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Google search trends and stock markets: Sentiment, attention or uncertainty?

Jan Jakub Szczygielski[a,e], Ailie Charteris[b], Princess Rutendo Bwanya[c], Janusz Brzeszczyński[d,f,*]

[a] Department of Finance, Kozminski University, ul. Jagiellońska 57/59, Warsaw, 03-301, Poland
[b] Department of Finance and Tax, University of Cape Town, Rondebosch, Cape Town, 7700, South Africa
[c] Department of Accounting and Financial Management, Newcastle Business School (NBS), Northumbria University, Newcastle upon Tyne, NE1 8ST, United Kingdom
[d] Aberdeen Business School, Robert Gordon University, Garthdee Road, Aberdeen, Scotland, AB10 7QE, United Kingdom
[e] Department of Financial Management, University of Pretoria, Private Bag x20, Hatfield, Pretoria, 0028, South Africa
[f] Department of Capital Market and Investments, Faculty of Economics and Sociology, University of Łódź, ul. POW 3/5, Łódź, 90-225, Poland

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ABSTRACT

Keyword-based measures purporting to reflect investor sentiment, attention or uncertainty have increasingly been used to model stock market behaviour. We investigate and shed light on the narrative reflected by Google search trends (GST) by constructing a neutral and general stock market-related GST index. To do so, we apply elastic net regression to select investor relevant search terms using a sample of 77 international stock markets. The index peaks around significant events that impacted global financial markets, moves closely with established measures of market uncertainty and it is predominantly correlated with uncertainty measures in differences, implying that GST reflect an uncertainty narrative. Returns and volatility for developed, emerging and frontier markets widely reflect changing Google search volumes and relationships conform to *a priori* expectations associated with uncertainty. Our index performs well relative to existing keyword-based uncertainty measures in its ability to approximate and predict systematic stock market drivers and factor dispersion underlying return volatility both in-sample and out-of-sample. Our study contributes to the understanding of the information reflected by GST, their relationship with stock markets and points towards generalisability, thus facilitating the development of further applications using internet search data.

1. Introduction

Information drives stock markets. Firms, governments and other institutions provide information which is disseminated by the media. Investors receive information from media sources which influences trading decisions and translates into stock price movements (Aouadi, Arouri, & Roubaud, 2018; Wang, 2018). The media, therefore, plays a critical role in the dissemination and interpretation of information (Agarwal, Kumar, & Goel, 2019; Strycharz, Strauss, & Trilling, 2018). This is known as information supply, where investors passively receive information from the media. However, the development and widespread usage of the internet has revolutionised information dissemination and processing, giving investors the opportunity to search for information actively as opposed to limiting investors to the passive reception of information (Agarwal et al., 2019; Wang, Rao, & Peng, 2015). Actively sought information can be viewed as demand side information.

The role of information in financial markets is well-established in existing literature. When new information is released, stock prices, trading volume and volatility are impacted (Vlastakis & Markellos, 2012). Likewise, active searches for information by investors have an impact on stock prices and volatility. As the demand for information increases and the number of informed investors rises, prices become

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* Corresponding author at: Aberdeen Business School, Robert Gordon University, Garthdee Road, Aberdeen, AB10 7QE, Scotland, United Kingdom.
E-mail addresses: jszczygielski@kozminski.edu.pl, kuba.szczygielski@up.ac.za (J.J. Szczygielski), ailie.charteris@uct.ac.za (A. Charteris), princess.bwanya@northumbria.ac.uk (P.R. Bwanya), j.brzeszczynski@rgu.ac.uk (J. Brzeszczyński).

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more reflective of current events (Grossman & Stiglitz, 1980). Since information is not directly observable, any study of the impact of information on financial markets relies on the use of proxies. Keyword-based measures of information are particularly useful as they filter information based on the frequency with which words appear in media sources. The plethora of traditional news outlets, online news services and social media such as Twitter has given rise to several information supply keyword-based indices. The availability of Google search trends (GST) has opened an avenue for the creation of information demand keyword-based indices as investors must actively search for information by using specific terms. These indices, both supply and demand side, differ in *subject*, such as a focus on the economy *versus* the stock market, and *narrative*, such as uncertainty, sentiment or attention (see for example Baker, Bloom, & Davis, 2016; Castelnuovo & Tran, 2017; Manela & Moreira, 2017; Szczygielski, Charteris, & Obojska, 2023). Understanding these distinctions is important in ascertaining the *what* – the subject – and the *why* – the narrative – that different keyword-based indices quantify and how they impact stock returns and volatility.

Examples of information supply keyword-based indices that are hypothesised to reflect an uncertainty narrative are the United States (US) economic policy (EPU) and equity market uncertainty (EMU) indices of Baker et al. (2016), the equity market volatility (EMV) index of Baker, Bloom, Davis, and Kost (2019) which is closely related to the EMU index, the news-based implied volatility index (NVIX) of Manela and Moreira (2017) and the Twitter economic (TEU) and market uncertainty (TMU) indices of Baker, Bloom, Davis, and Renault (2021). Brogaard and Detzel (2015) and Özyeşil and Tembelo (2020) show that the EPU and EMU indices can predict and explain US stock returns. Su, Fang, and Yin (2019) and Fang, Qian, Chen, and Yu (2018) demonstrate that the NVIX has predictive power for long-term US and (other) developed market volatility. Zhu, Liu, Wang, Wei, and Wei (2019) find that EMV outperforms the Chicago Board of Exchange's (CBOE) S&P500 volatility index (VIX) in forecasting US stock return volatility. The indices of Tetlock (2007), Garcia (2013), Smales (2016) and Xu, Wang, Chen, and Liang (2023) reflect a sentiment narrative through the explicit choice of economic and financial market terms that convey sentiment. These indices are shown to predict stock returns. Supply side indices may also reflect an attention narrative (see El Ouadghiri, Guesmi, Peillex, & Ziegler, 2021; Fisher, Martineau, & Sheng, 2017), although these are less common than uncertainty and sentiment narratives.

GST-based indices have increasingly gained traction in explaining or predicting stock returns. The subject of these indices ranges from the stock market to the economy to the COVID-19 pandemic. However, in contrast to information supply keyword-based measures, the choice of words in GST indices does not always reflect a particular narrative. Instead, in many instances scholars project divergent narrative*s* on their GST-based index by drawing on existing literature that uses GST to quantify investor uncertainty, attention or sentiment. Consequently, there remains a lack of clarity as to precisely what narrative GST reflect. Without a clear understanding of the underlying narrative, it is difficult to determine how GST-based indices may be useful for the purposes of analysis, econometric modelling and further application. Moreover, this prevents meaningful testing and analysis as sentiment, uncertainty and attention are distinct concepts that have a varying impact on investor behaviour and the understanding of financial markets.

In this study, we construct a *general* stock market-orientated GST index and use this index to shed light on the narrative reflected by GST. Our first contribution is the creation of a unique general and neutral stock market-orientated GST-based index using Google search terms for "stock market" and "stock markets" and related queries. Notably, this approach differs from existing GST-based indices that focus either on the economy, a specific topic, such as COVID-19 or particular stocks (see for example, Bijl, Kringhaug, Molnár, & Sandvik, 2016; Dzielinski, 2012; Lyócsa, Baumöhl, Výrost, & Molnár, 2020). Our second contribution is a methodological one: by using elastic net regression and terms indicated by Google as searched for by economic agents, we reduce subjectivity in the selection of terms used to construct the index. Consequently, keywords comprising the index are not those considered by us as being important but rather those that economic agents are searching for. Our third contribution relates to the broad sample of 77 national market aggregates comprising developed, emerging and frontier markets that are used in the construction of our GST index and subsequent analyses. By considering such a large sample, we are able to construct a stock-market specific index that can be used across a broad sample of national markets for analytical purposes. Our fourth contribution is particularly important and relevant: we set out to determine the narrative reflected by our GST-based index without imposing an interpretation from the onset. We compare our general stock market GST-based index with existing measures of uncertainty, sentiment and attention through diagrammatic and empirical analysis. Once we have established a narrative, we demonstrate how such an index can be used to gain insight into stock market behaviour and that models employing our index conform to *a priori* expectations in terms of relationships between returns, volatility and the narrative reflected by the index. Finally, we proceed with an evaluation of the ability of our GST-based index to approximate the systematic drivers of returns and factor dispersion underlying return volatility relative to the class of keyword-based measures to which our index belongs. We also assess the value and usefulness of our index relative to its class in terms of generalisability by studying its performance out-of-sample. Our study contributes to the understanding of the information reflected by GST, and thus aids the development of further applications using internet search and return data.

Our GST-based stock market-orientated index reflects important events and most closely approximates measures of uncertainty. Given an uncertainty narrative, we undertake further analysis to confirm that our index produces relationships that conform to *a priori* expectations in line with the expected impact of uncertainty on returns and volatility. We find that there is variation between how developed, emerging and frontier markets respond to uncertainty which we attribute to varying integration levels and risk aversion. Next, we assess the performance of our index relative to other keyword-based uncertainty measures in approximating the common drivers of returns and dispersion driving volatility. In-sample, our index outperforms other uncertainty measures in approximating factor scores reflecting common return and volatility drivers. In the out-of-sample period, our index continues to exhibit notable explanatory power and some predictive power suggesting that it is generalisable beyond the return data used to construct it. Given the performance of our index relative to other keyword-based measures and ease of access to Google search data together with a clearer narrative, we propose that GST-based indices can be used to study the impact of general and event-specific uncertainty on financial markets. This knowledge can be used to formulate investment strategies that favour resilient markets and limit exposure to losses and heightened volatility associated with uncertainty.

The remainder of this study is structured as follows. Section 2 outlines the literature on the use of GST to model stock returns and the different narrative*s* associated with GST. Section 3 describes the data and methodology. Section 4 presents our index and establishes the narrative with Section 5 demonstrating an application of our index and confirming *a priori* expectations. In Section 6, we compare the ability of our index to approximate and predict the drivers of returns and volatility relative to other keyword-based uncertainty measures. Section 7 discusses implications and Section 8 concludes.

2. Literature review

Google is the dominant internet search engine accounting for more than 85% of queries worldwide since 2016 (Statista, 2021). As such, Google search patterns are representative of the population's general search behaviour. Studies that utilise GST as a proxy for investor uncertainty draw on economic psychology suggesting that economic agents respond to heightened uncertainty by increasing their search for information (Castelnuovo & Tran, 2017; Donadelli, 2015; Liemieux & Peterson, 2011). Bontempi, Frigeri, Golinelli, and Squadrani (2019) state that if uncertainty can be reduced by increasing knowledge, then the intensity of searching for more knowledge using information gathering tools is a reasonable measure of the level of uncertainty, which can be captured by GST. This suggests that the narrative is one of uncertainty. Castelnuovo and Tran (2017), similarly to Dzielinski (2012) and Bontempi et al. (2019), show that their GST index comprising economic terms, in levels, is correlated with common measures of uncertainty such as the S&P100 volatility index (VXO) (0.58) and EPU (0.28).

Uncertainty impacts stock prices *via* two channels: it contributes to decreased expected future cash flows and increased risk aversion leading to a higher risk premium in the discount rate (Andrei & Hasler, 2015; Cochrane, 2018; Smales, 2021). Consequently, a negative relationship is expected between GST and stock returns. Moreover, greater uncertainty will lead to more upward and downward revisions in the stock price and hence greater volatility (Engle, Focardi, & Fabozzi, 2008; Szczygielski, Brzeszczyński, Charteris, & Bwanya, 2022). Dzielinski (2012), Preis, Moat, and Stanley (2013) and Donadelli (2015) confirm that uncertainty, quantified by GST related to economic and financial terms, negatively impacts US stock returns. Bilgin, Demir, Gozgor, Karabulut, and Kaya (2019) obtain similar results for Turkey. Dzielinski (2012) also shows that increased Google searches trigger heightened volatility. Lyócsa et al. (2020) and Szczygielski, Bwanya, Charteris, and Brzeszczyński (2021), among others, utilise GST to quantify uncertainty surrounding the COVID-19 pandemic with their findings confirming that increased uncertainty negatively impacts stock returns and is associated with heightened volatility. Szczygielski et al. (2021) also illustrate that GST related to the COVID-19 pandemic are highly correlated with other measures of uncertainty, such as the VIX and TMU.

Another strand of literature proposes that GST are a proxy for investor attention, indicating investor interest in a particular stock, the stock market or broader economy (Da, Engelberg, & Gao, 2011). GST captures retail investor attention as these investors are more likely to rely on Google searches as opposed to institutional investors who utilise a variety of professional sources such as Bloomberg (Smales, 2021). As such, the narrative of these GST indices is argued to be attention. However, Da et al. (2011) illustrate that GST exhibit low correlation with other common proxies of attention including news, extreme returns and trading volume. This is attributed to the widespread use of search engines by both investors and non-investors and heterogeneous interpretations by investors.

Two theories have been proposed to explain the impact of attention on returns. According to the price pressure hypothesis, increased investor attention on a stock will contribute to increased prices and trading volumes (Barber & Odean, 2008). Contrastingly, the investor recognition hypothesis proposes that stocks with less media coverage should earn a higher return as investors have less information about these stocks and are exposed to greater risk (Merton, 1987). Bijl et al. (2016), Chen (2017) and Perlin, Caldeira, Santos, and Pontuschka (2017) construct indices using various Google search terms (such as stock tickers, index names and the term "stock") to capture attention. They find that an increase in investor attention results in a negative impact on US and international stock returns, consistent with the investor recognition hypothesis (see also Iyke & Ho, 2021; Nguyen, Schinckus, & Nguyen, 2019; Salisu, Ogbonna, & Adediran, 2021). Contrastingly, evidence of a positive impact of investor attention quantified by GST is documented in several countries, such as India, Turkey and Botswana (Ekinci & Bulut, 2021; Iyke & Ho, 2021; Swamy & Dharani, 2019). Studies also report that increased investor attention triggers heightened volatility (Andrei & Hasler, 2015; Dimpfl & Jank, 2016; Perlin et al., 2017; Vlastakis & Markellos, 2012). Smales (2021) and Salisu and Vo (2020) show that GST related to the COVID-19 pandemic, which they use as a measure of investor attention, have a deleterious impact on returns and volatility.

GST have also been used to quantify investor sentiment. This approach proposes that keywords that are deemed to be positive or negative convey sentiment, as opposed to general stock market terms or firm names which do not capture feelings about the subject matter. Measuring the extent to which these words are inquired about on Google captures investor feelings (Da, Engelberg, & Gao, 2015) and the narrative of these indices is sentiment. Da et al. (2015) select economic words that have negative and positive sentiment but find that negative terms better capture the psychological intuition behind sentiment than positive terms. Accordingly, they create an index comprising only negative keywords. They find the index to be highly correlated with traditional survey measures of sentiment. Analysis further reveals that the index impacts S&P500 returns, with the influence larger than that of VIX and EPU, and triggers heightened volatility in returns. These results are consistent with theoretical expectations as sentiment results in investors incorrectly extrapolating future cash flow forecasts (Baker & Wurgler, 2007) with negative sentiment causing prices to fall. Moreover, increased sentiment-based trading introduces more noise into the market leading to greater volatility. Beer, Hervé, and Zouaoui (2013) and Brochado (2020) confirm that local country sentiment-based GST have a deleterious impact on French and Portuguese stock returns, respectively. Fang, Gozgor, Lau, and Lu (2020) construct a sentiment-driven Baidu search index and find that negative (positive) sentiment predicts increased (decreased) volatility for the Shanghai stock market.

Joseph, Wintoki, and Zhang (2011) propose that Google searches for company tickers proxy for sentiment as tickers are only likely to be searched for by an individual wishing to obtain information about the company's stock price (compared to a company name which could be searched for a variety of other reasons). This search is more valuable for an individual considering a buy than a sell decision because for the latter, the individual will already know the company's recent stock price performance. Hence, greater search volumes associated with a company ticker reflect positive sentiment. This contrasting view creates ambiguity as to whether some of the GST attention indices described (such as Bijl et al., 2016 or Perlin et al., 2017) could reflect a sentiment narrative. Further to this, other GST indices, such as those of Castelnuovo and Tran (2017), include sentiment-related keywords as well as more general terms and therefore obfuscate the distinction between sentiment and uncertainty narratives. Moreover, some studies which use GST to quantify sentiment use generic keywords without explicit motivation for their choice and/or use the terms attention and sentiment interchangeably (see for example Kim, Lučivjanská, Molnár, & Villa, 2019; Song, Ji, Du, & Geng, 2019; Wang, Ye, Zhao, & Kou, 2018).

Several findings emerge from the literature. First, information demand keyword-based indices impact stock markets, resulting in (mostly) negative returns and higher volatility. Second, for these GST-based indices, the subject of the index is determined by the choice of keywords. However, the choice of keywords does not always clearly reflect the narrative. Typically, the narrative is projected from schools of thought and a researcher's choice of framing. As such, some keywords are used in an index argued to reflect sentiment while similar keywords are used in an index argued to reflect uncertainty or attention. This creates ambiguity as to precisely what narrative search trends capture: uncertainty, sentiment or attention. Third, with respect to information demand indices, less attention has been given to identifying a suitable stock market-orientated index.

3. Data and methodology

3.1. Stock market data

Our sample comprises MSCI country indices in US dollars for countries classified as developed, emerging and frontier markets by MSCI Inc spanning the period from 1 June 2016 to 31 May 2022. It covers 77 international markets out of which 23 are classified as developed, 27 as emerging and 27 as frontier markets. We divide the period into two subperiods: 1 June 2016 to 31 May 2021, which we define as the in-sample period, and 1 June 2021 to 31 May 2022, which we designate as the out-of-sample period. The in-sample period is used to construct our index, investigate the narrative reflected by GST, demonstrate how GST may be used for analytical purposes once the narrative has been established and examine the relationship between returns, volatility and the index while confirming that established relationships conform to *a priori* expectations. We use in-sample and out-of-sample data to compare the explanatory and predictive performance of our index relative to other similar measures. Returns are defined as logarithmic differences in daily index levels. Descriptive statistics for the return series are reported in Table 1.

3.2. Google search trends data

Our aim is to construct a GST-based index that reflects searches for neutral stock market-related terms which we view as reflecting the behaviour of participants in the economy, namely economic agents. We view Google searches as a reflection of the spontaneous behaviour of individuals and beliefs of the broader population. Importantly, searches enable individual investors to gain information about the economy and financial markets (Brochado, 2020; Da et al., 2015; Dzielinski, 2012; Smales, 2021). The relevance of Google searches to economic agents and stock markets broadly follows from the information that is conveyed about the narrative reflected by GST. As new information reflective of either uncertainty, attention or sentiment enters the market, there is uncertainty about what this means for expected profitability. This results in a process of price discovery leading to upward and downward movements in stock prices as investors attempt to determine the true value of assets following the arrival of new information (Engle, 2004; Engle et al., 2008; Nwogugu, 2006).

We begin by obtaining worldwide search data for a single Google search term that is specific to stock markets, namely “stock market” and obtain search data for the top 25 search terms related to this term between 1 June 2016 to 31 May 2021. We then repeat this process using the term “stock markets”.[1] This yields 25 related search terms. In total, we obtain daily data for 46 unique Google search terms, including the terms “stock market” and “stock markets”. Weekend data is excluded for consistency with financial data when formulating indices (see Da et al., 2015; Dimpfl & Jank, 2016).[2] Each search term index is then rescaled by adjusting the highest value to 100 with remaining values adjusted accordingly relative to this base. Index values are differenced to obtain $\Delta TERM_t$, where $TERM_t$ refers to a specific search query (see Table A1 in the Appendix for a list of stock market-related Google search terms considered).[3]

The terms that we select are neutral and unrelated to crises or specific events. This differs from the approach of Baker et al. (2019) who, in their construction of the newspaper-based tracker that moves with the VIX, specify terms related to the economy, stock market and volatility with the latter featuring terms such as “uncertainty”, “realised volatility” and “VIX”. Our approach depends on two terms, “stock market” and “stock markets” and, therefore, does not require the specification of subjective key terms. Our keywords are neutral in that they are not chosen to capture sentiment in comparison to those of Da et al. (2015), who rely on dictionaries that classify words into different categories such as “positive” or “negative”. Their index is also subject to the specification of keywords, with the risk of excluding relevant terms. The latter is true for many similar indices such as those of Castelnuovo and Tran (2017) and Bontempi et al. (2019), among others.

Additionally, our approach permits us to create an index that has international applicability, contrasting with existing studies that propose indices relevant to a single market (such as that of Castelnuovo & Tran, 2017; Chen, 2017).

[1] Google search data was obtained from the Google Trends service (https://trends.google.com/). When selecting the geography for which Google search data is obtained, we extracted “Worldwide” search trends and selected the “Include low search volume regions” option. Data was gathered from Google Trends over intervals of 270 days to ensure that the scaling of the data is consistent. Intervals of 270 days (nine months) are used as Google Trends reports data at a weekly frequency for queries exceeding nine months. Data was obtained for the period 29 March 2016 to 31 May 2021 although the index is constructed over the 1 June 2016 to 31 May 2021 period.

[2] Differences in individual search terms are calculated by subtracting search levels on Friday from those of the following Monday. Information arrivals during weekends will either contribute to increased uncertainty or uncertainty resolution. Therefore, Monday index levels should reflect the outcome of information arrivals contributing to uncertainty over the weekend, positively or negatively, in line with the dynamics of financial times series.

[3] A potential limitation of using Google searches to construct indices is that search terms in a given language may not be applicable in markets where that language is not spoken (see Da et al., 2011, 2015; Castelnuovo & Tran, 2017; Beer et al., 2013; Dimpfl & Kleiman, 2019 for examples of studies using English, French and German search terms in the US, French and German markets, respectively). Nevertheless, some studies have used English search terms to investigate the relationship between stock markets and Google searches in non-English language markets. For example, Liu, Peng, Hu, Dong, and Zhang (2019) find that English Google searches have a significant impact on company stock returns whereas Chinese language searches in Baidu do not have any impact. In a cross-country study, Akarsu and Süer (2021) use English language Google search terms. They exclude countries that do not have English as one of their official or recognised languages (such as China and Japan) but still include countries such as Germany, Brazil and Chile where English is widely used. Their results show that English language Google searches impact stock returns in several countries. The impact is not dependent on the language of the country with both English-speaking (such as New Zealand and the United Kingdom) and non-English-speaking (such as Germany and the Netherlands) among the affected markets. These studies reveal that English language search terms are associated with market movements in non-English speaking countries. A potential explanation for this finding is that economic agents use English search terms as the language is the dominant business lingua franca (Neeley, 2012; Rao, 2019). We undertook a comparison of English language search results against home-language search results for a sample of non-English speaking markets which shows that English language search terms follow similar patterns to home-language search terms in terms of the magnitude and timing of peaks and troughs. This confirms that English language searches are closely aligned with home language searches. It also supports the proposition that English search terms reflect business lingua franca. Finally, an analysis of Google Trends “Interest by region” maps for the search terms suggests that even in non-English speaking countries economic agents are searching for English language stock market-related search terms. This further supports the proposition that English search terms reflect business lingua franca. We thank an anonymous Referee for the comment on the role of language in searches, which prompted us to explore this issue deeper.

Table 1
Descriptive statistics for stock index return series

Index	Obs.	Mean	Median	Maximum	Minimum	Std. dev.	Skewness	Kurtosis	Shapiro-Wilk
Developed markets									
1. Australia	1564	0.0002	0.0005	0.0697	-0.1105	0.0126	-1.3773	16.5835	0.8779***
2. Austria	1564	0.0002	0.0004	0.1076	-0.1578	0.0172	-1.0464	14.5120	0.8886***
3. Belgium	1564	-0.0002	3.84E-05	0.0760	-0.1735	0.0136	-1.5800	23.7108	0.8700***
4. Canada	1564	0.0003	0.0004	0.1182	-0.1364	0.0120	-1.8951	38.4525	0.7660***
5. Denmark	1564	0.0003	0.0002	0.0528	-0.0869	0.0119	-0.4181	6.7411	0.9630***
6. Finland	1564	0.0001	0.0000	0.0672	-0.1175	0.0127	-1.0309	13.9360	0.9116***
7. France	1564	0.0002	0.0007	0.0815	-0.1403	0.0128	-1.1408	19.4663	0.8615***
8. Germany	1564	4.52E-05	0.0006	0.0996	-0.1422	0.0129	-0.9201	19.5099	0.8702***
9. Hong Kong	1564	9.77E-05	0.0002	0.0535	-0.0715	0.0109	-0.4398	7.1350	0.9488***
10. Ireland	1564	2.34E-05	0.0004	0.0749	-0.1273	0.0143	-1.0930	14.1982	0.8978***
11. Israel	1564	-5.63E-05	0.0002	0.0984	-0.1169	0.0126	-0.9740	15.7361	0.8857***
12. Italy	1564	0.0001	0.0006	0.0834	-0.1966	0.0150	-2.4043	32.2534	0.8446***
13. Japan	1564	0.0001	0.0000	0.0733	-0.0726	0.0104	-0.0980	8.0546	0.9515***
14. Netherlands	1564	0.0003	0.0008	0.0871	-0.1121	0.0126	-0.6044	12.0066	0.9114***
15. New Zealand	1564	2.70E-05	0.0000	0.0720	-0.0799	0.0122	-0.0948	6.6459	0.9666***
16. Norway	1564	0.0002	0.0002	0.0702	-0.1352	0.0145	-1.1087	12.7370	0.9187***
17. Portugal	1564	0.0002	0.0002	0.1037	-0.1296	0.0134	-0.8097	14.1304	0.9201***
18. Singapore	1564	-1.85E-05	1.00E-06	0.0705	-0.0778	0.0104	-0.3217	10.4533	0.9261***
19. Spain	1564	1.22E-05	8.63E-05	0.0779	-0.1635	0.0140	-1.8769	27.0512	0.8653***
20. Sweden	1564	0.0002	0.0004	0.0692	-0.1330	0.0140	-1.2246	15.1681	0.9066***
21. Switzerland	1564	0.0002	0.0006	0.0599	-0.1040	0.0093	-1.1017	16.2833	0.9131***
22. United Kingdom	1564	3.98E-05	0.0005	0.0992	-0.1330	0.0122	-1.3917	21.8697	0.8449***
23. United States	1564	0.0004	0.0005	0.0899	-0.1292	0.0119	-1.1191	23.0584	0.8159***
Emerging markets									
1. Argentina	1564	-0.0001	0.0000	0.1187	-0.5089	0.0274	-4.3537	81.0391	0.8031***
2. Brazil	1564	0.0002	0.0006	0.1516	-0.1943	0.0216	-1.3812	17.2147	0.8849***
3. Chile	1564	-3.29E-05	0.0000	0.1118	-0.1674	0.0172	-0.9358	17.4642	0.8787***
4. China	1564	0.0001	0.0003	0.1359	-0.0796	0.0139	0.1959	10.7535	0.9461***
5. Colombia	1564	8.83E-05	4.66E-05	0.1594	-0.2190	0.0191	-1.6906	33.7510	0.7954***
6. Czech Republic	1564	0.0003	0.0002	0.0666	-0.1199	0.0128	-1.5270	18.1650	0.8674***
7. Egypt	1564	-0.0004	0.0000	0.1017	-0.3893	0.0181	-7.2348	148.5165	0.6544***
8. Greece	1564	-0.0003	0.0000	0.0979	-0.2450	0.0202	-1.5828	21.4588	0.8825***
9. Hungary	1564	-1.52E-05	0.0002	0.1007	-0.1841	0.0184	-1.7172	20.7798	0.8487***
10. India	1564	0.0003	0.0006	0.0928	-0.1479	0.0125	-1.5549	22.7252	0.8622***
11. Indonesia	1564	0.0001	0.0000	0.1548	-0.1022	0.0149	-0.1415	15.9654	0.8875***
12. Korea	1564	0.0002	0.0000	0.1055	-0.0700	0.0136	-0.1083	8.2073	0.9476***
13. Kuwait	1564	0.0005	0.0002	0.0450	-0.2261	0.0110	-6.2603	125.0979	0.6866***
14. Malaysia	1564	-0.0001	0.0000	0.0730	-0.0575	0.0083	-0.4095	11.7765	0.9227***
15. Mexico	1564	3.73E-05	0.0001	0.0685	-0.1118	0.0154	-0.9117	9.5353	0.9340***
16. Pakistan	1564	-0.0009	-0.0002	0.0650	-0.0879	0.0147	-0.4474	7.1208	0.9465***
17. Peru	1564	0.0001	3.52E-05	0.1018	-0.1356	0.0171	-0.9296	12.4164	0.9017***
18. Philippines	1564	-0.0001	0.0000	0.0832	-0.1414	0.0135	-1.2515	17.2373	0.8999***
19. Poland	1564	-8.36E-05	0.0000	0.1004	-0.1670	0.0166	-1.1573	16.9059	0.9028***
20. Qatar	1564	0.0002	0.0000	0.0598	-0.1387	0.0108	-1.5481	25.2263	0.8306***
21. Russia	1564	-0.0084	8.89E-05	0.2877	-12.8582	0.3262	-39.1241	1541.6270	0.0223***
22. Saudi Arabia	1564	0.0005	0.0000	0.0665	-0.1721	0.0111	-2.7214	45.5824	0.7920***
23. South Africa	1564	7.34E-05	0.0000	0.0831	-0.1271	0.0185	-0.7307	7.5751	0.9538***
24. Taiwan	1564	0.0005	0.0000	0.0747	-0.0687	0.0115	-0.3424	7.7049	0.9475***
25. Thailand	1564	8.42E-05	0.0000	0.0788	-0.1207	0.0117	-1.2924	23.2575	0.8363***
26. Turkey	1564	-0.0005	0.0000	0.1949	-0.1806	0.0221	-0.5438	15.4800	0.8873***
27. United Arab Emirates	1564	0.0002	0.0000	0.0860	-0.1541	0.0116	-1.9121	37.8706	0.7509***
Frontier markets									
1. Bahrain	1564	0.0004	0.0000	0.0793	-0.1757	0.0126	-2.6018	44.3619	0.7749***
2. Bangladesh	1564	-8.99E-05	0.0000	0.0822	-0.0931	0.0097	0.2902	20.8506	0.8177***
3. Bosnia Herzegovina	1564	0.0001	0.0000	0.0887	-0.0662	0.0114	0.3065	12.7214	0.8438***
4. Botswana	1564	-0.0006	0.0000	0.1542	-0.2113	0.0151	-3.5236	61.1116	0.5511***
5. Bulgaria	1564	7.79E-05	2.25E-06	0.0674	-0.1522	0.0135	-1.3454	18.9844	0.8954***
6. Croatia	1564	9.45E-05	0.0002	0.0411	-0.1207	0.0086	-2.1016	31.4365	0.8705***
7. Estonia	1564	1.97E-06	5.85E-05	0.0783	-0.1317	0.0135	-1.0657	19.6666	0.8469***
8. Jamaica	1564	0.0005	0.0000	0.0626	-0.0873	0.0134	-0.2789	8.3596	0.9269***
9. Jordan	1565	-0.0002	0.0000	0.0655	-0.4561	0.0148	-18.5004	573.0681	0.3968***
10. Kazakhstan	1564	0.0004	0.0000	0.1776	-0.2452	0.0221	-1.8089	27.8680	0.8036***
11. Kenya	1564	-1.21E-05	0.0000	0.0463	-0.0713	0.0115	-0.6162	7.2921	0.9427***
12. Lebanon	1564	0.0005	0.0000	1.6002	-1.5950	0.0611	-0.4391	602.9428	0.1371***
13. Lithuania	1564	7.78E-06	0.0002	0.0775	-0.1466	0.0106	-2.0855	35.8863	0.8271***
14. Mauritius	1564	-6.06E-05	0.0000	0.1314	-0.1530	0.0136	-1.3937	34.2963	0.7801***
15. Morocco	1564	4.92E-05	0.0000	0.0463	-0.0987	0.0088	-1.4435	20.4942	0.8659***
16. Nigeria	1564	-0.0003	0.0000	0.0678	-0.2905	0.0140	-6.4187	130.0021	0.6918***
17. Oman	1564	5.71E-05	0.0000	0.0429	-0.1261	0.0084	-2.4481	41.1360	0.7981***
18. Romania	1564	0.0003	0.0004	0.0914	-0.1641	0.0135	-1.6132	23.4255	0.8564***
19. Serbia	1564	6.93E-05	0.0000	0.1890	-0.0904	0.0119	1.7302	49.2054	0.8057***
20. Slovenia	1564	0.0002	0.0008	0.0642	-0.1262	0.0125	-1.7756	19.5552	0.8803***
21. Sri Lanka	1564	-0.0008	0.0000	0.1008	-0.1719	0.0160	-1.9452	27.3611	0.7548***

(*continued on next page*)

Table 1 (*continued*)

Index	Obs.	Mean	Median	Maximum	Minimum	Std. dev.	Skewness	Kurtosis	Shapiro-Wilk
22. Trinidad & Tobago	1564	-4.87E-05	0.0000	0.1058	-0.1126	0.0133	0.2641	20.0901	0.7376***
23. Tunisia	1564	-7.48E-05	-0.0002	0.0539	-0.0533	0.0091	-0.2899	7.3434	0.9494***
24. Ukraine	1564	-0.0005	-9.31E-05	0.3049	-0.4861	0.0252	-4.1962	114.5534	0.6345***
25. Vietnam	1564	0.0003	0.0006	0.0535	-0.0715	0.0119	-0.7330	7.5784	0.9314***
26. WAEMU	1411	-0.0003	-0.0003	0.0782	-0.1055	0.0139	0.0613	10.9233	0.8724***
27. Zimbabwe	1564	0.0043	0.0000	0.1839	-0.2534	0.0371	0.0404	11.7120	0.8199***

Notes: This table reports descriptive statistics for the return series in our sample spanning the period from 1 June 2016 to 31 May 2022. All series are in US dollars. Returns are defined as logarithmic differences in index levels. *** indicates statistical significance at the 1% level. Obs. refers to number of observations and Std. dev. to the standard deviation. Shapiro-Wilk is the Shapiro-Wilk test statistic for normality. WAEMU refers to the West African Economic and Monetary Union.

3.3. Search term identification

Next, we identify relevant stock market-related Google search terms. If GST proxy for uncertainty, sentiment or attention that is relevant to stock markets and reflect information about the spontaneous behaviour of and beliefs held by economic agents, then GST will be associated with market movements and will constitute a part of the composite factor set influencing returns. Consequently, search terms that are relevant to investors can be identified by relating them to factor score series that proxy for the common drivers of returns.

We extract statistical factor scores from all markets with a full return history between 1 June 2016 and 31 May 2021. The resultant factor scores may be interpreted as representations of composite *common* factors reflective of the pervasive influences associated with stock market movements across the developed, emerging and frontier markets in our sample (Szczygielski, Brümmer, Wolmarans, & Zaremba, 2020). To identify the number of latent factors that characterise the return generating process, the minimum average partial (MAP) test is applied. This test identifies the number of factors that most closely result in an approximation of the assumption of uncorrelated residuals, $E(\varepsilon_{it}, \varepsilon_{jt} = 0)$, that underlies factor models in the form of the diagonality assumption (Van Rensburg, 2002; Zwick & Velicer, 1986). Once factor scores have been derived, they are subjected to varimax rotation and then are used to identify and select search terms that proxy for common influences across markets.

We could use individual stock returns to identify relevant Google search terms. However, such an approach has limitations. While using factor scores constitutes an abstraction from individual market dynamics, it avoids the complexity of subjectively determining which terms are relevant across an extensive sample of stock markets. Some search terms will likely have limited explanatory power and/or will exhibit statistically significant explanatory power limited to individual markets or market groupings and therefore there is likely to be variability across markets in the relevant set of search terms. Complexities introduced by the need to subjectively decide which search terms are applicable across markets on the basis of an analysis of individual markets in the presence of variability will detract from the generalisability of our resultant index considering that our sample comprises 77 national markets and includes 46 Google search terms. Relatedly, because factor scores are a summary representation of the influences driving all markets in the sample, their use simplifies and facilitates the selection of a *parsimonious* and general set of Google search terms. By identifying a parsimonious set of search terms that are generalisable and by eliminating subjectivity associated with search term selection, we present a readily implementable approach to the construction of Google search-based indices that can be used to study stock market behaviour (see implications discussed in Section 7).

Not all search terms are likely to be relevant. For example, while search terms such as "futures markets" can be viewed as being more technical in nature and, therefore, likely to be associated with searches undertaken by investors, searches such as "what is the stock market" may be attributable to non-investors (see Table A1 in the Appendix). Da et al. (2015) only include search terms that have historically been related to stock market returns, as determined by a regression of each search term against contemporaneous returns. The methodology that we use to identify Google search terms that are associated with the drivers of returns draws upon the field of machine learning. Specifically, we apply the elastic net estimator to identify relevant terms in a specification relating derived factor scores, $F_{k,t}$, to differences in search index term k, $\Delta TERM_{k,\ t-\tau}$:

$$F_{k,t} = \alpha_i + \sum_{k=1}^{m} \beta_{\Delta TERM_k} \Delta TERM_{k,t-\tau} + \varepsilon_{k,t} \tag{1}$$

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

where λ is the penalty parameter determined by cross-validation and α controls the amount of the penalty applied and n is the number of observations in a sample. The elastic net estimator combines a mixture of LASSO (L1 norm, $\sum_{k=1}^{m} |\beta_{\Delta TERM_k}|$) and Ridge (L2 norm, $\sum_{k=1}^{m} \beta^2_{\Delta TERM_k}$) penalties, where the L1 norm is a sparsity inducing penalty and the L2 norm is a coefficient shrinkage penalty that performs well in the presence of multicollinearity (Zou & Zhang, 2009). We also include a time operator, τ, taking on a value of zero and 1, 2 and 3. This permits the algorithm to identify stock market related search terms that are explanatory and have a contemporaneous association with markets and also predictive components whereby markets respond to information reflected in stock market-related GST (see Canova & De Nicolo, 1995; Dzielinski, 2012; Szczygielski, Charteris, Bwanya & Brzeszczynski, 2023 for examples of the use of leads, lags and contemporaneous terms to model return behaviour).[4]

To select relevant Google search terms, an iterative process is followed. Eq. (1) is first estimated relating each factor score series to the full set of Google search terms. This is then repeated for each factor score series until only those measures for which coefficients are non-zero for λ_{min}, λ_{1SE} and λ_{2SE} remain where λ_{1SE} and λ_{2SE} are penalties one and two standard errors from λ_{min}. Search terms that are taken forward are those for which coefficients are not shrunk to zero in the final iteration across all penalties.

Elastic net regression is well-suited to the selection of relevant search terms. Stock market related search terms are likely to exhibit high levels of pairwise correlation, leading to multicollinearity and making it difficult to determine relative importance. Additionally, in the presence of multicollinearity, coefficients will be sensitive to small changes in

[4] King (1966) and Chen (1983) show how factor-analytically derived scores can be used to represent the return generating process whereas Chen, Roll, and Ross (1986) use factor scores to confirm the identity of macroeconomic variables proxying for pervasive influences associated with stock market comovements.

model specification and the precision of estimates will be reduced alongside a reduction in the power of significance tests (Alin, 2010). The elastic net estimator in eq. (2) draws upon machine learning; computational methods that learn and adapt to new data and identify patterns without human intervention (Alpaydin, 2020). Elastic net makes use of k-fold cross-validation whereby all data is partitioned into k sets and each set is individually used as a test set for model validation whereas the remaining sets are used for feature selection (model building) (Bergmeir & Benítez, 2012; Jung, 2018; Zhang, Sun, & Wu, 2019). Elastic net, by combining LASSO and Ridge penalties, automatically performs feature selection while preventing overfitting and performs well under multicollinearity (Goeman, Meijer, & Chaturvedi, 2018; Liu, Liang, Siegmund, & Lewinger, 2018; Zou & Hastie, 2005; Zou & Zhang, 2009).

By following this approach, we are able to identify the most relevant stock market related Google search terms that are related to factor scores while accounting for multicollinearity and attaining a degree of confidence that the search terms selected should remain relevant out-of-sample.

3.4. Index construction

We formulate three versions of the GST-based index comprising all terms selected by applying the procedure outlined in Section 3.3:

$$cGST_t = \sum_{k=0}^{m} c_k TERM_{k,t-\tau} \tag{3}$$

$$sGST_t = \sum_{k=0}^{m} s_k TERM_{k,t-\tau} \tag{4}$$

$$eGST_t = \frac{1}{n}\sum_{k=0}^{m} TERM_{k,t-\tau} \tag{5}$$

where $cGST_t$ is a factor-weighted Google search index and c_k represents the proportion of *total* shared variance explained by factor k (reported in Table 3), $sGST_t$ is a Google search index that weights each term by the proportion of shared variance explained by each factor, s_k, and $eGST_t$ is an equal-weighted GST index where n is the number of search terms identified. We view the latter as an unoptimised version of the index that does not account for the relative weighting of the search terms. At this stage of the analysis, the GST-based indices are formulated using search term series that have been scaled and are in levels (see Section 3.2). We also construct six naïve indices. The first two comprise the primary terms, "stock market" and "stock markets", respectively, denoted as $stock\_market_t$ and $stock\_markets_t$. The third is an arithmetic average of both terms denoted as ave_sms_t. The fourth and fifth indices are arithmetic averages of all Google search terms associated with and including the terms "stock market" and "stock markets", respectively, denoted as $ave\_stock\_market_t$ and $ave\_stock\_markets_t$. The final index comprises an arithmetic average of all Google search terms, ave_terms_t.

In the next step, we formulate composite factor score series from the factor scores used to identify relevant stock market-related Google search terms. To do so, we weight each factor score series by the respective proportion of total shared variance explained, c_k, and by the proportion of shared variance explained by each factor, s_k, as follows:

$$F_{c,t} = \sum_{k=1}^{m} c_k F_{k,t} \tag{6}$$

$$F_{s,t} = \sum_{k=1}^{m} s_k F_{k,t} \tag{7}$$

where $F_{c,t}$ is the c_k-weighted composite factor score series and $F_{s,t}$ is the s_k-weighted composite factor score series. These composite factor score series are then regressed onto the naïve indices and (differenced) $cGST_t$, $sGST_t$ and $eGST_t$ indices in single factor regressions and comparisons are made across explanatory power, as measured by the adjusted coefficient of determination, $\bar{R}^2$, Akaike information criterion (AIC) and Bayesian information criterion (BIC), where AIC and BIC reflect the ability of each index to approximate factor scores and the underlying data generating process, respectively. Lower values are preferable (Spiegelhalter, Best, Carlin, & Linde, 2014).

By following this approach, we confirm that the selection procedure results in the selection of Google search terms that are relevant to investors and those searched for by investors (Spyridis, Sevic, & Theriou, 2012; Szczygielski et al., 2020). We confirm this by showing that the indices constructed from terms selected using the approach outlined in Section 3.3 approximate factor scores and the data generating process in-sample and compare their performance to naïve indices.

3.5. Interpretation

To determine which stock market-related GST index performs best, two approaches are employed. The first approach compares our index in levels against established measures of uncertainty, sentiment and attention diagrammatically to determine which of these measures our index most closely approximates (see Baker et al., 2016 and Baker et al., 2019 for a similar approach in comparing the EPU and EMV trackers to the VIX and Manela and Moreira's, 2017 NVIX in the case of the latter).

As proxies of stock market uncertainty, we use the CBOE VIX (VIX_t),[5] the Twitter-based Market (TMU_t) and Economic Uncertainty (TEU_t) indices (Baker et al., 2021), the news-based US Economic Policy Uncertainty index (EPU_t) (Baker et al., 2016) and the newspaper-based US Equity Market Uncertainty index (EMU_t) (Baker et al., 2019). Although these indices are constructed using US data or English language Tweets (in the case of TMU_t and TEU_t), we nevertheless elect to use these indices because of data availability. Most indices are US centric and US market uncertainty is more likely to be reflected by global markets whereas global markets are less likely to drive US market uncertainty (Smales, 2019). Therefore, we can reasonably consider these indices to be proxies for general uncertainty, even if somewhat focused on the US. The sentiment proxies used are the Société Générale Global Sentiment index (SGS_t), the Credit Suisse Ravenpack Artificial Sentiment index (AIS_t), the US Federal Reserve Bank of San Francisco Daily News Economic Sentiment index (SFN_t) and the Credit Suisse Fear Barometer (CFB_t).

It is difficult to identify a direct proxy for investor attention (Da et al., 2011). For this reason, various indirect measures have been historically used. These include extreme returns, trading volume, news and headlines, advertising expenses, price limits, analyst coverage and Bloomberg searches (see for example, Barber & Odean, 2008; Da et al., 2011; Strycharz et al., 2018; Yung & Nafar, 2017). However, literature using these measures typically focuses on investor attention on individual stocks (Aouadi, Arouri, & Teulon, 2013; Da et al., 2011). In summary, very few measures quantify attention at market level although investors also pay attention to market movements at the aggregate level (Peng, Xiong, & Bollerslev, 2007). Consequently, we adapt and construct proxies that capture general market attention, with existing firm level proxies forming the basis for market level proxies.

Barber and Odean (2008) argue that when a stock experiences abnormally high trading volume, investors are more attentive. They find

[5] Although this is the US version of the index, Smales (2019) shows that VIX captures global market uncertainty and has been used by several other authors for this purpose (see also Dimic, Kiviaho, Piljak, & Äijö, 2016; Salisu & Akanni, 2020).

that abnormal trading volume is a better measure of attention than excess returns or news. Consequently, we calculate abnormal trading volume for the MSCI All Country World and Frontier Markets index which encompasses the markets in our sample, denoted as ABV_t, as an indirect measure of attention (see also Da et al., 2011; Yung & Nafar, 2017).[6] We also calculate extreme returns as a measure for investor attention, EXA_t. News about the market which contributes to extreme returns will likely catch the attention of some investors, while extreme returns will catch the attention of others (Barber & Odean, 2008; Da et al., 2011).[7] The final proxies for attention comprise the Predata Country Attention index for the US ($PRUS_t$) and equal and value-weighted attention indices constructed from Predata Country Attention indices for the US, China, Japan, France, the United Kingdom, Canada and Germany, denoted as PRE_t and PRV_t, respectively.[8]

The second approach is empirical. We apply the iterative selection procedure outlined in Section 3.3, replacing $F_{k,t}$ in eq. (1) with the (differenced) GST index found to be optimal and $\sum_{k=1}^{m}\beta_{TERM_k}\Delta TERM_{k,t-\tau}$ with $\sum_{k=1}^{m}\beta_{PROXY_k}\Delta PROXY_{k,t-\tau}$, where $\Delta PROXY_{k,t-\tau}$ is an established (differenced) measure of uncertainty, attention or sentiment, as outlined above. Each measure enters the set contemporaneously and with three lag terms ($\tau = 0, 1, 2, 3$). Permitting an intertemporal structure constitutes a test of whether stock market-related GST are a response to changes in uncertainty, sentiment or investor attention or whether GST are a contemporaneous proxy, or both. As a further test, we report the ten absolute largest ordinary and Spearman correlations between changes in the selected GST index and changes in uncertainty, sentiment and attention proxies.

4. Results

4.1. Factor structure, search measure selection and index selection

Table 2 presents the results of factor analysis with six factor score series extracted. The first factor is the most important with $F_{1,t}$ explaining 32.53% of shared variance. $F_{2,t}$ and $F_{3,t}$ explain 4.61% and 3.24% of shared variance, respectively, and for the remaining factors, shared variance declines to 1.87% for $F_{6,t}$. These six factors summarise almost half of shared return variance: 47.74% (see Fig. A1 in the Appendix for scree plot).[9] Average communalities indicative of common variation reflected by these six factors across developed, emerging and frontier markets are 0.6954, 0.4447 and 0.1846, respectively. This suggests that for developed markets, these six factors capture most of the common variation in returns and for emerging markets, they capture just less than half of common variation. The lower communality for frontier markets is expected, given lower integration levels with global markets (Berger, Pukthuanthong, & Yang, 2011; Zaremba & Maydybura, 2019).

Table 2
Factor structure summary

Factor	Proportion of total shared variance (c_k)	Proportion of explained variance (s_k)	Cumulative proportion
$F_{1,t}$	0.3253	0.7141	0.3253
$F_{2,t}$	0.0461	0.1064	0.3714
$F_{3,t}$	0.0324	0.0551	0.4038
$F_{4,t}$	0.0301	0.0546	0.4339
$F_{5,t}$	0.0248	0.0403	0.4586
$F_{6,t}$	0.0187	0.0295	0.4774

Notes: This table reports the results of factor analysis applied to returns for 76 markets over the period 1 June 2016 and 31 May 2021. As the WAEMU series does not have a full return history for the sample period, it is excluded from factor analysis. c_k represents the proportion of total shared variance explained by the extracted factor scores. s_k is the proportion of explained variance. Cumulative proportion is the cumulative proportion of total shared variance explained.

Table 3 reports the selection of relevant stock market-related Google search terms. As numerous iterations are required to identify a limited set of search terms that are associated with each factor score series, we report the number of iterations needed to arrive at the final iteration together with the results of the final iteration. Six Google search terms are identified, with a single term associated with each factor score series. The respective terms associated with $F_{1,t}$, $F_{2,t}$, $F_{3,t}$, $F_{4,t}$, $F_{5,t}$ and $F_{6,t}$, are *dow_jones*$_t$, *stock_market_futures*$_t$, *live_stock_market*$_{t-1}$, *futures_market*$_t$, *asian_stock_markets*$_t$ and *today_stock_market*$_t$. Our analysis also suggests that GST are mostly explanatory, i.e. all terms are in contemporaneous form (not lagged) except for *live_stock_market*$_{t-1}$, which is associated with $F_{3,t}$ (descriptive statistics for these search terms are reported in Table A2 of the Appendix).

The results in Table 4 show the explanatory power associated with the constructed Google search indices and the naïve indices. $cGST_t$ and $sGST_t$ outperform all indices in terms of explanatory power and their ability to approximate actual factor scores and the data generating process. Specifically, the $\bar{R}^2$, AIC and BIC values are 0.0991, 0.5497 and 0.5576 and 0.0903, 0.5594 and 0.5673 when communality-weighted, c_k (Panel A) and 0.0978, 2.1154 and 2.1233 and 0.0893, 2.1248 and 2.1327 when weighted by proportion of shared variance explained, s_k (Panel B). In comparison, the naïve index that yields the highest weighted $\bar{R}^2$ and lowest AIC and BIC values is *ave_stock_markets*$_t$ with respective $\bar{R}^2$, AIC and BIC values of 0.0814, 0.5692 and 0.5771 for $F_{c,t}$ and 0.0789, 2.1361 and 2.1440 for $F_{s,t}$.

Of the two optimised indices, the c_k weighted index, $cGST_t$, is associated with the highest explanatory power and performs best at approximating factor scores and the data generating process underlying the extracted factor scores. We therefore take this index forward in the analysis (see Fig. A2 in the Appendix for a juxtaposition of the individual search terms used to construct the index against $cGST_t$ in levels).[10]

Broader naïve indices (comprising more terms than our index) *may*

[6] Abnormal trading volume for the index on day t is calculated as the difference between the daily index trading volume on day t and the average index trading volume over the previous 252 trading days (one year) divided by the standard deviation of the index trading volume over the previous 252 trading days (Bajo, 2010; Da et al., 2011).

[7] The excess return on day t is calculated as the absolute value of the difference between the index return on day t and the average index return over the previous 252 trading days divided by the standard deviation of the index return over the previous 252 trading days.

[8] Predata Country Attention indices measure digital attention surrounding a country's political situation by tracking anomalies in web pages relating to a country's government, political structure, policy makers and financial institutions. While not specifically focused on financial markets nor directly derived from market indices, these indices nevertheless consider factors that investors are likely to pay attention to and the movements of which are likely to be reflected in market movements (PreData, 2021).

[9] To confirm that these six factors are sufficient, we examine the scree plot of eigenvalues reported in Fig. A1. The scree plot suggests that factors beyond the sixth factor (and arguably the third and fourth factors) increasingly lie on a flat gradient implying that they are trivial and that a six factor solution extracted on the basis of the MAP test is sufficient and congruent with an approximation of the diagonality assumption (see Kryzanowski & To, 1983; Van Rensburg, 2002).

[10] We also investigated whether using search data averaged over Saturday, Sunday and Monday may produce a superior index. The respective search terms identified are: *stock_market_news*$_t$, *stock_markets_live*$_t$, *asian_markets*$_t$, *futures_market*$_t$, *today_stock_market*$_{t-3}$ and *today_stock_market*$_{t-3}$. There is apparent variability in the search terms identified. We go on to formulate a communality weighted index using the above terms in the same manner as for $cGST_t$. A visual comparison with $cGST_t$ shows close co-movement although the alternative index appears to be far noisier. As $cGST_t$ is less noisy, we proceed with this index.

Table 3
Results of final iteration of elastic net regularisation for stock market-related Google search terms

	$F_{1,t}$: 4 iterations				**$F_{2,t}$: 2 iterations**		
	λ_{min}	λ_{1SE}	λ_{2SE}		λ_{min}	λ_{1SE}	λ_{2SE}
α_i	0.0003	2.71E-12	2.71E-12	α_i	0.0002	7.08E-11	7.08E-11
Δdow_jones_t	-0.0445	-1.49E-09	-1.49E-09	$\Delta asian\_markets_t$	-0.0033	0	0
$\Delta live\_stock\_market_t$	-0.0111	0	0	$\Delta financial\_markets_t$	0	0	0
$\Delta stock\_market\_index_t$	-0.0041	0	0	$\Delta futures\_market_t$	-0.0040	0	0
$\Delta stock\_market\_news_t$	-0.0151	0	0	$\Delta live\_stock\_market_t$	0	0	0
				$\Delta market\_news_t$	0	0	0
				$\Delta share\_market_t$	-5.21E-05	0	0
				$\Delta stock\_futures_t$	-0.0015	0	0
				$\Delta stock\_market\_crash_t$	0	0	0
				$\Delta stock\_market\_futures_t$	-0.0187	-1.43E-08	-1.43E-08
				$\Delta stock\_markets\_dow\_jones_{t-2}$	0.0011	0	0
				$\Delta stock\_markets\_live_t$	0	0	0
				$\Delta today\_stock\_market_{t-3}$	0	0	0
				$\Delta world\_markets_t$	-0.0075	0	0
				$\Delta world\_markets_{t-1}$	0	0	0
d.f.	4	1	1	*d.f.*	7	1	1
L1	0.0750	1.49E-09	1.49E-09	L1	0.0363	1.44E-08	1.44E-08
R^2	0.0870	2.99E-09	2.99E-09	R^2	0.0436	2.66E-08	2.66E-08
	$F_{3,t}$: 4 iterations				**$F_{4,t}$: 5 iterations**		
	λ_{min}	λ_{1SE}	λ_{2SE}		λ_{min}	λ_{1SE}	λ_{2SE}
α_i	-0.0001	-1.53E-12	-1.53E-12	α_i	0.0005	7.36E-12	7.36E-12
Δdow_jones_{t-1}	0.0260	0	0	Δdow_{t-3}	-0.0177	0	0
Δdow_jones_{t-2}	-0.0243	0	0	$\Delta futures\_market_t$	-0.0249	-1.02E-09	-1.02E-09
$\Delta live\_stock\_market_{t-1}$	0.0211	3.94E-10	3.94E-10	$\Delta stock\_futures_t$	-0.0068	0	0
$\Delta live\_stock\_market_{t-2}$	-0.0105	0	0	$\Delta stock\_martket_{t-3}$	0.0012	0	0
$\Delta stock\_market\_news_{t-1}$	0.0092	0	0	$\Delta stock\_markets_{t-3}$	-0.0192	0	0
$\Delta stock\_market\_news_{t-2}$	-0.0126	0	0	$\Delta stock\_markets\_live_t$	-0.0122	0	0
$\Delta the\_stock\_market_{t-1}$	0.0079	0	0				
d.f.	7	1	1	*d.f.*	6	1	1
L1	0.1118	3.96E-10	3.96E-10	L1	0.0825	1.03E-09	1.03E-09
R^2	0.1312	9.87E-10	9.87E-10	R^2	0.0528	1.48E-09	1.48E-09
	$F_{5,t}$: 7 iterations				**$F_{6,t}$: 7 iterations**		
	λ_{min}	λ_{1SE}	λ_{2SE}		λ_{min}	λ_{1SE}	λ_{2SE}
α_i	0.0002	9.91E-06	9.91E-06	α_i	-0.0002	-1.26E-05	-1.26E-05
$\Delta asian\_stock\_markets_t$	-0.0225	-0.0019	-0.0019	$\Delta stock\_exchange\_market_t$	-0.0116	0	0
$\Delta stock\_markets_t$	-0.0252	0	0	$\Delta stock\_market\_futures_{t-3}$	-0.0151	0	0
				$\Delta stock\_markets\_today_t$	0.0051	0	0
				$\Delta today\_stock\_market_t$	0.0291	0.0031	0.0031
				$\Delta what\_is\_stock\_market_{t-1}$	0.0114	0	0
d.f.	2	1	1	*d.f.*	5	1	1
L1	0.0479	0.0020	0.0020	L1	0.0724	0.0031	0.0031
R^2	0.0419	0.0039	0.0039	R^2	0.0412	0.0024	0.0024

Notes: This table reports the results of the final iteration of the elastic net-based selection and identification procedure, using daily data for the period 1 June 2016 to 31 May 2021. The procedure is repeated until only Google search terms for which coefficients are non-zero for the λ_{min}, λ_{1SE} and λ_{2SE} penalties remain. *d.f.* is the number of measures with non-zero coefficients and L1 is the sparsity inducing penalty. R^2 is the coefficient of determination for Google search terms with non-zero coefficients. All search terms are in first differences, denoted by Δ.

outperform our selected index for individual markets or for specific market groupings although this does not appear to be the case overall, as suggested by results in Table 4. However, broader indices will not incorporate search terms that are truly relevant and are therefore less precise (Dimpfl & Kleiman, 2019). By following the regression-based approach set out in Section 3.3, we ensure that only terms that are truly associated with market movements are included in the final GST-based index. The use of regression based-approaches (alternatively correlation-based approaches) to constructing narrower search-term indices is common in the literature. Da et al. (2015) develop the FEARS[11] index to measure investor sentiment by aggregating Google queries related to household concerns, arguing that a regression-based approach permits the "data to speak for itself" and is objective rather than subjective (i.e., imposed by the researcher; see also Kogan, Levin, Routledge, Sagi, & Smith, 2009). Motivated by Da et al. (2015), Brochado (2020) constructs positive and negative sentiment indices for Portugal by selecting ten search terms that are most positively and negative correlated with aggregate market returns. Both Da et al. (2015) and Brochado (2020) opt to reduce the number of search terms and construct indices comprising fewer terms than the initial search sets that could be considered as *broad* naïve indices. A regression-based approach will inevitably limit the number of search terms identified. However, our approach ensures that relevant search terms are used, is objective, yields a more parsimonious set of search terms simplifying index construction and offers greater precision in capturing an inherent narrative. Resultant indices will continue to explain a substantial amount of variation in returns by occupying a significant portion of the factor space explained by broader indices. As the wider contribution of our study is to provide insight into the narrative reflected by Google search trends, objectivity and precision are of great importance.

[11] Financial and Economic Attitudes Revealed by Search (FEARS).

Table 4
Comparison of optimised and naïve Google search indices

Index	Panel A: $F_{c,t}$			Panel B: $F_{s,t}$		
	$\bar{R}^2$	AIC	BIC	$\bar{R}^2$	AIC	BIC
$\Delta cGST_t$	0.0991	0.5497	0.5576	0.0978	2.1154	2.1233
$\Delta sGST_t$	0.0903	0.5594	0.5673	0.0893	2.1248	2.1327
$\Delta eGST_t$	0.0714	0.5800	0.5879	0.0702	2.1455	2.1534
$\Delta stock\_market_t$	0.0553	0.5971	0.6001	0.0538	2.1629	2.1709
$\Delta stock\_markets_t$	0.0423	0.6108	0.6187	0.0400	2.1773	2.1853
Δave_sms_t	0.0529	0.5996	0.6076	0.0508	2.1661	2.1740
$\Delta ave\_stock\_market_t$,	0.0642	0.5877	0.5956	0.0625	2.1537	2.1617
$\Delta ave\_stock\_markets_t$	0.0814	0.5692	0.5771	0.0789	2.1361	2.1440
Δave_terms_t	0.0804	0.5703	0.5782	0.0781	2.1369	2.1448

Notes: This table reports the results of regressions of composite factor scores onto two optimised versions of the stock market-related Google search indices, $cGST_t$ and $sGST_t$, an average of the six stock market-related terms identified by the iterative procedure as reflected by $eGST_t$, and naïve indices formed from stock market-related Google search terms over the period 1 June 2016 to 31 May 2021. All search terms of a daily frequency are in first differences, denoted by Δ. In factor score regressions, composite factor scores are used. $F_{c,t}$ in Panel A is the composite factor score series formed by weighting each of the six factor scores by associated communalities, c_k, representative of the proportion of total shared variance explained. $F_{s,t}$ in Panel B is the composite factor score series formed by weighting each of the six factor scores by the proportion of total shared variance explained by each factor score series, s_k. $\bar{R}^2$ is the adjusted coefficient of determination, indicative of explanatory power. AIC is the Akaike information criterion indicative of how well a specification approximates observed data series and BIC is the Bayesian information criterion approximating how well a specification approximates the data generating process. Indices that produce lower AIC and BIC values are preferred.

4.2. Diagrammatic comparisons

Fig. 1 plots $cGST_t$ index levels and identifies a number of significant events while Figs. 2 to 4 juxtapose $cGST_t$ against uncertainty, sentiment and attention measures. In Fig. 1, we note that $cGST_t$ exhibits pronounced spikes in reaction to various events. The series responds to several notable political events such as the British European Union Referendum ("Brexit") (24/06/2016), the election of Donald Trump and Joe Biden as US presidents (09/11/2016 and 08/11/2020, respectively), the US-China trade war (14/05/2019 and 15/08/2019) and the storming of Capitol Hill (06/01/2021). Spikes around political events are also reflected in VIX_t levels (Fig. 2). The finding that political news, such as "Brexit" (Baker et al., 2016), US presidential election outcomes (Goodell & Vähämaa, 2013) and the US-China trade war (Burggraf, Fendel, & Huynh, 2020) drive stock market uncertainty is consistent with prior studies of the VIX_t.

$cGST_t$ levels also rise between 18 February 2020 and 31 March 2020 around the COVID-19 pandemic (Szczygielski et al., 2021). The rapid spread of the virus globally, the declaration by the World Health Organization (WHO) of COVID-19 as a pandemic and the implementation of national lockdowns contributed to a palpable sense of uncertainty experienced by stock markets during this period (Altig et al., 2020; Baker et al., 2020). VIX_t also experienced sharp increases during the COVID-19 period (see Fig. 2).

Fig. 2 suggests that $cGST_t$ moves closely with measures of uncertainty exhibiting spikes around major US and (to a lesser extent) global stock market movements (06/02/2018, 11/10/2018, 27/12/2018). On 6 February 2018 investors traded on concerns about higher interest rates and market corrections (Zurcher, 2018). Similar views motivated trading on 11 October 2018 (Kollmeyer, 2018). The VIX_t, with which $cGST_t$ moves closely, also reflect spikes coinciding with these events. This is consistent with the view that uncertainty rises (falls) as markets decline (rise) (Whaley, 2009). Accordingly, the spike in $cGST_t$ on 27 December 2018 is surprising as this coincides with the largest one day rise in US markets in nine years. The VIX_t surged two trading days prior (24/12/2018), coinciding with a large market downturn, and declined on 27 December 2018 in reaction to the subsequent recovery in the stock market. The $cGST_t$ spike appears to lag this stock market decline and recovery. This may be attributable to delayed investor searches due to the Christmas holiday.

Confirmation that $cGST_t$ moves closely with the VIX_t is provided by ordinary correlation (ρ_o) of 0.9318 and Spearman correlation (ρ_s) of 0.9287 between the two series in levels (see Table A3 in the Appendix). Similarly high positive ρ_o (ρ_s) correlations are noted between $cGST_t$ and other measures of financial market uncertainty, namely TMU_t and EMU_t, of 0.6892 (0.8300) and 0.7826 (0.8631), respectively. The correlation of $cGST_t$ with the economic-based uncertainty measures is marginally lower with ρ_o of 0.6593 and ρ_o of 0.7299 for EPU_t and TEU_t, respectively, confirming that economic- and equity market-focused uncertainty indices capture different trends. Notably, correlation between $cGST_t$ and the VIX_t exceeds the correlation between stock market-focused uncertainty indices, TMU_t and EMU_t and the VIX_t with ρ_o (ρ_s) of 0.8057 (0.8153) and 0.7227 (0.8300), respectively. This suggests that our choice of keywords in $cGST_t$ performs as well as, or even better, than comparable stock market-orientated indices (such as those of Baker et al., 2019; French, 2021). Overall, correlations and diagrammatic evidence suggests that $cGST_t$ quantifies uncertainty.

There is ambiguity related to GST as a measure of sentiment (see Section 2). Da et al. (2015) maintain that increased searches for negative keywords reflect heightened negative sentiment whereas Joseph et al. (2011) argue that increased searches for company tickers reflect positive sentiment. $cGST_t$ differs from the index of Da et al. (2015) as it comprises neutral keywords, while also differing from that of Joseph et al. (2011) as the keywords are defined for the general stock market and not firm tickers. It is, therefore, unclear whether either of the explanations apply to $cGST_t$. We juxtapose $cGST_t$ levels against sentiment measures in Fig. 3 to better understand how $cGST_t$ relates to common sentiment measures. By construction, SFN_t and CFB_t are both lower when negative sentiment is higher (Frankel, 2009; FRBSF, 2020). $cGST_t$ does not exhibit particularly close co-movement with any of the sentiment proxies, although the index does exhibit some movements concurrently with the sentiment measures around major events. For example, at the onset of the COVID-19 pandemic, all four sentiment indicators experience notable declines, coinciding with a sharp increase in $cGST_t$. Brexit resulted in a protracted decline in all sentiment indicators, following an increase in $cGST_t$. Similarly, the increase in $cGST_t$ following the election of Donald Trump (09/11/2016) coincided with a notable decline in CFB_t and somewhat of a lesser decline in AIS_t and SGS_t (while SFN_t increased). The finding that negative sentiment increased around Brexit (Hudson, Urquhart, & Zhang, 2020), US elections (Becker, McGurk, & Hale, 2022) and COVID-19 (Biktimirov, Sokolyk, & Ayano, 2021; Haroon & Rizvi, 2020) is consistent with prior literature. $cGST_t$ is negatively correlated with SFN_t and CFB_t (ρ_o of -0.5830 and -0.6556, respectively) suggesting that higher internet searches are associated with negative sentiment, as reported by Da et al. (2015), even though the keywords in our index do not have negative connotations. However, the correlation between $cGST_t$ and sentiment is not as strong as for uncertainty. When taking Spearman correlations into account, the relationship is weak for CFB_t and turns

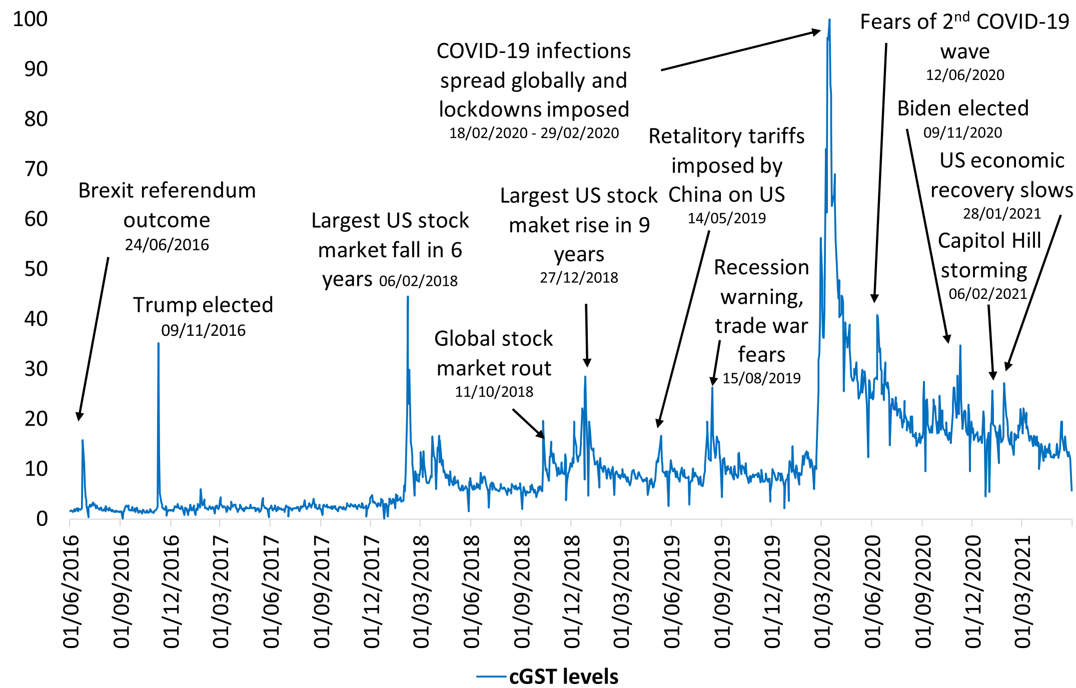

Fig. 1. ***$cGST_t$* in levels with significant events**

Notes: Fig. 1 plots $cGST_t$ in levels from 1 June 2016 to 31 May 2021. $cGST_t$ is constructed using six search terms related to "stock market" and "stock markets" that are found to drive stock returns, namely: "dow jones", "stock market futures", "live stock market", "futures market", "asian stock markets" and "today stock market". Dates and explanations for significant events are documented.

positive for SFN_t (-0.0010 and 0.2155). In contrast, $cGST_t$ is positively correlated with AIS_t and SGS_t (respective ρ_o of 0.4347 and 0.5954 and ρ_s of 0.9294 and 0.9154), which is surprising as this suggests that higher searches are associated with positive sentiment.[12] In summary, there is little evidence overall to suggest that $cGST_t$ quantifies sentiment.

Attention coincides with stock market movements during the COVID-19 pandemic (Huynh, Foglia, Nasir, & Angelini, 2021), Brexit (Guidolin & Pedio, 2021) and periods of notable market declines (Yu & Hsieh, 2010). Fig. 4 juxtaposes $cGST_t$ levels against attention measures, showing that movements in $cGST_t$ differ from those of attention measures over time and sharp increases around major events do not always coincide. For example, the COVID-19 induced spike in $cGST_t$ occurs at approximately the same time as the spike in ABV_t in March 2021, but occurs earlier than for PRE_t, while that of EXR_t is notably more delayed. In relation to political events, $cGST_t$ responds to Trump's election similarly to PRV_t, while PRE_t exhibits substantial spikes for a sustained period prior to the election outcome and ABV_t responds later, which is a pattern also seen surrounding the 2020 US elections results. With respect to notable US and global stock market movements in 2018, there is some similarity in EXR_t and $cGST_t$ movements, but not with any other attention measures. The correlation between $cGST_t$ and the attention measures is highest for stock-market derived measures, namely ABV_t and EXR_t (ρ_o of 0.3128 and 0.1608 and ρ_s of 0.7595 and 0.7931, respectively). This confirms diagrammatic evidence that these indices move in the same direction but there are periods during which their movements are distinct. Ordinary correlation coefficients show little relation between $cGST_t$ and the Predata attention measures, although a stronger positive relationship is captured by Spearman correlations. The Predata indices focus more on attention related to the political situation of a country and thus a lower correlation between $cGST_t$ and political-related attention measures can be expected (see Section 3.5). However, as seen diagrammatically, in times of political events which affect stock markets, co-movement is much higher. The evidence suggests that while $cGST_t$ moves in conjunction with some measures of attention, the relationship is much weaker than with uncertainty measures.

Overall, the diagrammatic analysis and correlations suggest that $cGST_t$ closely approximates the VIX_t and other measures of uncertainty and shows limited resemblance to sentiment and attention measures.

4.3. Empirical comparisons

We now turn to the empirical relationship between changes in $cGST_t$ and changes in the uncertainty, attention and sentiment measures.[13] Panel A of Table 5 reports final iterations of the selection procedure based on elastic net regression relating changes in $cGST_t$ to differenced uncertainty, sentiment and attention measures. Panels B and C report respective ordinary and Spearman correlations between $cGST_t$ and these proxies.

The results in Panel A point towards $cGST_t$ proxying for market uncertainty, as suggested by $cGST_t$'s positive and contemporaneous association with VIX_t and TMU_t. Correlations between $cGST_t$ and the measures in Panels B and C are also dominated by uncertainty measures, although measures of sentiment and attention also feature. For example, in Panel B the measures that are most highly correlated with $cGST_t$ are TMU_t (ρ_o of 0.3955), VIX_t (ρ_o of 0.3231) and TEU_t (ρ_o of 0.2511). In Panel C, the measure most highly correlated with $cGST_t$ is TMU_t (ρ_S of 0.2959), whereas the VIX_t (ρ_S of 0.2399) is the third most highly correlated

[12] We approach these results with caution given the discrepancy between ordinary and Spearman correlations, which suggests that these results may be impacted by the properties of the data.

[13] For empirical comparisons, we use changes in our GST index and changes in the alternative measures. To confirm that differences are stationary, we apply the Augmented Dickey-Fuller and non-parametric Phillips–Perron unit root tests and the Kwiatkowski-Phillips-Schmidt-Shin stationarity test. Tests are applied assuming an intercept with the number the number of lags selected using the AIC. Each series is shown to be stationary following differencing (see Table A4 in the Appendix).

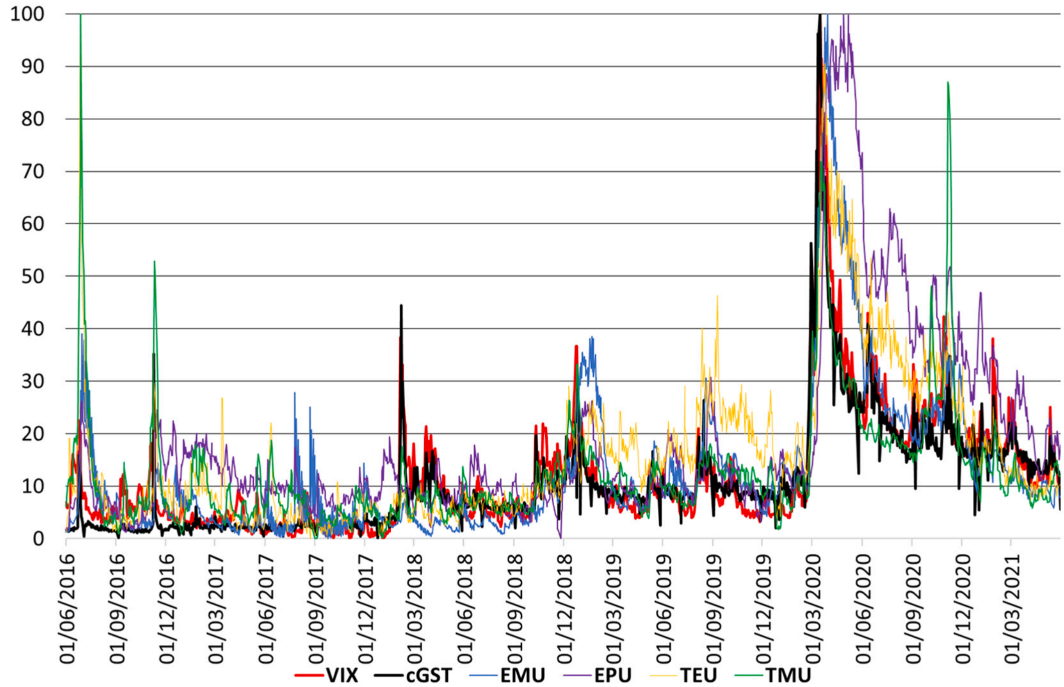

Fig. 2. ***cGST$_t$* in levels with uncertainty measures**

Notes: Fig. 2 plots *cGST$_t$* against common uncertainty measures in levels from 1 June 2016 to 31 May 2021. The uncertainty measures include the CBOE VIX (*VIX$_t$*), Twitter-based Economic and Market Uncertainty indices (*TEU$_t$* and *TMU$_t$*), Economic Policy Uncertainty index (*EPU$_t$*) and the Equity Market Uncertainty index (*EMU$_t$*).

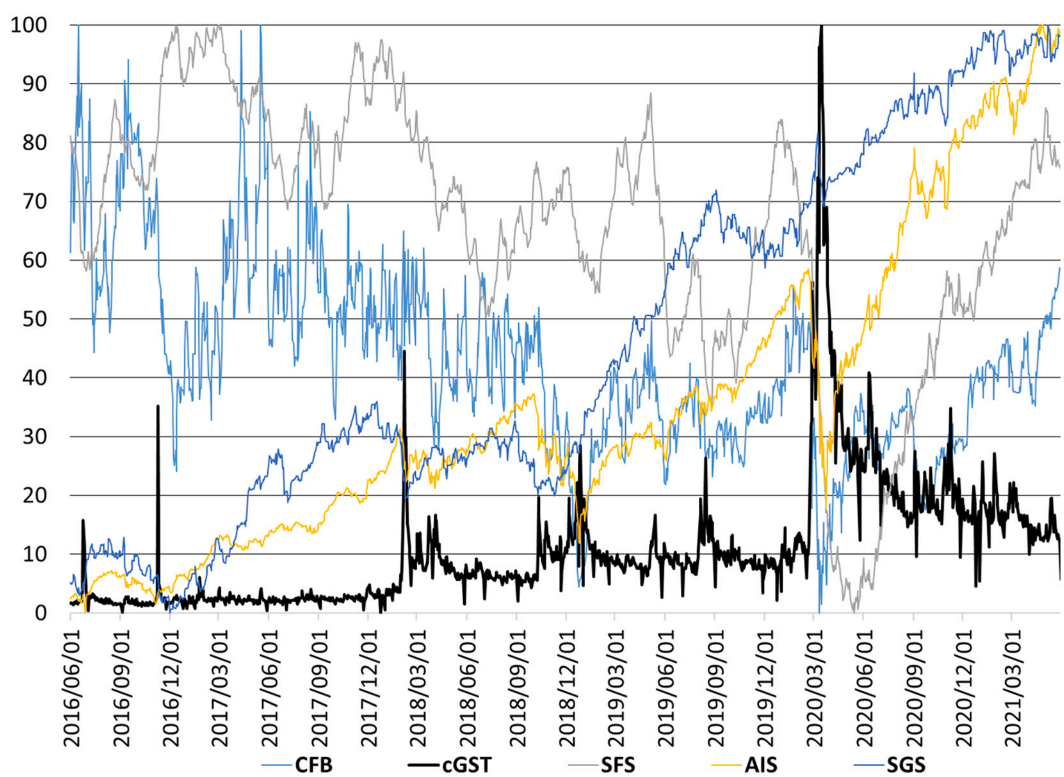

Fig. 3. ***cGST$_t$* in levels with sentiment measures**

Notes: Fig. 3 plots *cGST$_t$* against common sentiment measures in levels from 1 June 2016 to 31 May 2021. The sentiment measures include the Société Générale Global Sentiment index (*SGS$_t$*), the Credit Suisse Ravenpack Artificial Sentiment index (*AIS$_t$*), the US Federal Reserve Bank of San Francisco Daily News Economic Sentiment index (*SFN$_t$*) and the Credit Suisse Fear Barometer (*CFB$_t$*).

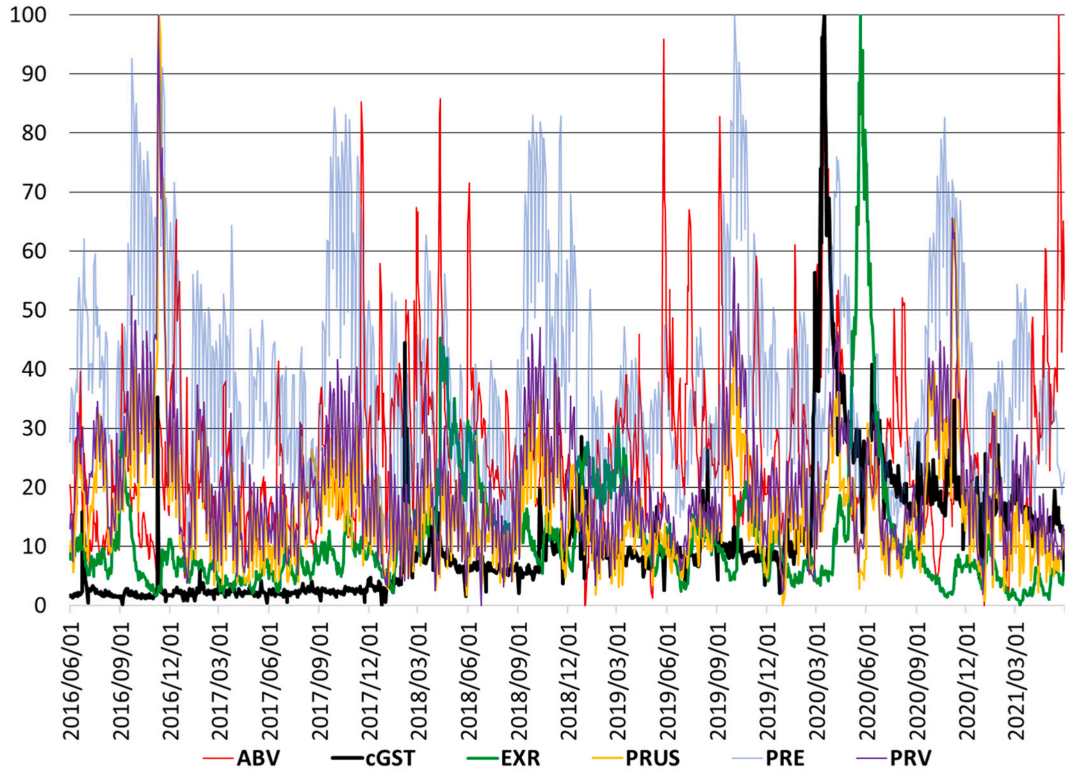

Fig. 4. $cGST_t$ in levels with attention measures

Notes: Fig. 4 plots $cGST_t$ against common attention measures in levels from 1 June 2016 to 31 May 2021. The attention measures include abnormal trading volume (ABV_t) and extreme returns (EXA_t) for the MSCI All Country World and Frontier Markets index, the Predata Country Attention index for the US ($PRUS_t$) and equal- and value-weighted Predata Country Attention indices for the US, China, Japan, France, the United Kingdom, Canada and Germany (PRE_t and PRV_t, respectively).

Table 5
Relationships between $cGST_t$ and attention, uncertainty and sentiment measures

	Panel A: Elastic net (4 iterations)			Panel B: Ordinary correlations		Panel C: Spearman correlations	
	λ_{min}	λ_{1SE}	λ_{2SE}		$\Delta cGST_t$		$\Delta cGST_t$
α_i	0.0003	0.0010	0.0013	ΔTMU_t	0.3955***	ΔTMU_t	0.2959***
ΔVIX_t	0.1650	0.0693	0.0264	ΔVIX_t	0.3231***	ΔPRV_{t-1}	0.2450***
ΔVIX_{t-1}	0.1646	0.0511	0.0011	ΔTEU_t	0.2511***	ΔVIX_t	0.2399***
ΔTMU_t	0.1072	0.0628	0.0402	ΔAIS_t	-0.24215***	ΔPRE_t	0.2317***
				ΔVIX_{t-1}	0.2131***	$\Delta PRUS_t$	0.2288***
				ΔABV_t	0.1927***	ΔABV_t	0.2066***
				ΔAIS_{t-1}	-0.1301***	ΔVIX_{t-1}	0.1658***
d.f.	3	3	3	$\Delta PRUS_t$	0.1291***	ΔPRE_{t-2}	-0.1608***
L_1	0.4371	0.1842	0.0690	ΔTMU_{t-2}	-0.1248***	ΔPRV_{t-3}	-0.1576***
R^2	0.2836	0.1967	0.1035	ΔEMU_t	0.1150***	ΔAIS_t	-0.1520***

Notes: Panel A reports the results of the final iteration of the elastic net-based identification procedure whereby differences in $cGST_t$ are regressed onto differences in each of the alternative measures over the period 1 June 2016 to May 2021. All measures are in first differences, denoted by Δ. The procedure is repeated until only the uncertainty, attention and sentiment measures for which coefficients are non-zero for the λ_{min}, λ_{1SE} and λ_{2SE} penalties remain. *d.f.* is the number of measures with non-zero coefficients and L_1 is the sparsity inducing penalty. R^2 is the coefficient of determination for proxy measures with non-zero coefficients. Panels B and C report the ordinary and Spearman correlation between $cGST_t$ and the alternative measures of uncertainty, sentiment and attention. Coefficients are ranked according to absolute magnitude. Each alternative measure enters the correlation matrix contemporaneously and with up to three lags. ***, ** and * indicate statistical significance at the respective 1%, 5% and 10% levels.

measure. Interestingly, TMU_t is the market uncertainty measure that is most highly correlated with $cGST_t$. This may potentially be explained by a shared reliance upon keywords to formulate this index and $cGST_t$, although our approach to selecting keywords differs. TMU_t is constructed by selecting keywords related to financial markets, e.g., "equity markets" and variants of the word "uncertainty" (Baker et al., 2021; French, 2021). In contrast, our approach relies upon directly selecting only two keywords, "stock market" and "stock markets", and related keywords and then applying elastic net regression to determine which of these terms are related to proxies for common return drivers. This presents a more objective keyword selection approach. Other proxies for uncertainty that feature amongst the top ten correlations, in both Panels B and C, are lags of VIX_t, VIX_{t-1} (ρ_o of 0.2131 (5th); ρ_S of 0.1658 (7th), respectively) and TMU_{t-2} (ρ_o of -0.1248 (9th)) and EMU_t (ρ_o of 0.1158 (10th) in Panel B. $cGST_t'$s strong and mostly positive and mostly contemporaneous correlation with these established market uncertainty measures suggests that increases in search volumes coincide with rising market uncertainty. Such a finding supports the hypothesis that economic agents respond to uncertainty by searching for information more intensively (Donadelli, 2015; Dzielinski, 2012; Liemieux & Peterson, 2011).

We also consider the presence of other measures in Panels B and C. Changes in $cGST_t$ are negatively correlated with changes in AIS_t (ρ_o of -0.2422) and AIS_{t-1} (ρ_o of -0.1301) in Panel B and with AIS_t (ρ_s of -0.1520) in Panel C. As contemporaneous correlation dominates, it appears that uncertainty rises concurrently with declining sentiment as opposed to responding to changes in sentiment. If $cGST_t$ is indeed a proxy for uncertainty, then a negative relationship between $cGST_t$ and sentiment proxies is expected. Epstein and Schneider (2008) argue that when investors face heightened uncertainty, decisions will be based upon the worst-case scenario given that investors are unable to arrive at a clear set of probabilities relating to future returns. Consequently, investors will become more pessimistic as uncertainty increases. Bird and Yeung (2012) confirm that there is an asymmetric response to good and bad earnings news during times of uncertainty, with investors ignoring good news during times of high uncertainty and reacting to bad news. They argue that this confirms that uncertainty breeds pessimism. Zhang (2019) propose that as uncertainty increases, firms delay investment decisions and begin facing financial pressures resulting in investor pessimism. Chen, Liu, and Zhao (2020) find that heightened market uncertainty, measured by the VIX, drives negative sentiment, inducing investors (in Bitcoin) to search for more information, a finding similar to that of this study. In light of these arguments, we view GST as a proxy for market uncertainty and not as a direct (*versus* indirect) proxy for sentiment. Declines in investor sentiment are the result of rising market uncertainty, accounting for negative correlation between $cGST_t$ and sentiment measures.

A number of attention measures are also correlated with changes in $cGST_t$, although correlation is weaker than that for the uncertainty proxies. In Panel B, we observe a positive correlation between ABV_t (ρ_o of 0.1927) and $PRUS_t$ (ρ_o of 0.1291). In Panel C, both PRV_{t-1} (ρ_S of 0.2450) and PRE_t (ρ_S of 0.2450) are positively correlated with $cGST_t$. As in Panel B, $cGST_t$ is also positively correlated with ABV_t (ρ_S of 0.2066) and negatively with lags of two attention measures, PRE_{t-2} (ρ_S of -0.1608) and PRV_{t-3} ((ρ_S of -0.1576). As positive and mostly contemporaneous correlation dominates, Google searches appear to increase around times of heightened attention. Vlastakis and Markellos (2012) suggest that when investor attention increases, concern around the impact of new information increases, resulting in higher return volatility. As $cGST_t$ is positively related to VIX_t, a similar mechanism is likely to apply. Peng et al. (2007) suggest that system wide shocks increase uncertainty, shifting limited investor attention away from specific assets to the market level as investors attempt to process new information. Aouadi et al. (2013) propose that investors who are paying attention will search for information. Dimpfl and Jank (2016) interpret increased Google searches as a measure of retail investor attention, proposing that retail investors may be viewed as uninformed noise traders. They argue that volatility shocks result in increased trading by noise traders which is reflected by increases in overall trading volume and further increases in volatility. This argument supports observations of positive correlation between $cGST_t$ and PRV_{t-1} and PRE_t, $PRUS_t$ and especially ABV_t, namely abnormal trading volume, in Panel C. Following the arrival of new information which constitutes a general shock which focuses attention on stock markets, i.e. the outbreak and milestones in the evolution of the COVID-19 pandemic, investors respond by searching for information (and news) relating to global markets.

What emerges from this discussion is that our index, $cGST_t$, is primarily a proxy for market uncertainty. This is suggested by the dominance and magnitude of correlations between $cGST_t$ and established measures of market uncertainty, notably the VIX_t and TMU_t measures. However, the story is incomplete without considering correlations between $cGST_t$ and the sentiment and attention measures although these tend to be of a lower magnitude. During times of heightened uncertainty, pessimism abounds, resulting in negative correlations between $cGST_t$ and the sentiment measures. During periods of heightened attention, stemming from the arrival of new information, investors react by searching for information in the face of greater uncertainty contributing to positive correlation. While uncertainty, attention and sentiment are related, what is perhaps most notable is that the results of the iterative procedure in Panel A of Table 5 identify only measures of uncertainty (VIX_t and TMU_t) as being related to $cGST_t$. Consequently, we can conclude that $cGST_t$ is most closely associated with measures of uncertainty, which is also supported by diagrammatic comparisons and established correlations.[14]

5. Google search trends, stock market returns and volatility

Given that $cGST_t$ appears to proxy for uncertainty, we demonstrate how a GST-based index can be used for analytical purposes and provide further confirmation that our index proxies for uncertainty using market returns and volatility directly. Our *a priori* expectation is that because $cGST_t$ reflects uncertainty, the relationship between returns and differences in $cGST_t$ should be negative. Heightened uncertainty is likely to be associated with declining expected cash flows to firms (Ramelli & Wagner, 2020). Additionally, during times of heightened uncertainty, investors will require a higher risk premium which will be reflected by the forward-looking discount rate (Andrei & Hasler, 2015; Cochrane, 2018; Smales, 2021). Lower expected cash flows and a higher discount rate translate into lower stock prices implying a negative relationship between changes in $cGST_t$ and returns. We test this relationship and conduct our analysis by regressing differences in $cGST_t$ onto returns for developed, emerging and frontier markets.[15]

To ascertain whether changes in $cGST_t$ are associated with volatility triggering across countries, we use the ARCH/GARCH framework.[16] We control for common factors in our sample by using statistically derived factors adjusted for $\Delta cGST_t$. The number of factors is identified by applying the MAP test. The mean equation is as follows:

$$r_{i,t} = \alpha_i + \sum_{k=1}^{m} \beta_{i,k} F^{RES}_{k,\Delta cGST_t} + \gamma_i r_{i,t-\tau} + \varepsilon_{i,t} \tag{8}$$

where $\sum_{k=1}^{m} \beta_{i,k} F^{RES}_{k,\Delta cGST_t}$ is the set of statistically derived factors from the return series, $r_{i,t}$, adjusted for $\Delta cGST_t$. To ensure parsimony, only significant proxy factors are retained. If required, autoregressive terms, $r_{i,t-\tau}$, of order τ, identified from an analysis of a residual correlogram, are included to address remaining autocorrelation.

We begin with an ARCH(p) model and proceed to estimate a GARCH (p,q) model if the former exhibits residual heteroscedasticity or non-linear dependence. If heteroscedasticity or non-linear dependence are still present, the number of ARCH(p) and/or GARCH(p,q) parameters is increased. We also consider IGARCH(p,q) specifications if ARCH and GARCH parameters are close to unity (Engle & Bollerslev, 1986) and the TGARCH(p,q) model if asymmetry is evident in the residual volatility series. The respective ARCH(p), GARCH(p,q), IGARCH(p,q) and TGARCH(p,q) conditional variance equations are as follows:

[14] Given that $cGST_t$ appears to proxy for market uncertainty, we apply the elastic net procedure to determine which market uncertainty proxy most closely approximates the VIX_t as a form of confirmatory analysis, but now include $cGST_t$ in the candidate measure set while VIX_t is now treated as the independent variable. $cGST_t$ is the only remaining measure in the uncertainty measure set, confirming its role as proxy for uncertainty.

[15] Estimated using least squares regressions. We use a contemporaneous estimate of $cGST_t$ in the regressions as it is found to dominate lagged values of $cGST_t$.

[16] We investigate the impact of $cGST_t$ on returns and volatility separately to avoid challenges associated with the convergence of coefficients when the same variable features in both the mean and conditional variance (see Bush & Noria, 2021).

$$h_{i,t} = \omega_i + \sum_{j=1}^{p} \alpha_i \varepsilon_{i,t-j}^2 + \varphi_{i,\Delta cGST} \Delta cGST_t \tag{9a}$$

$$h_{i,t} = \omega_i + \sum_{j=1}^{p} \alpha_i \varepsilon_{i,t-j}^2 + \sum_{k=1}^{q} \beta_i h_{i,t-k} + \varphi_{i,\Delta cGST} \Delta cGST_t \tag{9b}$$

$$h_{i,t} = \sum_{j=1}^{p} \alpha_i \varepsilon_{i,t-j}^2 + \sum_{k=1}^{q} \beta_i h_{i,t-k} + \varphi_{i,\Delta cGST} \Delta cGST_t \tag{9c}$$

$$h_{i,t} = \omega_i + \sum_{j=1}^{p} \alpha_i \varepsilon_{i,t-j}^2 + \gamma \varepsilon_{i,t-1}^2 D_{0,1} + \sum_{k=1}^{q} \beta_i h_{i,t-k} + \varphi_{i,\Delta cGST} \Delta cGST_t \tag{9d}$$

where $h_{i,t}$ is the conditional variance and $D_{0,1}$ in eq. (9d) is a dummy equal to one if $\varepsilon_{i,t}$ is less than zero, or zero otherwise. The impact of positive values of $\varepsilon_{i,t}$ on conditional variance is captured by α_i while the impact of negative shocks is captured by $\alpha_i + \gamma$. Maximum likelihood estimation is used and if residuals are non-normal, equations are re-estimated using quasi-maximum likelihood with Bollerslev-Wooldridge standard errors and covariance (Fan, Qi, & Xiu, 2014).[17] If $cGST_t$ reflects uncertainty, then the *a priori* expectation is that the relationship between conditional variance and $cGST_t$ is positive. Uncertainty can be viewed as being associated with information arrivals: 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 leading to volatility as market participants are not sure about the true value of assets following information arrivals (Engle et al., 2008; Szczygielski et al., 2022).

Panels A to C in Table 6 report results of regressions of returns onto changes in $cGST_t$ for developed, emerging and frontier markets, respectively. $cGST_t$ has a statistically significant and negative effect on stock returns for all 23 developed countries (average $\beta_{i,\Delta cGST}$ of -0.0022). Italy and Belgium are most impacted (respective $\beta_{i,\Delta cGST}$s of -0.0031 and -0.0029), while Hong Kong and New Zealand are least impacted ($\beta_{i,\Delta cGST}$s of -0.0014). A similar pattern arises for emerging markets, with $cGST_t$ coefficients statistically significant and negative for 23 out of 27 countries. The average $\beta_{i,\Delta cGST}$ of -0.0019 is marginally smaller than the developed market average. Among this group of countries, $cGST_t$ has the largest effect on returns for Greece and Argentina ($\beta_{i,\Delta cGST}$s of -0.0029 and -0.0027, respectively) and the smallest for Kuwait and the UAE ($\beta_{i,\Delta cGST}$s of -0.0010). For frontier markets, the negative impact of $cGST_t$ on returns is more muted, with an average $\beta_{i,\Delta cGST}$ of -0.0009, lower than those of developed and emerging markets, and significant for 13 out of 27 countries. In this grouping, Bulgaria and Kazakhstan are most impacted ($\beta_{i,\Delta cGST}$s of -0.0023) and Serbia and WAEMU are least impacted ($\beta_{i,\Delta cGST}$s of -0.0001). The conclusion that the impact of $cGST_t$, on average, is highest for developed markets followed by emerging and then frontier markets, is consistent with the respective average $\bar{R}^2$s of 0.0702, 0.0328 and 0.0225.

The finding of a negative effect of changes in $cGST_t$ on stock returns is in line with *a priori* expectations. This finding is consistent with Dzielinski (2012), Bijl et al. (2016) and Chen (2017), amongst others. For example, Chen (2017) documents a significant negative impact of country-specific stock market GST on one-month ahead stock returns using a panel of 67 countries. In contrast, Swamy and Dharani (2019), Akarsu and Süer (2021), Ekinci and Bulut (2021) and Iyke and Ho (2021) obtain mixed evidence, with returns for some countries negatively impacted and others positively impacted by GST. Our finding of a deleterious impact of $cGST_t$ on returns is also consistent with studies of the influence of COVID-19 related GST on stock market returns and importantly, consistent with an uncertainty narrative (Lyócsa et al., 2020; Smales, 2021; Szczygielski et al., 2021).

These results are also congruent with literature which detects an inverse relationship between VIX and stock returns across markets (Dimic, Orlov, & Piljak, 2015; Sarwar & Khan, 2017, 2019). Likewise, studies (such as Su et al., 2019; Fang et al., 2018; Özyeşil & Tembelo, 2020) have shown that an increase in EMU and NVIX, other established measures of uncertainty, negatively impacts stock returns. This provides further support for the diagrammatic and empirical analyses in Sections 4.2. and 4.3 that point towards GST reflecting uncertainty.

The finding that uncertainty has a greater effect on developed and emerging markets than frontier markets may be attributed to differences in market integration levels.[18] Frontier markets are less integrated with more developed markets (Berger et al., 2011; Zaremba & Maydybura, 2019) and are therefore likely to be less impacted by uncertainty reflected by $cGST_t$ and, instead, more impacted by domestic factors.[19]

We confirm the observation of Chen (2017) and Akarsu and Süer (2021) that developed country stock returns are most impacted by GST. We find that emerging markets are also impacted, although less so than developed countries. The finding that $\Delta cGST_t$ has a more muted impact on frontier markets is similar to the conclusion of Iyke and Ho (2021) but differs from that of Chen (2017) who documents a significant impact on this grouping. A possible explanation for some of the different findings lies in the GST measure. Our index comprises worldwide stock market-related search terms. Iyke and Ho (2021) also used a worldwide GST index related to COVID-19 whereas Chen (2017) and Akarsu and Süer (2021) develop separate indices for each country comprising terms related to the national market aggregate and constituent stocks, respectively. Accordingly, the results in this study and those of Iyke and Ho (2021) compared to those of Chen (2017) and Akarsu and Süer (2021) may suggest that emerging markets are more impacted by global rather than country-specific uncertainty, whereas the opposite is true for frontier markets. Additionally, internet penetration rates are lower in frontier market economies compared to developed and emerging countries making GST less relevant and reflective.[20]

[17] Broydon-Fletcher-Goldfarb-Shanno (BFGS) optimisation is used, however in the case that models do not converge, EViews legacy optimisation is employed. This approach relies on the Gauss-Newton with Marquardt or line search steps.

[18] As a confirmatory step, ARCH/GARCH models are estimated with differences in $cGST_t$ in mean and variance along with factor augmentation in the mean equation (this is an extension of the ARCH/GARCH model explained in Section 5 that includes $cGST_t$ in the variance only). The results are reported in Table A5 in the Appendix with the mean results in Panels A/C/E and the variance results in Panels B/D/F for developed, emerging and frontier markets respectively. $cGST_t$ shows consistency in terms of significance and direction of impact on returns across countries, with all 23 (23) developed country coefficients, 24 (23) of 27 emerging market coefficients, and 18 (16) of 27 frontier market coefficients significant with $cGST_t$ in mean and variance (in mean only). However, notably, the impact is smaller in magnitude after including $cGST_t$ in both mean and variance, especially for developed countries (average $\varphi_{i,\Delta cGST}$s of -0.0011, -0.0013 and -0.0005 with $cGST_t$ in mean and variance compared to -0.0022, -0.0019 and -0.0009 for developed, emerging and frontier markets). The story that emerges from these results is that the impact of $cGST_t$ differences on returns is similar in magnitude although emerging markets are most affected.

[19] The mean communalities reported in Section 4.1 suggest that this is indeed the case, given that the six common factors explain under a fifth of common variation in frontier market returns. Nevertheless, the mean communality for these markets is substantially above zero suggesting that common factors and $cGST_t$ still play a role in these markets as suggested by the results in Tables 6 and 7.

[20] As of 2021, 90% of individuals in developed countries use the internet compared to 57% in developing countries and 27% in the least developed countries (ITC, 2021). Frontier markets are considered more developed than the least developed countries and are typically classified alongside emerging markets under the umbrella term "developing". Hence, it is likely that internet penetration will be higher among the more developed of the developing countries, namely emerging markets, than the less developed developing countries, namely frontier markets.

Table 6
Mean specification estimated using least squares

Panel A: Developed Markets				Panel B: Emerging Markets				Panel C: Frontier Markets			
Country	α_i	$\beta_{i,\Delta cGST}$	$\bar{R}^2$	Country	α_i	$\beta_{i,\Delta cGST}$	$\bar{R}^2$	Country	α_i	$\beta_{i,\Delta cGST}$	$\bar{R}^2$
1.Australia	0.0003	-0.0024***	0.0773	1.Argentina	-0.0003	-0.0027***	0.0198	1.Bahrain	0.0002	-0.0008	0.0128
2.Austria	0.0004	-0.0027**	0.0577	2.Brazil	0.0003	-0.0023	0.0216	2.Bangladesh	-3.57E-05	-0.0006**	0.0111
3.Belgium	-0.0001	-0.0029***	0.0947	3.Chile	-0.0001	-0.0019***	0.0275	3.Bosnia Herzegovina	-0.0002	-0.0005*	0.0029
4.Canada	0.0003	-0.0024**	0.0834	4.China	0.0005	-0.0018***	0.0466	4.Botswana	-0.0013***	-0.0003	-0.0003
5.Denmark	0.0004	-0.0019***	0.0659	5.Colombia	-0.0002	-0.0026*	0.0376	5.Bulgaria	3.82E-05	-0.0023**	0.0666
6.Finland	0.0003	-0.0019***	0.0495	6.Czech Rep	0.0002	-0.0017**	0.0440	6.Croatia	0.0002	-0.0015**	0.0595
7.France	0.0004	-0.0025***	0.0878	7.Egypt	-0.0002	-0.0011***	0.0080	7.Estonia	-1.50E-05	-0.0013*	0.0261
8.Germany	0.0003	-0.0026***	0.0906	8.Greece	-0.0002	-0.0029***	0.0424	8.Jamaica	0.0005	0.0002	-0.0001
9.Hong Kong	0.0003	-0.0013***	0.0332	9.Hungary	0.0004	-0.0024***	0.0517	9.Jordan	-0.0004	-0.0003	0.0011
10.Ireland	0.0002	-0.0022***	0.0541	10.India	0.0004	-0.0021***	0.0579	10.Kazakhstan	0.0008	-0.0023**	0.0339
11.Israel	2.47E-05	-0.0021***	0.0587	11.Indonesia	3.97E-05	-0.0019***	0.0318	11.Kenya	0.0003	-0.0012**	0.0223
12.Italy	0.0003	-0.0031***	0.0951	12.Korea	0.0005	-0.0018***	0.0380	12.Lebanon	-0.0001	-0.0018	0.0009
13.Japan	0.0003	-0.0015***	0.0480	13.Kuwait	0.0004	-0.0010	0.0227	13.Lithuania	0.0002	-0.0020***	0.0855
14.Netherlands	0.0006	-0.0023***	0.0954	14.Malaysia	-0.0001	-0.0015***	0.0638	14.Mauritius	-0.0002	-0.0009	0.0076
15.New Zealand	0.0002	-0.0013***	0.0269	15.Mexico	8.20E-06	-0.0022***	0.0417	15.Morocco	0.0002	-0.0008	0.0149
16.Norway	0.0002	-0.0027***	0.0746	16.Pakistan	-0.0006	-0.0014***	0.0181	16.Nigeria	-0.0005	-0.0006*	0.0023
17.Portugal	0.0002	-0.0027***	0.0939	17.Peru	0.0002	-0.0015	0.0180	17.Oman	-0.0001	-0.0005	0.0104
18.Singapore	0.0001	-0.0014***	0.0413	18.Philippines	-0.0001	-0.0019***	0.0410	18.Romania	0.0004	-0.0018***	0.0406
19.Spain	0.0001	-0.0026***	0.0767	19.Poland	0.0002	-0.0026***	0.0621	19.Serbia	0.0002	-0.0001	-0.0004
20.Sweden	0.0004	-0.0023***	0.0616	20.Qatar	0.0001	-0.0011**	0.0280	20.Slovenia	0.0005	-0.0018**	0.0562
21.Switzerland	0.0003	-0.0020***	0.1082	21.Russia	0.0004	-0.0022**	0.0387	21.Sri Lanka	-0.0003	-0.0004	0.0011
22.United Kingdom	0.0001	-0.0024***	0.0805	22.Saudi Arabia	0.0004	-0.0012**	0.0315	22.Trinidad & Tobago	-0.0001	-0.0002	-0.0002
23.United States	0.0006	-0.0020**	0.0586	23.South Africa	0.0002	-0.0027***	0.0435	23.Tunisia	0.0001	-0.0003	0.0020
				24.Taiwan	0.0007	-0.0017***	0.0484	24.Ukraine	-4.45E-05	-0.0020**	0.0325
				25.Thailand	0.0001	-0.0023***	0.0753	25.Vietnam	0.0005	-0.0012**	0.0211
				26.Turkey	-0.0006	-0.0017***	0.0137	26.WAEMU	-0.0004	-0.0001	-0.0008
				27.UAE	0.0001	-0.0010	0.0207	27.Zimbabwe	0.0037	0.0005	-0.0003
Average	**0.0003**	**-0.0022**	**0.0702**	**Average**	**0.0001**	**-0.0019**	**0.0328**	**Average**	**0.0002**	**-0.0009**	**0.0225**

Notes: This table reports the results of regressions for returns on developed, emerging and frontier markets in Panels A, B and C, respectively onto changes in $cGST_t$ over the sample period 1 June 2016 to 31 May 2021. Least squares with Newey-West heteroscedasticity and autocorrelation consistent (HAC) standard errors are used for estimation purposes. $\bar{R}^2$ is the adjusted coefficient of determination. ***, ** and * indicate statistical significance at the respective 1%, 5% and 10% levels.

We now turn to the relationship between volatility and $cGST_t$. The results in Panel A of Table 7 show that $cGST_t$ has a statistically significant positive effect on return volatility for 18 of 23 developed countries, with an average $\varphi_{i,\Delta cGST}$ of 0.1010. The most impacted stock markets are Austria and Spain ($\varphi_{i,\Delta cGST}$s of 0.2780 and 0.2320, respectively) while Italy and Sweden are least impacted (respective $\varphi_{i,\Delta cGST}$s of 0.0279 and 0.0289). The average $\varphi_{i,\Delta cGST}$s for emerging and frontier markets are 0.1698 (Panel B) and 0.0860 (Panel C), respectively. The $\varphi_{i,\Delta cGST}$ coefficients are statistically significant for 24 out of 27 emerging markets, ranging from 1.0700 for Egypt and 0.4110 for Brazil (largest) to 0.0379 for Kuwait and 0.0445 for Malaysia (lowest). Among the frontier markets, 17 out of 27 have significant coefficients, largest for Zimbabwe and Kazakhstan (respective $\varphi_{i,\Delta cGST}$s of 0.9220 and 0.3910) and smallest for Trinidad and Tobago, and Botswana (respective $\varphi_{i,\Delta cGST}$s of 0.0000 and 0.0042).[21]

These results provide confirmation that as investors become more uncertain and search for information, equity prices become more volatile, which is in line with *a priori* expectations. A number of studies have also documented evidence of heightened volatility in response to increased Google searches (Vlastakis & Markellos, 2012; Andrei & Hasler, 2015; Perlin et al., 2017) and COVID-19 related GST (Smales, 2021; Szczygielski et al., 2021; Szczygielski et al., 2022). Notably, our results are similar to those obtained on the impact of the VIX on stock market volatility across developed, emerging and frontier markets (Zhu et al., 2019; Badshah, Bekiros, Lucey, & Uddin, 2018; Cheuathonghua et al., 2019).

Cross-country analysis reveals that return volatility for emerging markets is most impacted by $cGST_t$ followed by that of developed markets and finally frontier markets. This differs from the impact of $cGST_t$ on stock returns where developed country returns are most impacted. These results are congruent with the greater susceptibility of emerging markets to fluctuating risk tolerance in general (Froot & O'Connell, 2003; FitzGerald, 2007), especially during times of crises (such as the Global Financial Crisis in 2007/2008) (McCauley, 2013) and to uncertainty surrounding the COVID-19-induced health and economic crises (Szczygielski et al., 2021). Szczygielski et al. (2023) also illustrate that emerging market volatility is more responsive to COVID-19 related GST than that of developed markets. In contrast, frontier markets, due to their low integration with global markets (as outlined above), are less susceptible.[22] Most studies in this area focus on individual countries, particularly the US (Vlastakis & Markellos, 2012; Andrei & Hasler, 2015; Xu et al., 2023), and cross-country comparisons are rare. Our results mirror those of Cheuathonghua et al. (2019) who find that the impact of VIX is stronger for developed market returns and volatility than for emerging markets.

The analysis above confirms *a priori* expectations, i.e. that the relationship between changes in $cGST_t$ and returns is negative, while that between volatility and changes in $cGST_t$ is positive. Differences in impact can be attributed to differing levels of integration and risk aversion. Using our index, we investigate how the impact of uncertainty differs across developed, emerging and frontier markets. Such an analysis would not be viable or useful if Google searches remain without a clear interpretation.

6. Comparison against other uncertainty proxies

For GST-based indices to offer a useful alternative to existing keyword-based uncertainty measures, such indices should perform relatively well in explaining and predicting returns and volatility across a broad sample of markets. We undertake in-sample (1 June 2016 to 31 May 2021) and out-of-sample (1 June 2021 to 31 May 2022) comparisons of explanatory and predictive performance for the uncertainty measures considered and our index.

Out-of-sample analyses are common in literature assessing the suitability of uncertainty indices such as EPU and VIX (see Liu, Liu, Zeng, & Wu, 2022; Liu & Zhang, 2015). For the out-of-sample analysis, $cGST_t$ is constructed in the manner outlined in Section 4.1, using in-sample communality weightings and updated constituent Google search terms. We draw upon the methodology of Semper and Clemente (2003) who propose modelling the conditional mean and variance of factor scores derived from returns. By modelling factor scores, we summarise the impact of uncertainty measures across market groupings and investigate whether these measures drive returns and factor dispersion underlying return volatility. For the in-sample analysis, we use the composite communality-weighted factor score series for the all market grouping (Section 4.1) and derive three factors from developed and emerging market returns each and a single factor from frontier market returns. For the out-of-sample analysis, we permit a fully dynamic return generating process by deriving factor scores for the period 1 June 2021 to 31 May 2022 (see Section 3.4) for all market groupings.[23] Ten, five, four and one factor are derived for the all, developed, emerging and frontier market groupings, respectively. Except for the latter grouping, this suggests that the return generating process is dynamic (non-static in terms of underlying factor structure). A diagrammatic analysis of communality-weighted squared factor score series indicates that they exhibit time-varying volatility-like features (see Figs. A3 and A4 in the Appendix for in-sample and out-of-sample series, respectively).

We relate composite factor scores to changes in $cGST_t$ and each of the respective uncertainty measures using least squares regressions. This permits us to establish the ability of these measures to approximate the return generating process. Following Gorodnichenko and Weber (2016), we estimate variance equations directly. Instead of using squared returns or squared residuals as the dependent variable, we use composite squared factor scores which we interpret as reflecting dispersion associated with factors driving underlying volatility (Lehmann, 1990; Szczygielski et al., 2020). The mean and variance specifications are as follows:

$$F_{c,g,t} = \alpha_i + \sum_{k=1}^{m} \beta_{\Delta UNg} \Delta UN_{t-\tau} + \varepsilon_{c,g,t} \tag{10}$$

$$F^2_{c,g,t} = \omega_i + \sum_{k=1}^{m} \varphi_{\Delta UN_g} \Delta UN_{t-\tau} + \varepsilon_{c,g,t} \tag{11}$$

where $\Delta UN_{t-\tau}$ in the mean and variance specifications in Eqs. (10) and (11), respectively, is either $cGST_t$ or one of the measures of uncertainty: VIX_t, EMU_t, EPU_t, TEU_t and TMU_t. $\beta_{\Delta UN_g}$ reflects the impact of $\Delta UN_{t-\tau}$ on communality-weighted factor score series, $F_{c,g,t}$, for grouping g. $\varphi_{\Delta UN_g}$ reflects the association of $\Delta UN_{t-\tau}$ with the dispersion reflected in $F^2_{c,g,t}$ for group g. Eqs. (10) and (11) are first estimated for

[21] Lebanon is the exception as $cGST_t$ has a negative impact on volatility with $\varphi_{i,\Delta cGST}$ of -0.5690.

[22] With $cGST_t$ differences included in both mean and variance (see Table A4 in the Appendix), $cGST_t$ continues to contribute to heightened volatility across markets (Panels B/ D/ F). The impact is larger for developed markets (average $\varphi_{i,\Delta cGST}$s of 0.1383 with $cGST_t$ in mean and variance compared to 0.1010) but smaller for emerging and frontier markets (average $\varphi_{i,\Delta cGST}$s of 0.1566 and 0.0592 with $cGST_t$ in mean and variance compared to 0.1692 and 0.0860, respectively). The coefficients for all 23 (18) developed countries, 24 (24) out of 27 emerging markets and 16 (17) out of 27 frontier markets are individually significant with $cGST_t$ in mean and variance (in variance only). Emerging markets remain most impacted by $cGST_t$, followed by developed and frontier markets. These results thus confirm that $cGST_t$ affects stock market return volatility across countries.

[23] For developed, emerging and frontier markets both in-sample (1 June 2016 to 31 May 2021) and out-of-sample (1 June 2021 to 31 May 2022), we apply the MAP test to determine the number of latent factors when characterising the factor structure underlying the return generating process. We also apply the MAP test for all markets over the out-of-sample period.

Table 7
ARCH/GARCH estimates for conditional variance with $cGST_t$

Panel A: Developed Markets

Country	ω_i	α_1	α_2/γ	β_1	β_2	$\varphi_{i,\Delta cGST}$
1.Australia	1.62E-06***	0.0466***		0.9269***		0.1180***
2.Austria		0.0488***		0.7438***	0.2074	0.2780***
3.Belgium	7.85E-06***	0.2106***		0.6797***		0.0359
4.Canada	1.37E-06***	0.0644***		0.9048***		0.0632***
5.Denmark	5.73E-06**	0.0722***		0.8545***		0.0827***
6.Finland	6.74E-06*	0.0991***		0.7786***		0.0480
7.France	4.27E-06**	0.1059***		0.8494***		0.1700***
8.Germany	-8.37E-09	0.0016*		0.9985***		0.0363***
9.Hong Kong	2.22E-07	0.0278***		0.9699***		0.1430***
10.Ireland	2.54E-06**	0.0668***		0.8877***		0.0751**
11.Israel	2.06E-06***	0.0143*		0.9609***		0.1290***
12.Italy	3.16E-06***	0.0499	0.0952*^{y}	0.8251***		0.0279
13.Japan	9.35E-07**	0.0096	0.0299*^{y}	0.9603***		0.0997***
14.Netherlands	8.40E-07	0.0369		0.9505***		0.1490***
15.New Zealand	7.28E-07*	0.0266***		0.9659***		0.1300***
16.Norway	2.40E-06*	0.0445***		0.9225***		0.0956**
17.Portugal	-2.63E-08	0.0021*		0.9976***		0.1340***
18.Singapore	1.27E-06***	0.0391***	0.0061^{y}	0.9370***		0.1160***
19.Spain	3.96E-06***	0.0318***	0.0558***^{y}	0.9050***		0.2320***
20.Sweden	4.20E-06***	0.1466***		0.7534***		0.0289
21.Switzerland	5.66E-07***	0.0408***		0.9356***		0.0426***
22.United Kingdom	1.40E-06***	0.0655***		0.8904***		0.0434
23.United States	2.34E-06***	0.1681***		0.7875***		0.0454***
Average	**2.46E-06**	**0.0617**	**0.0468$^{\gamma}$**	**0.8863**	**0.2074**	**0.1010**

Panel B: Emerging Markets

Country	ω_i	α_1	α_2/γ	β_1	β_2	$\varphi_{i,\Delta cGST}$
1.Argentina	2.84E-05***	0.4915	-0.1496^{y}	0.6169***		0.1930*
2.Brazil	1.10E-05**	0.0643***		0.9034***		0.4110***
3.Chile	1.11E-05***	0.3708***		0.6100***		0.0680*
4.China	7.75E-06**	0.0549	0.0236	0.8579***		0.1390***
5.Colombia	6.11E-06***	0.0724***		0.8930***		0.2850***
6.Czech Republic	9.27E-07***	0.0222**	0.0092	0.9555***		0.0677***
7.Egypt‡	0.0003***	0.1348**		0.5855***		1.0700***
8.Greece	1.79E-05***	0.1089***		0.8269***		0.1280
9.Hungary	3.62E-06**	0.0468***		0.9240***		0.1500***
10.India	3.01E-06***	0.0539**		0.9144***		0.1010
11.Indonesia	3.31E-06***	0.1027***		0.8753***		0.0763
12.Korea	1.74E-06***	0.0335***		0.9418***		0.1190***
13.Kuwait	2.63E-06***	0.1226***		0.8210***		0.0379***
14.Malaysia	3.57E-07**	0.0434***		0.9435***		0.0445***
15.Mexico	7.73E-06**	0.0894***		0.8609***		0.2150***
16.Pakistan	5.63E-06***	0.1027***		0.8710***		0.1170***
17.Peru	8.60E-06**	0.1399*		0.6010	0.1721	0.0809**
18.Philippines	1.67E-06***	0.0414***		0.9423***		0.1570***
19.Poland	3.71E-06***	0.0264	0.0537**^{y}	0.9129***		0.1270***
20.Qatar	1.84E-05***	0.1695***		0.6228***		0.0918***
21.Russia	5.32E-06***	0.0572***	0.0562***	0.8834***		0.1320***
22.Saudi Arabia	2.66E-06***	0.1356***		0.8370***		0.0532***
23.South Africa	3.88E-06**	0.0321***		0.9467***		0.2060**
24.Taiwan	1.90E-06*	0.0449*		0.9201***		0.0691***
25.Thailand	1.10E-06**	0.0607***		0.9260***		0.1110***
26.Turkey	1.98E-05***	0.0910***		0.8643***		0.2880***
27. UAE	2.83E-06***	0.0798***		0.8497***		0.0462**
Average	**1.78E-05**	**0.1035**	**0.0339/-0.0289$^{\gamma}$**	**0.8410**	**0.1721**	**0.1698**

Panel C: Frontier Markets						
Country	ω_i	α_1	α_2/γ	β_1	β_2	$\varphi_{i,\Delta cGST}$
1.Bahrain	1.55E-05***	0.2338***		0.0725	0.4762***	0.0566***
2.Bangladesh	7.70E-06***	0.2827***		0.4116**	0.2066	0.0359***
3.Bosnia Herzegovina	6.18E-06***	0.0564***		0.8835***		0.0179
4.Botswana	1.79E-04***	0.0145	0.3104	0.1944		0.0042
5.Bulgaria	3.18E-06**	0.0327***		0.9375***		0.1460**
6.Croatia	8.68E-06***	0.1512***		0.6080***		0.0295***
7.Estonia	4.63E-07	0.0155*		0.9768***		0.1020***
8.Jamaica	6.10E-06**	0.0745***		0.8959***		0.0369
9.Jordan	7.24E-05	0.1910				0.0716***
10.Kazakhstan	1.14E-04***	0.0458***		0.5643***		0.3910***
11.Kenya	1.46E-05***	0.1580***		0.7258***		0.0879***
12.Lebanon	0.0004	0.0176	-0.0205 $^{\gamma}$	0.5892*		-0.5690***
13.Lithuania	1.59E-06**	0.0762***		0.8867**		0.0328
14.Mauritius	3.49E-06***	0.0592***		0.9122***		0.1070***
15.Morocco	2.93E-06***	0.0745***		0.8736***		0.0686***
16.Nigeria	0.0001***	0.8839**				0.0641
17.Oman		0.2379***		0.6395***		0.0396***
18.Romania	2.80E-06***	0.0526***		0.9246***		0.1540***
19.Serbia	9.68E-05***	0.1958**				0.0869
20.Slovenia	2.09E-06*	0.0231**		0.9486***		0.0772
21.Sri Lanka	1.01E-05***	0.0948*		0.8212***		0.0152
22.Trinidad & Tobago		0.0002	0.0444***	0.9554***		0.0000
23.Tunisia	4.79E-06***	0.1405***		0.8048***		0.0612***
24.Ukraine	2.64E-05***	0.1518***		0.1175		0.0337
25.Vietnam	4.93E-06***	0.1214***		0.8390***		0.1220***
26.WAEMU	0.0000**	0.1877***		0.2543	0.5087**	0.1260***
27.Zimbabwe‡	0.0004***	0.3463***		0.4494***		0.9220***
Average	**5.93E-05**	**0.1452**	**0.1774/ -0.0205** $^{\gamma}$	**0.6786**	**0.3972**	**0.0860**

Notes: This table reports conditional variance incorporating differences in $cGST_t$ modelled as an ARCH/GARCH process for each developed, emerging and frontier market in Panels A, B and C, respectively over the period from 1 June 2016 to 31 May 2021. Models are estimated using maximum likelihood. If residuals depart from normality, quasi-maximum likelihood estimation is applied. γ denotes the coefficient on the asymmetric ARCH if the TGARCH model was used. Coefficients on $cGST_t$ differences are scaled by 10 000. ***, ** and * indicate statistical significance at the respective 1%, 5% and 10% levels of significance.

Table 8
In-sample factor score regression results

	Factor scores									Squared factor scores								
	τ = 0			τ = 1, 2, 3			τ = 0, 1, 2, 3			τ = 0			τ = 1, 2, 3			τ =0, 1, 2, 3		
	$\bar{R}^2$	AIC	BIC	$\bar{R}^2$	AIC	BIC	$\bar{R}^2$	AIC	BIC	$\bar{R}^2$	AIC	BIC	$\bar{R}^2$	AIC	BIC	$\bar{R}^2$	AIC	BIC
Panel A: All markets																		
$\Delta cGST_t$	0.0991	0.5497	0.5576	0.0188	0.6366	0.6525	0.1376	0.5083	0.5282	0.1473	1.6249	1.6328	0.0279	1.7574	1.7733	0.1811	1.5867	1.6065
ΔTMU_t	0.0773	0.5736	0.5815	0.0140	0.6415	0.6574	0.1138	0.5355	0.5553	0.0413	1.7420	1.7499	0.0394	1.7456	1.7614	0.0905	1.6917	1.7115
ΔTEU_t	0.0189	0.6350	0.6429	0.0266	0.6286	0.6445	0.0830	0.5697	0.5895	0.0211	1.7628	1.7708	0.0181	1.7674	1.7833	0.0671	1.7170	1.7368
ΔVIX_t	0.2345	0.3868	0.3948	0.0541	0.6000	0.6158	0.3323	0.2524	0.2723	0.1364	1.6376	1.6455	0.0076	1.7781	1.7939	0.1498	1.6242	1.6440
ΔEPU_t	0	0.6548	0.6627	0.0016	0.6540	0.6699	0.0013	0.6550	0.6749	0	1.7843	1.7922	0.0104	1.7753	1.7912	0.0116	1.7748	1.7947
ΔEMU_t	0	0.6542	0.6621	0	0.6556	0.6715	0.0020	0.6544	0.6742	0.0030	1.7812	1.7891	0.0300	1.7553	1.7712	0.0306	1.7554	1.7752
Panel B: Developed markets																		
$\Delta cGST_t$	0.0750	1.8075	1.8155	0.0133	1.8736	1.8895	0.1037	1.7783	1.7981	0.1152	3.8224	3.8303	0.0297	3.9162	3.9320	0.1513	3.7831	3.8029
ΔTMU_t	0.0536	1.8304	1.8383	0.0199	1.8669	1.8828	0.0917	1.7916	1.8115	0.0356	3.9085	3.9164	0.0525	3.8924	3.9083	0.0999	3.8418	3.8617
ΔTEU_t	0.0127	1.8727	1.8806	0.0289	1.8577	1.8735	0.0741	1.8108	1.8306	0.0230	3.9216	3.9295	0.0250	3.9211	3.9369	0.0828	3.8606	3.8805
ΔVIX_t	0.1268	1.7498	1.7578	0.0536	1.8319	1.8478	0.2216	1.6373	1.6571	0.0819	3.8594	3.8673	0.0119	3.9343	3.9502	0.1029	3.8385	3.8583
ΔEPU_t	0	1.8862	1.8942	0.0019	1.8851	1.9009	0.0012	1.8865	1.9064	0	3.9449	3.9528	0.0080	3.9383	3.9541	0.0091	3.9379	3.9578
ΔEMU_t	0.0001	1.8854	1.8933	0	1.8872	1.9031	0.0012	1.8866	1.9064	0.0052	3.9396	3.9476	0.0275	3.9184	3.9343	0.0320	3.9146	3.9345
Panel C: Emerging markets																		
$\Delta cGST_t$	0.0471	0.9670	0.9749	0.0421	0.9738	0.9897	0.0967	0.9158	0.9357	0.1015	2.2308	2.2388	0.0299	2.3090	2.3249	0.1522	2.1750	2.1949
ΔTMU_t	0.0598	0.9536	0.9615	0	1.0176	1.0334	0.0697	0.9453	0.9651	0.0193	2.318297	2.3262	0.0089	2.3304	2.3463	0.0329	2.3067	2.3266
ΔTEU_t	0.0086	1.0066	1.0145	0.0131	1.0036	1.0194	0.0409	0.9758	0.9956	0.0067	2.3311	2.3391	0.0080	2.3313	2.3472	0.0261	2.3136	2.3335
ΔVIX_t	0.3228	0.6255	0.6335	0.0277	0.9887	1.0046	0.3462	0.5925	0.6124	0.1538	2.1708	2.1787	0.0468	2.2915	2.3073	0.1940	2.1245	2.1443
ΔEPU_t	0	1.0160	1.0239	0.0017	1.0151	1.0309	0.0018	1.0157	1.0356	0.0003	2.3375	2.3455	0.0081	2.3312	2.3471	0.0111	2.3290	2.3488
ΔEMU_t	0.0002	1.0151	1.0230	0.0064	1.0104	1.0262	0.0057	1.0118	1.0316	0	2.3383	2.3463	0.0038	2.3355	2.3514	0.0030	2.3371	2.3569
Panel D: Frontier markets																		
$\Delta cGST_t$	0.1076	-0.9173	-0.9093	0.0299	-0.8322	-0.8164	0.1566	-0.9714	-0.9516	0.1383	-0.4695	-0.4616	0.0435	-0.3636	-0.3477	0.2019	-0.5439	-0.5241
ΔTMU_t	0.0412	-0.8456	-0.8376	0.0106	-0.8125	-0.7967	0.0617	-0.8648	-0.8450	0.0253	-0.3463	-0.3384	0.0270	-0.3465	-0.3306	0.0577	-0.3778	-0.3580
ΔTEU_t	0.0112	-0.8147	-0.8067	0.0165	-0.8185	-0.8027	0.0510	-0.8535	-0.8336	0.0070	-0.3277	-0.3198	0.0054	-0.3246	-0.3087	0.0229	-0.3416	-0.3217
ΔVIX_t	0.1112	-0.9213	-0.9134	0.0643	-0.8683	-0.8525	0.1957	-1.0190	-0.9992	0.1766	-0.5151	-0.5071	0.0268	-0.3463	-0.3305	0.2008	-0.5426	-0.5227
ΔEPU_t	0.0031	-0.8066	-0.7986	0	-0.8002	-0.7843	0.0017	-0.8029	-0.7831	0	-0.3199	-0.3120	0.0045	-0.3237	-0.3078	0.0043	-0.3227	-0.3029
ΔEMU_t	0	-0.8034	-0.7955	0	-0.8014	-0.7855	0.0003	-0.8015	-0.7817	0.0009	-0.3216	-0.3136	0.0120	-0.3312	-0.3154	0.0114	-0.3299	-0.3101

Notes: This table reports the results of communality-weighted factor regressions for changes in $cGST_t$ and changes in the alternative measures of uncertainty over the period from 1 June 2016 to 31 May 2021. Factor scores are derived from the all, developed, emerging and frontier market groupings. Factor score series are first regressed onto each measure in contemporaneous form (explanatory), followed by a regression onto three lags of each alternative measure (predictive) and then a regression onto a combination of contemporaneous and lagged form with three lags of each measure (combined). All measures are in first differences, denoted by Δ. $\bar{R}^2$ is the adjusted coefficient of determination measuring explanatory power. AIC is the Akaike information criterion reflecting the ability of a measure to approximate actual factor score values. BIC is the Bayesian information criterion reflecting the ability of each measure to approximate the data generating process.

$\tau = 0$ (explanatory), for $\tau = 1$, 2 and 3 (predictive) and finally for $\tau = 0$, 1, 2 and 3 (combined). To assess how well our uncertainty measures perform relative to each other, we report $\bar{R}^2$, AIC and BIC values for Eqs. (10) and (11) for brevity.[24]

6.1. In-sample performance

In-sample analysis shows that $cGST_t$ dominates other keyword-based measures in contemporaneous form across market groupings in terms of explanatory power ($\tau = 0$) for factor scores (left side), except for emerging markets (Panel C, Table 8). When $cGST_t$ lags are considered ($\tau = 1, 2, 3$), the index continues to perform well but does not always outperform all keyword-based measures. For example, for all markets, TEU_t is the only keyword-based measure that outperforms $cGST_t$ (Panel A, Table 8). A similar observation is made for developed markets, but not for emerging and frontier markets where lags of $cGST_t$ dominate all keyword-based measures. Combining $cGST_t$ in contemporaneous form with lags ($\tau = 0$, 1, 2, 3) yields the highest $\bar{R}^2$ across panels. The closest competitor to $cGST_t$ in terms of its ability to explain and approximate factor scores and the underlying return generating process (measured by AIC and BIC, respectively) that is somewhat similarly constructed using keywords relating to equity markets and uncertainty is TMU_t. TMU_t outperforms $cGST_t$ in contemporaneous form in emerging markets. In terms of predictive power, $cGST_t$ outperforms TMU_t across all markets, emerging and frontier markets. For emerging markets, TMU_t appears to have no predictive power compared to $cGST_t$'s $\bar{R}^2$ of 0.0421. When factor score regressions are estimated with TMU_t contemporaneously and with lags, TMU_t underperforms in approximating factor scores and the return generating process relative to $cGST_t$ across groupings. The VIX_t outperforms $cGST_t$ in approximating factor scores and the underlying influences driving returns across groupings. Lagged VIX_t terms outperform $cGST_t$ for all groupings except emerging markets. When VIX_t is combined with lagged terms, the VIX_t outperforms $cGST_t$ across all groupings with differences in $\bar{R}^2$ greatest for all markets and lowest for frontier markets. The VIX is derived from US S&P500 option prices and is therefore a proxy for market uncertainty directly constructed from financial data (Bekaert & Hoerova, 2014). Consequently, the superior performance of the VIX is not surprising.

Regressions of squared factor scores onto uncertainty measures show that $cGST_t$ in contemporaneous form outperforms all keyword-based measures (right side, Table 8) across all groupings. TMU_t is the closest competitor in its ability to explain (measured by $\bar{R}^2$) and approximate squared factor scores (AIC) and the process underlying squared factor score series (BIC). TMU_t is a better predictor of squared factor scores for all and developed markets (Panels A and B, Table 8) but not for emerging and frontier markets. When contemporaneous and predictive $cGST_t$ terms are combined, $cGST_t$ outperforms all keyword-based measures across groupings.

Interestingly, $cGST_t$ outperforms VIX_t in contemporaneous regressions of squared factor scores across all markets and for developed markets. A possible reason may be that $cGST_t$ reflects other information, such as sentiment and/or investor attention, over and above that which is reflected in the VIX_t (Dergiades, Milas, & Panagiotidis, 2015). It may be that sentiment and attention measures play a greater role in developed markets relative to emerging and frontier markets and therefore $cGST_t$ has greater explanatory power for developed markets because it also reflects these components, although to a lesser extent.[25] When predictive power is considered, the VIX_t outperforms $cGST_t$ for emerging markets but not across all, developed and frontier market groupings. Dimic et al. (2015), in their study of the impact of the VIX on markets with varying levels of integration document that the largest impact is on frontier markets, followed by emerging and developed markets. When contemporaneous and predictive VIX_t terms are combined, VIX_t outperforms $cGST_t$ for developed markets and has comparable explanatory power for frontier markets. $cGST_t$ outperforms the VIX_t across all markets and emerging markets.

Given that $cGST_t$ may reflect other information not captured by the VIX_t, we re-estimate eq. (10) after orthogonalising $cGST_t$ against VIX_t to control for shared information reflected by both series (see Wurm & Fisicaro, 2014). Explanatory power for factor scores and squared factor scores declines relative to that observed prior to controlling for the VIX_t (see Table A6 in the Appendix for results). This is expected if $cGST_t$ reflects uncertainty that is also reflected by the VIX_t or a portion thereof. However, with the exception of emerging markets, the $\bar{R}^2$s overall decline substantially but do not decline to zero.[26] This latter observation holds true for all market groupings, including emerging markets, when squared factor scores are considered. The reduction in explanatory power further suggests that $cGST_t$ reflects uncertainty. Non-zero $\bar{R}^2s$ suggest that $cGST_t$ may reflect components of uncertainty not reflected by the VIX_t. Habibah, Rajput, and Sadhwani (2017) finds that GST-based indices reflect information not captured by VIX. They suggest that Google searches may reflect wider views, i.e. the views of not only retail participants but also non-investors who are interested in market trends, whereas the VIX reflects institutional investor views. This could explain any remaining residual explanatory power, as observed in Table A6. These findings also suggest that Google searches partially reflect investor sentiment and/or attention, but to a lesser extent given the declines in explanatory power. This is suggested by the results of Panel B and C of Table 5, which indicate that while uncertainty measures dominate in terms of the magnitude of correlation with $cGST_t$, sentiment and attention measures also feature.

Our analysis suggests that $cGST_t$ outperforms other keyword-based measures in proxying for market uncertainty in both returns and variance. A finding that factor scores and squared factor scores are contemporaneously and significantly related to $cGST_t$ and that $cGST_t$ in

[24] Eqs. (10) and (11) are estimated using least squares with Newey-West standard errors. The joint mean-volatility dynamics could also be modelled using the ARCH/GARCH methodology. However, we elected to model the mean and volatility dynamics separately for three reasons. First, we aim to assess and compare the ability of $cGST_t$ or one of the measures of uncertainty, VIX_t, EMV_t, EPU_t, TEU_t and TMU_t, to approximate and/or predict proxies for the drivers of returns and volatility. To do so, we need to calculate factor-weighted $\bar{R}^2$, AIC and BIC values that are not impacted by varying autoregressive and conditional variance structures across factor score series. Such variation may arise because of the need to achieve convergence within the ARCH/GARCH framework. Consequently, any differences in the factor-weighted $\bar{R}^2$, AIC and BIC values may be partially attributable to differences in the mean and variance structures and not uncertainty measures. Second, by estimating mean and variance specifications separately as opposed to simultaneously, we can obtain separate $\bar{R}^2$, AIC and BIC values for each measure across the mean and variance specifications as opposed to factor-weighted values for a model that simultaneously models the mean and variance equations and therefore limits direct comparisons. This increases the ease and granularity of comparisons. Third, by modelling the means and variances separately using the least squares methodology with Newey-West standard errors, we no longer need to worry about residual serial correlation or non-linear dependence when the derivation of factor-weighted $\bar{R}^2$, AIC and BIC values are of primary importance.

[25] The results in Panels B and C of Table 5, where attention and sentiment measures feature amongst the top ten correlations with $cGST_t$, suggest this is the case. Notably, in Panel C of Table 5, six of the ten most correlated measures are attention measures, namely PRV_{t-1}, PRE_t, $PRUS_t$, ABV_t, PRE_{t-2} and PRV_{t-3}. When Dimpfl and Jank (2016) add changes in the VIX to their regression of realised volatility against GST, the role of Google searches is reduced but not eliminated. This confirms that Google searches may capture other types of information and hence explanatory power remains in the presence of VIX (see also Dergiades et al., 2015).

[26] *Very minor* increases in the $\bar{R}^2$s may occur in instances where the VIX_t had a negligible $\bar{R}^2$ or even a negative $\bar{R}^2$ to begin with, implying that mean values yielded a better approximation of actual factor/squared factor scores.

Table 9
Out-of-sample factor score regression results

	Factor scores									Squared factor scores								
	τ = 0			τ = 1, 2, 3			τ = 0, 1, 2, 3			τ = 0			τ = 1, 2, 3			τ =0, 1, 2, 3		
	$\bar{R}^2$	AIC	BIC	$\bar{R}^2$	AIC	BIC	$\bar{R}^2$	AIC	BIC	$\bar{R}^2$	AIC	BIC	$\bar{R}^2$	AIC	BIC	$\bar{R}^2$	AIC	BIC
Panel A: All markets																		
$\Delta cGST_t$	0.1999	0.1173	0.1446	0.0169	0.3308	0.3855	0.1908	0.1400	0.2083	0.0135	-0.3777	-0.3504	0.0128	-0.3694	-0.3147	0.0448	-0.3986	-0.3303
ΔTMU_t	0.2446	0.0598	0.0871	0	0.3500	0.4046	0.2533	0.0596	0.1279	0.0024	-0.3665	-0.3392	0.0373	-0.3946	-0.3399	0.0471	-0.4010	-0.3327
ΔTEU_t	0.0535	0.2853	0.3126	0.0000	0.3534	0.4080	0.0705	0.2786	0.3469	0.0019	-0.3660	-0.3387	0.0173	-0.3740	-0.3194	0.0250	-0.3781	-0.3098
ΔVIX_t	0.2064	0.1091	0.1365	0.0572	0.2890	0.3436	0.2841	0.0175	0.0857	0	-0.3603	-0.3330	0.0120	-0.3686	-0.3139	0.0082	-0.3610	-0.2927
ΔEPU_t	0.0131	0.3271	0.3545	0.0140	0.3338	0.3884	0.0177	0.3338	0.4021	0	-0.3613	-0.3340	0.0000	-0.3470	-0.2924	0	-0.3420	-0.2737
ΔEMU_t	0.0000	0.3439	0.3712	0	0.3582	0.4129	0.0000	0.3651	0.4334	0	-0.3619	-0.3346	0.0041	-0.3606	-0.3060	0.0006	-0.3534	-0.2851
Panel B: Developed markets																		
$\Delta cGST_t$	0.1643	1.5287	1.5560	0.0271	1.6883	1.7429	0.1596	1.5457	1.6140	0.0015	2.7182	2.7455	0.0075	2.7197	2.7743	0.0163	2.7146	2.7829
ΔTMU_t	0.1913	1.4960	1.5233	0.0206	1.6950	1.7496	0.2016	1.4944	1.5627	0	2.7234	2.7507	0.0348	2.6919	2.7465	0.0320	2.6985	2.7668
ΔTEU_t	0.0478	1.6592	1.6865	0	1.7222	1.7768	0.0519	1.6663	1.7345	0	2.7234	2.7507	0.0185	2.7086	2.7632	0.0158	2.7151	2.7834
ΔVIX_t	0.1467	1.5495	1.5768	0.0229	1.6927	1.7473	0.1798	1.5214	1.5897	0	2.7235	2.7509	0.0000	2.7312	2.7858	0.0081	2.7229	2.7912
ΔEPU_t	0.0173	1.6908	1.7181	0.0206	1.6950	1.7496	0.0237	1.6956	1.7639	0	2.7229	2.7502	0.0000	2.7369	2.7915	0	2.7425	2.8108
ΔEMU_t	0	1.7114	1.7387	0.0000	1.7251	1.7797	0.0000	1.7301	1.7984	0	2.7218	2.7491	0	2.7228	2.7775	0.0006	2.7304	2.7987
Panel C: Emerging markets																		
$\Delta cGST_t$	0.2247	0.0792	0.1065	0.0376	0.3030	0.3576	0.2270	0.0876	0.1558	0.0594	0.4608	0.4881	0.0218	0.5076	0.5623	0.1188	0.4070	0.4753
ΔTMU_t	0.2695	0.0197	0.0470	0.0068	0.3344	0.3891	0.2645	0.0378	0.1060	0.0547	0.4658	0.4931	0.0287	0.5005	0.5551	0.1079	0.4193	0.4876
ΔTEU_t	0.0533	0.2790	0.3063	0.0003	0.3410	0.3956	0.0680	0.2747	0.3429	0.0152	0.5068	0.5341	0.0238	0.5056	0.5603	0.0563	0.4755	0.5438
ΔVIX_t	0.1062	0.2215	0.2488	0.0435	0.2968	0.3514	0.1621	0.1682	0.2365	0.0000	0.5254	0.5527	0.0006	0.5291	0.5837	0	0.5366	0.6049
ΔEPU_t	0.0101	0.3235	0.3508	0.0113	0.3299	0.3846	0.0136	0.3313	0.3996	0.0000	0.5230	0.5503	0.0000	0.5395	0.5942	0.0000	0.5451	0.6134
ΔEMU_t	0.0002	0.3335	0.3608	0.0000	0.3500	0.4046	0.0000	0.3505	0.4188	0	0.5258	0.5531	0.0007	0.5290	0.5836	0.0000	0.5364	0.6047
Panel D: Frontier markets																		
$\Delta cGST_t$	0.1536	2.8005	2.8278	0.0229	2.9517	3.0063	0.1639	2.7996	2.8679	0.0640	6.0243	6.0517	0.0226	6.0752	6.1299	0.1085	5.9871	6.0553
ΔTMU_t	0.2634	2.6616	2.6889	0.0000	2.9779	3.0325	0.2614	2.6756	2.7439	0.0952	5.9905	6.0178	0.0153	6.0827	6.1373	0.1259	5.9673	6.0355
ΔTEU_t	0.0529	2.9129	2.9402	0.0240	2.9506	3.0052	0.0897	2.8846	2.9529	0.0230	6.0672	6.0945	0.0279	6.0698	6.1244	0.0572	6.0429	6.1112
ΔVIX_t	0.0481	2.9180	2.9453	0.0426	2.9313	2.9859	0.1029	2.8700	2.9383	0	6.0942	6.1215	0.0000	6.1006	6.1553	0.0000	6.1083	6.1766
ΔEPU_t	0.0094	2.9578	2.9852	0.0043	2.9706	3.0252	0.0126	2.9659	3.0342	0	6.0935	6.1208	0.0000	6.1065	6.1611	0.0000	6.1139	6.1822
ΔEMU_t	0.0000	2.9711	2.9984	0.0000	2.9781	3.0328	0.0000	2.9838	3.0520	0	6.0943	6.1216	0.0000	6.1012	6.1559	0.0000	6.1089	6.1772

Notes: This table reports the results of communality-weighted factor regressions for changes in $cGST_t$ and changes in the alternative measures of uncertainty over the period from 1 June 2021 to 31 May 2022. Factor scores are derived from the all, developed, emerging and frontier market groupings. Factor score series are first regressed onto each measure in contemporaneous form (explanatory), followed by a regression onto three lags of each alternative measure (predictive) and then a regression onto a combination of contemporaneous and lagged form with three lags of each measure (combined). All measures are in first differences, denoted by Δ. $\bar{R}^2$ is the adjusted coefficient of determination measuring explanatory power. AIC is the Akaike information criterion reflecting the ability of a measure to approximate actual factor score values. BIC is the Bayesian information criterion reflecting the ability of each measure to approximate the data generating process.

contemporaneous form has the greatest explanatory power and ability to approximate factor scores and the return generating process confirms that $cGST_t$ reflects return drivers. The superior performance of $cGST_t$ contemporaneously relative to lagged terms implies that $cGST_t$ is predominantly a contemporaneous proxy for market uncertainty rather than a predictor in-sample. Nevertheless, $cGST_t$ appears to have some limited predictive power as suggested by non-zero $\bar{R}^2$s across panels.[27] When contemporaneous and lagged $cGST_t$ terms are combined, $cGST_t$ outperforms all keyword-based measures.

6.2. Out-of-sample performance

The main implication of the preceding discussion is that if we wish to use a keyword-based measure to model and investigate the impact of uncertainty on financial markets, GST outperforms all other widely used measures. The question that we now turn to is whether our GST-based index can both explain and predict factor scores derived from return series that were not used to construct the index. An analysis of out-of-sample explanatory and predictive performance allows us to ascertain the broader usefulness of the methodology employed to construct the index and that of the index itself. This is especially pertinent given that the structure of the return generating process across all, developed and developing markets appears to differ from the return generating process underlying the in-sample period.

Out-of-sample analysis indicates that $cGST_t$ continues to perform favourably in terms of contemporaneous explanatory power ($\tau = 0$) for factor scores (Table 9, left side) for the all (Panel A) and emerging market groupings (Panel C). For these groupings, explanatory power is comparable to that of the VIX_t and its ability to approximate factor scores (AIC) and the return generating process (BIC). However, TMU_t outperforms $cGST_t$ across market groupings, with outperformance greatest for frontier markets (Panel D of Table 9, $\bar{R}^2$ of 0.2634 and 0.1536, respectively). The inverse is true for $cGST_t$'s predictive ability ($\tau = 1, 2, 3$) which exceeds that of all other keyword-based measures except for frontier markets where TEU_t marginally outperforms $cGST_t$. $cGST_t$ exhibits predictive power that exceeds that of TMU_t for this grouping and TEU_t ($\bar{R}^2$ of 0.0240) outperforms $cGST_t$ ($\bar{R}^2$ of 0.0229) (Panel D of Table 9). With the exception of the developed market grouping where $cGST_t$ marginally outperforms the VIX_t, the VIX_t outperforms all remaining measures in terms of predictive power, its ability to approximate factor score series (AIC) and the underlying return generating process (BIC). When contemporaneous and lagged terms are combined ($\tau = 0, 1, 2, 3$), TMU_t is the best performing measure across market groupings, followed by $cGST_t$. Nevertheless, $cGST_t$ continues to exhibit noteworthy overall explanatory and predictive ability that exceeds that observed in-sample for a combination of contemporaneous and lagged terms, with respective $\bar{R}^2s$ of 0.1908, 0.1596, 0.2270 and 0.1639 across market groupings. In contrast, the respective $\bar{R}^2s$ in-sample for the all, developed, emerging and frontier markets are 0.1376, 0.1037, 0.0967 and 0.1566 for combinations of contemporaneous and lagged terms. A potential reason for GST performing better out-of-sample is that GST have increasingly come to reflect uncertainty given continually growing Google search utilisation and accessibility and general internet penetration (see Szczygielski, Charteris, & Obojska, 2023). Furthermore, although TMU_t outperforms $cGST_t$ in terms of contemporaneous explanatory power, $cGST_t$ outperforms TMU_t in terms of predictive power out-of-sample and its predictive performance is broadly comparable to in-sample performance (respective $\bar{R}^2$s of 0.0169, 0.0271, 0.0376 and 0.0229 out-of-sample *versus* in-sample $\bar{R}^2$s of 0.0188, 0.0133, 0.0421 and 0.299 for all, developed, emerging and frontier market groupings).

For squared factor score regressions, all measures of uncertainty, including VIX_t, perform poorly in contemporaneous form across the all and developed market groupings. A possible reason is that during this period, heightened volatility is relatively short-lived in comparison to the in-sample period which encompasses numerous events that contributed to heightened market volatility and comprises a longer sample (see Figs. A3 and A4 and Szczygielski et al., 2021). Fig. A3 (in the Appendix) suggests that spikes in volatility are short-lived, occurring mostly around the outbreak of the Russian-Ukrainian war on 24 February 2022. For emerging markets, $cGST_t$ outperforms TMU_t (with an $\bar{R}^2$ of 0.0594 *versus* 0.0547) and for frontier markets, TMU_t outperforms $cGST_t$ ($\bar{R}^2$ of 0.0952 and 0.0640, respectively). However, both appear to have explanatory power suggesting that both proxy for factors driving heightened volatility. The VIX_t appears to have no explanatory power.[28]

This finding may point towards market segmentation in emerging and frontier markets limited to this period. TMU_t and $cGST_t$ may be better proxies for uncertainty over this specific sample period relative to the VIX_t. In terms of predictive power, TMU_t outperforms $cGST_t$ across the all, developed and emerging market groupings although for the emerging market grouping, the difference in $\bar{R}^2$s is almost negligible ($\bar{R}^2$ of 0.0218 and 0.0287, respectively) and the $\bar{R}^2s$ are generally low across groupings (similarly as for in-sample predictive squared factor score regressions). For the frontier market grouping, $cGST_t$ outperforms TMU_t ($\bar{R}^2$ of 0.0226 and 0.0153, respectively) although TEU_t ($\bar{R}^2$ of 0.0279) outperforms both. In terms of combined explanatory and predictive power ($\tau = 0, 1, 2, 3$), the VIX_t performs poorly whereas the performance of both $cGST_t$ and TMU_t is approximately comparable across all, emerging and frontier markets although TMU_t marginally outperforms $cGST_t$ (respective $\bar{R}^2s$ of 0.0471, 0.0320, 0.01079 for TMU_t and 0.1259 vs 0.0448, 0.0163, 0.1179 and 0.01085 for $cGST_t$ across market groupings). The other notable keyword-based uncertainty measure that has explanatory power across all market groupings is TEU_t although this measure noticeably underperforms both TMU_t and $cGST_t$.

We investigate residual explanatory power associated with Google searches after adjusting $cGST_t$ for common information reflected by the VIX_t (see Table A7). $\bar{R}^2$ values decline for factor scores suggesting that $cGST_t$ reflects information captured by the VIX_t, but are greater than those in-sample. The same holds for squared factor scores with the exception of developed markets for which the $\bar{R}^2$ is close to zero. These observations again (as in the in-sample analysis) suggest that $cGST_t$ captures information not reflected by VIX_t such as investor sentiment, attention, wider investor views and/or better captures uncertainty at specific points in time (see Habibah et al., 2017).

The out-of-sample analysis produces encouraging results. $cGST_t$ has significant contemporaneous explanatory power for composite factor scores across market groupings, which is greater than that observed in-sample. Admittedly, our index underperforms TMU_t in contemporaneously approximating factor scores. However, in terms of predictive ability, $cGST_t$ outperforms the other keyword measures, including TMU_t. When it comes to modelling factor dispersion underlying return volatility, results are mixed. $cGST_t$ has poor explanatory power across the all and developed marking groupings – but so do the other measures including the VIX_t and TMU_t. This is possibly due to uncertainty being either relatively short-lived given the shorter sample period that constitutes the out-of-sample and/or a changing return generating process suggested by a differing number of factors extracted. In terms of predictive power, $cGST_t$ performs somewhat worse for all and developed markets but comparably well to the other measures in emerging and frontier markets. In terms of both explanatory and predictive power, $cGST_t$ marginally underperforms TMU_t in approximating factor

[27] We confirm that the $\bar{R}^2$s for each grouping are non-zero where applicable using the *F*-test.

[28] We confirm that VIX_t, TMU_t and $cGST_t$ are significantly correlated, suggesting that all reflect uncertainty components to varying degrees.

dispersion.

The question that we address by undertaking an out-of-sample analysis is whether our GST-based index can both explain and predict factor scores derived from return series that were not used to construct the index. This constitutes a more robust test than only our in-sample tests. $cGST_t$'s combined explanatory and predictive power remains notable, suggesting that our index continues to be a viable alternative to keyword-based stock market uncertainty measures beyond the sample which was used in its construction. This provides support for the generalisability and application of both the methodology used to construct the index and the index itself beyond this study. As the out-of-sample analysis provides evidence in support of our index, the analysis thus also supports our broader aim of investigating the narrative reflected by Google search trends.

7. Implications

Keyword based indices are increasing in popularity. They are varied in their underlying construction and utilise different sources to extract information. GST-based indices form part of this category of indices yet there is no agreement as to what GST reflect: sentiment, attention or uncertainty. Without a clear understanding of the underlying narrative it is difficult to determine how GST-based indices may be useful for the purposes of econometric modelling, analysis and application. In this study, our approach is to establish rather than impose a narrative and the narrative that emerges is one of GST reflecting uncertainty. A better understanding and insight into the narrative aids in the use of GST-based indices for the purposes of investment and portfolio management and market analysis. Thus, market participants can utilise our stock market-orientated GST index and other indices similarly constructed to quantify uncertainty across a broad range of stock markets with rising index values (commensurate with increased searches) reflecting heightened uncertainty. This measure is easy to understand, reflects retail investor views and presents an alternative to established measures of uncertainty, such as VIX and more recent keyword-based measures such as TMU. Further to this, GST offer the potential to formulate event-specific uncertainty indices by selecting keywords linked to specific events. For example, GST can be utilised to measure and quantify uncertainty surrounding election outcomes, recession fears or the COVID-19 pandemic. This provides a notable benefit over a generic financial market index such as the the VIX (see Smales, 2021; Szczygielski, Charteris, & Obojska, 2023).

In Section 5, we confirm that returns are negatively related to our index and that volatility is positively related to its movements. This is consistent with theoretical assertions regarding the relationship between uncertainty and stock markets and with prior empirical studies (Engle, 2004; Engle et al., 2008; Andrei & Hasler, 2015; Cochrane, 2018; Smales, 2021). Equipped with a better understanding of the narrative underlying Google search trends within the context of stock markets, we demonstrate an analytical application of our index by investigating how the impact of uncertainty differs across markets characterised by differing levels of development. The association of our index with stock markets is widespread across market groupings, showing that not only are developed and emerging markets impacted by uncertainty, as prior literature shows, but also frontier markets. These results further illustrate the importance for market participants of tailoring their investment strategies to account for uncertainty due to its pervasive and harmful impact. Our application demonstrates that GST have the potential to convey useful information to investors and researchers across a broad range of markets. Having an easily accessible and understandable measure to quantify uncertainty, such as the GST-based index, facilitates the consideration of uncertainty in portfolio construction. For example, if uncertainty is high, portfolio weights can be tilted towards markets more resilient to uncertainty.

In Section 6, we undertake an in-sample and out-of-sample analysis to compare the performance of our GST-based stock market index against the VIX and keyword-based measures in reflecting the impact of uncertainty in both returns and variance. In-sample analysis demonstrates that our index outperforms other keyword-based measures in approximating the underlying forces that drive stock markets. In terms of predictive power, it also performs well relative to other keyword-based measures. When it comes to approximating factor dispersion underlying time-varying volatility, our index outperforms its closest keyword-based competitor, the TMU index, in closely approximating the VIX. The results of the out-of-sample analysis are encouraging. Our GST-based index continues to have significant explanatory power that exceeds that of the in-sample analysis, even if it somewhat underperforms its closest competitor, i.e. the TMU index. However, it outperforms its closest competitor and all other keyword-based measures when it comes to predictive power. When modelling factor dispersion, our index performs favourably in approximating factor dispersion underlying emerging and frontier markets. Combined explanatory and predictive power for both our index and the TMU index is comparable and noteworthy. If we wish to use a keyword-based measure to reflect uncertainty experienced by financial markets in a given period of time that has lapsed, GST offer an alternative uncertainty measure to existing keyword-based measures. Moreover, out-of-sample analysis suggests that the GST-based index is generalisable. While Twitter is available to most internet users, gathering data to formulate a Twitter-based stock market uncertainty index requires advanced knowledge and programming to extract relevant terms. In contrast, GST data can be readily obtained. Given that a GST-based uncertainty index is a viable alternative to existing keyword-based uncertainty measures and the ease with which Google data can be obtained, the implication is that GST-based indices are more readily implementable.

We demonstrate how elastic net regression can be used to identify search terms that are used to formulate our index. We do not impose search terms that we as authors feel are important and, therefore, reflect a specific pre-determined narrative. Similarly to Feng, Giglio, and Xiu (2020), who apply regularised regression to establish the asset pricing contribution of over 150 factors, we use elastic net regression to sort important search terms that are related to returns. By taking this approach, we ensure that the search terms that are associated with market movements are investor relevant. Our application of machine learning not only assists in the construction of a general stock market uncertainty index using GST, but also demonstrates how information complexity can be reduced in empirical applications. Feature selection by machine learning can indicate which information markets respond to specifically and reduce information processing costs (Pernagallo & Torrisi, 2020). The application of such methods may be an attractive approach for analysts who seek to determine what information matters most by separating relevant information from the (at times) deafening noise emanating from the media and internet-based sources.

8. Conclusion

We construct a general stock market-related index using GST and a comprehensive sample of national stock markets. We proceed to investigate and clarify the narrative reflected by Google search data. Diagrammatic and empirical comparisons suggest that GST reflect an uncertainty narrative. We confirm that there is a relationship between our GST-based index and returns and volatility across developed, emerging and frontier markets and that this relationship conforms to *a priori* expectations associated with uncertainty. Our GST-based index outperforms other keyword-based indices in terms of explanatory power when approximating the drivers of stock returns and volatility in-sample and shows favourable performance out-of-sample. This makes it a viable alternative to other keyword-based measures given the ease with which Google search data can be obtained.

For researchers, we shed light on the narrative that GST reflect. For practitioners and investors, we show that GST can be used to reflect uncertainty and can be applied for analytical purposes. These findings, coupled with the availability of Google data, provide motivation for the development of Google-based indices and the application thereof for research, measurement and investment management. Given an established narrative, we propose that GST can be adapted to reflect general and/or event-specific uncertainty. Finally, we demonstrate the application of machine learning for identifying search terms that are relevant to markets and, by implication, to investors. Our paper shows how this approach may be applied to reduce information complexity and our findings may also assist in the development of further applications using various search data.

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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:** Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Princess Rutendo Bwanya:** Writing – original draft. **Janusz Brzeszczyński:** Writing – original draft, Writing – review & editing

Declaration of Competing Interest

None.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.irfa.2023.102549.

References

Agarwal, S., Kumar, S., & Goel, U. (2019). Stock market response to information diffusion through internet sources: A literature review. *International Journal of Information Management, 45*, 118–131.

Akarsu, S., & Süer, Ö. (2021). How investor attention affects stock returns? Some international evidence. *Borsa Istanbul Review, 2021*(09), 001.

Alin, A. (2010). Multicollinearity. *Wiley Interdisciplinary Reviews: Computational Statistics, 2*(3), 370–374.

Alpaydin, E. (2020). *Introduction to Machine Learning* (4th ed.). Massachusetts: MIT Press.

Altig, D., Baker, S., Barrero, J. M., Bloom, N., Bunn, P., Chen, S., … Mizen, P. (2020). Economic uncertainty before and during the COVID-19 pandemic. *Journal of Public Economics, 191*, Article 104274.

Andrei, D., & Hasler, M. (2015). Investor attention and stock market volatility. *Review of Financial Studies, 28*(1), 33–72.

Aouadi, A., Arouri, M., & Roubaud, D. (2018). Information demand and stock market liquidity: International evidence. *Economic Modelling, 70*, 194–202.

Aouadi, A., Arouri, M., & Teulon, F. (2013). Investor attention and stock market activity: Evidence from France. *Economic Modelling, 35*, 674–681.

Badshah, I., Bekiros, S., Lucey, B. M., & Uddin, G. S. (2018). Asymmetric linkages among the fear index and emerging market volatility indices. *Emerging Markets Review, 37*, 17–31.

Bajo, E. (2010). The information content of abnormal trading volume. *Journal of Business Finance & Accounting, 37*(7-8), 950–978.

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives, 21*(2), 129–152.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics, 131*(4), 1593–1636.

Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., & Viratyosin, T. (2020). The unprecedented stock market reaction to COVID-19. *Review of Asset Pricing Studies, 10*(4), 742–758.

Baker, S. R., Bloom, N., Davis, S. J., & Kost, K. J. (2019). *Policy news and stock market volatility*. Working Paper No. w25720. National Bureau of Economic Research. https://www.nber.org/papers/w25720.

Baker, S. R., Bloom, N., Davis, S. J., & Renault, T. (2021). *Twitter-derived measures of economic uncertainty*. https://www.policyuncertainty.com/twitter_uncert.htm.

Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies, 21*(2), 785–818.

Becker, M., McGurk, Z., & Hale, M. (2021). Structural changes in sentiment and returns: Evidence from the Trump election. *Applied Economics Letters, 29*(1), 901–905.

Beer, F., Hervé, F., & Zouaoui, M. (2013). Is big brother watching us? Google, investor sentiment and the stock market. *Economics Bulletin, 33*(1), 454–466.

Bekaert, G., & Hoerova, M. (2014). The VIX, the variance premium and stock market volatility. *Journal of Econometrics, 183*(2), 181–192.

Berger, D., Pukthuanthong, K., & Yang, J. J. (2011). International diversification with frontier markets. *Journal of Financial Economics, 101*(1), 227–242.

Bergmeir, C., & Benítez, J. M. (2012). On the use of cross-validation for time series predictor evaluation. *Information Sciences, 191*, 192–213.

Bijl, L., Kringhaug, G., Molnár, P., & Sandvik, E. (2016). Google searches and stock returns. *International Review of Financial Analysis, 45*, 150–156.

Biktimirov, E. N., Sokolyk, T., & Ayanso, A. (2021). Sentiment and hype of business media topics and stock market returns during the COVID-19 pandemic. *Journal of Behavioral and Experimental Finance, 31*, Article 100542.

Bilgin, M. H., Demir, E., Gozgor, G., Karabulut, G., & Kaya, H. (2019). A novel index of macroeconomic uncertainty for Turkey based on Google-Trends. *Economics Letters, 184*, Article 108601.

Bird, R., & Yeung, D. (2012). How do investors react under uncertainty? *Pacific-Basin Finance Journal, 20*(2), 310–327.

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

Brochado, A. (2020). Google search based sentiment indexes. *IIMB Management Review, 32*(3), 325–335.

Brogaard, J., & Detzel, A. (2015). The asset-pricing implications of government economic policy uncertainty. *Management Science, 61*(1), 3–18.

Burggraf, T., Fendel, R., & Huynh, T. L. D. (2020). Political news and stock prices: Evidence from Trump's trade war. *Applied Economics Letters, 27*(18), 1485–1488.

Bush, G., & Noria, G. L. (2021). Uncertainty and exchange rate volatility: Evidence from Mexico. *International Review of Economics and Finance, 75*, 704–722.

Canova, F., & De Nicolo, G. (1995). Stock returns and real activity: A structural approach. *European Economic Review, 39*(5), 981–1015.

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

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

Chen, N. F. (1983). Some empirical tests of the theory of arbitrage pricing. *Journal of Finance, 38*(5), 1393–1414.

Chen, N. F., Roll, R., & Ross, S. A. (1986). Economic forces and the stock market. *Journal of Business, 59*(3), 59383–59403.

Chen, T. (2017). Investor attention and global stock returns. *Journal of Behavioral Finance, 18*(3), 358–372.

Cheuathonghua, M., Padungsaksawasdi, C., Boonchoo, P., & Tongurai, J. (2019). Extreme spillovers of VIX fear index to international equity markets. *Financial Markets and Portfolio Management, 33*(1), 1–38.

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

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *Journal of Finance, 66*(5), 1461–1499.

Da, Z., Engelberg, J., & Gao, P. (2015). The sum of all FEARS investor sentiment and asset prices. *Review of Financial Studies, 28*(1), 1–32.

Dergiades, T., Milas, C., & Panagiotidis, T. (2015). Tweets, Google trends, and sovereign spreads in the GIIPS. *Oxford Economic Papers, 67*(2), 406–432.

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

Dimic, N., Orlov, V., & Piljak, V. (2015). The political risk factor in emerging, frontier, and developed stock markets. *Finance Research Letters, 15*, 239–245.

Dimpfl, T., & Jank, S. (2016). Can internet search queries help to predict stock market volatility? *European Financial Management, 22*(2), 171–192.

Dimpfl, T., & Kleiman, V. (2019). Investor pessimism and the German stock market: Exploring Google search queries. *German Economic Review, 20*(1), 1–28.

Donadelli, M. (2015). Google search-based metrics, policy-related uncertainty and macroeconomic conditions. *Applied Economics Letters, 22*(10), 801–807.

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

Ekinci, C., & Bulut, A. E. (2021). Google search and stock returns: A study on BIST 100 stocks. *Global Finance Journal, 47*, Article 100518.

El Ouadghiri, I., Guesmi, K., Peillex, J., & Ziegler, A. (2021). Public attention to environmental issues and stock market returns. *Ecological Economics, 180*, Article 106836.

Engle, R. F. (2004). Risk and volatility: Econometric models and financial practice. *American Economic Review, 94*(3), 405–420.

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

Engle, R. F., Focardi, S. M., & Fabozzi, F. J. (2008). ARCH/GARCH models in applied financial econometrics. In F. Fabozzi (Ed.), *Vol. III. Handbook of Finance* (pp. 689–700). Hoboken: John Wiley & Sons, Inc.

Epstein, L. G., & Schneider, M. (2008). Ambiguity, information quality, and asset pricing. *Journal of Finance, 63*(1), 197–228.
Fan, J., Qi, L., & Xiu, D. (2014). Quasi-maximum likelihood estimation of GARCH models with heavy-tailed likelihoods. *Journal of Business & Economic Statistics, 32*(2), 178–191.
Fang, J., Gozgor, G., Lau, C. K. M., & Lu, Z. (2020). The impact of Baidu Index sentiment on the volatility of China's stock markets. *Finance Research Letters, 32*, Article 101099.
Fang, L., Qian, Y., Chen, Y., & Yu, H. (2018). How does stock market volatility react to NVIX? Evidence from developed countries. *Physica A: Statistical Mechanics and its Applications, 505*, 490–499.
Federal Reserve Bank of San Francisco (FRBSF). (2020, April 06). *News sentiment in the time of COVID-19*. FRBSF Economic Letter https://www.frbsf.org/economic-research/publications/economic-letter/2020/april/news-sentiment-time-of-covid-19/.
Feng, G., Giglio, S., & Xiu, D. (2020). Taming the factor zoo: A test of new factors. *Journal of Finance, 75*(3), 1327–1370.
Fisher, A. J., Martineau, C., & Sheng, J. (2017). *Media attention, macroeconomic fundamentals, and the stock market*. University of British Columbia Working paper. https://www.cb.cityu.edu.hk/ef/doc/2017%20finance%20conf/Fisher.pdf.
FitzGerald, V. (2007). International risk tolerance, capital market failure and capital flows to emerging markets. In G. Mavrotas, & A. Shorrocks (Eds.), *Advancing Development: Core Themes in Global Economics* (pp. 299–318). London: Palgrave Macmillan.
Frankel, D. (2009, April 14). *Credit Suisse rolls out fear barometer*. Reuters. https://www.reuters.com/article/uk-creditsuisse-fear-barometer-idUKTRE53D6K020090414.
French, J. J. (2021). # Bitcoin, # COVID-19: Twitter-based uncertainty and Bitcoin before and during the pandemic. *International Journal of Financial Studies, 9*(2), 28–35.
Froot, K. A., & O'Connell, P. G. (2003). *The risk tolerance of international investors*. Working Paper no. w10157. National Bureau of Economic Research (NBER) https://www.nber.org/papers/w10157.
Garcia, D. (2013). Sentiment during recessions. *Journal of Finance, 68*(3), 1267–1300.
Goeman, J., Meijer, R., & Chaturvedi, N. (2018). *L1 and L2 penalized regression models*. Vignette R Package Penalized https://mran.microsoft.com/snapshot/2016-05-19/web/packages/penalized/vignettes/penalized.pdf.
Goodell, J. W., & Vähämaa, S. (2013). US presidential elections and implied volatility: The role of political uncertainty. *Journal of Banking & Finance, 37*(3), 1108–1117.
Gorodnichenko, Y., & Weber, M. (2016). Are sticky prices costly? Evidence from the stock market. *American Economic Review, 106*(1), 165–199.
Grossman, S. J., & Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *American Economic Review, 70*(3), 393–408.
Guidolin, M., & Pedio, M. (2021). Media attention vs. sentiment as drivers of conditional volatility predictions: An application to Brexit. *Finance Research Letters, 101943*.
Habibah, U., Rajput, S., & Sadhwani, R. (2017). Stock market return predictability: Google pessimistic sentiments versus fear gauge. *Cogent Economics & Finance, 5*(1), 1390897.
Haroon, O., & Rizvi, S. A. R. (2020). COVID-19: Media coverage and financial markets behavior—A sectoral inquiry. *Journal of Behavioral and Experimental Finance, 27*, Article 100343.
Hudson, R., Urquhart, A., & Zhang, H. (2020). Political uncertainty and sentiment: Evidence from the impact of Brexit on financial markets. *European Economic Review, 129*, Article 103523.
Huynh, T. L. D., Foglia, M., Nasir, M. A., & Angelini, E. (2021). Feverish sentiment and global equity markets during the COVID-19 pandemic. *Journal of Economic Behavior & Organization*.
International Telecommunications Union (ITC). (2021). *Measuring digital development*. Facts and figures 2021. Geneva Switzerland: ITC. https://www.itu.int/en/ITU-D/Statistics/Documents/facts/FactsFigures2021.pdf.
Iyke, B. N., & Ho, S. Y. (2021). Investor attention on COVID-19 and African stock returns. *MethodsX, 8*, Article 101195.
Joseph, K., Wintoki, M. B., & Zhang, Z. (2011). Forecasting abnormal stock returns and trading volume using investor sentiment: Evidence from online search. *International Journal of Forecasting, 27*(4), 1116–1127.
Jung, Y. (2018). Multiple predicting K-fold cross-validation for model selection. *Journal of Nonparametric Statistics, 30*(1), 197–215.
Kim, N., Lučivjanská, K., Molnár, P., & Villa, R. (2019). Google searches and stock market activity: Evidence from Norway. *Finance Research Letters, 28*, 208–220.
King, B. F. (1966). Market and industry factors in stock price behavior. *Journal of Business, 39*(1), 139–190.
Kogan, S., Levin, D., Routledge, B. R., Sagi, J. S., & Smith, N. A. (2009, May). Predicting risk from financial reports with regression. In *Proceedings of human language technologies: 2009 annual conference of the North American chapter of the Association for Computational Linguistics* (pp. 272–280).
Kollmeyer, B. (2018, October 11). *Global equities tumble in wake of Wall Street rout, but pressure on U.S. eases*. MarketWatch. https://www.marketwatch.com/story/global-markets-tumble-us-stock-futures-point-to-continued-selloff-on-wall-street-2018-10-11.
Kryzanowski, L., & To, M. C. (1983). General factor models and the structure of security returns. *Journal of Financial and Quantitative Analysis, 18*(1), 31–52.
Lehmann, B. N. (1990). Fads, martingales, and market efficiency. *Quarterly Journal of Economics, 105*(1), 1–28.
Liemieux, J., & Peterson, R. (2011). Purchase deadline as a moderator of the effects of price uncertainty on search behavior. *Journal of Economic Psychology, 32*(1), 33–44.
Liu, J., Liang, G., Siegmund, K. D., & Lewinger, J. P. (2018). Data integration by multi-tuning parameter elastic net regression. *BMC Bioinformatics, 19*(1), 1–9.
Liu, L., & Zhang, T. (2015). Economic policy uncertainty and stock market volatility. *Finance Research Letters, 15*, 99–105.
Liu, Y., Peng, G., Hu, L., Dong, J., & Zhang, Q. (2019). Using Google trends and Baidu index to analyze the impacts of disaster events on company stock prices. *Industrial Management & Data Systems, 120*(2), 350–365.
Liu, Z., Liu, J., Zeng, Q., & Wu, L. (2022). VIX and stock market volatility predictability: A new approach. *Finance Research Letters, 48*, Article 102887.
Lyócsa, Š., Baumöhl, E., Výrost, T., & Molnár, P. (2020). Fear of the coronavirus and the stock markets. *Finance Research Letters, 36*, Article 101735.
Manela, A., & Moreira, A. (2017). News implied volatility and disaster concerns. *Journal of Financial Economics, 123*(1), 137–162.
McCauley, R. N. (2013). Risk-on/risk-off, capital flows, leverage and safe assets. *Journal of Financial Perspectives, 1*(2), 1–10.
Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information. *Journal of Finance, 42*, 483–510.
Neeley, T. (2012, May). *Global business speaks English*. Harvard Business Review. https://hbr.org/2012/05/global-business-speaks-english
Nguyen, C. P., Schinckus, C., & Nguyen, T. V. H. (2019). Google search and stock returns in emerging markets. *Borsa Istanbul Review, 19*(4), 288–296.
Nwogugu, M. (2006). Further critique of GARCH/ARMA/VAR/EVT stochastic-volatility models and related approaches. *Applied Mathematics and Computation, 182*(2), 1735–1748.
Özyeşil, M., & Tembelo, H. (2020). Does uncertainty affect investor behaviours and returns in stock exchanges? A new generation analysis for the US equity markets. *Revista Argentina de Clínica Psicológica, 29*(5), 1223–1239.
Peng, L., Xiong, W., & Bollerslev, T. (2007). Investor attention and time-varying comovements. *European Financial Management, 13*(3), 394–422.
Perlin, M. S., Caldeira, J. F., Santos, A. A., & Pontuschka, M. (2017). Can we predict the financial markets based on Google's search queries? *Journal of Forecasting, 36*(4), 454–467.
Pernagallo, G., & Torrisi, B. (2020). A theory of information overload applied to perfectly efficient financial markets. *Review of Behavioral Finance*, 1940–5979.
PreData. (2021). https://www.predata.com.
Preis, T., Moat, H. S., & Stanley, H. E. (2013). Quantifying trading behavior in financial markets using Google Trends. *Scientific Reports, 3*(1), 1–6.
Ramelli, S., & Wagner, A. F. (2020). Feverish stock price reactions to COVID-19. *Review of Corporate Finance Studies, 9*(3), 622–655.
Rao, P. S. (2019). The role of English as a global language. *Research Journal of English, 4*(1), 65–79.
Salisu, A. A., & Akanni, L. (2020). Constructing a global fear index for the COVID-19 pandemic. *Emerging Markets Finance and Trade, 56*(10), 2310–2331.
Salisu, A. A., Ogbonna, A. E., & Adediran, I. (2021). Stock-induced Google trends and the predictability of sectoral stock returns. *Journal of Forecasting, 40*(2), 327–345.
Salisu, A. A., & Vo, X. V. (2020). Predicting stock returns in the presence of COVID-19 pandemic: The role of health news. *International Review of Financial Analysis, 71*, Article 101546.
Sarwar, G., & Khan, W. (2017). The effect of U.S. stock market uncertainty on emerging market returns. *Emerging Markets Finance and Trade, 53*(8), 1796–1811.
Sarwar, G., & Khan, W. (2019). Interrelations of US market fears and emerging markets returns: Global evidence. *International Journal of Finance and Economics, 24*(1), 527–539.
Semper, J. D. C., & Clemente, I. M. (2003). Value at risk calculation through ARCH factor methodology: Proposal and comparative analysis. *European Journal of Operational Research, 150*(3), 516–528.
Smales, L. A. (2016). Time-varying relationship of news sentiment, implied volatility and stock returns. *Applied Economics, 48*(51), 4942–4960.
Smales, L. A. (2019). *How does policy uncertainty influence financial market uncertainty across the G7?*. Working Paper No. 3427659. University of Western Australia. https://papers.ssrn.com/sol3/Papers.cfm?abstract_id=3427659.
Smales, L. A. (2021). Investor attention and global market returns during the COVID-19 crisis. *International Review of Financial Analysis, 73*, Article 101616.
Song, Y., Ji, Q., Du, Y. J., & Geng, J. B. (2019). The dynamic dependence of fossil energy, investor sentiment and renewable energy stock markets. *Energy Economics, 84*, Article 104564.
Spiegelhalter, D. J., Best, N. G., Carlin, B. P., & Linde, A. (2014). The deviance information criterion: 12 years on. *Journal of the Royal Statistical Society, Series B: Statistical Methodology, 76*(3), 485–493.
Spyridis, T., Sevic, Z., & Theriou, N. (2012). Macroeconomic vs. statistical APT approach in the Athens Stock Exchange. *International Journal of Business, 17*(1), 39–64.
Statista. (2021). *Worldwide desktop market share of leading search engines from January 2010 to September 2021*. http://www.statista.com/statistics/216573/worldwide-market-share-of-search-engines/.
Strycharz, J., Strauss, N., & Trilling, D. (2018). The role of media coverage in explaining stock market fluctuations: Insights for strategic financial communication. *International Journal of Strategic Communication, 12*(1), 67–85.
Su, Z., Fang, T., & Yin, L. (2019). Understanding stock market volatility: What is the role of US uncertainty? *North American Journal of Economics and Finance, 48*, 582–590.
Swamy, V., & Dharani, M. (2019). Investor attention using the Google search volume index–impact on stock returns. *Review of Behavioral Finance, 11*(1), 56–70.
Szczygielski, J. J., Brümmer, L. M., Wolmarans, H. P., & Zaremba, A. (2020). Are macroeconomic factors adequate proxies for systematic influences in stock returns? A South African perspective. *Investment Analysts Journal, 49*(1), 34–52.
Szczygielski, J. J., Brzeszczyński, J., Charteris, A., & Bwanya, P. R. (2022). The COVID-19 storm and the energy sector: The impact and role of uncertainty. *Energy Economics, 105258*.

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

Szczygielski, J. J., Charteris, A., Bwanya, P. R., & Brzeszczyński, J. (2023). Which COVID-19 information really impacts stock markets? *Journal of International Financial Markets Institutions and Money, 10152*.

Szczygielski, J. J., Charteris, A., & Obojska, L. (2023). Do commodity markets catch a cold from stock markets? Modelling uncertainty spillovers using Google search trends and wavelet coherence. *International Review of Financial Analysis, 102304*.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *Journal of Finance, 62*(3), 1139–1168.

Van Rensburg, P. (2002). Market segmentation on the Johannesburg stock exchange II. *Studies in Economics and Econometrics, 26*(1), 83–99.

Vlastakis, N., & Markellos, R. N. (2012). Information demand and stock market volatility. *Journal of Banking & Finance, 36*(6), 1808–1821.

Wang, J. X., Rao, Y. L., & Peng, D. F. (2015). What drives the stock market 'media coverage effect': Expected media attention or unexpected media attention. *Systems Engineering - Theory & Practice, 35*(1), 37–48.

Wang, X., Ye, Q., Zhao, F., & Kou, Y. (2018). Investor sentiment and the Chinese index futures market: Evidence from the internet search. *Journal of Futures Markets, 38*(4), 468–477.

Wang, Y. (2018). *Media and Google: The impact of information supply and demand on stock returns*. Working Paper https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2180409.

Whaley, R. E. (2009). Understanding the VIX. *Journal of Portfolio Management, 35*(3), 98–105.

Wurm, L. H., & Fisicaro, S. A. (2014). What residualizing predictors in regression analyses does (and what it does not do). *Journal of Memory and Language, 72*, 37–48.

Xu, Y., Wang, J., Chen, Z., & Liang, C. (2023). Sentiment indices and stock returns: Evidence from China. *International Journal of Finance and Economics, 28*(1), 1063–1080.

Yu, H. Y., & Hsieh, S. F. (2010). The effect of attention on buying behavior during a financial crisis: Evidence from the Taiwan stock exchange. *International Review of Financial Analysis, 19*(4), 270–280.

Yung, K., & Nafar, N. (2017). Investor attention and the expected returns of REITS. *International Review of Economics and Finance, 48*, 423–439.

Zaremba, A., & Maydybura, A. (2019). The cross-section of returns in frontier equity markets: Integrated or segmented pricing? *Emerging Markets Review, 38*, 219–238.

Zhang, B. (2019). Economic policy uncertainty and investor sentiment: Linear and nonlinear causality analysis. *Applied Economics Letters, 26*(15), 1264–1268.

Zhang, F., Sun, K., & Wu, X. (2019). A novel variable selection algorithm for multi-layer perceptron with elastic net. *Neurocomputing, 361*, 110–118.

Zhu, S., Liu, Q., Wang, Y., Wei, Y., & Wei, G. (2019). Which fear index matters for predicting US stock market volatilities: Text-counts or option based measurement? *Physica A: Statistical Mechanics and its Applications, 536*, Article 122567.

Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society, Series B: Statistical Methodology, 67*(2), 301–320.

Zou, H., & Zhang, H. H. (2009). On the adaptive elastic-net with a diverging number of parameters. *Annals of Statistics, 37*(4), 1733–1751.

Zurcher, A. (2018, February 6). *US stock plunge sparks global sell-off*. BBC News https://www.bbc.co.uk/news/business-42942921.

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