

UNIVERSITY OF KWAZULU-NATAL

**GEOPOLITICAL RISK EFFECTS ON THE QUALITY OF
EXCHANGE-TRADED FUNDS IN DEVELOPED AND
EMERGING MARKETS**

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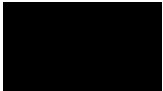
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January 2026

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ABSTRACT

Exchange-Traded Funds (ETFs) have gained popularity as the demand for low-cost and easily accessible investment vehicles. However, ETFs may be significantly influenced by Geopolitical Risks (GPR). GPR plays an important role in shaping market quality by affecting returns, volatility, and liquidity in both emerging and developed markets, and often lead to heightened uncertainty and market disruptions. Although several studies in the literature have examined the GPR effect on ETF returns, volatility, or liquidity individually, studies that jointly examine the GPR effect on ETF market quality remain scarce. Therefore, this study examines the GPR effect on the quality of ETFs in developed and emerging markets. To achieve the objective of this research, the study makes use of fourteen ETFs that track broad market indices, comprising of seven ETFs from emerging markets and seven from developed markets, and trade in their respective home countries. The sample period spans from each ETF inception date up to 31 December 2024. This study employs a Markov Regime-Switching model to examine the effect of GPR on ETF returns, a GARCH-MIDAS model to examine the effect of GPR on ETF volatility, and NARDL model to investigate the effect of GPR on ETF liquidity.

The findings from this study show that GPR has limited effect on ETF returns, with global GPR exhibiting little direct effect, while country-specific GPR shows stronger and more persistent effects on returns, particularly in developed markets. GPR significantly affects ETF volatility, with emerging market ETFs exhibiting greater sensitivity to global GPR, while developed market ETFs show higher volatility persistence following geopolitical shocks. In addition, GPR affects ETF liquidity asymmetrically, with ETFs from emerging markets exhibiting stronger and more unstable long-run and short-run liquidity responses to both global and country-specific GPR, while ETFs from developed markets display muted and stable liquidity reactions. These findings indicate that investors should not assume that holding ETFs from different asset classes will automatically spread-out risk. As a result, investors may need to take proactive adjustments during periods of elevated GPR. Policy makers should ensure market stability because emerging markets are highly volatile and rapidly lose liquidity during geopolitical shocks.

Key words: Exchange-Traded Funds; Geopolitical risk, returns; volatility; liquidity.

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LIST OF ACRONYMS

ADF:	Augmented Dicker-Fuller
AIC:	Akaike Information Criterion
AMH:	Adaptive Market Hypothesis
APs:	Authorized Participants
APT:	Arbitrage Pricing Theory
ARCH:	Autoregressive Conditional Heteroskedasticity
ARDL:	Autoregressive Distributed Lag
BPT:	Behavioural Portfolio Theory
BRICS:	Brazil, Russia, India, China, and South Africa
CAPM:	Capital Asset Pricing Model
CD:	Cross-sectional Dependence
CML:	Capital Market Line
COVID-19:	Coronavirus
DCC:	Dynamic Conditional Correlation
DiD:	Differences-in-Difference
EMH:	Efficient Market Hypothesis
EPU:	Economic Policy Uncertainty
ESG:	Environmental, Social, and Governance
ETF:	Exchange-Traded Fund
FDI:	Foreign Direct Investment
GARCH:	Generalised Autoregressive Conditional Heteroskedasticity
GDP:	Gross Domestic Product
GPR:	Geopolitical Risk
GT:	Geopolitical Threat
HQIC:	Hannan-Quinn Information Criterion
IT:	Information Technology
JB:	Jarque Bera
KPSS:	Kwiatkowski- Phillips Schmidt- Shin
LM:	Lagrange Multiplier
LR:	Likelihood Ratio
LSDV:	Least Squares Dummy Variable
MPT:	Modern Portfolio Theory

MS-DR:	Markov Switching Dynamic Regression
NARDL:	Nonlinear Autoregressive Distributed Lag
NAV:	Net Asset Value
OLS:	Ordinary Least Squares
PP:	Phillips Perron
REIT:	Real Estate Investment Trust
RMSFE:	Root Mean Square Forecast Errors
S.A:	South Africa
S&P:	Standard & Poor
SBIC:	Schwarz Bayesian Information Criterion
SBIC:	Total Net Asset Value
U.S:	United States
VAR:	Vector Autoregression

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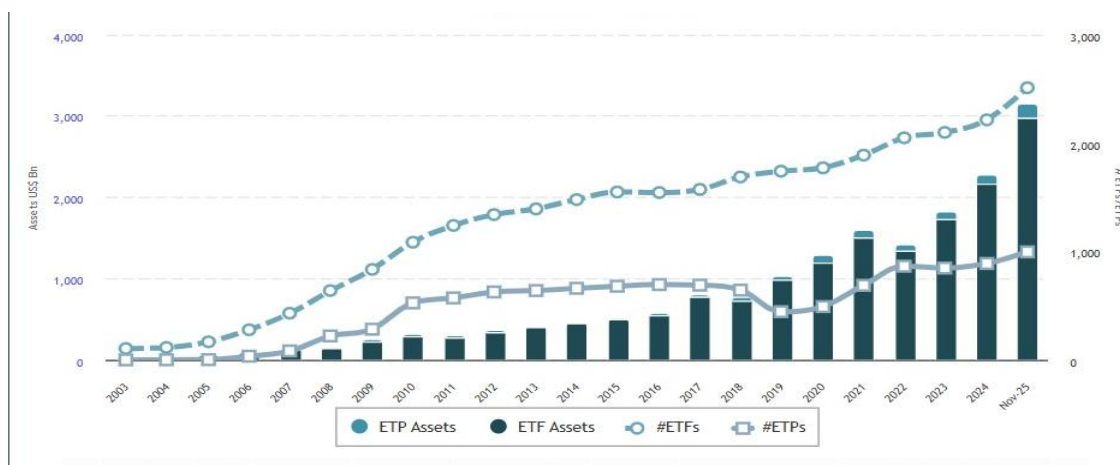
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CHAPTER 1: INTRODUCTION

1.1 Introduction and Background

Exchange-Traded Funds (ETFs) have revolutionised global financial markets by providing diversified exposure to different asset classes, such as stocks, bonds, commodities, and real estate, at relatively low costs. According to Kunjal (2023), an ETF is a pooled investment fund replicating a benchmark's components to track its performance. Globally, ETFs have experienced substantial growth in recent years. The assets invested in the global ETF industry reached a record high of \$2 216 billion by the end of 2024 up from \$1 116 billion in December 2020 (ETFGI, 2025). Similar growth trends can be seen in the South African (S.A) ETF market, where Assets under Management (AuM) more than doubled from approximately R111 billion to R225 billion by 2024, indicating the growing adoption of ETFs in S.A (ETFSA,2025). This strong upward trend is further illustrated in Figure 1.1, which shows the steady growth of global ETF assets over the past ten years. Additionally, this growth underscores the increasing appeal of ETFs among investors worldwide (Lenz and Mayer, 2023). This expansion of the ETF market is driven by lower fees, enhanced market liquidity, and greater trading flexibility compared to mutual funds (Clifford et al., 2024). Unlike mutual funds, ETFs trade continuously on stock exchanges, allowing intraday buying and selling. They also feature a unique creation and redemption mechanism that adjusts the number of shares based on demand, combining the flexibility of closed-end funds with the structural benefits of open-end funds (Bae and Kim, 2020). These advantages have positioned ETFs as a dominant investment vehicle worldwide, underpinning significant improvements across multiple dimensions of market quality.

Figure 1.1: Growth in the Global ETF Industry



Source: ETFGI (2025)

According to Indriawan (2020), market quality includes factors of financial markets, such as bid-ask spreads, trading volume, price efficiency, transaction costs, returns, volatility, and liquidity, all of which work together to determine how well markets support efficient and equitable trading. Specifically, returns refer to the loss or profit an investor earns by holding an ETF over a given period (Gutierrez, Martinez and Tse, 2009). Volatility refers to variations in a security's price brought on by uncertainty (Feng, Yang, Gong, and Chang, 2021). Market liquidity is defined as the ease with which financial assets can be traded (Leirvik, Fiskerstrand and Fjellvikas, 2017). Returns, volatility, and liquidity are significant determinants of market quality, as they directly influence trading efficiency, price stability, and investor confidence. High liquidity enables smooth trade execution with fewer disruptions in the financial markets while, low volatility guarantees price stability, and high returns draws investments (Chung and Chuwonganant, 2018). Therefore, market quality is important because it fosters a stable and efficient financial environment, which is essential for economic growth, capital formation, and the effective allocation of resources (Box, Davis and Fuller, 2019).

Market quality is strongly affected by geopolitical risks (GPR), which significantly influence returns, volatility, and liquidity in developed and emerging markets and frequently leading to heightened uncertainty and market disruptions. By definition, GPRs are uncertainties and possible negative outcomes arising from political events, conflicts, tension, or disruptions in international relations that can affect economies, financial markets, and investments (Ali, Anik, Hasan and Kamal, 2023). This definition is consistent with the framework proposed by Caldara and Iacoviello (2022), whose GPR index captures the occurrence and intensity of adverse geopolitical events. Recent geopolitical events that have increased global risk include attacks by the United States (U.S) and Israel on Iran's nuclear facilities, China's strategic use of rare-earth minerals, and disruptions of U.S foreign policy (Bukhari and Mujaddid, 2025). These geopolitical events extend on earlier developments, most notably the Russian invasion of Ukraine on February 24, 2022, which led to a sharp rise in geopolitical threats, which peaked during a significant week (Hosssain and Masum, 2022). Furthermore, Kunjal (2023) highlights additional examples of geopolitical events, including, tensions between the US and Japan in the East China Sea, the long-standing border tensions between China and India, and the Syrian civil war involving regional and international powers. Recent evidence from Fiorillo et al. (2023) indicates that GPR significantly affects financial markets by increasing uncertainty, reducing return predictability, and straining liquidity. These risks also raise volatility, further complicating market conditions and impacting long-term performance.

Ali et al. (2023) stated that GPRs affect ETF market quality by increasing volatility and altering investor sentiment, thereby directly weakening key dimensions of market quality, resulting in increased transaction costs, broader bid-ask spreads, and decreased liquidity. These results suggest that during times of increased geopolitical uncertainty, trading efficiency and price discovery in ETF market quality decline. In addition, their study found that sector ETFs in Information Technology and Financials showed resilience, maintaining strong returns during geopolitical threats, indicating that the effect of GPR on market quality may differ across ETFs. However, Monnonen (2025) highlights that high-rated Economic, Social and Governance (ESG) ETFs did not consistently outperform traditional benchmarks and lacked evidence of abnormal returns during geopolitical crises, suggesting that characteristics of ESG do not necessarily protect ETF market quality from geopolitical shocks. These mixed findings suggest that the impact of GPR on ETF market quality is not uniform and may depend on ETF characteristics and prevailing market conditions.

While some studies have investigated the effects of GPR on ETF returns, the literature remains limited, existing studies such as Jung, Lee, and Lee (2021) and Nasouri (2025) provide indirect insights from stock markets, showing that heightened GPR is generally associated with declining returns and increased uncertainty, particularly in geopolitically exposed or structurally weaker markets. However, these findings cannot be directly extended to ETFs due to their diversified structure and unique trading mechanisms, highlighting the need to analyse the impact of GPR on ETF returns in both developed and emerging markets, particularly under bull and bear market conditions.

Furthermore, while previous studies have examined the effects of GPR on stock markets, fewer studies have examined how GPR affects the volatility of ETFs in developed and emerging markets. For instance, Zhang et al., (2023) investigated how GPR affects stock markets globally and discovered that GPR affects emerging economies, countries that export crude oil, and nations that are not engaged in active conflicts are more affected, suggesting that the volatility response to GPR is stronger and more noticeable in specific markets. Similarly, Salisu et al. (2022) showed that GPR positively affects stock market volatility, supporting the idea that these risks increase financial market uncertainty, indicating a widespread, generally positive volatility effect in all markets. Caldara and Iacoviello (2022) further noted that the increase in GPRs has a significant impact on financial markets, increasing volatility in the stock market performance, without comparing between different types of markets, which contradicts with the evidence of heterogenous volatility effects reported by Zhang et al., (2023). Despite

these insights in stock markets, little is known about the direct impact of GPR on the volatility of ETFs in both developed and emerging markets. It is crucial to fill this gap so that investors and policymakers can develop an understanding of how domestic and global GPR affect the volatility of ETFs in developed and emerging markets.

Lastly, the literature on liquidity is even more limited and presents mixed findings. For instance, Kunjal (2023) examined the impact of GPR on ETF flows and liquidity across eight emerging markets (Brazil, Chile, China, Egypt, the Philippines, South Africa, and Taiwan). The results showed that GPR had a significant positive effect on ETF flows in most emerging markets studied, while the Philippines exhibited a significant negative response, suggesting that while GPR can increase ETF liquidity in some emerging markets, it can also decrease it in others. Similarly, Lui et al. (2024) examined the effect of geopolitical uncertainty on stock liquidity using Taiwan's misfired missile event as a natural experiment, and the results showed that because of increased stock price risk and information asymmetry, such uncertainty significantly decreased stock liquidity in Taiwan-related firms, demonstrating how geopolitical shocks have a negative impact on liquidity. Furthermore, Lui and Zhao (2024) examined the effects of liquidity spillovers among ETFs that tracked S&P sector indices during COVID-19 news shocks. The results showed that these effects were more noticeable when the news was bad, implying that negative news about GPR can amplify the decline in liquidity across ETFs. Despite these findings, there is a gap in the literature about how GPR affects ETFs' liquidity in developed and emerging markets, as existing studies presents contradictory findings of liquidity responses both negative and positive based on the structure of the market and the nature of geopolitical shock

Due to limited research on how GPR affects the quality of ETFs, the differences between ETFs in developed and emerging markets remain largely unexplored. Firstly, emerging markets tend to be more politically and economically unstable compared to developed markets, which raises the volatility and risk of ETFs (Ben Ghazzi and Chaibi, 2022). Secondly, emerging market regulatory frameworks are frequently weaker, leading to decreased efficiency and transparency, which causes a negative impact on investor confidence and ETF performance. In contrast, ETFs in developed markets gain access to established and strict regulatory systems that are intended to safeguard investors and improve transparency (Ben Ghazzi and Chaibi, 2022). Considering these dynamics, comparing developed and emerging markets is essential to understanding ways in which GPR affects ETF market quality differently. These comparative studies can offer insightful information that can help investors and policymakers create customised strategies.

Overlooking the relationship between GPR and ETFs' resilience and capacity as effective investments in volatile markets may lead to underestimating the risks and opportunities associated with geopolitical events. However, some studies argue that ETFs may already internalised geopolitical information through quick price discovery, which could lessen GPR incremental effect on their performance. This concern becomes even more pressing given the mounting influence of ETFs in global financial markets and their expanding usage in emerging markets (Zaremba, Cakici, Demir, and Long, 2022). GPR often destabilises economic stability, alters investor sentiment, and provokes capital withdrawals, which can significantly affect ETF stability. However, ETFs may be better able to withstand shocks than other investment vehicles due to their intraday tradability and diversification features, especially in developed markets. Given that ETFs are frequently linked to a diverse set of underlying asset classes, any shock to their structure or performance can be transmitted across markets, amplifying volatility and posing systemic risks to broader financial systems. Although the extent to which this transmission may vary across markets.

Therefore, this study aims to address a gap in the literature by comparing the effects of global and country-specific GPR on ETFs in both developed and emerging markets. Specifically, this study will evaluate ETF returns under both bullish and bearish conditions, analyse ETF volatility in response to country-specific and global GPR, assess how these risks influence ETF liquidity across different markets. By incorporating insights from stock market studies on asset classes, this study aims to enhance understanding of GPRs impact on ETF market quality across developed and emerging markets.

1.2 Problem Statement

In recent years, ETFs have become popular as the demand for low-cost, easily accessible investment vehicles soar (Kraus, Ehsani, and Lein, 2024). Remarkably, the global ETF market has grown from \$372 billion to \$1.3 trillion, which represents an approximate 249.5% increase over the last decade (ETFGI, 2025).. This rapid expansion has raised concerns about the potential systematic implications of ETFs, particularly their role in transmitting or absorbing shocks across financial markets. Ben-David, Franzoni, and Moussawi (2017) found that ETF liquidity and volatility shocks spill over to underlying assets, suggesting that ETFs may act as mechanisms of market instability rather than neutral investment vehicles. A critical but unresolved issue is whether ETFs function as stabilising instruments or as channels of risk transmission during periods of heightened uncertainty. This ambiguity becomes particularly relevant when considering GPR, which has emerged as a major driver of financial markets

dynamics. GPR and uncertainty are key factors influencing financial markets. GPR and uncertainty have increased globally due to conflicts like the war in Ukraine and Russia, the US-China trade tensions, and the conflict between Japan and China (Ali et al., 2022). This steady increase in GPR has grown to be a significant factor in determining the dynamics of financial markets, highlighting the need to understand how increased geopolitical uncertainty impacts ETF markets, particularly returns, volatility, and liquidity.

These risks have the potential to seriously upset financial markets by raising volatility, lowering equity returns, triggering capital outflows and causing shifts toward safe haven assets. Salisu, Lasisi, and Tchankam (2022) indicate that the threat of geopolitical events on stock returns frequently has a more negative effect than the actual events. Furthermore, a study by Chatziantoniou, Gabauer, and Stenfors (2025) on sector-specific effects showed that different GPRs, such as terrorism or military threats, have different effects on market volatility in different sectors, showing heterogeneous effects that contradict the idea of uniform market responses. While the effects of GPR on stock markets are well documented, empirical evidence on its impact on ETF market quality, particularly returns, volatility, and liquidity remains limited. Existing studies mainly focus on traditional equity markets, leaving ETFs underexplored despite their growing importance.

This lack of evidence creates a gap in the literature, it remains unclear whether ETFs mitigate geopolitical shocks by providing diversification and liquidity, or whether they amplify such shocks through volatility and liquidity to underlying assets. This uncertainty poses significant concerns for investors, policymakers, and financial stability, as ETFs may either spread GPR during periods of geopolitical stress. Therefore, understanding these dynamics is important because it allows policy makers and investors to recognise risks, create efficient risk management strategies, and lessen systematic spillovers in both emerging and developed markets. Furthermore, comparing developed and emerging markets is important as they differ in terms of market structure and investor behaviour, providing information about markets where ETFs are more vulnerable or resilient. Accordingly, this study aims to explicitly examine how GPR affects ETF market quality in both developed and emerging markets, thereby addressing the unresolved question of whether ETFs act as stabilisers of risk under geopolitical uncertainty.

1.3 Research Problem

Based on the problem statement discussed above, the primary focus of this study is to answer the following question:

- How does GPR influence the quality of ETFs trading in developed and emerging markets?

1.4 Aim and Research Objectives

This study examines the effect of GPR on the quality of ETFs in developed and emerging markets. To achieve this goal, the following objectives have been developed, and each objective is achieved by answering specific research questions:

1. To examine the influence of GPR on the returns of ETFs in developed and emerging markets.
 - (i) How do GPR affect the returns of ETFs in developed and emerging markets in bullish and bearish market conditions?
2. To investigate the impact of GPR on ETF volatility in developed and emerging markets.
 - (i) How does GPR influence ETF volatility in emerging and developed markets?
3. To explore the effect of GPR on the liquidity of ETFs in developed and emerging markets
 - (i) How does GPR affect the liquidity of ETFs in emerging and developed markets?

1.5 Scope and Method of This Study

1.5.1 Scope of the Study

To achieve the research objectives, this study utilizes ETFs from both developed and emerging markets. The study employs fourteen ETFs, seven trading in emerging markets and seven in developed markets. These ETFs track broad-based market indices and trade in their respective home countries. Additionally, these ETFs are randomly selected for each market to ensure that results are not influenced by the unique features of any ETFs or country, and to avoid selection bias. The study further includes the global and country-specific GPR indices as proxies for GPR, to purposely examine the varying GPR effects on returns, volatility, and liquidity of ETFs. Furthermore, this study covers the period from each ETFs inception date up to 31 December 2024 for both developed and emerging markets. This sample period captures major events in both economic and political history and likely to influence ETF market quality for developed and emerging markets.

Regarding the data frequency, monthly data is employed to study the effect of GPR on ETF returns in emerging and developed markets, because Mahmoudi and Ghaneei (2022), employed a monthly data frequency to maintain consistency across variables and investigate how structural regimes are influenced by fluctuations in the market. Additionally, the study also employs monthly data to examine GPR effect on ETF liquidity. This is because the control variables that will be included are inherently low-frequency measures that do not change meaningfully at daily horizons. Lastly, a combination of daily and monthly data is used to examine the GPR effect on ETF volatility in developed and emerging markets, since Salisu and Gupta (2021) and Li and Yoon (2024) argue that daily data is better at capturing volatility and GARCH-MIDAS (Mixed Data Sampling) model is suitable for accommodating data with mixed frequencies.

1.5.2 Method of the Study

To examine the effect of GPR on the returns of ETFs in emerging and developed markets, the Markov-Regime-Switching model is employed to examine the time- varying effects of returns. Additionally, the influence of ETF volatility in emerging and developed markets is investigated using the GARCH-MIDAS model, as it can effectively separate conditional variance into short and long-term, and can accommodate data with mixed frequencies. Lastly, the effect of GPR on the liquidity of ETFs in developed and emerging markets is explored using the Non-linear Autoregressive Distributed Lag (NARDL) model to capture asymmetric liquidity responses to positive and negative shocks in GPR. Before the estimation of the empirical models, preliminary data analysis such as stationarity and unit root test, descriptive statistics are conducted to ensure that the variables employed are appropriate and suitable for model estimation. After each model is estimated, diagnostic tests for heteroskedasticity and autocorrelation are conducted to confirm the accuracy and reliability of the results obtained.

1.6 Contribution of the Study

Despite the increasing popularity of ETFs in developed and emerging markets, studies in the literature have focused more on examining the impact of GPR on stock markets. Relatively fewer studies have focused on examining the effects of GPR on ETF markets. Although it is important to examine how GPR affects ETF markets because ETFs combine a variety of assets and are frequently used for risk management and diversification. As a result, geopolitical shocks to ETFs can have a greater impact on the overall market stability than shocks to

individual stocks. Therefore, this study contributes to existing literature by looking specifically in the ETF markets in developed and emerging markets. Moreover, previous studies in the literature have focused only on one aspect of market quality. Firstly, the study by Ali et al., (2023) examined ETF liquidity and volatility, it did not examine how different dimensions of GPR affect ETFs under varying market conditions. Similarly, studies by Ciner, Gurdgiev and Lucey (2013) and Ji, Zhang, and Zhao (2020) focused on market behaviour and volatility but overlooked ETF returns across distinct phases of the market cycle, such as bull and bear markets. Although some studies have considered ETF returns, these studies often fail to account for the time-varying and state-dependent nature of return behaviour. Secondly, Zhang et al. (2023) and Salisu et al., (2022) extensively investigated the impact of GPR on stock returns, they did not focus on ETFs, which differ from stocks due to their index-tracking nature and exposure to a broad set of asset classes. Thirdly, previous studies by Kunjal (2023) and Madhavan and Sobczyk (2016) focused on examining the effects of liquidity on ETFs. Therefore, it is important to examine the aspects of market quality jointly because these dimensions influence one another, implying that focusing on one aspect of market quality can results in misleading conclusions about the overall stability of the ETF market.

The majority of existing studies have focused on developed markets rather than emerging markets, which substantially differ from developed markets with respect to market size and structures. Therefore, this study focuses on comparing developed and emerging markets because these two market types may experience different effects from GPR in terms of returns, volatility, and liquidity due to differences in market structure and regulatory frameworks. Furthermore, existing studies in the literature have made use of only one measure of GPR, which is global GPR. However, markets may be more sensitive to domestic GPR because of local political unrest, causing investors to promptly reprice domestic assets. Therefore, this study make use of global and country-specific GPR as they capture different dimensions of GPR. The global GPR index captures international geopolitical tensions, while the country-specific GPR index captures GPRs that are specific to individual countries.

1.7 Structure of the Thesis

This thesis consists of six chapters that are structured as follows:

➤ Chapter 1: Introduction

This chapter outlines the background of the study. In addition, it presents the problem

statement, research aims and objectives, and the contribution of the study.

➤ **Chapter 2: Theoretical Foundations**

This chapter builds a framework of concepts relating to traditional and behavioural finance. In addition, it discusses the theoretical foundations of ETFs.

➤ **Chapter 3: Review of Empirical Studies**

Chapter 3 provides a review of existing studies on the effect of GPR on ETF returns, followed by an examination of studies on GPR effect on ETF volatility. Thereafter analyses studies that investigate how GPR influences ETF liquidity in developed and emerging markets. In addition, it identifies gaps in the existing literature based on the empirical studies reviewed.

➤ **Chapter 4: Data and Methodology**

This chapter outlines different aspects related to the data and methodology employed in the study, beginning with a description of the sample period, data frequency, ETF sample selection, and computation of main variables used. It then provides a detailed discussion of preliminary data analysis and model diagnostic tests, followed by the presentation of the methodology employed to examine the effect of GPR on ETF market in developed and emerging markets.

➤ **Chapter 5: Data Analysis and Results**

This chapter analyses and reviews the results obtained from the preliminary data analysis and presents a detailed discussion of the results of the models estimated using the methodology outlined in Chapter 4.

➤ **Chapter 6: Conclusion and Recommendations**

This is the final chapter of the thesis, which provides a summary of the results from the estimated models used to answer the research questions posed. In addition, this chapter discusses the implications of the study's findings for various stakeholders and offers recommendations for future research.

CHAPTER 2: THEORETICAL FOUNDATIONS

2.1 Chapter Overview

Traditional finance theories have been the dominant paradigm for several decades (Kamoune, and Ibenrissoul, 2022). However, at the start of twenty first century, many investors, statisticians, and economists started to argue that asset prices were relatively predictable (Rashid, Ahmad, and Tariq, 2022). To address this, behavioural finance theories have become an alternative. Accordingly, Chapter 2 provides an overview of the theories underpinning this study. This chapter is organized into 3 sections, with the first section conceptualizing GPR and reviewing theories related to GPR. The second section provides a review of theories relating to market quality with a clear distinction between traditional and behavioural finance theories. This section discusses the structure of ETFs, advantages and disadvantages of ETFs. The third and last section provides summary of theoretical considerations.

2.2 Conceptualization of Geopolitical Risk

GPRs are defined as uncertainties and possible negative outcomes arising from political events, conflicts, tension, or disruptions in international relations that can affect economies, financial markets, and investments (Ali, Anik, Hasan, and Kamal, 2023). Caldara and Iacoviello (2022) define GPR as the risk associated with terrorist acts, wars, and interstate conflicts that interfere with regular international relations, measuring its intensity using news-based index. In contrast, Salisu et al., (2022) consider GPR as global uncertainty that is driven by disputes over policies, political activities, and conflicts that affect financial market outcomes and economic expectations. These definitions highlight GPR as both the source of geopolitical tension and as well as channel through which political uncertainty is transmitted into financial markets. The primary sources of GPR include terrorism, wars, trade and economic sanctions, military conflicts, and political violence. Given these sources, GPR has important implications for returns, volatility, and liquidity, which in turn significantly affects financial markets, economies, and investors.

Firstly, GPR has a negative impact on financial markets by increasing uncertainty, which results into reduced investments, greater downside risk and increased market volatility (Ali et al., 2023). In response, investors shift their funds to safe assets while capital outflows from riskier markets particularly emerging markets resulting in reduced liquidity. Secondly, GPR can impact economies by decreasing investment, lowering growth, causing trade disruptions,

and weakening investor confidence. Additionally, it may result in job losses, increased inflation, and currency depreciation. Lastly, GPR impact investments by making investors delay or reduce capital allocation especially in emerging economies. Moreover, it can slow down investment activity and market growth by increasing risk aversion and decreasing Foreign Direct Investment (FDI). Given the significant impact of GPR on financial markets, economies and investments, it is crucial to have a reliable measure of GPR (Salisu et al., 2022).

GPR can be measured using GPR index developed by Caldara and Iacoviello (2018), which is a monthly index based on newspaper articles that counts how frequently articles discussing important terms relating to GPR appear in 11 major national and international newspapers (Wang, Wu, and Xu, 2024). In this study, the primary source of GPR is derived from this Caldara and Iacoviello index, which is based on media coverage of geopolitical events and tensions. Moreover, the GPR index constructed by Caldara and Iacoviello (2022) is used to examine the effect of GPR on financial markets because it is developed by economists at the Federal Reserve board, and it separates geopolitical acts (such as wars, terrorist attacks) and geopolitical threats (such as tensions) (Wang, Wu, and Xu (2024). However, GPR is divided into global and country-specific GPR indices. Global GPR index represents more general geopolitical tensions on a global scale, which may have an impact on markets, whereas country-specific GPR index captures variances that vary greatly between countries and offers a targeted assessment of domestic GPR (Hoque and Zaidi, 2020). Both global and country-specific GPR indices have been widely used in the literature to examine the effect of GPR on financial markets, including studies by Salisu et al., (2022), Agoraki, Kouretas, and Laopodis (2022), Salisu, Lasisi, and Tchankam (2022), Ali et al., (2023), and Coen and Desfleurs (2024).

Although GPR index is a commonly used for measuring GPR, there have been several criticisms regarding it. One of its main criticisms is the heavy reliance on newspaper articles which raises the possibility of media bias events that gain more media attention regardless of their true impact increasing the index while underreported but significant risks may go unnoticed (Nomikou, 2024). In terms of limitations of GPR index, it often fails to offer a detailed regional breakdown, which results in a global metric that might not fairly represent risk unique to a specific country (Nomikou, 2024). This is particularly a problem for investors and analysts who are interested in localized exposures. In contrast, the common criticism of GPR is that it is often difficult to define and measure, which may lead to interpretation bias. This means that this may cause inconsistent response and assessments based on what analysts

perceives as a significant geopolitical threat being viewed by other analysts as a diplomatic problem that can be resolved (Caldara and Iacoviello, 2022). Furthermore, a key limitation of GPR is that geopolitical events can take unexpected turns and have disproportionate effects that are hard to predict or model (Caldara and Iacoviello, 2022).

Considering these limitations and criticisms, Roy (2025) proposed alternative measures and proxies to capture GPR more comprehensively, including the BlackRock's GPR Dashboard which evaluates risk levels by combining real-time market data with professional judgment. This method uses data from analysts and financial indicators such as equity volatility and foreign exchange fluctuations to score possible geopolitical flashpoints according to perceived likelihood and severity. Secondly, the Eurasia Group's Top Risks Report identifies and ranks the top geopolitical threats to the world economy. In this report, each risk is assessed based on its likelihood, severity, and potential worldwide impact through a qualitative index based on expert judgment. The ranking itself represents a hierarchy of geopolitical importance, despite the report's lack of formal scoring or weighting methodology. The report is useful for long-term strategic decision-making in both governmental and corporate contexts because it is based on the premise that seasoned analysts are better able to anticipate and contextualize complex risks than purely algorithmic or market-based measures. Another proxy for the GPR index is the International Country Risk Guide (ICRG), which combines quantitative and qualitative assessments. It assesses countries in terms of their economic, financial, and political aspects, with a focus on institutional stability and good governance. The political risk component comprises elements with fixed weights, such as corruption, law and order, internal and external conflict, and government stability (Roy, 2025). In addition, the index is updated on a monthly basis using internal expert analysis and global information sources.

2.2.1 Theories Underpinning Geopolitical Risks

The theoretical foundations of GPR include international relations, political economy and risk management, institutional theory, and realism. While liberal theory stresses the role of institutions in reducing tensions and constructivism emphasizes the influence of ideas and identities, realists believe that changes in the balance of power drive state behaviour and potentially lead to conflict (Hu and Lu, 2016). These risks are linked, through political economy, to economic interdependence, where global markets are disrupted by events such as trade wars and sanctions. In finance, GPR is viewed as a type of systematic, non-diversifiable

risk, and frequently captured by modelling it using probability and uncertainty theory due to its low probability but high impact characteristics (Wang, Wu, and Xu, 2024).

To better understand the theories underpinning GPR, institutional theory and realism are two useful theories which are explained below. Institutional theory explains how adherence to international norms and institutions shapes state behaviour, while realism explains the role of power, security competition, and rivalry. Together, these theories provide a framework for understanding how political events translate into measurable economic and market risk (Hu and Lu, 2016).

2.2.1.1 Institutional Theory

According to Kauppi (2022), DiMaggio and Powell (1983) developed institutional theory which explains how norms and shared belief systems influence actor's behaviour instead of just rational self-interest. According to this theory, states and organizations strive for legitimacy by adhering to global governance frameworks. In the context of GPR, institutional theory describes how instability arises when institutions weaken, lose credibility, or are violated. The uncertainty and conflict between states are escalated by violations of international law, the collapse of diplomatic norms, and the shortcomings of multilateral organizations. Furthermore, trade regimes, sanctions, and security alliances demonstrate how institutional pressures shape the behaviour of the state. When institutional trust is damaged, geopolitical tensions rise and cooperation decreases, leading to the emergence of GPR.

2.2.1.2 Realism

Realism is one of the most important theories of international relations developed by Stephen Walt (1985). The theory is based on the idea that the international system is anarchic, meaning that each state must rely on its own strength to survive and that there is no central authority above the states. According to realism, states are rational actors motivated by the desire for power, security, and national interest. Moreover, according to Walt (1997), states form alliances to counter perceived threats as well as to balance power. In the context of GPR, realism explains that state behaviour is motivated by the desire of security and power, whereby territorial disputes, arms races power struggles, and military rivalries all inherently contribute to conflict and instability (Korab-Karpowicz, 2010). As a results, the shifts in power among the major states increase uncertainty and possibility of conflict.

2.3 Theoretical Foundations of Market Quality

The previous section discusses GPR and its underlying theories. The following section discusses the theoretical foundations of market quality, starting with a summary of its key dimensions. It then reviews traditional finance theories related to market quality. Moreover, it discusses behavioural finance theories. Lastly, it will discuss Adaptive Market Hypothesis (AMH), which aims to bridge the gap between EMH and behavioural finance.

2.3.1 Dimensions of Market Quality

Market quality includes various factors of financial markets, including returns, volatility, and liquidity, all of which work together to determine how well markets support efficient and equitable trading (Indriawan, 2020). Marsh and Payne (2012) and Indriawan (2020) acknowledge that dimensions of market quality include returns, volatility, and liquidity. These are important determinants of market quality since they impact price stability and trading efficiency, this is because strong liquidity enables smooth trade execution with fewer disruptions in financial markets, while low volatility guarantees price stability, and high returns draws investments (Chung and Chuwonganant, 2018). Returns refer to gain or loss generated by an investment over a specified period (Gutierrez, Martinez, and Tse, 2009). Volatility refers to the degree of variation in an asset's return over time, it is commonly used as a proxy for risk and measured using standard deviation (Feng, Yang, and Chang, 2021).

Market quality is important as it fosters a stable and efficient financial environment, which is essential for economic growth, capital formation, and effective allocation of resources (Box, Davis, and Fuller, 2019). However, elevated GPR can undermine these aspects of market quality by raising volatility, decreasing liquidity, widening bid-ask spreads, and increasing uncertainty. These effects compromise the stability and effectiveness necessary for capital formation and economic growth (Habibi, 2024). In addition, increased uncertainty brought on frequently lowers expected returns as investors demand higher risk premiums, while market participants may decrease trading activity or increase bid-ask spreads.

2.3.2 Traditional Finance Theories Underpinning Market Quality

Whilst the previous section discusses the dimensions of market quality, this section examines common theories of finance such as traditional finance theories. Traditional finance theories

look at how people behave when it comes to maximising wealth (Fakhry, 2016). Traditional finance theories discussed in this section include EMH, MPT, and APT. Notably, these theories do not relate to overall market quality, but they relate to individual components of market quality.

2.3.2.1 Efficient Market Hypothesis

Efficient Market Hypothesis (EMH) developed by Fama (1970) posits that asset prices fully reflect all available information either relating to a specific security or broader market, implying that financial markets are efficient. Fama (1970) explain EMH as “a market with great number of rational, profit-maximisers actively competing, with each other trying to predict future market values of individual securities, and where current important information is almost freely available to all participants”. Moreover, Fama (1970) stated that there are three forms of efficiency namely, weak, semi-strong, and strong form. A weak-form EMH refers to a scenario in which the prices of securities accurately reflect historical data on previous prices and returns, making it impossible for investors to utilize this information alone (Nisar, and Hanif, 2012). The weak form theory supports the idea that investors cannot achieve abnormal profits from investing in these financial assets. Therefore, this implies that weak form EMH follows a random walk model (Titan, 2015). Random walk model concludes that past price movements and changes cannot be used to predict future price changes, assuming that subsequent price changes are sovereign and uniformly distributed random variables (Suleman, Ali Shah and Imdad 2017).

Compared to the weak form EMH, semi-strong form assumes that the prices of financial assets always reflect all available information on the market, including historical prices and other historical data. In addition, it also assumes that prices change quickly and impartially to consider any new information that is made available to the public (Nhlapo, 2023). When a capital market exhibits a semi-strong form of the EMH, neither technical nor fundamental analysis can tell an investor how to allocate money to maximize profits compared to investing in a random portfolio of financial asset (Titan, 2015). A strong form assumes that prices consider all the information that is available about a market, including all private information about a financial asset, all new public information (semi-strong form), and historical financial information (weak form). For investors, EMH suggests the use of diversified investments such as ETFs or index funds instead of trying to beat the market through active trading. This is because returns are mainly driven by risk rather than investor skill, volatility reflects the

incorporation of new information into prices, and strong liquidity guarantees quick price adjustments.

In the context of this study, EMH implies that GPR as a form of new information should be rapidly incorporated into ETF prices, particularly under the semi-strong form of efficiency. This suggests that increases in GPR are expected to immediately affect ETF returns through price adjustments, while also increasing volatility as markets react to new uncertainty. Furthermore, liquidity may temporarily decrease during periods of heightened GPR, as information asymmetry and uncertainty increase transaction costs and reduce market participation (Janabi, 2024). However, under EMH, such effects should be short-lived, as prices adjust quickly to reflect new information. Importantly, the efficiency and speed with which GPR is incorporated into ETF prices may differ between developed and emerging markets. Developed markets, which are generally more liquid and informationally efficient, are expected to adjust more rapidly to geopolitical shocks, resulting in shorter periods of volatility and quicker recovery in liquidity. In contrast, emerging markets may exhibit slower information diffusion, leading to more persistent volatility, reduced liquidity, and potential short-term predictability in returns, which deviates from the assumptions of market efficiency (Nhlapho, 2023).

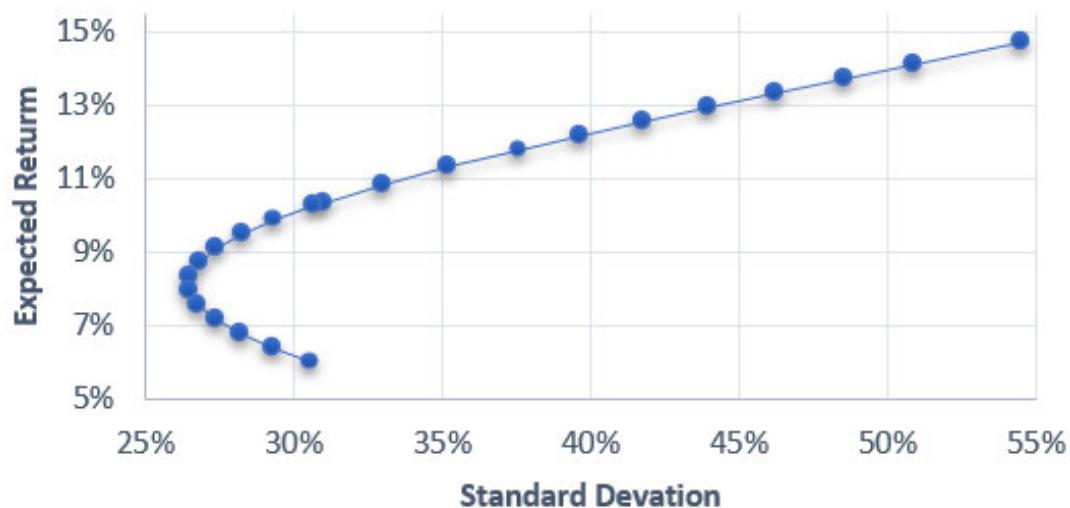
Heightened GPR can challenge these EMH assumptions by introducing sudden uncertainty, causing sharp volatility, and disrupting liquidity, which may temporarily hinder market's ability to process information efficiently (Suleman, Ali Shah and Imdad 2017). Disruptions including panic selling have the potential to cause irrational investor behaviour, causing prices to temporally diverge from the fundamental values of EMH and violating the assumption of fully efficient markets. In addition, persistent geopolitical shocks can also increase risk premiums and lower investor confidence, possibly causing returns to follow predictable patterns as markets gradually adapt to increasing uncertainty, thereby resulting in longer-term inefficiencies and weakened market stability.

2.3.2.2 Modern Portfolio Theory

In 1952, Markowitz (1952) introduced the Modern Portfolio Theory (MPT), which asserts that investors build portfolios by focusing on the mean and variance of their one period holding return. Furthermore, Markowitz (1952) claims that investors want to construct portfolios that

are mean-variance efficient that is, investors attempt to maximise the return of their portfolio given the level of variance and minimise the variance of their portfolios' return given the level of return (Kunjal, Peerbhai, and Muzindutsi, 2024). In addition, Markowitz popularised the concept of efficient portfolio, which minimises risk for a prescribed level of expected return, subject to constraints (Shkolnik et al., 2024). The concept of efficient portfolio is central to MPT, in which portfolios on the efficient frontier represent the set of optimal investment portfolios that provide the highest expected return for a specific level of risk, or the lowest risk for a given level of return (Buttelt,2010). Graphically, efficient frontier is illustrated as a curve, as shown in Figure 2.1, where x- axis represent risk measured using standard deviation, the y-axis represents expected return, and the curve represents an efficient portfolio. In the graph, points below the efficient frontier are inefficient meaning that it is possible to get a better return for the same risk or less risk for the same return. In contrast, points above the efficient frontier are unachievable meaning that they are outside the bounds of possibility given the assets and constraints (Buttelt, 2010).

Figure 2.1: Efficient Frontier Graph



Source: Author's own illustration based on existing literature

The efficient frontier in MPT denotes portfolios that optimize return for a given level of risk. ETF returns can be shifted and made more volatile by GPR, which reduces the optimality of previously effective portfolios. Additionally, high GPR can make it more difficult to trade ETFs at reasonable prices. As a result, ETFs may temporarily fall below the efficient frontier,

and investors may need to modify their portfolios in order to preserve the optimal risk-return ratio (Yang, 2021). In conclusion, market quality is influenced by MPT, which assumes high liquidity for costless rebalancing and encourages efficient diversification to maximise returns for a given level of risk (volatility). In practice, this implies that investors can remain closer to the efficient frontier when there is improved market quality which can be achieved by stable volatility, accurate pricing, and strong liquidity. MPT reflects MPT principles by providing diversified, inexpensive, and liquid access to a range of asset classes, allowing investors to effortlessly modify their risk-return profile along the CML (Shkolnik et al., 2024). While shifts in GPR can change the correlations between financial asset classes, undermining diversification benefits and shifting the efficient frontier.

2.3.2.3 Arbitrage Pricing Theory (APT)

In 1976, Stephen Ross introduced Arbitrage Pricing Theory (APT), a multi-factor pricing model, which provides a different framework for understanding the relationship between risk and macroeconomic factors (such as, inflation, industrial production, risk premiums and the slope of the term structure of interest rates). The APT is a substitute for the well-known Capital Asset Pricing model (CAPM) proposed by Sharpe (1964), which only explains the expected return of financial asset in terms of single market index (Ross, 2013). APT assumes that arbitrageurs will take action to eliminate mispricing and return prices to equilibrium if prices diverge from the expected return forecasted by macroeconomic factors (Nguyen, 2010). In addition, this theory heavily relies on the basis that markets are frictionless, no arbitrage opportunities and, homogeneous investor beliefs that the random returns on assets are generated by the linear k-factor model (Nguyen, 2010).

The APT implies that investors should be compensated for their exposure to GPR, since GPR represents a systematic risk factor which cannot be reduced through diversification (Kara and Karabiyik, 2015). In contrast to idiosyncratic risks, which can be mitigated by diversification, GPR events impact numerous asset classes and large market segments at the same time. These shocks can change risk premiums, discount rates, and expected cashflows across economies, which means that investors who hold assets sensitive to geopolitical events, will demand higher expected returns to offset this extra source of uncertainty. Furthermore, APT also helps in explaining the varying effects of GPR in developed and emerging markets. Emerging markets are generally more vulnerable to geopolitical shocks due to their weaker institutions and

increased political unpredictability, therefore GPR shocks typically result in higher volatility and more severe liquidity disruptions. In contrast, developed market ETFs are able to absorb geopolitical shocks because of their stronger regulatory frameworks and increased investor diversification, resulting in lower volatility and increased liquidity (Maitra, 2025).

2.3.4 Behavioural Finance Theories Underpinning Market Quality

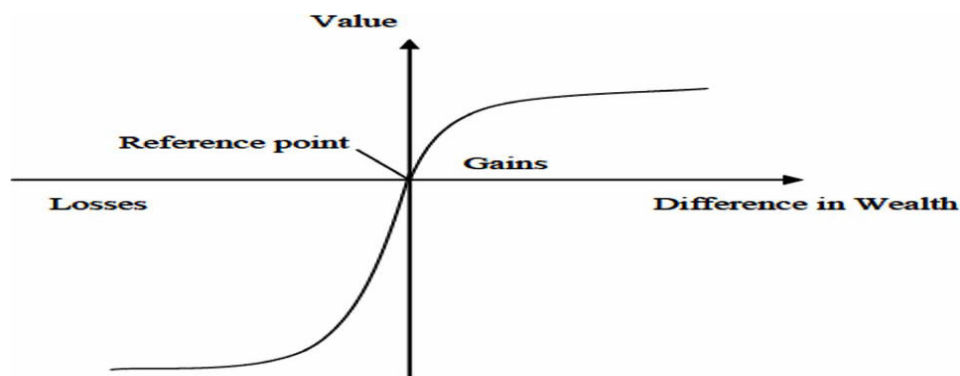
The previous section discusses traditional finance theories, this section examines behavioural finance theories. Behavioural finance theories are the psychological study of market participants and interactions with financial markets, and these market participants may be individual households or organisations (Fakhry, 2016). Additionally, behavioural finance theories discussed in this section include prospect theory and BPT.

2.3.4.1 Prospect Theory

Kahneman and Tversky (1979) introduced prospect theory, a behavioural economic theory that explains how people make choices in the face of risk and uncertainty. Prospect theory is an alternative model for expected utility theory of the economic model, because the expected utility theory was insufficient and unreliable in explaining the human decision-making process (Saliya, 2020). Prospect theory holds that when making decisions, people consider gains and losses in relation to a reference point rather than the final gains and losses. Based on this finding, they discovered a value function describing gains and losses in relation to the reference point. They also noted that the expected utility theory function is too simple to use probability as the weight directly (Pan, 2019). Instead under uncertainty, individuals determine their final decision value by adding all potential future value functions through decision weighting function (Pan, 2019).

Furthermore, Prospect theory proposes three important elements (Kahneman and Tversky, 1979). Firstly, individual's attitudes towards risk vary (Tversky and Kahneman, 1991). The second element of prospect theory states that individuals calculate each prospect's worth using a reference point (Kahneman and Tversky, 1979). According to Schmidt and Zank (2012) the third element of prospect theory is that people are loss averse, meaning that they prioritise losses over gains. The three elements result in the creation of an asymmetric 'S' shaped value function that is steeper in the domain of losses, concave for gains, and convex for losses (List, 2004). Notably, the utility function of the conventional expected utility theory is replaced by the value function of the Prospect theory shown in Figure 2.2 below.

Figure 2.2: Value Function of the Prospect theory



Source: Kahneman and Tversky (1979)

Expanding upon these behavioural foundations, prospect theory provides meaningful information about how risk-averse investor decision-making can affect aspects of market quality such as returns, volatility and liquidity. According to the theory, investors react more strongly to losses than to comparable gains because they have loss aversion and assess outcomes in relation to a reference point. This asymmetry can cause disposition effect, where investors prematurely realise gains but hold onto losing positions, thereby affecting price trends and realised returns (Hens, 2011). Additionally, probability weighting increases sensitivity to extreme market outcomes and causes overreaction to low probability events, which leads to excess volatility (Barberis, Jin, and Wang, 2021). During times of market stress, flight-to-safety dynamics may be triggered by loss-averse behaviour, which lowers demand for risky assets and tightens liquidity conditions as trading activity becomes more extreme (Henderson, 2012). In addition, these behavioural tendencies provide an explanation of why financial markets consistently deviate from outcomes predicted by traditional rational expectations model (Saliya, 2020).

Prospect theory offers a behavioural explanation of how GPR impact ETF returns, volatility, and liquidity in both developed and emerging markets. When GPR rises, investors tend to overweight possible losses and sell ETFs aggressively, which can result in negative returns, especially in risk sensitive markets (Barberis, Jin, and Wang, 2021). Furthermore, GPR is linked to increased volatility, particularly under favourable regimes or during times of market stress. Increased anxiety also causes investors to pull out of high-risk assets, which lowers trading depth and raises liquidity frictions (Pasquarillo, 2007). In contrast, investors tend to re-enter markets more gradually during times of improving geopolitical conditions, leading to asymmetric liquidity responses.

The prospect theory further explains why the impact of GPR vary across markets. Investors view emerging markets as riskier and more vulnerable. Therefore, loss aversion is more intense during GPR shocks, leading to greater volatility spikes, more severe liquidity contractions, and more stronger responses to global GPR (Nguyen, 2019). In contrast, developed markets have more improved diversification, strong financial markets, and regulatory frameworks, all of which lowers the perceived downside risk. As a result, investors in these markets are less likely to panic selling, explaining lower volatility and increased resilience.

2.3.4.2 Behavioural Portfolio Theory

Another popular behavioural finance theory is the Behavioural Portfolio Theory (BPT) introduced by Shefrin and Statman (2000) as an alternative to MPT. BPT suggests that investors should organise their portfolios into layers that correspond to various risk tolerances and financial objectives (Kapoor and Prosad, 2017). This layered structure directly reflects the behavioural biases identified in prospect theory, particularly loss aversion and the tendency to evaluate outcomes relative to specific reference points. The key differences between BPT and MPT is that risk in BPT is associated with the likelihood that the return will fall below the pre-determined threshold level as opposed to the variance of the returns measured by the MPT (Kunjal, Peerbhai, and Muzindutsi, 2024). Secondly, while BPT allows investors to see their holdings as a group of sub-portfolios that correspond to different accounts, MPT views the portfolio as a single, integrated whole. In addition, under MPT, the emphasis is on diversifying the portfolio to maximize the overall risk-return profile rather than creating distinct sub-portfolios to satisfy various psychological or goal specific requirements (Mittal, Battacharya, and Mandal, 2022).

By contrast, BPT allows investors to mentally divide their wealth into layers, like a pyramid, each reflecting different risk attitudes and goals (Jiang, Ma, and An, 2013). At the base of the pyramid, investors hold low-risk assets such as savings accounts and government bonds to protect their wealth. In the middle layers, they invest in moderate risk assets like blue-chip stocks to generate steady returns for medium term objectives. At the top of the pyramid, they take on high risk investments such as growth stocks and cryptocurrencies, aiming for large potential gains (Sapkota, 2022). This behaviour is consistent with prospect theory, as investors seek to avoid losses in lower layers while accepting higher risk in upper layers for potential gains.

Under BPT, investors have tendency to mentally build portfolios that has implications for market quality. Top layers, which are made up of high-risk assets, have the potential to generate big losses as well as exceptional returns in favourable conditions, which raises the variability of the overall portfolio return. These top-layer investments typically experience larger price fluctuations, which raises market volatility, particularly during times of sharply shifting sentiment. Due to their higher trading volume, liquidity is frequently concentrated in these speculative segments, while the lower- risk assets are held for longer periods of time, resulting in uneven liquidity across markets. This imbalance has the potential to erode market resilience and stability because shocks in speculative layers can amplify downturns and hinder the system's ability to recover. A vulnerability that can further be worsen by heightened GPR, which frequently causes sudden changes in capital flows and severe reductions in liquidity (Sapkota, 2022).

BPT provide an explanation of why GPR shocks cause more intense and persistent volatility in some markets than others. Under increased geopolitical uncertainty, investors with safety-oriented goals respond more to forcefully increased geopolitical uncertainty, increasing volatility through coordinated selling. This effect is more noticeable in emerging markets, where ETFs are seen as riskier and less resilient, resulting in sharper volatility responses, compared to developed markets with more stable financial systems (Akin and Akin, 2024). In terms of liquidity, BPT suggests that investors pull out of higher-risk portfolio layers during times of elevated GPR, which lowers market participation in affected ETFs (Mike and Farmer, 2008). This leads to reduced liquidity and larger bid-ask spreads, especially in emerging markets. In contrast, developed market ETFs may see comparatively stable or even improved liquidity as a result of portfolio rebalancing into safer markets.

2.4.3 Adaptive Market Hypothesis

The Adaptive Market Hypothesis (AMH) proposed by Lo (2004) states that market efficiency and inefficiencies can coexist in an intellectually coherent way. Under AMH, the traditional idea of all-or-nothing efficiency does not apply to market efficiency, rather, it develops over time (Urquhart and McGroarty, 2016). According to Sing and Singh (2024), AMH is based on the concept of evolutionary principles and bounded rationality to explain financial market behaviours. This means that investors learn from their past experiences and modify their

strategies accordingly, much like natural species do. Furthermore, under AMH investors frequently use heuristics, also known as mental shortcuts, which are tools used for making decisions that are not related to money. In addition, the percentage of investors who employ these heuristics instead of more successful strategies adapted to specific economic contexts determines how much of an impact these biases have on financial markets (Lo, 2005).

Lo (2004) acknowledges that there are several implications of AMH. Firstly, AMH acknowledges that market behaviour is strongly influenced by prevailing market regimes, such as expansion, crisis, or recovery, and that strategies frequently work in one regime but not in another. This suggests that active and passive investment strategies can coexist, with active strategies showing greater potential during periods of structural change and passive strategies proving more effective in stable, competitive markets. The relationship between risk and return is likely to vary over time under AMH since risk tolerance varies in response to recent market events, volatility, and changes in wealth.

In relation to market quality, AMH suggests that returns are not constant but rather change with market regimes (Wong and Shum, 2010). Abnormal returns are more likely to occur during times of structural change than during competitive times. Similarly, volatility is regime-dependent, rising sharply during crises as investors quickly modify their strategies while staying comparatively low and predictable in calm markets. Additionally, liquidity is dynamic, it tends to be abundant during times of high confidence but declines during times of instability as participants pull out and market depth shrinks (Mandac, Taskin, and Ergün, 2019). AMH further suggests that the effect of GPR on market quality is caused by shifts in investor competition, trading strategy for survival in the market. Under AMH, investors constantly change their trading strategies in response to shifting market conditions, including geopolitical shocks. Occurrence of geopolitical shock in the market results into the abandonment of strategies that are not effective, and lead to the rise of more resilient strategies, shifting returns, volatility and liquidity (Belhoula et al., 2023). The next section provides a conceptual overview of ETFs, which form the primary focus of this study.

2.5 Theoretical Foundations of ETFs

ETFs have emerged as one of the most popular passive investment vehicles among both retail and professional investors because of high liquidity and low transactional costs (Kunjal, 2023). This is because ETF shares are traded on stock exchanges, and investors can take short or long

positions. Additionally, ETFs may obtain index exposure by holding a basket of securities passively (physical replication), enter into derivative contracts that deliver the performance of an index (synthetic replication), or adopt a combination of the two (Ben-David, Franzon, and Moussawi, 2017). Similar to index mutual funds, ETFs enable investors to gain passive exposure to broad market indices. However, ETFs are traded continuously on an exchange, in contrast to closed end or open-end funds. ETFs thus incorporate features of both closed end and open-end funds (Leibi, 2020). On this basis, this section discusses the structure of ETFs, how they operate, and how their shares are created and redeemed. The key advantages and disadvantages associated with ETFs are also examined.

2.5.1 The Structure of ETFs

Structurally, while ETF holds a portfolio, it does not directly engage with capital markets like mutual funds (Arthur, 2013). Instead, the ETF manager enters into a formal agreement with one or more Authorized Participants (APs), usually specialised market makers or large financial institutions who then communicate with the markets (Kaur, 2025). Specifically, the ETF manager can issue or redeem shares with APs in big blocks, called creation units, for cash or variety of securities. This process is called the creation/ redemption mechanism (where creation refers to increasing the supply of ETF shares and redemption refers to a decrease in the shares outstanding of the ETF, and it allows the ETF shares to be adjusted in response to supply and demand (Lettau and Madhavan, 2018). This aligns with the Dynamic Equilibrium Model of ETFs introduced by Malamud (2016) which posits that the ETF market structure is characterised by two tiers, the primary and secondary market.

The primary market includes transactions between APs and ETF issuer, where the APs can redeem ETF shares by returning them in exchange of the underlying securities, or they can create new ETF shares by delivering a basket of the underlying securities to the issuer. This creation/redemption process makes sure that supply can grow or shrink in response to demand by operating in big blocks (Malamud, 2016). Whereas secondary market involves investors trading with one another on stock exchanges. Here, supply and demand pressures may cause ETF prices to momentarily deviate from NAV. The price of the ETF is pushed back toward NAV by APs using the primary market process to profit from arbitrage if there is a large price deviation (Malamud, 2016). When this happens, APs engage in arbitrage, if the NAV is greater than ETF price, they buy ETF shares and redeem them for the underlying securities, whereas,

if the NAV is less than ETF price, they buy the underlying securities and exchange them for newly created ETF shares. In both scenarios, APs sell the ETF shares or securities back to the market, gaining from the price difference while helping to realign the NAV with ETF price (Lettau and Madhavan, 2018).

2.5.1.1 Advantages of ETFs

ETFs have become a preferred investment vehicle because of the benefits they provide over mutual funds. One of their main advantages is diversification, which helps investors spread risk and reduce the impact of unfavourable events in any single market by providing wide exposure to various asset classes (Arthur, 2013). In most cases diversification is beneficial when it comes to reducing exposure to GPR, because the funds of the investor are not tied to one country. Another key advantage of ETFs is efficiency, where investors can access thousands of underlying holdings with a single transaction, which together represent a particular market segment or adhere to rules-based security selection strategy set by the index sponsor (Baiden, 2011). As a result, ETFs allow investors to quickly acquire targeted exposure to a variety of markets with little administrative complexity.

ETFs offer significant advantages in terms of both tax efficiency and hedging opportunities. ETFs are more tax efficient than many conventional investment vehicles because their special creation and redemption mechanism, which uses in-kind transactions rather than cash sales to minimise capital gains distributions to investors (Moussawi, Shen, and Velthuis, 2019). This creation and redemption mechanism also helps ETF prices remain closely aligned with their underlying NAV, as APs arbitrage away mispricing by creating or redeeming ETF shares, which enhances price efficiency and stability even during periods of geopolitical uncertainty. This structure allows investors to control the timing of their tax liabilities better, thereby improving after-tax returns. Additionally, ETFs offer flexible and affordable hedging opportunities, because they can be used to hedge against market risk, country-specific risk, interest rate risk, currency risk, and even GPR (Liebi, 2020). During times of increased uncertainty, investors use ETFs to protect portfolios by taking long or short positions or combine them with options.

In addition to the abovementioned advantages of ETFs, another benefit ETFs provide is greater liquidity levels. ETFs offer investors more liquidity through intraday trading than mutual funds,

which are only available for trading at the end of the day at their closing NAVs (Ben-David, et al., 2017). The intraday trading combined with the creation and redemption mechanism further supports liquidity by allowing continuous adjustment of supply and demand through APs, which is particularly important during periods of heightened GPR when trading activity and liquidity conditions may fluctuate. ETFs offer significant trading flexibility because they are listed on stock exchanges and can be bought or sold at market prices throughout the trading day. Due to intraday trading flexibility, investors can react fast to changes in the market and modify portfolio exposures in real time. ETFs offer more control over trade execution by supporting a variety of order types, including limit and stop orders. Additionally, they can also be used in conjunction with derivatives enabling advanced investment strategies like hedging (Ben-David, Franzon, and Moussawi, 2017). Overall, ETFs offer investors with a powerful and flexible investment vehicle that can be easily tailored to meet diverse financial objectives while adapting swiftly to changing market conditions, by combining broad diversification, operational efficiency, tax efficiency, hedging opportunities, and greater liquidity levels.

2.5.1.2 Disadvantages of ETFs

Even though ETFs are popular investment vehicles because of the benefits they offer to investors who seek to maximise returns for a given level of risk, they also have disadvantages and concerns that need to be considered. One of the main concerns with ETFs is the tracking error caused by the ETFs being unable to exactly replicate the performance of its underlying index because of transaction costs, sampling methods, and trust expenses (Baiden, 2011). Another concern is market risk. Although investment diversification reduces the effect of a decline in the performance of any one security in the ETF portfolio, it does not reduce the risk of broad market declines caused by economic events or policy changes affecting the underlying index (Kaur, 2025). As a result, an ETF can lose a significant value if the overall sector or market experiences a downturn. Because ETFs are designed to passively mimic index, they cannot actively avoid market risk, meaning that investors remain fully exposed to market risk. Moreover, another concern with ETFs is the limited professional management associated with passively managed ETFs that track an index, while professional management of active ETF strategies may be available, but they come with higher fees and less widespread adoption (Kaur, 2025).

Other concerns with ETFs include liquidity risk that occurs when an ETF has little trading activity or when underlying securities, it holds are not liquid. In such cases, investors might have to deal with larger bid-ask spreads, more expensive transactions, and difficulty in executing trades without having a big effect on the price (Box, *et al.*, 2021). Lastly, other concerns with ETFs include premiums and discounts to NAV which occurs when the market price of an ETF differs from the value of its underlying assets, this often happens during times of market stress or in funds with illiquid holdings (Kuar, 2025). Overall, the concerns about ETF markets suggest that ETFs can disrupt broader financial markets. Therefore, although they are many benefits to investing in ETFs, there are some concerns to ETFs that must be considered before making an investment decision. However, little is known about how ETFs react to GPR, despite their increasing popularity as investment vehicles. Therefore, this highlights the need for further research on how GPR affects ETF market quality.

2.6 Chapter Summary

This current chapter reviewed different theories underpinning market quality of ETFs and GPR. GPR is underpinned by institutional theory and realism. Institutional theory emphasizes that GPR arises when international norms and institutions weaken, reducing corporation and increasing uncertainty, while realism highlights how security concerns, power competition, and shifts in the balance of power inherently cause conflict and instability. Together these theories explain how failures and power-driven state behaviour convert into systematic risks affecting both financial systems and global economic. The theories underpinning market quality jointly explain how GPR affects ETF market quality across returns, volatility, and liquidity in developed and emerging markets. The EMH suggests that GPR should have weak or temporary effects on ETF returns, as markets are expected to incorporate new information quickly. In contrast, APT predicts that GPR represents a systematic factor, suggesting a positive risk premium on ETF returns, particularly in more exposed markets. Prospect theory explains heightened ETF volatility during periods of elevated GPR as overreaction amplify price fluctuations. The AMH further indicates that GPR effects are regime-dependent, varying across bull and bear markets as investor behaviour changes. Lastly, institutional theory highlights liquidity disruptions under GPR, with stronger and more persistent effects in emerging markets due to weaker institutions. Overall, ETFs are passive investment vehicles that trade continuously on stock exchanges and relying on the creation and redemption mechanism involving APs. Their key advantages include diversification, high liquidity, trading flexibility,

tax efficiency, operational efficiency, and hedging opportunities. However, ETFs also have limitations such as tracking error, limited professional management, liquidity risk, and premiums or discounts to NAV.

CHAPTER 3: REVIEW OF EMPIRICAL STUDIES

3.1 Chapter Overview

While the previous chapter reviewed theories that are fundamental to the objectives of this study, the current chapter aims to conduct a review of empirical research on the effects of GPR on financial markets. However, given that there is limited empirical evidence on the effects of GPR on the ETF markets, inferences are drawn from studies on other financial markets where appropriate. This chapter is structured as follows: Section 3.2 provides a review of empirical studies on the effects of GPR on returns in emerging and developed markets. Section 3.3 reviews empirical studies of GPR effects on volatility in developed and emerging markets. Section 3.4 examines empirical studies on GPR effects liquidity in developed and emerging markets. For each study reviewed, the methodologies employed are outlined to inform the development of an appropriate empirical methodology for addressing the objectives of this study

3.2 Geopolitical Risk Effects on Returns

The following section discusses previous studies examining the effects of GPR on returns in emerging and developed markets. Due to limited empirical evidence of studies examining the GPR effect on ETF returns, inferences are drawn from studies examining the influence of GPR on stock markets.

3.2.1 Xaba, Moroke, and Rapoo (2019)

Xaba, Moroke, and Rapoo (2019) employed a Markov Switching Dynamic Regression (MS-DR) to examine the stock returns of BRICS (Brazil, Russia, India, China, and South Africa) countries over the sample period of January 1997 to January 2017. The main aim of this study is to examine GPR effect on stock returns, as well as the shift in returns between two regimes for the five stock market returns. Following Hamilton (1993), the two state Markov Regime-Switching model is based on the idea that the behaviour of the dependent variable is governed by distinct market regimes.

The results revealed that stock returns exhibit nonlinear effects and regime dependence across all BRICS countries. Specifically, the study found that predictability is stronger in bear markets than bull, although the magnitude and persistence of this predictability differ across countries. This implies that during times of increased uncertainty such as financial stress, market behaviour becomes more sensitive to underlying risk factors. Although the study does not

specifically include GPR as an explanatory variable, the regime shifts are found consistent with the times when geopolitical uncertainty is high, especially in emerging markets. Furthermore, the findings demonstrate varying regime durations and transition probabilities across countries, suggesting that some BRICS markets experience bear regimes for longer than others. These differences in markets suggests that returns react asymmetrically based on market structure and that emerging markets differ in their ability to withstand shocks, which may include geopolitical disturbances.

An important inference from this study is that asset returns are highly regime-dependent, with the bull and bear market conditions having a significant impact on returns. This finding directly motivates the current study by suggesting that the effect of GPR on ETF returns is likely to differ between developed and emerging markets as well as market regimes. When compared to Coen and Desfleurs (2024) who reported that GPR is a priced factor affecting REIT returns in U.S under the linear asset pricing model, Xaba et al., (2019) report the significance of nonlinear, regime-switching behaviour in explaining return dynamics. These studies suggest that while GPR may be priced in asset returns, its effect may differ significantly across market regimes.

3.2.2 Salisu, Lasisi, and Tchankam (2022)

Salisu Lasisi, and Tchankam (2022) explored the effect of global GPR on stock returns in advanced economies, specifically the G7 countries (Canada, Germany, France, Japan, Italy, United Kingdom, and United States) and Switzerland. The advanced economies were selected based on several factors, specifically, these economies are the most developed, export diversified and financially integrated in the world. They contribute more than 40% of the world's total output and have the highest Gross Domestic Product (GDP) per capita, at around \$25 000, as a result, any shock to them would therefore have a big effect on the world economy. Using a historical monthly stock index described as S&P 300 Composite Index (for Canada), CDAX Composite Index (for Germany), CAC All-Traded Index (for France), Nikkei 225 Index (for Japan), Banca Commerciale Italian Index (for Italy), the FTSE All share Index (for UK), S&P Index (for the US), and All Share Stock Index (for Switzerland). Along with sub-indices which include geopolitical acts and geopolitical threats. Oil prices are included as control variables and represented by West Texas Intermediate in the study.

The empirical framework of this study is based on APT, which assumes that stock returns react to systematic risks, of which GPR is modelled as one of the risk factor. This study employed bias-adjusted Ordinary Least Squares (OLS) estimators in accordance with Lewellen (2004), Westerlund (2012) and Narayan (2015), to address endogeneity, persistence, and conditional heteroscedasticity, which are common in financial time series. The model formulation is based on the idea that stock market investments should experience a decline in value during periods of GPR. The predictive models expand the constant return (historical average) benchmark to incorporate GPR indices, expressed in log form. The findings from this study revealed that GPR significantly affect stock returns, except for Italy. Furthermore, the results demonstrated that GPR consistently reduces returns, proving that advanced economies stock markets are not good hedges and are sensitive to geopolitical uncertainty. In addition, the study revealed that GPR based models perform better than benchmark models in both in-sample and out-of-sample forecast, and their robustness is preserved when the dynamics of oil prices are added as important global factor.

Notably, the findings from this study emphasize the importance of research objective one because they indicate that GPR significantly predicts stock returns in advanced economies and challenges the idea that only emerging markets are highly exposed to GPR. This suggests that even in highly developed markets, GPR is a systematic and priced risk factor, and these findings imply that ETF returns are likely to be exposed to GPR through their underlying equity holdings. However, the limitation of this study is that it does not account for how GPR effects differ across different market conditions. Since financial markets exhibit regime switching behaviour. Accordingly, examining how GPR affects ETF returns across markets as well as different market regimes addresses an important gap in the existing literature.

3.2.3 Ben Ghozzi and Chaibi (2022)

Ben Ghozzi and Chaibi (2022) examined the effects of political risk on stock market returns in developed and emerging markets. By using a sample of 46 stock markets, consisting of 23 emerging and 23 developed markets from the period of 1995 to 2019. The study employs Fixed effect model in line with previous studies of Goodell and Vahamaa (2013) and Dimic et al., (2015) to capture the effects of political risk on stock markets in developed and emerging markets. The model employed in this study is useful as it mitigates several country characteristics which may have a greater effect on stock market than political risk in that

country. The study revealed that in both developed and emerging markets, high stock market returns are associated with lower political risk. Notably, developed stock markets returns are more sensitive to political risk than emerging stock markets, suggesting that while emerging stock markets are frequently thought of as more volatile, developed stock market returns might be more sensitive to political fluctuations. This heightened sensitivity in developed markets can be caused by their increased exposure to international capital flows, which allow rapid transmission of political uncertainty into asset prices. In contrast, emerging market often exhibit structural frictions and reduced market efficiency, which may mitigate the immediate pricing of political uncertainty into stock returns.

The key finding from this study is that the effect of political risk on asset returns differs depending on the type of the market. This finding directly relates to the present study, as ETFs are highly liquid and are globally traded instruments that may increase the transmission of GPR into returns across different markets. Furthermore, the observed sensitivity differences suggest that the effect of GPR on ETF returns may be regime-dependent and vary across bull and bear market conditions as investor behaviour changes across market conditions.

3.2.4 Agoraki, Kouretas, and Laopodis (2022)

The study by Agoraki, Kouretas, and Laopodis (2022) examined the effect of GPR and Economic Policy Uncertainty (EPU) on stock returns. By using unbalanced panel models capable on examining data with the number of observations that differs across observations. This study uses monthly data of stock returns for 22 countries from 1985 to 2020, this sample period also accounts for the impact of the global financial crises from 2007 to 2009. The results show that there is strong negative correlation between the EPU index and stock returns, while the GPR index shows positive correlation. In addition, the findings from this study confirm that GPR is a priced and unfavourable factor in equity markets by showing that increases in global GPR consistently lowers stock market returns across countries. Furthermore, the EPU also negatively affects stock returns, but its effect is weaker relative to that of GPR. These findings are related to those of Salisu, Lasisi, and Tchankam, (2022), who similarly revealed that increases in GPR consistently reduce stock returns.

3.2.5 Ali et al. (2023)

To examine the relationship between geopolitical threats and equity returns in global markets, the study used geopolitical threat index. The geopolitical threat index incorporates a wide range of crises and only considers geopolitical events and is preferred over previous political risk measures. The study covers a period from 2005 to 2021 because of ETF data availability and consists of daily price data from the U.S stock market, which is used to calculate returns, the five precious metals, global bond yields, and the major G7 equity markets during this period. In addition, the study includes 11 ETFs used to track the equity market at the sectoral level (these ETFs include, Communication ETF, Information Technology ETF, Consumer Discretionary ETF, Consumer Staples ETF, Energy ETF, Health ETF, Financial ETF, Material ETF, Industry ETF, Utility ETF, and Real Estate ETF). By employing the Markov Regime-Switching model with two volatility regimes low and high, the study examines how changes in geopolitical threats (expressed as $\Delta GPR Threat$) affect asset returns, while controlling for unemployment, inflation, term premium, credit spreads, and trade volume. The Markov regime switching model is expressed in Equation (3.1) as follows:

$$R_t = a_0 + \varphi_{st1}\Delta GPT Threat_t + \varphi_{st2}\Delta GPT Threat_{t-1} + \varphi_{st3}\Delta CPI_t + \varphi_{st4}\Delta UNEMPL_t + \varphi_{st5}\Delta Bond Yield Spread_t + \varphi_{st6}\Delta Trade Volume_t + \varepsilon_t \quad (3.1)$$

In Equation (3.1) above, $\varepsilon_t \sim N(0, \sigma_{st}^2)$ is a discrete regime indicator that can take values as $\{1, 2, \dots, n\}$ according to the n state Markov regime switching process. In addition, two-regime models with regime dependent constant variances were evaluated. The results from Markov regime switching model suggested that geopolitical threats are major factor in equity returns, and the effects vary across regimes, sectors, and asset classes. Furthermore, the U.S equities are an effective hedge at the aggregate level and in high volatility periods. However, the effect diminishes when macroeconomic control variables such as inflation, credit spreads, term premium, unemployment, and trade volume are added. In addition, the U.S markets continue to be volatile in low-volatility periods.

In sectoral analysis, it is also noted that Information and Communication ETFs are strong hedges because they consistently have positive and significant returns regardless of regime. Energy and Materials sectors have high-volatility environments, whereas Utilities and Healthcare have low-volatility and serve as effective hedges. Gold and Silver are precious

metal that remain safe haven, while bonds and U.S dollar are less sensitive to GPR. Overall, this study emphasises sectoral diversification and the specific safe-haven sectors that investors can rely on when GPR intensify. These results therefore infer that ETF returns are directly affected by GPR and that the direction and magnitude of this effect depend on prevailing market regimes and sectoral characteristics. These findings emphasize the importance of research question one because not enough research has been done on how ETF returns behave over time in relation to different market conditions in developed and emerging markets. that of GPR.

3.2.6 Coen and Desfleurs (2024)

Coen and Desfleurs (2024) examined the role played by GPR in explaining the returns of REITs in U.S. Using monthly data covering the period from January 2000 to December 2023. This study employs extended conditional Fama and French (1993) pricing model to examine the influence of two components of GPR such as geopolitical threat and geopolitical acts on the returns of REITs. The results from the study revealed that in U.S, GPR is a priced factor securitised real estate market, which in comparison to conventional Fama and French factors, has statistically significant but comparatively lower economic effects. Furthermore, the results show that geopolitical acts have a greater effect on REIT returns than geopolitical threats. Additionally, this study also emphasises how different REIT portfolios are affected by GPR, showing the importance of firm characteristics in determining exposure to GPR.

Despite these contributions, the study has several limitations. While it shows strong evidence that GPR is priced in the U.S REIT market. However, it focuses solely on single developed market. In addition, the use of Fama and French models implies constant relationships overtime and thus fail to capture potential regime-dependent effects of GPR, such as changes between bull and bear market conditions. Lastly, although this study confirms that GPR is a priced factor, more research is required to determine whether similar effects exist for ETFs trading in developed and emerging markets under different market conditions.

In conclusion, reviewed studies collectively show that GPR plays an important role in shaping asset returns across different markets. Studies by Bouras, Christou, and Gupta (2018), Yang et al. (2021), and Salisu et al., (2022) consistently suggest that GPR is mainly transmitted through heightened and persistent volatility rather than predictable returns. Studies by Xaba et al., (2019) and Arenas and Gil-Lafuente, (2021) show that asset returns may differ across market

conditions. While studies focusing on developed markets by Salisu et al., (2022), Ben Ghoszi and Chaibi (2022), and Coen and Desfleurs (2024) provide evidence that GPR is a priced risk affecting returns with varying sensitivity across markets and asset classes.

3.3 Geopolitical Risk and ETF Volatility

The following section reviews empirical studies that examine the effect of GPR on ETF volatility. Due to limited studies on the literature, inferences were drawn from studies that examined GPR effects on stock markets in either developed or emerging markets.

3.3.1 Bouras, Christou, and Gupta (2018)

Bouras, Christou, and Gupta (2018) investigated the role of global and country-specific GPR in driving the movement of 18 emerging stock markets, mainly focusing on the volatility response to geopolitical uncertainty. The main objective of this study is to examine whether GPR represents a significant source of uncertainty that affect investor behaviour and stability of markets in emerging markets, and whether global GPR outweigh domestic geopolitical shocks. The study employed monthly data of 18 emerging stock market, covering period from November 1998 to June 2017. As well as GPR indices to measure global and country-specific indices. These indices do not relate only to geopolitical events of the global world but also include country-specific levels of 18 emerging stock markets. The analysis of this study is conducted using Panel Generalized Autoregressive Conditional Heteroskedasticity (GARCH) approach. This methodology is advantageous as it accounts for possible Cross-sectional Dependence (CD) compared to time series GARCH model (Single country) that is unable to incorporate such behaviour which is considerably important given the strong interconnectedness between emerging economies financial markets in a modern day. In addition, the main contribution of the methodology lies in directly incorporating GPR measures into conditional variance equation to examine their effect on market volatility.

The findings from this study revealed that global GPR has a strong effect on stock market volatility across emerging markets, whereas country-specific GPR has a weak effect on stock market volatility. In contrast, neither country-specific GPR nor global GPR significantly impact stock returns of emerging markets. These results suggest that in emerging markets, geopolitical uncertainty is mainly transmitted through volatility rather than expected returns, reflecting increased risk aversion, instability, and uncertainty during times of high geopolitical

tension. Despite its contributions, this study has limitations. Firstly, it focuses mainly on stock market indices, thereby ignoring other asset classes such as ETFs, whose volatility dynamics may differ due to liquidity and arbitrage mechanisms. Secondly, the study is limited to emerging markets, which makes it less applicable to developed markets. Thirdly, the study does not explicitly focus on whether the volatility response to GPR differs across different markets, as it focuses solely on emerging markets. An important inference from this study is that GPR is the main driver of market volatility rather than returns in emerging economies, with global GPR playing a dominant role. This insight provides a motivation for this research by implying that ETF volatility may be particularly vulnerable to GPR, given ETFs high liquidity and quick information transfer.

3.3.2 Yang et al., (2021)

Yang et al., (2021) examined the effect of GPR based on two categories (Geopolitical act and geopolitical threat) on the volatility of China's stock market. The study looked at China as it is the world's biggest emerging economy and has experienced huge growth in both investment and trade. In addition, China has stood out as the only major economy to maintain positive economic growth, making it a critical case for understanding the impact of GPR on emerging markets. The study uses data from 18 emerging economies, GPR acts index, GPR threat index, and the CSI 300 Index to thoroughly investigate the overall trends and movements of the Chinese A-share market. In this study, the main stock market indicator is the CSI 300 Index. To capture GPR in different directions, the study employs global GPR index together with categorical indices such as, GPR Act, GPR Threat, GPR Broad indices, GPR Narrow indices and GPR indices from 18 emerging economies. The sample period used in the study spans from the period of September 2011 to July 2020. Moreover, the study employs GARCH-MIDAS (Mixed Data Sampling) model developed by Engle, Ghysels, and Sohn (2013), which connects the long-term component of stock volatility to macroeconomic fundamentals such as industrial production and inflation.

The study employs GARCH-MIDAS model with realised volatility as it benchmarks model and GARCH-MIDAS model with realised volatility and GPR indices as extended model. The results from the study revealed that GPR significantly increase the volatility of China's stock returns, suggesting that higher levels of GPR leads to increased uncertainty in the Chinese stock market. According to the findings, GPR threat have a stronger and more consistent effect on

volatility than GPR acts. This suggests that the anticipation on GPR is more important to Chinese investors than the actual occurrence of geopolitical events. Furthermore, the results indicate that severe GPR have a greater impact, implying that market participants tend to react more strongly when risks are perceived as serious or extreme.

The study also examines how other countries GPR affect China's stock market. Ten countries GPR in 18 emerging economies showed a significant relationship with the volatility of the CSI Index. Noteworthy, GPR from countries like Turkey, Indonesia, Korea, Columbia, Saudi Arabia, Malaysia, and Philippines reduces volatility in China's stock market. This is due to diversification or indirect stabilizing effects. Whereas, Brazil, Venezuela, and China's GPR increases volatility in the CSI 300, which may be explained by geographic proximity, dependence on petroleum economics, or investment linkages. These findings demonstrate that GPR spillovers are diverse and dependent on how interconnected countries are financial and economically.

In comparison with the study by Bouras, Christou, and Gupta (2018), both studies highlight that GPR primarily affect markets through volatility in emerging markets. However, while Bouras, Christou, and Gupta (2018) rely on Panel GARCH model and focus on aggregate volatility responses across 18 emerging markets, Yang et al, (2021) offer a more detailed analysis by decomposing GPR into acts and threats and modelling long-run volatility using GARCH-MIDAS model. Therefore, this highlights the advantage of GARCH-MIDAS model in capturing persistent geopolitical uncertainty, which this study employs to ETF volatility in developed and emerging markets.

3.3.3 Dutta and Dutta (2022)

Dutta and Dutta (2022) examined the effect of GPR on the volatility of renewable energy ETF returns. According to the study, the GPR may affect energy assets via four channels. First, investors perception of the alternative energy sector may be influenced by their expectations for future changes in supply and demand for oil, which may be reflected in their investment decisions. Secondly, rising GPR can also increase crude oil prices, encouraging a substitution toward renewable energy sources and improving the operating conditions and performance of clean energy firms. Thirdly, heightened geopolitical tensions often accelerate the shift toward energy self-sufficiency and renewable energy, prompting greater interest from investors and

policy makers. Fourthly, increased GPR frequently results in increased uncertainty, which is rapidly transmitted to financial markets, making clean energy assets more sensitive to geopolitical developments.

To capture these dynamics and investigate how GPR affect the probability of being in low-and high volatility regimes across different clean energy assets. The study employs Markov Regime- Switching model, and a sample period from April 2008 to March 2020. In addition, the study includes monthly GPR data due to data availability of daily data, three ETFs such as Invesco daily Wilderhill Clean Energy ETF, Invesco Global Clean Energy, and Invesco Solar Energy ETF. The findings from this study reveals that employing the Markov regime switching model is a useful tool for understanding how market volatility and GPR interact. A rise in the GPR index specifically raises the probability of being in a low- volatility regime and decreases the likelihood of staying in a high volatility regime. These results can be explained by the behaviour of market participants when there is increased geopolitical uncertainty. As a result, of how easily geopolitical tensions can affect crude oil, investors frequently turn their attention to clean energy as a more reliable and sustainable option. This change raises the stock prices of startup energy companies, stabilizing the market and reducing volatility overall.

The methodology employed in this study is well suited for capturing nonlinear volatility and sudden shifts between high and low volatility regimes, which traditional linear models may be unable to detect. However, the Markov Regime-Switching model does not explicitly model the persistence or long-term transmission of GPR into volatility, instead it treats regime transitions as latent and probabilistic. Which makes it more difficult for the model to differentiate between persistent geopolitical uncertainty and short-run geopolitical shocks. A key limitation of this study is that GPR data are only available at a monthly frequency, which may mitigate short-term geopolitical shocks that could have an immediate impact on the volatility of ETFs. In conclusion, the findings from this study indicate that the impact of GPR on volatility is asset specific, with some sectors, such as renewable energy ETFs, possibly experiencing stabilizing effects as a result of portfolio reallocation during times of increased uncertainty. This suggests that different assets have different volatility responses to GPR and emphasizes the importance of research on ETF volatility to consider nonlinear volatility dynamics using GARCH-MIDAS model.

3.3.4 Salisu, Ogbonna, Lasisi, and Olaniran (2022)

Salisu et al., (2022) investigated the relationship between GPR and stock market volatility in emerging markets. Using a sample period from January 1997 to May 2020. This study employs GARCH-MIDAS model which separates conditional variance into short and long-run components. The short-run component consists of daily stock returns, while long-run component consists of log of GPR index which serves as predictor. In this study, the models were estimated separately since global and country-specific GPR cannot be included in the same model to avoid multicollinearity.

The results from the study revealed that GPR has a positive significant effect on the long-run volatility component, implying that increases in GPR results into higher long-term market uncertainty. The ARCH and GARCH parameters, which captures the short-run GARCH dynamics, confirm the presence of persistent daily volatility, as the sum of ARCH and GARCH term is close to unity. Furthermore, when global economic factors are considered, stock market volatility in emerging markets becomes more predictable. Regardless of whether the measure of GPR is country-specific or global, an increased frequency of geopolitical crises tends to create fear in the stock markets. This study makes a significant contribution by clearly identifying GPR as a long-term volatility driver rather than short term shock.

However, this study is limited to emerging markets only, which highlights the need for more research on different markets. Moreover, the methodology employed in this study is similar to Yang et al., (2021), who employed GARCH-MIDAS model to examine how GPR affect long-run volatility of China's market. Together, these studies show consistent evidence that GPR is included in the emerging markets long-term volatility structure, however, they do not provide evidence on whether long-run volatility exists in developed markets, thereby highlighting the need to examine the GPR effect on ETF volatility in developed and emerging markets using a GARCH-MIDAS model.

3.3.5 Zhang et al., (2023)

The study by Zhang et al., (2023) aims at expanding the body of literature by examining the effects of GPR on stock market volatility from a global perspective. By using sample period from March 2017 to March 2022, the study uses data from 32 countries and regions across Europe, Asia, Australia, America, and the Middle East, and constructs measures of realised

volatility using daily returns. Furthermore, it then employs the bias-corrected Least Squares Dummy Variable (LSDV) estimator in a dynamic framework to deal with volatility persistence and endogeneity. By using this method, this study makes a unique contribution to existing literature, unlike relying on country specific time series methods.

The findings from the study revealed that increases in GPR significantly raise stock market volatility. This effect is maintained even when additional control variables such as jump components, returns, CBOE Volatility Index (VIX), and CBOE Crude Oil Volatility Index (OVX) are included. This reliability suggests that traditional based uncertainty measures fail to capture the incremental information about volatility that is found in GPR. The findings also imply that GPR produce widespread and persistent uncertainty that spreads throughout the global equity markets. Furthermore, the findings also reveal varying effects among various economic groups. Particularly emerging markets, nations that export crude oil, and countries at peace are more affected by GPR. This finding suggests that countries are exposed to external shocks are more sensitive to immediate increases in global geopolitical uncertainty.

3.3.6 Nilsson (2024)

Nilsson (2024) investigated whether GPR indices can predict the stock market volatility in 21 developed markets. Using a sample period from 1985 to 2021, the study utilises data of stock market indices, country-specific GPR index, and global GPR index, sourced from the work of Caldara and Iacoviello (2022). Following the work of Salisu et al., (2022), the study employs the GARCH-MIDAS model to examine the predictability of GPR indices when forecasting stock market volatility in developed markets. The results from the study revealed that GPR indices can predict stock market volatility but not in all developed markets. It also showed that the predictive power of GPR indices varies among developed market, which shows the significance of assessing each country's forecasting ability independently. Furthermore, the results also demonstrate that GPR indices can increase forecasting accuracy for both long-run and short-run total variance, although improvements are mainly associated with long-term variance.

Notably, the study emphasises the importance of research objective two, by demonstrating how both global and country-specific GPR can predict stock market volatility in developed markets. This, in turn, shows the need to examine how GPR influences ETF volatility in both emerging

and developed markets. Furthermore, these findings are in line with previous studies employing GARCH-MIDAS models, which demonstrate that GPR generates persistent uncertainty in financial markets. However, they contrast with the findings of Zhang et al., (2023) who reported that similar volatility effects across countries. Overall, the findings suggest that different countries respond differently to GPR and that relying solely on broad market indices may hide significant differences in how different financial instruments respond to such risk.

3.3.7 Nasouri (2025)

Nasouri (2025) examined and compared the effect of GPR on equity markets and financial stress in both developed and emerging markets. The main aim of the study is to understand how GPR influences market returns, volatility, and overall financial stability across markets. Using monthly Geopolitical threat (GT) index sourced from the work of Caldara and Iacoviello (2022), daily stock returns of emerging markets and G7 countries. The GARCH-MIDAS model developed by Engle et al., (2013) is employed to capture the long-run and short-run volatility dynamics associated with GPR. The results from the study revealed that there are notable differences on the effects of GPR in developed and emerging markets. The U.S equity market exhibit positive returns during periods of high geopolitical threat, particularly, in the financial and information technology sectors. In contrast, emerging markets respond to GPR with higher stock market volatility. Increases in GPR exacerbates financial stress in emerging markets, particularly in cases where financial conditions are already strained. In addition, GPR effects are mainly seen in the stock markets of G7 countries.

The finding that emerging markets respond to GPR with higher volatility are consistent with Bouras, Christou, and Gupta (2018) and Yang et al., (2021) who found that GPR is transmitted mainly through heightened volatility rather than systematic return predictability. An important inference from this study is that the transmission of GPR varies across markets, because developed markets may be better able to absorb shocks, while emerging markets tend to experience financial stress and heightened volatility. These findings support the view that GPR act as long-run source of volatility in emerging markets, whereas its effects in developed markets are more associated with positive return responses.

In conclusion, these studies collectively examine how GPR affects volatility. Bouras, Christou, and Gupta (2018) found that global GPR significantly increase volatility in 18 emerging markets, while returns are not significantly affected and country-specific GPR effects are weak.

Yang et al., (2024) revealed that GPR increases long-run volatility in China, with geopolitical threats having stronger effects than geopolitical acts, and show heterogenous GPR effects across emerging economies. Dutta and Dutta (2022) show that higher GPR increases the probability of renewable energy ETF being in a low-volatility regime, demonstrating an asset specific volatility response. Salisu et al., (2022), Zhang et al., (2023), and Nilsson (2024) all suggest that GPR is associated with higher volatility, with GARCH-MIDAS results indicating stronger long-run volatility effects. While Nasouri (2025) find asymmetric effects across markets, with emerging markets exhibiting higher volatility under elevated geopolitical threat, while the U.S shows

3.4 Geopolitical Risk and ETF liquidity

The following section reviews empirical studies of GPR effect on liquidity. However, relatively few studies have been available for the review due to limited studies on the literature, although some insights were drawn from studies on stock liquidity.

3.4.1 Kunjal (2023)

To investigate the effect of GPR on ETF flows in emerging markets, Kunjal (2023) make use of Vector Autoregressive (VAR) models developed by Sims (1980) together with their impulse response functions and granger causality tests. The methodology used in this study is motivated by the stationarity of the variables at levels since these models are traditionally developed for stationary variables. Therefore, this study uses sample period from July 2013 to June 2023 for all its 8 broad equity market ETFs namely Brazil, China, Chile, India, Philippines, Taiwan, South Africa, and Egypt. The VAR model in the study is estimated for each ETF as shown in Equation (3.2).

$$\begin{bmatrix} LnFlow_t \\ LnGPR_t \end{bmatrix} = \begin{bmatrix} \alpha_{LnFlow} \\ \alpha_{LnGPR} \end{bmatrix} + \sum_{m=1}^M A_m \begin{bmatrix} LnFlow_{t-m} \\ LnFlow_{t-m} \end{bmatrix} + \sum_{n=0}^N B_n \begin{bmatrix} LnR_{t-n} \\ LnAmihud_{t-n} \end{bmatrix} + \begin{bmatrix} e_{LnFlow,t} \\ e_{LnGPR,t} \end{bmatrix} \quad (3.2)$$

In the above Equation (3.2), the main variables of interest are GPR and ETF flows are represented by $LnGPR_t$ and $LnFlow_t$, the control variables, ETF liquidity and ETF returns are represented by $LnAmihud_t$ and LnR_t . To account for alternative sources of ETF flows, LnR_t which captures the ETF's log returns and $LnAmihud_t$ which captures the ETF's liquidity are included as exogenous variables in the VAR equation. a and e represent the constant and error terms, whereas the optimal lags of the endogenous and exogenous variables which are chosen using the information criterion are represented by M and N . Lastly A_m and B_n represent

parameter estimates.

In conclusion, the findings from the study revealed that the dynamics of ETFs in emerging markets are significantly influenced by GPR. Majority of countries including Brazil, China, Chile, India, Egypt, South Africa, and Taiwan, increases in GPR causes ETF flows to rise. This is a result of a flight-to-safety reaction, in which investors reallocate capital to ETFs because they are comparatively safer instruments during times of increased uncertainty. This positive correlation aligns with prospect theory, which postulates that investors' perceptions of risk motivate them to safeguard their wealth rather than seek out new opportunities for profit. However, Philippines is a noteworthy exception, where growing GPR results in lower ETF flows. This is in line with limited market participation, as investors pull out of financial markets when uncertainty is high. Lastly, the results show that, although the effect is not uniform, GPR tends to promote inflows and boost ETF markets in emerging economies.

3.4.2 Fiorillo et al. (2023)

Fiorillo et al. (2023) uses an international sample of publicly listed firms and GPR indexes developed by Caldara and Iacoviello (2022), from the period of 1995 to 2021 to investigate the relationship between GPR and stock liquidity. In addition, this study examines the relationship between geopolitical uncertainty and stock liquidity by focusing on elements such as information asymmetry and financial constraints, which have been found to be the primary causes of declining stock liquidity in previous studies. This perspective is consistent with the findings from Taiwan misfired missile event, where increased uncertainty amplifies these channels and ultimately decrease liquidity in the Chinese A-share market. The findings from the study shows that GPR significantly reduces stock liquidity, emphasising that uncertainty arising from geopolitical threats rather than real world events have a huge impact in shaping investor behaviour. Furthermore, the results showed that higher levels of information asymmetry, greater financial constraints, and preexisting low liquidity all increase the effects of GPR on liquidity. This suggests that during times of increased geopolitical uncertainty, investors tend to gravitate toward safer and more liquid assets and away from riskier, less transparent, and financially constrained companies. Overall, the findings demonstrate that information asymmetry and financing limitations are two major ways that GPR uncertainty reduces stock liquidity.

3.4.3 Lui et al., (2024)

Lui et al. (2024) examined the effect of geopolitical uncertainty on stock liquidity in China's A-Share market, focusing on the case of Taiwan's misfired missile event on 1 July 2016, a natural experiment that resulted in the fatality of a fisherman. By employing the Differences-in-Difference (DID) model which compares the changes in outcomes over time between treatment group (firms with close ties to Taiwan) and a control group (firm without close ties to Taiwan), the study make use a sample period from 1 January 2016 to 31 December 2016. The DID model allows for the determination of the causal impact of an exogenous geopolitical shock on market liquidity. Therefore, the results from using bid-ask spreads as a measure of liquidity revealed that the event significantly decreased stock liquidity of Taiwan related firms. On average, the bid-ask spreads of Taiwan related firms widened by 0.32 basis points when compared to firms without close ties to Taiwan. Furthermore, the mechanism tests from the study demonstrated that the primary ways that geopolitical uncertainty reduces stock liquidity is through stock price risk and information asymmetry.

The findings provide evidence that geopolitical uncertainty can reduce market liquidity by raising the risk and adverse selection faced by market participants. However, this study is restricted on one emerging market, one geopolitical event, and shorter sample period, which limits the extent to which the findings can be applied to comprehensive and persistent measures of GPR. In addition, the study only used the bid-ask spread as a measure of liquidity. Despite these limitations, this study is particularly useful especially for research examining the effect of GPR on ETF liquidity across developed and emerging markets. ETFs rely on both the primary and secondary markets which are highly sensitive to information asymmetry and underlying uncertainty. Consequently, the liquidity reducing channels identified by Lui et al., (2024) suggest that GPR may have greater effect on ETF liquidity, especially for ETFs with exposure to emerging markets.

In conclusion, the studies by Kunjal (2023), Fiorillo et al., (2023), and Lui et al., (2024) collectively examine how GPR affects financial markets through liquidity channels. Kunjal (2023) show that rising GPR results into increased ETF flows in emerging markets, reflecting a flight-to-safety behaviour, though effects are not the same across countries. Fiorillo et al., (2023) find that GPR significantly reduce stock liquidity globally, through financial constraints and heightened information asymmetry. Lui et al., (2024) show the evidence that geopolitical

shock reduces stock liquidity in China's A share market by raising risk and adverse selection. Overall, these studies suggest that geopolitical uncertainty changes investor behaviour by affecting market liquidity.

3.5 Chapter Summary

Chapter three reviewed existing studies on the literature surrounding the effect of GPR on the quality of ETFs in developed and emerging markets. This chapter reviews these existing studies separately for ETF returns, volatility, and liquidity. Table 3.1 presents the summary of empirical studies reviewed in Chapter 3. Although the studies in Table 3.1 examined important aspects of market quality, a comparative reading of these studies reveals both similarities and differences in their findings across markets and dimensions of market quality. It is evident from Table 3.1 that the empirical research surrounding the effect of GPR on ETF market quality remains limited. The reviewed studies show that there are gaps in the literature.

Firstly, the evidence on ETF specific effects remains limited, since most studies of Dutta and Dutta (2022), Ali et al., (2023), and Kunjal (2023) focuses on stock indices or REITs, with few studies directly examining ETFs which differ in structure. This indicates that findings from related asset classes may not fully translate to ETF markets, highlighting a gap in ETF specific evidence. Secondly, the studies by Bouras, Christou, and Gupta (2018), Yang et al., (2021), and Salisu et al., (2022) show evidence that GPR increases volatility in emerging markets, and markets more sensitive to external shocks. In contrast, studies by Nilsson (2024) and Nausori (2025) show mixed evidence for developed markets, indicating that these markets are better able to withstand geopolitical shocks, resulting to less uniform volatility across countries. Taken together, these findings suggest the impact of GPR on volatility is not homogenous and varies depending on market structure and level of development.

Thirdly, the studies that looked at GPR effect on liquidity either focus on stocks globally or in a single country, limiting the comparison across markets. As a result, there is limited evidence on how liquidity responses differ between developed and emerging ETF markets under geopolitical stress. Fourthly, the reviewed studies show that findings are not fully consistent with studies by Bouras, Christou, and Gupta (2018) and Salisu et al., (2022) showing that GPR primarily impact financial markets through higher volatility, especially in emerging markets. In contrast, studies by Salisu, Lasisi, and Tchankam (2022) and Coen and Desfleurs (2024)

show evidence that GPR is priced in developed markets assets and generate positive return responses during periods of high geopolitical uncertainty. These mixed findings suggest that the effect of GPR on returns may depend on market conditions, investor behaviour, and the type of market considered. Taken together, these gaps highlight the need for a detailed analysis that jointly examine ETF returns, volatility, and liquidity across developed and emerging markets.

Table 3.1: Summary of Studies Reviewed

Authors	Method Employed	Findings
GPR and Returns		
Xaba, Moroke, and Rapoo (2019)	Markov Switching Dynamic Regression (MS-DR)	Return dynamics differ across countries, suggesting asymmetric responses to shocks across regimes.
Ben Ghozzi and Chaibi (2022)	Fixed-effects panel model	Political risk negatively affects stock returns across developed and emerging markets, with developed markets experiencing greater sensitivity than emerging markets.
Agoraki, Kouretas, and Lapodis (2022)	Unbalanced panel regression models	Increases in global GPR consistently lower stock market returns across countries, proving GPR as a priced and unfavourable risk factor, with stronger effects than EPU.
Ali et al., (2023)	Markov Regime-Switching model	The effect of geopolitical threats on asset returns is regime and sector dependent. Certain ETFs and sectors act as hedges during high volatility periods, while others are more exposed to GPR.
Coen and Desfleurs (2024)	Augmented Fama-French asset pricing model	GPR is a priced factor in U.S REIT returns, with geopolitical acts exhibiting stronger effects than geopolitical threats.
GPR and Volatility		
Bouras, Christou, and Gupta (2018)	Panel GARCH	Global GPR increases stock market volatility across emerging markets, while country-specific GPR has a weak effect.
Yang et al., (2021)	GARCH-MIDAS	GPR significantly increase volatility in China's stock markets
Dutta and Dutta (2022)	Markov Regime-Switching model	A rise in GPR increases the probability of being in a low volatility regime and reduces the likelihood of remaining in a high volatility regime for renewable energy ETFs.

Salisu et al., (2022)	GARCH-MIDAS	GPR has a positive and significant effect on the long-run volatility component in emerging markets, suggesting that increases in GPR raises long-term market uncertainty.
Zhang et al., (2023)	Bias-corrected Least Squares Dummy Variable (LSDV)	Increases in GPR significantly raise stock market volatility across 32 countries.
Nilsson (2024)	GARCH-MIDAS	GPR indices can predict stock market volatility in developed markets.
Nasouri (2025)	GARCH-MIDAS	GPR effects vary across market, with emerging markets reacting with higher volatility and increased financial stress, while the U.S equity market exhibits positive returns during periods of high geopolitical threat.
GPR and Liquidity		
Kunjal (2023)	Vector Autoregressive (VAR) model	GPR significantly influences ETF flows in emerging markets. In most countries higher GPR levels results into increased ETF flows, consistent with flight-to-safety behaviour.
Fiorillo et al., (2023)	Panel regression model	GPR significantly reduces stock liquidity at the global level.
Lui et al., (2024)	Difference-in Differences (DID) model	Taiwan's misfired missile event significantly reduced stock liquidity in China's A-share market.

CHAPTER 4: DATA AND METHODOLOGY

4.1 Chapter Overview

The previous chapters reviewed the theoretical foundations and empirical studies of the effect of GPR on ETF market quality, as well as the empirical methodologies employed in each study reviewed, to inform development of appropriate methods for this study. This study employs different methodologies, including the Markov Regime Switching model, GARCH-MIDAS, and NARDL models, to analyse ETFs in emerging and developed markets. The chapter begins with a description of the data and variables used, followed by a discussion of the methodologies applied to address the research questions.

4.2 Data Description

4.2.1 Sample Period

Choosing the right sample period and data frequency is essential because these decisions have a direct impact on the analysis's robustness and reliability, providing valuable insights into long-term trends and patterns (Lopez and Whitehead, 2013). Additionally, using longer study period lowers the possibility of biases or erroneous results from data mining while simultaneously improving validity and accuracy of the results (Kunjai and Peerbhai, 2021). Therefore, this emphasizes the importance of using a longer sample period in this study when examining the effect of GPR on ETF market quality in both developed and emerging markets. Since GPR is not constant and varies in response to geopolitical events, ETF returns, volatility, and liquidity may also respond differently in different markets. If a sample period is longer, the results are more representative and trustworthy, while enabling the analysis to capture several geopolitical events.

To ensure reliability, this study covers the period from each ETFs inception date up to 31 December 2024 for both developed and emerging markets. This sample period captures major events in both economic and political history and likely to influence ETF market quality for developed and emerging markets. These major events include the terrorist attacks of September 2001, the 2008 global financial crisis, the onset Syrian civil war in 2011, the U.S-China trade war in 2018, the COVID 19 pandemic in 2020, the Russian invasion of Ukraine in 2022, and the Israel-Hamas conflict in 2023. Furthermore, previous studies in the literature have incorporated longer sample periods to account for these geopolitical events, while others have included shorter sample periods to account for unique exposures to specific markets or sectors.

4.2.2 Data Frequency

Equally important to sample period is choosing data frequency because it affects how well the analysis captures market dynamics and the effects of geopolitical events on returns, volatility and liquidity. Data frequency is important because it reflects market dynamics where high frequency data such as daily data can identify short-term fluctuations and immediate response to events, whereas low frequency data such as monthly data reduces out noise and highlights long-term trends (Narayan and Sharma, 2015). Therefore, it is essential to find a balance between the two to ensure that there is no noise in the series and that low frequency data does not cause information loss (Salvador, Floros, and Arago, 2014).

The global and country-specific GPR indices employed in this study are sourced from the work of Caldara and Iacoviello (2022). The use of monthly data arises because the indices are created by methodically aggregating newspaper articles and other media sources, a process that needs to be smoothed to reduce noise and guarantee consistent measurement of GPR overtime. Many studies in the literature have made extensive use of the index in this format. As evidenced by studies of Caldara et al. (2022), Iacoviello et al. (2024), and Yilmazkuday (2024). In contrast, the other variables used in this study such as turnover ratio, market liquidity (proxied by Amihud illiquidity measure), ETF age, and Total Net Asset value (TNA), are available at a monthly frequency, allowing more detailed investigation of ETF market behaviour.

Monthly data is employed to study the effect of GPR on ETF returns in developed and emerging markets. Some studies in the literature have employed the same frequency, including the studies by Chen and Kawaguchi (2018) made use of monthly data in asset pricing research through reliance on Fama-French factor portfolios. In addition, the study employs Markov Regime-Switching model, for which monthly data frequency is particularly suitable as it guarantees consistency across and enhances the detection of regime changes. Another study by Mahmoudi and Ghaneei (2022), employed a monthly data frequency to maintain consistency across variables and investigate how structural regimes are influenced by fluctuations in the crude oil market. Similarly, in this study the ETF specific variables are employed in monthly format to ensure robustness and comparability. Moreover, the study will also employ monthly data to examine GPR effect on ETF liquidity. This is because the control variables that will be included are inherently low frequency measures that do not change meaningfully at daily horizons (Narayan and Sharma, 2015)

A combination of daily and monthly data is used to examine the GPR effect on ETF volatility in developed and emerging markets. Daily ETF data is used to capture short-term dynamics of volatility, while GPR indices are available in monthly format. Darrat, Rahman, and Zhong (2003) argue that high frequency data (daily data) should be used to analyse price volatility because financial markets adjust quickly. However, because of the disparity in data frequencies between monthly GPR indices and daily ETF specific data, a model that can accommodate both frequencies is needed. Therefore, GARCH-MIDAS model can be used since there are studies by Salisu and Gupta (2021) and Li and Yoon (2024) that have made use of this model that accommodate mixed frequencies.

4.2.3 Sample Selection

This study centres on the analysis of ETFs that track broad equity market indices in developed and emerging markets. The motivation for choosing ETFs that track broad equity market indices and trade in their own country stems from the fact that these ETFs are a representative indicator of overall market performance and investor behaviour and have sufficient historical data available for the study period. Secondly, these indices serve as an anchor in the ETF market, due to their strong ties to well- established benchmark indices that serves as a guide for risk assessment, investor expectations, and asset allocation decisions (Buetow and Henderson 2012). Particularly in the periods of market stress, where their trading activity, liquidity, and volatility frequently have an impact on more specialised ETFs. Lastly, the indices capture a broad cross-section of businesses from various industries and sectors (Buetow and Henderson 2012). Unlike sector-specific indices, which might be overly impacted by idiosyncratic shocks, broad based market indices offer a more trustworthy framework for analysing the effects of systematic factors such as GPR. Furthermore, in both developed and emerging markets, ETFs that follow broad equity market indices are frequently very liquid and widely traded (Kostovetsky and Warner, 2025).

To examine the effect of GPR on ETF market quality, this study employs 14 ETFs with seven trading in developed markets and seven in emerging markets. By choosing an equal number of ETFs for each market, this is to make sure that it easier to compare these markets and examine how GPR affect market quality of these ETFs. In addition, these ETFs are randomly selected for each group to ensure that results are not influenced by the unique features of any ETFs or

country, and to avoid selection bias¹(Kunjal, 2023). For ease of reference, Table 4.1 provides a list of ETFs used in this study that trade in developed and emerging markets.

Table 4.1: List of ETFs in Developed and Emerging Markets

Emerging Market ETFs				
No.	Country	Name of ETF	Benchmark Index Tracking	Inception Date
1	China	HSBC MSCI China ETF	MSCI China Index	2011/01/31
2	South Africa (S.A)	Satrix 40 ETF	FTSE/JSE Top 40 Index	2000/11/30
3	India	Nippon India ETF Nifty 50 BeES	Nifty 50 Index	2002/02/31
4	South Korea	KODEX 200 ETF	KOSPI 200 Index	2002/10/31
5	Mexico	iShares NAFTRAC	S&P/BMV IPC	2002/04/30
6	Indonesia	Premier ETF LQ-45	LQ45 Index	2009/01/30
7	Tawain	Yuanta/P-shares Taiwan Top 50 ETF	TAIEX 50 Index	2003/06/30
Developed Market ETFs				
1	United Kingdom (U.K)	Vanguard FTSE 100 ETF	FTSE 100 Index	2012/05/31
2	France	Lyxor CAC 40 ETF	CAC 40 Index	2000/12/29
3	United States (U.S)	Schwab U.S Broad Market ETF	Dow Jones U.S Broad Stock Market Index	2000/01/31
4	Japan	Nikko AM Japan Equity ETF	Nikkei 225 Index	2013/11/29
5	Australia	Vanguard Australian Shares Index ETF	S&P/ASX 300 Index	2009/05/29
6	Switzerland	UBS ETF (CH) MSCI Switzerland 20/35 ETF	MSCI Switzerland Index	2013/11/29
7	Germany	Xtrackers DAX UCITS ETF	DAX 30 Index	2007/01/31

Source: Compiled by author

4.2.4 Types of Data and Sources of Data

To meet the objectives of this study, the following secondary data are employed; daily and monthly closing prices of each ETF, daily and monthly shares outstanding of each ETF, monthly Total Net Assets (TNA) for each ETF, monthly turnover ratios for each ETF, monthly global GPR index, monthly country-specific GPR index for each ETF, monthly Amihud illiquidity measure for each ETF, and age of each ETF. Except for GPR indices, all the secondary data employed in this study is sourced from Bloomberg. Data for GPR indices is sourced from the work of Caldara and Iacoviello (2022)²

¹ Selection bias occurs when the sample used in the study is not a true representation of the population that is being examined, because of the observations chosen (Wei and Young, 2024).

² Available at: <https://www.matteoiacoviello.com/gpr.htm>

4.2.5 Computation of Main Variables

To achieve the objectives of this study, which examine how GPR affects ETF returns, volatility and liquidity in developed and emerging markets, the computation of ETF returns and turnover ratios is required. ETF returns are computed at a monthly frequency for Research Objective 1 and 3, and at a daily frequency for Research Objective 2. Market liquidity is proxied using the Amihud illiquidity measure. The following subsections explain in detail the computation of these variables employed in this study.

4.2.5.1 ETF Returns

ETF returns are a key indicator of market exposure since they theoretically reflect the performance of the underlying index. They serve as an important foundation for assessing investment performance and risk-adjusted results, and they reveal market efficiency by demonstrating how closely ETFs track their benchmarks (Arenas and Gil-Lafuent, 2021). In the literature, ETF returns are widely used to study the effects of geopolitical events and macroeconomic factors as they provide a direct measure of how shocks are transmitted to financial markets. Furthermore, previous study by Moodley, Lawrence and Tabash, (2025) investigated the effect macroeconomic variables on ETF returns, which is important for understanding systematic risk. In addition, ETF returns provide a meaningful comparison between developed and emerging markets and capture the differential responses of these markets to similar macroeconomic or geopolitical shocks (Ali et al, 2023). Thereby reflecting differences in market structure, liquidity and investor behaviour.

To maintain methodological consistency with previous research, this study uses ETF returns in line with the studies of Petijisto (2017), Broman and Shum (2018), and Bouras et al, (2019). These studies preferred log returns since they offer two key advantages. These advantages include time additive, which makes it easier to sum returns over multiple periods, secondly, they have statistical characteristics that brings them closer to a normal distribution, which makes econometric analysis easier and increases the validity of hypothesis testing. These characteristics make log returns useful in asset pricing, volatility modelling, and risk management research, where consistency and reliable statistical inference are important (Panna, 2017). Therefore, this study follows the same approach and uses log of ETF returns as defined in Equation (4.1).

$$r_{i,t} = 100 \times (\ln(P_{i,t}) - \ln(P_{i,t-1})) \quad (4.1)$$

In the above Equation (4.1) $r_{i,t}$ represents the return of ETF i at time t and $P_{i,t}$ represents the price of ETF i at time t (closing price on day t or month t), while $P_{i,t-1}$ represents the price of ETF i at the previous period $t - 1$. In addition, the above Equation 4.1 is applied to calculate monthly ETF returns for research objective one using monthly closing prices , while daily ETF returns for research objective two are calculated using closing prices with the same formula.

4.2.5.2 Geopolitical Risk Index

To measure GPR, this paper utilises the GPR Index constructed by Caldara and Iacoviello (2018), which is widely acknowledged for its dependability and resilience in capturing how geopolitical events affect financial and economic variables. The GPR index of Caldara and Iacoviello (2022) is based on the frequency of newspaper articles discussing geopolitical tensions providing a thorough and dynamic assessment of global geopolitical uncertainty. According to Ali et al., (2023), the raw data for the GPR index is based on the monthly count of newspaper articles that mention words related to GPR, which is then used to quantify the intensity of geopolitical uncertainty. Ali et al., (2023) further articulated that the GPR index is important because it focuses solely on GPR and allows for the inclusion of a wider range of geopolitical events compared to earlier measures. For example, the closest index to GPR is the Economic Policy Uncertainty (EPU), which tends to rise in the run-up to presidential elections and disagreements over fiscal policy. In contrast to EPU, GPR is less affected by economic downturns and presidential elections.

The literature has made extensive use of this GPR index including studies of Salisu et al., (2022), Ali et al., (2023) and Kunjal (2023), indicating its widespread acceptance and suitability for examining the consequences of GPRs. It is especially pertinent for researching financial instruments like ETFs and ensures that it captures real-time changes in GPR. However, this study make use of global and country-specific GPR indices as they capture different dimensions of GPR. The global GPR index captures geopolitical tensions that can impact global investor sentiment and capital flows, which can impact ETFs across markets (Salisu et al., 2022). While country-specific GPR index consider GPRs that are specific to a country and have an immediate effect on ETFs that trade there (Caldara and Iacoviello, 2022). By using both indices, it is possible to gain a more thorough understanding of how domestic and global shocks affect the quality of ETF market in developed and emerging markets. In

conclusion, this study adheres to previous studies by using monthly frequency of the global and country-specific GPR indices, since this frequency is suitable for capturing the changes in GPR overtime and is consistent with data availability.

4.2.5.3 Turnover Ratio

There are several ways in which liquidity can be measured, where each measure captures different aspects of trading activity and costs. The first class of measures involves measuring trading costs directly, however quoted prices are not always available across markets (Lesmond, 2005). A second class of measures is created using firm-level data to overcome this constraint. A third class uses price behaviour to indirectly infer trading costs, with the benefit that only price data and no trading volume is required. In addition, Lesmond et al., (1999) proposed a different indirect approach that relies on the occurrence of zero returns. Considering the different methods of liquidity measures (Lesmond, 2005).

In this study, turnover ratio is included as an ETF specific control variable for Research Objective 1 and 2, due to its widespread use as a proxy for trading activity and liquidity indicating how frequently ETFs are traded in relation to their size. Its inclusion helps in controlling for changes in market quality that could affect how GPR affect ETF returns and volatility. Previous studies such as Clifford, Fulkerson, and Jordan, (2014) have also included the turnover ratio as a control variable when examining factors that drives ETF flows. However, for Research Objective 3, turnover ratio is not included as a control variable. Since the focus is solely on ETF liquidity and it is another measure of liquidity. In this case, Amihud illiquidity measure is employed since it better analyses liquidity patterns by capturing price impact effects as opposed to trading frequency (Tucker, 2019). Thus, turnover ratio is used more where it provides valuable control for market activity, but when liquidity becomes a primary variable of interest, it is replaced with a more accurate liquidity measure (Clifford, Fulkerson, and Jordan, 2014).

4.2.5.4 Amihud Illiquidity Measure

Following its proven application in capturing the characteristics of liquidity by considering the price impact of trades, this study uses Amihud's (2002) illiquidity measure as a proxy for liquidity, to examine the effect of GPR on ETF liquidity in developed and emerging markets. The Amihud's (2002) illiquidity measure shows the sensitivity of ETF prices to trading

volume. In financial literature, this measure is associated with market liquidity, which refers to the ease and speed with which assets such as ETFs, stocks, or bonds can be bought or sold on the market without significantly changing its price (Coën and de La Bruslerie, 2019). In addition, Amihud's illiquidity ratio is a direct indicator of market liquidity and is suitable for analysing GPR effect on ETF liquidity (Coën and de La Bruslerie, 2019). A lower Amihud's illiquidity ratio denotes lower transaction costs, as stated by Bedowska-Sojka (2018), highlighting the importance of this metric in evaluating liquidity dynamics, whereas a high Amihud's illiquidity ratio indicate that even a small trading volume can lead to large price movements, reflecting low market liquidity. This indicates that the asset is illiquid, which implies that it is difficult to trade without significantly affecting its price (Bedowska-Sojka, 2018). Moreover, Fong, Holden, and Trzcinka (2017) found that Amihud's measure is the best monthly cost-per dollar volume proxy for liquidity. In addition, this measure establishes the price impact per unit of trading volume. The Amihud's illiquidity measure is defined in Equation (4.2) as:

$$Amihud_{i,j} = \frac{|r_{i,j}|}{Volume_{i,t}} \quad (4.2)$$

Where Amihud's illiquidity measure for the i_{th} ETF on day j is indicated by $Amihud_{i,j}$, $r_{i,j}$ is the absolute return of ETF i on month t , and $Volume_{i,t}$ is the trading volume of ETF on month t . This measure is available at a daily level. However, to ensure consistency with other variables that are used to achieve Research Objective 3. The Amihud's illiquidity ratio is computed for each ETF by aggregating or averaging the daily Amihud's illiquidity ratio over positive trading volume days only, in line with by studies of Brennan, Huh, and Subrahmanyam, (2013) and Kunjal (2022) which used this measure as a dependent variable.

4.2.5.5 Total Net Assets

Total Net Assets (TNA) are defined as the total market value of all assets held by a fund such as mutual fund or ETF, after subtracting liabilities, and is computed by adding all the securities and cash in the fund's portfolio minus any obligations or debts (Gempesaw, Henry, and Xiao, 2024). Previous studies of Jun, Marethe, and Shawky (2003), Ben-David, Franzoni, and Moussawi (2018), and Da and Shive (2018) have included TNA as a control variable because fund size can affect returns and liquidity. In addition, TNA is not just a measure of size, it offers a perspective of ETF operations and how it is viewed by investors. Larger TNAs typically indicate high investor confidence because they reflect the increased capital invested in the fund, which can lower transaction costs and increase liquidity (Reinganum, 1999).

Moreover, TNA can also have an impact on how funds behave because ETFs with large AuM can more accurately replicate their benchmark indices and withstand market shocks, whereas smaller funds might be more volatile and subject to illiquidity pressures (Gempesaw, Henry, and Xiao, 2024). This study uses the log of TNA because it allows for percentage-based interpretation of ETFs and can reduce the influence of larger values (Ramos, 2012). This is consistent with the studies of Ramos (2012) and Ben-David et al., (2018) who have used the variable in this format.

4.2.5.6 Age of ETF

The age of ETF is a measure of how long an ETF has been trading since it was first introduced in the market (Webster, 2002). ETF age is considered as a useful control variable for liquidity studies, because it captures characteristics that evolve over time, such as investor familiarity, an investor base, consistent creation or redemption activity by Authorised Participants (APs), and the gradual build-up of secondary market trading. All these characteristics tend to improve liquidity and stabilise trading dynamics (Tucker, 2019). Young ETFs may display illiquidity, and weaker AP activity, making them more vulnerable to shocks such as elevated GPR, whereas older ETFs typically show more consistent liquidity including higher turnover ratios (Ali et al., 2023). Therefore, this study includes the age of ETF as explanatory variable because it is easy to determine whether observed liquidity responses to geopolitical shocks are a reflection of market stress (Clifford, Fulkerson, and Jordan, 2014). Additionally, a study by Clifford, Fulkerson, and Jordan, (2014) included the age of ETF as a control variable when looking at liquidity. In this study, the age of ETF is logged to ensure consistency with studies by Ben-David et al., (2018) who used this variable logged to show the idea that the effect of age on liquidity diminishes as ETFs get older.

4.2.6 Preliminary Data Analysis

Prior to the estimation of empirical models, preliminary data analysis is conducted to ensure suitability and reliability of the data. This involves checking for stationarity using unit root tests, examining descriptive statistics, and conducting correlation analysis.

4.2.6.1 Unit Root Tests

In this study, before estimating the empirical models, it is important to examine the time series of the variables by conducting unit root tests, to determine whether the data employed is stationary or non-stationary. Stationarity is defined as the characteristic of a stochastic process where the statistical properties such as mean, variance, and autocovariance do not change overtime. Whereas non-stationarity is the opposite of stationarity and the statistical properties change overtime (Ryan, Haslbeck, and Waldorp, 2025). The commonly used methods to test for stationarity in time series analysis includes Augmented Dicker-Fuller (ADF) test, ADF test with unit root break point, Phillips-Perron (PP) test, and Kwiatkowski Phillips Schmidt Shin (KPSS) test. These unit root tests are discussed in the following subsections:

i. Augmented Dicker-Fuller (ADF) test

Augmented Dicker-Fuller test developed by Dickey and Fuller (1979) states that, ADF is only appropriate if error term ε_t is a white noise. However, if error term is autocorrelated, this issue can be addressed by including p lagged term of dependent variable in the regression. This lagged term reduces the problem of autocorrelation. Therefore, the ADF equation is defined in Equation (4.3) as follows:

$$\Delta Y_t = \psi Y_{t-1} + \sum_{i=1}^p \gamma_i \Delta Y_{t-1} + \varepsilon_t \quad (4.3)$$

Where ΔY_t denotes first difference of series, ψ denotes unit root, γ is the time trend that is included, when necessary, ε_t is the white noise disturbance, and p denotes the number of lags. The information criteria used to determine the ideal lag of dependent variable (Vrieze, 2012), includes Akaike Information Criterion (AIC) developed by Akaike (1973), it helps in choosing the best statistical model from a set of models by balancing fit and complexity. In addition, a model with better fit receives a lower score (Akaike, 1998). Schwarz's Bayesian Information Criterion (SBIC) introduced by Schwaz (1978) is similar to AIC and penalises model complexity while choosing the best statistical model. However, it penalises additional parameters as sample size increases (Drton and Plummer, 2017). Lastly, Hanna and Quinn Information Criterion (HQIC) developed by Hannan and Quinn (1979), is used for model selection, balancing goodness of fit and model complexity. In addition, it employs a different penalty term that grows more slowly than SBIC (Beretvas and Murphy, 2013). The equations for these information criteria are defined as follows:

$$AIC = 2K - 2Ln (L) \quad (4.4)$$

$$SBIC = Ln (n)k - 2Ln (L) \quad (4.5)$$

$$HQIC = -2k + 2kln (Ln (L)) \quad (4.6)$$

In the above Equations (4.4, 4.5, and 4.6), n represents the number of data points, K denotes the number of free parameters to be estimated, and L represents the maximised value of the likelihood function of the model. According to Vrieze (2012) AIC is more suitable for small samples, since it commonly selects longer lag orders, while SBIC is more appropriate for large samples and usually favours shorter lag orders. Lastly, HQIC lies in between AIC and SBIC criterions. Using the ADF test, the following hypothesis test is established:

$$H_0: \text{The series has a unit root}$$

$$H_1: \text{The series is stationary}$$

If the test statistic (t-stat) is less than the critical value (crit-value), the null hypothesis is rejected in favour of the alternative hypothesis that the series is stationary, at the specified significance level. However, if the t-stat is above crit-value, the null hypothesis of a unit root cannot be rejected, implying that the series is non-stationary (Mushtaq, 2011). Lastly, all the variables employed in this study are tested for stationarity using the ADF test as they change overtime and stochastic.

ii. Augmented Dickey Fuller (ADF) with Unit Root Break Test

According to Perron (1990), traditional ADF tests assumes that the underlying data series is stable over time and fail to take into consideration structural breaks and sudden changes in mean or trend that may arise due to policy changes and geopolitical shocks. To overcome this constraint, Zivot and Andrews (2002) developed a sequential test that used a completed sample and a distinct dummy variable for each potential break, treating structural break as an endogenous occurrence. In simple terms, Zivot and Andrews (2002) choose the break date that produces the minimal t-stat by running the ADF unit root test for each potential observation (Chipunza et al., 2025). The null and alternative hypothesis for the ADF test with unit root break test are as follows:

$$H_0: \text{The series has a unit root}$$

$$H_1: \text{The series is stationary}$$

If the t-stat is less than the crit-value, the null hypothesis of a unit root is rejected, indicating that the series is stationary with a structural break. Conversely, if the t-stat is above the crit-value, the null hypothesis cannot be rejected, implying that the series has a unit root even after accounting for the structural break. Given that the sample period employed in this study covers period from each ETFs inception date to 2024, a period that consists of many major economic and geopolitical events, which may have led to structural changes in the data series observed, and these structural breaks can bias the ADF causing misleading conclusions about the stationarity of the variables. Therefore, the study employs ADF test with unit root break point to ensure that any differences in the results between the ADF test and the ADF test with break point test shows actual data as opposed to disruptions brought on by unaccounted structural

iii. Phillips Perron Test

The Phillips Perron (PP) Test is another method used to test for stationarity of series. This test was developed by Phillips and Perron (1988). The advantage of PP test is that it is non-parametric, as no generating model for time series needs to be specified. This is different from ADF, which is based on autoregressive specification, at least as an approximation to underlying model (Schwert, 1989). In addition, compared to ADF test which uses additional lags of first differenced variable, PP test makes use of Newey-West (1987) standards errors to account for serial autocorrelation. Moreover, studies by Schwert (1989) put forward that the PP test can experience significant size distortions, even in samples that are moderately large (Leybourne and Newbold, 1999). The equation for PP test is defined as follows:

$$\Delta\gamma_t = \alpha + \beta t + \gamma_{t-1} + \varepsilon_t \quad (4.7)$$

Where γ_t represents the time series tested, α represents the intercept, β represents trade term that is included, when necessary, γ_{t-1} denotes the lagged level of the series, and ε_t represents the error term. The PP test accounts for autocorrelation and heteroscedasticity in the residuals by adjusting the test statistic (t-stat), which changes the ADF. Eviews (2019) presents the PP test (Z_α) statistic base on the equation written below:

$$Z_\alpha = t_\alpha \left(\frac{\gamma_0}{f_0} \right)^{\frac{1}{2}} - \frac{T(f_0 - \gamma_0)(s\epsilon(\hat{\alpha}))}{2f_0^{\frac{1}{2}}s} \quad (4.8)$$

In the above Equation (4.8), t_α represents the t-ratio of α , T represents the sample size, $s\epsilon(\hat{\alpha})$ represents the coefficient standard error, $\hat{\alpha}$ represents the estimate, f_0 represents an estimate of the residual spectrum computed at frequency zero, γ_0 represents the estimate of error

variance, and s represents the standard error of the test regression (Del Barrio Castro, Rodrigues, and Taylor, 2015). In addition, the probability values for PP t-stat are provided by Eviews, and PP test adjust the t-stat to take heteroscedasticity and autocorrelation in residuals into account, thereby changing the ADF. Therefore, the PP t-stat is defined as follows:

$$PP\ t - stat = \frac{\hat{y}}{SE(\hat{y})} \quad (4.9)$$

Where $\hat{y}$ denotes the estimated coefficient form regression and $SE(\hat{y})$ denotes the standard error of the coefficient adjusted for heteroscedasticity and autocorrelation using the non-parametric method (Del Barrio Castro, Rodrigues, and Taylor, 2015). The hypothesis for the tests are as follows:

H_0 : *The series has a unit root (non – stationary)*

H_1 : *The series is stationary*

The null hypothesis of time series is rejected when the p-value is less than the specified level of significance in favour of the alternative hypothesis that the series is stationary. Conversely, the null hypothesis is not rejected when the p-value is above the specified level of significance. However, if the time series is found to be non-stationary, the natural log transformation is then used to reduce the correlation amongst the trend and the volatility of the trend (Beard et al. 2019).

iv. Kwiatkowski Phillips Schmidt Shin (KPSS) test

The Kwiatkowski Phillips Schmidt Shin (KPSS) Test was introduced by Shin and Schmidt (1992). It was created to supplement unit root tests because the ADF and PP tests mentioned above have low power for long-run trend processes and near unit root processes (Kagalwala, 2022). In addition, the ADF and PP test have non-stationarity as their null hypothesis whereas, the KPSS test flips this, using stationarity as the null hypothesis and non-stationarity as the alternative hypothesis. The equation for the KPSS test is expressed as follows:

$$x_t = r_t + \beta_t + \varepsilon_t \quad (4.10)$$

In the above Equation (4.10), the KPSS test is defined by 3 variables, where r_t denotes the random walk, β_t denotes deterministic trend and ε_t denotes the stationary error term. The hypotheses for KPSS test are expressed as follows:

H_0 : The series is stationary

H_1 : The series is non – stationary

The null hypothesis that the series is stationary is rejected when the LM-stat (Lagrange Multiplier) is greater than the crit-value at the specified significance level in favour of the alternative hypothesis that the series is non-stationary. The KPSS test is designed to be used in conjunction with unit root tests. However, when the results of the KPSS test conflict with those of the unit root tests, the KPSS test is preferred over the ADF and PP tests (Sjösten, 2022). This preference is caused by the fact that the ADF and PP tests look for the presence of unit root, whereas the KPSS tests for stationarity. In addition, the null hypothesis can only be rejected or confirmed but cannot be proven (Kagalwala, 2022).

4.2.6.2 Descriptive Statistics

The descriptive statistics analysed in this study includes the following:

(i) Mean

According to De Carvalho (2016), the mean represents the average value of the data and provides a central point for comparison. It is computed by summing up all the observations and then dividing by the number of observations. The mean equation is defined as follows:

$$\bar{x} = \frac{\sum_{i=1}^n x_i}{n} \quad (4.11)$$

In the above equation, x_i represents individual observation and n represents total number of observations (Martinez and Batholomew, 2017).

(ii) Standard Deviation

Standard Deviation (SD) is a measure of how spread out the values in a data set are around the mean (Lee and Lee, 2015). A low standard deviation indicates that the data points are tightly clustered around the mean, suggesting consistency in the variable being measured. Whereas high standard deviation indicates greater variability because the values are widely dispersed from the mean (Martinez and Batholomew, 2017). Standard deviation is calculated as follows:

$$SD = \sqrt{\frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n-1}} \quad (4.12)$$

In the above equation, x_i represents a random observation in the series, $\bar{x}$ represents mean value of series and n represents the total number of observations in the series.

(iii) Skewness

Skewness measures the symmetry of data distribution whether it is positive or negative (Demir, 2022). Specifically, skewness indicates which side a has a longer distribution. Where, positive skewness indicates a longer right tail and negative skewness indicates a longer left tail. Normally distributed series has a skewness of zero (Blanca, Arnau, Lopez-Montiel, and Bendayan, 2013). The value of skewness is determined using the following equation (4.13):

$$\text{Skewness } (S) = \frac{1}{N} \sum_{i=1}^N \left(\frac{x_i - \bar{X}}{\hat{\sigma}} \right)^3 \quad (4.13)$$

In the above equation, x_i , $\bar{X}$, and n follows the same explanation as in the above Equation (4.13). $\hat{\sigma}$ measures the samples standard deviation calculated using biased estimate of variance and is calculated as follows:

$$\hat{\sigma} = \sigma \sqrt{\frac{(N-1)}{N}} \quad (4.14)$$

Where standard deviation is explained in Equation (4.12).

(iv) Kurtosis

Kurtosis measures how flat or peaked the data distribution is compared to a normal distribution, where a higher value represents a more peaked distribution, whereas a lower value represents a flatter distribution (Demir, 2022). The kurtosis value is calculated as follows:

$$\text{Kurtosis } (K) = \frac{1}{N} \sum_{i=1}^N \left(\frac{x_i - \bar{X}}{\hat{\sigma}} \right)^4 \quad (4.15)$$

In the above equation X , N , $\bar{X}$, are previously explained in Equation (4.15). Since the kurtosis value of a normal distribution is 3, a series distribution is said to be peaked (flat) if the kurtosis value is greater (less) than 3 (Demir, 2022).

(v) Jarque-Bera

Jarque-Bera also known as (JB) examines whether the data follows a normal distribution based on the skewness and kurtosis (Jarque and Bera, 1980). In addition, the JB t-stat depends on the

sample's calculated skewness (S) and kurtosis (K) measures, and the theoretical values of S and K under normality are 0 and 3 respectively (Thadewald and Büning,2007). The t-stat JB of Jarque-Bera is computed by using the following equation:

$$\text{JB test statistic} = \frac{\eta}{6} \left(S^2 + \frac{(K-3)^2}{4} \right) \quad (4.16)$$

In the above equation, η denotes how many coefficients were used to generate a series, while S and K represent the series skewness and kurtosis values. The null and alternative hypothesis are expressed as follows:

$$\begin{aligned} H_0: & \text{Series is normally distributed} \\ H_1: & \text{Series is not normally distributed} \end{aligned}$$

JB is asymptotically chi-squared distributed with two degrees of freedom, since JB is simply the sum of two asymptotically independent standardized normal (Thadewald and Büning, 2007). In addition, the P-value associated with JB t-stat can be used to determine whether the null hypothesis is rejected or not. The null hypothesis is rejected when p-value is less than the specified level of significance implying that series is not normally distributed. Whereas, null hypothesis cannot be rejected when p-value is above the specified level of significance, indicating that series is normally distributed.

4.2.6.3 Correlation Analysis

Correlation analysis is a statistical technique employed to assess the relationship between two variables (Franzese and Iuliano, 2018). When evaluating correlation, certain assumptions must be made, the relationship is linear in that a unit increase or decrease in one variable is associated with a constant proportional change in the other (Ali, Bhaskar, and Sudheesh, 2019). The Pearson correlation coefficient can be applied, and it is computed as follows:

$$\rho = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{[\sum_{i=1}^n (X_i - \bar{X})^2 \sum_{i=1}^n (Y_i - \bar{Y})^2]^{1/2}} \quad (4.17)$$

In the above equation ρ denotes Pearson correlation coefficient, $\bar{X}$ is the mean of observations X , X_i is the i th observation of variable X and Y_i is the i th observation of the variable Y , $\bar{Y}$ is the

mean observation of the variable Y . Moreover, correlation analysis can either be positive or negative, and the Pearson correlation coefficient that lies within the range of -1 and $+1$. Where a positive correlation amongst variables means that the variables move in the same direction, and when one variable increase or decreases, the other variable will also increase or decrease. Whereas negative correlation analysis amongst variables means that the variables move in opposite directions, and when one variable increases, the other variable decreases, vice versa. However, if there is no relationship between the variables, the correlation coefficient is equivalent to zero (Escudero-Gomez, Garcia-Gonzalez, and Martinez-Navaro, 2023).

According to Stapor (2020) high correlation between explanatory variables leads to multicollinearity, a situation in which explanatory variables provide overlapping information about the dependent variable. As a result, it may be difficult to figure out the specific impact of each variable, often leading to unstable coefficients estimates. Conversely, a low correlation between explanatory variables is preferable, as it suggests that each variable makes a unique contribution to the model and supports more reliable empirical analysis.

4.3 Methodology Employed to Examine GPR Effect on ETF Returns, Volatility, and Liquidity

To answer the research objectives of this study, the Markov Regime-Switching model, the GARCH-MIDAS model, and the NARDL models are employed. The following subsections outline the models employed to achieve the objectives of the study.

4.3.1 Methodology for Research Objective 1- Markov Regime-Switching Model

To achieve the first objective, the study employs the Markov Regime-Switching model proposed by Hamilton (1989). This model is renowned for capturing intricate dynamic patterns by permitting regime transitions and incorporating multiple structures corresponding to distinct regimes, aligning with the behaviour of time series data (Afreem, 2021). Consequently, Markov Regime-Switching models have gained popularity in modelling time-varying dynamics of financial market returns (Ahmed and Sarkodie, 2021). Unlike traditional linear models, which assume constant and a single stable data generating. Therefore, when analysing financial time series that exhibit Regime-Switching behaviour especially during times of economic or geopolitical stress, traditional linear models become less effective (Chipunza, Muguto,

Muguto, and Muzindutsi, 2025). Markov Regime-Switching model is useful for capturing non-linear dynamics in financial and economic time series, because it permits parameters to vary between various regimes, such as bull and bear. In addition, it offers transition probabilities that show the possibility of shifting between regimes, providing information about how long market conditions will last (Guidolin, 2011). In line with these advantages, previous studies of Xaba, Moroke, and Rapoo (2019), Arenas and Gil-Lafuente (2021), and Chipunza, Muguto, Muguto, and Muzindutsi (2025) have employed this model in the literature to examine time-varying effects of returns.

To begin, the simplest case of a model that incorporates switching dynamics can be expressed as:

$$y_t = \mu_{S_t} + \epsilon_t \quad (4.18)$$

In the above Equation (4.18), μ is the intercept, $S_t = 1..k$, ϵ_t follows a normal distribution with zero variance and mean given by $\sigma_{S_t}^2$. Moreover, the intercept changes according to the state of an indicator variable S_t , this implies that there are k states, there will be k values of σ^2 and μ (Perlin, 2015). According to Hamilton (1993), Markov Regime-Switching model assumes that the development of y_t can be explained by regimes, where a two state Markov Regime-Switching model can be expressed as follows:

Regime 1:

$$y_t = \mu_{S_t} + \epsilon_t \quad (4.19)$$

Where $\epsilon_t \sim (0, \sigma_1^2)$

Regime 2:

$$y_t = \mu_{S_t} + \epsilon_t \quad (4.20)$$

Where $\epsilon_t \sim (0, \sigma_2^2)$

The above Equation (4.19) and (4.20) assumes that Equation (4.18) has two states ($k = 2$). In addition, Equation (4.19) and (4.20) indicates that the dependent variable y_t follows two distinct processes. When the state at time t is 1 (2), the expected value of y_t is μ_1 (μ_2) and the variance is σ_1^2 (σ_2^2) (Perlin, 2015).

To determine whether the determinants of returns differ in bull and bear market, the analysis assumes that the regime-generating processes follow a Markov chain with finite number of

regimes S_t . In the two-regime state, if $S_t = 1$ the process is in regime one and if $S_t = 2$ the process is in regime 2 (Chipunza et al, 2025). Furthermore, it is assumed that S_t cannot be observed directly and can only be inferred from the observed behaviour of y_t , while the transition between regimes is stochastic, meaning that regime changes occur unpredictably (Tan, 2013). In addition, the transition probability matrix is also used in the model to capture the likelihood of a switch between regimes. In the two-state regime p_{11} and p_{22} represent the probabilities of remaining in regime one and regime two, respectively. These parameters govern the persistence of each regime and control the transition probabilities between two regimes (Tan, 2013). Transition matrix, P , is assumed to be constant, as it controls for the probability of a switch from one regime to regime two (Xaba, Moroke, and Rapoo, 2019). The transition matrix P can be expressed as follows:

$$P = \begin{pmatrix} \Pr(s_t = 1|s_{t-1} = 1) = p_{11}, \Pr(s_t = 1|s_{t-1} = 2) = p_{21} \\ \Pr(s_t = 2|s_{t-1} = 1) = p_{12}, \Pr(s_t = 2|s_{t-1} = 2) = p_{22} \end{pmatrix} = \begin{pmatrix} 1 - p_{12}, p_{21} \\ p_{12}, 1 - p_{21} \end{pmatrix}$$

In the above transition matrix P , p_{12} represents the probability that the process switches from regime one to regime two in the next period, while p_{21} represents the probability that the process switches from regime two to regime one in the next period (Baharami, Shamsuddin, and Uylangco, 2019). A regime is considered persistence if transition probability is greater than 50% (Baharami, Shamsuddin, and Uylangco, 2019). The expected duration is calculated using transition probabilities of staying in a regime. In addition, the expected duration of staying in the bull and bear market is calculated as follows:

$$E[D_i] = \frac{1}{1-p_{ii}} \quad (4.21)$$

In the above Equation (4.21), $E[D_i]$ is the expected duration of staying in bull or bear market, p_{ii} represents the transition probability of remaining in state i .

The Markov regime-switching models are estimated as follows:

$$R_t^{ETFR}|s_t = a_{s_t} + \beta_{1,s_t}ETFR_{t-1} + \beta_{2,s_t}GGPR_t + \beta_{3,s_t}Turnover\ Ratio_t + \beta_{4,s_t}TNA_t + \varepsilon_{s_t} \quad (4.22)$$

$$R_t^{ETFR}|s_t = a_{s_t} + \beta_{1,s_t}ETFR_{t-1} + \beta_{2,s_t}CGPR_t + \beta_{3,s_t}Turnover\ Ratio_t + \beta_{4,s_t}TNA_t + \varepsilon_{s_t} \quad (4.23)$$

Where: $\varepsilon_{s_t} \sim iid\ N(0,1)$

To achieve the objectives of this study, the effect of global GPR and country-specific GPR on returns is analysed using two separate models shown in the above Equations (4.22) and (4.23). The monthly logarithm of ETF returns is the dependent variable and is expressed as ($ETFR$). Chen and Diaz (2015) found that autocorrelation in ETF returns is addressed by including the lagged variable $ETFR_{t-1}$. The turnover ratio and TNA are represented by the variables *Turnover Ratio*, and *TNA*. The turnover ratio measure liquidity, indicating how well ETFs withstand disruptions which can help stabilise returns during periods of volatility, while TNA capture the ETF's size as large funds that tracks broad equity market indices may be more stable during geopolitical shocks (Clifford, Fulkerson, and Jordan, 2014). Additionally, s_t represents a latent state-dependent variable ε_{s_t} represents a state-dependent error term, and β_{i,s_t} captures the state-dependent effects of the independent control variables such as *Turnover Ratio*, and *TNA*.

i. **Likelihood Ratio Test**

The Likelihood Ratio (LR) test is a statistical tool for comparing the fit of two competing models, typically a simpler model (restricted) versus a more complex (unrestricted model) model (Coelho, 2025). In essence, it indicates the degree to which the data is more likely under one model than the other. The LR ratio is defined as follows:

$$LR = -2 \ln \left(\frac{L_0}{L_1} \right) = 2[\ln L_1 - \ln L_0] \quad (4.24)$$

In the above Equation (4.24), L_0 represents the maximum likelihood of the restricted model, while L_1 represents the maximum likelihood of the unrestricted model. $\ln L_1$ and $\ln L_0$ represents the natural logarithms of the likelihoods. A higher value of the LR indicates that the unrestricted model fit data significantly better than the restricted model, whereas a lower value of the LR suggests that the restricted model fits data significantly better than the unrestricted model (Bickel, 2025). Additionally, the LR test is assumed to follow a chi-square distribution with degrees of freedom equivalent to the difference in the number of parameters between the two models. Therefore, in Markov Regime-Switching models, the LR test is employed to compare the regime switching specification against a single-regime alternative.

4.3.2 Methodology for Research Objective 2: GARCH-MIDAS Model

Previous studies by Xu and Yin (2017) and Ali et al. (2023) have used Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework to examine how GPR impacts volatility of stock market. However, non-linear techniques such as GARCH-type models can be used to determine ETF price volatilities effectively (Kantar, 2021). This is because GARCH-type models are useful for analysing financial price volatilities as they capture time-varying variance and volatility clustering, which its characteristics are frequently seen in financial returns (Lundbergh and Teräsvirta, 2002). In addition, this model is good for modelling and forecasting market uncertainty because it takes persistence and heteroskedasticity into account, unlike constant variance models (Bauwens, Laurent, and Rombouts, 2006). In this study, the GARCH-MIDAS model is estimated under the assumption of a Gaussian (normal) distribution of the error terms, and Quasi-Maximum Likelihood Estimation (QMLE) with robust standard errors is employed to ensure consistent parameter estimate in the presence of potential non-normality, skewness, and leptokurtosis commonly observed in financial return series. However, Kunjal, Peerbhai, and Muzindutsi (2024) argue that conventional GARCH-type models might not be sufficient to capture the primary factors influencing long-term volatility in financial markets. Therefore, they support the GARCH-MIDAS (Mixed Data Sampling) model, which was put forth by Engle, Ghysels, and Sohn (2013) and has clear benefits over traditional GARCH techniques.

These benefits include its ability to handle data with mixed frequencies meaning that it allows combining low frequency data (daily) and high frequency data (monthly or quarterly) data. Secondly, the model makes a distinction between long-lasting, persistence effects from geopolitical shocks and high frequency market shocks (Engle et al., 2013). In addition, they improve volatility forecasting by incorporating important low-frequency variables, this model typically provides more accurate volatility forecasts compared to traditional GARCH models (Conrad and Kleen, 2020). As a result of the benefits offered by GARCH-MIDAS model previous studies of Salisu et al., (2022), Nilsson (2024), and Nasouri (2025) have used it to examine GPR effects on stock market volatility. The GARCH-MIDAS model primarily captures key volatility characteristics such as volatility clustering, persistence, and the decomposition of volatility into short-run and long-run components. However, while the baseline specification used in this study is symmetric, this choice is maintained due to the focus on overall volatility behaviour rather than directional asymmetry (Engle et al., 2013), and the

inclusion of GPR as an explanatory variable in the long-run component helps capture persistent shocks associated with geopolitical events. However, a limitation of this symmetric model is that it does not capture asymmetric effects of volatility, where negative shocks tend to have a stronger effect on volatility than positive shocks, which is a common feature of financial markets.

To achieve the objective of this study, GARCH-MIDAS model is used to examine how GPR affect price fluctuations, as it can effectively separate total conditional variance into short-term and long-term components. This is particularly suitable because volatility is best captured at high frequencies, such as daily. By combining daily and monthly data, the GARCH-MIDAS models allow for a more accurate analysis of how GPR influence ETF volatility overtime. The use of the GARCH (1,1) specification for the short-run component is justified because of its ability to capture volatility clustering.

Under the GARCH-MIDAS model, the return series as proposed by Engle et al., (2013) comprises of two parts, the conditional variance and the conditional mean which is constant and defined as follows:

$$r_{i,t} = \mu + \sqrt{\tau_{i,t} + h_{i,t}} \times \varepsilon_{i,t} \quad (4.25)$$

With: $\varepsilon_{i,t} | \mathcal{F}_{i,t-1} \sim N(0,1)$

Where in the above Equation (4.25), μ represents the unconditional mean of the ETF return, and $\mathcal{F}_{i,t-1}$ denotes the information setup to day $t - 1$.

The short-term volatility component that is assumed to follow a GARCH (1,1) is defined as follows:

$$h_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i,t-1} - \mu)^2}{\tau_t} + \beta h_{i,t-1} \quad (4.26)$$

In Equation (4.26) above, α represents the ARCH term and β represents the GARCH term and satisfies the following conditions: $\alpha > 0$, $\beta \geq 0$, and $\alpha + \beta = 1$. τ_t captures the long-run component that include exogenous macroeconomic series, and it incorporates the monthly value across all the days within that month (Salisu et al., 2022). Moreover, the long-term volatility component is defined as the smoothed realised volatility of the MIDAS regression:

$$\tau_t = m + \theta \sum_k^K \phi_k(\omega_1, \omega_2) \text{GPR}_{t-k} \quad (4.27)$$

Where GPR_{t-k} represents the explanatory variable of interest, which is GPR proxy (either GGPR or CGPR) included in the model using its natural logarithm form. θ is a predictability measure of GPR and is represented by the slope coefficient. Furthermore, m represents the long-run constant term that serves as a benchmark for analysing how GPR shocks affect long-run volatility, representing the baseline level of ETF volatility when GPR is at its average level. In addition, the weighting scheme $[\phi(\omega_1, \omega_2)]$ follows the Beta weighting scheme because it is more adaptable and frequently utilised to accommodate different lag structures (Wang et al., 2020) and is defined as follows:

$$\phi(\omega_1, \omega_2) = \frac{(k/(k+1))^{\omega_1-1} \times (1-k/(k+1))^{\omega_2-1}}{\sum_j^K (j/(k+1))^{\omega_1-1} \times (1-j/(k+1))^{\omega_2-1}} \quad (4.28)$$

The sum of the weights $\phi(\omega_1, \omega_2) \geq 0, k = 1, \dots, K$ must equal to 1. In this study, beta weighting scheme will be transformed from the two-parameter to one parameter called beta polynomial weighting scheme, similar to the studies by Colacito, Engle, and Ghysels, (2011), Hoque and Zaidi (2020), and Salisu et al., (2022). This means that to obtain the optimal weighting function that decreases consistently, ω_1 is set to one and $\omega_2 = \omega$. Moreover, to determine the lag structure for K , tests will be conducted between 12, 24, and 36 lags, and the optimal lag length will be selected using information criteria such as AIC, SBIC, and HQIC explained in Equations (4.6), (4.7), and (4.8) and log likelihood. Extending from Equation (4.27), the following model is employed to examine how GPR affect ETF price volatility which reflect market uncertainty in both developed and emerging markets. In addition, the models will run separately for each ETF.

Several diagnostic tests are employed to assess the estimated model's dependability. For the GARCH-MIDAS model, to ensure the accuracy of the models estimated, the ARCH-LM test is employed to identify any residual ARCH effects.

(i) Test for ARCH effects

According to Engle (1982), in the presence of Autoregressive Conditional Heteroskedasticity (ARCH) effects the Ordinary Least Squares (OLS) estimator is not consistent. ARCH effects

happen when the variance of the error term changes based on previous squared error terms rather than being constant. Thus, it is important to identify ARCH effects since they imply time-varying volatility, which makes GARCH models more suitable (Scott Hacker, and Hatemi-J*, 2005). Engle (1982) suggested the use of Lagrange Multiplier (LM) test for testing ARCH effects. The t-stat for LM-test is given by (Demos and Sentana 1998):

$$\xi = TR^2 \quad (4.29)$$

Where ξ is the LM t-stat, R^2 is the coefficient of determination from the auxiliary regression, and T represents the number of observations. The null and alternative hypothesis associated with the ARCH LM t-stat are:

$$\begin{aligned} H_0: & \text{No ARCH effects} \\ H_1: & \text{ARCH effects are present} \end{aligned}$$

LM t-stat follows a chi-squared distribution with degrees of freedom equivalent to q (Demos and Sentana 1998). The above null hypothesis of no ARCH effects is rejected when t-stat is greater than the critical chi-squared value, implying that ARCH effects are present and there is conditional heteroskedasticity. Whereas, if t-stat is below the critical chi-squared value, null hypothesis of no ARCH effects cannot be rejected, this implies that there is homoskedasticity.

4.3.3 Methodology for Research Objective 3: ARDL and NARDL Models

Related studies by Husnain, Hashmi, and Ahmed (2021), Kunjal (2022), and Bharat et al., (2024) have employed Auto Regressive Distributed Lag (ARDL) model which allows variables to be integrated of different orders. In addition, they are other related studies by Kunjal (2023) which employed Vector Auto Regressive (VAR) model which requires variables to be stationary at levels. However, this study employs ARDL model proposed by Pesaran, Shin, and Smith (1999), to examine GPR effect on ETF liquidity in developed and emerging markets. An ARDL model is defined as an econometric model used to examine dynamic links between time series variables, it may be used to both short-term and long-term relationships and is useful when working with variables with mixed orders of integration (Menegaki, 2019). In addition, ARDL make estimating short and long-term relationships between variables in the system easier, by capturing the inherent heterogeneity effects in the coefficient estimates brought on by cross-sectional differences (Salisu and Isah, 2017). Other benefits of ARDL model

mentioned by Rana (2018) is that ARDL model employs only a single reduced form equation while conventional cointegration methods estimate the long-run relationships within the context of a system of equations. Secondly, ARDL model is suitable even when sample size is small, while other cointegration techniques are sensitive to the size of the sample. Lastly, the ARDL models accommodates data with mixed orders of integration. Before estimating an ARDL model, variables are tested for unit root, using tests like ADF, PP test, and KPSS test discussed above. The study then employ ARDL bounds testing.

Bounds testing was developed by Pesaran et al., (1999) within the ARDL framework and is used to check the existence of cointegration between variables to identify if a long-run relationship exists between dependent and independent variables. A key advantage of this test is that it can be used to test the presence of cointegration between variables regardless of whether they are integrated of order zero $I(0)$, or order one $I(1)$. In addition, they are not similar to traditional cointegration tests such as Johansen and Engle-Granger cointegration tests because they can be applied when variables are integrated of different orders (Ran, 2018). The null and alternative hypothesis for bounds tests is:

H_0 : *No long – run relationship exists between variables*

H_1 : *Long – run relationship exists*

To determine if a long-run relationship exists based on the bounds test, calculated F-statistic is compared with critical values tabulated by Pesaran et al. (1999). If F-stat is above upper bound critical value, the null hypothesis that there is no long-run relationship between variables is rejected in favour of alternative hypothesis that long-run relationship exist. Contrarily if F-stat is below the lower bound critical value the null hypothesis that long-run relationship does not exist is cannot be rejected. However, if F-stat falls between the upper and lower bound critical values, the results are regarded as inconclusive. In addition, if the order of integration of variables is known and all variables are integrated of order one, the decision is made based on the upper bound. Whereas, if the order of integration is $I(0)$, the decision is made based on the lower bound (Pesaran and Shin, 2001).

If the regression produces a significant F-stat, there is evidence of cointegration (Nkoro and Uko, 2016). The Bound's testing procedure is estimated in the following linear ARDL model:

$$\Delta LM_t = a_o + \sum_{j=1}^n \beta_j \Delta LM_{t-j} + \sum_{i=0}^n \delta_j \Delta GPR_{t-j} + \sum_{i=0}^n \varphi_j \Delta Age_{t-j} + \sum_{i=0}^n \vartheta_j \Delta TNA_{t-j} + \gamma_1 LM_{t-1} + \gamma_2 GPR_{t-1} + \gamma_3 Age_{t-1} + \gamma_4 TNA_{t-1} + \varepsilon_t \quad (4.30)$$

The above equation will run separately for individual ETFs, where ΔLM_t represents the first difference of market liquidity measured using Amihud's illiquidity measure. $\beta_j, \delta_j, \varphi_j, \theta_j, \vartheta_j$ denotes short-run coefficients whereas $\gamma_1 - \gamma_5$ denotes long-run coefficients, ε_t denotes error term and a_o is a constant. In addition, information criteria is used to determine the number of lags to be used in the model.

The second step of linear ARDL model is to estimate the long-run coefficients. In the notation ARDL (x, y, z, l) , alphabets represent the optimal lag lengths for each variable, which are typically selected using information criteria. The regression equation used to estimate long-run coefficients is derived from the Equation (4.30), and is presented below:

$$LM_t = a_o + \gamma_1 LM_{t-1} + \gamma_2 GPR_{t-1} + \gamma_3 Age_{t-1} + \gamma_4 TNA_{t-1} + \varepsilon_t \quad (4.31)$$

The third and last step in the linear ARDL approach is estimating Error Correction Model (ECM) linked to each long-run regression and is used to ascertain the short-run dynamics

The ECM has the following specifications and is obtained from Equation (4.31) and is defined as follows:

$$\Delta LM_t = a_o + \sum_{j=1}^n \beta_j \Delta LM_{t-j} + \sum_{i=0}^n \delta_j \Delta GPR_{t-j} + \sum_{i=0}^n \varphi_j \Delta Age_{t-j} + \sum_{i=0}^n \vartheta_j \Delta TNA_{t-j} + \lambda ECT_{t-1} + \varepsilon_t \quad (4.32)$$

Where ECT_{t-1} measures the deviation from long run equilibrium in period $t - 1$, while λ denotes the speed of adjustment to equilibrium after a deviation (Shuaibu et al. 2022). The following diagnostics tests are performed to check the validity of the model:

(i) Test for Autocorrelation

The Breusch-Godfrey (BG) test is considered one of the most important tests for detecting autocorrelation, as it is particularly helpful in detecting higher-order autocorrelation, and remains valid even when there are stochastic regressors present, such as lagged values of the dependent variable (Rois et al, 2012). In addition, it is also known as the likelihood-based two-

sided LM test. The BG test is developed under the following hypothesis test:

H_0 : *There is no autocorrelation*

H_1 : *There is autocorrelation*

Moreover, the BG t-stat for detecting autocorrelation at lag order h is obtained by estimating an auxiliary regression in which the residuals ε_t are regressed on the original explanatory variables together with lagged residuals $(\varepsilon_{t-1}, \dots, \varepsilon_{t-h})$, where the first h residuals are set to zero (Charemza and Deadman, 1997). The R^2 from this auxiliary regression is then used to calculate the LM t-stat as follows:

$$LM\ t - Stat = (T - h)R^2 \quad (4.33)$$

In the above Equation (4.33), T represents number of observations, h represents the number of lags of the error terms, and R^2 represents the coefficient of determination from auxiliary regression. The LM t-stat is asymptotically distributed as chi-squared with one degrees of freedom (Hyun et al., 2010). The above null hypothesis of no autocorrelation is rejected against alternative hypothesis, when LM t-stat is greater than critical chi-squared value (Brooks, 2002:66).

(ii) Test for Heteroskedasticity

The White (1980) heteroskedasticity test is used to detect the presence of heteroskedasticity in the linear model that could results into unreliable, inefficient but consistent parameter estimates. The White test is based on the multiple correlation coefficient R^2 from the auxiliary regression. In the auxiliary regression, the squared residuals are regressed on the initial independent variables, cross-products and squares. The auxiliary regression will capture dependence if the variance of the errors is related to regressors. For White's test, the t-stat is computed as nR^2 , where n is the size of the sample and R^2 represents coefficient of determination from the auxiliary regression (Berenguer-Rico and Wilms, 2021). The t-stat follows a chi-squared distribution where the number of degrees of freedom are equivalent to the number of explanatory variables excluding constant. The null and alternative hypothesis for White's test are:

H_0 : *Error terms are homoskedastic*

H_1 : *Error terms are heteroskedastic*

If t-stat is above the critical chi-squared value, the null hypothesis that error terms are homoscedastic is rejected against the alternative hypothesis that error terms are heteroskedastic. Whereas, if the t-stat is below the critical chi-squared value, the null hypothesis that error terms are homoscedastic cannot be rejected.

The NARDL model is estimated because it captures both the asymmetric long-run and short-run relationships (Ewodo-Amougou et al. 2023). Specifically, it breaks down changes in GPR into positive and negative components, allowing the model to determine whether increases in GPR have a different impact on ETF liquidity than decreases. Examining asymmetry is particularly important in the context of GPR, as ETFs may respond differently to positive and negative shocks (Ewodo-Amougou et al. 2023). The choice between the ARDL and NARDL model is based on the evidence of asymmetry. The Wald test is then applied to test for the presence of both long-run and short-run asymmetry by examining whether the coefficients of positive and negative GPR changes are statistically equal. Specifically, the null hypothesis for the Wald test is that the effects of positive and negative GPR changes are equal, while the alternative hypothesis is that they differ significantly, indicating the presence of asymmetry. Rejecting the null hypothesis provides evidence of asymmetric effects of GPR on ETFs in both the long-run and short-run. Accordingly, the NARDL model is estimated as follows:

$$\begin{aligned} \Delta LM_t = & a_o + \sum_{j=0}^{n-1} \beta_j \Delta LM_{t-j} + \sum_{j=0}^{n-1} (\delta_j^+ \Delta GPR_{t-j}^+ + \delta_j^- \Delta GPR_{t-j}^-) + \sum_{j=0}^{n-1} (\varphi_j^+ \Delta Age_j^+ + \\ & \varphi_j^- \Delta Age_j^-) + \sum_{j=0}^{n-1} (\vartheta_j^+ \Delta TNA_j^+ + \vartheta_j^- \Delta TNA_j^-) + \gamma_1 LM_{t-1} + \gamma_2^+ GPR_{t-1}^+ + \gamma_3^- GPR_{t-1}^- + \\ & \gamma_4^+ Age_{t-1}^+ + \gamma_5^- Age_{t-1}^- + \gamma_6^+ TNA_{t-1}^+ + \gamma_7^- TNA_{t-1}^- + \varepsilon_t \end{aligned} \quad (4.34)$$

In the equation above, the null hypothesis of no cointegrating relationship means that $\gamma_1 = \gamma_2^+ = \gamma_3^- = \gamma_4^+ = \gamma_5^- = \gamma_6^+ = \gamma_7^- = 0$. If there is a cointegrating relationship, the ECM associated with NARDL is estimated. The equation is defined as follows:

$$\begin{aligned} \Delta LM_t = & a_o + \sum_{j=0}^{n-1} \beta_j \Delta LM_{t-j} + \sum_{j=0}^{n-1} (\delta_j^+ \Delta GPR_{t-j}^+ + \delta_j^- \Delta GPR_{t-j}^-) + \sum_{j=0}^{n-1} (\varphi_j^+ \Delta Age_j^+ + \\ & \varphi_j^- \Delta Age_j^-) + \sum_{j=0}^{n-1} (\vartheta_j^+ \Delta TNA_j^+ + \vartheta_j^- \Delta TNA_j^-) + \lambda ECT_{t-1} + \varepsilon_t \end{aligned} \quad (4.35)$$

Based on the ARDL and NARDL models used for this research objective, Equation (4.31) and (4.34) are used to examine long-run linear and non-linear effects of GPR on ETF liquidity, whereas Equations (4.32) and (4.35) are used to examine the short-run effects. This analysis

will examine the effect of both, focusing on ETFs that track broad equity market indices within individual countries. The models run separately for each ETF, as well as individually for global and country-specific GPR, to capture the unique impact of each risk type on ETF liquidity. The results from both ARDL and NARDL models are compared to assess whether asymmetric effects are present in the short and long-run.

4.4 Chapter Summary

Chapter 4 provided a detailed discussion of the methods employed to examine the GPR effect on ETF market quality in developed and emerging markets. This study is conducted on ETFs that track broad equity market indices and trade in their own country. In addition, the ETFs are randomly selected for each group to ensure that results are not influenced by unique features of any ETFs or country, and to avoid selection bias. Notably, the sample period begins on the inception date for each ETF and ends in December 2024. Before the estimation of the results, preliminary data analysis including unit root tests, descriptive statistics, and correlation analysis to detect potential data issues and ensure that the variables behave as expected. In addition, model diagnostic tests including test for autocorrelation, test for heteroskedasticity, and test for ARCH effects, are conducted to determine the validity, reliability, and suitability of a fitted model for the data. In conclusion, Table 4.2 provides a summary of methods employed in this study.

Table 4.2: Summary of Empirical Models Employed

Research Question	Empirical Model	Motivation for Methodology Employed
How does GPRs affect the returns of ETFs in developed and emerging markets under bullish and bearish market conditions?	Markov Regime-Switching models	This model is employed to capture the time-varying effects of ETF returns and to analyse their behaviour under different market conditions, such as the bull and bear regimes.
How does GPR influence ETF volatility in developed and emerging markets?	GARCH-MIDAS model	This model is used to examine the effect of GPR on ETF volatility by separating short and long-term volatility components, providing a strong framework for modelling volatility with mixed-frequency data.

How does GPR affect the liquidity of ETFs in emerging and developed markets	ARDL and NARDL models	The ARDL/ NARDL models are employed to assess both short-run and long-run relationships between GPR and ETF liquidity, with NARDL specifically capturing potential symmetric effects of positive and negative GPR shocks on ETF liquidity.
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CHAPTER 5: RESULTS AND ANALYSIS

5.1 Chapter Overview

The previous chapter discussed data description, including sample period, data frequency, sample selection, and data used to achieve the objectives of the study, and outlined the preliminary tests conducted. The current chapter attempts to answer the research questions of the study by analysing the results obtained from the methodologies employed and explained in Chapter 4. Before analysing the results, preliminary data analysis is explained to ensure that the data employed is accurate and suitable for this study. This is followed by diagnostic tests to verify the reliability of the results, and subsequently an analysis of the empirical results. Particularly, the results from the Markov Regime-Switching model are discussed to examine the influence of GPR on ETF returns. Thereafter, the results from the GARCH-MIDAS model are discussed to examine the GPR effect on ETF volatility. Lastly, the results from the ARDL model are discussed to examine the effect of GPR on ETF liquidity in developed and emerging markets.

5.2 Preliminary Data Analysis

5.2.1 Stationarity of Variables

Prior to estimating the main models, it is important to examine the time-series properties of the variables used in this study outlined in Section (4.2.5). The stationarity of these variables is assessed using the ADF, PP test, and KPSS test outlined in Section (4.2.6.1). For Research Objective 1, the results of stationarity and unit root tests for developed and emerging markets are presented below in Tables 5.1 and 5.2. The results from the ADF tests for both emerging and developed market ETFs conducted at levels indicated that all the variables including Global GPR, Country-specific GPR, turnover ratio and TNA are stationary at levels. This implies that the null hypothesis that the series has a unit root is rejected in favour of the alternative hypothesis that the series has no unit root at 1% significance level. Moreover, the results for the break point unit root test for both developed and emerging market ETFs presented in Tables 5.1 and 5.2 showed that the ADF break t-stats are more negative than the critical values at the 1% significance level. This implies that the null hypothesis of a unit root is rejected in favour of the alternative hypothesis that the series are stationary after accounting for structural breaks within the sample period.

Table 5.1: Stationarity and Unit Root Test Results for ETFs in Emerging Markets

Emerging Markets					
Country	Variable	ADF Test	ADF Test with Break Point	PP Test	KPSS Test
Global	GPR Index	-5.8841*	-8.1344*	-5.7136*	0.4346
China	Country- Specific GPR	-5.9065*	-7.6199*	-5.7360*	1.0368
	ETF Returns	-13.7855*	-14.4584*	-13.5924*	0.0922
	Turnover Ratio	-3.7171*	-15.8129*	-6.1992*	0.6053
	DTNA	-11.9095*	-15.0139**	-11.9278*	0.0545
South Africa	Country- Specific GPR	-6.1378*	-11.8996*	-11.7513*	0.2035
	ETF Returns	-18.0201*	-18.5751*	-17.9880*	0.1152
	Turnover Ratio	-4.6880*	-8.5987*	-11.0083*	1.0085
	DTNA	-18.6321*	-20.4944*	-18.7830*	0.4413
India	Country- Specific GPR	-11.5918*	-13.1716*	-12.4575*	0.4094
	ETF Returns	-15.5196*	-16.8849*	-15.5197*	0.7780
	Turnover Ratio	-5.3497*	-6.0908*	-5.0831*	0.1884
	DTNA	-14.4982*	-23.7696*	-14.7900*	0.4801
South Korea	Country- Specific GPR	-9.4123*	-10.5691*	-10.3924*	0.5131
	ETF Returns	-16.5210*	-17.1559*	-16.5512*	0.1818
	Turnover Ratio	-4.6259*	-7.6004*	-7.0102*	0.1386
	DTNA	-10.2474*	-16.8636*	-20.3925*	0.1023
Mexico	Country- Specific GPR	-7.8250*	-13.2786*	-13.8269*	0.1373
	ETF Returns	-15.6483*	-16.5877*	-15.7814*	0.3764
	Turnover Ratio	-2.4647*	-5.9907*	-5.5162*	0.5297
	DTNA	-15.9671*	-17.2619*	-15.9893*	0.1249
Indonesia	Country- Specific GPR	-8.3076*	-9.2718*	-8.7467*	0.2842
	ETF Returns	-12.7665*	-14.6749*	-12.8064*	0.4952
	Turnover Ratio	-8.3076*	-23.4029*	-5.0079*	0.8769
	DTNA	-8.0042*	-13.7099*	-10.7262*	0.1652
Taiwan	Country- Specific GPR	-2.4733*	-12.1914*	-3.3302*	0.0519
	ETF Returns	-15.4087*	-16.3306*	-15.5012*	0.1003
	Turnover Ratio	-4.2574*	-12.0690*	-11.0483*	0.6789
	DTNA	-2.3229*	-16.5578*	-16.8861*	0.8346

Notes:

1. * Represents statistical significance at 1%.

In addition to the ADF test and break point unit root test results, the PP unit root test is conducted on all variables for both ETFs from developed and emerging markets. As shown in Tables 5.1 and 5.2, the null hypothesis that the series has a unit root is rejected in favour of the alternative hypothesis that the series is stationary at the 1% significance level. Moreover, the results of KPSS test using the LM statistic for emerging and developed markets showed that all the variables had values less than the critical values at 1% significance level, implying that the null hypothesis that the series is stationary cannot be rejected. Overall, after performing the ADF test, the ADF test with a structural break, the PP test, and the KPSS test, the results in Table 5.1 and 5.2 indicate that the variables employed in Research Objective 1 are stationary at levels. Consequently, no further differencing is required before continuing with the empirical analysis.

Table 1.2: Stationarity and Unit Root Test Results for ETFs in Developed Markets

Developed Markets					
Country	Variable	ADF Test	ADF Test with Break Point	PP Test	KPSS Test
Switzerland	Country- Specific GPR	-8.7383*	-9.5301*	-8.7754*	0.3154
	ETF Returns	-13.0738*	-13.5205*	-13.3273*	0.0417
	Turnover Ratio	-2.4052*	-14.3342*	-7.7506*	0.3152
	DTNA	-11.4458*	-12.7740*	-11.4849*	0.0314
Australia	Country- Specific GPR	-2.5005*	-12.1942*	-8.8136*	0.0560
	ETF Returns	-14.0862*	-16.3306*	-14.6146*	0.0398
	Turnover Ratio	-3.0061*	-12.0690*	-8.2209*	0.8427
	DTNA	-13.9739*	-16.5578*	-13.9729*	1.9150
Germany	Country- Specific GPR	-5.6691*	-7.5818*	-5.5451*	0.9156
	ETF Returns	-13.9819*	-14.7557*	-13.9623*	-0.0937
	Turnover Ratio	-12.8282*	-11.6294*	-7.8582*	0.9914
	DTNA	-12.6748*	-14.3864*	-12.7391*	0.0640
Japan	Country- Specific GPR	-6.9836*	-10.1313*	-10.7468*	0.2299
	ETF Returns	-15.0767*	-16.4493*	-15.0844*	0.1871
	Turnover Ratio	-4.8932*	-6.4264*	-4.0990*	1.2863
	DTNA	-19.4900*	-20.5495*	-19.5648*	0.5782
	Country- Specific GPR	-8.7992*	-12.1987*	-9.4456*	0.5664
	ETF Returns	-14.0111*	-16.2443*	-14.0629*	0.0803

U.K	Turnover Ratio	-2.9474*	-11.6869*	-8.3356*	0.0425
	DTNA	-11.7667*	-12.5835*	-11.7634*	0.4250
France	Country- Specific GPR	-8.9536*	-11.0400*	-9.1507*	0.4952
	ETF Returns	-15.7186*	-16.6392*	-15.7106*	0.2216
	Turnover Ratio	-3.5985*	-174.35*	-43.6380*	0.8110
	DTNA	-18.8823*	-19.4364*	-18.7712*	0.2974
U.S	Country- Specific GPR	-6.4891*	-7.9457*	-8.7754*	0.1960
	ETF Returns	-16.9838*	-18.1399*	-17.0197*	0.3964
	Turnover Ratio	-2.5795*	-5.0700*	-4.8020*	0.4694
	DTNA	-20.9410*	-22.3867*	-21.1547*	0.7201

Notes:

1.* represents statistical significance at 1%.

Table 5.3: Stationarity and Unit Root Test Results for ETFs in Emerging Markets

Country	Variables	ADF Test	ADF Test with Break Point	PP Test	KPSS Test
China	ETF Returns	-61.0394*	-61.4627*	-61.2068*	0.0780
	LGPR_G	-10.6865*	-16.9676*	-30.2416*	0.1355
	LGPR_C	--11.5761*	-17.1689*	-79.5692*	0.5000
S.A	ETF Returns	-78.8252*	-79.3344*	-79.3547*	0.0930
	LGPR_G	-12.6967*	-23.1540*	-29.5304*	0.1053
	LGPR_C	-19.9913*	-25.0668*	-89.1554*	0.5000
India	ETF Returns	-73.0522*	-74.1913*	-73.0485*	0.0767
	LGPR_G	-12.4677*	-22.7280*	-28.5941*	0.1079
	LGPR_C	-19.6553*	-24.6217**	-87.7535*	0.5000
South Korea	ETF Returns	-75.3783*	-76.5024*	75.4112*	0.2149
	LGPR_G	-11.5000*	-22.2556**	89.1554*	0.5000
	LGPR_C	-10.6865*	-96.9676*	30.2416*	0.1355
Mexico	ETF Returns	-53.7093*	-70.9194*	-70.3959*	0.4414
	LGPR_G	-13.1685*	-21.8643*	-36.3371*	0.2246
	LGPR_C	-12.1154*	-29.3546*	-13.2002*	0.3320
Indonesia	ETF Returns	-45.2378*	-66.2511*	-65.1335*	0.6617
	LGPR_G	-11.6194*	-14.2951*	-14.3350*	0.0941
	LGPR_C	-12.4651*	-19.5814*	-66.9374*	0.5000
Taiwan	ETF Returns	-73.0770*	-73.7980*	-73.1529*	0.1135
	LGPR_G	-11.8262*	-21.0819*	-37.8254*	0.3698
	LGPR_C	-14.7599*	-24.5362*	-39.3303*	0.0520

Table 5.4: Stationarity and Unit Root Test Results for ETFs in Developed Markets

Country	Variables	ADF Test	ADF Test with Break Point	PP Test	KPSS Test
U.K	ETF Returns	-57.4164*	-58.9050*	-57.4605*	0.0435
	LGPR G	-10.4434*	-16.5989*	-28.4550*	0.1336
	LGPR C	-12.8255*	-18.5872*	-39.1219*	0.0486
France	ETF Returns	-79.9853*	-80.4430*	-80.3583*	0.1726
	LGPR G	-12.4459*	-22.6883*	-28.4356*	0.1070
	LGPR C	-14.9101*	-21.2694*	-49.2191*	0.0854
U.S	ETF Returns	-30.0634*	-13.2151*	-25.6488*	0.3758
	LGPR G	-14.1612*	-18.5490*	-17.6717*	0.1426
	LGPR C	-15.1229*	-18.8709*	-30.9118*	0.0939
Japan	ETF Returns	-60.1261*	-83.6320*	-84.5902*	0.4407
	LGPR G	-11.3952*	-22.5338*	-27.2629*	0.1037
	LGPR C	-17.5974*	-17.6058*	-63.5955*	0.1520
Australia	ETF Returns	-66.6994*	-67.5714*	-66.6428*	0.0169
	LGPR G	-16.2873*	-17.2408*	-20.2403*	0.0813
	LGPR C	-14.0138*	-22.2064*	-50.1762*	0.1069
Switzerland	ETF Returns	-52.6790*	-54.2676*	-52.7313*	0.0280
	LGPR G	-14.4108*	-15.1751*	-25.4248*	0.1584
	LGPR C	-14.1603*	-17.3260*	-39.4514*	0.1655
Germany	ETF Returns	-68.5778*	-69.7160*	-68.5880*	0.0517
	LGPR G	-12.4618*	-19.0168*	-33.1550*	0.2421
	LGPR C	-11.9687*	-18.6002*	-25.8903*	0.0457

In Table 5.3 and 5.4 the ADF tests for both emerging and developed market ETFs conducted at levels indicated that, for all the variables including daily ETF returns, monthly global GPR index and monthly country-specific GPR index are stationary at 1% significance levels. The ADF test with unit root break point further supports these results, confirming that variables remain stationary even after accounting for structural breaks within the sample period. Similarly, the PP unit root test indicated that the variables are stationary at 1%. Additionally, the results of KPSS test using the LM statistic revealed that the values are less than the critical values at, implying that the null hypothesis that the series is stationary cannot be rejected. Overall, these results show that variables used for Research Objective 2 are stationary at levels.

Table 5.5 and 5.6 below present the results of the stationarity and unit root tests conducted for the variables used in Research Objective 3. The log of Amihud illiquidity Ratio is found to be stationary for ETFs in both developed and emerging markets predominantly at the 1% significance level. This is confirmed by the ADF test, ADF with breakpoint, PP test, and KPSS test, indicating that no differencing is required for this variable. In contrast, the log of the age of ETF is found to be non-stationary at levels but becomes stationary after first differencing,

indicating that it is integrated of order one. Table 5.5 and 5.6 confirms these results by showing stationarity for this variable only after differencing. Overall, the stationarity and unit root test results suggest that the variables employed in Research Objective 3 are integrated of mixed orders.

Table 5.5: Stationarity and Unit Root Test Results for ETFs in Emerging Markets

Country	Variables	ADF Test	ADF Test with Break Point	PP Test	KPSS Test
China	LM	-14.3224*	-8.4489*	-32.4219*	0.1193
	LAge	-9.8843*	-23.3155*	-19.5420*	0.1391
S.A	LM	-3.5415*	-7.7170*	-7.3527*	0.5698
	LAge	-4.1489*	-6.5062*	-2.1591*	1.7282
India	LM	-9.9662*	-18.2262*	-16.7550*	0.1413
	LAge	-4.6781*	-7.4507*	-2.0678*	1.6553
South Korea	LM	-16.8499*	-4.4928*	-29.1320*	0.1935
	LAge	-3.4814*	-9.7192*	-3.4548*	1.8225
Mexico	LM	-13.1911*	-26.2298*	-37.6126*	0.3405
	LAge	-6.0427*	-(6.8948*	-3.4543*	1.6396
Indonesia	LM	-2.9045*	-6.6287*	-6.8914*	1.0477
	LAge	-3.4674*	11.3399*	-3.4646*	1.5804
Taiwan	LM	-12.3395*	-5.9424*	-54.1365*	0.5000
	LAge	4.9693*	10.5194*	-28.1909*	0.1810

Table 5.6: Stationarity and Unit Root Test for Developed Market ETFs

Country	Variables	ADF Test	ADF Test with Break Point	PP Test	KPSS Test
U.K	LM	-4.8841*	-8.4186*	-5.4196*	0.2218
	Lage	-9.3007*	-12.6171*	-3.3489*	1.2938
France	LM	-12.7095*	-5.5225*	-9.6790*	0.7303
	Lage	-6.0858*	-8.3771*	-3.4530*	1.7190
U.S	LM	-11.6411*	-4.9491*	-7.3561*	0.7390
	Lage	-9.1129*	-9.5821*	-9.2549*	0.6621
Japan	LM	25.5235*	-4.9525*	-36.0511*	0.9086
	Lage	-13.8120*	-15.7800*	-8.5319*	1.6665
Australia	LM	-11.8600*	-8.4596*	-22.8514*	1.0016
	Lage	-6.8743*	-8.1107*	-5.5539*	1.5538
Switzerland	LM	-5.6543*	-11.0300*	-6.0297*	1.5359
	Lage	-3.9260*	-15.3526*	-8.0895*	1.2698
Germany	LM	12.5696*	-18.2262*	-7.3527*	0.1413
	Lage	-5.9623*	-7.4507*	-2.1591*	1.6553

5.2.2 Descriptive Statistics

Similarly, the descriptive statistics results are presented separately for each research objective in this study. However, variables such as monthly GPR indices and TNA are not repeated in the other tables, as these variables are already included in the descriptive statistics for Research Objective 1.

Table 5.7: Descriptive Statistics Results for Emerging Markets ETFs

Country	Variable	Mean	Standard Dev.	Skewness	Kurtosis	Jarque -Berra	Prob. (JB)
China	ETF Returns	0.0019	0.0604	-0.1584	4.5659	17.7591	0.0001
	GPR C	2.9317	0.7337	1.0478	4.4757	45.7076	0.0000
	Turnover Ratio	3.6448	0.7852	6.1860	5.0958	17.0702	0.0000
	TNA	2.7807	4.4644	1.6939	9.1365	46.2699	0.0000
S.A	ETF Returns	0.0078	0.0496	-0.2443	3.9775	14.3832	0.0007
	GPR C	0.0466	0.0367	1.3816	5.2055	15.5131	0.0000
	Turnover Ratio	820.88	0.7158	2.8869	14.9048	21.0803	0.0000
	TNA	29.0307	0.3058	0.3787	7.0741	20.5600	0.0000
India	ETF Returns	0.0114	0.0611	-0.8846	7.7434	29.3684	0.0000
	GPR C	0.2198	0.1026	1.5455	8.5392	46.06	0.0000
	Turnover Ratio	15.8975	16.2124	2.1421	8.2901	53.0988	0.0000
	TNA	0.0789	0.7120	2.1421	14.1378	22.3820	0.0000
South Korea	ETF Returns	3.0094	0.7254	0.8185	3.5450	32.9931	0.0000
	GPR C	0.2448	0.1626	1.4410	5.2388	14.7622	0.0000
	Turnover Ratio	76.4732	33.3516	1.0678	4.2184	67.0091	0.0000
	TNA	1.9910	4.6711	0.0069	7.8798	26.9316	0.0000
Mexico	ETF Returns	0.0072	0.0480	-0.4954	4.3376	31.4074	0.0000
	GPR C	0.1215	0.0690	1.5525	6.4082	11.0352	0.0000
	Turnover Ratio	43.3708	28.7510	0.9596	4.3537	62.5163	0.0000
	TNA	2.4808	3.9309	0.3955	7.9509	28.8924	0.0000
Indonesia	ETF Returns	0.0036	0.0739	-0.5062	8.4784	24.7007	0.0000
	GPR C	0.2042	0.0943	0.8764	3.9390	31.4684	0.0000
	Turnover Ratio	18.4178	35.5686	6.1723	45.1967	15.3830	0.0000
	TNA	14.2476	42.4800	-0.9606	19.0225	20.7246	0.0000
Taiwan	ETF Returns	0.0061	0.0529	-0.4814	4.6096	37.8194	0.0000
	GPR C	2.9685	0.7004	0.9392	4.1126	51.2418	0.0000
	Turnover Ratio	20.7292	10.0226	2.8743	14.2385	17.1300	0.0000
	TNA	1.5709	1.3010	2.4335	18.9714	29.9600	0.0000

Notes:

1. Prob. Refers to probability value

Table 5.8: Descriptive Statistics Results for Developed Markets ETFs

Country	Variable	Mean	Standard Dev.	Skewness	Kurtosis	Jarque -Berra	Prob. (JB)
Switzerland	ETF Returns	0.0048	0.0353	-0.3561	2.8628	2.7603	0.0250
	GPR_C	0.0580	0.0692	3.9462	25.1903	30.7397	0.0000
	Turnover Ratio	37.8623	27.7234	3.2229	21.8953	22.0885	0.0000
	TNA	11.2059	0.7800	0.1984	6.9613	87.8306	0.0000
Australia	ETF Returns	0.0062	0.0529	-0.4814	4.6097	37.88194	0.0000
	GPR_C	0.0745	0.1028	2.8743	14.2385	17.1300	0.0000
	Turnover Ratio	20.7292	0.2522	1.3159	5.0346	11.8951	0.0001
	TNA	1.5709	0.13001	2.4335	18.9714	29.9600	0.0002
Germany	ETF Returns	0.0051	0.0544	-0.6804	4.4990	36.7168	0.0000
	GPR_C	0.3929	0.2611	2.1409	9.8103	57.9728	0.0000
	Turnover Ratio	16.658	0.2118	3.7426	20.2118	31.5579	0.0000
	TNA	21.0161	0.0441	5.7293	8.0428	54.8826	0.0000
Japan	ETF Returns	0.0048	0.0535	-0.0727	5.0302	73.2708	0.0000
	GPR_C	0.2256	0.1445	1.5496	5.3616	17.7760	0.0000
	Turnover Ratio	11.8687	13.9778	2.2196	9.6319	17.4568	0.0000
	TNA	1.8410	0.1711	0.1022	9.8823	55.5067	0.0000
U.K	ETF Returns	0.0025	0.0351	-0.7116	5.4511	50.5469	0.0000
	GPR_C	0.0443	0.0534	3.4440	20.9342	23.2211	0.0000
	Turnover Ratio	15.2919	0.3457	3.0060	15.5301	12.1616	0.0000
	TNA	23.66	0.1008	0.1588	4.2231	10.0470	0.0065
France	ETF Returns	0.0009	0.0517	-0.6341	4.7884	57.5131	0.0000
	GPR_C	0.5563	0.2976	3.0993	20.1849	40.0404	0.0000
	Turnover Ratio	27.0452	0.9223	2.6129	9.8714	89.4296	0.0000
	TNA	10.2731	0.5608	-0.1647	4.3945	24.6390	0.0000
U.S	ETF Returns	0.0049	0.0445	-0.6614	4.0708	36.0814	0.0000
	GPR_C	2.9653	0.1356	2.9794	18.2142	33.2610	0.0000
	Turnover Ratio	32.6177	0.2479	1.8952	6.5257	15.9285	0.0000
	TNA	2.0409	0.3710	-0.0855	6.5716	15.9285	0.0000

Notes:

1. Prob. Refers to probability value

Table 5.7 shows the descriptive statistics for ETFs trading in emerging markets. For ETF returns, the results show that average monthly returns may differ across emerging markets, with India and South Korea having the highest mean returns which could indicate increased capital inflows, whereas China and Indonesia have the lowest mean returns indicating reduced investor confidence during sample period and regulatory restrictions. Specifically, India's ETF have an average return of 0.0114, followed by South Africa with 0.0078 and Mexico with 0.0072. In contrast, China's ETF has the lowest average return of 0.0019 and Indonesia is 0.0036, suggesting lower level of short-term profitability for investors. In terms of volatility measured using the standard deviation, majority of ETFs exhibit moderate risk, ranging from 0.0480 for Mexico to 0.0739 for Indonesia, with Mexico being the least volatile. The high

volatility indicate that it is more vulnerable to currency fluctuations, economic uncertainty, and market shocks. In contrast, the low volatility in Mexico indicates comparatively more stable ETF price movements, which makes it more attractive risk-averse investors looking to gain exposure to emerging markets. While the results of ETFs in developed markets presented in Table 5.8 show that, Australia, Germany, and Japan have the highest average returns of 0.0062, 0.0051, and 0.0048 compared to other ETFs. This means that these ETFs have the strongest performance, suggesting that investors received more returns in a month. In contrast, France has the lowest average return of 0.0009 suggesting that investors received minimal returns per day during the sample period, which could indicate slower economic growth and weaker ETF performance.

The results of global GPR index for ETFs in emerging markets in Table 5.7 show that the average global GPR is low across ETFs, indicating that global risk is stable during the sample period. However, Taiwan and Indonesia show high average values of 0.2001 and 0.061, which may indicate increased sensitivity to trade disruptions and political uncertainty. In addition, this indicate that these ETFs are more sensitive to global geopolitical shocks compared to other ETFs. Similarly, Table 5.8 shows that developed markets exhibit low global GPR values for most countries indicating that developed market ETFs can withstand geopolitical shocks. U.S and Switzerland exhibit high average values of 0.0610 and 0.0127, indicating that these ETFs may be more exposed to global geopolitical shocks. Volatility patterns show significant variation in GPR exposure across markets. ETFs from S.A and India exhibit high standard deviation of 0.8070 and 0.8209, suggesting that GPR is highly unstable. This increased volatility may stem from increased sensitivity to geopolitical events. In contrast, Indonesia and South Korea exhibit significantly lower volatility of 0.0944 and 0.1146, implying more stable GPR. Developed market exhibit similar pattern of differences, with the highest volatility shown by Japan and France of 0.8267 and 0. 8222. This suggests that GPR can fluctuate overtime in developed markets, potentially affecting capital flows and ETF prices.

Similarly, the results of country-specific GPR index in emerging markets showed that India has the highest average of 9.3305, indicating high political uncertainty which could affect ETF pricing. Mexico and South Africa also have an average country-specific GPR values of 1.3906 and 0.9010 possibly indicating recurring political developments. In contrast China, South Korea, and Taiwan have the lowest average values. Volatility patterns show significant differences in the predictability of country-specific GPR, with Taiwan and Indonesia having

the highest standard deviation of 0.9075 and 0.7038, indicating that GPR in these ETFs is more unstable, whereas India, South Korea exhibit more stable country-specific risk. Among developed markets, Japan and U.S have the highest average values while U.K, France, Australia, and Germany show relatively low average values, consistent with more stable political environment. Moreover, the volatility in developed markets for U.K and U.S show more stable risk, suggesting that GPR in these ETFs tends to change more gradually rather than showing sudden fluctuations

The turnover ratio and TNA also show strong cross-country differences. With China having an average turnover ratio of 3.6448 indicating stable trading activity. While S.A have a high average turnover ratio of 820, reflecting measurement differences. India and Indonesia have a lower average turnover ratio of 15.8975 and 18.4178, indicating unstable trading activity, which could indicate lower secondary market liquidity and inconsistent investor participation, raising transaction costs and decreasing ETF price efficiency. In contrast, South Korea and Mexico have higher average turnover ratios of 76.4732 and 43.3708, accompanied by higher standard deviations, indicating more active but inconsistent trading. The pattern observed in these ETFs suggests that although they have more liquidity, they may also experience increased short-term capital flows, which could lead to unstable trading dynamics. Taiwan shows moderate turnover ratio of 20.7292 with standard deviation of 10.0226, suggesting a more balanced trading environment with consistent investor participation and lower turnover. These findings suggests that turnover ratio differs across ETFs, with higher averages linked to greater instability in trading volumes.

TNA show huge differences in ETF size across emerging markets. S.A has the highest average value of 29.0307 with a lower standard deviation of 0.3058, suggesting large and stable asset holdings. While Indonesia follows with an average value of 14.2476 and a high standard deviation of 42.4800, indicating extreme fluctuations in fund size. China and Mexico have moderate averages of 2.7807 and 2.4808, with standard deviation of 4.4644 and 3.9309, respectively. Furthermore, South Korea has an average of 1.9910 and Taiwan is 1.5709 with standard deviation of 4.6711 and 1.3010, indicating smaller and unstable assets. For developed market ETFs, U.K has the highest mean of 23.668 followed by Germany with 21.0161, whereas ETFs from Australia and U.S has the lowest mean of 1.5709 and 2.0409. The standard deviation of TNA in developed markets show stability of ETF fund sizes with U.K having high standard deviation of 0.1008 followed by Switzerland with standard deviation of 0.7800, suggesting that

fund size fluctuate over time. In contrast, Germany's low standard deviation of 0.0441 indicate that ETF sizes are consistent and stable.

As explained in section 2.6.2, JB test determines whether the data is normally distributed based on the kurtosis having a value of 3 and skewness value of 0. The result for ETF returns across all emerging markets deviate from normality. Most ETFs show negative skewness suggesting that returns are slightly biased towards losses. Except for the ETF trading in South Korea, it has a positive skewness, suggesting higher positive returns. In terms of kurtosis, all ETFs show greater values that are above 3, indicating that the return distribution is bell-shaped. This effect is evident for ETFs trading in India with 7.7434 and Indonesia with 8.4784, showing a higher likelihood of extreme fluctuations in returns. In addition, JB test statistic is significant at 1% significant level, suggesting that ETF returns for all emerging markets are not normally distributed. However, according to Adu, Alagidene, and Karimu (2015) the assumption of normality in asset returns is extremely unrealistic, particularly for the BRICS countries, which have significant growth fluctuations and are susceptible to political and regulatory changes that could cause asset returns to drastically deviate from normality assumption.

The results from skewness and kurtosis of GPR index for all emerging and developed market ETFs indicate that the results are positively skewed and exhibits leptokurtic distributions. The skewness values range from 0.8764 for Indonesia to 1.5525 for Mexico, indicating that most countries tend to experience more extreme increases in GPR than decreases. Kurtosis values are extremely high especially for Switzerland, U.K, Mexico, and India , with coefficients of 25.1903, 20.9342, 6.4082, and 8.5392, indicating higher likelihood of extreme deviations from the mean. The JB test statistic is significant at 1% for all ETFs, indicating that the GPR for all ETFs is not normally distributed. These results are consistent with Bouras et al., (2019) who argue that the GPR index is not normally distributed because geopolitical events are rare and often have very large impacts.

Similarly, turnover ratios exhibit strong positive skewness, especially for Indonesia, U.S, France, China, and Taiwan, with coefficients of 6.1723, 2.974, 3.0993, 6.1860, 14.2385, indicating that there are more frequent turnover ratios than low ones. While the kurtosis is extremely high for all ETFs with S.A having 14.9098, Taiwan 17.1300, France 9.8714, U.K 15.5301, and Indonesia with 45.1967 showing a higher chance of extreme turnover values. In addition, the Jarque-Berra test is significant at the 1% level for all ETFs suggesting that the

turnover ratio is not normally distributed. These results are consistent with Gimeno, Sarto, and Vicente (2022) who found the turnover ratio of the fund not normally distributed, suggesting that ETF trading is irregular, with frequent extreme spikes rather than smoothly clustered around the mean.

Lastly, TNA for all ETFs is not normally distributed. Majority of ETFs exhibit positive skewness, mostly with China, India, and Taiwan having high values of 1.6939, 2.1421, and 2.4335. However, Indonesia is the only ETF with negative skewness of -0.9609, indicating a tendency toward smaller fund sizes. The high consistency of kurtosis across ETFs, from Taiwan, Australia, Germany, and Indonesia, as well as the significant JB statistics confirm that TNA is not normally distributed. These results are consistent with the findings of Gimeno, Sarto, and Vicente (2022) who found that TNA is not normally distributed because fund sizes are uneven and large changes in fund value make the distribution skewed and irregular.

Table 5.9: Descriptive Statistics Results for Emerging and Developed Market ETFs

Panel A Emerging Markets							
	Variable	Mean	Standard Dev.	Skewness	Kurtosis	JB- Test	Prob. (JB)
China	D_Returns	3.2905	0.0068	0.0443	7.5005	29.66	0.0000
S.A	D_Returns	0.0001	0.0057	-0.1018	6.3749	28.6686	0.0000
India	D_Returns	0.0002	0.5069	-0.4914	13.1864	24.8992	0.0000
South Korea	D_Returns	0.0001	0.0057	-0.2687	11.4022	16.2122	0.0000
Mexico	D_Returns	0.0001	0.4049	-0.0523	9.0398	86.9685	0.0000
Indonesia	D_Returns	0.0001	0.6800	-0.6859	23.7366	59.5824	0.0000
Taiwan	D_Returns	0.0200	0.5500	-0.3357	9.0335	81.4828	0.0000
Panel B Developed Markets							
	Variable	Mean	Standard Dev.	Skewness	Kurtosis	JB- Test	Prob. (JB)
U.K	D_Returns	5.2205	0.4007	-0.7965	14.6208	18.2460	0.0000
France	D_Returns	0.0002	0.0060	-0.2195	9.4408	106.3960	0.0000
U.S	D_Returns	0.0924	0.5027	0.2272	7.5868	54.5200	0.0000
Switzerland	D_Returns	0.8620	0.04000	-1.2739	17.5103	25.1220	0.0000
Australia	D_Returns	7.6505	0.0042	-0.6580	8.5512	53.7171	0.0000
Germany	D_Returns	0.0983	0.0059	-0.5318	13.6153	21.6629	0.0000
Japan	D_Returns	0.0924	0.0057	0.2272	7.5868	54.5201	0.0000

Notes:

1. Prob. refers to probability value
2. D_Returns refers to daily returns

Table 5.9 show the descriptive statistics for ETFs trading in emerging and developed markets. The results illustrate clear differences in both daily average returns and volatility measured using standard deviation. Among ETFs trading in emerging markets, China has the highest mean return of 3.2905, which may indicate higher growth expectations during the sample period. In contrast, ETFs from S.A, South Korea, India, Mexico, and Taiwan show lower average returns below 0.0500, indicating that they are fewer opportunities for investors to make short-term profits. In terms of volatility, ETFs from China and S.A show relatively low standard deviations of 0.0068 and 0.0057, suggesting stronger market depth. Whereas ETFs from Indonesia, Taiwan, and India show relatively high standard deviation of 0.6800, 0.5500, and 0.5069, suggesting greater risk and uncertainty. In developed markets, ETFs from Australia and U.K show the highest average returns of 7.6505 and 5.2205, showing stronger macroeconomic conditions. In contrast, ETFs from France and U.S have low average returns of 0.0200 and 0.0924, suggesting more developed market conditions with lower short-term growth potential. In developed markets, volatility is more stable with ETFs from France, Australia, Germany and Japan exhibiting low standard deviation ranging from 0.0042 to 0.0060, indicating lower uncertainty. However, ETFs from U.S and U.K experience higher standard deviation of 0.5027 and 0.4007, possibly indicating increased vulnerability to monetary policy changes and international capital flows.

The daily ETF returns from both emerging and developed market exhibit skewness values that are negative, indicating that their distribution is titled to the left, with exception of China which exhibit positive skewness. This suggests than there is more downside risk for investors because extreme negative returns are more likely than extreme positive returns in most ETFs. Regarding the kurtosis values, for all the variables in Table 5.9 have kurtosis values above 3, indicating that variables are peaked and leptokurtic. This highlights the existence of increased vulnerability to sudden market shocks indicating that extreme return events happen more frequently than would be expected under normal distribution. In financial markets, this kind of leptokurtic behaviour is common and frequently linked to liquidity constraints. In addition, JB- stat for all the variables in Table 5.9 have probability values less than the 5% significant level. Suggesting that the null hypothesis of a normally distributed series is rejected in favour of alternative hypothesis that the series is not normally distributed. Overall, the skewness, kurtosis, and JB-statistics values indicate that all the variables are not normally distributed. However, since daily ETF returns and the

GPR indices are not normally distributed, this suggests that asymmetry and fat tails are present. This non-normality supports the use of GARCH-type models, which are made to manage volatility clustering and heavy tailed data (Engle, Ghysels, and Sohn, 2013).

Table 5.10: Descriptive Statistics Results for Emerging and Developed Market ETFs

Panel A- Emerging Market ETFs							
	Variable	Mean	Standard Dev.	Skewness	Kurtosis	JB- Test	Prob.
China	LM	-21.6565	0.9406	0.2190	12.6315	78.8358	0.0000
	LAge	0.0833	0.3000	0.0950	3.6574	32.5246	0.0000
S.A	LM	21.2683	0.7635	-0.9609	3.9447	55.4094	0.0000
	LAge	2.1866	0.9726	-0.1652	6.3775	27.7158	0.0000
India	LM	2.9707	0.2747	0.6417	6.5620	17.5727	0.0000
	LAge	2.1373	0.9715	-0.6934	6.3625	26.1944	0.0000
South Korea	LM	30.5785	0.4155	0.5568	3.0095	30.0752	0.0000
	LAge	2.1044	0.9696	-0.6778	6.2500	24.2778	0.0000
Mexico	LM	25.2884	0.8099	0.5871	3.5727	17.6955	0.0001
	LAge	2.1264	0.9707	-0.6840	6.2889	25.2077	0.0000
Indonesia	LM	20.3675	0.3373	-0.0244	3.3318	36.5988	0.0000
	LAge	1.7758	0.9620	-0.6382	6.0433	15.9720	0.0000
Taiwan	LM	3.8647	0.6510	0.2279	3.4180	0.8997	0.0000
	LAge	2.0742	0.9687	-0.6721	6.2155	23.2903	0.0000
Panel B- Developed Market ETFs							
	Variable	Mean	Standard Dev.	Skewness	Kurtosis	JB- Test	Prob.
U.K	LM	2.5007	0.2000	0.5820	8.4327	25.0331	0.0000
	LAge	1.5442	0.9518	-0.5800	5.7006	10.9447	0.0000
France	LM	2.0030	0.0342	0.5179	3.2844	19.0178	0.0000
	LAge	2.1808	0.9696	-0.6807	6.2622	26.3297	0.0000
U.S	LM	22.3249	0.9647	0.4995	5.5237	37.5943	0.0000
	LAge	2.1657	0.9720	-0.6940	6.3560	26.1055	0.0000
Japan	LM	22.7422	0.6203	0.4299	3.4658	11.8696	0.0003
	LAge	21.0276	0.2904	-0.6040	5.6190	19.8673	0.0000
Australia	LM	30.3460	0.6502	0.3347	3.9176	23.2012	0.0014
	LAge	17.5686	0.9560	-0.6026	5.8146	14.5288	0.0000
Switzerland	LM	9.3186	0.7637	0.3936	6.9714	70.9318	0.0000
	LAge	1.4323	0.9366	-0.5719	5.5988	92.2021	0.0001
Germany	LM	3.4412	0.2747	0.6417	6.5620	23.5680	0.0000
	LAge	0.5688	0.6879	0.0950	3.6574	16.1793	0.0000

Table 5.10 above present the descriptive statistics for the variables used in Research Objective 3. The log of Amihud illiquidity ratio shows that the average of Amihud illiquidity ratio is high across ETFs in emerging markets, with Taiwan having the lowest mean of 3.8647 and South Korea having the highest mean of 30.5785. Whereas, in developed markets, France has the lowest mean of 2.0030 and Australia has the highest mean of 30.3460. Indicating that some ETFs have significantly higher average Amihud ratios, especially South Korea and Australia, this means that trading these ETFs may result in greater price impacts per unit of trading volume. In addition, higher Amihud illiquidity imply high transactional costs which may discourage investor participation and lower overall market efficiency. In terms of standard deviation, most ETFs in emerging markets such as Mexico has the highest standard deviation of 0.8099, and in developed markets U.S has the highest standard deviation of 0.9647. This indicates that ETFs illiquidity varies significantly overtime, with some periods being significantly more illiquid than others. This changing illiquidity imply that macroeconomic shocks have an impact on liquidity conditions which can increase volatility.

The log of ETF age shows that most ETFs in emerging markets have an average of age ranging between two and three years, suggesting that these ETFs are relatively new in the market. Except for China and Indonesia with lower mean ages of 0.0833 and 1.7758, indicating that these ETFs have been recently established in the market. In developed markets, majority of ETFs fall within the same ranges, except for Japan and Australia with higher means of 21.0276 and 17.5686, suggesting that they have been trading for many years in the market.

In terms of standard deviation, majority of ETFs in emerging market exhibit a higher standard deviation above 0.9000, except for China with standard deviation of 0.3000, suggesting wide variation in ETF ages. While in developed markets, majority of ETFs also have high standard deviation, except for Japan with standard deviation of 0.2904, suggesting that ETF ages are relatively consistent. This consistency in ETF age in developed market ETFs may indicate a more established ETF industry, where ETFs have longer track records and investors can depend more on past performance when making investment decisions.

Moreover, majority of ETFs in both developed and emerging markets show that for both log of Amihud illiquidity ratio and log of age of ETF exhibit positive skewness, indicating that their distribution is tilted to the right. The kurtosis values show values that are above 3, indicating that their distribution is bell-shaped, this suggests that both Amihud illiquidity and

log of ETF age are characterized by fat tails, indicating that there are more extreme observations than would be expected by a normal distribution. In addition, the JB-test statistic is significant at 1% level for all ETFs, indicating that both log of Amihud illiquidity ratio and log of ETF age are not normally distributed.

5.2.3 Correlation Analysis

Correlation coefficients are computed to assess the strength of linear relationships among the variables used in this study. Specifically, correlation analysis is conducted for variables included in the Markov Regime-Switching model to investigate how they interact under different market conditions. Table 5.11 presents the correlation coefficients between ETF variables for emerging market ETFs, while Table 5.12 presents the correlation coefficients between ETF variables for developed market ETFs. However, correlation analysis was not performed for other models, such as GARCH-MIDAS and NARDL, since these models focus on capturing volatility dynamics and short and long-run relationships, rather than linear relationships among variables.

Correlation analysis in Table 5.10 and 5.11 below indicates that, for most ETFs, global GPR and ETF returns exhibit low, positive correlation. This means that, although the relationship is very small, ETF returns tend to increase slightly as GPR increases. This relationship may suggest that investors demanded higher expected returns to compensate for increasing geopolitical uncertainty. In emerging markets, the correlation ranges from 0.0043 for India to 0.0887 for Mexico, suggesting a minimal positive correlation, with the exceptions of Indonesia -0.0378 and China -0.0241, which show a minimal negative correlation, indicating that higher global GPR is slightly associated with lower ETF returns in these markets. This negative correlation in these markets may occur because emerging markets are frequently more sensitive to capital outflows during times of increased uncertainty.

Similarly, for most ETFs in developed markets, there is low, positive correlation, ranging from 0.0022 for Switzerland to 0.1105 for France, suggesting that global GPR has only a minor positive effect on ETF returns. This minor positive effect in developed market ETFs may be associated with stronger financial institutions, which helps more effectively in absorbing geopolitical shocks. Except for Australia and Germany which has low, negative correlation of -0.0499 and -0.0090, indicating that slight declines in ETF returns in these markets are

associated with increases in global GPR. These differences between emerging and developed market ETFs may indicate that ETFs in emerging markets tend to be more vulnerable to global GPR, because during times of increased uncertainty, investors view them as riskier. In contrast, developed markets appear more stable because of their stronger institutional stability.

Correlation between country-specific GPR and ETF returns exhibits a low, positive correlation in emerging markets, ranging from 0.0162 for Indonesia to 0.0887 for Mexico, suggesting that increases in country-specific GPR are associated with only a minimal rise in ETF returns. This relationship indicate that investors demand higher expected returns when country-specific GPR increases. However, India and Taiwan exhibit low, negative correlations of -0.0370 and -0.0384 respectively, this indicates that ETF returns are slightly lower in these two ETFs due to increased country-specific GPR. This negative correlation suggests that GPR is perceived by investors to be more disruptive to economic stability, resulting to capital outflows.

Overall, emerging market ETFs tend to be more sensitive to political uncertainty due to weaker institutional frameworks and greater exposure to macroeconomic volatility, which can increase the effect of country-specific GPR. In addition, for both developed and emerging market ETFs, the global GPR and country-specific GPR indices show strong, positive correlation, indicating that country-specific GPR across markets are closely correlated with increases in global GPR. This suggest that country-specific GPR is sometimes driven by global GPR. However, developed market ETFs may be better able to withstand shocks compared to emerging market ETFs who may not be able to withstand geopolitical shocks.

Table 5.11: Correlation Coefficient Results for Emerging Market ETF Variables

		ETF_Returns	GPR_G	GPR_C	Turnover Ratio	TNA
China	ETF_Returns	1.0000				
	GPR_G	-0.0241	1.0000			
	GPR_C	0.0704	0.5159	1.0000		
	Turnover Ratio	-0.0895	-0.2407	-0.1211	1.0000	
	TNA	-0.2049	-0.0459	-0.0496	-0.0245	1.0000
		ETF_Returns	GPR_G	GPR_C	Turnover Ratio	TNA
S.A	ETF_Returns	1.0000				
	GPR_G	0.1121	1.0000			
	GPR_C	0.0255	0.1823	1.0000		
	Turnover Ratio	0.0538	-0.0435	0.0769	1.0000	
	TNA	-0.0678	-0.0588	-0.0177	-0.1193	1.0000
		ETF_Returns	GPR_G	GPR_C	Turnover Ratio	TNA

India	ETF Returns	1.0000				
	GPR_G	0.0043	1.0000			
	GPR_C	-0.0370	0.3949	1.0000		
	Turnover Ratio	0.0675	-0.2057	0.2155	1.0000	
	TNA	0.0483	0.1470	0.0431	-0.0419	1.0000
		ETF Returns	GPR_G	GPR_C	Turnover Ratio	TNA
South Korea	ETF Returns	1.0000				
	GPR_G	0.0089	1.0000			
	GPR_C	0.0077	0.0516	1.0000		
	Turnover Ratio	0.0035	0.0806	-0.0068	1.0000	
	TNA	0.0563	-0.0155	-0.0369	-0.0001	1.0000
		ETF Returns	GPR_G	GPR_C	Turnover Ratio	TNA
Mexico	ETF Returns	1.0000				
	GPR_G	0.0887	1.0000			
	GPR_C	0.0887	0.3142	1.0000		
	Turnover Ratio	0.0630	-0.2624	-0.0741	1.0000	
	TNA	-0.0427	0.0344	0.0837	-0.0619	1.0000
		ETF Returns	GPR_G	GPR_C	Turnover Ratio	TNA
Indonesia	ETF Returns	1.0000				
	GPR_G	-0.0378	1.0000			
	GPR_C	0.0162	0.4426	1.0000		
	Turnover Ratio	0.4090	-0.1724	0.0761	1.0000	
	TNA	-0.0290	-0.0293	0.0538	-0.0431	1.0000
		ETF Returns	GPR_G	GPR_C	Turnover Ratio	TNA
Taiwan	ETF Returns	1.0000				
	GPR_G	0.0169	1.0000			
	GPR_C	-0.0384	0.3952	1.0000		
	Turnover Ratio	-0.0958	-0.1255	-0.3361	1.0000	
	TNA	0.0170	0.0728	0.1289	-0.1095	1.0000

Table 5.12: Correlation Coefficients Results for Developed Market ETF Variables

		ETF Returns	GPR_G	GPR_C	Turnover Ratio	TNA
Switzerland	ETF Returns	1.0000				
	GPR_G	0.0022	1.0000			
	GPR_C	0.0037	0.1692	1.0000		
	Turnover Ratio	0.0529	0.0121	0.1399	1.0000	
	TNA	-0.1581	-0.0175	-0.0182	-0.0649	1.0000
		ETF Returns	GPR_G	GPR_C	Turnover Ratio	TNA
Australia	ETF Returns	1.0000				
	GPR_G	=0.0499	1.0000			
	GPR_C	-0.0616	-0.1399	1.0000		
	Turnover Ratio	-0.0363	0.2219	-0.1571	1.0000	
	TNA	-0.0566	-0.1078	0.0249	-0.1787	1.0000
		ETF Returns	GPR_G	GPR_C	Turnover Ratio	TNA

Germany	ETF Returns	1.0000				
	GPR_G	-0.0090	1.0000			
	GPR_C	-0.0442	0.0361	1.0000		
	Turnover Ratio	-0.0775	0.0290	-0.1958	1.0000	
	TNA	-0.0850	-0.0122	-0.0746	-0.0084	1.0000
		ETF Returns	GPR_G	GPR_C	Turnover Ratio	TNA
Japan	ETF Returns	1.0000				
	GPR_G	0.0122	1.0000			
	GPR_C	-0.0184	0.5384	1.0000		
	Turnover Ratio	-0.0708	-0.0898	-0.1701	1.0000	
	TNA	-0.0330	-0.0102	-0.0032	-0.1096	1.0000
		ETF Returns	GPR_G	GPR_C	Turnover Ratio	TNA
U.K	ETF Returns	1.0000				
	GPR_G	0.0470	1.0000			
	GPR_C	-0.0228	0.3819	1.0000		
	Turnover Ratio	0.0912	(0.2343)	-0.2197	1.0000	
	TNA	-0.0558	-0.0601	-0.0194	0.1344	1.0000
		ETF Returns	GPR_G	GPR_C	Turnover Ratio	TNA
France	ETF Returns	1.0000				
	GPR_G	0.1105	1.0000			
	GPR_C	0.0241	0.5348	1.0000		
	Turnover Ratio	-0.1871	0.2059	-0.1312	1.0000	
	TNA	0.0159	0.0654	0.0282	0.0395	1.0000
		ETF Returns	GPR_G	GPR_C	Turnover Ratio	TNA
U.S	ETF Returns	1.0000				
	GPR_G	0.0952	1.0000			
	GPR_C	0.0985	0.9980	1.0000		
	Turnover Ratio	-0.0241	-0.1282	-0.1472	1.0000	
	TNA	-0.0977	-0.0229	-0.0163	(0.1482)	1.0000

Furthermore, correlation between turnover ratio and ETF returns for most emerging market ETFs exhibit a low, positive relationship, indicating that higher trading activity is associated with higher returns, except for China and Taiwan which exhibit low, negative correlations of -0.0895 to -0.0958, suggesting that higher turnover is associated with lower returns in these markets. In developed market the opposite pattern is observed, as turnover ratio and ETF returns exhibit low, negative relationship for most ETFs ranging from -0.0241 for U.S to -0.1871 for France. This indicates that increased trading activity is associated with lower returns, except for U.K and Switzerland. For developed markets, this inverse relationship may suggest that higher turnover is associated with short-term trading, which can reduce rather than increase returns. Moreover, global GPR and turnover ratio for most emerging markets exhibit a low, negative relationship, which is the similar case for country-specific GPR and turnover

ratio, suggesting that lower trading activity is associated with higher GPR. This pattern may imply that heightened geopolitical uncertainty may decrease market liquidity which could result to decreased trading activity in more sensitive emerging markets. In contrast, majority of ETFs exhibit positive correlation ranging from 0.1472 for U.S to 0.1958 for Australia, but there is negative correlation between country-specific GPR and turnover. This may suggest that while domestic geopolitical uncertainty tend to suppress trading by raising perceived risk and uncertainty, global geopolitical events can occasionally encourage hedging in developed markets.

Notably, in both developed and emerging markets, the correlation between TNA and other variables including ETF returns, global GPR, country-specific GPR, and turnover ratio is low and negative. Indicating that larger TNA are associated with lower returns, lower exposure to global and country-specific GPR. However, because of low correlation explained, these relationships are not strong, suggesting that ETF size does not have a significant effect in shaping ETF returns, GPR exposure, and turnover in either developed or emerging markets.

Overall, the results from correlation analysis for developed and emerging markets indicate that the variables used are weakly related to one another suggesting that there is no variable that drives another, showing little to no correlation. This weak interdependence supports the idea that ETF returns, GPR, liquidity function through different transmission channels rather than tightly linked linear relationships. Although there are few correlations observed among the variables (between returns and GPR, returns and turnover ratios in some ETFs), these correlations suggest that increases in GPR are generally associated with small declines in performance. Therefore, weak correlation among variables suggests that multicollinearity is not a cause for concern, meaning that there is low risk of multicollinearity, and variables are suitable to be used together.

5.2.4 Model Diagnostic Tests

Model diagnostic tests are employed to determine the validity, reliability, and suitability of a fitted model for data. Since they support the identification of problems such as inaccurate estimates, poor fit, and violation of model assumptions. In this study, different diagnostic tests are performed based on the research objectives. For all research objectives, tests for serial correlation and heteroskedasticity are performed. For research objective one, the LR test is

performed. For research objective two the ARCH-LM test is performed to identify any residual ARCH effects only on GARCH-MIDAS model. Lastly, for research objective three, the bounds test is performed to identify long-term cointegration of variables. The results of these diagnostic tests are presented and discussed below.

5.2.4.1 Test for Serial Correlation

For research objective one and three, Breusch-Godfrey test explained in section 4.2.6.4 was used to detect the presence of serial correlation. The test was conducted using the default options in EViews. Table 5.13 and 5.14 below show the F-stat and probability values of ETFs from emerging and developed markets.

Table 5.13: Results of Breusch-Godfrey Test for Emerging and Developed Market ETFs

Emerging Markets			Developed Markets		
	F-stat	Prob.		F-stat	Prob.
China	0.0096	0.9900	Switzerland	1.2383	0.2934
S.A	0.5300	0.5892	Australia	2.1525	0.1183
India	0.7150	0.4901	Germany	2.8314	0.0612
South Korea	0.2104	0.8104	Japan	2.3742	0.0950
Mexico	0.2901	0.7484	U.K	1.3011	0.2754
Indonesia	0.7832	0.4585	France	1.5260	0.2192
Taiwan	2.1525	0.1183	U.S	2.5109	0.0829

Notes:

1. Null hypothesis: No evidence of autocorrelation

Table 5.14: Results of Breusch-Godfrey Test for Emerging and Developed Market ETFs

Emerging Markets			Developed Markets		
	F-stat	P-value		F-stat	P-value
China	63.6153	0.7275	Switzerland	19.3615	0.1123
S.A	23.5111	0.8891	Australia	8.5016	0.4308
India	7.5547	0.229	Germany	6.5712	0.3756
South Korea	42.5600	0.6300	Japan	3.5311	0.1711
Mexico	14.2137	0.3014	U.K	28.7613	0.2792
Indonesia	14.9820	0.1548	France	61.9074	0.3016
Taiwan	4.3810	0.1119	U.S	14.0173	0.1361

In Table 5.13 and 5.14 above, given that the level of significance (that is 5%) is greater than the associated probability values, this imply that the null hypothesis of no autocorrelation cannot be rejected. This indicates that the results for objective one and three, concerning ETFs trading in developed and emerging markets do not exhibit serial autocorrelation. Suggesting that each observation is not systematically dependent on past values over time.

5.2.4.2 Test for Heteroskedasticity

In this study, the White test is conducted to detect the presence of heteroskedasticity for research objective one and three. Table 5.15 below present the results of the White test for emerging and developed markets ETFs (research objective one), while Table 5.16 presents the results of the White test for emerging and developed markets (research objective three).

Table 5.15: White Test Results for ETFs in Emerging and Developed Market ETFs

	Emerging Markets				Developed Markets		
	Chi-Squared	df	Prob.		Chi-Squared	df	Prob.
China	36.5806	14	0.0001	Switzerland	14.7650	14	0.0102
S.A	30.6130	14	0.0063	Australia	21.2443	14	0.0945
India	11.3985	14	0.0016	Germany	37.6423	14	0.0467
South Korea	27.5018	14	0.0166	Japan	33.7902	14	0.0092
Mexico	20.5527	14	0.0117	U.K	28.0087	14	0.0142
Indonesia	14.7524	14	0.0245	France	40.8266	14	0.0002
Taiwan	34.0684	14	0.0020	U.S	43.0450	14	0.0001

Table 5.16: White Test Results for ETFs in Emerging and Developed Market ETFs

	Emerging Markets				Developed Markets		
	Chi-Squared	df	Prob.		Chi-Squared	df	Prob.
China	70.3305	35	0.0004	Switzerland	52.1745	38	0.0020
S.A	48.8037	38	0.0000	Australia	48.9876	32	0.0000
India	47.5044	32	0.0000	Germany	77.8050	32	0.0000
South Korea	19.5319	34	0.0000	Japan	108.5628	40	0.0004
Mexico	68.59	33	0.0000	U.K	67.8265	39	0.0029
Indonesia	54.6850	35	0.0000	France	48.2580	33	0.0040
Taiwan	61.3813	45	0.0911	U.S	69.9140	32	0.0001

Notes:

1. Null hypothesis: Error terms are homoscedastic
2. df refers to degrees of freedom

The results of the White test above show that the probability values and chi-squared statistics are greater than 0.01, 0.05, and 0.10. Thus, at the 1%, 5%, and 10% level of significance, the null hypothesis of homoskedasticity (no heteroskedasticity) in the errors of the respective ETF models cannot be rejected. This indicates that the residuals of the models estimated for research objectives one and three does not exhibit heteroskedasticity. Overall, the results of the diagnostic tests conducted for the models suggest that the estimated models for research objectives one and three are reliable and unbiased. Additionally, for research objective three, the White test indicated no evidence of heteroskedasticity in the error terms, supporting the

adequacy of model specification. In terms of the Markov Regime-Switching model, the results showed that the model effectively captures the regime-dependent dynamics in the data.

5.2.4.3 Test for ARCH Effects

Prior to estimating the GARCH-MIDAS (1,1) models, the ARCH-LM test was conducted for Research Objective 2, on daily ETF returns to determine whether the daily ETF returns exhibited ARCH effects explained in section 4.2.6.4. Table 5.17 below presents the results of ARCH-LM test for both emerging and developed market ETFs.

Table 5.17: Results of ARCH-LM Test for Emerging and Developed Market ETFs

Emerging Markets			Developed Markets		
Country	LM-Stat	Prob.	Country	LM T-Stat	Prob.
China	228.9854	0.0000	U.K	58.5506	0.0010
S.A	941.1153	0.0000	France	18.5919	0.0000
India	744.9416	0.0000	U.S	4.9140	0.0266
South Korea	246.2275	0.0000	Japan	31.8981	0.0000
Mexico	134.8914	0.0001	Australia	4.5208	0.0335
Indonesia	84.6630	0.0000	Switzerland	16.8031	0.0000
Taiwan	296.0099	0.0000	Germany	239.7755	0.0000

The results from ARCH-LM test above correspond to LM-stat defined in Equation 4.33. The LM-stat for all ETFs have probability values below the 5% significance level, indicating that daily ETF returns exhibits ARCH effects, implying that these returns exhibit volatility clustering and time-varying conditional variance. Overall, given the presence of ARCH effects for all ETFs in developed and emerging markets, this justifies the use of GARCH-MIDAS model to capture time-varying volatility.

5.3 Research Objective 1: Geopolitical Risk and ETF Returns

This section presents and interprets the results obtained from the Markov regime switching model explained in Section (4.3.1) for fourteen ETFs tracking broad based market indices in developed and emerging markets. This analysis distinguishes between models using the global and country-specific GPR indices as explained in Section (4.2.5.2), since they capture different dimensions of GPR and to avoid multicollinearity. In addition, these models are therefore estimated separately. Given that the study examines 14 ETFs and the models are estimated individually for each ETF, a uniform lag structure was used to ensure consistency across estimated models.

Before interpreting the results from the Markov Regime-Switching models, it is crucial to differentiate between the different market regimes. In accordance with existing literature, the regime specific standard deviations are used to determine the bull and bear market regimes, as summarized below in Table 5.18 and 5.19. For each ETF, the regime with the lower standard deviation is characterized by lower volatility and thus represent the bull market regime. While the regime with the higher standard deviation represents the bear market regime. The results from the Markov Regime-Switching model from Table 5.18 and 5.19 reveal significant differences in the behaviour of ETFs across market regimes when comparing models that incorporate global and country-specific GPR indices. Specifically, most emerging market ETFs are more sensitive to GPR, reflected in higher volatility and shorter durations, whereas developed market ETFs tend to maintain longer bull regimes and demonstrate greater resilience to geopolitical shocks. These results are consistent with Madondo and Kunjal, (2025) who reported that developed market ETFs are characterized by low financial volatility compared to those in emerging markets.

Table 5.18: Regime Classification Results for ETFs in Emerging Markets

Country	Regime 1				Regime 2			
	Std Dev	Market	$P_{1,1}$	$D_{1,1}$	Std Dev	Market	$P_{2,2}$	$D_{2,2}$
China (Global)	0.8258	Bear	0.8258	5.7415	0.0412	Bull	0.9188	12.3144
China (Country-specific)	0.0822	Bear	0.6811	3.1361	0.0429	Bull	0.8969	9.7023
S.A (Global)	0.0381	Bull	0.9823	56.4834	0.0739	Bear	0.9405	16.7955
S.A (Country-specific)	0.0740	Bear	0.5493	2.2189	0.0383	Bull	0.9610	25.6182
India (Global)	0.0889	Bear	0.3389	1.5127	0.0473	Bull	0.9556	22.5233
India (Country-specific)	0.0342	Bull	0.2081	26.7260	0.0485	Bear	0.9626	1.2627
South Korea (Global)	0.0605	Bear	0.9934	1.151.56	0.0298	Bull	0.9788	47.2023
South Korea (Country-specific)	0.0458	Bull	0.9746	39.3225	0.0518	Bear	0.9601	25.0910
Mexico (Global)	0.0712	Bear	0.8395	7.6634	0.0365	Bull	0.9610	25.6497
Mexico (Country-specific)	0.0745	Bull	0.5142	19.8989	0.0310	Bear	0.9497	2.0586
Indonesia (Global)	0.0545	Bear	0.2836	1.3959	0.0527	Bull	0.9656	29.1135
Indonesia (Country-specific)	0.1065	Bear	0.4661	1.8707	0.0508	Bull	0.9572	23.3386
Taiwan (Global)	0.0387	Bull	0.9818	54.8489	0.0886	Bear	0.9158	11.8716
Taiwan (Country-specific)	0.0388	Bull	0.9794	48.5610	0.0893	Bear	0.9057	10.6019

Table 5.19: Regime Classification Results for ETFs in Developed Markets

Country	Regime 1				Regime 2			
	Std Dev	Market	$P_{1,1}$	$D_{1,1}$	Std Dev	Market	$P_{2,2}$	$D_{2,2}$
U.K (Global)	0.0221	Bull	0.6460	2.8245	0.0433	Bear	0.3827	1.6199
U.K (Country-specific)	0.0236	Bull	0.8994	8.2922	0.0502	Bear	0.5580	2.2624
France (Global)	0.0368	Bull	0.7181	3.5484	0.0586	Bear	0.2818	1.3924
France (Country-specific)	0.0403	Bull	0.1669	1.2003	0.0408	Bear	0.8331	5.9922
U.S (Global)	0.0239	Bull	0.4821	1.9311	0.0458	Bear	0.5179	2.0741
U.S (Country-specific)	0.0247	Bull	0.4947	1.9792	0.0451	Bear	0.5053	2.0213
Switzerland (Global)	0.07669	Bear	0.1825	1.2233	0.0256	Bull	0.8936	9.3970
Switzerland (Country-specific)	0.0393	Bear	0.7616	4.1951	0.0143	Bull	0.6690	3.0208
Australia (Global)	0.0335	Bear	0.9755	1.2654	0.0160	Bull	0.2097	40.7947
Australia (Country-specific)	0.0342	Bear	0.9866	74.7951	0.0081	Bull	0.3249	1.4813
Germany (Global)	0.0351	Bull	0.9473	18.9863	0.0749	Bear	0.8988	9.8860
Germany (Country-specific)	0.0361	Bull	0.9446	18.0608	0.0772	Bear	0.8806	8.3759
Japan (Global)	0.0569	Bear	0.2717	1.3730	0.0381	Bull	0.5192	2.0798
Japan (Country-specific)	0.0491	Bull	0.9924	13.8134	0.0981	Bear	0.5548	2.2463

The first key finding from the models incorporating both global and country-specific GPR shows that emerging market ETFs exhibits higher sensitivity to regime shifts, while ETFs from developed markets tend to remain more persistently in bull regimes characterized by lower volatility and longer average expected durations. Specifically, the models incorporating global

GPR show that ETFs from emerging markets exhibit high probabilities of being in a bear market regime, while ETFs from developed markets exhibit higher probabilities of being in a bull market regime. For instance, the ETF from China demonstrate a relatively high standard deviation of 0.8258 and an expected duration of 5.7415 periods in regime 1, while the ETF from Mexico has a lower standard deviation of 0.0605 and a slightly longer expected duration of 7.6634. These results indicate that global GPR increase market instability and accelerates transitions into high-volatility regimes in emerging markets. Moreover, the shorter duration of the bear regime suggests that this volatility may be very temporary, followed by quicker transitions to more stable market conditions rather than prolonged downturns. In contrast, ETFs from S.A and Taiwan has a lower standard deviation of 0.0381 and 0.0387 exhibiting higher average expected duration of 56.4834 and 54.8489 indicating a bull regime. This suggest that although ETFs from emerging markets can still maintain relatively stable bull regimes.

Similarly, most developed market ETFs especially those from U.K, France, U.S, and Germany are characterized by lower standard deviation and longer average expected durations, demonstrating persistent bull market conditions. With a standard deviation ranging from 0.0221 for U.K to 0.0361 for Germany, with longer duration of 2.8245 and 18.9863. This suggests that developed markets are less vulnerable to destabilizing effects of geopolitical tensions. However, certain developed market ETFs, particularly those from Switzerland, Australia, and Japan, have higher standard deviation of 0.0766 for Switzerland, 0.0335 for Australia, and 0.0569 for Japan, with shorter durations of 1.2233, 1.2654, and 1.3730. Reflecting sensitivity patterns similar to those observed in some emerging market ETFs.

The models incorporating country-specific GPR show a broadly consistent regime pattern, in which emerging market ETFs continue to show sensitivity to GPR but with relatively stronger persistence in bull regimes compared to the global GPR. For instance, emerging market ETFs from India, South Korea, and Mexico has standard deviations of 0.0342, 0.0458, 0.0758, with average durations of 26.7260, 39.2225, and 19.8989. This suggest that domestic GPR are less disruptive than global shocks in emerging markets. This implies that domestic investors may be better able to interpret and respond to domestic political events, leading to more stable regime persistence. Similarly, the Taiwanese ETF remains in a bull regime under both global and country-specific GPR with a higher standard deviation of 0.0387 and duration of 54.8489 under global GPR and standard deviation of 0.0388 with duration of 48.5610 under country-specific GPR, indicating persistent market stability regardless of the type of GPR. Among

developed market ETFs, those from U.K, France, U.S, Switzerland, and Germany continue to exhibit bull regimes under both global and country-specific GPR indices. This consistency suggests that ETFs in developed markets maintain similar regime allocations under both global and country-specific GPR.

Overall, comparing across developed and emerging markets, and considering regimes, transition probabilities, and expected durations, the results indicate that GPR affects intensity and the persistence of volatility instead of shifting the ETF return pattern, with emerging markets continuing to be more vulnerable to high volatility regime shifts and developed markets showing greater regime stability. In addition to GPR, ETF specific variables such as turnover ratio and TNA also influence returns across regimes. The results presented below in Table 5.20 and 5.21 show how these ETF specific variables influence ETF returns in developed and emerging markets, based on two separate models, one including the global GPR index and the other including country-specific GPR index. In addition, the results are classified into bull and bear regimes according to the standard deviation.

Table 5.20: Estimation Results for Emerging Market ETFs

Global GPR							
	China	S.A	India	South Korea	Mexico	Indonesia	Taiwan
Bull Regime							
Constant	-0.0032	-0.0028	0.0211***	0.0040	-0.0161	-0.0014	0.0105
ETF Returns (-1)	0.4856	-0.8975	0.7369	-0.1125	-0.7351	-0.4898	0.1475
GPR_G	0.0088	0.0008	-0.0006	0.0002	0.0080	-0.0013	0.0048
Turnover Ratio	7.9109**	-2.6708***	-2.3009*	-2.5509**	3.6509***	9.1908*	-7.9308***
TNA	-3.4710*	1.0812	3.9413*	7.0915**	-1.0312**	-4.6111***	-1.2313*
Bear Regime							
Constant	-0.0032	-0.0035	-0.2391*	0.0015	-0.0251	-0.7253*	0.0386
ETF Returns (-1)	0.0222	-2.5893	-0.0091	-0.0489	-0.0003	-0.1196	-0.0642
GPR_G	0.0108	0.0029	0.0215	0.0007	-0.0017	0.1637*	-0.0161
Turnover Ratio	-6.3108*	8.1608**	5.9207*	3.1909	8.6308	4.8607*	-5.4909
TNA	-3.1210*	-1.8012	2.1211***	1.2114**	1.5812*	8.5410***	1.5012
Country-Specific GPR							
	China	S.A	India	South Korea	Mexico	Indonesia	Taiwan
Bull Regime							
Constant	0.5263***	0.0104**	0.0281	0.0063	-0.0883	0.0014	0.0254*
ETF Returns (-1)	-0.7489	-0.4778	-0.6415	-0.0031	-0.4174	0.7001	0.4117

GPR C	0.0108	-0.0807	-1.3510*	-0.0589**	0.4154	-0.0325	0.0026
Turnover Ratio	-6.3108*	7.6808**	9.2807*	2.5308***	7.9308	9.3708*	-8.3608**
TNA	-3.1210*	-1.0612	6.6011*	2.1314**	4.1212	-7.4711	-1.5013
Bear Regime							
Constant	-0.0052*	-0.4030	0.0212*	0.0267	0.0082	0.1252	0.0050
ETF Returns (-1)	0.0217	-0.1317	-0.0080	-0.1430	-0.0014	-0.1157	-0.0669
GPR C	0.0088	0.6717	-0.0201	0.1737*	0.0182	-1.4497	-0.0994
Turnover Ratio	7.9109	-1.6808	-1.4408	-9.5108**	1.2212	2.0607**	-2.0208
TNA	3.4710	-6.1612	3.7213*	-1.2114	-3.2189	2.0809	1.7912

Notes:

1. *ETF_Returns* represents the lag of ETF returns

Table 5.21: Estimation Results for Developed Market ETFs

Global GPR							
	Switzerland	Australia	Germany	Japan	U.K	France	U.S
Bull Regime							
Constant	-0.0627*	0.0609	0.0041	0.0184	0.0197	0.0037	0.0294
ETF Returns (-1)	-0.5586	0.1006	0.8170	-0.9144	-0.1982	-0.0031	0.4032
GPR_G	-0.0053***	-0.0635	0.0024	0.0019	-0.0051	-0.0057	-0.0057
Turnover Ratio	4.4508*	5.4809	1.4407	4.1809	7.2909	6.0509	3.7409
TNA	-5.1411	2.3510	-1.3811**	-1.0313**	2.8612	-4.0311	-1.2912**
Bear Regime							
Constant	-0.0059	0.0207	0.0569	-0.0164	0.0351	-0.0258	-0.0242
ETF_Returns (-1)	-0.1937	-0.0578	-0.0560	0.1659**	0.2780	-0.0507	-0.0309
GPR_G	-0.0021	-0.0037	-0.0232	-0.0006	-0.0093	0.0065	0.0073
Turnover Ratio	-1.5109	-2.2508	-7.7808	5.7708***	1.6207	-6.8708*	-3.2809
TNA	1.1710	-1.2811	-6.7912	1.6214	-5.8410	1.6110***	-4.4813
Country-Specific GPR							
	Switzerland	Australia	Germany	Japan	U.K	France	U.S
Bull Regime							
Constant	0.0029	0.0112	0.0165***	0.0140**	-0.0042	-0.0891	0.0354
ETF Returns (-1)	-0.1987	-0.6873	0.5930	0.5412	0.0008	-0.4711	-0.1140
GPR_C	0.0187	-0.0176	-0.0139	-0.0120	-0.0894	0.1040*	-0.0074
Turnover Ratio	3.5008***	-2.1108	1.3807	-3.1808	-6.7008	-4.6008**	3.2409***
TNA	-4.0011	-9.2112	-1.2611**	-5.3114***	1.7810	2.3610*	-1.3312***
Bear Regime							
Constant	-0.0042	0.0121	-0.0016	0.0383*	0.0029	0.0276*	-0.0322***
ETF_Returns (-1)	-0.2511**	-0.0658	-0.0592	0.0939	-0.2510**	-0.0646	-0.0200
GPR_C	-0.0892	-0.0176	-0.0073	-1.2998*	0.0189	-0.0250**	0.0096*
Turnover Ratio	-6.7008	-2.1108	-2.0907	-4.0908	3.5008***	-1.3008	-3.0109
TNA	1.7810	-9.2112	-6.4012	-4.8713	-4.0011	-2.7811	4.7413

Notes:

1. *ETF_Returns (-1)* represents the lagged ETF returns

An important finding from these results reveals that the effect of global GPR on ETF returns between emerging and developed markets differs. For emerging market ETFs, the global GPR index is statistically insignificant for all ETFs. This indicates that the global GPR does not significantly affect ETF returns in these markets, suggesting that returns of ETFs in emerging markets are relatively immune to global GPR. This is consistent with the EMH, which implies that publicly available information may already be rapidly incorporated into prices, limiting predictable effects of returns. In contrast, for developed market ETFs, the global GPR index is also statistically insignificant in both bull and bear regimes, except for an ETF from Switzerland with a coefficient of -0.0053, where it is statistically significant at the 10% level under the bull regime, indicating that this ETF is typically unaffected by global geopolitical shocks. This finding suggests that the global GPR has a limited direct effect on ETF returns across developed and emerging markets, suggesting that global GPR mostly affects volatility rather than returns. This aligns with the MPT, where diversification across markets reduces the direct impact of global shocks on returns but not on volatility.

Conversely, another key finding relates to the effect of country-specific GPR on ETF returns from developed and emerging markets. For emerging market ETFs, country-specific GPR has a relatively weak direct effect, particularly during periods of market stress. This is evidenced by the country-specific GPR index being statistically insignificant for most ETFs, with limited exceptions for ETFs in India and South Korea, where coefficients of -1.3510 and -0.0589 indicate significance during the bull regime and, in the case of South Korea, also during the bear regime with the coefficient of 0.1737. These results indicate that among emerging market ETFs, South Korea shows the highest sensitivity to country-specific GPR, while most other emerging market ETFs appear to be largely resilient to country-specific GPR. For developed market ETFs, however, the findings reveal that the country-specific GPR index is statistically significant for all ETFs except France with a coefficient of -0.1040 under the bull regime, suggesting that domestic geopolitical tensions affect ETF returns more consistently in developed markets. This suggests that ETF returns in developed markets are more strongly and consistently impacted by country-specific GPR compared to emerging markets, indicating higher sensitivity to local political conditions. Additionally, these findings indicate that country-specific GPR influences returns compared to global GPR, especially in developed markets. This is consistent with the prospect theory, where investors in developed markets may react more strongly to country-specific shocks due to loss aversion leading to more pronounced price adjustments.

From a liquidity perspective, the turnover ratio plays an important role in explaining ETF returns, particularly in emerging markets. It is statistically significant for all emerging market ETFs during bull regimes, suggesting that turnover ratio is important during times of market optimism. In contrast, during bear regimes, turnover ratio becomes largely insignificant, except for ETFs trading in South Korea and Indonesia with coefficients of -2.5509 and 9.1908 indicating that liquidity driven trading weakens when investor sentiment decreases. These results imply that while other emerging market ETFs show less reliance on liquidity during market downturns, South Korea and Indonesia exhibit higher sensitivity to liquidity effects. These findings are consistent with the study by Bekaert, Harvet, and Lundbald (2007), who reported that emerging markets are less prone to domestic political risk due to their exposure to global risk factors. For developed market ETFs, the turnover ratio exhibits mixed significances across market and regimes. It is statistically insignificant for ETFs trading in Switzerland, Australia, Germany, and the U.S, but statistically significant for ETFs in Japan at 10% and France at the 1% level, with coefficients of 5.7708 and -6.8708, suggesting that trading activity affects returns only in specific developed market ETFs, under particular market conditions. This suggests that the sensitivity of liquidity is concentrated in few ETFs from developed markets.

Lastly, TNA is statistically insignificant across all emerging market ETFs in both regimes, implying that fund size does not play a significant role in explaining ETF returns in emerging markets. This indicates that the size of ETF in emerging markets does not meaningfully affect returns in emerging markets. Furthermore, this suggests that larger ETFs are usually more liquid and can respond to changes in the market more effectively, regardless of the state of the market. For developed market ETFs, TNA is statistically insignificant under the bull regime except for ETFs trading in Germany, U.S, and Japan, while under the bear regime only the ETF from France is statistically significant at the 10% level with a coefficient of 1.6110. These results suggest that the ETF size has regime dependent effect, affecting returns of fewer ETFs in developed markets.

In conclusion, the results from Markov Regime-Switching model indicated that ETFs from emerging markets exhibit greater resilience to both global and country-specific GPR, whereas ETFs from developed markets are more sensitive to country-specific GPR. Global GPR seems to have a minimal direct impact on ETF returns, while country-specific GPR shows stronger and more persistent effect, especially in developed markets. These findings are consistent with

the studies of Hoque and Zaidi (2020) and Salisu et al., (2022) who reported that GPR affects markets unevenly across asset classes and countries, highlighting the importance of distinguishing between global and country-specific GPR.

5.4 Research Objective 2: Geopolitical Risk and ETF Volatility

To achieve Research Objective 2 of investigating the impact of GPR on ETF volatility for ETFs trading in emerging and developed markets, a GARCH-MIDAS model explained in Section 4.3.2 is employed. The main aim is to examine the influence of global and country-specific GPR indices on ETF returns across emerging and developed markets. To achieve the objective of this study, two separate GARCH-MIDAS models are estimated for each ETF, one with global GPR index and the other including corresponding country-specific GPR index. This is consistent with Engle, Ghysels, and Sohn (2013) who designed GARCH-MIDAS model such that the long-run component uses one explanatory variable. In addition, the GARCH-MIDAS models are estimated using an optimal lag structure of 36 months, to capture and examine both the persistent and short-term influence of GPR on ETF volatility. The 36-months lag structure is selected and consistently employed across all estimated empirical models, and this choice is further supported by the SBIC, which is minimised at 36 lags for all models estimated. Therefore, Table 5.22 and 5.23 below illustrate the GARCH-MIDAS results for both emerging and developed market ETFs when the country-specific GPR and global GPR indices are included in the model, with Panel A showing estimates for emerging market ETFs and Panel B showing estimates for developed market ETFs.

Table 5.22: Estimation Results with Country-Specific GPR Index

Panel A: Emerging Markets						
	μ	α	β	θ	ω	m
China	0.0002*	0.1484**	0.8372*	2.5832*	8.7953*	0.9287*
S.A	0.9559*	0.3482*	0.6517*	0.8592*	-1.1732*	0.6792*
India	0.0314**	0.6081*	0.3919*	-5.2099*	10.4297*	-2.0517*
South Korea	0.0765**	0.1547*	0.8421*	-0.6991	4.7049	0.5818*
Mexico	0.1491*	0.5029*	0.4971*	-9.5371*	0.1275*	0.5917
Indonesia	-0.1479*	0.1200*	0.8722*	-0.0254*	-0.1340**	0.1340***
Taiwan	0.6396*	0.2053*	0.3102*	0.1195*	0.5198**	0.3310*
Panel B: Developed Markets						
	μ	α	β	θ	ω	m
U.K	0.0056*	0.8412**	0.0578*	0.8145*	-0.1563*	0.3782*
France	0.0042*	0.4366*	0.5634*	-1.6887*	2.5332*	0.5708*
U.S	0.0203*	0.1638*	0.8354*	-0.2026*	-11.4249*	2.5669*

Switzerland	0.0059*	0.6365*	0.3634*	2.4187*	1.9142	0.7178*
Australia	0.0065	0.7898*	0.2103*	-3.5826	1.6143	0.2634
Germany	0.0161*	0.8324*	0.1676*	1.4967*	0.0017*	0.1154*
Japan	-0.0311*	0.2119*	0.7881*	0.0001*	-3.9060*	0.6284*

Table 5.23: Estimation Results with Global GPR Index

Panel A: Emerging Markets						
	μ	α	β	θ	ω	m
China	0.0011**	0.1651*	0.7882*	0.0160**	2.3652**	0.6342**
S.A	0.6199*	0.3800*	0.6199*	0.8802*	0.5589*	0.4285*
India	0.1284*	0.1239*	0.8543*	-3.8674**	2.5543*	-10.3974*
South Korea	0.6349	0.1571*	0.8428*	-1.8768*	-1.1692	0.3719*
Mexico	1.4058	0.4473*	0.5527*	0.4139	0.5956	0.5136*
Indonesia	-0.9733*	0.1112*	0.8880*	3.1459*	-0.0345	-0.0297
Taiwan	0.4340*	0.3351*	0.4661*	-0.0040*	0.3212**	1.0204*
Panel B: Developed Markets						
	μ	α	β	θ	ω	m
U.K	0.0252*	0.1020*	0.8563*	-0.8960*	0.8502*	0.1023*
France	0.0024*	0.4097*	0.5903*	-0.7186*	0.7887*	0.6794*
U.S	0.0100*	0.0767*	0.9230*	1.7262	0.1830	2.1052*
Switzerland	0.0263	0.2730*	0.7269*	-0.8255*	7.4743*	0.6452*
Australia	0.0049*	0.1406*	0.8594*	0.1835*	-8.2517*	0.0634*
Germany	0.0258	0.3537*	0.6463*	-4.4704	-0.0996	0.9713
Japan	-0.0267*	0.2120*	0.7880*	0.0013*	-1.7270*	0.6322*

Prior to examining the impact of country-specific GPR on the volatility of ETFs in emerging and developed markets, it is important to note the unconditional mean of ETF returns (μ), which indicates whether ETFs delivered positive or negative average daily returns throughout the sample period. As presented in Table 5.22, the unconditional mean of ETF returns in both Panel A and B indicate that, in emerging markets, China, India, South Korea, and Taiwan have positive and significant average daily returns over the period, suggesting that these ETFs have delivered average gains. In contrast, ETFs from S.A, Mexico, and Indonesia have negative and significant average ETF daily returns, indicating losses over the sample period. In developed markets, majority of ETFs have positive and significant average daily returns, with the exception of Japan with negative and significant average daily returns of -0.0311, suggesting that this ETF delivered losses over the sample period. This highlights differences in baseline performance across markets, which may influence how volatility responds to geopolitical shocks.

Once the baseline returns have been determined, the study examines the short-term volatility dynamics that follow GARCH (1,1) specified in Equation (4.28), as captured by the α (ARCH) and β (GARCH) term. The results from Panel A and B in Table 5.22 show the ARCH and GARCH terms that are positive and significant for all ETFs in emerging and developed markets, indicating that volatility is driven by both temporal shocks and past volatility. According to Setiawan et al., (2021), this suggests that current volatility is influenced by both current shocks and past volatility, implying the persistence of volatility and the market sensitivity of external shocks. Notably, most emerging markets ETFs have the sum of ARCH and GARCH terms that is less than 1, suggesting that the effects of any shock on emerging markets are typically temporary but may last for a longer time, given that the sum is close to one. However, India and Mexico have the sum of ARCH and GARCH term that is equal to one, suggesting that volatility shocks are permanent and do not fully revert to a long-run mean. These results are similar to the study by Salisu et al., (2022) who reported that when the sum of ARCH and GARCH terms is less than one there is evidence of high but mean reverting volatility persistence whereas, the study by Bonga (2019) reported that when the sum of ARCH and GARCH term is equal to one there is evidence that volatility shock in the market is persistent implying that the market takes longer to return to normal levels after shocks.

In developed markets, ETFs from U.K, U.S, and Switzerland have the sum of ARCH and GARCH term that is less than one, indicating that even though volatility responds to previous shocks, these ETFs stabilize faster following spikes in volatility. By contrast, ETFs from France, Australia, Germany and Japan have the sum of ARCH and GARCH term that is equal to one, suggesting that volatility shocks are highly persistence and that the market takes long time to stabilize following shocks. This is similar to the study by Setiawan et al., (2021) who reported that volatility shocks decay over time when the sum of ARCH and GARCH term is less than one, volatility is highly persistent, and market takes longer to stabilize when ARCH and GARCH term is equal to one. These results imply that when uncertainty is persistent in developed markets, they may react to geopolitical shocks with prolonged volatility regardless of their depth.

To evaluate how country-specific GPR impact ETF volatility, this is done by examining the slope coefficient (θ) specified in Equation (4.29) from the MIDAS component. The results presented in the above Table 5.22, Panel A shows that θ of ETFs from emerging markets is

positive and significant at 1% level, with values of 2.5832, 0.8592, and 0.1195 for China, S.A, and Taiwan, suggesting that increases in country-specific GPR increases volatility in these markets. However, for India, South Korea, and Mexico the slope θ is negative and statistically significant at 1% significance level, with coefficients of -5.2099, -0.6991, and -9.5371, suggesting that country-specific GPR is associated with reduced volatility rather than heightened instability. Importantly, this suggests a volatility dampening effect rather than a lack of predictive power, which is consistent with the idea that investors in these markets may interpret domestic geopolitical developments with greater confidence. In developed markets, the results shown in Panel B indicates that, ETFs from U.K, Switzerland, Germany and Japan have θ that is positive and significant, with coefficients of 0.8145, 2.4187, 1.4967, and 0.0001, suggesting increased volatility responses to country-specific GPR shocks. Whereas ETFs from France, U.S, and Australia have negative and significant θ at 1% significance level with coefficients of -1.6887, -0.2026, and -3.5826, suggesting that higher country-specific GPR reduces ETF volatility in this market. Overall, these results indicate that the impact of country-specific GPR on ETF volatility is based on the markets, indicating differences in the sensitivity of GPR across both markets. This finding is consistent with the previous studies of Hoque and Zaidi (2020) and Salisu et al., (2022) which reported that in ETFs where θ is negative, the muted volatility response suggests that when geopolitical tensions increase, investors seem more assured and do not respond with panic. Additionally, country-specific GPR does not uniformly increase volatility, particularly in well-diversified markets.

Moreover, the adjusted beta weights explained in Section 4.3.2 further explains the temporal influence of past GPR shocks, showing which lags most strongly impact long-run volatility. The estimates of adjusted beta weights ω in Panel A for China, India, South Korea, Mexico, and Taiwan are positive, significant, and above one suggesting that when country-specific GPR increases, ETF volatility usually rise because of immediate country-specific GPR shocks. While adjusted beta weights for S.A and Indonesia are negative, significant, and above 1, suggesting an inverse relationship between country-specific GPR and ETF volatility. In developed markets, France and Germany have the adjusted beta weights that are above one, positive and significant, suggesting that higher country-specific GPR increases ETF volatility. However, U.K, U.S, and Japan have estimated coefficients that are above one, negative, and significant, this suggests that country-specific GPR decreases ETF volatility. Based on this, it is evident that the impact of country-specific GPR on ETF volatility is heterogenous across

ETFs and markets. As a result, both emerging and developed markets react differently to GPR. In addition, these findings are similar to the studies by Setiawan et al., (2021), Hoque and Zaidi (2020) who reported that higher country-specific GPR increases volatility if the beta weights are positive and reduces volatility if beta weights are negative, implying that the GPR is not uniform.

To complement the country-specific results, the study further examines the impact of global GPR on ETF volatility using the results in Table 5.23. The unconditional mean results in emerging markets showed that most ETFs such as China, S.A, India, and Taiwan have positive and significant average ETF returns of 0.0011, 0.6199, 0.1284, and 0.4340. In contrast, the ETF from Indonesia has negative and significant average return of -0.9733, while ETs from South Korea and Mexico are insignificant. In developed markets, ETFs from U.K, France, Australia, and U.S have positive and significant returns of 0.0252, 0.0024, 0.0049, and 0.0100, while the ETF from Japan is negative and significant and ETFs from Germany and Switzerland are not significant. These results suggest that a positive unconditional mean of returns indicates that ETFs generated average gains, while a negative unconditional mean implies that ETFs experienced average losses.

Regarding volatility persistence under the global GPR, most emerging market ETFs have the sum of ARCH and GARCH term that is less than one when global GPR is included, except for Mexico which has the sum of ARCH and GARCH term equal to one. Suggesting that the impact of shocks on emerging market ETFs is temporal. In contrast, developed market ETFs from U.K, U.S, and Switzerland display mean-reverting volatility shocks. However, ETFs from France, Australia, Germany, and Japan exhibit permanent volatility shocks. These findings are consistent with the studies by Engle et al., (2013) and Lamine and Zribi (2024) who documented that many global GPR have persistent effects on volatility, providing a reason as to why most developed market ETFs exhibit the sum of ARCH and GARCH term that is equal to one.

The estimated slope coefficients further indicate that global GPR increases volatility in most emerging market ETFs, while reducing volatility in most developed market ETFs, except Australia and Japan. This suggests that ETFs from emerging markets are more vulnerable to global shocks, whereas developed market ETFs benefits from diversification and hedging opportunities. This difference highlights a key distinction between country-specific and global

GPR, because global GPR amplifies volatility mainly in emerging markets, while country-specific GPR produces more heterogeneous effects. Lastly, the adjusted beta weights results indicates that, only ETFs from China and India in emerging markets have polynomial weights that are above one and significant, while ETFs from S.A, and Taiwan are positive, less than one and significant. This suggests that recent GPR causes ETF volatility to react more strongly, while older shocks become less significant. This is the same for ETFs in developed markets except for U.S, implying that the effects of global geopolitical shocks on volatility are temporally concentrated.

Overall, the key findings of these results shows that baseline performance differs systematically across developed and emerging markets. This is because emerging market ETFs show heterogeneous unconditional mean returns, whereas developed market ETFs generally exhibit positive and significant unconditional mean returns. This finding demonstrates the structural differences in return generating capacity, which influence how volatility reacts to GPR. The second key finding shows that volatility persistence is present in both markets, but it is stronger in developed markets, indicating that these ETFs absorb shocks more slowly once volatility escalates. The third key finding shows that the impact of country-specific GPR on ETF volatility is asymmetrical across markets, demonstrating that country-specific GPR does not always increase volatility, especially in markets with stronger institutions or greater diversification. The fourth key finding indicates that global GPR destabilizes emerging markets more severely, suggesting that emerging market ETFs are disproportionately vulnerable to global geopolitical shocks. The fifth finding reveals that Global GPR lowers volatility in developed markets while raising it in emerging markets, showing a key contrast that while global GPR may stabilize developed market ETFs, it increases risk in emerging markets.

In conclusion, these findings show evidence that baseline performance, sensitivity of GPR, and persistence of volatility differs across emerging and developed markets. Emerging market ETFs show greater sensitivity to global geopolitical shocks, while ETFs from developed markets show greater volatility persistence once shocks occur. The country-specific GPR has asymmetric and market dependent effects, showing that domestic political risk does not always increase volatility and may, in certain situations, reduce market instability. These findings combined show that global GPR play a more destabilizing role in emerging markets, whereas country-specific GPR generate heterogeneous volatility responses.

5.5 Research Objective 3: Geopolitical Risk and ETF liquidity

This section presents and interprets the results obtained from the ARDL and NARDL models, explained in Section 4.3.3. For the linear ARDL models, the models for ETFs were estimated separately for both emerging and developed markets using the global and country-specific GPR indices. For each ETF, the Eviews statistical program assessed more than 8 500 alternative model specifications, from which the optimal lag structures such as ARDL (2,0,1,0) were selected. The full results from which the optimal linear NARDL specifications for ETFs in emerging and developed markets are presented and reported in Appendix A. These models were chosen by Eviews because they minimize the SBIC. Similarly, for the NARDL models, the Eviews statistical program assessed over 9 120 model specifications for each ETF in developed and emerging markets. As with the ARDL models, SBIC minimization was used to choose the NARDL models. Based on a comparison of the information criteria, SBIC favours the ARDL models over the NARDL models for ETFs in both developed and emerging markets, because the linear specification is more parsimonious. However, both the ARDL and NARDL models were estimated to evaluate the potential asymmetric effects of GPR on ETF liquidity as well as the presence of long-run relationships.

The Bound's testing procedure is employed to examine the existence of long-run relationships in both ARDL and NARDL models, and the results are presented in Table 5.24 and 5.25. The results indicate that for both emerging and developed market ETFs, the F-statistics for all ETFs is statistically significant 5% level and is greater than the lower and upper bound critical values. This implies that the null hypothesis that there is no long-run cointegration amongst variables is rejected in favour of the alternative hypothesis that long-run cointegration is present. Therefore, the results indicate that long-run cointegration is present between GPR, TNA, and ETF age. Given that there is evidence of long-run cointegration, the following step is to estimate and interpret long-run coefficients. However, prior to interpreting these coefficients, Wald tests are conducted to assess whether the effects of GPR are symmetric or asymmetric in the long run. The Wald test results shown in Appendix B and C for ETFs in developed and emerging markets, indicate that the probability values of F-statistics are below the significant values for all ETFs. This suggests that the short-run and long-run positive and negative shocks are significant, implying that ETF liquidity responds asymmetrically.

Table 5.24: ARDL Bounds Test Results for Emerging and Developed Markets

Global GPR							
Emerging Markets				Developed Markets			
Country	F-Stat	Lower Bound	Upper Bound	Country	F-Stat	Lower Bound	Upper Bound
China	6.4128**	2.790	3.670	U.K	7.7134**	2.790	3.670
S. A	4.8651**	2.370	3.200	France	5.5326**	2.790	3.670
India	9.8544**	2.790	3.670	U.S	8.3771**	2.790	3.670
South Korea	5.2412**	2.790	3.670	Japan	7.5017**	2.790	3.670
Mexico	5.2377**	2.790	3.670	Australia	5.8109**	2.790	3.670
Indonesia	6.7196**	2.790	3.670	Switzerland	11.3406**	2.790	3.670
Taiwan	28.0840**	2.790	3.670	Germany	25.8945**	2.790	3.670
Country-Specific GPR							
Emerging Markets				Developed Markets			
Country	F-Stat	Lower Bound	Upper Bound	Country	F-Stat	Lower Bound	Upper Bound
China	6.0674**	2.790	3.670**	U.K	7.0915**	2.790	3.670
S.A	4.263**	3.200	3.510**	France	4.5744**	2.790	3.670
India	9.7266**	3.650	4.660	U.S	6..3691**	2.790	3.670
South Korea	5.2107**	2.790	3.670**	Japan	7.0554**	2.790	3.670
Mexico	6.6397**	2.790	3.670**	Australia	4.8448**	2.790	3.670
Indonesia	6.2052**	2.790	3.670**	Switzerland	10.7991**	2.790	3.670
Taiwan	25.6679**	2.790	3.670**	Germany	25.7010**	2.790	3.670

Notes:

1. ** represents the 5% level of significance

Table 5.25: NARDL Bounds Test Results for Emerging and Developed Markets

Global GPR							
Emerging Markets				Developed Markets			
Country	F-Stat	Lower Bound	Upper Bound	Country	F-Stat	Lower Bound	Upper Bound
China	11.1369**	2.790	3.670	U.K	6.5543**	2.790	3.670
S.A	5.3176**	2.790	3.200	France	4.0031**	2.790	3.670
India	6.4972**	2.790	3.670	U.S	9.1302**	2.790	3.670
South Korea	4.1894**	2.790	3.670	Japan	11.5034**	2.790	3.670
Mexico	9.1374**	2.790	3.670	Australia	9.1836**	2.790	3.670
Indonesia	6.3179**	2.790	3.670	Switzerland	4.1694**	2.790	3.670
Taiwan	5.0023**	2.790	3.670	Germany	6.3479**	2.790	3.670
Country-Specific GPR							
Emerging Markets				Developed Markets			
Country	F-Stat	Lower Bound	Upper Bound	Country	F-Stat	Lower Bound	Upper Bound
China	3.9062**	2.790	3.670	U.K	6.0461**	2.790	3.670
S.A	4.4713**	3.200	3.510	France	3.8901**	2.790	3.670

India	7.2203**	3.650	4.660	U.S	4.1943**	2.790	3.670
South Korea	4.6179**	2.790	3.670	Japan	9.0019**	2.790	3.670
Mexico	6.8846**	2.790	3.670	Australia	6.7903**	2.790	3.670
Indonesia	9.1374**	2.790	3.670	Switzerland	9.1100**	2.790	3.670
Taiwan	0.3316**	2.790	3.670	Germany	9.7546**	2.790	3.670

Notes:

1. ** represents the 5% level of significance

Accordingly, although the SBIC favours the ARDL models, the existence of long-run asymmetry justifies focusing the analysis on the long-run coefficients obtained from the NARDL models, as these models provide deeper insights of how positive and negative changes in GPR affect ETF liquidity in developed and emerging markets. The results of long-run coefficients are presented in Table 5.26 and 5.27, where Table 5.26 show the results for models incorporating global GPR, while Table 5.27 presents the results for models incorporating country-specific GPR.

Table 5.26: Long-Run Coefficients Results from the NARDL Model with Global GPR

Panel A: Emerging Market ETFs							
	GPR_{t-j}^+	GPR_{t-j}^-	TNA_{ij}^+	TNA_{ij}^-	Age_{ij}^+	Age_{ij}^-	Constant
China	0.9752**	0.8211***	-0.1647	-0.6908***	0.6827	-0.0968	-0.5742*
S.A	-0.1424	-0.2243**	-0.0429	0.3617*	0.0020	0.3500*	0.4157*
India	-0.4165	-0.0186*	0.4503	-1.2171	0.4200	-1.4589	-0.4599*
South Korea	-0.1105	0.2158*	-0.4689***	-0.3717*	0.0500	0.0500	0.2400*
Mexico	-0.3238	-0.9088*	-0.8467*	0.7109*	0.8439	0.5697*	0.4424*
Indonesia	0.6791***	0.9476***	-0.0523*	-0.2104*	0.2146	0.8130	-0.4794*
Taiwan	0.1608	0.1761	-0.3789*	-0.4334*	-0.2408	0.6315*	0.6904*
Panel B: Developed Market ETFs							
	GPR_{t-j}^+	GPR_{t-j}^-	TNA_{ij}^+	TNA_{ij}^-	Age_{ij}^+	Age_{ij}^-	Constant
U.K	0.5395**	0.3513	-0.8037***	0.3610	0.6583	0.4555	0.5226*
France	0.0943	-0.0588	-0.1451	0.2117	-0.0793	0.0359	0.2396*
U.S	0.4329***	-0.1034	-0.0419***	0.8886	-0.3198	0.6133	-0.5715*
Japan	0.3524**	0.4544**	-0.1044	-0.3394*	-0.4518*	0.6179	-0.2856*
Australia	-0.4087**	0.0480	-0.8470*	-0.7191*	0.3158**	-0.4268***	0.3675*
Switzerland	-0.1666*	-1.3047	0.8633	2.0502	0.6499*	-0.6149	0.6467*
Germany	-0.3920	-0.4537***	0.1753*	-0.1760*	0.2995*	0.1870	0.7470*

Notes:

1. *, **, *** represent statistical significance at a 1%, 5%, and 10% level of significance, respectively.

In Table 5.26, ETFs from China and Indonesia show that both increases and decreases in the global GPR exhibit positive effects on ETF liquidity with coefficients of 0.9752 and 0.6791,

respectively. This suggest that ETF liquidity in these markets increases even though there is an increase or decrease in global GPR, suggesting that increased geopolitical uncertainty may encourage trading as investors seek to rebalance their portfolios or engage in speculative trading. This implies that during times of global uncertainty, ETFs from China and Indonesia might serve as liquidity enhancing tools, benefitting from higher demand rather than experiencing a withdrawal of liquidity. Among emerging markets, China is more sensitive to global GPR, because of its greater response to liquidity. In contrast, ETFs from S.A, India, and Mexico show that decreases in GPR exhibit negative effects on ETF liquidity, with coefficients of -0.2243, -0.0186, and -0.9088. This implies that lower trading activity in these ETFs is linked to times of decreasing global GPR. When global conditions stabilize, investor capital may be reallocated from emerging market ETFs to alternative assets, which could result into reduced liquidity.

In developed markets, the ETF from Japan exhibit positive effects to both increases and decreases in global GPR, implying a consistent strong liquidity environment that is resistant to shifts in the global geopolitical shocks. Similarly, ETFs from the U.K and U.S show that increases in GPR exhibit positive effects with coefficients of 0.5395 and 0.4329, suggesting that increases in GPR lead to a rising demand for ETFs in these markets, and are used as liquid vehicles for risk management. Among developed market ETFs, Japan is more sensitive to global GPR due to consistent liquidity response across positive and negative shocks. In addition, emerging markets are more sensitive to global GPR compared to developed markets, as liquidity responses are larger.

The long-run NARDL model show that TNA has a negative effect on ETF liquidity across emerging and developed markets. In emerging markets, ETFs from South Korea, Indonesia, and Taiwan show negative effect on ETF liquidity when there is an increase and a decrease in TNA, suggesting that changes in fund size tend to decrease trading activity. In contrast, ETFs from China and S.A exhibit positive and negative effects on ETF liquidity when TNA decreases, suggesting that decreases in fund size may improve liquidity. In developed markets, the ETF from Australia exhibit negative effect to both increases and decreases in TNA. Similarly, the ETFs from U.K and U.S exhibit negative liquidity responses to increases in TNA, with coefficients of -0.8037 and -0.0419, indicating that if there is an expansion on ETF size, it may lead to reduction in ETF liquidity.

The age of ETF affects liquidity differently across markets. In emerging markets, the ETFs from S.A, Mexico, and Taiwan exhibit positive liquidity responses to decreases in ETF age, with coefficients of 0.3500, 0.0597, and 0.6315, respectively. This imply that newly established ETFs may draw more trading activity. In developed markets, the ETFs from Switzerland and Germany show positive liquidity effects when there is an increase in ETF age. In contrast, the Australian ETF exhibit negative liquidity response when there is a decrease in the age of ETF. This implies that lower investor confidence brought on by shorter maturity may dampen trading activity.

Table 5.27: Long-Run Coefficients Results from the NARDL Model with Country-Specific GPR

Panel A: Emerging Market ETFs							
	GPR_{t-j}^+	GPR_{t-j}^-	$TNA_{i,j}^+$	$TNA_{i,j}^-$	$Age_{i,j}^+$	$Age_{i,j}^-$	Constant
China	0.4355***	0.4245	-0.8048**	-0.0141*	-0.0057	0.6692*	-0.5547*
S.A	-0.0143	2.2288**	-0.5520	-0.1672	-2.5870	2.1061**	1.2796***
India	0.0454	0.2562	0.3601	0.1523	-3.4563	0.3645	-0.5827*
South Korea	0.0205	0.0215	-0.3669*	-0.3690*	0.0774	0.6950	-0.2266*
Mexico	0.1061*	-0.2455*	-0.7886*	0.6817*	0.1032**	0.8963	-0.4356*
Indonesia	0.0136	-0.5027*	-0.0543	0.1248***	0.2695	0.6670	-0.3794*
Taiwan	0.0453***	0.0280	-0.4583*	-0.4155*	-0.4628*	-0.5396*	-0.6991*
Panel B: Developed Market ETFs							
	GPR_{t-j}^+	GPR_{t-j}^-	$TNA_{i,j}^+$	$TNA_{i,j}^-$	$Age_{i,j}^+$	$Age_{i,j}^-$	Constant
U.K	-0.0828***	-0.0930**	-0.7600***	-0.2077	0.6513	-0.4189	-0.4922*
France	0.4659	-0.3158	0.2236	-0.0222	-0.3982***	0.3649	0.2123*
U.S	0.4742***	-0.0270	-1.0271***	0.8310	-0.3181	0.1136*	0.5751*
Japan	0.0837	0.1125	-0.0670	-0.2449**	-0.3849**	-0.6603*	-0.2676*
Australia	0.0185	-0.6896*	-0.4971*	-1.3595*	0.0933	0.2345	-0.4188*
Switzerland	-0.8665*	-0.3734*	0.6483*	0.0415*	-0.3786*	-0.8867	0.7063*
Germany	-0.1145*	-0.1250	0.0708	-0.0084	0.0558	0.9310	-0.7814*

Table 5.27 present the results of long-run coefficients from NARDL models for models incorporating the country-specific GPR index. Among emerging market ETFs, those from China and Taiwan exhibit positive liquidity responses to increases in country-specific GPR. This suggests that rising country-specific GPR lead to increases in trading activity in these markets. Whereas the ETF from Mexico exhibit both positive and negative liquidity responses to both increases and decreases in country-specific GPR, suggesting an unstable market. In addition, the ETF from Indonesia exhibits negative liquidity responses to decreases in country-specific GPR, with a coefficient of -0.5027, implying that lowering domestic risk causes

trading activity to decline as investors turn their focus away from ETFs. In developed markets, the ETFs from U.K and Switzerland show that both increases and decreases in country-specific GPR exhibit negative effect on ETF liquidity, indicating that domestic geopolitical developments in these markets continue to dampen trading activity. By contrast, the ETF from U.K show that increases to country-specific GPR exhibit positive effects on ETF liquidity, indicating that this ETF can be used as liquid instruments during times of increased domestic uncertainty. These findings show that, among emerging market ETFs, the ETF from Mexico is the most sensitive ETF to country-specific GPR, because of its response to increases and decreases in country-specific GPR. While in developed markets, the ETF from the U.S is the most sensitive, because when domestic GPR increases, liquidity rises. Overall, there is a greater sensitivity to domestic geopolitical conditions because emerging market ETFs show greater and more varied liquidity responses compared to ETFs from developed markets.

The results from the long-run NARDL indicated that the impact of TNA on ETF liquidity is asymmetric. For ETFs from China, South Korea, and Taiwan, both increases and decreases in TNA exhibit negative long-run effects to liquidity, indicating that growth in fund size may reduce trading efficiency because of decreased marginal trading activity as ETFs become larger. In contrast, ETFs from Mexico and Indonesia show that decreases in TNA exhibit positive significant effect on ETF liquidity with coefficients of 0.6817 and 0.1248, respectively. This suggests that the reductions in fund size may improve liquidity by encouraging trading flexibility.

In developed markets, the ETF from Switzerland show positive liquidity responses to both increases and decreases in TNA, demonstrating that strong institutional support is reflected in liquidity, which is stable regardless of changes in fund size. In contrast, the ETF from Australia exhibit negative liquidity effects to both increases and decreases in TNA, indicating that the fluctuations in fund size consistently hinder liquidity. Additionally, the ETF from U.K and U.S exhibit negative liquidity effects linked to increases in TNA, with coefficients of -0.7600 and -1.0271, suggesting that if ETF size is increased beyond a certain point, the declining marginal trading intensity may cause liquidity to be reduced. Overall, these results suggest that the impact of TNA on ETF liquidity is stronger in emerging markets, while the effect of liquidity in developed markets remain relatively stable.

The results from the long-run NARDL indicate that the age of ETF affects liquidity asymmetrically across ETFs. For emerging market ETFs from China and S.A, decreases in ETF age exhibit positive effects on liquidity with coefficients of 0.6692 and 2.1061, suggesting that newly established ETFs may attract higher trading activity because of increased investor interest. In contrast, the ETF from Taiwan exhibit negative liquidity effects on decreases in ETF age, suggesting that the reduced market maturity may weaken trading activity. In developed markets, the ETF from Japan exhibit negative liquidity effects to both increases and decreases on ETF age, suggesting that changes in fund maturity continuously lower trading activity, perhaps as a result of stable investor preferences. Similarly, ETFs from France and Switzerland exhibit negative liquidity effects on increases to ETF age, with coefficients of -0.3982 and -0.3786, respectively. This implies that trading activity may decrease as ETFs becomes older as there will be less need for portfolio adjustments.

Table 5.28: Short-Run Coefficients Results from the NARDL Model with Global GPR

Panel A: Emerging Market ETFs							
	ΔGPR_{t-j}^+	ΔGPR_{t-j}^-	ΔTNA_{ij}^+	ΔTNA_{ij}^-	ΔAge_{ij}^+	ΔAge_{ij}^-	ECT_{t-1}
China	-0.1984	-0.5148	-0.5809*	-0.6178*	-0.2230*	-0.3253*	-0.5742*
S.A	0.4560	0.7800*	-3.2242*	-4.7920*	-0.0056*	0.9600	-0.3353*
India	1.9678*	1.7796**	2.5689	-1.5046	-2.7148*	-4.4256*	-0.4598*
South Korea	-0.1105	-0.1244*	-0.3882*	-0.3717*	0.0500	0.6489*	-0.2400*
Mexico	-0.1755	-0.6320*	0.6179	0.7166	0.4423*	0.2254*	-0.4424*
Indonesia	0.2379	0.6103	-0.0511	-0.6731	0.6300	0.6314	-0.4794*
Taiwan	-0.0381	-0.4374*	-0.0380*	-0.5649	-0.2922*	-0.6174*	-0.6904*
Panel B: Developed Market ETFs							
	ΔGPR_{t-j}^+	ΔGPR_{t-j}^-	ΔTNA_{ij}^+	ΔTNA_{ij}^-	ΔAge_{ij}^+	ΔAge_{ij}^-	ECT_{t-1}
U.K	0.5687	-0.1990*	1.2043**	1.9247***	0.8888*	0.8226*	-0.5248*
France	0.0132	0.0918*	0.7340	0.6127**	0.6257	0.1252	-0.2396*
U.S	0.6701	1.4140**	0.4380	0.9837	1.3694*	0.1436	-0.2057*
Japan	0.4971	-0.1149*	0.8610***	-0.2383	1.6981*	-1.9703*	-0.5607*
Australia	-0.1588**	0.3786	0.0480	0.0969	0.8565	-1.4512*	-0.5174*
Switzerland	0.6626	-0.7020*	0.1169*	0.2667**	0.8188*	-0.7013*	-0.6654*
Germany	0.3524**	0.4544**	-0.8467*	0.7109*	0.8439	0.5697*	-0.5011*

The above Table 5.28 show the results of short-run coefficients from the NARDL model, incorporating global GPR. In emerging markets, the ETF from China exhibits significant positive effect to ETF liquidity responses on both increases and decreases in global GPR, suggesting that short-term trading activity increases during times of geopolitical uncertainty. This suggest that the Chinese ETF is actively utilized for quick risk adjustment and portfolio

rebalancing. In contrast, ETFs from South Korea, Mexico, and Taiwan exhibit negative liquidity responses when there are decreases in global GPR, with coefficients of -0.1244, -0.6320, and -0.4374, suggesting that short-run trading activity decreases when geopolitical tensions decrease. In addition, the Mexican ETF is the most sensitive to global GPR in the short run because of its larger liquidity response. In developed markets, the ETF from Germany exhibit positive effects on ETF liquidity to both increases and decreases in global GPR, indicating a strong short-term liquidity structure that effectively absorb geopolitical shocks. While ETFs from the U.K, France, and Japan exhibit negative liquidity responses to decreases in ETF liquidity. Notably, the ETF from U.S exhibit positive significant effect to decreases in changes in global GPR, with coefficients of 1.4140, indicating increased short-run trading when global conditions stabilize. Among ETFs from developed markets, the U.S ETF show greater sensitivity to global GPR.

The results of short-run NARDL indicate that TNA affects ETF liquidity asymmetrically across ETFs. In emerging markets, ETFs from China, S.A, and South Korea exhibit negative liquidity responses to both increases and decreases in TNA, indicating that the fluctuations in fund size tend to disturb trading activity. The ETF from Taiwan also exhibit negative liquidity responses to increases in TNA, with a coefficient of -0.0380, suggesting that expansions in the short-term may decrease trading efficiency. In contrast, developed market ETFs from U.K, Switzerland exhibit positive liquidity responses to both increases and decreases in TNA, with coefficients of 0.8610 and 0.6127, implying that trading activity in these markets is improved by short-term changes in ETF size. In emerging markets, majority of ETFs from emerging markets exhibit negative liquidity responses to both increases and decreases in ETF age, suggesting that changes in fund maturity are linked to reduced trading activity. In contrast, majority of ETFs from developed markets exhibit positive liquidity responses to both decreases and decreases in ETF age, indicating that when ETFs mature, liquidity tends to improve.

Table 5.29: Short-Run Coefficients Results from the NARDL Model with Country-Specific GPR

Panel A: Emerging Market ETFs							
	ΔGPR_{t-j}^+	ΔGPR_{t-j}^-	ΔTNA_{ij}^+	ΔTNA_{ij}^-	ΔAge_{ij}^+	ΔAge_{ij}^-	ECT_{t-1}
China	0.6520	-0.6179**	-0.6553*	-0.8992	-0.6745*	0.5099*	-0.5547*
S.A	0.0021	-0.0014	0.0051	0.0598	0.3289	0.0058	-0.3320*
India	1.5645	0.5647	-2.5648	-1.7986	-8.6648	-4.1991*	-0.5025*
South Korea	-0.0116	-0.1168*	-0.5952*	-0.6788*	0.5989	-0.5963	-0.2266*

Mexico	-0.6149	-0.1179*	0.3691**	0.0688**	0.4536*	0.0860*	-0.4356*
Indonesia	0.4365	-0.4412*	-0.6025*	0.6319	0.9416	0.8863	-0.3794*
Taiwan	0.3916	-0.1373*	0.1948*	0.6947*	-0.5413*	-0.3013*	-0.6991*
Panel B: Developed Market ETFs							
	ΔGPR_{t-j}^+	ΔGPR_{t-j}^-	$\Delta TNA_{t,j}^+$	$\Delta TNA_{t,j}^-$	$\Delta Age_{t,j}^+$	$\Delta Age_{t,j}^-$	ECT_{t-1}
U.K	-0.8776	-0.0132	0.9671***	0.2284**	0.2220	-0.6147*	-0.4922*
France	-0.3994**	0.5412*	0.9399	0.2154***	0.5147	-0.0695*	-0.5522*
U.S	-0.5980	-0.3181	0.2547	-0.1317	0.0344	1.4016	-0.5130*
Japan	0.7832	0.6565*	0.1604	1.7104*	0.4459	-1.8420*	-0.7975*
Australia	0.6501	-0.4516*	-0.2622**	-0.7121	0.0078***	-0.7559***	-0.8790*
Switzerland	0.2638	-0.4983*	-0.2430*	-0.7932**	0.4923	0.9080	-0.7078*
Germany	0.7896	-0.1034*	0.0696	0.4471	0.1728*	0.1256*	-0.7813*

In Table 5.29, the results indicate that emerging market ETFs from China, South Korea, Mexico, Indonesia, and Taiwan exhibits negative liquidity responses to decreases in country-specific GPR, with coefficients of -0.6179, -0.1168, -0.1179, -0.4412 and -0.1373. This indicates that when domestic geopolitical tension decreases, short-run trading activity decreases. In addition, China and Indonesia show greater sensitivity to changes in country-specific GPR. In developed markets, similar patterns are observed in liquidity following decreases in country-specific GPR for ETFs in Australia, Switzerland, and Germany, with coefficients of -0.4516, -0.4983, and -0.1034. However, ETFs from France and Japan show positive liquidity responses to decreases in country-specific GPR. These results indicates that ETFs from emerging markets are more sensitive to country-specific GPR compared to developed markets. In both developed and emerging markets, the ECT in the short-run NARDL models is negative and statistically significant for models incorporating both global and country-specific GPR, with coefficients ranging between negative one and zero. This indicates the presence of a stable long-run equilibrium and a consistent adjustment towards it following short-run shocks. The size of the ECT indicates a quick speed of adjustment, suggesting that ETF markets efficiently return to their long-run equilibrium levels and that liquidity shocks brought on by GPR are not persistent.

Overall, the key findings from these results indicate that the ETFs from emerging markets are more exposed to both global and country-specific GPR, whereas ETFs from developed markets show more muted liquidity responses. Furthermore, the global GPR dominates in explaining the short-run liquidity effects, especially during periods of decreasing uncertainty, when trading activity adjusts quickly. In contrast, country-specific GPR play a significant role in

shaping long-run liquidity adjustments in emerging markets, where domestic political developments have continuous effects on the behaviour of investors. In addition, the observed asymmetric and stronger liquidity responses in emerging markets indicate that GPR serves as an important channel of liquidity instability in these markets. By comparison, developed markets ETFs tend to benefit from diversification and greater investor confidence, which help to ease both short-run and long-run liquidity disruptions caused by GPR. This pattern is consistent with the flight-to-safety theory, where investors reallocate capital away from riskier emerging markets toward safer developed markets during periods of heightened geopolitical uncertainty, leading to reduced liquidity in emerging markets.

5.6 Chapter Summary

Chapter 5 discuss and presents the results obtained from different models estimated using different methodologies. Firstly, the results from the Markov-Regime Switching model show that ETFs from emerging markets exhibit stronger resilience to both global and country-specific GPR, whereas the ETFs from developed markets are more prone to country-specific GPR. Additionally, global GPR has limited impact on ETF returns, whereas country-specific GPR exhibit stronger and persistence effects, especially in developed markets. Secondly, the results from GARCH-MIDAS models show that sensitivity to GPR and volatility persistence is different across emerging and developed market ETFs. ETFs from emerging markets are more sensitive to global geopolitical shocks, suggesting increased exposure to international uncertainty, while ETFs from developed markets show higher volatility persistence when shocks occur, indicating slower adjustment to increased risk. Additionally, the country-specific GPR exhibit asymmetric effects, indicating that domestic risks do not uniformly increase volatility, and may in some cases decrease market instability. Lastly, the results from the NARDL models indicates that emerging market ETFs are more exposed to both global and country-specific GPR in terms of liquidity, whereas developed market ETFs exhibit muted liquidity responses. The global GPR dominates short-run liquidity dynamics during periods of decreasing uncertainty when trading activity adjusts quickly. In contrast, country-specific GPR is more relevant for long-run liquidity adjustments in emerging markets, where domestic GPR exhibit persistent effects on investor behaviour. In conclusion, the results from different methodologies employed in this study show structural differences between emerging and developed market ETFs and their response to GPR. The global GPR primarily increases short-term instability in emerging markets, while country-specific GPR show market-specific effects, especially in developed markets.

CHAPTER 6: CONCLUSION AND RECOMMENDATIONS

6.1 Introduction

ETFs have revolutionized global financial markets by providing diversified exposure to different asset classes at relatively low costs. Globally, ETFs have experienced substantial growth in recent years. The expansion of the ETF market is driven by enhanced market liquidity and greater trading flexibility. As a result, these advantages have made ETFs a preferred investment vehicle globally, contributing to various dimensions of market quality. Additionally, market quality is greatly influenced by GPR, which significantly affect returns, volatility, and liquidity in developed and emerging markets and often results in heightened uncertainty and market disruptions.

Overlooking the relationship between GPR and ETF's resilience and capacity as effective investments in volatile markets may lead to underestimating risks and opportunities associated with geopolitical events. This concern becomes even more pressing given the mounting influence of ETFs in global financial markets and their usage in emerging markets. GPR often destabilises economic stability, alters investor sentiment, and provokes capital withdrawals, which can significantly affect ETF stability. Given that ETFs are frequently linked to a diverse set of underlying asset classes, any shock to their structure or performance can be transmitted across markets, amplifying volatility and posing systemic risks to broader financial systems. Therefore, this study aims to address this gap in the literature by comparing the effects of GPR on ETFs from emerging and developed markets. Specifically, the study will examine the influence of GPR on market quality of ETFs in developed and emerging markets.

Against this background, the study aims to achieve three research objectives namely:

- To examine the influence of GPRs on the returns of ETFs in developed and emerging markets.
- To investigate the impact of GPR on ETF volatility in developed and emerging markets.
- To explore the effect of GPRs on the liquidity of ETFs in developed and emerging markets

In line with the above research objectives, this study employs three distinct methodologies, with the results discussed in the subsequent chapter. In addition, the following section presents a summary of the main findings and addresses the research question posed in this study.

6.2 Summary of Main Findings

6.2.1 Research Question One- To Examine the influence of GPRs on the Returns of ETFs in Developed and Emerging Markets?

The results of the estimated Markov Regime-Switching models indicated that, emerging market ETFs are more sensitive to both local and global GPR, often exhibiting shorter bull durations and higher volatility. In contrast, developed market ETFs tend to maintain longer bull regimes and demonstrate greater resilience to geopolitical shocks. When models incorporating the country-specific GPR index are estimated, emerging market ETFs shift toward bull regimes with lower volatility and longer durations. The results show that global GPR have a stronger and more widespread negative effect on emerging markets, while developed markets exhibit greater resilience. Emerging market ETFs tend to transition to bear regimes under global GPR, whereas developed market ETFs often transition to bull regimes. However, on country-specific GPR indices, emerging market ETFs exhibit improved stability, suggesting that domestic GPR are relatively less disruptive. In contrast, developed market ETFs show little difference between domestic and global GPR, reflecting their capacity to absorb and diversify geopolitical shocks. Overall, these results show a distinct difference between emerging and developed markets, because emerging markets are extremely sensitive to global shocks, while developed markets exhibit immunity to both country-specific and global geopolitical shocks.

6.2.2 Research Question Two- To Investigate The impact of GPR on ETF volatility in Developed and Emerging Markets?

The results from the estimated GARCH-MIDAS model for ETFs in developed and emerging markets, using the global and country-specific GPR index as explanatory variables, indicate strong persistence of volatility and market sensitivity to external shocks. The results indicated that GPR significantly influence ETF volatility. However, the effect differs between emerging and developed markets. ETFs in emerging markets are more vulnerable to geopolitical shocks, whereas ETFs in developed markets demonstrate that they can absorb shocks more effectively. Additionally, the empirical results confirm that GPR is a significant driver of ETF volatility in both emerging and developed markets. Overall, these results effectively address the research objective by showing that, although GPR has a substantial impact on ET volatility, its destabilizing effect is much more noticeable in emerging than developed markets. This demonstrate how GPR is translated into financial volatility is significantly influenced by market structure.

6.2.3 Research Question Three- How Does GPR Affect the Liquidity of ETFs in Emerging and Developed Markets?

The results from the NARDL models for ETFs in both developed and emerging markets indicate that ETFs from emerging markets are more exposed to both global and country-specific GPR, while ETFs from developed markets show muted liquidity responses. Moreover, the global GPR is better at explaining the short-run liquidity effects, particularly during periods of declining uncertainty. In contrast, country-specific GPR play an important role in shaping the long-run liquidity adjustments in emerging markets, where domestic political developments have continuous effects on the behaviour of investors. Overall, these results suggest that developed market ETFs tend to benefit from diversification, which helps to ease both short-run and long-run liquidity disruptions caused by GPR.

6.3 Implications of the Findings

The Efficient Market Hypothesis suggest that markets do react to GPR, but they do not always respond instantaneously or symmetrically. The more persistence and stronger response of emerging market ETFs to global GPR, show that although geopolitical information is eventually priced, the adjustment process is uneven. While the comparatively muted reaction to GPR in developed markets is consistent with higher information efficiency, where stronger institutions allow shocks to be absorbed and reduced more quickly. In contrast, more persistent and greater regime shifts, and volatility found in emerging markets indicate incomplete or delayed adjustment to geopolitical information, indicating deviations from EMH, particularly weak- form EMH.

Furthermore, the Modern Portfolio Theory, diversification is used to minimize risk by putting together assets with low correlations. The results of the study, however, indicate that during times of increased geopolitical tensions, global GPR function as a common systematic factor that reduces the diversification of owning emerging market ETFs. Many emerging market ETFs have a tendency to move together into riskier regimes when global GPR intensifies, which increases return co-movements and reduces the effectiveness of diversification across ETFs. In contrast, ETFs from developed markets show stronger resistance during these times indicating that they continue to offer hedging and diversification advantages that MPT predicts even in situations of high geopolitical uncertainty. As such these findings offer valuable insights to investors and policy makers, and scholars.

- Investors should re-evaluate their diversification strategies under MPT assumptions because during times of increased global GPR, the diversification advantages of investing in emerging market ETFs are diminished. Additionally, investors should not assume that holding ETFs from different countries will automatically spread-out risk, they may need to take proactive adjustments or take precautions.
- Policy makers should ensure market stability and liquidity because emerging markets are highly volatile and rapidly lose liquidity during geopolitical shocks. Therefore, policy makers should establish backup liquidity measures. These actions will help in maintaining market order and lessen disturbances brought on by delays in the way new information is reflected in prices. In addition, given the stronger liquidity decrease and volatility in emerging markets during periods of increased GPR, investors may consider reducing exposure to emerging market ETFs and increasing allocation to more stable developed market ETFs.
- Scholars will gain valuable knowledge from this study, by understanding that GPR is not just a background macroeconomic factor, but rather a significant and systematic driver of ETF behaviour with distinct effects on returns, volatility, and liquidity.

6.4 Recommendations for Future Studies

The study had few limitations, mainly arising from ETFs having different inception dates, as the sample of ETFs focused primarily on ETFs that track broad market indices and trade in their respective home countries. As a result, the sample period of ETFs begins at the ETFs individual inception date, since they were randomly selected to avoid selection bias. Following these research limitations, future studies are encouraged to:

- Consider ETFs with the same inception dates and trade within a single market to improve sample comparability and alignment.
- Secondly, future research should expand the measurement of GPR beyond the measures used in this study such as global and country-specific GPR, this can be done by incorporating alternative indices such as geopolitical threat index and geopolitical act index.
- Thirdly, since the study employed Markov Regime-Switching empirical model to examine the effect of GPR on ETF returns under bull and bear market conditions, future research could extend this empirical model by combining Markov Regime-Switching model with time-varying parameter models to more accurately map regime transitions

and quantify state-dependent sensitivities.

- Since this study employed GARCH-MIDAS model to investigate the GPR effect on ETF volatility, the model only included GPR as the explanatory variable. However, future research could extend this approach by including additional control variables. This would follow the study by Salisu et al., (2022), who estimated empirical models both with and without control variables, using GPR as the main explanatory variable and compared the results.
- Lastly, since the study looked at the asymmetric effects of GPR on ETF liquidity, future research could investigate whether these asymmetric GPR effects also apply to other asset classes such as bonds.

6.5 Conclusion

By using the Markov Regime-Switching Model, the GARCH-MIDAS model, and the NARDL models, this study aimed to examine the effect of GPR on ETF returns, volatility, and liquidity in emerging and developed markets. The study used ETFs that track broad-based market indices, with seven trading in emerging and seven trading in developed markets. The results indicated that GPR has a strong and systematic effect on ETF returns, volatility, and liquidity, with distinct differences between emerging and developed markets. As a result, emerging market ETFs exhibit greater volatility, stronger liquidity disruptions, and more frequent transitions into bear regimes due to their increased sensitivity to geopolitical shocks. In contrast, during times of increased GPR, developed market ETFs exhibit greater resilience, with more stable return regimes, lower volatility responses, and more stable liquidity conditions. In conclusion, these results confirm that the financial impact of GPR is significantly more persistent and pronounced in emerging than developed markets. These Findings also contribute to the literature by providing a different econometric models that captures regime shifts, volatility dynamics, and asymmetric effects of GPR across different markets.

APPENDICES

Appendix A: Optimal Lag Length Selection for Emerging and Developed Market ETFs

Emerging Market ETFs			Developed Market ETFs		
ETF	Type of GPR	Selected Lags	ETF	Type of GPR	Selected Lags
China	GGPR	NARDL (2.0.0.0.0.2)	Switzerland	GGPR	NARDL (2.0.2.1.0.2)
	CGPR	NARDL (2.0.1.0.2.0)		CGPR	NARDL (1.2.0.2.2.2)
S.A	GGPR	NARDL (2.0.1.0.1.2)	Australia	GGPR	NARDL (2.1.2.0.1.2)
	CGPR	NARDL (2.0.2.0.2.2)		CGPR	NARDL (2.0.1.2.0.2)
India	GGPR	NARDL (2.1.0.1.0.0)	Germany	GGPR	NARDL (2.0.1.0.1.1)
	CGPR	NARDL (2.1.0.2.1.0)		CGPR	NARDL (2.1.1.1.2.0)
South Korea	GGPR	NARDL (2.0.2.0.2.2)	Japan	GGPR	NARDL (1.1.2.2.2.0)
	CGPR	NARDL (2.1.1.0.0.0)		CGPR	NARDL (2.1.1.2.0.0)
Mexico	GGPR	NARDL (2.0.0.2.2.2)	U.K	GGPR	NARDL (2.0.1.0.0.1)
	CGPR	NARDL (2.0.0.2.2.0)		CGPR	NARDL (2.0.2.1.1.1)
Indonesia	GGPR	NARDL (2.2.1.1.1.1)	France	GGPR	NARDL (2.2.1.1.1.1)
	CGPR	NARDL (2.0.1.1.0.1)		CGPR	NARDL (2.1.1.2.2.1)
Taiwan	GGPR	NARDL (1.2.0.1.1.0)	U.S	GGPR	NARDL (2.2.0.1.1.1)
	CGPR	NARDL (2.2.1.1.2.0)		CGPR	NARDL (2.0.1.2.0.1)

Notes:

1. GGPR represents global GPR index, while CGPR represents country-specific GPR index.

Appendix B: Wald Test NARDL Results of ETFs with Global GPR

Panel A: Emerging Market ETFs						
	$\gamma_2^+ = \gamma_3^-$	$\gamma_4^+ = \gamma_5^-$	$\gamma_6^+ = \gamma_7^-$	$\sum_{i=0}^{n-1} \delta_1^+ = \sum_{i=0}^{n-1} \delta_2^-$	$\sum_{i=0}^{n-1} \varphi_1^+ = \sum_{i=0}^{n-1} \varphi_2^-$	$\sum_{i=0}^{n-1} \vartheta_j^+ = \sum_{i=0}^{n-1} \vartheta_2^-$
China	11.5689*	5.4874**	8.4100*	4.4156*	9.4568*	6.4187**
S.A	4.0031*	6.7810**	5.4613*	6.1874**	4.7489*	6.4789*
India	5.6417*	8.4723*	6.3178*	7.4159*	5.4201*	8.4891**
South Korea	11.1963**	9.1100*	7.4173**	5.8816*	5.0346*	9.4158*
Mexico	3.0013*	6.7212*	7.9971**	6.9564*	8.1480**	6.9206**
Indonesia	5.8835*	9.4678**	8.7668*	5.6821**	3.2569*	5.2954*
Taiwan	6.3227*	7.4038**	8.6204*	6.3881*	4.1407*	7.0922*
Panel B: Developed Market ETFs						
	$\gamma_2^+ = \gamma_3^-$	$\gamma_4^+ = \gamma_5^-$	$\gamma_6^+ = \gamma_7^-$	$\sum_{i=0}^{n-1} \delta_1^+ = \sum_{i=0}^{n-1} \delta_2^-$	$\sum_{i=0}^{n-1} \varphi_1^+ = \sum_{i=0}^{n-1} \varphi_2^-$	$\sum_{i=0}^{n-1} \vartheta_j^+ = \sum_{i=0}^{n-1} \vartheta_2^-$
U.K	9.8461*	5.4784*	6.4887*	3.4875**	7.4785*	5.0214*
France	8.4366*	5.4198*	5.4756*	5.6149*	5.5547*	6.3874*
U.S	5.4136*	6.4875*	9.1478*	4.2014*	4.3574*	5.4789*
Japan	5.3394**	5.4874**	11.4897*	6.3092*	4.2091*	15.2629**
Australia	7.4985*	5.3187*	18.4471*	9.4875*	6.1943*	6.2580*
Switzerland	6.1572*	4.2149*	6.5519*	9.2718*	5.5162*	16.5102*
Germany	8.3229*	15.4029*	5.9907**	7.1818*	6.5877**	5.9907**

Notes:

1. *, **, *** denotes statistical significance at a 1%, 5%, and 10% level of significance, respectively

Appendix C: Wald Test NARDL Results of ETFs with Country-specific GPR

Panel A: Emerging Market ETFs						
	$\gamma_2^+ = \gamma_3^-$	$\gamma_4^+ = \gamma_5^-$	$\gamma_6^+ = \gamma_7^-$	$\sum_{i=0}^{n-1} \delta_1^+ = \sum_{i=0}^{n-1} \delta_2^-$	$\sum_{i=0}^{n-1} \varphi_1^+ = \sum_{i=0}^{n-1} \varphi_2^-$	$\sum_{i=0}^{n-1} \vartheta_j^+ = \sum_{i=0}^{n-1} \vartheta_2^-$
China	4.4875*	10.1174*	14.4875*	9.1031*	7.8954*	6.4875*
S.A	9.4087*	8.2553*	9.1974*	11.5148**	18.0001*	6.0173*
India	8.0179**	16.4087*	19.4875*	9.3346*	10.1143*	15.4369*
South Korea	9.1562*	7.4097*	12.9437*	6.4985*	5.0142*	8.4891*
Mexico	9.4875**	8.9456*	6.8418*	9.6148**	10.3784*	9.9410*
Indonesia	13.5748**	15.091*	9.1064**	7.2054**	9.1100*	7.4173**
Taiwan	5.3250*	9.5834*	4.0870*	10.5987*	6.7212*	7.9971**
Panel B: Developed Market ETFs						
	$\gamma_2^+ = \gamma_3^-$	$\gamma_4^+ = \gamma_5^-$	$\gamma_6^+ = \gamma_7^-$	$\sum_{i=0}^{n-1} \delta_1^+ = \sum_{i=0}^{n-1} \delta_2^-$	$\sum_{i=0}^{n-1} \varphi_1^+ = \sum_{i=0}^{n-1} \varphi_2^-$	$\sum_{i=0}^{n-1} \vartheta_j^+ = \sum_{i=0}^{n-1} \vartheta_2^-$
U.K	10.2211*	5.81678**	8.5447*	10.5582*	9.5003*	6.1572**
France	9.4330*	23.5112*	9.6179**	7.6620*	4.2091*	15.2629**
U.S	5.8871*	5.5547*	5.4975*	16.1970*	5.8835*	9.4678**
Japan	8.9999*	4.3574*	10.9412*	4.9999**	6.9206**	10.0000*
Australia	5.4512**	4.2091*	13.9175*	11.5691*	5.2954*	10.4697*
Switzerland	6.1074*	11.1963**	9.1100*	7.4173**	7.0922*	12.9437*
Germany	4.9417*	3.0013*	6.7212*	7.9971**	4.4875*	6.8418*

Notes:

1. *, **, *** denotes statistical significance at a 1%, 5%, and 10% level of significance, respectively

Appendix D: Ethical Clearance Letter



14 July 2025

Miss Anelisiwe Dladla (221025288)
School Of Acc Economics&Fin
Westville

Dear Miss Anelisiwe Dladla,

Original application number: 00031725

Project title: Geopolitical risk effects on the quality of exchange-traded funds in developed and emerging markets

Exemption from Ethics Review

In response to your application received on 9 July 2025, your school has indicated that the protocol has been granted **EXEMPTION FROM ETHICS REVIEW**.

Any alteration/s to the exempted research protocol, e.g., Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through an amendment/modification prior to its implementation. The original exemption number must be cited.

For any changes that could result in potential risk, an ethics application including the proposed amendments must be submitted to the relevant UKZN Research Ethics Committee. The original exemption number must be cited.

In case you have further queries, please quote the above reference number.

PLEASE NOTE:

Research data should be securely stored in the discipline/department for a period of 5 years.

I take this opportunity of wishing you everything of the best with your study.

Yours sincerely,

Prof Claire Lauren Vermaak
Academic Leader Research
School Of Acc Economics&Fin

Appendix E: Turnitin Report

Masters Thesis

ORIGINALITY REPORT

15%	12%	11%	5%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

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2	www.mdpi.com Internet Source	1%
3	core.ac.uk Internet Source	<1%
4	faba.bg	<1%

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