Delta IDEMV_t$, ΔEMV_t and $\Delta CV19_t$, with this potentially being attributable to $\Delta IDEMV_t$ and ΔEMV_t not approximating ΔVIX_t.[14] These results again point towards $\Delta CV19_t$ reflecting topic-specific uncertainty, following from the observation that $\Delta CV19_t$ is better at approximating VIX components and is related to uncertainty proxies that are also significantly related to ΔVIX_t, namely ΔTMU_t and ΔTEU_t.

5. Implications and discussion

Google, along with other search engines, is a technological tool that offers direct access to the thoughts and attitudes of economic agents. This access provides valuable understanding of how new information is processed. Google search data is readily available at varying frequencies, has advantages over survey-based measures of prevailing views and reduces the likelihood of economic agents being influenced by external parties (Dietzel et al., 2014). The COVID-19 pandemic is characterised by novelty, as are other crises to differing degrees. We utilise Google searches in conjunction with the machine learning technique of elastic net regression, to isolate and construct an index that quantifies uncertainty linked to COVID-19. This analysis spans an extended period, encompassing the initial outbreak and its subsequent aftermath.

Our analysis shows that the response to the outbreak of COVID-19 resulted in a significant increase in uncertainty, as revealed by the extensive levels of association between $\Delta CV19_t$ and ΔVIX_t (see also Jun et al., 2021; Section 4.1). The onset of the global pandemic led to unprecedented restrictions on economic activity and government interventions, presenting economic agents with the challenge of comprehending the potential consequences thereof, compounded by a large quantum of information. Global markets reacted to the outbreak

[11] While the COVID-19 crisis had a significant impact on financial markets and society, another crisis followed shortly thereafter: the first truly global energy crisis (Birol, 2023). The impact of energy price uncertainty on financial markets and the economy is recognised in the literature (see Brown and Yücel, 2002; Degiannakis et al., 2018; Korosteleva, 2022). A number of events contributed to soaring oil, natural gas and coal prices such as the rapid post-COVID-19 economic recovery, excess demand for oil, a European wind drought in 2021, the lead up to the Russian invasion of Ukraine and the invasion (February 2022), sanctions on Russian energy imports, supply chain disruptions, and bidding wars for energy products as European countries sought to secure energy supplies (Ajdin, 2022; Benton et al., 2022; Logan, 2022). We isolate components reflective of energy price uncertainty using Google searches and an extension of our methodology. The search set comprises a total of 95 terms that include and are related to 'oil price', 'oil prices', 'natural gas price', 'natural gas prices', 'coal price' and 'coal prices' over the period 1 June 2021 and 31 January 2023. The AutoSEARCH (general-to-specific) algorithm of Sucarrat and Escribano (2012) is used for an initial screening of search terms related to ΔVIX_t. Next, elastic net regression is applied to reduce the search term set and to take advantage of k-fold cross-validation. Keywords for which coefficients are non-zero for λ_{min}, λ_{1SE} and λ_{2SE} enter the subsequent iteration of the elastic net regression and fitted values are used to proxy for energy price uncertainty, $\Delta ENPU_t$ (see Table B1 in Appendix B). Our extension isolates and approximates ΔVIX_t components while reducing the number of iterations, permitting a more flexible structure and assigning weights to search terms. Abridged results are reported in Appendix B. Full results are available upon request. Fig. B1 plots the spectrogram for $\Delta ENPU_t$ and ΔVIX_t with coherence reflecting events that fuelled energy price uncertainty. Entropies are plotted in Fig. B2. Between October and December 2021, the first coal and natural gas price peak occurred, with fears of a possible Russian invasion of Ukraine driving energy prices upwards (region A). Russia's invasion of Ukraine in February 2022 contributed to concerns about Europe's dependence on Russian oil and sanctions were imposed in March 2022 (Benton et al., 2022). In April 2022, European countries began considering energy rationing while in May 2022, they began seeking substitutes for Russian gas through imports, contributing to rising natural gas prices (Gill and Kose, 2022; Logan, 2022). Steel, chemical and fertilizer producers began shutting down factories in Europe in June 2022 due to rising oil and gas prices (region B). In July 2022, Fatih Birol, head of the International Energy Agency (IEA), stated that the world has never witnessed such a complex and extensive energy crisis and that the worst may still be ahead (Stringer, 2022). Russia stopped gas supplies to Europe via the Nord Stream 1 pipeline and explosions ruptured the Nord Stream 1 and 2 pipelines in September 2022 (region C). In October 2022, Russia and Saudi Arabia slashed oil production by 2 million barrels citing global economic uncertainty and in November 2022, global demand for floating liquified natural gas storage and regasification rose dramatically as countries sought to boost natural gas imports. European countries began facing potential shortfalls in natural gas in December 2022, paving the way for the energy crisis to worsen with warnings that the energy crisis could last several years (region D) (IAE, 2022). Table B2 indicates that $\Delta ENPU_t$ approximates over a quarter of the variation in ΔVIX_t ($\overline{R}^2$ of 0.2699) and that there are no structural breaks in the relationship. Table B3 confirms that $\Delta ENPU_t$ and ΔVIX_t impact global stock market returns negatively, as expected, and trigger volatility. Table B4 reports the results of Granger causality tests assuming energy price movements and energy price volatility or both drive energy price uncertainty. The null hypothesis is broadly rejected suggesting that energy prices and energy price volatility drive $\Delta ENPU_t$. Our main conclusion continues to hold; Google searches can be used to isolate and approximate topic-specific components of overall uncertainty (as measured by ΔVIX_t).

[12] We devised a two-step test for this purpose. First, we established the ability of these indices to approximate the VIX by regressing ΔVIX_t onto $\Delta IDEMV_t$, ΔEMV_t, ΔTEU_t and ΔTMU_t and compare them against $\Delta CV19_t$. We report *standardised coefficients* which can be interpreted similarly to correlation coefficients and treat the adjusted coefficient of determination, $\overline{R}^2$, as the ability of each index to approximate ΔVIX_t (see Nimon and Oswald, 2013). In the second step, we regress each of these indices onto $\Delta CV19_t$. As our index is topic-specific, we expect our index to approximate components of these broader indices. By following this approach, we are able to establish the significance and strength of the relationship while accounting for the varied nature of these indices.

[13] We investigate this further by permitting intertemporal relationships using leads and lags. The relationship between ΔVIX_t and $\Delta IDEMV_t$ becomes marginally significant (first two of three lags are significant, significant Wald F-statistic) when lags are considered ($\overline{R}^2$ of 0.0056).

[14] Szczygielski et al. (2023b), in their study of the narrative reflected by *general* stock market-related Google searches, also report a weak relationship between ΔEMV_t and Google searches and find that ΔEMV_t has no noticeable explanatory or predictive power for factors driving returns and volatility in an extensive sample of stock markets.

severely (Section 4.3), with the COVID-19 outbreak triggering significant volatility. Nevertheless, as the pandemic progressed markets reacted in a more muted manner which can be attributed to normalising investor expectations, facilitated by economic support measures and a reversion to a more natural state. Markets became more rational and less reactive, with other events increasingly playing a role in driving market dynamics.

We use continuous wavelet transform which provides detailed insights into interdependence between two series, including shocks and persistent correlations. It surpasses regular regression analysis, which lacks temporal and frequency variation insights. Advanced methods such as the DCC-GARCH model are needed to investigate time-varying correlations (Jensen and Whitcher, 2014). The refinement that we develop, directional wavelet coherence, permits the modelling of interdependencies over different horizons with greater precision, assisting in the understanding of how specific events contributed to heightened market volatility. This refinement can benefit researchers utilising non-traditional quantitative methods to study interdependencies in finance and economics (see Bouri et al., 2020; Mensi et al., 2021). For example, our analysis revealed that while the designation of COVID-19 as a pandemic (11 March 2020) had a long-term contributory effect on stock market uncertainty, the emergence of the Omicron variant in late November 2021 (Fig. 2, area E), resulted in uncertainty that was relatively short-lived. Although certain elements of the COVID-19 pandemic remained novel, overall, it was no longer considered a completely new or unfamiliar situation. This insight would not have been possible without utilising wavelet analysis and, in particular, directional wavelet coherence. Knowledge derived from our analysis can be exploited when designing international diversification strategies or for identifying resilient markets. Moreover, investors can use our approach to model uncertainty spillovers in specific markets (as in Fig. 4) and to determine which markets recover quickest from shocks. Information from directional spectrograms can also be used to form expectations about how long heightened uncertainty will persist and when uncertainty resolution can be expected. While the future is unpredictable, better-informed decisions can be undertaken by exploiting knowledge about the effects of past events.

The value of a technique that allows for the modelling of crisis evolution at high frequencies and the identification of uncertainty-related phases is substantial. The COVID-19 pandemic stands as one of the most impactful and disruptive events in recent history (Cruz-Cárdenas et al., 2021). Much like wars and sociopolitical shifts, its impact is far reaching with substantial declines in income, employment and productivity (see Ceylan et al., 2020; Goodell, 2020). In such circumstances, policy responses are critical. Our analysis indicates that Google searches are more responsive to policies aimed at mitigating a crisis relative to the VIX, suggesting that GST may be a better proxy for gauging the effectiveness of interventions (see Section 4.2.). Therefore, our approach presents a more comprehensive and broader measure that can be utilised to assess the efficacy of government interventions at a high frequency and may be particularly useful for the monitoring of the later stages of future pandemic-like crises (and crises in general) when restrictive measures are relaxed or withdrawn and support measures take effect. In an environment of uncertainty, our approach offers valuable insights for market participants aiming to mitigate downside risk throughout all stages of a crisis (see Akhtaruzzaman et al., 2021).

Relatedly, our study shows that information campaigns and economic support measures were particularly effective, having a negative accumulated impact on $\Delta CV19_t$ (see Fig. A3 in Appendix A). policymakers can use this knowledge – awareness of which responses are effective – to plan for anticipated crises and can adapt or discard those that were ineffective. While a pandemic-like situation may be unlikely in the near future, these measures can serve as viable policy responses in any future crisis. A prominent example of an emerging crisis following the COVID-19 pandemic is what is termed as the first truly global energy crisis, starting in June 2021 (Birol, 2023; see Appendix B). The projected consequences of escalating energy prices include an increase in inflation, highly restrictive monetary policy, a decrease in productive capacity, a decline in global GDP and a setback in the global economy's recovery from the COVID-19 pandemic (Guenette et al., 2022; Korosteleva, 2022; Yagi and Managi, 2023). Responses to this crisis will naturally depend on several factors and will be the result of the superposition of different economic and political considerations. Information campaigns and economic support packages have their merits and can prove to be beneficial. However, it may also be necessary to develop new crisis-specific measures in response to the evolving situation. The approach presented here will aid policymakers in rapidly assessing the effectiveness of new measures.

By using elastic net regression to select COVID-19-associated search terms that are related to a measure of overall uncertainty, we isolate and capture uncertainty around a specific crisis. Our approach demonstrates how machine learning can be used to filter 'infobesity' (Karhade et al., 2021). Our index comprises just seven Google search terms whereas the search set consists of 110 terms. Investors have limited computational capacity yet must deal with large information flows, leading to potential departures from market efficiency if information flows become too large and costly to process (Pernagallo and Torrisi, 2020). Our methodology enables us not only to determine which keywords are utilised by economic agents to reflect uncertainty experienced by market participants, thus ensuring true objective relevance, but also demonstrates how information costs and complexity can be reduced by extracting only the most important and relevant search terms. This methodological approach offers a broader application, allowing for the identification and analysis of numerous factors, whether they are characteristic-based or macroeconomic in nature, that play a role in traditional asset pricing. It is not limited to the formulation of keyword-based indices but can be utilised to assess the influence of various factors on asset pricing more generally. Specifically, as suggested by Feng et al. (2020), it can be used to 'tame the [asset pricing] factor zoo'.

Our approach defines and sets the narrative by relating search terms to a well-known measure of uncertainty. Without a clear narrative, as is often the case when Google searches and other keyword-based measures are used to model stock market behaviour, it is difficult to determine how GST-based indices may be useful for the purposes of analysis, econometric modelling and application within the context of modelling stock market dynamics (see Da et al., 2011; Brochado, 2020 for examples of studies differing on narrative). A clear narrative assists in the application of GST-based indices for the purposes of investment decision making and portfolio management and facilitates broader analysis and research while permitting the measurement of the impact of specific events using search terms that are relevant to economic agents. The approach expounded can be generalised to assign different narratives, such as sentiment, attention or general economic uncertainty, by relating Google searches to a pre-selected general proxy that reflects a desired narrative. This conclusion stems from the idea that Google searches serve as indicators of the views of economic agents. In light of this, our study contributes to developing a systematic approach to shaping narratives and measuring their impact. This allows researchers, econometricians and analysts to explore the effects of a particular narrative concerning a specific topic or event on stock markets.

We show that Google searches reflect uncertainty about an outcome that is not perfectly forecastable and contribute to an understanding of the information captured by GST (see Section 4.1). GST can reflect uncertainty around a *specific* event, depending upon the keywords used in index formulation. An important implication arises from this finding: economic agents directly disclose their views by utilising specific search terms. By using GST, researchers, econometricians and analysts can decompose the effects of uncertainty – or any other narrative – associated with specific events or categories of events such as wars, geopolitical risk and recessions, and no longer need to rely upon general proxies that may confound narratives around specific events with general narratives. Furthermore, Google search data can be readily obtained, is free, available at a high frequency and does not require advanced programming skills meaning that researchers can use this data, combined with the approach demonstrated here, to achieve a level of analytical specificity on a topic of interest with greater ease than using newspaper or Twitter data (see Dietzel et al., 2014; Balcilar et al., 2018; Będowska-Sójka et al., 2022).

While this study is concerned with modelling the evolution of the COVID-19 crisis – nowcasting – at a high frequency using Google searches, it can be adapted for forecasting purposes. Dietzel et al. (2014), Bijl et al. (2016), Kim et al. (2019) and Brochado (2020) demonstrate that GST can predict financial market dynamics and asset prices in the short and longer run. As Google search data is available at varying frequencies, predictive narrative-based indices can be constructed by taking into account intertemporal relationships between a given proxy and GST. As an illustration, in the construction of a predictive sentiment index similar to the approach taken by Brochado (2020), terms that exhibit a correlation with a sentiment proxy in a previous time period can be utilised. These terms can be employed to create an index that enables the prediction of how shifts in sentiment may influence future economic and financial market dynamics. Moreover, Google searches have been shown to predict variables such as unemployment suggesting that our approach can be applied in areas other than narrative modelling (see D'Amuri and Marcucci, 2017; Niesert et al., 2020). As elastic net incorporates the use of k-fold cross-validation, search terms selected using this approach are more likely to have predictive power out-of-sample. In a more general context, this approach mitigates model overfitting (Bergmeir et al., 2018).

6. Conclusion

Crises have a profound impact on society and COVID-19 stands out as one of the most impactful and economically disruptive events in recent times. Its unprecedented nature and the responses that ensued resulted in heightened levels of uncertainty that had an initially profound impact on financial markets. We model the evolution of the pandemic by relating Google searches associated with COVID-19 to an overall measure of stock market uncertainty, the VIX, using elastic net regression. We isolate and quantify the impact of resultant uncertainty. Our measure of topic-specific uncertainty is economic agent-determined, relying upon COVID-19-related search terms that economic agents searched for and are related to the VIX. This follows from the proposition that if economic agents are searching for specific keywords, and these keywords are correlated with an established measure of uncertainty, then such keywords can be used to formulate a topic-specific uncertainty index. Further testing of our index confirms that it is a proxy for topic-specific uncertainty and we confirm its ability to model the influence of uncertainty on global market returns and volatility using ARCH/GARCH modelling. Our index outperforms two other keyword based-measures of uncertainty, namely the TMU and TEU indices, in approximating the VIX. We use Shannon Time-Energy Entropy to propose a contribution-based interpretation for COVID-19-related uncertainty to overall uncertainty.

The COVID-19 pandemic can be characterised by five phases, designated as 'shock', 'emergence', 'transition', 'resolution' and 'resurgence'. They are delineated by the initial outbreak of the virus, which is characterised by high levels of novelty compounded by speculation about its consequences, the imposition of unprecedented restrictions and support measures, the emergence of variants, prospects of effective vaccines and vaccine rollouts. The initial outbreak contributed to highly persistent levels of uncertainty. Our analysis is facilitated by the application of wavelet coherence combined with a refinement that discriminates between negative and positive associations, designated as directional wavelet coherence. Causality tests suggest that responses to the pandemic played a significant role in driving uncertainty, with $\Delta CV19_t$ seemingly more responsive to interventions than ΔVIX_t. A potential reason for this is because Google searches proxy for uncertainty experienced by retail investors and may reflect other components such as sentiment or attention.

Global markets experienced a significant and pronounced reaction during the initial stages of the crisis, exhibiting extreme volatility in response to COVID-19-related uncertainty. Our assertion is that this reflects the anticipation of a substantial economic downturn, exacerbated by an overwhelming and ambiguous influx of information, which in turn fuelled speculation. Our analysis further suggests that with time, expectations normalised and as the pandemic evolved. This was aided by rescue packages that restored confidence and an adjustment to a 'new normal'. As the pandemic progressed, other events became a source of uncertainty impacting global stock markets.

Our research presents a comprehensive analysis of the progression of the COVID-19 pandemic, spanning a prolonged duration that surpasses numerous existing studies primarily focused on its initial stages. The results and insights that follow, and the methodology applied should be of interest to researchers, econometricians, market analysts and policymakers. Several implications follow. First, Google searches can be used to gain an understanding of how economic agents process information. Second, directional wavelet analysis offers a complementary analytical tool that, unlike traditional wavelet coherence, permits the modelling of positive and negative associations while overcoming some of the limitations of regression analysis. Third, Google searches are more responsive to interventions than the VIX, offering a potentially useful measure of the impact of public policy, and analysis suggests that information campaigns and economic support measures contributed to reducing uncertainty. While these measures will likely be useful in future crises, an approach that permits the high-frequency monitoring of the effectiveness of crisis-response measures will assist in formulating appropriate future crisis-specific responses. Our study makes a valuable contribution to the development of a systematic methodology for shaping narratives and quantifying their influence. Moreover, this study lays the groundwork for future extensions and advancements in modelling topic-specific narratives, opening possibilities for adapting the methodology for forecasting variables beyond narrative proxies.

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CRediT authorship contribution statement

Jan Jakub Szczygielski: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration. **Ailie Charteris:** Investigation, Writing – original draft, Writing – review & editing. **Lidia Obojska:** Methodology, Software, Validation, Formal analysis, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Janusz Brzeszczyński:** Conceptualization, Writing – review & editing.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

Appendix A and B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.techfore.2024.123319.

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Jan Jakub Szczygielski is an Assistant Professor of Finance at Kozminski University in Poland and an extraordinary lecturer at the University of Pretoria in South Africa. His research interests are in empirical finance, financial econometrics, asset pricing and information transmission. He has published in Finance Research Letters, International Review of Financial Analysis, Energy Economics, Journal of International Financial Markets, Institutions and Money and the Journal of Portfolio Management.

Ailie Charteris is an Associate Professor of Finance at the University of Cape Town in South Africa. Her research interests include capital markets, investments, behavioural finance, and commodities. She has published in journals including Energy Economics, International Review of Financial Analysis, Finance Research Letters, Journal of International Financial Markets, Institutions and Money and the Investment Analysts Journal among others. She is an associate editor of the Investment Analysts Journal.

Lidia Obojska is an Associate Professor of Mathematics at Kozminski University (KU) in Poland. Before joining KU, she worked at Space Research Centre of Polish Academy of Sciences in Warsaw. She has also worked for AARHUS Institute of Advanced Studies in Denmark, was a member of the "International Advisory Council for the Metanexus Global Network Initiative" of Metanexus Institute for interdisciplinary researchers in New York and is an expert in EU Horizon 2020. She also serves as a reviewer for AMS: Mathematical Reviews. She has published in the International Review of Financial Analysis, Chaos Solitons and Fractals, Journal of Physics Communications and Review of Symbolic Logic.

Janusz Brzeszczyński is a Professor of Finance in the Business School at the Edinburgh Napier University (ENU) in Edinburgh. Before joining ENU, he worked at the Robert Gordon University (RGU) in Aberdeen, at Northumbria University in Newcastle upon Tyne and at Heriot-Watt University in Edinburgh. He is also a Professor at the Faculty of Economics and Sociology at the University of Łódź. Janusz Brzeszczyński was awarded Fulbright scholarship (Senior Grant) at the Arizona State University in the USA, Humboldt Fellowship for Experienced Researchers at the University of Münster in Germany, ESKAS federal scholarship at the Swiss Institute of Banking of Finance at the University of St. Gallen in Switzerland and DAAD research scholarship at the Kiel University in Germany. His editorial work currently includes the Associate Editor role at the Finance Research Letters journal and Senior Editor role at the International Journal of Emerging Markets.