

UNIVERSITY OF CAPE COAST

ECONOMIC UNCERTAINTY AND FINANCIAL ASSET RETURNS

BY

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This thesis has been submitted to the Department of Finance, School of Business within the College of Humanities and Legal Studies at the University of Cape Coast, as part of the fulfillment of prerequisites for the conferment of a Master of Commerce Degree in Finance.

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### DECLARATION

I hereby assert that this thesis epitomizes my original contribution, and no section of it has been proffered for any other academic credential, whether within the confines of this university or beyond.

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#### Validation by Supervisors

We officially attest that the formulation and presentation of this thesis were conducted under our guidance, adhering to the directives for thesis supervision established by the University of Cape Coast.

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## ABSTRACT

Economic uncertainties pose a major problem to global economies. The issue of economic uncertainties in recent times has become a cause of excessive worry to investors and policymakers. This study examines the effect of economic uncertainty proxied by country-level and global economic policy uncertainty (EPU), oil volatility index (OVX) and geopolitical risk (GPR) on the returns of financial assets (G7 stocks, gold, Bitcoin, and the European Union Allowance Future market). Considering data spanning from 1<sup>st</sup> January 2012 to 31<sup>st</sup> December 2022, the study employed the Variational Mode Decomposition (VMD) based quantile regression and quantile-on-quantile regression analysis, followed by the wavelet analysis and the Disk and Panchenko causality test. The findings from the VMD-based quantile regression revealed that the influence of global and country-level EPU, OVX and GPR on the returns of financial assets is dependent on the market condition and investment horizons. The results of the quantile regression revealed that financial assets are greatly affected adversely during the bearish market conditions. Likewise results from the wavelet analysis revealed an economic uncertainty-led adverse comovement during times of high uncertainty. Again, the Disk and Panchenko causality test supported the findings of the quantile regression and wavelet techniques, where the study observed a short term causal nexus between economic uncertainties and the financial assets under study. The significant adverse effect of economic uncertainty on the returns of financial assets is of interest and relevance to investors and policymakers as the findings have practical application to enlighten their decision-making.

## KEY WORDS

Disk and Panchenko Causality Test

Economic Uncertainty

Financial Asset Returns

Quantile Regression

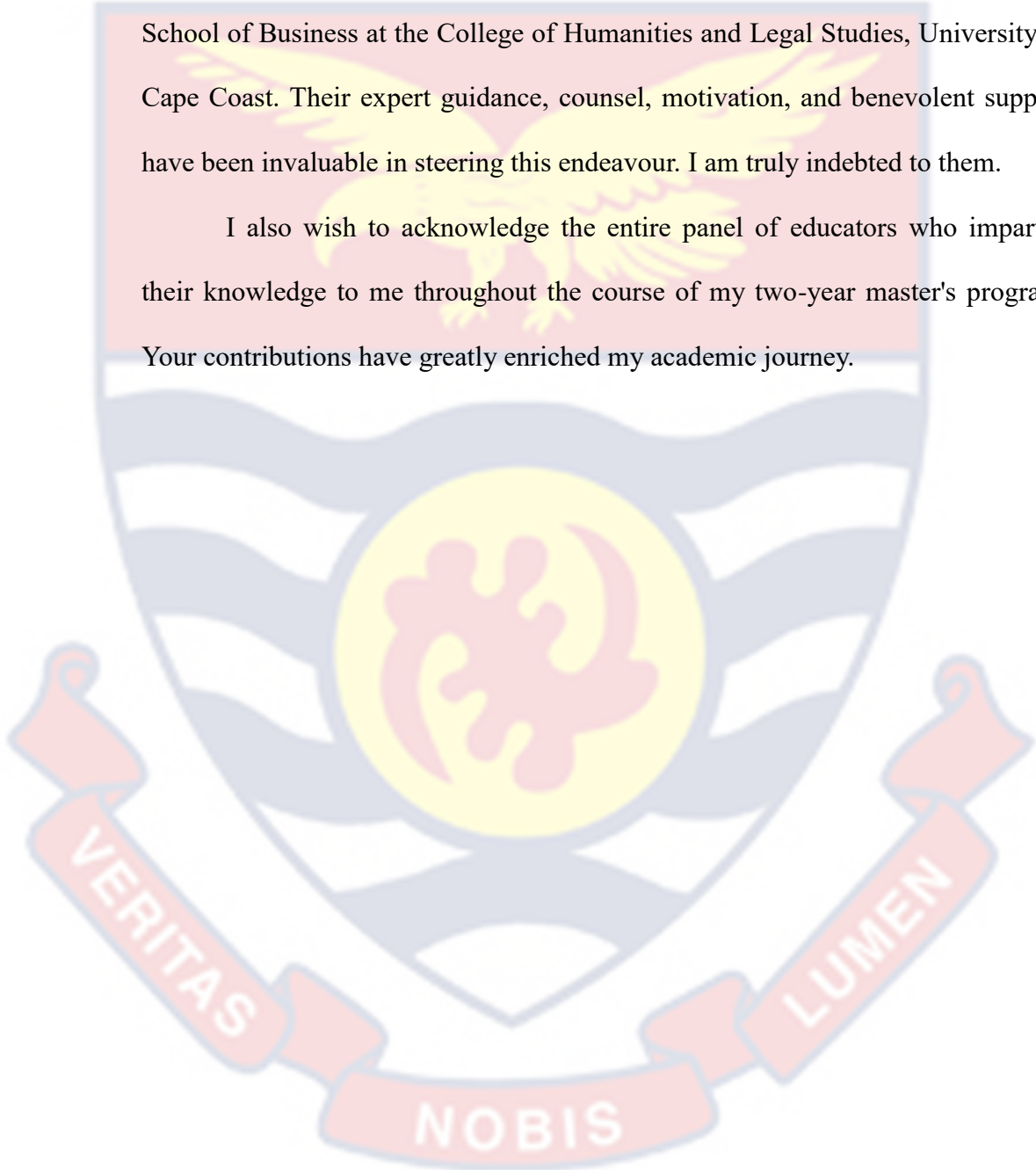
Wavelet Estimation Technique



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**DEDICATION**

To my myself and Family.





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**LIST OF ACRONYMS**The background of the page features a large, semi-transparent watermark of the University of Cape Coast crest. The crest is a shield-shaped emblem with a yellow eagle with outstretched wings in the upper half. Below the eagle is a yellow circle containing a red figure of a person. At the bottom of the shield is a red banner with the Latin motto "VERITAS NOBIS LUMEN" in white capital letters.

ADF	Augmented Dickey Fuller
AMH	Adaptive Market Hypothesis
BTC	Bitcoin
CBOE OVX	Chicago Board Options Exchange Oil Volatility Index
CL-EPU	Country-Level Economic Policy Uncertainty
EUAF	European Union Allowance Futures
G7	Group of Seven
GEPU	Global Economic Policy Uncertainty
GFC	Global Financial Crisis
GPR	Geopolitical Risk
HMH	Heterogeneous Market Hypothesis
PP	Phillip Perron
QQR	Quantile-in-quantile Regression
QR	Quantile Regression
VMD	Variational Mode Decomposition



## CHAPTER ONE

### INTRODUCTION

Numerous significant issues have surfaced in recent years, leading to unrest in the political and economic landscapes of the world. The first of these was the "Arab Spring," which caused political unrest in the near-east and among the advanced countries of the world. Concerns regarding the future of the Euro and European economic policy have been voiced in the wake of the Brexit referendum, in which the UK decided to exit the EU. Again, concerns regarding uncertain policies, particularly those relating to economic policies and investment decisions, have grown and expanded in recent times as a result of significant global mishaps like the COVID-19 pandemic and the conflict between Russia and Ukraine (Ozili, 2022; Cui & Maghyereh, 2023). Issues like rising oil price fluctuations associated with economic uncertainties have further complicated global economies (Al-Thaqeb & Algharabali, 2019). Since globalisation has changed how we live, there is more uncertainty than ever before, and it is more relevant than ever (Al-Thaqeb & Algharabali, 2019). In light of these recent developments, the primary aim of this study is to investigate how economic uncertainty affects the G7 stocks, Gold, Bitcoin, and the European Union Allowance futures returns (carbon market).

#### **Background to the Study**

The contemporary world is rife with uncertainties. Considering the inherently unpredictable nature of human existence, it is challenging to envision a world devoid of such uncertainties. Recent events, including the pandemic,

political divisions, international disputes, and economic crises, have all heightened concerns regarding escalating economic uncertainty. Despite the undeniable importance of uncertainty, the literature does not offer a universally accepted definition of the term.

Some scholars define uncertainty as the inconsistency of monetary, regulatory, and fiscal policy which eventually fuels market unsteadiness. Unexpected changes to the economic environment and how they impact businesses through variations in monetary, fiscal, or other administrative policies are more specifically referred to as economic uncertainty (Abel, 1983). Global economic uncertainties raise the prospect that firms and consumers would postpone acquisitions and investments because of an unsteady market (Abel, 1983; Al-Thaqeb, Algharabali, & Alabdulghafour, 2022).

According to Altig et al. (2020), firms' and households' indecision about the government's forthcoming governing agenda, taxation, spending, monetary policies, and healthcare initiatives touched its limit during the recent COVID-19 pandemic. Similarly, Al-Thaqeb and Algharabali (2019) postulate that future policy ambiguity has a long-term effect on economies. It is apparent that a variety of components influence uncertainty. While certain factors, like currency fluctuations, have an impact on uncertainty both in the short and long-term, other factors, like variations in oil prices, only have a short-term impact. This calls for finding measurements of the uncertainties triggered by these numerous factors. In this regard, this study seeks to employ four uncertainty measurements as a proxy for economic uncertainty.

The study intends to employ the country-level and global economic policy uncertainty index (GEPUI), Chicago board options exchange crude oil market volatility index (OVX) and the geopolitical risk index (GPR) as the four proxies for economic uncertainty and intends to examine its asymmetric effect on the returns the financial assets under study. The study also assesses the comovement and the causal association between economic uncertainty indices and the variables under study. With regard to the financial assets, this research intends to focus on the G7 stocks, gold, Bitcoin, and the European Union Allowance Future market (carbon market). The study finds the need to employ the aforementioned uncertainty indices because recent global occurrences are linked to the indexes under study. For instance, the country-level EPU, global EPU and the OVX indexes peaked at the height of the coronavirus pandemic (Baker, Davis & Levy, 2022), with the GPR index also peaking in recent times when the Russia-Ukraine conflict began (Caldara & Iacoviello, 2022). This implies that the uncertainty indexes employed reflect the trend in recent global happenings.

This study, unlike existing empirical works that focused exclusively on the U.S. equity market, investigates the influence of economic uncertainty on G7 stock markets, which Feng et al. (2017) emphasize. The focus on the nexus between economic uncertainties and G7 countries' returns is noteworthy for three significant reasons. To begin with, the G7 markets encompass a share exceeding 44% of the GDP when considering nominal valuation, and a substantial 30.7% of the planetary GDP on the basis of purchasing power parity as of 2021. They also account for 58% of the world's net riches (\$317 trillion) (World Economic

Outlook Report, 2022). Second, the G7 region is home to the biggest and most significant stock exchanges, according to the Financial Times. Again, the combined market value of companies listed on the G7 stock exchanges exceeds 41 trillion dollars, accounting for over two-thirds of the global market capitalisation. Additionally, the G7 is made up of a diverse group of nations.

In light of the diversity of the G7 stock market, it is observed that although the G7 nations all have sizable, industrialised economies, there are frequent variations in their financial conditions and responses to times of global upheavals, such as Brexit, the coronavirus outbreak, and the Russia-Ukraine war are not alike. Additionally, their economies show notable variances in terms of the role of policy, monetary structure, and financial laws; as a result, comparing how their stock markets react to shocks caused by economic uncertainty is extremely helpful (Bastianin et al., 2016).

Although a vast number of literature consistent with the adaptive market hypothesis, the heterogeneous market hypothesis and the arbitrage pricing theory have established an adverse association concerning EPU and stock returns, some research works have established that some stocks are less susceptible to the effect of EPU (Gao et al., 2019; Li et al., 2020; Guo et al., 2018). For instance, Guo, Zhu, and You (2018) in investigating the influence of EPU on G7 equity markets arrived at the conclusion that EPU shocks do not reduce the returns of UK and France.

In contrast, the empirical findings of Huang and Liu (2022) revealed that GEPU has an asymmetric impact on equity returns in France and the UK. Again,



there is divergence in the pattern and intensity of the nexus concerning the GEPU index and equity markets on the stock exchange markets. Some research indicates that due to credit restrictions, GEPU upsurge has a greater impact on emerging countries (Carriere-Swallow & Cespedes, 2013), nevertheless, others contend that the consequence is minor in emerging markets as compared to the developed market (Das & Kumar, 2018).

For decades, studying the makeup and bases of relationships in relation to economic uncertainties have surfaced as a relevant area of academic research. Consequently, a growing corpus of research has looked at the nexus between equities and macroeconomic factors (see, Adam & Tweneboah, 2008; Asafo-Adjei, Owusu Junior & Adam, 2021). As the existing works persists to examine these associations with several econometric techniques, a relevant section in the scholarly works that remains dominant in public argument is the association concerning oil prices and equity returns and how macroeconomic factors respond to volatility in the oil market (for instance, see, Salisu, Swaray & Oloko, 2019; Balcilar, Gabauer & Umar, 2021; Ratti & Vespignani, 2016).

The discussion of the influence of the oil market on equity returns may theoretically emanate from the seminal paper of Huang, Masulis and Ng (1996). Huang et al. (1996) postulate that investors can determine the value of a stock by discounting all projected subsequent earnings from the investment. In this sense, variations in the value of oil may have a unswerving implication on a firm's profitability (Xiao, Hu, Ouyang & Wen, 2019) and may also indirectly alter the discount rate (Degiannakis, Filis & Arora, 2018), affecting the stock's value.

Therefore, accurate measurement of uncertainty in oil price is crucial to reducing market risk. To this purpose, the Chicago Board Options Exchange's (CBOE) recently released oil price implied volatility index (OVX) is utilised as a proxy of market uncertainty.

Although the theoretical association concerning crude oil and equity markets is clear, there is conflicting empirical proof to support this relationship. Studies have been few, and their findings have been murky in the overall G7 setting. For instance, Feng, Wang & Yin (2017), found that there are statistically significant effects of oil prices on equity markets based on their study of the oil-stock nexus in the G7 setting. On the other hand, Lee, Yang and Huang (2012), found that stock index variations in each G7 member nation are not significantly impacted by changes in oil prices. These inconsistencies in the research papers further motivate this study to investigate the oil volatility and G7 stock returns nexus. This is notwithstanding the substantial effect of GPR on the G7 stock market.

Recent literature has established that reports of a change in geopolitical risk brought on by an increase in uncertainty from political regime changes, military tensions and terrorist acts can disturb economic activities and households' revenue (Pereira et al., 2022). Studies have concentrated more on emerging markets than established economies since it is widely believed in the literature that developing markets are more strongly vulnerable to GPR than advanced economies (Hoque & Zaidi, 2020).



This study fails to accept the aforementioned analogy founded on numerous reasons. First off, with a GDP per capita of nearly \$25,000 and a contribution to the world's total output of more than 40% (in PPP terms), these advanced economies are extremely industrialised, trade-diversified, and financially linked economies in the world. As a result, any shock to them would have a big influence on the world economy, and the same is true of any threat to the world economy (Salisu, Lasisi, & Tchankam, 2022). Consequently, terrorists and other agitators have so traditionally targeted these economies in an effort to increase their visibility and influence abroad. In a similar vein, political tensions between these leading economies have risen recently. Moreover, globalisation and economic interdependence have also made it essential to investigate the nexus concerning GPR and equity returns in developed markets, especially for policy and investment decisions given that awareness of systematic perils, of which GPR is a member, is a crucial component in pricing of stocks (Caldara & Iacoviello, 2022).

Several commodities have been recognised to provide a hedge against economic uncertainty. However, gold is among the key commodities that is widely known in literature to provide a hedge against economic uncertainty. Gold has been acknowledged as a resource that may be utilised for exchange purposes as well as an asset that is stored and thought to be resistant to material damage (Jones & Sackley, 2016). During recession and political unpredictability, gold has recently been perceived as a safe haven (Gao & Zhang, 2016; Arouri et al., 2015; Beckmann et al., 2015). Furthermore, it is viewed as a way to protect against risks

such as geopolitical risk, exchange rate risk, inflation risk, and price fluctuations for oil (Beckmann & Czudaj, 2013; Balcilar et al., 2016; Beckmann et al., 2015). Investors and the media both highlight these two qualities of gold (Balcilar et al., 2016).

Another attractive asset similar to gold is Bitcoin, a totally decentralized cryptocurrency created in the midst of the global monetary crisis and independent of any institutional power (Urquhart et al., 2016; Nadarajah & Chu, 2017). Due to its resemblance to gold (refer to Selmi et al., 2018; Selgin, 2015; Shahzad et al., 2019) and its distinctive approach to pricing, there has been a frequent assertion that the introduction of Bitcoin aimed to address the lack of faith within the current financial system. And that in instances where certain fund managers lose confidence in orthodox currencies or the overall economy, they can resort to Bitcoin as an alternative (Bouri et al., 2017a; Dyhrberg et al., 2016; Wang et al., 2019). Another strand of research argues against the efficiency of Bitcoin due to its decrease in dominance in the crypto market from 90% in 2013 to around 40% in 2022. Again, Jiang et al. (2018), Cheah et al. (2018), and Nadarajah and Chu (2017) demonstrate that the Bitcoin market is inept, and studies by Kristoufek (2018) and Tiwari et al. (2018) confirm this claim with the exception of certain time periods. But Vidal-Tomás and Ibañez (2018) and Urquhart (2016) contend that Bitcoin has improved in efficiency over the period. The above findings on Bitcoin and the economic uncertainty nexus have led to inclusiveness in its robustness against uncertainty.

On the carbon market front, Boutabba (2014), and Andriamahery and Qamruzzaman (2022) posit that from the 1970s, damage to the environment and changes in climate conditions have become a pertinent and divisive global problem, and there is a rising body of worldwide consensus that these serious issues must be quickly addressed. Insight from the World Bank's Carbon Emissions Inventory, carbon dioxide emissions (CO<sub>2</sub>) have recently surged at an alarming rate, rising significantly from 22.76 billion metric tonnes in 1990 to 37.12 billion metric tonnes in 2021. Amidst the goal of curtailing pollution and mitigating degradation, countries have devised and put into action strategies for safeguarding the environment to counteract the repercussions of climate change. The foremost among global agreements addressing climate management has been the 1997 Kyoto Protocol, a pivotal treaty that focuses on curtailing carbon emissions.

In pursuit of its objectives to achieve carbon emission reduction targets in accordance with the 1997 Kyoto Protocol, the European Union (EU) assumed a pioneering stance by orchestrating the conception of the European Union Emissions Trading System (EU ETS), a pragmatic blueprint that has subsequently served as a paradigm for the institution of analogous carbon markets. The carbon trading market has been seen as a significant market mechanism for carbon reduction since the commencement of the EU ETS in 2005. Rooted in the "cap-and-trade" framework, the EU ETS facilitates recognition for the exchange of European Union Allowances (EUAs) among duly listed enterprises and other consequential stakeholders.

Across the span of the last sixteen (16 years), the EU ETS has traversed three pivotal stages: Phase I (2005–2007), Phase II (2008–2012), and Phase III (2013–2020), with the ongoing Phase IV (2021–). Throughout each of these successive phases, the roster of contributors, trading magnitude, adaptability, and market fluidity within the EUA domain have witnessed substantial augmentation, propelling the EU ETS into its position as the preeminent and most vibrant carbon market on an international scale (Ibikunle et al., 2016). In light of the growing international agreement that these major challenges associated with increased carbon emissions must be addressed immediately, recent research works have started paying attention to factors that enhance the reduction in carbon emissions. In this regard, Researchers have examined the determinants that underpin the progression of carbon prices, and they primarily pay attention to how the carbon market affects other traditional commodities and financial assets (e.g., the equity and oil markets) (Gong, Shi, Xu & Lin, 2021; Zhou, Wu & Zhang, 2022). However, it is surprising that so few research have looked into how policy uncertainty affects the dynamics of carbon prices.

EPU has exhibited a marked rise over recent decades, owing to the erratic economic upheavals observed globally. The influence of EPU on financial markets has become of interest to policymakers greatly as a consequence of its dire effect on the returns of financial assets. Jiang et al. (2019), for instance, look at the ecological ramification of EPU on the emissions of carbon dioxide (CO<sub>2</sub>) and discover that policy uncertainties influences how economic entities make decisions, which results in an upsurge in the emissions of CO<sub>2</sub>. Nonetheless, the



contrary outcome is presented by Adedoyin and Zakari (2020), revealing that EPU leads to a decline in both energy usage and economic expansion, consequently resulting in a decline in CO<sub>2</sub> emissions. Despite the conflicting results showcased by these investigations, they suggest the presence of a potential cascade effect flowing from EPU into carbon pricing.

Dutta (2018) also looks at how the oil volatility index affects the carbon market and arrives at the conclusion that carbon emission prices are extremely susceptible to oil market volatility. While Anser, Syed and Apergis (2021) examine the effect of GPR on the release of CO<sub>2</sub> and conclude that GPR escalates the emission of CO<sub>2</sub>.

In light of the aforementioned arguments, this study examines the effect of economic uncertainties on the returns of financial assets. The findings of this study will enlighten investors in the financial market and economic policymakers as to how recent uncertainties affect the returns of financial assets and as well guide them in decision-making.

### **Statement of the Problem**

According to existing literature, economic uncertainty may make businesses suspend vital investments or choices that could affect future financial outcomes and cash flow (Al-Thaqeb, Algharabali, & Alabdulghafour, 2022). And as future cash flows are often correlated with the stock price, this may put downward pressure on stock prices. Additionally, a sizable number of current empirical works show that EPU spikes of the kind suggested by Baker et al.

(2016) amplify volatility in the financial market (Bekiros, Gupta, & Kyei, 2016; Gao, Zhu, O'Sullivan, & Sherman, 2019; Li et al., 2020).

In this regard, numerous research papers have examined the consequences of EPU in areas such as the market for commodities (Wang, Zhang, Diao & Wu, 2015), economic development (Asafo-Adjei et al., 2020; Adjei & Tweneboah, 2022), and comovement of equity markets (Li & Peng, 2017). These aforementioned studies also show the potency of policy intervention on the broader economy, particularly equity markets, is greatly impacted by EPU.

This is remarkably worrying considering the current rise in uncertainty ensuing the recent COVID-19 pandemic and the effect of the conflict concerning Russian and Ukraine, which has further resulted in oil price hikes. The geopolitical risk index as advanced by Caldara and Iacoviello (2022), revealed that the index is constructed based on a count of newspaper articles discussing geopolitical pressures. Caldara and Iacoviello further posits that in 2022, the GPR index peaked at an all-time high since 2015. The dire effect of an increased GPR on the financial market is emphasised by Ozili (2022) and Cui and Maghyereh (2023). Again, according to the recent Financial Stability Report, which was released in April 2020, the COVID-19 pandemic has a substantial bearing on the financial systems, and future escalation of the crisis will worsen its impact on global financial stability. The World Bank's Global Economy Prospects report released in January 2021 revealed that the global economy as a result of the COVID-19 pandemic experienced a contraction of about 3.5% in 2020, a



considerably more severe downturn than the global financial crises experienced during 2008–2009 (World Bank, 2021).

According to the Global Financial Stability Report (2020), the COVID-19 pandemic exerted a bizarre bearing on financial assets, with the equity market witnessing the fastest decline in history. For instance, in March 2020, the US equity market encountered an extraordinary scenario where circuit breakers were tripped four times in the course of ten days. This phenomenon, originally introduced in 1987, had been activated only once before in 1997. Simultaneously, equity markets in Europe and Asia underwent declines in parallel with the US downturn. Notably, on March 12, 2020, the FTSE, the principal index for the UK, suffered its most substantial plummet since 1987, exhibiting a decline of over 10%. Moreover, the Japanese equity market witnessed a decline exceeding 20% from its climax in December 2019.

The World Bank in their Global Economic Prospect Reports (2023), projects global growth to decline to 1.7% in 2023. It is anticipated that investment growth in markets that are emerging and developing economies would continue to be below the average of the last 20 years. Additionally, any negative upheaval could result in a recession in the international economy. These setbacks in the financial market per the reports reviewed are attributed primarily to the effect of COVID-19 and the enduring conflict concerning Russian and Ukraine. These setbacks pose a huge problem for investors and fund managers as to the best way to construct an effective portfolio to diversify the risk posed by the

growing uncertainties in the world (Boako & Alagidede, 2020; Owusu Junior et al., 2021).

On the association concerning economic uncertainties and stock returns. It can be observed from existing literature that there are contradictory findings with regard to the effect of EPU on stock returns in advanced countries and it appears that the findings change over time. For example, Guo, Zhu and You (2018) in analysing the asymmetric impact of EPU on the equity returns of BRICS and the G7 arrived at the conclusion that EPU does not reduce the equity returns of France and UK. The findings of Huang and Liu (2022) contradict that of Guo et al. (2018). The findings of Huang and Liu (2022) suggested that EPU reduces the equity returns of France and the UK but has no substantial impact on Germany's equity returns. The aforesaid findings depicts the diverse finding with regard to the effect of EPU on the returns of stocks which confirms the changing trend in uncertainty and stock returns nexus.

On the oil volatility front, new developments such as the coronavirus pandemic and the conflict between Russia and Ukraine in recent times have also contributed to the continued rise in the price of crude oil (Prabheesh et al., 2020; Ozili, 2022). When the Russian-Ukraine crisis began, for instance, oil prices shot through the roof, going from roughly \$76 per barrel at the outset of the year to above \$110 per barrel on 4th March 2022. Given the prevailing increase in economic unpredictability, it is foreseeable that investors are unwavering in their quest to identify alternative risks and potential gains in order to fulfil their portfolio goals.

Regardless of the effort made in prior studies to assess the nexus between economic uncertainties and their effect on stock returns, there still exist gaps in the literature that this research paper seeks to fill. To begin with, the nexus between EPU and G7 stocks in particular depicts contradictory findings (see, Guo, Zhu & You 2018; Huang & Liu, 2022). This contradiction in the findings could be a result of the different time periods in which the research work was carried out. This reinforces the need to examine the effect of EPU on stock returns in recent times to arrive at a conclusion on the effect of EPU on stock returns and the subsequent examination of their diversification potential. Again, this study is distinct from other studies in the sense that this study will make a comparative analysis of how country-level EPU and the global EPU affect the G7 stock market, which has not been captured in previous works.

The gap that exists between oil volatility shocks and stock returns nexus that this study seeks to fill is that the vast majority of studies that examined the oil volatility and stock market nexus used the WTI oil spot prices index (for instance, see Feng et al., 2017; Khalfaoui et al., 2015; Tiwari et al., 2020) which captures historical information on oil price uncertainty. While others used the oil volatility risk premium (Feng et al., 2017) and realised volatility (Bastianin & Manera, 2018) as a measure of the oil price index.

This study unlike other studies employs the novel CBOE oil volatility index which offers a precise gauge of uncertainty within the crude oil market, as it encompasses both past data on oil prices and investor outlooks regarding future anticipations of oil price shifts (Xiao et al., 2018; Xiao et al., 2019). With

reference to the literature, this study is the first to investigate, in light of recent global catastrophes, the diverse impact of the CBOE oil volatility index on the G7 stock market. This research paper will as well add to the scant literature on the nexus concerning GPR and the stock market of the G7.

The position of gold as a customary shelter or protective strategy for financial investors amid periods of economic ambiguity has been extensively examined in academic works (for instance, Baur & Lucey, 2010; Agyei-Ampomah et al., 2014; Hood & Malik, 2013). While the majority of these investigations have presented substantiating data endorsing gold's function as a refuge, granting investors an avenue to uphold value during market declines, there remains limited comprehension regarding how gold's return patterns react to sudden disruptions in the market, both in the short and long term.

According to existing literature, the efficacy of gold as a dependable haven could potentially shift based on the prevailing economic circumstances (Zhang et al., 2021), particularly in times of heightened stress (Raza et al., 2018). The impact of economic uncertainty on the price of gold is also demonstrated to fluctuate throughout varying time intervals (Balcilar et al., 2016; Huang et al., 2023). Furthermore, the influence on both gold returns and volatility is noted to significantly intensify throughout periods of crisis, such as those witnessed during the Global Financial Crisis and the European Debt Crisis (Gozgor et al., 2019).

It can be observed from the preceding statement that the influence of economic uncertainties on the returns of gold varies and that calls for recent findings in light of the conflict concerning Russia and Ukraine. Furthermore, it



can be inferred from the preceding discussion that the manner in which gold responds to economic uncertainties in both the immediate and extended timeframes holds considerable significance for determining the timing and efficacy of risk management tactics.

To that end, this study fills a gap in the nexus between economic uncertainties and returns of gold by employing a VMD-based quantile regression-and wavelet technique to reveal the heterogeneous and time-frequency evidence in the nexus between economic uncertainties and the returns of gold.

Certain scholars posit that Bitcoin, similar to other assets like gold, possesses the capacity to serve as a partial hedge against uncertainty (for instance, Bouoiyour, Selmi, & Wohar, 2019). However, divergent perspectives exist among other scholars regarding the hedging potential of Bitcoin. For instance, as exemplified by Baur, Hong, and Lee (2018), Shahzad et al. (2019), and Dutta, Das, Jana, and Vo (2020), findings indicate that Bitcoin lacks comparable hedging attributes to gold and exhibits significantly restricted utility as a currency. A focal reason for the inconsistent conclusion on risk hedging of Bitcoin is possibly due to the fact that prior works on the nexus neglected the nonlinear effect of uncertainty on Bitcoin prices.

The existing gap in the uncertainty-Bitcoin returns nexus is that a review of existing literature shows inconsistencies in the hedge properties of Bitcoin against uncertainties. Again, Bitcoin's decline in dominance in the cryptocurrency space has the potential to reveal new dynamics in the nexus between economic uncertainties and Bitcoin returns. For instance, according to Bloomberg, the



dominance of Bitcoin in terms of market capitalisation stood around 94% in 2013 because no alternative coins existed at the time. This dominance has plummeted to 40% as of December 2022. This decline in market dominance may alter the dynamics between economic uncertainties and the Bitcoin dynamics. This reiterates the need to assess how uncertainties affect Bitcoin in light of current global uncertainties and the current position of the Bitcoin market. Finally, this study employs quantile regression and wavelet techniques to explain the non-linear nexus between uncertainties and Bitcoin to avoid bias estimations as argued by Bouri, Gupta, Lahiani, and Shahbaz (2018), and Ciner (2001).

Concerning the carbon market, findings by Andriamahery and Qamruzzaman (2022) demonstrate that the carbon market essentially functions as an intricate model of volatility. The price of carbon could potentially be influenced by a number of factors, including the broader macroeconomic landscape and uncertainties stemming from climate and economic policies. According to the Intercontinental Exchange (ICE) statistics, the European Union Allowance future market (EUAF) which was created as a market for reducing carbon emission has experienced frequent and rapid price oscillations due to uncertainties in economic and climate policies. Such volatile carbon prices compromise the effectiveness of the carbon market, potentially undermining the impact of efforts aimed at reducing carbon emissions.

Given this background, it becomes essential to examine the influence of economic uncertainties on carbon prices, establish a robust mechanism for pricing carbon assets, and ultimately shape a well-functioning carbon market. Aligned

with the previously mentioned assertion, researchers have delved into the factors influencing the fluctuations of carbon prices. Mainly, they concentrate on the interconnectedness concerning the carbon market and traditional commodity and financial assets (such as the oil and equity markets). However, it is notable that only a limited number of investigations have delved into the repercussions of economic uncertainty on the dynamics of carbon prices.

This research intends to close the knowledge gap in the areas of the carbon market and economic uncertainty in the following ways. To begin with, there have been few research papers on the nexus between EPU and the carbon market. Specifically, it has been observed from literature that only two studies have been conducted on the effect of EPU on the European carbon market. Ye, Dai, Nguyen and Huynh (2021) assessed the linear nexus between US EPU, UK EPU and European Union Allowance Future prices and found that there was no linear relationship but from the multiscale multifractal perspective, the study arrives at the conclusion that there exists a robust cross-correlation between both the EPU of UK and the EPU of US on the returns of EU carbon futures. Again, Dai, Xiong, Huynh and Wang (2022) analysed the impact of EPU on the fluctuations of the European carbon market using the GARCH-MIDAS model for a duration of 2008 to 2015 and arrived at a conclusion that European global EPU will aggravate the long-term fluctuations of the European carbon spot return.

This study differs from the aforementioned study in many ways. First, this study unlike the work by Ye et al. (2021) employ the GEPU as a measure of EPU which captures economic uncertainties globally. Providing a broader scope to how

economic uncertainties around the globe affect the efficiency of the carbon market. Again, Unlike the work by Ye et al. (2021) who utilises a linear model in assessing the nexus between US and UK EPU on the EUAF market, this study uses the quantile regression and wavelet analysis to examine the heterogeneous and time-varying association between global EPU and EUAF market returns. Secondly, the work by Dai et al. (2022) covers a duration of 2008 to 2015 which covers halfway into the Phase III of the EUA futures market, limiting the scope of the study as it does not cover all four phases of the EUA futures market. And as stated by Ye et al. (2021) the EPU-EUA futures market relationship varies with respect to the various phases. This research paper bridges the gap in the aforementioned literature by covering a duration of 2010 to 2022 which captures the relationship in full and reflects the current dynamics between EPU and the EUA futures.

Another novelty of the study is that, unlike the studies by Anser, Syed and Apergis (2021) and Bildirici (2018b) who examined the nexus between GPR and CO<sub>2</sub> emissions in general, this study examines the effect of GPR on the EUAF market returns (carbon market). With reference to literature, this is the first of its kind.

### **Purpose of the Study**

This study examines the asymmetric relationship between economic uncertainties and financial asset returns, as well as the time-varying comovement between economic uncertainties and the returns of financial assets.

## Research objectives

The specific objectives of the study are the following:

1. To examine the asymmetric effect of economic uncertainty on the returns of the G7 stocks, Bitcoin, Gold, and the European Union Allowance Future.
2. To analyse the comovement between economic uncertainty and the G7 stocks, Bitcoin, Gold, and the European Union Allowance Future returns.

## Research Questions

The study aims to answer the following questions:

1. What is the relationship between economic uncertainty and financial asset returns across bearish, normal, and bullish market conditions?
2. Is there any significant co-movement between economic uncertainty and the financial assets across time and frequencies?

## Significance of the Study

Insights drawn from existing literature have proposed that a rise in economic uncertainty adversely affects overall investment, the employment rate, and financial assets (Baker et al., 2016; Gao, Zhu, O'Sullivan, & Sherman, 2019). In this context, recent worldwide crises have resulted in various consequences for global markets, prompting investors to seek out fresh avenues for diversification (Boako & Alagidede, 2020; Owusu Junior et al., 2021). In line with the aforementioned supposition, this study is motivated to examine the effect of economic uncertainty on financial assets to assist investors in the financial market



and economic policymakers in the diversification opportunities in the financial market amid recent global uncertainties, as well as the repercussions of policy decisions during times of uncertainties.

Moreover, this study captures a broad range of financial assets which effectively captures the nexus between economic uncertainties and the financial market at large. The G7 stock market for instance plays a significant role in the global financial market and the results of economic uncertainty-return nexus for G7 stocks can well represent global equity markets' major behaviour (Andrikopoulos, Angelidis & Skintzi, 2014). Again, this study considers the effect of economic uncertainties on the European Union Allowance futures which is Europe's largest market aimed at reducing carbon emissions. Understanding the carbon market price dynamics with respect to economic uncertainties will help the market and policy makers in the carbon space achieve its primary aim of reducing carbon emissions.

### **Delimitation**

The study is based on a duration of 10 years (2012–2022). Although the period under study captures times of high uncertainty, other notable periods, such as the 2008–2009 global financial crisis, are not captured in the study due to the lack of data for some uncertainty indices and assets such as the EUAF market. The scope of the study is limited in terms of indices employed for economic uncertainty with relevant uncertainties such as the climate policy uncertainty not considered by the study. Again, the study did not consider the bond market which is a major market in the financial market due to data constraints.



### Limitations of the Study

The methodology employed in the study is limited to examining the asymmetric and co-movement between the variables under study. Other econometrics techniques such as the GARCH models if employed could have effectively captured the volatility that exists in the markets under study.

### Definition of Terms

The subsequent operational explanations of the pivotal terms employed within this study are specified as follows:

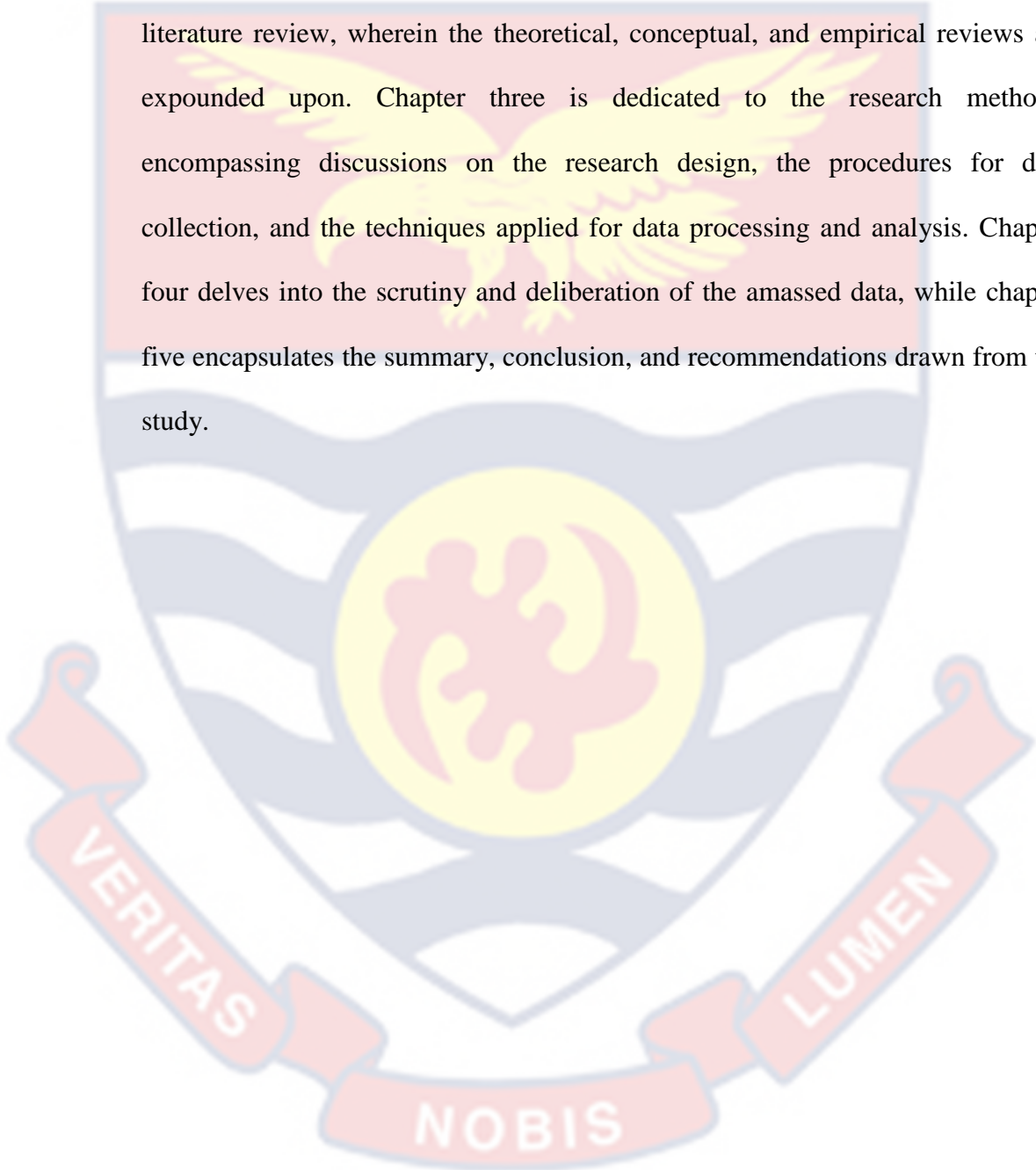
**Economic uncertainty:** Çolak, Güney and Hacıhasanoğlu (2020) defined economic uncertainty as the case where the future path of an economy is uncertain. This study employs the Country-level EPU and Global EPU, CBOE crude oil volatility index and the geopolitical risk indexes as the four proxies of economic uncertainties.

**Financial assets:** Financial assets refer to intangible assets that represent a claim to a future stream of economic benefits or a right to receive a payment. They are typically owned or held by individuals, businesses, or institutions as investments or for trading purposes. Financial assets can take the form of stocks, bonds, derivatives, commodities, and currencies. Financial assets considered under this study include the G7 stocks, gold, Bitcoin, and the European Union Allowance future market.

### Organisation of the Study

The study is structured across five chapters, spanning from chapter one to chapter five. In chapter one, the introduction encompasses various focal aspects,

including the study's background, the articulation of the problem, the study's purpose, its research objectives and inquiries, the significance it holds, the defined boundaries, and the explication of key terms. In chapter two, the focus turns to the literature review, wherein the theoretical, conceptual, and empirical reviews are expounded upon. Chapter three is dedicated to the research methods, encompassing discussions on the research design, the procedures for data collection, and the techniques applied for data processing and analysis. Chapter four delves into the scrutiny and deliberation of the amassed data, while chapter five encapsulates the summary, conclusion, and recommendations drawn from the study.



## CHAPTER TWO

### LITERATURE REVIEW

#### Introduction

In this study, the second chapter is devoted to an exploration of theories and literature. Its primary aim is to scrutinise the effect of country-level and global economic policy uncertainty (EPU), oil price volatility, and geopolitical risk on the stock returns of the G7 nations, Bitcoin, Gold, and the European Union Allowance Future prices. The initial section delves into the theoretical review, while the subsequent section delves into the conceptual review. The third section focuses on the empirical review, delving into the association between the dependent and independent variables. This section also brings attention to the existing gaps in research and the contribution this research paper makes to the current body of knowledge. The study also provides a conceptual framework showing the relationship that exist between the independent and the dependent variables under study. Finally, the chapter is summarized to consolidate its key points.

#### Theoretical Review

##### Adaptive Market Hypothesis

The efficient market hypothesis believes that individual investors are rational economic people, and behavioural finance believes that investors are bound rational. In order to integrate the two schools of thought, the adaptive market hypothesis (AMH), a novel financial market theory, was put forth by Lo (2004). This hypothesis characterizes the degree of efficiency of financial markets

to several elements, including the volume of competitors within the market, the opportunity to make profits, and the flexibility of investors.

The adaptive market hypothesis (AMH) posits that investors don't fit exclusively into categories of complete rationality or complete irrationality. Instead, they are adaptable and rational economic agents, possessing the capacity to make suitable adjustments based on prevailing conditions. As per Lo (2004), alterations in the external environment can lead to biased behaviour among investors. This behaviour shouldn't be solely labelled as irrational within financial markets; rather, it might represent a "maladaptive" behavioural progression.

Empirical findings support the fact that after a major global uncertainty event, influenced by the effect of information dissemination through the internet, mass investors show increasing interest in the event. This heightened interest often result in increased short-term speculation, consequently impacting the returns and volatility of stocks associated with the event (Ouadghiri & Uctum, 2020; Baker et al., 2016; Guo et al., 2018; Jinfang et al., 2020). According to AMH (Lo, 2004), substantial changes or economic shocks trigger an evolutionary transformation in the market's environment. This suggests that the efficient market hypothesis (EMH) might not remain applicable during periods of rapid change, heightened stress, or anomalous circumstances. This signifies that different market conditions have different effects on the returns of financial assets as a result of investor behaviour. The adaptive market hypothesis justifies the adoption of the QR and the wavelet techniques with regard to how investors behave under different market conditions.

### **Heterogeneous Markets Hypothesis (HMH)**

The HMH by Muller et al. (1997) hypothesizes that diverse economic entities formulate investment choices across varying timeframes, driven by their distinct risk and return inclinations, while evaluating historical and present-day news. This implies that amid periods of economic uncertainties such as the COVID-19 pandemic and the incursion of Ukraine by Russia, investor conduct undergoes shifts as these upheavals occur. Given that markets operate within a broader context, the asymmetrical and time-sensitive nature of investor behaviour becomes evident in market pricing. The HMH from the aforementioned suppositions clearly supports the notion that changes in economic conditions affect assets in the financial market as a result of investor behaviour.

The existing literature makes it evident that the nexus between economic uncertainty and the returns of financial assets is not a straightforward one-to-one connection. Instead, it follows a non-linear and asymmetric pattern. Furthermore, the current body of literature firmly establishes that investor behavioural patterns commonly exhibit variations over time. Moreover, as postulated by Wu and Huang (2009), the reaction of market participants to information at varying points in time generates exceedingly noisy market data. As a result studies (Owusu Junior et al., 2021; Hassani, Dionisio, & Ghodsi, 2010) argue that if the noise in the data is not dealt with it may affect the result of the study.

This study, therefore, decomposes the return series by employing the variational mode decomposition technique to shed light on the diverse investment timeframes of market participants (short, medium, and long term). This reflexion



aligns with the concepts outlined in the HMH and AMH as proposed by Muller et al. (1997) and Lo (2004) respectively. Further, the use of the quantile regressions and the wavelet technique addresses the complexities that exist in the data as a result of the non-linearity, asymmetries, adaptiveness, and noise that exist between the returns series of economic uncertainty and the financial asset variables.

### **Arbitrage Pricing Theory**

Ross formulated the arbitrage theory of capital asset pricing as an alternative to the traditional mean-variance capital asset pricing model (CAPM). Roll and Ross (1984) characterise the arbitrage pricing theory (APT) as a multifactor model for pricing assets. This theory is rooted in the concept that the returns of an asset can be deduced by scrutinising the connection between the asset's anticipated return and other macroeconomic pointers that inculcate market risk. The theory was created with the presumption that a variety of variables, which may be classified as macroeconomic have an impact on the values of securities.

Roll and Ross (1984) go on to say that an asset's sensitivity to unforeseen changes in economic indicators determines its riskiness and, consequently, its average long-term return. The argument by Roll and Ross (1984), falls in line with the principal aim of the study in identifying the nexus between economic uncertainty and financial asset returns.

Again, as argued by Cizmesija, Lolic, and Soric (2017), Casteinuovo, Lim and Pellegrino (2017), and Su, Fang, and Yin (2019), changes in proxies for

economic uncertainty indices such as the global EPU, oil volatility index and geopolitical risks are driven by natural catastrophes as well as changes in macroeconomic fundamentals. And in line with the Arbitrage pricing theory, systematic risks such as macroeconomic factors cannot be diversified away and hence affect the returns of assets. It therefore stands to reason that changes in proxies for economic uncertainties as defined earlier have an effect on the returns of financial assets since these proxies are driven by changes in macroeconomic factors. This assertion therefore support the notion of a relationship between economic uncertainties and the returns of financial assets.

### **Conceptual Review**

This section reviews relevant concepts supporting the study. Major concepts like economic uncertainty and financial asset returns are discussed.

#### **Economic uncertainty**

Çolak, Güney and Hacıhasanoğlu (2020) defined economic uncertainty as the case where the future path of an economy is uncertain. In situations of rising uncertainty, agents in the economy are unable to predict the effect of their actions because their expectations are clouded. The world in recent times has seen an unprecedented number of significant negative shocks, which has increased uncertainty among businesses and people over the future economic path (Al-Thaqeb & Algharabali, 2019; Prabheesh et al., 2020; Ozil, 2022). Increased heights of uncertainty have had a negative effect on the world economies in the past years by affecting economic agents in all parts of the economy, encompassing

individuals, businesses, banks, financial markets, and policymakers as well (Walmsley, Rose & Wei, 2021).

Shocks to uncertainty have a variety of effects on economic activity. They influence the economy's demand for goods and services through the demand side channel. Which includes decisions concerning the level of consumption and investment behaviour. Uncertainty in an economy can also have an effect on the supply aspect of the economy which is mainly the production machinery of the economy. Therefore, it is essential to comprehend these implications in order to choose the right policy action. The EPU index captured in the study proxies for uncertainties with regard to future government policies. CBOE crude oil volatility proxies for volatility in the oil market while the geopolitical risk index proxies for uncertainties as a result of acts of war and terrorism.

### **Financial assets**

Financial assets refer to intangible assets that represent a claim to a future stream of economic benefits or a right to receive a payment. They are typically owned or held by individuals, businesses, or institutions as investments or for trading purposes. Arguably the most widespread among financial markets are stock markets. Within these platforms, companies list their shares, which are subsequently traded by traders and investors. The derivatives market which is also covered in this study is a secondary market wherein the worth of its securities' is exclusively contingent upon the valuation of the primary security to which they are intrinsically linked. Conversely, commodities markets serve as platforms where vendors and consumers convene to trade tangible commodities,

such as energy products and precious metals. The cryptocurrency markets consist of decentralized digital assets that are based on blockchain technology.

Assets employed in this study cut across various assets in the financial market. They include the G7 stocks, gold, Bitcoin, and the European Union allowance future market. These markets have gone through unheard-of volatility with reference to global economies, especially during the global financial crises, COVID 19, and the conflict concerning Russia and Ukraine (Agyei, 2023; Bossman, Gubareva & Teplova, 2023). This volatility hurts the financial market's ability to function normally and raises its level of risk and uncertainty (Okicic, 2015; Yao & Li, 2020; Dai, Xiong, Liu, Huynh & Sun, 2021). It is especially crucial to monitor the fluctuation of the financial returns precisely in order to lessen this uncertainty. This is due to the fact that positive growth in economies of developed economies is generally linked to the positive growth of assets in the financial market (Guru & Yadav, 2019; Van Eyden, Difeto, Gupta & Wohar, 2019). Therefore, assessing how various uncertainty elements affect financial asset returns are required for positive economic growth.

### **Empirical Review**

This section assesses the present status of the topic under study and presents findings from previous research. The objective of this section is to survey the current literature relevant to the study and aid in pinpointing areas where gaps exist in the existing body of research.

### **Economic policy uncertainty and the stock market**

Using the quantile regression technique, Guo, Zhu, and You (2018) investigated the asymmetric dependency between EPU, and equity returns in the BRIC and G7 stock markets. The study's conclusion was that EPU lowers equity market returns, with the exemption of equity returns in UK and France. Similarly, Huang and Liu (2022) used the quantile regression technique to investigate the asymmetric impact of EPU on G7 equity returns. According to the study, asymmetric effects do occur since EPU increases have a bigger impact on the returns of the G7 equity returns than a decrease in EPU does. In contrast to Guo et al. (2017), the analysis discovered that EPU has an asymmetric influence on equity returns in UK and France.

In order to determine the rate of spillovers and investigate the length of the spillover impact of EPU and equity markets, Ma, Wang, and He (2022) applied a Fourier transformation technique. They discover that there are some geographical commonalities and a relatively strong spillover impact of EPU on equity market volatility, particularly in Canada, Japan, and the United States. According to Ma et al. (2022), EPU has lengthier spillover impact on the equity markets of France, Italy, and, Germany with the biggest effects occurring over a period of 3 to 18 months. Last but not least, the study argued that significant economic occurrences like the financial predicament and Brexit exacerbated the level and duration of EPU transmission.

Gao, Zhu, O'Sullivan and Sherman (2019) created a new uncertainty index for the UK and examined the stock's sensitivity to the newly created index using a



dynamic factor-augmented vector autoregressive model. The study's data revealed that UK EPU is a relevant aspect in understanding the distribution of UK stock yields.

Similarly, using the panel VAR technique, Christou, Cunado, Gupta, and Hassapis (2017) examined the effect of own-country EPU on the equity returns of 6 Pacific-rim nations (China, Canada, Australia, Korea, Japan, and the US). The findings of the panel VAR Monthly data estimate from 1998 to 2014 showed that the EPU of one's home nation has an adversative effect on equity yields in the countries around the Pacific Ocean. Chang (2020) used the linear regression technique to investigate how variance in EPU affected the return on Japanese stocks. An adverse correlation suggests that increased EPU will result in worse returns for Japanese stocks.

In a study to show the immediate and long-term bearing of EPU on the equity prices of the G7 nations Nusiar and Al-Khasawneh (2022) using monthly data, used the nonlinear and linear ARDL models. The findings showed that EPU has a considerable short-term adverse effect on the equity values of every G7 nation. Only Canada and Japan experience this detrimental long-term impact. The nonlinear ARDL model, conversely, demonstrated that fluctuations in EPU have a notable short-term effect on equity prices across all countries in the G7 framework. Moreover, these short-term effects extend into the long term for all G7 countries, excluding the UK. Notably, all countries, excluding the UK, display indications of heterogeneity in short and long terms.

To assess the causal nexus between EPU and equity markets over monthly intervals from 2003 to 2014 in nine countries, Wu, Liu, and Hsueh (2016) study applied the bootstrap panel Granger causality test introduced by Kónya (2006). The finding of the research provided support for a causal association from EPU to the G7 equities.

In the US, the causal link between the equities market and EPU was studied by Ajmi, Aye, Balcilar, Montasser, and Gupta (2015). The research employed daily data from 1st January 1985 to 14th June 2013 for the indices created by Baker et al. (2013). The findings of the nonlinear causality tests demonstrate that the nexus between EPU and the equity market is highly predictive. The research discovered proof that EPU may assist in predicting the movements in the equity market.

### **Oil volatility and the stock market**

The association between stock market volatility and oil has only recently come under scientific scrutiny. Several empirical investigations have sought to comprehend the effect of oil variations on stock returns in both advanced and developing countries. To align with and build upon these empirical findings, our emphasis in this section lies in reviewing previous evidence from G7 countries.

Studies haven't been done much in the context of the G7 as a whole, and their findings are hazy. Khalfaoui et al. (2015) used a novel methodology that combines the wavelet-based MGARCH and the GARCH-BEKK techniques to explore the transmission of both mean and volatility effects between the oil market (WTI) and equity markets. Their findings suggest that there are

considerable volatility relays between the WTI and equity markets. They also discover dynamic connections for a couple of market pairings. However, the findings of the wavelet analysis signify that the WTI market dominated the stock markets.

Employing oil fluctuation risk premium as an indicator for oil shocks, Feng et al. (2017) reviewed the nexus concerning oil and equities from the perspective of the G7 countries. Upon accounting for several common macroeconomic indicators, they discover economically and significant impacts of oil prices on equity market yields. Conversely, Lee et al. (2012) reveal that equity index variations in each G7 member country are not significantly impacted by changes in oil prices in their analysis, which spans the years 1991 to 2009. Nevertheless, they discover that fluctuations in equity prices in the US, the UK, and Germany cause variations in oil prices.

Diaz, Molero, and Gracia (2016) investigated the nexus between fluctuations in oil prices and equity yields in the G7 nations (France, Canada, Germany, Japan, Italy, US, and UK) considering monthly intervals for the duration 1970 to 2014. To gauge oil volatility, the study considered world, nominal and real oil prices. The study then used a vector autoregressive model to estimate the nexus concerning oil prices and equity returns of the G7 nations. The empirical findings reveal an adverse reaction of G7 equity markets in the face of heightened oscillations in oil price fluctuations.

For the United States, empirical evidence yields conflicting results. According to several studies, there are large spillovers in stock market volatility

from oil prices. In order to characterise the transmission effect between oil and the US equity market in several frequency aspects, Liu et al. (2017) used a wavelet-based GARCH-BEKK model. They discover that the correlation between oil prices and equity market volatility is altering in the short term but diminishing over the long term.

Çevik, Atukeren, and Korkmaz (2018) used the dynamic Granger-causality tests to assess the Granger-causal links concerning variations in the price of oil and variations in global equity returns. The equities of the G7 nations were represented in the research using the daily yields from Morgan Stanley Capital International (MSCI) G7. The findings of the dynamic Granger-causality-in-mean tests showed a causal association between variations in the price of oil and equity returns in the G7 countries. Results of the dynamic Granger-causality-in-variance test showed proof of causal relationships between oil prices and global equity market yields, but only for specified time periods. The study's findings also provide proof that, depending on market volatility, the influence of fluctuations in the value of oil on equity returns may vary.

#### **Geopolitical risk index and the stock market**

In the continuing geopolitical confrontation between Russia and Ukraine, Agyei (2023) looked into the heterogeneous association between GPR and the equity markets of the leading seven emerging (E7) nations, comprising Russia, India, Mexico, Turkey, China, Brazil, and Indonesia. Including daily information spanning the time frame from January 1, 2022, to July 25, 2022. The findings from the wavelet analysis highlight varied and uneven coherence and temporal



sequence trends that are specific to each market. This reveals the intricate interconnectedness of GPR on E7 equities. Notably, the results suggest strong correlations between the Russian-Ukrainian upheaval and market volatility. Particularly in the studied era, Mexico and India show fewer diversity features. While countries providing a safe haven and hedges from GPR include Brazil, China, Indonesia, Turkey, and Russia.

Bossmann and Gubareva (2023) utilised the quantile-on-quantile regression model to assess the heterogeneity in the nexus between the ongoing Russia-Ukrainian conflict and the advanced (G7) and emerging (E7) equity markets. The findings reveal that the bearing of GPR on equity markets is market-specific and asymmetrical. The study finds that all G7 and E7 stocks, with the exception of Russia and China, react well to GPR in normal circumstances. Again, stock markets from Russia, Brazil, Turkey, and China (Japan, France, and the US) among the E7 (G7) nations were found to be resistant to GPR in bearish periods.

Salisu, Lasisi, and Tchankam (2022) looked into the effects of several types of GPR on the economy of advanced nations (Switzerland and G7). The work develops a prediction model, adopting the strategies proposed by Lewellen (2004) and Westerlund and Narayan (2014). Their research shows that advanced economies' stock returns are susceptible to GPR (with the exception of Italy) and that GPR threats, such as terrorism and war, exert a more adverse influence on market returns than their actual occurrence.

A non-parametric causality-in-quantiles test was used by Bouri, Demirer, Gupta, and Marfatia (2019) to investigate the causative association between GPR



and the returns and variation dynamics of Islamic equities and bond markets spanning the timeframe from 2005 to 2017. The findings demonstrated that geopolitical risks forecast Islamic bond returns as well as volatility measures.

Using the dynamic conditional correlation model by Engle (2009) and the rolling correlation model, Chiang (2021) examined the influence of a variation in EPU and GPR on the yields of equities, gold, and bonds in the Chinese equity market. The findings showed that Chinese equity returns are adversely impacted by both EPU and GPR. The influence of the conflict regarding Russia and Ukraine on the companies that make up the top equity market indexes of the G7 nations was examined by Abassi, Kumari, and Pandey (2022) using the event study approach to offer insight on the susceptibility of enterprises to war-related events. The authors show that whereas enterprises in Germany, Japan, and the UK saw an adverse cumulative returns over the event window, those in Canada and Italy showed positive cumulative impacts.

Nonparametric causality-in-quantiles tests were used by Balcilar, Bonato, Demirer, and Gupta (2017) to investigate the bearing of geopolitical uncertainty on the yield and fluctuation dynamics in the BRICS equity markets. The findings revealed that there were variations in the way that geopolitical risks (GPRs) affected the BRICS stock markets. GPRs are typically observed to exert an adverse influence on measures of equity market volatility, often displaying such effects at return quantiles situated below the median. This suggests that GPRs play a role in these markets as a source of unfavourable volatility. The findings further demonstrated that India is the sturdiest BRICS country in the duo, whereas

Russia exhibits the highest level of risk exposure to GPRs, evident in both volatility and returns.

By using the quantile regression approach, Kannadhasan and Das (2019) examined and contrasted the impacts of shocks related to EPU and GPR on the Asian emerging equity markets. The study discovers that the nexus between GPR and equity returns is asymmetrical, with an adverse association between GPR and lower quantiles and a positive association between GPR and intermediate and upper quantiles of stock returns. Similarly, empirical results by Jiang, Tian, Wu and Mo (2020) indicate that GPR has an adverse impact on tourism stock return that is both long-lasting and more substantial at low quantiles than at high quantiles.

GPR, exchange rate (EXCH), and EPU were evaluated for their effects on the South Korean equity market by Adebayo, Akadiri, and Rjoub (2022). Their study employed the innovative non-parametric causality-in-quantiles test developed by Balcilar et al. (2017), utilising a monthly dataset spanning from 1997 to 2021. The analysis unveiled that both the mean and variance of the equity market reflect the causal influence of EPU and GPR on equity returns. However, no evidence of causation in the variance was found, and the causal impact of EXCH on the equity market is discernible solely in the mean.

### **Economic policy uncertainty and the gold market**

The dynamic impact of EPU on return and volatility in gold futures was examined by Zhang, Demirer, Huang, Huang, and Suleman (2021) using the dynamic parameter VAR model with stochastic volatility applied to high-

frequency data. The study shows that the volatility and gold returns' impulsive responses to EPU shocks alternatively display asymmetric patterns and are time-varying.

Any degree of uncertainty surrounding policies impedes the economy's growth since economic policies are crucial in determining how an economy develops. In this context, Raza, Shah, and Shahbaz (2018) used monthly data from January (1995) through March (2017) to explore the nexus between EPU and the price of gold. The findings from the traditional linear Granger causality test establishes that there is no causal nexus between the price of gold and the uncertainty of economic policy.

Also, Wang et al. (2015) used the prices of 23 commodities EPU index of Baker et al. (2016) to research the connection between the prices of commodity prices and EPU nexus in the US. The finding of the research paper revealed that the prices of commodities can serve as a predictive indicator to forecast the unpredictability of economic policy.

The non-parametric causality-in-quantiles method was used by Balcilar et al. (2017a) to investigate the nexus between the volatility of gold prices and the uncertainty of policies that are economic in nature. Their empirical findings using monthly and daily data showed that EPU has an effect on the return, volatility, and price of gold. According to the research, investor sentiment has a substantial causal impact on volatility jumps only at the higher and lower quantiles, which implies that extreme levels of fear correspond to heightened positive volatility surges in gold yields, while extreme confidence is linked to negative volatility

increases. Jones and Sackley (2016) explored the nexus between EPU and gold prices. They came to the conclusion that rising EPU causes gold prices to upsurge.

Wu, Tong, Yang, and Derbali (2019) calculated the hedging and safe-haven attributes of gold and BTC against EPU shocks using the GARCH model and quantile regression utilising dummy variables. According to the analysis, neither gold nor BTC can act as a reliable hedge against EPU under average market conditions. Secondly, the study unveiled that even though gold retains its resilience with comparatively lower hedge and safe-haven coefficients, Bitcoin demonstrates greater susceptibility to shocks stemming from economic policy uncertainty.

The effect of various levels of EPU spillover on the Chinese stock, oil, and the market for gold was examined by Gao, Zhao, and Zhang (2021). The study's results unveiled that EPU transmits the least growth and volatility transmission to the oil market while transmitting the highest heights of growth and volatility spillover to the market for gold.

Gao, You, and Chen (2019) examined the dynamic response pattern of gold prices to EPU using a structural vector autoregression with the dynamic stochastic volatility model. The results from the seven developing nations and the thirteen developed nations showed that the impacts of the GEPUs upsurge on the prices of gold changes over various time intervals. The impacts were negative during 2009–2012, but positive during 2006–2008 and 2013–2017, suggesting that the effectiveness of gold as a safe haven is not constant and is dependent on economic circumstances. The instability of gold as a safe haven with reference to



literature reiterates the need to assess how current global mishaps affect the gold market.

Bilgin, Gozgor, Lau, and Sheng (2018) investigated the asymmetry link between the prices of gold and WTI crude oil, U.S. exchange rates, and several uncertainty indicators (VIX index, GEPU, and Partisan Conflict Index) using the Nonlinear Autoregressive-distributed Lag Model. The findings indicate a significant positive correlation between gold price and economic uncertainty. This finding suggests that rising levels of uncertainty cause gold prices to climb. The study however found that a decline in gold prices is unrelated to an improvement in the state of economic policy.

#### **Oil volatility and the gold market**

Using the GARCH-jump model, Dutta (2018) found that there was a sizable price transfer from the market for oil to the industrial metals sector. The research paper also showed that there are dynamic jumps in the returns on the fundamental metal market. The analysis also reveals that oil volatility upsurge have an effect on the silver and gold markets. Particularly, an upsurge in OVX has a favourable effect on gold returns. Third, the study found that the effects of OVX persisted during both the crisis and post-crisis eras when assessing the GFC affected the nexus between the metal and oil markets. The analysis also revealed that there exist significant asymmetries in the relationships between the markets for industrial metals and oil.

To investigate the volatility behaviour of three important commodities—silver, gold, and copper—when exposed to shocks in interest rates and crude oil,



Hammoudeh and Yuan (2008) used a number of GARCH-type models. The empirical results posited that the three metals are all not affected by the recent oil shock equally. The findings from the EGARCH model however revealed that gold and silver can be a wise investment in case of economic downturns.

Ewing and Malik (2013) examined the fluctuations of oil futures and gold using the bivariate and univariate GARCH models. The results of the study furnished compelling substantiation for a pronounced transmission of volatility between the returns on oil and gold.

Using GARCH and GJR models, Behmiri and Manera (2015) examined the price fluctuations of metals. The authors take into account the current spot prices for metals such as platinum, gold, silver, palladium, lead, copper, tin, and zinc on a daily basis. The results revealed that the gold market's fluctuations is decreased by negative oil price shocks but is unaffected by positive oil price variations.

Another contemporary research by Roboredo and Ugolini (2016) demonstrates that throughout the pre- and post-financial crisis periods, significant swings in oil prices had an effect on a number of precious and industrial metals. In a similar vein, Bakhat and Würzburg (2013) demonstrate that the prices of nickel and aluminium are integrated with the prices of world oil. The Granger causality tests also show that the value of oil affects the value of nickel and aluminium.

Bildirici and Türkmen (2015) used the BDS test, non-linear ARDL methodology, and the non-linear Granger causality approaches in Turkey to

analyse the correlation regarding oil prices and the prices of silver and gold. The study's results revealed a distinct long-run association regarding the prices of oil and the price of silver, gold, and copper as well as a one-way Granger causality between oil prices and the prices of valued metals.

### **Geopolitical risk and the gold market**

Huang, Li, Suleman, and Zhang (2023) used high-frequency data to investigate the causal nexus regarding GPR and the gold market from January 2000 to November 2017. They used a causality-in-quantiles approach. According to the findings, geopolitical risks have an upshot on gold market volatility other than returns. The research paper also showed that under the bull and normal market situations, geopolitical concerns had a greater causal relationship with the jump component.

Researchers have analyzed the potential of gold to serve as a hedge against geopolitical risk due to its role as a hedging mechanism (Yilanci & Kilci 2021; Baur & Smales 2018, 2020; Li, Huang, & Chen 2021a; Gkillas, Gupta, & Pierdzioch 2020; Li et al., 2021b). Baur and Smales (2020) investigated the question of whether gold exerts a hedging impact on geopolitical risk. The findings of the study showed that gold indeed exhibits a hedging potential on geopolitical events. According to Triki and Maatoug (2021), there is a stronger association between the equity market and gold when geopolitical risk events take place. The study however revealed that in instances of geopolitical upheavals, gold can be used to mitigate risk. Yilanci and Kilci (2021) ascertained that a unidirectional causal association existed between political risk and the price of

gold. They employed the dynamic Hacker and Hatemi (2012) causality test to reach this conclusion.

Based on a wavelet coherence analysis, Cheng, Zhang, and Cao (2022) investigated whether precious metals could be utilised to mitigate GPR and whether there were any asymmetries in the hedging potential when GPR increased or decreased in the time and frequency domains. The lead-lag association regarding GPR, and precious metals was also determined by the investigation under various time-frequency effects. The ensuing is a summary of the key findings. First, in the near and medium terms, gold and silver provide suitable assets to use as a hedge against GPR. Second, when there is an upsurge and decline in GPR, there is a noticeable imbalance in the link regarding GPR and precious metals. The study also discovered that silver and gold are pioneers in GPR modifications.

### **Economic policy uncertainty and the Bitcoin market**

Bivariate and multivariate wavelet techniques were utilised by Al-Yahyee, Rehman, Mensi, and Al-Jarrah (2019) to review the correlation between the Bitcoin (BTC) and Volatility Uncertainty Index (VIX). This was accomplished by considering the influences of three primary global determinants, to wit GPR, the U.S. EPU Index, and OVX. The findings demonstrated that there are temporal and frequency variations in the BTC-VIX association. Finally, correlations between BTC-uncertainty indices were found to be dependent upon investment horizons. Similar conclusions were reached based on the research of Mokni, Ajmi, Bouri, and Vo (2020), who claimed that after the December 2017 Bitcoin crash, there

was a bad correlation between EPU and the US equity market. But, before the Bitcoin crisis, EPU hikes had a favourable impact on BTC returns.

Huynh, Wang, and Vo (2019) looked at the potential of EPU to forecast three different aspects of Bitcoin, namely the return, volume, and volatility. The Transfer Entropy model with stationary and non-stationary assumptions was used in the investigation. The study's empirical findings indicate that Global EPU has a detrimental consequence on the volumes, returns, and unpredictability of Bitcoin. Consequently, in times of uncertain regimes, fund managers incline to being risk-averse when engaging in trading activities, contributing to a reduction in market volatility.

Wang, Li, Shen, and Zhang (2020) investigated the impact of EPU on local currency-denominated BTC markets. The study's results showcased a notable discrepancy in returns between days marked by the highest EPU and those with the lowest EPU. Furthermore, after EPU upsurge days, the EPU of US boosts the trading and volatility volume of BTC, whereas the EPU of UK does not exhibit these characteristics. In addition, it is observed from the study that there is a transmission influence from the EPU of USU to the BTC market of UK.

To investigate the dynamic correlation regarding EPU and BTC, Wang et al. (2019) further constructed the dynamic conditional correlation (DCC)-GARCH model to that effect. The results show that the US EPU has a stronger influence on Bitcoin/USD than the EPU of UK has on Bitcoin/GBP. It can be noted from the above literature that the results of Wang et al. (2019) on EPU increasing the volatility and trading volume of BTC contradicts that of Huynh et



al. (2019) who asserted that EPU spike decreases BTC volatility. The differences in findings could be attributed to different the EPU indexes used as well as the methodology employed.

Demir, Gozgor, Lau, and Vigne (2018) assesses the EPU's index's ability to forecast daily BTC returns over a period of seven years (2010-2017). The research paper demonstrates that EPU has the potential to forecast the yields of Bitcoin, utilising the Bayesian Vector Autoregressive model, ordinary least squares, and Quantile regression estimations. The study found out that essentially, EPU has an adverse association with the yields of Bitcoin. The effect remains negative and statistically relevant, both at upper and lower quantiles of Bitcoin returns and EPU.

Mokni (2021) looked into the causality moving from EPU to BTC yields and volatility for the top 10 nations hosting Bitcoin nodes. The study used the linear and non-linear causality in-quantiles test to achieve this. According to the results, EPU in the majority of countries, can better estimate the returns of Bitcoin when the market is extremely volatile. However, at the average and upper, EPU increases Bitcoin volatility. Further analysis taking into account the non-linear causality in quantiles demonstrates that the causality flowing from EPU to the yields of Bitcoin is obtained from elevated EPU levels, whereas the causality from EPU to Bitcoin volatility is sourced from the decline in EPU (negative variations).



## Oil volatility and the Bitcoin market

The realm of Bitcoin trading stands out as highly uncertain, showcasing characteristics diverging from Gaussian patterns, encompassing elements such as non-linearity and heavy tails (Gkillas & Katsiampa, 2018; Gangwal & Longin, 2018; Kristjanpoller, Bouri, & Takaishi, 2020). Furthermore, it remains vulnerable to speculative bubbles, a susceptibility highlighted by studies such as those by Bouri, Shahzad, and Roubaud (2020) and Cheah and Fry (2015). In light of this, much research has been conducted to determine how Bitcoin compares to other assets. While just a handful of research papers have explored the impact of oil volatility on the BTC market, it's noteworthy given that BTC is a hybrid commodity, and its dynamics are influenced by fluctuations in crude oil prices. In this regard, Baur, Hong, and Lee (2018) looked at the correlation regarding BTC and other conventional commodities like bonds, stocks, and commodities in both calm and turbulent times and came to the conclusion that there isn't an association between BTC and the conventional asset classes under study. Similarly to this, Klein, Thu, and Walther (2018) compared the qualities of BTC and Gold in a portfolio and found that they have fundamentally distinct characteristics.

According to Bouri et al. (2020), Bitcoin is more effective than gold and other commodities at hedging extremely negative changes in equity market indices. Yet, other studies have contested the diversification and hedging advantages of cryptocurrencies (see for instance, Chowdhury, 2016 & Klein et al., 2018). In recent times few studies have considered the influence of oil price volatility on the Bitcoin market.

A DCC-GARCH model was used by Dutta, Das, Jana, and Vo (2020) to evaluate the safe haven qualities of gold and BTC in light of the coronavirus outbreak. According to empirical findings from the study, gold serves as a place of refuge for the world's oil markets, but BTC just plays the role as a diversifier for crude oil.

The nonlinear autoregressive distributed lag model was used by Long, Pei, Tian, and Lang (2021) to analyse the performance differences between BTC and gold under the influence of three different indexes of uncertainties, namely the US equity market VIX, GEPV, and OVX. The findings showed that when faced with upsurge of various uncertainty, BTC is unable to act as a safe haven, whereas gold can, to variable degrees, hedge against uncertainties.

The Granger causality test was used in Li, Hong, Wang, Xu, and Pan's (2022) study of the excessive risk transfer between the BTC and crude oil markets to determine if there is a causative connection for both severe and non-extreme shocks. The findings from the time-varying estimations demonstrated that the link between the price of crude oil and BTC is asymmetric as it changes over time.

### **Geopolitical risk and the Bitcoin market**

Aysan, Demir, Gozgor, and Lau (2019), investigated the effectiveness of the GPR index in predicting the volatility and daily returns of BTC from July 2010 to May 2018. When taking into account the Bayesian Graphical Structural Vector Autoregressive (BSGVAR) approach, the study discovered that GPR has the potential to predict both BTC returns and volatility. The Quantile-on-Quantile

(QQ) estimation results showed that the impact of GPR on BTC returns is favourable at the upper quantiles but unfavourable at lower quantiles.

Bouri, Gupta, and Vo (2022) examined the relationships between GPR spikes and the cryptocurrency market from 2013 to 2019. According to the projected outcomes, it was discovered that Bitcoin was the only cryptocurrency whose price increases were positively correlated with increases in the degree of geopolitical risk. This outcome offers proof that BTC may be utilised as a hedge against political risk.

Su, Qin, Tao, Shao, Albu, and Umar (2020) investigated how the Bitcoin currency could help people avoid and overcome the hazards related to global geopolitical events and circumstances. The findings from the Granger causality test revealed that geopolitical risks (GPR) and Bitcoin price (BCP) have a detrimental impact on bitcoin prices.

According to Chibane and Janson (2020), the degree of GPR has a considerable effect on the fluctuations of BTC prices. The study finds that when geopolitical risk is high, BTC price hikes are particularly much more predominant to emerge. On the other hand, the analysis discovers that Bitcoin returns are roughly averagely distributed and do not appear to promote asset pricing spikes when geopolitical risk is moderate.

An examination of the existing literature indicates that several established empirical observations regarding BTC no longer hold true when we incorporate the GPR index into the analysis of BTC returns. This suggests that delving deeper into the influence of geopolitical actions on the cryptocurrency market across

diverse market conditions could offer valuable understandings into the potential of GPR to exert an impact on cryptocurrency prices.

### **Economic policy uncertainty and the carbon market**

To explore the interrelation between the EU carbon market future returns from the UK and the USA, Ye, Dai, Nguyen, and Huynh (2021) apply the linear analysis and the cross-correlation estimations. According to the empirical results of the linear assessment, there was no association regarding the return on EU carbon futures and either country's EPU (EPU-USA and EPU-UK). The study also revealed that the EU carbon futures return can cause UK EPU but cannot cause USA EPU. The study however disclosed that the country-specific EPU under study cannot cause the returns in the EU carbon futures market.

Using the GARCH-MIDAS model for the period of 2008 to 2015, Dai, Xiong, Huynh and Wang (2022) investigated the impact of EPU on the fluctuations of the European carbon market. The findings demonstrate that the long-run fluctuations of the European carbon return will be exacerbated by both global and European EPU, with the former having a bigger effect when the change is the same.

Similarly to the aforementioned study, Hemrit and Benlagha (2021) explored the effects of the worldwide pandemic and EPU on the index of renewable energy using daily measurements from January 2005 to June 2020. The quantile regression findings showed that the global pandemic had a large and positive influence on the renewable energy index, but the EPU had a negative impact.



In a similar vein, Wang, Liu, Zhong, and Lobont (2022) use a wavelet-based quantile-on-quantile regression technique to examine the diverse responses of the Chinese carbon emission trading price (CETP) to various temporal frequencies of EPU. The empirical findings show that the coefficients regarding EPU and CETP are dynamic and even shift in reverse directions when EPU is in various quantiles and frequencies, demonstrating the instability of their connection.

Accounting for the influence of U.S. EPU, Adekoya, Oliyide, and Noman (2021) investigated the propagation of volatility risks across different frequency ranges among the EU carbon market and diverse commodities and financial markets. The study's findings underscore the intricate and diverse nature of connections between the carbon market and other domains. Notably, as the frequency cycle extends, the intensity of volatility interdependence rises, emphasizing that risk transmission becomes most pronounced when assets are held over longer durations. The analysis concludes by highlighting the significant role played by U.S. EPU in establishing interconnections regarding the carbon market and the various other markets.

Dou, Li, Dong, and Ren (2022) examined the impact of US EPU on carbon futures returns using the causality test, quantile regression, and wavelet approach. The carbon futures prices and EPU index data from January 22, 2013, through July 2, 2021, were utilised. The study's findings showed that EPU shocks are unable to forecast the return of carbon futures. However, EPU was shown to have a considerable adverse long-term influence on the return on prices of carbon



futures. Nevertheless, the outcome of the causality test showed that there is an asymmetric causal association between EPU and the carbon market throughout the whole spectrum of the yields of carbon futures.

### **Oil volatility and the carbon market**

Existing research has demonstrated that a variety of factors, including institutional actions, climate conditions, the macroeconomic and financial markets, and the market for energy, have an effect on the price of carbon (Aatola et al., 2013; Alberola et al., 2009). Among these, the energy market, particularly the market for crude oil, may be the one that is most strongly linked to variations in the price of carbon (Zhuang et al., 2014; Alberola et al., 2009). By applying the threshold co-integration approach, Peri and Baldi (2011) claimed that there is a long-run asymmetric correlation between the values of Brent oil and EUA futures.

According to Aatola et al. (2013), who used the Granger causality test, Vector Auto-Regression, and OLS estimation, the oil and carbon markets are positively correlated, and the price of the EUA causes the price of oil. Contrarily, Hammoudeh et al. (2014) used a quantile regression approach and observed that, during periods of elevated carbon prices, an upsurge in crude oil price could lead to a significantly lower price for those commodities. The return series of the prices of carbon and crude oil were shown to be strongly cross-correlated by Zhuang et al. (2014) using the cross-correlation technique.

Yu, Li, and Tang (2015) investigated the non-linear association between the EUA and Brent futures prices. A dynamic conditional correlation (DCC) model was utilised to reveal the non-linear association between the two markets.

The findings revealed that generally, the findings revealed that there is a clear positive association between the EUA and Brent markets. Furthermore, the empirical work also showed that such a dynamic spillover impact changes with time and exhibits a relatively diminished magnitude in Phase III as compared to Phase II. Additionally, the connection mechanism is structurally altered by economic events like economic downturns and political shifts.

Sarker, Bouri, and Marco (2023) applied the non-linear autoregressive distributed lags model to data spanning from January 2001 to December 2021. Their study aimed to explore the non-linear impacts of, geopolitical perils, crude oil prices and climate policy uncertainty (CPU) on clean energy prices (CEP). The study shows that the impact of GPR, CPU, and WTI oil prices on CEP's yields and realised fluctuations changes in the immediate and long terms, signifying its non-linearity. The study revealed that while a spike in WTI has short-term impact on CEP's yields and realised volatility, a decline in WTI has long-term effects.

### **Geopolitical risk and the carbon market**

Various indicators denoting geopolitical uncertainties (including conflicts, terrorism, and political turbulence) have been utilised in previous research investigating the correlation between geopolitical instabilities and CO<sub>2</sub> emissions. While numerous scholarly works in the literature adopt terrorism as a substitute for GPR, a case in point is the study by Bildirici and Gokmenoglu et al. (2020) that scrutinises the effect of terrorism on nations such as Pakistan, the Philippines, Afghanistan, Nigeria, Thailand, and Yemen, concerning ecological degradation.

The study uses the panel ARDL technique. The study's conclusions demonstrated that rising CO<sub>2</sub> emissions are a result of terrorism.

Similar to this, Bildirici (2020) uses the DOLS and FMOLS estimator to analyse the influence of economic growth, energy consumption, FDI, and terrorism, on CO<sub>2</sub> emissions for Turkey, Israel, China, and India. According to the findings, FDI, terrorism, and energy use all raise CO<sub>2</sub> emissions.

Militarization is used in other studies as a stand-in for geopolitical threats. For example, Bildirici (2017b) also investigates the influence of economic development, energy use, and militarism on CO<sub>2</sub> emissions in the G7 nations. The findings demonstrate that militarization increases carbon dioxide emissions. Additionally, there is a Granger causation between CO<sub>2</sub> emissions and militarism.

Accordingly, Chowdhury et al. (2021) investigated the impact of global uncertainty, pandemics and GPR on the energy markets and equity markets using quantile regression for the duration 1996 to 2020. The analysis discovered that although the epidemic and global uncertainty have a detrimental impact on the markets, there exist significant differences across the quantiles. GPR also has a negative effect on the markets. Global uncertainty, the occurrence of geopolitical risk, and pandemics, all have a one-way causal nexus with the energy and equity markets.

Recently, Gokmenoglu et al. (2020) investigated Turkey's CO<sub>2</sub> emissions and ecological footprint in relation to financial development, military, and energy use. To determine a long-term nexus and the path of causality between the variables, the study uses FMOLS and causality approaches. The results showed

that energy use and militarization accelerate environmental damage. Additionally, it was observed that there was a unidirectional causal association between militarization and CO<sub>2</sub> emissions.

Similar to the aforementioned study, Bildirici (2018b) uses FMOLS and DOLS estimations to examine how economic growth and military actions affect the emission of CO<sub>2</sub> for the G7 nations. The findings provide an explanation for how these economies' high levels of CO<sub>2</sub> emissions are a result of both militarization and economic growth.

In contrast, Ullah et al. (2020) note that military actions results in a decrease in CO<sub>2</sub> emissions in India and Pakistan. The research paper also revealed that military action has a non-linear impact on CO<sub>2</sub> emissions. Parallel to this, numerous research look at the impact of political (in)stability on environmental quality as an indicator for geopolitical risks.

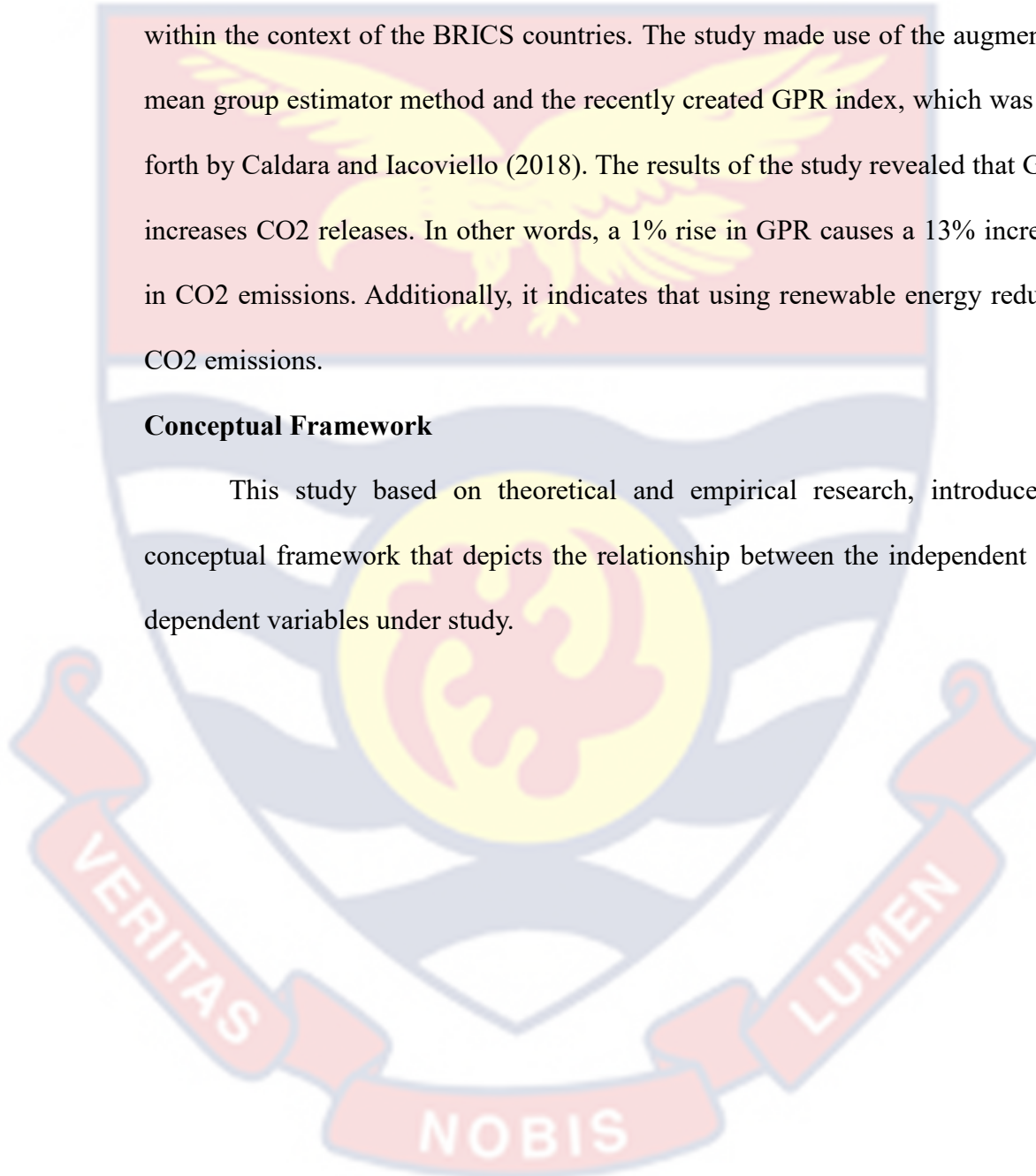
Sofuoğlu and Ay (2020) investigate the connection regarding climate change, wars, and political unrest in MENA countries. The result demonstrate that there is a unidirectional causal association linking political unrest and climatic change. Abid (2016) also looks into how institutional, social, and economic issues affect CO<sub>2</sub> emissions. The results show that increased CO<sub>2</sub> emissions are a result of political instability. Recently, Adams et al. (2020) used the panel ARDL model, and causality to assess the effects of GPR threats and EPU on CO<sub>2</sub> emissions for the resource-rich nations. The results show that geopolitical concerns drive up CO<sub>2</sub> emissions in the short term but drive them down in the long term.



Accounting for the influence of GDP, population, non-renewable energy utilisation, and renewable energy usage, Anser, Syed, and Apergis (2021) delved into the influence of geopolitical perils (GPR) on CO<sub>2</sub> emanations in particular within the context of the BRICS countries. The study made use of the augmented mean group estimator method and the recently created GPR index, which was put forth by Caldara and Iacoviello (2018). The results of the study revealed that GPR increases CO<sub>2</sub> releases. In other words, a 1% rise in GPR causes a 13% increase in CO<sub>2</sub> emissions. Additionally, it indicates that using renewable energy reduces CO<sub>2</sub> emissions.

### **Conceptual Framework**

This study based on theoretical and empirical research, introduces a conceptual framework that depicts the relationship between the independent and dependent variables under study.



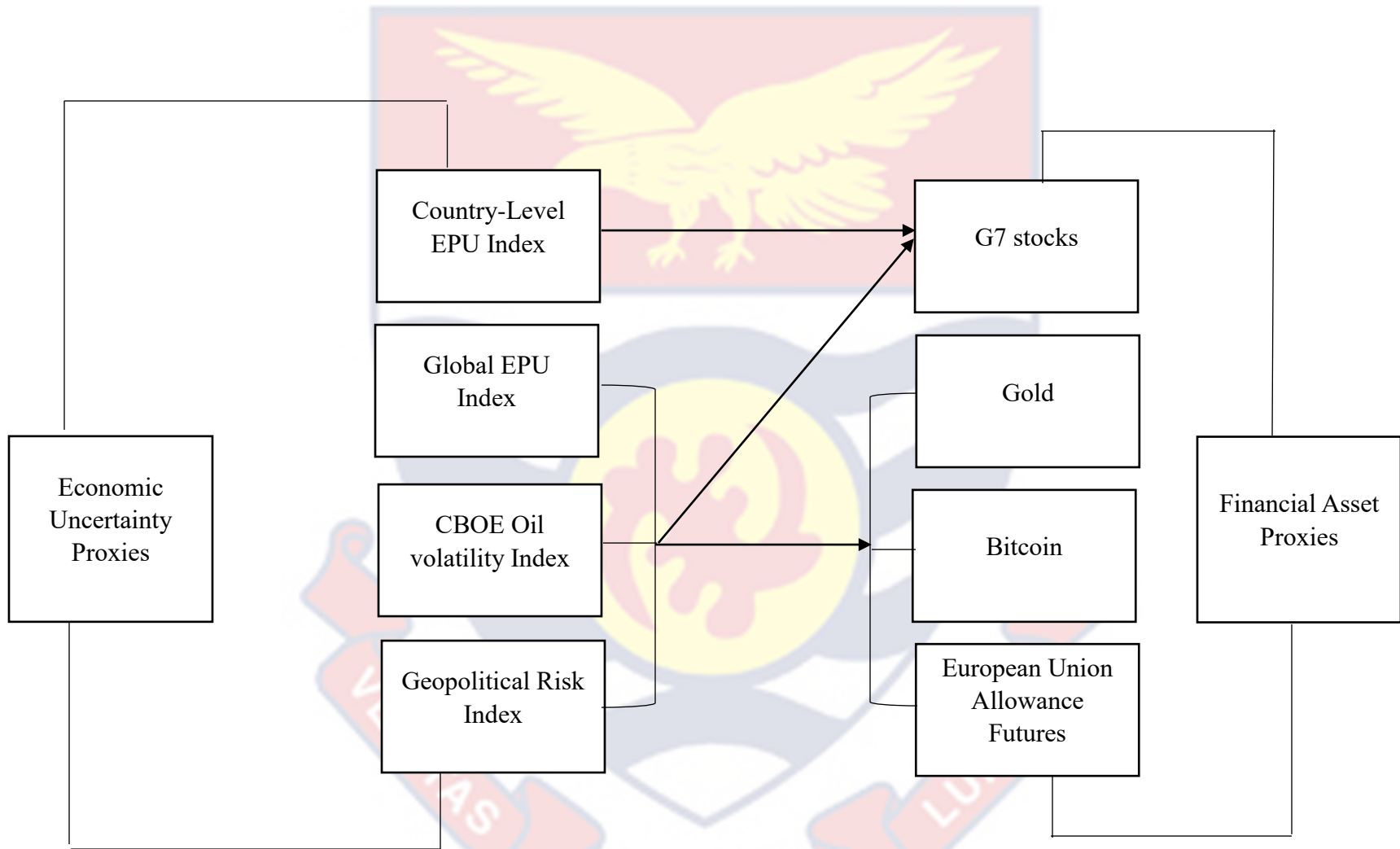


Figure 1: Conceptual framework.

The conceptual framework above depicts the relationship that exists between the independent variables (economic uncertainty proxies) and the dependent variables (financial assets). Economic uncertainties as shown in Figure 1 indicate that it is proxied by four indices (country-level EPU, global EPU, CBOE oil volatility index and geopolitical risk). This in line with the adaptive market hypothesis, heterogeneous market hypothesis and arbitrage pricing theory are presumed to affect the returns of the financial assets under study (G7 stocks, gold, bitcoin, and European Union allowance futures). The study examines the effect of country-level EPU, global EPU, oil volatility, and geopolitical risk on the returns of the G7 stocks. On the other hand, the study examines the effect of Global EPU, oil volatility, and geopolitical risk on the returns of gold, bitcoin, and the European Union Allowance futures.

### **Chapter Summary**

The second chapter of this research scrutinised the literature review concerning the asymmetrical interplay and concurrent movements among Country-level and global economic policy uncertainty (EPU), the oil volatility index, geopolitical risk, and the G7 stock market, alongside the examination of their interactions with gold, Bitcoin, and the carbon market. The study is underpinned by the Adaptive market hypothesis, Heterogeneous market hypothesis and the Arbitrage pricing theory.

## CHAPTER THREE

### RESEARCH METHODS

#### Introduction

This section encompasses the systematic steps used to examine the asymmetric relationship between economic uncertainties and the returns of financial assets under study. This chapter goes on to discuss the analytical technique employed to reveal the comovement as well as the causal nexus that exists between the variables under study. The causality test was however employed to serve as a robustness test for the quantile regression and wavelet techniques. Furthermore, this segment elaborates on the research design, research methodology, sample selection and sampling methodology, operationalisation and quantification of variables, data analysis methods, and the manner in which findings are presented, all in alignment with the study's objectives.

#### Research Design

According to Zikmund, Babin, Carr, and Griffin, (2013) the research design effectively serves as a guide for conducting the entire study. Selecting a research design is crucial because it establishes the optimal course of action to address the study's hypotheses (Sekaran & Bougie, 2010). It assists the researcher by tackling matters such as the importance of the study, the nature of enquiry, the level of complexity, the geographical setting, the time frame, and the focal subject of analysis. Saunders and Lewis (2012) state that there are three types of research designs: exploratory, explanatory, and descriptive. The amount to which one or



more factors influence another variable is determined via an explanatory study, also referred to as causal research (Zikmund, Babin, Carr, & Griffin, 2013).

In this regard, the study employs explanatory research design to accomplish the aims set forth in this study. The explanatory design aims to describe the links between two variables through the analysis of a situation or a particular issue. The explanatory design also has the benefit of being replicable if required. Additionally, because the study subjects are carefully chosen, the explanatory design is associated with higher stages of internal legitimacy (Zikmund et al., 2013). In this regard, this research employs the explanatory research design to examine the asymmetric nexus between economic uncertainties and the returns of financial assets, as well as investigate the comovement and causal relationship between the aforesaid variables.

The primary danger with explanatory research is that coincidences in events might be mistaken for causal linkages. Using the results of an explanatory research study to draw inferences on causality can sometimes be challenging. This is a result of the influence of several elements and variables on the economic and social environment. To put differently, even while causality might be inferred, it couldn't be demonstrated with absolute confidence. Despite the aforementioned explanatory study's shortcomings, it is seen to be the best option for the study's goal since it enables analysis of how economic uncertainty affect financial assets.

### **Research Paradigm**

According to Hallebone and Priest (2008), a research paradigm is the viewpoint that guides scientific inquiry and the methodological framework that is

thought to be very relevant given the aim, setting, and subject matter of the study. This empirical work uses the post-positivist framework, which emphasises a deductive line of thought. Post-positivism acknowledges that earlier experience and present social settings impact our perceptions and form our awareness, in contrast to positivism, which emphasises the researcher's independence from the unit of study (Bergman, 2016). Panhwar, Ansari, and Shah (2017) assert that post-positivism paradigm also promotes methodological pluralism, which is predicated on the idea that the methodology to be used in a given study should be chosen in accordance with the research question it is attempting to answer. This paradigm promotes the study's use of a variety of techniques to accomplish its various goals.

### **Research Approach**

To attain its objectives, the study uses a quantitative research methodology. According to Aliyu, Singhry, Adamu, and Abubakar (2015) and Babbie (2010), quantitative research aims to collect statistical information and generalise it across various groups or elucidate an explicit occurrence. The primary purpose of quantitative research is to find the nexus regarding the study variables and their cause-and-effect relationships.

According to Babbie (2010), quantitative research is centred around statistics, logic, and an objective point of view in addition to measurable and dynamic data, accuracy, and convergent thinking. In addition to emphasising how a modified variable affects another variable in a specific context and environment, it enables the reproduction of the same phenomena at a greater degree of

dependability (Plonsky & Oswald, 2014). The quantitative method is deemed appropriate for this research paper since the purpose is to assess the non-linear nexus between economic uncertainties and the returns of financial assets, as well as investigate the comovement and causal relationship between the aforesaid variables.

### **Source of Data Collection**

The data utilised in this research work are of two broad categories. Firstly, the study employs four economic uncertainty indices (Global EPU, Country-level EPU, CBOE Crude oil volatility index and Geopolitical risk index). The Global EPU, Country-level EPU and Geopolitical risk index are sourced from [www.policyuncertainty.com](http://www.policyuncertainty.com) while data for CBOE Crude oil volatility index is sourced from [www.yahoofinance.com](http://www.yahoofinance.com). With regard to financial assets, the study employs the G7 stock indices, Bitcoin, Gold, and the European Union Allowance Future prices. The data on G7 stocks and Gold future prices are sourced from [www.yahoofinance.com](http://www.yahoofinance.com), data on Bitcoin is retrieved from CoinDesk at [www.coindesk.com/price](http://www.coindesk.com/price), while data for the European Union Allowance Future Prices is sourced from the Intercontinental Climate Exchange.

All indices employed for this data are monthly observations spanning from January 2012 to December 2022. The suggested time frame was opted because it covers major global happenings such as Brexit, the beginning of COVID-19 as a worldwide disease outbreak, and the conflict concerning Ukraine and Russia. The markets included in this study are dependent on trading volume and market capitalisation. All the markets examined are accessible to foreign portfolio

investment, notwithstanding variations in the degree of openness. The analysis is based on monthly returns, which are computed as  $r_t = \ln P_t - \ln P_{t-1}$ , where  $P_t$  and  $P_{t-1}$  are the recent and prior indices, correspondingly, and  $r_t$  is the continuously compounded return.

### **Definition and Measurement of Variables**

The variables incorporated in this research are delineated to exclusively encompass only dependent and independent variables. The dependent variables for the research work are the financial assets under study (the G7 stocks, BTC, gold and the EUAF returns), the independent variables include the global EPU, country-level EPU, CBOE crude oil volatility index and geopolitical risk index. The indices of the G7 stocks employed are Germany (GDAXI), Italy (MIB), France (FCHI), UK (FTSE 100), Japan (N225), Canada (GSPTSE), and US (S&P 500). For Gold futures, Bitcoin and the EUAF returns, the study uses the GCM4, BTC and EUAF indices respectively.

### **Economic uncertainty**

The study employs four main measures of global uncertainties in light of recent global mishaps. They are: Global EPU, country-level EPU, CBOE crude oil volatility index (OVX) and geopolitical risk index (GPR).

The EPU index constitutes a newly developed gauge of uncertainty devised by Baker et al. (2020), formulated from the regularity of mentions in the media regarding the count government tax law provisions projected for repeal in the forthcoming years. It also reflects discord among economic prognosticators regarding variables pertinent to policy and uncertainties in economic strategies.



Baker et al. (2016) found the index for EPU to be trustworthy, impartial, and consistent with the other uncertainty metrics.

On the other hand, the CBOE oil volatility index offers a precise representation of indecision in the oil market since it includes both past data on oil prices and investor perceptions of expected forthcoming changes in oil prices (Xiao et al., 2018; Dutta et al., 2017; Xiao et al., 2019). The GPR index, created by Caldara and Iacoviello (2022), quantifies the likelihood of terrorist attacks, conflicts, and nation-to-nation hostilities that obstruct normal international interactions. The GPR index is derived from text searches of terms often used in 11 significant worldwide newspapers that are relevant to geopolitical issues. More uncertainty or fear in the market is represented by higher values in the uncertainty index, whilst less market ambiguity is represented by lower numbers.

The global uncertainty indices employed by this study captures significant global upheaval such as the Brexit, the crude oil crash, the COVID-19 outbreak and Russia's armed operation in Ukraine. The potential of the uncertainty index to capture the previously mentioned global events and many others will contribute to examine how economic uncertainties in recent times affect the returns of financial assets.

### **Financial assets**

Financial assets are intangible items that reflect a right to money or a claim to a future stream of benefits. Stocks, bonds, derivatives, commodities, and currencies are some examples of them. Gold futures, Bitcoin, the European Union



Allowance futures market, and the G7 equities are among the financial assets taken into account in this study.

To achieve a more precise assessment of the dependence structure, this study utilises exchange rates sourced from Investing.com to change the home prices of stocks into dollars. The stock benchmark of the G7 nations include Germany (GDAXI), Italy (MIB), France (FCHI), the UK (FTSE 100), Japan (N225), Canada (GSPTSE) and the US (S&P500). These G7 markets were chosen because of their important roles in the global market. Again, the econometric findings of the uncertainty and asset return relationship from these countries would show the main market behaviour in the international equities market (Andrikopoulos, Angelidis & Skintzi, 2014). It is important to acknowledge that the selection of countries and the chosen timeframe is influenced by the accessibility of data. While our research is confined to specific countries concerning the stock market, it encompasses a substantial share of the global economy.

The study again employed the gold futures, Bitcoin and the European Union Allowance future prices which effectively represents their respective market. Gold for instance is known for its hedging properties against economic downturns (Hood & Malik, 2013; Baur & Lucey, 2010; Agyei-Ampomah et al., 2014; Baur & McDermott, 2010). Conversely, Bitcoin dominates the cryptocurrency, boasting of a formidable market capitalisation of \$593.32bn in June 2023 (yahoofinance.com). The European Union Allowance future market is the largest carbon market in Europe (Xu & Zhai, 2022) which aims to achieve the

Kyoto protocol and the COP 27 agreement which is aimed at achieving a substantial reduction in carbon emissions. An insight as to how economic uncertainties affect these dominant financial assets will inform investors and policymakers about the bearing of recent economic uncertainties on the financial market at large.

### **Estimation techniques**

This empirical work employs the methodology developed by Koenker and Bassett (1978). The first objective of the study is to examine the asymmetric nexus between economic uncertainties and financial asset returns. In line with the first objective of the study, this research employed a three-step approach encompassing the Variational Mode Decomposition (VMD) method, as well as the techniques of Quantile Regression Analysis (QRA) and Quantile-in-Quantile Regression (QQR). The incentive for the adoption of the VMD and quantile regressions techniques is founded on skewness and the non-linear nature of the data employed in the study. The use of the VMD technique stems from the literature reviewed as well as the theories employed in the study. The adaptive market hypothesis and the heterogeneous market hypothesis as put out by Lo (2004) and Muller et al. (1997) posit that investors are not completely rational but bound rational. This implies that during times of economic uncertainties, investors' conduct on the financial market changes, resulting in irregular trading patterns over various time horizons, including short, medium, and long term. This motivated the study to utilise the VMD method to segregate the return series into

different time horizons (M1 denotes short term, M2 and M3 denote medium term, while MA<sub>gg</sub> denote long term).

On the other hand, the study employed the Quantile regressions technique due to the non-linear nature of the return series of the data as established by the Jarque-bera test. The Jarque-bera test as shown in Table 1 reveal that the return series are not normally dispersed. Again, the descriptive statistics also revealed that the data is largely negatively skewed. This motivated the study to embrace the quantile regressions technique to effectively capture how economic uncertainty affect returns of assets across different time horizons.

To begin with, the study commences by introducing the Variational Mode Decomposition (VMD) methodology put forth by (Dragomiretskiy & Zosso, 2013), which is sequentially followed by the application of QR and QQR techniques. In this procedural framework, the output yielded by the VMD process serves as the input data stream for the subsequent QR analysis.

Within the context of VMD, the Intrinsic Mode Function (IMF) is distinctly characterised as a signal that exhibits both amplitude modulation and frequency modulation. Formally, the  $k_{th}$  mode, denoted as  $U_k(t)$ , is represented as follows:

$$U_k(t) = A_k(t) \cos(\phi_k(t)), \quad (1)$$

In the given expression,  $A_k(t)$  signifies simultaneous amplitude,  $\phi_k(t)$  represents the instantaneous phase, and its derivative  $\omega_k(t) = \phi_k'(t)$  is identified as the simultaneous scale.

In the analysis of each specific mode  $U_k(t)$ , the VMD approach incorporates the Hilbert transmute to derive the diagnostic signal and to estimate the inherent frequency band. In this regard,  $U_k(t)$  represent the return of each variable to be decomposed (returns for economic uncertainties and financial assets). Following this, the mode's spectrum is transitioned to the baseband through the application of the shift property within the Fourier transform. Subsequent to this transition, the bandwidth is projected using a Gaussian smoothing process denoted by  $H^1$ . The overarching optimisation objective is to minimise the aggregate spectral widths across all mode functions, aiming to achieve the utmost reduction:

$$\frac{\min}{\{u_k\}, \{\omega_k\}} \left\{ \sum_{k=1}^K \partial_t \left\| \left[ \left( \delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e_2^{-j\omega_k^t} \right\| \right\} \quad (2)$$

$$\text{s.t.} \quad \sum_{k=1}^K u_k = f,$$

In this context,  $\{u_k\}$  symbolises the collection of mode ensembles, while  $\{\omega_k\}$  represents the corresponding ensemble of center frequencies, where  $K$  denotes the observation of modes (in context, M1, M2, M3 and Magg), representing short term, medium term (M2&M3) and long term correspondingly. The underlying signal can be expressed as the cumulative total of these modes, which serves as the underlying constraint. In order to transform the earlier constrained optimization problem into an unconstrained one, an exponential penal factor and a Lagrangian multiplier are initiated, resulting in the following formulation:

$$L(\{u_k\}, \{\omega_k\}, \lambda) = \alpha \sum_{k=1}^K \left\| \partial_t \left[ \left( \delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e_2^{-j\omega_k^t} \right\|_2^2 + \left\| f(t) - \sum_{k=1}^K u_k(t) \right\|_2^2 + \lambda(t), f(t) - \sum_{k=1}^K u_k(t), \quad (3)$$



In this context, the parameter  $\alpha$  represents the penal factor, and  $\lambda$  signifies the Lagrangian multiplier. To address this equation iteratively, the Alternating Direction Method of Multipliers (ADMM) is employed by the VMD. Ultimately, the initial signal undergoes decomposition into  $K$  intrinsic mode function (IMF) elements. In the context of the study the intrinsic mode function – IMF, is defined as  $M1$  denoting short term,  $M2$  &  $M3$  denoting medium term and  $MA_{agg}$  denoting long term. The code for implementing the VMD technique is accessible through Hamilton and Ferry's (2017) suite named "VMD."

### **The QR and QQR approaches**

To scrutinise the interplay between economic uncertainty and financial asset returns across different frequencies, this study commences with linear regression analyses before transitioning into a QR framework. The utilisation of quantile QRA, a methodology presented by Koenker and Bassett (1978), has evolved into a commonplace technique for modelling the dynamic extent and configuration of interdependence. It encompasses a collection of regression lines that diverge over assorted quantiles of the conditional distribution of the response variable. These quantiles encapsulate distinct phases of the dependent variable's time-varying behaviour. In contrast to conventional linear correlation or regression approaches, quantile functions furnish a better evaluation of the covariates' influence on the dependent variable. Moreover, they capture potential non-stationarity within the series, offering a more nuanced perspective on the complex relationships present (as discussed in Koenker & Ng, 2005).

Furthermore, the utility of employing QRA is underscored by its capacity to furnish insights into tail dependence, encompassing both higher and lower tails, in supplement to the median. The study employed the Quantile regressions technique owing to the non-linear nature of the return series of the data as established by the Jarque-bera test. The Jarque-bera test as shown in the descriptive statistics reveal that the return series are not normally dispersed. Again, the descriptive statistics also revealed that the data is largely negatively skewed. This motivated the study to embrace the quantile regressions technique to effectively capture how economic uncertainty affect returns of assets across different time horizons.

Nonetheless, it's important to acknowledge a limitation inherent to the QRA methodology – its incapability to encapsulate dependency in its completeness. In particular, while QRA can effectively calculate the heterogeneous correlation regarding financial asset returns and economic uncertainty across different locations of the conditional distribution of the former, it falls short in encompassing the potential impact of the magnitude (i.e., magnitude of uncertainty) on the nexus among financial assets and economic uncertainty. This nuanced facet, unfortunately, eludes quantile regressions.

Accordingly, instead of resorting to the conventional QRA method, the present study aligns with the approach set forth by Sim and Zhou (2015), introducing a QQR methodology. This QQR paradigm enables the modelling of financial asset return quantiles, encompassing diverse frequencies, in relation to the quantiles of the economic uncertainty index. This strategic alignment offers

the advantage of acknowledging potential variations in the nexus among these variables across diverse points of their respective distributions. The QQR technique, as such, furnishes a more comprehensive depiction of interdependency.

Its application involves selecting multiple quantiles of uncertainty and subsequently assessing the localised influence exerted by these specific uncertainty quantiles on a range of financial asset return quantiles.

Within the confines of this investigation, our focus is directed toward this interrelation, commencing with the following equation:

$$FR_t = \beta^\theta (EU_t) + \mu_t^\theta \quad (4)$$

where  $FR_t$  represent the returns of financial assets and  $EU_t$  represents the uncertainty indices (i.e global EPU, country-level EPU, OVX and GPR indices) at period t. The term  $\beta^\theta(\cdot)$  signifies the coefficient characterising the association between the returns of financial assets and the uncertainty indices at a specific conditional level, while the  $\theta^{\text{th}}$  quantile of  $FR_t$  in equation (4), which is conditionally distributed is denoted by  $\theta$ . Additionally,  $\mu_t^\theta$  is the error term corresponding to the  $\theta^{\text{th}}$  quantile. Equation (4) can be construed as a foundation for the quantile regression, thereby forming the basis for the subsequent derivation of QQR.

Through a primary Taylor expansion of the  $\tau$  quantile of FR, equations (4) is extended, resulting in equation (5) presented as follows:

$$\beta^\theta FR_t \approx \beta^\theta (EU^\tau) + \beta^{\theta'} (EU^\tau)(EU_t - EU^\tau) \quad (5)$$

The derivative of  $\beta^\theta FR_t$  is defined by  $\beta^{\theta'}$ , signifying a proportional effect resembling the slope. Notably,  $\theta$  embodies the functional depiction of  $\beta^\theta FR_t$  as well as  $\beta^\theta(EU^\tau)$ , from equation (4), while  $\tau$  encapsulates the functional representation of  $EU$  and  $EU^\tau$  in relation to equation (5). Hence,  $\theta$  and  $\tau$  serve as functional renderings of  $\beta^\theta(EU^\tau)$  and  $\beta^{\theta'}(EU^\tau)$ , respectively, within equation (5). Upon substituting  $\beta^\theta(EU^\tau)$  and  $\beta^{\theta'}(EU^\tau)$  from equation (5) for  $\beta_0(\theta, \tau)$  and  $\beta_1(\theta, \tau)$ , equation (6) is inferred as follows:

$$\beta^\theta(FR_t) \approx \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(EU_t - EU^\tau) \quad (6)$$

Equation (5) can now be inserted into equation (4), leading to the formulation of equation (7) as:

$$FR_t = \beta_0(\theta, \tau) + \beta_1\left(\frac{\theta}{(*)}, \tau\right)(EU_t - EU^\tau) + \mu_t^\theta \quad (7)$$

Where the term  $(*)$  results in the conditional quantile of  $\theta$ th quantile of returns on  $EU$  as presented in equation (7). This expression also effectively illustrates the actual responsiveness of  $FR(\tau$ th) to disturbances stemming from the  $\theta$ th quantile of  $EU$ , denoting the factors  $\beta_0$  and  $\beta_1$  with corresponding indices  $\theta$  and  $\tau$  in relation to equation (7).

Similar to the situation encountered in the Ordinary Least Squares (OLS) framework, we employ a comparable minimization process, leading to the formulation of the subsequent equation.

$$\min_{b_0, b_1} \sum_{i=1}^n p^\theta [FR_t - b_0 - b_1(EU_t - EU^\tau)] K \left( \frac{F_n(EU_t) - \tau}{h} \right) \quad (8)$$



In this particular case, the mathematical definition of the quantile loss function,  $\rho_{\theta}(u)$  is,  $\rho_{\theta}(u) = u(\theta - I(u < 0))$ , wherein  $I$  serves as an indicator function. The kernel density function (KDF), represented by  $K(\bullet)$ , and the bandwidth parameter,  $h$ , play pivotal roles. The observations of  $EU_{\tau}$  are endowed with weights through the KDF, with these weights inversely linked to the distribution of  $EU_{\tau}$ , expressed as  $F_n(EU_{\tau}) = (1/n) \sum_{k=1}^n I(EU_k < EU_{\tau})$ . The bandwidth chosen for the quantiles employed in this study for the QQR analysis ranges from  $h = [0.05 \text{ to } 0.95]$ , aligning with the criteria established by Sim and Zhou (2015). The bandwidth, which stands for the distributions of the quantiles, determines how smoothly the estimated results are distributed. It is advised to use smaller bandwidths rather than bigger ones because the latter could result in inaccurate estimates of the coefficients (Sim & Zhou, 2015).

### Wavelet Approach

The study employed the wavelet approach, which was first pioneered by Goupillaud et al. (1984), to study the time-frequency dependence of financial asset returns and global uncertainty. The flexibility of financial time series in response to operational shifts that transpire over different time periods (Lo, 2004), combined with the heterogeneity inherent in the series at different inherent intervals (Müller et al., 1997), necessitates examinations conducted from time and frequency standpoints. This underscores the indispensability of wavelet methodologies in the dynamic evaluation of financial time-series data.

In the context of this investigation, the utilisation of the biwavelet approach proves pertinent for the exploration of co-movements existing between

two variables over both time and frequency domains. This underscores that the biwavelet methodology is confined to the analysis of solely two variables at any given temporal instance. Unlike the quantile regression which doesn't reveal time and frequency nexus as well as the lead-lag association, the biwavelet technique determines the comovement and lead or lag relationship among the proxies for economic uncertainties and financial assets over investment times (short, medium, and long-term). The methodologies utilised in this contemporary investigation have found broader utilisation across an array of inquiries within the realm of financial and economic literature (Fernández-Macho, 2012; Adebayo & Akinsola 2021; Haseeb et al., 2020; Boateng et al., 2022a; Asafo-Adjei et al., 2021; Owusu Junior et al., 2021a).

The roots of wavelets ( $\psi$ ) go back to the Morlet family of wavelets. The equation for  $\psi(t)$  is

$$\psi(t) = \pi^{-1/4} e^{-i\omega t} e^{-\frac{1}{2}t^2}, p(t), t = 1, 2, 3 \dots T \quad (9)$$

$\psi$ , which includes the parameters frequency ( $z$ ) and spatial disposition ( $h$ ).

Whereas  $z$  regulates the enlarged wavelet to localise different frequencies (that is, short term (2-4 months), medium term (4-16 months) and long term (above 16 months)), the major function of the ( $h$ ) stricture is to determine a wavelet's specific position in time by swapping the wavelet.  $\psi_{h,z}$  can formerly be achieved by transforming  $\psi$ . The ensuing alteration can be described as follows.:

$$\psi_{h,z}(t) = \frac{1}{\sqrt{z}} \psi\left(\frac{t-n}{z}\right), h, z \in \mathbb{R}, z \neq 0 \quad (10)$$

The perpetually oscillating wavelet can be synthesised through the mathematical operation involving  $\psi$ , which functions in relation to parameters  $h$

and  $z$ , under the condition of being presented with the temporal sequence information denoted by  $f(t)$ :

$$w_p(h, z) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{z}} \psi\left(\frac{t-h}{z}\right) dt \quad (11)$$

The recreated times series  $f(t)$  with the  $\psi$  coefficient is

$$f(t) = \frac{1}{c_\psi} \int_0^{\infty} \left[ \int_{-\infty}^{\infty} |w_f(a, b)|^2 da \right] \frac{db}{b^2} \quad (12)$$

The study employs the wavelet coherence method founded on the second goal of the current investigation. The key advantage of the wavelet coherence method over the quantile regression methodology is that it allows the research to depict any association regarding the two-time sequences  $f(t)$  and  $j(t)$  in joint time-frequency-based comovement. The following is the time series' cross wavelet transform (CWT):

$$w_{F_j}(h, z) = w_f(h, z) \overline{w_j(h, z)} \quad (13)$$

Whereas  $W_f(h, z)$  and  $W_j(h, z)$  stand for the respective CWT of two time series,  $f(t)$  and  $j(t)$  (Kirikkaleli, 2019).  $f(t)$  denotes the returns of financial assets (G7 stocks, gold, BTC and EUAF), while  $j(t)$  denotes the returns of economic uncertainties proxies (Global EPU, OVX, and GPR). The equation for the quadratic wavelet coherence is provided by Orhan, Kirikkaleli, and Ayhan (2019).

$$R^2(h, z) = \frac{|c(z^{-1}w_{fj}(h, z))|^2}{C(z^{-1}|W_f(h, z)|^2)C(z^{-1}|W_j(h, z)|^2)} \quad (14)$$

where  $C$  displays the levelling process across time, alongside  $0 \leq R^2(h, z) \leq 1$ . Obtaining a value of zero for  $R^2(h, z)$  in the wavelet coherence Figures demonstrates that there is no association regarding the time-series variables  $f(t)$

and  $j(t)$ . As  $R^2(h, z)$  approaches 1, this scenario is depicted in blue in the image and implies that the variables  $f(t)$  and  $j(t)$  correspond on a specific scale (Kirikkaleli, 2019). In context, the output of  $R^2(h, z)$  denotes the time varying relationship between the returns of economic uncertainties and financial assets. Torrence and Compo (1998) proposed a technique for detecting the wavelet coherence discrepancies over pointers of deferments in the vacillating of two time series' since getting the value of  $R^2(h, z)$  does not offer any means of discriminating an adverse association from a positive association (Pal & Mitra, 2017). The wavelet coherence difference phase equation is developed as

$$\phi_f(h, z) = \tan^{-1} \left( \frac{L\{C(Z^{-1}W_{fj}(h, z))\}}{O\{C(Z^{-1}W_{fj}(h, z))\}} \right) \quad (15)$$

Where L stands for an imaginary operator and O represents a real operator. The variance in wavelet coherence, which emerges, draws attention as a wellspring of inspiration shaping the phase-pattern dimension within the map of wavelet coherence. In the graphical depiction of the biwavelet, arrows are employed to denote rightward and leftward movements, as well as upward and downward movements. Correspondingly, rightward, and upward arrows signify downward and leftward, while rightward and downward arrows symbolise upward and leftward directions, indicating the precedence between the first and second variables respectively. Regions with a profusion of shared movements are denoted by a red (warm) hue, while areas with fewer shared movements are depicted in blue (cool) tones (Agyei et al. 2022). The findings bear limited relevance beyond the confines of the sphere of influence (COI).



### Diks and Panchenko Nonlinear Causality Test

Ultimately, this investigation employs the non-linear causality assessment formulated by Diks and Panchenko (2006) in order to scrutinise the underlying causal connection between economic uncertainties and the yields of financial assets. This examination in turn serves as a robustness test for the quantile regression and wavelet techniques employed in the study.

Diks and Panchenko (2005, 2006) assert that their devised methodology mitigates the risk of overly discarding the null hypothesis of absence of causality, a phenomenon noted in the Hiemstra and Jones (1994) approach. The approach set forth by Diks and Panchenko (2006) introduces a novel nonparametric test for Granger non-causality, adept at averting undue rejections, achieved by substituting the comprehensive test statistic with an amalgamation of local measures of conditional dependence. Grounded in these rationales, the present inquiry employs the Diks and Panchenko (2006) nonlinear causality assessments as a cornerstone of this study's analytical framework.

Let's consider that  $X_t^{lX} = (X_{t-\ell X + 1}, \dots, X_t)$  and  $Y_t^{lY} = (Y_{t-\ell Y + 1}, \dots, Y_t)$  represent the delay vectors, where  $\ell X$  and  $\ell Y$  are both greater than or equal to 1. Again,  $\ell X$  and  $\ell Y$  represent the returns of the response and predictor variables. In context,  $\ell X$  represents the returns of Global EPU, OVX and GPR while  $\ell Y$  represents the returns of the G7 stocks, gold, BTC and EUAF. The null hypothesis, denoting that  $X_t^{lX}$  encompasses supplementary information regarding  $Y_{t+1}$  is formally expressed as follows:

$$H_0 = Y_{t+1} | (X_t^{lX}; Y_t^{lY}) \sim Y_{t+1} | Y_t^{lY} \quad (16)$$

The null hypothesis transmutes into an assertion concerning the unchanging dispersion of the  $(\ell X + \ell Y + I)$  dimensional vector, denoted as  $W_t = (X_t^{\ell X}, Y_t^{\ell Y}, Z_t)$ , where  $Z_t = Y_t + 1$ . In case we disregard the temporal marker and presume that  $\ell X = \ell Y = 1$ , then the dispersion of  $Z$ , given the condition  $(X, Y) = (x, y)$ , mirrors that of  $Z$ , given  $Y = y$ . To put it differently,  $X$  and  $Z$  exhibit conditional independence, given  $Y = y$ , for every fixed value of  $y$ . Consequently, the joint probability density function  $f_{X, Y, Z}(x, y, z)$  and its individual marginal distributions must conform to the subsequent relationship:

$$\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} = \frac{f_{X,Y}(x,y)}{f_Y(y)} \frac{f_{X,Z}(y,z)}{f_Y(y)} \tag{17}$$

Diks and Panchenko (2006) demonstrate that the reformulated null hypothesis leads to the following implication:

$$q \equiv E [f_{X,Y,Z}(X, Y, Z) f_Y(Y) - f_{X,Y}(X, Y) f_{Y,Z}(Y, Z)] = 0 \tag{18}$$

where  $\hat{f}_w(W_i)$  symbolizes a restricted intensity estimator of a dW-variate random vector  $W$  at the point  $W_i$ , as demonstrated by:

$$\hat{f}_w(W_i) = (2\varepsilon_n)^{-d} W (n-1)^{-1} \sum_{j \neq i} I_{ij}^w, \text{ where } I_{ij}^w = I\left(\|W_i - W_j\| < \varepsilon_n\right), I(\cdot) \text{ the indicator function and } \varepsilon_n \text{ the bandwidth, contingent on the sample size } n,$$

play pivotal roles. The test statistic, a scaled empirical counterpart of  $q$  in equation (18), is streamlined to:

$$T_n(\varepsilon_n) = \frac{n-1}{n(n-2)} \cdot \sum_i (\hat{f}_{X,Z,Y}(X_i, Z_i, Y_i) \hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i, Y_i) \hat{f}_{X,Z}(Y_i, Z_i)) \tag{19}$$

where  $T_n$  is comprised of a weighted mean of local contributions,  $(\hat{f}_{X,Z,Y}(X_i, Z_i, Y_i) \hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i, Y_i) \hat{f}_{X,Z}(Y_i, Z_i))$  that progressively converge to

zero in terms of probability within the confines of the null hypothesis. Diks and Panchenko (2006) furnish a proof that stipulates, under the condition  $\varepsilon_n = Cn^{-\beta}$  ( $C > 0, \frac{1}{4} < \beta < \frac{1}{3}$ ) for a single lag, then the test statistic as presented in

equation (19) satisfies the subsequent criterion:

$$\sqrt{n} \frac{(T_n(\varepsilon_n) - q)}{S_n} \xrightarrow{D} N(0,1) \quad (20)$$

Where  $\xrightarrow{D}$  signifies convergence in distribution, and  $S_n$  represents an estimator for the asymptotic variance of  $T_n(\cdot)$ .

### Chapter Summary

This section expounded upon the methodologies harnessed in the execution of the investigation. The study operates within the framework of the post-positivism research paradigm, adopting a quantitative research approach. Furthermore, the study is characterised by its utilisation of an explanatory research design, as its primary objective is to scrutinise the intricate interplay between economic uncertainty and the yields of financial assets. The time frame of the study covered a monthly data series from January 2012 to December 2022. The chapter also brings to bear the source and measurement of the variables under study.

This chapter highlights the descriptive statistics as well as the trend analysis that motivated the empirical technique the study employed. The study employed the VMD technique to segregate the data series and also utilised the QR technique to assess the asymmetric nexus regarding the dependent and independent variables. The quantile-on-quantile regression technique was employed as a robust test for the quantile regression estimates. The wavelet

analysis was conducted to reveal the time and frequency domain comovement between the dependent and independent variables. Finally, the Diks and Panchenko non-parametric causality was employed to test the causal nexus regarding the dependent and independent variables as well as a robustness test for the quantile regression and wavelet technique.





## CHAPTER FOUR

### RESULTS AND DISCUSSION

#### Introduction

In this section, the exposition and deliberation of the estimation outcomes are presented. The chapter begins by showcasing the descriptive statistics pertaining to the variables under study. It further encompasses the computation of trend analyses concerning the time-varying prices and returns of economic uncertainty variables, in addition to the assets under examination. This examination extends to both the original (signal) series and the segregated series (M1, M2, M3, and MAgg). Regarding the segregated series, M1 represent the short term, M2 and M3 represent the medium term and MAgg represents the long term. The study highlights and discusses the findings for both the quantile regressions estimations and the wavelet technique in relation to the objectives and with orientation to the empirical literature review in this study. The study further presents the quantile-on-quantile estimates as a robustness test for the QR estimates.

The Diks and Panchenko (2006) nonlinear causality test is also employed by the study to examine the causal relationships that exist in the variables under study and in turn to serve as robustness test for the quantile regression and wavelet techniques employed in the study. It is relevant to note that for want of space and brevity, the study presents the descriptive statistics for the uncertainty indices and the decomposed trend plots of uncertainty indices and financial assets in Appendix A, while the M3 quantile results are presented in Appendix B. The

study presents the M3 quantile results in Appendix B because of the similarity in finding with M2 for which both represent the medium term.

### **Descriptive Statistics**

This section examines the fundamental attributes of the variables employed in the study. Consequently, the mean serves as a representation of the arithmetic average of each of the variables, the median corresponds to the middle observation within the variables. The standard deviation provides insight into the temporal fluctuations within the time series, offering a measure that can elucidate the volatility present among the returns within the variables. The skewness and kurtosis encapsulate the distribution characteristics of the returns in the time series. The Jaque-bera test examines the returns of the series for normality. The test criteria are that if the test statistics are further away from zero, then it implies that the data is not normally distributed. The Augmented Dickey-Fuller (ADF) and Phillips and Perron Test (PP) unit root test determines whether the return series is stationary.

**Table1: Summary Descriptive Statistics of Financial Asset Returns**

Statistics	US	UK	France	Germany	Italy	Japan	Canada	Gold	BTC	EUAF
					Signal					
Mean	0.0082	0.0001	0.0036	0.0043	0.0016	0.0042	0.0011	0.0004	0.0622	0.0173
Std. dev.	0.0417	0.0465	0.05374	0.0558	0.0690	0.0432	0.0494	0.0415	0.2761	0.1382
Skewness	-0.6261	-0.5879	-0.0943	-0.3530	-0.3902	-0.3284	-0.9746	0.1443	1.8100	-0.6719
Kurtosis	0.9752	1.7349	1.4775	0.5317	1.4898	0.8552	3.7486	-0.1376	9.2363	0.5641
Jarque Bera	14.622***	25.564***	13.256***	4.6595*	16.67***	6.9761**	102.25***	0.51297	558.08***	12.178***
ADF	-5.163***	-4.772***	-4.389***	-4.837***	-4.465***	-4.591***	-4.818***	-4.794***	-4.368***	-3.658**
PP	-137.81***	-128.01***	-134.43***	-122.95***	-139.78***	-123.89***	-137.18***	-122.97***	-110.75***	-158.18***
					M1					
Mean	0.0079	0.0000	0.0014	0.0023	0.0005	0.0027	0.0005	0.0002	0.0586	0.0138
Std. dev.	0.0070	0.0109	0.0147	0.0136	0.0197	0.0099	0.0118	0.0080	0.0706	0.0331
Skewness	-0.9043	0.1638	0.2456	-0.0333	0.1108	-0.2431	0.2200	0.4222	0.0713	0.3723
Kurtosis	0.6845	-0.0786	-0.4573	-0.9740	-0.9384	-0.1832	-0.1105	0.1663	-0.6626	-0.8433
Jarque Bera	21.424***	0.61052*	2.3201*	4.9156*	4.7992*	1.4377*	1.1132*	4.2661*	2.2754**	6.7301**
ADF	-5.0167***	-5.1836***	-4.7069***	-5.4282***	-4.6039***	-5.8795***	-4.9701***	-3.5731**	-4.3404***	-4.6519***
PP	-2.3382	-16.022	-16.017	-10.296	-16.5	-9.3133	-11.386	-6.8361	-4.0971	-5.9218
					M2					
Mean	0.0000	0.0000	0.0003	0.0003	0.0002	0.0002	0.0001	0.0000	0.0010	0.0006
Std. dev.	0.0055	0.0074	0.0104	0.0100	0.0146	0.0090	0.0074	0.0098	0.0729	0.0276
Skewness	-0.6632	-0.2210	-0.2304	-0.1448	-0.0469	-0.0886	-0.0125	-0.0802	0.0675	-0.3209
Kurtosis	1.3119	0.0269	-0.5961	-0.5438	-0.7560	0.0986	-0.0623	-0.6451	-1.1243	-0.1938
Jarque Bera	20.345***	1.1284*	2.9154*	1.8811*	2.9138**	0.29417*	0.0051656	2.1846**	6.7038**	2.4426**
ADF	-6.5054***	-8.2021***	-6.7079***	-7.914***	-6.262***	-6.8929***	-7.847***	-6.9215***	-4.7856***	-5.0091***

Table 1, Continued

PP	-36.839***	-42.975***	-40.713***	-37.653***	-40.052***	-36.623***	-43.603***	-40.411***	-21.315**	-34.626***
	M3									
Mean	0.0000	0.0000	0.0001	0.0001	0.0000	0.0001	0.0000	0.0000	0.0001	0.0001
Std. dev.	0.0123	0.0135	0.0192	0.0184	0.0229	0.0135	0.0134	0.0074	0.1175	0.0507
Skewness	-0.1472	-0.1629	0.0027	-0.0852	-0.0184	0.0020	-0.1500	0.0673	0.1067	0.0013
Kurtosis	0.8584	1.9876	0.6242	1.2995	0.1764	-0.4512	1.0455	-0.8785	2.6201	-0.9640
Jarque Bera	5.1179*	24.03***	2.5411**	10.417***	0.28618**	0.93409*	7.2516**	4.0384*	40.538***	4.7854*
ADF	-10.548***	-11.523***	-12.161***	-10.946***	-12.536***	-11.174***	-10.957***	-9.7727***	-11.195***	-10.236***
PP	-42.246***	-41.829***	-37.156***	-47.048***	-37.229***	-41.569***	-44.007***	-44.629***	-42.34***	-31.53***
	M(Agg)									
Mean	-0.0002	0.0000	-0.0018	-0.0016	-0.0008	-0.0011	-0.0005	-0.0001	-0.0020	-0.0026
Std. dev.	0.0341	0.0355	0.0393	0.0418	0.0510	0.0330	0.0384	0.0325	0.1876	0.1050
Skewness	-0.0813	-0.0465	-0.0863	-0.0368	0.1497	0.0492	0.3603	-0.0177	-1.0666	0.3259
Kurtosis	0.8327	0.1915	-0.0471	0.2422	0.1546	0.0822	2.6258	-0.0687	8.3700	0.4479
Jarque Bera	4.5191*	0.36652*	0.16747*	0.49897**	0.73114*	0.14658	43.374***	0.010206	427.13***	3.7698*
ADF	-6.1774***	-6.6584***	-7.8708***	-7.9767***	-7.6381***	-6.9998***	-7.661***	-8.7586***	-6.7527***	-7.0996***
PP	-156***	-155.06***	-171.63***	-148.81***	-172.73***	-143.39***	-161.62***	-138.41***	-155.77***	-192.05***

Note: \*\*\*, \*\*, and \* indicate significance levels of 1%, 5%, and 10% respectively. The dataset encompasses monthly observations totaling 133 instances for each variable, recorded within the time span from 01/01/2012 to 31/12/2022. Descriptive statistics have been computed across seven distinct assessments for financial assets, spanning various frequencies including short-term, medium-term, and long-term, alongside the original series. The null hypothesis for the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests presumes the existence of unit roots. It is pertinent to note that the return series associated with the financial assets demonstrate a departure from normal distribution across all frequencies, whereas the majority of return series exhibit stationary behaviour.



Table 1 presents the descriptive statistics of the original (signal) as well as the decomposed data at M1 (short-term), M2 and M3 (medium-term), and the MAgg (long-term) frequency levels. It can be remarked that the majority of stock returns with the exception of MAgg (long-term), exhibit a positive mean, implying a potential for enhanced performance of the market. From the signal, it is evident that BTC has the highest average return in comparison to all other assets under study. It is however not surprising that BTC has the highest standard deviation indicating higher fluctuation in returns and higher risk.

The negative skewness for the majority of the asset returns indicates a fatter left-sided tail signifying that a higher occurrence of negative returns was observed during the studied period. The kurtosis statistics largely depict leptokurtic behaviour for the original return series but vary between positive and negative kurtosis across the decomposed series. The null hypothesis of normality for the original series as measured by the Jarque-Bera statistics is rejected at the 1% significance level, indicating that the returns of financial assets are not normally distributed. Additionally, the research paper compares the ADF and PP tests for the robustness of stationarity. It can be noticed from the ADF and PP test that all of the return series are stationary but for M1.

On the other hand, looking at the uncertainty indices as depicted in Table 2 of Appendix A, the global EPU indices have a positive mean value, alongside a comparatively modest standard deviation. In contrast, the German EPU index has the highest standard deviation, indicating that it transmits the most risk. Furthermore, the J-B statistics of the signal highlight that the majority of series do

not follow a normal distribution, with the exception being the EPU of the UK, France, Germany, and Canada. It can however be observed that US EPU at MAgg is normally distributed. The ADF and PP statistics collectively indicate that all the return series exhibit stationarity. The significance of using an asymmetric statistical technique capable of exposing associations across diverse market conditions is highlighted by the fact that the majority of return series, especially the signal is not normally distributed. This provides a compelling rationale for predominantly depending on a quantile-based approach which can effectively account for the presence of heavy-tailed distributions.

Conversely, in the case of risk and uncertainty indices (Global EPU, country-level EPU, OVX and GPR), the study observes that returns of the indices were highly volatile during the years 2020 and 2022 which reflect the spikes in the uncertainty indices during such global mishaps. In a general sense, it is apparent that the return series for the analysed assets display the phenomenon of volatility clustering, aligning with the commonly observed patterns found in the dynamics of various financial assets (Adam & Owusu Junior, 2017).

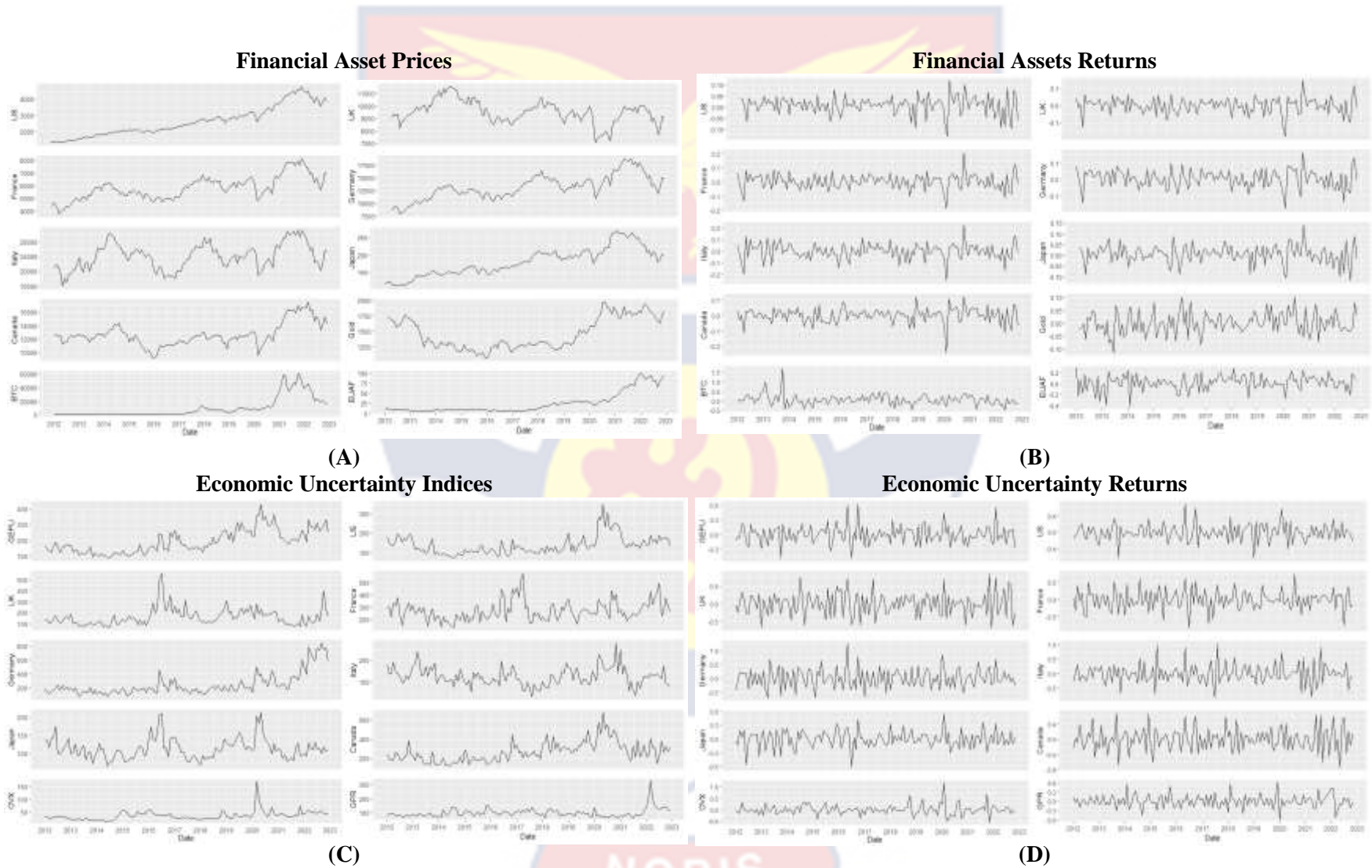


Figure 2: Plots of prices and returns for financial assets and uncertainty indices (original series).

Figure 1 (A-D) presents the time-varying prices and returns of Assets and Uncertainties for both the original (signal) and the disassembled series (M1, M2, M3, and MAgg). It can be particularly observed from the plots in Figure 1(A) that the prices of all the assets under consideration showed an upward trend from 2017 to early 2019. It is also evident that there was a sharp fall in the prices of all the assets (with the exception of Gold and BTC) in 2020, which can be related to the repercussions of the COVID-19 pandemic. There was again, a downward fall in prices of all the assets under study during the year 2022 which could be linked to the commencement of Russia's military operation in Ukraine and the associated spike in oil prices. It can however be observed that the price trend for most markets exhibits an upward trend subsequent to a downward dip. In other words, prices undergo a swift escalation, aligning with the observation posited by Zhang, Hu, and Ji (2020) that markets tend to recuperate following periods of stress. The phenomenon is attributed to the adaptive capacity of most businesses and economies to endure and recover from challenging circumstances.



## Quantile Regression Analysis

The study presents the findings of the frequency-dependent quantile regression for the original and segregated series. This paper utilises 19 quantiles to examine the asymmetric relationship between economic uncertainty and the financial assets under study. The study defines three market conditions from the threshold range ( $\tau = 0.05, 0.10, 0.15, \dots, 0.95$ ). For lower quantiles (bearish market), ( $\tau = 0.05, 0.1, 0.15, 0.20, 0.25, 0.30$ ) for intermediate quantiles (normal market), ( $\tau = 0.35, 0.40, 0.45, 0.50, 0.55, 0.60$ ) and ( $\tau = 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95$ ) for upper quantiles (bullish market).

### **Asymmetric relationship between economic uncertainties and the returns of financial assets.**

In harmony with the first aim of the study, this study examines the asymmetric nexus between economic uncertainties and returns of financial assets under study across the signal and segregated series (M1, M2, M3 and MAgg) using the VMD-based-quantile regressions technique.

**Table 3. Quantile Regression Results of GEPU and Financial Assets (Signal)**

Quantiles	US	UK	France	Germany	Italy	Japan	Canada	Gold	BTC	EUAF
0.05	-0.1070**	-0.1662**	-0.1790**	-0.1789***	-0.1836**	-0.1076**	-0.0926	-0.0257	-0.5178**	-0.3195**
0.10	-0.0613	-0.0583*	-0.0634	-0.0895	-0.1321**	-0.1195***	-0.0904**	-0.0014	-0.3910**	-0.1837**
0.15	-0.0520	-0.0497*	-0.0351	-0.0520	-0.0751	-0.0736*	-0.0791**	0.0320	-0.2947**	-0.2976**
0.20	-0.0336	-0.0729***	-0.0449	-0.0722	-0.0987**	-0.0488	-0.0573	0.0027	-0.3089*	-0.2569**
0.25	-0.0548**	-0.0610**	-0.0527**	-0.0639*	-0.0388	-0.0395	-0.0401	0.0247	-0.2224	-0.2070**
0.30	-0.0553**	-0.0487*	-0.0494*	-0.0787***	-0.0361	-0.0471**	-0.0061	0.0193	-0.1467	-0.2242**
0.35	-0.0402	-0.0432*	-0.0276	-0.0747**	-0.0437	-0.0501***	0.0118	0.0181	-0.2192	-0.2317**
0.40	-0.0368	-0.0213	-0.0204	-0.0861***	-0.0324	-0.0491***	0.0217	0.0407	-0.1488	-0.2589***
0.45	-0.0215	-0.0270	-0.0279	-0.0794***	-0.0541	-0.0539***	0.0225	0.0240	-0.0826	-0.2282**
0.50	-0.0205	-0.0354**	-0.0466	-0.0728***	-0.0691**	-0.0453*	0.0171	0.0124	-0.0285	-0.2297**
0.55	-0.0029	-0.0328*	-0.0586*	-0.0594**	-0.0458	-0.0520***	0.0139	0.0245	-0.1159	-0.1696
0.60	0.0048	-0.0283	-0.0675**	-0.0611*	-0.0503	-0.0468**	-0.0063	0.0203	-0.1450	-0.1460
0.65	0.0071	-0.0356	-0.0732**	-0.0420	-0.0337	-0.0406*	-0.0131	0.0019	-0.2053	-0.0817
0.70	0.0087	-0.0315	-0.0685**	-0.0509	-0.0496	-0.0526**	-0.0141	-0.0072	-0.1869	-0.0994
0.75	0.0070	-0.0229	-0.0323	-0.0213	-0.0510	-0.0558**	-0.0083	-0.0111	-0.2812	-0.0976
0.80	0.0013	-0.0411	-0.0417	-0.0323	-0.0251	-0.0249	0.0033	0.0274	-0.2133	-0.2042
0.85	0.0115	-0.0320	-0.0179	-0.0333	-0.0204	0.0234	0.0099	0.0412	-0.2424	-0.1953
0.90	0.0177	-0.0203	0.0076	0.0056	0.0289	0.0040	0.0015	0.0433	-0.1871	-0.0500
0.95	-0.0025	-0.0018	0.0025	0.0305	0.0577	0.0278	0.0167	0.0374	-0.2823	-0.0171

Note: \*\*\*, \*\*, and \* indicate statistical significance at levels of 1%, 5%, and 10%, respectively. ( $\tau = 0.05, 0.1, 0.15, 0.20, 0.25, 0.30$ ) denote bearish market, ( $\tau = 0.35, 0.40, 0.45, 0.50, 0.55, 0.60$ ) denote normal market, ( $\tau = 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95$ ) denote bullish market condition.

Table 3 displays the coefficient estimates derived from the quantile regression analysis of the original return series. Generally, it can be observed that the return of the Global EPU index has an adverse influence on the returns of the majority of the G7 stocks, BTC and the EUAF. Specifically, it is apparent from Table 3 that the Global EPU index has an adverse effect on the lower to intermediate quantiles of US stock returns but has a positive effect on the upper quantiles (with the exception of 0.95 quantile). This empirical result rests well with the findings of Guo, Zhu and You (2018) who argued based on empirical evidence that the EPU and the US equity market exhibit an asymmetric and tail dependence structure in the bearish and bullish markets.

Consistent with the findings of Gao, Zhu, O'Sullivan and Sherman (2019), the study observes that UK stock return is adversely affected by global EPU. The France, Germany, Italy, and Japan stock returns are negatively and statistically affected across varying quantiles, however, the study observes a positive relationship with EPU at 0.9 and 0.95 quantiles. The Canadian stock returns depict different dynamics as it shows positive and negative effects across their quantiles.

On the other hand, gold is seen to be positively correlated with the returns of global EPU which is consistent with the result of Jones and Sackey (2016) who came to the conclusion that rising EPU causes an increase in the returns of gold as a result of rising prices. With regard to the effect of GEPU on BTC and EUAF returns, the study observes that the BTC and EUAF returns are most affected by the Global EPU as it is negatively affected across all quantiles.

**Table 4. Quantile Regression Results of GEPU and Financial Assets (M1)**

Quantiles	US	UK	France	Germany	Italy	Japan	Canada	Gold	BTC	EUAF
0.05	-0.0515*	-0.0566	-0.0723	-0.0097	-0.0241	-0.0427	-0.0415	0.0412*	0.21248	0.06193
0.10	-0.0467**	-0.0369	-0.0219	0.02886	0.01116	-0.0165	-0.0364	0.0277	0.01490	0.1639*
0.15	-0.0389*	-0.0284	-0.0244	0.02745	-0.0127	-0.0029	-0.0174	0.0066	-0.0885	0.11674
0.20	-0.0193	-0.0141	-0.0388	-0.0079	0.01194	6.62E-05	-0.0151	0.0046	0.02972	0.08189
0.25	-0.0142	-0.0112	-0.0272	-0.0133	0.03049	-0.0030	-0.0237	0.0351	-0.0157	0.04473
0.30	-0.0027	-0.0279	-0.0265	-0.0069	0.02911	-0.0104	-0.0149	0.0336	-0.0851	0.06591
0.35	0.0054	-0.0279	-0.0087	-0.0034	-0.0064	-0.0138	-0.0054	0.0527	-0.1645	0.04618
0.40	0.0009	-0.0269	-0.0158	-0.0028	-0.0211	-0.0141	-0.0091	0.0370	-0.0799	-0.0521
0.45	-0.0017	-0.0217	-0.0292	-0.0016	-0.0219	-0.0104	-0.0009	0.0134	-0.0422	-0.041
0.50	-0.0004	-0.0239	-0.0269	-0.0116	-0.0207	-0.0153	0.0040	0.0118	-0.1961	-0.0405
0.55	-0.0033	-0.0208	-0.0174	-0.0166	-0.0132	-0.0264	0.0008	0.00208	-0.0789	-0.0826
0.60	-0.0042	-0.0190	-0.0165	-0.0277	-0.0365	-0.0454*	0.0088	-8.39E-05	-0.0253	-0.0819
0.65	0.0032	-0.0163	-0.0323	-0.0254	-0.0293	-0.0277	0.0065	-0.0063	-0.0739	-0.0627
0.70	-0.0021	-0.0136	-0.0162	-0.0426	-0.0683*	-0.0185	-0.0124	0.00547	-0.0617	-0.0035
0.75	0.0019	-0.009	-0.0255	-0.0386	-0.0717**	-0.0133	-0.0271	-0.0094	-0.0097	0.00893
0.80	0.0112	-0.0016	-0.0187	-0.0366*	-0.0807**	-0.0011	-0.0332	-0.0088	0.04071	0.00176
0.85	0.0079	-0.0223	-0.0306	-0.0455*	-0.0541*	0.01421	-0.0273	-0.0342	0.12790	-0.0259
0.90	-0.0047	-0.0204	-0.0347**	-0.0259	-0.0438	0.03768	-0.0228	-0.0542*	0.16055	-0.0249
0.95	0.0123	-0.0066	-0.0413*	-0.0279	-0.0537	0.05643*	-0.0159	-0.0525*	0.31137**	0.01217

Note: \*\*\*, \*\*, and \* indicate statistical significance at levels of 1%, 5%, and 10%, respectively. ( $\tau = 0.05, 0.1, 0.15, 0.20, 0.25, 0.30$ ) denote bearish market, ( $\tau = 0.35, 0.40, 0.45, 0.50, 0.55, 0.60$ ) denote normal market, ( $\tau = 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95$ ) denote bullish market condition.



**Table 5. Quantile Regression Results of GEPU and Financial Assets (M2)**

Quantiles	US	UK	France	Germany	Italy	Japan	Canada	Gold	BTC	EUAF
0.05	0.037785	-0.37439***	-0.4230***	-0.38716***	-0.6382***	-0.17466***	0.10337	0.1569***	0.43284	-0.1542
0.10	-0.11544	-0.36046***	-0.4442***	-0.41879***	-0.6265***	-0.23732***	-0.11851	0.1448***	-0.1250	-0.4133**
0.15	-0.14113	-0.33407***	-0.4541***	-0.42782***	-0.6340***	-0.23549***	-0.09142**	0.1005***	-0.5644	-0.4602***
0.20	-0.11787**	-0.32408***	-0.4400***	-0.41024***	-0.6180***	-0.22467***	-0.1432**	0.0239**	-0.6565	-0.4164**
0.25	-0.10685***	-0.33065***	-0.4735***	-0.38671***	-0.6082***	-0.20735***	-0.1748***	0.0049**	-0.7003**	-0.3509**
0.30	-0.10237***	-0.31141***	-0.4562***	-0.36936***	-0.5979***	-0.21556***	-0.1446***	0.0075*	-0.5877***	-0.26168
0.35	-0.08753***	-0.31463***	-0.4291***	-0.36105***	-0.5845***	-0.18544***	-0.1303***	0.0044*	-0.5547***	-0.21779
0.40	-0.0828***	-0.30394***	-0.4435***	-0.34987***	-0.5847***	-0.14822***	-0.1313***	0.0005	-0.5532***	-0.17998
0.45	-0.08917***	-0.28318***	-0.4437***	-0.34426***	-0.5966***	-0.1549***	-0.1364***	-0.007	-0.5644***	-0.24339
0.50	-0.10342***	-0.29032***	-0.4254***	-0.3386***	-0.5837***	-0.14841***	-0.1515***	-0.0039	-0.6419***	-0.23824
0.55	-0.10945***	-0.29207***	-0.4278***	-0.3494***	-0.5906***	-0.16504***	-0.1730***	-0.0159	-0.7296***	-0.26239
0.60	-0.10835***	-0.29985***	-0.4181***	-0.3486***	-0.5976***	-0.16052***	-0.2207***	-0.0101	-0.6908***	-0.20058
0.65	-0.10665***	-0.3102***	-0.4308***	-0.2884***	-0.5743***	-0.15909***	-0.2473***	0.0039*	-0.5712***	-0.2510**
0.70	-0.10656***	-0.30142***	-0.4256***	-0.2932***	-0.568***	-0.16181***	-0.2824***	0.0347**	-0.5325*	-0.3110***
0.75	-0.10351***	-0.28795***	-0.4060***	-0.2397***	-0.5280***	-0.15334***	-0.2625***	0.0642**	-0.53303	-0.3008**
0.80	-0.09168***	-0.28202***	-0.4285***	-0.2251***	-0.5256***	-0.14976***	-0.2572***	0.0833***	-1.1566***	-0.1962**
0.85	-0.09646***	-0.28722***	-0.4086***	-0.1762***	-0.5254***	-0.1405***	-0.2119***	0.1380***	-1.2367***	-0.2097*
0.90	-0.08977***	-0.26817***	-0.3723***	-0.1572***	-0.553***	-0.1158***	-0.1993***	0.1310***	-1.2962***	-0.0063
0.95	-0.05036*	-0.27375***	-0.3439***	-0.1575***	-0.4483***	-0.0967**	-0.1735***	0.09489	-0.7201*	0.12919*

Note: \*\*\*, \*\*, and \* indicate statistical significance at levels of 1%, 5%, and 10%, respectively. ( $\tau = 0.05, 0.1, 0.15, 0.20, 0.25, 0.30$ ) denote bearish market, ( $\tau = 0.35, 0.40, 0.45, 0.50, 0.55, 0.60$ ) denote normal market, ( $\tau = 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95$ ) denote bullish market condition.

In the short term (M1) as observed in Table 4, the asymmetric association regarding global EPU and the financial asset under consideration differs a bit. The US stock return in the short term is adversely and statistically affected by global EPU across all quantiles (except 0.05 quantile). A similar trend is observed for UK, Germany, France, Japan, Italy, Canada, BTC and EUAF market. Gold is however the only asset that is seen to have a positive and statistically significant nexus with GEPU at lower and intermediate quantiles (except 0.45 – 0.60 quantile) in the short term. It is apparent that in the short term, the EUAF market, BTC and the G7 stock market returns are negatively correlated with GEPU.

Tables 5 and 6 represent the medium-term trend of the decomposed series. Following from Table 5, it can be generally observed that although global EPU has an adverse effect on the majority of the financial asset returns under study, it is apparent that it is largely statistically insignificant in comparison to its short-term dynamics. It is relevant to note that gold which had a statistically positive nexus with global EPU in the short term, now with the exception of the 0.05 quantile, has an adverse nexus with global EPU. From Table 6 (M3), which is presented in Appendix B, gold is adversely related with global. This corroborates the finding of Jones and Sackey (2018) who also found a heterogeneous relationship between global EPU and the returns of gold. Regarding the EUAF returns, the study largely observes positive nexus with global EPU in the bearish market, negative relationship during normal market conditions and positive nexus in the bullish market. BTC on the other hand also depict heterogeneity in its relationship with global EPU

**Table 7. Quantile Regression Results of GEPU and Financial Assets (Magg)**

Quantiles	US	UK	France	Germany	Italy	Japan	Canada	Gold	BTC	EUAF
0.05	0.0446	-0.0007	-0.02443	0.0917	0.0046	-0.0171	0.01926	0.0118	-0.3944	-0.4357***
0.10	0.0243	-0.0038	-0.05599	0.0519	0.0026	0.0031	0.01467	0.0174	-0.1481	-0.2727*
0.15	0.0527	-0.0402	-0.03555	-0.0179	0.0079	0.0138	0.04488	0.0108	-0.2023	-0.265**
0.20	0.0196	-0.0042	-0.04193	-0.0065	0.0131	0.0092	0.00022	0.0143	-0.1042	-0.1922*
0.25	0.0157	-0.0035	-0.04823	-0.0235	0.0070	-0.0026	0.00387	0.0156	-0.0891	-0.2356***
0.30	0.0117	-0.0182	-0.01908	-0.0154	-0.0122	-0.0234	0.00625	0.0240	-0.0686	-0.2086***
0.35	0.0078	-0.0121	-0.01219	0.00247	-0.0239	-0.0263	0.02155	0.0093	-0.1786	-0.2121***
0.40	0.0092	-0.0082	-0.02063	-0.0025	-0.0099	-0.0066	0.02171	0.0144	-0.2090*	-0.2110***
0.45	-0.0010	0.0015	-0.02402	0.00578	0.0051	-0.0213	0.02380	0.0042	-0.2079	-0.1313
0.50	0.0046	-0.0041	0.004151	0.00834	0.0190	-0.0178	0.02501*	0.0167	-0.1795	-0.1189
0.55	-0.0014	-0.0006	0.007473	0.00508	0.0189	-0.0327	0.01709	0.0061	-0.1563	-0.0861
0.60	-0.0039	-0.0025	-0.00028	-0.0087	-0.0071	-0.0140	0.02294	-0.007	-0.2457	-0.1268**
0.65	-0.0204	-0.0103	-0.00619	-0.0281	-0.0332	-0.0122	0.03639*	0.0005	-0.2388	-0.1500**
0.70	-0.0107	-0.0157	-0.00257	-0.0323	-0.0085	-0.0374	0.02223	-0.004	-0.2563	-0.21***
0.75	-0.0102	-0.0395	-0.00918	-0.0436	0.0168	-0.0422	0.00235	-0.0152	-0.1897	-0.2147***
0.80	-0.0069	-0.0263	-0.00656	-0.0255	-0.0025	-0.0462	-0.0151	0.0091	-0.2537*	-0.286***
0.85	-0.0076	-0.0013	-0.00591	-0.0417	-0.0261	-0.0429	-0.0383	-0.0103	-0.311**	-0.236***
0.90	-0.0249	-0.0267	-0.00489	-0.0419*	-0.0482	-0.0417	0.0115	-0.0205	-0.371**	-0.1783**
0.95	-0.0682	-0.1019**	-0.07865**	-0.0489	-0.0871	-0.0465	-0.0651	-0.0097	-0.6501***	-0.1999

Note: \*\*\*, \*\*, and \* indicate statistical significance at levels of 1%, 5%, and 10%, respectively. ( $\tau = 0.05, 0.1, 0.15, 0.20, 0.25, 0.30$ ) denote bearish market, ( $\tau = 0.35, 0.40, 0.45, 0.50, 0.55, 0.60$ ) denote normal market, ( $\tau = 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95$ ) denote bullish market condition.

In the long term, Canadian stock returns provides a positively and significantly correlated with global EPU at 0.50 and 0.65 quantiles while gold is also positively correlated with EPU across varying quantiles. Again, it can be noticed that the dependence structure between global EPU and the financial assets changes over time with the long-term relationships portraying to be largely less adversely and significantly affected by global EPU. The only exception is the EUAF return which is adversely and significantly affected by global EPU even in the long term.

The general intuition on the examination between global EPU and financial asset returns is that overall, global EPU has an adverse effect on the returns of financial assets under study. With regard to the G7 stock markets, just as Guo, Zhu and You (2018) asserted, EPU indices have an adverse impact on the bearish market of all G7 stock market returns. Insight from the relationship that exists between the EPU indices, and the US stock returns (original signal) suggests an asymmetric and tail dependence structure in the bearish and bullish market, which corroborates well with the finding of Guo et al. (2018).

Again, the study observes that during the short term, the adverse effect of the EPU indices on stock returns is strong but it tends to weaken over the long term. This finding is supported by the work of Nusair and Al-Khasawneh (2022) who argued that the adverse effect of EPU on G7 stock returns lasts into the long term, but the effect is less significant as compared to the short term. The results of this study find asymmetry in the relationship that exists between EPU and stock



returns which is consistent with the Adaptive and heterogeneous market hypothesis.

On the gold-global EPU front, gold as established by numerous studies (Gao & Zhang, 2016; Arouri et al., 2015; Beckmann et al., 2015), is positively correlated with global EPU across some selected quantiles in the short and medium term. It should however be remarked that gold, in the long term is adversely associated with global EPU in the long term. This finding compliments the argument by Baur and Lucey (2010) that the safe haven attribute of gold is transient, depicting the heterogeneous relationship between global EPU and gold. Impliedly, investors with investment objectives geared towards the short and medium term might consider gold as a robust sanctuary and hedge in that respect.

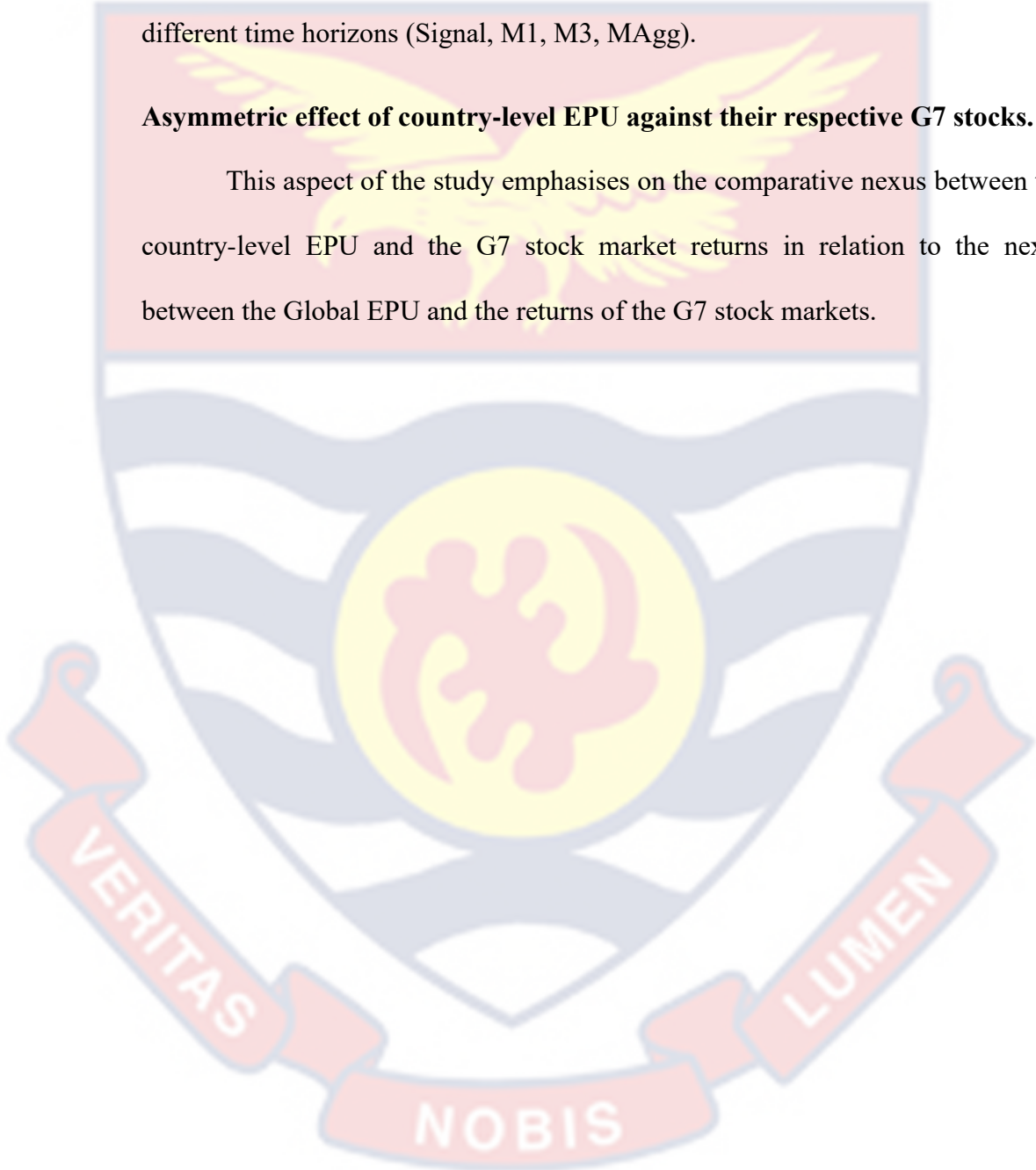
In harmony with the result of Wu et al. (2019), Smales (2019) and Mokni et al. (2021) the study finds that generally, bitcoin is extra receptive to global EPU changes. However, the results contradict that of Umar et al. (2021) who argued that BTC is positively correlated with EPU. The variance in the research findings could be because of the different data spans employed by Umar et al. (2021). Again, the contradiction in the findings reaffirms the study's initial position that the decline in BTC's market capitalisation could as well affect its potency as a safe haven as suggested by earlier studies.

Empirical evidence on the global EPU and the European Union allowance futures market (EUAF) posit that the market is largely affected negatively by EPU which is consistent with the finding of Dai, Xiong, Huynh and Wang (2020). Again, Wang et al. (2020)'s argument about the heterogeneous response of

China's carbon emission market against EPU is consistent with this study, since it can be observed that the EUAF market returns are largely positively correlated with global in the medium term (M2) although it is adversely affected across different time horizons (Signal, M1, M3, MA<sub>agg</sub>).

#### **Asymmetric effect of country-level EPU against their respective G7 stocks.**

This aspect of the study emphasises on the comparative nexus between the country-level EPU and the G7 stock market returns in relation to the nexus between the Global EPU and the returns of the G7 stock markets.

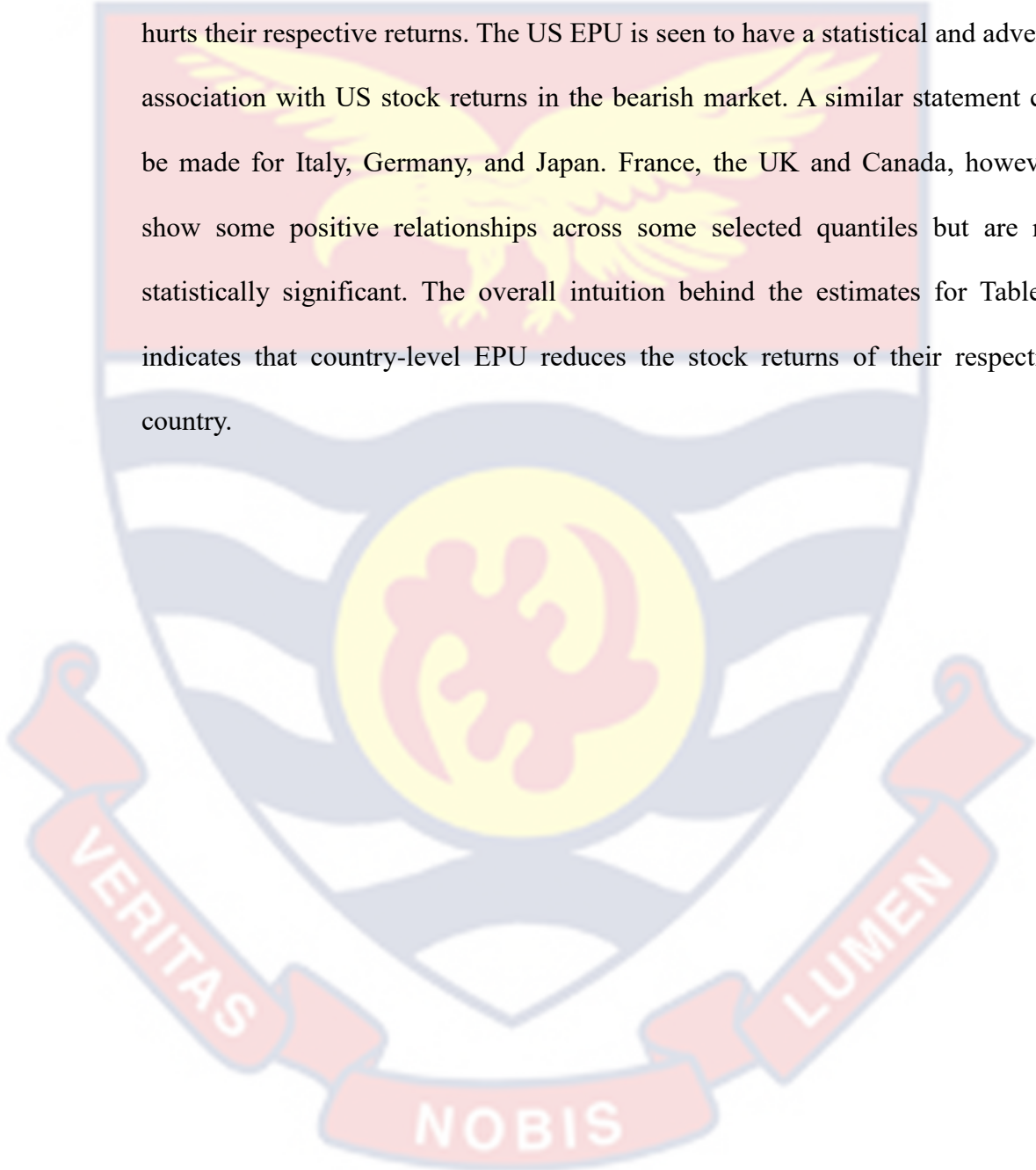


**Table 8. Quantile Regression Results of Country-Level EPU and the G7 Stock Returns (Signal)**

Quantiles	US	UK	France	Germany	Italy	Japan	Canada
0.05	-0.10843**	-0.03291	-0.02278	-0.06051	-0.15848**	-0.08811**	-0.00782
0.10	-0.11142**	-0.03795	0.009961	-0.04784	-0.09027**	-0.08746***	-0.01478
0.15	-0.09818***	-0.02402	-0.01058	-0.04182*	-0.09029**	-0.06696	-0.01211
0.20	-0.07191***	-0.02423	-0.03662	-0.03591**	-0.07143***	-0.04245	-0.01555
0.25	-0.06127***	-0.02664	-0.02801	-0.03374***	-0.07058**	-0.03256	-0.00289
0.30	-0.05568***	-0.02987*	-0.02353	-0.03752***	-0.06028***	-0.04691*	0.004053
0.35	-0.05486***	-0.01972	-0.02615	-0.0346***	-0.05334***	-0.04738*	0.005221
0.40	-0.03747**	-0.01902	-0.0268	-0.04447***	-0.04888**	-0.04688*	0.004422
0.45	-0.02595	-0.02278	-0.02565	-0.05064***	-0.05227***	-0.03352	-0.00011
0.50	-0.01961	-0.02032	-0.04248**	-0.04585***	-0.03689**	-0.04163*	-0.00786
0.55	-0.01637	-0.01843	-0.02617	-0.04222***	-0.03999**	-0.04824*	-0.01234
0.60	-0.01124	-0.01804	-0.01996	-0.03143*	-0.02715*	-0.04951*	-0.01144
0.65	-0.00771	-0.01934	-0.00668	-0.03462*	-0.03013*	-0.06201**	-0.00725
0.70	-0.00156	-0.00715	0.004514	-0.04253**	-0.02648*	-0.05132*	-0.00569
0.75	0.000254	-0.00056	0.013054	-0.02879	-0.01972	-0.04751	0.003722
0.80	-0.00495	-0.00406	0.022411	-0.01556	-0.01216	-0.03674	0.005427
0.85	-0.01808	0.005134	0.027262	-0.01214	-0.02933	-0.01685	-0.01288
0.90	-0.00842	0.01052	0.019431	-0.02219*	-0.02541	0.004178	-0.00704
0.95	-0.00208	-0.00042	-0.0003	-0.04848	0.003068	0.012341	-0.00523

Note: \*\*\*, \*\*, and \* indicate statistical significance at levels of 1%, 5%, and 10%, respectively. ( $\tau = 0.05, 0.1, 0.15, 0.20, 0.25, 0.30$ ) denote bearish market, ( $\tau = 0.35, 0.40, 0.45, 0.50, 0.55, 0.60$ ) denote normal market, ( $\tau = 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95$ ) denote bullish market condition.

Table 8 presents the original signal of the quantile regression coefficients of dependence between specific country-level EPU and the associated country. It can be generally observed that the country-level EPU of the respective countries hurts their respective returns. The US EPU is seen to have a statistical and adverse association with US stock returns in the bearish market. A similar statement can be made for Italy, Germany, and Japan. France, the UK and Canada, however, show some positive relationships across some selected quantiles but are not statistically significant. The overall intuition behind the estimates for Table 8 indicates that country-level EPU reduces the stock returns of their respective country.



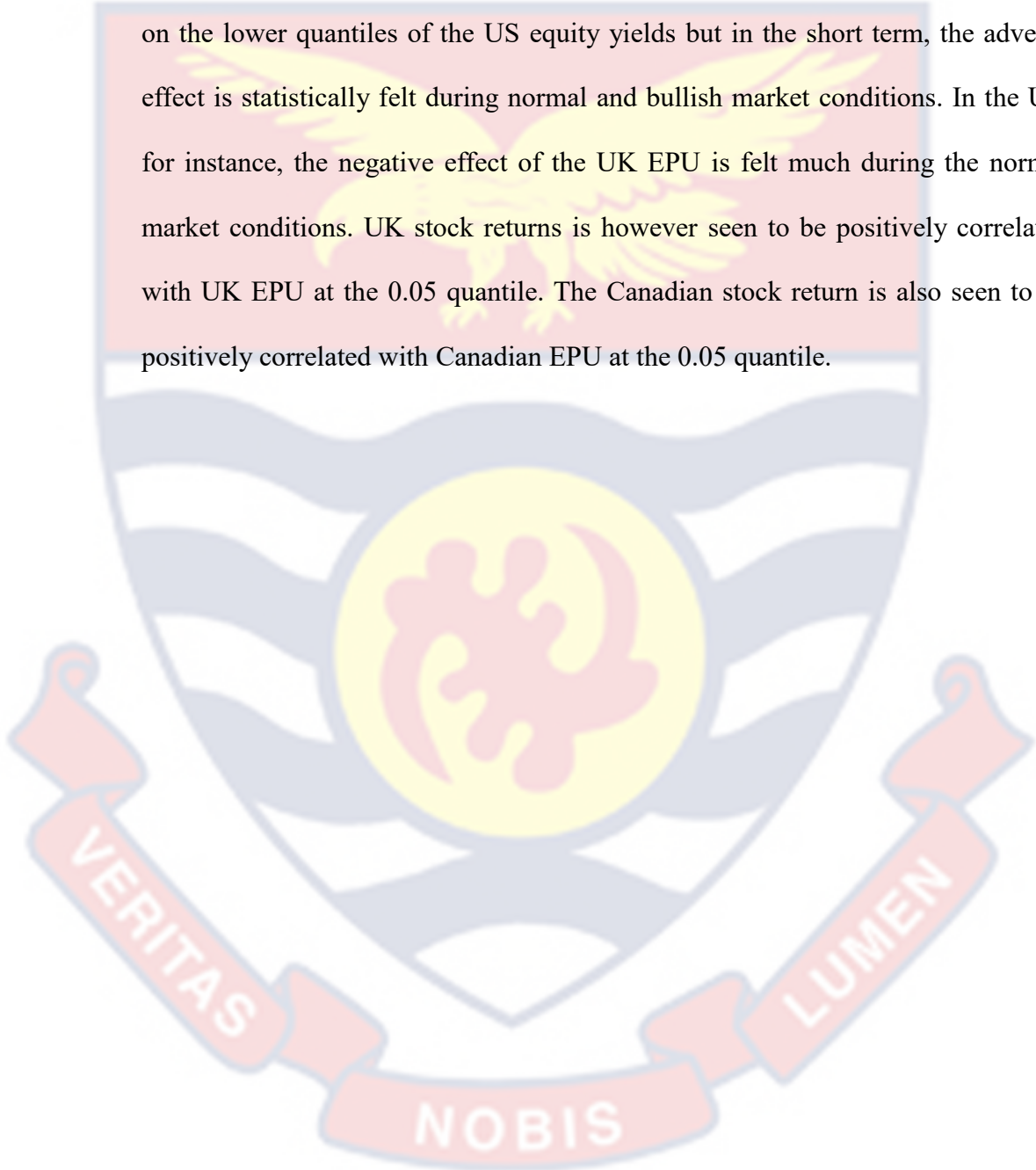


**Table 9. Quantile Regression Results of Country-Level EPU and G7 Stocks (M1)**

Quantiles	US	UK	France	Germany	Italy	Japan	Canada
0.05	0.035285	0.0486***	-0.03646	-0.05207	-0.1465***	-0.5017***	0.074793**
0.10	-0.07768	0.02479	-0.04225	0.00537	-0.1763***	-0.4087***	0.013944
0.15	-0.00969	-0.0021	-0.01876	-0.00136	-0.2175***	-0.3875***	0.008484
0.20	-0.04893	-0.0083	-0.01116	-0.01852	-0.2516***	-0.3486***	0.01722
0.25	-0.04707	-0.0122	-0.0232	-0.01405	-0.2406***	-0.3002***	0.004822
0.30	-0.0579	-0.029*	-0.02746	-0.01187	-0.2349***	-0.2896***	0.023087
0.35	-0.05633	-0.0387***	-0.02736	-0.02582	-0.2200***	-0.2739***	0.038519
0.40	-0.0919**	-0.0382***	-0.00309	0.001443	-0.2381***	-0.2242***	0.039109
0.45	-0.0881***	-0.0447***	0.006953	1.29E-05	-0.2318***	-0.2285***	-0.0036
0.50	-0.0735***	-0.0540***	0.013403	-0.00392	-0.2522***	-0.2137***	0.010957
0.55	-0.0608***	-0.0426***	0.003955	-0.02771	-0.2539***	-0.2003***	-0.01676
0.60	-0.0532**	-0.0447***	0.008316	-0.03418	-0.2521***	-0.1982***	-0.03507
0.65	-0.0572***	-0.0446***	0.038241	-0.0311	-0.2532***	-0.1846***	-0.02878
0.70	-0.0471**	-0.0333*	0.013593	-0.01689	-0.2494***	-0.1879***	-0.02156
0.75	-0.0416**	-0.0350*	0.01664	-0.00651	-0.2320***	-0.2079***	-0.03059
0.80	-0.05068**	-0.0203	-0.02011	-0.00329	-0.1903***	-0.2249***	-0.04408
0.85	-0.0545***	-0.0112	-0.01933	-0.00073	-0.1576***	-0.2193***	-0.09814
0.90	-0.0417***	-0.0971**	-0.01961	-0.01497	-0.1694***	-0.1760***	-0.1553***
0.95	-0.0317***	-0.1028***	-0.0709	-0.00515	-0.1482***	-0.1665***	-0.1602***

Note: \*\*\*, \*\*, and \* indicate statistical significance at levels of 1%, 5%, and 10%, respectively. ( $\tau = 0.05, 0.1, 0.15, 0.20, 0.25, 0.30$ ) denote bearish market, ( $\tau = 0.35, 0.40, 0.45, 0.50, 0.55, 0.60$ ) denote normal market, ( $\tau = 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95$ ) denote bullish market condition.

The short-term decomposition trend as depicted in Table 9 shows quite different dynamics with regard to the country-level EPU and stock returns. It is evident that in the original signal, US EPU had an adverse and significant effect on the lower quantiles of the US equity yields but in the short term, the adverse effect is statistically felt during normal and bullish market conditions. In the UK for instance, the negative effect of the UK EPU is felt much during the normal market conditions. UK stock returns is however seen to be positively correlated with UK EPU at the 0.05 quantile. The Canadian stock return is also seen to be positively correlated with Canadian EPU at the 0.05 quantile.



**Table 10. Quantile Regression Results of Country-Level EPU (M2)**

Quantiles	US	UK	France	Germany	Italy	Japan	Canada
0.05	-0.0373*	-0.0180	-0.01098	-0.02647	-0.01013	-0.0743**	-0.01446
0.10	-0.0361**	-0.01104	-0.0309**	-0.02341	-0.00317	-0.0214	-0.01117
0.15	-0.0361**	0.000813	-0.0353**	-0.01502	-0.00789	-0.0033	-0.00268
0.20	-0.0287*	0.004273	-0.03046	-0.01187	0.004145	0.0087	0.001981
0.25	-0.01784	0.002691	-0.01091	-0.00869	-0.01331	0.0036	0.004667
0.30	-0.00371	0.00414	-0.01766	-0.01645	-0.0176	-0.00522	0.011955
0.35	-0.00078	0.0064	-0.01201	-0.01036	-0.0093	-0.00459	0.011475
0.40	-0.0015	0.0008	-0.0149	-0.00881	-0.00523	-0.0054	0.009737
0.45	-0.00302	-0.0080	-0.01	-0.0039	-0.01915	-0.0025	0.009825
0.50	-0.00225	-0.0141	0.010433	0.000522	-0.01808	0.007288	0.006836
0.55	-0.0064	-0.0078	0.011632	-0.00163	-0.02126	-0.00231	0.002907
0.60	-0.00807	-0.0045	0.012827	-0.00422	-0.01714	-0.00894	0.003586
0.65	0.001603	-0.0023	0.014851	-0.01302	-0.01374	-0.01886	0.00487
0.70	-0.00425	-0.0036	0.010563	-0.01592	-0.03033	-0.02674	0.0126
0.75	-0.00743	-0.0017	0.000439	-0.01811	-0.0057	-0.01027	0.00675
0.80	0.005527	-0.0031	0.0066	-0.00936	0.019584	-0.01148	0.001437
0.85	0.002317	-0.0186*	0.0234*	-0.00331	-0.00141	0.004668	-0.00283
0.90	-0.00264	-0.0199	0.03242**	-0.00772	0.006178	0.016461	0.001341
0.95	0.014149	-0.0217	0.02085*	-0.00728	0.023908	0.02046	-0.01699

Note: \*\*\*, \*\*, and \* indicate statistical significance at levels of 1%, 5%, and 10%, respectively. ( $\tau = 0.05, 0.1, 0.15, 0.20, 0.25, 0.30$ ) denote bearish market, ( $\tau = 0.35, 0.40, 0.45, 0.50, 0.55, 0.60$ ) denote normal market, ( $\tau = 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95$ ) denote bullish market condition.

**Table 12. Quantile Regression Results of Country-Level EPU M(Agg).**

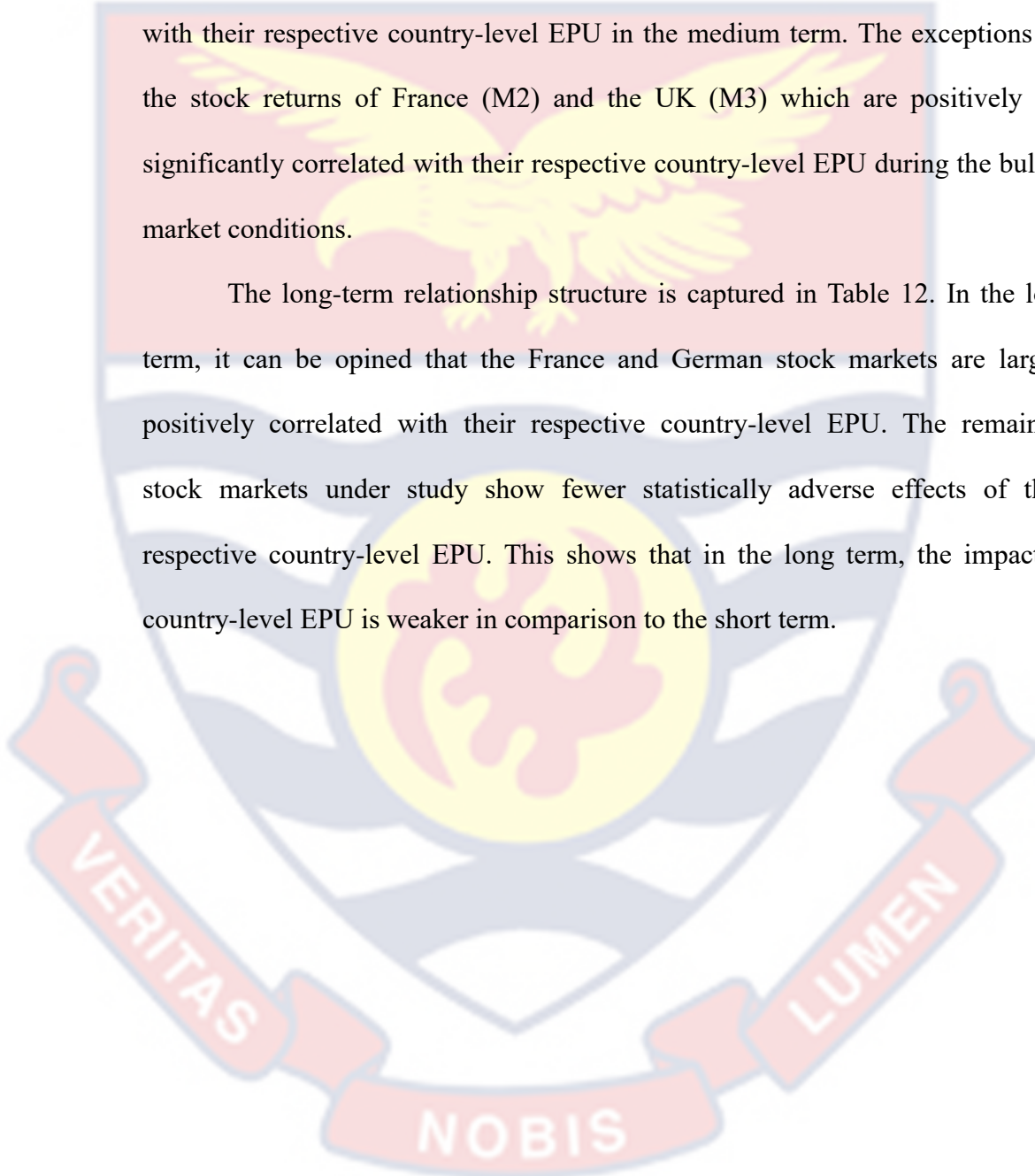
Quantiles	US	UK	France	Germany	Italy	Japan	Canada
0.05	0.030055	-0.01267	0.007594	0.034167	0.046085	0.004479	-0.00847
0.10	-0.01165	-0.01961	0.0037*	0.01275*	-0.0175	0.028518	0.035902
0.15	-0.02343	0.015703	-0.0108	-0.01584	-0.00514	0.003161	0.029825
0.20	-0.02829	0.009164	0.038574	-0.03432	-0.01576	0.016446	0.000157
0.25	-0.01764	-0.01907	0.022593	-0.02631	-0.02083	0.001508	0.002741
0.30	-0.0073	-0.02395	0.021857	-0.02026	-0.02964	0.013707	0.014028
0.35	5.88E-05	-0.03687	0.007243	-0.01266	-0.0396**	0.006349	0.014614
0.40	-0.00549	-0.02736	0.00382	-0.00078	-0.0285*	0.003688	0.009446
0.45	-0.00664	-0.02156	-0.00548	0.004455	-0.0244	0.021976	0.005396
0.50	-0.00825	-0.01189	-0.00799	0.009351	-0.0166	0.023158	0.003399
0.55	-0.00515	-0.00786	0.000967	0.00678	-0.0236	0.020992	0.007198
0.60	-0.01788	-0.01146	-0.00031	-0.00579	-0.0312	0.009783	0.010686
0.65	-0.01595	-0.02364	-0.00774	-0.02019	-0.0451**	-0.00464	0.016994
0.70	-0.00477	-0.01982	-0.00192	-0.01927	-0.0406**	-0.00903	0.016631
0.75	-0.0109	-0.01616	0.007194	-0.02636	-0.0305**	-0.02203	0.006889
0.80	0.017266	-0.00504	0.016172	-0.01533	-0.0289**	-0.03772	0.045557
0.85	0.001295	0.00035	0.016067	-0.02443	-0.0270	-0.03772	0.036662
0.90	-0.01172	-0.00433	0.020474	-0.02443	-0.03859	-0.04531	0.01852
0.95	-0.04336	-0.04169	0.05912*	-0.0128*	-0.03092	-0.05582	0.009175

Note: \*\*\*, \*\*, and \* indicate statistical significance at levels of 1%, 5%, and 10%, respectively. ( $\tau = 0.05, 0.1, 0.15, 0.20, 0.25, 0.30$ ) denote bearish market, ( $\tau = 0.35, 0.40, 0.45, 0.50, 0.55, 0.60$ ) denote normal market, ( $\tau = 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95$ ) denote bullish market condition.



Tables 10 and 11(Appendix B) examine the medium-term asymmetric nexus between the country-level EPU and the G7 stock returns. The evaluations from the table show that the G7 stock markets are largely adversely correlated with their respective country-level EPU in the medium term. The exceptions are the stock returns of France (M2) and the UK (M3) which are positively and significantly correlated with their respective country-level EPU during the bullish market conditions.

The long-term relationship structure is captured in Table 12. In the long term, it can be opined that the France and German stock markets are largely positively correlated with their respective country-level EPU. The remaining stock markets under study show fewer statistically adverse effects of their respective country-level EPU. This shows that in the long term, the impact of country-level EPU is weaker in comparison to the short term.



### **Summary of comparative analysis between the effect of country-level EPU and global EPU on the G7 stock returns.**

Insight from the quantile regression estimate of both global EPU, country-level EPU and the G7 stock returns indicate that, generally, the effect of country-level EPU on the stock returns of the respective G7 stock returns is larger than the effect of global EPU on the return of the G7 stock market. Particularly, the US, Germany and Italy are affected the most by its country-level EPU. The underlying reason for a stronger effect of CEPU on their respective stock market could be elucidated by the fact that CEPU measures the economic policy uncertainties in a particular country and that in line with AMH and HMH theories, these country-level economic policies will have a stronger effect on its respective stock markets. This phenomenon can also be explained using the Arbitrage pricing theory. In line with the arbitrage pricing theory, changes in macroeconomic indicators, which form part of the measure of economic uncertainties, form part of the system risk in a market which in turn reflects in asset pricing. In this regard, it is reasonable for the country-level EPU of a country to have a strong effect on its respective stock market.

On the other hand, the Global EPU (GEPU) is an average measure of EPU of 21 countries and so it does not represent the uncertainty of a particular country. In that regard, the uncertainty captured by the GEPU index may not necessarily reflect an uncertainty in a particular country hence a less adverse effect will be observed in relation to its stock returns.

### Asymmetric effect of oil volatility on the returns of financial assets

In this section, the study discusses the effect of oil volatility on the returns of the financial assets under study. The study first analyses the asymmetric association between OVX and the G7 stock returns, followed by the effect on gold, BTC and EUAF returns.



**Table 14. Quantile Regression Results of OVX and Assets (Signal)**

Quantiles	US	UK	France	Germany	Italy	Japan	Canada	Gold	BTC	EUAF
0.05	-0.1379***	-0.1851***	-0.1741***	-0.1285***	-0.2168***	-0.0467	-0.1406***	-0.0266	-0.16794	-0.04126
0.10	-0.1010***	-0.1358***	-0.1248***	-0.1413***	-0.1599***	-0.1285***	-0.1590***	-0.0289	-0.07499	-0.13944
0.15	-0.1091***	-0.1367***	-0.1268***	-0.1473***	-0.1682***	-0.0940***	-0.1551***	-0.0498	-0.1596**	-0.2730***
0.20	-0.1066***	-0.1284***	-0.1311***	-0.1562***	-0.1412***	-0.0943***	-0.1351***	-0.0332	-0.1863**	-0.1865***
0.25	-0.1042***	-0.1306***	-0.1252***	-0.1444***	-0.1521***	-0.0757***	-0.1011***	-0.0485*	-0.1678**	-0.1995***
0.30	-0.1132***	-0.1369***	-0.1391***	-0.1347***	-0.1521***	-0.0775***	-0.1022***	-0.0405	-0.1832**	-0.2024***
0.35	-0.1096***	-0.1283***	-0.1344***	-0.1351***	-0.1386***	-0.0808***	-0.1088***	-0.0292	-0.1992**	-0.2164***
0.40	-0.1130***	-0.1153***	-0.1413***	-0.1430***	-0.1306***	-0.0726***	-0.0953***	-0.0284	-0.212**	-0.1831***
0.45	-0.0986***	-0.1099***	-0.1334***	-0.1459***	-0.1308***	-0.0578***	-0.0914***	-0.0036	-0.2329**	-0.1785***
0.50	-0.0924***	-0.1029***	-0.1209***	-0.1542***	-0.1396***	-0.0518***	-0.1081***	-0.0047	-0.17649	-0.1711***
0.55	-0.0921***	-0.1055***	-0.1219***	-0.1443***	-0.1004***	-0.0569***	-0.1117***	-0.0087	-0.19996	-0.1727***
0.60	-0.0750***	-0.1188***	-0.1235***	-0.1375***	-0.1149***	-0.0636***	-0.1184***	-0.0116	-0.22926	-0.1527**
0.65	-0.0709***	-0.1166***	-0.0917***	-0.1255***	-0.1221***	-0.0662***	-0.1158***	-0.0211	-0.28507	-0.0996
0.70	-0.0815***	-0.1084***	-0.0937***	-0.1202***	-0.1281***	-0.0766***	-0.1193***	-0.0225**	-0.2902*	-0.0757
0.75	-0.0819***	-0.1021***	-0.0824***	-0.1241***	-0.1428***	-0.0796***	-0.1112***	-0.0281**	-0.22798	-0.1026
0.80	-0.0766***	-0.0869***	-0.0969***	-0.1002***	-0.1268***	-0.0705***	-0.1189***	-0.0161	-0.06189	-0.1302
0.85	-0.0809***	-0.0881***	-0.1133***	-0.1107***	-0.1579***	-0.0658***	-0.1282***	-0.0332	-0.13254	-0.1179
0.90	-0.0843***	-0.0987***	-0.1267***	-0.1238***	-0.1385***	-0.06614***	-0.1421***	-0.0259*	-0.19498	0.00717
0.95	-0.1007***	-0.1140***	-0.1350**	-0.1239**	-0.11248	-0.07838	-0.1497***	-0.0697	-0.01477	-0.0277

Note: \*\*\*, \*\*, and \* indicate statistical significance at levels of 1%, 5%, and 10%, respectively. ( $\tau = 0.05, 0.1, 0.15, 0.20, 0.25, 0.30$ ) denote bearish market, ( $\tau = 0.35, 0.40, 0.45, 0.50, 0.55, 0.60$ ) denote normal market, ( $\tau = 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95$ ) denote bullish market condition.



Following from Table 14, the quantile coefficient shows that OVX spikes have a statistically negative effect on the returns of all G7 stocks which resonates well with the findings of Feng et al. (2017) as well as Diaz, Molero and Gracia (2016) who argued based on empirical findings that OVX has an adverse effect on G7 stocks. The repercussions stemming from adverse OVX shocks can be rationalised based on the prevailing circumstance that the majority of G7 nations function as significant oil importers, thus rendering a surge in oil prices capable of exerting detrimental ramifications on both their stock markets and broader economies.

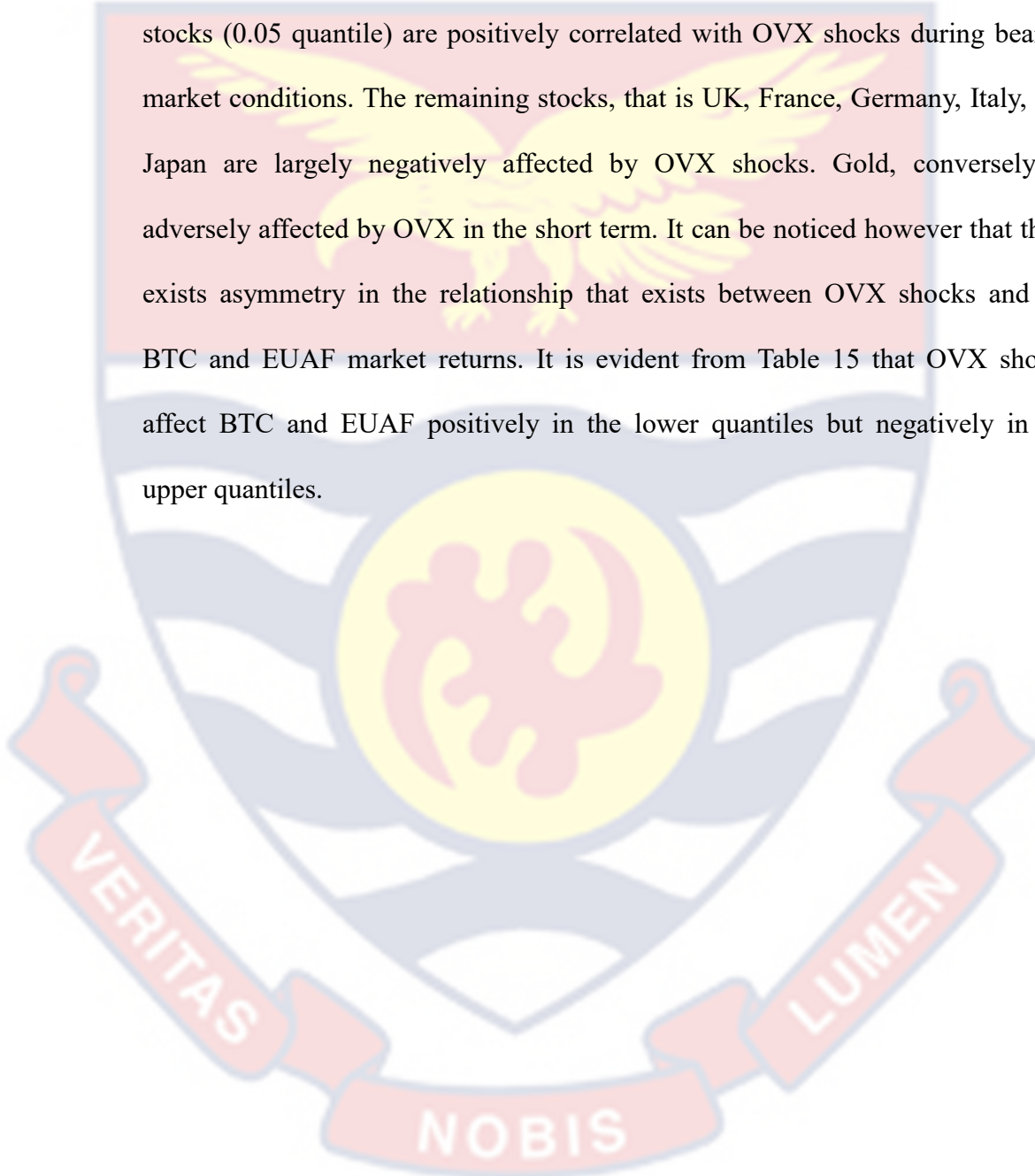
Similar to the findings of Hammoudeh et al. (2014), the study asserts that OVX shocks result in a substantial drop in the EUAF market returns. Similar negative trends with OVX are realised for the gold and BTC as evident in Table 14. The adverse effect of OVX on BTC returns is in line with the result of Long et al. (2021) and Dutta et al. (2020) who established an adverse association between OVX and BTC returns using the NARDL model and a DCC-GARCH model respectively.

**Table 15. Quantile Regression Results of OVX and Assets (M1).**

Quantiles	US	UK	France	Germany	Italy	Japan	Canada	Gold	BTC	EUAF
0.05	0.10857***	-0.1197***	-0.1878***	-0.1139**	-0.0885	-0.1764**	0.0416**	-0.022	0.5035	0.0706
0.10	0.0889*	-0.0905***	-0.1307***	-0.0620**	-0.1884*	-0.0937**	0.0039	0.0220	0.1737	0.1520**
0.15	0.0097	-0.0714**	-0.1122***	-0.0837**	-0.2285***	-0.0384	-0.0349	-0.0011	0.0448	0.1442*
0.20	0.01473	-0.0865***	-0.1082***	-0.1184***	-0.2209***	-0.0309	-0.0777*	-0.0028	-0.0212	0.11107*
0.25	-0.0046	-0.1065***	-0.1009***	-0.1087***	-0.1856***	-0.0379*	-0.0989***	-0.0004	-0.0859	0.02466
0.30	-0.0064	-0.1169***	-0.1000***	-0.0975***	-0.1900***	-0.0402**	-0.1074***	-0.0036	-0.1453	-0.0013
0.35	-0.0186	-0.1181***	-0.0993***	-0.0950***	-0.1564***	-0.0364*	-0.0969***	-0.0090	-0.2482*	0.01535
0.40	-0.0119	-0.1238***	-0.1030***	-0.0690*	-0.1439***	-0.0269	-0.0973***	-0.0156	-0.3706***	0.01188
0.45	-0.0182	-0.1296***	-0.1152***	-0.0674*	-0.1412***	-0.0045	-0.0950***	-0.0244	-0.3933***	0.0191
0.50	-0.0198	-0.1188***	-0.1118***	-0.0761**	-0.1631***	-0.0027	-0.0999***	-0.0199	-0.4085***	-0.0135
0.55	-0.0241**	-0.0935***	-0.1162***	-0.0981***	-0.1416***	-0.0115	-0.1153***	-0.038	-0.4401***	-0.0013
0.60	-0.0268***	-0.0948***	-0.1399***	-0.1145***	-0.1481***	-0.0216	-0.1207***	-0.0392	-0.3476**	-0.0128
0.65	-0.0301***	-0.0833***	-0.1354***	-0.1204***	-0.1526***	-0.0354*	-0.1037***	-0.0424	-0.2981*	-0.0165
0.70	-0.0319***	-0.0868***	-0.1445***	-0.1200***	-0.1553***	-0.0509**	-0.1023***	-0.0246	-0.2922	-0.0518
0.75	-0.0367***	-0.0946***	-0.1605***	-0.1192***	-0.1938**	-0.0531***	-0.1037***	-0.0253	-0.429*	0.01252
0.80	-0.0418***	-0.1209***	-0.1819**	-0.1202***	-0.2443**	-0.0671***	-0.1119***	-0.0204	-0.4865	-0.0734
0.85	-0.0426***	-0.1053**	-0.0657	-0.1323**	-0.12662	-0.0713***	-0.1219***	0.05614	-0.8048	-0.0281
0.90	-0.0474***	-0.1507***	-0.12189	-0.0664	-0.1487	-0.0782***	-0.1384***	0.04394	-0.4551	-0.0383
0.95	-0.0610***	-0.1739***	-0.1987**	-0.1252***	-0.15094	-0.0847***	-0.2038***	0.02342	-0.3149*	-0.1178

Note: \*\*\*, \*\*, and \* indicate statistical significance at levels of 1%, 5%, and 10%, respectively. ( $\tau = 0.05, 0.1, 0.15, 0.20, 0.25, 0.30$ ) denote bearish market, ( $\tau = 0.35, 0.40, 0.45, 0.50, 0.55, 0.60$ ) denote normal market, ( $\tau = 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95$ ) denote bullish market condition.

Table 15 represents the short-term relationship that exists between OVX shocks and returns of the financial assets under study. With regard to the G7 stocks, it can be observed that only US (0.05 and 0.10 quantiles) and Canadian stocks (0.05 quantile) are positively correlated with OVX shocks during bearish market conditions. The remaining stocks, that is UK, France, Germany, Italy, and Japan are largely negatively affected by OVX shocks. Gold, conversely, is adversely affected by OVX in the short term. It can be noticed however that there exists asymmetry in the relationship that exists between OVX shocks and the BTC and EUAF market returns. It is evident from Table 15 that OVX shocks affect BTC and EUAF positively in the lower quantiles but negatively in the upper quantiles.

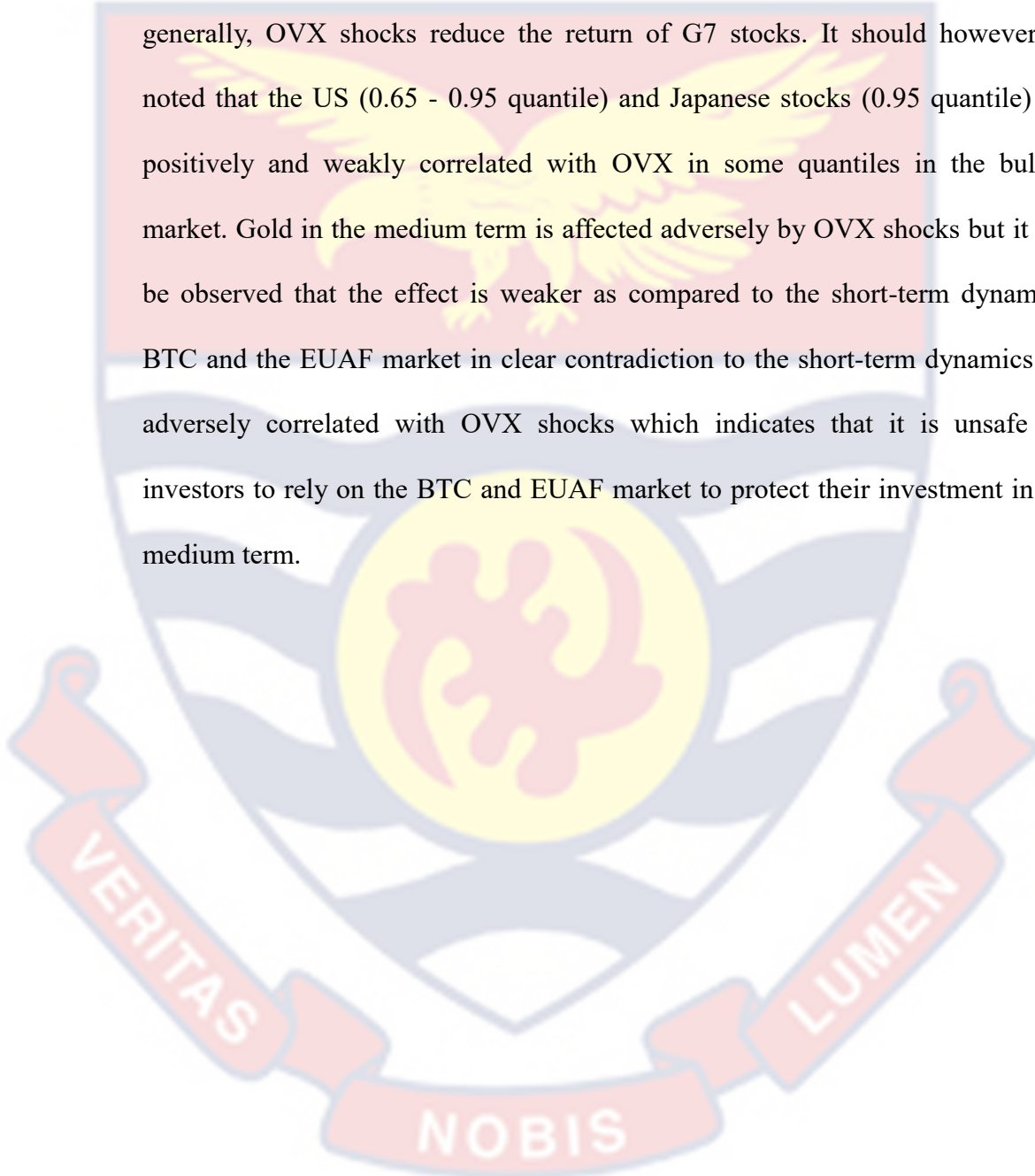


**Table 16. Quantile Regression Results of OVX and Assets (M2).**

Quantiles	US	UK	France	Germany	Italy	Japan	Canada	Gold	BTC	EUAF
0.05	-0.0425***	-0.0479***	-0.0610***	-0.0268	-0.0389	-0.0642***	-0.0637***	-0.0365	0.0546	0.0853
0.10	-0.0496***	-0.0422***	-0.0630***	-0.0438**	-0.0571*	-0.0601***	-0.0568***	-0.0140	0.0119	0.0334
0.15	-0.0372**	-0.0414***	-0.0699***	-0.0484**	-0.0519*	-0.0473*	-0.0525***	-0.0057	-0.1069	-0.0263
0.20	-0.0318**	-0.0317**	-0.059***	-0.0543***	-0.0568**	-0.0273	-0.0447***	0.0018	-0.1368	-0.0428
0.25	-0.0301**	-0.0269**	-0.0554***	-0.0397**	-0.0473*	-0.0214	-0.0431***	0.0031	-0.1706**	-0.0466
0.30	-0.0312**	-0.0212*	-0.0540***	-0.0431**	-0.0576**	-0.0197*	-0.0439***	0.0143	-0.1910*	-0.0301
0.35	-0.01619	-0.0260**	-0.0513**	-0.0424**	-0.0443	-0.0091	-0.0468***	0.0148	-0.2136*	-0.0534
0.40	-0.01059	-0.0288***	-0.04324	-0.02521	-0.0486*	-0.0101	-0.0494***	0.0018	-0.0904	-0.0357
0.45	-0.00576	-0.0274***	-0.03653	-0.00227	-0.0442**	-0.0074	-0.0471***	0.0035	-0.0915	-0.0484
0.50	-0.00482	-0.0357***	-0.02494	0.007056	-0.0353*	0.0057	-0.0428***	0.0097	-0.0202	-0.0251
0.55	-0.00527	-0.0304***	-0.02155	0.006358	-0.0347*	-0.0018	-0.0485***	-0.0005	0.03531	-0.0535
0.60	-0.00588	-0.0288**	-0.01352	0.002358	-0.0322	-0.0006	-0.0418***	0.0031	0.09479	-0.0372
0.65	0.001632	-0.0333***	-0.01988	-0.00214	-0.0397	0.0003	-0.0348**	-0.0007	0.25761	0.0113
0.70	0.003165	-0.0324**	-0.0291*	-0.00353	-0.0443	0.0021	-0.0314**	-0.0038	0.23420	0.0075
0.75	0.001306	-0.0257**	-0.02389	-0.00512	-0.023	0.0100	-0.0325**	-0.0096	0.11719	0.0068
0.80	0.007636	-0.0319***	-0.01729	-0.01446	-0.024	-0.0010	-0.0279**	-0.0205	0.08495	0.0014
0.85	0.01394	-0.0258**	-0.0216*	-0.00239	-0.0125	0.0103	-0.0249	-0.0287***	0.11468	0.0195
0.90	0.019434	-0.01476	-0.0224**	0.001631	-0.0033	0.0233	-0.0267	-0.0263**	0.13603	0.0551
0.95	0.006753	-0.00341	-0.01204	0.00234	-0.0194	0.0441***	-0.0376*	-0.0593*	0.13108	-0.0519

Note: \*\*\*, \*\*, and \* indicate statistical significance at levels of 1%, 5%, and 10%, respectively. ( $\tau = 0.05, 0.1, 0.15, 0.20, 0.25, 0.30$ ) denote bearish market, ( $\tau = 0.35, 0.40, 0.45, 0.50, 0.55, 0.60$ ) denote normal market, ( $\tau = 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95$ ) denote bullish market condition.

In the medium term, as shown in Tables 16 and 17, there are similarities in the relationship observed in the short term. With regard to the G7 stock returns, OVX has a significant adverse effect on all G7 stocks. This is to say that generally, OVX shocks reduce the return of G7 stocks. It should however be noted that the US (0.65 - 0.95 quantile) and Japanese stocks (0.95 quantile) are positively and weakly correlated with OVX in some quantiles in the bullish market. Gold in the medium term is affected adversely by OVX shocks but it can be observed that the effect is weaker as compared to the short-term dynamics. BTC and the EUAF market in clear contradiction to the short-term dynamics are adversely correlated with OVX shocks which indicates that it is unsafe for investors to rely on the BTC and EUAF market to protect their investment in the medium term.





**Table 18. Quantile Regression Results of OVX and Assets (M Agg).**

Quantiles	US	UK	France	Germany	Italy	Japan	Canada	Gold	BTC	EUAF
0.05	-0.1099***	-0.1649***	-0.1642**	-0.1257**	-0.1202	-0.0067	-0.1357***	-0.07198	-0.30738	-0.0885
0.10	-0.1051***	-0.1134***	-0.0976	-0.1527**	-0.1574**	-0.0391	-0.1519***	-0.01152	-0.15054	-0.0081
0.15	-0.1255***	-0.0988***	-0.0773**	-0.0895**	-0.1252**	-0.05*	-0.1438***	-0.00573	-0.15859	-0.0535
0.20	-0.1078***	-0.1042***	-0.0852***	-0.0855**	-0.1005*	-0.0529*	-0.1279***	-0.01752	-0.17261	-0.1093
0.25	-0.0989***	-0.1195***	-0.0885***	-0.1175***	-0.0892**	-0.0601**	-0.1182***	-0.02216	-0.19533	-0.1685
0.30	-0.0905***	-0.1141***	-0.1065***	-0.1103***	-0.1156***	-0.0558**	-0.0989***	-0.03514	-0.14783	-0.2089**
0.35	-0.0769**	-0.1099***	-0.1146***	-0.1038***	-0.1167***	-0.0484**	-0.1056***	-0.02777	-0.21098	-0.2274***
0.40	-0.0807***	-0.1007***	-0.1042***	-0.1165***	-0.1269***	-0.0484**	-0.0999***	-0.02525	-0.3098**	-0.2449***
0.45	-0.0903***	-0.1045***	-0.1049***	-0.1224***	-0.1298***	-0.0599**	-0.0862***	-0.03821**	-0.3536**	-0.2633***
0.50	-0.0704**	-0.1134***	-0.1273***	-0.13106***	-0.1213***	-0.0647*	-0.0889***	-0.0358***	-0.3376**	-0.2686***
0.55	-0.0823**	-0.121***	-0.1226***	-0.14096***	-0.1179***	-0.0774*	-0.0868***	-0.03419	-0.3228**	-0.2592***
0.60	-0.0874***	-0.1259***	-0.1247***	-0.14872***	-0.1289***	-0.0808	-0.0798***	-0.02894	-0.2998*	-0.2429***
0.65	-0.0988***	-0.1217***	-0.1232***	-0.14796***	-0.1457***	-0.0729	-0.0829***	-0.02182	-0.2317*	-0.2334***
0.70	-0.1013***	-0.1169***	-0.1097***	-0.14387***	-0.1649***	-0.0807	-0.0837**	-0.01612	-0.2005*	-0.2434***
0.75	-0.1019***	-0.1093***	-0.1099***	-0.1301***	-0.1577***	-0.0772	-0.0744*	-0.00996	-0.1819*	-0.2633***
0.80	-0.1080***	-0.1061***	-0.1050***	-0.1213***	-0.1445***	-0.0689	-0.1018**	-0.02113	-0.1824*	-0.2571***
0.85	-0.1017***	-0.0942***	-0.0905***	-0.1119***	-0.1376***	-0.0539	-0.1061**	-0.01116	-0.1515	-0.1372
0.90	-0.0959***	-0.0917***	-0.1085***	-0.1125***	-0.1331***	-0.0428	-0.1424**	-0.00307	-0.1959	-0.0797
0.95	-0.0642*	-0.0679	-0.0999***	-0.1250***	-0.1428***	-0.0236	-0.14575**	0.013758	0.07888	-0.0049

Note: \*\*\*, \*\*, and \* indicate statistical significance at levels of 1%, 5%, and 10%, respectively. ( $\tau = 0.05, 0.1, 0.15, 0.20, 0.25, 0.30$ ) denote bearish market, ( $\tau = 0.35, 0.40, 0.45, 0.50, 0.55, 0.60$ ) denote normal market, ( $\tau = 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95$ ) denote bullish market condition.

In the long-term, the nexus that exists between OVX and the asset under study is not significantly different from what was observed in the original signal.

The coefficient of the quantile regression estimates shows that OVX shocks affect all G7 shocks adversely and significantly. This clearly shows the devastating effect oil price volatility has on equity markets. Again, gold, which is known to be a safe haven asset against some asset (Barson et al., 2022; Gao & Zhang, 2016; Beckmann et al., 2015) and commodities classes (Naeem, Hasan, Arif, Suleman, & Kang, 2022; Ji, Zhang & Zhao, 2020) is unable to protect investors from the adverse effect of the volatility in oil prices.

BTC and the EUAF market, similar to the relationship observed in the medium term are adversely affected by OVX shocks. Conclusively just as reported by Dutta, Das, Jana and Vo (2020), BTC is generally seen to be affected adversely across the majority of the investment horizons (except the short-term). Conversely, the outcome of the adverse effect of OVX on EUAF future prices is in line with the study by Peri and Baldi (2011) and Hammoudeh et al. (2014). This study, however, contradicts the results of Aatola et al. (2013) who posited that carbon market prices are positively correlated with the price of oil. The contradiction may be a result of the OLS estimation technique used which is unable to capture the non-normal distribution of the time series data thereby affecting the accuracy of the result.

The general observation from the analysis of the nexus between OVX and the G7 stock returns under study shows that OVX largely affects financial assets adversely. This finding is largely congruous with the findings of Feng et al. (2017) who indicated that the volatility of oil prices have a substantial impact on equity market returns.

With regard to the gold market, the findings of this research are in line with that of Dutta (2018), who posited that there exists asymmetry in the nexus between the gold and oil market. The BTC and EUAF markets in line with the works of Dutta, Das, Jana, and Vo (2020), and Long, Pei, Tian and Lang (2021) are observed to be largely adversely affected by OVX shocks.

#### **Asymmetric effect of geopolitical risk on the returns of financial assets.**

This section of the study analyses the asymmetric nexus between the returns of geopolitical risk (GPR) index and the financial assets under study. The study first examines the effect of the GPR returns on the returns of the G7 stocks, followed by gold, BTC and the EUAF market returns.

**Table 20. Quantile Regression Results of GPR and Assets (Signal).**

Quantiles	US	UK	France	Germany	Italy	Japan	Canada	Gold	BTC	EUAF
0.05	0.0297	0.0751**	0.0344	0.0385	0.0715	0.0432*	-0.0059	-0.0123	-0.0752	-0.3285*
0.10	0.0469	0.0381	0.0173	0.0390	0.0209	0.0571	0.0366	-0.0320	-0.0389	-0.3232
0.15	0.0137	0.0216	0.0071	0.0349	0.0092	0.0265	0.0447	-0.0031	-0.0225	-0.1639
0.20	-0.0168	0.0033	0.0186	0.0175	0.0292	0.0109	0.0213	0.0001	0.12994	-0.0606
0.25	-0.0329	-0.0002	-0.0093	-0.0012	0.03181	-0.0004	0.0185	0.0032	0.0773	-0.0734*
0.30	-0.0292	0.0127	-0.0142	-0.0054	-0.0071	-0.0052	0.0119	0.0164	0.10091	-0.0566
0.35	-0.0067	-0.0159	-0.0204	-0.0064	-0.0089	-0.0157	-0.002	0.0096	0.1311	-0.0667
0.40	-0.0123	-0.0286	-0.0139	-0.0188	-0.0221	-0.0165	-0.006	0.0204	0.1266	-0.0555
0.45	-0.0174	-0.0176	-0.0327	-0.0307	-0.0299	-0.0233	-0.004	0.0146	0.1507	-0.0431
0.50	-0.0178	-0.0216	-0.0317	-0.0244	-0.0105	-0.0191	-0.0077	0.0111	0.1986*	-0.0317
0.55	-0.0108	-0.0185	-0.0227	-0.0135	-0.0169	-0.0177	-0.0173	0.0119	0.2115*	0.0061
0.60	-0.0076	-0.0371	-0.0203	-0.0266	-0.0031	-0.0029	-0.0253	0.0230	0.1599	0.0352
0.65	0.0010	-0.0405*	0.0075	-0.0349	0.00192	-0.0152	-0.0334	0.0261	0.1425	0.0451
0.70	0.0022	-0.0161	0.0356	-0.0451	0.02774	-0.0186	-0.0253	0.0409*	0.1318	0.0253
0.75	0.0005	-0.0278	0.0385	-0.0348	0.02813	-0.0076	-0.0212	0.0300	0.1123	0.0411
0.80	-0.0097	-0.0285	0.0208	-0.0015	0.02056	-0.0268	-0.0373	0.0264	0.1413	0.0003
0.85	-0.0197	-0.0301	0.0116	0.0045	-0.0251	-0.0396	-0.0349	0.0001	-0.0502	-0.0174
0.90	-0.0220	-0.0704*	0.0097	0.0216	-0.0419	-0.0653	-0.0621*	-0.0172	-0.0607	0.0799
0.95	-0.1076*	-0.1029*	-0.0737	-0.0708	-0.0021	0.0071	-0.0511	-0.0229	-0.0047	0.0987

Note: \*\*\*, \*\*, and \* indicate statistical significance at levels of 1%, 5%, and 10%, respectively. ( $\tau = 0.05, 0.1, 0.15, 0.20, 0.25, 0.30$ ) denote bearish market, ( $\tau = 0.35, 0.40, 0.45, 0.50, 0.55, 0.60$ ) denote normal market, ( $\tau = 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95$ ) denote bullish market condition.



Table 20. presents the signal quantile coefficient on the nexus between the returns of GPR and the financial assets under study. In the G7 context, it can be observed that GPR affects the G7 stock markets both positively and negatively across varying quantiles. This is to say that there exists asymmetry in the nexus between the returns of GPR and the G7 stocks which is in line with the study of Kannadhasan and Das (2019) who found an asymmetric nexus between GPR risk and the Asian equity returns.

It is evident from estimates of the original signal that in the bearish market conditions, the G7 stocks are largely positively correlated with GPR returns, negatively correlated in normal market conditions, and positively correlated in the bullish market. Specifically, the UK and France stock returns are the only two stocks among the G7 that are seen to be positively and statistically correlated with GPR in the bearish market (0.05 quantile). With regard to the gold market, GPR return affects it both positively and negatively across different quantiles. It can be seen that gold is significantly and positively correlated with GPR in the bullish market (0.70 quantile). BTC on the other hand is positively and significantly correlated with GPR in normal market conditions (0.50 and 0.55 quantiles) while EUAF returns per the estimates of the original signal show that it is adversely affected by GPR across the majority of the quantiles.



**Table 21. Quantile Regression Results of GPR and Assets (M1).**

Quantiles	US	UK	France	Germany	Italy	Japan	Canada	Gold	BTC	EUAF
0.05	0.0321	0.0101	-0.0454	-0.0586**	-0.0595	-0.0317	-0.0189	-0.0313	0.2439	0.0728
0.10	0.0389	0.0203	-0.0630	-0.0519	-0.0367	-0.0721	0.0413	0.0628	0.2504	0.0929
0.15	-0.0274	0.0056	-0.0535	-0.0756*	-0.0341	0.0047	0.0304*	0.0206	0.1195	0.0342
0.20	-0.0218	-0.0047	-0.0251	-0.0567	-0.0639	-0.0013	0.0423**	0.0125	0.0097	0.1224
0.25	-0.0143	-0.0034	-0.0299	-0.0579	-0.0361	-0.0177	0.0419*	-0.0017	0.0390	-0.0701
0.30	-0.0043	0.0108	-0.0257	-0.0803	-0.0517	-0.0449	0.0193	0.0019	-0.1045	-0.0996
0.35	-0.0049	0.0225	-0.0248	-0.0721	-0.0373	-0.0614	0.0081	0.0014	-0.0954	0.0246
0.40	-0.0193	0.0313	-0.0184	-0.0584	-0.0336	-0.0572	0.0098	0.0009	-0.0469	0.0095
0.45	-0.0250	0.0435	-0.0156	-0.0326	-0.0141	-0.0402	-0.004	0.0028	-0.0962	0.0352
0.50	-0.0302	0.0521	-0.0344	-0.0285	0.0317	-0.0128	-0.0164	-0.0005	-0.1194	0.0956*
0.55	-0.0185	0.0636	-0.0346	-0.0575	0.0469	-0.0197	-0.0175	-7.75E-06	-0.1995	0.1052**
0.60	-0.0066	0.0581	-0.0057	-0.0289	0.0868	-0.0473	0.00737	0.0167	-0.1143	0.1212**
0.65	-0.0049	0.0326	0.0445	0.04836	0.0326	-0.0393	0.0013	0.0022	-0.1630	0.0914
0.70	-0.0072	0.0038	0.0035	0.0496	0.0075	-0.0088	-0.002	-0.0154	-0.1434	0.0121
0.75	-0.0206	-0.0152	0.0417	0.0745	-0.0278	0.0247	-0.0198	-0.0505*	0.0877	-0.0659
0.80	-0.0238	-0.0351	0.0569	0.0622	0.0092	0.0399	-0.0431	-0.0608*	0.0825	-0.1135
0.85	-0.0034	-0.0049	0.0448	0.0765*	0.0455	0.0418	-0.0627	-0.0765*	-0.4406	-0.0750
0.90	-0.0080	0.0077	0.0236	0.0817***	0.0691	0.0418	-0.0363	-0.1114**	0.2114	0.0029
0.95	0.0346*	0.0238	0.0105	0.0817***	0.0160	0.1056*	0.0289	-0.0491	0.3530	0.0821

Note: \*\*\*, \*\*, and \* indicate statistical significance at levels of 1%, 5%, and 10%, respectively. ( $\tau = 0.05, 0.1, 0.15, 0.20, 0.25, 0.30$ ) denote bearish market, ( $\tau = 0.35, 0.40, 0.45, 0.50, 0.55, 0.60$ ) denote normal market, ( $\tau = 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95$ ) denote bullish market condition.

**Table 22. Quantile Regression Results of GPR and Assets (M2).**

Quantiles	US	UK	France	Germany	Italy	Japan	Canada	Gold	BTC	EUAF
0.05	0.021679	-0.01491	0.046608	0.013385	0.0699***	0.000408	0.003173	0.0185	0.3395	0.1289
0.10	0.017606	0.010681	0.035048	0.023195	0.0544**	0.011709	-0.02457	0.0204	0.1127	0.0839
0.15	-0.00116	0.015908	0.041567	0.018721	0.0430	-0.01604	-0.00593	0.0178	0.0464	0.1063**
0.20	0.001308	0.022852	0.020605	0.023496	0.0313	-0.02462	0.000574	0.0349	0.0165	0.1038
0.25	0.007358	0.0286*	0.005298	0.012829	0.0304	-0.0201	0.018897	0.0338	-0.0051	0.0990
0.30	-0.00046	0.0334*	0.003507	0.015876	0.0416	-0.00377	0.029018	0.0507**	0.0859	0.0346
0.35	0.001283	0.03092*	0.015251	0.013315	0.0121	0.003741	0.020249	0.0458*	0.0122	0.0453
0.40	-0.00182	0.028897	0.011731	-0.0022	-0.0121	0.009441	0.02973*	0.0442	-0.0648	0.0508
0.45	-0.00523	0.022481	0.031553	0.006894	0.0309	-0.00222	0.019404	0.0474	-0.0362	0.0190
0.50	-0.0072	0.042394	0.02861	0.004484	0.0396	-0.00743	0.021216	0.0425	-0.2149	0.0337
0.55	-0.01204	0.027763*	0.030544	-0.00276	0.0292	-0.00631	0.016374	0.0273	-0.1807	0.0046
0.60	-0.01059	0.034717*	0.037784	0.010016	0.0189	0.001608	0.025762	0.0231	-0.1468	-0.0015
0.65	-0.00904	0.025603	0.025875	0.010819	0.0206	-0.00724	0.021748	0.0267	-0.1236	-0.0488
0.70	-0.01614	0.021677	0.028694	0.010896	0.0298	-0.00799	0.02958	0.0224	-0.0646	-0.0516
0.75	-0.02032	0.017586	0.038484	0.023494	0.0060	-0.00071	0.024783	0.0228	0.0229	-0.0437
0.80	-0.02025	0.005379	0.039576	0.049874	0.0288	0.005626	0.015601	0.0158	-0.1326	-0.0567
0.85	-0.01942	-0.0087	0.047653	0.050248	0.0158	-0.00583	0.005952	-0.0046	-0.1994	-0.1013*
0.90	-0.00055	-0.00991	0.052461	0.03202	0.0314	-0.01417	0.004711	-0.0286	-0.2261	-0.1569***
0.95	0.014059	0.01441	0.036577	-0.02513	0.0358	0.005843	-0.01491	-0.0401***	0.22179	-0.1574**

Note: \*\*\*, \*\*, and \* indicate statistical significance at levels of 1%, 5%, and 10%, respectively. ( $\tau = 0.05, 0.1, 0.15, 0.20, 0.25, 0.30$ ) denote bearish market, ( $\tau = 0.35, 0.40, 0.45, 0.50, 0.55, 0.60$ ) denote normal market, ( $\tau = 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95$ ) denote bullish market condition.

In the short term, it can be observed from Table 21 that the nexus between the GPR returns and financial assets under study alters. The US stock market, in particular, is seen to be positively correlated with GPR returns at the 0.95 quantile, Germany positively correlated with GPR from 0.85 to 0.95 quantiles, Japan positively correlated with GPR at 0.95 quantile while the Canadian stock returns are positively correlated with GPR in some selected quantiles (0.15 – 0.25) in the bearish market. Gold and BTC on the other hand are seen to be adversely associated with GPR returns in the short-term. The EUAF market returns, on the other hand, are positively and significantly correlated with GPR returns in some selected quantiles (0.50 – 0.60) in normal market conditions.

Tables 22 and 23 inform the study about the medium-term relationship between GPR and financial asset returns. From Table 22 (M2) in particular, it can be observed that the UK stock returns are positively and significantly correlated with GPR returns in some selected quantiles in the bearish and normal market conditions. A similar statement can be made for the Italian stock market where the study observes a statistically positive relationship with GPR in some selected quantiles in the bearish market. The Canadian stock market is however observed to be positively correlated with GPR only at the 0.40 quantile.

It is important to note that, France and German stock returns are positively correlated with GPR return in most cases but statistically insignificant. As shown in Table 22 (medium term), gold is positively correlated with GPR returns in the normal market (0.30 and 0.35 quantile) conditions while Table 21(short term) demonstrates that gold is positively correlated with GPR during the bearish

market (0.05 quantile). In the medium term, it can be observed that both BTC and the EUAF markets are positively correlated with GPR in some selected quantiles in the bearish market.



**Table 24. Quantile Regression Results of GPR and Assets (Magg).**

Quantiles	US	UK	France	Germany	Italy	Japan	Canada	Gold	BTC	EUAF
0.05	-0.0434	-0.0943***	-0.0409	-0.0723*	0.07949	-0.0604	-0.0571	-0.0468	0.2235	-0.2074
0.10	-0.0391	-0.0623**	-0.0264	-0.0012	0.03529	-0.0433	-0.0210	-0.0161	0.1874	-0.0505
0.15	-0.0141	-0.05283*	-0.0472	-0.0164	-0.0059	-0.0189	-0.0056	0.00336	0.2111**	-0.0078
0.20	0.00655	-0.0349	-0.0125	0.01865	-0.0096	-0.0157	-0.0006	-0.0158	0.1435	-0.0415
0.25	0.01015	-0.0215	-0.0024	-0.0117	-0.0125	-0.0046	-0.0176	-0.0175	0.0376	-0.0253
0.30	-0.0108	-0.0138	0.00898	-0.0034	-0.0243	-0.0064	-0.0102	-0.0145	0.0345	-0.0239
0.35	-0.0211	-0.0122	-0.0091	0.01104	-0.0199	0.01051	-0.019	-0.0058	0.1538	-0.0197
0.40	-0.0213	-0.0147	-0.0076	-0.0021	-0.0273	0.00102	-0.0151	0.01058	0.1314	-0.0047
0.45	-0.0217	-0.0218	-0.0147	0.00195	-0.0189	0.00110	-0.0153	0.01255	0.0984	-0.0095
0.50	-0.0183	-0.0292	-0.0124	0.01296	-0.0239	0.00479	-0.0185	0.01938	0.0832	-0.0224
0.55	-0.0139	-0.0209	-0.0294	0.01532	-0.0164	0.01598	-0.0172	0.01593	0.0877	-0.0038
0.60	-0.0107	-0.0245	-0.0207	0.00198	-0.0067	0.02095	-0.013	0.01249	0.0545	0.01867
0.65	-0.0060	-0.0262	-0.0158	-0.0026	-0.0188	0.02091	-0.0211	0.01178	0.1007	-0.0173
0.70	0.00612	-0.0072	-0.0263	-0.0127	0.00925	0.0318	-0.0242	-0.0048	0.0740	-0.0292
0.75	0.01746	-0.0282	-0.0074	0.00159	0.01619	0.0254	-0.0381	-0.0109	0.0789	-0.0315
0.80	0.01692	-0.0215	0.00183	0.02597	0.00408	0.0272	-0.0332	-0.0224	-0.0522	-0.1216
0.85	0.00234	-0.0018	-0.0108	-0.0002	-0.0233	0.0030	-0.0264	-0.0175	-0.0124	-0.2049
0.90	-0.0043	-0.0063	-0.0135	-0.0048	-0.0052	-0.0181	0.00229	-0.0134	-0.1562	-0.2332
0.95	-0.0443	0.00272	-0.0112	-0.0059	-0.0629	-0.0007	-0.0156	-0.0247	-0.2521	-0.3102

Note: \*\*\*, \*\*, and \* indicate statistical significance at levels of 1%, 5%, and 10%, respectively. ( $\tau = 0.05, 0.1, 0.15, 0.20, 0.25, 0.30$ ) denote bearish market, ( $\tau = 0.35, 0.40, 0.45, 0.50, 0.55, 0.60$ ) denote normal market, ( $\tau = 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95$ ) denote bullish market condition.



In the long term, the empirical evidence as depicted in Table 24 shows that the G7 stocks are affected adversely by GPR signifying that the adverse effect of GPR on the G7 stock returns travels into the long term. The quantile estimate for the BTC market shows that BTC largely is positively but not statistically correlated with GPR. The EUAF market returns on the other hand are adversely affected by GPR risk indicating that a risk in GPR risk can frustrate the effort of policymakers to reduce global carbon emissions using the EUAF carbon emission trading system. This is so because an adverse effect on the returns of the EUAF market will make the market unattractive to investors which may frustrate the goal of the market in building an efficient active market to trade carbon credits to reduce carbon emissions.

In summary, the study observes that consistent with the study by Salisu, Lasisi and Tchankam (2022), advanced economies (G7) are susceptible to GPR shocks. Again, in line with the study by Abassi, Kumari, and Pandey (2022) the study asserts that the stock returns of Japan, Germany, and the UK are more susceptible to GPR shocks while the stock returns of Italy and Canada are less affected adversely by GPR shocks. The study also observes that the effect of GPR on equity returns is strong, especially in the short term but weakens in the long term. The asymmetry in the relationship resonates well with the adaptive and heterogeneous market hypothesis that hypothesizes the different investor reactions in the market, given different market conditions. On the other hand, BTC and the EUAF market returns exhibit heterogeneity in its relationship with GPR.

### Quantile-on-quantile regression analysis

In accordance with Tweneboah, Owusu Junior and Kumah (2020), this research paper compares the QQR estimates with the QR coefficients in order to investigate the robustness of the QR estimations. The QQR approach is perceived as a deconstruction of estimations derived from fundamental quantile regression, affording the opportunity to scrutinise individual estimations corresponding to specific quantiles of the independent variable, as elucidated by Iqbal et al. (2020). Employing the QR technique entails the regression of financial asset return quantiles against shifts in uncertainty, resulting in coefficients uniquely linked to the index  $\theta$ . In contrast, within the QQR framework, coefficients are indexed by both  $\theta$  and  $\tau$ , given that the QQ method conducts regressions between  $\theta$  quantiles and  $\tau$  quantiles of alterations in uncertainty.

The QQR method, as opposed to the QR method, gives a more detailed understanding of the nexus between uncertainty changes and financial asset returns because the explanatory variable may vary between quantiles. The basic characteristics of the QR are preserved by QQR estimations because the QQR technique has an intrinsic deconstruction component (Sim & Zhou, 2015); otherwise, this approach would be methodologically flawed and produce inaccurate findings (Lin & Su, 2020).

It is important to acknowledge that due to the non-parametric nature inherent in the QQR estimations, the determination of significance levels for coefficients becomes impractical. Nevertheless, the credibility of QQR estimates finds validation through alignment with the QR outcomes, as elaborated upon

within this section. Again, for want of space and brevity, the study presents only the QQR plots for the original series. The validity of the decomposed series is however confirmed by the Disk and Panchenko (2006) non-linear causality test.



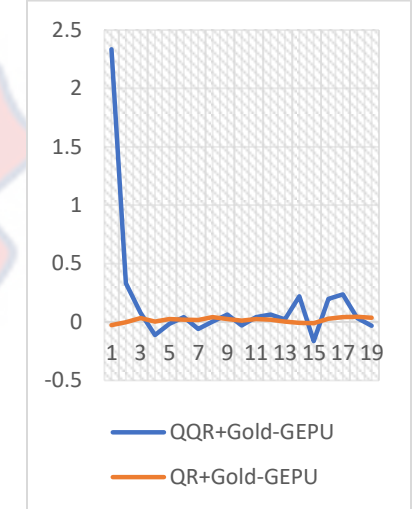
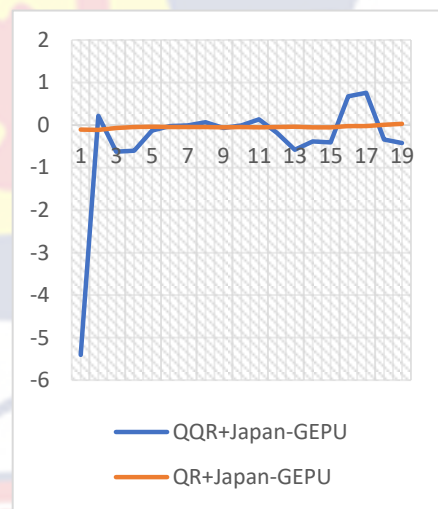
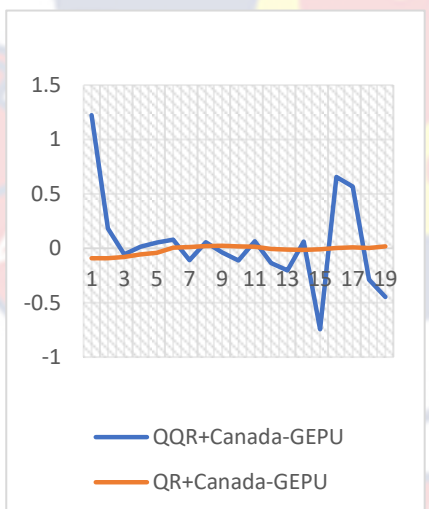
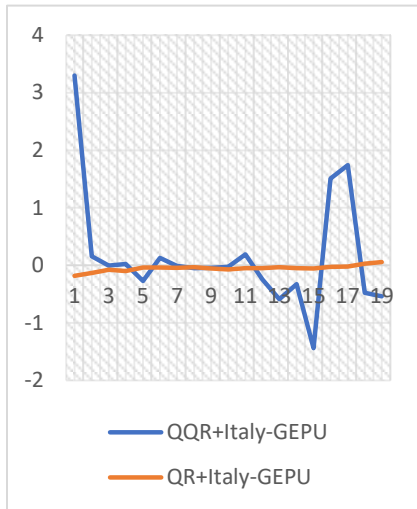
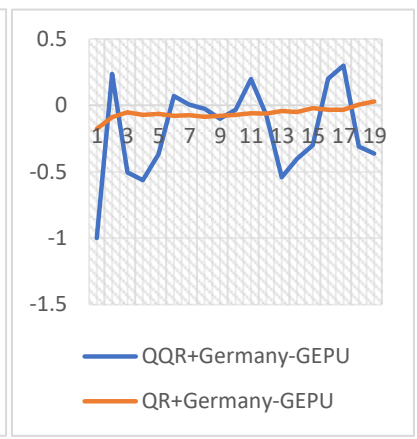
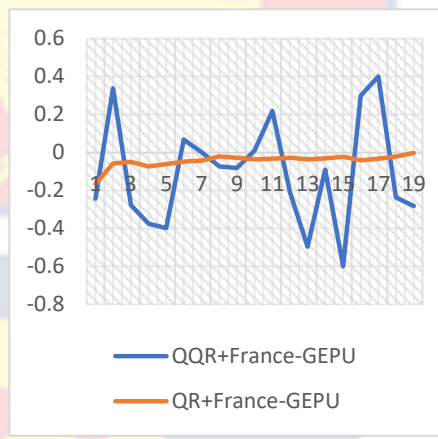
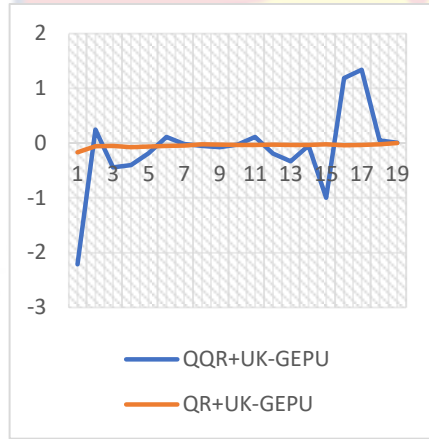
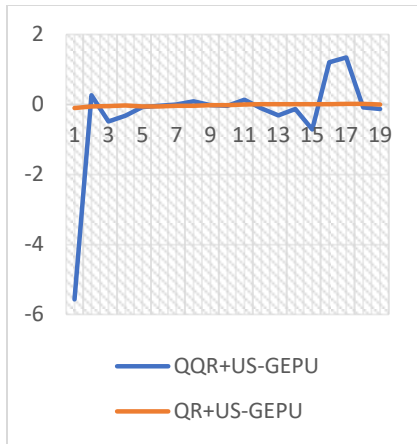


Figure 5: continued

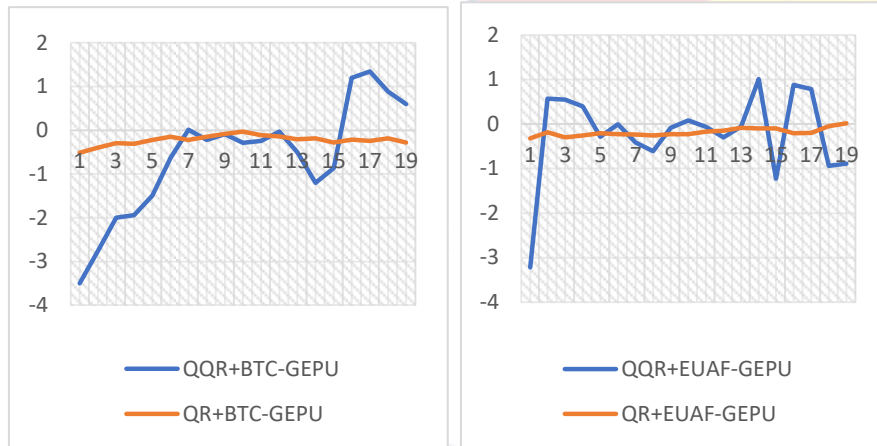


Figure 5: Contrast between the mean QQR and QR coefficients across various percentiles of GPEU shocks and returns on financial assets. Annotations: This diagram portrays a linear plot illustrating QQR and QR approximations. Blue markers signify QQR gradients, while orange markers represent QR approximations. The x-axis on each chart indicates quantiles, while the y-axis illustrates the coefficient gradient.



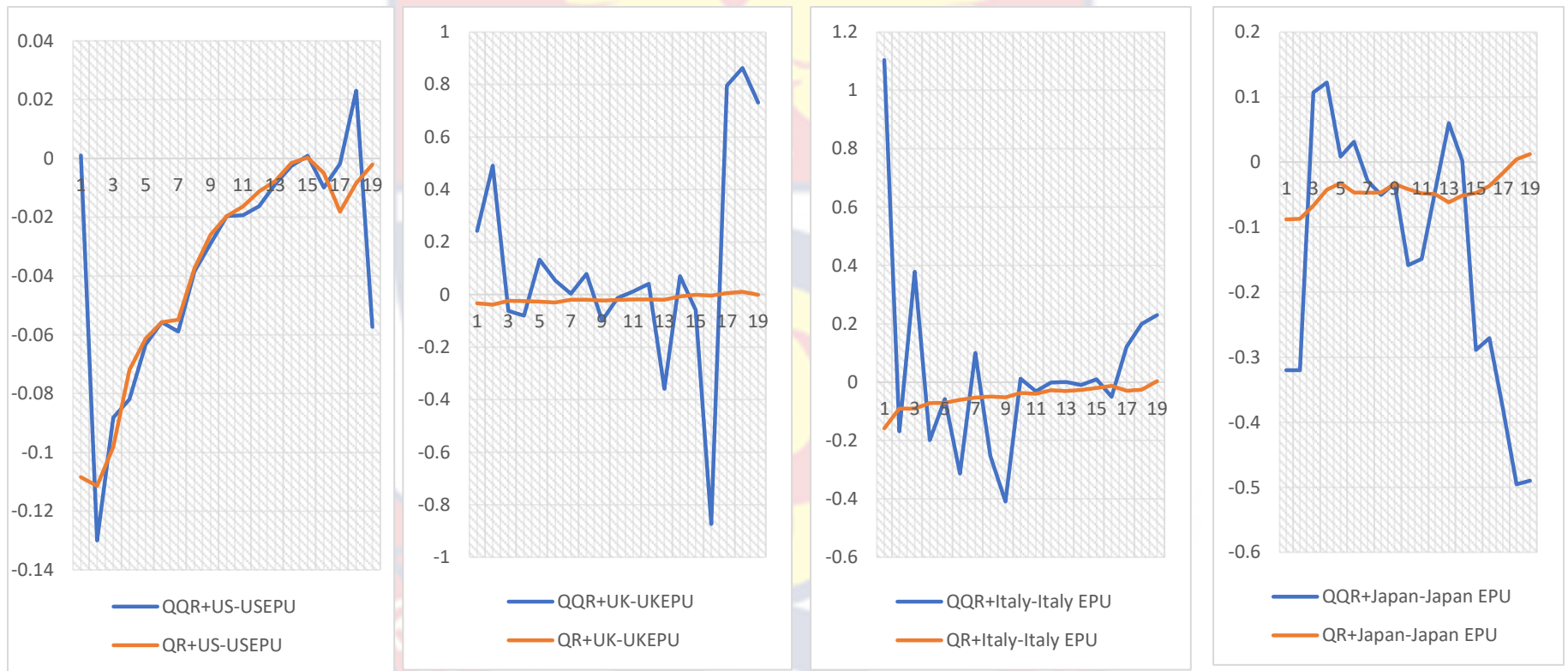


Figure 6: Comparison of the average QQR and QR coefficients at different quantiles of Country Level-EPU shocks and the G7 stock returns.

Figure 6: Continued

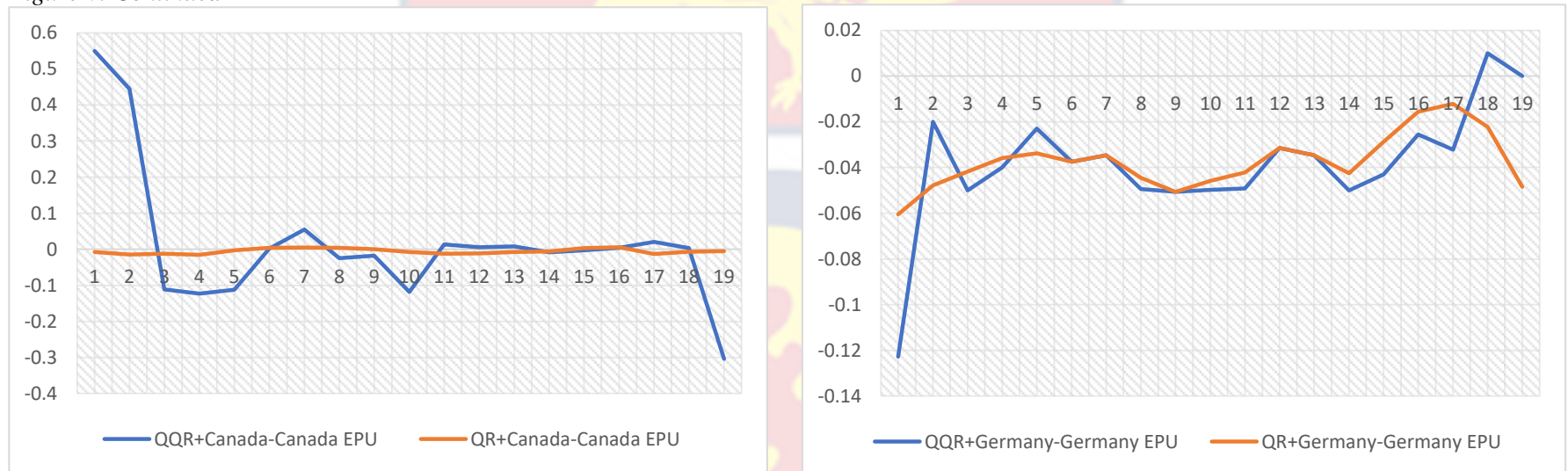


Figure 6: Comparison of the average QQR and QR coefficients at different quantiles of Country Level-EPU shocks and the G7 stock returns.

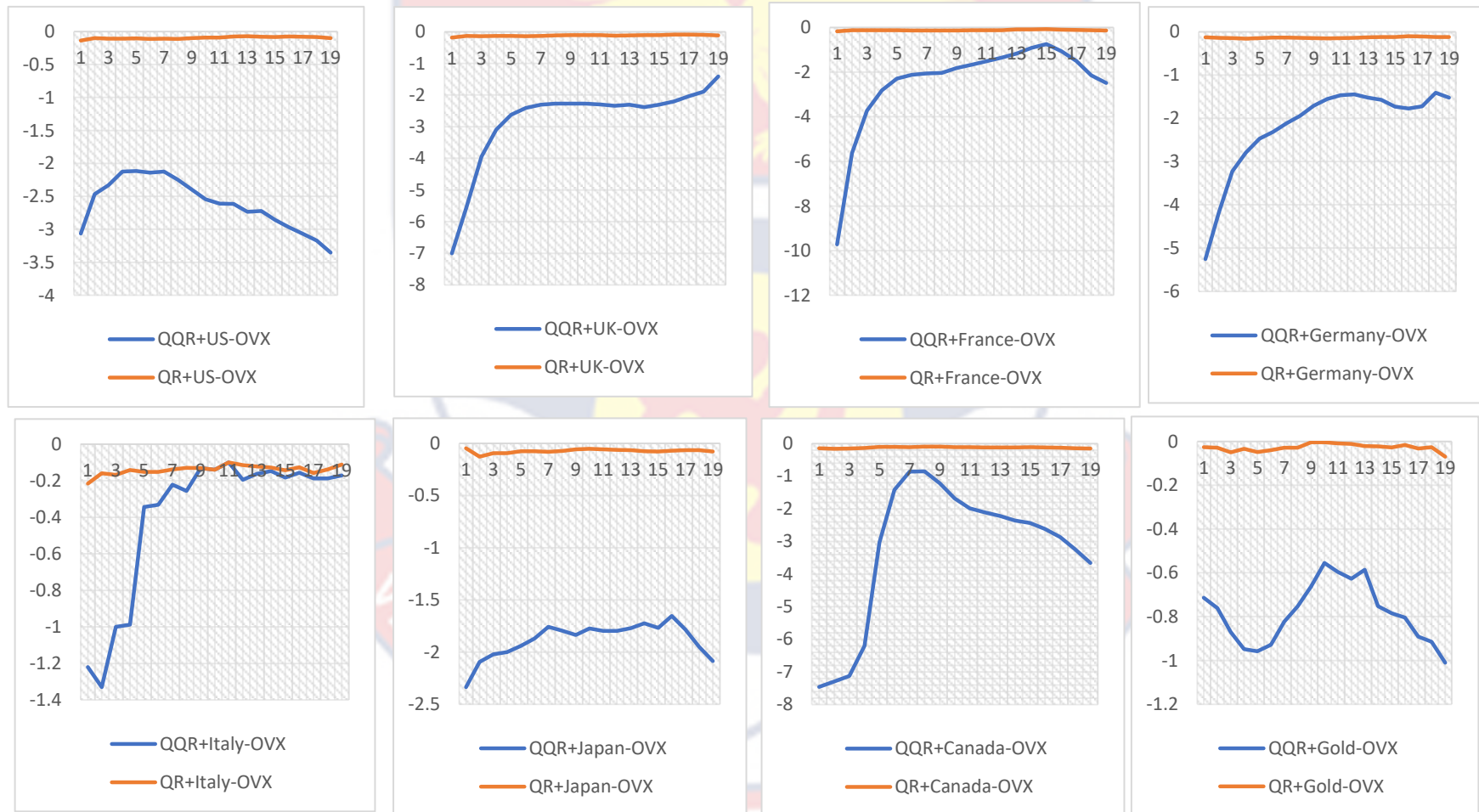


Figure 7: Contrast between the mean QQR and QR coefficients across various percentiles of OVX shocks and returns on financial assets.

Figure 7: Continued

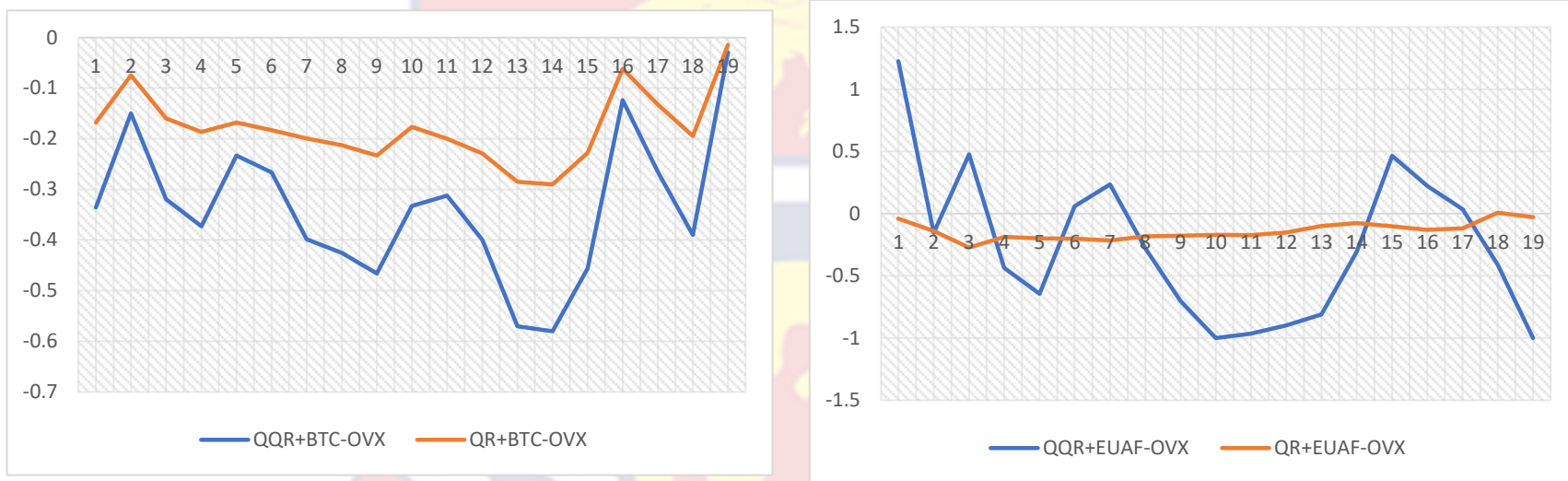


Figure 7: Contrast between the mean QQR and QR coefficients across various percentiles of OVX shocks and returns on financial assets. Annotations: This diagram portrays a linear plot illustrating QQR and QR approximations. Blue markers signify QQR gradients, while orange markers represent QR approximations. The x-axis on each chart indicates quantiles, while the y-axis illustrates the coefficient gradient.



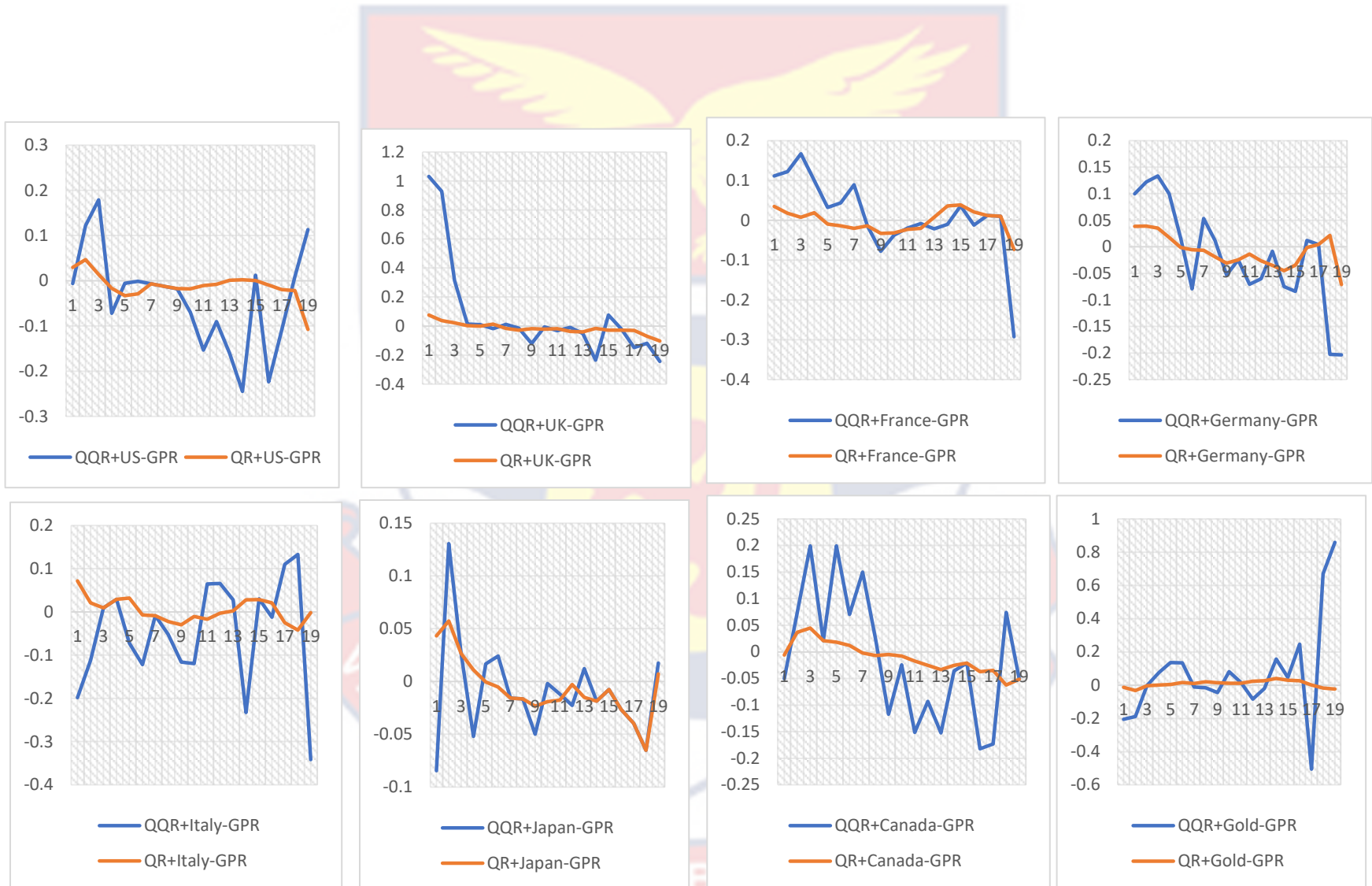
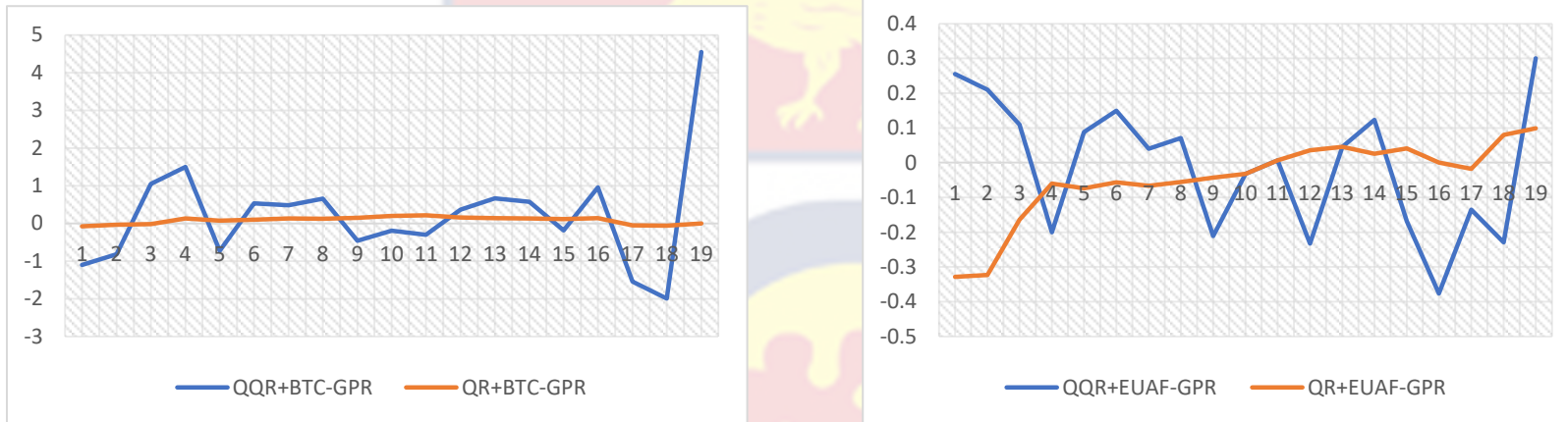


Figure 8: Contrast between the mean QQR and QR coefficients across various percentiles of GPR shocks and returns on financial assets.

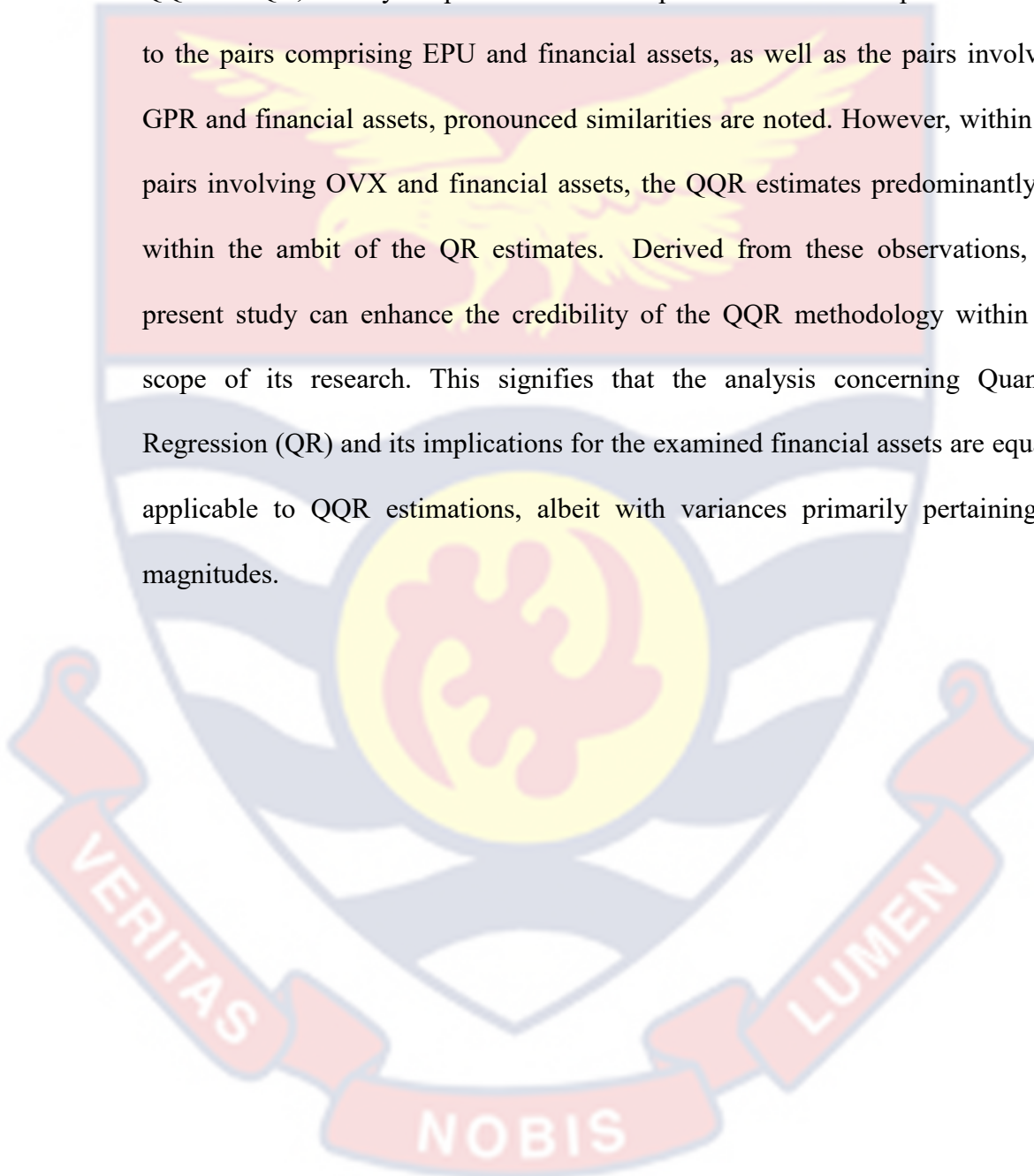


Figure 8: continued



*Figure 8:* Contrast between the mean QQR and QR coefficients across various percentiles of GPR shocks and returns on financial assets. Annotations: This diagram portrays a linear plot illustrating QQR and QR approximations. Blue markers signify QQR gradients, while orange markers represent QR approximations. The x-axis on each chart indicates quantiles, while the y-axis illustrates the coefficient gradient.

In Figures 5-8, the study observes that while disparities exist between the QQR and QR, notably the plots show similar patterns for the most part. In relation to the pairs comprising EPU and financial assets, as well as the pairs involving GPR and financial assets, pronounced similarities are noted. However, within the pairs involving OVX and financial assets, the QQR estimates predominantly lie within the ambit of the QR estimates. Derived from these observations, the present study can enhance the credibility of the QQR methodology within the scope of its research. This signifies that the analysis concerning Quantile Regression (QR) and its implications for the examined financial assets are equally applicable to QQR estimations, albeit with variances primarily pertaining to magnitudes.



## Wavelet Analysis

The examination of this research's objective two was accomplished through the utilisation of wavelet methodologies. In order to explore the comovement between economic uncertainties and the financial asset returns under study, the bivariate wavelet methodologies are employed. This section presents the empirical results from the squared wavelet coherence (SWC)-based lead-lag relationship between economic uncertainty and financial asset returns. Since this study utilises monthly data we set,  $l_j, j = 1, \dots, 4$  which follows Boateng et al. (2020), and Idun et al. (2022) to define its intrinsic time horizons. In line with the aforesaid studies, this study defines 2-4 months to represent the short-term relationships, 4-16 months to represent medium-term relationships and above 16 months to present the long-term. The comovement patterns that reveal the extractable lead-lag dynamics are showcased within the scalograms. The x-axes portray the calendar time, and the y-axes represent the frequency (intrinsic time), quantified in terms of months. They formulate the framework within the domain of time and frequency when combined (Boateng et al. 2022; Owusu Junior et al. 2021a).

In accordance with Gouhier et al. (2013), the study proposes that warmer colours (red and yellow) symbolize heightened coherence, while cooler colours (blue and green) represent diminished coherence within the pair. Visually, arrows oriented  $\rightarrow$  and  $\leftarrow$  indicate coherence in-phase (movement in the same direction) and out-phase (movement in the opposite direction), respectively. Specifically, leftward arrows signify negative correlations, while rightward arrows indicate

positive correlations. Arrows oriented to the right and upward ( $\nearrow$ ) or left and downward ( $\swarrow$ ) denote a leading or precedence position for the initial variable. Conversely, arrows pointing right and downward ( $\searrow$ ) or left and upward ( $\nwarrow$ ) indicate a leading or precedence role for the second variable, identified as financial assets. Significant focus is given to the phase difference association situated within the cone of influence, illustrating the pronounced comovement dynamics between the examined pairs. The COI is evident on the scalogram as the non-faded region, signifying that lead-lag dynamics within (outside) these clear areas are considered significant (insignificant).

#### **Comovement between GEPU and financial asset returns**

This section discusses the time and frequency comovement between global EPU and the financial assets under study. The study first discusses the comovement between the individual G7 stocks followed by gold, Bitcoin and the EUAF returns.



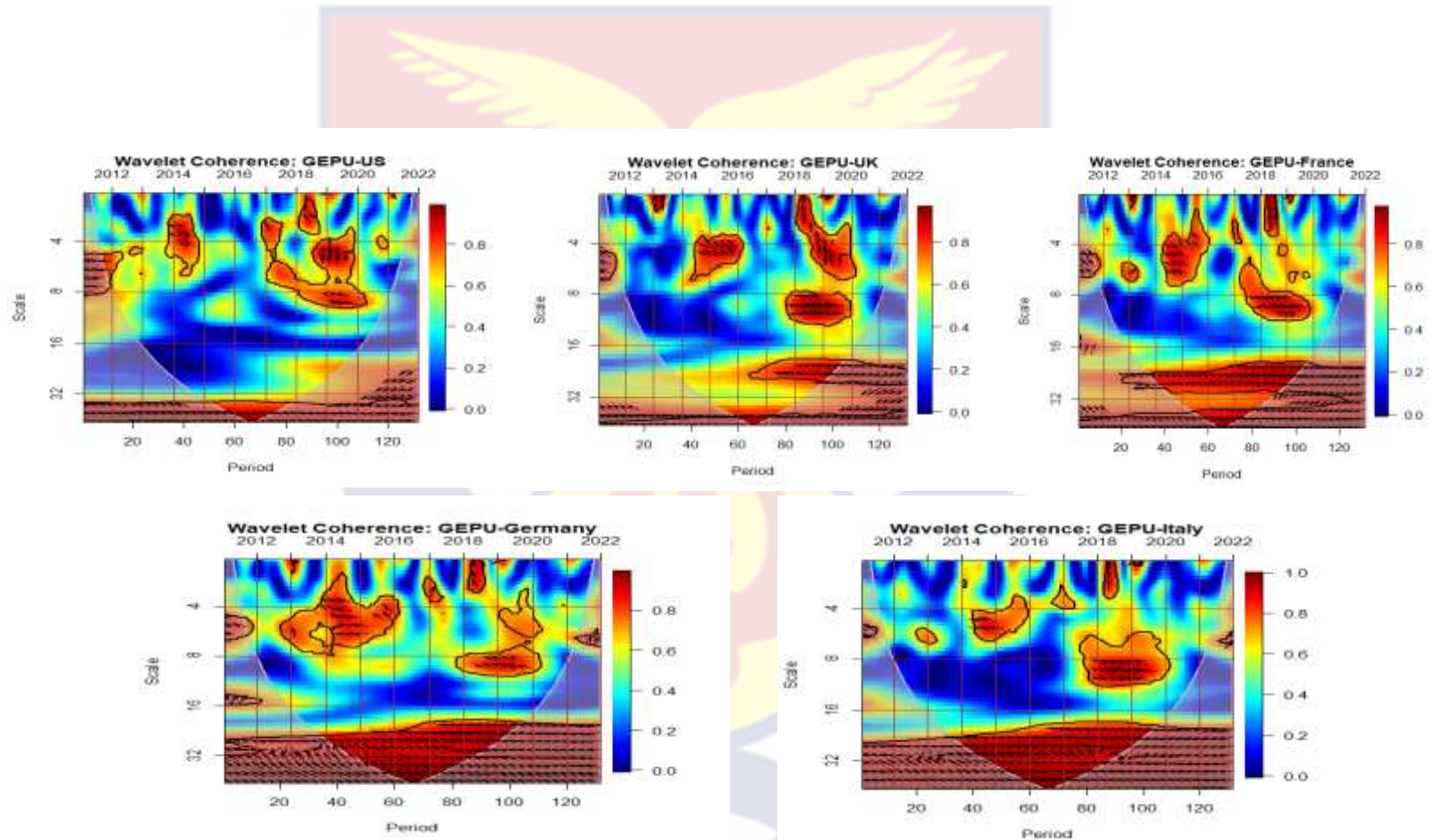


Figure 9: Comovement between Global EPU and Financial asset returns.

Notes: This diagram depicts the squared wavelet coherence. The x-axes (y-axes) represent years (frequency in months). The observed period starts from 01/01/2012 to 31/12/2022. Arrows  $\leftarrow$  and  $\rightarrow$  denote comovement in-phase and anti-phase, respectively; arrows  $\nearrow$  or  $\swarrow$  indicate a precedence of the first variable (GEPU);  $\searrow$  or  $\nwarrow$  indicate a precedence of the second variable (asset returns). The gradient bar illustrates the intensity of comovements – warmer (from yellow to red) indicate strong comovements and cooler shades (from green to blue) indicate weak comovements.





Figure 9: Continued

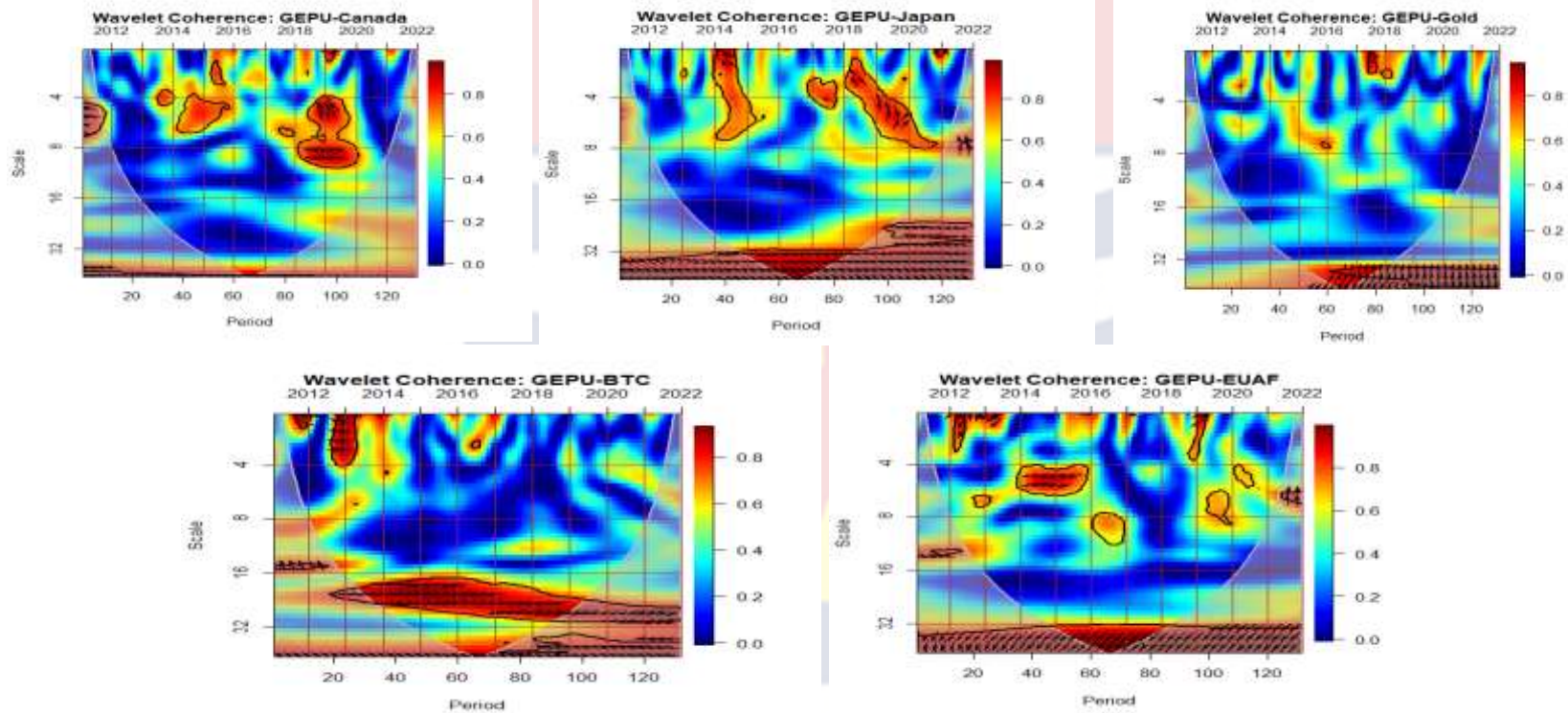


Figure 9: Comovement between Global EPU and Financial asset returns.

Notes: This diagram depicts the squared wavelet coherence. The x-axis (y-axis) represents years (frequency in months). The observed period starts from 01/01/2012 to 31/12/2022. Arrows  $\leftarrow$  and  $\rightarrow$  denote comovement in-phase and anti-phase, respectively; arrows  $\nearrow$  or  $\swarrow$  indicate a precedence of the first variable (GEMU);  $\searrow$  or  $\nwarrow$  indicate a precedence of the second variable (asset returns). The gradient bar illustrates the intensity of comovements – warmer (from yellow to red) indicate strong comovements and cooler shades (from green to blue) indicate weak comovements.

### GEPU and US stocks

Figure 9 depicts the SWC-based lead-lag dynamics between GEPU and the US stock returns. Within this GEPU-US pairing, the investigation reveals a range of coherence levels spanning between high, medium, and low levels. Notably, concerning the US, it is crucial to observe that the heatmap predominantly exhibits red shading in the context of short and medium terms, indicating high comovement, while the patches of blue regions indicate low comovement in the long term. This is observable, especially during the years 2014, 2017-2020. The enduring prevalence of pronounced coherence is evidence of the high comovement between GEPU shocks propagated by significant global mishaps such as the BREXIT, and the COVID-19 pandemic.

During the early part of 2014, the cloud of left-upward pointing arrows indicates that the US stock was adversely leading GEPU in the short to medium term (approximately 2-7 monthly cycles). The patches of red regions with left-upward pointing arrows are again observed from 2017-2018 within the short and medium term. The study however observes that in 2019 (within 1-2 monthly cycles), GEPU adversely leads US stock returns. This is to say that a rise in GEPU shocks leads to a fall in the US stock returns. Within 4-8 monthly cycles the left upward pointing arrows still indicate a leading role by GEPU. The lead-lag dynamics however changed within 8-12 monthly cycles where it is observed that the US stock returns adversely lead GEPU. At this point, an increase in the US stock returns is occasioned by a fall in the GEPU index.

### GEPU and UK stocks

Figure 9 depicts the SWC-based lead-lag dynamics between GEPU and UK stock returns. For this pair (GEPU-UK), the investigation reveals a range of coherence levels spanning between high, medium, and low levels. The dynamics in the comovement between this pair are quite different from what was observed in the GEPU-US pair. It is evident from the scalogram that, unlike the GEPU-US pair, the patches of red regions extend to the long term, especially during 2017-2020 signifying strong comovement during the stated duration. The enduring prevalence of pronounced coherence is evidence of the high comovement between GEPU shocks propagated by significant global events such as the British exiting the European Union, and the COVID-19 pandemic.

From the GEPU-UK pair, GEPU led UK stock returns in the early part of 2013 during the short term. This is to say that an increase in GEPU results in a reduction in the returns of UK stocks. From the latter part of 2014 to early 2016, the study observes a strong comovement between GEPU and UK stock returns between (4-7 monthly cycles). Again, the cloud of left-upwards pointing arrows of the latter indicates a strong negative drive from UK stock returns to GEPU. Similar to the dynamics observed in the GEPU-US pair, it is observed from the scalogram that during 1-2 monthly cycles the left-downward pointing arrow indicates that GEPU was driving UK stock returns negatively in the short term. The cloud of upward-pointing arrows from 2018 to mid-2019 indicates that GEPU led UK stock returns. The patches of red and left-pointing arrows indicate

an adverse nexus between GEPU, and the UK stock returns during the medium and long term, especially between 2018 and mid-2020.

### **GEPU and France stocks**

The scalogram as shown in Figure 9, depicts the GEPU-France pair. Consistent with the findings observed in the GEPU-UK pair, the study observes patches of strong comovement across the short, medium, and long term. Specifically, during the early part of 2013, the study observed a cloud of left-downward pointing arrows which signifies that GEPU leads the France stock market returns in the short term. That is to say that the left-downward pointing arrows indicate that an upsurge in GEPU results in a fall in the returns of France's stock market.

Again, in the medium term (approximately 5-7 monthly cycles), the study observes a red region with a right upward arrow which indicates that GEPU led the returns of France positively. Across the years 2014-2018, the study observes patches of red with left-upward pointing arrows across the short-term, medium-term and long-term. The cloud of left-upward pointing arrows indicates that the France stock market led GEPU within the aforementioned times. Within the stated time, the study observes from the scalogram that there exists high comovement between the GEPU-France pair. Unlike what was observed in the GEPU-UK pair, it is evidenced from the scalogram of the GEPU-France pair that, there exist patches of orange colours across 2-8 monthly cycles during the year 2019-2020 which signifies somewhat of a weaker comovement between the pair as compared to say the GEPU-UK pair. This signifies that during the COVID-19 pandemic,



there was less comovement between GEPU and the returns of France's stock market. However, the study observes a strong adverse comovement between GEPU and France stock returns within 8-12 monthly cycles.

#### **GEPU and Germany stocks**

The scalogram observed in Figure 9 depicts the GEPU-Germany pair. It can be observed that there exist patches of orange and red regions distributed across the scalogram which signifies high comovement between the GEPU and Germany returns. The left downward pointing arrows between 1-2 monthly cycles of 2013 and 2019 show that GEPU drove the German stock returns negatively in the stated period. However, in the medium and long term across varying times it is seen that the German stock returns negatively drove GEPU which is represented by left-upward pointing arrows.

#### **GEPU and Italy stocks**

The GEPU-Italy pair is represented by the scalogram in Figure 9. Very similar to the findings in the GEPU-Germany pair, the study observes patches of orange and red regions distributed across the scalogram which signifies high comovement between GEPU and Italy stock returns. Generally, the study observes a stock return led comovement between the GEPU-Italy pair across various sections of the scalogram with the exception of the 1-2 monthly cycles of 2019 where GEPU is seen to negatively drive the Italian stock market.



### **GEPU and Canada stocks**

The patches of orange and red as observed in the GEPU-Canada pair signify strong comovement within the regions. The cloud of left downward pointing arrows within 1-2 monthly cycles of 2019 signifies that GEPU leads the Canadian stock market adversely. It can however be observed that during 4-10 monthly cycles, the Canadian stock market leads GEPU adversely. This means that an increase in the stock returns of Canada decreases the GEPU index and vice versa.

### **GEPU and Japan stocks**

The GEPU-Japan pair as observed in Figure 9 shows strong comovement in the short term as indicated by the orange and red patches in the scalogram. The patches of blue colours across the regions in the scalogram indicate weak comovement between the GEPU-Japan pair in the long term. The patches of left-upward pointing arrows from 2014 to 2019 across the short and medium term indicate that the Japan stock returns led GEPU within the frame under consideration. The study however observes a lead role by GEPU in the medium term (approximately 4-8 monthly cycles).

### **GEPU and Gold stocks**

The scalogram as shown in Figure 9, depicts the GEPU-Gold pair. In a clear contradiction to what was observed in the comovement between GEPU and the G7 stock returns, the study observes a weak to moderate comovement between the GEPU-Gold pair generally across the medium and long term. The scalogram however shows strong comovement between GEPU and the returns of

gold specifically in the short term. It is evident from the biwavelet plot that during mid-2017, the plot depicts a patch of a red region with a right-upward pointing arrow within 1-2 monthly cycles. The evidence of a right-upward pointing arrow indicates that GEPU was leading gold. The right-upward pointing arrow indicates a mild positive correlation between GEPU and gold. This is to say that an increase in GEPU resulted in an increase in the returns of gold.

### **GEPU and BTC**

Following from Figure 9, the biwavelet plot for the GEPU-BTC pair is seen to be quite similar to what was observed in the GEPU-Gold pair. The study observes strong comovement between GEPU and bitcoin returns within the short term of the years, 2012-2014. The cloud of right-downward pointing arrows as seen in 1-2 monthly cycles of 2012 indicates a lead role by BTC. Getting to the latter of 2013 to mid-2013, the study observes left-upward pointing arrows which also support the lead role of BTC against GEPU.

Across the years 2014-2022, the study spots weak comovement between the GEPU-BTC pair in the short term with the exclusion of 2017 where the region in the short term captures the strengthened comovement between GEPU and BTC during the December 2017 BTC crash. But in the long term, evidence from the biwavelet plot indicates an adverse correlation between GEPU and the returns of Bitcoin. The left-downward pointing arrows indicate a lead role by GEPU in the long term which is in direct contradiction with what was seen in the short term. Again, the strong comovement observed in the long term shows that GEPU has a long-term relationship with BTC returns.

## GEPU and EUAF

The general intuition from the scalogram as depicted in Figure 9 indicates that among the variables under study, the European Union allowance futures market is most adversely affected by GEPU. The study observes patches of red and orange regions across the scalogram which depicts strong comovement between the GEPU-EUAF pair. From 2012 to the latter part of 2013, the red region in the scalogram with left-downward pointing arrows within 1 to 3 monthly cycles indicates a strong adverse comovement between GEPU and EUAF. This implies that an upsurge in GEPU shocks consequently results in a fall in the returns of the EUAF market. A similar conclusion can be drawn for the medium-term dynamics observed between 2014-2016, and the short-term relationship observed at the beginning of 2019.

Unlike the relationship observed between the GEPU-BTC pair, the study observes no comovement between GEPU and EUAF returns in the long term. This signifies that GEPU comoves with EUAF mostly in the short and medium term. This impliedly shows the inability of the EUAF market to hedge against GEPU risk in the short and medium term.

In conclusion, the examination of the comovement between GEPU and the G7 stock market returns shows that, consistent with the work by Ma, Wang and He (2022), GEPU comoves with G7 stock market returns across the stipulated investment horizons (short, medium and long term) with the exception of US and Canadian stock returns where the study finds weaker comovement with GEPU in the long term. Again, it can be seen that significant economic occurrences like

Brexit and the COVID-19 pandemic exacerbated the comovement between GEPU and G7 stocks. This finding resonates well with the findings of Ma, Wang and He (2022) and Arouri et al. (2016). It can also be observed that the G7 stock returns usually adversely relate to the GEPU shocks, with the G7 stocks generally having a lead role. Another key observation from the analysis is that in line with the work by Ko and Lee (2015), the study found GEPU to be adversely associated with G7 stock returns usually between the short-term and medium-term duration of 2014 and 2020. This could be explained by the significant global decline in oil prices as well as the impact of COVID-19 respectively.

With regards to the gold market, the large patches of blue colours indicate weak comovement between the GEPU and gold pair especially in the long term. However, in the short term, the biwavelet plot suggests patches of strong comovement in the short term. This is to say that, in the long term the study, based on the plots doesn't see any significant comovement between GEPU and gold. The aforementioned finding aligns partly with the outcome by Yu-Xin et al. (2021), who found a strong comovement and lead-lag relationship between EPU and gold returns in the short term in US and UK. Again, in line with the findings of Jones and Sackey (2018) and Bilgin, Gozgor, Lau, and Sheng (2018), the right upward pointing arrow as observed in the biwavelet plot indicates a positive association between EPU and gold returns. In essence, an escalation in EPU leads to a corresponding rise in gold returns.

An analysis of the comovement between GEPU and the return of bitcoin suggests that in the short term (except in 2012 and 2013), the study observes weak



comovement between the GEPU-BTC pair. It is however worth noting in the long term (between the latter part of 2013 to 2020) there is a strong negative comovement between GEPU and the BTC returns. The aforementioned finding partly aligns with the outcome of Al-Yahyaee, Rehman, Mensi, and Al-Jarrah (2019), who asserted that the positive and negative comovements between EPU and BTC returns are dependent upon investment horizons.

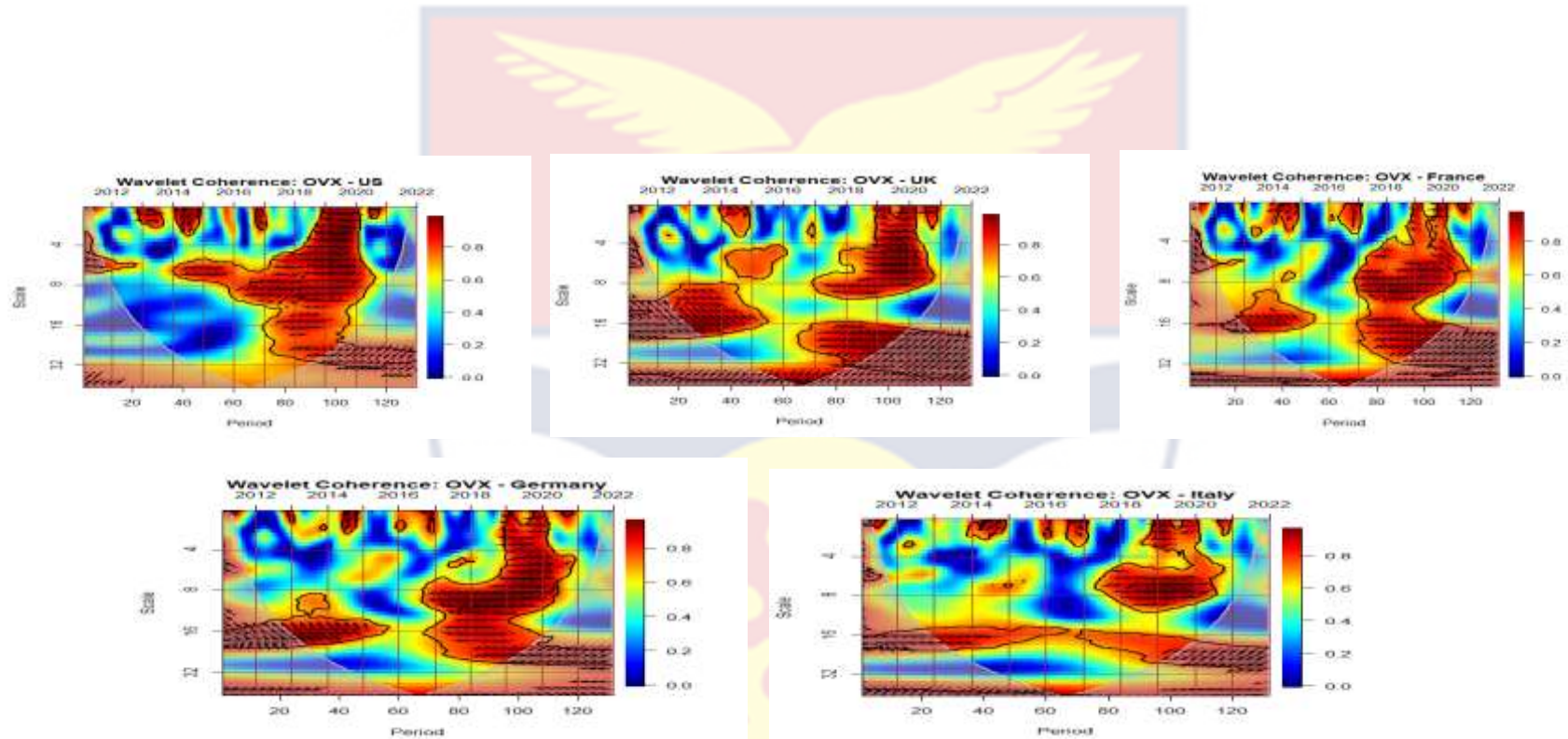
Consistent with the findings of Adekoya, Oliyide, and Noman (2021), the analysis of the comovement between GEPU and EUAF largely suggests a negative comovement between the GEPU-EUAF pair within the short and medium-term investment horizons. The study however observes weak comovement between GEPU-EUAF in the long term.

This study concludes by saying that the dynamics of numerous markets have been reshaped by the impact of COVID-19. The low and strong comovements exhibited within the time and frequency domain are demonstrative of the HMH proposed by Müller et al. (1997), as well as the AMH proposed by Lo (2004). Additionally, the variation in the heterogeneity in the patterns of leading or lagging asset returns dynamics across time frequencies elucidates the principles underlying the HMH and AMH.

#### **Comovement between oil volatility index and financial asset returns.**

This section examines the time and frequency comovement between oil volatility and the financial assets under study. The study first discusses the time varying relationship between oil volatility and individual G7 stocks, followed by gold, Bitcoin, and the European Union Allowance future returns.





*Figure 10:* Comovement between Oil volatility index and financial asset returns.

Notes: This diagram depicts the squared wavelet coherence. The x-axes (y-axes) represent years (frequency in months). The observed period starts from 01/01/2012 to 31/12/2022. Arrows  $\leftarrow$  and  $\rightarrow$  denote comovement in-phase and anti-phase, respectively; arrows  $\nearrow$  or  $\swarrow$  indicate a precedence of the first variable (OVX);  $\searrow$  or  $\nwarrow$  indicate a precedence of the second variable (asset returns). The gradient bar illustrates the intensity of comovements – warmer (from yellow to red) indicate strong comovements and cooler shades (from green to blue) indicate weak comovements.

Figure 10: Continued

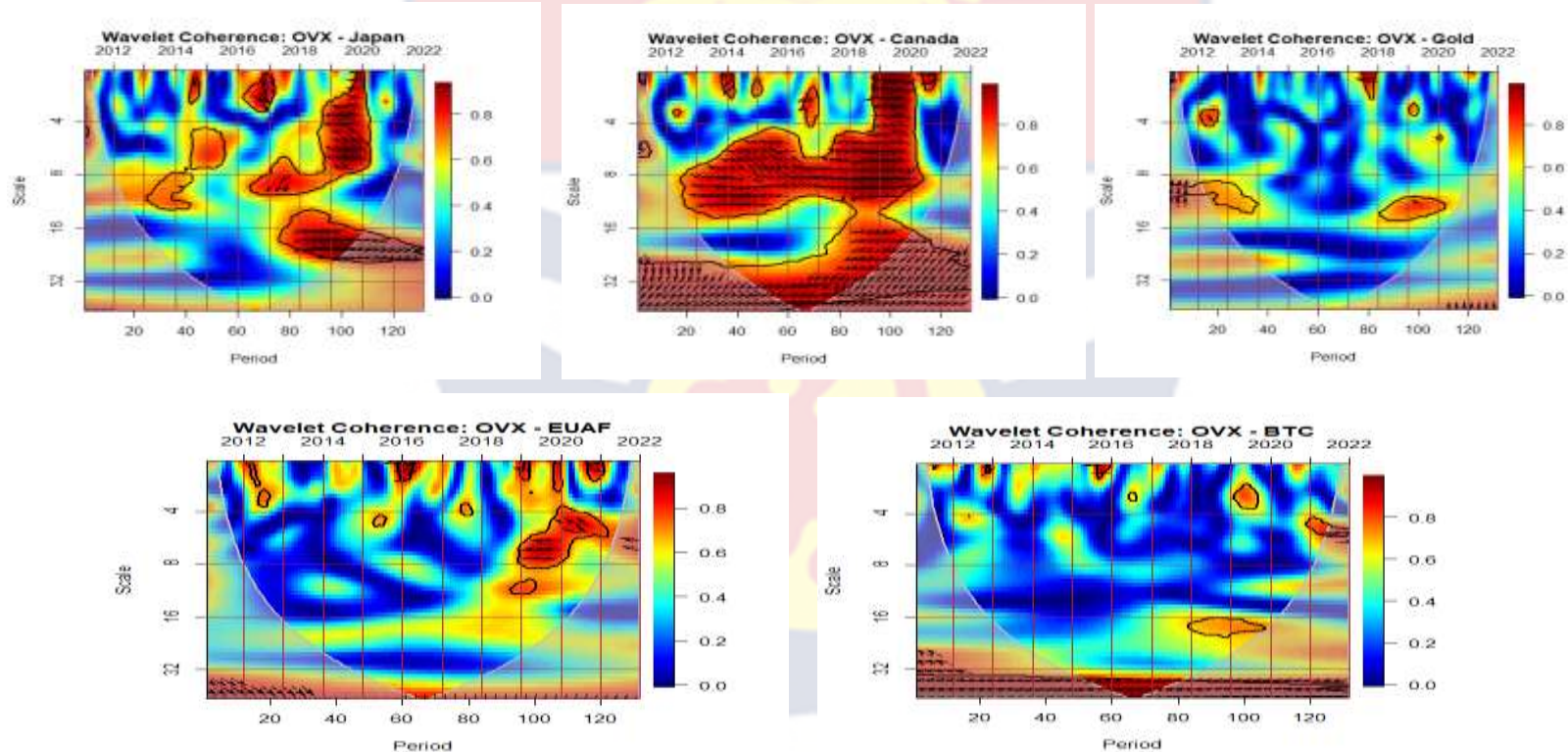


Figure 10: Comovement between Oil volatility index and financial asset returns.

Notes: This diagram depicts the squared wavelet coherence. The x-axes (y-axes) represent years (frequency in months). The observed period starts from 01/01/2012 to 31/12/2022. Arrows  $\leftarrow$  and  $\rightarrow$  denote comovement in-phase and anti-phase, respectively; arrows  $\nearrow$  or  $\swarrow$  indicate a precedence of the first variable (OVX);  $\searrow$  or  $\nwarrow$  indicate a precedence of the second variable (asset returns). The gradient bar illustrates the intensity of comovements – warmer (from yellow to red) indicate strong comovements and cooler shades (from green to blue) indicate weak comovements.

### OVX and US stock returns

Figure 10 depicts the SWC-based lead-lag and comovement dynamics between OVX and US stock returns. For this pair of OVX-US, the investigation reveals a range of coherence levels spanning between high, medium, and low levels. Notably, concerning the US, it is crucial to observe that the heatmap predominantly exhibits red shading in the context of short and medium terms across the 2012–2016 time scales, signifying high comovement between the pair. From 2017–2020, the biwavelet plot depicts a strong comovement between the pair across all investment horizons (short, medium, and long term). In 2013 (1-2 monthly cycles), the left downwards pointing arrows signify an OVX-led adverse comovement. This means that a rise in OVX shocks is occasioned by a subsequent fall in the returns of the US stock market. A similar trend is observed during the short and medium-term cycles of 2014. At the end of 2017, the study observed a US stock return-led comovement within the short term. The dynamics in the medium term however show an adverse comovement between the pair under study.

Within 2019–2021, the wavelet plot shows high coherence between the OVX-US pair signifying that the market underwent significant market stress during the aforesaid period. During the year 2019–2020, the scalogram infers a negative US stock return-led comovement in the short term. Across the 7–32 monthly cycles, the scalogram infers an adverse OVX-led comovement. This signifies that OVX shocks drove the US stock market under the aforesaid time



period, which implies that the OVX index serves as an effective proxy for gauging fear in the US stock market.

### **OVX and UK stock returns**

The biwavelet plot as depicted in Figure 10 represents the comovement that exists between the OVX-UK pair. Following from the biwavelet plot, the patches of red regions across the plot signify high comovement between the pair under study. Across the medium and long-term scale in 2013-2015, the biwavelet plot reflects an adverse UK-led comovement signifying that during the aforesaid duration, the UK stock returns drove OVX shocks. Across 2019-2021 which denotes the COVID-19 period, the biwavelet plots reflect an adverse UK-led comovement with OVX shocks. It can, however, be observed that there was a different dynamic in the long term where the study observes an adverse OVX-led comovement. This signifies that through the COVID-19 period, an upsurge in OVX shocks led to a fall in UK stock returns.

### **OVX and France stock returns.**

Quite similar to the comovement dynamics between the OVX-UK stock return pair, the biwavelet plot as evidenced in Figure 10, shows varying levels of high coherence across the plot. Similar to the OVX and UK stock returns pair, the study observes a negative France-led comovement in the short-term of 2019-2021. The pattern continues into medium term (specifically, 4-9 monthly cycles). Above 10 monthly cycles, the study observes a strong OVX-led adverse comovement with the France stock returns. This shows that the impact of OVX on



the France stock returns continues deep into the long term and has a devastating effect on the France stock returns especially during times of high uncertainties.

#### **OVX and Germany stock returns.**

With regard to the OVX-German stock returns, again the study observes a similar trend with regard to the OVX-France pair. In general, the biwavelet plot confirms a strong coherence between the pairs during the COVID pandemic era. This implies that during times of uncertainties, the comovement between OVX and the German stock returns strengthens and the adverse comovements prolong into the long term.

#### **OVX and Italy stock returns.**

The OVX-Italy pair as evidenced in Figure 10 shows that during the year 2014-2015, OVX shocks adversely led the Italian stock market in the short term with largely low comovement in the medium term. In the long term, the left-upward arrows as shown in scalograms infer an adverse Italy stock-led comovement. During the years 2018-2020, the scalogram largely reveals an adverse association between OVX shocks and Italian stock returns across the short, medium and long term.

#### **OVX and Japan stock returns.**

The scalogram as depicted in Figure 10 shows that in comparison to the previously reviewed pairs, the study finds low coherence across the scalogram. Again, significant lead-lag relationships are observed during the years 2014, 2016 and 2019-2020. The short-term comovement between the OVX-Japan pair in 2014 and 2017 reveals a positive Japan stock return-led comovement. It is evident

that during the COVID-19 era as represented by the time frame 2019-2020, the study observes a negative nexus between OVX and Japanese stock returns in the short term, a negative Japan stock return-led comovement within the 4-8 monthly cycle, and a negative OVX-led comovement in beyond 16 monthly cycles.

#### **OVX and Canadian stock returns.**

Figure 10 depicts the SWC-based lead-lag and comovement dynamics between the OVX-Canada pair. The large red region across the scalogram implies high comovement between the pair under study. During the later part of 2014 to early 2014 (1-2 monthly cycles), the scalogram reflects an OVX-led adverse comovement with the Canadian stock returns. In the medium term, the scalogram generally reflects an adverse Canadian stock return-led comovement. In the long term, the scalogram reflects an OVX-driven market. Considering the time frame 2019-2021, the scalogram reflects a negative association between the OVX-Canada pair in the short and medium term. In the long-term, it is seen that OVX negatively leads the Canadian stock returns.

#### **OVX and Gold returns.**

Figure 10 depicts the SWC-based comovement dynamics between the OVX-Gold pair. The large portions of blue regions as shown in the scalogram show weak comovement between the pair under study. It is obvious that the comovement between the OVX-Gold pair is significantly different from the OVX-G7 stock market pair. Specifically, during the year 2013, the study observes a right downward pointing arrow which suggests a positively gold-led comovement during the short term. In the medium term, the study finds an orange

region which suggests somewhat of a strong comovement between the variable. During the 2019-2021 period, the left-upward pointing arrow suggests a negatively gold-led comovement between the pair. This signifies that gold drove OVX shocks considering the time frame in question.

#### **OVX and BTC returns.**

Similar to the findings of the OVX-Gold pair, the scalogram largely infers a weak comovement between the OVX-BTC pair across the times under study. A few exceptions are made for the short-term dynamics where the scalogram infers an OVX-led comovement during 2012, 2013 and the later part of 2016. Again, during the 2019-2020 season, the study observes a high comovement between the pair in the short and long term.

#### **OVX and EUAF returns.**

The scalogram of the OVX-EUAF pair largely depicts weak comovement across the medium to long-term horizons between 2012 to 2017. In the short-term, specifically in 2016, the left-downward pointing arrows imply an OVX-led comovement which suggests that an increase in OVX shocks leads to a fall in EUAF stocks. During the year 2020-2021, the scalogram reflects an EUAF-led comovement with OVX within 4-8 monthly cycles.

In conclusion, the general observation on the OVX-G7 stock market pair is that OVX shocks are seen to be highly correlated with the G7 stock market across different investment horizons (short, medium and long-term). Again, the study observes that during times of high uncertainties, the comovement between the OVX-G7 stock market pair tightens. This resonates well with the finding of

Antonakakis et al. (2015) who argued that there is an increase in correlation of uncertainty indexes and assets during periods of high uncertainty. It is however worth noting that during the short term, the study observes a Stock return-led adverse comovement with OVX shocks but in the long term, the biwavelet plot indicates an OVX-led adverse comovement with the G7 stock returns which depicts heterogeneity in the relationship between the aforesaid variables which aligns with the HMH proposed by Muller et al. (1997).

Consistent with the finding of Khalfaoui et al. (2015) the study can also affirm that the oil market typically demonstrates a strong comovement in the long term with other stock markets. In contradiction to the study by Lee et al. (2012), the study observes that each G7 member country's stock returns are substantially impacted by the upsurge in oil prices. Again, unlike the finding of Liu et al. (2017) who discovered that the correlation between oil prices and the stock market is altering in the short term but diminishing in the long term, the study finds similar trends from 2012-2017 but the relationship alters into the long term during the COVID-19 pandemic specifically. The difference in findings could be explained by the duration of the study as well as the analytical techniques employed. This reiterates the need to re-evaluate the nexus between macroeconomic variables in light of recent happenings.

With regards to the gold and bitcoin market, the biwavelet plot largely reveals a weak comovement between the assets and the OVX pair. In line with the finding of Dutta (2018), the study finds heterogeneity in the relationship between OVX and gold returns. Selmi et al. (2018) argue that gold and bitcoin serve as a

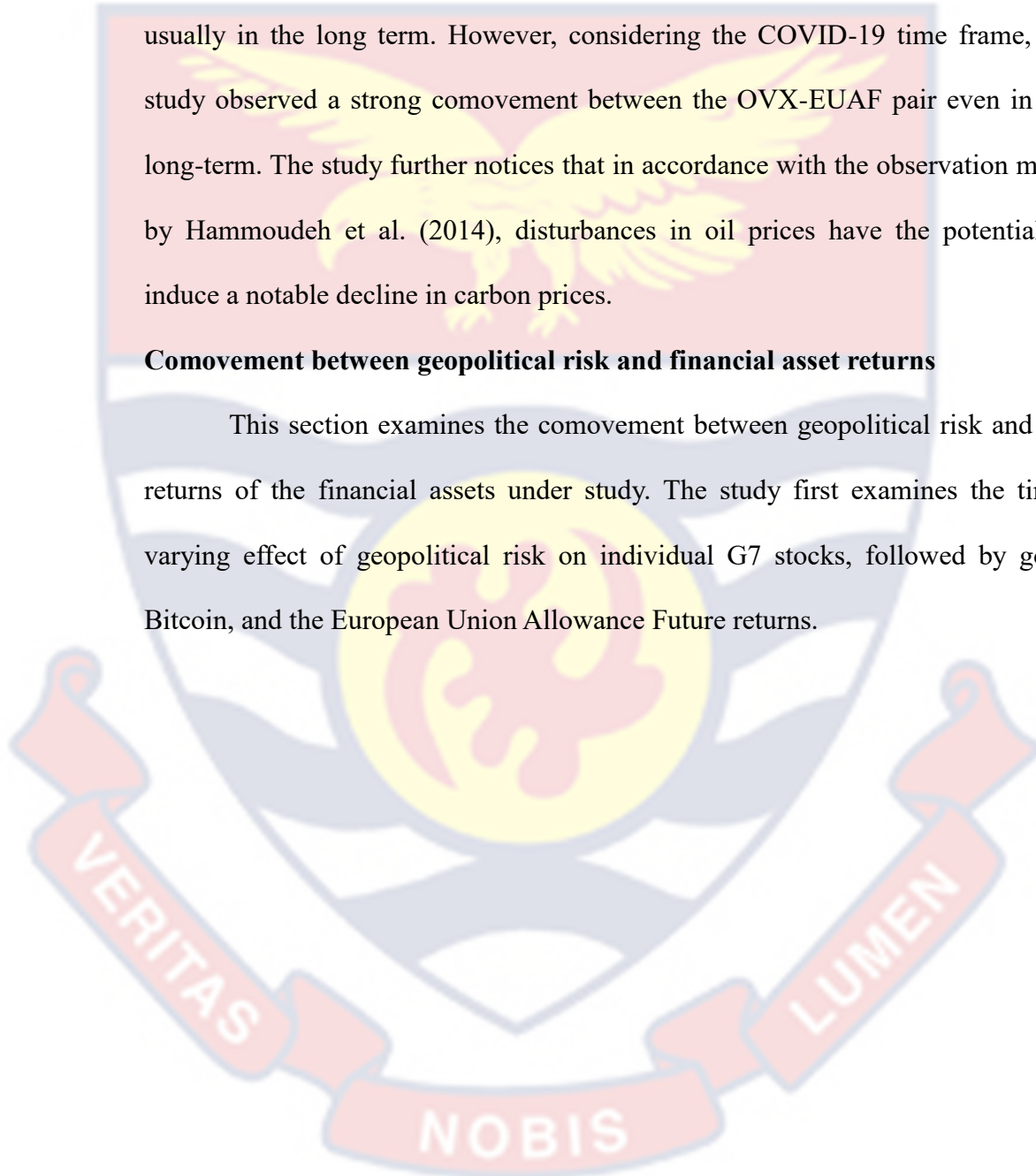


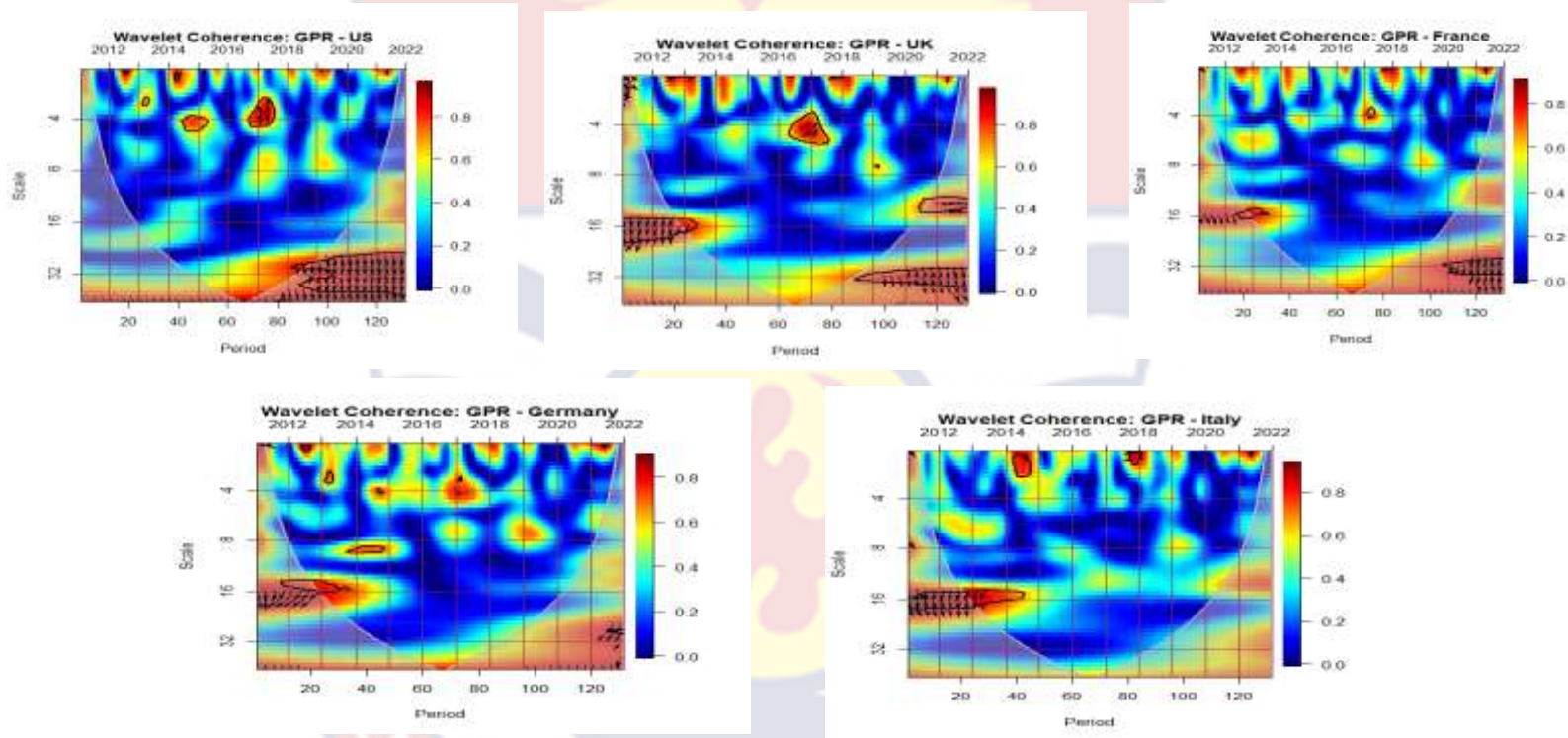
hedge, safe haven and diversifier against oil prices as a result of the insensitivity of gold and bitcoin against oil prices.

The comovement between the OVX-EUAF pair also seems to be weak usually in the long term. However, considering the COVID-19 time frame, the study observed a strong comovement between the OVX-EUAF pair even in the long-term. The study further notices that in accordance with the observation made by Hammoudeh et al. (2014), disturbances in oil prices have the potential to induce a notable decline in carbon prices.

### **Comovement between geopolitical risk and financial asset returns**

This section examines the comovement between geopolitical risk and the returns of the financial assets under study. The study first examines the time-varying effect of geopolitical risk on individual G7 stocks, followed by gold, Bitcoin, and the European Union Allowance Future returns.





*Figure 11: Comovement between GPR index and financial asset returns.*

Notes: This diagram depicts the squared wavelet coherence. The x-axes (y-axes) represent years (frequency in months). The observed period starts from 01/01/2012 to 31/12/2022. Arrows  $\leftarrow$  and  $\rightarrow$  denote comovement in-phase and anti-phase, respectively; arrows  $\nearrow$  or  $\swarrow$  indicate a precedence of the first variable (GPR);  $\searrow$  or  $\nwarrow$  indicate a precedence of the second variable (asset returns). The gradient bar illustrates the intensity of comovements – warmer (from yellow to red) indicate strong comovements and cooler shades (from green to blue) indicate weak comovements.

Figure 11: Continued

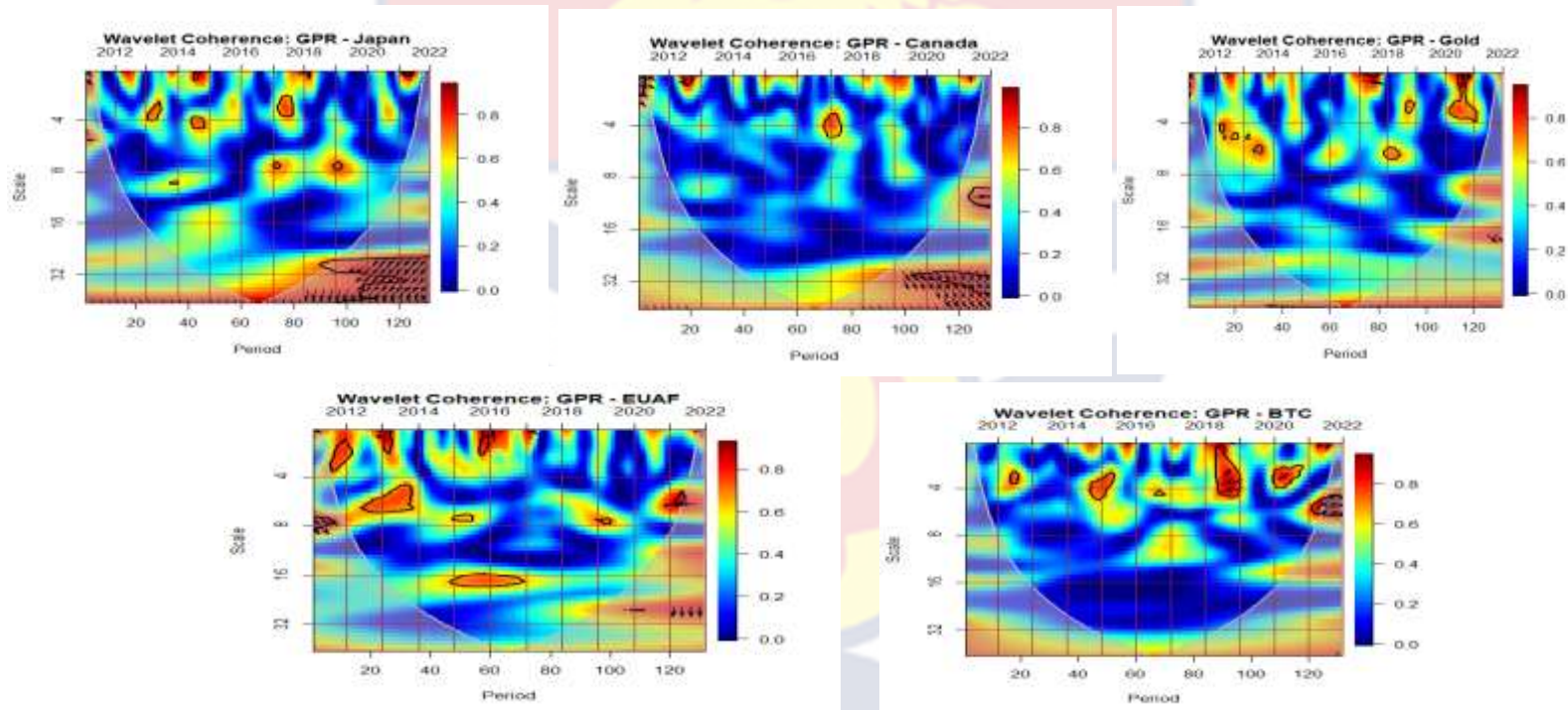


Figure 11: Comovement between GPR index and financial asset returns

Notes: This diagram depicts the squared wavelet coherence. The x-axes (y-axes) represent years (frequency in months). The observed period starts from 01/01/2012 to 31/12/2022. Arrows  $\leftarrow$  and  $\rightarrow$  denote comovement in-phase and anti-phase, respectively; arrows  $\nearrow$  or  $\swarrow$  indicate a precedence of the first variable (GPR);  $\searrow$  or  $\nwarrow$  indicate a precedence of the second variable (asset returns). The gradient bar illustrates the intensity of comovements – warmer (from yellow to red) indicate strong comovements and cooler shades (from green to blue) indicate weak comovements.

### **Geopolitical risk and US stock returns.**

Findings from Figure 11 divulge the comovements between the GPR-US pair. The biwavelet plot as seen in Figure 11 shows large patches of blue regions especially in the medium and long term. These patches imply weak comovement between geopolitical risks and the returns of the US. The study however observes patches of strong comovement as indicated by the patches of regions in the short term. During the early part of 2017, the biwavelet plot shows a cloud of upward-pointing arrows which indicates a GPR-led role against the US stock returns. Taking a look at the dynamics captured in 2022 which inferably captures the effect of the Russian-Ukraine conflict, the study observes a right-downward arrow which indicates a positive US stock return-led comovement.

### **Geopolitical risk and UK stock returns.**

Quite similar to what was observed in the GPR-US pair, the biwavelet plot as shown in Figure 11 indicates largely, weak comovement between the GPR-UK pair in the medium and long term. During the years 2013-mid 2014, the biwavelet plot seems to suggest an adverse UK stock return-led comovement with GPR in the short-term. The study observes patches of high comovement across the short-term frequency of 2014, 2017, 2018 and 2022. Considering 2017 in particular, the cloud of right-upward pointing arrows the positive effect of UK stock returns on GPR shocks. This is to say that UK stock returns drive GPR given the particular time frame in question. With an emphasis on the mid-section of 2022, the study inferably observes an adverse GPR-led comovement, signifying that GPR negatively drove UK stock returns at the early stages of the Russian-Ukraine



conflict. Further, the study observes weak comovement into the medium term as the adverse seems to be neutralised.

#### **Geopolitical risk and France stock returns.**

The biwavelet plot of the GPR-France pair shows intermittent patches of red and orange regions which signifies high comovement across the short and medium term. The lead-lag dynamics between the pair are seen in the biwavelet plot. However, during the later part of 2017, the study observed left-downward pointing arrows which signify that GPR was driving the returns of France stocks negatively. This is to say that an upsurge in GPR shocks results in a fall in the returns of France stocks. Inference from the dynamics observed in 2022 revealed that during the Russia-Ukraine conflict, the study observes a right-downward pointing arrow which indicates a positive France stock-led comovement.

#### **Geopolitical risk and Germany stock returns.**

Figure 11 depicts the comovement between the GPR-Germany pair. The patches of red regions distributed mainly during the short term signify a high comovement between the pair during the years under study (2012-2022). The lead-lag dynamics are established during mid-2022 where the study observes a positive German stock-return led comovement indicating that a fall in the German stock return is occasioned by a confirming fall in GPR.

#### **Geopolitical risk and Italy stock returns.**

The study observes from the GPR-Italy pair that there exists weak comovement between GPR and Italian stock returns in the medium and long term with the exception of 2013 where the biwavelet plot depicts an inverse GPR-

driven comovement. Left-downward pointing arrows within 1-2 of 2018 also indicate an adverse GPR-led comovement with Italy stock. The study observes a right-downward pointing arrow in 2022 which signifies that during the onset of the Russia-Ukraine conflict, the Italian stock market positively drove GPR.

### **Geopolitical risk and Japan stock returns.**

The GPR-Japan pair as depicted in Figure 11 shows only small regions of red and orange patches across the scalogram with no significant lead-lag dynamics. The study observes strong comovement usually in the short term of the following years: 2013-2017, 2018, and 2021-2022. In the medium term, the study observes strong comovement between the GPR-Japan pair across the years 2013-2020. In the long term, the study observes largely weak comovement between the pair, with the exception of 2016-2019, where the red region beyond the 32 monthly scales signifies a strong comovement between the pair.

### **Geopolitical risk and Canada stock returns.**

A quick scan of the biwavelet plot of the GPR-Canada pair shows that in the medium and long term, there exists weak comovement between the pair. In the short term, the biwavelet plot shows little patches of strong comovement in the short term (usually 1-2 monthly scales) with no significant lead-lag relationships.

### **Geopolitical risk and gold returns.**

Figure 11 depicts the comovement between the GPR-Gold pair. The study observes a positive Gold-led comovement between the pair within 1-2 monthly cycles in 2018. The study again observes a positive Gold-led comovement

between the pair in the short term in 2021. Generally, there exists weak comovement between the GPR-Gold pair in the long term.

### **Geopolitical risk and Bitcoin returns.**

Similar to the dynamics observed in the GPR-Gold pair, the patches of red and orange regions are mainly concentrated in the short term and medium term. Thus, the scalogram depicts a weak comovement between the GPR-BTC pair in the long term. During the year 2019 (2-4 monthly cycles), the study observes a positive GPR-driven comovement. At this juncture, an upsurge in GPR is prompted by a corresponding elevation in BTC returns. The dynamics however changed in 2021 when the study observed an adverse GPR-driven comovement. This means that an increase in GPR shocks leads to a subsequent fall in BTC. During the year 2022, the biwavelet plot shows a cloud of left-downward pointing arrows during the short term which indicates a GPR-led negative comovement with BTC returns.

### **Geopolitical risk and European Union allowance futures returns.**

Following from Figure 11, the study observes patches of red regions scattered across the short, medium and long term. The study however finds no lead-lag relationships with the exception of 2014 and 2022. In the short term, the study observes a EUAF-led comovement between the pair. The direction of the arrow indicates a negative relationship. In 2022 which captures the duration of the Russian-Ukraine conflict, the study observes a GPR-led negative comovement with the EUAF returns. This signifies that a spike in the GPR index resulted in a decrease in the return of the EUAF market.

In summary, the biwavelet analysis of geopolitical risk and financial asset returns indicates that generally, GPR has a weak comovement with financial assets especially in the long term. In the short and medium term, the study observes that the G7 stock market usually positively drives GPR. The dynamics however alter during times of significant geopolitical events. For instance, during the later part of 2017, the study observes an adverse GPR-led comovement between the pairs of UK, France, and Italy stocks. But quite surprisingly during the current Russian-Ukraine conflict, the study observes that the majority of the G7 stock returns (US, France, Japan, and Canada) positively correlated with GPR, especially in the short term. It can be therefore be inferred that the Russian-Ukraine conflict had no adverse impact on the G7 returns. The aforesaid finding lends support to the finding of Bossman and Gubareva (2023) who asserted that the majority of the G7 stocks are resilient to GPR shocks and most especially during the Russian-Ukrainian conflict. Furthermore, similar to the finding of Agyei (2023) who studied the lead-lag nexus between GPR and the Emerging seven markets, this study highlights asymmetric market-specific coherence and lead-lag behaviours regarding the comovement between GPR and the G7 equities.

For the above phenomena, a plausible reason underlying the differences in the relationships between GPR and the G7 stock returns stems from behavioural finance. According to the behavioural finance literature (AMH and HMH), the empirical findings are attributed to over and under-reaction of investors to how they trade on the stock markets as a result of good or bad news that is caused by geopolitical risk. As the consequences of under- and overreaction for investors are



different, this may lead to differing relationships between GPR and G7 stocks with respect to different countries.

Another possible explanation for the differing relationship between GPR and the G7 stock returns can be associated with the heterogeneous character of markets, in terms of geographical location and economic class (Agyei et al., 2022; Bossman et al., 2023). Again, in light of the diversity of the G7 stock markets in terms of variations in their economic conditions and responses to global upheavals (Bastianin et al., 2016), it is expected that the effect of GPR on their respective markets will not be alike.

With regard to the gold market, the study observes a weak comovement between the GPR-Gold pair especially in the medium and long term. In the short term, the study observes a few patches of red regions signifying high comovement. This study, therefore, provides findings commensurate with the work of Cheng, Zhang, and Cao (2022) that there is a strong correlation between gold and GPR when GPR events take place. In line with the study by Cheng, Zhang and Cao (2022), this study generally observes a gold-led comovement against GPR. Finally, the positive comovement between the GPR-Gold pair as observed during the Russian-Ukraine conflict lends support to the finding of Chiang (2021) who revealed that higher GPR results in higher returns for gold.

Similar to the GPR-Gold pair, the biwavelet plot for the GPR-BTC pair shows weak comovement between the pair in the long term. During the year 2019, the study observes that consistent with the finding of Bouri et al. (2022), GPR positively leads the GPR-BTC pair. But considering 2021 and 2022, the

study observes an adverse comovement between the pair. This signifies that GPR shocks had an adverse effect on the returns of BTC. The latter statement resonates well with the results of Bouri et al. (2022) and Su et al. (2020) who argued that during stressful market conditions (as observed in 2021 and 2022 due to the COVID-19 pandemic and the Russian-Ukraine conflict) GPR is adversely correlated with BTC returns.

The GPR-EUAF pair showed glimpses of strong comovement across the short, medium and long term. The study observes from the biwavelet plot that during the year 2022, GPR negatively led the EUAF market, causing a decrease in the returns of the EUAF market in the medium term. The finding of this study, therefore, lends support to the work by Chowdhury et al. (2021) who revealed that GPR impacts energy and stock markets adversely, especially during stressful market conditions, which in this case can be hypothesized with the Russian-Ukraine conflict observed in 2022.

### **The Uni-directional Causal Relationship between Economic Uncertainty and Financial Asset Returns**

#### **Global economic policy uncertainty and financial asset returns**

This study employed the Diks and Panchenko (2006) non-linear causality test as a robustness test for the quantile and wavelet techniques. The Diks and Panchenko causality test is a non-parametric test. It does not rely on assumptions about the underlying parametric models of the data distributions and instead uses kernel-based methods to estimate densities. This allows it to effectively capture and test for non-linear relationships between time series datasets without the

constraints imposed by parametric approaches (Diks & Panchenko, 2006). Motivated by the non-linear nature of the time series as shown in the descriptive statistics. It is more appropriate to employ the Diks and Panchenko (2006) causality to effectively capture and test for the non-linear relationships in the variables under study. In this regard, this study examines the uni-directional causal relationship flowing economic uncertainties to the financial asset returns under study. A pivotal insight drawn from the wavelet coherence analysis indicates that there are causal connections between the independent and dependent variables. While the wavelet coherence plot illustrates these linkages across time and frequency domains, this study employs the Diks and Panchenko (2006) nonparametric causality test to validate the causal relationship that exists between economic uncertainties and financial asset returns.

The results of the non-parametric Diks and Panchenko (2006) causality examination between GEPU and financial asset returns are showcased in Table 26. The investigation delves into the degree of one-way causation existing between the variables, aiming to determine whether the behaviour of the studied financial assets can be forecasted by economic uncertainty indices. Drawing from the data's behaviour, the research introduces five data series to vividly demonstrate the scope of causality. The findings are encapsulated in Table 26, showcasing the results of the Diks and Panchenko (2006) nonparametric causality assessment between economic uncertainties and financial asset returns across decomposed frequencies and signals. The most prevalent frequency within the decomposed data is M1 (pertaining to the short-term). This is consistent with the

findings from the wavelet estimations as well as the quantile regression estimations where the study finds a high comovement and strong effect of economic uncertainties on financial asset returns in the short-term.





**Table 26. Disk and Panchenko nonparametric causality between GEPU and financial asset returns**

GEPU $\neq$ US	GEPU $\neq$ UK	GEPU $\neq$ France	GEPU $\neq$ Germany	GEPU $\neq$ Italy	GEPU $\neq$ Japan	GEPU $\neq$ Canada	GEPU $\neq$ Gold	GEPU $\neq$ BTC	GEPU $\neq$ EUAF
					Signal				
0.815	0.307	0.407	-0.289	0.185	-0.113	0.475	-1.223	-0.449	-0.193
					M1				
0.667	1.280*	1.749**	2.069***	2.244***	2.011**	0.761	0.450	1.427*	1.116*
					M2				
0.029	0.590	0.596	0.623	0.008	0.774	0.594	0.286	0.839	-0.883
					M3				
-0.367	0.955	0.574	1.333*	-0.592	0.369	-0.642	-0.840	-0.463	-0.745
					M <sub>Agg</sub>				
0.704	-0.054	-0.983	-1.427	0.119	-1.344	0.136	0.252	-1.094	0.365

Notes: This Table reports the t-values of the Diks and Panchenko causality tests. The arrow " $\neq$ " denotes the causality null hypothesis that GEPU does not cause Financial assets; embedding dimension = 2, and bandwidth = 0.5000 (Diks & Panchenko, 2006). The interpretation of the Disk and Panchenko causality test involves comparing the calculated p-value to the chosen significance level. If the p-value is less than  $\alpha$ , we reject the null hypothesis and infer the presence of Granger-causality. If the p-value is greater than  $\alpha$ , we fail to reject the null hypothesis, suggesting no strong evidence for a causal relationship based on the available data. \*\*\*, \*\*, and \* denote significance at the 1%, 5% and 10% levels, respectively.

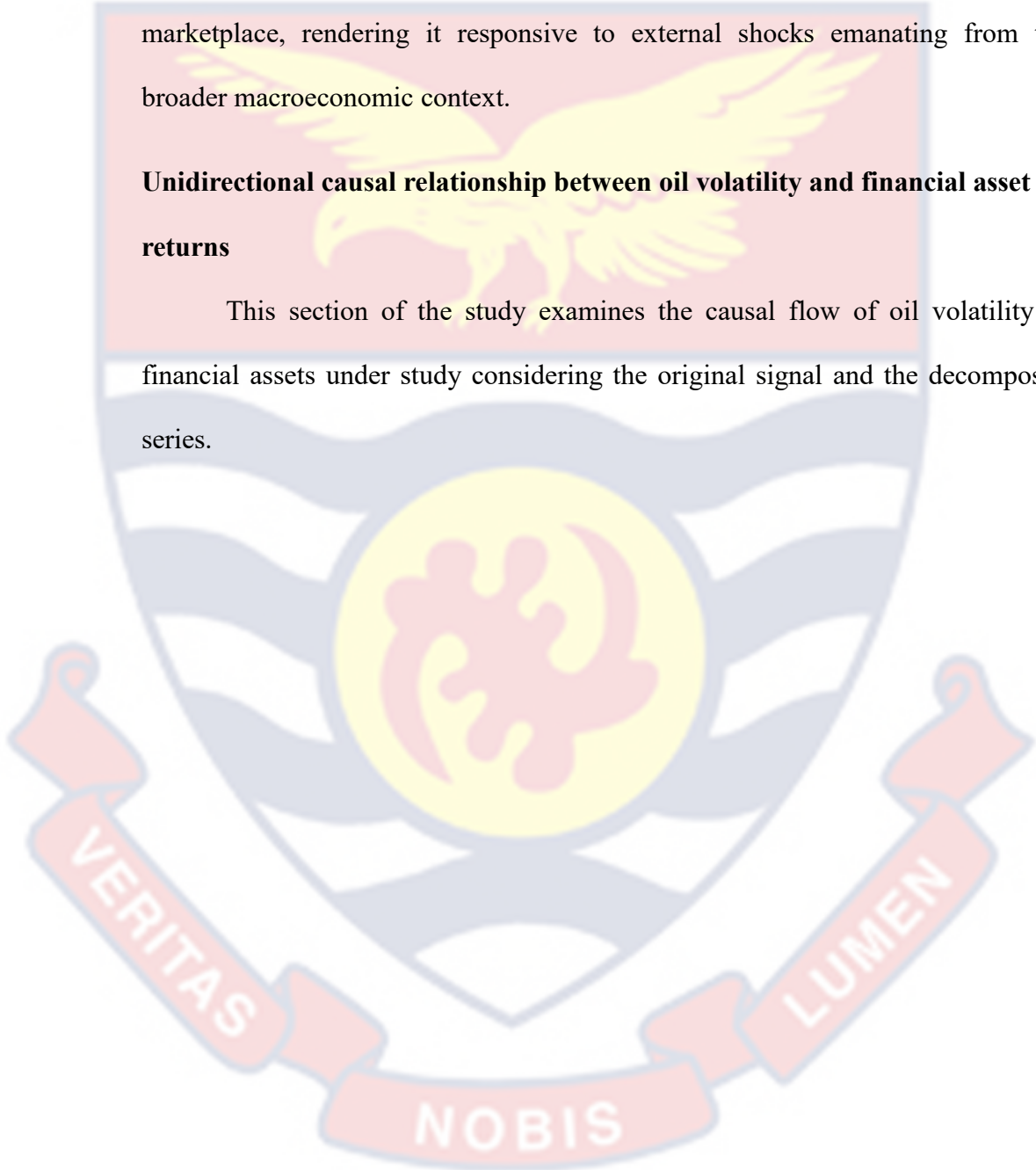
Regarding the G7 stocks, the study finds that GEPU causes the stocks of the UK, France, Germany, Italy, and Japan in the short term. This signifies that short-term volatilities in GEPU on the G7 stocks are prominent compared to the medium-term and long-term (with the exception of German stocks where the study finds a unidirectional causal relation with GEPU in the medium-term). Consequently, this implies that shocks from EPU hold substantial implications for investors engaged in stock markets. It appears that the investor community within the UK, France, Germany, Italy, and Japan, which is largely composed of sophisticated individuals (such as fund managers, arbitragers, and speculators), assigns notable significance to the forthcoming policy decisions. These findings align harmoniously with research conducted by Wu, Liu, and Hsueh (2016), Antonakakis et al. (2013), Kang and Ratti (2013), and Dzielinski (2012), all of which identify a pronounced influence of policy uncertainty on stock prices. For instance, Dzielinski (2012) asserted a negative association between EPU and stock returns, indicating that the impact flows from EPU to stock prices.

On the causal nexus between GEPU and gold, the study observes that GEPU does not cause gold. This finding is commensurate with the finding by Raza, Shah, and Shahbaz (2018) who employed the Granger causality test to reveal that there is no causal nexus between the price of gold and uncertainties of economic policy. Consistent with the finding of Mokni (2021), the study observes a causal relationship flowing from GEPU to bitcoin returns in the short-term. This suggests GEPU predicts BTC returns in the short term.

In line with the finding of Dou et al. (2021), the study finds that GEPU has the ability to predict EUAF returns. This aligns precisely with the expectation of the study, as the carbon market fundamentally operates as a policy-oriented marketplace, rendering it responsive to external shocks emanating from the broader macroeconomic context.

### **Unidirectional causal relationship between oil volatility and financial asset returns**

This section of the study examines the causal flow of oil volatility to financial assets under study considering the original signal and the decomposed series.



**Table 27. Disk and Panchenko nonparametric causality between OVX and financial asset returns**

OVX≠US	OVX≠UK	OVX≠France	OVX≠Germany	OVX≠Italy	OVX≠Japan	OVX≠Canada	OVX≠Gold	OVX≠BTC	OVX≠EUAF
Signal									
0.752	-0.187	0.138	-0.596	0.301	0.096	0.987	1.093	0.476	-0.913
M1									
1.634**	1.285*	1.579**	-0.039	-0.783	1.280*	2.102***	1.049**	0.651	1.170
M2									
1.104	-1.092	-0.083	0.013	1.701**	0.553	1.031	0.781	1.593**	-1.287
M3									
-1.092	-0.049	1.417*	1.050	0.365	-1.156	-0.566	0.962	-1.063	-0.820
MAgg									
-0.144	-0.983	0.854	-0.065	0.987	-0.821	0.589	-0.999	0.711	-0.127

Notes: This Table reports the t-values of the Diks and Panchenko causality tests. The arrow “≠” denotes the causality null hypothesis that OVX does not cause Financial assets; embedding dimension = 2, and bandwidth = 0.5000 (Diks & Panchenko, 2006). The interpretation of the Disk and Panchenko causality test involves comparing the calculated p-value to the chosen significance level. If the p-value is less than  $\alpha$ , we reject the null hypothesis and infer the presence of Granger-causality. If the p-value is greater than  $\alpha$ , we fail to reject the null hypothesis, suggesting no strong evidence for a causal relationship based on the available data. \*\*\*, \*\*, and \* denote significance at the 1%, 5% and 10% levels, respectively.



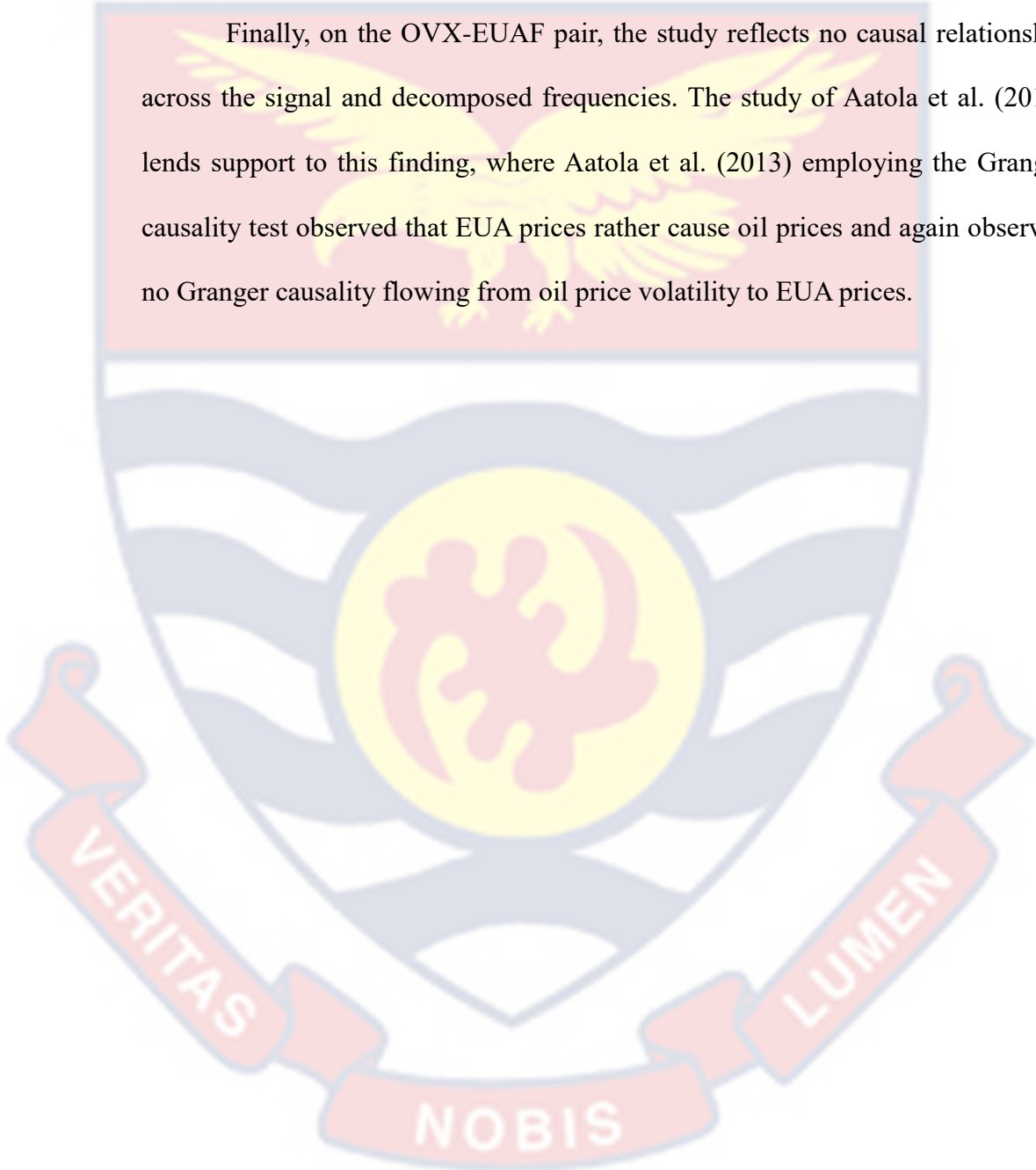
Table 27 presents the Diks and Panchenko (2006) non-linear causality between OVX and financial asset returns. With regard to the G7 stock markets, the study observes that OVX can predict the majority of G7 stocks. Specifically, the study observes that OVX causes the returns of the US, UK, France, Japan and Canadian stock returns in the short term. In the medium term, the study observes a causal relationship flowing from OVX to Italy and France stocks. The outcome of the study resonates well with the findings of Çevik, Atukeren, & Korkmaz (2018) who employed the Granger causality test to examine the causal association between Brent oil volatility and the G7 stocks returns (Morgan Stanley Capital International index). The time-varying Granger causality test indicated evidence of causal linkages flowing from oil prices to the stock of the G7. The studies of Feng et al. (2017) and Diaz, Molero, and Garcia (2016) also support the evidence of a significant impact of oil volatility on the returns of the G7 stocks.

With regard to the gold market, the study observes that OVX causes gold returns in the short-term. A similar finding was revealed by Bildirici and Turkmen (2015) who found a unidirectional Granger causality between oil prices and precious metal price. Roboredo and Ugolini (2016) also employed the Granger causality test and revealed that oil prices granger cause the prices of precious metals. A similar finding was revealed by Ewing and Malik (2013) who also found an association between oil prices and gold prices.

On the other hand, consistent with work by Li, Hong, Wang, Xu, and Pan (2022), who found a time-varying causality between OVX and Bitcoin, this study observes that OVX can predict BTC returns in the medium term. The findings of

Long, Pei, Tian, and Lang (2021) on the adverse effect of GEPV and oil volatility on the prices of Bitcoin infer a causal relationship between OVX and Bitcoin prices.

Finally, on the OVX-EUAF pair, the study reflects no causal relationship across the signal and decomposed frequencies. The study of Aatola et al. (2013) lends support to this finding, where Aatola et al. (2013) employing the Granger causality test observed that EUA prices rather cause oil prices and again observed no Granger causality flowing from oil price volatility to EUA prices.



### Unidirectional causal relationship between geopolitical risk and financial asset returns

This section of the study examines the causal flow of geopolitical risk to financial asset under studies considering the original signal and the decomposed series.

**Table 28. Disk and Panchenko nonparametric causality between GPR and financial asset returns**

GPR≠US	GPR≠UK	GPR≠France	GPR≠Germany	GPR≠Italy	GPR≠Japan	GPR≠Canada	GPR≠Gold	GPR≠BTC	GPR≠EUAF
					Signal				
-0.328	0.462	-0.197	-0.485	-0.134	-0.102	-0.492	-0.638	-0.522	-0.958
					M1				
-0.958	1.602**	2.550***	2.052**	-0.320	2.167***	1.452*	0.978	1.754**	0.316
					M2				
1.050	1.232	-0.452	0.534	-0.016	0.323	1.039	0.039	1.121	0.975
					M3				
0.609	-0.942	1.652**	-1.169	0.679	-1.338	0.555	0.507	-0.350	-0.543
					MAgg				
0.950	1.026	-0.708	-0.504	-0.573	-0.556	-0.463	1.296*	0.501	-0.562

Notes: This Table reports the t-values of the Diks and Panchenko causality tests. The arrow “≠” denotes the causality null hypothesis that GPR does not cause Financial assets; embedding dimension = 2, and bandwidth = 0.5000 (Diks & Panchenko, 2006). The interpretation of the Disk and Panchenko causality test involves comparing the calculated p-value to the chosen significance level. If the p-value is less than  $\alpha$ , we reject the null hypothesis and infer the presence of Granger-causality. If the p-value is greater than  $\alpha$ , we fail to reject the null hypothesis, suggesting no strong evidence for a causal relationship based on the available data. \*\*\*, \*\*, and \* denote significance at the 1%, 5% and 10% levels, respectively.

Table 28 reveals the nonparametric causality estimate between GPR and financial assets. In the short term, it is evident from Table 28 that there exists a short-term causal relationship flowing from GPR to the UK, France, Germany, Japan, and Canada. In the medium term, the estimates from Table 28 shows that there is a causal relationship flowing from the GPR to the French stock market. This implies that GPR can forecast the stock returns of the aforesaid stock markets which is consistent with the finding of Adebayo, Akadiri, and Rjoub, (2022) who observed a causal influence of GPR on stock returns of South Korea. Again, the study infers causality from the works by Agyei (2023), Bossman and Gubareva (2023), and Salisu, Lasisi, and Tchankam (2022) who observed a statistically significant impact of GPR on the stock returns of emerging and advanced economies.

The Gold market on the other hand only experiences a long-term causal flow from GPR. The finding of the study is supported by the work of Huang, Li, Suleman, and Zhang (2023) who employed a nonparametric causality-in-quantiles methodology to assess the causal nexus between GPR and the returns of gold. The outcomes of the study revealed a causal association between GPR and gold market volatility. Likewise, Yilanci and Kilci (2021) identified a unidirectional causal link between mainland margin political risk and gold prices through the application of the dynamic Hacker and Hatemi-J (2012) bootstrap causality test.

With regard to the BTC market, the study observes GPR can predict the stock returns of BTC in the short term. The findings of this study resonate well with work by Al-Yahyee, Rehman, Mensi, and Al-Jarrah (2019) who employed



the wavelet technique to conclude that there exists a causal association between GPR and BTC prices. Again, the study by Aysan, Demir, Gozgor and Lau (2019) established that GPR has the ability to forecast both Bitcoin returns and volatility, which sits well with the findings of this study.

The study however observes a long-term causal relationship between GPR and the EUAF market. This finding is corroborated by the study of Gokmenoglu et al. (2020). Gokmenoglu et al. (2020) on the effect of militarization, on CO<sub>2</sub> emissions and the ecological footprint in Turkey revealed a long-run association and a flow of causality between the variables. Furthermore, Sofuoğlu and Ay (2020) observed a unilateral causal relationship extending from political instability to climate change, subsequently impacting returns within the carbon market.

In summary, the research paper utilising the Diks and Panchenko (2006) non-linear causality test reveals that economic uncertainties proxied by Global EPU, OVX and GPR cause the returns of the financial assets under study across different investment horizons but more specifically in the short and medium terms. This finding resonates well with the finding of the quantile regression and wavelet results. It can be recalled from the findings of the quantile estimations that there was a high level of statistically significant effect of the economic uncertainty indices on the returns of financial assets in the short and medium term. It was observed that in the long term, this adverse effect weakens significantly. A similar conclusion can be drawn for the wavelet analysis which shows high comovement between economic uncertainty indices and financial

asset variables usually in the short and medium term. The estimations from the Diks and Panchenko (2006) non-linear causality test confirms the robustness of the quantile regression and wavelet techniques. In light of the findings on the adverse effect of economic uncertainty indices on the returns of financial assets, it is essential for policymakers on economic policies and investors on the financial market to mitigate the impact of these uncertainties, especially during market stress conditions.

### **Chapter Summary**

Within this chapter, an analysis of the time series characteristics of all variables employed in the study was conducted, followed by their presentation and subsequent discussion. Preliminary and diagnostics tests such as the Jarque-Bera test, Augmented Dickey-Fuller and Phillip Perron tests were conducted to determine the appropriate estimation technique to employ as well as to ensure accurate results. The results from the Jarque-Bera test revealed that the data was not normally distributed. The estimations from the ADF and PP test also revealed that the returns of variables under study were stationary. These diagnostic tests motivated the study to employ non-linear models such as the VMD technique, QR and QQR models, wavelet model and the Disk and Panchenko non-parametric causality test.

The results obtained by the quantile regression model on the relationship between economic uncertainties and financial asset returns is that overall, economic uncertainties proxied by Global and Country-level EPU, OVX and GPR have an adverse effect on the returns of financial assets. With regard to the G7

stock market, the study observed that economic uncertainty indices largely affected the stocks of the G7 adversely in the bearish market. The adverse effect is however seen to weaken in the medium and long-term.

The comparative analysis between the effect of country-level EPU and Global EPU on G7 stock market revealed that a country's respective country-level EPU has a larger statistical impact on the stock returns of its country.

The analysis on the relationship between economic uncertainties and the returns of gold shows that the return of gold is generally robust to the adverse effect of economic uncertainties. It should however be noted that the robustness of gold returns against economic uncertainties is short-lived. That is, gold's robustness against uncertainties is strong in the short term, but then weakens in the medium and long term. Bitcoin on the other hand is generally more responsive to economic uncertainties as compared to gold.

The empirical evidence on the nexus between economic uncertainties and the EUAF market revealed that the EUAF market is largely and significantly affected across various investment horizons. It is paramount to note that the robustness of the QR estimates was confirmed by QQR plots.

The analysis of the comovement between economic uncertainties and the financial assets under study revealed heterogeneity in the uncertainty and financial asset dynamics. The aforesaid statement is motivated by patches of strong and weak comovement observed in the scalogram as well as the altering lead-lag relationships.

On the causality front, the study observed that economic uncertainties generally affect financial assets in the short and medium terms. This reiterates the significance of employing the VMD technique to reveal the time-varying relationship between the aforesaid variables.





## CHAPTER FIVE

### SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

#### Introduction

This chapter serves as a focal point for summarising the entirety of the study. Additionally, it offers a concise overview of the findings, conclusions, recommendations, and suggestions for potential future research endeavours.

#### Summary of the Research

Concerns regarding uncertain policies, particularly those relating to economic policies and financial decisions, have grown and expanded in recent years as a result of significant global events like the COVID-19 pandemic and the Russia-Ukraine conflict (Ozili, 2022; Cui & Maghyreh, 2023). Al-Thaqeb, Algharabali, and Alabdulghafour (2022) argue that economic uncertainty may make firms postpone important investments or decisions that could affect future financial outcomes and cash flow. And as future cash flows are often correlated with the stock price, this may put downward pressure on stock prices. Several reports including the Global Financial Stability Report (2020) and the World Economic Outlook Report (2020) revealed that uncertainties, especially the COVID-19 pandemic had a devastating impact on the financial market.

In light of these recent developments, this study aimed to investigate how economic uncertainty affects the G7 stocks, Gold, Bitcoin and the European Union Allowance futures returns. An insight into how the uncertainty indices employed affect the financial assets under consideration provides investors with a detailed analysis of the uncertainty and financial asset dynamics in recent times. It

again assists investors in building a diversified portfolio since the study discusses the asymmetric effect of economic uncertainty on the returns of the financial assets under study. To policymakers, the findings of the study serve as a guide in policymaking during periods of high uncertainty. The revelation on how uncertainties proxied by current happenings affect the carbon market (EUAF market) gives insight to policymakers as to how to improve and maintain the effectiveness of the carbon market and the ultimate aim of a reduction in carbon emissions.

The theories underpinning the nexus between economic uncertainty and financial asset returns are the arbitrage pricing theory, the heterogeneous market hypothesis and the adaptive market hypothesis. The empirical review of the nexus between economic uncertainties and financial asset returns largely showed an adverse relationship but the study however observes that the relationship differs with respect to countries and the assets in question. Nevertheless, the conflicting outcomes noted in the empirical review may potentially arise from distinct economic circumstances peculiar to individual countries, variations in the adopted estimation methodologies, discrepancies in data frequency, and disparities in the timeframes considered within the studies.

The research was grounded in the post-positivism research paradigm and employed a quantitative research approach. Furthermore, the study utilised an explanatory research design to facilitate the estimation of diverse models. Furthermore, monthly data for the period of 2012 to 2022 was employed for the estimation techniques utilised in the study. The study employed five estimation

techniques. The study first employed the Variational Mode Decomposition (VMD) technique to segregate the data into diverse investment horizons (short, medium and long-term). Following the VMD technique, the research paper utilised the quantile and the quantile-on-quantile regressions which sought to examine the asymmetry in the relationship between the independent and dependent variables and the robustness of the quantile regression technique respectively. The fourth technique, which is the wavelet analysis, sought to reveal the time and frequency comovement between the dependent and independent variables whereas the fifth technique, which is the Disk and Panchenko non-linear causality test, aimed at examining the causal nexus between the independent and dependent variables as well as examining the robustness of the quantile and wavelet techniques.

To advance the study's objectives, descriptive statistics were employed to elucidate the attributes of each variable. These descriptive statistics encompassed key metrics such as the mean, standard deviation, Jarque-Bera test, Augmented Dickey-Fuller test, and Phillip Peron test. The mean offered insight into the average returns of the assets, while the standard deviation shed light on the level of market risk observed during the examined time frame. The Jarque-Bera test confirmed the non-normality of the data series which motivated the use of non-linear estimation techniques in the study. The ADF and PP tests were employed to test for stationarity in the variables. The PP test in particular examines the stationarity of variables while considering structural breaks which prevents spurious regression results.

## Summary of Findings

This study sought to first, examine the asymmetric relationship between economic uncertainties and the returns of financial assets employed in the study.

Second, assess the comovement between economic uncertainty and the returns of financial assets.

From the results of the first objective, strong evidence was found that firstly, there exists an asymmetry in the nexus between economic uncertainty and the returns of financial assets. Secondly, with regard to the G7 stock market, the study observed that economic uncertainty indices proxied by Global and Country-level EPU, OVX and GPR largely affected the stock returns of the G7 adversely during bearish market conditions. The adverse effect is however seen to weaken in the medium and long term.

It is paramount to note that the QQR technique was employed to assess the robustness of the findings of the QR. Since the QQR plots followed a similar trend as the QR line plot, the study affirms the robustness of the quantile regression results. The results of the Disk and Panchenko test also validated the QR results of the decomposed series. The causality test revealed a significant short- and medium-term effect of economic uncertainty on the returns of the financial assets which is consistent with the findings from the QR estimates as well as the wavelet analysis.

Results from the second objective, which was the wavelet technique revealed a heterogeneous relationship between economic uncertainties and the financial assets under study. The aforesaid statement is motivated by the patches



of strong and weak comovement observed in the scalogram as well as the altering lead-lag relationships. The study observed that during times of high uncertainties, the wavelet analysis revealed economic uncertainty-led adverse comovement but during periods which were not reflective of harsh economic conditions, the study observed an asset-led positive comovement. The change in the dynamics of the lead-lag association between the dependent and independent variables is consistent with the HMH (Muller et al., 1997) and the AMH (Lo, 2004). These two theories argued that investors react differently given different market conditions which affect the performance of the financial market positively or negatively depending on the perception and actions of investors.

Lastly, one significant finding of the study which is worth discussing is the effect of economic uncertainty on the European Union Allowance future market, which is Europe's largest active carbon market. The findings from all three estimation techniques employed revealed that economic uncertainties affect the carbon market negatively. This in turn puts the true purpose of the carbon market which runs a cap-and-trade system in disarray. This is because the prices of the carbon unit will no longer be determined exclusively by the forces of demand and supply (cap and trade) but the prices will be determined to some extent by the effect of economic uncertainties. This will in turn destroy the main purpose of the carbon market which was set up to motivate the reduction of carbon emissions. It is imperative to also state that an unstable carbon market will not draw investors to invest in such a market for fear of losing investment.

## Conclusion

The study's outcomes unveiled that the influence of global and country-level EPU, OVX and GPR on the returns of the financial assets under study is dependent on the market condition and investment horizons. The most substantial uncertainty index is the OVX, succeeded by EPU and GPR. Analysis of the estimation techniques employed suggests that economic uncertainties generally have an adverse effect on the returns of financial assets. The results of the quantile regression revealed that the financial assets are greatly affected adversely during the bearish market conditions likewise results from the wavelet analysis revealed an economic uncertainty-led adverse comovement during times of high uncertainty. Again, the Disk and Panchenko non-parametric causality test supported the findings of the quantile regression and wavelet techniques, where the study observed a causal nexus between economic uncertainties and the financial assets under study.

## Recommendations

The findings of the study provide several recommendations to investors on the financial market and policymakers who deal with economic policies.

To investors on the financial market:

Investors should monitor the effect of economic policy uncertainties, oil volatility and geopolitical risk in order to hedge their investment against potential risk exposures from the aforementioned economic uncertainties. It is recommended that investors should diversify their portfolio with an investment in gold during times of uncertainty since the returns of gold is largely seen to be

robust against economic uncertainties. It should however be noted that the robustness of gold against economic uncertainties is short-lived and that investors should be cautious on investing in gold as the robustness of the returns of gold against economic uncertainties is limited to the short-term.

With regard to oil volatility, the US stock market is seen to be dominant in its robustness against oil shocks. It is therefore recommended that investors hedge against uncertainties from the oil market with US stocks, specifically the S&P 500 stocks. Again, inferring from the wavelet analysis which reveals the time-varying relationship between GPR and the G7 stocks, it can be established that the ongoing Russia-Ukraine conflict is seen to have no significant adverse effect on the G7 stocks and therefore it is recommended that investors invest in the stocks of the G7 stocks since they are robust to geopolitical risks.

To economic policymakers:

It is established from the findings of the study that during heightened periods of economic uncertainties, financial assets are to a greater extent affected adversely. In light of this, policymakers on economic policies are advised to do the following during times of heightened uncertainties:

Firstly, policymakers on the capital market should maintain the drive of capital performance and regulate the financial market to sustain financial stability. This can be accomplished by providing incentives to boost investors in the financial market and establishing a stable capital market fund by benchmarking it to a certain safety level such as the circuit breaker protocol.

Secondly, in light of the challenges faced by the carbon market (EUAF market) as a result of recent global uncertainties. It is recommended that policymakers in the carbon space put in place appropriate measures to curb the heightening of economic uncertainties in order to maintain a stable and effective carbon market. This can be done in the following ways:

To begin with, policymakers should provide clear and consistent communication regarding their economic policies and intentions. This helps to reduce ambiguity and confusion, enabling investors to make informed decisions.

Secondly, policymakers should aim to create policies that provide a long-term vision for economic growth and development. By creating a long-term policy framework, policymakers can reduce uncertainty and build confidence among market participants.

Thirdly, policymakers should ensure stakeholder engagement and policy coordination. Policymakers should seek the input of businesses, industry experts and academia to fully comprehend the implications and challenges associated with their decisions. Again, policymakers can ensure policy coordination by supporting policies from different government administrations and agencies. These, when taken into consideration will go a long way to curbing economic uncertainties and their associated effect on financial assets.

### **Suggestions for Further Research**

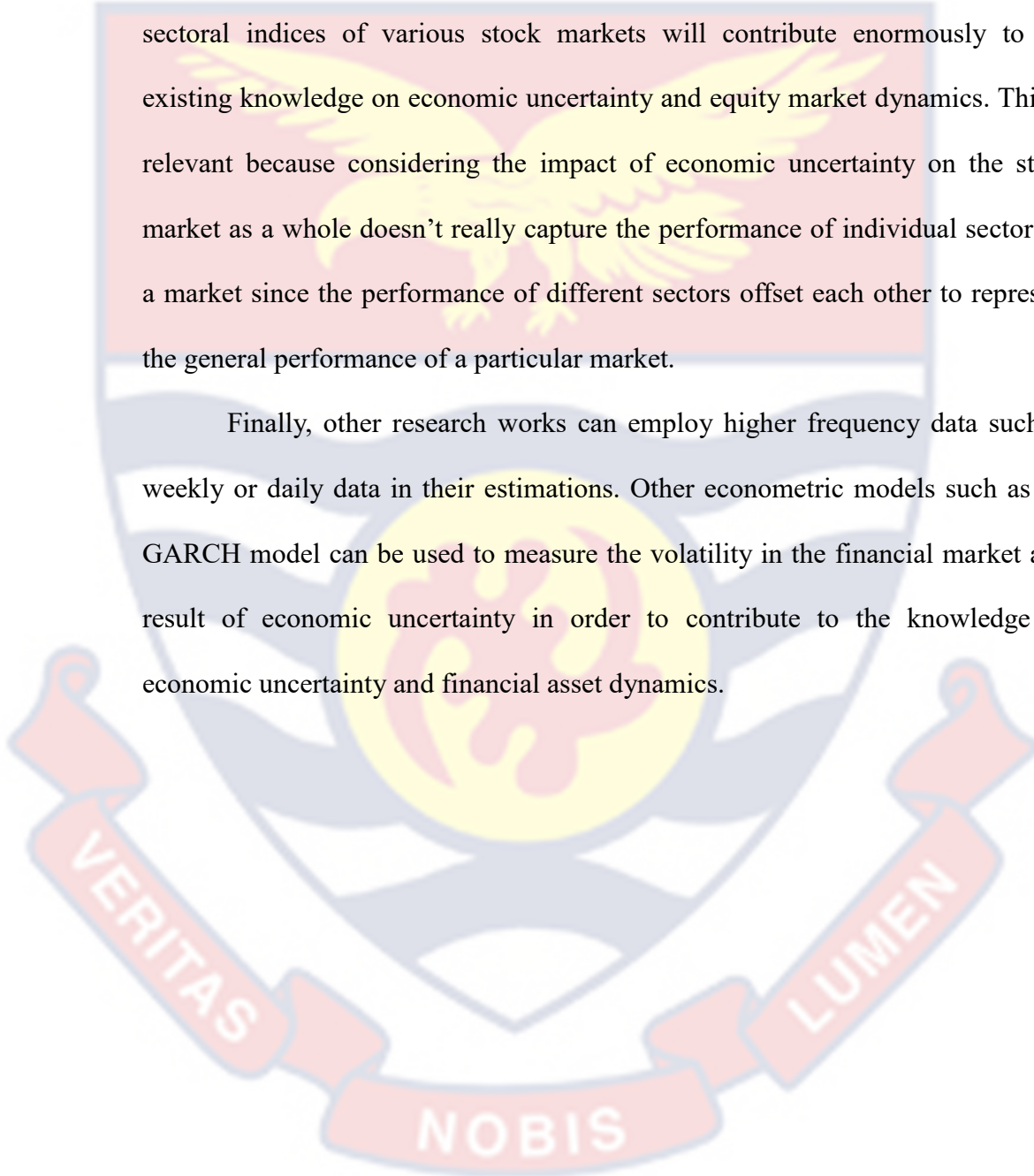
In the future, an intriguing avenue for expansion would involve extending this study to encompass an examination on the role of economic uncertainty



indices on other emerging cryptocurrencies as well as other assets in the financial market such as bonds and Non-Fungible Tokens (NFTs).

Additionally, an examination of how economic uncertainties affect the sectoral indices of various stock markets will contribute enormously to the existing knowledge on economic uncertainty and equity market dynamics. This is relevant because considering the impact of economic uncertainty on the stock market as a whole doesn't really capture the performance of individual sectors in a market since the performance of different sectors offset each other to represent the general performance of a particular market.

Finally, other research works can employ higher frequency data such as weekly or daily data in their estimations. Other econometric models such as the GARCH model can be used to measure the volatility in the financial market as a result of economic uncertainty in order to contribute to the knowledge on economic uncertainty and financial asset dynamics.



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## APPENDICES

## APPENDIX A

**Table 2. Summary Descriptive Statistics of the Uncertainty Indices**

Statistics	GEPU	US EPU	UK EPU	France EPU	Germany EPU	Italy EPU	Japan EPU	Canada EPU	OVX	GPR
Signal										
Mean	0.0034	-0.0021	0.0016	-0.0007	0.0084	-0.0062	-0.0018	0.0021	0.0019	0.0027
Std. dev.	0.1860	0.2103	0.3268	0.2889	0.3470	0.3422	0.1844	0.3023	0.2252	0.2062
Skewness	0.4193	0.0736	0.1283	-0.0895	0.3512	0.4605	-0.2513	0.1800	1.3368	0.2474
Kurtosis	1.2943	1.1198	-0.2716	0.2444	0.2140	0.8366	1.0587	-0.2267	5.8130	0.8196
Jarque Bera	14.033***	7.7659**	0.65519	0.65244	3.1354	9.1177***	8.2748***	0.90832	233.1***	5.5807*
ADF	-5.4883***	-5.6569***	-5.3954***	-6.497***	-6.7154***	-5.3706***	-6.1295***	-5.2361***	-5.7213***	-6.885***
PP	-141.8***	-143.17***	-146.86***	-139.24***	-136.58***	-172.61***	-124.6***	-146.78***	-112.3***	-142.52***
M1										
Mean	0.0011	-0.0005	0.0002	0.0000	0.0004	-0.0016	-0.0007	0.0003	0.0004	0.0004
Std. dev.	0.0296	0.0344	0.0661	0.0671	0.0789	0.0588	0.0271	0.0379	0.0451	0.0404
Skewness	-0.4431	0.0815	0.0747	-0.0333	0.0235	-0.2917	-0.0239	0.0593	0.6862	0.2737
Kurtosis	-0.2428	0.3560	-0.3489	0.1594	-0.2505	-0.2601	-0.4001	-1.0625	0.6163	0.4338
Jarque Bera	4.6409*	1.0625*	0.64825	0.26253	0.2512	2.1763*	2.1763*	5.9459**	13.079***	2.9875*
ADF	-5.1952***	-4.1202***	-6.2748***	-8.527***	-8.1672***	-4.9239***	-4.9239***	-6.8457***	-3.7674**	-4.5387***
PP	-19.844*	-26.382***	-41.012***	-39.137***	-45.625***	-25.434***	-25.434***	-38.138***	-33.776**	-40.177***
M2										
Mean	0.0001	-0.0001	0.0000	0.0000	0.0002	-0.0001	-0.0001	0.0000	0.0001	0.0001
Std. dev.	0.0493	0.0590	0.0846	0.0791	0.0935	0.0664	0.0626	0.0983	0.0727	0.0520
Skewness	0.0189	0.0291	-0.0010	0.0268	0.0276	0.0092	-0.0131	0.0132	0.1116	0.0277
Kurtosis	-0.8889	0.0163	-0.7013	0.0400	-0.0994	-0.8621	-0.6744	-0.4267	0.7406	-0.0105
Jarque Bera	4.0436*	0.040618*	2.4404	0.057478	0.033771	3.7851*	2.2482*	0.8286	3.7818*	0.02416*



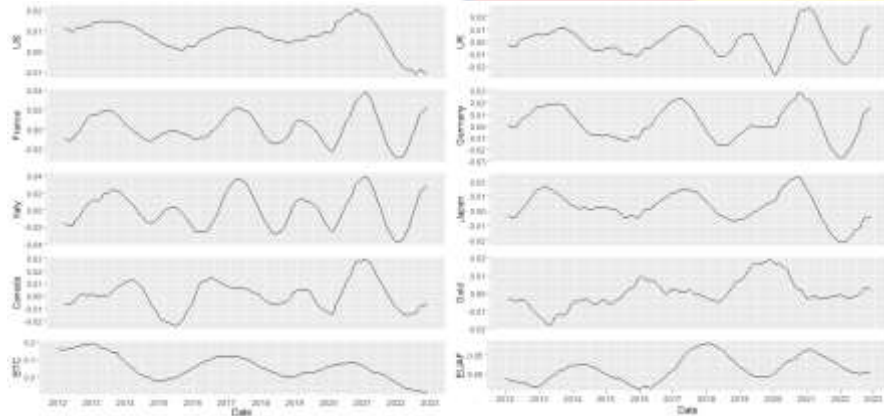
Table 2, continued.

ADF	-13.091***	-11.832***	-12.703***	-12.985***	-11.878***	-12.094***	-9.6843***	-12.543***	-8.9714***	-7.8806***
PP	-43.856***	-43.186***	-33.027***	-34.937***	-29.245***	-31.692***	-45.416***	-74.431***	-44.97***	-45.583***
M3										
Mean	0.0000	0.0000	0.0000	0.0000	0.0001	-0.0001	0.0000	0.0000	0.0000	0.0001
Std. dev.	0.0611	0.0696	0.1336	0.0991	0.1193	0.1374	0.0717	0.0971	0.0858	0.0642
Skewness	0.0392	0.0398	0.0129	-0.0031	0.0050	0.0615	0.0022	-0.0245	0.0303	0.0185
Kurtosis	0.4704	2.0833	0.0562	-0.3128	-0.6298	-0.0876	0.4756	-0.7765	1.2851	0.3221
Jarque Bera	1.5421*	25.725***	0.0621	0.40612	1.9375	0.095221	1.5382	3.0451	10.055***	0.77282
ADF	-15.016***	-15.243***	-12.975***	-12.218***	-13.483***	-12.503***	-14.142***	-16.693***	-14.027***	-12.353***
PP	-66.421***	-45.615***	-105.8***	-92.359***	-76.49***	-102.07***	-35.366***	-33.206***	-28.004***	-29.237***
M(Agg)										
Mean	-0.0021	0.0014	-0.0013	0.0007	-0.0076	0.0044	0.0010	-0.0017	-0.0014	-0.0021
Std. dev.	0.1384	-0.0457	0.2173	0.2024	0.2436	0.2525	0.1317	0.2242	0.1549	0.1596
Skewness	-0.0611	-0.0457	-0.2030	0.0703	-0.0439	-0.3195	0.3185	-0.0601	-0.6071	-0.1330
Kurtosis	-0.0942	0.2362	0.1370	-0.3851	-0.5091	0.7421	0.0718	-0.1786	4.4655	0.8266
Jarque Bera	0.097545	0.49636*	1.1163	0.766	1.2628	5.812**	2.3612	0.18202	123.66***	4.7082*
ADF	-7.4565***	-5.604***	-4.4357***	-4.6512***	-4.133	-8.5037***	-6.6257***	-6.8986***	-4.0065***	-3.4585**
PP	-196.61***	-202.22***	-215.42***	-220.15***	-220.86	-214.98***	-190.01***	-215.98***	-183.32***	-192.85***

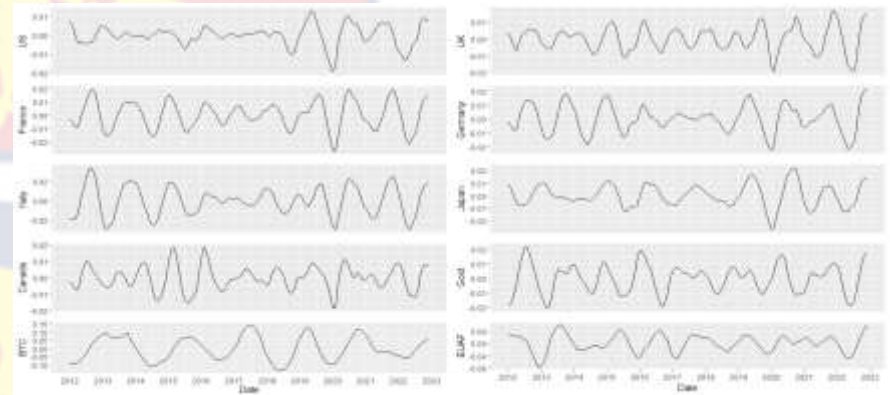
NB: \*\*\*, \*\*, and \* denote significance at 1%, 5%, and 10%, respectively. The monthly data observed are 133 for each variable sampled from 01/01/2012 to 31/12/ 2022. Descriptive statistics are presented for 7 tests for uncertainty indices at various frequencies (short-, medium-, and long-term) in addition to the original series. The null hypothesis for ADF and PP tests is the presence of unit roots. The return series for the uncertainty indices depict nonnormal distribution at all frequencies, whereas most return series are stationary.



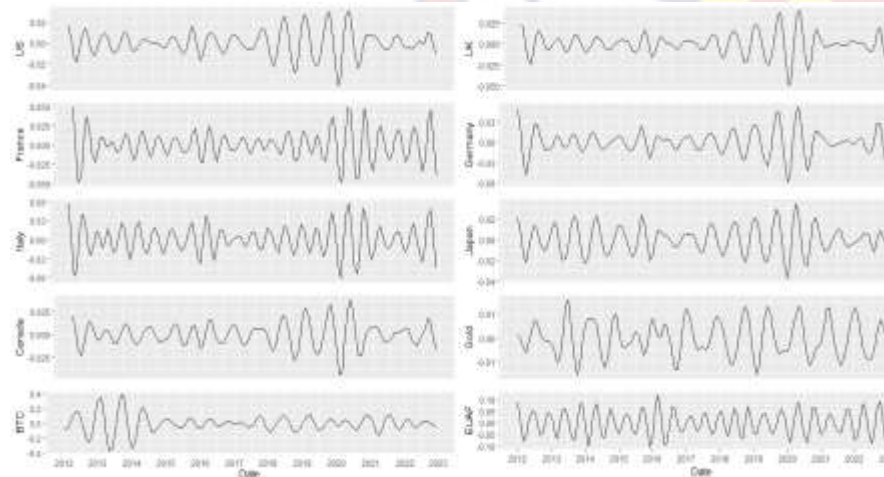
**Short-term Returns of Financial Assets (M1)**



**Medium-term Returns of Financial Assets (M2)**



**Medium-term Returns of Financial Assets (M3)**



**Long-term Returns of Financial Assets (MAgg)**

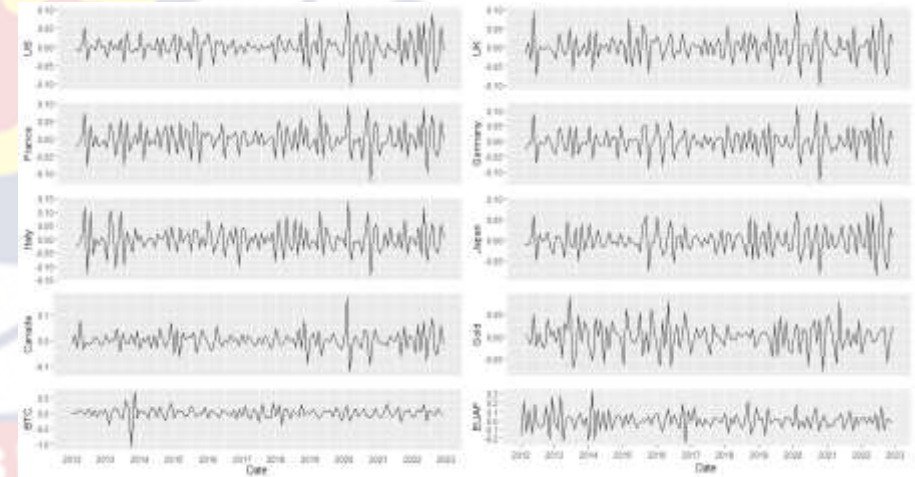


Figure 3: The time-varying returns of the financial assets.

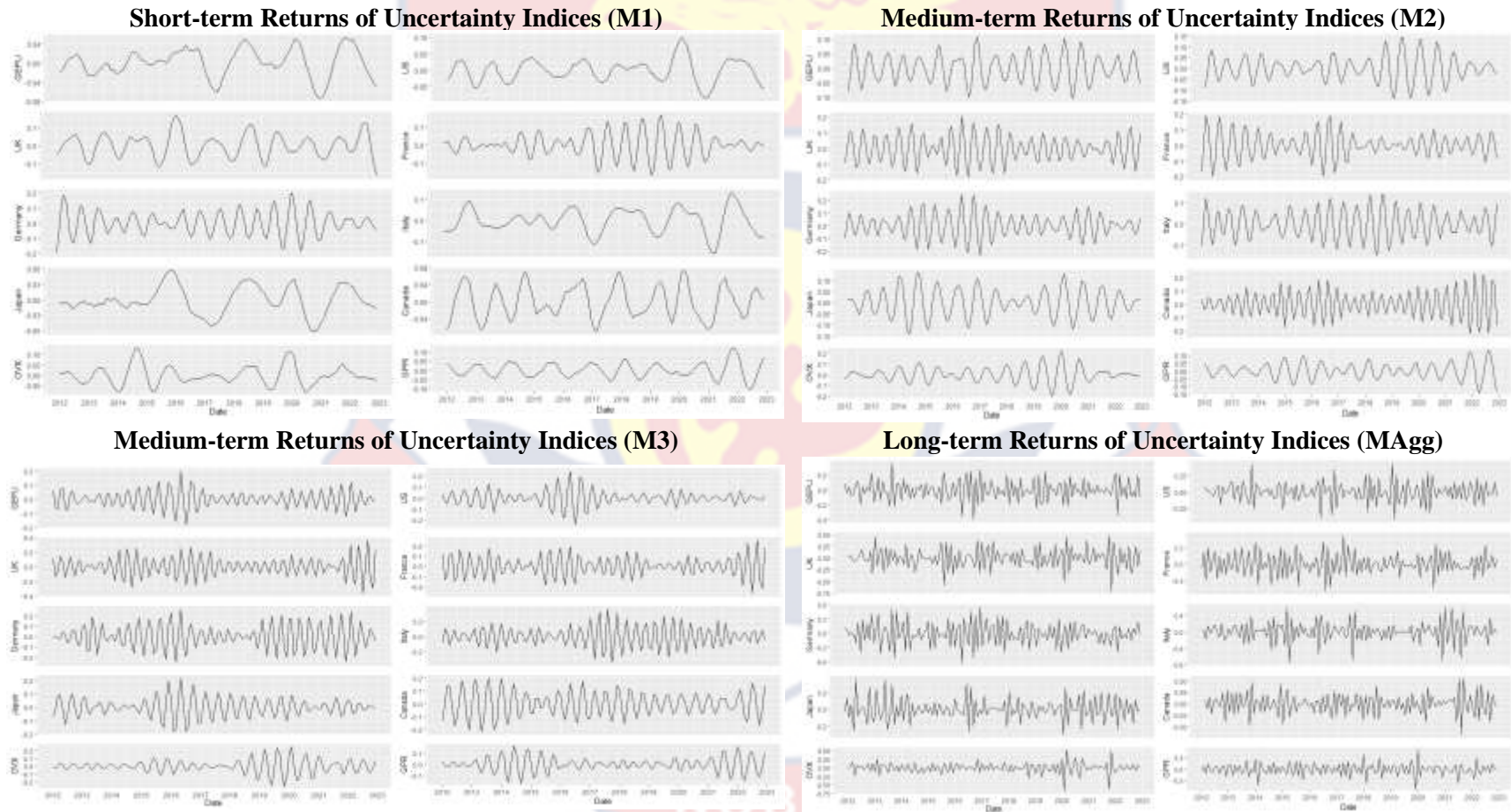


Figure 4: The time-varying returns of economic uncertainty indices.

## APPENDIX B

Table 6. Quantile Regression Results of GEPU and Financial Assets (M3)

Quantiles	US	UK	France	Germany	Italy	Japan	Canada	Gold	BTC	EUAF
0.05	-0.0592	-0.0523	0.0055	-0.0501	-0.1006	0.02219	-0.0562	-0.0176*	1.3530	-0.0883
0.10	-0.0479	-0.0636	-0.0071	-0.0885	-0.0872	-0.0150	-0.0419	-0.0244	0.1501	-0.1513
0.15	-0.0018	-0.0478	-0.0323	-0.085**	-0.0581	-0.0026	-0.0017	-0.0167	0.1525	-0.1689**
0.20	-0.0076	-0.0201	-0.0272	-0.084***	-0.0581	-0.0162	0.00257	-0.0264	0.0276	-0.1443***
0.25	-0.0009	-0.0291	-0.0297	-0.0553*	-0.0520	-0.0031	0.00698	-0.0092	0.0522	-0.1926***
0.30	-0.0058	-0.0285*	-0.0318	-0.0438**	-0.0332	-0.0089	0.00484	0.0028	0.0129	-0.1674**
0.35	-0.0104	-0.0219	-0.0149	-0.0363*	-0.0064	-0.0124	-0.0025	0.0022	0.1337	-0.1809*
0.40	-0.0009	-0.0099	-0.0280	-0.0412*	-0.0270	-0.0198	-0.0079	0.0033	0.1066	-0.0946
0.45	0.0012	-0.0073	-0.0373	-0.0229	-0.0424	-0.0154	-0.0045	0.0009	0.0630	-0.0068
0.50	0.0003	0.00142	-0.0354	-0.0168	-0.0598	-0.0163	-0.0038	0.0139	-0.0943	-0.0100
0.55	-0.0013	-0.0123	-0.0425	-0.0049	-0.0421	-0.0151	-0.0103	0.0109	-0.0609	-0.1597
0.60	-2.41E-05	-0.0095	-0.0382	-0.0141	-0.0551	-0.0051	-0.0153	0.0168	-0.0041	-0.1146
0.65	0.0111	-0.0116	-0.0303	-0.0093	-0.0546	-0.0153	-0.0199	0.0146	-0.0116	-0.1367
0.70	0.0003	-0.0107	-0.0189	-2.38E-05	-0.0477	-0.0141	-0.0193	0.0156	-0.0943	-0.1415
0.75	-0.0087	-0.0118	-0.0047	-0.0041	-0.0406	-0.0283	-0.0259	0.0208	-0.0403	-0.1279
0.80	-0.0057	-0.0054	-0.0133	0.00141	-0.0507	-0.0361	-0.0171	0.0193	-0.0860	-0.0897
0.85	0.0032	0.01083	-0.0451	0.01967	-0.0364	-0.0159	-0.0198	0.0064	-0.2143	-0.0364
0.90	0.0329	0.02827	-0.0233	0.06695	-0.0535	-0.0109	0.01096	0.0019	-0.1266	-0.0806
0.95	0.0759	0.05673	0.12411	0.01284	0.05144	-0.0150	0.04739	-0.0034	-0.5335	-0.1294

Note: \*\*\*, \*\*, and \* indicate statistical significance at levels of 1%, 5%, and 10%, respectively. ( $\tau = 0.05, 0.1, 0.15, 0.20, 0.25, 0.30$ ) denote bearish market, ( $\tau = 0.35, 0.40, 0.45, 0.50, 0.55, 0.60$ ) denote normal market, ( $\tau = 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95$ ) denote bullish market condition.



**Table 11. Quantile Regression Results of Country-Level EPU and G7 Stocks (M3)**

Quantiles	US	UK	France	Germany	Italy	Japan	Canada
0.05	-0.01471	-0.00821	-0.01187	-0.02263	0.023941	-0.0068	-0.02709
0.10	-0.01064	-0.00361	-0.01434	-0.05589	0.025857	-0.0379	-0.02452
0.15	-0.01665	-0.00136	-0.04416	-0.02112	0.005562	-0.0502**	-0.01855
0.20	-0.00406	-0.00217	-0.03944	-0.00561	-0.00021	-0.0427**	-0.01512
0.25	-0.01043	-0.00112	-0.02083	-0.01736	-0.00219	-0.0360**	-0.00631
0.30	-0.01339	-0.0047	-0.02414	-0.02345	-0.0021	-0.0331*	-0.00317
0.35	-0.02343	-0.00894	-0.01567	-0.01961	-0.00395	-0.03002	-0.01036
0.40	-0.02618	-0.00715	-0.00851	-0.0084	-0.00428	-0.01994	-0.01629
0.45	-0.01948	-0.00175	0.001762	-0.00691	-0.00519	-0.01222	-0.01268
0.50	-0.00997	0.000841	0.002514	0.000641	-0.01414	-0.00466	-0.0109
0.55	-0.00669	-0.00127	-0.00159	-0.00173	-0.0226	-0.01735	-0.011
0.60	-0.00811	0.000159	0.005622	-0.00638	-0.01452	-0.0003	-0.01608
0.65	-0.0082	-0.00021	0.015947	0.003878	-0.01735	-0.00894	-0.00545
0.70	-0.01367	0.000847	0.001568	-0.00081	-0.01925	-0.0138	-0.00866
0.75	-0.00973	0.006961	0.002568	-0.00224	-0.0057	-0.01821	-0.01018
0.80	-0.00609	-0.00176	-0.00834	0.006075	0.004538	-0.03878	-0.02304
0.85	0.002456	0.01359*	-0.00644	0.026901	-0.00708	-0.02887	-0.02257
0.90	-0.02613	0.006019	-0.01136	0.029831	-0.01235	-0.03063	-0.0391*
0.95	-0.06439	-0.0072	-0.01439	0.067764	0.016361	-0.02182	-0.0522*

Note: \*\*\*, \*\*, and \* indicate statistical significance at levels of 1%, 5%, and 10%, respectively. ( $\tau = 0.05, 0.1, 0.15, 0.20, 0.25, 0.30$ ) denote bearish market, ( $\tau = 0.35, 0.40, 0.45, 0.50, 0.55, 0.60$ ) denote normal market, ( $\tau = 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95$ ) denote bullish market condition.



**Table 17. Quantile Regression Results of OVX and Assets (M3).**

Quantiles	US	UK	France	Germany	Italy	Japan	Canada	Gold	BTC	EUAF
0.05	-0.0283	-0.06671	-0.1659***	-0.0547	-0.1651***	-0.0033	-0.0473	-0.0159	-0.4747	-0.2011***
0.10	-0.0696**	-0.0782*	-0.1661***	-0.1113*	-0.1880***	-0.0275	-0.0479	-0.0073	0.01014	-0.2844***
0.15	-0.0767**	-0.0845**	-0.1679***	-0.0887*	-0.2125***	-0.0469	-0.0405	-0.0109	-0.0232	-0.2324**
0.20	-0.0492**	-0.0769***	-0.1555***	-0.0722*	-0.1933***	-0.0534*	-0.0672**	-0.0076	-0.0155	-0.3165***
0.25	-0.0582**	-0.0789***	-0.1518***	-0.0840**	-0.1993***	-0.0449**	-0.0675*	-0.0029	-0.0022	-0.3373***
0.30	-0.0644**	-0.0817***	-0.1578***	-0.0638*	-0.1906***	-0.0477*	-0.0569*	0.0009	-0.0297	-0.3322***
0.35	-0.0564**	-0.0705***	-0.1605***	-0.0709**	-0.1779***	-0.0525**	-0.0539	0.0023	-0.0451	-0.3555***
0.40	-0.0524**	-0.0688***	-0.1661***	-0.0738*	-0.1781***	-0.0607*	-0.0543*	0.0008	-0.0359	-0.3265***
0.45	-0.0495**	-0.0601***	-0.1651***	-0.0697**	-0.1799***	-0.0528*	-0.0474	-0.0059	-0.0712	-0.3437***
0.50	-0.0506**	-0.0569**	-0.1556***	-0.0586*	-0.1850***	-0.0438*	-0.0296	-0.0096	-0.1021	-0.3313***
0.55	-0.0435**	-0.0559**	-0.1489***	-0.0504	-0.1948***	-0.0512*	-0.0531	-0.0096	-0.1144	-0.3537***
0.60	-0.0400**	-0.0521**	-0.1483***	-0.0401	-0.1886***	-0.0456	-0.0480*	-0.0180	-0.096	-0.3423***
0.65	-0.0483*	-0.0466*	-0.1427***	-0.0361	-0.1815***	-0.0477	-0.0458	-0.0149	-0.022	-0.3159***
0.70	-0.0412	-0.04023	-0.1423***	-0.0419	-0.1696***	-0.0520	-0.0358	-0.0266**	0.0488	-0.3074***
0.75	-0.0358	-0.0476*	-0.1518***	-0.0442	-0.1628***	-0.0411	-0.0349	-0.0185*	0.0729	-0.3178***
0.80	-0.0244	-0.0498	-0.1453***	-0.0336	-0.1795***	-0.0446	-0.0504*	-0.0181	0.0771	-0.2549***
0.85	-0.0246	-0.0615*	-0.1449***	-0.0272	-0.1816***	-0.0351	-0.0565*	-0.0217	0.06818	-0.2305***
0.90	-0.0342	-0.0396	-0.1674***	-0.0426	-0.1822***	-0.0333	-0.0479	-0.0107	0.0649	-0.2281***
0.95	-0.0471	-0.0486	-0.1537***	-0.0480	-0.1950***	-0.0257	-0.0466	-0.0033	-0.1619	-0.2726**

Note: \*\*\*, \*\*, and \* indicate statistical significance at levels of 1%, 5%, and 10%, respectively. ( $\tau = 0.05, 0.1, 0.15, 0.20, 0.25, 0.30$ ) denote bearish market, ( $\tau = 0.35, 0.40, 0.45, 0.50, 0.55, 0.60$ ) denote normal market, ( $\tau = 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95$ ) denote bullish market condition.

**Table 23. Quantile Regression Results of GPR and Assets (M3).**

Quantiles	US	UK	France	Germany	Italy	Japan	Canada	Gold	BTC	EUAF
0.05	0.077088	0.038657	0.03861	0.0169	0.0337	-0.0183	0.0452	0.0201*	-0.5748	-0.1279
0.10	0.015265	-0.02168	-0.0284**	-0.0478	-0.061	0.0164	-0.0230	0.0139	-0.0186	-0.1174
0.15	0.000232	-0.00795	-0.0647*	-0.0472	-0.0182	0.0003	-0.0145	0.0001	-0.0487	-0.1066
0.20	-0.01294	-0.01173	-0.05682	-0.0435*	-0.02498	0.0108	-0.0092	-0.0060	0.1499	-0.1345
0.25	-0.0065	-0.00996	-0.04015	-0.0318*	-0.04619	0.0057	0.0054	-0.0038	0.1211	-0.2114*
0.30	-0.00802	-0.01065	-0.06299	-0.0356**	-0.05431	-0.0077	-0.0012	0.0042	0.1799	-0.2438**
0.35	-0.01347	-0.01373	-0.07958	-0.0414**	-0.0687*	0.0014	0.0073	0.0082	0.1352	-0.2217**
0.40	-0.01415	-0.00716	-0.08662	-0.0332	-0.0910***	-0.0062	0.0081	0.0073	0.1032	-0.2803***
0.45	-0.01489	-0.00545	-0.09175	-0.0240	-0.0907**	-0.0079	-0.0096	0.0075	0.1741	-0.2885***
0.50	-0.02217*	-0.00367	-0.09263	-0.0224	-0.0839**	-0.0108	-0.0136	0.0064	0.1803	-0.2985***
0.55	-0.02575**	-0.0102	-0.08161	-0.0346**	-0.0867***	-0.0155	-0.0199	0.0053	0.1446	-0.2429**
0.60	-0.02339*	-0.01072	-0.07093	-0.0369**	-0.0792**	-0.0058	-0.0165	0.0059	0.0668	-0.21932*
0.65	-0.02083*	-0.01751	-0.06405	-0.0483**	-0.0767**	-0.0004	-0.0144	0.0158	0.1377	-0.2202*
0.70	-0.01746	-0.01705	-0.06065	-0.0443*	-0.04914	0.00857	-0.0127	0.0198	0.1409	-0.1840*
0.75	-0.01125	-0.01565	-0.06086	-0.0270	-0.03072	0.00648	-0.0119	0.0201	0.2680	-0.2301***
0.80	-0.00138	-0.03556	-0.04943	-0.0335	-0.03436	-0.0018	-0.0193	0.0176	0.2957	-0.2102***
0.85	-0.00152	-0.05715**	-0.0539*	-0.0632*	-0.02648	-0.0101	-0.0237	0.0072	0.2005	-0.1956**
0.90	-0.03718	-0.03984	-0.0805*	-0.0871**	-0.01336	-0.0048	-0.0353	0.0164	0.0654	-0.13051
0.95	-0.0851	0.01249	0.033939	-0.0191	0.027278	-0.0205	-0.0122	0.0132	-0.2522	-0.0783

Note: \*\*\*, \*\*, and \* indicate statistical significance at levels of 1%, 5%, and 10%, respectively. ( $\tau = 0.05, 0.1, 0.15, 0.20, 0.25, 0.30$ ) denote bearish market, ( $\tau = 0.35, 0.40, 0.45, 0.50, 0.55, 0.60$ ) denote normal market, ( $\tau = 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95$ ) denote bullish market condition.