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Energy in turmoil: Industry resilience to uncertainty during the global energy crisis

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HIGHLIGHTS

- We analyse the impact of energy price uncertainty (ENPU) stemming from the global energy crisis on global industry groups.
- Returns and volatility reflect distinct channels of influence.
- The 'Overall Impact of Uncertainty' (OIU) measure is used to jointly quantify the impact of ENPU.
- The impact of ENPU is heterogeneous across industry groups.
- Energy prices have relatively weak explanatory power relative to that of ENPU.

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ABSTRACT

We investigate the resilience of global industry groups to energy price uncertainty (ENPU) during the global energy crisis. Diversified financials reflect the greatest return response, being vulnerable to investment delays and discretionary spending, whereas industry groups producing necessities are most resilient. Volatility triggering is highest for automobiles & components due to ambiguous risk-return prospects requiring greater investor learning whereas the food & staples retailing group is most resilient. Differences in ranked return and volatility responses point towards distinct transmission channels. We expound a measure, the 'Overall Impact of Uncertainty' (OIU), that considers both effects jointly and reflects a dominant effect. According to the OIU, the most and least impacted groups are automobiles & components and food & staples retailing, respectively. Energy prices have a relatively weak impact relative to ENPU, suggesting that ENPU reflects a broader transmission channel, encompassing other forms of uncertainty.

1. Introduction

From mid-2021, a series of global developments disrupted energy markets, leading to what is commonly recognised as the first Global Energy Crisis (GEC) [61].[1] The surge in energy demand, which outpaced supply during the post-COVID-19 economic recovery, translated into substantial increases in oil, natural gas and coal prices. Limited supply was compounded by reduced renewable energy production due to adverse weather conditions in 2021 including droughts in Europe, Central Asia and Brazil, a summer wind drought in Europe and severe winter cold in the northern hemisphere [95,172]. Natural gas prices reached record highs fuelled by concerns over reduced natural gas flows

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from Russia to Europe in late 2021 and following Russia's invasion of Ukraine in February 2022 [92]. In response, Europe increased natural gas imports from various countries leading to further natural gas price increases and shortages in countries such as Pakistan and Bangladesh. The Russia-Ukraine war also contributed to oil and coal price increases given Russia's substantial production of both these energy commodities [165,229]. Several European countries delayed coal-fired power station closures due to natural gas shortages, further driving coal demand and prices upwards [119,165]. Sanctions on Russian energy exports and the Nord Stream 1 and 2 pipeline sabotage exacerbated shortages and further destabilised energy markets [29]. As of June 2022, crude oil (West Texas Intermediate, WTI), natural gas (Dutch Title Transfer Facility, TTF) and coal (Newcastle) prices were 53%, 116% and 126% higher, respectively, compared to a year earlier.

The resulting GEC had far-reaching economic ramifications. Households grappled with escalating energy prices, intensified by significant inflation in the prices of goods and services, as businesses revised their pricing strategies to counteract the increase in energy-related expenses [25]. The surge in inflation reduced purchasing power and consumer confidence which, in turn, exacerbated the strain on firms' cash flows. Central banks around the world responded to rampant inflation by raising interest rates, leading to increased borrowing costs, diminished investment, reduced employment and slowing economic growth [89,217]. Global stock markets experienced declines and higher volatility in response to the adverse economic conditions during the crisis.

The GEC, as is the case for all crises, is characterised by pervasive levels of uncertainty [101,205]. Uncertainty reflects the 'unknown unknowns', distinct from risk which quantifies the 'known unknowns' [136]. Energy prices impact financial markets through various channels, including uncertainty. This broad conduit encompasses other channels through which energy prices are proposed to affect stock markets. It reflects how uncertainty contributes to firms delaying investment, consumers postponing durable purchases, higher inflation and interest rate expectations, lower economic growth and investors demanding a higher risk premium and adjusting their risk-return expectations [67,212]. With the uncertainty channel providing such extensive scope, this motivates for an investigation of the impact of the GEC on stock markets through the lens of uncertainty. Uncertainty prevailing during the GEC stems from surging energy prices, which are linked to ambiguity about inflation and monetary policy, influencing both firm profits and aggregate output [205]. It follows that economic growth during the GEC is impacted not only by the direct ramifications of rising energy prices but also by the indirect effects of heightened uncertainty around possible economic consequences [34,101]. Global stock markets were also adversely impacted during the GEC due to prevailing uncertainty which resulted in lower returns and higher volatility [205]. However, not all industrial sectors are expected to respond in the same manner to uncertainty, given the varied nature of crises, the types of goods produced (necessities versus luxuries), the investment risk faced by consumers or firms and ambiguity regarding the future risk-return outlook faced by firms that constitute an industry [55,82,212]. To the best of our knowledge, no study has considered the heterogeneous and comprehensive impact of energy price uncertainty on industry groups [165].

Studies that investigate the impact of energy price uncertainty across industries tend to focus on one aspect, oil price uncertainty, as measured by the Chicago Board Options Exchange's (CBOE) Crude Oil Volatility Index (OVX). For example, Luo and Qin [152], Dupoyet and Shank [74] and Xiao et al. [221] find that the returns for the energy, metals and mining sectors are negatively impacted by oil price uncertainty whereas healthcare, utilities and clean energy are more resilient, reflecting a muted or small positive effect. However, a drawback of using oil price uncertainty as a measure of energy price uncertainty is its failure to consider natural gas and coal price shocks, which are key characteristics of the GEC. Kilian [134] and Dang et al. [66] demonstrate that oil prices are not a good proxy for energy prices as energy prices also reflect natural gas, coal and renewables prices and the markets for each are distinct. Accordingly, oil price uncertainty is not necessarily an appropriate measure of energy price uncertainty. Afkhami et al. [4], Xu et al. [223] and Dang et al. [66] develop monthly measures of energy market uncertainty, which provide a comprehensive overview of uncertainty relating to energy prices, energy demand and supply, and other macroeconomic factors. However, these measures do not specifically quantify energy price uncertainty. On the other hand, Yoon and Ratti [225], Punzi [177] and Chiah et al. [55] employ more focused metrics of energy price uncertainty, but these measures are of a low frequency (monthly). Additionally, little is known about the specific effects of energy price uncertainty on stock returns and volatility at a high frequency, particularly across industries.

In this study, we quantify the impact of energy price uncertainty arising from the GEC on 24 MSCI global industry groups and set out to determine which groups are most and least impacted. To assist us in answering this question, we employ the 'overall impact of uncertainty' (OIU) measure proposed by Szczygielski et al. [201,202]. This measure proposes that the impact of uncertainty should be quantified by jointly considering its effects on both returns and volatility. To the best of our knowledge, this is the first such study to do so. Uncertainty arising from the GEC, which is deemed to have begun in 2021 (see [166,173] for consensus on the start of the crisis), emanates from rapidly increasing energy prices and associated events, deteriorating energy security, concerns around the sustainability of the green energy transition and the broader economic consequences of the GEC [18,137]. We designate the start of the GEC as 1 June 2021, following observed rapid increases in energy prices which are most notable for natural gas and coal prices. To quantify energy price uncertainty, we use the Google-based energy price uncertainty (henceforth ENPU) measure of Szczygielski et al. [205] which approximates energy price-related components of the CBOE's Volatility Index (VIX). The advantages of this measure are that it is of a high frequency (daily), encompasses uncertainty stemming from oil, natural gas and coal price shocks and directly reflects investor concerns about rapidly increasing energy prices. Its theoretical foundation is rooted in economic psychology, which suggests that economic agents increase their searches for information when confronted with uncertainty [150,211]. We apply least squares regressions and ARCH/GARCH modelling to quantify ENPU's impact on industry returns and volatility. The application of the OIU measure, which we demonstrate to be a more comprehensive indicator of the impact of uncertainty than the effect on returns or variance individually, allows us to gain a deeper understanding of how uncertainty influences stock markets beyond the conventional approach of modelling its effects on both moments of the return distribution separately.

We contribute to the literature in several areas. First, to the best of our knowledge, the effect of ENPU on stock markets during the first truly global energy crisis has not yet been thoroughly examined. Importantly, uncertainty is one of the transmission channels through which energy prices impact financial markets [41]. Several studies examine how the Russia-Ukraine war influenced the relationship between energy prices and stock markets. For example, Basdekis et al. [26] observe significant short-term coherence between the S&P500 and Brent crude oil prices at the war's outset. The two series are positively correlated with weak evidence of oil leading the stock market. Adekoya et al. [3] report that oil prices had a greater impact on developed stock markets during the war's initial phase. Alam et al. [7] and Umar et al. [208] find increased connectedness between Russian stocks and bonds, crude oil and natural gas and global markets during the crisis. Szczygielski et al. [205] find that ENPU negatively impacted global stock returns and triggered volatility, particularly following Russia's invasion of Ukraine, whereas policy responses seemingly contributed to reducing the effect of uncertainty. Other studies, such as Guan et al. [100] and Hutter and Weber [116], focus on the macroeconomic impact of the GEC, while Pollit [173] evaluates the European Union's policy responses to the crisis. We study the effects of the crisis through the lens of ENPU – a specific component of overall uncertainty – as this broad conduit incorporates other channels through which energy prices affect stock markets. Additionally, the GEC, as in all crises, is characterised by heightened levels of ambiguity [205]. In doing so, we contribute to the relatively nascent literature on the consequences of this unprecedented crisis and its impact on stock markets. This is especially pertinent considering the possibility of future energy crises [102,115].

Second, we undertake research into the impact of ENPU on financial markets.[2] Uncertainty surrounding energy prices significantly impacts financial markets [41]. Numerous studies, such as those of Dutta et al. [78], Bouri et al. [39] and Xiao et al. [222], confirm that oil price uncertainty quantified by the OVX negatively affects stock returns and triggers volatility. This effect varies across industry groups [152,221]. However, focusing solely on oil price uncertainty overlooks the substantial contributions of natural gas (27%) and coal (24.3%) to the global energy supply (where oil accounts for 33%) [181]. Other studies, such as those of Yoon and Ratti [225] and Chiah et al. [55], use the conditional variance of changes in the real *monthly* United States (U.S.) Fuel and Related Products and Power series to measure ENPU. Xu et al. [223] and Dang et al. [66] construct monthly broad energy market uncertainty indices but these do not exclusively focus on energy *price* uncertainty. These studies predominantly examine the effects of energy price/market uncertainty on energy prices, output or firm decisions, with limited analysis of the impact on stock returns. Exceptions include Chiah et al. [55], who focus on the value premium, and Szczygielski et al. [205], who investigate the impact on *global* stock returns and volatility. Zhao et al. [230] state that researchers have focused their attention mainly on oil price movements when studying the effect of energy price volatility on economic growth, attributing this to the extensive use of oil and suggesting that the influence of other energy prices is often ignored. Consequently, knowledge of the effects of broader ENPU beyond that stemming from oil prices, on stock markets, especially at an industry level, remains limited. We use a comprehensive, high-frequency measure of ENPU developed by Szczygielski et al. [205], which quantifies uncertainty stemming from oil, natural gas, and coal price shocks, with the latter characterising the GEC more than oil price shocks alone. Szczygielski et al. [205] show that ENPU outperforms the OVX in approximating the VIX and is better at explaining global market returns. The ENPU index is constructed by correlating energy price-related Google searches with the VIX and using search terms to isolate and approximate VIX components. It is motivated by the proposition that economic agents directly disclose their views around topics and events by utilising *specific* search terms which reflect intensified searches for information during periods of heightened uncertainty [51,64,79,174]. Google search data has advantages over survey-based measures of prevailing views and reduces the likelihood of economic agents being influenced by external parties [69].

Third, we focus on industry effects, as some industry groups may be more resilient than others owing to their reduced or limited reliance on energy inputs, the nature of goods produced (luxuries versus necessities), their use of hedging and business prospects [98,201,202,226]. Uncertainty components (stemming from COVID-19, trade and economic policy, for example) are shown to have a heterogeneous impact on industry returns and volatility [32,179,201,202]. Understanding the heterogeneous impact of ENPU across industries can lead to better decision-making and more effective investment and risk management strategies. For investors, this granular assessment has the potential to facilitate more informed asset allocation, diversification and risk management [98,226]. For example, our results suggest that investors should tilt their portfolios away from the automobiles & components and consumer services industry groups given their large exposure to ENPU. For firms, our results point to the need to develop strategies to build resilience to ENPU, such as corporate diversification [111]. For instance, firms producing durable goods or services could consider diversifying into necessities. For policymakers, knowledge of industry effects is crucial for devising targeted measures to mitigate the adverse impact of the GEC and potential future energy crises which are likely to have heterogenous effects across industries, including those deemed as strategic. According to Amaglobeli et al. [11], during the GEC, while many policies focused on protecting consumers, support measures aimed at firms – such as electricity and gas price brakes (which differ somewhat from price caps), proved to be highly successful in reducing ENPU. Additionally, the success of targeted assistance for energy-intensive firms and subsidies to energy firms to support short-term procurement, as seen in Germany, demonstrates the need for the tailoring of policies across industry groups based on their exposure to ENPU [11].

Our final contribution lies in the development and application of the OIU measure. Uncertainty impacts stock returns and volatility through distinct channels. Uncertainty forces firms to delay investments and households to reduce spending on durable goods, lowering a firm's expected cash flows [80]. Uncertainty also leads to investors demanding a higher risk premium, raising the forward-looking discount rate [125]. Lower expected cash flows and a higher discount rate result in lower stock returns. Uncertainty about a firm's risk-return outlook also complicates the determination of a firm's intrinsic value. Consequently, the arrival of new information triggers volatility in stock returns due to investor learning [168,169,212]. While many studies examine the effects of uncertainty on either stock returns or volatility [190,221,228], Sarwar and Khan [184] emphasise the need to capture the effects on both to fully quantify the transmission of new information to asset prices. Some studies, such as those of Sarwar and Khan [184], Chiang [56], Kundu and Paul [140] and Szczygielski et al. [201,202], address this. We build on this research by not only investigating the effects of ENPU on both stock returns and volatility on industry groups separately to understand both transmission channels, but also jointly using the OIU measure of Szczygielski et al. [201]. The OIU offers a more comprehensive method for gauging the joint influence of uncertainty on stock markets by unifying the transmission channels through which returns and volatility respond to uncertainty. Our analysis further suggests that the OIU reflects another dimension to uncertainty – dominance – which identifies the origin of a return series' sensitivity to uncertainty fluctuations. We develop this measure by expounding a mathematical framework. Relatedly, by quantifying the cumulative performance of industry groups during the GEC, we can identify which performed favourably and which suffered overall. Insights gained from this analysis, combined with the identification of industry groups resilient to ENPU, offer potentially valuable knowledge for investors, firms and policymakers.

Our results show that all industry group returns are negatively affected by ENPU, with the extent of the impact varying based on the composition of firms within each industry group. The magnitude of the impact of ENPU on returns can be attributed to its effect on cash flows. Industries that comprise firms producing necessities, such as household & personal products and food & staples retaining, are the least impacted, whereas diversified financials, consumer services and software & services are most impacted. We attribute the response of volatility to ambiguity about risk-return expectations and interpret this as the intensity with which investors respond to information as it enters the market. ENPU triggers volatility for most industry groups, with automobiles & components, consumer services and media & entertainment among the most impacted and utilities, pharmaceuticals, biotechnology & life sciences and food & staples retailing least impacted. Relative rankings of industry groups based on the intensity of response differ from those determined by the magnitude of impact, suggesting that both moments reflect different information. For a number of industry groups, the OIU

[2] This research also builds upon the broader literature exploring the impact of various types of uncertainty – such as that originating from trade policy, economic policy and COVID-19 – on stock returns and volatility [108,126,184,201,224]. This approach is warranted as market participants do not respond uniformly to different types of information [126].

produces relative rankings that differ from those determined by either magnitude of impact or intensity alone. According to this measure, the least impacted groups are food & staples retailing, pharmaceuticals, biotechnology & life sciences and materials whereas the most impacted groups are automobiles & components, consumer services and media & entertainment. We go on to show that the OIU reflects a third dimension of responses to uncertainty, namely the dominance effect. This knowledge can be useful when seeking to identify the source of an industry's resilience. Interestingly, energy prices by themselves have a weak impact on returns in comparison to that of ENPU. This suggests that ENPU encompasses a broader transmission channel, potentially reflecting uncertainty about economic factors, other types of uncertainty and risk perceptions. Further analysis suggests that this is indeed the case, as ENPU is associated with shifting global and U.S.-specific factors, financial conditions and risk perceptions. An analysis of cumulative abnormal returns (CARs) shows that despite the GEC, most industry groups yield positive returns and that when averaged, CARs are positive. The message is that ENPU is one aspect of the crisis; there are profitable opportunities for investors and investors should engage in diversification.

The remainder of this study is structured as follows: Section 2 reviews the literature on the impact of energy prices and ENPU on industry returns and volatility. Section 3 outlines the data and methodology employed to examine the effects of ENPU on returns and volatility, with the results presented and analysed in Section 4. Section 5 discusses the implications of our findings and Section 6 concludes.

2. Literature review

Energy prices influence stock markets through various channels. The stock valuation hypothesis posits that asset prices are determined by discounted expected cash flows [192]. According to the input conduit, rising energy prices increase production costs for most firms due to their reliance on energy as a major input, negatively impacting cash flows and stock prices [114,145]. The output conduit proposed by Hamilton [104] suggests that increased energy prices decrease demand as individuals allocate a greater share of their budgets towards energy expenses, leading to lower total production in the economy and, subsequently, reduced expected cash flows for firms. According to the monetary channel, higher energy prices lead to increased expected inflation and real interest rates which, in turn, raise discount rates, resulting in lower discounted cash flows and stock prices [67,114]. Additionally, higher interest rates increase borrowing costs, limiting investment in value-enhancing projects and depressing stock prices [192].

The uncertainty conduit encompasses the preceding channels [41]. Increasing energy prices result in elevated uncertainty regarding economic conditions due to the impact of uncertainty on demand, output, inflation and interest rates. As a result, firms delay investments and households reduce spending on durable goods which impedes economic growth, lowers firms' forecasted cash flows and reduces stock prices [80,103]. According to Elder and Serletis [81] and Jo [125], heightened uncertainty also forces investors to demand a higher risk premium translating into an increased forward-looking discount rate. Moreover, uncertainty influences investors' expectations regarding a firm's risk-return outlook. Pástor and Veronesi [168,169] propose that increased ambiguity among investors about a firm's risk-return outlook makes it challenging to determine the firm's intrinsic value. Consequently, when new information emerges, there are more pronounced upward and downward revisions stemming from the price discovery process [170,201,202]. Veronesi [212] refers to this as investor learning (the process of acquiring new knowledge and information), with a more intense learning process leading to greater volatility as the price determination process evolves. Elevated uncertainty also amplifies economic agents' responsiveness to economic conditions and market signals, driving increased reactions to news arrivals and contributing to volatility [34]. It, therefore, follows that uncertainty attributable to rising energy prices and the consequences thereof reflect a potentially broader transmission pathway than the preceding conduits. Uncertainty encompasses both macro and micro effects arising from the input, output and monetary channels, impacting both stock returns and volatility.

Studies of the impact of ENPU on stock markets predominantly focus on the effects of oil price uncertainty. Maghyereh et al. [153], Dutta et al. [78], Bouri et al. [39] and Xiao et al. [222] confirm that heightened oil price uncertainty, as measured by the OVX, contributes to lower returns and increased volatility. At an industry level, Luo and Qin [152] and Xiao et al. [221] find that energy, metals and mining returns are adversely affected by oil price uncertainty. Other sectors display varying degrees of resilience, with some experiencing a minimal negative effect, no impact (such as healthcare) and even a positive effect for oil-substitute industries such as clean energy. Elyasiani et al. [84] find that the returns for seven of 13 U.S. industry groups, notably those in oil-user sectors such as transportation, machinery and chemicals, respond positively to oil price volatility which proxies for oil price uncertainty.[3] This positive effect is attributed to the ability of firms in these industries to adjust their prices more readily in response to volatile oil prices. However, the contrasting impact relative to other studies may stem from the use of a different uncertainty proxy, namely conditional volatility rather than the OVX, or reflect the nature of the oil price shock over the sample period. Dutta [75] and Luo and Qin [152] confirm that the OVX has a much larger impact on stock returns than oil price volatility because the former is forward-looking (and stock prices reflect expectations about cash flows) while the latter is backwards looking. Alsalman [9] argues that volatility by itself may be a poor proxy because uncertainty depends on more than only past variance. Caporale et al. [47] find that the Chinese financial, and oil and gas sectors are negatively affected by oil price uncertainty during periods characterised by supply-side shocks whereas industrials and technology are positively impacted by oil price uncertainty during periods characterised by demand-side shocks. They show that returns do not respond to oil price uncertainty following precautionary demand shocks.[4] Dupoyet and Shank [74] find that oil price uncertainty has a significant negative effect on nine out of ten U.S. industries, with energy and utilities most and least impacted respectively. Furthermore, oil price uncertainty has a greater impact when compared to that of oil price movements. Dutta et al. [77] report that three U.S. transport sub-sectors - trucking, airlines and marine - respond negatively to the OVX, with the largest response observed for the trucking sector. The impact is time-varying and asymmetric. The findings discussed above reveal that industries respond differently to oil price uncertainty. This suggests that certain industries are likely to be more (less) resilient to the GEC when analysed through the lens of a broader ENPU measure.

In contrast to the numerous studies of the impact of oil price uncertainty on industry returns, a limited number investigate the response of industry return volatility to oil price uncertainty, with the focus being predominantly on the relationship at the aggregate market level (see [39,60,78]). Studies that consider the industry level are limited to single sectors. For example, Dutta [75] illustrates that return volatility for the clean energy industry rises with increased levels of the OVX, indicating investors' significant learning in adjusting risk-return expectations due to this industry's status as an oil substitute. Conversely, Dutta [76] finds that OVX movements lead to reduced volatility in the U.S. ethanol sector. This aligns with the notion that heightened oil price uncertainty encourages investment in biofuels such as ethanol, reducing investor learning. The lack of studies investigating the heterogeneous response of

[3] This approach is consistent with other studies that quantify oil price uncertainty as the one-step ahead forecast error from a GARCH model of changes in the oil price (such as [9,54]). Another approach (as used by [46,183], among others) is to measure uncertainty as the variance of oil price returns.

[4] Precautionary demand shocks reflect market-specific changes in precautionary demand due to uncertainty about possible future oil supply deficits.

industry sector return volatility to oil price uncertainty – and more broadly ENPU – reveals a gap in the literature.

Kilian [134] and Dang et al. [66] argue that oil prices alone do not adequately represent energy prices. Energy consumption relies on several sources beyond oil including natural gas, coal and renewable energy, each with unique demand and supply dynamics. Therefore, changes in oil prices may not reflect shifts in other energy sources accurately. Accordingly, a broader measure than oil price uncertainty is needed to evaluate the impact of ENPU. Several studies construct (or use existing) energy market uncertainty indices, covering not only price uncertainty but also supply conditions and regulation. Dutta [76] utilises the U.S. energy sector VIX (VXXLE), which measures uncertainty for U.S. energy stocks (but which was discontinued in February 2022). Findings reveal bi-directional causality between oil prices and energy market uncertainty (see [151,162] for further use of this index). Xu et al. [223] develop a monthly energy market uncertainty index that reflects energy prices, demand, supply, inventories and relevant macroeconomic and financial variables. Their results show that energy market uncertainty negatively affects oil returns. Text-based energy market uncertainty indices have also been created. Afkhami et al. [4] formulate a weekly Google search-based index for a broad set of energy market-related keywords and find that energy market uncertainty results in higher oil and natural gas price volatility. Dang et al. [66] develop a monthly Energy Uncertainty Index (EUI) by analysing keywords reflecting energy sector trends in the Economist Intelligence Reports. The EUI combines separate counts of energy market- and uncertainty-related terms, potentially capturing general rather than specific energy market uncertainty. The EUI spikes during crises such as the COVID-19 pandemic and the Russia-Ukraine war, events that correlate with both energy market *and* general uncertainty. Higher EUI levels are linked to a decline in economic output.

Narrower and more specific measures of ENPU – contrasting with more general measures of energy market uncertainty – have been developed. Yoon and Ratti [225] and Chiah et al. [55] utilise the one-step ahead forecast error from a GARCH model of changes in the real monthly U.S. Fuel and Related Products and Power series to quantify this uncertainty (similarly to Elyasiani et al.'s [84] use of the conditional oil price volatility to quantify oil price uncertainty). Yoon and Ratti [225] find that heightened ENPU reduces firm investment, especially for growth firms, with a larger effect observed in low energy intensity industries. Chiah et al. [55] report that ENPU affects stock prices, with a larger value premium observed during periods of elevated uncertainty, attributable to asset flexibility for value firms. Punzi [177] shows that ENPU, measured by the realised volatility of the monthly global energy price index, prompts households to reduce consumption in favour of precautionary savings, leading to increased short-term investment and economic output. Szczygielski et al.'s [205] ENPU index uses Google search terms exclusively linked to ENPU during the GEC. The keywords in this index are more focused and determined by economic agents compared to the broader and preselected set of energy market search terms used by Afkhami et al. [4]. Moreover, this daily measure provides a higher frequency metric for quantifying ENPU compared to those used by Yoon and Ratti [225], Punzi [177] and Chiah et al. [55]. Szczygielski et al.'s [205] findings reveal that ENPU negatively impacts global stock market returns and triggers increased return volatility, although the effects vary over time. Notably, however, no studies explore and compare the effects of ENPU across industries, particularly during the GEC.

Several key findings and implications emerge from the preceding discussion. The uncertainty channel linking energy prices to financial markets has wide-ranging macro and micro effects that encompass the input, output and monetary channels. Given this breadth, the focus on ENPU as a conduit through which the GEC influences financial markets is a natural avenue for inquiry. Studies that seek to model the impact of ENPU on financial markets focus on oil price uncertainty, usually quantified using the OVX. The emphasis is on its impact on stock returns; literature on the impact of oil price uncertainty on return volatility across industrial sectors is sparse, reflecting a gap. We argue that the OVX is not adequate within the context of the GEC as it does not reflect uncertainty stemming from natural gas and coal price shocks. Furthermore, while the OVX has been shown to heterogeneously impact sectors, the response of industries to a broad (and more appropriate) measure of ENPU during the GEC has not yet been studied. This could be due to the scarcity of comprehensive ENPU measures. Existing measures, while broader than oil price uncertainty, tend to be of a low frequency, potentially confound general uncertainty with specific uncertainty components and tend not to fully reflect ENPU. Where the role of ENPU is examined, the exploration of its impact on stock markets and more specifically at the industry level, is limited [55,205]. Consequently, our study fills a gap in knowledge by modelling the impact of ENPU on returns and volatility, using Szczygielski et al.'s [205] daily ENPU index, across a broad sample of global industry groups.

3. Data and methodology

3.1. Data

Global industry performance is measured using 24 second-tier MSCI industry group indices. Daily data in U.S. dollars is obtained for the period 1 January 2019 to 31 January 2023 and returns are defined as logarithmic differences in index levels. Table 1 lists the global industry groups that comprise the sample and reports descriptive statistics. While we utilise an extended sample for estimation purposes, we adopt a 'milestone' approach to identify the onset of the GEC. This involves pinpointing economically or financially pivotal events to mark the beginning of the GEC on 1 June 2021 (see [132]). The start of the GEC is defined by a notable and almost simultaneous increase in all major energy price benchmarks which coincides with the post-COVID-19 economic recovery and is followed by a surge in prices (see Fig. 1 which plots the energy price benchmarks considered). Global energy markets began rebounding in early 2021 following the COVID-19 pandemic, which saw reduced demand for energy commodities and underinvestment in oil and gas production capacity. Energy prices spiked significantly in August/September 2021, particularly for natural gas and coal, and showed substantial coincident increases from around 1 June 2021 (see Fig. 1) [15,91]. This occurred after a wind shortage in Europe during the summer of 2021, leading to heightened demand for coal and natural gas, thereby inflating prices, and was followed by other events that contributed to rising energy prices, such as the build-up to Russia's invasion of Ukraine [94]. While the oil market experienced disturbances in early 2020 as the COVID-19 pandemic progressed, natural gas and coal markets were relatively undisrupted. The disruption in the oil market resulted from an unparalleled negative demand shock, rather than a combination of rising demand and tightening supply occurring simultaneously. Selecting 1 June 2021 as the commencement date accounts for heterogenous energy market behaviour while acknowledging significant events around this time (e.g., such as the European rain and wind droughts in 2021). A visual inspection of differenced energy price benchmark series reflects changing energy price dynamics (see Fig. A1 in the Appendix), with volatility increasing significantly after 1 June 2021 and remaining elevated thereafter. In summary, the approach adopted here considers the complexity of energy markets by pinpointing a specific start date and factoring in the events that led up to spikes in prices and changing price trends.

3.2. Google search-based energy price uncertainty index and validation

3.2.1. Theoretical development and methodology

Risk represents 'known unknowns,' where outcomes are unknown but governed by a known probability distribution, while uncertainty refers to 'unknown unknowns,' where neither outcomes nor probability distributions are known [136]. Asset pricing theory, supported by

Table 1
Descriptive statistics for global industry group returns

Industry group	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Shapiro-Wilk Wilk
Automobiles & components	0.0004	0.0005	0.0902	−0.0973	0.0178	−0.2246	61.111	0.9588***
Banks	0.0003	0.0005	0.0501	−0.0814	0.0097	−0.3735	113.625	0.9183***
Capital goods	0.0003	0.0004	0.0980	−0.1097	0.0129	−0.6983	162.664	0.8752***
Commercial & prof. Services	0.0004	0.0009	0.0807	−0.1042	0.0112	−0.8863	155.191	0.8951***
Consumer durables & apparel	0.0005	0.0011	0.0933	−0.1109	0.0137	−0.3035	116.554	0.9182***
Consumer services	0.0002	0.0006	0.1207	−0.1333	0.0148	−0.7376	179.624	0.8621***
Diversified financials	0.0001	0.0005	0.0891	−0.1096	0.0139	−10.642	170.204	0.8585***
Energy	0.0002	0.0007	0.1395	−0.1995	0.0192	−15.132	231.251	0.8494***
Food & staples retailing	0.0003	0.0009	0.0678	−0.1028	0.0151	−0.5562	78.862	0.9471***
Food, beverages & tobacco	0.0003	0.0003	0.0616	−0.0923	0.0095	−0.8513	179.633	0.8742***
Healthcare equip. & services	0.0002	0.0003	0.0626	−0.0849	0.0096	−0.5030	134.241	0.8980***
Household & personal products	0.0002	0.0006	0.0496	−0.0960	0.0090	−14.809	202.977	0.8514***
Insurance	0.0004	0.0008	0.1116	−0.1188	0.0142	−0.8195	189.365	0.8525***
Materials	0.0003	0.0008	0.0927	−0.1094	0.0125	−0.9292	148.877	0.9010***
Media & entertainment	0.0000	0.0001	0.0423	−0.0841	0.0084	−10.864	161.178	0.8961***
Pharma., biotech. & life sciences	0.0004	0.0007	0.0867	−0.1202	0.0127	−0.8772	167.761	0.8743***
Real estate	0.0000	0.0005	0.0763	−0.1349	0.0122	−16.733	243.971	0.8320***
Retailing	0.0003	0.0011	0.0690	−0.1103	0.0153	−0.6096	83.486	0.9389***
Semicond. & semicond. Equip.	0.0008	0.0012	0.0892	−0.1041	0.0152	−0.4229	89.205	0.9366***
Software & services	0.0003	0.0009	0.0998	−0.1132	0.0119	−15.113	252.023	0.8156***
Tech. hardware & equip.	0.0005	0.0011	0.0974	−0.1360	0.0167	−0.4584	112.746	0.9197***
Telecommunication services	0.0008	0.0013	0.0935	−0.1305	0.0183	−0.4842	76.165	0.9582***
Transportation	0.0003	0.0004	0.0738	−0.0926	0.0113	−0.9604	147.088	0.8965***
Utilities	0.0002	0.0007	0.0793	−0.1158	0.0114	−0.9801	227.681	0.8226***

Notes: This table reports the descriptive statistics for returns on the 24 MSCI second-tier industry groups that comprise the sample over the period 1 December 2019 to 31 January 2023. Returns are calculated as logarithmic differences in index levels. Each series comprises 1066 observations. Std. Dev. refers to the standard deviation. Shapiro-Wilk is the Shapiro-Wilk normality test statistic. *** indicates statistical significance at the 1% level.

empirical evidence, suggests that when economic agents are unsure about the correct probability law governing asset returns, they demand a higher premium [24,87]. Events can generate varying levels of uncertainty, with greater uncertainty arising when they are less predictable, have limited or no precedent or involve highly complex and interconnected factors. In such cases, the unknown aspects of an event are more pronounced, making it difficult or impossible to assign probabilities to potential outcomes. Even events with lower levels of uncertainty – because they are somewhat more predictable, have some historical precedent or are less complex – still involve unknown unknowns, distinguishing them from risk [163]. For example, droughts generate uncertainty, but precedents from similar events, despite no two being identical, provide some insight that helps to reduce the quantum and scope of unknowns. This does not preclude the existence of risk associated with specific events. Instead, it defines uncertainty as a changing variable that is a component of any crisis determined by a lack of precedent, complexity and interconnected factors.

As uncertainty is a latent variable and cannot be perfectly measured [128], proxies are used. These include market-based measures such as implied volatility indices, notably the VIX, and realised volatility [48], news-based measures such as the economic policy uncertainty (EPU) index of Baker et al. [20], econometric-based measures from structural models [128], and survey-based measures capturing market participants' views [10]. Market-based measures, such as the VIX, are available daily, reflect overall market conditions and contribute to future volatility. In contrast, survey-based measures, though less frequent, provide sector- or market-specific insights about uncertainty, with 'market' understood as a group of market participants [48].

Our study is framed within the paradigm of 'unknown unknowns', capturing varying depths of uncertainty across events that occurred during the GEC. First, the Google search-based measure of ENPU is constructed using the VIX which is a broadly recognised measure of stock market uncertainty [191,213]. Second, as we show in Section 4.1, the periods during which ENPU was most influential coincide with the invasion of Ukraine in February 2022 and the sabotage of the Nord Stream 1 and 2 pipelines in September 2022. Both events are unprecedented in recent history and, arguably, predicting associated future outcomes with any probability is extremely difficult, if not impossible. Contrastingly, the early phases of the crisis coincided with a rebounding global economy and a European wind drought, which, while still marked by uncertainty, benefit from some historical precedents.

To quantify and model the impact of ENPU on global industry returns and volatility, we use Szczygielski et al.'s [205] Google search-based ENPU index. Their approach is motivated by the work of Szczygielski, Charteris and Obojska [204] and John and Li [126] who show that Google searches can be used to isolate and model topic/event-specific uncertainty. Given Google's dominance in facilitating internet searches, accounting for over 80% of (desktop) worldwide search queries [31], Google may be viewed as representing the population's general search behaviour. The basis for using Google searches to proxy for uncertainty stems from economic psychology which suggests that during times of heightened uncertainty, economic agents increase searches for information [51,72,146]. It follows that if uncertainty around a specific topic can be reduced by increasing knowledge by gathering information, then search volumes reflect the level of uncertainty [35,206]. As Google permits the use of keywords that are related to specific topics or events, searches will therefore proxy for *topic-specific* uncertainty components.

To construct the index, Szczygielski et al. [205] identify six first-level search terms that exhibit rising trends around the start and during the GEC. These are 'oil price', 'oil prices', 'natural gas price', 'natural gas prices', 'coal price' and 'coal prices,' suggesting that the crisis is primarily driven by concerns about rapidly rising energy prices. Next, they obtain 25 second-level search terms related to each of the first-level terms and eliminate duplicates and terms unrelated to energy prices and aspects of the GEC. The use of related search terms identified by

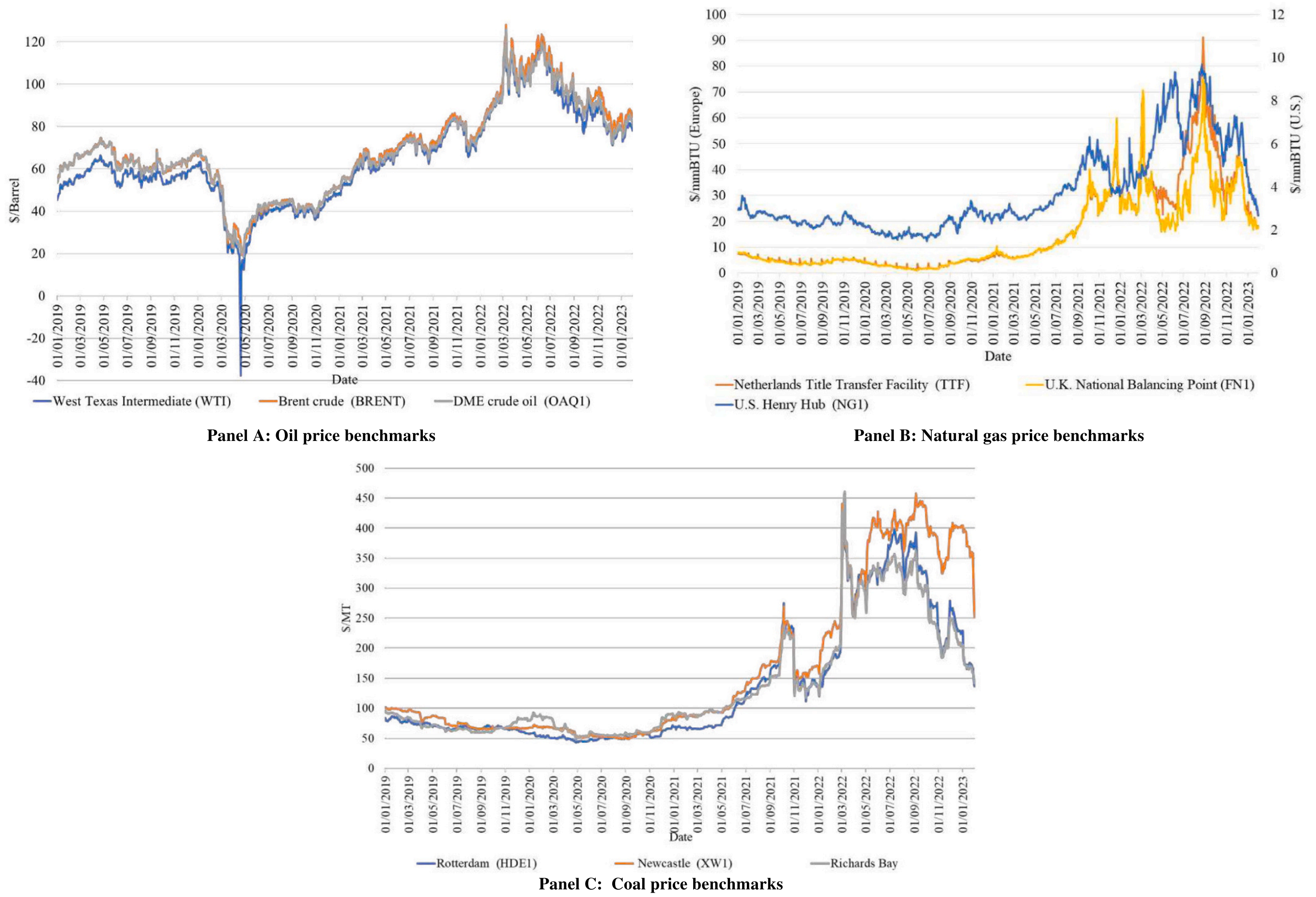

Fig. 1. Energy price benchmarks.
Notes: This figure plots oil, natural gas and coal price benchmarks over the period 1 January 2019 to 31 January 2023. For oil, benchmarks are the West Texas Intermediate (WTI_t), Brent Crude ($BRENT_t$) and Dubai Mercantile Exchange (DME) Oman Crude Oil ($OAQ1_t$) futures prices. Natural gas prices are represented by Dutch Title Transfer Facility (Europe) (TTF_t), Henry Hub (U.S.) ($NG1_t$) and the National Balancing Point (NBP) (United Kingdom, U·K) ($FN1_t$) futures prices. Newcastle (Australia) ($XW1_t$), Richards Bay (South Africa) ($XO1_t$) and API2 Rotterdam (Netherlands) ($HDE1_t$) futures prices are used to represent coal prices. For comparative purposes, price benchmarks are standardised in U.S. dollars and quantities. Oil prices are reported in U.S. dollars per barrel ($/Barrel), natural gas prices are reported in U.S. dollars per million British thermal units ($/mmBTU) and coal prices are reported in U.S. dollars per megaton ($/MT).

Google ensures that the constituents of the broader search set are objectively determined and used by economic agents and not subjectively selected by the researchers. Also, this approach ensures that the search set reflects a broader nomenclature, driven by and reflective of the multitude of events that contributed to rising energy prices. The broader search set comprises 95 unique search terms, with each series normalised by adjusting the highest value to 100. For compatibility with financial time series, weekends are excluded from Google search data which is available for seven days of the week. Then, the Auto-search/GETS (General-to-Specific) algorithm of Sucarrat and Escribano [198] is applied in a first-pass regression to identify search terms that approximate VIX components (see Table A1 in the Appendix for first pass search term selection). Although derived from S&P500 option prices, the VIX is widely recognised as a global benchmark for stock market uncertainty, reflecting the U.S. market's strong influence [191,213]. As economic agents respond to uncertainty by seeking information on a specific topic as uncertainty increases, there is a similarity between Google search trends and the VIX even if the underlying conceptual paradigms differ. As uncertainty increases, stock markets respond negatively and levels of the VIX increase. Consequently, both the VIX and Google search trends measure a variable that is not directly observable nor forecastable from the perspective of economic agents [128]. This suggested similarity implies that uncertainty components aggregated within the VIX may be identified by relating topic-specific proxies to the VIX (see [143,204]).

A particularly relevant feature of the Auto-search/GETS algorithm in the formulation of the ENPU index is the application of the Parsimonious Encompassing Test (PET), which ensures that any selected model encompasses rival models. The result is a more parsimonious solution without the loss of (true) explanatory power and an additional form of model validation [45,159]. As the algorithm eliminates insignificant search terms, it reduces multicollinearity and redundancy. Furthermore, because GETS modelling automates the search term selection process, it is efficient in handling large search sets, reducing human error and subjectivity in the selection of search terms [139]. The latter two properties are particularly important in the present context as they ensure that the search terms selected to approximate VIX components are relevant – that is, searched for by economic agents and reflective of stock market uncertainty – as opposed to being subjectively imposed by the researchers [175,205].[5] A second-pass elastic net regression is used to relate the search terms identified in the first-pass to movements in the VIX. This is to take advantage of *k*-fold cross-validation and to account for multicollinearity between search terms. In the final (third) pass, search terms with non-zero coefficients across penalties in the second-pass regression are related to the VIX using elastic net regression. Fitted values, $\Delta\widehat{ENPU}_t$, are treated as an approximation of VIX components (see Table A2 in the Appendix for the results of the final iteration of elastic net regularisation).

3.2.2. Validation

Szczygielski et al. [205] undertake extensive testing of $\Delta\widehat{ENPU}_t$ to demonstrate its effectiveness in approximating the VIX over the full sample period as well as during sub-periods that coincide with significant events. These include the lead-up to and the invasion of Ukraine, along with its immediate aftermath (January to May 2022), as well as the period coinciding with the sabotage of the Nord Stream 1 and 2 pipelines in September 2022, which resulted in sharp increases in energy prices. Over the entire sample period, $\Delta\widehat{ENPU}_t$ approximates 26.99% of the variation in ΔVIX_t and grows progressively between June 2021 and the end of September 2022 ($\overline{R}^2$s of 0.2461, 0.2641 and 0.3972, respectively) before approximative power declines from October 2022 onwards ($\overline{R}^2$ of 0.1805) (see Table A3 in the Appendix). The latter period saw decreasing energy prices which coincided with policymakers implementing measures aimed at shielding consumers from rising energy prices and extending existing measures aimed at addressing the GEC's consequences (see [1,8,62,91,106,127,142,167,186]). Next, the authors show that $\Delta\widehat{ENPU}_t$ outperforms the OVX in approximating the VIX, with the OVX widely used to proxy for oil price uncertainty and ENPU broadly, given that previous energy crises were synonymous with oil crises [147,162,221]. This is done by comparing the explanatory power of $\Delta\widehat{ENPU}_t$ to that of ΔOVX_t for ΔVIX_t over the entire sample period and sub-periods. Using a sample period that coincides with ours, they report that ΔOVX_t approximates 18.55% of the variation in ΔVIX_t whereas $\Delta\widehat{ENPU}_t$ approximates 26.99% (see Table A4 in the Appendix). We include an additional test whereby we adjust $\Delta\widehat{ENPU}_t$ for ΔOVX_t to confirm that $\Delta\widehat{ENPU}_t$ has approximative power over and above that of ΔOVX_t for ΔVIX_t and that the approximative power of $\Delta\widehat{ENPU}_t$ is not solely attributable to that of ΔOVX_t. Results show that $\Delta\widehat{ENPU}_t$s explanatory power declines somewhat over the entire sample period ($\overline{R}^2$ from 0.1855 to 0.1718) and over the sub-periods (from 0.2461 to 0.2041 and from 0.3972 to 0.3658 over the most acute periods of the energy crisis, coinciding with the invasion of Ukraine and the Nord Stream sabotage). While this is expected, as ΔOVX_t will reflect aspects of the GEC, $\Delta\widehat{ENPU}_t$ retains its approximative power over the full sample and sub-periods (see Tables A4 and A5 in the Appendix for comparison).

Szczygielski et al. [205] also report partial wavelet coherence between ΔVIX_t and ΔOVX_t after adjusting ΔOVX_t for $\Delta\widehat{ENPU}_t$. Following this adjustment, coherence is mostly insignificant in the short and medium run, except for limited significant coherence during the early phases of the GEC, which can potentially be attributed to the dominance of oil price uncertainty as a proxy for ENPU *prior* to the crisis and localised oil price peaks during the early stages of the GEC (see Figs. A2 and A3 in the Appendix for comparison). This, together with the approximative power of $\Delta\widehat{ENPU}_t$ that exceeds that of ΔOVX_t, indicates that $\Delta\widehat{ENPU}_t$ is a broader approximator of ENPU components reflected by ΔVIX_t. This is to be expected, given that it includes not only search terms associated with oil prices but also those related to natural gas and coal prices, increases in which characterise the GEC. As $\Delta\widehat{ENPU}_t$ is constructed by approximating ΔVIX_t components using Google searches, it is expected that there will be a relationship between $\Delta\widehat{ENPU}_t$ and ΔVIX_t.

We conduct an additional test that confirms that $\Delta\widehat{ENPU}_t$ is indeed a better approximator of ΔVIX_t relative to other keyword-based uncertainty proxies by regressing these measures onto ΔVIX_t. These are the Twitter-based Economic Uncertainty and Market Uncertainty Indices of Baker et al. [23] (ΔTEU_t and ΔTMU_t respectively), the news-based U.S Economic Policy Uncertainty Index of Baker et al. [20] (ΔEPU_t), the newspaper-based U.S. Equity Market Volatility Tracker of Baker et al. [21] (ΔEMV_t), the Geopolitical Risk Index (ΔGPR_t) of Caldara and Iacoviello [43] and the Infectious Disease Equity Market Volatility Tracker ($\Delta IDEMV_t$) of Baker et al. [22]. We also include ΔOVX_t for comparative purposes.[6] $\Delta\widehat{ENPU}_t$ outperforms each measure in approximating ΔVIX_t, with ΔTMU_t yielding the closest approximation (11.97%), though still second to that of $\Delta\widehat{ENPU}_t$. This demonstrates that $\Delta\widehat{ENPU}_t$ outperforms both broader (notably ΔTMU_t, ΔTEU_t and ΔEMV_t) and more specific measures (such as ΔGPR_t and $\Delta IDEMV_t$) that may also reflect elements of ENPU approximating ΔVIX_t and suggests that $\Delta\widehat{ENPU}_t$ encompasses uncertainty components that may be reflected by these measures (see Table A6 in the Appendix).

To confirm that $\Delta\widehat{ENPU}_t$ is driven by energy price shocks, measured by energy prices and energy price volatility derived from individual benchmarks and which reflect the multitude of events that drove energy prices, Szczygielski et al. [205] use Granger causality tests. The results confirm that energy price benchmarks drive $\Delta\widehat{ENPU}_t$; the null hypothesis of no causality is rejected for either prices and price volatility or both for

[5] We acknowledge that there are other Auto-search/GETS-type algorithms. Examples include those of Hoover and Perez [112], the PcGets algorithm of Hendry and Krolzig [109] and the Auto-metrics algorithm of Doornik [73]. The Auto-search/GETS algorithm of Succarat and Escribano [198] shows favourable performance in numerous aspects. For example, it identifies the maximum-minimum lag length dynamically whereas Hoover and Perez's [112] algorithm is limited to a maximum of two lags. This makes the former more flexible and robust in certain contexts when compared to the more rigid structure of other algorithms such as that of Hoover and Perez [112]. Moreover, Hoover and Perez's [112] algorithm is restricted to a maximum of ten search paths. In contrast, Auto-search/GETS is unlimited and determined by the number of insignificant variables in the generalised unrestricted model (GUM) (a total of 1,397,048,137 models were compared in the first pass when formulating the energy price uncertainty index!). Importantly, the superiority of the Auto-search/GETS algorithm stems from the introduction of log ARCH/GARCH terms which translates into more rapid convergence relative to the algorithms of Hendry and Krolzig [109] and Doornik [73] and makes it more suitable for application to financial data. The computational efficiency of the Auto-search/GETS algorithm makes it particularly suitable for large financial datasets and complex models. Moreover, owing to the *log* transformation, errors become independent and identically distributed, resulting in statistical tests having greater power. Consequently, irrelevant variables are less likely to be retained in comparison to PcGets, which is more likely to suffer from overfitting, or the Auto-metrics algorithm, which can be adversely affected by the number of variables exceeding that of observations. Succarat and Escribano [198] show that their Auto-search/GETS algorithm performs better in removing irrelevant variables and reducing overfitting relative to other algorithms.

[6] We estimate an AR-GARCH(1,1) model and juxtapose the resultant conditional variance (GARCH) series against $\widehat{ENPU}_t$ and OVX_t levels (see Figure A4 in the Appendix) to confirm similarity between these series. Conditional variance and $\widehat{ENPU}_t$ generally move closely together, especially from the end of 2021, more so the GARCH series and OVX_t levels. This suggests that global market volatility reflects ENPU, as do the MSCI ACWI returns.

all energy price benchmarks except for Henry Hub (U.S.) ($\Delta NG1_t$) prices.[7] As the relationship between energy prices and energy price uncertainty may be non-linear, Szczygielski et al. [205] validate these results using transfer entropy - a non-parametric, non-linear measure of directed information flows between two processes (see [70,117,149,171,207]) assuming that the relationship runs from energy price shocks to $\Delta\widehat{ENPU}_t$. This verifies that the approximative power of $\Delta\widehat{ENPU}_t$ for uncertainty components in ΔVIX_t can be attributed to $\Delta\widehat{ENPU}_t$ reflecting energy price shocks and is not purely by design (see Tables A7 and A8 in the Appendix).

Szczygielski et al. [205] also compare $\Delta\widehat{ENPU}_t$'s explanatory power for global markets as measured by returns on the MSCI All Country World Index (ACWI) to that of other keyword-based measures of uncertainty and also to that of ΔOVX_t.[8] $\Delta\widehat{ENPU}_t$ performs favourably in explaining ACWI returns ($\overline{R}^2$ of 0.1604), a series that is not used to construct $\Delta\widehat{ENPU}_t$. The keyword-based measure with the second highest explanatory power is ΔTMU_t ($\overline{R}^2$ of 0.1327), which is a general measure of stock market uncertainty. The explanatory power of $\Delta\widehat{ENPU}_t$ also exceeds that of ΔOVX_t ($\overline{R}^2$ of 0.0876) (see Table A9 in the Appendix). Szczygielski et al. [205] further report that the explanatory power of $\Delta\widehat{ENPU}_t$ for global market returns exceeds that of oil, natural gas and coal prices (joint $\overline{R}^2$ of 0.0286). This latter result suggests that the ENPU transmission channel is more encompassing of aspects of the crisis that are not reflected by energy price movements alone, such as rising inflation, stagnating economic growth and restrictive monetary policy.

This section outlines the approach used in constructing $\Delta\widehat{ENPU}_t$ and discusses the extensive tests conducted by Szczygielski et al. [205] in validating the index and demonstrating its feasibility as an uncertainty measure. These tests reveal that $\Delta\widehat{ENPU}_t$ outperforms ΔOVX_t in approximating components of stock market uncertainty and is a better approximator of ΔVIX_t relative to alternative keyword-based measures of uncertainty. $\Delta\widehat{ENPU}_t$ continues to have approximative power after adjusting for ΔOVX_t, indicating that it is a broader proxy for ENPU. We expect this to be the case given that search terms used to construct $\Delta\widehat{ENPU}_t$ are not limited to those associated with oil prices alone. Partial wavelet coherence confirms that $\Delta\widehat{ENPU}_t$ encompasses information reflected by ΔOVX_t, particularly as the crisis progressed. $\Delta\widehat{ENPU}_t$ outperforms ΔOVX_t and other keyword-based measures in approximating aggregate global returns. Importantly, causality testing confirms that $\Delta\widehat{ENPU}_t$ is driven by energy price shocks.

3.3. Methodology

We model the response of industry group returns to $\Delta\widehat{ENPU}_t$ as follows:

$$r_{i,t} = \alpha_i + \beta_{i,\Delta\widehat{ENPU}}\Delta\widehat{ENPU}_t + \beta_{i,\Delta OIL}\Delta OIL_t + \beta_{i,\Delta GAS}\Delta GAS_t + \beta_{i,\Delta COAL}\Delta COAL_t + \beta_{M\varepsilon}M_{\varepsilon,t} + \varepsilon_{i,t} \tag{1}$$

where $r_{i,t}$ is the return on index i at time t and $\beta_{i,\Delta\widehat{ENPU}}$ measures the impact of ENPU. ΔOIL_t, ΔGAS_t and $\Delta COAL_t$ are proxies for oil, natural gas and coal prices in the form of rotated factor scores constructed from differences in the energy price benchmarks (see Fig. 1).[9] M_ε is the residual market factor derived by regressing $\Delta\widehat{ENPU}_t$, ΔOIL_t, ΔGAS_t and $\Delta COAL_t$ onto MSCI ACWI returns, used to control for any additional common variables not reflected directly in eq. (1). Eq. (1) is estimated using least squares with Newey-West standard errors and *standardised* coefficients for the period 1 June 2021 to 31 January 2023 incorporating $\Delta\widehat{ENPU}_t$ and energy prices separately and then jointly, and the resultant $\overline{R}^2$s are reported as indicators of explanatory power.

$\beta_{i,\Delta\widehat{ENPU}}$ quantifies the impact of $\Delta\widehat{ENPU}_t$ on returns which we expect to be negative and heterogenous across industry groups [14,41,80]. Uncertainty, including firm-specific, macroeconomic, stock market and oil price uncertainty, has a significant negative impact on investment and durables consumption [50,81,129,221]. Firms face not only the decision of which irreversible investment to commit resources to but also the timing of that decision. Increased uncertainty regarding future returns on investments will result in firms delaying investment decisions. Similarly, consumers, driven by a precautionary motive, are less willing to spend on durable goods and luxuries in the face of uncertainty [34,80]. Firms that sell durable goods or services, and/or whose products or services require substantive investment decisions by other companies or themselves, will experience increased sensitivity to uncertainty [82]. Investors may also demand a higher risk premium from investing in these firms due to increased uncertainty, resulting in a higher discount rate [55,216]. In contrast, firms which sell non-durable goods and services, and/or are less reliant on firms making substantive investment decisions, or whose own investment decisions are less significant, will exhibitlower sensitivity to uncertainty.

Variance is modelled separately as a GARCH*(p,q)* process incorporating $\Delta\widehat{ENPU}_t$, while adjusting for common influences in the mean with $\Delta\widehat{ENPU}_t$ excluded. By modelling the mean and variance separately, we avoid challenges associated with model convergence that may potentially arise from the estimation of the mean and conditional variance which simultaneously include the regressor of interest, $\Delta\widehat{ENPU}_t$ (see [42]). To control for common factors, factor scores derived from third-tier industry returns are regressed against $\Delta\widehat{ENPU}_t$ and we control for energy prices (see [200,210]).[10] The mean equation is as follows:

$$r_{i,t} = \alpha_i + \sum_{k=1}^{m}\beta_{i,k}F^{RES}_{k,\Delta\widehat{ENPU}} + \beta_{i,\Delta OIL}\Delta OIL_t + \beta_{i,\Delta GAS}\Delta GAS_t + \beta_{i,\Delta COAL}\Delta COAL_t + \gamma_i r_{i,t-\tau} + \varepsilon_{i,t} \tag{2}$$

where $\sum_{k=1}^{m}\beta_{i,k}F^{RES}_{k,\Delta\widehat{ENPU}}$ is the set of statistically derived factors from

[7] A likely reason for the absence of Granger causality for U.S. natural gas prices and volatility is that historically natural gas prices in Europe have been higher than in the U.S. because of the latter's significantly larger reserves, more diversified supplier base, oversupply from shale gas production and decoupling from European gas and crude oil prices. However, transfer entropy shows that $\Delta\widehat{ENPU}_t$ responds to volatility in U.S. natural gas prices ($\Delta NG1_t^2$) whereas this was not the case for Granger causality.

[8] We estimate an AR-GARCH(1,1) model and juxtapose the resultant conditional variance (GARCH) series against $\widehat{ENPU}_t$ and OVX_t levels (see Figure A4 in the Appendix) to confirm similarity between these series. Conditional variance and $\widehat{ENPU}_t$ increase generally move closely together, especially from the end of 2021, more so the GARCH series and OVX_t levels. This suggests that global market volatility reflects ENPU, as do ACWI returns.

[9] To derive composite proxies for energy prices, we factor analyse difference in the energy price benchmarks in Figure 1. A total of three factors are extracted. Following orthogonal varimax rotation, oil benchmark movements load onto the first factor (ΔOIL_t), natural gas price benchmark changes load onto the second factor (ΔGAS_t) and coal price benchmark movements load onto the third factor ($\Delta COAL_t$).

[10] The number of factors is identified by applying the minimum average partial (MAP) test and non-trivial factors are retained following the analysis of a scree plot. Factors are incorporated into the mean equation to control for dispersion in the residuals that would otherwise be attributable to omitted variables.

industry return series adjusted for $\Delta\widehat{ENPU}_t$. Adjusted factor scores that have a *marginal* contribution to explaining returns, as measured by $\overline{R}^2$, are excluded to avoid overspecification. *Q*-statistics are checked for linear and non-linear residual dependence to ensure that the retention of certain factor score series does not result in misspecification (see [200] for a detailed demonstration of this approach) and that the estimated GARCH(*p,q*) specifications account for heteroscedasticity. If required, autoregressive terms, $r_{i,t-\tau}$, of order τ, identified from an analysis of a residual correlogram, are included to address remaining autocorrelation.

We begin with a GARCH(*1,1*) model and proceed to increase the number of ARCH and/or GARCH parameters if heteroscedasticity or non-linear dependence is still present.[11] The GARCH(*p,q*) conditional variance equation incorporating $\Delta\widehat{ENPU}_t$ is as follows:

$$h_{i,t} = \omega_i + \sum_{p=1}^{n}\alpha_i\varepsilon_{i,t-p}^2 + \sum_{q=1}^{m}\beta_i h_{i,t-q} + \varphi_{i,\Delta EN\hat{P}U}\Delta\widehat{ENPU}_t D_{C,0,1} \tag{3}$$

where $h_{i,t}$ is the conditional variance and $D_{C,0,1}$ is a dummy denoting the crisis period. An extended sample period, 1 January 2019 to 31 January 2023, is used for estimation purposes to reduce biases in maximum likelihood estimates and the persistence of non-linear dependence associated with small sample sizes [118]. If residuals are non-normal, equations are re-estimated using quasi-maximum likelihood with Huber-White robust standard errors and covariance [93].

$\varphi_{i,\Delta EN\hat{P}U}$ quantifies the impact of $\Delta\widehat{ENPU}_t$ on variance, which we expect to be positive and vary across industry groups. Greater uncertainty results in increased ambiguity faced by investors about future risk and returns. When investors face increased ambiguity concerning the risk-return outlook for firms, it becomes more challenging to evaluate future asset values. This heightened uncertainty leads to a greater need for learning and, consequently, more price revisions, resulting in a more intense price discovery process inducing higher volatility [86,212]. Conversely, when investors have lower uncertainty regarding the risk-return outlook, there is greater clarity about future asset values. As a result, there is less need for extensive learning, leading to a more moderate process of price determination and, consequently, lower volatility. In summary, the greater (lower) the learning, the more (less) intense the stock price response.

3.4. Overall impact of uncertainty

Rising $\Delta\widehat{ENPU}_t$ is expected to impact stock returns negatively and to contribute to increased volatility. We model the *joint* impact of uncertainty on both returns and volatility using Szczygielski, Brzeszczyński et al.'s [201] OIU measure. The OIU_i for industry *i* captures the directional strength of the effect of uncertainty ($\beta_{i,\Delta EN\hat{P}U}$) amplified by the intensity with which information enters the market ($\varphi_{i,\Delta EN\hat{P}U}$) as follows:

$$OIU_i = \beta_{i,\Delta EN\hat{P}U}\cdot\varphi_{i,\Delta EN\hat{P}U} \tag{4}$$

Szczygielski, Brzeszczyński et al. [201] proposed the OIU to study the impact of COVID-19-related uncertainty on energy markets. However, they did not formalise the concept and instead relied upon an analogy of the effects of rainstorms on the environment. Szczygielski, Brzeszczyński et al. [201] argue that rainstorms can produce different amounts of water – equivalent to the magnitude component, $\beta_{i,\Delta EN\hat{P}U}$. The force of the rain and wind may also vary i.e., the 'volatility' of the storm, analogous to the intensity component, $\varphi_{i,\Delta EN\hat{P}U}$, which can range from low to high. The impact of a rainstorm is heaviest when there is heavy rain and, at the same time, the intensity of the storm is high (e.g., it is accompanied by gale force winds). This occurs when both $\beta_{i,\Delta EN\hat{P}U}$ and $\varphi_{i,\Delta EN\hat{P}U}$ are high. Conversely, the impact of a rainstorm on the environment is weak when there is only light rain and its intensity is low, i.e., both $\beta_{i,\Delta EN\hat{P}U}$ and $\varphi_{i,\Delta EN\hat{P}U}$ are low. Other combinations can occur, such as low intensity but high magnitude or vice versa. The OIU_i reflects all these possible situations. It follows that in the OIU_i, the magnitude of impact, $\beta_{i,\Delta EN\hat{P}U}$, quantifies the effect of uncertainty which induces firms to delay investment, households to postpone consumption and/or investors to demand a higher risk premium. This is reflected by the response of returns to uncertainty. Correspondingly, intensity, $\varphi_{i,\Delta EN\hat{P}U}$, reflects the effect of uncertainty on investors' risk-return expectations which necessitates learning and gives rise to price volatility stemming for the intensity of the price discovery process.

We introduce a general formalisation of the OIU below. If we define a function $f(r_{i,t}, h_{i,t})$ which[12] quantifies the joint impact of uncertainty on returns ($r_{i,t}$) and variance ($h_{i,t}$), the OIU_i becomes its partial derivative with respect to $\Delta\widehat{ENPU}_t$ i.e., $\delta f/\delta\Delta\widehat{ENPU}$. Following the rules of derivation applied to linear approximations of eqs. (2) and (3), we obtain:

$$\frac{\delta r_{i,t}}{\delta\Delta\widehat{ENPU}} = \beta_{i,\Delta EN\hat{P}U} \tag{5}$$

$$\frac{\delta h_{i,t}}{\delta\Delta\widehat{ENPU}} = \varphi_{i,\Delta EN\hat{P}U} \tag{6}$$

and

$$f(r_{i,t}, h_{i,t}) = \frac{1}{2}\left(\varphi_{i,\Delta EN\hat{P}U}\, r_{i,t} + \beta_{i,\Delta EN\hat{P}U} h_{i,t}\right) \tag{7}$$

Eq. (7) is one of many specifications that we can develop but opt for the simplest one.[13] Eqs. (5) and (6) reflect the impact of $\Delta\widehat{ENPU}_t$ on the mean and variance respectively. Since the function $f(r_{i,t}, h_{i,t})$ represents the general impact of uncertainty on a market, the OIU_i, being its partial derivative, can be seen as an overall measure of the impact of uncertainty related to $\Delta\widehat{ENPU}_t$. As the OIU_i captures the effect of uncertainty on returns and volatility, it can be seen as a *risk-adjusted impact of uncertainty*. Sarwar and Khan [184] argue that capturing the effect of uncertainty, proxied by the VIX in their study, on both returns and volatility represents a comprehensive transmission model, as it reflects the full effect of new information on asset prices. We build on this by combining the two effects into a single measure, namely the OIU_i. As such, the negative effect of uncertainty on returns is exacerbated by volatility leading to a greater overall impact.

As the OIU_i is the product of the magnitude of impact and its intensity, we demonstrate that the dominance of either the magnitude or intensity determines its overall size. We first standardise $\beta_{i,\Delta EN\hat{P}U}$ and $\varphi_{i,\Delta EN\hat{P}U}$ as follows:

$$std.\beta_{i,\Delta EN\hat{P}U} = \frac{\beta_{i,\Delta EN\hat{P}U} - \frac{1}{n}\sum_{i=1}^{n}\beta_{i,\Delta EN\hat{P}U}}{\sigma_{\beta_{\Delta EN\hat{P}U}}} \tag{8}$$

$$std.\varphi_{i,\Delta EN\hat{P}U} = \frac{\varphi_{i,\Delta EN\hat{P}U} - \frac{1}{n}\sum_{i=1}^{n}\varphi_{i,\Delta EN\hat{P}U}}{\sigma_{\varphi_{\Delta EN\hat{P}U}}} \tag{9}$$

where $\frac{1}{n}\sum_{i=1}^{n}\beta_{i,\Delta EN\hat{P}U}$ and $\frac{1}{n}\sum_{i=1}^{n}\omega_{i,\Delta EN\hat{P}U}$ are the respective means of $\beta_{i,\Delta EN\hat{P}U}$ and $\varphi_{i,\Delta EN\hat{P}U}$, and $\sigma_{\beta_{\Delta EN\hat{P}U}}$ and $\sigma_{\varphi_{\Delta EN\hat{P}U}}$ are the corresponding stan-

[11] We also considered the ARCH(*p*) specification and IGARCH(*p,q*) specifications if ARCH and GARCH parameters are close to unity [85]. The GARCH(*p,q*) specification with varying *p* and *q* proved to be sufficient in capturing volatility dynamics (see Table 3).

[12] We do not use the subscript *t* in eqs. (5)–(7) anymore so as to apply methods of differential calculus where we approximate difference models (2) and (3) by linear functions which do not depend on *t*.

[13] $\frac{\delta f}{\delta\Delta\widehat{ENPU}} = \frac{\delta f}{\delta r_i}\frac{\delta r_i}{\delta\Delta\widehat{ENPU}} + \frac{\delta f}{\delta h_i}\frac{\delta h_i}{\delta\Delta\widehat{ENPU}} = \frac{\varphi_{i,\Delta EN\hat{P}U}}{2}\beta_{i,\Delta EN\hat{P}U} + \frac{\beta_{i,\Delta EN\hat{P}U}}{2}\varphi_{i,\Delta EN\hat{P}U} = OIU_i$.

dard deviations. Next, we define the *dominance ratio* as:

$$DomR_i = \frac{std.\beta_{i,\Delta\widehat{ENPU}}}{std.\varphi_{i,\Delta\widehat{ENPU}}} \tag{10}$$

where $DomR_i$ indicates whether $\beta_{i,\Delta\widehat{ENPU}}$ or $\varphi_{i,\Delta\widehat{ENPU}}$ dominates. If $|DomR_i| > 1$, $\beta_{i,\Delta\widehat{ENPU}}$ dominates the OIU_i or if $|DomR_i| < 1$, $\varphi_{i,\Delta\widehat{ENPU}}$ dominates the OIU_i meaning that either effect determines the OIU_i-relative rank for industry group i. To demonstrate this, we add the position of $\beta_{i,\Delta\widehat{ENPU}}$ to $DomR_i$ and take the absolute sum when magnitude is dominant to arrive at an ordinal ranking that approximates that of the OIU_i. Conversely, we add the position of $\varphi_{i,\Delta\widehat{NEPU}}$ to $DomR_i$ when intensity dominates and take the absolute sum to arrive at an ordinal ranking that approximates that of the OIU_i. Correlations are estimated between the sum of $DomR_i$ and the dominant effect for each industry group and the OIU_i to confirm that dominance is indeed a determinant of the comparative OIU_i (rank)

4. Results and analysis

4.1. The evolution of ENPU

Before proceeding to model the impact of $\Delta\widehat{ENPU}_t$ on industry group returns and volatility in Sections 4.2. and 4.3., we provide an overview of the evolution of $\Delta\widehat{ENPU}_t$ in relation to ΔOVX_t and ΔVIX_t and show that it is part of the composite factor set driving industry group returns using rolling correlations. To model the dynamic relationship between overall stock market uncertainty as represented by ΔVIX_t and $\Delta\widehat{ENPU}_t$, we estimate rolling ordinary and Spearman correlations. For comparative purposes, we also estimate rolling correlations between ΔOVX_t, which we treat as a (commonly used) benchmark for ENPU, and ΔVIX_t. Results are reported in Fig. 2. To model the relationship between $\Delta\widehat{ENPU}_t$ and the factors that drive industry group returns, we begin by factor analysing returns. The MAP test is applied to identify the number of factors that characterise the return generating process. This test identifies the number of factors that are most congruent with the assumption of uncorrelated residuals, $E(\varepsilon_{i,t}, \varepsilon_{i,t})$, underlying linear factor models [231]. A total of three factors are extracted, approximating 73.67% of common return variation over the GEC. Next, we formulate a composite communality-weighted factor score series, $F_{c,t}$, to summarise these factors into a single factor by following the approach of Szczygielski, Charteris, Bwanya and Brzeszczyński [203].[14] Rolling correlations are then estimated for $\Delta\widehat{ENPU}_t$, $F_{c,t}$ and ΔOVX_t. Fig. 3 reports the results.

In Fig. 2 below, correlation patterns between $\Delta\widehat{ENPU}_t$ and ΔVIX_t, and ΔOVX_t and ΔVIX_t are comparable during the early stages of the crisis between June 2021 and March 2022. This suggests that initially energy-related uncertainty components of the VIX were primarily driven by oil price uncertainty. It also confirms that similarly to ΔOVX_t, $\Delta\widehat{ENPU}_t$ reflects oil price uncertainty. Furthermore, this may also suggest that initially, the GEC was viewed as an oil crisis by economic agents rather than one stemming from natural gas and coal price shocks. Divergence between correlations began around March 2022 with $\Delta\widehat{ENPU}_t$-ΔVIX_t correlations exceeding those of ΔOVX_t-ΔVIX_t. In Fig. 2, the early months of 2022 coincide with dramatic increases in coal and natural gas prices (see Panels B and C of Fig. 1). In late 2021, the decline in natural gas exports from Russia to Western Europe accelerated. Russia's invasion of Ukraine on 24 February 2022 further contributed to concerns about Europe's dependence on Russian energy. Sanctions were imposed in March 2022 with Canada and the U.S. banning Russian oil and gas imports (Benton et al., 2022). Coal prices soared during 2022 as countries sought substitutes for other energy sources [119]. Natural gas supplies from Russia were further disrupted when Russia stopped deliveries to Poland and Bulgaria because of their refusal to pay in Rubles towards the end of April 2022 and natural gas prices increased dramatically. In May 2022, Ukraine's state-owned gas grid operator reduced the transit of Russian natural gas to Europe and Russia halted supplies of natural gas to Finland because of Finland's refusal to pay in Rubles. Explosions ruptured the Nord Stream 1 and 2 pipelines in September 2022 in what was considered an act of sabotage, pushing natural gas prices to record highs and coal prices to near all-time highs. Furthermore, while ΔOVX_t-ΔVIX_t correlations decline between May and October 2022, $\Delta\widehat{ENPU}_t$-ΔVIX_t correlations increase and remain elevated. In July 2022, Fatih Birol, head of the IEA, stated that the world has never witnessed such a complex and extensive energy crisis and that the worst may still be ahead [196]. Fig. 2 confirms that the dramatic price increases in natural gas and coal prices and the numerous events that occurred during 2022 contributed to ENPU.

Fig. 3 suggests that $\Delta\widehat{ENPU}_t$ is more reflective of energy price shocks than ΔOVX_t. For example, $\Delta\widehat{ENPU}_t$-$F_{c,t}$ correlations become increasingly negative between July and August 2021, a period that coincides with early coal and natural gas price increases and is immediately followed by subsequent shocks to prices. This early period aligns with the rapid post-COVID-19 economic recovery, marked by rising energy prices, limited power generation capacity that could not be restored in time, and oil supplies struggling to meet the rebounding demand (Gaffen, 2022; Bettoli et al., 2023). Also, Europe and the Americas suffered renewable energy shortages which contributed to rising energy prices as demand for fossil fuels increased. $\Delta\widehat{ENPU}_t$-$F_{c,t}$ correlations remain negative and elevated (in absolute terms) following Russia's invasion of Ukraine in February 2022 and between June and September 2022, the latter period coinciding with the Nord Stream 1 and 2 sabotage, an event that resulted in worsening energy shortages, further instability in already fragile energy markets and natural gas prices reaching record highs [6,29,193]. This is not the case for ΔOVX_t-$F_{c,t}$ correlations which decrease in absolute magnitude from May 2022. $\Delta\widehat{ENPU}_t$-$F_{c,t}$ correlations only begin declining in absolute magnitude from October 2022, this coinciding with declining energy prices (see Fig. 1) and the implementation or extensions of policies aimed at shielding consumers from high energy prices towards the end of 2022. Examples are the €99bn German energy support scheme proposed in September 2022, the European Commission's interventions and gas price caps agreed upon in December 2022, and the U.K. government's energy price guarantee introduced from 1 October 2022 [1,91,142]. Other countries in the Americas, Africa and Asia (e.g., the U.S., South Africa and Korea) implemented less extensive measures [186]. While such measures may not have directly contributed to falling energy prices, they arguably reduced ENPU and the effects of energy price shocks. Declining $\Delta\widehat{ENPU}_t$-$F_{c,t}$ (absolute) correlations in Fig. 3 suggest that this is indeed the case while confirming that $\Delta\widehat{ENPU}_t$ is part of the composite factor set driving industry group returns during most of the sample period.

Next, we regress composite factor scores, $F_{c,t}$, onto $\Delta\widehat{ENPU}_t$, ΔOVX_t and ΔVIX_t. Here, we seek to confirm that $\Delta\widehat{ENPU}_t$ is indeed a component of the return generating process, as suggested by Fig. 3, and that there is approximate co-movement in explanatory power (as quantified by the $\overline{R}^2$s) between these three uncertainty measures. We also seek to quantify explanatory power in four distinct sub-periods. These are the start of the energy crisis (June to December 2021) which was characterised by early increases in energy prices as the global economy rebounded post-pandemic, the lead-up to the invasion of Ukraine and its immediate aftermath (January to May 2022), the period coinciding with the sabotage of the Nord Stream 1 and 2 pipelines (June to September 2022)

[14] Szczygielski, et al. [203] propose that a single composite factor score can be constructed by communality (c_k) weighting statistical factor scores, $F_{k,t}$, derived from returns as follows: $F_{c,t} = \sum_{k=1}^{m} c_k F_{k,t}$.

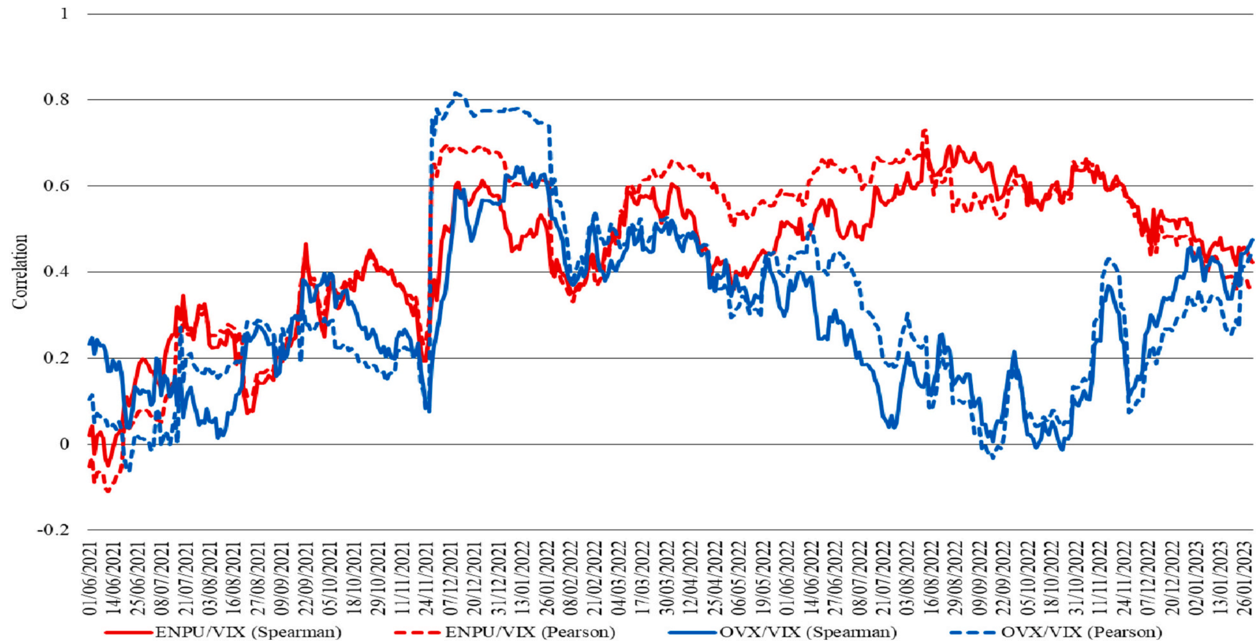

Fig. 2. Rolling correlations for $\Delta\widehat{ENPU}_t$, ΔOVX_t and ΔVIX_t.

Notes: This figure reports rolling ordinary and Spearman correlations between $\Delta\widehat{ENPU}_t$ and ΔVIX_t, and ΔOVX_t and ΔVIX_t. Rolling correlations are estimated using windows of 45 observations over the period 1 January 2021 to 31 January 2023 using a backcast of $\Delta\widehat{ENPU}$ and reported for the period 1 June 2021 to 31 January 2023.

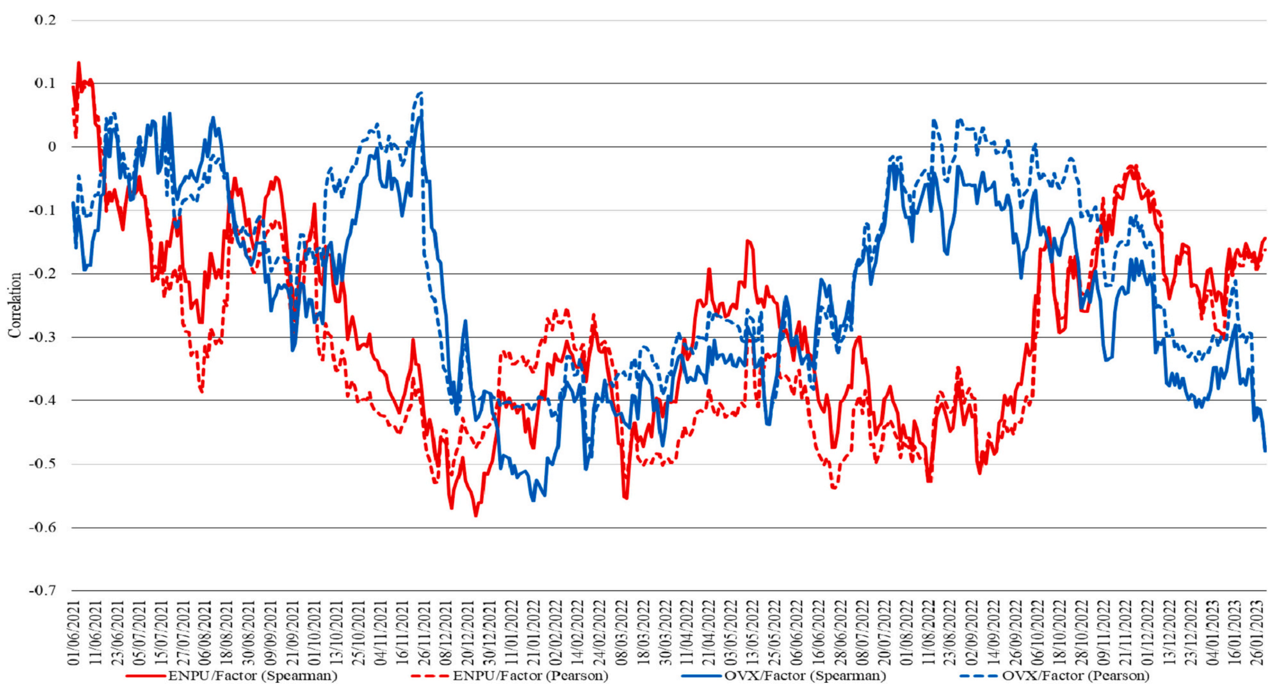

Fig. 3. Rolling correlations for $\Delta\widehat{ENPU}_t$, ΔOVX_t and $F_{c,t}$

Notes: This figure reports rolling ordinary and Spearman correlations between $\Delta\widehat{ENPU}_t$ and ΔOVX_t, and $F_{c,t}$ and ΔOVX_t. Rolling correlations are estimated using windows of 45 observations over the period 1 January 2021 to 31 January 2023, using a backcast of $\Delta\widehat{ENPU}$ and reported for the period 1 June 2021 to 31 January 2023.

and a final period characterised by rapidly declining energy prices (October 2022 to January 2023). Results in Table A10 confirm that $\Delta \widehat{ENPU}_t$ outperforms ΔOVX_t in approximating the return generating process ($\overline{R}^2$ of 0.1061 versus 0.0364, respectively) over the full sample period. The explanatory power attributable to ΔVIX_t exceeds that of $\Delta \widehat{ENPU}_t$. This is expected given that ΔVIX_t is a general measure of stock market uncertainty whereas $\Delta \widehat{ENPU}_t$ reflects a component thereof. The sub-period analysis also shows that there is approximate co-movement in explanatory power between these three uncertainty measures, which is expected if all three measures reflect ENPU components.

Standardised coefficients increase in magnitude for all three measures (see Table A10 in the Appendix) from the beginning of the energy crisis and peak between January and May 2022 ($\beta_{C,\Delta UN_2}$s of -0.2435, -0.2019 and -0.4795 for $\Delta \widehat{ENPU}_t$, ΔOVX_t and ΔVIX_t, respectively). At the onset of the energy crisis (the first sub-period), climatic conditions and the rapid post-COVID-19 rebound created uncertainty, although similar events in the past had provided some precedents. For example, rapid recoveries often trigger demand surges that outpace supply, fuelling inflation and prompting central banks to raise interest rates unexpectedly, creating uncertainty around borrowing costs. Harr and Spange [105] compare inflationary pressures during the COVID-19 recovery and Russia-Ukraine war to the 1970s, emphasising similarities (although limited) and the role of central banks in restoring price stability. Such recoveries, as seen following the pandemic, can also strain supply chains, causing input cost spikes from demand pressures, transportation bottlenecks and resource shortages. While recovery strategies for 'disruption events' are documented, they remain limited as each situation is unique [122]. Botzen et al. [36] suggest that countercyclical government spending, financial compensation and societal safety nets can be effective in mitigating the economic and distributional impacts of climate disasters. These and similar insights aided in mitigating the extent and variability of uncertainties during the first sub-period (see Section 3.2.1). The increasing impact of energy price uncertainty on returns during Russia's invasion of Ukraine (the second sub-period) aligns with the heightened unknowns of that period. Masters [156] emphasises that Russia's full-scale invasion, aimed at toppling President Zelenskyy, represents the largest conflict in Europe since World War II. The potential for dangerous escalation further amplified the range of possible outcomes and the scope of uncertainty. Similarly to our findings, Grebe et al. [97] report that the effects of uncertainty on financial markets and economic output were particularly high in the first few months of the war.

Between June and September 2022 (the third sub-period), coefficients decrease marginally but are significant for both $\Delta \widehat{ENPU}_t$ and ΔVIX_t ($\beta_{C,\Delta UN_3}$ of -0.2104 and -0.3571, respectively). The lack of significance associated with ΔOVX_t during this period may stem from the nature of the crisis. While oil prices began declining from June 2022, natural gas prices peaked between June and September 2022 (see Panels A and B in Fig. 1). As $\Delta \widehat{ENPU}_t$ is a broader measure of ENPU compared to ΔOVX_t, this may account for the observed difference. The continued substantial role of ENPU in the return generating process from June to September 2022 reflects persistent uncertainty surrounding the crisis. This period was marked by heightened tensions, including the suspected sabotage of the Nord Stream pipelines and Russian President Putin's nuclear threats, with U.S. President Biden stating that the 'risk of nuclear Armageddon was at its highest since the Cuban Missile Crisis' [148]. The unprecedented nature of the crisis, combined with energy shortages in Europe, highlights the complexity and interconnectedness of its effects, thereby justifying its heightened impact.

From October 2022 onwards (the fourth sub-period), $\Delta \widehat{ENPU}_t$ does not have a significant effect on $F_{c,t}$. This period coincides with steep decreases in energy prices as the European winter was less severe and policy measures aimed at shielding consumers from rising energy prices were implemented or extended [1,91,142,186]. Moreover, while the conflict in Ukraine continued, the threat of the escalation had not materialised reducing the quantum of unknowns. ΔOVX_t continues to have a significant (albeit weaker) impact during this sub-period whereas $\Delta \widehat{ENPU}_t$ does not. This may be attributed to the abatement of the GEC driven by sharp increases in natural gas and coal prices with the ΔOVX_t again potentially reflecting ENPU, given the importance of oil price volatility prior to the energy crisis [205].[15]

The analysis in this section confirms that $\Delta \widehat{ENPU}_t$ approximates ΔVIX_t using rolling correlations, with correlations strengthening during periods that coincide with rapidly increasing energy prices and significant events. $\Delta \widehat{ENPU}_t$ outperforms ΔOVX in approximating composite factor scores during the period coinciding with the Nord Stream 1 and 2 sabotage, as suggested by positive elevated correlations over this period in Fig. 2. It also approximates the return generating process over this period, as suggested by the negative non-zero correlations in Fig. 3, whereas ΔOVX does not. Regression results confirm that $\Delta \widehat{ENPU}_t$ is a component of the return generating process, outperforming ΔOVX over the entire sample period and most sub-periods, and exhibits co-movement with ΔOVX and ΔVIX_t in explanatory power indicating that it reflects ENPU components reflected by these measures. Moreover, sub-period analysis confirms that $\Delta \widehat{ENPU}_t$ was a larger component of the return generating process during periods of heightened uncertainty, namely that coinciding with Russia's invasion of Ukraine and its immediate aftermath, and that surrounding the sabotage of the Nord Stream pipelines. This contrasts with the first sub-period, which was still characterised by uncertainty but had some precedent from past events, and the fourth sub-period, during which uncertainty began subsiding.

4.2. The impact of ENPU and energy prices on returns

Table 2 reports the results of regressions of industry group returns onto $\Delta \widehat{ENPU}_t$ and energy prices. $\Delta \widehat{ENPU}_t$ has a statistically significant negative effect on returns for all industries (average standardised $\beta_{i,\Delta \widehat{ENPU}}$ of -0.3061), consistent with *a priori* expectations of a negative impact of uncertainty on returns. The diversified financials, consumer services and software & services industry groups are most impacted ($\beta_{i,\Delta \widehat{ENPU}}$s of -0.3969, -0.3927 and -0.3831, respectively). Energy, food & staples retailing and household & personal products are least impacted ($\beta_{i,\Delta \widehat{ENPU}}$s of -0.1506, -0.2207 and -0.2266, respectively) (see also Fig. 4). The magnitude of the impact of ENPU varies across industries in a manner consistent with our hypothesis that firms that sell durable goods or services and/or whose products or services require substantive investment decisions by other companies or themselves face large investment decisions, experience increased sensitivity to uncertainty [82]. Industry groups, such as software & services (3rd), healthcare & equipment (4th) and capital goods (6th) whose products and/or services require long-term investments are heavily impacted as uncertainty has a detrimental impact on firm-level investment thus lowering forecasted cash flows for companies in these industry groups. Firms that are heavily dependent on discretionary consumer spending are also among those most affected, such as consumer services (2nd), media & entertainment (7th) and retailing (9th) as consumers reduce optional spending, which includes luxury goods such as hotels, gambling and

[15] Squared standardised coefficients have the advantage of being more readily interpretable, given that they approximate the $\overline{R}^2$. It follows that in the final period ΔOVX_t approximates 1.43 % of the variation in $F_{c,t}$. Szczygielski et al. [205] find that $\Delta \widehat{ENPU}_t$ continues to have a significant effect on MSCI ACWI returns although the corresponding standardised coefficient is also low in magnitude (-0.0758). For completeness, we also regress the MSCI ACWI returns on ΔOVX_t. The coefficient on ΔOVX_t is -0.0616 and is statistically insignificant for the final period. This contrasts with the significant explanatory power of $\Delta \widehat{ENPU}_t$ for MSCI ACWI returns. Results are available upon request.

Table 2
Impact of $\Delta\widehat{ENPU}_t$ and energy prices on industry group returns.

Industry group	α	$\beta_{i,\Delta\widehat{ENPU}}$	$\beta_{i,\Delta OIL}$	$\beta_{i,\Delta GAS}$	$\beta_{i,\Delta COAL}$	$\beta_{M\varepsilon}$	$\overline{R}^2_{\Delta\widehat{ENPU}}$	$\overline{R}^2_{\Delta EN}$	$\overline{R}^2_{\Delta FULL}$
1. Diversified financials	−0.0001	−0.3969***	0.1122***	−0.0736***	−0.0667***	0.8330***	0.1653	0.0269	0.1809
2. Consumer services	−0.0002	−0.3927***	0.1030*	−0.0498**	−0.0858***	0.7392***	0.1589	0.0218	0.1725
3. Software & services	−0.0003	−0.3831***	0.0311	−0.0087	−0.0832***	0.8075***	0.1453	0.0038	0.1471
4. Healthcare equip. & services	−0.0001	−0.3659***	0.0314	−0.0426	−0.0439*	0.7261***	0.1360	0.0041	0.1346
5. Insurance	0.0003	−0.3489***	0.1286**	−0.1039**	−0.0779*	0.6653***	0.1313	0.0385	0.1570
6. Capital goods	−0.0001	−0.3407***	0.1859***	−0.0917***	−0.0945***	0.7977***	0.1256	0.0560	0.1689
7. Media & entertainment	−0.0009**	−0.3363***	0.0378	−0.0083	−0.0611***	0.7794***	0.1119	0.0009	0.1107
8. Commercial & prof. Services	−0.0001	−0.3307***	0.0673***	−0.0679**	−0.0532***	0.7694***	0.1139	0.0130	0.1192
9. Retailing	−0.0007	−0.3242***	0.0656*	−0.0235	−0.0775**	0.7732***	0.1056	0.0078	0.1097
10. Semicond. & semicond. Equip.	−0.0002	−0.3226***	0.0963***	0.0097	−0.0973***	0.7968***	0.1023	0.0132	0.1142
11. Real estate	−0.0003	−0.3222***	0.0889**	−0.0218	−0.0387	0.7161***	0.1052	0.0078	0.1085
12. Consumer durables & apparel	−0.0003	−0.3211***	0.1039***	−0.1206***	−0.0911***	0.7484***	0.1123	0.0382	0.1382
13. Transportation	−0.0002	−0.3167***	0.1255***	−0.0068	−0.0585**	0.7707***	0.1010	0.0162	0.1134
14. Tech. hardware & equip.	0.0000	−0.3100***	0.0610**	−0.0037	−0.0514**	0.8111***	0.0951	0.0019	0.0949
15. Automobiles & components	−0.0005	−0.2990***	0.0637**	−0.0043	−0.0878**	0.6630***	0.0880	0.0066	0.0930
16. Banks	−0.0001	−0.2983***	0.1464***	−0.1495**	−0.0963**	0.6859***	0.1006	0.0587	0.1448
17. Pharma., biotech. & life sciences	0.0001	−0.2927***	−0.0206	−0.0820**	−0.0351	0.6594***	0.0887	0.0083	0.0910
18. Food, beverage & tobacco	0.0000	−0.2866***	0.0593	−0.1596***	−0.0182	0.6127***	0.0929	0.0359	0.1151
19. Utilities	0.0000	−0.2715***	0.1051**	−0.0683*	−0.0342	0.5867***	0.0781	0.0170	0.0878
20. Materials	−0.0002	−0.2465***	0.3173***	−0.0655*	−0.0679***	0.7105***	0.0681	0.1104	0.1686
21. Telecommunication services	−0.0003	−0.2425***	0.1235***	−0.1097**	−0.0463	0.5837***	0.0654	0.0309	0.0870
22. Household & personal products	−0.0002	−0.2266***	−0.0727**	−0.1472**	−0.0701***	0.6025***	0.0558	0.0337	0.0824
23. Food & staples retailing	0.0001	−0.2207***	0.0512	−0.0669***	−0.0820***	0.6733***	0.0504	0.0111	0.0571
24. Energy	0.0008	−0.1506***	0.6255***	0.0265	−0.0066	0.4101***	0.0269	0.3948	0.4159
Average	**−0.0002**	**−0.3061**	**0.1099**	**−0.0600**	**−0.0636**	**0.7051**	**0.1010**	**0.0399**	**0.1339**

Notes: This table reports the results of regressions of returns for 24 industry groups onto $\Delta\widehat{ENPU}_t$, oil, natural gas and coal prices and the residual market factor, M_ε, over the GEC period 1 June 2021 to 31 January 2023. Regressions are estimated using least squares with Newey-West heteroscedasticity and autocorrelation consistent (HAC) standard errors. Standardised coefficients are presented. Numbers preceding each industry group reflect ranking according to the magnitude of impact as measured by $\beta_{i,\Delta\widehat{ENPU}}$. $\overline{R}^2_{\Delta\widehat{ENPU}}$ reflects the exclusive explanatory power of $\Delta\widehat{ENPU}_t$. $\overline{R}^2_{\Delta EN}$ reflects the exclusive explanatory power of ΔOIL_t, ΔGAS_t and $\Delta COAL_t$, the energy proxies derived from energy price benchmarks. $\overline{R}^2_{\Delta FULL}$ is the combined explanatory power of $\Delta\widehat{ENPU}_t$ and energy price proxies. ***, ** and * indicate statistical significance at the respective 1%, 5% and 10% levels.

restaurants (comprising the consumer services group) during times of heightened uncertainty [47]. Consistent with this argument, industries that provide necessities are less impacted; food & staples retailing (23rd) and household & personal products (22nd) are two of the least impacted industry groups along with utilities (19th) (see also Szczygielski, Charteris et al., [202]). Hirsch [110] documents that consumers prioritised purchasing necessities during the GEC. Luo and Qin [152] and Xiao et al. [221] similarly report that industries associated with the production or provision of necessities are less impacted by oil price uncertainty. Wu and Zhao [220] find that household consumption of necessities and luxuries declined due to heightened uncertainty driven by economic policy. Diversified financials (most impacted) bore the fallout from both changing patterns of investment by firms and expenditure by consumers as these reduce demand for credit and related services, thus lowering returns. Dai and Zhu [65] similarly find that the broad financials sector is impacted by economic policy uncertainty.

The energy sector is the most resilient. Heightened uncertainty caused by rising energy prices benefits firms comprising this industry group as cash flows increase in line with rising energy prices which can be passed on to consumers due to relatively inelastic demand [9]. Furthermore, higher energy prices provide a catalyst for expanded exploration and drilling by increasing investment that may not be economically viable during periods of lower prices. This, in turn, helps ensure the sustainability of revenue streams. Finally, according to Jin and Jorion [124], oil and gas industries that comprise the broader energy industry group extensively hedge oil and gas prices thus reducing the impact of uncertainty. Nevertheless, the energy industry group is not immune to the negative impact of the crisis, as evident from the significant and negative value of $\beta_{i,\Delta\widehat{ENPU}}$, for two reasons. The first is the negative impact of ENPU on global economic growth, with energy prices acting as a barometer for growth prospects. Higher expected cash flows attributable to rising energy prices will be offset by anticipated adverse economic conditions due to rising inflation and interest rates. The second is uncertainty surrounding the declining long-term demand for fossil fuels as the crisis accelerates the move to renewable energy sources [120].

The impact of energy prices on industry group returns, while significant, appears to be minor, with energy prices explaining just under 4% of variation in industry group returns on average (average $\overline{R}^2_{\Delta EN}$= 0.0399). Dupoyet and Shank [74] and Szczygielski et al. [205] also found that ENPU dominates the impact of energy prices on aggregate stock returns. Oil prices have a positive and significant impact on 18 industry groups while natural gas and coal prices have a negative and significant impact on 14 and 18 industry groups, respectively. Most of the explanatory power can be attributed to oil prices, whereas natural gas and coal prices, while significant, have limited explanatory power as suggested by the magnitude of the individual standardised coefficients and their averages of 0.1099, −0.0600 and −0.0636 for oil, gas and coal, respectively.[16]

The positive effect of oil is consistent with the demand-side shock that predated the GEC where the increase in the demand for oil

[16] One benefit of using standardised coefficients lies in their ability to serve as an indicator of explanatory power when squared comparable to the coefficient of determination. For example, the squared average standardised coefficient for oil is 0.0121, suggesting that oil prices explain 1.21 % of variation in returns on average. As standardised coefficients for natural gas and coal prices are small but significant, we validate our findings by estimating ordinary and Spearman correlations between the return indices and each energy source. Correlations are congruent with the results for energy prices in Table 2 in terms of the direction of association and frequency of significance.

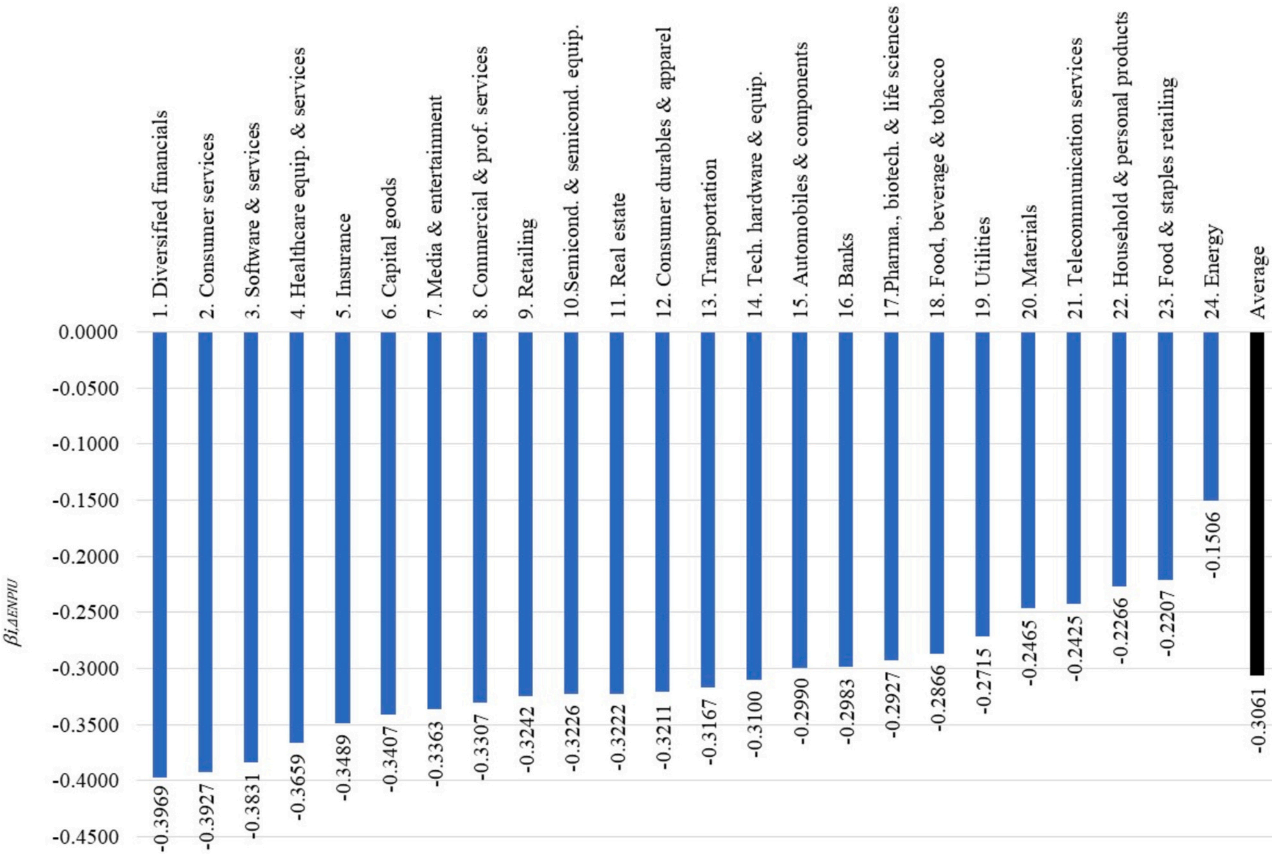

Fig. 4. Impact of $\Delta \widehat{ENPU}_t$ on industry group returns.
Notes: This figure plots the estimates of the impact of ENPU on returns for 24 industry groups and the average. Numbers preceding each industry group reflect ranking according to the magnitude of impact as measured by $\beta_{i,\Delta \widehat{ENPU}}$.

coincided with the post-COVID-19 pandemic economic recovery. As the crisis evolved, supply-side shocks began dominating. These types of shocks have been shown to have no noticeable impact on stock returns [40,135]. The adverse impact of both coal and natural gas price movements is in line with expectations following the dramatic price increases of both energy sources and mirrors findings from prior studies (such as [2,182]). Higher energy prices curtail economic activity, thus driving stock prices lower and the results attest to this. Amaro [12] argues that Europe is heading towards a recession as firms and consumers bear the brunt of the unprecedented shortage of natural gas and rising prices. According to Proctor [176], while the availability of coal enabled countries to reduce their reliance on natural gas as a source of energy, the unprecedented coal price increases driven by this surge in demand, dampened economic prospects. This negative effect contrasts with the positive effect documented for oil. While oil prices rose, the causes of this were not, at least initially, for the same reason as for natural gas and coal (shortage of supply for natural gas and consequent demand for coal versus increased demand for oil due to increased output) which may account for the varying findings for natural gas and coal compared to oil. Specifically, this crisis was sparked by natural gas shortages and price increases, with the rapid increase in the demand for coal partly driven by conditions in the natural gas market [119]. The negative impact of natural gas and coal prices across industries, albeit small but contrasting with that of oil, constitutes further evidence that the GEC is driven by natural gas and coal prices and not oil prices.

Industry groups most impacted by changes in oil prices are energy, materials and capital goods ($\beta_{\Delta OIL}$s of 0.6255, 0.3173 and 0.1859, respectively). The positive and significant impact on the energy group is not surprising given that oil and oil-related activities are a key output for this sector. As oil prices increase, cash flows to firms comprising this sector increase [9,161]. The materials and capital goods industry groups have a long-term orientation and/or require substantial investment and their performance depends on long-term economic prospects. The positive impact reflects oil's role as a proxy for economic conditions, whereby in the period before and the early months of the crisis, these sectors were recovering as aggregate economic activity increased [145].

Banks experience relatively large exposure to energy prices overall ($\bar{R}^2_{\Delta EN}$of 0.0587) which reflects spillovers from other sectors as lower consumer incomes and lower firm profits attributable to higher energy prices harm bank profitability [17,161]. The capital goods sector also responds to energy prices overall ($\bar{R}^2_{\Delta EN}$of 0.0560), consistent with firms in this group facing higher energy costs due to their energy-intensive production processes, driving cash flows downwards [104]. The pharmaceuticals, biotechnology & life sciences industry group has low exposure to energy prices ($\bar{R}^2_{\Delta EN}$of 0.0019). According to Stewart [195], pharmaceutical manufacturers and biotechnology firms have implemented new less energy-intensive manufacturing processes, thus reducing the impact of energy prices on this industry group.

These results suggest that $\Delta \widehat{ENPU}_t$ matters more than energy price shocks in explaining returns. While shocks drive $\Delta \widehat{ENPU}_t$, the explanatory power attributable to Szczygielski et al.'s [205] proxy confirms that it reflects a broader transmission channel and is associated with a greater amount of information than that encapsulated by energy prices alone. Returns on industry groups that are more susceptible to firms delaying investments and/or consumers halting purchases are more negatively impacted by $\Delta \widehat{ENPU}_t$. This represents the magnitude of the impact of uncertainty. The negative impact of coal and natural gas prices is consistent with the crisis being driven by these two energy sources whereas the supply-side nature of oil price increases explains its limited impact.

4.3. The impact of ENPU on volatility

$\Delta\widehat{ENPU}_t$ triggers significant volatility for 15 of the 24 industry groups (average $\varphi_{i,\Delta\widehat{ENPU}}$ of 0.1955) (Table 3). Most impacted are automobiles & components, consumer services and media & entertainment ($\varphi_{i,\Delta\widehat{ENPU}}$s of 0.9060, 0.4480 and 0.4460, respectively). Food & staples retailing, pharmaceuticals, biotechnology & life sciences and utilities are least impacted ($\varphi_{i,\Delta\widehat{ENPU}}$s of 0.0173, 0.0475 and 0.0549, respectively) (see also Fig. 5). The ordering differs from that for returns. For example, the automobiles & components industry group is now most impacted whereas it was 15th for returns; the consumer durables & apparel group is 4th but was 12th for returns and technology hardware & equipment is 5th for volatility but was 14t^{h} for returns. In contrast, diversified financials and software & services are now 11th and 16th, respectively but were 1st and 3rd for returns. These differences in order, at times stark, suggest that the impact of uncertainty on volatility reflects different information associated with ENPU to that reflected by returns. However, there is similarity in rankings for several groups e.g., consumer services (ranked 2nd for returns and volatility) and food & staples retailing (23rd for returns and 24th volatility).

The overall positive effect of $\Delta\widehat{ENPU}_t$ on volatility is consistent with expectations that heightened uncertainty leads to greater volatility and findings of prior studies examining the effect of economic, oil price and stock market uncertainty [78,79]. The heterogeneous impact across industries is congruent with the proposition that in industries where uncertainty causes greater ambiguity in anticipated risk and returns, it becomes more challenging to assess future asset values. This leads to a more intensive price discovery process as greater investor learning occurs resulting in a larger effect. For example, the automobiles & components industry, which is most impacted by investor learning, is highly cyclical as demand for automobiles depends on economic conditions, falling sharply during recessions (as seen during COVID-19 and the global financial crisis (GFC)) and rising during boom periods [107]. According to Boudette [38], the GEC, which saw energy prices surge, high levels of inflation and persistent interest rate hikes, contributed to uncertainty about new car sales and fuelled ambiguity regarding the momentum in the transition to new and cleaner energy vehicles [180,199]. In short, forecasts of the business prospects of the industry were severely impacted by the prevailing ambiguity thus triggering heightened volatility in the returns for this industry group as investors respond to new information and learn as prices adjust to intrinsic values. Examples of other sectors that are highly cyclical and that suffer during uncertain economic conditions are consumer services, media & entertainment and consumer durables & apparel. Given their discretionary nature, there is greater uncertainty among investors about future risk and returns as households scale back on discretionary consumer spending [13].

The utilities, pharmaceuticals, biotechnology & life sciences and food & staples retailing industry groups experience the lowest volatility triggering effects. This is consistent with prior evidence that these sectors are more resilient to uncertainty (Abatipudi & Kumar, [1]; Szczygielski, Charteris et al., [202]). Our findings are also similar to those of Berry et al. [30], who observe that the utilities sector is relatively insensitive to macroeconomic innovations. The demand for the products of utilities and food & staples retailers is inelastic as their products are essentials. Consequently, risk-return expectations for these industry groups are less ambiguous and, as such, learning effects that arise when determining the intrinsic value are low, thus the price discovery process is less intense. The risk-return outlook for the pharmaceutical, biotechnology & life sciences industry group remains relatively clear as, according to Kemler [131], considerable investment has been made into this industry in recent years with long-term funding secured for research

Table 3

Impact of $\Delta\widehat{ENPU}_t$ on industry group conditional variance

Industry group	ω_i	α_1	α_2	β_1	β_2	$\varphi_{i,\Delta\widehat{ENPU}}$
1. Automobiles & components	7.16E−07	0.0656	0.0331	0.9064***		0.9060**
2. Consumer services	7.45E-07*	0.0193	0.0875**	0.8737***		0.4481***
3. Media & entertainment	1.15E-06	0.0373*	0.0291	0.3465	0.5668**	0.4460***
4. Consumer durables & apparel	1.11E-06**	0.0718***		0.9043***		0.2380**
5. Tech. hardware & equip.	5.30E-06	0.0939		0.4417***	0,3767***	0.2380*
6. Retailing	3.83E-07	0.0361*		0.9570***		0.2360**
7. Semicond. & semicond. Equip.	3.52E-06	0,0741**		0,8774***		0.2260
8. Healthcare equip. & services	2.97E-06	0.0729**		0.8432***		0.2130***
9. Commercial & prof. Services	9.97E-07**	0.1062***		0.8409***		0.1700***
10. Real estate	7,52E-07*	0,1010***		0,6980**	0.1857	0.1650*
11. Diversified financials	1.28E-07	0.0737***		0.9191***		0.1650***
12. Transportation	6.61E-07	0.0536		0.0970	0.8261***	0.1390
13. Food, beverage & tobacco	5.88E-07	0.0576		0.9032***		0.1385*
14. Insurance	1.55E-07	0.0583***		0.9324***		0.1320***
15. Capital goods	8.49E-07**	0.0815***		0.8875***		0.1308*
16. Software & services	1,15E-06**	0.1441***		0.8397***		0.1220
17. Household & personal products	5.70E-06	0,1598*		0.6196**		0.1140
18. Banks	6.33E-07*	0.1307***		0.8346***		0.1060**
19. Energy	1.88E-06	0.1156		0.8693***		0.0968
20. Telecommunication services	2.61E-07	0,2111***	-0.1806**	0,9567***		0.0853*
21. Materials	3.71E-06	0.1449**		0.7987***		0.0577
22. Utilities	1,97E-07*	0.0757***		0.9046***		0.0549**
23. Pharma., biotech. & life sciences	7.10E-06**	0.1521***	−0.0227	0.6548***		0.0475
24. Food & staples retailing	5.88E-07	0.1807***	−0.1278***	0.4611***	0.4669***	0.0173
Average	**1.86E-06**	**0.0966**	**−0.0302**	**0.7541**	**0.5114**	**0.1955**

Notes: This table reports the results of regressions of $\Delta\widehat{ENPU}_t$ onto conditional variance modelled as an ARCH/GARCH process for 24 industry group aggregates. An extended estimation sample is used for ARCH/GARCH modelling, beginning on 1 January 2019 and ending on 31 January 2023 with the energy crisis period designated by a dummy variable in the conditional variance specification (see eq. (3)). Regressions are estimated with maximum likelihood unless residuals depart from normality, in which case quasi-maximum likelihood estimation is applied. $\varphi_{i,\Delta\widehat{ENPU}}$ coefficients are scaled by 100,000 for ease of comparison. Numbers preceding each industry group reflect ranking according to impact on volatility as measured by $\varphi_{i,\Delta\widehat{ENPU}}$. ***, ** and * indicate statistical significance at the respective 1%, 5% and 10% levels.

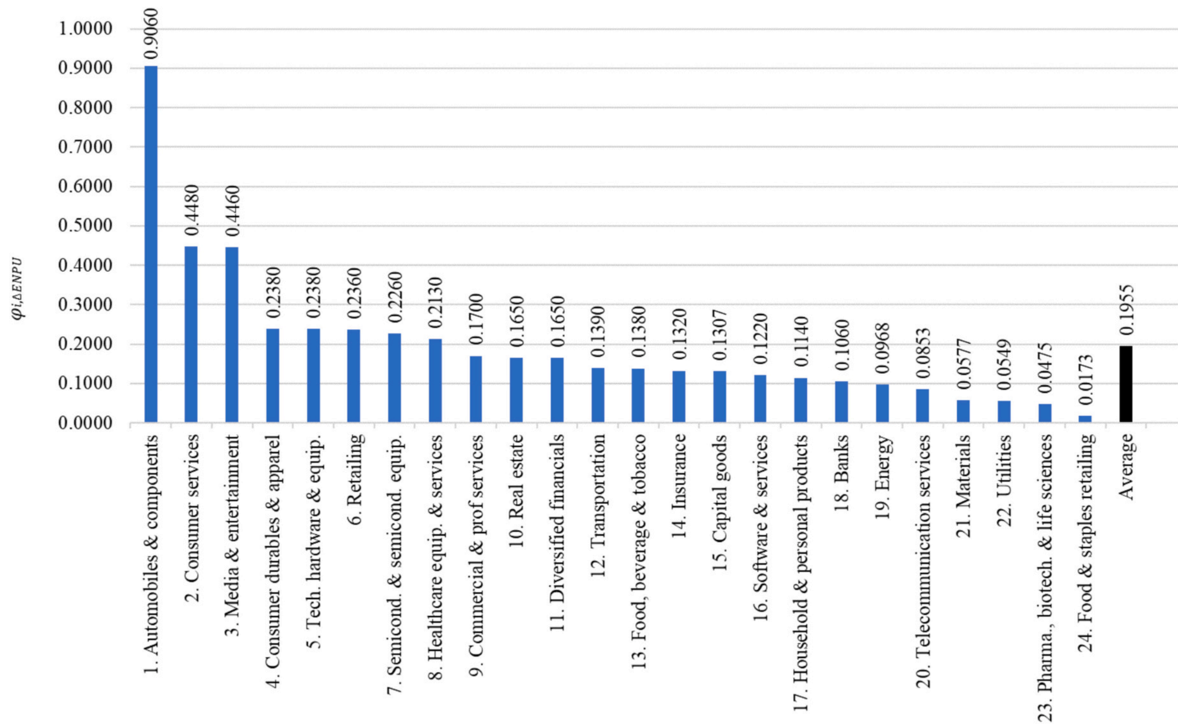

Fig. 5. **Impact of $\Delta\widehat{ENPU}_t$ on industry group conditional variances**
Notes: This figure plots the estimates of the impact of ENPU on conditional variance for industry groups and the average. Numbers preceding each industry group reflect ranking according to the impact on volatility as measured by $\varphi_{i,\Delta EN\hat{P}U_t}$. Estimates are scaled by 100,000 for ease of comparison.

and development. Current events therefore have a limited impact on this group's prospects. The similarity in ranking of consumer services (highest) and food & staples retailing (lowest) in both returns and variance demonstrates the luxury versus essential status of the products provided by these groups and how this affects sensitivity to uncertainty both through the consumer spending and investment channels, and risk-return expectations of these firms.

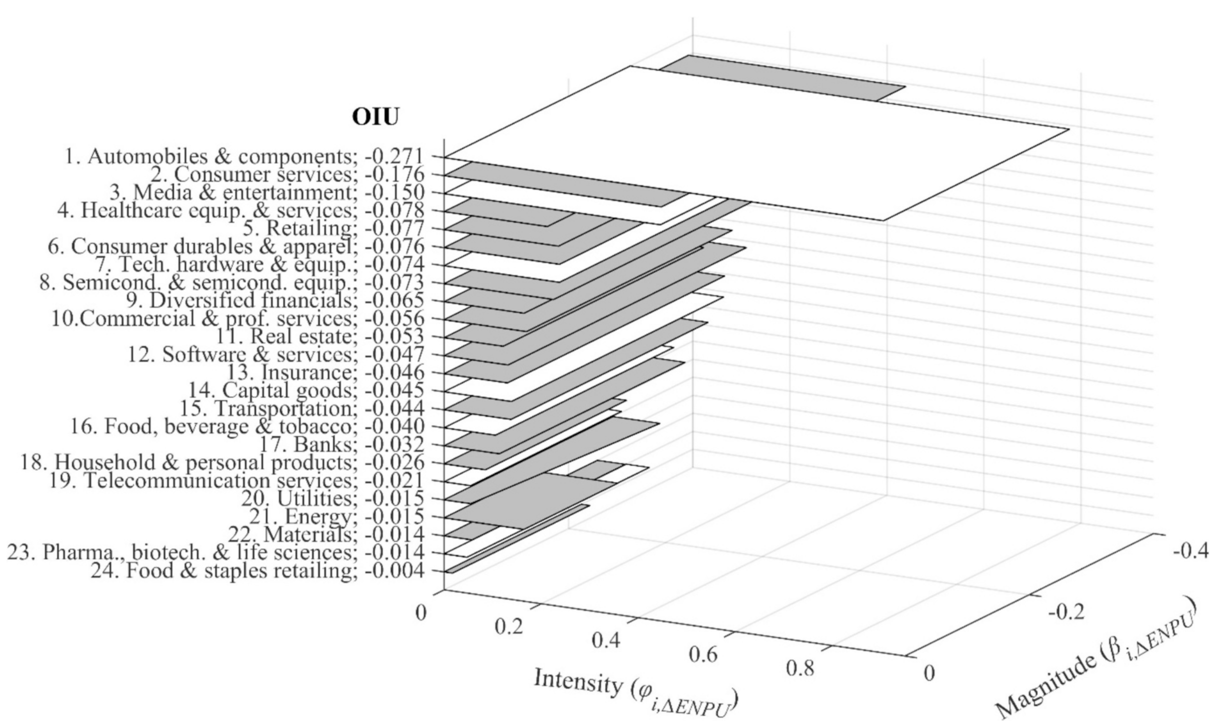

Fig. 6. Overall impact of energy price uncertainty on industry groups
Notes: This figure reports OIU values and summarises the relationship between magnitude ($\beta_{i,\Delta E\hat{N}PU}$), intensity ($\varphi_{i,\Delta EN\hat{P}U_t}$) and OIU. The size of each rectangle represents the size of the OIU for each industry group whereas the vertical axis reports OIU values for each group. Industry groups where the magnitude effect dominates are shaded in grey while industry groups where intensity dominates are shaded in white. Estimates of $\varphi_{i,\Delta EN\hat{P}U_t}$ are scaled by 100,000 for ease of comparison.

In summary, $\Delta\widehat{ENPU}_t$ triggers volatility in industry returns but the relative ranking of the intensity of the price determination process differs compared to that for returns. This suggests that a somewhat different mechanism is responsible for driving the volatility response than for returns. The results are consistent with the proposition that the sectors most impacted are those that have the most ambiguous prospects which are reflected by risk-return expectations. This requires more extensive learning about intrinsic asset values, resulting in a more intensive price determination process reflected in higher volatility.

4.4. The overall impact of ENPU

Fig. 6 reports the OIU_i for each industry group, while also reflecting magnitude, intensity and denoting the dominance effect (see Table 4). The automobiles & components, consumer services and media & entertainment industry groups are most impacted (OIU_is of -0.2709, -0.1759 & -0.1500, respectively). The least impacted industry groups are food & staples retailing, pharmaceuticals, biotechnology & life sciences and materials (OIU_is of -0.0038, -0.0139 and $-$ 0.0142, respectively). OIU_i rankings differ from either those of $\beta_{i,\Delta\widehat{ENPU}}$ or $\varphi_{i,\Delta\widehat{ENPU}}$ alone, in line with the argument that individually neither of these reflect the full transmission effect of uncertainty. For example, the automobiles & components group is ranked 15th according to $\beta_{i,\Delta\widehat{ENPU}}$ (-0.2927) but experiences the largest volatility triggering effects ($\varphi_{i,\Delta\widehat{ENPU}}$ of 0.9060). The resultant OIU_i indicates that this is the most impacted industry group. Similarly, the technology hardware & equipment group is ranked 14$^{\text{th}}$ according to $\beta_{i,\Delta\widehat{ENPU}}$ but 5$^{\text{th}}$ according to $\varphi_{i,\Delta\widehat{ENPU}}$. It is ranked 7$^{\text{th}}$ according to the *OI*. A further example is the consumer durables & apparel industry group, which is 12$^{\text{th}}$ according to $\beta_{i,\Delta\widehat{ENPU}}$, 4$^{\text{th}}$ based on $\varphi_{i,\Delta\widehat{ENPU}}$ but 6$^{\text{th}}$ according to the OIU_i. Likewise, the impact of $\Delta\widehat{ENPU}_t$ on the diversified financials industry group was greatest for returns (1$^{\text{st}}$), but low for volatility (11$^{\text{th}}$), with the OIU_i ranking this industry group 9$^{\text{th}}$.

OIU_i rankings illustrate that considering the impact of uncertainty on only one aspect – returns or volatility – does not capture the full extent of the impact as the effects of uncertainty result in changes to cash flows and/or the discount rate which are reflected by returns (magnitude) and risk-return forecasts impact volatility through the price discovery process (intensity) [184,201]. We propose that the OIU_i offers a more comprehensive measure of the pervasive effects of uncertainty on stock markets for investors, portfolio managers and policymakers.

The results in Table 4 indicate that most series are dominated by the magnitude of the impact of $\Delta\widehat{ENPU}_t$ (indicated by grey shading) rather than intensity as most dominance ratios are above 1 in absolute terms (17 of 24). Significant and highly positive ordinary and Spearman correlations between the OIU_i and the rank predicted by the absolute sum of the dominance ratio and the rank of the dominant effect confirm that the OIU_i reflects not only the effect of uncertainty on returns and variance jointly, but also the relative importance of a given effect. The dominance of the impact on returns across industries suggests that ENPU has a greater impact on cash flows through delayed investment or reduced consumption compared to the effect on risk-return expectations. This suggests that investors face less ambiguity about future returns and risk, particularly considering insights acquired during past crises, including the recent COVID-19 pandemic. This reasoning is consistent with the findings of Andrei and Hasler [14] and Choi [59] who illustrate that

Table 4
Industry groups ranked according to the absolute sum of the dominance ratio and dominant effect rank

Industry group	$DomR_i$	$\lvert DomR_i + \beta_{i,\Delta\hat{E}NPU} >\rvert$ $\lvert DomR_i + \varphi_{i,\Delta\hat{E}PNU} >\rvert$	$\beta_{i,\Delta\hat{E}NPU}$ rank	$\varphi_{i,\Delta\hat{E}NPU}$ rank	OIU_i rank
1. Consumer services	-1.0891	0.9109	2	2	2
2. Automobiles & components	0.0320	1.0320	15	1	1
3. Media & entertainment	-0.3823	2.6177	7	3	3
4. Technology hardware & equip	-0.2888	4.7112	14	5	7
5. Software & services	3.3254	6.3254	3	16	12
6. Health care equip & services	-10.8552	6.8552	4	8	4
7. Insurance	2.1399	7.1399	5	14	13
8. Retailing	-1.4212	7.5788	9	6	5
9. Capital goods	1.6959	7.6959	6	15	14
10. Semiconductors & semiconductor equipment	-1.7145	8.2855	10	7	8
11. Diversified financials	9.4533	10.4533	1	11	9
12. Consumer durables & apparel	-1.1186	10.8814	12	4	6
13. Commercial & professional services	3.0552	11.0552	8	9	10
14. Transportation	0.5923	12.5923	13	12	15
15. Real estate	1.6765	12.6765	11	10	11
16. Food, beverage & tobacco	-1.0782	16.9218	18	13	16
17. Banks	-0.2792	17.7208	16	18	17
18. Materials	-1.3748	18.6252	20	21	22
19. Household & personal products	-3.0991	18.9009	22	17	18
20. Energy	-5.0027	18.9973	24	19	21
21. Telecommunication Services	-1.8322	19.1678	21	20	19
22. Utilities	-0.7813	21.2187	19	22	20
23. Food & staples retailing	-1.5226	21.4774	23	24	24
24. Pharmaceuticals, Biotechnology & Life	-0.2886	22.7114	17	23	23
Ordinary correlation					0.9187***
Spearman correlation					0.8991***

Notes: In this table, the first column reports the dominance coefficient ($DomR_i$) attributing dominance to either magnitude or intensity. If $|DomR_i|>1$, then the OIU_i is dominated by magnitude while if $|DomR_i| < 1$, the OIU_i is dominated by intensity. The second column reports the absolute sum of the dominance ratio $DomR_i$, as determined by eq. (10), and the position of the dominant effect, $\beta_{i,\Delta\widehat{ENPU}} >$ or $\varphi_{i,\Delta\widehat{ENPU}} >$, as in Tables 2 and 3, respectively. OIU_i positions, as reported in Fig. 6, are reported in the fifth column. For ease of reference, groups for which magnitude, $\beta_{i,\Delta\widehat{ENPU}}$, is dominant are shaded in grey. Ordinary and Spearman correlations are correlations between the sum of $DomR_i$ and the dominant effect for each industry group and OIU_i. *** indicates statistical significance at the 1% level.

investors learn from prior market uncertainty.

For example, the impact of $\Delta\widehat{ENPU}_t$ on returns for diversified financials dominates the impact on volatility suggesting the risk-return outlook is not substantially affected owing to the sector's experience with crises [113]. The software & services grouping is also dominated by the effect on returns. In contrast, for automobiles & components, intensity dominates and substantially affects the overall ranking of this industry group (see Section 4.3). Intensity also dominates magnitude for utilities. Utilities' cash flows are expected to be robust amid uncertainty, given their essential products and price regulation [9]. However, the larger intensity impact indicates some ambiguity among investors, leading to a learning requirement. Other industry groups for which intensity dominates magnitude are media & entertainment, technology hardware & equipment, transportation, banks and pharmaceuticals, biotechnology & life sciences.

The preceding analysis suggests that an investigation of the impact of uncertainty should consider both magnitude and intensity as it yields additional insights about the transmission of uncertainty to stock markets. An industry group may appear relatively resilient, such as automobiles & components, if only returns are considered. The OIU measure also suggests that there is a third component, that of dominance, which determines how severely an industry group is impacted.

4.5. Further analysis and testing

To explore whether $\Delta\widehat{ENPU}_t$ interacts with other factors, we re-estimate unrestricted versions of eqs. (1) and (2) with additional variables included. These are the Baltic Exchange Dry Index (ΔBDI_t) which is used to proxy for global economic activity and supply chain pressures (see [28,154]), the U.S. Dollar Index (ΔDXY_t) to control for shifts in global and U.S. specific factors, financial conditions and risk perceptions [164], $\Delta IDEMV_t$ to account for remaining pandemic-related uncertainty, ΔGPR_t to control for geopolitical risk and ΔEPU_t to control for U.S. economic policy uncertainty. These variables are incorporated into eq. (1) which is used to obtain $\beta_{i,\Delta EN\hat{P}U}$ estimates and into eq. (2) which is the conditional mean equation associated with eq. (3) from which $\varphi_{i,\Delta EN\hat{P}U}$ estimates are obtained.

Results indicate that on an individual basis differences in the $\beta_{i,\Delta EN\hat{P}U}$s obtained from the restricted and unrestricted versions of eq. (1) are negligible (see Panel A of Table A11 in the Appendix). Significance is consistent across specifications for individual $\beta_{i,\Delta EN\hat{P}U}$s. The paired sample *t*- and Wilcoxon matched-pairs signed-rank tests confirm that overall the $\beta_{i,\Delta EN\hat{P}U}$s remain unchanged. Differences between the respective individual $\varphi_{i,\Delta EN\hat{P}U}$s are somewhat more pronounced for some industry groups, with declines observed for automobiles & components (from 0.9060 to 0.6413), media & entertainment (0.4460 to 0.3688), healthcare equipment & services (0.2130 to 0.1766) when ΔBDI_t, ΔDXY_t, $\Delta IDEMV_t$, ΔGPR_t and ΔEPU_t are incorporated into eq. (2) to control for associated dispersion in the conditional variance (see [144,200]). For others, the $\varphi_{i,\Delta EN\hat{P}U}$s decline marginally, examples being consumer services, commercial & professional services and food, beverage & tobacco (see Panel B of Table A11 in the Appendix). On an individual basis, $\Delta\widehat{ENPU}_t$ has a significant impact on the conditional variance of 16 industry groups when the restricted version of eq. (2) is estimated (Table 3) and on 11 groups when the unrestricted version is considered. Differences between the overall $\varphi_{i,\Delta EN\hat{P}U}$s (of 0.1955 and 0.1506 for the restricted and unrestricted versions of eq. (2), respectively) are statistically significant. Consequently, we test the hypothesis of whether the $\varphi_{i,\Delta EN\hat{P}U}$s obtained from the unrestricted equation differ significantly from zero. Both tests confirm that this is the case, indicating that overall $\Delta\widehat{ENPU}_t$ continues to impact the conditional variance. Taken together, these results suggest that interactions between $\Delta\widehat{ENPU}_t$ and ΔBDI_t, ΔDXY_t, $\Delta IDEMV_t$, ΔGPR_t and ΔEPU_t potentially play a role in informing investor learning reflected by the conditional variance.

To gain insight into these interactions, we estimate correlations between $\Delta\widehat{ENPU}_t$ and these variables. Correlations (ordinary (ρ_O) and Spearman (ρ_S)) are significant for $\Delta\widehat{ENPU}_t$ with ΔDXY_t (ρ_O of 0.1849 and ρ_S of 0.1681) and also (weakly) with $\Delta IDEMV_t$ (ρ_O of 0.0813 and ρ_S of 0.0819) (see Table A12 in the Appendix). Correlations suggestive of an interaction between $\Delta\widehat{ENPU}_t$ and ΔDXY_t are not unexpected. Part of the impact of $\Delta\widehat{ENPU}_t$ stems from changing financial conditions and risk perceptions which are part of any crisis, including the GEC [197]. Risk perceptions can influence how stakeholders distinguish between measurable risk (quantifiable with probabilities) and uncertainty (where probabilities are unknown). Higher perceived risk can lead to inflated measures of uncertainty as stakeholders react to both known risk and uncertainty (as per Knightian uncertainty, Section 3.2.1). As a final test, we orthogonalise $\Delta\widehat{ENPU}_t$ against all the variables above with the aim of quantifying $\Delta\widehat{ENPU}_t$'s explanatory power for ΔVIX_t that is not attributable to these variables. $\Delta\widehat{ENPU}_t$'s explanatory power declines (to 22.33% from 26.99%) but still exceeds that of other alternative uncertainty measures (see Section 3.2., Table A6 in the Appendix) confirming that although $\Delta\widehat{ENPU}_t$ may interact with other factors and sources of uncertainty, it continues to have independent approximative power.

Next, we consider the impact of inter-industry information spillovers to determine whether these impact $\beta_{i,\Delta EN\hat{P}U}$ and $\varphi_{i,\Delta EN\hat{P}U}$ estimates. To incorporate potential spillovers, we augment eqs. (1) and (2) with lagged returns for industry group *j*, $\sum_{\tau=1}^{\tau} r_{j,t-\tau}$, while controlling for further lags of $r_{i,t}$, by incorporating $\sum_{\tau=1}^{\tau} r_{i,t-\tau}$ where lag orders are 1, 3 and 5 ($\tau = 1, 3, 5$) (see [83,138,209]). To identify spillovers, we apply the Auto-search/GETS algorithm with $\sum_{\tau=1}^{\tau} r_{i,t-\tau}$ and $\sum_{\tau=1}^{\tau} r_{j,t-\tau}$ acting as search sets while retaining the specifications used to estimate the $\beta_{i,\Delta EN\hat{P}U}$s and $\varphi_{i,\Delta EN\hat{P}U}$s.[17] The results (reported in Panel A of Table A13 in the Appendix) for the $\beta_{i,\Delta EN\hat{P}U}$ estimates suggest that inter-industry information spillovers have an indiscernible impact on $\beta_{i,\Delta EN\hat{P}U}$ for individual industry groups and overall. All $\beta_{i,\Delta EN\hat{P}U}$s remain statistically significant across all lag orders. Average $\beta_{i,\Delta EN\hat{P}U}$s for each lag order (−0.3079 for $\tau = 1$, −0.3074 for $\tau = 3$, −0.3082 for $\tau = 5$) do not differ significantly from the average $\beta_{i,\Delta EN\hat{P}U}$ in Table 3 (of −0.3061). Some *limited* variability is observed for the $\varphi_{i,\Delta EN\hat{P}U}$ estimates (see Panel B of Table A13 in the Appendix). For example, $\varphi_{i,\Delta EN\hat{P}U}$ decreases for telecommunications and becomes insignificant as the lag order increases. Contrastingly, $\varphi_{i,\Delta EN\hat{P}U}$ estimates for the consumer durables & apparel industry group increase somewhat although there is no change in significance. Statistical significance is largely consistent across lags and, where changes are observed, these are ambiguous. For example, while the $\varphi_{i,\Delta EN\hat{P}U}$ coefficient for technology hardware & equipment is statistically significant in Table 3, it becomes statistically insignificant when spillovers are reflected with one (or five) lags but remains significant

[17] To ensure comparability to the $\beta_{i,\Delta EN\hat{P}U}$ s and $\varphi_{i,\Delta EN\hat{P}U}$s reported in Tables 2 and 3, respectively, eqs. (1) and (2) remain unchanged except for the incorporation of $\sum_{\tau=1}^{\tau} r_{i,t-\tau}$ and $\sum_{\tau=1}^{\tau} r_{j,t-\tau}$ so that eq. (1) now becomes $r_{i,t} = \alpha_i + \beta_{i,\Delta EN\hat{P}U}\Delta\widehat{ENPU}_t + \beta_{i,\Delta OIL}\Delta OIL_t + \beta_{i,\Delta GAS}\Delta GAS_t + \beta_{i,\Delta COAL}\Delta COAL_t + \beta_{M\varepsilon}M_{\varepsilon,t} + \sum_{\tau=1}^{\tau} r_{i,t-\tau} + \sum_{\tau=1}^{\tau} r_{j,t-\tau} + \varepsilon_{i,t}$ and eq. (2) becomes $r_{i,t} = \alpha_i + \sum_{k=1}^{m} \beta_{i,k} F_{k,\Delta EN\hat{P}U}^{RES} + \beta_{i,\Delta OIL}\Delta OIL_t + \beta_{i,\Delta GAS}\Delta GAS_t + \beta_{i,\Delta COAL}\Delta COAL_t + \gamma_i r_{i,t-\tau} + \sum_{\tau=1}^{\tau} r_{i,t-\tau} + \sum_{\tau=1}^{\tau} r_{j,t-\tau} + \varepsilon_{i,t}$. The $\gamma_i r_{i,t-\tau}$ remain and are used to control for serial correlation where present and are thus not part of the search sets. The inclusion of $\sum_{\tau=1}^{\tau} r_{j,t-\tau}$ in eq. (2) controls for dispersion in the residuals and the conditional variance (eq. (3)) that is potentially attributable to spillovers. As far as possible, the GARCH(*p*,*q*) specifications remain the same in terms of *p* and *q* to ensure that any differences in $\varphi_{i,\Delta EN\hat{P}U}$s are not attributable to changes in the GARCH(*p*, *q*) specification. Abridged results are reported in Table A13 in the Appendix and full results are available upon request.

when spillovers are modelled using three lags. Other examples are retailing and food, beverage & tobacco. The telecommunications services industry group is the only industry group for which $\varphi_{i,\Delta\widehat{ENPU}}$ is no longer significant at higher lag orders. Overall, average $\varphi_{i,\Delta\widehat{ENPU}}$s for each lag order ($-0.1945$ for $\tau=1$, -0.2029 for $\tau=3$, -0.1959 for $\tau=5$) do not differ significantly to those reported in Table 3 (of 0.1955). We conclude that our results are largely consistent after accounting for inter-industry spillovers and that spillovers have a limited and highly ambiguous effect (if at all) on investor learning about risk-return expectations.

4.6. Cumulative abnormal returns

Each crisis varies in its nature and therefore industry groups will be affected differently during each crisis. We investigate the cumulative performance of industry groups during the GEC. We estimate a market model relating industry group returns to returns on the MSCI ACWI in the lead-up to the crisis and use the resultant beta to calculate cumulative abnormal returns for each industry group, CAR_i, for the crisis period.[18] Results are reported in Table A14 in the Appendix.

Industry groups that experienced the largest negative CARs include media & entertainment (−40.92%), retailing (−33.23%) and automobiles & components (−29.35%). These groups are among those most affected by $\Delta\widehat{ENPU}_t$ according to the OIU_i (3rd, 6th and 1st, respectively). In contrast, groups with the highest CARs include energy (154.06%), insurance (39.18%) and banks (26.48%). These were moderately impacted by $\Delta\widehat{ENPU}_t$ in both the mean and variance according to the OIU_i (ranked 21st, 13th and 17th, respectively). Of the 24 industry groups comprising the sample, 13 yielded positive CARs suggesting that this crisis could be navigated by investing in firms belonging to industry groups which are more resilient to the negative effects of the crisis, such as financials, utilities and pharmaceuticals, biotechnology & life sciences and short selling firms in less resilient industry groups, such as automobiles & components, media & entertainment and retailing.

The nature and characteristics of the crisis are evident from the varying degrees to which certain industry groups performed. For example, healthcare's performance is moderately positive (0.21%). During COVID-19, healthcare was one of the top performers, owing to the nature of its business and that of the crisis (Szczygielski, Charteris et al., 2022). Energy outperforms all other industry groups during the GEC. This is consistent with increased cash flows attributable to rising energy prices. During the pandemic, the oil & gas industry group suffered because of lockdowns which curtailed economic activity and reduced demand for energy products. Chen and Yeh [53] similarly found that the oil & gas industry earned the most negative CARs during the height of the GFC as economic activity fell sharply.

Financials comprising insurance (2nd, 39.18%), banks (3rd, 26.48%) and diversified financials (6th, 12.20%) performed well. This can be attributed to rising interest rates which boosted profitability for financial institutions [68,227].[19] Insurance firms passed on inflationary pressures to consumers who view insurance as a necessity, especially after the COVID-19 pandemic [185]. The consumer staples sector, which includes the food, beverage & tobacco and food & staples retailing industry groups, also performed well (8th & 9th respectively with CARs of 9.45% & 8.19%). These groups comprise defensive stocks, as they provide necessities and thus should continue to perform well in tough economic conditions. In line with expectations, industry groups comprising cyclical stocks, which provide discretionary consumer goods, performed poorly. This includes media & entertainment, retailing and automobiles & components as well as consumer durables and apparel.

The underlying message is that in any crisis, including the GEC, opportunities exist to earn positive returns. This should prompt investors to evaluate how the GEC will interact with the line of business characterising industry groups and the firms that comprise these groupings. Although ENPU has a negative impact, these results illustrate that this factor alone is not solely responsible for performance.

5. Implications, coping strategies and policy recommendations

Although ENPU began falling from October 2022, coinciding with falling energy prices, the stabilisation of inventories and the implementation of policy measures aimed at shielding consumers from rising energy prices [16], the possibility of future energy crises, characterised by heightened ENPU, is high. This partially stems from elevated geopolitical risks and the increasing weaponisation of energy[20] [115,121,189]. Other potential contributors are natural disasters such as hurricanes or droughts, which have the potential to contribute to ENPU if major supply disruptions follow [63]. Also, there is considerable ambiguity stemming from the transition to a low carbon economy [102,214,215,219]. Considering these potential triggers of energy market disruptions, the lessons from the first GEC are relevant for investors, firms and policymakers, while also of significance for other types of crises.

Our analysis suggests that the effects of ENPU during the GEC were ubiquitous. Returns, reflective of cash flow effects and higher discount rates, respond negatively to ENPU for all industry groups. Energy price uncertainty triggers heightened volatility reflective of investor learning for most industry groups. It follows that investors can minimise their exposure to ENPU – and therefore hedge against energy market disruptions – by tilting towards firms that comprise the household & personal products, food & staples retailing and utilities groups (also see [221]). For firms that belong to these industry groups, future cash flows are less likely to be affected due to inelastic demand, the ability to pass on price increases to customers and the potential for government support. Also, investors are less likely to demand a higher risk premium, as there is limited increased risk, given that these firms produce necessities. To minimise volatility triggering, investors should focus on the utilities, pharmaceutical, biotechnology & life sciences and food & staples retailing industry groups, which are least impacted. Firms comprising these groups appear to have more certain risk-return expectations. Such a recommendation is similar to that of Ambatipudi and Kumar [13], who suggest that industries producing necessities should be favoured when economic policy uncertainty is high. Our findings suggest that uncertainty has less impact on these firms' risk-return outlook, leading to clearer business prospects and less investor learning when new information enters the market [168,169,212]. While uncertainty poses risks, it also presents opportunities for profitable long-short trading strategies [152,203]. Additionally, volatility stemming from ENPU can be profited from [37]. Our study, by identifying industry groups that are least and most resilient, can assist in facilitating risk and investment management strategies.

Our study expounds the OIU measure, which may be viewed as a tool for comprehensively reflecting the impact of uncertainty. Rankings based on the OIU differ from those based on returns or volatility alone,

[18] $r_{i,t} = \alpha + \beta_{i,m}R_{m,t} + \varepsilon_{i,t}$, where $R_{m,t}$ are the daily returns on the MSCI ACWI over the period 1 January 2019 to 30 April 2021. Using the estimated $\beta_{i,m}$, abnormal returns are calculated as follows: $AR_t = r_{i,t} - \alpha - \beta_{i,m}R_{m,t}$ for each day of the GEC period starting 1 June 2021. $AR_{i,t}$ is the daily abnormal return for industry group i. CAR_i is computed as $\prod_{t}^{T}(1 + AR_{i,t}) - 1$.

[19] Our study ends on 31 January 2023 prior to the banking crisis characterised by the collapse of Silicon Valley Bank which took place in March 2023.

[20] Slakaityte and Surwillo [189] define energy weaponisation / blackmail as the strategic manipulation of energy resources for political or economic gain which includes total or partial supply disruptions, coercive pricing strategies, leveraging existing energy debts or asset control.

reflecting the full transmission mechanism. For example, returns for the diversified financials group are most impacted (1^{st}) whereas this group is more resilient in terms of volatility triggering (11^{th}). Similarly, returns for technology hardware & equipment are relatively resilient (14^{th}) whereas volatility (5^{th}) is highly sensitive to ENPU. For both industry groups, the OIU provides an intermediate ranking (9^{th} and 7^{th}, respectively). Considering solely the impact on returns or, alternatively volatility, can therefore overstate or understate exposure. The OIU also reflects a third dimension, which we refer to as the dominant effect, revealing the source of an industry's (or firm's) resilience or lack thereof. Aside from this measure acting as a comprehensive analytical tool – in the present context, a measure which reflects transmission to returns and volatility jointly – it can also be utilised to tailor portfolios to investor preferences. Investors who are highly averse to losses may wish to tilt towards sectors where the dominant effect is intensity. Contrastingly, investors who are averse to heightened volatility, may favour investments where the dominant effect is magnitude. Thus, the OIU offers a measure that can assist investors in incorporating uncertainty into their portfolio decisions. As an analytical tool, the OIU provides a measure which investors can use to minimise the overall impact of the energy crisis on their portfolios. Accordingly, the OIU suggests that utilities, materials, pharmaceutical, biotechnology & life sciences and food & staples retailing are among the most resilient.

The CAR analysis in Section 4.6 emphasises the importance of considering the specific nature of a crisis. For example, the energy industry group performed poorly during the COVID-19 crisis but excelled during the GEC, while healthcare was the best performer during the COVID-19 crisis but yielded only a moderate positive abnormal return during the GEC [178]. This analysis demonstrates that earning positive returns during crises is possible. The message is that investors should not panic. Instead, careful consideration should be given to the nature of the crisis, the fundamentals of an industry, and how they intersect. Additionally, overall CARs are positive when averaged across industry groups, emphasising the importance of broad diversification and the avoidance of single-sector concentration [71]. For example, investing in a limited number of industry groups such as automobiles & components, software & services, and household products, would have resulted in significant losses. Substantial diversification, involving a greater number of groups, can reduce losses or generate gains, as 13 out of 24 industry groups experienced positive returns, offsetting the losses of the other 11 industries.

Our results point to the harmful effects of ENPU on firms across industry groups during the crisis although some are more resilient than others. Firms in industries for which returns are more sensitive to ENPU are those selling durable goods or services or those requiring significant investment decisions. Those for which volatility is more sensitive to ENPU are those with more ambiguous risk-return expectations. One strategy that may be beneficial in building resilience to ENPU – and, importantly, other sources of uncertainty that may arise during future crises - is corporate diversification. Khanna and Tice [133], Matvos and Seru [157] and Kuppuswamy and Villalonga [141] report that diversified firms respond to uncertainty more effectively, as exemplified by higher market values. This is attributed to their ability to access leverage at lower costs than non-diversified firms and due to competition in internal capital markets. Gopalan and Xie [99] and Aivazian et al. [5] find that productivity increases for diversified firms during crises. Corporate diversification thus aids in mitigating the harmful effects of uncertainty, acting as an insurance function [111]. For instance, a firm which produces durable goods could diversify into the production of non-durable goods. However, for firms in industries less exposed to ENPU (such as energy or utilities), such corporate diversification is less crucial. The results of this study can assist in raising awareness of the potential benefits and need for corporate diversification, particularly for firms belonging to industry groups that are most impacted.

Firms could also mitigate the impact of ENPU by diversifying their energy sources, particularly by incorporating renewables. While energy prices are one piece of the puzzle, Szczygielski et al. [205] show that ENPU is driven by energy price shocks. As such, if firms are less exposed to energy prices through the production of their own energy, this has the potential to reduce their exposure to uncertainty. Keller et al. [130] and Camargo et al. [44] highlight that industrial companies (such as those involved in manufacturing and construction) can invest in on-site generation from renewable sources such as wind, solar and energy storage systems. It follows from our results that firms belonging to industry groups such as automobiles & components, healthcare equipment & services and retailing should seek to diversify their energy sources. A policy implication also follows; governments may wish to assist industries in transitioning away from energy sources that contribute to ENPU, particularly if these are viewed as strategic in a national market. Our study helps identify industries that may particularly benefit from such assistance. Finally, and relatedly, hedging is a crucial strategy for firms to mitigate uncertainty arising from energy prices. This is especially pertinent given that ENPU has a greater impact on industry groups than energy prices alone. Jin and Jorion [124] note that oil and gas firms extensively hedge energy prices, thereby building resilience against energy price fluctuations. Based on our results, firms in industry groups such as diversified financials and software & services, should consider hedging energy price risk. Basher and Sadorsky [27] and Shahzad et al. [187] demonstrate that implied volatility indices, such as the VIX, are effective tools for hedging adverse stock price movements. It follows that using futures or options contracts on the VIX allows firms to hedge against broad stock market uncertainty, not just price movements. As ENPU is a component of overall uncertainty, proxied by the VIX, using the VIX would serve as a hedge against ENPU.

The widespread adverse effects of ENPU during the GEC on global industry groups motivate a reassessment of energy security by policymakers. Greater energy security results in enhanced stability of the energy supply, leading to more predictable energy prices and lower ENPU [194]. Clarke [63] highlights the importance of countries having a diverse global supply of energy resources, citing Europe's overreliance on Russian natural gas as a significant vulnerability. Clarke [63] refers to Singapore as an example of preparedness; despite its reliance on piped natural gas, Singapore constructed Liquified Natural Gas (LNG) import terminals to mitigate supply disruptions. Another example of this kind of energy security policy decision is Poland's construction of a LNG terminal on the Baltic Sea coast in 2015. This move allowed Poland to diversify energy sources by securing LNG deliveries from Norway, Qatar and the U.S., reducing their reliance on Russian oil before Russia's invasion of Ukraine in 2022 [88,188].[21] Clarke [63] underscores the value of LNG as a diversification tool due to its global availability. Similarly, McIntyre and Ashram [158] stress the need for energy diversification to reduce countries' susceptibility to oil price uncertainty. By diversifying its energy supply, a country is less dependent on any single energy source or supplier. This reduces the risk of significant price fluctuations due to supply disruptions, geopolitical tensions or market changes affecting a particular source, contributing to reduced ENPU. Importantly, reducing the risk of significant price fluctuations has the potential to reduce economic disruptions, which are reflected in rising uncertainty [96]. Our study highlights the importance of ENPU, emphasising the need to manage risks that can potentially heighten ENPU.

The findings of heterogeneous effects of ENPU across industry groups suggest that policymakers need to tailor responses to target specific sectors as not all sectors respond in the same manner. Examples of differentiated policies include Germany providing subsidies to energy firms to support short-term procurement, Norway's direct support to

[21] This idea was noticed and praised by the European Commission [90] when it was still at the development stage, as it would not only improve the energy supply and energy security of Poland, but also stimulate regional growth, competitiveness and investment.

their agriculture industry, the U.K. government providing a short-term bailout to a carbon dioxide manufacturer to prevent disruptions in the food supply chain, Italy establishing a fund to support the automotive sector and offering subsidies to the transport and agricultural sectors, Finland providing grants to the agricultural and logistics sectors, and Greece subsidising their industrial sector and farmers [11,155,160,186]. Additionally, in several countries, including the U.K., Norway, Italy, Germany and Cyprus, support was extended to energy-intensive users (which would predominantly be those in the utilities, materials, transportation, and automobiles & components industry groups). Utilities, in countries such as Denmark, Finland and Germany, also received direct assistance to ensure the continued provision of essential services such as electricity and water despite extremely high energy prices [186]. Amaglobeli et al. [11] emphasise the success of the targeted approaches implemented in Germany. To subsidise these support mechanisms, governments, such as those of Italy, Cyprus, Portugal and the U.K., introduced windfall taxes on firms in the oil and gas industry that were earning substantial profits due to the high energy prices (see [186]). However, the U.K.'s windfall tax, implemented until 2029, had adverse side effects. According to Jacobs [123], oil and gas production in the U.K. in 2023 was at its lowest level since 1977 and capital expenditure by these firms declined. Predictions suggest that this trend of reduced capital expenditure will continue, potentially leading to significant job losses, with estimates ranging between 40,000 and 100,000 jobs. This underscores the need for governments to regularly review and adjust policies. Ari et al. [16] and Castle et al. [52] motivate for the need to ensure that policy measures are temporary and are associated with incentive schemes. Croatia, for example, offered an electricity cost subsidy to energy-intensive firms, contingent upon firms conducting an energy audit and investing in projects that either significantly lower greenhouse gas emissions or increase the share of renewable energy sources in electricity consumption.

The literature (in Section 2) suggests that ENPU reflects a broad transmission channel to stock markets, including higher inflation [18,67,137]. Monetary policy tools, such as interest rates, are commonly used to counteract inflation stemming from energy price increases and have the potential to mitigate the harmful impact of ENPU [19]. However, interest rate adjustments also introduce monetary policy uncertainty, as market participants face uncertainty about the timing and magnitude of rate changes. This form of uncertainty has a documented negative impact on stock returns and results in increased volatility [57,218]. The effects of monetary policy uncertainty vary across industries, with sectors such as construction and manufacturing being particularly sensitive to interest rate changes (see [49,58]). For example, Wang, Xue and Song [214] show that in China returns for the real estate and information technology sectors are most negatively impacted by monetary policy uncertainty, while the financials and consumer staples sectors experience the highest volatility triggered by this uncertainty. These may be seen as industries where monetary policy uncertainty can amplify ENPU, further intensifying its impact [33]. This effect may be particularly pronounced in the short run, until interest rate changes effectively reduce inflation. Monetary authorities therefore need to carefully consider the impact of interest rate decisions on different industries when they respond to inflation stemming from an energy crisis, recognising that ENPU potentially reflects broader inflationary pressures and monetary policy uncertainty. We hope that the results of this study encourage greater attention to the interplay between monetary policy, broader policy responses and uncertainty.

6. Conclusion

Our study aims to examine the response of global industry groups to ENPU stemming from the GEC, with the goal of identifying the industry groups that are most and least resilient. To quantify and isolate ENPU, we use a Google search-based uncertainty measure developed by Szczygielski et al. [205] which isolates topic-specific (in this instance energy price-related) components in the VIX. This measure surpasses the OVX, a commonly used gauge of ENPU, in its scope by reflecting natural gas and coal price shocks which are central to the GEC (see Section 3.2). We further expound a measure, the OIU, which simultaneously considers the impact of ENPU on returns and volatility. We confirm that the ENPU measure approximates components of stock market uncertainty, outperforming the OVX, notably during the period coinciding with Nord Stream 1 and 2 sabotage, and is part of the composite factor set driving industry groups returns. Periods during which ENPU is a more substantial component of the return generating process - those coinciding with the invasion of Ukraine and the sabotage of the Nord Stream 1 and 2 pipelines - are unprecedented in recent history. The unprecedented events and interconnected factors that characterise these periods make it difficult to predict future outcomes, resulting in heightened uncertainty (Section 4.1.). We propose that there are two channels through which ENPU impacts stock prices. The first, the return effect, occurs through the impact of ENPU on expected cash flows which decline as uncertainty about the state of the real economy grows. This uncertainty contributes to firms delaying investment, consumers postponing durable consumption, ambiguity about inflation and interest rate expectations and, consequently, lower economic growth. The second, the volatility effect, arises from increasing uncertainty about a firm's risk-return prospects, leading to investor learning being reflected in the price discovery process as investors strive to ascertain the true intrinsic value. Ordering based on the magnitude (returns) and intensity (variance) of the impact of ENPU produces different results when the effect of uncertainty on industry groups is considered. The results are largely unaffected by considering alternative specifications that incorporate variables that account for global economic activity and supply pressures, shifting financial conditions, pandemic-related uncertainty, geopolitical risk, policy uncertainty and inter-industry information spillovers (Section 4.5).

ENPU impacts all industry group returns negatively and significantly and as expected, the impact is heterogeneous. The magnitude of impact is seemingly dependent upon the type of goods sold by firms comprising an industry group and whether firms are dependent upon large internal or external investments and consumer discretionary spending. For example, the software & services, healthcare & equipment and capital goods industry groups, which are reliant upon long-term investments, are among the most impacted. Groups that comprise firms heavily dependent upon discretionary spending, such as consumer services, media & entertainment and retailing, are also among the most affected. Those that comprise firms providing necessities are less impacted, notably utilities, household & personal products and food & staples retailing (Section 4.2). However, this represents only one part of the story, with volatility triggering constituting the other significant aspect. ENPU triggers volatility for most industry groups, which we propose is due to investor learning. It follows that industry groups that experience greater volatility triggering, namely automobiles & components, consumer services and media & entertainment, are those that experience greater ambiguity in anticipated risk and returns and thus require greater investor learning to assess future values. Industry groups that experience the least volatility triggering are utilities, pharmaceutical, biotechnology & life sciences and food & staples retailing. Groups that have secured long term funding, such as pharmaceutical, biotechnology & life sciences, or those producing essential goods with inelastic demand, such as utilities and food & staples retailers, face less ambiguous risk-return expectations and are therefore among the least impacted (Section 4.3).

The relative rankings based on the intensity of response (volatility) differ from those determined by the magnitude (returns) of impact. This suggests that volatility reflects information that differs from that reflected by returns, implying differing transmission channels. The OIU produces relative rankings that differ from those determined by either magnitude of impact or intensity alone, illustrating that considering the impact of uncertainty on only a single moment - returns or volatility - does not capture the full extent of the impact. Considering the separate impact of uncertainty on returns and volatility presents investors with a trade-off, potentially necessitating a choice between investing in industries that are resilient in terms of price but experience high levels of volatility. The OIU serves as a unified metric that goes some way to resolving this by offering a single measure reflective of both effects. Furthermore, the OIU reflects another dimension of uncertainty – that of dominance. Results show magnitude is the dominant effect for most industry groups. According to the OIU, the least impacted groups are food & staples retailing, pharmaceuticals, biotechnology & life sciences, and materials whereas the automobiles & components, consumer services and media & entertainment (Section 4.4.). This is useful knowledge for investors wishing to minimise the GEC's effects on cash flows while simultaneously avoiding increased levels of volatility.

The GEC should be viewed in a broader context, as part of a series of crises starting with COVID-19 in 2020. While uncertainty abounds, the analysis in Section 4.6 suggests that there are profitable opportunities for investors. More than half (13) of the industry groups demonstrated positive CARs. The best performing industry group, energy, is also the most resilient to ENPU according to the OIU. During the COVID-19 period, it was one of the worst performing. Aside from energy, the insurance and banks industry groups were the best performers whereas the media & entertainment, retailing and automobiles & components industry group were the worst performers during the GEC. The message here is that each crisis is different, and investors should be cognisant of this. This analysis also emphasises the importance of diversification, given that several industry groups performed positively, despite the energy crisis.

A notable finding is that the industry group which is central to this crisis, namely energy, is highly resilient to ENPU according to the magnitude of impact, intensity and the OIU. This suggests that firms in this group benefit from rising energy prices and associated uncertainty and higher energy prices act as a catalyst for expanded exploration. Relatedly, and within the broader context of the GEC and this study, the impact of energy prices appears to be minor relative to that of ENPU. When present, most explanatory power can be attributed to oil prices which have a positive effect on three quarters of industry groups. The positive impact is consistent with oil's role as a barometer for economic activity in line with heightened demand in the lead-up to the crisis, whereas its muted magnitude can be attributed to the supply-side nature of oil price increases. Natural gas and coal prices have a negative effect on half and more than three-quarters of industry groups respectively. The negative impact of these two energy sources on returns, albeit limited, is consistent with the nature of the GEC. The relatively weak explanatory power of energy prices on stock returns suggests that ENPU encompasses a broader transmission channel, reflecting a greater amount of information than that encapsulated by energy prices alone. This information reflects uncertainty about inflation, economic growth and monetary policy – economic variables impacted by energy price shocks. The implication here for investors is that what is of greater concern are the broader economic consequences of the GEC, rather than energy price shocks alone.

Although the future is unpredictable, the insights and implications that follow from this analysis can assist investors and policymakers in making better-informed investment decisions, managing portfolio risk and responding appropriately (see Section 5). By identifying resilient industry groups, investors can tilt towards industries that are less impacted. The OIU measure, by reflecting both transmission channels and the dominant effect, may be particularly useful in this regard, especially given heterogeneous investor preferences. An implication that follows is that corporate diversification may be beneficial – not only in terms of resilience to the GEC but also in other crises. Furthermore, given that the response to ENPU varies across industries, policymakers may wish to consider differentiating their responses when implementing assistance packages and other policies to mitigate the impact of the GEC. Our findings also motivate for increasing energy security, by diversifying energy sources with the aim of reducing the risk of significant price fluctuations which have the potential to drive ENPU. Relatedly, governments may wish to assist industries in transitioning away from energy sources that contribute to ENPU, particularly for industry groups which are strategic and heavily impacted. A final implication is that given the breadth of ENPU as a transmission channel, policymakers should consider the interaction of policy tools and uncertainty.

Our study opens several avenues for further research. The findings suggest that the impact of ENPU is through a transmission channel that potentially reflects the effect of innovations in numerous economic variables, risks and uncertainties. Further analysis suggests that ENPU interacts with the U.S. Dollar Index which can be viewed as a proxy for changing global and U.S.-specific factors, financial conditions and risk perceptions, and (weakly) pandemic-related equity market volatility. While such interactions are not unexpected, they call for further exploration of the nature of the transmission channel through which ENPU impacts financial markets. Having a measure that quantifies and isolates ENPU from overall uncertainty by relating Google searches to a widely recognised measure of stock market uncertainty, the VIX, can assist in disentangling the macroeconomic effects of uncertainty stemming from the GEC. This may be of interest to policymakers, aiding the formulation, implementation and monitoring of policies aimed at reducing the impact of increasing energy prices. Importantly, the interaction between fiscal and monetary policy responses and ENPU is particularly important. It may be that some policy responses contribute to increasing uncertainty whereas others may reduce it. The question is therefore which policies increase (decrease) ENPU and how long such increases (decreases) persist. Then, while we apply the OIU to comprehensively quantify the impact of ENPU, the OIU may be adapted for the purposes of measuring the effect of any variable which impacts both moments of the return distribution. Another avenue for further research lies in investigating the relationship between the OIU and industry (or firm) fundamentals such as size, earnings yields, book-to-market ratios and sustainability performance. Such an analysis – that relies upon a measure that captures both the magnitude and intensity of impact – has the potential to offer valuable insights into why some industries (or firms) may be more resilient than others. Further research should also consider why different industry groups are dominated by either magnitude or intensity effects in the OIU. Consideration should be given to what could be done from a policy, governance and financing perspective to reduce sensitivity to adverse events. However, before this can be done, the source of sensitivity must be identified, which is a task where the OIU can assist. Finally, an extension to our study is to consider national market resilience to ENPU during the GEC and to determine why certain markets are likely to be more impacted during this crisis.

CRediT authorship contribution statement

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

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2025.125351.

Data availability

Data will be made available on request.

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