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Do commodity markets catch a cold from stock markets? Modelling uncertainty spillovers using Google search trends and wavelet coherence☆

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ABSTRACT

We investigate stock market uncertainty spillovers to commodity markets using wavelet coherence and a general stock market-related Google search trends (GST)-based index to proxy for uncertainty. GST reflect stock market uncertainty over short-, medium- and long-term horizons. Periods of association between GST and the VIX, a widely used proxy for stock market uncertainty, coincide with economic, financial, and geopolitical events. The association between the VIX and GST has grown over time. In line with economic psychology, this implies that during times of heightened uncertainty investors increasingly search for stock market-related information. Our analysis further reveals that some commodities are more susceptible to uncertainty spillovers from stock markets, notably energy commodities. We demonstrate how GST may be used to isolate the impact of specific events and show that COVID-19 had a disproportionate impact on commodity price volatility. We also find that energy, livestock and precious metals are increasingly integrated with stock markets. Spillover analysis repeated using the VIX produces similar results and reflects information that is also reflected in GST, confirming an uncertainty narrative. The use of wavelet analysis and GST to proxy for general and event specific uncertainty offers an alternative perspective to traditional econometric approaches and may be of interest to econometricians, analysts, investors and researchers.

1. Introduction

A substantial increase in the importance of commodities to investors over the past two decades has resulted in growing integration between commodity and stock markets (Adams & Glück, 2015; Baldi, Peri, & Vandone, 2016; Karyotis & Alijani, 2016) leading to increased volatility spillovers. A shock to one market – the equity or commodity market – may spur investors to rebalance their portfolios by investing in the other market resulting in volatility spillovers. Numerous studies document volatility spillovers from stock to commodity markets and vice versa (Baldi et al., 2016; Mensi, Beljid, Boubaker, & Managi, 2013; Mensi, Shafiullah, Vo, & Kang, 2021; Vardar, Coşkun, & Yelkenci, 2018; Wen, Cao, Liu, & Wang, 2021). Among commodities, oil is most frequently studied (Boubaker & Raza, 2017; Khalfaoui, Sarwar, & Tiwari, 2019; Olson, Vivian, & Wohar, 2014; Sarwar, Shahbaz, Anwar, & Tiwari, 2019; Sarwar, Tiwari, & Tingqiu, 2020) alongside gold and other precious metals (He, Takiguchi, Nakajima, & Hamori, 2020; Jiang, Fu, & Ruan, 2019; Lin, Kuang, Jiang, & Su, 2019; Mensi et al., 2021; Uddin, Hernandez, Shahzad, & Kang, 2020; Vardar et al., 2018). Studies have also investigated agricultural commodities and industrial metals (Ahmed & Huo, 2021; Baldi et al., 2016; Mensi et al., 2013; Wen et al., 2021). Volatility spillovers are typically more pronounced from stock to commodity markets (Mensi et al., 2013; Olson et al., 2014; Vardar et al., 2018) although oil impacts the stock markets of major oil exporting and importing countries (Khalfaoui et al., 2019; Sarwar et al., 2019; Sarwar et al., 2020). The magnitude of stock market spillovers differs across commodities and there is evidence of sizeable spillovers to energy, precious metals and agricultural commodities (Ahmed & Huo, 2021; Baldi et al., 2016; Mensi et al., 2021). Evidence also reveals that volatility spillovers are time-varying and intensify during and following

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crisis periods (Boubaker & Raza, 2017; Jebabli, Kouaissah, & Arouri, 2021; Mensi et al., 2021; Wen et al., 2021).

Uncertainty is a latent variable that cannot be directly observed. Return volatility, measured by realised variance (unconditional) or based on an ARCH(q)/GARCH(p,q) model (conditional variance) (see for example, Ahmed & Huo, 2021; Mensi et al., 2013; Mensi et al., 2021; Reboredo, Ugolini, & Hernandez, 2021) is a common proxy for uncertainty (Salisu, Gupta, Karmakar, & Das, 2022). As such, studies of volatility spillovers across financial markets provide insight into uncertainty spillovers. However, other measures of market uncertainty are frequently used such as the Chicago Board of Exchange (CBOE) Volatility Index (VIX) (Bekaert & Hoerova, 2014; Smales, 2022), corporate spreads and Economic Policy Uncertainty (EPU) index (Baker, Bloom, and Davis' 2016). These measures of uncertainty are a source of stock market volatility and volatility spillovers to international stock markets (Cheuathonghua, Padungsaksawasdi, Boonchoo, & Tongurai, 2019; Škrinjarić & Orlović, 2020; Su, Fang, & Yin, 2019), with spillovers exhibiting variation over time (Cheuathonghua et al., 2019). For example, Su et al. (2019) and Balli, Hasan, Ozer-Balli, and Gregory-Allen (2021) confirm that United States (U.S.) stock market uncertainty is a major source of stock market spillovers to other markets. However, there is limited research examining whether stock market uncertainty, a driver of stock market volatility, translates into increased volatility in commodity markets. Zhang, Chevallier, and Guesmi (2017) show that the VIX is associated with spillover effects to crude oil and natural gas volatility. Bakas and Triantafyllou (2018) find that shocks to economic and financial uncertainty result in persistent increases in commodity price volatility, notably for energy, and go on to observe that the impact of macroeconomic uncertainty is greater than financial market uncertainty. Amar, Belaid, Youssef, Chiao, and Guesmi (2021) document spillovers from stock markets to commodity markets which intensify during the COVID-19 period and illustrate that these spillovers are linked to various measures of uncertainty.

A growing number of studies have investigated the impact of general economic, financial and event-specific Google search trends (GST) on stock markets (Da, Engelberg, & Gao, 2011; Da, Engelberg, & Gao, 2015; Smales, 2021a; Smales, 2021b; Szczygielski, Brzeszczyński, Charteris, & Bwanya, 2022; Szczygielski, Bwanya, Charteris, & Brzeszczyński, 2021). One strand of literature treats GST as a measure of uncertainty, stock market-related and economic in nature. For example, Szczygielski et al. (2021) show that COVID-19-related GST move closely with the VIX during the onset of the COVID-19 pandemic (from December 2019 to June 2020). They go on to find that GST impact returns on regional market aggregates and are associated with heightened volatility (see also Lyócsa, Baumöhl, Výrost, & Molnár, 2020; Szczygielski, Brzeszczyński et al., 2022; Szczygielski, Charteris, Bwanya, & Brzeszczyński, 2022). Castelnuovo and Tran (2017) construct monthly GST economic uncertainty indices for Australia and the U.S. and find that they correlate positively with existing proxies of uncertainty (see also Bontempi, Frigeri, Golinelli, & Squadrani, 2019; Dzielinski, 2012). Dzielinski (2012), Preis et al. (2013) and Donadelli (2015) document that uncertainty, measured by GST related to economic and financial terms, negatively impacts U.S. stock returns. Dzielinski (2012) reports that increased GST are associated with heightened stock market volatility. GST as a measure of uncertainty finds a basis in economic psychology. Economic agents search for information when there is greater uncertainty and increasing Google searches on a topic therefore reflect increasing uncertainty associated with that topic (Castelnuovo & Tran, 2017; Donadelli, 2015; Liemieux & Peterson, 2011). Other literature, however, treats GST as a measure of retail investor attention directed at a particular stock or commodity, the stock or commodity market or broader economy (Afkhami, Cormack, & Ghoddusi, 2017; Da et al., 2011; Han, Li, & Yin, 2017). Nevertheless, GST have been shown to exhibit low correlation with common proxies of attention including news, extreme returns and trading volume (Da et al., 2011). Another strand of literature uses GST to quantify financial and economic sentiment (Da et al., 2015; Fang, Gozgor, Lau, & Lu, 2020; Joseph, Wintoki, & Zhang, 2011). What emerges is that there is ambiguity as to the narrative reflected by GST – uncertainty, attention or sentiment?

There are a limited number of studies that have focused on the association between Google searches for commodity-linked keywords and commodity markets. Mišečka, Ciaian, Rajčániová, and Pokrivčák (2019) use individual GST for corn, wheat and soybeans and find that increased searches for "corn" ("wheat") positively impact corn (wheat) prices in the short and long run but searches for the term "soybeans" have no impact on soybean prices (see also Miao, Khaskheli, Raza, & Yousufi, 2022). Han et al. (2017) and Kou, Ye, Zhao, and Wang (2018) confirm that GST-linked to a specific commodity impact commodity returns for a wide range of commodities, from grains to gold. Afkhami et al. (2017) observe that GST related to energy commodities trigger heightened return volatility. Wei, Guo, Yu, and Cheng (2021) document evidence of volatility triggering effects for metal futures attributable to Google searches related to metal prices, financial crises and earthquakes (see also Song, Ji, Du, & Geng, 2019). GST related to gold, silver, oil and natural gas prices have also been shown to impact dynamic correlations between these four commodity markets (Prange, 2021). However, whether stock market uncertainty, as reflected by GST related to equity markets, has spillover effects on commodity markets is unclear.

In this paper, we study the impact of stock market uncertainty spillovers on the volatility of six aggregate commodity indices using a novel GST-based index developed by Szczygielski, Charteris, Bwanya, and Brzeszczyński (2023) that relies upon neutral stock market-related Google search terms to measure prevailing equity market uncertainty. Our iteration of the index differs in numerous respects to existing keyword-based indices. It is of a daily frequency and spans a period of 10 years. It is based upon five keywords that were objectively selected and have been shown to impact market returns and trigger volatility across a comprehensive sample comprising 77 stock markets. Given the ambiguity reflected by keyword-based GST indices, we first demonstrate that this index proxies for stock market uncertainty. We do this by analysing the association between GST and an established measure of stock market uncertainty, the VIX, using wavelet coherence (Bekaert, Hoerova, & Duca, 2013; Smales, 2022). Wavelet coherence has a number of advantages over traditional regression analysis. It provides information about the relationship between different components of time series, permitting insight into associations at varying time horizons. To our knowledge, this is the first study to investigate spillover effects into commodity markets using GST to proxy for stock market uncertainty by applying wavelet coherence.

Our study contributes in a number of areas. First, it demonstrates that GST are a proxy for *general* stock market uncertainty and therefore adds to the literature on the narrative reflected by GST. It does so using non-traditional econometric approaches. To our knowledge, we are the first to use wavelet analysis to study the association between GST and an established measure of stock market uncertainty. Our analysis shows that the long-term association between GST and the VIX has steadily grown over the last 10 years and that GST reflect short-, medium- and long-term uncertainty and persistence thereof, with this becoming more evident towards the end of our sample. Growing association is potentially attributable to increased Google accessibility and utilisation, resulting in GST rapidly reflecting stock market uncertainty. Second, we use wavelet analysis to model stock market uncertainty spillovers to commodity price volatility. We find that some commodities reflect uncertainty spillovers to a greater extent, these being energy, livestock and precious metals. Grains and industrial metals are impacted to a lesser extent, even during the COVID-19 pandemic, implying that these commodities may be held as a hedge against uncertainty in stock markets. Our analysis suggests periods of increased spillovers coincide with significant geopolitical, financial and economic events. Third, we isolate the effects of COVID-19-related uncertainty on commodity volatility using COVID-19-related GST and report evidence suggesting that some commodity series show increasing integration with stock markets after accounting for COVID-19-related uncertainty spillovers. In doing so, we demonstrate how GST and wavelet analysis can be used to quantify and isolate the impact of specific events on commodity markets as opposed to limiting ourselves to a less detailed analysis that relies upon using general uncertainty measures. Finally, by applying wavelet analysis we demonstrate how this methodology can be used to gain new insights into the interaction between asset markets and its evolution. These insights offer a different perspective to that provided by the application of traditional econometric approaches and thereby potentially demonstrate a more accessible form of analysis to those without a background in financial econometrics.

This study proceeds as follows: Section 2 outlines the data and methodology. Section 3 investigates the relationship between the GST-based index used in this study and the VIX and uses the GST-based index to model stock market uncertainty spillovers to commodity price volatility. Section 4 outlines implications and Section 5 concludes.

2. Data and methodology

2.1. Commodity price data

Our commodity price data spans six commodity groups, as defined by the Bloomberg commodity index methodology, namely energy, precious metals, industrial metals, livestock, grains and softs between 1 January 2012 and 31 December 2021.[1] According to Tilton, Humphreys, and Radetzki (2011), commodity spot prices reflect changes in fundamentals that affect producer supply, and consumer and investor demand (also see Zaremba, Umar, & Mikutowski, 2019). As uncertainty is likely to impact commodity prices through demand and supply channels, the use of spot prices is deemed to be appropriate.[2] Each series is of a daily frequency and returns are derived from logarithmic differences. Table 1 lists the commodity groups considered, together with descriptive statistics.

2.2. GST-based stock market uncertainty index

Our stock market-related GST index is based upon that of Szczygielski, Charteris et al. (2023) which the authors show closely approximates existing measures of stock market uncertainty, namely the VIX, the Twitter-based market and economic uncertainty (TMU and TEU) indices of Baker, Bloom, Davis and Renault (2021), a news-based U.S. Economic Policy Uncertainty (EPU) index (Baker et al., 2016) and a newspaper-based U.S. Equity Market Volatility tracker (EMV) (Baker, Bloom, Davis, & Kost, 2019). The TMU, TEU, EPU and EMV are constructed using keywords from different sources. In contrast, Szczygielski, Charteris et al.'s (2023) index is a general index that uses neutral stock market-related Google search terms to construct the index without the imposition of a narrative as to what is reflected by the index and the index is calibrated to returns and not volatility. The authors first identify 46 unique Google search terms that are related to and include the terms "stock market" and "stock markets". Then, they use elastic net regression to select six search terms (from a search term set that includes the two terms above) that are related to factor scores representative of common return drivers underlying a sample of 77 markets comprising developed, emerging and frontier countries. The search terms that are widely related to stock market movements are "dow jones", "stock market futures", "live stock market", "futures market", "asian stock markets" and "today stock market". The authors go on to show that their index outperforms other keyword-based measures of uncertainty when it comes to explaining returns and proxying for factor dispersion underlying stock return volatility. We construct a similar index by equal weighting each term but exclude "asian stock markets", owing to the sparse number of searches during the first half of our sample period; our index spans a period that is approximately five years longer than that of Szczygielski, Charteris et al. (2023) which begins on 1 June 2016. Our iteration begins on 1 January 2012 and ends on 31 December 2021. GST data are obtained for each of the five terms. The highest value is adjusted to 100 with remaining values adjusted accordingly relative to this base. For compatibility with the financial time series which comprise five days of the week, we exclude weekends from our GST data which are available for seven days of the week. Next, individual index values are added and the sum is divided by five. The resultant index is then differenced and designated as ΔGST_t.[3] Fig. 1 below plots individual GST levels for each search term together with the resultant aggregated index.

2.3. Commodity volatility series

As we are interested in modelling uncertainty spillovers from stock markets to commodity price volatility, we need to generate approximations of volatility. To do so, we use squared returns for each commodity price series where returns, $r_{i,t}$, are derived from logarithmic differences in the levels for commodity index i at time t, $S_{i,t}$:

$$r_{i,t} = ln\left(\frac{S_{i,t}}{S_{i,t-1}}\right) \tag{1}$$

and

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

where $V_{i,t}$ is the realised volatility for commodity index i at time t. The use of realised volatility offers a method of constructing volatility series that does not require an explicit model specification such as an ARCH(q) or GARCH(p,q) model and/or other parametric models that are complex and restrictive. Squared returns offer a simple nonparametric volatility measurement that is straightforward to calculate, reflects short- and long-term dynamics and permits volatility to be modelled directly using standard time series techniques (Golosnoy, Gribisch, & Liesenfeld, 2015; Lobato & Savin, 1998; Zheng, Qiao, Takaishi, Stanley, & Li, 2014). Realised volatility represented by squared returns has been used by Dimpfl and Jung (2012), Zheng et al. (2014), Golosnoy et al. (2015), Nakajima (2017) and Gupta and Pierdzioch (2021) to study spillovers and information transmission between markets and asset classes.

2.4. Wavelet coherence

Our primary approach to the analysis of spillover effects of GST-proxied stock market uncertainty to commodity volatility is based upon wavelet coherence (Torrence & Compo, 1998). Wavelet coherence provides information about the co-movement between two signals, $x_{1,t}$ and $x_{2,t}$, in the frequency domain which can be interpreted as different time (or alternatively investment) horizons. It is based on the continuous wavelet transform, which serves to identify relationships, evaluate their

[1] Energy: crude oil, WTI and Brent, ULS diesel, natural gas and RBOB gasoline. Precious metals: gold, platinum and silver. Industrial metals: aluminium, copper, lead, nickel, tin and zinc. Livestock: live cattle and lean hogs. Grains: corn, soybeans, soybean oil, soybean meal and wheat. Softs: cocoa, coffee, cotton and sugar.

[2] Although we use spot prices, we also undertake an analysis using commodity futures' prices which (also) frequently feature in the literature (see for example Kang, McIver, & Yoon, 2017). There are no significant differences in the results.

[3] In calculating differences in GST indices over weekends, changes are calculated by subtracting aggregate index 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 will reflect the outcome of information arrivals contributing to uncertainty over the weekend, positively or negatively, much like for financial time series.

Table 1
Descriptive statistics for returns on Bloomberg commodity indices

Commodity	Energy	Precious metals	Industrial metals	Livestock	Grains	Softs
Mean	−2.16E-05	2.84E-05	0.0001	3.64E-05	2.96E-05	2.82E-05
Median	0.0003	0.0000	0.0000	0.0000	0.0000	0.0000
Maximum	0.0988	0.0823	0.1823	0.0772	0.0629	0.2161
Minimum	−0.1450	−0.1038	−0.1516	−0.0627	−0.0640	−0.1888
Std. dev.	0.0177	0.0113	0.0117	0.0108	0.0121	0.0134
Kurtosis	9.6990	10.6568	36.6813	6.7893	5.3746	43.5932
Skewness	−0.4651	−0.5230	0.5872	−0.1787	0.1005	0.6347
SW	0.9332***	0.9220***	0.8995***	0.9642***	0.9764***	0.8890***

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

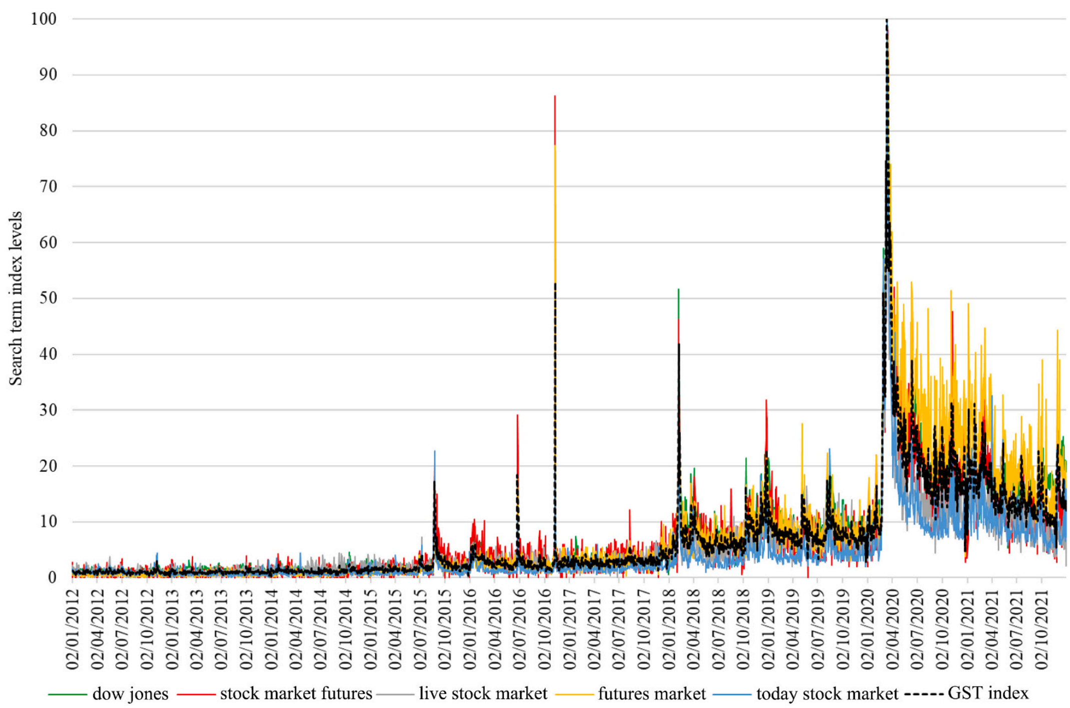

Fig. 1. Stock market-related searches over time as captured by GST
Notes: This figure plots scaled levels of general stock market-related Google search terms (maximum = 100) that have been shown to move international stock markets and an equal-weighted GST index comprising five terms, namely "dow jones", "stock market futures", "live stock market", "futures market" and "today stock market" over the period 1 January 2012 to 31 December 2021.

strength and persistence, and localises them over time. Wavelet analysis captures shocks and persistent correlations between series allowing for a better understanding of the interdependence between $x_{1,t}$ and $x_{2,t}$. In contrast, regression analysis provides information about correlation but does not yield insight into its evolution over time and frequency. More advanced regression methods, such as the DCC-GARCH model, are required to investigate time-varying correlations (Jensen & Whitcher, 2014). Several studies have used variations of wavelet analysis to examine co-movement and dependence across asset classes (see for example Abid & Kaffel, 2018; Bouri, Shahzad, Roubaud, Kristoufek, & Lucey, 2020; Jena, Tiwari, & Roubaud, 2018; Mensi et al., 2021; Tiwari, Jana, & Roubaud, 2019; Zaremba et al., 2019).

In this study, we use the Morlet wavelet as a mother wavelet which provides the best balance between time and frequency localisation (Aguiar-Conraria & Soares, 2011). Wavelet absolute squared coherence between $x_{1,t}$ and $x_{2,t}$ is given by:

$$R^2_{x1,x2} = \frac{\left|S\left(WPS_{x1,x2}\right)(\tau,s)\right|^2}{S(|WPS_{x1}(\tau,s)|)S(|WPS_{x2}(\tau,s)|)} \tag{3}$$

where

$$WPS_{x1,x2}(\tau,s) = WPS_{x1}(\tau,s)WPS^*_{x2}(\tau,s) \tag{3a}$$

$$WPS_{xn}(\tau,s) = \left|W_{xn,\phi}(\tau,s)\right|^2 = \left|\int_{-\infty}^{\infty} x_t \frac{1}{\sqrt{|s|}}\phi^*\left(\frac{t-\tau}{s}\right)dt\right|^2 \tag{3b}$$

where $R^2_{x1,x2}$ represents wavelet squared coherence between $x_{1,t}$ and $x_{2,t}$, $WPS_{x1,x2}(\tau,s)$ is the cross-wavelet power spectrum of $x_{1,t}$ and $x_{2,t}$ showing areas of co-movement between two series, S is a smoothing operator, ϕ is a wavelet function (a mother wavelet), the star operator * denotes a complex conjugate, τ denotes a time lag, i.e., a parameter determining the time location of the wavelet and s is the scaling parameter. Wavelet coherence takes on values between 0 and 1, with one indicating maximum coherence and zero a lack thereof.

Results are represented using spectrograms (alternatively contour plots). The horizontal axis reflects the date, whereas the vertical axis is expressed in the number of days and represents the time horizon. Higher horizons (periods) indicate a longer investment horizon. Values of (approximately) between 1 and 32 days are defined as the short run, 33 to 128 days are defined as the medium run and values greater than 129 days represent the long run. Wavelet analysis thus enables us to analyse correlations at different time horizons (scales); we can analyse relationships over the short, medium and long run as defined above. To do this we use a maximal overlap discrete wavelet transform (MODWT) with a mother wavelet fk4[4] which can be applied to financial data because of its decomposition of time series into frequencies (Boubaker & Raza, 2017; Jensen & Whitcher, 2014). Dark red areas are indicative of strong coherence whereas dark blue areas are indicative of no coherence where coherence can be interpreted as the association between series. Consequently, wavelet coherence can be seen as a scale-specific squared correlation between series $x_{1,t}$ and $x_{2,t}$. In addition, this approach allows us to study lead-lag relationships between series which are represented by arrows on spectrograms. A right (left) pointing arrow indicates that the two series are positively (negatively) correlated. A downward pointing arrow (including downward left and downward right) indicates that $x_{1,t}$ responds to $x_{2,t}$, and an upward pointing arrow (including upward left and upward right) indicates that $x_{2,t}$ follows $x_{1,t}$.

We begin our analysis by establishing wavelet coherence between ΔGST_t and ΔVIX_t, where the VIX is treated as an established measure of stock market uncertainty (Bekaert & Hoerova, 2014). The role of the VIX as a measure of stock market uncertainty can be explained by outlining how the VIX relates to stock market behaviour and how uncertainty impacts stock markets.[5] The VIX is a U.S.-orientated forward-looking proxy for stock market volatility. It can be (and is) used to proxy for global stock market uncertainty given that U.S. market uncertainty is transmitted across global markets and not vice-versa (Smales, 2022). The VIX spikes during periods of market turmoil - turmoil that may impact the price and volatility of other assets - and movements in the VIX are inversely related to contemporaneous stock returns. For this reason, the VIX is considered to be a measure of stock market uncertainty and an investor fear gauge (Fleming, Ostdiek, & Whaley, 1995; Whaley, 2009). Uncertainty is associated with declining expected cash flows to firms as a result of uncertainty about aggregate demand and supply conditions, which are highly relevant to commodities (Bouri, Lucey, Saeed, & Vo, 2021; Ramelli & Wagner, 2020). Furthermore, increased risk aversion during times of heightened uncertainty means that investors will require a higher risk premium which is reflected in the forward-looking discount rate (Andrei & Hasler, 2015; Cochrane, 2018; Smales, 2021a). Lower expected cash flows and a higher discount rate translate into lower stock prices. The resultant process of price discovery as economic agents react to uncertainty results in asset price volatility as market participants are uncertain about the true value of assets following the arrival of new data (Engle, 2004; Engle, Focardi, & Fabozzi, 2008; Nwogugu, 2006). While the VIX is forward looking in terms of volatility expectations but reacts to market movements contemporaneously, GST reflect current searches. Economic psychology proposes that increased searches reflect rising uncertainty as economic agents respond to uncertainty by searching for information around a specific issue or topic (see Section 1). It therefore follows that there should be similarity between GST and the VIX as measures of uncertainty even if the paradigms that these two measures draw upon differ. As uncertainty increases, economic agents search for information more intensively, this intensity being reflected by increased Google searches. As uncertainty increases, stock markets respond negatively and levels of the VIX increase. Both the VIX and GST measure a variable that is not perfectly forecastable from the perspective of economic agents (Jurado, Ludvigson, & Ng, 2015).[6] Given the apparent similarity in terms of measuring uncertainty, we aim to confirm that ΔGST_t is indeed a proxy for stock market uncertainty by analysing the relationship between ΔGST_t and ΔVIX_t.

Numerous studies have taken the approach of relating GST to the VIX to show that GST can be used to proxy for uncertainty. Dzielinski (2012) proposes a GST-based index to capture investor uncertainty around the state of the economy arguing that the benefit of internet-based searches is that they are generated by spontaneous investor behaviour. The author goes on to show that the GST-based economic uncertainty index is significantly and positively correlated with other uncertainty measures, which include the VIX, and exhibits a significant relationship with aggregate stock returns and volatility. Szczygielski et al. (2021), Szczygielski, Brzeszczyński, et al. (2022) and Szczygielski, Charteris et al. (2022, 2023) show that there is a relationship between GST - COVID-19-related and general stock market-related - and the VIX using approaches that are more commonly used in the discipline of finance, namely correlation analysis, rolling correlations and diagrammatic comparisons and are applicable to short horizons. Castelnuovo and Tran (2017) show that their U.S. and Australian orientated Google economic uncertainty indices correlate positively with the VIX, and other measures of financial, interest rate, real activity, and monetary policy uncertainty. Chen, Liu, and Zhao (2020) construct a two search term COVID-19-related GST index to proxy for sentiment and investigate the relationship between COVID-19-related sentiment and the VIX, which they interpret as a measure of market uncertainty. They find that investor fear around COVID-19 – as measured by GST – is positively correlated with financial market uncertainty.[7] Vlastakis and Markellos (2012) study the relationship between information demand, quantified by GST, and the VIX. They find that GST are significantly and contemporaneously related to the VIX implying that higher information demand is associated with higher implied volatility measures.

By applying wavelet analysis, we extend and provide a different perspective as to the interpretation of the narrative reflected by the informational content of our GST index by relating it to a well-known and widely accepted proxy for stock market uncertainty in the form of the VIX. Additionally, we are also able to depict the evolution of GST as a proxy of stock market uncertainty over an extended period of time. In

[4] fk4 stands for the Fejér-Korovkin mother orthogonal wavelet, i.e., a scaling filter with four coefficients.

[5] We would like to thank an anonymous reviewer for a comment relating to the nature of the VIX as well as for other comments which helped in improving this study.

[6] For example, the economic consequences of the COVID-19 pandemic were not known, understood or perfectly predictable at the time of the outbreak of the pandemic. Nevertheless, it can be argued that economic agents searched for COVID-19-related information using Google in an attempt to better understand the potential consequences of the pandemic which were not fully known at present (Szczygielski et al., 2021). It follows that when economic agents search for information on a specific topic, they are uncertain about the future state of a specific variable given current events and information flows which prompt intensified searches in the present.

[7] Realised volatility can also be used as a proxy for uncertainty (Cascaldi-Garcia et al., 2021; Salisu et al., 2022). However, we are of the opinion that the VIX is a more appropriate proxy because of its widespread acceptance as a measure of (global) stock market uncertainty, its widespread application in the literature to proxy for stock market uncertainty and specifically, usage in literature that seeks to interpret information reflected in GST by relating GST to the VIX (also see Berger, Dew-Becker, & Giglio, 2020 who argue that expected volatility rather than realised volatility captures uncertainty). Nevertheless, we re-estimated all spectrograms using realised volatility derived from returns on the MSCI All Country (AC) World Index, treating this as an alternative global uncertainty proxy. The results, available upon request from the authors, are closely comparable.

calculating wavelet coherence between ΔGST_t and ΔVIX_t, ΔGST_t replaces $x_{1,t}$ while ΔVIX_t replaces $x_{2,t}$ in Eq. (3). Tiwari et al. (2019) also use wavelet analysis to examine the co-movement dynamics between EPU and VIX.

Next, we turn to the analysis of the relationship between ΔGST_t and the volatility series, $V_{i,t}$. We investigate whether ΔGST_t reflects stock market uncertainty by modelling stock market uncertainty spillovers to commodity price volatility. While we do not expect all commodities to reflect uncertainty spillovers from stock markets (Ahmed & Huo, 2021; Baldi et al., 2016; Mensi et al., 2021), we expect to see coherence between some of the commodity volatility series and ΔGST_t if there are uncertainty spillovers from stock markets *and* ΔGST_t proxies for stock market uncertainty (Zhang et al., 2017). Due to the approach that we follow, we will be able to establish the nature of the intertemporal relationships if spillovers occur. In calculating wavelet coherence between ΔGST_t and $V_{i,t}$, $x_{1,t}$ now becomes $V_{i,t}$ and $x_{2,t}$ becomes ΔGST_t.

3. Results and analysis

3.1. Google search trends as a measure of market uncertainty

In this section, we apply wavelet analysis to study the evolution of the relationship between ΔGST_t and ΔVIX_t.

Fig. 2 indicates that over the medium and long horizons, ΔGST_t increasingly becomes associated with stock market uncertainty as evident from increased medium- and long-term coherence during the second half of the sample period (beginning of 2017 onward). A possible explanation is the growing accessibility and utilisation of Google as a search engine by the general public, including investors. Between 2009 and 2017, the percentage of internet users across the world increased dramatically; Asia, Europe, North America, Latin America, Africa, Middle East and Oceania saw the number of internet users increase by 153%, 55%, 23%, 117%, 351%, 151% and 33%, respectively (Statista, 2021). Additionally, in 2015, Google introduced a search algorithm for mobile devices providing "on the go" accessibility (Gravoc, 2015). Prior to this, in the 2000s, Google positioned itself as a one-stop destination for information through the integration of numerous services and its superior search algorithm (Stross, 2008). This suggests increased relevance, accessibility and utilisation coincided with investors increasingly searching for stock market-related information during times of heightened uncertainty resulting in GST increasingly reflecting uncertainty.

Importantly, Google searches related to financial and economic terms are likely to reflect retail investor search activity because institutional investors rely on professional information services (Dimpfl & Jank, 2016; Smales, 2021a). There has been a notable rise in the number of retail investors in recent years with the availability of easy-to-use apps (such as Robinhood, *E*-Trade and Webull). Many of these investors are new to investing, increasing the likelihood that they will search for stock market-related information (Aharon & Qadan, 2020; Aramonte & Avalos, 2021; Deloitte, 2021) especially when uncertainty increases.[8] Aharon and Qadan (2020) confirm that retail investors engage in more information gathering when uncertainty prevails. As such, the increased number of retail investors who utilise Google as a source of stock market information may have contributed to the growing association between GST and VIX as Google searches began reflecting stock market uncertainty more rapidly through stock market-related searches attributable to broader accessibility and utilisation.

A further observation that suggests that accessibility and utilisation may increasingly be driving the association of both indices is that up until October 2017, lead-lag relationships between ΔVIX_t and ΔGST_t exhibited less stability, especially in the short run but also in the medium run (region A). For example, between October 2012 and May 2013, ΔGST_t follows ΔVIX_t (downward pointing arrows). In contrast, between May 2013 and April 2014, ΔGST_t precedes ΔVIX_t (upward pointing arrows). Nevertheless, the relationship becomes increasingly synchronous over time (rightward pointing arrows).

Additionally, in Panel B of Table 2 we note that during the first half of the sample period, 1 January 2012 to 31 December 2016, ΔGST_t and ΔVIX_t are uncorrelated ($\rho_1 = 0.0171$) over two-day horizons although correlation becomes significant for longer horizons (four days and above). This contrasts with the second period in Panel C, 1 January 2017 to 31 December 2021, for which ρ_2 is statistically significant for all horizons and greater in magnitude relative to the first period. We interpret this as implying that ΔGST_t took longer to reflect stock market uncertainty as reflected by ΔVIX_t and did so to a lesser extent potentially due to lower utilisation and less timely (due to accessibility) stock market-related searches taking place in response to rising stock market uncertainty. Stronger correlation across all horizons during the second period in Panel C suggests that ΔGST_t became more responsive to stock market uncertainty reflected by ΔVIX_t and that this uncertainty was reflected quicker by ΔGST_t. We note that correlations are significant for all horizons in Panel A, the entire sample period, and that they grow over longer horizons again implying that stock market-related Google searches exhibit a protracted increase as stock market uncertainty increases. Correlations during the second half of the sample period are greater than correlations during the entire sample period suggesting that overall correlations are driven by the strengthening of the association between ΔVIX_t and ΔGST_t during the second half of the sample.

Over the short run, increased coherence can be observed mostly (but not exclusively) towards the end of the sample period. Increased short-run coherence is most evident between January 2015 and August 2016 (bottom of regions C and D), around July 2017 (bottom right corner of region A), around February 2018 (region E) and then increasingly from November 2018 onwards. Short-term coherence prior to the end of 2015 is of a shorter duration and of a lower frequency (occurrence).

To confirm and gain further insight into short-run dynamics, we estimate breakpoint regressions for ΔGST_t onto ΔVIX_t with breakpoints identified using the Bai-Perron test (Bai & Perron, 1998).

Results in Table 3 indicate that there is a positive and significant short-term relationship over the full sample period between ΔGST_t and ΔVIX_t. Significant and positive associations are observed between February 2015 and August 2016 (see the event overview that follows, region C, $\bar{R}^2$ of 0.2805), February 2018 and March 2020 (regions E, F, part of G, $\bar{R}^2$ of 0.3019) and March 2020 to December 2021 (regions G, H, $\bar{R}^2 = 0.0738$). Overall, the results in Table 3 are congruent with short-run associations reflected in Fig. 2 and similarly suggest that coherence has grown over time, most notably during the second half of the sample period.

Association between both indices appears to coincide with significant economic, financial market and political developments. Medium-run coherence increased between October 2012 and February 2014 (region B), coinciding with rising fears of a breakup of the Euro area, continuation of the European sovereign debt crisis (Casiraghi, Gaiotti, Rodano, & Secchi, 2013), the start of the Ukrainian conflict in early 2014 and the resulting deterioration in Russia-West relationships. Short-term associations between June and September 2015 coincide with the Chinese stock market crash which saw the Shanghai Stock Exchange Composite Index decline by 34% (Yousaf & Hassan, 2019). Other notable events coinciding with increased association are the Brexit referendum in June 2016 and the international market contagion that followed (Escribano & Íñiguez, 2021; Podgorski, 2020) Donald Trump's victory in the U.S. presidential elections in November 2016 (region D), the Dow Jones plummeting by 12% in February 2018 amid concerns around rising inflation and potential interest rate hikes in the U.S. (Kim & Kim, 2022), the start of the U.S.-China trade war in January 2018 which continued into 2019 (regions E, F) (Mason, 2019) and associated

[8] Searching for information as a form of reassurance seeking among individuals is also seen in medical searches (McManus, Leung, Muse, & Williams, 2014).

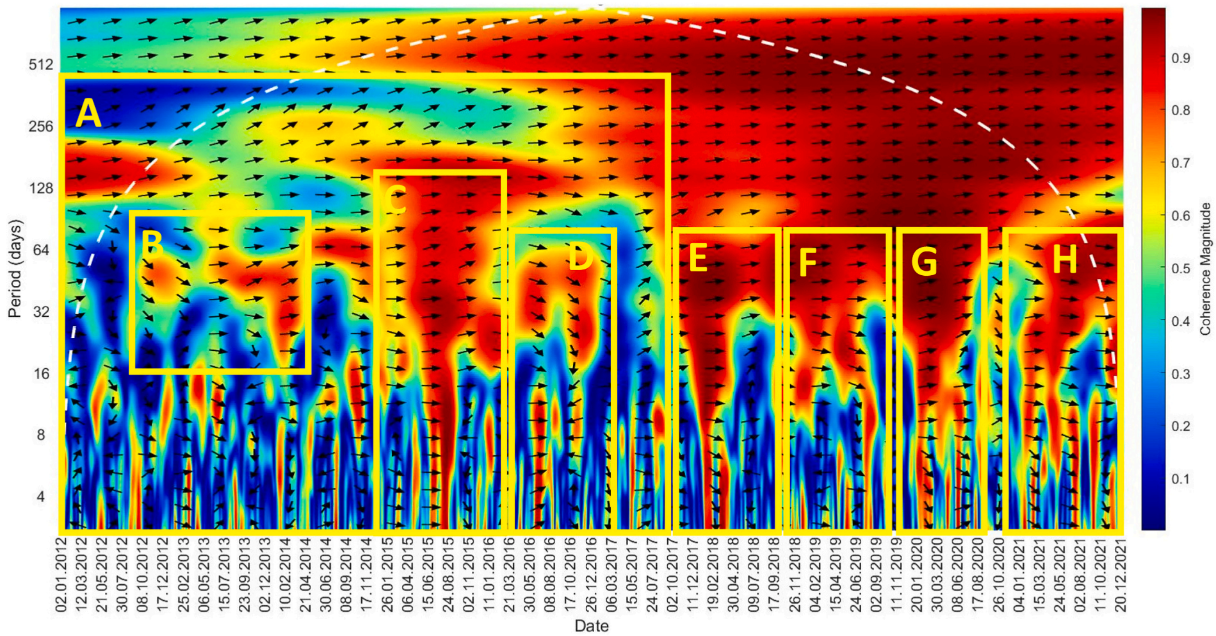

Fig. 2. Spectrogram for ΔGST_t and ΔVIX_t

Notes: Fig. 2 presents a spectrogram for ΔGST_t and ΔVIX_t in three dimensions where time is on the horizontal axis, the frequency domain is on the vertical axis expressed in the number of days and wavelet coherence values (contour map). Higher frequencies indicate a longer investment horizon. Values of (approximately) between 1 and 32 days are defined as the short run, 33 to 128 days are defined as the medium run and values greater than 129 days are considered to represent the long run. Coherence takes on values between zero (0) and one (1), with one indicating maximum coherence and zero a lack thereof. Dark red areas are indicative of strong coherence whereas dark blue areas are indicative of no coherence where coherence can be interpreted as association between the two indices. The white dashed line indicates the 5% significance level for edge effects occurring in coherence data. A right (left) pointing arrow indicates that the two series are positively (negatively) correlated. A downward pointing arrow (including downward left and downward right) indicates that ΔGST_t responds to ΔVIX_t whereas an upward pointing arrow (including upward left and upward right) indicates that ΔVIX_t follows ΔGST_t.

Table 2
Correlations between ΔGST_t and ΔVIX_t over different time horizons

Horizon	Panel A	Panel B	Panel C
	ρ_{full}	ρ_1	ρ_2
2	0.2179***	0.0171	0.2859***
4	0.3284***	0.1540***	0.4016***
8	0.4897***	0.2026***	0.5986***
16	0.5798***	0.2978***	0.6831***
32	0.7514***	0.5346***	0.8332***
64	0.8172***	0.6580***	0.8927***
128	0.8689***	0.7468**	0.9175***
256	0.8832***	0.5279	0.9531**

Notes: This table reflects ordinary correlations over different horizons estimated using MODWT. Both series (ΔGST_t, ΔVIX_t) have been decomposed into frequencies, i.e. investment horizons that are non-overlapping, and correlations for the respective horizons were then estimated. For example, a 2-day horizon for ΔGST_t, is correlated with the 2-day horizon for ΔVIX_t. Given that for each time horizon we have multiple wavelet decompositions, the most probable outcomes are chosen on the basis of adjusted *p*-values. As a result we obtain correlations calculated over investment horizons and not specific to certain observations. Panel A reports correlations for the entire sample period, 1 January 2012 to 31 December 2021, Panel B reports correlations for the first half of the sample period, 1 January 2012 to 31 December 2016, and Panel C reports correlations for the second half of the sample period, 1 January 2017 to 31 December 2021. Values of (approximately) between 1 and 32 days are defined as the short run, 33 to 128 days are defined as the medium run and values greater than 129 days are considered to represent the long run. Asterisks ***, ** and *, indicate statistical significance at the respective 1%, 5% and 10% levels of significance.

Table 3
Short run relationships

Period	α	$\beta_{\Delta VIX_{t,\pi}}$	$\bar{R}^2$
Full	0.0052	0.3834***	0.0841
01/01/2012	0.0006	0.0088	0.0000
09/07/2013	0.0004	0.0166	0.0008
12/02/2015	0.0068	0.3593***	0.2805
12/08/2016	0.0667	−0.0914	0.0000
12/02/2018	0.0525	0.8103***	0.3019
13/03/2020	−0.1351	0.3493***	0.0738

Notes: This table reports the results of least squares regressions for ΔGST_t onto ΔVIX_t estimated with Newey-West heteroscedasticity and autocorrelation consistent (HAC) standard errors. “Full” in the period column refers to estimates over the entire sample period whereas sub-periods are indicated by a date corresponding to the beginning of that sub-period as identified by applying the Bai-Perron test for 1 to M globally determined breaks. α is the intercept and $\beta_{\Delta VIX_{t,\pi}}$ is the coefficient associated with the ΔVIX_t for segment π. $\bar{R}^2$ is the adjusted coefficient of determination. Asterisks *** indicate statistical significance at the 1% level of significance.

uncertainty which negatively impacted the global investment environment (Plummer, 2019). The beginning of 2020 coincides with the COVID-19-induced market crash (February to April 2020) (region G) (Frazier, 2021). The emergence of the Delta COVID-19 variant in May/June 2021 led to further stock market volatility together with concerns about creeping inflation in early 2021 (Calhoun, 2021; Clifford & Rap, 2021). A number of other events in 2021 also contributed to ongoing market volatility (e.g. slowing rebound, Evergrande’s likely default, gas supply shortages) (region H). Furthermore, Aharon and Qadan (2020) also show that retail investors pay more attention to their trading accounts following market shocks and macroeconomic announcements as well as when there are extreme movements in the VIX. Likewise, Szczygielski et al. (2021) show increased Google searches related to COVID-19 as the virus spread globally but declined over time (see also Smales, 2021a, 2021b; Szczygielski, Charteris et al., 2022; Szczygielski, Brzeszczyński et al., 2022). This is consistent with Fig. 2 regarding increased information searches following market shocks and other major events.

The preceding discussion suggests that short-run associations can be explained by uncertainty surrounding specific events. However, uncertainty associated with these events persists in the medium and long run as is evident in Fig. 2. We expect this to be the case given that market volatility has been shown to exhibit long memory and persistence (Ferreira, 2020; Huang, Tu, & Chou, 2015). Additionally, the evolution of a number of events, such as the European sovereign debt crisis (at the beginning of the sample), the COVID-19 pandemic and the emergence of new variants (towards the end of the sample), was protracted. This contributed to medium- and long-term associations which are reflected by coherence between ΔGST_t and ΔVIX_t. The association between ΔGST_t and ΔVIX_t is generally consistent with the still limited number of studies that utilise GST to proxy for uncertainty. Szczygielski et al. (2021) show that COVID-19-related GST move closely with the VIX during the onset of the COVID-19 pandemic (December 2019 to June 2020) (see also Lyócsa et al., 2020; Szczygielski, Brzeszczyński et al., 2022). Castelnuovo and Tran (2017) construct monthly GST economic uncertainty indices for Australia and the U.S. and find that they correlate positively with existing proxies for uncertainty (see also Dzielinski, 2012).

In summary, our analysis reveals that the relationship between ΔGST_t and ΔVIX_t has grown over time. This may be partially attributable to increased Google accessibility and utilisation. Although less stable and sporadic in the short run, there is a relationship between ΔGST_t and ΔVIX_t nevertheless, as suggested by Fig. 2 and the results in Tables 2 and 3, notably for the full period in regression analysis. Short-run coherence over the full period is likely attributable to increased coherence later in the sample. The relationship appears to strengthen around events that increase stock market uncertainty and exhibits increasing stability over the mid- and long-run horizons. Given these findings, we postulate that GST increasingly reflect stock market uncertainty and persistence that is associated with uncertainty. We aim to investigate this further by modelling stock market uncertainty spillovers to commodity price volatility using ΔGST_t next.

3.2. Stock market uncertainty spillovers

3.2.1. Uncertainty spillovers and commodity price volatility

Having shown that coherence between ΔGST_t and ΔVIX_t has grown over time and that there is mostly a contemporaneous relationship between these indices which supports the stock market uncertainty narrative, we use ΔGST_t to model uncertainty spillovers to commodity price volatility. Fig. 3 points towards substantial stock market uncertainty spillovers to all volatility series over short horizons (32 days and less). All $V_{i,t}$ series exhibit sporadic but frequent coherence with ΔGST_t over this horizon implying that commodity price volatility series reflect short-term uncertainty originating from stock markets. For some series, notably energy, industrial metals and precious metals, the frequency of short-run coherence appears to increase towards the second half of the sample.

Spillovers to energy, industrial metals, livestock, precious metals and softs volatility series are most evident and persistent over medium- and long-term horizons (over 32 days) and coherences appear to grow over time for most commodities, with the exception of grains. As increased coherences over the medium and long run coincide with and correspond to significant events, we focus on these in the discussion that follows.

For energy commodities, coherence between the energy series and ΔGST_t is highly evident for medium- and longer-term horizons (regions A, B). Arrows predominantly point downwards in these periods, indicating that energy commodity return volatility responds to ΔGST_t. This points towards stock market uncertainty spilling over to energy commodity volatility. This finding is similar to that of Zhang et al. (2017) who report that the VIX transmits uncertainty to oil and natural gas markets (which form part of the Bloomberg energy index used in this study). This finding is also consistent with the broader literature that finds stock market volatility spillovers to energy commodities in general (Olson et al., 2014), and oil (Boubaker & Raza, 2017; Jebabli et al., 2021; Khalfaoui et al., 2019; Sarwar et al., 2019; Sarwar et al., 2020) and natural gas individually (Jebabli et al., 2021).

Smales (2021c) and Wen et al. (2021) document that periods of increased stock market uncertainty spillovers to oil and energy commodities coincide with economic, financial and geopolitical events. Studies find that spillovers from stock markets to commodity markets intensified during the global financial crisis (GFC), implying that links between asset markets increase during financial crisis (Boubaker & Raza, 2017; Khalfaoui et al., 2019; Olson et al., 2014). Coherence denoted by dark red in 2012 (region A) coincides with the after effects of oil price shocks of 2011, when oil averaged over $100 a barrel in part due to the Arab Spring and civil war in Libya (US Energy Information Administration (EIA), 2012). As our sample begins in January 2012, we view this as residuum of strong coherence. This is consistent with prior findings of increased volatility following uncertainty surrounding the Arab Spring (Chau, Deesomsak, & Wang, 2014) and increased spillovers from stock markets to oil markets during the Arab Spring (Amar et al., 2021; Jebabli et al., 2021; Mousavi & Ouenniche, 2014). Heightened spillovers from ΔGST_t to energy commodity volatility in early 2014, 2015–2016 (region B) and late 2017/early 2018 (region C) coincide with the Russian-Ukrainian conflict over Crimea (and subsequent sanctions on Russia), Russian involvement in Syria and geopolitical risk in Venezuela,[9] respectively. These events resulted in the oil price increasing as a result of rising uncertainty (Holodny, 2015; European Central Bank (ECB), 2018; Moran, 2022). Studies confirm increased stock market volatility (Baker et al., 2019; Indārs, Savin, & Lublóy, 2019) and document heightened volatility spillovers from stock to energy markets over these periods (Amar et al., 2021; Jebabli et al., 2021).

Stock market uncertainty spillovers to energy commodities strengthen over medium- and long-term horizons at the outbreak of the COVID-19 pandemic in early 2020 which coincided with the Russia-Saudi Arabia oil price war (region D). Amar et al. (2021), Jebabli et al. (2021) and Wen et al. (2021) document notable spikes in spillovers from stock markets to energy markets since the onset of the COVID-19 pandemic, with Jebabli et al. (2021) showing that spillovers from stock markets to energy commodities exceed those during the GFC. Adekoya and Oliyide (2021) confirm that during the COVID-19 outbreak from January to July 2020 there was increased connectedness between financial and commodity markets. Their findings suggest that the pandemic significantly raised uncertainty among investors and policy makers and altered the global financial cycle which in turn impacted flows of capital across asset markets. Dissipation over medium-run horizons seen in Fig. 3 is also consistent with patterns reported in these studies. These findings mirror literature that shows that COVID-19 magnified stock market uncertainty spillovers (Guru & Das, 2021; Yousfi, Zaied, Cheikh, Lahouel, & Bouzgarrou, 2021) and that uncertainty spillovers to other stock markets intensify during extreme market conditions (Cheuathonghua et al., 2019).

Uncertainty spillovers to grain volatility are mostly negligible over the long run. Periods of (relatively) stronger coherence occur only over medium horizons (regions A and B). During these periods, arrows predominantly point downwards indicating that grain return volatility responds to ΔGST_t (notably in region B). The timing of increased association between stock market uncertainty and grain volatility coincides with that observed for energy commodities (although to a far lesser extent) suggesting that these spillovers are also attributable to geopolitical, financial and/or economic events. Baldi et al. (2016), Ahmed and Huo (2021) and Wen et al. (2021) similarly report stock

[9] Agreements by OPEC and non-OPEC members to curb production going into 2018 may also have been a contributing factor (ECB, 2018).

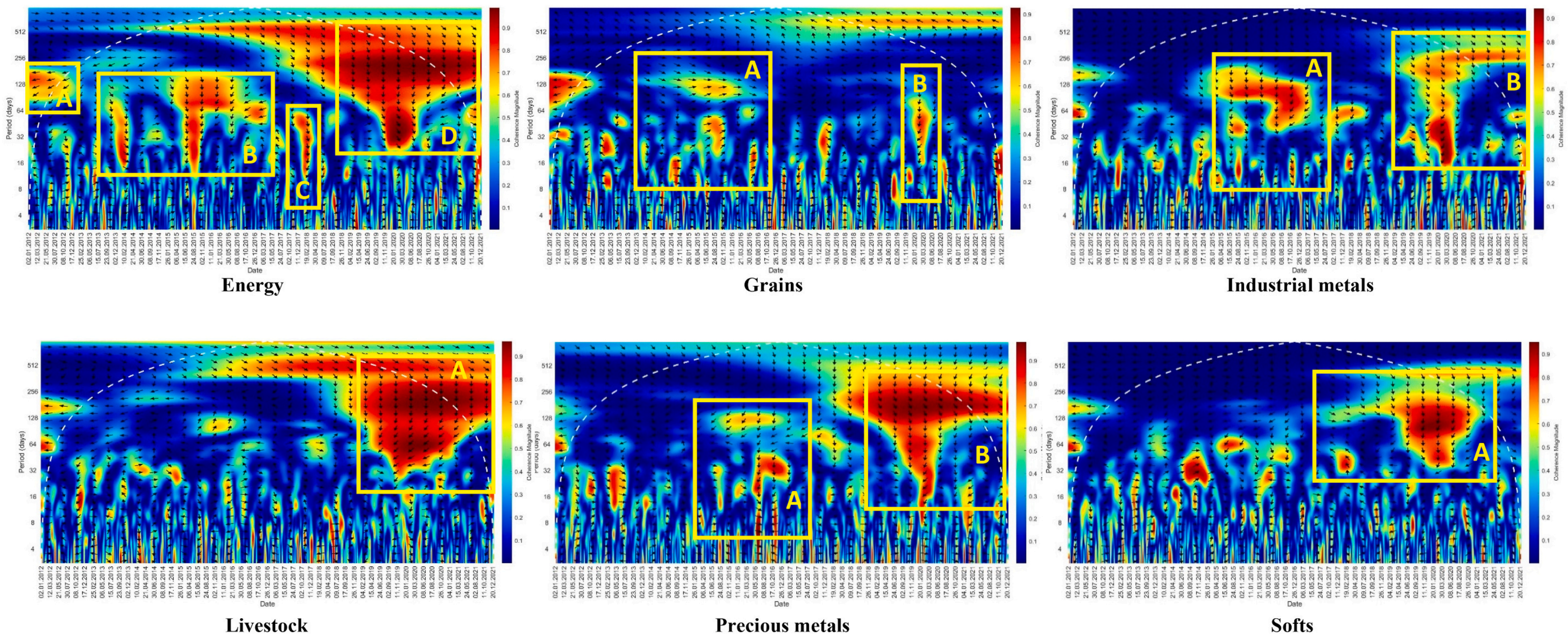

Fig. 3. Spectrogram for ΔGST_t and commodity realised volatility series, $V_{i,t}$

Notes: Fig. 3 reports spectrograms of $V_{i,t}$ for each commodity spot price index and ΔGST_t in three dimensions where time is on the horizontal axis, the frequency domain is on the vertical axis expressed in the number of days and wavelet coherence values (contour map). Higher frequencies indicate a longer investment horizon. Values of (roughly) between 1 and 32 days are defined as the short run, 33 to 128 days are defined as the medium run and values greater than 129 days are considered to represent the long run. Coherence takes on values between zero (0) and one (1), with one indicating maximum coherence and zero a lack thereof. Dark red areas are indicative of strong coherence whereas dark blue areas are indicative of no coherence where coherence can be interpreted as association between the two indices. The white dashed line indicates the 5% significance level for edge effects occurring in coherence data. A right (left) pointing arrow indicates that the two series are positively (negatively) correlated. A downward pointing arrow (including downward left and downward right) indicates that $V_{i,t}$ responds to ΔGST_t whereas an upward pointing arrow (including upward left and upward right) indicates that ΔGST_t follows $V_{i,t}$.

market spillovers to wheat and grains around these major events. However, the magnitude of spillovers reported in these studies is much larger. Differences suggest that stock market spillovers to grains are not driven to the same extent by stock market uncertainty (as is the case for energy) but instead reflect changing fundamentals linked to demand and supply (such as an economic recession or drought) (Gaetano, Emilia, Francesco, Gianluca, & Antonio, 2018).[10] This is consistent with these commodities representing necessities (International Grains Council, 2022) which are less likely to be impacted by uncertainty. Mensi et al. (2013) also find that spillovers from the S&P500 are much smaller for wheat than oil and gold.

Softs show a similar pattern to grains in terms of the timing, persistence and strength of spillover effects from stock market uncertainty, although with a notable difference. Stock market uncertainty at the time of the COVID-19 pandemic has a much greater and more persistent impact on softs' return volatility as suggested by greater coherence around the time of the outbreak of the pandemic towards the end of 2019 (region A). Softs and grains are similar in that they are grown (or farmed) rather than mined and thus a similar response to stock market uncertainty is not unexpected. However, significant spillovers at the time of the COVID-19 pandemic suggest that softs are more sensitive to uncertainty, possibly because they are less essential for consumers. The overall pattern of spillovers observed for softs resembles that reported by Wen et al. (2021) in their analysis of stock market spillovers to commodity markets, including the reaction to the COVID-19 outbreak.

For industrial metals and livestock, Fig. 3 reveals that contours are almost identical to those of softs, reflecting limited spillovers until periods of heightened geopolitical risk and the COVID-19 outbreak. Industrial metals show increased coherence with stock market uncertainty from mid-2015 to mid-2017 (region A). The Chinese stock market suffered substantial losses in the period 2015 to 2016 amidst an economic downturn, as global stock markets fell amidst fears that this downturn would trigger a global financial crisis (Duggan, 2015; Lahart, 2017). This uncertainty spilled over to industrial metals as demand for these commodities is heavily influenced by economic activities in China (Sedov & Budanov, 2017) but would also be impacted by a global downturn. Industrial metals also experienced stronger spillovers since the COVID-19 outbreak that persisted to the end of the sample (region A for livestock and region B for industrial metals). This may be due to the COVID-19 pandemic impacting uncertainty levels and global flows of capital (Adekoya & Oliyide, 2021) or it may suggest increased integration between stock and commodity markets in line with the growing financialisation of commodities (Adams & Glück, 2015; Baldi et al., 2016; Karyotis & Alijani, 2016; Zhang et al., 2017) (see Section 3.2.3 that follows). The volatility of both livestock and industrial metals also responds (is not contemporaneous) to ΔGST_t as indicated by downward arrows. These findings mirror those of Reboredo et al. (2021) who find that the livestock commodity class experiences low spillovers from stock markets, similarly to agricultural commodities, compared to industrial metals and energy which experience much larger spillovers from stock markets. The authors also report a substantial spike in spillovers from stock markets to commodities collectively during the peak of the COVID-19 crisis in 2020.

Increased coherence for industrial metals beginning in 2020 can be attributed to their role in construction and production. A consequence of the COVID-19 pandemic was a slowdown in global economic activity, amplified by lockdowns and uncertainty about its consequences. It follows that the accompanying decline in real activity would impact the demand for materials used in the construction and production of goods and would be exacerbated by lockdowns and economic uncertainty. Moreover, the demand for many of these metals soared due to their role in the green economy transition,[11] likely making them more susceptible to market uncertainty. Díaz, Hansen, and Cabrera (2021) confirm that copper price volatility is impacted by uncertainty as measured by VIX, EPU and geopolitical risk. Wen et al. (2021) show no spillovers from stock markets to industrial metals, except for a brief spike around 2015, and then a strong and relatively sustained impact from 2020 into 2021 (although tapering). The pattern reflected in Fig. 3 for industrial metals coincides with that noted by Wen et al. (2021); increased association towards the end of 2019/beginning of 2020 that is followed by a tapering from mid-2020 onwards.

Finally, for precious metals, the response is weaker relative to energy commodities but significant at the same points over the medium and long horizons suggesting that it is also driven by geopolitical risk, financial and economic events. While gold is often seen as a safe haven during times of uncertainty (Uddin et al., 2020), research has shown that other precious metals such as silver, platinum and palladium also act as a safe haven at various times (Lahiani, Mefteh-Wali, & Vasbieva, 2021; Li & Lucey, 2017). Although returns on precious metals may provide a safe haven, this does not preclude uncertainty spillovers resulting in heightened volatility. Specifically, we observe increased coherence which suggests persistent spillovers from mid-2016 to mid-2017 (region A) and from early 2020 to the end of the sample period (region B). The first period can again be attributed to rising geopolitical risk around Russia's involvement in the 2016 U.S. presidential elections and North Korea's nuclear programme prompting more aggressive actions (sanctions and other measures) from the U.S. government. Such fears caused movements away from risky assets and into assets considered safe havens (Caplinger, 2017). The second period of increased spillovers from stock market uncertainty to precious metals coincides with the outbreak of COVID-19. The gold price soared as investors fled stock markets at the outbreak of the pandemic and other precious metal prices also saw renewed investment following the easing of lockdowns (Koh & Baffes, 2020). Gao, Zhao, and Zhang (2021) show that another uncertainty index, the EPU, is also associated with substantial spillover effects to gold and that this intensified during the GFC. The evidence for overall stock market spillovers to precious metals is somewhat more mixed, with Ahmed and Huo (2021) finding that gold is largely immune to stock market spillovers. This contrasts with Wen et al. (2021) who observe substantial spillovers to precious metals including during the COVID-19 period. Our results are in line with those of Wen et al. (2021), pointing towards the presence of uncertainty spillovers to precious metal price volatility.

Overall, the analysis of medium- and long-term spillovers suggests that 1) ΔGST_t can be considered a proxy for stock market uncertainty and provides support for the analysis in Section 3.1 and 2) that ΔGST_t can be used to model uncertainty spillovers between asset markets. Periods of increased coherence over medium- and long-run horizons coincide with significant events, geopolitical, financial and economic in nature. Uncertainty spillovers appear to strengthen during times of crisis and tend to persist. Spillovers into commodity price volatility are most evident towards the end of the sample period, coinciding with the outbreak of the COVID-19 pandemic. Encouragingly, our observations are similar to those of other studies of spillovers from stock to commodity markets. We also note that there are sporadic increases in coherence over short horizons for all commodities suggesting that commodity price volatility reflects short-term increases in stock market uncertainty reflected by ΔGST_t. Not all commodities appear to be similarly sensitive to spillovers. Energy volatility is most reflective,

[10] Brümmer, Korn, Schlüßler, and Jamali Jaghdani (2016) study the drivers of price volatility for oilseeds and vegetable oils. Although they find that volatility in the dollar exchange rate is one of the main determinants, weather and stock levels also play a role.

[11] For example, copper (widely used in the production of electronic devices), lithium (batteries), aluminium and silver (solar panels, wind turbines) and cobalt (a catalyst used in the production of clean fuels) are key metals in the move to greener technologies.

followed by livestock and precious metals whereas grains appear to be least impacted by prevailing uncertainty.

3.2.2. Uncertainty spillovers and the VIX

We compare spillover patterns for ΔVIX_t to those for ΔGST_t in Fig. 3 to confirm that ΔGST_t reflects stock market uncertainty. In Fig. 4, spectrograms for ΔVIX_t are closely comparable to those for ΔGST_t, especially towards the end of the sample. This implies that both have a similar association with realised volatility series. Similarly to ΔGST_t, ΔVIX_t spillovers are most notable for the energy volatility series, followed by livestock and precious metals whereas grains are least impacted. The strength and patterns of coherence do however differ somewhat, this being more noticeable during the first half of the sample. This is observable over the medium-term horizon for the energy, industrial metals, precious metals and softs commodity volatility series (see regions denoted as A for these respective commodities in Fig. 4). We expect this to be the case; ΔVIX_t and ΔGST_t are not perfectly interchangeable. The ΔVIX_t is based upon the Standard and Poor's 500 Index (SPX) and reflects expected volatility by aggregating weighted prices of SPX puts and calls over a wide range of strike prices (CBOE, 2021). In contrast, ΔGST_t is a keyword-based proxy for stock market uncertainty. We also note in Fig. 2 that coherence between ΔVIX_t and ΔGST_t grows significantly from the end of 2017 onwards (regions E, F, G and H). Prior to the end of 2017, notable periods of coherence arise although these are shorter in duration and somewhat weaker (notably regions B and C in Fig. 2). Nevertheless, overall patterns of coherence are comparable across both measures in Figs. 3 and 4 and observed differences are minor. Importantly, periods of strengthened coherence correspond to the significant events identified in Section 3.2.1. across both measures and commodity groupings.

Next, we investigate whether the informational content reflected by ΔVIX_t is similar to that reflected by ΔGST_t. To isolate the impact of ΔGST_t, we apply partial wavelet coherence (Hu & Si, 2021; Mihanović, Orlić, & Pasarić, 2009), which corresponds to partial correlation in time-series analysis. This approach permits us to estimate the resulting association between two variables, ΔVIX_t and $V_{i,t}$, after eliminating a common factor. In this instance, the factor that we postulate is common is ΔGST_t. Partial wavelet coherence is defined as follows:

$$R^2_{x1,x2,z} = \frac{\left|R_{x1,x2}(s,\tau) - R_{x1,z}(s,\tau)R_{z,x2}(s,\tau)^*\right|^2}{\left(1 - R^2_{x1,z}(s,\tau)\right)\left(1 - R^2_{x2,z}(s,\tau)\right)} \tag{4}$$

where $x_{1,t}$ now becomes $V_{i,t}$, $x_{2,t}$ is ΔVIX_t and z_t becomes ΔGST_t. If ΔGST_t reflects similar information to ΔVIX_t, coherence between the ΔVIX_t and realised volatility should decrease substantially. Any remaining coherence will be the result of residual information not captured by ΔGST_t.

Spectrograms, reported in Fig. A1 of the Appendix, indicate a significant reduction in coherence across all horizons for all commodity volatility series. This is further evidence, in addition to the comparison of coherence patterns in Figs. 3 and 4, of common informational content related to stock market uncertainty in both ΔVIX_t and ΔGST_t. Remaining residual coherence is expected given that ΔVIX_t is derived from stock market data whereas ΔGST_t is an indirect proxy for stock market uncertainty.

3.2.3. Increasing spillovers: Integration or COVID-19?

An interesting observation in Fig. 3 is that the impact of spillovers appears to have grown over time as suggested by extended periods of strong coherence towards the end of the sample, most notable for the energy, livestock, precious metals, industrial metals and softs volatility series (see regions D, A, B, A, and A, respectively). There are potentially two reasons for this. The first is that there is increasing integration between stock and commodity markets, as a result of the financialisation of commodity markets with commodities becoming a popular asset class for investors similarly to stocks and bonds. This implies that during times of crisis, investors are more likely to rebalance their portfolios by selling stocks and purchasing safe haven assets which include certain commodities and shorting other commodity types (i.e. agricultural commodities) as a result of changes in risk appetite (Adams & Glück, 2015; Baldi et al., 2016; Cheng, Kirilenko, & Xiong, 2015; Cheng & Xiong, 2014; Karyotis & Alijani, 2016; Zhang et al., 2017). In this instance, increasing integration would imply that spillovers have an increasing and more persistent impact on commodity price volatility over time. The second is that increased coherence towards the end of the sample period is driven by uncertainty around the COVID-19 pandemic. COVID-19-related uncertainty may have a disproportionate impact given its unprecedented nature. To investigate whether integration or spillovers of COVID-19-related uncertainty account for increased coherence towards the end of the sample, we control for COVID-19-related uncertainty by using the GST-based COVID-19 uncertainty[12] index of Szczygielski, Bwanya et al. (2021) and Szczygielski, Brzeszczyński et al. (2022) and estimate partial coherences for the volatility series and ΔGST_t.

Fig. 5 shows that controlling for the impact of COVID-19-related uncertainty results in a reduction in medium- and long-horizon coherence towards the end of the sample period across all realised volatility series. Reductions are most notable for energy, industrial metals, livestock, precious metals and softs. Grains also show a reduction in coherence, although the strength and duration of coherence was minor to begin with (see region A in Fig. 5 for all commodity indices). This suggests that high levels of coherence towards the end of the sample are likely to have been driven by COVID-19. To confirm that is the case and that the second GST-based index considered, $\Delta CV19_t$, isolates the impact of COVID-19-related uncertainty, we plot coherence between $\Delta CV19_t$ and ΔVIX_t below.

Fig. 6 indicates that for all horizons there is an association between $\Delta CV19_t$ and ΔVIX_t from the beginning of 2020, the approximate start of COVID-19. We view this as confirmation that $\Delta CV19_t$ reflects COVID-19-related uncertainty. The coherence pattern in Fig. 6 approximates that observed towards the end of the sample for energy (region D in Fig. 3), livestock (region A) and precious metals (region B), and to a lesser degree for industrial metals (region B) and softs (region A). Fig. 6, together with Figs. 3 and 5, indicates that by using $\Delta CV19_t$ – which is a topic specific GST-based index unlike ΔGST_t which is general – we are able to isolate the impact of COVID-19-related uncertainty.

The spectrograms in Fig. 5 suggest that some commodities continue to reflect increasing uncertainty spillovers towards the end of the sample, even after accounting for uncertainty associated with COVID-19. While coherence weakens significantly for grains, industrial metals and softs, for energy, livestock and precious metals, coherence remains more protracted and of a greater magnitude than that observed during the first half of the sample. This suggests that volatility for these commodities increasingly reflected stock market uncertainty during the second part of the sample (that is not COVID-19 specific), pointing towards increasing integration with stock markets for these three commodities.

[12] Individual terms comprising this index are "coronavirus", "COVID19", "COVID 19", "COVID", "COVID-19", "SARS-CoV-2", "SARS-COV", "severe acute respiratory syndrome-related coronavirus" and "severe acute respiratory syndrome". Each shows rising search volumes shortly after 16 December 2019. An overall search term index is constructed by combining trends for the terms above. Index values are then differenced to obtain the COVID-19-related uncertainty index. Szczygielski et al. (2021) and Szczygielski, Brzeszczyński et al. (2022) demonstrate that this index is correlated with ΔVIX_t and other general measures of COVID-19-related uncertainty from the beginning of the COVID-19 period and also exhibits co-movements in levels with these alternative measures.

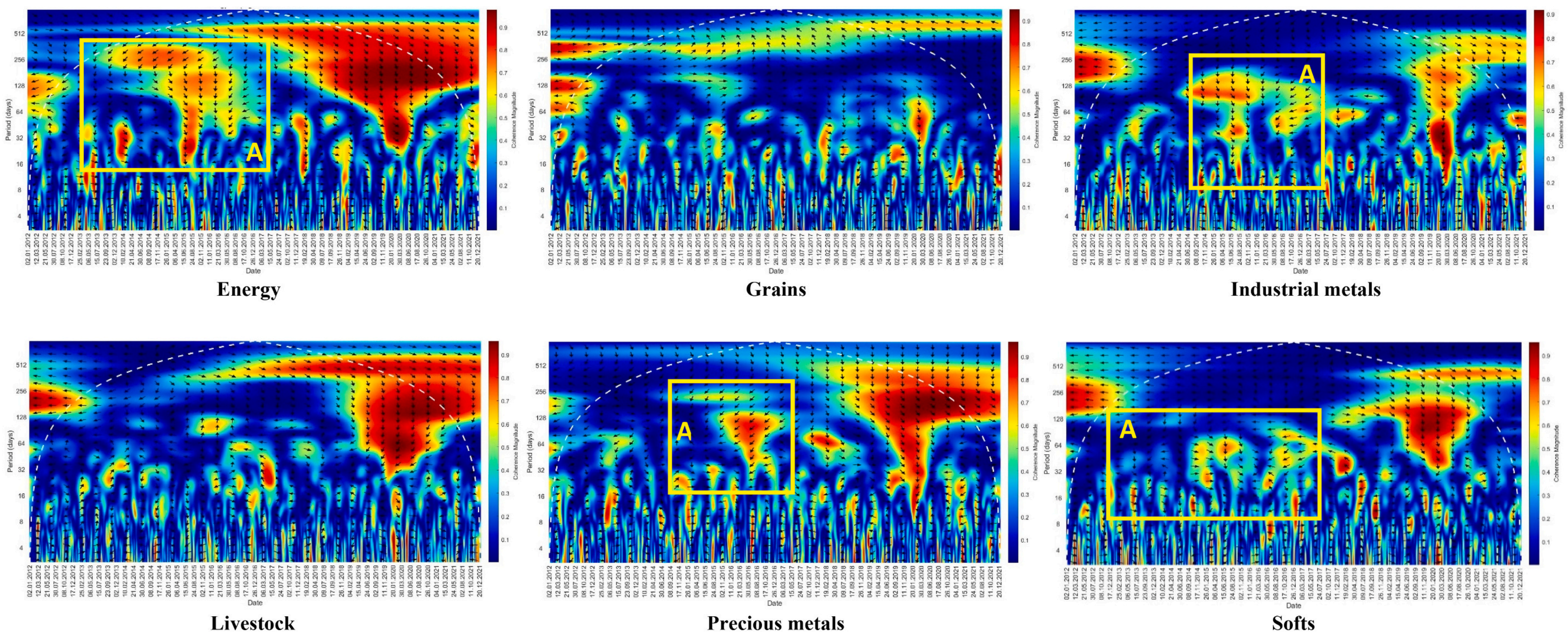

Fig. 4. Spectrograms for ΔVIX_t and commodity realised volatility series, $V_{i,t}$

Notes: Fig. 4 reports spectrograms for $V_{i,t}$ series for each commodity spot price index and ΔVIX_t in three dimensions where time is on the horizontal axis, the frequency domain is on the vertical axis expressed in the number of days and wavelet coherence values (contour map). Higher frequencies indicate a longer investment horizon. Values of (roughly) between 1 and 32 days are defined as the short run, 33 to 128 days are defined as the medium run and values greater than 129 days are considered to represent the long run. Coherence takes on values between zero (0) and one (1), with one indicating maximum coherence and zero a lack thereof. Dark red areas are indicative of strong coherence whereas dark blue areas are indicative of no coherence where coherence can be interpreted as association between the two indices. The white dashed line indicates the 5% significance level for edge effects occurring in coherence data. A right (left) pointing arrow indicates that the two series are positively (negatively) correlated. A downward pointing arrow (including downward left and downward right) indicates that $V_{i,t}$ responds to ΔVIX_t whereas an upward pointing arrow (including upward left and upward right) indicates that ΔVIX_t follows $V_{i,t}$.

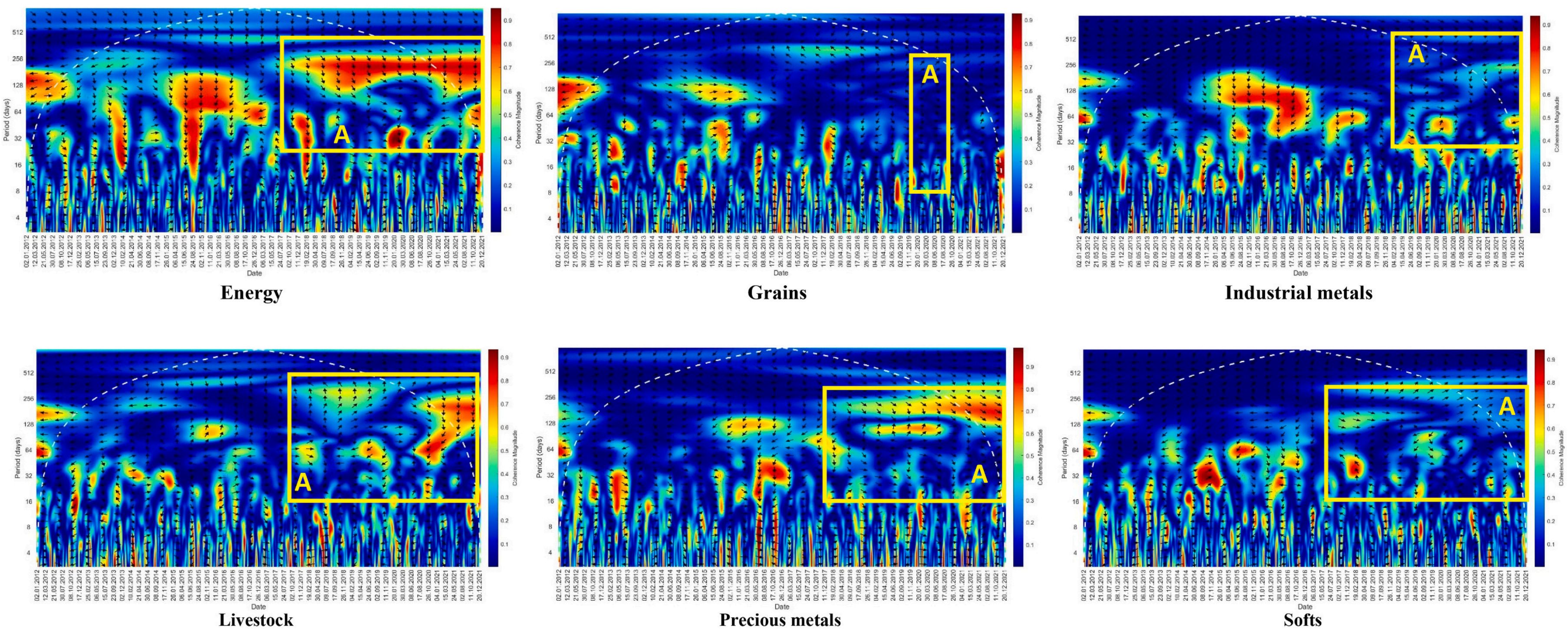

Fig. 5. Spectrograms for ΔGST_t and commodity realised volatility series, $V_{i,t}$, after adjusting for COVID-19-related uncertainty, $\Delta CV19_t$

Notes: Fig. 5 reports spectrograms for $V_{i,t}$ for each commodity spot price index and ΔGST_t in three dimensions after controlling for the influence of COVID-19-related uncertainty measured using GST, $\Delta CV19_t$, where time is on the horozontal axis, the frequency domain is on the vertical axis expressed in the number of days and wavelet coherence (contour map). Higher frequencies indicate a longer investment horizon. Values of (roughly) between 1 and 32 days are defined as the short run, 33 to 128 days are defined as the medium run and values greater than 129 days are considered to represent the long run. Coherence takes on values between zero (0) and one (1), with one indicating maximum coherence and zero a lack thereof. Dark red areas are indicative of strong coherence whereas dark blue areas are indicative of no coherence where coherence can be interpreted as association between the two indices. The white dashed line indicates the 5% significance level for edge effects occurring in coherence data. A right (left) pointing arrow indicates that the two series are positively (negatively) correlated. A downward pointing arrow (including downward left and downward right) indicates that $V_{i,t}$ responds to ΔGST_t whereas an upward pointing arrow (including upward left and upward right) indicates that ΔGST_t follows $V_{i,t}$.

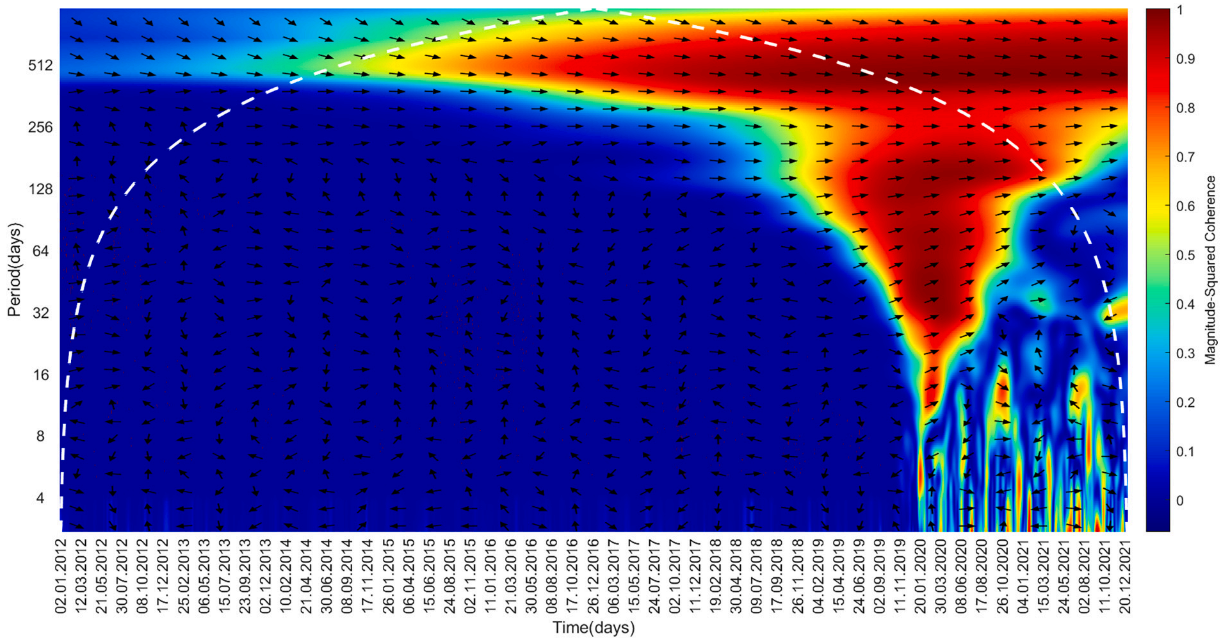

Fig. 6. Spectrogram for $\Delta CV19_t$ and ΔVIX_t

Notes: Fig. 6 presents a spectrogram for $\Delta CV19_t$ and ΔVIX_t in three dimensions where time is on the horizontal axis, the frequency domain is on the vertical axis expressed in the number of days and wavelet coherence values (contour map). Higher frequencies indicate a longer investment horizon. Values of (approximately) between 1 and 32 days are defined as the short run, 33 to 128 days are defined as the medium run and values greater than 129 days are considered to represent the long run. Coherence takes on values between zero (0) and one (1), with one indicating maximum coherence and zero a lack thereof. Dark red areas are indicative of strong coherence whereas dark blue areas are indicative of no coherence where coherence can be interpreted as association between the two indices. The white dashed line indicates the 5% significance level for edge effects occurring in coherence data. A right (left) pointing arrow indicates that the two series are positively (negatively) correlated. A downward pointing arrow (including downward left and downward right) indicates that $\Delta CV19_t$ responds to ΔVIX_t whereas an upward pointing arrow (including upward left and upward right) indicates that ΔVIX_t follows $\Delta CV19_t$.

4. Implications and discussion

Keyword-based indices, which include GST indices, and their association with stock markets is an increasingly popular topic of research. A limitation of such indices lies in the ambiguity about the narrative that they represent. Do they reflect sentiment, attention or uncertainty? The analysis in Section 3.1. demonstrates that there is a growing association between the VIX and GST over time that persists across different time horizons and is most notable over the medium and long term. This is evidence that GST reflect uncertainty. Additional support is provided by spillover patterns for GST and realised commodity price volatility which closely resemble coherence patterns between the VIX and GST in Fig. 4 (Section 3.2.2.). 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 application. In this study, we uncover and demonstrate a clear uncertainty narrative. A clear narrative will aid in the application of GST-based indices in investment management, market analysis and portfolio analysis.

A key question within the finance discipline is what information impacts asset markets. The GST index used in this study comprises neutral keywords related to stock markets and can be viewed as a general proxy for stock market uncertainty. However, GST differ from other existing and established measures of uncertainty, such as the VIX, which can be seen as reflecting *general* information about risk and risk aversion (Bekaert et al., 2013). GST, given their nature, can reflect uncertainty around a *specific* event, depending upon the keywords used in the construction of the index. In this study, we also quantify COVID-19-related uncertainty spillovers using GST (Section 3.2.3.) to isolate uncertainty associated with COVID-19. We find that for certain commodities, extensive uncertainty spillovers are the result of COVID-19 towards the end of the sample period. Commodities that are significantly impacted by COVID-19 are energy, livestock, precious metals, industrial metals and softs. In contrast, the impact on grains is minor. By using GST, econometricians and analysts can decompose the effects of uncertainty associated with specific events or categories of events such as wars, geopolitical risk and recessions. Such knowledge may be useful to investors aiming to avoid volatility associated with specific events or categories of events and extends its potential application beyond studying cross-market volatility spillovers.

We also demonstrate an alternative approach to analysing relationships between variables. The "workhorse" of financial econometrics is regression analysis. Traditional regression analysis can be used to establish short- and long-term relationships by estimating relationships between differenced series or cointegrated series (Shahbaz, Lahiani, Abosedra, & Hammoudeh, 2018). However, it does not provide a comprehensive overview at different horizons. Wavelet coherence permits us to analyse relationships at various horizons, without restricting us to specific horizons and reflects associations between variables of interest diagrammatically. Several other studies have used variations of wavelet analysis to examine co-movement across asset classes (such as Zaremba et al., 2019; Bouri et al., 2020; Mensi et al., 2021). For example, in Section 3.2.1., we observed that ΔGST_t reflects short-term uncertainty which spills over to commodity realised volatility series. However, we are also able to observe the effects of spillovers over the medium and long term. Periods of heightened volatility coincide with events that are of a geopolitical, financial and economic nature. Furthermore, by relying on spectrograms, we can not only observe the impact of specific events (see Section 3.2.1.) but can also quantify persistence of uncertainty over longer horizons. In our analysis, we observed (and also confirmed) that COVID-19 resulted in the largest and most persistent uncertainty spillovers into commodity return volatility over different horizons. Such information is valuable from an analytical perspective.

Relatedly, by using wavelet analysis and GST, we are also able to observe the evolving relationship between stock and commodity markets. In Section 3.2.1., we observe that coherence is stronger towards the end of the sample, especially over medium- and long-term horizons. We then argued in Section 3.2.3. that this could be the result of the financialisation of commodity markets or driven by COVID-19. We proceeded to isolate the impact of COVID-19 by using COVID-19-related GST that have been shown to reflect uncertainty related to the pandemic. This is possible because of the nature of GST-based proxies which rely upon specific keywords (see preceding discussion). We observe that energy, livestock and precious metals continue to reflect increased uncertainty spillovers during the second half of the sample to a greater extent than in the first half of the sample. As we adjust for the impact of COVID-19-related uncertainty, this implies that remaining spillovers can potentially be attributed to increased interdependence between these commodities and stock markets stemming from the financialisation of commodities. This form of analysis offers an alternative approach to investigating relationships between asset markets and can be extended to gain a more detailed insight into the integration between international stock markets which will not be obtained using regression or correlation analysis. Such knowledge may be useful when designing international diversification strategies.

Finally, the analysis undertaken in this study using wavelet coherence yields insights that can assist investors in making investment decisions. Specifically, our analysis indicates that not all commodities are equally impacted by uncertainty in stock markets. Commodities that appear to be more resilient to uncertainty spillovers are grains and industrial metals (Fig. 3). Spillovers appear to have a less persistent impact on variance for these two commodities and this is also the case for the COVID-19 period. A similar observation can be made for softs although this commodity class is impacted by spillovers during the COVID-19 period to a greater extent than grains and industrial metals. However, for most of the sample period until the COVID-19 period, this commodity group is relatively insulated from uncertainty. The same may be said about livestock in relation to the first half of the sample period although livestock commodities show a very significant response to COVID-19. Our analysis suggests that if investors wish to avoid stock market-related uncertainty, they should consider investing in grain commodities and also potentially in softs and industrial metals.

5. Conclusion

In this study, we bring two strands of literature together. We study the impact of stock market uncertainty on commodity markets using a keyword-based measure in the form of GST to proxy for stock market uncertainty. The index that we use differs in a number of important respects relative to other keyword-based indices constructed using Google data and also Twitter and news headlines. Our index is neutral in that there is no narrative that is imposed in its construction, it is stock market specific, spans a period of 10 years and is of a daily frequency. Before we model spillovers, we show that stock market-related GST increasingly reflect an uncertainty narrative, this likely attributable to increased accessibility and utilisation of Google by investors and the broader public. To confirm the uncertainty narrative by investigating the relationship between the GST index and VIX, we apply wavelet analysis which offers a different perspective from traditional regression analysis. We then demonstrate that GST can be used to model uncertainty spillovers in commodity markets and go on to show that using the VIX produces similar results, and that GST reflects information that is common to both the VIX and GST. This is further confirmation of the uncertainty narrative reflected by GST measures. We find that not all commodities reflect stock market uncertainty spillovers to the same extent. Energy commodities appear to be most vulnerable whereas grains are least susceptible. Using GST to proxy for uncertainty allows us to demonstrate that GST can proxy for general and event-specific uncertainty. Our analysis points towards growing integration between stock and some commodity markets even after COVID-19-related uncertainty is taken into consideration.

Our study has a number of implications that may be of interest to econometricians, researchers, analysts and investors. By undertaking this study, we shed light on the nature of GST and the relationship between commodity markets and GST using wavelet coherence. For researchers in general, we contribute to the discussion about the nature of information reflected in GST. This is important, given the recent proliferation of studies that use GST to model the behaviour of financial assets. For practitioners and investors, we provide further evidence indicating that GST can be used to reflect general stock market uncertainty and show that GST can also reflect uncertainty that is associated with specific events. This has the potential to open further avenues of research on the impact of specific events on asset markets. We hope that these findings and the ease with which Google data can be obtained motivate practitioners and investors to develop Google-based indices and to apply these indices for the purposes of analysis, measurement and investment management. The application of GST in practice is an area for further research. Finally, for econometricians, we demonstrate the application of wavelet analysis which offers a diagrammatic representation of the relationship between variables over multiple (and readily customisable) horizons. Additionally, this form of analysis also offers a perspective that differs from that provided by traditional econometric analysis. Using diagrams to represent relationships constitutes a form of analysis that is potentially more accessible to non-econometricians.

CRediT authorship contribution statement

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

Declaration of Competing Interest

None.

Data availability

Data will be made available on request.

Appendix

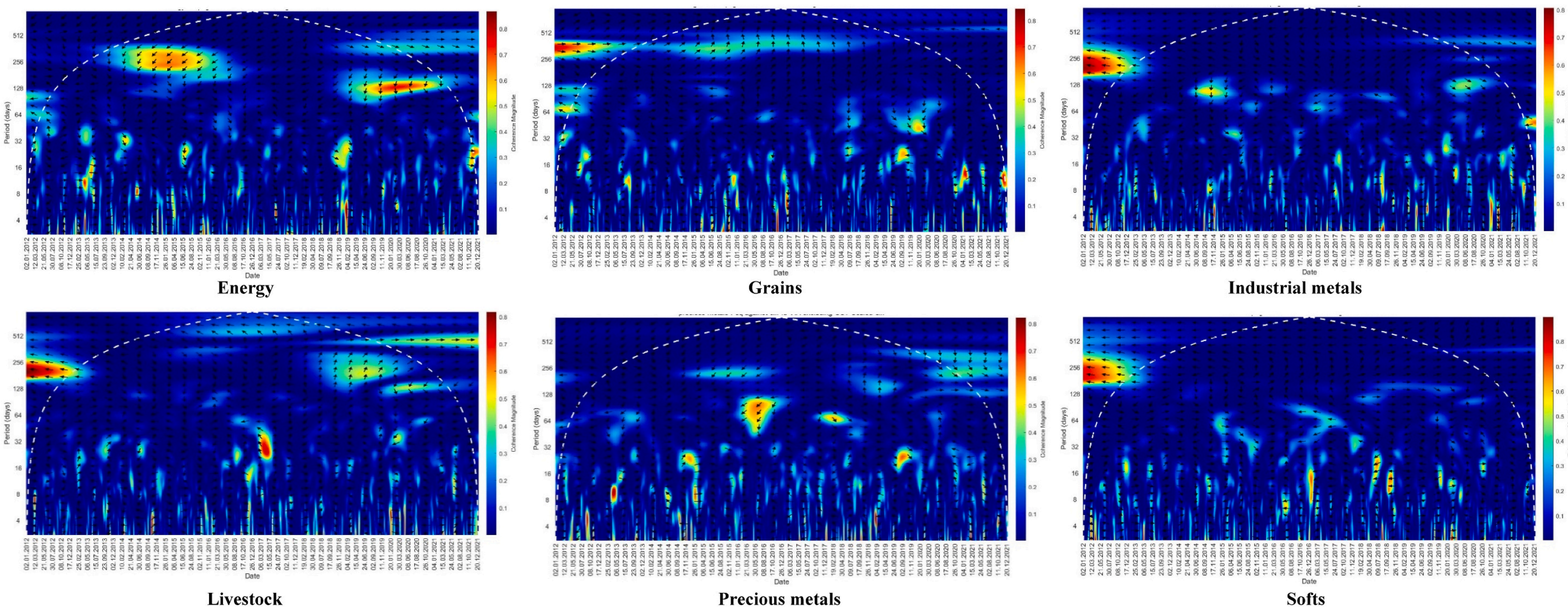

Fig. A1. Spectrogram for ΔVIX_t and commodity realised volatility series, $V_{i,t}$, after adjusting for the effects of ΔGST_t

Notes: Fig. A1 reports spectrograms for $V_{i,t}$ for each commodity spot price index and the ΔVIX_t in three dimensions after controlling for the influence of ΔGST_t where time is on the horizontal axis, the frequency domain is on the vertical axis expressed in the number of days and wavelet coherence values (contour map). Higher frequencies indicate a longer investment horizon. Values of (roughly) between 1 and 32 days are defined as the short run, 33 to 128 days are defined as the medium run and values greater than 129 days are considered to represent the long run. Coherence takes on values between zero (0) and one (1), with one indicating maximum coherence and zero a lack thereof. Dark red areas are indicative of strong coherence whereas dark blue areas are indicative of no coherence where coherence can be interpreted as association between the two indices. The white dashed line indicates the 5% significance level for edge effects occurring in coherence data. A right (left) pointing arrow indicates that the two series are positively (negatively) correlated. A downward pointing arrow (including downward left and downward right) indicates that $V_{i,t}$ responds to ΔVIX_t whereas an upward pointing arrow (including upward left and upward right) indicates that ΔVIX_t follows $V_{i,t}$.

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