Recession fears and stock markets: an application of directional wavelet coherence and a machine learning-based economic agent-determined Google fear index.

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Abstract

Recession fears play a pivotal role in investment decision-making and policy development aimed at reducing the likelihood of a recession and managing its impact. Using machine learning, we develop an economic agent-determined daily recession fear index using Google searches that isolates recession-related fears from overall stock market uncertainty. We study the evolving impact of recent recession fears on stock markets using directional wavelet analysis that distinguishes between positive and negative associations. Recession fears negatively impact world and G7 stock markets and trigger heightened volatility, with Japan being the most resilient. Monetary policy tightening in response to record inflation levels significantly contributes to persistent recession fears, suggesting that policymakers should consider co-ordinating responses to avoid an excessive global economic slowdown. Our methodology offers a high frequency monitoring tool that can be applied to analyse evolving relationships between variables and can be generalised to study the influence of specific events on financial markets by isolating topic-specific components from general proxies for uncertainty, attention or sentiment.

Keywords: recession fears, uncertainty, elastic net regression, machine learning, Google search, directional wavelet analysis

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1. Introduction

Events since December 2021 have triggered recession fears globally. The perceived likelihood of Russia invading Ukraine increased significantly towards the end of December 2021 as Russia threatened a military response if its demands, which included Ukraine abstaining from NATO membership and NATO reducing its presence in Eastern Europe, were not met (Roth, 2021). While energy prices were already rising due to shortages attributable to the post-COVID-19 economic recovery and climatic conditions (i.e., the European wind drought of 2021), prices soared in response to a deteriorating security situation with natural gas prices reaching record highs. Oil prices increased sharply following the outbreak of the Russia-Ukraine war in February 2022 and the conflict resulted in rising wheat, fertilizer and metal prices. Natural gas and coal prices reached unprecedented highs driven by supply shortages (Logan, 2022).[1]

Inflation accelerated to unparalleled levels in the United States (U.S.), Europe, Brazil and Turkey, among other countries, due to pent-up consumer spending, low interest rates, global supply chain disruptions and rising energy and food prices. In response to surging inflation, central banks (75 in total) raised interest rates (Smialek & Nelson, 2022). Rapid and sizeable interest rate increases by the U.S. Federal Reserve (the Fed) led to the U.S. yield curve inverting in March 2022, signalling growing expectations of an economic slowdown. As of July 2023, yield curve inversion reached levels not seen since 1981. Economic contractions began occurring worldwide, such as in Germany, France and Brazil, fuelling fears of a global recession. Furthermore, U.S. consumer confidence diminished in the face of rising inflation and tight monetary policy, coupled with dwindling surplus savings accumulated during the COVID-19 pandemic which partially shielded the U.S. economy from the difficult economic

[1] We would like to thank the participants of the 31st Southern African Finance Association Conference (January 2023, Cape Town, South Africa), the 2nd Spring Workshop on Fintech (April 2023, Ghent, Belgium) for comments and suggestions that assisted in improving this manuscript.

conditions (Moore, 2023; Ngo, 2022; Randall & Barbuscia, 2023). China's weak economic recovery and property market crisis also raised concerns globally (Yao & Cash, 2023).

These factors are amongst a multitude of factors that contributed to an unprecedented economic situation characterised by energy price shocks, high inflation and restrictive monetary policy which led to growing recession fears. Google searches for the term "recession" reflect this, reaching a new peak since the COVID-19 pandemic in March 2020, commensurate with levels seen during the 2008-2009 Global Financial Crisis (GFC). Since December 2021, various events have heightened concerns about a recession with a number of these, including oil price shocks and unexpected monetary policy tightening, often signalling the onset an economic downturn (Leduc & Sill, 2004; Stock & Watson, 2012; Kilian & Vigfusson, 2017).

Fear is an important driver of stock returns. In response to rising fear, investors lower future cash flow expectations and risk aversion increases, translating into a higher required risk premium (Baker & Wurgler, 2007). Consequently, increased fear levels are inversely related to stock market returns. Increased fear also contributes to heightened volatility due to greater market noise (Black, 1986). A common financial market "fear gauge" reflecting stock market uncertainty is the Chicago Board of Exchange (CBOE)'s Volatility Index (VIX) (Bekaert & Hoerova, 2014). Using the VIX, the theoretical expectation of fear exerting a negative influence on both current and future stock returns and contributing to increased volatility has been validated (Whaley, 2009; Smales, 2017a). The impact of fear intensifies during crisis periods such as the GFC and COVID-19 (Smales, 2017a; Just & Echaust, 2020). Fear can also be quantified using indices that reflect the frequency of internet and media searches for fear-related terms. Economic psychology suggests that economic agents intensify their search for information to reduce fears (Vasileiou, 2022; Liu et al. 2023). For example, Da et al.'s (2015) Google search-based fear index, called the Financial and Economics Attitudes Revealed by Search (FEARS) index, comprises negative financial and economic terms (e.g., "recession", "unemployment", "bankruptcy"). Movements in this index have a greater impact on S&P500 returns than the VIX.

General fear proxies, such as the VIX and FEARS, reflect various sub-components of fear, such as stock market, recession and health-related fears. Specific components can, however, be quantified and isolated using topic-specific Google searches (Smales, 2021; Szczygielski et al., 2022). John and Li (2021) emphasize the importance of studying the impact of various fear components as market participants respond differently to different information. Recession fears are a critical component of aggregate fear given that investors consider the macroeconomic outlook when valuing companies. Recession risk is typically measured using survey estimates (such as the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters) or probability models that utilise financial market variables including the yield curve slope, leading economic indicators (such as initial unemployment insurance claims) or the macroeconomic state (Estrella & Mishkin, 1998; Benzoni et al., 2018;

Engstrom & Sharpe, 2019; Davig & Hall, 2019; Kiley, 2022a). Probability models provide a likelihood assessment of a recession occurring. Although Powell and Treepongkaruna (2012) refer to these probability assessments as *ex-ante* estimates of recession fears, they, similarly to survey forecasts, do not quantify the emotional response of market participants to the perceived threat of a recession.[2] Instead, they quantify the response to news which may signal an increased likelihood of a recession (Gilbert & Karahalios, 2010; Audrino et al., 2020). Even if these probability assessments are used to gauge recession fears, they are available monthly or quarterly due to variable input frequencies (Kiley, 2022b). The alternative to quantifying recession fears is to use a broad high-frequency measure of stock market uncertainty such as the VIX which reflects a plethora of other fears and does not directly isolate recession fears (Tsai, 2014).

In this study, we isolate and quantify recession fears using daily Google searches and examine the impact thereof on world and G7 stock returns and volatility during the post-COVID-19 period. Our analysis of this period is motivated by several notable events that define it, offering insight into the evolution of recession fears at a high frequency and their effect on global markets. Notable events include the economic rebound following the COVID-19 pandemic, rising interest rates in response to rapidly increasing inflation, the outbreak of a conflict in Europe – the first major European conflict since World War 2 - and its widespread consequences and, what has been described as the world's first global energy crisis (Marchant & Chainey, 2022). This period is characterised by a heightened sense of uncertainty, with concerns about an economic downturn abounding.

Our study contributes in several ways. First, we add to the literature on the construction and application of internet search-based fear indices. We quantify recession fears by developing an explanatory Google search-based index comprising recession-related terms selected using elastic net regression, a machine learning methodology. Google searches can be viewed as a measure of uncertainty or fear surrounding a *specific* topic. This follows from economic agents searching more intensively for information when faced with greater uncertainty (see Liemieux & Peterson, 2011; Donadelli, 2015). For example, COVID-19-related Google searches have been used to reflect pandemic-related fears (Chen et al., 2020; Vasileiou, 2022). An advantage of using internet searches is that they can be used to isolate and quantify fears around a specific topic because they reflect economic agent concerns and state of mind (John & Li, 2021; Szczygielski, Charteris & Obojska, 2023). The risk of an economic recession is of major concern for financial market participants and policymakers and fears will be reflected in overall uncertainty proxies such as the VIX. General fear proxies such as the VIX are used to quantify recession fears during periods when recession fears abound (see Tsai, 2014). However, the usefulness of such proxies in reflecting recession fears is limited by their tendency to also capture confounding events that

[2] Variables that are utilized in probability models, such as the yield curve, may capture participants' attitude towards the risk of a recession. These variables, however, may also reflect other factors such as monetary policy expectations and business conditions (Benzoni et al., 2018). Accordingly, they do not directly measure market participants' fears around a looming recession.

are part of broader fear. Any observed impact during periods of high recession fears may not necessarily be attributable to recession fears alone. Measures that predict the probability of a recession draw on financial and economic indicators but do not quantify the fear of market participants regarding a recession. They are also of a low frequency and thus are not useful for analysing the real time evolution of recession fears. An easily accessible and timeous measure of recession fears, which we develop and which differs from existing low frequency measures and general proxies, will be a source of useful information. Our index and approach to its construction, combined with an analysis undertaken using directional wavelet coherence, will provide policymakers with timely insight into events and policy decisions that reduce/increase recession fears. Moreover, this approach is not limited to recession fears; it is generalisable and can be applied to model the influence of specific events on financial markets. Such events might include inflation-related concerns and rising energy prices. Our approach may be of particular interest for policy makers, investors, and market participants who require insights into the influence of specific events on market dynamics at a high frequency.

Second, our recession fear index is fully economic agent-determined, comprising keywords reported by Google as those searched for by economic agents. This differs from existing Google search-based indices where terms are chosen by researchers and are therefore subject to potential bias and a lack of true investor relevance (Da et al., 2015; Chen et al., 2020). Third, we use elastic net regression to select relevant search terms for inclusion in the index. Elastic net can automatically perform measure selection while preventing overfitting. By applying this approach, we identify and isolate terms that reflect recession-related fears that are relevant and reflect components of general stock market uncertainty. This approach performs well under multicollinearity which is particularly relevant for Google searches which are related. Examples of existing studies that utilise elastic net for variable selection and machine learning techniques for information extraction and text mining are those of Topuz et al. (2018), Baradaran Rezaei et al. (2022), Guo et al. (2020) and Jiang et al. (2018). Our analysis demonstrates the usefulness and applicability of machine learning for developing (relative) high-frequency internet search-based indices. Such indices are becoming increasingly popular in finance applications and our approach should be of interest to researchers and econometricians. We therefore contribute to developing a systematic approach to shaping narratives and measuring their impact.

Fourth, using our index, we analyse the interaction between G7 stock markets and recession fears from December 2021 to September 2023. As of 2022, G7 stock markets represented 77.3% of global stock market capitalisation (Eagle, 2023). Jointly, they constitute a significant international trading platform with interconnected dynamics, mirroring macroeconomic fundamentals driving industrialised economies (Su, 2020). Although BRICS (Brazil, Russia, India, China and South Africa) and other developing markets have become more open and integrated with developed markets, developing markets are more susceptible to financial spillovers from G7 markets than the other way round (Fang et al., 2021). G7 markets are exporters of risk whereas others, including BRICS, are receivers (Zhang, 2021). Although global market dynamics are changing, G7 stock markets continue to dominate global markets. What happens in these markets impacts the rest and therefore the focus on these markets is warranted, especially during turbulent times. During the period under consideration, world equity markets experienced their worst calendar year since 2008, down almost 20% in 2022. Assessing the impact of recession fears on financial markets is therefore of great importance. While a few studies examine the effects of the Russia-Ukraine war on financial markets (such as Będowska-Sójka et al., 2022; Boubaker et al., 2023; Wu et al., 2023), our study broadly focuses on recession fears while accounting for this and other notable events. Accordingly, our analysis provides unique insights on an evolving period of crisis and demonstrates how our approach can be applied for the purposes of monitoring and decision making, such as portfolio management and risk hedging.

Finally, to model the interaction between markets and recession fears, we use wavelet coherence that directly discriminates between positive and negative associations, which we term "directional coherence analysis". This represents a refinement to the wavelet analysis methodology, encoding lead-lag relationships in a manner that permits the identification of events driving recent recession fears with greater precision. As wavelet analysis represents relationships using diagrams, this approach offers a different perspective to that provided by the application of traditional econometric approaches and thereby potentially constitutes a more accessible form of analysis to those without a background in financial econometrics.

Our study provides an analysis of how economic agents respond to information. We interpret positive (negative) associations between recession fears, as measured by our index, and overall market uncertainty, as measured by the VIX, as a growing (declining) contribution of the former to the latter. Periods of growing contribution, as identified by us and as supported by existing literature, coincide with significant geopolitical events, such as Russia's invasion of Ukraine, and the subsequent economic repercussions, including energy price shocks, surging inflation, and monetary policy tightening in the U.S. and around the world. We confirm this using regression analysis. Other information plays a less prominent role in the changing contribution of recession fears to overall stock market uncertainty. Following the invasion of Ukraine and its immediate economic repercussions, recession fears are seemingly associated with a plethora of economic news which we postulate are interpreted within the context of the possibility of a recession. Beyond global markets, recession fears negatively impact G7 stock returns and volatility, with the impact varying over time and across markets. Japan is the most resilient market while the U.S. is most affected. Importantly, our analysis reveals cross-border spillovers from monetary policy tightening suggesting that policymakers should consider co-ordinating their responses to avoid an excessive slowdown of the global economy.

The remainder of this study is structured as follows: Section 2 reviews the theory and empirical evidence of the impact of fear on stock markets. Section 3 details the data and methodology used for creating our recession fears index and analysing the influence of recession fears on stock returns and volatility. Section 4 presents the results. Section 5 outlines the implications of our study and Section 6 concludes.

2. Literature review

The stock valuation hypothesis proposes that stock prices are determined by discounted expected cash flows (Smyth & Narayan, 2018). Although classical finance theory leaves little room for irrational investor behaviour, market participants may be influenced by sentiment and fear (Black, 1986; Smales, 2017b).[3] Fear negatively impacts stock returns through two channels. First, investors revise expectations of future cash flows downwards due to concerns that a firm will not be able to operate as usual and/or may incorrectly extrapolate future cash flow forecasts (Baker & Wurgler, 2007). Second, fear results in investors being more risk-averse, leading to a higher risk premium being reflected in an increased forward-looking discount rate (Guiso, 2012; Smales, 2017b). Fear pervades during crises and increases investor risk aversion, as shown by Guiso (2012) during the GFC. Fear also leads to greater fluctuations in stock prices, reflected as time-varying volatility, due to uncertainty surrounding future market conditions, sentiment-based trading, and flight-to-quality as investors sell riskier stocks and move to safe-haven assets (Black, 1986; Durand et al., 2011).

Aggregate fear comprises sub-components such as stock market, geopolitical, recession and health-related fears. John and Li (2021) suggest that different categories of information elicit responses of varying intensity from market participants, especially during times of great stress. This motivates for an analysis of how specific fears impact stock markets, instead of focusing solely on aggregate fear. Recession fears are an important subset of general fear as market participants consider the economic outlook when forming expectations about future cash flows and undertaking investment decisions. Firm performance is strongly correlated with business conditions, with periods of economic downturns associated with reduced consumer and business spending to smooth consumption (Gómez-Cram, 2022). It therefore follows that increased recession fears will lower cash flow forecasts, driving stock prices lower. At the same time, increased recession fears lead to increased risk aversion resulting in investors demanding a higher risk premium (Fama & French, 1989). Recession-related fears also fuel market volatility as investors, lacking complete insight into the recession's scope and impact, shift towards safer assets. Furthermore, government policies aimed at stimulating the economy can introduce uncertainty, exacerbating volatility during times of economic downturns (Hamilton & Lin, 1996; Lim et al., 2014).

Investor fear is widely quantified using the CBOE implied volatility index, VIX, which is a measure of market expectations of future stock return volatility and is often referred to as an investor "fear gauge"

[3] Sentiment and uncertainty (fear) are distinct concepts. Sentiment reflects the overall mood of market participants whereas uncertainty reflects the lack of clarity regarding future outcomes. Szczygielski et al. (2024) demonstrate that uncertainty (fear) measures, such as VIX and economic policy uncertainty among others, differ from sentiment measures. They further demonstrate that indices based on Google searches, without a predefined narrative, more accurately measure uncertainty rather than sentiment.

(Whaley, 2000; Smales, 2022). A strand of literature examines the impact of fear on stock returns and volatility using the VIX. For example, Whaley (2000, 2009), Fernandes et al. (2014), Lim et al. (2014) and Smales (2017b) report a negative relationship between U.S. aggregate stock returns and investor fear as measured by the VIX in line with *a priori* expectations. Durand et al. (2011), Lim et al. (2014) and Smales (2017b) reveal that U.S. style factor returns are impacted by fear; fear has a positive impact on the value premium but a negative impact on the size premium. This is consistent with a flight-to-quality effect showing that in the face of heightened fear, investors move towards safer value and large stocks rather than riskier glamour and small stocks. With regards to volatility, Fleming et al. (1995), Giot (2005), Blair et al. (2010) and Zhu et al. (2019) confirm theoretical assertions that increased fear drives U.S. stock market fluctuations. Moreover, the results of these latter studies point to VIX exhibiting predictive power for realised volatility both in- and out-of-sample.

Pathak and Deb (2020) report that investor fear, measured using country-specific implied volatility indices, has a negative effect on stock returns across a sample of developed and emerging markets. Li et al. (2019) document similar findings for China. Frijns et al. (2010), Pati et al. (2018), Dai et al. (2020) and Fassas and Siriopoulos (2021) show that heightened domestic investor fear contributes to increased stock market volatility in several developed and developing countries. The effects of fear on stock markets are not limited to domestic fear. Wang et al. (2014), Tsai (2014), Dutta (2018) and Owusu Junior et al. (2021) illustrate that the VIX impacts stock returns in other developed (non-U.S.) and emerging markets. Smales (2022) shows that the U.S. investor fear gauge (VIX) affects G7 and BRICS fear indices but not *vice versa*. Thus, fear is spread from the U.S. market to global markets, meaning that the VIX can be used as a fear proxy for global markets.

Fear can also be measured using alternative measures. Da et al. (2015) construct a broad fear index comprising negative keywords searched for on Google, known as the FEARS index. The FEARS index has a negative impact on U.S. stock returns and triggers heightened return volatility. Following Da et al. (2015), Goel et al. (2022) construct a FEARS index for India and find increased fear negatively affects Indian stock returns across return quantiles although the magnitude of impact is smaller than observed in the U.S. This is attributed to lower internet penetration rates in emerging markets and cultural differences across countries. In contrast to search-based indices which reflect information demand, the Thompson Reuters' MarketPsych fear index is constructed from textual analysis of news and social media, reflecting information supply related to fear. Using this index, Griffith et al. (2020) find that fear has a significant but delayed impact on S&P500 returns and contributes to heightened volatility. Dhaene et al. (2012) construct a fear index (FIX) using option data accounting for market risk through the VIX, liquidity risk via implied liquidity indicators and systemic risk through the concept of comonotonicity.

What is common to these fear measures – the VIX, FEARS, MarketPysch fear index and FIX – is their general orientation. These measures do not differentiate between fears related to specific events or economic conditions. The limitation of the broad scope of such measures could potentially be mitigated by utilising internet searches, which, due to their specific nature, can more accurately reflect fears concerning a particular topic (Smales, 2021; John & Li, 2021). The basis for using searches for information to measure and reflect fear stems from economic psychology, which suggests that increased searches on a topic correlate with heightened fear associated with that topic (Vasileiou, 2022; Liu et al. 2023).

COVID-19-related fears dominated global markets in 2020 spurring the use of Google searches to quantify pandemic-related fears. Smales (2021) observes that investor fears about the COVID-19 pandemic, quantified by domestic and global Google searches for the term 'coronavirus', negatively impacted G7 stock returns. Emerging market returns were also adversely affected, with the impact of global COVID-19 fears dominating that of local COVID-19 fears. G7 stock markets also experienced increased volatility in response to heightened fear surrounding the pandemic. Smales (2022) attributes the impact of fear on stock markets to investors searching for information to reduce fear rather than searching for information on potential stocks to buy (see also Da et al., 2015). Subramaniam and Chakraborty (2021) and Vasileiou (2022) report that COVID-19 fears, measured by Google searches, had a negative impact on U.S., Brazilian and Indian stock returns which persisted over time. Su et al. (2022) and Liu et al. (2023) employ Baidu searches to quantify COVID-19 fears in China, finding that searches had a negative and persistent impact on Chinese stock returns. John and Li (2021) decompose COVID-19 fears into five categories (COVID-19, market, lockdown, banking and government relief) using Google searches. They find that these components contribute to or reduce overall stock market fear, as quantified by VIX. The authors go on to illustrate that heightened COVID-19 and market fears resulted in increased stock market and banking sector return volatility whereas government relief efforts reduced volatility.

Geopolitical risk and wars began playing an increasingly prominent role post-COVID-19. Będowska-Sójka et al. (2022) find increased association between geopolitical risk, measured using the geopolitical risk (GPR) index of Caldara and Iacoviello (2022) which is constructed using the frequency of newspaper articles mentioning geopolitical events, and global stock returns following Russia's invasion of Ukraine. Boubaker et al. (2023) and Kumari et al. (2023) attribute the negative reaction of European markets at the outbreak of the Russian-Ukraine war to fear regarding the war's consequences. This is consistent with Ngo et al.'s (2022) findings that information about the Russia-Ukraine war impacted investor sentiment and beliefs. Khalfaoui et al. (2023) quantify fears surrounding the Russian-Ukraine war using Google searches for war-related terms and find that these fears negatively affected G7 stock returns although the impact varied across market regimes and frequency horizons. Using Baidu searches related to the Russia-Ukraine war, Zhou and Lu (2023) report that China's stock markets experienced heightened volatility in response to investor fears. The use of searches related specifically to the Russia-Ukraine war, as per Khalfaoui et al. (2023) and Zhou and Lu (2023), provides a more direct quantification of war-related fears than the broader GPR index used by Będowska-Sójka et al. (2022).

According to Tsai (2014), the VIX is used to analyse shifting expectations of a potential recession. However, recession fears are a sub-component of total fear quantified by the VIX, which will reflect uncertainty and fears around a multitude of coincident events.[4] Recession risk can be measured using probability assessments or professional forecasters (see Section 1; Benzoni et al., 2018; Davig & Hall, 2019). Rudebusch and Williams (2009) show that estimates from a probit model using the yield curve slope are more accurate than predictions obtained from surveys (the U.S. Survey of Professional Forecasters). Davig and Hall (2019) confirm that a naïve Bayes model (closely allied to the probit model) also outperforms the survey forecasts. Powell and Treepongkaruna (2012) argue that these recession probability assessments provide a measure of *ex ante* recession fear. They find that recession fears have little impact on stock returns which they attribute to the lead-lag relationship between recession turning points and subsequent stock market recoveries (see also Resnick & Shoesmith, 2002). Importantly, this suggests that that there is no tool to measure and quantify the impact of recession fears on stock markets.

The literature yields several conclusions. Heightened fear negatively impacts stock returns and leads to greater volatility. Reactions differ depending on the nature of information, with fears related to specific events having the potential to elicit diverse market responses. This is evident from market responses to COVID-19 or the Russia-Ukraine war. Fears related to these events are a sub-set of aggregate fear. Similarly, recession fears are another component of aggregate fear that have important implications for stock valuations, yet little attention has been given to quantifying these fears. The focus has instead been on predicting the occurrence of recessions. Although Powell and Treepongkaruna (2012) argue that these probability assessments represent recession fears, this is not a common interpretation as they do not explicitly quantify the emotional response of market participants to an impending recession. According to Gilbert and Karahalios (2010), investors exhibit an emotional response to negative news, such as fear, panic or pessimism. Thus, probability assessments reflect news which leads to shifts in the emotional state of market participants who exhibit heightened fear in response to emerging information. Moreover, if they are to be used as a recession fear index, they are reliant on monthly or quarterly data. This contrasts with high frequency measures such as the VIX which are available daily but are general in scope, reflecting a myriad of other fears. This motivates for a high frequency recession fear measure that isolates recession-related components in the VIX using Google recession-related searches. We

[4] Recession fears may also be part of fears related to specific events like the Russia-Ukraine war or the COVID-19 pandemic, but event-related fears are multifaceted thus necessitating considering recession fears in isolation.

construct such a measure and use the resultant index to model the evolving impact of recession fears on stock markets.

3. Data and methodology

3.1. Financial data

Our data comprises U.S. dollar denominated MSCI indices for global (MSCI All Country World Index (ACWI)) and individual G7 stock markets (U.S., Canada, United Kingdom (U.K.), Germany, France, Italy and Japan), spanning the period 1 December 2021 to 15 September 2023. The start of the sample is determined by a search of news headlines which show increased early mentions of a looming recession in G7 markets from December 2021. Returns are defined as logarithmic differences in daily index levels, $R_{i,t}$. Descriptive statistics for the return series are reported in Table 1. All return series are leptokurtic, revealing that they are characterised by non-stationary variance, a common feature of financial time series arising from the intensification of the influence of events concentrated in time. German and French stock returns are positively skewed suggesting that these markets are more likely to yield positive returns whereas the remaining return series are negatively skewed. Various explanations have been proposed for negative skewness, including the presence of the leverage effect, volatility feedback effects, the existence of stochastic bubble microstructures and temporary market disequilibria (Ekholm & Pasternack, 2005; Mantalos et al., 2020; Yang et al., 2022). The assumption of normality is rejected for all series except for Canada based on the Shapiro-Wilk test. All return series are stationary, as indicated by the rejection of the null hypothesis of a unit root based on the results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests.

Table 1: Descriptive statistics for returns on MSCI indices

Country	World	U.S.	Canada	U.K.	Germany	France	Italy	Japan
Index	**MSCI ACWI**	**MSCI U.S.**	**MSCI Canada**	**MSCI U.K.**	**MSCI Germany**	**MSCI France**	**MSCI Italy**	**MSCI Japan**
Mean	-0.0001	-0.0001	-0.0001	0.0001	-0.0003	0.0000	0.0001	-0.0001
Median	-0.0002	0.0000	0.0000	0.0000	0.0000	0.0000	0.0006	0.0000
Maximum	0.0428	0.0554	0.0390	0.0401	0.0900	0.0815	0.0792	0.0480
Minimum	-0.0372	-0.0442	-0.0365	-0.0527	-0.0585	-0.0610	-0.0751	-0.0442
Std. dev.	0.0102	0.0128	0.0119	0.0123	0.0158	0.0150	0.0164	0.0119
Skewness	0.0127	-0.0952	-0.0168	-0.4728	0.2020	0.0793	-0.4504	-0.0097
Kurtosis	4.0630	4.1229	3.3420	5.3402	6.1125	6.0054	6.0611	4.1620
SW	0.9899***	0.9861***	0.9964	0.9660 ***	0.9677 ***	0.9690***	0.9596***	0.9892***
ADF	-18.7429***	-21.4662***	-19.5053***	-21.1876***	-21.6246***	-21.9742***	-21.7914***	-23.5746***
PP	-18.4729***	-21.4761***	-19.4755***	-21.1878***	-21.6257***	-21.9770***	-21.7937***	-22.6618***

Notes: This table reports descriptive statistics for the indices in our sample over the period 1 December 2021 to 15 September 2023. Returns are defined as logarithmic differences in index levels. Data is daily in U.S. dollars. SW is the Shapiro-Wilk test statistic verifying normality. ADF and PP are the Augmented Dickey-Fuller and Phillips-Perron test statistics, respectively, with the null hypothesis positing that each series has a unit root. Both tests are conducted assuming only an intercept. *** indicates statistical significance at the 1% level.

3.2. Economic agent-determined recession fear index

Our approach to constructing a recession fear index draws upon Szczygielski, Charteris and Obojska (2023) who demonstrate that Google searches can be used to isolate event-specific uncertainty from general uncertainty and thereby will reflect fears around a specific topic (see also John & Li, 2021).

Two assumptions underlie our approach. First, economic agents respond to uncertainty by searching for information (Liemieux & Peterson, 2011; Donadelli, 2015). Second, searches reflect investor concerns – fears – around real events (Manela & Moreira, 2017; Larsen, 2021). It follows that by obtaining data for a proxy of investor fears, we can measure and quantify fears around a specific topic or event. Google search data can be readily obtained on a regular frequency without the need to resort to advanced programming methods to obtain data. Google search data is therefore more readily accessible, and indices are more readily implementable than indices that rely upon Twitter data, for example.

The approach followed to construct the index is summarised in Figure 1. First, we identify six search terms that contain the word "recession" suggested by the Google Autocomplete feature, which indicates the most common queries on a given topic. These are designated as first level search terms. Accordingly, our index is "economic agent-determined" as the search terms used are those searched for by economic agents and not those perceived by us as being relevant (as in Da et al., 2015). The six search terms are "recession", "recession 2022", "recession 2023," "recession us", "recession stocks" and "recession meaning".[5] We obtain daily data for these first level and related (second level) terms containing the word "recession" from Google Trends, resulting in a total of 98 unique search terms (see Table A1 in Appendix A for a list of search terms and level designations).

Next, we employ the elastic net estimator which draws upon machine learning to identify which search terms approximate recession fear components that are reflected in the VIX. Elastic net makes use of k-fold cross-validation, whereby data is partitioned into k sets and each set is individually used as a test set for model validation while the remaining sets are used for feature selection (model building, search term selection in the present context) (Jung, 2017; Zhang et al., 2019). By combining LASSO and Ridge penalties, elastic net performs keyword selection while mitigating overfitting and performing well under multicollinearity (Zou & Hastie, 2005; Zou & Zhang, 2009; Liu et al., 2018). We use the elastic net estimator to relate keywords to the VIX – the "fear gauge" – which acts as a general stock market uncertainty measure. Although the VIX is a measure of U.S. fear, Smales (2022) illustrates that U.S. fear is transmitted across global markets (but not vice versa).

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

where

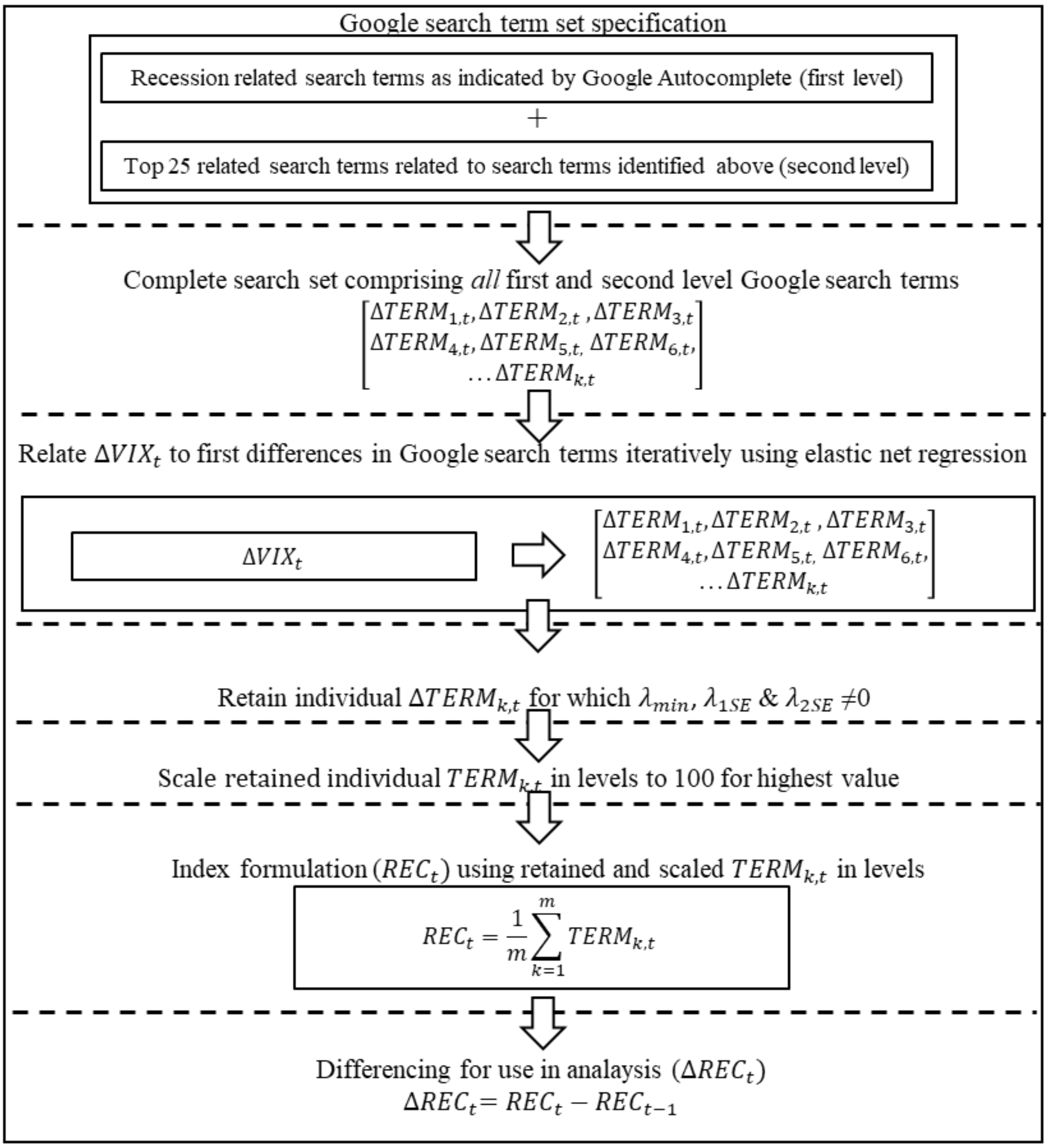
$$\beta_{\Delta TERM,k}(\text{enet}) = \arg\min \begin{bmatrix} \frac{1}{2n}\sum_{t=1}^{n}\left(\Delta VIX_t - \sum_{k=1}^{m}\beta_{\Delta TERM,k}\,\Delta TERM_{k,t}\right)^2 + \\ \lambda\left(\frac{1-\alpha}{2}\sum_{k=1}^{m}\beta_{\Delta TERM,k}^2 + \alpha\sum_{k=1}^{m}\left|\beta_{\Delta TERM,k}\right|\right) \end{bmatrix} \tag{2}$$

[5] To ensure that the recession-related terms that we select are unbiased, we use the Google.com domain with the no country redirect parameter and clear all history and cookies so that Autocomplete suggestions are not influenced by prior user searches. Search terms with sufficient observations permitting the construction of continuous series are included in the final search set.

where ΔVIX_t and $\Delta TERM_{k,t}$ are respective first differences in VIX and search term levels and n is the number of observations. λ is a penalty parameter determined by cross-validation, α controls the penalties applied and $\sum_{k=1}^{m}|\beta_{\Delta TERM,k}|$ and $\sum_{k=1}^{m}\beta_{\Delta TERM,k}^{2}$ are LASSO (L1 norm) and Ridge (L2 norm) penalties. Equation (1) is recursively estimated until terms for which coefficients are non-zero for λ_{min}, λ_{1SE} and λ_{2SE}, where λ_{1SE} and λ_{2SE} are penalties one and two standard errors from λ_{min}, remain. Search terms taken forward to formulate the recession fear index are those for which coefficients are not shrunk to zero in the final iteration across all penalties, ensuring that they remain valid out of sample. The index, REC_t, is formulated by adjusting the highest value to 100 and all other values relative to the highest value in each series in levels, and then obtaining an equal-weighted average of all m terms in levels:

$$REC_t = \frac{1}{m}\sum_{k=1}^{m} TERM_{k,t} \tag{3}$$

Figure 1: Economic agent-determined Google search index construction methodology



Notes: Figure 1 depicts the steps followed in the construction of the recession fears index, REC_t.

The recession fear index, REC_t is then differenced (ΔREC_t) for the purposes of analysis in line with convention used in financial time series analysis.[6] By linking event-specific searches that reflect real world events and economic agents' state of mind to the VIX, we isolate recession-related uncertainty components from general stock market uncertainty and assign a *narrative* to our index by associating terms used by economic agents to reflect fear. Similarly, by using different narrative setting proxies instead of the VIX that, for example, reflect broader sentiment or attention, we can create an index that isolates and quantifies sentiment or attention around a specific topic.[7]

3.3. Wavelet analysis and directional wavelet coherence

We first demonstrate that our index reflects recession-related uncertainty by undertaking a visual comparison of REC_t and VIX_t followed by rolling correlations between differences. We then estimate wavelet coherence between ΔREC_t and ΔVIX_t to establish which events are associated with increased recession-related searches (Aguiar-Conraria & Soares, 2011; Szczygielski, Charteris & Obojska, 2023):

$$r^2_{\Delta RECt,\Delta VIXt} = \frac{\left|S(WPS_{\Delta RECt,\Delta VIXt})(\tau,s)\right|^2}{S(|WPS_{\Delta RECt}(\tau,s)|)S(|WPS_{\Delta VIXt}(\tau,s)|)} \tag{4}$$

where

$$WPS_{\Delta RECt,\Delta VIXt}(\tau,s) = WPS_{\Delta RECt}(\tau,s)WPS^*_{\Delta VIXt}(\tau,s) \tag{5a}$$

$$WPS_{xn}(\tau,s) = \left|W_{xn,\phi}(\tau,s)\right|^2 = |\int_{-\infty}^{\infty} x_t \frac{1}{\sqrt{|s|}}\phi^*(\frac{t-\tau}{s})dt\,|^2 \tag{5b}$$

where $r^2_{\Delta RECt,\Delta VIXt}$ represents wavelet squared coherence between ΔREC_t and ΔVIX_t, $WPS_{\Delta RECt,\Delta VIXt}(\tau,s)$ is the cross-wavelet power spectrum (covariance), S is a smoothing operator, ϕ is a wavelet function (a mother wavelet), * denotes a complex conjugate, τ denotes a time-lag and s is the scaling parameter. Wavelet coherence takes on values between 0 and 1, with one indicating maximum coherence and zero a lack thereof.

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 continuous wavelet transform, which serves to identify relationships, evaluate their strength and persistence, and localises them over time. Wavelet analysis captures shocks and

[6] We use differences to reflect short-term dynamics. An average of differenced terms, instead of an average of scaled levels which is then differenced, may also be used and will produce identical results. Arguably, this offers a simpler approach to formulating an index that can be applied in econometric analysis. However, an index in levels prior to differencing is appealing for its simplicity in terms of a visual representation of evolving recession fears (see Figure 2). Weekend data is excluded for consistency with financial data when formulating the final index.

[7] Examples of proxies for sentiment are the Société Générale Global Sentiment Index and U.S. Federal Reserve Bank of San Francisco Daily News Economic Sentiment Index. Examples of attention proxies are the Predata Country Attention Indices and extreme returns. It follows that any topic-specific search terms that are related to a narrative proxy will reflect and isolate the defined narrative associated with that topic.

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 variation over time and frequency and aggregates the association between variables over intervals.

As we have a frequency dimension, we obtain information about the direction of association between ΔREC_t and ΔVIX_t represented by phase-angle as follows:

$$\theta_{\Delta RECt,\Delta VIXt}(\tau,s) = \tan^{-1}\frac{Im(WPS_{\Delta RECt,\Delta VIXt}(\tau,s))}{Re(WPS_{\Delta RECt,\Delta VIXt}(\tau,s))} \tag{6}$$

Im and *Re* denote the imaginary and real parts of $WPS_{\Delta RECt,\Delta VIXt}(\tau,s)$ estimated for ΔREC_t and ΔVIX_t at location τ and scale s. If $\theta_{\Delta RECt,\Delta VIXt}(s,\tau) \in \left(-\frac{\pi}{2},\frac{\pi}{2}\right)$, ΔREC_t and ΔVIX_t are in-phase, they are positively correlated, otherwise, ΔREC_t and ΔVIX_t are out-of-phase, i.e., they are negatively correlated. In this study, we codified associations as follows:

$$A_{\Delta RECt,\Delta VIXt}(\theta_{\Delta RECt,\Delta VIXt}(s,\tau)) = \begin{cases} r^2_{\Delta RECt,\Delta VIXt}: & \theta_{\Delta RECt,\Delta VIXt}(s,\tau) \in \left(-\frac{\pi}{2},\frac{\pi}{2}\right) \\ -r^2_{\Delta RECt,\Delta VIXt}:: & \theta_{\Delta RECt,\Delta VIXt}(s,\tau) \in \left(-\pi,-\frac{\pi}{2}\right) \cup \left(\frac{\pi}{2},\pi\right) \end{cases} \tag{7}$$

Classical coherence, by definition, takes on only positive values. Traditionally, arrows, which represent lead-lag dynamics, are used in spectrograms to illustrate the direction of relationships between variables. However, an excessive number of arrows can complicate interpretation whereas a sparse number of arrows results in a lack of precision. Arrow directions are determined by phase-angles represented by imaginary numbers, indicating coherences (eqs. (4) and (6)). Consequently, we assign plus or minus signs to coherence for positive or negative correlations which are colour coded in red or green, respectively (eq. (7)) and transform the lead-lag relationships to positive/negative correlations. All significant coherences at the 10% level are plotted using the Monte Carlo method, reflecting significant associations and their direction of association. We designate this refinement as directional wavelet coherence.

Wavelet analysis, and specifically directional wavelet analysis, offers several advantages over regression-based methods applied to model relationships. Regression analysis aggregates information across horizons, returning an average measure of the strength of a relationship without considering changes in its persistence. To capture time-varying correlations, advanced regression methods such as the DCC-GARCH model must be applied (Jensen & Whitcher, 2014). Beyond capturing dynamic correlations over time, wavelet analysis provides insight into the frequency domain, which can be understood as the investment horizon. This reflects the length over which the analysis is conducted, providing information about the persistence of temporal relationships and coherence patterns, revealing dynamic shifts in relationships between variables. Periods of highly persistent coherence tend to coincide with significant events characterised by novel information, indicating how long a shock is expected to affect the relationship (Vetterli et al., 2014). Relative to traditional wavelet analysis, we can gain a more detailed understanding of the evolution of recession fears by readily delineating periods during which the influence of recession fears increases or decreases. Relative to regression analysis, directional wavelet coherence provides more refined insights into the timing, duration, and direction of the influence of recession fears.

In the second part of the analysis, we model the influence of recession fears on global and G7 stock returns and variance (proxied by squared returns, $R_{i,t}^2$) using directional wavelet coherence.

4. Results and discussion

4.1. Recession fears and stock market uncertainty

Panel A of Table 2 reports the results of the final iteration of elastic net regularisation (eqs. (1) and (2)) applied to select recession-related search terms that approximate ΔVIX_t components associated with recession-related fears.[8] Panel B summarises descriptive statistics for differences in the resultant index, designated as ΔREC_t (see Figure 1).

Figure 2 plots REC_t and VIX_t in levels. Higher REC_t levels reflect increased recession-related searches and signal increased fear of an impending recession. REC_t exhibits an upward trend from the beginning of the sample, spiking sharply from June and August 2022 before declining rapidly. It increases gradually from early September 2022 before resuming a downward trend from October 2022. Overall, from March 2022 onwards, co-movement between REC_t and VIX_t increases, with both indices exhibiting a concurrent upward and then downward trend. Towards the end of the sample period, in August 2023, both indices exhibit a brief, sharp increase. Rolling correlations in Figure 3 confirm that recession-related searches increased substantially with VIX_t between January and August 2022 pointing towards overall stock market uncertainty reflecting recession-related fears. Although correlations are lower in magnitude from August 2022, they are still mostly positive between September 2022 and May

[8] We consider alternative methodologies for search term selection, namely the Auto-search/GETS algorithm of Sucarrat and Escribano (2012), (single-pass) LASSO and stepwise regression. We do not test least squares regression as a selection procedure given the ensuing multicollinearity that follows from the consideration of similar terms (see McNeish, 2015). As with the iterative procedure, the VIX is related to the search term set (eq. (1)) using each of these methods. For the Auto-search/GETS algorithm and stepwise regressions, we use *p*-values of over 10% as a cut-off point. The Auto-search/GETS algorithm identifies 15 search terms and the resultant index approximates 3.094% of the variation in ΔVIX_t. LASSO regularisation selects a total of 51 search terms. While this number vastly exceeds that of search terms selected by the elastic net procedure (16), the resultant index approximates 2.746% of VIX movements. A larger number of search terms does not yield a better approximation of the VIX. Stepwise regression identifies 13 terms, and the resultant index approximates 2.220% of ΔVIX_t. These results confirm that elastic net regression applied iteratively enables us to construct the best approximation of ΔVIX_t. We also consider correlations between ΔREC_t and the recession fear indices formulated with the aid of these alternative search term selection methods. Ordinary (Spearman) correlations are 0.6885 (0.6282) for LASSO and 0.8690 and 0.8383 for Auto-search/GETS. Alternative search term identification procedures produce indices that are similar but less effective in approximating VIX movements.

2023. From June 2023, correlations are briefly negative and thereafter increase sharply suggesting that overall stock market uncertainty again increasingly reflects recession-related fears.

Figure 4 shows limited meaningful directional coherence between ΔREC_t and ΔVIX_t from December 2021 to the end of January 2022 (Area A) although ΔREC_t contributes positively (red) to ΔVIX_t in the medium run from early January 2022. Record U.S. inflation and expectations of interest rate increases by the Fed likely contributed to these early recession fears. Directional coherence grows between February and May 2022 (Area B) over the short run, implying rising recession fears.

Table 2: Search term identification

Panel A: Final iteration of elastic net regularisation relating ΔVIX_t to recession-related Google searches

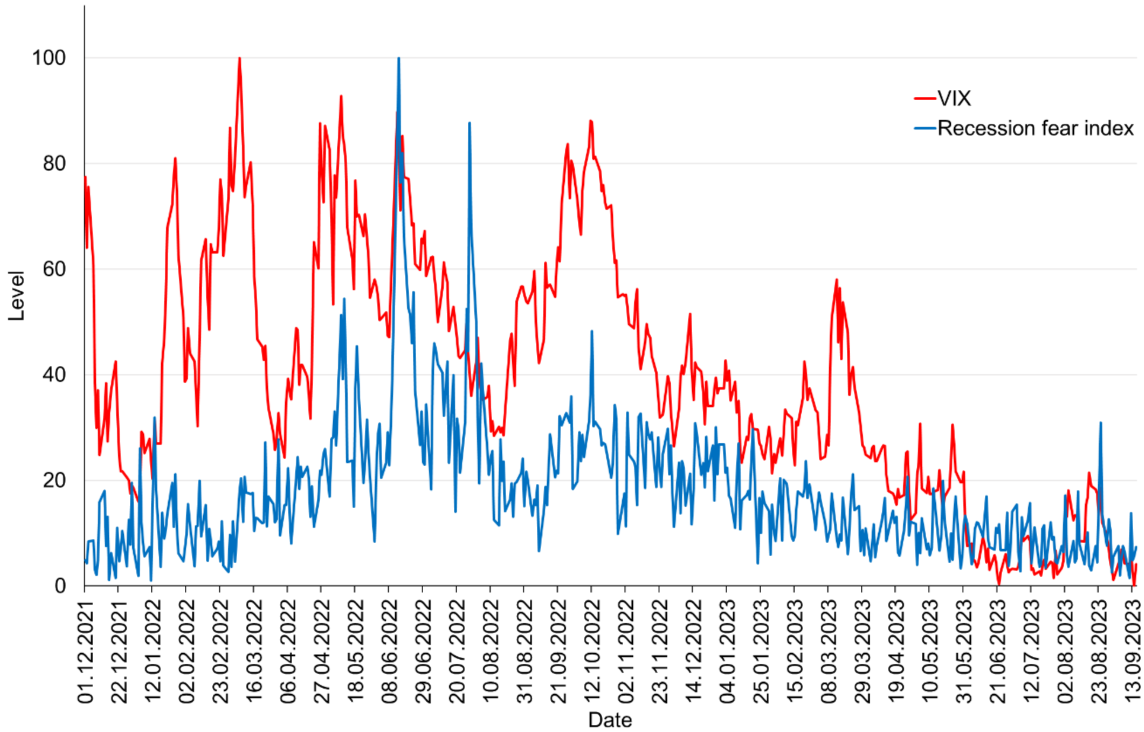
	λ_{min}	λ_{1SE}	λ_{2SE}
α_V	-0.0805	-0.0805	-0.0805
$\Delta BEST\_RECESSION\_STOCKS_t$	0.0075	0.0073	0.0073
$\Delta LAST\_RECESSION_t$	0.0401	0.0390	0.0390
$\Delta MARKET\_RECESSION\_2022_t$	0.0004	0.0002	0.0002
$\Delta RECESSION\_2022_t$	0.0090	0.0068	0.0068
$\Delta RECESSION\_COMING_t$	0.0488	0.0485	0.0485
$\Delta RECESSION\_DEFINITION_t$	-0.0784	-0.0724	-0.0724
$\Delta RECESSION\_NEWS\_2022_t$	0.0081	0.0077	0.0077
$\Delta STOCKS\_IN\_A\_RECESSION_t$	0.0181	0.0178	0.0178
$\Delta STOCKS\_TO\_BUY\_DURING\_A\_RECESSION_t$	0.0100	0.0097	0.0097
$\Delta STOCKS\_TO\_BUY\_IN\_A\_RECESSION_t$	0.0142	0.0137	0.0137
$\Delta STOCKS\_TO\_BUY\_IN\_RECESSION_t$	0.0125	0.0122	0.0122
$\Delta US\_IN\_RECESSION\_2022_t$	0.0281	0.0268	0.0268
$\Delta WILL\_THERE\_BE\_A\_RECESSION\_IN\_2022_t$	0.0111	0.0108	0.0108
$\Delta ECONOMY\_RECESSION\_MEANING_t$	0.0086	0.0081	0.0081
$\Delta RECESSION\_MEANING\_TAMIL_t$	-0.0076	-0.0072	-0.0072
$\Delta STOCK\_MARKET\_RECESSION_t$	0.0158	0.0150	0.0150
d.f.	16	16	16
L1	0.3988	0.3835	0.3835
R^2	0.0976	0.0961	0.0961

Panel B: Descriptive statistics for recession fears index

Mean	Median	Max	Min	Std. dev	Skew.	Kurt.	SW	ADF	PP
0.0073	0.1607	26.4836	-14.5382	4.8716	0.5174	5.9442	0.9692***	-15.2441***	-56.0091***

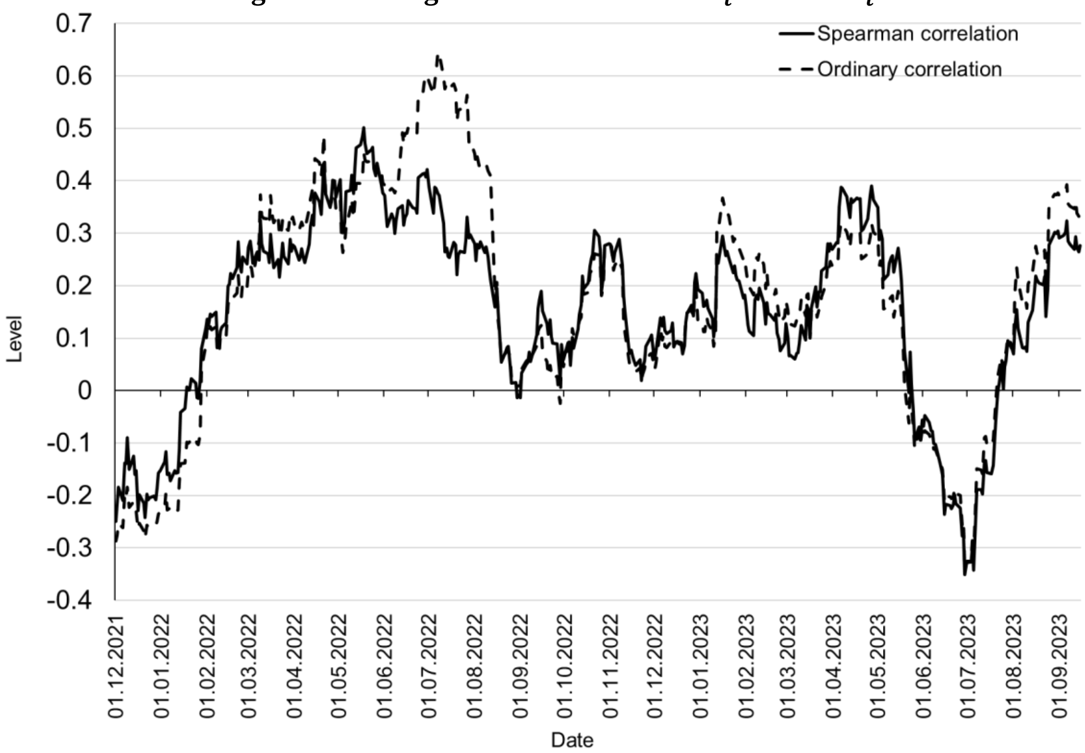
Notes: Panel A reports the results of the final iteration of the elastic net-based selection and identification procedure for recession-related keywords relating. The procedure is repeated until only Google search terms for which coefficients are non-zero for the λ_{min}, λ_{1SE} and λ_{2SE} penalties remain. *d.f.* is the number of measures with non-zero coefficients and L1 norm is the sparsity inducing penalty. R^2 is the coefficient of determination for Google search terms with non-zero coefficients. The VIX and the search term series are in first differences. Prior to first differencing, each series value is scaled to 100 by dividing each observation by the highest value in each series and multiplying by 100. Panel B reports the descriptive statistics for differences in the resultant recession fears index, ΔREC_t. SW is the Shapiro-Wilk test statistic verifying normality. ADF and PP are the Augmented Dickey-Fuller and Phillips-Perron test statistics, respectively, with the null hypothesis positing that each series has a unit root. Both tests are conducted assuming only an intercept. *** indicates statistical significance at the 1% level.

Figure 2: Recession fear index and VIX levels



Notes: Figure 2 plots levels in the recession fear index, REC_t, constructed from Google search terms, against levels of VIX_t, which is treated as a proxy for general stock market uncertainty, over the period 1 December 2021 to 15 September 2023.

Figure 3: Rolling correlations for ΔREC_t and ΔVIX_t

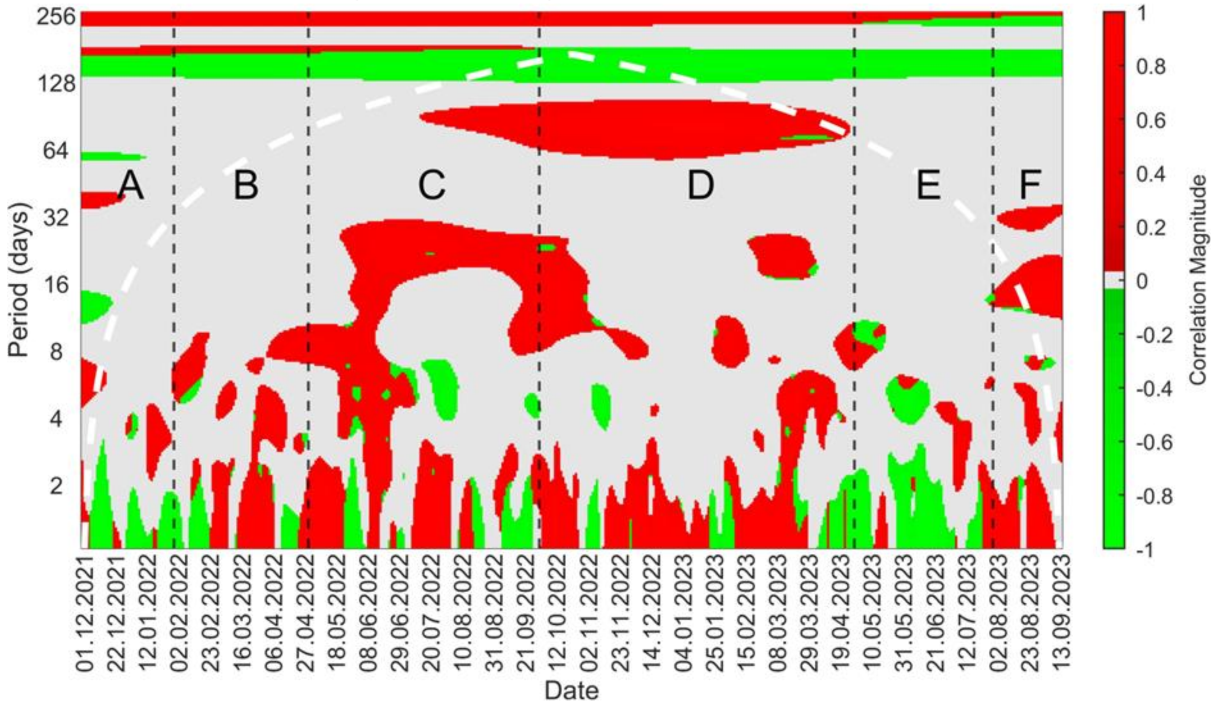


Notes: Figure 3 plots rolling ordinary and Spearman correlations between ΔREC_t and ΔVIX_t over the period 1 December 2021 to 15 September 2023. Both series are in first differences. Rolling correlations are estimated using rolling windows of 45 observations.

Notable growing positive association between ΔREC_t and ΔVIX_t coincides with the invasion of Ukraine (24 February), the Fed increasing rates by 0.5% (16 March), the inversion of the yield curve (also March 2022), and mounting concerns over supply chain disruptions. The combination of these factors contributed to rising expectations of a potential recession amongst economic agents. The outbreak of the Russia-Ukraine war appears particularly relevant in driving recession fears. The immediate aftermath is characterised by soaring energy prices, leading to concerns about economic growth. Astrov et al. (2022) and Korosteleva (2022), writing at the start of the war, argue that restricting Russian energy imports could trigger higher inflation, tighter monetary policy, and a global recession, particularly impacting Western economies dependent upon Russian energy, with the European Union most affected. Yagi and Managi (2023) quantify the impact of increased oil prices following Russia's invasion, revealing a 2.85% decline in global Gross Domestic Product (GDP), equivalent to $2.7 trillion. Guénette and Khadan (2022) assert that the war not only jeopardised near-term global economic prospects but also impeded the post COVID-19 economic recovery, exacerbated poverty and intensified inflationary pressures in developed and emerging economies through higher energy prices. The inversion of the yield curve is also a notable driver of increased recession fears during this period, as it is viewed as a reliable indicator of a future recession; an inverted U.S. yield curve has predicted every recession since 1955 except one (Randall & Barbuscia, 2023).

Mid-April to early November 2022 (Area C) sees extensive positive short-run association between ΔREC_t and ΔVIX_t that extends into the long run coinciding with the intensifying effects of Chinese COVID-19 lockdowns and the growing impact of the Russia-Ukraine war on fuel and food prices. During this period, global food prices increased to record-breaking levels and energy prices remained inflated. From mid-May 2022 there is pervasive coherence between recession-related searches and uncertainty across all horizons. While short-run directional coherence becomes sporadic (in early June/July), searches reflecting persistent uncertainty extend into the medium and long run. The primary driver of recession fears over this period can be attributed to the U.S. Fed's decision to increase interest rates by an unprecedented 0.75% in both June and July 2022 to curb soaring inflation. According to Cox (2022), this represented the most stringent consecutive action since the Fed began using the overnight funds rate as the main monetary policy tool in the early 1990s. Ross (2022) argues that these interest rate hikes fuelled recession fears, with risks of a global recession also rising as other central banks, including the European Central Bank (ECB), Bank of England and Reserve Bank of India, raised rates. Given the size of the U.S. economy and the adverse impact of high interest rates on the global economy, it is expected that such unprecedented hikes in U.S. rates will have significantly impacted uncertainty. In addition, China – the world's second largest economy – faced severe disruptions in April and May 2022, with major cities, such as Shanghai, under lockdown (Chin, 2022). This drove fear regarding the country's economic prospects. Although the reopening of the economy in July resulted in a rebound in retail spending, Gao (2022) highlights that fear abounded due to the growing property sector crisis, the possibility of a global recession and the ability of Chinese authorities to continue to provide economic stimulus. These fears explain the positive association between recession fears and overall uncertainty that extends into the long run.

Figure 4: Spectrogram for ΔREC_t and ΔVIX_t



Notes: Figure 4 presents a spectrogram for ΔREC_t and ΔVIX_t in three dimensions: time on the horizontal axis, frequency domain on the vertical axis expressed in the number of days and directional wavelet coherence values (contour map). Both series are in first differences. Regions in red (green) reflect a positive (negative) association, at the 10% significance level, between ΔREC_t and ΔVIX_t indicating that recession fears positively (negatively) contribute to overall uncertainty. The white dashed line indicates the 5% significance level for edge effects occurring in coherence data. Higher horizons (periods) indicate a longer investment horizon and more persistent associations. Values of (approximately) between 1 and 8 days are defined as the short run, 9 to 32 days are defined as the medium run and values greater than 33 days are designated as the long run.

Positive coherence between ΔREC_t and ΔVIX_t continued from October 2022 to April 2023 over short-run horizons while long-run recession fears persisted (see Area D). According to Smith, M. (2023), despite a fairly resilient U.S. economy, consumer confidence dropped to its lowest level in nine months, in line with heightened expectations of a recession. Accumulated savings from the COVID-19 pandemic bolstered ongoing consumer expenditure throughout 2022, cushioning the economy against the full impact of elevated inflation and rising interest rates. However, by late 2022, dwindling savings gave rise to expectations that the effects of the difficult prevailing economic conditions (high inflation and high interest rates) would be more severely felt by consumers and businesses going forward (Ngo, 2022). Krauskopf (2022) and Mikolajczak (2022) argue that in December 2022, U.S. stock prices continued their downward trajectory due to increased recession fears. The dominant narrative among economists and investors at this time was of a looming U.S. recession. Figure 4 reflects this narrative; recession fears have a lingering long-run contribution to overall uncertainty (reflected in the upper part of Area D). Furthermore, the Eurozone officially slipped into a recession in the first quarter of 2023 with two consecutive periods of negative growth attributable to the impact of the cost-of-living crisis (Partington, 2023).

A change occurs from May to July 2023 (Area E) with ΔREC_t contributing negatively to ΔVIX_t (green shaded areas in Figure 4). This can be interpreted as recession-related Google searches decreasing while overall stock market uncertainty increases (see Figure 5) implying that other considerations are now driving ΔVIX_t. This reprieve in recession fears is consistent with positive economic conditions in the U.S. The U.S. economy grew faster than expected in the second quarter of 2023, supported by strong consumer confidence, lower inflation, a resilient labour market and increased firm investment (Mutikani, 2023; Pickert, 2023). Other economic indicators, such as retail sales, housing market activity, wages and job growth, gave credence to a "soft landing" in the U.S. (the avoidance of a recession following inflationary pressure and monetary policy tightening) (Cox, 2023; Smart, 2023). These positive sentiments were echoed in Europe as inflation stabilised (relatively quickly) due to falling energy prices, and some European countries, such as France and Spain, experiencing economic growth (Chadwick, 2023; Thompson, 2023). In contrast, Yao and Cash (2023) highlight China's frail pace of growth and the need for stimulus to support economic activity in the country. This mix of positive and negative developments is consistent with the limited and sporadic positive medium-run associations between ΔREC_t and ΔVIX_t over this period.

The reduction of recession fears is short-lived. Coherence between ΔREC_t and ΔVIX_t becomes positive from August 2023 onwards (Area F). Despite the resilience of the U.S. economy, Rao (2023) reports that consumer confidence fell markedly in the third quarter of 2023 due to worsening business conditions and stubbornly high prices, especially for groceries and gasoline. The U.S. Consumer Confidence Survey results confirm that consumer fears about an impending recession rose, with the yield curve inversion in the U.S. continuing to signal a recession and the Fed forecasting a two in three possibility of a recession by July 2024 (Ermey, 2023; Moore, 2023). According to Curtis (2023), the end of the third quarter of 2023 would see the depletion of pandemic-era excess savings by U.S. consumers. This is anticipated to have ramifications for the economy as consumers and firms reduce spending due to depleted savings, elevated inflation and high interest rates. Furthermore, Inman (2023) and Martinez (2023) highlight that the recovery in European economic output was short-lived, with reduced German industrial output and a shrinking U.K. economy contributing to recession fears. This coincides with persistent concerns about the sustainability of China's growth trajectory, given the country's property sector crisis and falling consumer confidence (Amaro, 2023 July 25).

The analysis in Figure 4 permits us to ascribe an interpretation to evolving recession fears. The changing contribution of ΔREC_t to ΔVIX_t is tied to several economic and geopolitical events and news. The event that significantly contributed to rising inflation, is the Russian invasion of Ukraine (Area B). U.S. monetary policy tightening in June and July 2022 led to persistent and heightened recession fears (Area

C). Acute recession fears began to abate from the beginning of the fourth quarter of 2022 implying that economic agents had grown accustomed to the restrictive monetary policy environment in the U.S (and also globally). From the end of 2022, the contribution of recession fears to overall uncertainty became less persistent but remained mostly positive, driven by news about the global economic climate (Area D). A brief dissipation (Area E) occurred following positive news about the U.S. economy and a short-lived European economic recovery. A resurgence of rising recession fears occurred from the third quarter of 2023 coinciding with falling consumer confidence, stubbornly high inflation levels and concerns about China's growth trajectory (Area F). Our analysis offers valuable insights into how economic agents process information and reflects a degree of adaptation, particularly in response to the swift tightening of monetary policy in the U.S.

4.2. Further tests

4.2.1. Entropy analysis

To confirm that positive associations reflect contributions of recession-related fears to overall uncertainty, we apply Wavelet Shannon Time Energy Entropy (WSTEE). Shannon entropy can be viewed as a classic measure of uncertainty (Shannon, 1948; Schuster & Just, 2006) and, as our study is concerned with uncertainty, its application is arguably appropriate. Shannon entropy can be defined as:

$$H = -\sum_i p_i \ln(p_i) \colon \sum_i p_i = 1 \tag{8}$$

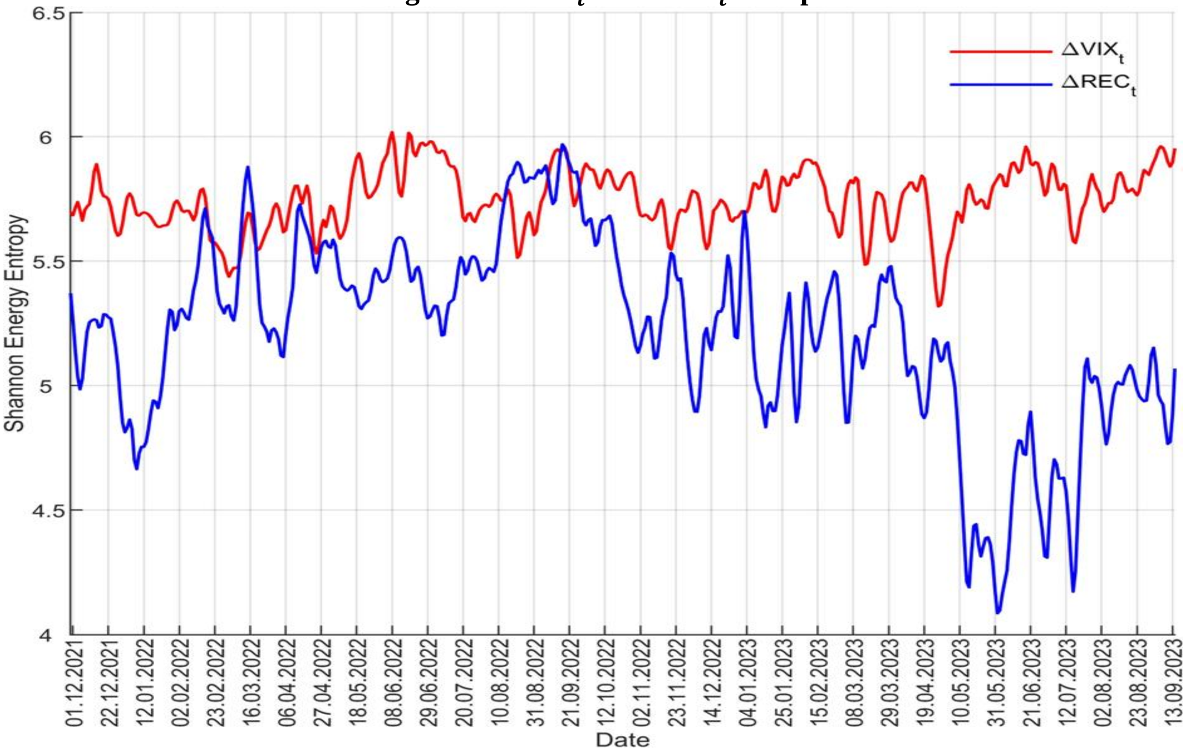
where H indicates Shannon entropy and p_i is a probability distribution estimated within time. In probability theory, entropy quantifies the average flow of information per unit of time. Therefore, entropy represents a loss of information, i.e., the growth of uncertainty – which proxies for fear. WSTEE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

$$WSTEE = -\sum_i p_i \ln(p_i) \; ; p_i = \frac{D_i(t)^2}{\sum_i D_i(t)^2} ; \sum_i p_i = 1; \tag{9}$$

where $D_i(t)^2$ denotes energy at scale *i* and time *t*, and $\sum_i D_i(t)^2$ denotes total energy (at all scales) at time *t* calculated using squared power spectrum wavelet coefficients.

When association between ΔREC_t and ΔVIX_t is positive (negative) in Figure 4, recession fears increasingly (diminishingly) contribute to overall uncertainty. Shannon entropies in Figure 5 support this interpretation. When ΔREC_t and ΔVIX_t entropies increase (decrease) *simultaneously,* this corresponds to positive association between ΔVIX_t and ΔREC_t observed in Figure 4. When ΔREC_t entropies increase (decrease) and ΔVIX_t entropies decrease (increase), negative or no association between ΔVIX_t and ΔREC_t occurs. However, negative associations do not mean that our index no longer reflects recession-related fears. Instead, this indicates that recession-related fears contribute less to overall uncertainty (Sulthan et al., 2017).

Figure 5: ΔREC_t and ΔVIX_t entropies



Notes: Figure 5 presents Wavelet Shannon Time-Energy Entropy for ΔREC_t (blue line) and ΔVIX_t (red line). Dates are stated on the horizontal axis and energy entropy levels are on the vertical axis. Vertical dashed lines delineate phases.

For example, in Figure 4 we observe a positive association between ΔREC_t and ΔVIX_t following Russia's invasion of Ukraine in February 2022 where both entropies move together up until the beginning of April before moving in opposite directions until the end of April 2022 in Figure 5. Thereafter, we again observe co-movement in the same direction until mid-May 2022, coinciding with short-term positive association between ΔREC_t and ΔVIX_t. Contrastingly, between April and early July 2023, coherence is largely negative in Figure 4 implying that ΔREC_t has a lower contribution to overall uncertainty. This is consistent with co-movement in opposite directions in Figure 5 during this period. This interpretation can further be confirmed by comparing the slopes for consecutive points lying on each entropy curve which precisely indicate movements in the same or opposing directions. Relying upon an analysis of slopes is particularly useful when positive contributions follow shocks (such as that in June 2022 attributable to the unprecedented rate hikes by the Fed) that are short-lived but result in recession-related fears that extend over longer horizons.[9] Nevertheless, at no point does ΔREC_t entropy decline to zero implying that recession fears contributed to overall uncertainty throughout the period, although the extent of contribution varies.

[9] Entropy series and slopes are available upon request, permitting a more precise analysis of co-movement or movement in opposite directions.

4.2.2. Explanatory power

To directly quantify the explanatory power of our index and to confirm its applicability, we regress ΔVIX_t onto ΔREC_t as follows:

$$\Delta VIX_t = \alpha_V + \beta_{\Delta REC}\Delta REC_t + \varepsilon_{V,t} \qquad (10)$$

Results in Table 3 confirm a positive and significant short-term relationship over the full sample period, with ΔREC_t approximating almost 6% of ΔVIX_t ($\bar{R}^2$ of 0.0578). When eq. (10) is estimated with sub-periods approximately corresponding to dates defining the areas designated in Figure 4 (Areas A, B, C, D, E and F), significant and positive associations are observed from the beginning of February 2022 onwards until the end of March 2023. This indicates that ΔREC_t approximates ΔVIX_t components over these sub-periods, with the $\bar{R}^2$ peaking between February and May 2022. Towards the end of the sample, from August 2023 onwards, the $\bar{R}^2$ is 0.1162, implying that recession-related fears again increased following a period of relative optimism. The results in Table 3 are congruent with coherence patterns reflected in Figure 4 and similarly demonstrate that recession-related fears increasingly contributed to VIX movements around significant geopolitical and economic events, notably during the first half of the sample period.

Table 3: Relationship between ΔVIX_t and ΔREC_t

Period	α	$\beta_{\Delta REC_\pi}$	$\bar{R}^2$
Full	-0.0801	0.2085***	0.0578
01/12/2021	-0.1535	0.1487	0.0000
01/02/2022	0.2853	0.4383**	0.0680
01/05/2022	-0.0348	0.2478**	0.1236
01/10/2022	-0.2863	0.1468**	0.0321
01/05/2023	-0.0937	-0.1108	0.0082
01/08/2023	0.0137	0.2101***	0.1162

Notes: This table reports the results of least squares regressions for ΔVIX_t onto ΔREC_t estimated with Newey-West heteroscedasticity and autocorrelation consistent (HAC) standard errors. Both series are in first differences. "Full" in the period/start column refers to estimates over the entire sample period, 1 December 2021 to 15 September 2023. Approximate sub-periods are designated on the basis of patterns in Figure 4 with dates corresponding to the start of each sub-period in the first column. A is the intercept and $\beta_{\Delta REC_\pi}$ is the coefficient associated with the ΔREC_t for sub-period π. $\bar{R}^2$ is the adjusted coefficient of determination. *** and ** indicate statistical significance at the 1% and 5% levels of significance, respectively.

We expect ΔREC_t to exhibit significant but limited explanatory power over an extended sample period as recession fears may be more acute during certain periods, such as around the invasion of Ukraine and record U.S. rate hikes. Regression analysis aggregates the empirical relationship between ΔVIX_t and ΔREC_t and does not capture localised relationships in the same manner as coherence analysis. Coherence analysis, on the other hand, does not directly quantify the strength of the relationship between two series. We therefore also estimate rolling regressions for ΔVIX_t onto ΔREC_t which confirm that aggregation over the intervals in Table 3 understates the localised approximative power of ΔREC_t (see Figure A1 in Appendix A). The approximative power of ΔREC_t increases significantly from February 2022, peaking in early July 2022 (with rolling $\bar{R}^2$s reaching over 0.5). Thereafter, the $\bar{R}^2$

exhibits localised peaks, aligning with periods of significant positive coherence in Figure 4. Rolling regressions thus confirm that ΔREC_t approximates components of ΔVIX_t and, as expected, recession fears exhibit a time-varying contribution to overall uncertainty. These regressions approximately quantify this contribution, while directional coherence analysis precisely localises changes in the relationship and reveals information about the persistence of recession fears.

4.2.3. Control variables

To confirm the robustness of our results, we regress ΔVIX_t onto ΔREC_t and variables representative of energy prices (as a category), real activity, interest rates, sentiment, global financial conditions, and investor risk perceptions, individually and jointly. The Baltic Exchange Dry Index (ΔBDI_t) is used to proxy for global economic activity (see Makridakis et al., 2020) and the FTSE World Government Bond Index ($\Delta WGBI_t$) proxies for global interest rates.[10] We consider composite proxies for oil (ΔOIL_t), natural gas (ΔGAS_t) and coal ($\Delta COAL_t$) prices in the form of rotated factor scores constructed from differences in major energy price benchmarks.[11] Global market sentiment is measured using the Société Générale Global Sentiment Index (ΔSGS_t) (Ghosh et al, 2023). The U.S. Dollar Index, ΔDXY_t, is used to control for shifts in various global and U.S. specific factors, financial conditions and risk perceptions (Obstfeld & Zhou, 2023).

Results (reported in Table A2 in Appendix A) indicate that ΔREC_t continues to approximate ΔVIX_t when considered with control variables individually and jointly, with the relationship remaining statistically significant and positive. $\beta_{\Delta REC}$ is stable in magnitude, declining only when considered with ΔSGS_t and ΔDXY_t revealing that ΔREC_t reflects components of market sentiment and risk perceptions. This is not unexpected; sentiment deteriorates, and risk perceptions increase as recession fears grow (Smales, 2017b). In the unrestricted regression which combines all variables and ΔREC_t, ΔVIX_t responds negatively to $\Delta WGBI$ indicating that increases (decreases) in interest rates contribute positively (negatively) to overall stock market uncertainty (row (6) of Table A2 in the Appendix).[12] This is in line with the patterns in Area C of Figure 4 which are attributed to unprecedented interest rate hikes. The only energy commodity that impacts ΔVIX_t is ΔGAS. The rapid post-COVID-19 economic recovery, the outbreak of the Russia-Ukraine war and the aftermath resulted in rapidly increasing energy prices. Unlike oil prices which have historically exhibited high levels of volatility, the sharp increases in natural gas and coal prices are unprecedented in recent history and therefore constitute an economic shock (Szczygielski, Charteris, Obojska & Brzeszczyński, 2023). Overall, this analysis indicates that

[10] Preliminary analysis shows that movements in this index are negatively and correlated with changes in yields on 90-day U.S. Treasury Bills and 10-year U.S. government bonds.

[11] For oil, we use DME Oman Crude, Brent and WTI futures' prices. For coal, we use Newcastle, Rotterdam and Richards Bay futures' prices. Dutch TTF, U.S. Henry Hub and U.K National Balancing Point futures' prices are used to proxy for natural gas prices. Composite proxies are constructed by factor analysing differences in these series and using factors that load onto each energy commodity.

[12] This follows from the negative relationship between $\Delta WGBI$ and interest rates; as interest rates increase (decrease), $\Delta WGBI$ decreases (increases).

ΔREC_t continues to approximate ΔVIX_t after accounting for other factors that reflect changing macroeconomic and financial conditions, sentiment and risk perceptions. Importantly, it demonstrates that ΔREC_t reflects a distinct component of overall stock market uncertainty.

4.2.4. Comparison against other keyword-based uncertainty measures

We compare the approximative power of our index to that of other daily keyword-based uncertainty measures. These are the newspaper-based U.S. economic policy uncertainty (EPU) index of Baker et al. (2016) and U.S. equity market uncertainty (EMU) index of Baker et al. (2019), the Twitter-based equity market and economic uncertainty (TMU and TEU, respectively) indices of Baker et al. (2021) and the geopolitical risk index (GPR) of Caldara and Iacoviello (2021).

The results (reported in Table A3 of Appendix A) indicate that only ΔTMU_t outperforms ΔREC_t with higher explanatory power for ΔVIX_t ($\bar{R}^2$ of 0.0744). However, the ΔTMU_t series ends in late April 2023 (at the time of writing).[13] An advantage of Google search data is that it is readily available and up to date. Then, ΔREC_t is a topic-specific index whereas ΔTMU_t is a general stock market uncertainty index. Given its greater breadth, it is not unexpected that this index may be a better approximator of ΔVIX_t. Even so, it marginally outperforms ΔREC_t in approximating ΔVIX_t when considered using the data available.[14] None of the other indices outperform ΔREC_t in approximating ΔVIX_t. Explanatory power is marginal for ΔTEU_t and non-existent for ΔEMU_t, ΔEPU_t and ΔGPR_t. Finally, we consider the similarity between these uncertainty measures and ΔREC_t by estimating correlations. ΔREC_t and ΔTMU_t are weakly but significantly correlated based on both ordinary and Spearman correlations (ρ_O of 0.1284 and ρ_S of 0.1047) whereas only ordinary correlation between ΔREC_t and ΔTEU_t is significant (ρ_O of 0.0883).[15] Correlations between ΔREC_t and ΔEMU_t, ΔEPU_t and ΔGPR_t are insignificant. We expect some similarity between ΔREC_t and ΔTMU_t as both aim to proxy for stock market uncertainty at a high frequency using keywords. However, our index reflects a topic-specific component of uncertainty.

4.3. Recession fears and global stock markets

4.3.1. Global market reactions

The impact of recession fears on global stock markets is presented in Figure 6. Panel A shows ΔREC_t becomes negatively and persistently associated with returns following Russia's invasion of Ukraine and subsequent oil price increases (Area B). This is in line with expectations that heightened recession fears translate into reduced cash flows for firms due to lower consumer and firm spending and/or a higher forward-looking discount rate attributable to heightened risk aversion (Guiso, 2012; Smales, 2017b; Gómez-Cram, 2022). Khalfaoui et al. (2023) similarly report that increased Google searches for war-

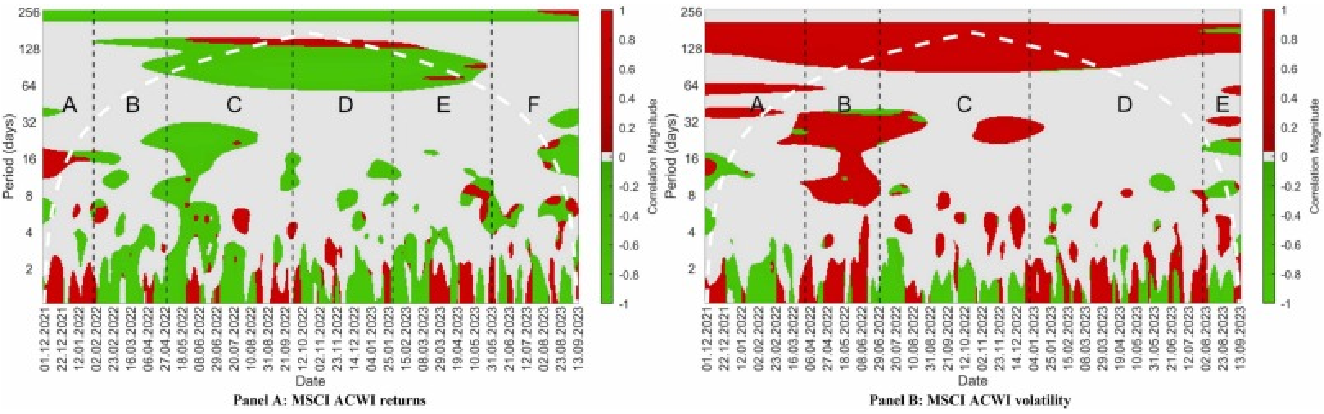
[13] This index is no longer being updated due to the removal of Academic Research access to the Twitter/X API.
[14] Between 1 December 2021 and 24 April 2023, ΔREC_t approximates 6.59% of ΔVIX_t.
[15] Results are available upon request. Significance is reported at the 10% level.

related terms negatively impacted stock returns at this time. Moreover, Boubaker et al. (2023) and Kumari et al. (2023) propose that the negative reaction of stock markets to the outbreak of the Russia-Ukraine war can be explained by fear. Relatedly, Będowska-Sójka et al. (2022) document more pervasive coherence between geopolitical risk and developed and emerging stock markets following Russia's invasion.[16] From the end of April to July 2022 (Area C), the association between ΔREC_t and $R_{w,t}$ extends into the medium run, commensurate with rising food and energy prices, supply-side constraints and ongoing conflict in Ukraine. This period also coincides with unprecedented rate increases in the U.S. and globally, the effect of which is also reflected in Figure 4. These factors have the potential to erode expected cash flows as they adversely impact consumer spending in response to a cost-of-living crisis and increase firm production costs. At the same time, as inflation increases, so do discount rates, reflecting monetary policy tightening. Towards the end of this sub-period, short-run coherence becomes sporadic, alternating between positive and negative. This coincides with a brief market upturn attributable to positive earnings reports and continued consumer spending in the U.S. (Macheel & Pound, 2022). According to Kose et al. (2017), positive economic conditions in the U.S. are expected to be reflected by global stock markets. Nevertheless, recession fears persist over the medium and long run in-line with rising concerns around high U.S. inflation and Fed rate increases (June and July 2022) (Cox, 2022; Ross 2022). Notably, persistence – indicated by negative coherence that extends into the medium and long run – suggests that the likelihood of a recession is increasingly being accepted by economic agents.

From October 2022 to January 2023 (Area D), short-run coherence becomes less sporadic and is mostly negative, with negative long-run coherence implying persistent recession fears. At this time, the narrative among economists and investors was that of an impending U.S. recession (Krauskopf, 2022; Mikolajczak, 2022) while the Eurozone experienced an economic downturn implying decreased aggregate demand in these economies (Partington, 2023). However, from March to May 2023 (Area E) short-run positive associations (red) between ΔREC_t and $R_{w,t}$ again point towards decreasing recession fears. This abatement is in line with the approximate coherence patterns in Figure 4 which suggest that ΔREC_t contributed less to overall stock market uncertainty, consistent with perceptions of a soft landing for the U.S., rising U.S. consumer confidence, stabilising inflation in Europe, falling global energy prices and the resilience of economies such as France and Spain which experienced economic growth (Smart, 2023; Chadwick, 2023). Nevertheless, long-run coherence remains negative reflecting ongoing concerns around slowing Chinese growth and the real estate slump (Yao & Cash, 2023). Additionally, Pazzanese (2023) notes that market participants were pricing negative economic growth into valuations at this time.

[16] Będowska-Sójka et al. (2022) show the intensity of the relationship but do not distinguish between positive and negative associations.

Figure 6: Spectrograms for ΔREC_t, global stock market returns $R_{w,t}$ and realised variance, $R^2_{w,t}$



B: MSCI ACWI volatility

Notes: Figure 6 reports spectrograms for ΔREC_t against global stock returns ($R_{w,t}$) and realised volatility ($R^2_{w,t}$) in Panels A and B, respectively in three dimensions: time on the horizontal axis, frequency domain on the vertical axis expressed in the number of days and directional wavelet coherence values (contour map). The performance of global stock markets is represented by the MSCI ACWI index over the period 1 December 2021 to 15 July 2022. Returns are calculated as logarithmic differences in the MSCI index levels and the recession fear index is in first differences. Regions in red (green) reflect a positive (negative) association between ΔREC_t and $R_{w,t}/R^2_{w,t}$ at the 10% significance level. The white dashed line indicates the 5% significance level for edge effects occurring in coherence data. Higher horizons (periods) indicate a longer investment horizon and more persistent uncertainty spillover components. Values of (approximately) between 1 and 8 days are defined as the short run, 9 to 32 days are defined as the medium run and values greater than 33 days are designated as the long run.

From the end of May 2023, the persistent negative impact of recession fears on stock returns dissipates although short- and medium-run associations remain and are predominantly negative (Area F). This coincides with news around falling U.S. consumer confidence and dwindling household savings which would reduce consumer spending and have an adverse impact on firms' future cash flows. These effects extend beyond the U.S., with Europe and China also experiencing increasing economic difficulties (Amaro, 2023; Inman, 2023).

Panel B of Figure 6 shows that ΔREC_t has a short-run positive (red) association with market volatility, as measured by realised variance, $R^2_{w,t}$, briefly around the outbreak of war in Ukraine in late February 2022. Medium- and long-run coherence persists from end January to end March 2022 due to ongoing assessments by economic agents of the impact of monetary policy tightening on earnings growth and fears around an impending Russian-Ukraine conflict (Area A) (Holland et al., 2022). Russia's invasion of Ukraine does not cause immediate positive short-run association between recession fears and volatility revealing that geopolitical risk contributes to increased volatility but is not necessarily a critical driver thereof. This is consistent with the findings of Wu et al. (2023) that the Russia-Ukraine war had a delayed impact on global stock market volatility. They attribute this delay to government military spending which decreased the uncertainty of firms' future cash flows. This, however, is offset as the war proceeds and the long-term consequences of military action are processed by market participants. Global market volatility, similarly to returns, becomes increasingly associated with recessionary fears towards end March 2022 (Area B) across all horizons showing that record-breaking global food prices, high oil prices, a slowdown in China's economic growth and – notably – U.S. interest rate hikes translated into general stock market unease. In early/mid-June 2022, coherence becomes more pronounced, signalling that recession fears increasingly coincided with persistently higher volatility, aligning with U.S. May inflation of 8.6% (10 June), at that time the highest since 1985 (Choe & Troise, 2022) and the subsequent rate hikes that followed. In response to these rate hikes, U.S. stock prices plunged, and entered bear territory (Iacurci, 2022).

Up until this point, the association between ΔREC_t and variance coinciding with record-breaking U.S. inflation is more distinct than that of prior news releases (i.e., China's economic slowdown), given that high inflation is associated with rising interest rates which negatively impact consumer and capital expenditure. The predominant positive association of recession fears with stock return volatility is consistent with theoretical expectations that fear contributes to noise in stock prices as investors seek to ascertain true value during a negative economic outlook (Black, 1986) and mirrors international evidence related to general fears (Whaley, 2009; Smales, 2017b) and COVID-19-related fears (John & Li, 2021).

From June to December 2022 (Area C), there is limited positive association between recession fears and stock market volatility (red) with negative associations (green) dominating in the short run. This implies that investors had already priced in a recession over the short term and hence news, such as the consecutive U.S. interest rate hikes, did not contribute to substantial upward and downward stock price revisions (Zhan, 2022). In January 2023, there is a resurgence of sporadic positive short-run associations between ΔREC_t and $R^2_{w,t}$ that continues until July 2023 (Area D). Thus, while a reduction in recession fears due to the potential of a "soft landing" and resilience in European economies positively impacted stock returns, it triggered volatility as markets priced in this news (Yeh & Lee, 2000; Brenner et al., 2009). No clear coherence pattern emerges towards the end of the sample period, with coherence alternating between positive and negative (Area E). Recession fears surged again at this time, contributing to overall stock market uncertainty. This coincided with increased U.S. yield curve inversion, negative consumer sentiment, and sticky inflation. However, this did not translate into stock market volatility, suggesting that economic agents became accustomed to the possibility of a recession.

Our analysis shows that recession fears began playing a more prominent role in driving stock market returns and volatility from the outbreak of the war in Ukraine. At this time, escalating energy prices were anticipated to fuel inflation and prompt tighter monetary policy. This came to pass, with record inflation rates in recent history observed globally and notably in the U.S. Monetary policy became more restrictive with the Fed increasing rates by 0.75% in June 2022. Figure 4 suggests that this was a major contributor to overall stock market uncertainty that, as revealed by Figure 6, impacted global markets. While this was not the end of the tightening cycle in the U.S., economic agents seemingly became accustomed to this environment as no singular event thereafter is associated with such prominent coherence. What follows are more sporadic and less prominent associations between ΔREC_t, returns and volatility which implies that recession fears continued to affect markets. Economic news related to deteriorating consumer confidence, changing global economic growth prospects and the inversion of the U.S. yield curve contributed to lingering recession fears reflected by both moments. In summary, market responses to recession fears are driven by both sentiment and economic fundamentals. There is some variation in coherence patterns for stock returns and volatility, which is to be expected as returns reflect the direct reaction of stock prices to information whereas volatility reflects the intensity of price revisions as economic agents seek to interpret information.[17]

[17] We also model recession fears between January 2020 and November 2021. This period is treated separately from the post-COVID-19 period because of its unique characteristics and the relatively unadulterated role of COVID-19 in driving recession fears. Recession fears during the first half of 2020 are attributable to supply side shocks driven by government-imposed lockdowns and other restrictive measures that impacted economic activity. While the initial stages were characterised by supply-side constraints, reduced and uncertain incomes translated into declining exports, falling commodity prices, shrinking travel and tourism, and declining remittances from abroad, this translated into falling consumption, investment spending and consequently falling aggregate demand (Jomo & Cowdhury, 2020). The COVID-19 pandemic is one of the most impactful and disruptive events in recent history (Cruz-Cárdenas et al., 2021). Following its outbreak, projections were that the global economy would contract by 3% in 2020, a more severe contraction than during the GFC. Recovery was projected to occur in 2021, with the global economy growing by 5.8% (IMF, 2020). Global stock markets crashed in response to the outbreak in March 2020, returning to pre-outbreak levels by October 2020. Coherence for the VIX and a recession fears index, ΔREC_t, constructed for the period January 2020 to November 2021 using eight search terms from a search set of 51 terms, reflects the severity of recession fears during the acute phase of the COVID-19 crisis in early 2020 (see Figure B1 in Appendix B). The $\bar{R}^2$ is 0.2578 implying that recession fears played a more significant role in driving overall uncertainty relative to the post-

4.3.2. Confirmatory analysis

To confirm that ΔREC_t models recession fears reflected by global market returns and volatility, we compare the results of regressions of returns and realised variance onto both ΔREC_t and ΔVIX_t over the full sample period and for sub-periods corresponding to the areas in Panels A and B in Figure 6. Results in Panel A of Table 4 for the full period indicate that ΔREC_t explains just over 5% of variation in returns whereas ΔVIX_t explains 53.53%. Lower explanatory power, as measured by $\bar{R}^2$, is expected if ΔREC_t approximates specific components in ΔVIX_t, given that ΔVIX_t is a proxy for overall stock market uncertainty and that the contribution to recession fears varies over time and will be more acute during certain periods relative to others. Rolling regressions of $R_{i,t}$ onto ΔREC_t confirm that this is indeed the case; rolling $\bar{R}^2$s indicate that the explanatory power of ΔREC_t for $R_{i,t}$ peaks between 0.4 and 0.5 (depending upon rolling window size, see Panel A of Figure A2 in Appendix A) between February and September 2022. This result suggests that regression analysis understates the *localised* impact of recession fears (see Section 4.2.2.). Similarly, directional wavelet analysis provides further and more detailed insight by precisely localising associations, revealing how the impact varies in intensity over time and reflecting the growth of persistence around significant events. At times, negative associations are short lived, but nevertheless significant such as around the time when the U.S. yield curve inverted (March 2022), the dominant narrative was of a recession (December 2022), consumer confidence in the U.S. was low (April 2023) and countries in the Eurozone slipped into a recession (June 2023) (Krauskopf, 2022; Mikolajczak, 2022; Moore, 2023, Partington, 2023).

COVID-19 period, congruent with the highly disruptive and unprecedented nature of the COVID-19 crisis. Coherence between ΔREC_t and ΔVIX_t is highly persistent, notably around mid-February and end-March 2020, extending into the long run. It becomes less persistent from April 2020 until February 2021. This can be explained by normalising expectations, government rescue packages restoring investor confidence and economic agents beginning to adapt to restrictions and gaining a better understanding of COVID-19 information (Szczygielski, Charteris, Bwanya & Brzeszczyński, 2023). The combination of these factors contributed to falling recession fears. We also plot directional coherence between ΔREC_t and returns and realised variance for the MSCI ACWI (see Panels A and B of Figure B2 in Appendix B). Coherence between ΔREC_t and returns is negative and highly persistent between February and March 2020, becoming limited to the short run from April 2020 onwards. Coherence between ΔREC_t and realised variance reflects similar patterns indicative of an acute market response around the outbreak of COVID-19. The association between ΔREC_t and realised variance is highly pervasive and positive from February to March 2020, extending into the long run before becoming limited to short-run horizons from April 2020. The outbreak of the COVID-19 pandemic offers valuable insight into how economic agents process information. The outbreak and subsequent response measures sparked expectations of a serious economic fallout, fuelled by media hype, fake news, and speculation about adverse effects (Vasterman, 2005; Nicomedes & Avila, 2020). Early in the crisis when economic data was limited, predictions about a severe impact on corporate profitability led investors to anticipate lower future cash flows (Mamaysky, 2020). The information overload and unprecedented nature of the situation together with restrictions impacting economic activity posed a significant challenge for economic agents, resulting in substantial stock market responses (Zaremba et al., 2020; Bakry et al., 2022). As the pandemic progressed, markets reacted in a more muted manner to recession fears which can be attributed to normalising investor expectations, facilitated by economic support measures and a reversion to a more natural state. Economic agents no longer had to process such a large quantum of information as was the case following the designation of COVID-19 as a pandemic and the implementation of unprecedented responses (Szczygielski, Charteris, Bwanya & Brzeszczyński, 2023). Despite the ongoing nature of the pandemic and the emergence of new concerns, such as COVID-19 variants that fuelled fears of additional lockdowns, markets began to behave more rationally and became less sensitive to immediate COVID-19 developments (Meyer, 2021).

Regression results for returns in Panel A of Table 4 indicate that between February 2022 and the end of September 2022, the explanatory power for both ΔREC_t and ΔVIX_t increased before declining and is highest for ΔREC_t between May and September 2022. These patterns reflect the pervasiveness of coherence in Panel A of Figure 6, most notably for Area C which shows highly persistent associations. In Panel B of Table 4, the relationship between $R^2_{w,t}$ and both ΔREC_t and ΔVIX_t is strongest and significant between April and June 2022, with an $\bar{R}^2$ of 0.1862. This again reflects coherence patterns observed in Panel B of Figure 6, with Area B coinciding with rapidly rising inflation and subsequent interest rate increases which fuelled recession fears. When explanatory power for ΔREC_t approaches that of the ΔVIX_t, as in Panel B in Table 4 from August 2023 onwards, this illustrates that recession fears are the dominant component in overall stock market uncertainty. Co-movement in explanatory power confirms that ΔREC_t is a component of ΔVIX_t and that recession fears drove stock market volatility.

Rolling $\bar{R}^2$s confirm that the strength of the relationship between $R^2_{w,t}$ and ΔREC_t peaks between April and June 2022, with ΔREC_t briefly approximating over 30% of realised variance around this time (see Panel B of Figure A2 in Appendix A). This is congruent with the positive and persistent coherence in Area B of Panel B in Figure 6.

Table 4: Comparison of ΔREC_t and ΔVIX_t explanatory power

Panel A: Returns

		ΔREC_t			ΔVIX_t	
Period	**α**	$\boldsymbol{\beta_{\Delta REC_\pi}}$	$\bar{R}^2$	**α**	$\boldsymbol{\beta_{\Delta VIX_{t,\pi}}}$	$\bar{R}^2$
Full	-0.0001	-0.0005***	0.0543	-0.0003	-0.0018***	0.5353
01/12/2021	-0.0003	5.81E-05	0.0000	-0.0005	-0.0013***	0.6752
01/02/2022	-0.0012	-0.0011***	0.1139	-0.0008	-0.0017***	0.6810
01/05/2022	-0.0015	-0.0007***	0.1481	-0.0016*	-0.0021***`	0.6052
01/10/2022	0.0018	-0.0001	0.0000	0.0009	-0.0025***	0.3751
01/02/2023	0.0001	-0.0004**	0.0315	-0.0001	-0.0016***	0.5773
01/06/2023	0.0007	-6.08E-05	0.0000	-0.0004	-0.0017***	0.3227

Panel B: Variance

		ΔREC_t			ΔVIX_t	
Period	**α**	$\boldsymbol{\beta_{\Delta REC_\pi}}$	$\bar{R}^2$	**α**	$\boldsymbol{\beta_{\Delta VIX_\pi}}$	$\bar{R}^2$
Full	0.0001***	6.15E-06*	0.0245	0.0001***	8.41E-06*	0.0342
01/12/2021	6.99E-05***	8.91E-06	0.0114	0.0001***	9.07E-06*	0.0390
01/04/2022	0.0002***	1.87E-05**	0.1862	0.0002***	2.63E-05***	0.3519
01/07/2022	0.0001***	3.76E-06	0.0013	0.0001***	4.76E-07	0.0000
01/01/2023	4.88E-05	1.38E-06	0.0000	4.85-05***	-8.80E-07	0.0000
01/08/2023	3.84E-05***	5.22E-06*	0.1256	3.83E-05***	9.81E-06	0.1395

Notes: This table reports the results of least squares regressions of returns, $R_{w,t}$, and realised variance, $R^2_{w,t}$, for the MSCI ACWI onto ΔREC_t and ΔVIX_t, estimated with Newey-West heteroscedasticity and autocorrelation consistent (HAC) standard errors. Returns are calculated as logarithmic differences in the MSCI index levels, and the recession fear index and the VIX are in first differences. "Full" in the period column refers to estimates over the entire sample period, 1 December 2021 to 15 July 2022. Approximate sub-periods are designated on the basis of the areas defined in Panels A and B in Figure 6 with dates corresponding to the start of each sub-period. A is the intercept and $\beta_{\Delta REC_t,\pi}$ and $\beta_{\Delta VIX_t,\pi}$ coefficients associated with the ΔREC_t and ΔVIX_t respectively for sub-period π. $\bar{R}^2$ is the adjusted coefficient of determination. Asterisks *, **, *** indicate statistical significance at the respective 10%, 5% and 1% levels of significance.

In an unreported test, we confirm information commonality in both ΔREC_t and ΔVIX_t by regressing returns and realised variance onto ΔREC_t after adjusting ΔREC_t for ΔVIX_t. If ΔREC_t's explanatory power for returns and variance stems from its ability to reflect recession-related fears that are also reflected by ΔVIX_t, then $\bar{R}^2$s should decline substantially (see Wurm & Fisicaro, 2014; Szczygielski et al., 2024). This is indeed the case; ΔVIX_t-adjusted ΔREC_t explains 0.15% of the variation in returns (a decrease from 5.43%) and 0.12% of realised variance (decrease from 2.45%). Residual explanatory power can be attributed to Google searches reflecting the views of not only retail and potentially institutional investors, but also non-investors and other narratives reflected by Google searches, such as attention or sentiment.[18]

4.4. Recession fears and G7 stock markets

The association between ΔREC_t and G7 stock market returns in Figure 7 is predominantly negative (green) and becomes more prominent for all countries following Russia's invasion of Ukraine, coinciding with rising global food and oil prices, record inflation and interest rate increases. Khalfaoui et al. (2023) similarly find that fears related to the Russia-Ukraine war negatively impacted G7 stock returns, with the impact varying across market states and frequency horizons. Figure 7 shows that European countries, having greater trade exposure to the region, are more impacted, unlike Japan, which is less impacted. Inflation remains relatively low in Japan as decades of stagnation mean that companies

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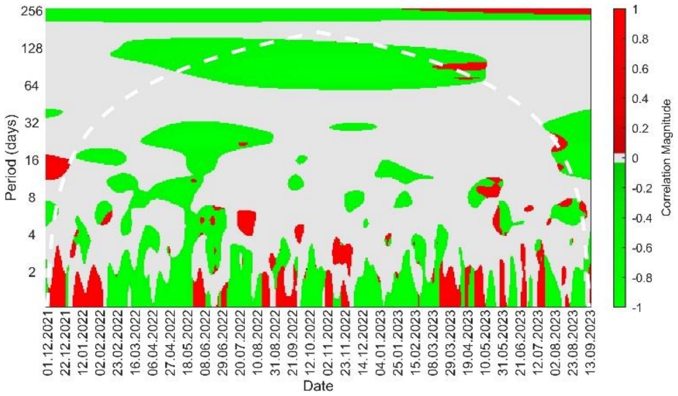
[18] As additional analysis, we consider whether ΔREC_t retains its explanatory power for returns after controlling for the variables considered in Section 4.2.3. ΔREC_t continues to exert a negative and significant influence on MSCI ACWI returns (see Table A4 in Appendix A) across specifications. When energy prices are considered, ΔOIL_t exerts a significant positive effect whereas ΔGAS_t has a significant negative impact (row (1) in Table A4). ΔOIL_t's positive impact is attributable to its role as a barometer for global economic activity. Economic expansion drives the demand for oil, resulting in price increases (Lv & Wu, 2022). Szczygielski, Charteris, Obojska and Brzeszczyński (2023) find that although the relative importance of oil as a barometer of economic activity fell during the 2021-2023 global energy crisis, oil continues to act as a measure of economic activity. Conversely, the anticipated economic impact of rising natural gas prices is negative, especially in Western economies where natural gas is a crucial input (Astrov et al., 2022; Korosteleva, 2022). The negative and significant relationship between returns and ΔGAS_t confirms this. The relationship between returns and $\Delta WGBI_t$ is positive and significant. This is expected, given the relatively high negative correlation between $\Delta WGBI_t$ and interest rates. Increases in $\Delta WGBI_t$ reflect falling interest rates, implying decreases in discount rates will be associated with rising stock prices. ΔBDI_t, viewed as a leading indicator of economic activity, has a significant and negative impact on $R_{w,t}$ (row (3) in Table A4). While a positive relationship is expected as increased demand drives shipping costs upwards owing to the inelasticity of shipping capacity, numerous factors, such as exchange rates movements and inflation, can distort the BDI (Lin et al., 2019). For example, it may be that during times of higher inflation, the BDI increases not because of rising economic activity but owing to rapidly increasing prices. The correlation between BDI and stock returns is negative for some markets, amongst these the U.S., which represents a substantial component of the MSCI ACWI (Graham et al., 2016; Sartorius et al., 2018). These results reveal that while there is a relationship between returns and ΔBDI_t, the transmission channel may suffer from distortions. The relationship between $R_{w,t}$ and ΔSGS_t is significant and positive, implying that improving sentiment is associated with positive global market movements whereas ΔDXY_t has a negative impact. $\beta_{\Delta REC_\pi}$ decreases in magnitude when considered together with all factors jointly (row (6) in Table A4) and ΔOIL_t and ΔGAS_t no longer impact returns suggesting that the explanatory power attributable to ΔOIL_t and ΔGAS_t is subsumed by the remaining factors. $\Delta WGBI_t, \Delta BDI_t$, ΔSGS_t and ΔDXY_t retain their significance. Together with the results in Section 4.2.3, which show that ΔREC_t reflects a distinct component of overall stock market uncertainty, this analysis confirms the presence of a recession fears effect in global market returns. As in Section 4.2.4. and because ΔREC_t is constructed by relating search terms to ΔVIX_t, we consider the explanatory power of the alternative measures for $R_{w,t}$ and $R^2_{w,t}$ - series that are not used to construct ΔREC_t. For returns, the best performing measure is ΔTMU_t ($\bar{R}^2$ of 0.1164), outperforming ΔREC_t. The $\bar{R}^2$ for ΔREC_t up until 24 April 2023, the same period for which data for ΔTMU_t and ΔTEU_t is available, is 0.065. Superior performance can be ascribed to ΔTMU_t's general and broader nature. The explanatory power for ΔTEU_t and ΔGPR_t is significant but marginal for returns whereas ΔEPU_t and ΔEMU_t lack explanatory power. For realised variance, ΔREC_t outperforms all alternative keyword measures, which have no significant explanatory power (see Table A5 of Appendix A for results).

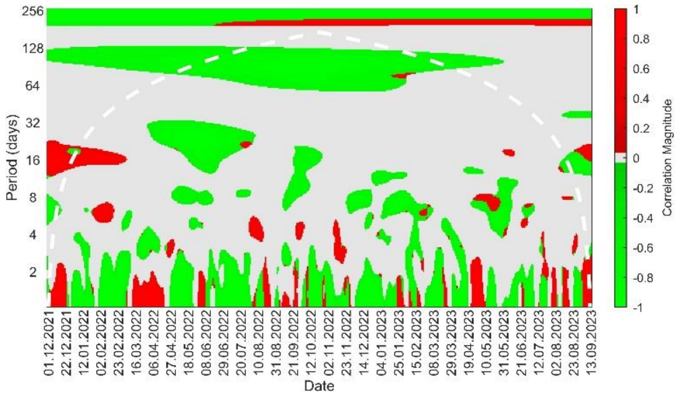
rarely pass on price increases and workers do not demand higher wages (Inagaki & Harding, 2022). Additionally, the Bank of Japan maintained zero interest rates in 2022. Consequently, recession fears driven by rising inflation and interest rates are less of a concern for Japan relative to other G7 markets.

European market returns exhibit short-run negative association with recession fears earlier (in December 2021-January 2022) relative to the U.S., Canada and Japan, coinciding with an increased likelihood of a recession due to renewed lockdowns and supply chain bottlenecks. Supply chain bottlenecks (as seen with computer chips, for example) may contribute to a recession due to the inability to produce goods and services (e.g., automobiles, consumer electronics products, etc.) resulting in a fall in output. Shortages of goods also have the potential to contribute to inflation, further hurting economies. The heightened negative coherence seen in the U.S. in April 2022 is in line with food prices rising at a pace not seen for forty years. Although global food prices were rising rapidly due to supply disruptions caused by the Russia-Ukraine war and increasing energy costs facing producers (Baffes & Temaj, 2022), Adjemian et al. (2023) highlight that U.S. food prices were further fuelled by domestic factors such as avian influenza, disruptions at meat-packaging plants, increased demand due to COVID-19 fiscal and monetary stimulus, and lingering supply problems from COVID-19 lockdowns. European and Canadian markets appear somewhat more insulated from spiralling global food prices relative to the U.S. Except for Japan, all G7 markets reflect prominent negative coherence that extends into the medium run around May and June 2022, coinciding with steepening Federal fund rate increases (50 and 75 basis points, respectively). This reveals that these rate increases were associated with spillovers to most other G7 markets. Furthermore, from May/June 2022 onwards, lingering recession fears in the long run are evident for all markets and are most persistent for the U.S., Canada and Japan. This points towards economic agents increasingly accepting an imminent recession as well as increased confidence in their central banks' ability to curb inflation – contributing to reduced negative short-run associations but growing medium- and long-run associations. In contrast, European central banks delayed raising interest rates, resulting in an increased likelihood of a recession that influenced stock returns (Ellyatt, 2022). Accordingly, central banks that show seriousness in fighting inflation appear to be able to calm fears among market participants (de Larosière, 2022; Lehtimäki, & Palmu, 2022).

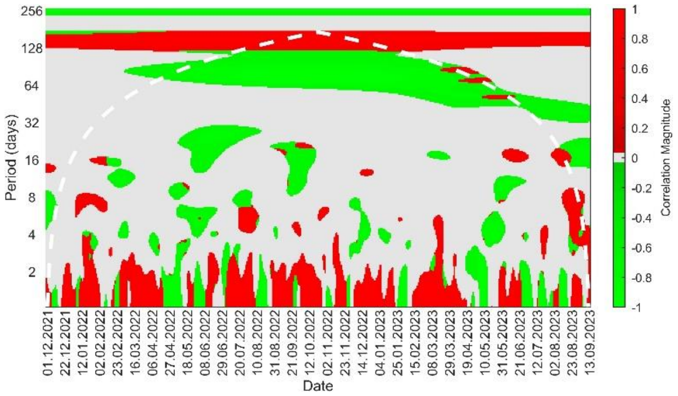
Figure 7: Spectrograms for ΔREC_t and individual G7 country stock market returns, $R_{i,t}$



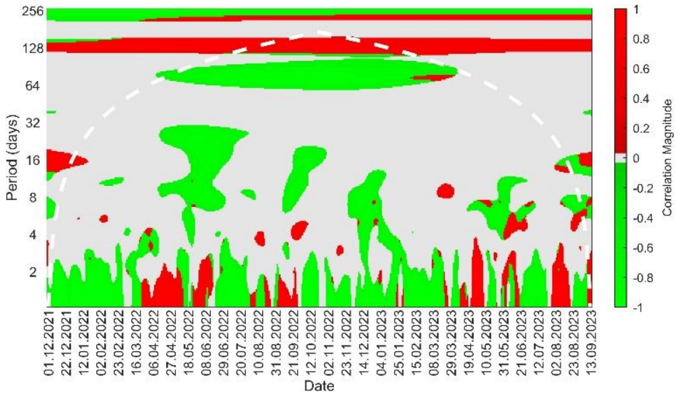
Panel A: U.S.



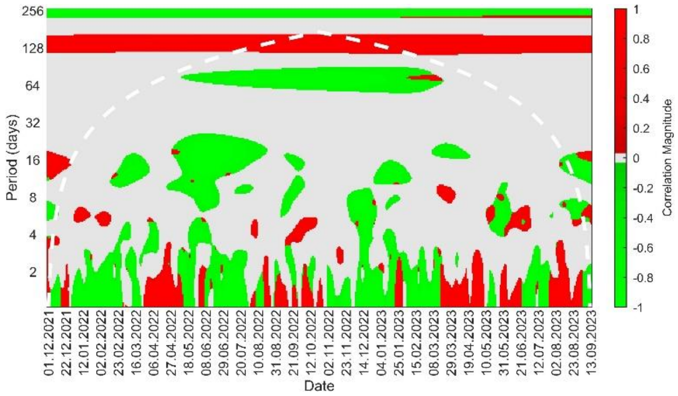
Panel B: Canada



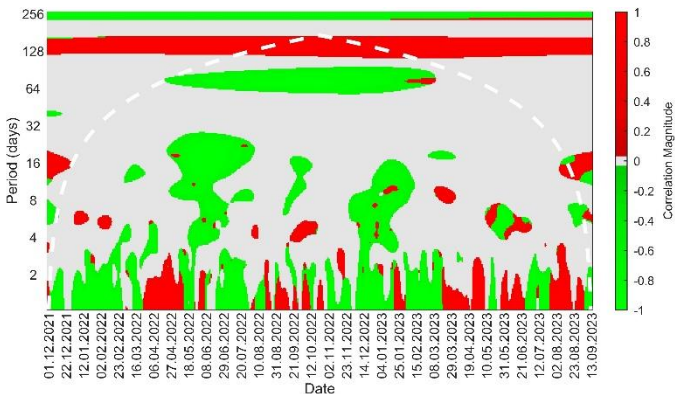
Panel C: Japan



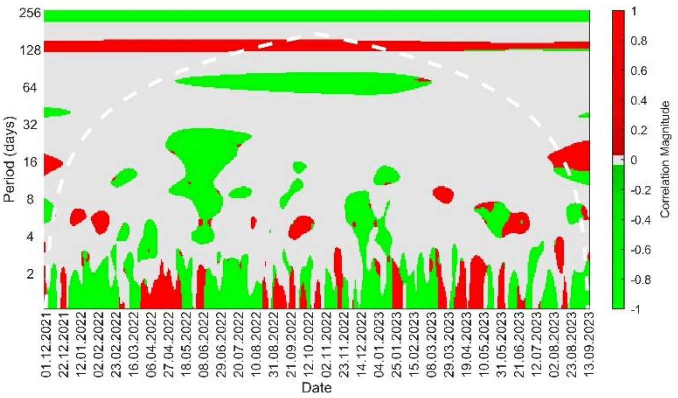
Panel D: U.K.



Panel E: Germany



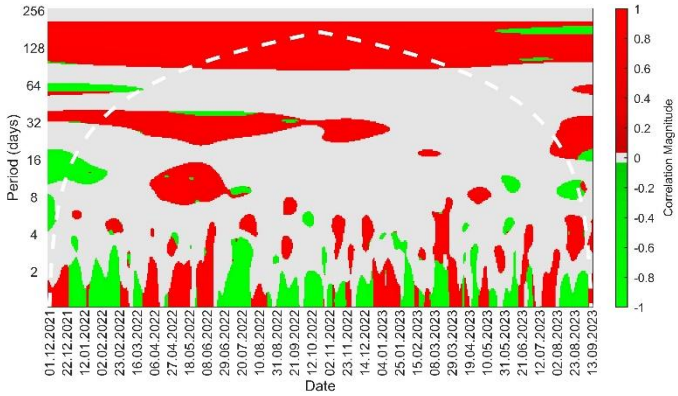
Panel F: France



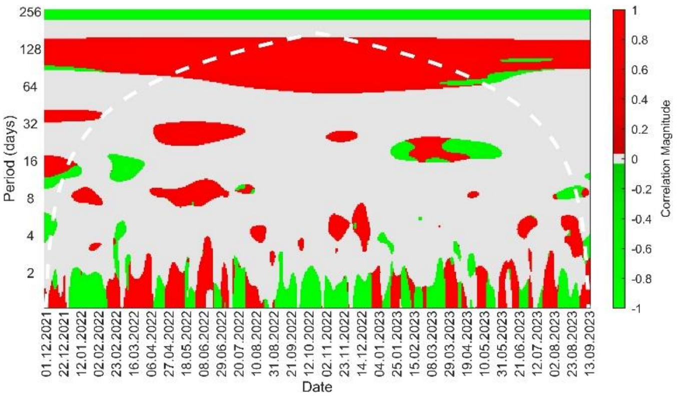
Panel G: Italy

Notes: Figure 7 reports spectrograms for ΔREC_t against individual G7 stock returns ($R_{i,t}$) in three dimensions: time on the horizontal axis, frequency domain on the vertical axis expressed in the number of days and directional wavelet coherence values (contour map). The performance of individual G7 stock markets is represented by MSCI country indices over the period 1 December 2021 to 15 July 2022. Returns are calculated as logarithmic differences in MSCI index levels and the recession fear index is in first differences. Regions in red (green) reflect a positive (negative) association at the 10% significance level. The white dashed line indicates the 5% significance level for edge effects occurring in coherence data. Higher horizons (periods) indicate a longer investment horizon and more persistent uncertainty spillover components. Values of (approximately) between 1 and 8 days are defined as the short run, 9 to 32 days are defined as the medium run and values greater than 33 days are designated as the long run.

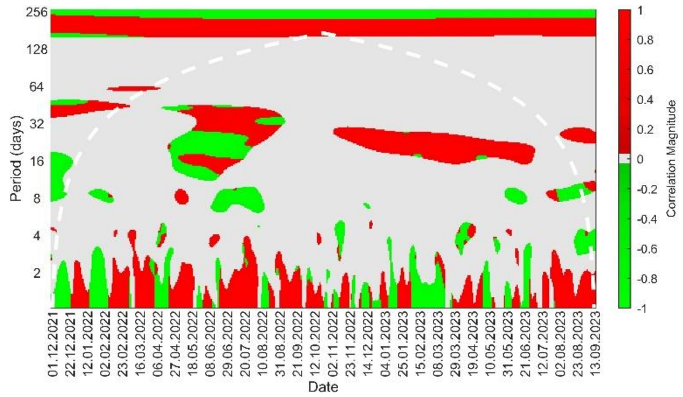
Figure 8: Spectrograms for ΔREC_t and individual G7 country stock market realised variance, $R_{i,t}^2$



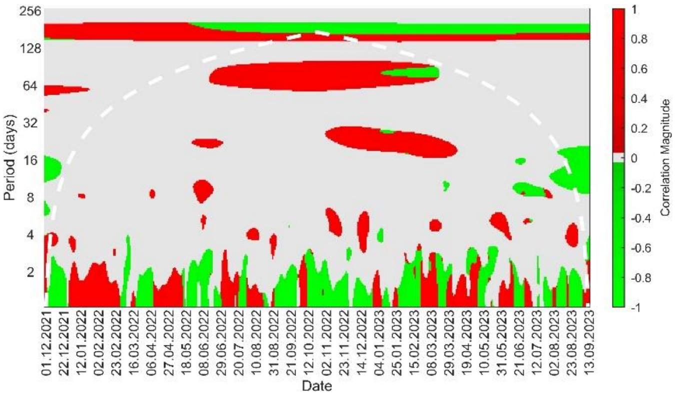
Panel A: U.S.



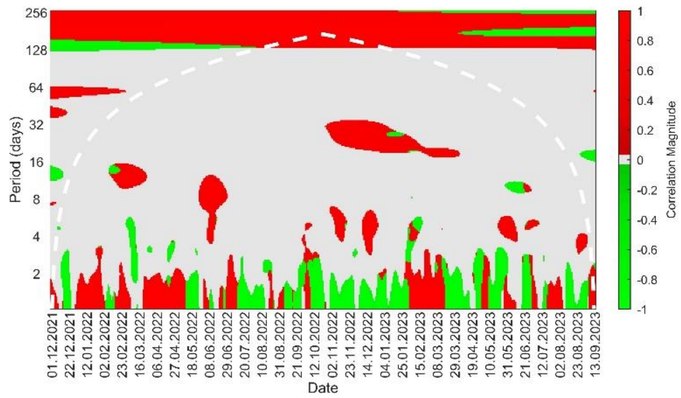
Panel B: Canada



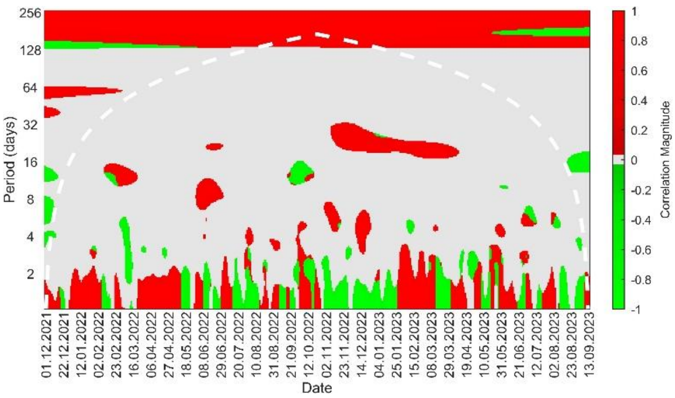
Panel C: Japan



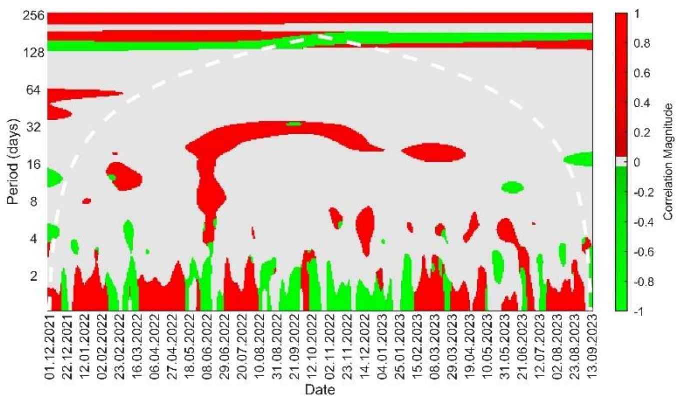
Panel D: U.K.



Panel E: Germany



Panel F: France



Panel G: Italy

Notes: Figure 8 reports spectrograms for ΔREC_t against individual G7 stock market return realised variance ($R_{i,t}^2$) in three dimensions: time on the horizontal axis, frequency domain on the vertical axis expressed in the number of days and directional wavelet coherence values (contour map). Realised variance is the squared return for individual G7 stock markets as represented by MSCI country indices over the period 1 December 2021 to 15 July 2022. Returns are calculated as logarithmic differences in MSCI index levels and the recession fear index is in first differences. Regions in red (green) reflect a positive (negative) association at the 10% significance level. The white dashed line indicates the 5% significance level for edge effects occurring in coherence data. Higher horizons (periods) indicate a longer investment horizon and more persistent uncertainty spillover components. Values of (approximately) between 1 and 8 days are defined as the short run, 9 to 32 days are defined as the medium run and values greater than 33 days are designated as the long run.

Short- and medium-term negative associations between returns and recession fears become more prominent in all markets except Japan from December 2022 to March 2023. During this period, the prevailing consensus among economists was of an impending recession in the U.S. Moreover, consumer confidence was low in the U.S. due to persistent inflation, high interest rates and dwindling COVID-19 savings (Ngo, 2023; Smith, M., 2023). This is reflected in stock market performance, with the S&P500 declining by over 5% in December 2022, which Krauskopf (2022) and Mikolajczak (2022) attribute to recession fears driven by the Fed's restrictive monetary policy. European economies were also confronted with challenging economic conditions at that time which were pushing these countries to the verge of a recession and fuelling fears of an economic downturn (Bank of England Monetary Policy Committee, 2022). This includes record-high inflation, with prices expected to peak at year-end 2022, energy supply bottlenecks, difficulties in sourcing raw materials, and labour shortages (ifo Institute, 2022; Aldama et al., 2022). These conditions constrained production, leading to increased costs, while consumer spending decreased, collectively impacting stock returns negatively. The European Commission's autumn forecast predicted that EU countries were likely to contract in the last quarter of 2022, consistent with country specific forecasts (Aldama et al., 2022; Ciocca & Costagli, 2022; ifo Institute, 2022). Carlssson-Szlezak and Swartz (2022) maintain that although the global energy price shock in the first half of 2022 was a major challenge for the U.S. economy, the Eurozone felt the effects more intensely. France, Italy, Germany and the UK were also impacted by U.S. recession concerns as events in the world's largest economy impact other developed countries (Roos & Zaun, 2016). In August 2023, ΔREC_t is again negatively associated with U.S. stock returns in the short and medium run. This aligns with the views of the Fed, economists and other market participants of a high probability of a recession as suggested by the inverted U.S. yield curve (Moore, 2023). Contrastingly, Japan reported a surge in growth in the second quarter of 2023, explaining the sporadic negative short-term coherence for the remainder of the sample period (Dooley, 2023).

ΔREC_t contributes to individual G7 stock market volatility (Figure 8) but less so than for returns. European markets again show initial short-run positive association earlier, coinciding with the emergence of concerns around slow economic growth in late 2021 whereas the U.S., Canada and Japan are somewhat insulated as evident from sporadic positive or mostly negative association. Short-term coherence becomes more pervasive in all G7 markets from mid-March to April 2022 (except for the U.K. which commences only in April). The Russia-Ukraine war thus does not have an immediate impact on G7 stock market volatility as seen for world markets (Section 4.2) and similarly observed by Wu et al. (2023). However, by late March 2022, the effects of the war on energy and food prices which fuelled inflation, along with China's slow economic growth and the Fed adopting a hawkish monetary policy stance, contributed to recession fears and resulted in stock price volatility (Zhou & Lu, 2023).

For the U.S., Canada, Japan and Italy, coherence becomes more prominent in the short-run and extending into the medium-run between May and June 2022 coinciding with the acceleration of U.S.

monetary policy tightening. This is consistent with the findings of Caldara et al. (2022) of spillover effects from the rapid pace of Fed rate increases. We interpret this as U.S. monetary tightening causing less unease in the remainder of the European markets considered. The persistent coherence for Italy over medium-term horizons from June to November 2022 reflects the country being among the most reliant on Russia for its energy in Europe and its precarious economic position due to an already high debt-to-GDP ratio and government deficit (Kazmin, 2022). Consequently, market participants are likely to be more concerned about recession fears and consider this in their stock valuations as the probability of a recession, and the severity of a recession, will be greater in Italy due to the aforementioned factors (Égert, 2015). The U.K. also exhibits coherence over the long run during this period in line with the ubiquitous cost-of-living crisis in the country and allied recession fears (Haq, 2022).

The negative short-lived association between ΔREC_t and $R^2_{w,t}$ from November 2022 to January 2023 in the U.K., France, Italy and Germany occurs at the time of the enactment or extension of policies aimed at reducing the impact of rising energy prices on consumers. The U.K implemented a gas price guarantee from 1 October 2022; the European Commission adopted interventions to address high energy prices from October 2022; Germany implemented a €99bn energy support scheme in December 2022; and France capped the electricity price increase (Abnett, 2022; Kurmayer, 2022; European Commission, 2023; Jha, 2023). Jha (2023) acknowledges that these policies were successful in stabilising inflation and supporting central bank monetary policy tools with the goal of avoiding a recession. This, in turn, aided in calming markets as market participants anticipated no additional rate hikes by the ECB than were already anticipated in 2023 (Amaro, 2023).

European markets experienced a limited resurgence in recession fears as suggested by positive short-term coherence from February 2023. At this time, news emerged that several European countries had managed to avoid the recession predicted for the winter of 2022. This coincided with other positive developments namely falling natural gas prices, a resilient labour market and improving economic sentiment. Positive coherence nevertheless suggests that European economies were still beset with challenges that contributed to uncertainty and recession fears as economic agents sought to understand the implications of high energy costs, high inflation, continued monetary policy tightening, weak consumption and negative real wage growth (Koranyi, 2023; Smith, E., 2023). Short-run associations between ΔREC_t and $R^2_{w,t}$ are most prominent for Italy (Panel G) from the beginning of 2023 until the end of the sample. Jones and Cinelli (2023) highlight Italy's continued precarious economic situation in 2023 with the country only marginally avoiding a technical recession in the third quarter in addition to difficulties caused by interest rate hikes by the ECB and problems in meeting policy conditions for COVID-19 relief funds promised by the European Commission.

Consistent with the analysis for global markets in Section 4.3, the analysis of individual G7 markets confirms that recession fears, as measured by our index, contribute to market movements, and to a lesser degree market variance, in line with major events that drive recession fears during the early part of the sample period. Notable amongst these is rising inflation and subsequent monetary policy tightening in the U.S., the effects of which spill over to almost all markets, with the exception being Japan which is relatively unimpacted. Considering the parallel economic trends globally, it is expected that G7 stock markets will be affected by recession fears as central banks worldwide raise interest rates in response to escalating inflation while economic output declines or stagnates. Resilience during some parts of the sample period can be attributed to structural characteristics of an economy, such as in the case of Japan with historically low interest rates, or domestic orientation. Subsequent drivers of recession fears are news releases about the economic state and prospects.

5. Implications

Google, along with other search engines, is a technological tool that offers direct access to the thoughts and attitudes of economic agents. Economic agents directly disclose their views by utilising specific search terms, providing valuable insight into how new information is processed. Google search data has advantages over survey-based measures of prevailing views and reduces the likelihood of economic agents being influenced by external parties (Dietzel et al., 2014). It can be freely obtained, is available at high frequencies and does not require advanced programming skills. Researchers can readily use this data, combined with the approach expounded here, to achieve a level of analytical specificity on a topic of interest with greater ease relative to using newspaper or Twitter data (see Dietzel et al., 2014; Balcilar et al., 2018; Będowska-Sójka et al., 2022). According to Powell and Treepongkaruna (2012), the probability risk assessment of a recession based on macroeconomic and financial indicators, commonly employed in the literature and industry, can be viewed as a measure of recession fears. However, these methods are designed to assess the probability of a recession occurring and not to quantify the emotional response of market participants to news about a recession i.e. the fear that the news of an impending recession and its impact elicits. The alternative to quantifying recession fears at a high frequency is to use a broad-based measure of stock market uncertainty such as the VIX that reflect a plethora of other fears and uncertainties (Tsai, 2014). We contribute to the literature by using Google searches in conjunction with elastic net regression to develop an economic agent-determined high frequency measure that isolates and quantifies recession fears.

We apply this measure to study the evolution of recession fears post-COVID-19. Results reveal that recession fears began playing a significant role in driving overall stock market uncertainty following the outbreak of the Russia-Ukraine war. This event was followed by increasing energy prices, a stall in the post COVID-19 economic recovery and monetary tightening in the U.S and elsewhere as central banks responded to rising inflation (Section 3.1.). This is suggested by pervasive coherence between recession fears and global market returns and volatility between February to June 2022 (Figure 6). Nevertheless, while recession fears persisted over the long run, global market reactions became more muted in the short and medium run. This implies normalising investor expectations and a return to a more typical state, providing insights into how economic agents process information. Following shocks, there is a process of adaptation and mean-reversion (Yarovaya et al., 2021).

Relatedly, examining G7 stock markets yields insight into how these economies respond to shocks, with their stock markets serving as indicators of economic outlook and responsiveness. The impact of recession fears varies over time and across markets. For instance, Japan exhibits greater resilience to concerns about recessions. Such resilience may be due to the general characteristics and structure of a particular economy or the nature of a particular shock. Some economies may be more resilient to certain types of shocks relative to others. More broadly, by gaining an understanding of how markets react to specific concerns, whether they are related to recessions or, for instance, pandemics, investors can strive for enhanced diversification across geographic markets and more effective portfolio risk management. In an environment of uncertainty, our approach offers valuable insights for market participants aiming to mitigate downside risk throughout all stages of a crisis.

A high-frequency tool that measures fears around a specific topic can assist policymakers in formulating responses to shocks and events that drive these concerns. The analysis of the G7 stock markets demonstrates that a contributing factor to recession fears across markets was U.S. monetary policy tightening . In response to rising inflation levels, central banks around the world embarked on tightening not seen since the 1970s. This raised concerns about adverse international monetary policy spillovers with arguments being made in favour of co-ordinating responses to rising inflation in a manner that will not lead to an unintended contraction of global economic activity (Caldara et al., 2022). Our results suggest that such spillovers do indeed exist and point towards a rising risk of underestimating the economic impact of increasingly restrictive monetary policy. These findings provide further motivation for policymakers to coordinate their responses at a global level. At a national level, they suggest that consideration should be given to strategies that prevent excessive tightening given the actions of external central banks. Another example is the implementation of policies aimed at reducing the impact of energy prices on consumers towards the end of 2022 and beginning of 2023 in European countries. Around this time, recession fears were a smaller contributor to market variance suggesting that such policies had a calming effect during the energy crisis. The availability of a high-frequency tool that can measure spillover effects associated with monetary policy and policy in a broader sense, as well as its impact on markets, could be advantageous in helping policymakers formulate effective strategies.

Our study relies upon continuous wavelet transform which provides detailed insights into interdependence between two series, including shocks and persistent correlations. It surpasses regular regression analysis, which lacks temporal and frequency variation insights. Advanced regression methods are needed for investigating time-varying correlations (Jensen & Whitcher, 2014). Directional wavelet coherence permits the modelling of interdependencies over different horizons with greater precision, assisting in the understanding of how specific events contributed to market uncertainty.

Notable amongst these events are the Russia-Ukraine war, rapidly increasing energy prices, increasing inflation and monetary policy tightening in the U.S (and globally) (Areas B and C, Figure 4). The refinement presented here can benefit researchers utilising non-traditional quantitative methods to study interdependencies in finance and economics (see Bouri et al. 2020; Mensi et al., 2021). Moreover, investors can use this refinement to model spillovers in specific markets (as in Section 3.4.) to determine which markets recover quickest from shocks. Information from directional spectrograms can be used to form expectations about how long heightened fears attributable to coincident events may persist and when uncertainty resolution can be expected. While the future is unpredictable, better-informed decisions can be undertaken by exploiting knowledge about the effects of past events.

By using elastic net regression to select recession-related search terms that are associated with an overall uncertainty measure, we isolate and capture topic-specific fears. Our approach demonstrates how machine learning can be used to filter "infobesity" (Karhade et al., 2021). Our index comprises 16 Google search terms whereas the starting search set comprises over 98 terms. Investors have limited computational capacity yet must deal with large information flows, leading to departures from market efficiency if information flows become too large and costly to process (Pernagallo & Torrisi, 2020). This approach enables us to not only determine which terms are utilised by economic agents to reflect fears experienced by market participants, thus ensuring objective relevance, but also demonstrates how information costs and complexity can be reduced by extracting only the most relevant search terms. Additional analysis suggests that the iterative elastic net regression-based procedure (Section 2.2.) outperforms alternative feature selection methodologies (see footnote 8). This approach can be applied more broadly, allowing for the identification and analysis of numerous factors, whether they are characteristic-based or macroeconomic in nature, that play a role in traditional asset pricing. It is not limited to the formulation of search term-based indices and can be utilised to assess the influence of various factors on asset pricing more generally. As suggested by Feng et al. (2020), it can be used to "tame the [asset pricing] factor zoo."

Our approach defines and sets the narrative by relating search terms to a well-known measure of uncertainty. Without a clear narrative, it is difficult to determine how Google search-based indices may be useful for the purposes of analysis, econometric modelling and application to stock market dynamics (see Da et al., 2011; Brochado, 2020 for examples of differing narratives). A clear narrative assists in the application of Google search-based indices for investment decision making and portfolio management and facilitates broader analysis and research while permitting the measurement of the impact of specific events using search terms that are relevant to economic agents. The approach expounded can be readily generalised to assign different narratives, such as sentiment, attention, or general economic uncertainty, by relating Google searches to a pre-selected general narrative proxy. This stems from the proposition that Google searches reflect economic agents' views and concerns about a particular topic. Researchers, econometricians and analysts can decompose the effects of narratives associated with specific events or categories of events such as wars, geopolitical risk and recessions. Our study contributes to developing a systematic approach to shaping narratives and measuring their impact.

While this study is concerned with modelling the evolution of recession fears – "nowcasting" – at a high frequency using Google searches, it can be adapted for forecasting purposes. Dietzel et al. (2014), Bijl et al. (2016), Kim et al. (2018) and Brochado (2020) demonstrate that Google searches can predict financial market dynamics and asset prices in the short and long run. For example, a recession fear index can be constructed to predict stock market movements in-sample and can be tested for predictive power out-of-sample. As Google search data is available at varying frequencies, predictive narrative-based indices can be constructed by accounting for intertemporal relationships between a given proxy and Google searches. As an illustration, in the construction of a predictive sentiment index similar to the approach taken by Brochado (2020), terms that exhibit a correlation with a sentiment proxy in a future time period can be utilised. These terms can be employed to create an index that enables the prediction of how shifts in sentiment may influence future economic and financial market dynamics. Moreover, Google searches have been shown to predict variables such as unemployment suggesting that our approach can be applied in areas other than narrative and stock market dynamic modelling (see D'Amuri & Marucci, 2017; Niesert et al., 2020).

6. Conclusion

Recession fears are a critical component of decision-making as economic agents consider the economic outlook when valuing stocks. This study expounds an approach for quantifying recession fears at a high frequency and constructs a recession fear index for the tumultuous period from December 2021 to September 2023. Our analysis suggests that the invasion of Ukraine, the subsequent surge in inflation, and monetary policy tightening in the U.S. and worldwide are major contributors to widespread recession fears. G7 markets reflect these shocks although the reaction is heterogenous. Such knowledge is valuable for stock market investors who are seeking diversification opportunities. Our analysis yields insights into how economic agents process information revealing that they adapted to unfavourable economic news although long-run recession fears persisted.

While this study quantifies and investigates the evolution of recession fears and their impact on stock markets, our approach provides a methodology for isolating and identifying events that matter most to markets with greater precision; namely monetary policy tightening on the heels of rising inflation, more so than other economic and geopolitical events. The findings imply that policymakers should further explore alternative tools, such as energy price caps, rather than solely relying on interest rates to control inflation which have persistent effects. Our analysis points toward spillovers from monetary policy tightening in the U.S. Central banks often overlook the effects of cross-border spillovers raising the risk of underestimating their impact. Globally, policymakers should consider co-ordinating their responses, while at a national level, they should consider strategies to prevent excessive tightening given the actions of foreign central banks.

A limitation of our study is that the sample is restricted to global markets as an aggregate and G7 stock markets individually. Other market groupings, such as BRICS, may be considered. The question is whether Google searches can be used to model their behaviour, given that internet penetration in a number of these countries (e.g., South Africa and India) is relatively lower and therefore may not be reflective of concerns about specific events to the same extent as in G7 countries. A further avenue of research relates to interlinkages between G7 and BRICS markets. Our results suggest that spillovers from the outbreak of the Russia-Ukraine war and subsequent monetary policy tightening had an impact on most G7 stock markets. Research may be undertaken to determine whether other market groupings reflect these spillovers and to what extent. Consideration should also be given to whether our approach can be applied to other asset classes, such as real estate, cryptocurrencies, commodities, and bonds. The response of these asset classes to recession fears may point towards diversification opportunities. Further research may consider whether increased searches for recession-related terms precede economic downturns. Google searches of varying frequencies, which reflect the concerns of economic agents, including retail investors, could provide more timely indications of the early and subtle signs of worsening economic conditions.

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Highlights

- We investigate the influence of recession-related fears on global and G7 stock markets.
- Recession-related fears are isolated and quantified using an economic agent-determined Google search-based index.
- We apply directional wavelet analysis that distinguishes between positive and negative associations.
- Not all stock markets react equally to recession-related fears.
- Key recession-related fear drivers are record inflation levels and tightening monetary policy.
- Our methodology is generalizable and can be applied to isolate and study the impact of specific events on stock markets.

Author 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 **Janusz Brzeszczyński:** Writing - Review & Editing

Appendix A

Recession fears and stock markets: An application of directional wavelet coherence and a machine learning-based economic agent-determined Google fear index

Table A1: Recession related Google search terms used in the formulation of REC_t

2008 recession	last recession*	recession uk
2008 us recession	last us recession	**recession us**
2022 recession	market recession 2022*	recession us 2022
2023 recession	meaning of recession	stock market recession*
2023 recession prediction	news on recession	stocks during recession
are we in a recession 2022	**recession**	stocks for recession
are we in recession	recession 2008	stocks in a recession*
are we in recession 2022	recession 2020	stocks to buy during a recession*
bbc news recession	**recession 2022***	stocks to buy during recession
best recession stocks*	**recession 2023**	stocks to buy in a recession*
best stocks during recession	recession 2023 usa	stocks to buy in recession*
best stocks for a recession	recession 2024	the great recession
best stocks for recession	recession coming*	the meaning of recession
best stocks in a recession	recession definition*	the recession
best stocks in recession	recession in 2022	the recession 2023
buy stocks during recession	recession in 2023	uk recession
coming recession 2022	recession in hindi	uk recession news
definition recession	recession in the us	us economic recession
economic recession	recession in us	us economy recession
economic recession meaning*	recession in us 2022	us great recession
economy recession	recession in us economy	us in a recession
economy recession meaning	**recession meaning**	us in recession 2022*
good recession stocks	recession meaning hindi	us recession
great recession	recession meaning in english	us recession 2022
in recession meaning	recession meaning in tamil	us recession 2023
india recession	recession meaning tamil*	what happens in a recession
india recession news	recession news	what is a recession
inflation recession	recession news 2022*	what is recession
is recession coming	recession news india	what is the meaning of recession
is the us in a recession	recession news today	what us a recession
is the us in recession	recession proof stocks	will there be a recession in 2022*
is us in a recession	**recession stocks**	will there be a recession in 2023
is us in recession	recession stocks to buy	

Notes: This table lists Google search terms used to formulate the recession fear index, REC_t (ΔREC_t in differences). Search terms in **bold** are those suggested by the Google Autocomplete feature when entering the keyword "recession". These are designated as first level search terms. All other search terms, designated as second level search terms, are related to the first level search terms that contain the word "recession". * denotes search terms that have been used in the construction of the recession fear index, REC_t, following identification using the iterative procedure (see Table 1).

Table A2: Relationship between ΔVIX_t and ΔREC_t with control variables

	$\boldsymbol{\alpha}$	$\boldsymbol{\beta_{\Delta REC_{\pi}}}$	$\boldsymbol{\beta_{\Delta OIL}}$	$\boldsymbol{\beta_{\Delta GAS}}$	$\boldsymbol{\beta_{\Delta COAL}}$	$\boldsymbol{\beta_{\Delta WGBI}}$	$\boldsymbol{\beta_{\Delta BDI}}$	$\boldsymbol{\beta_{\Delta SGS}}$	$\boldsymbol{\beta_{\Delta DXY}}$	$\boldsymbol{\bar{R}^2}$
(1)	-0.0753	0.2050***	-0.3294	0.4542**	0.2968					0.0757
(2)	-0.1114	0.2058***				-0.7638				0.0615
(3)	-0.0742	0.2087***					0.0946			0.0564
(4)	-0.0467	0.1730***						-0.2488***		0.3283
(5)	-0.1232	0.1805***							2.1732***	0.1357
(6)	-0.1056	0.1631***	0.1999	0.2216	0.1081	-0.7753**	0.0789	-0.2610***	1.5480***	0.3549

Notes: This table reports the results of least squares regressions for ΔVIX_t onto ΔREC_t and control variables estimated using least squares regression with Newey-West heteroscedasticity and autocorrelation consistent (HAC) standard errors over the period 1 December 2021 to 15 September 2023. All series are in first differences. Control variables are oil (ΔOIL_t), coal ($\Delta COAL_t$) and natural gas (ΔGAS_t) prices, the FTSE World Government Bond Index ($\Delta WGBI_t$), the Baltic Dry Index (ΔBDI_t), the Société Générale Global Sentiment Index (ΔSGS_t) and the U.S. Dollar Index (ΔDXY_t). Row (6) reports the results of the unrestricted regression combining ΔREC_t with all control variables. In this equation, ΔDXY_t is orthogonalised against $\Delta WGBI$ and ΔSGS whereas ΔSGS is orthogonalised against $\Delta WGBI$ to account for possible multicollinearity. $\bar{R}^2$ is the adjusted coefficient of determination. *** and ** indicate statistical significance at the 1% and 5% levels of significance, respectively.

Table A3: Relationship between ΔVIX_t and keyword-based uncertainty

	$\boldsymbol{\alpha}$	$\boldsymbol{\beta_{\Delta UN}}$	$\boldsymbol{\bar{R}^2_{\Delta UN}}$
ΔEPU_t	-0.0784	0.0067	0.0000
ΔEMU_t	-0.0787	-0.0066	0.0000
ΔTEU_t	-0.0707	0.0548**	0.0123
ΔTMU_t	-0.0567	0.1903***	0.0744
ΔGPR_t	-0.0788	0.0306	0.0021

Notes: This table reports the results of regressions of ΔVIX_t onto keyword-based uncertainty measures, ΔUN_t, over the period 1 December 2021 to 15 September 2023 for ΔEPU_t and ΔEMU_t and 1 December 2021 to 24 April 2023 (owing to data availability for the two latter measures). Regressions are estimated using least squares with Newey-West heteroscedasticity and autocorrelation consistent (HAC) standard errors. $\bar{R}^2$ is the adjusted coefficient of determination. ΔEPU_t are changes in the economic policy uncertainty index, ΔEMU_t are changes in the U.S. equity market uncertainty index, ΔTEU_t and ΔTMU_t are changes in the Twitter-based economic and market uncertainty indices and ΔGPR_t are changes in the geopolitical risk index. ** and ** indicate statistical significance at the 1% and 5% levels of significance, respectively.

Table A4: Relationship between $R_{w,t}$ and ΔREC_t with control variables

	α	$\beta_{\Delta REC_{\pi}}$	$\beta_{\Delta OIL}$	$\beta_{\Delta GAS}$	$\beta_{\Delta COAL}$	$\beta_{\Delta WGBI}$	$\beta_{\Delta BDI}$	$\beta_{\Delta SGS}$	$\beta_{\Delta DXY}$	$\bar{R}^2$
(1)	-0.0002	-0.0005***	0.0014**	-0.0010*	-0.0009					0.0828
(2)	0.0002	-0.0005***				0.0074***				0.1394
(3)	-0.0002	-0.0005***					-0.0009*			0.0621
(4)	-0.0002	-0.0004***						0.0007***		0.3740
(5)	5.95E-05	-0.0004***							-0.0097***	0.3153
(6)	0.0001	-0.0003***	-0.0001	-0.0004	-0.0004	0.0074***	-0.0009*	0.0006***	-0.0071***	0.4808

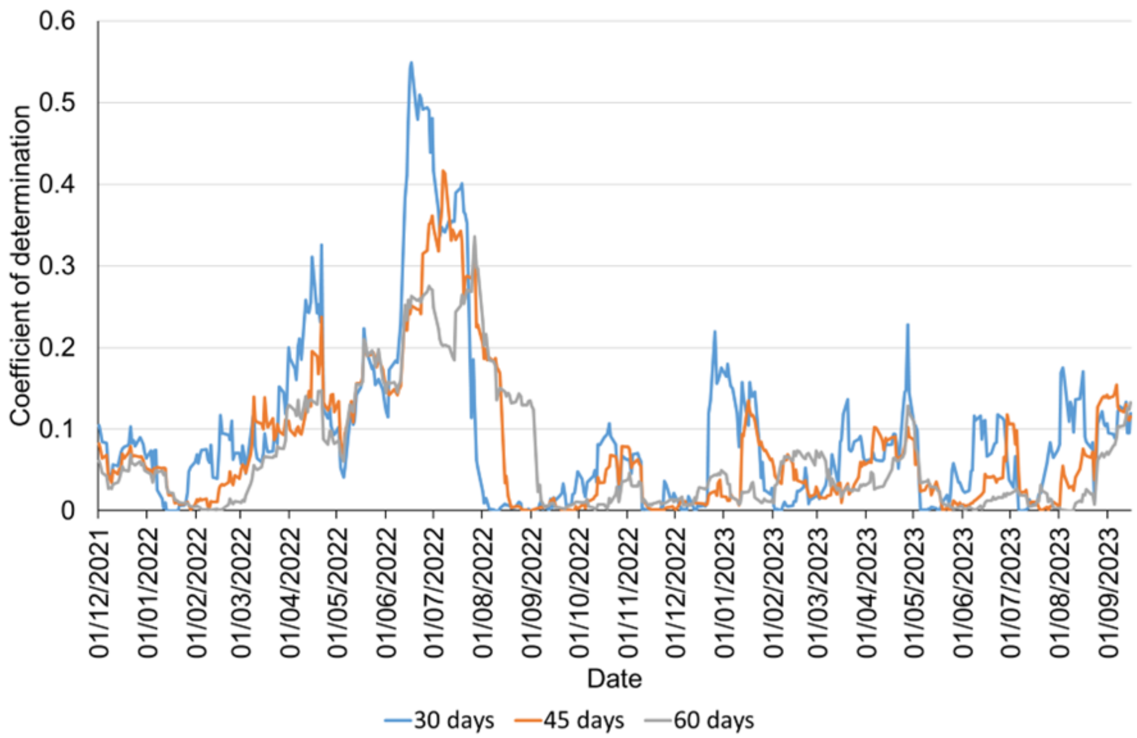
Notes: This table reports the results of least squares regressions for returns on the MSCI ACWI, $R_{w,t}$, onto ΔREC_t and control variables estimated with Newey-West heteroscedasticity and autocorrelation consistent (HAC) standard errors over the period 1 December 2021 to 15 September 2023. All series are in first differences except for returns on the MSCI ACWI, which are estimated as logarithmic differences. Control variables are oil (ΔOIL_t), coal ($\Delta COAL_t$) and natural gas (ΔGAS_t) prices, the FTSE World Government Bond Index ($\Delta WGBI_t$), the Baltic Dry Index (ΔBDI_t), the Société Générale Global Sentiment Index (ΔSGS_t) and the U.S. Dollar Index (ΔDXY_t). Row (6) reports the results of the unrestricted regression combining ΔREC_t with all control variables. In this equation, ΔDXY_t is orthogonalised against $\Delta WGBI$ and ΔSGS whereas ΔSGS is orthogonalised against $\Delta WGBI$ to account for possible multicollinearity. $\bar{R}^2$ is the adjusted coefficient of determination. ***, ** and * indicate statistical significance at the 1% and 5% levels of significance, respectively.

Table A5: Explanatory power of uncertainty measures for MSCI ACWI returns and variance

	α	$\beta_{\Delta UN}$	$\bar{R}^2_{\Delta UN}$
Panel A: Returns			
ΔEPU_t	-0.0001	-1.46E-05	0.0000
ΔEMU_t	-0.0001	-2.22E-07	0.0000
ΔTEU_t	-0.0003	-0.0002***	0.0207
ΔTMU_t	-0.0004	-0.0006***	0.1164
ΔGPR_t	-0.0001	-8.08E-05*	0.0027
Panel B: Variance			
	α	$\beta_{\Delta UN}$	$\bar{R}^2_{\Delta UN}$
ΔEPU_t	0.0001***	-4.46E-07	0.0000
ΔEMU_t	0.0001	-7.43E-08	0.0000
ΔTEU_t	0.0001***	1.39E-06	0.0021
ΔTMU_t	0.0001	-1.86E-07	0.0000
ΔGPR_t	0.0001***	2.74E-07	0.0000

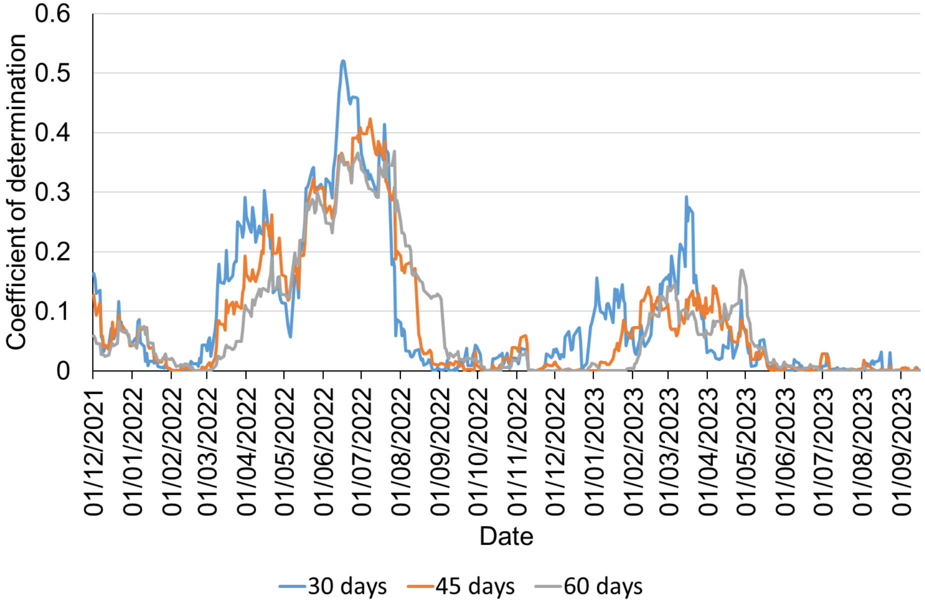
Notes: This table reports the results of regressions of returns and variance for the MSCI ACWI keyword-based uncertainty measures, ΔUN_t, over the period 1 December 2021 to 15 September 2023 for ΔEPU_t and ΔEMU_t and 1 December 20221 to 24 April 2024 (owing to data availability for the two latter measures). Regressions are estimated using least squares with Newey-West heteroscedasticity and autocorrelation consistent (HAC) standard errors. $\bar{R}^2$ is the adjusted coefficient of determination. ΔEPU_t are changes in the economic policy uncertainty index, ΔEMU_t are changes in the U.S. equity market uncertainty index, ΔTEU_t and TMU_t are changes in the Twitter-based economic and market uncertainty indices and ΔGPR_t are changes in the geopolitical risk index. *** and * indicate statistical significance at the 1% and 10% levels of significance, respectively.

Figure A1: $\bar{R}^2$ for rolling regressions of ΔVIX_t onto ΔREC_t

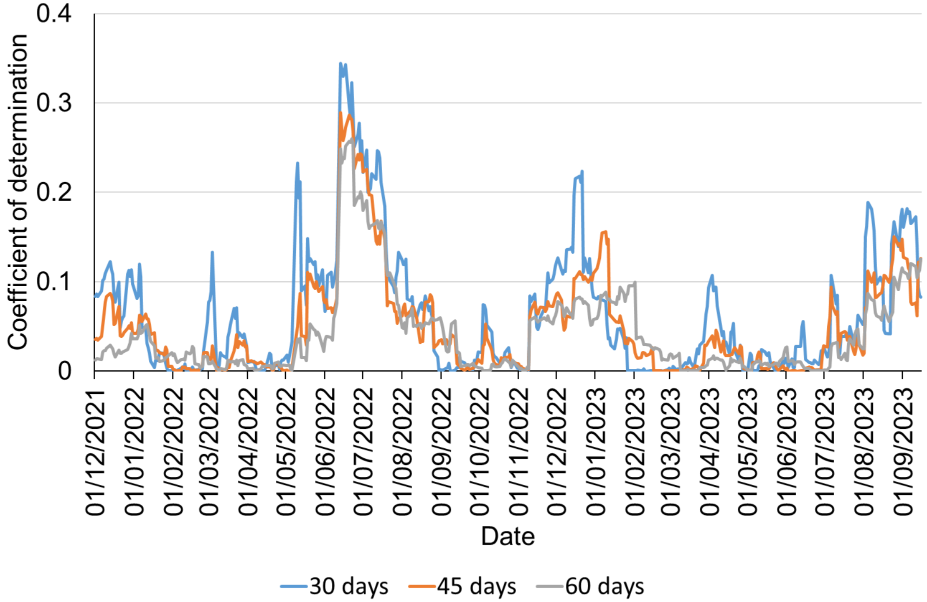


Notes: This figure plots $\bar{R}^2$s for rolling regressions of $\Delta \mathrm{VIX_t}$ onto $\Delta \mathrm{REC_t}$ over 30, 45 and 60 days. The resultant $\bar{R}^2$s are treated as a measure of the ability of the recession fear index, ΔREC_t, to approximate ΔVIX_t.

Figure A2: Plot of $\overline{R}^2$s for regressions of $R_{i,t}$ and $R^2_{w,t}$ onto ΔREC_t



Panel A: Rolling $\overline{R}^2$ for $R_{i,t}$



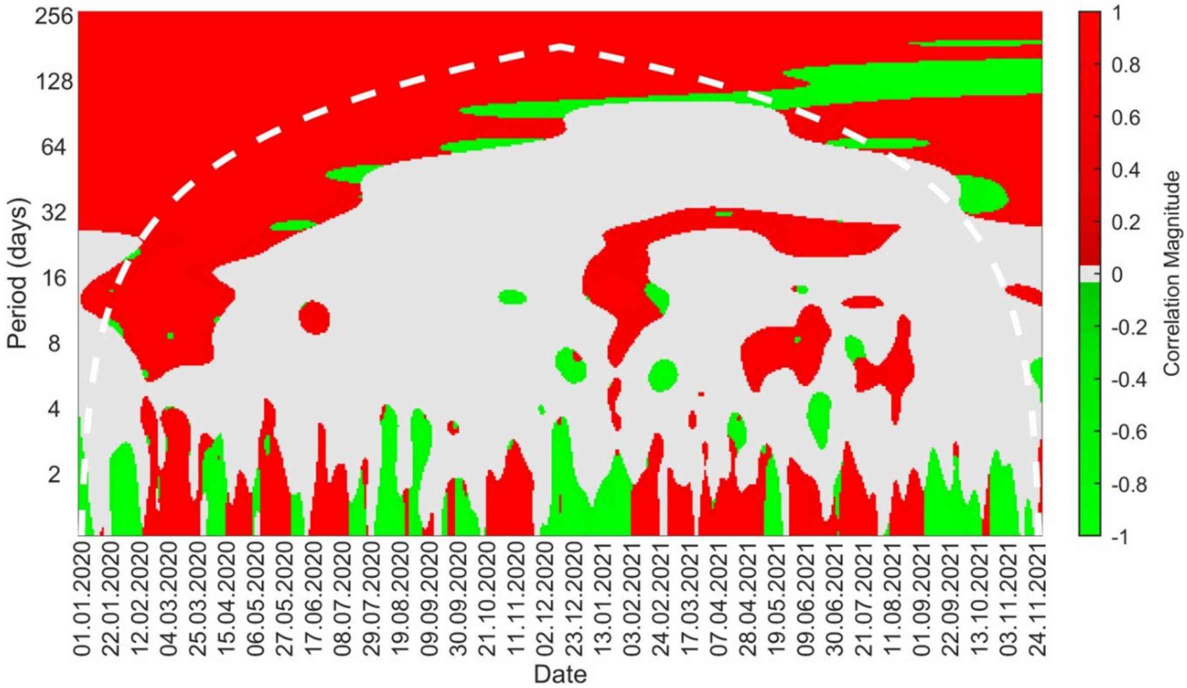
Panel B: Rolling $\overline{R}^2$ for $R^2_{w,t}$

Notes: This figure plots rolling $\overline{R}^2s$ for a regression of global market returns, $R_{i,t}$, and realised variance, $R^2_{w,t}$, estimated from logarithmic differences in MSCI ACWI levels, onto the recession fears index, ΔREC_t, over 30, 45 and 60 days.

Appendix B

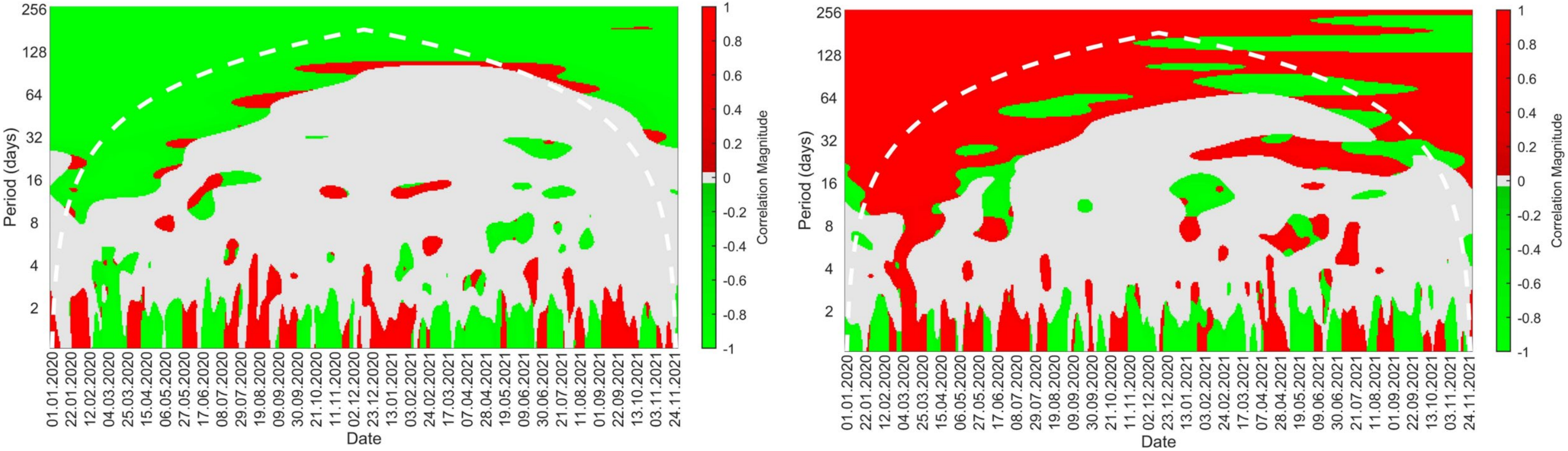
Recession fears and stock markets: An application of directional wavelet coherence and a machine learning-based economic agent-determined Google fear index

Figure B1: Spectrogram for ΔREC_t and ΔVIX_t for the COVID-19 crisis



Notes: Figure B1 presents a spectrogram for ΔREC_t and ΔVIX_t in three dimensions: time on the horizontal axis, frequency domain on the vertical axis expressed in the number of days and directional wavelet coherence values (contour map) over the COVID-19 crisis designated from 1 January 2020 to 30 November 2021. Both series are in first differences. Regions in red (green) reflect a positive (negative) association, at the 10% significance level, between ΔREC_t and ΔVIX_t indicating that recession fears positively (negatively) contribute to overall uncertainty. The white dashed line indicates the 5% significance level for edge effects occurring in coherence data. Higher horizons (periods) indicate a longer investment horizon and more persistent associations. Values of (approximately) between 1 and 8 days are defined as the short run, 9 to 32 days are defined as the medium run and values greater than 33 days are designated as the long run.

Figure B2: Spectrograms for ΔREC_t, global stock market returns $R_{w,t}$ and realised variance, $R^2_{w,t}$ for the COVID-19 crisis



Panel A: MSCI ACWI returns

Panel B: MSCI ACWI volatility

Notes: Figure B2 reports spectrograms for ΔREC_t against global stock returns ($R_{w,t}$) and realised volatility ($R^2_{w,t}$) in Panels A and B, respectively in three dimensions: time on the horizontal axis, frequency domain on the vertical axis expressed in the number of days and directional wavelet coherence values (contour map). The performance of global stock markets is represented by the MSCI ACWI over the COVID-19 crisis designated from 1 January 2020 to 30 November 2021. Returns are calculated as logarithmic differences in MSCI ACWI levels and the recession fear index is in first differences. Regions in red (green) reflect a positive (negative) association between ΔREC_t and $R_{w,t}/R^2_{w,t}$ at the 10% significance level. The white dashed line indicates the 5% significance level for edge effects occurring in coherence data. Higher horizons (periods) indicate a longer investment horizon and more persistent uncertainty spillover components. Values of (approximately) between 1 and 8 days are defined as the short run, 9 to 32 days are defined as the medium run and values greater than 33 days are designated as the long run.