LIQUIDITY DYNAMICS OF EXCHANGE-TRADED FUNDS IN DEVELOPING MARKETS

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A Doctoral Thesis Submitted in Fulfilment of the Requirements for the Award of Doctor of Philosophy Degree in Finance

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ABSTRACT

Market liquidity remains a significant challenge in emerging markets, hindering the development of capital markets. To address this issue, there have been suggestions that innovations, such as new asset classes, could help alleviate market frictions. Exchange Traded Funds (ETFs) have emerged as an asset class that has gained traction over the past few decades in developed markets and is now gaining acceptance in emerging markets. The increasing use of ETFs has led to a diversification of investor types, investment strategies, and investment classes, which has sparked academic and policy interest in this investment instrument.

The purpose of this research is to analyse the effects of ETFs on capital markets, with a particular focus on liquidity, which has often eluded emerging economies. To achieve this aim, three objectives are addressed: first, to analyse how the introduction of ETFs has impacted liquidity; second, to explore the liquidity risk associated with ETFs; and third, to examine the effects of ETFs on market efficiency.

The analysis reveals that, in most countries studied, ETFs are associated with a reduction in liquidity. Further cross-sectional analysis indicates a shift in the financial market architecture. The study also demonstrates a moderate to high liquidity risk during periods of market turmoil. The final objective highlights transitory effects of ETFs where ETFs play different roles in the price formation process, with varying impacts on short- and long-run efficiency. Consequently, the results align more closely with the Adaptive Market Hypothesis rather than the Efficient Market Hypothesis.

The findings of this study suggest a need for a renewed emphasis on maintaining market integrity, stability, and investor protection. This may necessitate new regulations or increased oversight to effectively address the evolving landscape of ETF-influenced markets.

DECLARATION

I, Gladness Lennie Monametsi, declare that this research report is my own work except as indicated in the references and acknowledgements. It is submitted in fulfilment of the requirements for the degree of Doctor of Philosophy in Finance at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

GMonametsi

Signed at………………………………………

On the………**25**…………………day of…………**July**…………….**2025**

DEDICATION

To my parents, Nnaniki Monametsi and Joseph Rakabane Monametsi whose support, and sacrifices have been the foundation of all my achievements.

ACKNOWLEDGEMENT

Completing this PhD has been both a challenging and rewarding experience, and I am profoundly grateful to all those who supported me along the way. First and foremost, I extend my sincere thanks to my supervisor, Prof Odongo Kodongo, for the intellectual guidance that has been instrumental in shaping this study.

To my colleagues who lent a sympathetic ear and offered encouragement during moments of doubt, your support has been invaluable. Your willingness to listen and provide perspective has helped me navigate the challenges of this academic journey.

I would also like to express my gratitude to Wits University for the partial funding of my study through the Postgraduate Merit Award. I also acknowledge the Postgraduate Writing Resources, which offered writing expertise that significantly aided my writing process.

Finally, I thank God, in whom are hidden all the treasures of wisdom and knowledge.

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CHAPTER ONE: INTRODUCTION

1.1 Overview

Liquidity is critical to market growth, determining essential metrics such as systemic risk, return, and market efficiency. A few of the notable financial events of the past have been driven by liquidity events: for example, fears of market illiquidity exacerbated the global financial crisis of 2007-2008 (Xu et al., 2018). Equally, the flash crash of 2010 was caused by a sudden liquidity dry up that wiped out one trillion dollars in market value (Aldrich et al., 2017); and the Covid-19 pandemic caused panic pull-out of investments from emerging markets as investors opted for safety amid fears of possible economic fallout (Dutta et al., 2020). Countries with an upward trend of confirmed Covid-19 infections showed a related decrease in market liquidity as investors lost confidence in those markets (Haroon & Rizvi, 2020). The liquidity dry-up was due to the global liquidity shock that caused sudden shifts from the perceived riskier assets of affected markets to perceived safer liquid assets in less-affected markets (Gubareva, 2021). The crisis period and subsequent move to liquid assets highlight the influence of monetary economic analysis, where agents are primarily concerned with the uncertainty of future market conditions and hence the focus on liquidity as vital to financial markets (Minsky, 1986). Studies on liquidity are necessary to understand the technical construction of financial markets as prompted by reactions to financial crises.

1.2 Background of the Study

Liquidity has emerged as a significant influence on the financial markets of developing countries (Kumar & Misra, 2015). The well-established low liquidity of emerging markets (Chowdhury et al., 2018; Kundlia & Verma, 2021) has been the object of literature, chiefly to identify the factors that influence it, including macro-economic variables such as inflation, stability of the currency, and money supply (Igbinosa & Uhunmwangho, 2019; Kapingura, 2015), which potentially increases systematic risk or information shock, causing investors to opt for safer asset holdings in advanced markets, thus usurping liquidity from the emerging market (Chowdhury et al., 2018). Other challenges to liquidity are the technical and institutional developments that include trading infrastructure and central depository systems and financial liberalisation, all of which are believed to be less robust for developing markets than advanced markets (Rokhim & Min, 2020; Saliya, 2020). Illiquid markets are generally undesirable for investors as they pose high risks of loss due to significant transaction costs

Despite the reforms towards financial market liberalisation in developing markets, their development still lags quite considerably. Akinsola and Odhiambo (2017) found that while financial liberalisation positively impacted development for some Sub-Saharan African countries, low-income countries showed a negative relationship. Their findings bolster the concerns of those who suggest that illiquidity will continue to persist as a problem due to the constraints of the level of economic development (Agbo & Udeh, 2019). While there has been some growth of stock markets, the problem of illiquidity persists in most African countries (Agbo & Odo, 2020). Though calls for integrating Africa's stock markets as well as other emerging markets have increased to overcome illiquidity (Ntim, 2012), this has yet to materialise.

Yartey and Adjasi (2007) asserted that one of the ways advanced countries have managed to overcome illiquidity and consequently develop their stock markets was by introducing new financial products that allowed for more investment. A diversification of financial instruments plays an important role in the movement of capital flows to the domestic economy. The more the diversity in financial instruments, the easier the financing constraints for industrial and investment projects. Attendant to the introduction of new financial products is the emergence of new investors in the financial markets. These two factors, among others, have helped overcome the challenges experienced by developing countries. Historically, developing markets have offered a narrow range of products, resulting in a government crowding out effect where government dominates trading activity in the capital market (see, for example, Al-Majali, 2018; Hasnat & Ashraf, 2018). Exchange traded funds (ETFs) are a relatively new product in developing markets whose impact on developing countries is not yet fully explored. However, they are yet to be introduced in many of these markets (Odera, 2012).

An ETF is a type of investment fund that tracks an underlying index, commodity, or basket of assets, and trades on a stock exchange like a common stock and provides investors with exposure to a diversified portfolio of securities through the purchase of a single security. They are the most rapidly expanding financial instrument in the market and are instruments that invest a large portion of their portfolio in economic activities (Alhaj & Awn, 2020). The advancement of ETFs has been facilitated by the diffusion of information and communication technologies that eliminate frictions in trading. Russia’s ETF growth is attributed to the need to develop instruments that meet the requirements of the new digital economy and appeal to investors (Loginov & Tatyannikov, 2019). The digital revolution and the increasing internet use have facilitated the expansion and development of innovative financial instruments such as ETFs. Marszk and Lechman (2021) showed how ICT and internet use positively influenced the development and share of ETF markets in ten European countries. It is thus expected that with the strive towards digitisation in developing and emerging countries, ETFs will be introduced and further developed.

1.2.1 Overview of Exchange Traded Funds

Exchange-traded funds (ETFs) are a relatively new phenomenon in the equities market, having appeared for the first time only in 1993 in the US and Canadian exchanges. Since their introduction, they have proliferated, holding assets worth almost $80 billion between 1993 and 2001 in the US, an annual growth rate of about 132% (Madhavan, 2016). By 2013, the US-based ETFs had $1.7 trillion worth of assets under management (Da & Shive, 2018). Other countries/regions that have seen large growth in the ETF market include Australia, which had grown to $25 billion by the first quarter of 2017 (Cunningham, 2017), and Europe, whose ETF market represented $183 billion in assets under management by July 2009 (Blitz et al., 2012). The enthusiasm by researchers and practitioners for ETFs and their increasing global share of the equities market has spurred growth in emerging markets. Thus, the uptake of ETFs in the emerging stock markets has expectedly seen an increase. India, for example, saw a 37% annual increase in ETFs between 2006 and 2011 (Prasanna, 2012); by 2019, India had 60 indexed funds registered on the stock exchange.

To fully understand the mechanics of ETFs, it is essential to examine the key players and processes involved in their operation. ETF transactions primarily involve three parties: the ETF provider, an authorised participant, and the investor. The unique structure of ETFs revolves around two fundamental processes: share creation and share redemption(Lettau & Madhavan, 2018). ETF shares are created when an authorised participant deposits a basket of securities with the ETF provider, who then issues ETF shares proportionate to the deposit. The authorised participants can then retain the shares or sell the shares to investors via the stock exchange. The redemption process is the reverse of the creation process, where the authorised participant can redeem ETF shares in exchange for securities. The authorised participants, i.e., financial institutions, play a crucial role in making ETFs relatively advantageous compared with mutual funds.

Facilitating the share creation/redemption process ensures that the ETF closely tracks its benchmark by reflecting investors' daily demand (Jun Chen et al., 2017). If ETF shares are trading at a discount, the authorised participant buys the shares from the market and redeems them with the ETF provider, causing the ETF shares' value to increase closer to its benchmark. On the other hand, if ETF shares trade at a premium, the authorised participants are incentivised to purchase the underlying assets and create more ETF shares to sell in the market; this will decrease the value of the ETF shares closer to the value of the underlying assets (Petajisto, 2017). These two operations, the creation and redemption, give the ETF its advantage of being liquid and, by extension, the ability to track the underlying portfolio's value closely.

Because ETFs combine elements of both open-ended and close-ended funds, they are deemed as a superior product. For example, like ETFs, open-ended funds have a limitless number of shares that can be traded throughout the day. However, unlike ETFs, their value is determined at the end of the day by the net asset value of the underlying portfolio. With close-ended funds, the similarity is with the intraday price determination based on demand and supply. However, a fixed number of shares is available, unlike the limitless supply offered by ETFs and open-ended funds (Wu et al., 2021). Combining the positive elements of both types of funds into one product makes ETFs, theoretically, a highly liquid product.

The accessibility that ETFs provide to retail investors and the innovative ways they are used in portfolios by institutional investors have caused an increase in their use. Balchunas (2016) notes that they are used in small portions and for specific needs, typically as tools to adjust portfolio exposures, manage cash or for liquidity. On the other hand, ETF popularity amongst retail investors gives investors access to a diversified range of assets (Alemanni et al., 2021; Cunningham, 2017). For example, the index fund industry in India was spurred when the government utilised ETFs as disinvestment for public sector undertakings as well as when the government consented to employees' provident fund organisations investing up to 15% in ETFs (Dhabolkar & Reddy, 2019). In South Africa, ETFs have been increasingly recognised as a way of strengthening retirement savings cost-effectively. Their higher liquidity, transparency, and service for targeting specific risk exposures make them ideal in retirement savings. Additionally, more and more investment products are designed to benchmark indices to capture specific macroeconomic risks such as currency and commodity exposures, shari'ah compliance, and sector exposures (Malhotra & Sinha, 2023; Tripathi & Sethi, 2022). Such a portfolio requires strategic asset allocation beyond traditional asset classes such as bonds, equities, and property.

1.2.2 Emerging Market Context

Despite the increasing popularity in ETF trading, emerging markets constitute a relatively small proportion of AUM. However, these markets have been gaining traction, with the Asia Pacific emerging as the fastest growing ETF market in the world as of 2020. This growth in ETF trading within emerging markets presents both opportunities and challenges that remain to be thoroughly examined. The expanding literature on the subject indicates that some of these opportunities and challenges are region-specific and influenced by distinct specific macro-economic factors that vary significantly across emerging markets (Nielsen et al., 2018). Consequently, a body of literature has developed that compares the performance of ETFs in developed markets with those in emerging and developing markets.

Zawadzki (2020) analysed the differences between developed and emerging markets considering regional diversity and found significant and negative tracking errors in both types of markets, suggesting that ETFs provide no benefits relative to trading in the underlying basket. Furthermore, the study revealed that emerging markets experience compounded tracking errors which are more pronounced than those in developed markets. The author recommended expanding the analysis to include different models and other factors such as market liquidity to better understand the reasons for the deviations. Similarly, Miziołek and Feder-Sempach (2019) conducted a study that compared the performance of emerging market and developed market ETFs. Consistent with other studies, they identified larger tracking error in emerging market ETFs compared to those in developed markets. They also concluded that additional research is necessary to determine the underlying causes of these discrepancies, including an examination of liquidity factors and volatility.

The studies referenced above have the common sampling method of ETFs that are domiciled in developed markets but track an index in the emerging markets. As such, the comparisons are of ETFs that have exposure to the domestic market assets or an index in emerging markets with ETFs that track developed market indexes. Research documenting ETFs that are domiciled in emerging markets and track local indices is considerably less common. Neto et al. (2021) assessed the tracking error of emerging markets ETFs and found that, consistent with ETFs domiciled in developed countries, they exhibited a greater tracking error than those of developed markets. Almudhaf and Alhashel (2020) demonstrated that Saudi ETFs traded at a premium to their NAVs, a premium that did not diminish after a day of trading. They also identified a positive and significant relationship between volume traded and volatility. The authors noted a decline in ETF investment, hazarding low liquidity and market inefficiency as contributing factors. Omar et al. (2021) likewise proposed that certain market characteristics and liquidity issues could contribute to market inefficiency, warranting further investigation.

The structural differences of emerging markets with developed markets have a pronounced effect on market quality characteristics. Developed markets are more efficient than the developing markets, for example (Gazel, 2020). ETFs being a relatively new addition to emerging markets amplify these market conditions.

1.3 Statement of the Problem

The surge in ETF popularity has attracted increased regulatory scrutiny due to potential risks associated with their rapid growth and innovation. A primary concern is the build-up of systemic risk, particularly stemming from ETF pricing strategies and the increasing complexity in the types and structures of strategies used to generate returns (Kosev & Williams, 2011). While ETFs have become the fastest-growing investment product worldwide, this growth paradoxically introduces various risks to the market, including counterparty risk, liquidity risk, and collateral risk (Dannhauser & Hoseinzade, 2021; Foucher & Gray, 2014). These factors collectively contribute to regulators' apprehension about the overall systemic risk in the market. This has led to a heightened focus on price discovery as a critical area of ETF research. Regulators are especially interested in understanding how ETF pricing mechanisms might impact overall market stability and efficiency.

While some studies provide evidence for improved price efficiency and report negligible adverse effects on the financial markets (Bhojraj et al., 2020; Jilong Chen et al., 2020; Xu et al., 2019), others contend that ETFs do indeed negatively affect financial markets (Ben-David et al., 2017; Bhattacharya & O'Hara, 2018; Clements, 2020b). The particular concern stems from ETFs' arbitrage trading mechanism characteristic that can propagate liquidity shocks and reduce pricing efficiency. These concerns have not been adequately examined, and therefore the potential effects of ETFs, are not yet clearly understood especially in emerging markets which have peculiar characteristics such as thin trading, inadequate analyst following, and low market capitalisation (Alhashel & Almudhaf, 2021; Konku et al., 2018; Yao & Liang, 2019), among others, some of which may arguably be improved by ETFs.

The impact of ETFs on market dynamics is further complicated by the trading behaviour and investor sentiment of market participants, which can significantly influence market volatility and efficiency across various asset classes. While research on the behavioural aspects of ETF trading in emerging markets is still developing, there are indications that ETFs affect volatility differently in these markets compared to developed ones. Costa Neto et al. (2019) found that emerging market investors engage in feedback trading, in contrast to their developed market counterparts, whose trading is more driven by fundamentals. This difference in behaviour can have significant implications for market dynamics.

Moreover, investor biases, such as overconfidence, contribute to market anomalies like increased volatility (Kunjal & Peerbhai, 2021). The growth of ETFs, combined with the information asymmetry characteristic of emerging markets, creates arbitrage opportunities that can lead to increased volatility (Jhunjhunwala & Sethi, 2022). These investment behaviours can hinder the incorporation of fundamental information into ETF prices, potentially causing inefficiency. Additionally, emerging markets are typically more influenced by noise traders and investor sentiments, further increasing volatility (Chen et al., 2021).

As research in this field progresses, market liquidity has emerged as a crucial factor in emerging markets ETFs. Converse et al. (2020) demonstrate that ETF investors place significant importance on liquidity regardless of the country's economic conditions. Their study concludes that emerging markets ETFs exhibit greater global co-movement than mutual funds, suggesting liquidity merits further exploration. The need to understand the effect of ETF on market liquidity is further accentuated by Omar et al. (2021), who point out that it (liquidity) is among the important market characteristics that contribute to market inefficiency. Coupled with this is the familiar position in the theoretical literature (e.g., Holden & Nam, 2019; Saglam et al., 2019) that ETFs potentially proffer liquidity enhancement benefits to the market for the underlying assets

The growing theoretical and empirical literature necessitates a closer examination of ETFs' impact on developing market liquidity. Some studies (Holden & Nam, 2019; Saglam et al., 2019) posit that ETFs can enhance market liquidity and, consequently, efficiency. However, mixed results from developed markets (Box et al., 2019; Fiedor & Katsoulis, 2020; Liebi, 2020) indicate that the relationship between ETFs and market liquidity is more complex and warrants further exploration, particularly in the context of developing economies. Several emerging markets have adopted the use of ETFs. A study of these markets before and after adoption of ETFS would help shed light on the liquidity effects of ETFs on the market as well as whether ETFs make a significant difference to liquidity, liquidity risk and overall efficiency of the market. This study is an important first attempt to undertake a comprehensive analysis of this kind.

The theoretical motivations for this study stem from the Kyle (1985) and the Holden and Subrahmanyam (1992) models that largely inform the assumptions in the studies of the effects of the introduction of ETFs to markets. These models assert that informed investors rapidly exploit rents of their private information for profit at the disadvantage of the uninformed traders. Uninformed traders, therefore, prefer to trade in the index market, which ostensibly always reflects all information of the underlying securities. The assertions made by the models rest on two main points. First, the index market is more informationally efficient than the underlying market, which means that the arbitrage opportunity is limited.

Samuelson's dictum, posited by Jung and Shiller (2005), suggests that the individual market for securities may be more informationally efficient than the index market, which opposes the Kyle (1985) and the Holden and Subrahmanyam (1992) models. Some studies affirm Samuelson's dictum (for example, Beikmanis & Sīlis, 2020; Glasserman & Mamaysky, 2019; Gumbo, 2017). Glasserman and Mamaysky (2016) suggest that this has implications for ETFs that need to be explored. The exploration of such implications will be that of liquidity and by extension, market efficiency and liquidity risk in this study.

The second assertion of the Kyle (1985) and the Holden and Subrahmanyam (1992) models involves the investor type. They assume that uninformed investors move from one market to the other to avoid informational exploits. Thus, in terms of ETFs, the question of investor type is pertinent. The models suggest that uninformed, implicitly, retail investors, who tend to increase market volatility more than other types of investors, are the most attracted to ETFs (Amihud & Mendelson, 1986). However, with the expansion of ETFs, new types of investors are becoming more and more prevalent in the market. For example, more institutional investors have adopted ETFs for more strategic uses (Balchunas, 2016) in, say, provident funds, as earlier mentioned. The role of other market participants, such as arbitrageurs, is yet to be concluded in the literature. The works of Brunnermeier and Pedersen (2009), Greenwood (2005) and Malamud (2016) imply that risk-averse arbitrageurs propagate volatility and liquidity shocks.

In line with other studies that examine the macroeconomic architecture of markets, this study delves into the broad-scale structural aspects of developing markets' liquidity and investigates how ETFs affect liquidity and the systemic risk of the underlying market, in particular, liquidity risk, and the implications thereof to market efficiency. Nascent research in the effects of ETF liquidity suggests that ETFs may not in fact have the liquidity benefits that are so touted by earlier research, especially of developed markets. For example, Clements (2020) refers to the liquidity illusions of ETFs, positing that due to their complex ecosystem, ETFs could cause a liquidity risk, possibly exacerbating illiquidity during times of financial crisis like a market crash. In part II of the study, Clements (2020a) further elaborated on the products of the ETF ecosystem being contagion effects, information cascades, both of which can distort the price discovery mechanism of the underlying assets and make markets inefficient. In both studies, the author argued for the need for more regulatory and academic attention to ETFs due to the systemic risk it poses to markets.

With the above study motivations in mind, the following research questions are asked:

1. How does the introduction of ETFs impact the liquidity of the underlying index?
2. To what extent does the liquidity of ETFs interact with the liquidity risk of the underlying index?
3. How do ETFs influence the market efficiency of the underlying index?

1.4 Research Objectives

The broad objective of this research is to understand the liquidity effects of the introduction of ETFs to a market. Specifically, based on the research questions, the research objectives are:

1. To analyse the effects of ETF introduction on the liquidity of the underlying security in emerging markets.

2. To examine the effects of ETF liquidity on the liquidity risk of emerging markets.
3. To assess the impact of ETFs on the market efficiency of emerging markets.

1.5 Contribution to the literature

A key insight from the existing literature is that ETFs' liquidity, when compared to their underlying portfolios, plays a crucial role in facilitating trading. This liquidity advantage impacts not only the net flows (aggregate demand) of ETFs but also distinctly affects their inflows and outflows. This study will undertake a detailed analysis of the liquidity differential between ETFs and their underlying portfolios. This research direction builds upon and extends the rich literature on the determinants and consequences of mutual fund flows, applying these insights to the rapidly evolving ETF market. By examining these liquidity dynamics, the aim is to provide a richer perspective of ETF behaviour and its implications for market efficiency. (see, for example, Ben-Rephael, 2017; Bu & Lacey, 2017; Christoffersen et al., 2018; Nanda & Wei, 2018) But that has yet to be explored extensively with ETFs specifically.

Specifically, this study is close to the recent work of (Holden & Nam, 2024), who investigate the effect of ETFs on the liquidity of underlying asset markets. Unlike their study, which focuses on bond markets in developed economies (arguably less accessible than developed equity markets), the study focuses on equity markets of emerging countries. The results suggest heterogeneity in the effects of ETFs on the liquidity of underlying assets with some markets reporting negative effects, consistent with models developed by Kyle (1985) and the Holden and Subrahmanyam (1992), which suggest that the introduction of ETFs would usurp liquidity from the underlying index; other report positive effects, consistent with the inferences in Jung and Shiller (2005) that the introduction of ETFs would make the underlying index more active. Interestingly, the study documents that the initial effect, positive or negative, diminishes or intensifies with time, again, depending on country-level idiosyncrasies.

This study also aims to contribute to the literature on the systemic risk that ETFs pose to the market, particularly focusing on the liquidity risk in developing markets, which are especially vulnerable to illiquidity conditions. Furthermore, the study seeks to evaluate the mechanism through which liquidity risk is propagated between the ETF market and the underlying assets. The findings reveal generally low connectedness between ETFs and the overall index under normal market conditions. However, significantly increased comovement and upper-tail dependence during periods of market stress is observed, indicating heightened vulnerability to illiquidity contagion. Specifically, the copula analysis demonstrates that diminished liquidity in one asset can trigger an illiquidity spiral, particularly during market downturns. These results highlight the need for adaptive liquidity risk management strategies to mitigate contagion risks.

In terms of market efficiency areas such as tracking errors, volatility, dealer behaviours, and the influence of market participants, demonstrate complex dynamics that require further exploration to enhance the understanding of ETFs in emerging markets. This study attempts to address this literature gap by providing a better understanding of the impact of ETFs in emerging markets in numerous ways. Firstly, this study's focus on local market contrasts with the extant literature that typically focuses on broad global indices. Secondly, the models deployed allow for asymmetric examination of ETFs' effect on market efficiency. This is a departure from the traditional linear models that assume symmetric relationships. Thirdly, by applying different models and variables to each, greater depth is given to the understanding of market efficiency. Namely, the methods allow for discussion on the price discovery process, the information flow, arbitrage effectiveness, market integration and feedback loops between the two markets.

The results highlight the challenges of implementing uniform policies across broad categories of markets and underscore the need for flexible, adaptable approaches that deliberately consider the institutional framework and policy environments of every financial market.

1.6 Conclusion

This chapter introduced the importance of liquidity as a developmental factor for financial markets. The fact of its illusiveness despite financial liberalisation reforms in developing markets was explicated. Further, the role of ETFs in liquidity supply to help alleviate the problem of illiquidity was highlighted, and the possible benefits it could have to other developing markets that are yet to adopt their use. In chapter 2, a literature review is undertaken to explicate the issues attendant to liquidity and ETFs to identify the literature gaps. Chapter 3 develops the models that will be used to test the hypotheses. The next chapter will be an analysis and presentation of the empirical results. The final chapter concludes.

CHAPTER TWO: LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Introduction

Liquidity has been identified as a critical factor that moderates the strength of stock market development. Ake (2010) showed a strong positive relationship between financial market development and economic growth for countries with highly liquid stock markets compared with those with less liquid markets. This sentiment echoes true in light of the poor market liquidity often descriptive of developing countries. In this chapter, the nexus between an efficient market, market liquidity, and ETFs' financial innovation is reviewed. Further, the chapter outlines the role of liquidity in financial markets and, more specifically, liquidity in markets with respect to ETFs.

2.2 Theoretical Framework

2.2.1 Efficient Market Hypothesis

The efficient market hypothesis (EMH) is a concept that has been developed over fifty years and is the bedrock of modern financial theory today. The EMH asserts that all available information is rapidly absorbed into the price of an asset; consequently, investors cannot hope to earn above-average risk-adjusted profit from an analysis of historical and present data. Moreover, no arbitrage opportunities are available for exploitation (Langevoort, 1992). The concept itself is a derivative from the economic discipline, more specifically, that of economic equilibrium. It is thought of as the theory of competitive equilibrium from the neoclassical tradition applied to the financial asset market. As such, the assumptions of perfect markets extend to EMH, being that market participants are rational, risk-averse, and profit-seeking (Fakhry, 2016).

The genesis of the EMH was in 1900 by a French mathematician, Louis Bachelier, in his thesis, *Theory of Speculation*. In his work, Bachelier (1900) argued that the movement of stock prices followed a Brownian motion. Five years later, the random walk concept was established by Pearson (1905). According to the random walk model, information comes into the market unpredictably, thus making asset prices random and independent. Later, Kendell (1953) found that stock prices indeed follow a random walk. In 1965, Fama defined efficient markets for the first time in his analysis of stock market prices that concluded with evidence of a random walk. In his definition, a market is considered efficient if all available information is fully reflected in the prices of assets trading in the market (Fama, 1965). In the same year (Samuelson, 1965), working independently from Fama, also made a formal economic argument for market efficiency. It was not until 1967 that the term efficient markets hypothesis was ingratiated into the literature by Harry Roberts, who also distinguished between weak and strong form efficient tests.

In reviewing evidence of random walk from the 1960s, Fama (1965) found no or weak empirical opposition to EMH. However, in the 1970s and 1980s, EMH started facing strong challenges (Guerrien & Gun, 2011). In this period, there were mixed empirical results in support of (e.g., Cox & Ross, 1976; Jensen, 1978; Scholes, 1972) and in opposition to (e.g., Ball, 1978; Beja, 1977; Grossman & Stiglitz, 1980; Shiller, 1981) the hypothesis. It has been argued that the lack of opposition to EMH in much of the earlier works was a result of testing bias or, more specifically, a joint hypothesis problem (Jensen, 1978). Jensen noted that tests of market efficiency also entailed tests of asset pricing models. A market efficiency test, thus, can fail due to faults of one or the other or failure of both hypotheses.

In a compilation of empirical studies, the special issue of the Journal of Economic Studies of 1978 published a series of articles testing the EMH. Where the EMH proved false, this was attributed to either a lack of efficiency in the market under study or a deficiency of the pricing model. In support of the EMH, Fama (1991) noted that the joint hypothesis problem was more pronounced than initially conceived, concluding that market efficiency is not directly observable and any valid test would have to be done in conjunction with a pricing model test. Nevertheless, that did not invalidate the EMH. Fama (1991) argued that though scholars disagree on the implication of EMH tests, the facts of the tests are not in dispute. Thus, the EMH is applicable as it has influenced practitioners and scholars' views on returns behaviour. In sum, during the period of the 1970s through 1980s, empirical evidence was mixed on EMH.

The 1990s discussions are best summarised by Haugen (1999), who asserted that the EMH is on one extreme of a spectrum of possible states of a market. Fridson (1994) presented variations of the EMH paradigm as follows. First is the weak form efficiency in which the assumption of rational behaviour is not met by market participants, which leads to some anomalies in asset prices. However, the anomalous prices are swiftly rectified by arbitrageurs. In the semi-strong form, there are persistent asset price deviations away from fundamental values for extended periods. Asset prices in strong form markets fully reflect all past and present public and private information. All these represent anomalies in markets. Latif et al. (2011) documented several causes of anomalies in the financial market, including calendar, under- and overreaction, and the equity risk premium puzzle, all representing shortcomings in the empirical evidence on the EMH.

Scheifler (2000) criticised the EMH, questioning the assumptions of the rationality of market participants. This criticism appears to have laid the foundation for the two essential inputs to behavioural finance (and thus, opposition to EMH): investor sentiment and limited arbitrage opportunities. Regarding the rationality of investors, it was demonstrated that judgements and decisions are influenced by sentiment towards the information available to them. One of the assumptions of EMH is that well-informed and rational arbitrageurs exist and will drive asset prices should they deviate from fundamental values. The behavioural finance literature has shown that the actions of these arbitrageurs do not thwart the actions of other market participants and that they can behave in a manner that causes further price deviation; thus, the limited opportunity for arbitrage argument. In general, behavioural finance proponents argue that market inefficiency is the norm rather than the exception. Shiller (2003) argues more fervently that EMH should be replaced by behavioural finance.

However, Fama (1998) explained that the EMH withstands criticism in the long-run predictability of market returns, observing that market over- or underreaction tends to course-correct to pre-anomaly state, where asset prices revert to their fundamental values before the event that triggered the reaction. Further, anomalies in the long term can be caused by methodological misapplications that, once addressed, fade away. Notwithstanding the criticisms of the EMH, it still is a benchmark used to explain asset prices. Moreover, as many supporters have put it, until there is a better alternative to explaining markets, it will remain one of the dominant theories in financial markets.

While supporters of the EMH contend that it stands up to scrutiny in the long term, they concede ground on its inability to explain short-term anomalies in returns. Such anomalies imply that in the short run, at least, security returns are predictable, and arbitrage opportunities may exist for short periods. Thus, it is important to understand specific attributes of securities markets that may facilitate such opportunities. For instance, illiquidity in the markets may cause temporary aberrations in asset prices from their equilibrium values (anomalies), opening up arbitrage opportunities (Avramov et al., 2017; Chordia et al., 2014; Rojo-Suárez et al., 2020). Hence this study’s focus on liquidity.

Cajueiro and Tabak (2004), while testing for market efficiency, concluded that liquidity plays a role in explaining the efficiency levels of each of the Asian stocks under investigation. Other studies have also documented the role of liquidity in predicting excess asset returns in the short run (Avramov et al., 2006; Timmermann & Granger, 2004). It is noteworthy that the EMH is silent on liquidity as it tacitly assumes continuous trading. Thus, when markets are inefficient, liquidity is an attribute of consequence that ought to be explored (Ariwa et al., 2017; Wei, 2018). Analysis of the world economic meltdown commonly cited as evidence of the failure of the EMH shows that illiquidity was a feature in credit and real estate markets (Ball, 2009). More recent evidence suggests that the higher the liquidity, the higher the efficiency of the market (Chung & Hrazdil, 2010; Holden et al., 2014; Wei, 2018; Zhang et al., 2020).

2.2.2 Liquidity Preference Theory

Keynes postulated liquidity preference theory in *A Treatise on Money* (1930) and *General Theory* (1936). The views in these works dissented noticeably from the prevailing textbook economics of the time. Keynes and other scholars such as Schumpeter and Minsky put forth a tradition of monetary economic analysis that asserted that monetary questions influence real-world economic agents. Liquidity is a central theme in this tradition.

It is helpful at this juncture to recall that the theory was developed in two publications, "A Treatise on Money" (Keynes, 1930) and "General Theory" (Keynes, 1936). The response to Keynes' propositions has been two main threads of literature, each stemming from the two publications. The response to *the Treatise* is more inclined to the applied world of bankers, investors, and policy makers. In particular, this thread is preoccupied with the portfolio choice of bankers. The resulting literature has spurred an interpretation of the liquidity preference aligned to the more practical use for analysing liquidity. This strand has been very influential in developing empirical models for assessing liquidity. In contrast, the *General Theory* thread is inclined more to the realm of theoretical economics. This thread is concerned with the demand and supply of money and seeks to find equilibrium between the returns of available assets.

Tobin (1958) conceptualised liquidity preference related to risk, explaining that asset prices are determined by portfolio rebalancing (Tobin, 1969). This strand of interpretation is commonly referred to as the portfolio rebalancing model. In this theory, liquidity means cash, and an investor decides what proportion to hold as cash or investment in risk-free government securities. Accordingly, the demand for money (liquidity) is the total investment balance net of the investment in government securities. Risk increases proportionally with the amount of investment in government securities; thus, the more securities are purchased, the more the returns are diminished until they get to a particular point (zero) equal to that of money. At this point, a risk-averse investor will no longer hold any more securities, as it is the same as holding cash. Under this view, asset prices are determined by portfolio rebalancing.

Tobin's liquidity preference differs rather significantly from Keynes' version. The main difference is that Tobin's theory does not account for an investor's acquisition of new knowledge that may cause them to alter their initial investment position. As such, the liquidity, i.e. the ease with which one can alter their portfolio to match their assessment of the newly acquired information, is rendered moot (Runde, 1994). Moreover, Tobin framed liquidity preference as behaviour toward risk, whereas Keynes framed it as behaviour towards uncertainty. According to Tobin's portfolio rebalancing perspective, the demand for liquidity is not a demand for liquidity but rather a demand for the most riskless asset.

Another popular scholarly derivative of Keynes' liquidity preference is that of Hicks (1962). Unlike Tobin, Hicks's interpretation focused on the concept of liquidity. He defined liquidity in a broader sense of marketability, requiring a structure made of active dealers. Hicks deconstructs the definition of liquidity put forth by Keynes, being an asset more certainly realisable at short notice without loss. To this end, some assets are more marketable than others because marketability depends on an expected certainty of a realisable price determined at short notice and will continue to be realisable in the future. The degree of liquidity is a determinant of the expected certainty of the realisable value of the asset. Consequently, marketability is a characteristic of liquid assets whose degree differs from one asset to the other. The analysis of the definition's 'without loss' aspect lends itself to a discussion of a statistical probability distribution of a portfolio. A decision-maker is concerned with two values, the standard deviation of the portfolio, i.e., the certainty (uncertainty) of returns and the mean value as a proxy for expectation.

Culham (2020a) argues that Hicks' interpretation of liquidity preference strays from Keynes's due to the ontological differences in the conception of money. The commodity view of money is that money derives its value from the commodity itself, and so money is a product of the most marketable or saleable commodity. Under this conception of money, liquidity preference is narrowed only to an analysis of marketability, or rather market liquidity. However, a different perspective of money, that is, the debt view of money, propounded by Mitchell-Innes (1914), necessarily broadens the scope of discussion of liquidity preference to more than just market liquidity. The debt view of money asserts that money is credit, particularly in the absence of being backed by a commodity. Therefore, Culham argues that liquidity preference is not merely about market liquidity from the debt view of money.

Stemming from the divergence between Keynes and Hicks' ontology of money, two criticisms are levelled against Hicks's liquidity preference interpretation. Firstly, there is no difference in realisable value in short notice or long notice, and there is a benchmark long notice realisable value against which the short notice is measured. This means that at one point, an asset has a value that would, in retrospect, be the benchmark value against which a future sale value will be compared. Therefore, perfect market liquidity is an asset realisable at its benchmark. The trouble inherent to this is the assumption of perfect market liquidity, which suggests that a benchmark value cannot be adequately ascertained. Secondly, the function of dealers in a market of determining tradeable prices of assets relative to a similar class of assets suggests that, in their absence, these prices cannot be obtained. Evidence for this is the illiquidity of markets during times of crisis. As such, the fundamental value of an asset is not a consideration under Hicks' liquidity preference.

Following the preceding discussion of liquidity preference theory and the subsequent interpretations flowing from Keynes' two publications, this section aims to operationalise the theory for application in analysing the research questions in this study. This study opts for the use of Hicks' interpretation of liquidity preference theory. The following arguments are made in justification. Firstly, analyses in many studies (e.g., Culham, 2020a; Runde, 1994) have shown that the way liquidity preference theory has been conceptualised and applied differs from Keynes' original thought; they do not offer alternative models for empirical analysis of liquidity.

Brown (2003) and Culham (2020b) argue that only the Keynesian liquidity preference theory can form the basis for an asset pricing model. A discussion on the interplay between asset prices and liquidity is outlined in an earlier section. It is essential to point out that the section indicates that the popular asset pricing models did not initially account for liquidity but have subsequently done so through empirical findings. The models themselves are not built on the axioms of Keynes' liquidity preference that intimates that a liquidity premium is essentially a cost of convenience. Instead, the models view liquidity premium as part of the carrying cost of an asset, market friction. Hence, the second reason for selecting Hicks' liquidity preference is that the empirical models in the literature implicitly adopt his interpretation.

Despite the criticisms outlined above, empirical literature relies heavily on market liquidity rather than the "convenience" model by Keynes. For example, Amihud and Mendelson's models of determining liquidity depend on volume and spread, a function of markets. Thirdly, while outlining the divergent aspects of Hicks's interpretation, Culham (2020) concedes that the Neo-Ricardian equilibrium model on which the Keynesian perspective of liquidity is built is not an appropriate model for analysing the day-to-day fluctuations in the prices of existing assets. Such analysis is necessary for an empirical study such as this. It is not to discount the limitation of the assumption of perfect market liquidity presented by the Neo-Walrasian general equilibrium model inherent in Hicks' interpretation. Indeed, it is the intent to overcome this limitation. However, the analysis ought to be possible in the first place. A comprehensive discussion of this issue follows in the methodology section.

The third reason for selecting Hicks' liquidity preference is its narrowly defined liquidity in terms of market liquidity. Market liquidity allows for the preservation of parsimony in analysis and leaves less ambiguity than would be presented by the Keynesian model that relies on the subjectivity of uncertainty. As mentioned earlier, Keynes's view on uncertainty relates to applying the *belief* of an outcome of an event in choosing between alternatives. On the other hand, Hicks' risk deals with a portfolio's more objective and easier ascertainable standard deviation. Having established and affirmed Hicks' version of liquidity preference, it is crucial to understand liquidity and, specifically, market liquidity. A discussion which is now presented.

2.3 Liquidity in Financial Markets

2.3.1 Defining Liquidity

Despite the extensive use of the concept of liquidity in the finance literature over many years, there is no universally accepted definition. This lack of consensus is primarily due to the varied perspectives from which liquidity can be examined. From a corporate standpoint, liquidity pertains to a firm's solvency and its capacity to meet its financial obligations. In contrast, when viewed from a liability perspective, liquidity implies funding liquidity, while from a broader monetary viewpoint, it refers to the liquidity of an entire economy. Keynes (1936) and Makower and Marschak (1938) posited that there is no absolute standard of liquidity; rather, it exists on a continuum that measures different characteristics of an asset. Keynes's conception of liquidity is based on the premise of holding assets in money or near-money forms to ensure immediate liquidity command. As such, it reflects a preference for assets with price protection features over those characterised by capital uncertainty. Its emphasis lies on liquidity itself, rather than on money.

However, as discussed in the theoretical framework section, this study interprets liquidity as empirically defined in much of the financial literature, grounded in Hicks's (1962) liquidity preference theory. In this context, with respect to investors, liquidity refers to the ease of trading an asset (Stange & Kaserer, 2009), its saleability without incurring a significant loss (Culham, 2020b), and its readiness for shiftability (Sayers, 1964). A unifying and consistent characteristic captured in the literature is the time required for an asset to be converted into funds for immediate consumption or reinvestment (Hicks, 1962). This liquidity characteristic is explicitly identified by Lippman and McCall (1986) as one of the most significant, and is implicitly acknowledged in studies by numerous other scholars. Time, in relation to liquidity, is influenced by four factors: first, the price at which the seller is willing to offer the asset; second, the frequency of offers from buyers; third, any impediments to the legal transfer of title; and fourth, the cost associated with holding the asset. Another integral property of liquidity, often included in its definition, is the predictability of an asset's pricing. Therefore, an asset is considered liquid if it can be sold quickly at a predictable price.

Asset sale price is dependent on the conditions of a market. A perfectly liquid market would have only one bid/ask spread at all times regardless of volumes traded. The assumption of perfect market liquidity is, of course, demonstrably flawed as all markets, even the most developed, do not adhere to this standard. Black (1970) outlined the following characteristics of a liquid market:

1) There are always bid and ask prices for investors who want to buy or sell small amounts of stock immediately.

2) The difference between the bid and ask prices (the spread) is always small.

3) An investor buying or selling a large amount of stock in the absence of unique information can expect to do so over a long period at a price not significantly different, on average, from the current market price.

4) An investor can buy or sell a large block of stock immediately, but at a premium or discount that depends on the size of the block. The larger the block, the more significant the premium or discount (Black, 1970: p.30)

Kyle (1985) further delineated three aspects of a liquid market: the tightness of the bid-ask spread, market depth, and market resilience (Bervas, 2006). The bid-ask spread quantifies the cost of reversing a position at short notice and serves as a direct measure of transaction costs. Market depth and resilience reflect the market's capacity to absorb volume without negatively impacting prices. The bid-ask spread compensates dealers for the immediate execution of transactions and constitutes a cost to the investor. The bid-ask price is influenced by the size and volatility of order flows[1] as well as information asymmetry between dealers and investors, and the processing costs incurred by dealers. From an alternative perspective, tightness, depth, and resilience may also be regarded as indicators of market imperfections.

A comprehensive discussion of liquidity must acknowledge the parameters that underpin trading activity within a market and, consequently, influence liquidity (Bourne & Zaidi, 2001). The first of these parameters is the spread, which has been previously mentioned. In a liquid market, the difference between the bid and ask prices represents the profit that a market maker derives from their role in providing immediacy of transactions to investors. The spread also serves as a buffer against adverse market movements that may impact the market maker. A tight spread results in increased transaction costs, whereas a wider spread offers greater incentives to the market maker, as it presents the potential for higher profits. Inventory limits constitute another parameter that governs the minimum and maximum quantities of assets that the market maker is permitted to trade. The minimum threshold is established at the level of inventory necessary to enable market makers to recover their costs. Conversely, a market maker anticipates the number of assets to retain prior to price fluctuations, which defines the maximum level. To enhance liquidity within a market, a larger maximum market size is deemed preferable.

[1] The bid-ask spread widens with order size. Order flow volatility negatively affects the bid-ask spread due to increased adverse selection costs.

Time and the predictability of pricing are more succinctly associated with market liquidity. Funding liquidity is a related, yet distinct form of liquidity often discussed in relation to assets. Funding liquidity can be defined as the ease with which one can acquire funding to trade an asset. Market liquidity and funding liquidity are frequently interconnected and reinforced through a feedback loop (Brunnermeier & Pedersen, 2009). An illustrative example of this feedback loop is the downward liquidity spiral observed in banks. When a bank experiences a liquidity shortfall (i.e., is unable to meet its liquidity requirements) and cannot procure liquidity from the interbank market, it is compelled to sell its assets, resulting in a decline in asset prices. This decrease in asset prices triggers liquidity outflows. Consequently, the bank is required to increase its margin, which necessitates further asset sales, leading to an additional reduction in market prices (thereby undermining market liquidity). Thus, a downward spiral of funding and market liquidity ensues (Drehmann & Nikolaou, 2013).

Further studies reiterate the relationship between funding and market liquidity (Czelleng, 2020). Macchiavelli and Zhou (2019) identified funding liquidity as a predictor of market liquidity in the context of corporate bonds. Their research demonstrated that dealers with more readily accessible funds were able to reduce transaction costs in market-making activities. The prevailing notion is that a reduction in margin requirements leads to an increase in trading volume of assets and a corresponding decrease in the bid-ask spread (Jylhä et al., 2019).

2.3.2 Liquidity and Asset Pricing Models

Early theoretical models provide the framework for which asset pricing is construed. The capital asset pricing model (CAPM) developed by Treynor, Sharpe, Lintner and Mossin is one such model. In this model, factors are priced only if these factors pose systematic risk. In the standard CAPM, the market beta captures systematic risk and is considered the sole source. However, the CAPM is empirically flawed, as many studies have shown that it does not adequately explain the cross-section of asset returns (Erdinç, 2017; Jan et al., 2021; Sattar, 2017). Thus, research has sought to identify and validate other factors which may explain asset returns. Liquidity has emerged as a factor commanding a premium in asset prices. Any investor who employs some form of leverage and faces a solvency constraint will require higher expected returns for holding assets that are difficult to sell when aggregate liquidity is low (Altay & Çalgıcı, 2019; McKane & Britten, 2018). Pástor and Stambaugh (2003) found that market-wide liquidity is an essential factor in asset pricing.

Holmström and Tirole (2001) critique of the CAPM is that while in the literature it is recognised that investment decisions are affected by the agency conflict, asset pricing models do not reflect this dynamic. As such, asset pricing models only capture retail consumption; expressly, consumers' intertemporal marginal rate of substitution and exclude the corporate level dynamics that contribute to asset prices. The assumption of perfect capital markets of CAPM that propagates the notion that firms can raise funds from the market commensurate with their income needs is belied by the fact that corporations have funding needs autonomous from the consumer market they trade. Due to the need for regulatory compliance to capital adequacy requirements, leverage ratios and savings compositions, liquidity in security holdings is sought after.

Corporations seeking to protect themselves from future credit rationing through various financial operations available in the market must hold securities that serve as a liquidity buffer. For example, when a company seeks a revolving credit line or a loan commitment which provides a type of insurance that can be drawn on when needed, the financial institution providing such insurance may require the maintenance of a compensatory balance. In other words, the company is required to maintain a certain level of liquidity. Consequently, liquid assets trade for a premium relative to illiquid assets. Holmström and Tirole (2001) suggested that the lack of linkage between the interchange of liquidity demand and supply at the corporate level with that at the retail level is an empirical limitation of the CAPM. Much of the investment management research now recognises liquidity in the models used for empirical tests. For instance, the liquidity adjusted CAPM (LCAPM) is now often used in the literature (Altay & Çalgıcı, 2019; Cheriyan & Lazar, 2017; Grillini et al., 2019). Undoubtedly, liquidity has emerged as an essential feature in the investment environment and a fundamental consideration in investment decisions.

2.3.3 Liquidity and Portfolio Management

Liquidity has also been identified as essential in portfolio management. Portfolio management literature delves into the optimal portfolio to hold in periods of market crisis. It has been the case that investors hold different securities to optimise returns. Markowitz (1952) Modern Portfolio Theory is the seminal work upon which portfolio management literature is anchored and from which asset pricing models such as CAPM have spawned. However, while still heavily cited, scholars agree that it suffers from the flawed assumption of frictionless markets. Liquidity is a consequence of market frictions and thus needs to be considered when forming portfolios.

Beyond its predictive power on returns, liquidity has been used to explain investors' trading behaviour, specifically a liquidity preference. Portfolio managers actively manage the liquidity of their portfolios in response to market volatility. The dominant view is that portfolio managers should sell off illiquid assets during a market crunch to reduce exposure (Radde, 2015; Vayanos, 2004). Nevertheless, it appears that that is not always what transpires. Under some market conditions, portfolio managers can preserve liquidity to be more strategic (Beber et al., 2009). The literature terms this as flight-to-liquidity. It appears that at specific points and in certain market conditions, there is a preference for liquidity by portfolio managers wherein a sell-off of illiquid stock occurs. For example, mutual funds reduce their holding of illiquid stock in periods of deteriorating market conditions (Ben-Rephael, 2017), a reaction by retail investors to lousy performance.

China's stock market exhibits this same phenomenon, demonstrating that an illiquidity premium exists, prompting investors' preference for liquidity in times of market stress (Li et al., 2019). Evidence of a reverse flight to liquidity is shown by other scholars (O'Sullivan & Papavassiliou, 2020; Rzeznik, 2017). In March of 2020, due to COVID-19, the financial markets experienced some turmoil, and in that time, money market funds sold their less liquid assets, a behavioural departure from normal market conditions (Avalos & Xia, 2021). The corporate bond mutual fund market was also affected by many redemptions during the month as investors sought liquidity (Liang et al., 2020). In contrast, there are instances where investors sell liquid assets in times of crisis, albeit with some caveat. Li et al. (2020) found that investors sell liquid assets with a lower price impact.

2.3.4 Liquidity and Returns

There are two costs attendant to the execution of a transaction. The first is the bid-ask spread, and the second is the less direct cost of any negative price swing resulting from the removal of liquidity from the market. In general, illiquid stocks are more difficult and expensive to trade, making them less attractive to investors than liquid stocks. Logically, it follows that since illiquidity carries costs to the investors such as demand pressures, exogenous trading costs, inventory risks, search frictions and symmetric information (Amihud et al., 2006), liquidity risk needs to be priced. Amihud and Mendelson (1988) demonstrated that trading costs of assets are substantial over the life of an asset and cannot be trivialised. Amihud and Mendelson (1986) established the relationship between liquidity and stock returns in their seminal work. Their study showed that investors get higher returns for illiquid stock as a recompense for illiquidity costs. Subsequent studies on this have shown similar findings. For example, Marozva (2019) found that illiquid stocks are associated with higher returns in the Johannesburg Stock Exchange study. Conversely, while illiquid assets demand a trade premium, liquid assets provide greater value since they command lower claims for future returns.

Thus, in theory, liquid assets should trade at a discount while illiquid assets should command a premium. Notwithstanding these findings, the empirical validity of the liquidity factor premium has been challenged. Evidence suggests that asset prices have shown a decreasing sensitivity towards liquidity (Azi et al., 2008). In earlier periods, there was more robust evidence of a liquidity premium that diminished over time to levels that the study found statistically indistinguishable from zero (Ben-Rephael et al., 2015). Contrarily, Chinese evidence supported a significant liquidity premium that was not only robust to several alternative liquidity measures (Ben-Rephael et al., 2015) but increased in significance over the years (An et al., 2020).

Market efficiency explanation lands itself as aligned to early asset pricing models because, as mentioned earlier, the main criticism of the CAPM is that it did not adequately account for systematic risk due to the flawed assumption of perfect markets. Incorporating liquidity, one of the factors not captured by the standard CAPM, leads to the empirical finding of a liquidity premium. However, as markets become more efficient, a liquidity premium gradually declines, and vice versa. Thus, one would expect that emerging or developing markets studies would support the Amihud and Mendeleson (1988) hypothesis, but that is not necessarily the case. For instance, Miralles-Quirós et al. (2017) found that more liquid assets tended to yield higher returns in the Portuguese stock market, in contrast to Amihud and Mendeleson (1988). Similarly, Vo and Bui (2016) documented a negative relationship between illiquidity and the Vietnamese stock exchange stock returns. Thus, different markets exhibit differences in the empirical pricing of liquidity.

Assefa and Mollick (2014) found that liquid securities yielded higher returns than illiquid securities in Africa's stock markets. The study involved sixteen African markets, and the results held for all markets except South Africa. This is ascribed to the South African market being more mature and developed than the other African markets in the sample. In line with the idea that the more efficient the market, the lower the illiquidity premium, the study found that when South Africa was included in the analysis, the relationship between liquidity and returns became statistically insignificant. Overall, the literature suggests that whether liquidity is a predictor of returns is not yet settled or explored conclusively.

2.3.5 Liquidity Commonality

In the literature, liquidity is often analysed through a microstructure lens. As discussed in previous sections, much of the research concerns the trading volumes, transactions costs and overall liquidity of individual securities, as is the case in microstructure literature. However, a strand of literature on liquidity seeks to explore the effects of broader market liquidity on the liquidity of individual securities, commonly referred to as liquidity commonality. Understanding liquidity commonality is important for investors because it implies a systematic risk that cannot be diversified away. Thus, it has implications for asset pricing, portfolio selection and market efficiency. In severe market conditions, the risk of illiquidity is greatly exacerbated by liquidity commonality and could lead to inventory risk and an inability of investors to either buy or sell. Liquidity commonality explains market crashes where co-movements in liquidity of individual securities resulted in wider market illiquidity, such as the financial crisis of 2007 and the flash crash of 2010.

Well documented measures of individual asset liquidity are trading volume, price and volatility. Chordia et al. (2000) determined that market risk can be understood in terms of inventory risk and asymmetric information on a market-wide level. General market price swings influence trading activity. Trading volumes determine the optimal levels of dealer inventory, which consequently affects the liquidity of assets. Additionally, large trades resulting from similar investing styles by institutional funds can exert inventory pressure across the market. As such, volatility can have a market component as liquidity co-moves with correlated inventory movements of individual assets. Regarding asymmetric information, the few privileged could possess private information, such as new technology, influencing an industry. A key question is the relative importance of inventory risk and asymmetric information in market-wide liquidity.

In contrast, Huberman and Halka (2001) found that while there is a systemic and time-varying liquidity component, it was not linked with inventory risk and asymmetric information. Results of commonality studies have, over the years, continued to yield differences, even from the earlier works. For example, Hasbrouck and Seppi (2001) failed to find any economically significant components of liquidity commonality in the market. Instead, they found that firm-specific liquidity effects were more prominent. On the other hand, Brockman and Chung (2002) found a significant market and industry-wide influence on liquidity commonality on firms' order flows. Similar findings were recorded by Galariotis and Giouvris (2007); Foran et al. (2015).

As the studies on commonality have gained ground, the objective moved from finding evidence of commonality to investigating the causes of commonality. Karolyi et al. (2012) first proposed the existence of global liquidity commonality, citing demand side and supply side sources. Demand-side sources include institutional ownership, investor sentiment and trading activity. Supply-side sources typically refer to funding constraints and are less influential than demand-side sources in liquidity commonality (Kumar & Prasanna, 2020). Accordingly, liquidity commonality literature has evolved to ascertain the sources of commonality worldwide and supply and demand-side sources. The supply-side hypothesis is that when funds are constrained, there will be negative returns in the market and thus fewer funds in securities, meaning less liquidity supply. This is usually associated with high interest rates, high volatility and poor financial market conditions (Brunnermeier & Pedersen, 2009). The demand side hypothesis refers to the trading behaviour of mostly institutional investors (Brunnermeier & Pedersen, 2009).

One of the most comprehensive studies that involved 39 markets over 15 years determined that liquidity commonality was higher in weaker, financially and economically volatile, poor investor protection and opaque information environments (Moshirian et al., 2017). This study also found that behavioural causes of liquidity commonality are negatively associated with markets defined by low levels of individualism and masculinity and higher levels of power distance and uncertainty avoidance. Furthermore, just as Chordia et al. (2000), asymmetric information was also a factor in liquidity commonality. The cultural differences identified lend credence to the idea of country differences. However, there are other demand-side possible mitigating sources of commonality, such as institutional ownership. Deng et al. (2018) and Gold et al. (2017), and Vo et al. (2021) found a negative relationship between foreign institutional ownership and global liquidity commonality. They also found evidence that foreign institutional ownership mitigates the effects of culture and a poor corporate governance environment. However, it exacerbated the impact of economic policy uncertainty.

While evidence of demand-side liquidity commonality has been documented in most developed markets or in studies that included a broad global data set, evidence of supply-side liquidity commonality has been documented typically in emerging markets. For example, Syamala et al. (2017) found that supply-side sources were more influential than demand-side sources of liquidity commonality in India. These results were attributed to the fact that India is a bank-based economy. Therefore, bank returns, exports and the exchange rate would logically be more influential than the trading behaviours of investors. Similarly, Będowska-Sójka and Echaust (2019) found that the emerging markets of Europe exhibited supply-side liquidity commonality. Some emerging market results have yielded evidence of both sources of liquidity commonality. Silva and Veras Machado (2020) found that foreign institutional investors drive liquidity commonality in the Brazilian stock market and do so at an increasing rate during times of financial crisis. Concurrently, the commonality during periods of a financial crisis is intensified by funding constraints. Another contradictory study was Kumar and Prasanna (2020), which also found conjoined supply-side and demand-side liquidity effects in the Indian stock market. This discussion serves as the basis for the selection of control variables and is further elaborated upon in Section 3.4.1, where control variables are addressed.

2.3.6 Liquidity in Order-driven and Quote-driven Markets

This section aims to analyse the dynamics of liquidity. Traders are required to make critical buy/sell decisions within a specified time frame. A central question that occupies traders is when to execute their buy/sell orders and whether to utilise a market order or a limit order. Research has indicated that liquidity levels in asset markets exhibit temporal variations. In other words, liquidity flows are subject to change over time, indicating that liquidity is not a static phenomenon. It was noted earlier that transactions can occur either within or outside a spread; consequently, liquidity is inherently dynamic. Given that the focus of this study is liquidity, it is essential to comprehend this dynamic behaviour. The literature distinguishes between the determinants of liquidity in order-driven markets and quote-driven markets.

An order-driven market does not have a market maker. All investors display the prices and quantities that they wish to trade. An individual decides whether to place a limit order and allows other investors to buy or sell by market order. Alternatively, they can put in a market order and allow a limit order to be executed. The compensation for providing liquidity in an order-driven market is given to investors who place limit orders (De Jong & Rindi, 2009). In order to understand this, two events that drive trading ought to be explained. The microstructure literature identifies liquidity events and information events as the economic drivers of trading (Handa et al., 1998). An information event affects the entire market and investors' assessment of the value of traded assets. Unless information asymmetry exists in the market, on the other hand, liquidity events are individual events dependent on the desire to balance cash flow and expenditure and thus unique to an investor.

Liquidity events provide the type of price elasticity needed for investors who place limit orders to get compensation. Say an investor places a buy limit order, and liquidity-motivated investors (i.e., those with unbalanced portfolios) make sell market orders, causing the price of an asset to decrease. The limit order will be executed, and the investor will profit. However, if there are buy market orders, the price will increase, and the investor can either buy inflated shares or not trade (Goettler et al., 2005).

Liquidity events cause a temporary shift in prices that revert to their original level before the liquidity events. This process is referred to as mean reversion and is associated with short-term accentuated price volatility. Numerous studies have found evidence of this phenomenon (Agrawal et al., 2018; Ahmed et al., 2018; Corbet & Katsiampa, 2020). Short-term accentuated price volatility brought on by liquidity events sets the basis for the operations of an order-driven market. It offsets losses for limit orders, hence incentivising investors to place more limit orders. The price volatility in the asset then causes other investors, particularly those looking to balance their portfolio, to place market orders as it would be too costly to pass up on executing the limit orders. The balancing of demand and supply of liquidity is reached when the short-run volatility is just enough to compensate the marginal limit order investor. When there is short-run volatility and prices fluctuate wildly, investors place limit orders, which are executed by market orders. Limit orders are then triggered and placed until the order book is filled and the effects of the liquidity event are neutralised. When this occurs, investors are no longer incentivised to place limit orders.

To clarify the dynamics of liquidity in this particular market structure, we move from theory to the empirical by presenting the results of a study. Daníelsson and Payne (2016) found clear evidence of predictability of demand and supply of liquidity in order-driven markets. For a thorough analysis, the study was broken down into three parts. The first level of analysis involved a study of liquidity not conditioned on any market characteristics or market events. They discovered that fresh liquidity is mainly introduced at the best limit price. At the second level of analysis, results were gathered after being conditioned on prior market events. Before a market buy, liquidity supply on the opposite end of the order book is reduced. It indicated that liquidity that was mopped up by trading activities on one end of the order book was not reciprocally resupplied.

Further to this, liquidity tended to cluster on one side in a way that predicts lower liquidity in tandem with the other side of the order book. Additionally, when extant book liquidity was low, limit order arrivals increased relative to market orders. At the final level of analysis, market depth was included, which showed that market volatility encouraged the arrival of new orders. However, these orders tended to be at lower prices, translating to wider spreads, or decreased liquidity. Overall, this study showed that the liquidity supply and demand are self-regulating except in periods of volatility and when trading activities are introduced. Reiteration from Foucault (1999) and Handa et al. (2003), and Biais et al. (1995) found similar dynamics of order flows in order-driven markets.

In quote-driven markets, a market maker dictates the bid and ask prices (Kumar & Misra, 2018). Investors purchase assets at the asking price and sell at the bid price. The profit that the market maker makes, the difference between the bid and ask spread, is the compensation they receive for providing immediacy (liquidity) to investors (Demsetz, 1968). Immediacy is the ability to transact any time while the market is open. The quote-driven market has market makers who act as intermediaries for buyers and sellers. In a price-driven market, the quote-driven spread reflects the difference between the bid and ask price. However, a quoted spread is typically an indicator of liquidity at a particular point in time, so transactions can occur within the spread or even outside. This variability can be assessed based on order flows that invariably affect liquidity (Hwang & Jindapon, 2020). For example, an increase in buy order flows would positively impact the asking price as there is increased aggregate demand.

Increased order flows may signal to other market participants that there might be some benefit to be gained that is yet unknown (information asymmetry) (Tripathi & Dixit, 2021). Sellers will then demand a premium for the asset, driving up prices. So, we see that market makers balance the demand and supply of investors. Market makers provide liquidity to investors for a price.

Market liquidity is dependent on dealers to supply liquidity to the market. Dealers adjust their bid-ask spread as their inventories of assets are drawn down or up (Treynor, 1987). Prices quoted by dealers are based on relative values rather than fundamental values. According to Treynor (1987), while dealers are not concerned about fundamental values, they are concerned with the outside spread. They rely on value investors, those concerned with the fundamental value, to provide the ultimate liquidity. The ultimate liquidity is set at the minimum and maximum price at which value investors are willing to go long or short, respectively, on the dealers' inventory (Mehrling, 2013). Besides the dealers in a market, other market makers operate within the confines of the outside spread (Baradel et al., 2019; Lepone & Wong, 2017). Market makers operate by skewing bid and offer prices. For example, inventory balances that are, for example, too short will cause the market maker to increase the relative price to match other market makers' prices. Equally, when inventory is too long, prices are lowered. These operations enable the rectification of flow imbalances by sharing amongst the market makers.

The two different types of markets have different market structures, and as a result, the dynamics, including those of liquidity, are different (Narayan & Zheng, 2010). For example, by comparing order-driven and quote-driven markets, Malinova and Park (2013) found that small trades in dealer markets resulted in smaller market width than order-driven markets and vice versa for large trades. Simultaneously, price impacts on small trades were higher in dealer markets than in order-driven markets and the opposite for large trades. There are many differences between order-driven and quote-driven markets that affect liquidity (Pereira et al., 2020). The most obvious is that order-driven markets do not have market makers. Market makers perform the essential function of providing liquidity by providing immediacy to traders.

In order-driven markets, the supply of liquidity is a function fulfilled by investors who place limit orders. In an order-driven market, there is no obligation on any market participant to place a limit order. As such, there is no liquidity supplier of last resort. This is because investors' primary objective is not to provide immediacy but rather to make decisions about their portfolio (Handa et al., 1998). In contrast, in a quote-driven market, as mentioned earlier, dealers and market makers, by working within the confines of the inside and outside spread, rely on value investors to be liquidity suppliers of last resort. Hence, order-driven markets are generally less liquid than quote-driven markets. However, they have an advantage over quote-driven markets, which is that they lower transaction costs (Flepp et al., 2017).

Quote-driven markets are relatively common in developed countries of the US, Australia, Canada, and the UK, but not in emerging markets. Some developing markets such as those in China, India, Kenya, Nigeria, Brazil, and South Africa operate as order-driven markets. However, some markets combine the attributes of both types of markets by, for example, allowing for the viewing of limit orders and showing the bid and ask quotes. The Nasdaq and the New York Stock Exchange are models for hybrid markets. "Both structures have their advantages, and neither can claim to be close to the economic ideal of a perfect market" (Schwartz & Weber, 1997, p.1). Market imperfections are the subject of the next section.

2.4 Market Imperfections

2.4.1 Asymmetric Information

George Akerlof first advanced the idea of asymmetric information in 1970 in the publication "*The market for lemons: quality uncertainty and the market mechanism*". In the paper, Akerlof describes a scenario wherein a seller is privy to certain information that buyers, reliant on market statistics, do not have and thus are motivated to sell a lower quality product to gain from this informational advantage. He contended that buyers rely on average market statistics to obtain information about a product, whereas a seller, more familiar with a specific product, has more product-specific information. The information advantage incentivises sellers to trade in a lesser quality product than the market average.

The application of information asymmetry has been broad in financial markets. Specifically, it has been used to explain several phenomena, including asset prices, asset returns, market flashes and crashes. Glosten and Milgrom (1985) were the first to link asymmetric information to liquidity. Their work puts forth the idea of a spread from an informational source. A market maker faces adverse selection risk. If investors are trading with superior information, the market maker risks loss unless profits from investors motivated by liquidity offset this. The offset of possible loss with profit is done through the setting of the bid-ask spread. Thus, Glosten and Milgrom (1985) proved that asymmetric information is negatively related to liquidity, a finding reiterated by Kyle (1985).

The consequence of asymmetric information in financial markets has been well documented in the literature. It is a reasonably well-established phenomenon in the literature that illiquidity results from asymmetric information (see, for example, García-Sánchez & Noguera-Gámez, 2017; Lee & Chou, 2018; Tripathi & Dixit, 2019). So pervasive is this relationship that models for measuring liquidity incorporate asymmetric information (Li et al., 2019). The current literature focuses on the dynamism between asymmetric information and liquidity in terms of size effects, time horizons, and how trading behaviour is influenced. For example, Hsieh (2017) attributed the difference in liquidity to asymmetric information, where illiquidity was higher before earnings announcements than post-earnings announcements in the London Stock Exchange. This paper focused on the impact of asymmetric information on liquidity at different periods of an information event.

Asymmetric information is more manifest in emerging markets than in developed markets. Emerging markets are characterised by ill-informed investors with unreliable access to information (Harrison & Moore, 2012). Disclosure requirements are not as robust as needed to adequately inform investors owing to poor legal and regulatory environments and weak minority investor rights (Sokolovska, 2017). In line with this is the conventional wisdom that market quality is improved when there is information disclosure. Disclosure crowds out private information and hence reduces asymmetric information (Goldstein & Yang, 2017). Beyond the differences between developed and emerging markets, the literature also highlights the differences in asymmetric information amongst investor types. Individual investors are generally thought of as uninformed and less sophisticated than institutional investors. They are at an informational disadvantage and face behavioural biases when making investment decisions. Studies such as Kim et al. (2019) find that individual investors show more asymmetric information than institutional investors in the Korean stock market. The same study revealed that the presence of foreign institutional investors tended to mitigate asymmetric information. In reiteration, Yang et al. (2017) and Agudelo et al. (2019) revealed that foreign and domestic institutional investors are more informed than individual investors.

2.4.2 Imperfect competition

Imperfect competition is a market imperfection closely related to information asymmetry because large trades are often the result of privately-held information. In a competitive market, asset prices are informed by the level of information acquired by traders, and this information is in turn acquired from the price of assets. Essentially, traders believe that the prices of assets reveal information and will thus make trades based on their belief of what this information is. As such, information acquisition and price equilibrium in the market coincide. This situation describes an ideal wherein individuals have access to the same information.

Empirical models based on competitive markets discount the traders' effects on the price of the asset. On the other hand, imperfect market models account for the effects of trading strategies of traders with asymmetric information on asset prices. For example, a monopolistic agent with private information is incorporated into prices at a slow and steady pace in a linear manner, and market depth (i.e., liquidity) is constant over time (Kyle, 1985). The single monopolistic agent optimally exploits its monopoly power over time. However, in the real world, it is more likely that instead of a single monopolistic agent, there will be multiple agents with private information.

So, later Holden and Subrahmanyam (1992) modelled this more realistic depiction of the financial markets. Their model included multiple agents with private information who seek to rapidly exploit this information as they operate under the assumption that other traders may soon acquire this information. The study revealed that multiple informed investors trade aggressively; thus, private information is reflected in asset prices quickly. The market is strong-form efficient, and as such, market depth is large (i.e., highly liquid). By subdividing trading periods by calendar time, it was further revealed that market depth was least in early periods when adverse selection is high but subsequently deepened with time as the effects of adverse selection diminished.

Further development of the Kyle (1985) model that assumed a single risk-neutral agent incorporated the Holden and Subrahmanyam (1992) multiple agents into a dynamic framework that assumed risk-averse traders. The study's findings revealed that both monopolistic and competing informed traders choose to rapidly exploit rents, causing an increasingly deepening market depth as time progresses (Holden & Subrahmanyam, 1994). The likely explanation for this result is that although a trader would like to exploit rents gradually, his risk-aversion means he is uncertain about the future expected value of assets, thus causing him to trade rapidly, unlike a risk-neutral agent. A risk-averse agent would not like to bear any unnecessary risk related to the expected value of assets in the future and will therefore trade more aggressively than a risk neutral agent. In this aspect this study differed from Kyle (1985) but was similar to Holden and Subrahmanyam (1992) in that non-cooperating competing informed traders exhibited similar aggressive trading regardless of risk assumption.

In sum, theoretically, it is understood that the relationship between liquidity and returns is moderated by imperfect competition. Future expected returns are reduced when there is increased information competition, as this reduces market inefficiency. Empirical studies have supported this assertion. For example, Chiu (2020) found that imperfect competition magnified the impact of macroeconomic uncertainty on liquidity in the Taiwanese market. In describing perfectly competitive financial markets, Lee and Kyle (2018) revealed that this occurs only when the number of traders approaches infinity.

2.4.3 Transaction Costs

Transaction costs are all-encompassing terms that refer to different inputs that go into a buy/sell transaction. In terms of trading in the financial asset market, transaction costs include the bid/ask spread, brokerage commission and transaction taxes. If we recall the definition of liquidity, which is the transference of an asset without significant loss, one can realise that transaction costs denote illiquidity. As transaction costs increase, the "without significant loss" aspect of liquidity is diminished as it takes away from the ready marketability of an asset. Transaction costs affect the market in terms of asset prices, investor behaviour and market returns. Amihud and Mendelson (1986) showed that assets with relatively high transaction costs tend to attract long-horizon investors, whereas low transaction costs attract short-horizon investors. The logic is that an investor would want to minimise transaction costs by trading infrequently and holding the asset for a longer period for the returns to compensate for the cost incurred.

Scale effects of transaction costs often relate not to the quantities transferred but to the size of an individual transaction or the market (Niehans, 1989). The most important effect of transactions is that they negatively impact the volume of transactions as traders seek to become economical amid rising costs. In a two-asset portfolio, the optimal structure is defined by the ratio of assets contained within the portfolio. In the absence of transaction costs, there is no constraint on the volumes traded. However, when transaction costs become a consideration, the optimal portfolio structure must account for this. The maximum expected utility is not simply the proportion of the two assets but also cost minimisation. In the face of transaction costs, an investor has the option to buy an asset x, buy an asset y or not trade at all. An increase in the cost of one of the two assets negatively impacts its demand, giving a first-order effect of transaction costs[2]. Consequently, there is a range of asset prices that induces zero trading.

However, the seminal work by Constantinides (1986) showed that transaction costs have a second-order effect on asset returns. He demonstrated that investors accommodate an increase in transaction costs by reducing the frequency and volume of trade. Directly affecting the three aspects of a liquid market identified by Kyle (1985): market depth, resilience, and the bid/ask spread. Furthermore, traders showed no sensitivity to significant deviations of the optimal proportion of the portfolio from the portfolio with transactions costs. Thus, a liquidity premium is enough to compensate investors for this deviation. Notwithstanding these findings, Constantinides (1986) does identify certain limitations in the study. Firstly, the model used a two-asset portfolio and assumed endogenously determined asset adjustment in the portfolio and thus an infinite horizon model as opposed to a model with multiple assets and single-period investments. Vayanos (1998) and Barclay et al. (1998) have obtained similar results, finding a second-order effect[3] of transaction costs on returns. The presence of only second-order effects of transactions costs explains pricing models that do not incorporate these costs.

Subsequent studies with different parameters revealed that the second-order effect argued by Constantinides (1986) relied on the assumption of an infinite investment opportunity. Jang et al. (2007) found that there is a first-order effect on the liquidity premium in a model with discontinuous investment opportunities. Vayanos & Vila (1999), again, while studying the effects of transaction costs on asset prices, found that when transaction costs are increased, the price of liquid assets increases while the price of illiquid assets increases if they were in ample supply or decreases if supply was small. In periods of market crisis, this holds especially true, where there is a flight to liquidity. Generally, there is increased demand for liquid assets, which attract prohibitively high transactions costs (O'Hara & Zhou, 2020).

[2] A first-order effect of transactions costs entails an increase in transaction costs which negatively affects bid price.
[3] Second-order effects of transaction costs result in reduction in volume and frequency of trades. In such instances, market depth and resilience are negatively affected.

Other studies have also contradicted the notion that transaction costs only have a second-order effect on asset prices (Albuquerque et al., 2020). Thus, from the literature, the question is not whether transaction costs are consequential; the question is the order of magnitude.

2.5 Hypothesis Development

2.5.1 Index Funds and Market Liquidity

Over the years, the utilisation of index funds has gained significant traction across various markets. This increase in popularity can be attributed to their cost-effectiveness, capacity to limit exposure to diversified market segments, and, in the case of ETFs, their intraday trading capability and tax efficiency (Lettau & Madhavan, 2018). However, these advantages are accompanied by certain negative repercussions. Gammill Jr and Perold (1989) predicted that the introduction of index funds would adversely affect the liquidity of individual stocks. Specifically, the presence of informed traders within a market compels market makers to compensate for potential losses incurred when trading with informed traders by widening the bid/ask spread. Consequently, the likelihood of loss is heightened in the individual stock market compared to the index market, due to the preference of uninformed investors to engage in trading within the index market.

The advantage of private information is diminished in the index market, resulting in a lower assessed adverse selection cost for the market maker compared to the market for individual stocks. The models proposed by Kyle (1985) and Holden and Subrahmanyam (1992), which assert that informed investors swiftly exploit the rents associated with their private information for profit at the expense of uninformed traders, indicate a preference among the latter group for trading in the index market. As previously noted, the impact of private information is less pronounced in the index market. The migration of uninformed traders from the individual stock market to the index market, coupled with the reduced adverse selection cost and overall transaction cost, culminates in more liquid index funds and diminished liquidity for individual stocks.

2.5.2 ETFs and Liquidity of Underlying Securities

The relationship between Exchange-Traded Funds (ETFs) and market liquidity has been a subject of ongoing debate in financial literature. Traditional models, such as those proposed by Kyle (1985) and Holden and Subrahmanyam (1992), assume that information in index funds, including ETFs, incorporates all available information from underlying securities. However, recent studies have challenged this assumption, highlighting the complexity of the ETF-liquidity relationship, particularly in emerging markets.

Building on this debate, Jung and Shiller (2005) introduced an alternative perspective based on Samuelson's dictum, which posits that markets are micro-efficient but not macro-efficient. This theory suggests that individual stock information is more accessible and varies more significantly than aggregate market information. Glasserman and Mamaysky (2016) argue that this has important implications for ETFs that warrant further exploration. Consequently, it can be hypothesised that investors might prefer investing in individual stocks over ETFs, or move between these markets based on perceived opportunities.

The impact of ETFs on the liquidity of underlying securities has been extensively studied, particularly in developed markets. Several studies have found a positive relationship between ETF introduction and increased liquidity of underlying assets (Hamm, 2014; Malamud, 2016; Saglam et al., 2019). However, this relationship may be moderated by the accessibility of individual securities. Holden & Nam (2019) found that ETFs improve liquidity when individual securities are not easily accessible, but may deteriorate liquidity when they are.

This moderation effect becomes particularly relevant when considering emerging markets, which are generally characterised by illiquidity (Marozva, 2020). For instance, Bayala and Bama (2019) noted poor market liquidity in the West Africa regional stock exchange due to investors' share conservation approach. Other studies have highlighted conditions of market turmoil as moderating the effects of ETFs on market liquidity. For example, Yousefi and Najand (2022) reported capital flight by international investors who perceived emerging markets as riskier during the Covid-19 pandemic. Thus, broader market sentiment often creates a reinforcing cycle of illiquidity, amplifying the adverse effects of ETFs (Kunjal, 2022). Converse et al. (2023) explain that this is because ETFs attract short-horizon clienteles who trade more often in response to shocks. Saha et al. (2022) affirmed that investor behaviour caused liquidity issues for ETFs' underlying assets during the pandemic. So, while the growth of ETFs in emerging markets has increased their interconnectedness with the global financial system, they have inadvertently exacerbated the markets' sensitivity to the global financial cycle.

Nonetheless, the complexity of ETFs offering diversification benefits is underscored by conflicting evidence in the literature where ETFs act as a liquidity catalyst. One significant finding is that the introduction of ETFs enhances market liquidity by providing retail and institutional investors with greater access to and participation in previously illiquid markets. For example, Fu and Jiang (2023) highlighted that ETF liquidity positively correlates with price efficiency, indicating that a more liquid ETF market can lead to better pricing of underlying assets. Saglam et al. (2019) found that stocks associated with ETFs are more liquid than those that are not. Hamm (2014) presented contrary evidence, suggesting that the liquidity of underlying stocks deteriorated with ETF introduction, an effect exacerbated by ETF diversification. Other studies have documented a bi-directional effect of liquidity between ETFs and their underlying portfolios (Marshall et al., 2015), adding another layer of complexity to the issue.

Further complicating matters, Pan and Zeng (2019) studied ETF arbitrage under liquidity mismatch conditions, finding that arbitrage activities are subject to frictions in both primary and secondary markets. These frictions can lead to persistent price mismatches between ETFs and the illiquid assets they track, potentially affecting market liquidity in ways not observed in more liquid markets. Another aspect of the negatives of arbitrage activities was noted by Jhunjhunwala and Sethi (2022), who illustrated that traders engaging in arbitrage across the entire basket of underlying securities can inadvertently increase the return co-movement of these assets, potentially diminishing the diversification benefits that ETFs are purported to provide . This can lead to a situation where assets that would typically exhibit diverse price behaviours become tightly correlated, negatively impacting overall market liquidity.

Moreover, inefficient ETF prices can distort market signals, increase volatility, and promote market instability (Fu & Jiang, 2023). Such distortions may deter potential investors from participating in the market, further exacerbating liquidity issues. Erratic price movements resulting from arbitrage actions may make markets appear riskier, dissuading liquidity provision. It is also important to consider the role of market conditions and regulatory environments in influencing arbitrage activity in emerging markets. Neto et al. (2021) found that tracking errors in emerging markets are generally higher compared to developed markets, reflecting limitations in the efficiency of arbitrage operations.

Given this inconclusive evidence, particularly in markets characterised by illiquidity, this study proposes to test the following hypothesis:

H1: The introduction of ETFs increases the liquidity of the underlying index.

This hypothesis is supported by Samuelson's dictum, which has been confirmed by several scholars (Beikmanis & Sīlis, 2020; Glasserman & Mamaysky, 2019; Gumbo, 2017). It also addresses the potential crowding-out effect on investors in the underlying market, as suggested by Ben-David et al. (2018).

The differences in asset microstructure between developed and developing countries, and their effects on liquidity, underscore the importance of investigating this hypothesis. While most studies showing a positive association between ETFs and market liquidity are from developed countries, the unique characteristics of emerging markets may lead to different outcomes. This study aims to address this gap in the literature and contribute to our understanding of ETF impacts in diverse market contexts, potentially shedding light on how these financial instruments interact with market liquidity in less developed financial ecosystems.

2.5.3 ETFs and Liquidity Risk

The conceptual foundation for this study is anchored in the models developed by Kyle (1985) and Holden and Subrahmanyam (1992), which relate the impact of ETFs to the volatility of market liquidity. These models assert that noise traders and convenience traders move to the ETF market rather than the individual securities market. Thus, the relationship between ETFs and volatility depends on the type of investors that are attracted to the ETF. Some empirical studies, such as Ben-David et al. (2018), have shown that stocks with higher ETF ownership often exhibit greater nonfundamental volatility. Moreover, Yuan and Zeng (2023) demonstrated that changes in ETF shareholding ratios can systematically affect the liquidity of underlying stocks, thereby modifying the volatility profile of the market. Given the yet unexplored types of investors drawn to ETFs in developing markets, an assessment of the impact on liquidity shock is essential. Still, as Ben-David et al. (2018) point out, some questions remain about whether ETFs have introduced different types of investors and their impact on systemic risk.

Further conceptualisation of this study is based on the theoretical work of Greenwood (2005), who asserted that non-fundamental shock is propagated to individual securities by risk-averse arbitrageurs. The arbitrage mechanism of ETFs that facilitates rapid rebalancing is the primary source of the volatility spillover to the individual securities. Wang and Xu (2019), for example, documented significantly increased overall and fundamental volatility of the index caused by daily ETF flows in the Chinese market. Further support was given by Malamud (2016), who showed that the arbitrage mechanism of ETFs leads to shock propagation to the underlying securities, which was strengthened by liquidity.

Additionally, the interaction between ETF-induced arbitrage and market microstructure becomes even more pronounced during periods of market stress. Tripathi and Sethi (2022) emphasise that in turbulent market periods, both positive and negative effects on pricing efficiency emerge, indicating that the volatility spillovers from ETFs are context dependent. Yavas and Rezayat (2016) extend this line of inquiry by showing that ETF returns are linked to volatility spillovers across different emerging markets, suggesting that the interconnectedness of these markets can exacerbate the transmission of liquidity shocks. This phenomenon is compounded by the presence of noise traders who are drawn to ETFs for their simplicity and low transaction costs, thereby potentially destabilising prices and reducing the quality of liquidity (Corbet, 2012; Weber et al., 2013).

The sensitivity of emerging markets to these ETF-induced effects is particularly notable. Emerging markets typically have lower overall liquidity and more fragile market structures, which magnifies the impact of rapid trading dynamics. Empirical studies in markets such as South Africa and Egypt provide evidence of these phenomena (see Matarutse & Sibanda, 2014; Otaify, 2023), suggesting that the liquidity dynamics in less mature markets are more prone to instability when influenced by ETF trading. Overall, the effects of ETFs on the volatility of liquidity in emerging markets are significant yet context dependent, necessitating continuous empirical investigation to delineate the conditions under which ETFs either stabilise or destabilise market liquidity. Accordingly, the following research question is addressed in this study: To what extent does the liquidity of ETFs interact with the liquidity risk of the underlying index? Thus, the following hypothesis is put forth:

H_2 = Higher ETF liquidity decreases the sensitivity of the underlying index's returns to market-wide liquidity shocks.

2.5.4 ETFs and Market Efficiency

The effects of the pricing efficiency of ETFs on the underlying market are often a relationship that encompasses several mechanisms, including impacts on pricing and volatility. And often, a discussion on market efficiency is intrinsically linked to that of market liquidity as the latter is typically a determinant of the other, particularly as it affects ETFs. Cespa and Foucault (2014) assert a positive relationship between liquidity and price informativeness; a loss of liquidity in one asset can have a spillover effect on the liquidity and price informativeness of another asset. Atanasova and Weisskopf (2020) reiterated this point further, finding that price convergence of ETFs and the underlying portfolio was driven by liquidity. Li and Zhu (2018) presented evidence that when the underlying assets of an ETF are illiquid, market participants tend to trade the ETF as an alternative to compensate for the restrictive arbitrage and high transactions costs of the underlying assets.

The arbitrage activities associated with ETFs ensure that market prices of the funds closely track the NAV of the underlying securities, enabling a converging effect that enhances informational efficiency (Broman & Shum, 2018; Lakshmi, 2022). By trading in the ETF, market participants circumvent the trading constraints of the underlying asset, leading to more informational efficient pricing. Glosten et al. (2021) also found that ETF activity was positively associated with greater informational efficiency, and that efficiency was contingent upon firms with weak information and imperfectly competitive environments. Other studies have indicated an improvement in the underlying securities of an ETF (Dias et al., 2024; Zhao et al., 2021).

However, dissent exists, such as that of Israeli et al. (2017), who showed that an increase in ETFs deteriorates the efficiency of the underlying securities. They hypothesised that as ETFs increased, transaction costs of the underlying securities increased proportionally, leading to a deterioration of pricing efficiency. Further support for this hypothesis was outlined by Al-Nassar (2021), who showed that the ETFs did not fully reflect the information from the underlying basket of securities. They attributed this to market frictions related to primary and secondary market liquidity factors. Secondary factors included a lack of active market for the ETF shares as well as their underlying securities, while the primary market factors were short selling restrictions and high costs of creation and redemption. The cause of the pricing inefficiencies by ETFs is the locking up of shares of the underlying market that limits the shares available for trading. Additionally, uninformed investors or noise traders move to the ETF market, leaving only informed investors in the underlying market who are disincentivised from trading with one another (Subrahmanyam, 1991). Amihud and Mendelson (1986) detailed the differences in investor type, noting that long-term investors tend to invest in assets with higher transaction costs and short-term investors, in assets with lower transaction costs. Thus, given the lower transaction costs of ETFs, they typically attract short horizon investors, consequently diminishing the trading activity in the underlying market and deteriorating pricing efficiency.

Extant literature has revealed that one of the key mechanisms through which ETFs affect market efficiency, the arbitrage activity, indicates divergence from the theoretical expectations. Theory suggests that arbitrage activity serves as a critical role in maintaining price alignment between ETFs and their underlying assets. As described by Ben-David et al. (2017), the arbitrage activity aims to eliminate price discrepancies, thereby enhancing market efficiency. Secondary market arbitrageurs, particularly market makers, play an essential role in this process, as they can take opposite positions in ETFs and their underlying securities to capitalise on transient mispricings. By providing investors with an immediate way to gain exposure to diversified asset classes, ETFs facilitate quicker adjustments to information, reflecting more rapid changes in fundamental valuations relative to traditional investment vehicles (Lakshmi, 2022).

However, the process of arbitrage can have unintended consequences on market efficiency and price dynamics. Xu and Pu (2022) found that the ETF share volume makes an important contribution to the price efficiency of the tracked stock market, which is weakened by the arbitrage activity across the markets. Similarly, Chen et al. (2024) found that an increase in ETF ownership reduced the pricing efficiency of the underlying stocks. They attributed this phenomenon to the arbitrage activity which triggers a noise contagion from the ETF to the underlying market. When significant volumes of arbitrage transactions occur, liquidity strains can emerge, particularly if the underlying stocks are illiquid, leading to inefficiencies characterised by higher bid-ask spreads. This dynamic can negatively impact price efficiency, as the underlying securities may reflect noise rather than fundamental values during periods of intensive arbitrage trading (Agarwal et al., 2018). It is the arbitrage mechanism that also allows liquidity shocks and volatility to be transmitted to the component assets potentially comprising market efficiency (Son et al., 2023). Jhunjhunwala and Sethi (2022) highlighted another aspect of arbitrage influences on market efficiency, noting that while arbitrage mechanisms are essential for ensuring that ETF prices do not deviate significantly from their underlying values, they can simultaneously increase return correlations among the underlying assets. This tendency can diminish the diversification benefits typically provided by ETFs, thereby raising concerns regarding the overall stability and efficiency of the market. Based on the above literature, and following on the preceding discussion of ETFs and liquidity, the following hypothesis is put forward:

H_3 = ETFs enhance the market efficiency of the underlying index.

2.6 Conclusion

This chapter established the theoretical framework underpinning this study and emphasised the significant gap in the literature concerning ETFs and their potential impacts on market liquidity. The existing literature predominantly focuses on ETFs in developed markets, highlighting the need for a thorough examination of liquidity differences between these markets and emerging markets. The variations in market macro-structure necessitate further investigation, particularly regarding market imperfections that are exacerbated in emerging markets. These imperfections raise concerns about the receptiveness of ETFs in such environments. Consequently, the persistent ambiguity surrounding liquidity in these markets, coupled with the potentially illusory liquidity benefits of ETFs arising from the ETF ecosystem, warrants exploration from the perspective of emerging markets. Furthermore, the literature review provided a foundation for the subsequent chapter on methodology by detailing the theoretical aspects and offering references for the investigations outlined in later chapters.

CHAPTER 3: METHODOLOGY

3.1 Introduction

Research methodology is informed by assumptions made concerning the nature of science. Objectivism and subjectivism are two approaches to research philosophy that determine ontology, epistemology, and methodology. Such philosophical assumptions shape the research outcome and are, therefore, critical to the choice of methodology. This chapter sets out the mode of enquiry for the study. Cognisance is given to the fact that the complexities of the phenomenon make it difficult to select methods that comprehensively capture the relationships of the objects of the study. As such, even the most objective and purist paradigms leave room for choice by the researcher. Nonetheless, the methodologies employed in the study are selected with the view to adequately addressing the research questions.

3.2 Population and Data

The population of this study consists of all emerging markets as defined in the MSCI database[4], which is twenty-five countries in total. Each of these countries has ETFs listed on their respective stock markets. The sample for this study was further screened based on the following criteria:

- The inclusion of equity ETFs that track a domestic index with companies operating across diversified sectors.
- The selection of passive managed ETFs with a full replication strategy.
- The choice of the largest ETF, in terms of assets under management, that meets the first two criteria.

This screening process resulted in a final sample size of thirteen countries that met the specified criteria. Table 1 below presents the countries, the corresponding ETFs, the indices they track, and the dates of introduction of these ETFs in the market. Further sampling for each objective is outlined in the relevant chapters.

[4] https://www.msci.com/our-solutions/indexes/emerging-markets

Table 1: Study Sample: Countries, Corresponding ETFs, Tracked Indices, and Market Entry Dates

Country	ETF	Index	ETF Inception Date
Brazil	Ishares Ibovespa (BOVA11)	Bovespa Index	28/11/2008
Bulgaria	Expat Bulgaria Sofix UCITS(BGX)	BSE Sofix	27/09/2016
Chile	Fundo Mutuo ETF IT NOW S&P IPSA	S&P CLX IPSA (SPIPSA)	01/12/2012
Colombia	Global X Colombia Select ETF	S&P Colombia Select Index	29/05/2014
Greece	ALPHA ETF FTSE Athex Large Cap Equity UCITS (AETF)	FTSE Large Cap Index	14/01/2008
Philippines	First Metro Phil EQTY ETF	PSE Index	02/12/2013
Qatar	QE Index ETF	QE Index	05/03/2018
Russia	FINEX RTS UCITS ETF	RTS Index	24/02/2016
South Africa	Satrix 40 ETF	ALSI 40	27/11/2000
Taiwan	Yuanta/P-shares Taiwan Top 50	TSEC Taiwan 50 Index	25/06/2003
Thailand	ThaiDEX SET50	SET50 Index	06/09/2007

3.2.1 Summary features of Market Microstructure of Sampled Countries

To properly contextualise and interpret the findings of this study, it is important to consider the underlying microstructure characteristics of the stock exchanges where these ETFs trade. Key microstructure variables, such as trading volume, market size, and the number of listed entities, provide valuable insights into the depth and breadth of the investment landscape. For instance, higher trading volumes and larger market capitalisations are generally associated with greater liquidity, as they attract more diverse and sophisticated participants, including institutional investors and market makers.

The regulatory framework governing a stock exchange can also shape the incentives and constraints faced by market participants, including ETF providers and authorised participants, which can, in turn, influence liquidity. Under a Limited Exchange Self-Regulatory Organisation (SRO) model, the collaborative nature of the regulation may promote transparency and stability, supporting market liquidity. Conversely, a pure Government model could potentially hinder the exchange's ability to respond quickly to market changes, while an Independent Member SRO model may foster innovation but introduce concerns about conflicts of interest, both of which could impact liquidity.

Furthermore, the sectoral composition of ETF portfolios and the concentration of their holdings can indicate the potential for idiosyncratic risks to impact the fund's performance and liquidity. The investment styles of the sampled ETFs, which include growth at a reasonable price (GARP), growth, and aggressive growth, can also influence their trading patterns and liquidity provision, as these strategies may attract different investor profiles with varying trading behaviours and holding periods. Finally, the expense ratio of an ETF reflects the costs associated with managing and operating the fund, which can affect investor demand and trading activity, ultimately impacting market liquidity. By considering these microstructure variables, the observed effects of ETFs on market liquidity can be better contextualised within the broader market ecosystem. These features are presented in Table 2.

Table 2:Selected Market Microstructure Characteristics for the Sampled Countries.

Samples Countries	Microstructure Characteristics Trading Volume (90 day Avg)	Market size	Number of listed entities	Regulatory model	Top 3 ETF Sector Holdings	ETF Growth Style	Percentage Held by Top 5 Holding	Expense Ratio
Philippines	24,690	324.833 billion US$	288	Limited Exchange SRO	Commercial Banks Department Stores Shipping & Ports	Growth	50.99	0.49%
Bulgaria	5,796	6.501 billion US$	385	Limited Exchange SRO	Conglomerates Real Estate Investment Trusts Commercial Bans	Growth	55.13	1.0%
Brazil	5,817,603	788.626 billion US$	463	Limited Exchange SRO	Other metals and mining Oil & Gas- Integrated Commercial Banks	Growth	34.38	0.3%
Greece	7,298	59.035 billion US$	164	Government (Statutory) Model	Commercial Bans Soft Drinks Utilities - Diversified	GARP	53.83	0.97%
Russia	4,800	78.427 billion US$	832	Government (Statutory)	Oil & Gas – Integrated Commercial Banks Oil & Gas – Exploration & Production	GARP	58.12	0.90%
Chile	134,979	187.79 billion US$	295	Limited Exchange SRO	Commercial Banks Department Stores Regulated Electric	Growth	45.73	0.50%
Colombia	549,399	92.363 billion US$	65	Independent Member SRO	Regulated Electric Construction Materials Oil & Gas – Integrated	GARP	43.18	0.486%
Qatar	2,999	640.81 billion USD$	51	Independent Member SRO	Oil & Gas – Integrated Financial Services Industrials	GARP	Not available	0.50%
South Africa	179,576	1.07 trillion US$	297	Strong Exchange S SRO	Commercial Banks Internet Retail Gold	Growth	36.65	0.30%
Thailand	1,001,492	519.96 billion US$	821	Limited Exchange SRO	Commercial Banks Electric Equipment & Parts Telecom Services	Growth	42,25	0.51%
Taiwan	42,533,301	1.97 trillion	1025	Limited Exchange SRO	Semi-Conductor	Aggressive	86.54	0.32%

	US$	Electronic Components Commercial Banks	Growth

Note: This table provides an overview of the market microstructure of the sample countries. SRO is self-regulatory organisation. GARP is Growth at a reasonable price

3.2.2 Data Imputation

In handling the data, particularly the control variables, there were some missing values due to inconsistent reporting from different countries. Consequently, data imputation was necessary in order to maintain a balanced panel and enable the use of statistical models for the objectives. There are various approaches to handling missing data as discussed in the literature. Complete case analysis (CC), also known as listwise deletion, is one such option. The advantage of CC is its ease of implementation and suitability when the missingness is less than 5%. However, CC analysis relies on strong assumptions that the missing data is either missing completely at random (MCAR) or missing at random (MAR), and in practice, missingness of less than 5% is uncommon (White & Carlin, 2010).

Data imputation is a widely accepted method for dealing with missing values and serves as an alternative to CC (Austin et al., 2021). The goal of data imputation is to reduce bias caused by missingness, and this can be accomplished through either single imputation or multiple imputation. Imputation involves using all observed variables in a dataset to predict the missing value using a regression model. This can be done through either single imputation or multiple imputation. If the values are MAR or MCAR, single imputation provides unbiased effect estimates but underestimates the standard errors of the estimate because it assumes complete data. On the other hand, multiple imputation takes into account the uncertainty of the missing values by performing imputation multiple times. Knol et al. (2010) compared CC with MI and found that when the data is MAR or MCAR, MI performs well even with missingness of up to 30%. However, both CC and MI are not suitable when the data is missing not at random (MNAR).

This study addressed the issue of missing data by employing the multivariate imputation by chained equation (MICE) method, specifically utilising classification and regression trees (CART) as the conditional models. MICE offers an alternative approach to traditional multiple imputation (MI) by allowing for increased flexibility in modelling variables (White et al., 2011). To elaborate, the MICE procedure consists of several steps. The initial step involves mean imputation for all missing values, followed by an iterative imputation based on a model derived from the non-missing values of the respective variable and other variables in the dataset. The missing values are then imputed based on this model. The third step entails sequentially processing each missing data point, creating a chain of imputation models, hence the name "chained equations". Step 4 involves repeating the imputation process 5-10 times to generate multiple complete datasets, each with different imputed values. Ultimately, the pooled results are utilised to produce overall parameter estimates and standard errors, accounting for the variability due to missing data (Azur et al., 2011; Wulff & Jeppesen, 2017; Zhongheng Zhang, 2016). The strength of MICE over other methods of handling missing data is the smaller standard errors and narrower confidence intervals (Chhabra et al., 2017). Combining MICE with machine learning algorithms helps to further reduce bias in estimation.

CART is a widely used algorithm for decision trees in machine learning. It is favoured for its ability to generate accurate prediction models with nonlinear and interactive effects, while also producing easily interpretable decision trees. The CART is a greedy algorithm, dividing the data and assigning predicted values to each division (Loh, 2014). For quantitative outcomes, the mean is used as the predicted value within each division. For categorical outcomes, the mode is used. The algorithm consists of three main elements: variable splitting, stopping criteria, and model selection. During the variable splitting stage, the algorithm selects the variable and partitioning value that yields the most homogeneous outcomes within each group when dividing the data into two groups (Jiao et al., 2020). The resulting groups are referred to as child nodes, with the original split being the parent node (Breiman, 2017). All predictor values are assessed as potential splitting values. For a regression tree with numeric outcomes, the variable and splitting value that minimises the sum of squared residuals are chosen to divide the node. A classification tree with categorical outcomes, the variable and splitting value that minimises the Gini Index (or other measures of entropy/information) are selected (Daniya et al., 2020). This splitting process is repeated on each child node until a stopping criterion is met. Stopping criteria may include a minimum improvement in prediction accuracy, a maximum tree depth, or a minimum sample size required to divide a node.

By combining CART with MICE, the imputation process benefits from CART's ability to capture non-linear relationships and interactions in the data. MICE, which is commonly used to implement MI, by default, cycles through variables imputation without accounting for interactions and non-linearity (Laqueur et al., 2022). The imputation model deployed must be as complex as the final analysis model (Klusowski & Tian, 2024; Seaman et al., 2012; Wulff & Jeppesen, 2017). Accordingly, the imputation model used in this study is non-parametric and adequately accounts for complex relationships in the data similar to the final analysis models such as the propensity score matching and the DiD analysis. By incorporating CART with MICE, we reduce bias in estimates (Burgette & Reiter, 2010; Chhabra et al., 2017; Slade & Naylor, 2020). Imputation was implemented using the MICE package in R (Van Buuren & Groothuis-Oudshoorn, 2011; Zhongheng Zhang, 2016). The proportion of missing variables before and after imputation is depicted in Appendix A.1. To ensure reliability and validity of the imputed data, Box plots were applied and are presented in Appendix A.2. T-Tests were also conducted for the same purpose, the results of which are presented in Appendix A.3.

3.3 Estimating Liquidity

It was noted earlier that liquidity is a multifaceted concept with no agreed-upon definitional construct. As such, empirical studies employ a wide range of proxies to capture different dimensions and characteristics of liquidity. The proxies selected by scholars converge on the five dimensions of liquidity posited by Bervas (2006), namely, breadth, depth, immediacy, resilience, and tightness. The liquidity measures selected for use depend on the dimension that one requires to capture in their study. Many measures capture one dimension, while others capture two or more dimensions. Often the choice of proxy is determined largely by the availability of data (Johann & Theissen, 2017).

Recent works that examine liquidity use high-frequency data (intraday measures), which are available lately in some databases. However, relatively low-frequency data (daily observations) are still prevalent, especially for developing markets. High-frequency data (HFD) consists of intraday transactions, in some instances measuring second-to-second price changes. Such data generates large volumes that require advanced computer programmes for analysis, hence the use of HFD in developed countries (Le & Gregoriou, 2020). Low frequency data (LFD) is more accessible to developing markets as their market infrastructure is, in general, not so advanced as to generate HFD. In a comparative study between a developed and emerging country, Będowska-Sójka (2019) found that low-frequency liquidity measures were effective in both countries. Fong et al. (2017) compared numerous liquidity measures and showed the robustness of low-frequency liquidity measures as proxies for high-frequency benchmarks. The study also revealed the results held across different countries and periods. This study will therefore use low-frequency data-based liquidity measures.

There have been numerous studies on the effectiveness of certain proxies in capturing liquidity in certain markets. According to Díaz and Escribano (2020), there are four types of proxies used in low-frequency liquidity measures in the literature. These are transactions costs and volume-based proxies. The next sections discuss each of these different proxies.

In selecting the choice of liquidity measures, it is important to consider the liquidity dimensions as identified by Kyle (1985). These are market tightness, depth and resilience. It is noteworthy that emerging markets lack the wealth of transactional level data present for developed markets, notably, the bid and ask prices. Consequently, any selection of liquidity proxy will be limited to the availability of data needed to run the models.

3.3.1 Volume Based Measures

Volume-based measures are based on the idea that liquidity is determined by the number of transactions of a security. The higher the volume, the more liquid the security (as represented by a small bid-ask spread) and vice versa. On one hand, a small bid-ask spread drives volume while on the other, a high trading volume leads to a small ask spread. Volume-based proxies reveal the depth and breadth of a market signified by the number and volume of transactions. Additionally, the number of transactions provides information for market dealers who use it to execute orders without incurring excessively risky inventory positions.

The most used volume-based and liquidity measure in general, in the finance literature, is the Amihud et al. (2006) (il)liquidity measure. The illiquidity ratio, sometimes referred to as the return to volume ratio, indicates the sensitivity of average absolute daily price to trading volume for a stock. The stock is considered illiquid if the return to volume ratio is high. Goyenko et al. (2009) showed that the Amihud illiquidity measure was the most effective in measuring price impact. Fong et al. (2017) reiterated this when they found that of the 43 stock exchanges under review, the closing per cent quoted spread (Chung & Zhang, 2014) and Amihud measures were among the best in cost per volume proxies. Kang and Zhang (2014) likewise found that the Amihud measure was the most effective liquidity proxy. The strength of the Amihud measure in emerging markets over others has been reiterated by other scholars (An et al., 2020; Będowska-Sójka, 2018; Fong et al., 2017). Marshall et al. (2018) demonstrated the efficacy of the Amihud in capturing liquidity in the ETF market.

Despite its proven effectiveness, the Amihud, and in fact, volume-based measures require volume data, which, given the markets that make up our sample and the periods under assessment, is inconsistent for some markets and not always available.

3.3.2 Transactions Cost-Based Measures

One of the most used proxies for transaction costs is the bid-ask spread that consists of order processing costs, information asymmetry and inventory cost (Saleemi, 2022). All these factors were discussed in previous sections. However, to summarise, information asymmetry presents as a cost as dealers need to compensate for the potential loss from an information event. Similarly, dealers increase the bid-ask spread due to the uncertainty of future returns of their inventory, also associated with the time to execution of transactions. Again, dealers increase spread when order processing costs are high as compensation (Brouty et al., 2024). As explained before, transaction costs are a market imperfection typically persistent in developing countries and, as such, are considered in this study.

This study utilises spread estimators as proxies for liquidity for several reasons. One of the most evident and practical reasons is that the necessary data for estimating spreads is readily available for all markets included in this study. Additionally, spread estimators provide a comprehensive understanding of market tightness, resilience, and immediacy, unlike volume-based measures which only capture market depth and breadth (Bernales et al., 2018; Cobandag Guloglu & Ekinci, 2022). Consequently, applying spread estimators allows for greater insights into the markets being examined. A narrow spread can be interpreted as an indication of market tightness, suggesting minimal price disparity. Furthermore, the spread serves as an indicator of a market's ability to handle trade orders without causing significant price impact, demonstrating its resilience. A narrow spread implies that larger trades can be accommodated without causing substantial price movements.

The ability to capture market resilience, immediacy, and tightness also enables the study to draw inferences about macroeconomic events through the lens of market sentiment, as signalled by the aspects of market liquidity that spread estimates represent. For example, the ability to execute trades immediately and efficiently can be influenced by market liquidity and the availability of counterparts, both of which may fluctuate in response to macroeconomic events. Such insights will prove valuable in analysing the second objective of this study, which focuses on the cross-market effects of liquidity, particularly under different economic conditions throughout the specified periods.

Over the years, there has been significant work towards the development of spread estimators driven by the desire to develop an estimate that closely simulates the features of real data. These features relate to market imperfections as discussed in section 2.4 and order flow as discussed in section 2.3.6.. Bleaney and Li (2015) studied the effects of bid-ask estimators under simulated conditions of real markets and found that some estimators were specifically designed for low frequency data, typically available in the emerging and developing markets in our sample. Using low frequency data for spread estimation presents the problem of the signal-to-noise ratio (SNR), which refers to the ratio of the strength of the signal (the spread) to the amount of random variation or "noise" present in the data (Le & Gregoriou, 2020). A higher SNR indicates that the signal (the true spread) is more distinguishable from the noise (random fluctuations in the spread) and thus corresponds to a more reliable and accurate bid-ask spread estimation. At low frequencies, the SNR is likely to be small compared to high frequency estimators, making low frequency estimators less reliable, some being more susceptible to the problem than others. Accordingly, this study uses various spread estimators which are limited to the ready availability of the inputs required for estimation. In support of this approach, (Johann & Theissen, 2017) concluded from their study that no single best estimate exists. These estimators are discussed in the next section. The estimators are of two classes, the Roll class and the High-Low class of estimators.

3.3.2.1 Roll Implicit Effective Spread Estimator (Roll)

Roll's (1984) implicit effective spread estimator was the first introduced estimator and remains one of the most extensively applied in the literature. The Roll spread estimator decomposes the observed transaction price changes into two components, the price change due to information arrival and the price change due to liquidity trading. This decomposition helps to isolate the impact of market liquidity on prices. The spread is then estimated by comparing the variance of the liquidity component with the variance of the total price change. This estimation is premised on the assumption that the liquidity component of price changes is directly related to the bid-ask spread, making it possible to infer the spread from the relative magnitudes of these variances(Le & Gregoriou, 2020).

$$Roll_i = \sqrt[2]{-cov_i} \tag{3.1}$$

where $Roll_i$ is the implicit spread of stock *i,* and *cov* represents the first-order serial covariance of returns requiring daily or weekly transaction prices.

The Roll is primarily sensitive to order processing costs, which are a key component of bid-ask spreads. This sensitivity is based on the assumption that markets are informationally efficient and that the observed price changes are due to the bid-ask bounce rather than changes in the fundamental value of the asset (Chen et al., 2019). This assumption aligns closely with the nature of order processing costs, which are relatively stable and unrelated to information flows. Thus, the estimator captures the tendency of prices to bounce between bid and ask levels, which is primarily driven by order processing costs. In the absence of new information, this bounce is the main source of price changes (Brouty et al., 2024). Unlike adverse selection costs, which vary with information flow, order processing costs are relatively stable. The Roll estimator's assumption of informational efficiency makes it less sensitive to information-driven components of the spread. The negative serial covariance in price changes that the Roll estimator measures is consistent with the short-term reversals expected from order processing costs (Saleemi, 2022). These reversals occur as trades bounce between bid and ask prices without fundamental value changes. The Roll model's simplicity aligns with the straightforward nature of order processing costs, which are generally consistent across trades and don't require complex modelling of information asymmetry or inventory risks.

The advantage of the Roll estimator is that it utilises readily available transaction data, allowing for estimation based on real trading activity in the market. It is also suitable for estimation in illiquid markets where bid-ask quotes are less frequent or reliable. The main disadvantage of Roll is the potential error in estimation due to sensitivities of the assumptions upon which it is predicated. The other problem is that it does not account for no trading days, which leads to bias in the estimated trading cost because the midpoint of the recorded bid-ask spread is devoid of transaction costs. Lastly, the implicit effective spread is undefined when serial covariance is positive, a common occurrence. Various models have since been developed to address the shortcomings of the Roll.

3.3.2.2 Corwin and Schultz High-Low Spread Estimator (CS)

The high-low spread of Corwin and Schultz (2012) is one of the alternatives to Rolls' measure that uses high and low prices. The authors suggest that the daily price ranges effectively represent the bid-ask spread as the high prices are almost always buyer-initiated while the low prices are almost always seller-initiated. The CS estimator uses daily high and low prices, which are influenced by informed trading. Larger price movements, driven by informed trading, result in a higher estimated spread, indirectly capturing higher adverse selection costs. Adverse selection costs arise from information asymmetry between informed and uninformed traders (Groß-KlußMann & Hautsch, 2013). When these costs are high, market makers widen the spread to protect themselves against potential losses from trading with better-informed counterparties (He et al., 2010). The CS estimator has been empirically validated in various markets, demonstrating its effectiveness in capturing adverse selection costs. Studies have shown that the estimator provides reliable estimates of the adverse selection component of the bid-ask spread, which aligns with theoretical predictions regarding the impact of information asymmetry on trading costs (Spulber, 2019; Wasan & Boone, 2010). The CS involves using the difference between the high and low prices over a specific period to estimate the bid-ask spread. It estimates the spread by firstly, computing the daily variance of the log price changes, which provides a measure of price volatility for each day. The spread is then estimated using the relationship between the variance of the log price changes and the bid-ask spread.

$$S_2 = \frac{2(e^{\alpha t} - 1)}{1 + e^{\alpha t}}$$

$$\alpha_t = \frac{\sqrt{2\beta_t} - \sqrt{\beta_t}}{3 - 2\sqrt{2}} - \frac{\gamma_t}{3 - 2\sqrt{2}}$$

$$\beta_t = (h_{t+1} - l_{t+1})^2 + (h_t - l_t)^2$$

$$\gamma_t = (\max\{h_{t+1}, h_t\} - \min\{l_{t+1}, l_t\}) \tag{3.2}$$

h and l are, respectively, natural logs of high and low prices. The estimator assumes that the variance of the log price changes is related to the bid-ask spread, allowing for the inference of the spread from the observed price volatility. When adverse selection costs are high due to significant information asymmetry, it often leads to increased price volatility. The CS estimator captures this volatility in its measurement of the high-low range. The CS assumes that the level of liquidity in the market remains relatively stable over the time period under consideration. In practice, liquidity can vary, and changes in market conditions can impact the accuracy of the spread estimate. The advantage of the high-low spread is that it has a low standard deviation in low-frequency data. The disadvantage of it is that it requires adjustments for non-trading periods because of the assumption that trades are continuous and that their values remain constant during those non-trading days. An empirically flawed assumption that reduces reliability of the measure.

3.3.2.3 The Abdi and Ronaldo Spread Estimator (AR)

The AR spread introduced by Abdi and Ranaldo (2017) is a recent effort to address the shortcomings of both the Roll measure and the High-low spread. The AR spread is based on the latter two models and hence has the same benefits as the two measures. It, however, unlike Rolls, is independent of trade direction but does need to be adjusted for non-trading days like the high-low spread (Le & Gregoriou, 2020). By using the absolute difference $c_{it} - \eta_{it+1}$, the estimator captures the magnitude of price changes regardless of direction. The AR spread is calculated as follows:

$$AR_{it} = \sqrt[2]{E[(c_{it} - \eta_{it+1})]} \qquad (3.3)$$

Where:

AR_{it}= spread estimator of stock *i* in day *t*

c_{it}= the close log-price of stock *i*

η= the midpoint of the daily high and low log price of stock *i*. $\eta_{it} = \frac{h_{it}+l_{it}}{2}$

The term $E[(c_{it} - \eta_{it+1})]$ represents the expected value (or average) of the difference between the observed transaction price (c_{it}) and the efficient price η_{it+1}. The AR estimator focuses on the price change between the closing price of one day and the opening price of the next day. This overnight period helps capture information flow and potential informed trading. The overnight price change captures how new information is incorporated into prices. Larger changes indicate more significant information arrival, reflecting higher adverse selection costs. By focusing on the transition from close to open, the AR estimator captures a critical period of price discovery, where informed traders have an advantage (Gao et al., 2019; Lee et al., 2022). Significant overnight price changes can indicate the presence of asymmetric information, a key driver of adverse selection costs. The AR estimator's focus on overnight price changes reduces the influence of extreme values on the overall spread estimation and makes it less affected by short-term, intraday volatility spikes. This makes it more robust to outliers and extreme price movements, which are common during volatile market conditions. In contrast, the Corwin and Schultz estimator may be more affected by outliers, leading to inflated spread estimates during periods of high volatility (Abad et al., 2023). Additionally, the AR emphasises the effective spread, which is calculated based on the observed transaction prices rather than just the quoted prices. This approach allows it to better capture the true cost of trading, as it accounts for the actual prices at which trades are executed. By focusing on effective spreads, the estimator mitigates the impact of transient volatility that may distort quoted spreads (Cadorel, 2024). Empirical studies have shown that the AR estimator tends to provide more stable estimates of the bid-ask spread across different market conditions, including periods of high volatility (Bekar, 2023; Borri & Shakhnov, 2022; Zhang et al., 2024).

3.3.2.4 Efficient Discrete Generalised Estimator

Thus far, there is one main problem with the aforementioned estimators: although each subsequent estimator improves upon the prior, they have yet to adequately address it. As earlier mentioned, this relates to the infrequency of trading in illiquid markets, where in such instances, the size of the SNR causes a downward bias of the low frequency spread estimators. Ardia et al. (2024) developed an estimator that utilises the full set of price data to minimise estimation variance, Efficient Discrete Generalised Estimator (EDGE). According to a simulation study, The EDGE outranked the Roll, CS and AR, which was attributed to the use of the full set of OHLC prices. Not only does the EDGE compensate for downward bias, but there is also an upward bias caused by the way in which the CS and AR models deal with negative estimates (Cosenza & Stalder, 2024). The CS and AR deal with negative estimates by resetting them to zero so that transaction costs estimates are non-negative. This generally leads to an overestimation of the spread, especially in illiquid markets where it is most likely to have a higher number of negative estimates. Because the EDGE exploits the full set of OHLC prices, it naturally reduces negative estimates. It is estimated as[5]

$$S^2 = \frac{\omega_1 \mathbb{E}[X_1] + \omega_2 \mathbb{E}[X_2]}{\omega_1 \omega_2 \left(\nu_{0=h,l} + \nu_{c=h,l}\right) - 1/2} \tag{3.4}$$

[5] In the mathematical expression $X_{1,t} = (\eta_t - o_t)(o_t - c_{t-1}) + (o_t - c_{t-1})(c_{t-1} - \eta_{t-1})$ and $X_{2,t} = (\eta_t - o_t)(o_t - \eta_{t-1}) + (\eta_t - c_{t-1})(c_{t-1} - \eta_{t-1})$ X_1 and X_2 are vectors derived from log returns so that $h_t = l_t = c_{t-1}$ whereas $\upsilon_{o=h.l}$ is computed as $(\nu_{o=h} + \nu_{o=l})/2$ where $\nu_{o=h}$ and $\nu_{o=l}$ are the fractions of times in which $o_t = h_t$ or $o_t = l_t$ respectively. $\omega_1 = \frac{Var[X_{2,t}]}{Var[X_{1,t}]+Var[X_{2,t}]}$, $\omega_2 = \frac{Var[X_{1,t}]}{Var[X_{1,t}]+Var[X_{2,t}]}$ are the optimal weights. Refer to Ardia et al., (2024) for a more extensive discussion of the estimation procedure.

Where S^2 is the mean squared spread. The estimation's advantages are derived from the Generalised Method of Moments (GMM). GMM estimators, including EDGE, are less sensitive to violations of distributional assumptions compared to traditional estimators like Ordinary Least Squares (OLS). This robustness makes EDGE a suitable choice in environments where the underlying assumptions of the model may not hold, thereby enhancing the credibility of the results (J. Wang & Croucher, 2021). Further derivative benefits from GMM that apply to the EDGE include handling of endogeneity (M. Kumar & Goswami, 2022) and discrete data common in financial markets (Akande & Kwenda, 2017). And by providing robust standard errors that account for potential heteroskedasticity and autocorrelation in the data, the EDGE provides better statistical inference (Kurnia et al., 2021).

3.4 Hypothesis 1: The Effects of ETF Introduction to Market Liquidity

The first hypothesis intends to evaluate the effects of introducing ETFs to the underlying securities market. Four liquidity measures that capture different aspects of the ETF market are used for veracity. A methodological extension of the difference in differences (DiD) research design is then used that accounts for multiple periods and variations in treatment timing. From the analysis, causal effect parameters are determined.

The DiD is one of the more prominent research designs used to analyse the impact of actions on outcomes. The DiD estimates the difference between the change in outcomes of a group before and after a treatment compared with the before and after outcome of a control group. The estimated coefficient on the interaction between the two periods is represented in the following equation:

$$y_{it} = \gamma + \gamma_{i.} TREAT_i + \gamma_{.t} POST_t + \beta^{2\times2} TREAT_i \times POST_t + \mu_{it} \tag{3.5}$$

The canonical DiD main assumption is that both groups would have followed a parallel path without treatment. Given this assumption, the average treatment effect is determinable by contrasting the difference in the treated group with the untreated group, i.e, ATT. A two-way fixed effects (TWFE) regression can be specified when there are numerous independent clusters of a treated and control population such that:

$$y_{it} = \alpha_{.i} + \alpha_{.t} + \beta^{DD} D_{it} + e_{it}$$

[3.6]

The TWFE accords more empirical applications than the canonical 2x2 set-up, because in most cases, treatments usually occur at different times. As such, equation 3 is estimated with dummies for cross-section units ($\alpha_{.i}$), time periods ($\alpha_{.t)}$ and a treatment dummy (D_{it}). The canonical DiD has met with other empirical limitations due to its restrictive assumptions. Consequently, the burgeoning literature on DiD extends the model with more relaxed assumptions to allow for non-bias coefficients. Roth et al. (2023) categorised these extensions into three main groups based on the assumption that the proposed extension relaxes for the canonical DiD.

The first category, as already alluded to, is the relaxation of the 2x2 set-up where there is no variation in treatment timing and units. Numerous authors have noted that the interpretation of the TWFE DiD model as in equation 3.6 is biased as it is not knowable how mean outcomes are compared across groups. Specifically, the TWFE model generates a coefficient that represents comparisons between the treated and control groups as well as comparisons between the already treated groups when heterogeneity is allowed in treatment timing. The biasness of the coefficient emanates from the later group comparison where the TWFE coefficient can have the opposite sign due to negative weightings. Goodman-Bacon (2021) notes that when comparison is made between already treated groups, changes in outcomes are subtracted from the overall TWFE estimator, hence the biasness when treatment timing differs. This can be represented mathematically thus:

$$\beta^{DD} = \frac{\sum_{i,t}(D_{i,t} - \widehat{D}_{i,t})Y_{i,t}}{\sum_{i,t}\left(D_{i,t} - \widehat{D}_{i,t}\right)^2} \qquad (3.7)$$

Where β^{DD} is the univariate regression coefficient between y_{it} and the $D_{i,t} - \widehat{D}_{i,t}$. The latter being the predicted value from equation 3 from a regression of $D_{i,t} = \alpha_{.i} + \alpha_{.t} + e_{it}$. This draws on the Frisch-Waugh-Lovell theorem that allows the reduction of multivariate regression into a univariate regression. Essentially, a regression of y on a set of x can be decomposed where x is split into x_1 and x_2, and this will give the same coefficient estimates of regressing y on x_2. The same concept is applied to this TWFE regression with various treatment effects. However, as in accord with the OLS regression with binary outcomes, a problem arises when the predicted variable is greater than one. Then $D_{i,t} - \widehat{D}_{i,t}$ will be negative regardless of treatment status, thus causing a negative weighting on β^{DD} . As such, the TWFE does not produce a reliable estimate with heterogeneous treatment effects.

An alternative to this static TWFE model is the dynamic TWFE that allows for regression specifications for period fixed effects represented in the following equation:

$$Y_{i,t} = \alpha_i + \alpha_t + \sum_{r \neq 0} 1[R_{i,t} = r]\beta_r + \epsilon_{i,t} \tag{3.8}$$

$R_{i,t} = t - G_i + 1$ denoting all possible treatment periods where G_i is the initial treatment period for unit i. And similar to the static TWFE, α_i, α_t are the unit and time fixed effects, respectively. However, Sun & Abraham (2021) demonstrated the problems of attempting to interpret the coefficients from this TWFE model. Firstly, it suffers from the same negative weighting of treatment of effect of some cross-section units as the static model, and secondly, there is cross-lag contamination for treatment effects on different cohorts. That is, the coefficient of a treatment effect of a cross-section unit may be affected by a lead or lag of another unit. Summarily, this implies that even a dynamic TWFE coefficient estimand is biased when there is variation in treatment timing and treatment effects.

Despite its popularity, emerging empirical literature suggests that it can produce misleading estimates (Borusyak et al., 2021). Imai & Kim (2021) suggested that the reliability of the TWFE rests on its modelling assumptions. Similar to the DiD, one of the assumptions is parallel trends, which literature has shown to hold quite consistently in applications. However, the assumption of constant treatment effect between groups and over time is empirically questionable (De Chaisemartin & d'Haultfoeuille, 2020; Sun & Abraham, 2021). Therefore, the TWFE is difficult to apply for heterogeneous treatment effects. Kropko & Kubinec (2018) demonstrated the difficulty in interpreting the results of the TWFE, recommending that it not be used by applied researchers except if the second assumption is met. Hill et al. (2020) documented twelve limitations of TWFE, which in addition to the above included low statistical power, limited external validity and erroneous causal inferences.

Given the timing differences in the introduction of ETFs in the study sample, the canonical DiD will not capture the true treatment effect. However, it is still applied as a baseline model. Other DiD methods that allow for the heterogeneous treatment timing effect are applied.

These models are the Goodman-Bacon (2021) decomposition analysis and the Callaway & Sant'Anna (2021) model, both of which are discussed in greater detail in chapter 4.

3.4.1 Control Variables

Various factors affect market liquidity that broadly can be classified into market microstructure and macrostructure. When examining liquidity dynamics across a sample of emerging economies, the use of macroeconomic factors as control variables offers several advantages over the reliance on market behaviour and sentiment indicators. First, macroeconomic variables provide a more fundamental and structural lens through which to analyse liquidity conditions in emerging markets. These economies are often characterised by rapid institutional and policy changes, as well as volatility in economic fundamentals (Harjoto et al., 2021). Macroeconomic factors, such as monetary policy, credit conditions, and capital flows, can better capture the underlying economic environment that shapes the overall availability and allocation of liquidity in these markets (Feyen et al., 2021). Additionally, Chowdhury et al. (2018) identified several key macroeconomic variables that affect market liquidity across various stock market sectors. These include money supply, government spending, private borrowing, bank rates, short-term interest rates, and government borrowing. Their research underscores the complex interplay of macroeconomic factors in determining liquidity in emerging stock markets. This structural perspective is particularly crucial when conducting cross-country comparisons.

Liquidity is often a key target of regulatory and reform efforts in emerging economies, and understanding the impact of such interventions requires a clear view of the macroeconomic landscape (Blitz et al., 2018). Accordingly, macroeconomic controls allow for a robust evaluation of policy effectiveness and institutional development in emerging markets. Some studies, like Syamala et al. (2017), emphasise the importance of domestic policies and institutional announcements in shaping market liquidity, as observed in the Indian context. Macroeconomic factors tend to exhibit more gradual and persistent trends, providing a more stable foundation for understanding liquidity dynamics over time (Olokoyo et al., 2020). This allows researchers to better differentiate between temporary market fluctuations and underlying structural changes that shape liquidity conditions. The choice to use macro structure variables hinges on supply-side liquidity as discussed in section 2.3.5, which posits that constraints in funding liquidity negatively impact general market liquidity. Such constraints include interest rates, money supply etc.

One of the more prevalent determinants of market liquidity in the literature is governments' monetary and fiscal policy. Numerous studies analysing developing/emerging markets have identified various of these macroeconomic variables which are considered in this study (Babarinde & Ogbeide, 2022; Chowdhury et al., 2018; Eleodinmuo et al., 2023; Igbinosa & Uhunmwangho, 2019; Naik & Reddy, 2024). For monetary policy, the aggregate money supply, bank rate are used as controls for this study. The bank rate refers to the rate at which the central bank provides credit to financial institutions. These two variables are indicators of funding conditions within economies. For example, a decline in the bank rate might signal increased liquidity, whereas an increase in rates may indicate increased illiquidity.

The fiscal policy variables used in this study are government expenditure and credit to the private sector. These are predicated on the influence that these interventions have on market liquidity. For example, government expenditure can stimulate liquidity by injecting funds into the economy, creating more demand for goods and services and affecting market sentiment and confidence. On the other hand, if government expenditures are not offset by revenue, it can cause higher interest rates due to excessive borrowing. Additionally, excessive spending by the government can lead to a crowding out effect where funds become unavailable for the private sector.

Other macroeconomic variables included in the study are Industrial Production. The nexus between industrial production and market liquidity is a complex one, underpinned by several interconnected economic mechanisms. Industrial production, as a key indicator of economic health and growth, exerts a multifaceted influence on market liquidity through various channels. Firstly, industrial production serves as a barometer for overall economic activity. When industrial production rises, it often signals economic expansion, which can lead to increased investor confidence and market participation. This heightened market activity typically results in improved liquidity conditions, as the volume of trades and the number of market participants tend to increase. Conversely, a decline in industrial production may portend economic contraction, potentially leading to reduced market activity and, consequently, diminished liquidity. This relationship is particularly pronounced in emerging markets, where economic indicators like industrial production can have a more direct and immediate impact on market sentiment. The inflation rate is another control variable considered in this study, which, like industrial production, can influence the actions of the central bank. Central banks often adjust interest rates to control the rates of inflation. Inflation also erodes purchasing power and asset valuations, thus causing a reduction in liquidity. This study uses the inflation rate (growth of consumer price index) to capture inflation development. Finally, market capitalisation is used to control for the size effects of the market.

There is a bidirectional relationship between Foreign Direct Investment (FDI) and market liquidity. While FDI can enhance liquidity, a more liquid market can also attract more FDI. A well-developed financial market can mitigate the adverse effects of liquidity shocks, thereby creating a more stable environment for foreign investors (Kirabaeva & Razin, 2009). FDI has also been associated with improved stock market liquidity by increasing the volume of transactions (Tite et al., 2022). FDI affects liquidity by providing stability, which enhances market confidence and encourages other investors to participate, thereby improving liquidity. Additionally, it introduces new sectors and industries to the host country's capital market, providing investors with a broader range of investment opportunities. This diversification can attract more investors, leading to increased trading activity and improved liquidity. On the inverse, liquidity tends to decrease more sharply for firms with larger FDI compared to those with foreign portfolio investment (Ng et al., 2022; Silva & Veras Machado, 2020). On the whole, foreign investment, including FDI, plays a crucial role in strengthening the financial sector and enhancing market liquidity (Almomani et al., 2024). A well-organised and liquid stock market is a potent incentive for foreign investors, facilitating inflows of foreign capital (Adebisi & Arikpo, 2017).

3.5 Hypothesis 2: Cross Market Effects of ETF Liquidity on Liquidity Risk

The models that predict the relationship between liquidity and liquidity risk are predicated on trading volume and can be classed into three categories, namely, competition, distribution mixture and information asymmetry (Haugom & Ray, 2017). The latter category of models, popularised by the seminal works of Kyle (1985) and Holden & Subrahmanyam (1992), predicts a positive relationship between trading volume and liquidity. Generally, liquidity shocks in one market may propagate volatility in another market. This hypothesis seeks to investigate the cross-market dynamic effects of ETF liquidity on market volatility of liquidity. The joint dynamics of liquidity and volatility of liquidity are studied, specifically, the liquidity-volatility spillovers between the ETF and their underlying securities. As a first step, the DCC-GARCH-copula, complemented by the TVP-VAR, are used to determine the liquidity risk spillover between the two markets.

3.5.1 Dynamic Conditional Correlation Generalised Autoregressive Conditional Heteroscedasticity

Financial time series typically exhibit non-random changes, and accordingly, volatility models have been developed to capture the clustering, leveraging and leptokurtosis effects of time series. Of these, the autoregressive conditional heteroscedasticity (ARCH) by Engle (1982) and the generalised ARCH (GARCH) proposed by Bollerslev (1986) have gained the most prominence. The ARCH models time-varying conditional variances using lagged disturbance, appropriate for time series where the conditional variance is autoregressive and returns consist of a stochastic process. Later, it was found that the ARCH model requires a high order ARCH process to capture the dynamic behaviour of the conditional variances. The introduction of a lag phase to conditional variance generalised the ARCH model so that the number of estimated parameters is decreased from infinity to two.

The GARCH model is particularly useful for analysing a time series' clustering and leptokurtosis effects. GARCH modelling is advantageous because it is easier to implement since the stochastic difference equations in discrete time match the discrete intervals in which financial data is often gathered. Moreover, the GARCH process produces fat tails like what is typically observed in financial time series. Further developments of the GARCH models were prompted by their limitation in capturing leverage effects due to their symmetric distribution. To address this shortcoming, several non-linear models have been developed, such as the GJR (Glosten et al., 1993), the exponential GARCH (EGARCH) (Nelson, 1991) and the APARCH (Ding et al., 1993).

Given that this study seeks to identify features of volatility of liquidity across different markets, multivariate models rather than the univariate models thus far described are needed. One of the difficulties in modelling a multivariate GARCH is the inversion of the iterations of the conditional covariance matrix, which makes it computationally demanding. Thus, an important consideration in MGARCH is parsimony while maintaining flexibility. Engle (2002) introduced a class of MGARCH, the Dynamic Conditional Correlation (DCC-GARCH), which has the flexibility of the univariate GARCH and models the parametric models correlation parsimoniously. The DCC-GARCH uses recent past information for estimating the current correlation between series. Additionally, the DCC-GARCH builds on the Diebold and Yilmaz (2012) methodology that is limited by its specific definition of volatility (involves daily high and low prices) and construction of spillover index within a VAR system that assumes that the covariance matrix is time-invariant. Gamba-Santamaria et al. (2017) proposed the DCC GARCH that avoids the need to define volatility and better models the volatility clustering and the time-varying correlations of time series.

To determine the time-varying correlations of returns, the DCC model is applied. The time-varying variance-covariance matrix $\boldsymbol{H}_t$ is defined as

$$\boldsymbol{H}_t = \boldsymbol{D}_t \boldsymbol{R}_t \boldsymbol{D}_t \tag{3.9}$$

Where $\boldsymbol{D}_t = diag(\sqrt{h_{11,t}} \ldots\ldots\ldots \sqrt{h_{nn,t}})$ is a diagonal matrix of square root conditional variances. $\boldsymbol{R}_t$ is the DCC based on the standardised residuals' conditional variance-covariance Q_t following a GARCH structure

$$\boldsymbol{R}_t = (\boldsymbol{Q}_t)^{-1/2} \boldsymbol{Q}_t diag(\boldsymbol{Q}_t)^{-1/2} \tag{3.10}$$

Where

$$\boldsymbol{Q}_t = (1 - a - b)\overline{\boldsymbol{Q}} + a z_{t-1} z'_{t-1} + b\boldsymbol{Q}_{t-1} \tag{3.11}$$

a and b are positive scalar parameters satisfying $a + b < 1$ to ensure stationarity. Further exposition of the DCC-GARCH is in chapter 4.

Caporin and McAleer (2013) have documented ten limitations of the DCC-GARCH model, primarily stemming from its mathematical properties. They argue that the model lacks asymptotic properties and testable regulatory conditions, both of which are essential in statistical analysis as they provide a framework for evaluating the model's performance in real-world scenarios. Asymptotic properties, in particular, allow for the assessment of convergence, consistency, and efficiency of estimators, enabling inferences to be made about how accurately the model captures the true underlying dynamics in the data. Caporin and McAleer (2013) conclude that due to these limitations, the DCC-GARCH model can be useful as a filter or diagnostic tool for capturing the dynamics of conditional correlations among assets.

Jiang et al. (2023) also note that while the DCC-GARCH model is valuable for assessing the contagion effect between assets by observing conditional correlation, it does not identify the source of this contagion. In other words, it does not reveal the dependence structure of assets. As a result, the model is often used in conjunction with other models for further analysis. For instance, Syed (2022) employed the DCC-GARCH model as a diagnostic tool to confirm the results of the TVP-VAR analysis in their study.

Given these limitations, this study will employ the DCC-GARCH model as a filter for further analysis, in line with the approach taken by other scholars. By initially applying the DCC-GARCH model, it serves as a preliminary tool to assess whether a contagion effect exists between the two markets under review. Indeed, upon satisfying the test's requirements and observing the conditional correlation, the presence of this contagion effect has been confirmed. The next section, copulas are applied to the data to reveal the dependence structure for further analysis.

3.5.2 Copulas

The DCC-GARCH model is often used in time series to describe autocorrelation, heteroscedasticity and volatility of joint distributions. However, it is ineffective in describing tail dependence, the probability of an occurrence of an extreme event in an asset given a similar occurrence in another asset. Due to the fat tail, non-normal and tail risk interdependence of financial data, similarly assessed in Section 5.3.1, copula models are employed to capture these complex dependency structures and better represent the joint distribution of the variables (Dewick & Liu, 2022). Four widely used copulas in empirical economic research (Naeem et al., 2020; Yeap et al., 2021) are applied in this analysis. A copula is a function that “couples” a bivariate distribution function, the marginal distribution that describes the behaviour of a single variable independently of the other and a dependence structure that captures the joint behaviour of the variables separately from their marginal distributions. Mathematically, $H(x, y) = C(F(x), G(y))$. Where $F(x), G(y)$ is the marginal distribution of each variable on the interval [0,1] (Größer & Okhrin, 2022).

Copulas are useful for this study because rather than, or more than, modelling just the influence of ETF liquidity on Index liquidity or vice versa, copulas determine how the two variables move and the strength of the concurrent movement over different points of the distribution (Kharoubi-Rakotomalala & Maurer, 2013). Accordingly, it serves to enhance understanding of the relationship between the variables beyond the DCC-GARCH. By separating the modelling of dependence between variables from the modelling of their marginal distributions, copulas allow for a comprehensive and more realistic modelling of financial data that often exhibits non-normal and complex dependencies (Dewick & Liu, 2022). Thus, copulas can help identify spurious correlations that may be caused by shared distributional properties rather than true economic linkages between variables. Also, the ability to model non-linear relationships is key to capturing similarly non-linear linkages in the tails of the distribution during market stress (J.-M. Kim, 2020). This is because copulas do not abide by restrictive assumptions of normal distributions. In this study, two classes of copulas were applied, the Archimedean and Elliptical copulas. The different copulas applied in this study are defined in chapter 5.

3.5.3 Time-Varying Parameter-Vector Autoregression

Antonakakis and Gabauer (2017) extended the Diebold and Yilmaz (2012) methodology of connectedness based on forecast error variance decomposition from vector autoregressions (VAR). Antonakakis and Gabauer (2017) proposed a measure that improves on the shortcomings of the Diebold and Yilmaz (2012) in three ways: (1) there is no loss of observations, (2) it is not outlier sensitive and (3) it eliminates the need to set a window size to carry out the rolling window estimation (Liew et al., 2022). They demonstrated that their proposed TVP-VAR (time varying parameter- vector autoregressions) measure adjusts immediately to events compared with the Diebold and Yilmaz (2012) model that either overreacts when the rolling window size is too small or smoothes out the effect when the window is too large. The TVP-VAR allows the variances to vary via a stochastic volatility Kalman Filter estimation to analyse the time varying transmission mechanism. By so doing, arbitrary selection of a rolling window size is not needed and accordingly, the estimation can be used to examine dynamic connectedness at low frequencies and limited time-series data. A TVP-VAR model can be represented as follows:

$$\boldsymbol{Y}_t = \beta_t \boldsymbol{Y}_{t-1} + \epsilon_t \qquad \epsilon_t|\boldsymbol{F}_{t-1} \sim N(\boldsymbol{0}, \boldsymbol{S}_t) \tag{3.12}$$

$$\beta_t = \beta_{t-1} + v_t \qquad v_t|\boldsymbol{F}_{t-1} \sim N(\boldsymbol{0}, \boldsymbol{R}_t) \tag{3.13}$$

$\boldsymbol{Y}_t = N \times 1$ conditional volatilities vector

$\boldsymbol{Y}_{t-1} = N_p \times 1$ lagged conditional vector

$\beta_t = N \times N_p$ dimensional time-varying coefficient matrix

$\epsilon_t = N \times 1$ dimensional error disturbance vector with an $N \times N$ time-varying variance-covariance matrix, $\boldsymbol{S}_t$. $\boldsymbol{F}_{t-1}$ is the information set.

The parameters β_t depend on their own lagged values and an $N \times N_p$ dimensional error matrix with an $N_p \times N_p$ variance-covariance matrix. The generalised forecast error variance decompositions (GFEVD) of Diebold and Yilmaz (2012) determine the time-varying coefficients and error covariances that estimate the generalised connectedness procedure. This is shown in Appendix B

In sum, the estimate of TVP-VAR analyses the effects of ETF liquidity on the volatility of liquidity of the underlying basket of securities. It is then also used to examine the spillovers between liquidity of the basket of securities and ETFs. This reveals how the liquidity of one market propagates liquidity risk to the other market. The specific manner in which this is achieved is presented in Chapter 5.

3.6 Hypothesis 3: Effect of ETFs on Market Efficiency

This study employs cointegration analysis as the baseline model to evaluate the impact of ETFs on stock market efficiency. Cointegration is a statistical property of a set of time series variables that are individually non-stationary but exhibit a stable long-term relationship. When two or more time series are cointegrated, it indicates that they share a common stochastic drift, which can be interpreted as a long-term equilibrium relationship, despite short-term deviations. This concept is particularly significant in economic modelling, where understanding the long-term relationships between variables such as prices, interest rates, and economic output can yield insights into market behaviour (Maslyuk & Smyth, 2009; Stern, 2000).

The characteristics of the data and the objectives of the study suggest that cointegration modelling represents the most suitable methodological approach. Some of the variables in the dataset are non-stationary, thereby excluding Ordinary Least Squares (OLS) regression modelling, which assumes data stationarity. Conversely, cointegration analysis is robust to non-stationary data, as it identifies long-term relationships among variables that may individually be non-stationary (Bojanic, 2012; Ghouse et al., 2021). Applying OLS under non-stationary conditions may result in spurious regression, where the findings do not accurately reflect the true relationships among the variables. Given that the research question revolves around exploring long-term equilibrium relationships, cointegration analysis is the more appropriate method.

Cointegration facilitates the identification of a stationary series, indicating a stable long-term relationship derived from a linear combination of non-stationary variables. This aspect is particularly relevant in economic contexts, where variables such as interest rates and exchange rates often exhibit trends over time (Ndoricimpa, 2021). Furthermore, cointegration analysis includes an error correction term that adjusts for short-term deviations from long-run equilibrium, enhancing the understanding of the dynamic adjustments of the variables in question.

3.6.1 Model Selection

The specific choice of the cointegration model was determined a priori based on the orders of integration of each variable. Prior to the analysis, unit root tests were conducted to ascertain the order of integration for each variable. The results are presented in chapter 6. Due to the varying orders of integration, the Engle and Granger method and the Johansen models were deemed inapplicable. The Autoregressive Distributed Lag (ARDL) model is capable of accommodating variables with differing orders of integration, up to I(1), thus making it suitable for this analysis. The ARDL model is particularly advantageous for small sample sizes, as traditional cointegration techniques, such as the Johansen test, may exhibit reduced power and reliability in such contexts. The ARDL bounds testing approach is recognised for its effectiveness even with limited observations, rendering it a preferred method in many empirical studies where data availability is constrained (Pahlavani et al., 2005). Sample size was a consideration for this study, given the recency of ETFs in developing markets, which limited the data to only a few years. Additionally, the ARDL model addresses endogeneity concerns by incorporating lagged values of both dependent and independent variables. This inclusion helps to mitigate potential biases in the estimation process and corrects for autocorrelated residuals, thereby enhancing the robustness of the ARDL model in the presence of such econometric issues (Mohamed & Saâdaoui, 2024).

3.6.2 Model Development

3.6.2.1 Independent Variable

ETF trading volume serves as a critical indicator of market activity, reflecting investor engagement and mechanisms of price discovery. This relationship can be examined from various perspectives, including its implications for market efficiency, investor behaviour, and price dynamics. The connection between trading volume and price discovery is particularly significant. Wallace et al. (2019) observed that as trading volumes increase, bid-ask spreads tend to decrease, thereby enhancing market efficiency and price discovery. This dynamic suggests that higher trading volumes facilitate more accurate ETF pricing by capturing a broader consensus among market participants regarding the value of the underlying assets (Jiayuan Chen, 2023).

Trading volume patterns also provide insights into investor behaviour and market dynamics. Giudici and Hu (2019) identified distinct intraday trading volume patterns that vary throughout the trading day, which can inform investor strategies. These patterns indicate that trading volume is not only a measure of activity but also a reflection of investor behaviour, influenced by factors such as economic indicators and sentiment. Glosten, Nallareddy and Zou (2021) asserted and affirmed that ETF activity is driven by speculations of systematic information. Further, Wang and Hui (2024) found information transfer from ETF trading volume to market efficiency.

This relationship further underscores the role of trading volume in reflecting underlying market dynamics and investor perceptions. By analysing trading volume, investors and analysts can gain valuable insights into market conditions, potential price movements, and overall investor sentiment, making it a crucial component of ETF market analysis. Consequently, this study utilises trading volume to assess how activity in the ETF market contributes to market efficiency.

3.6.2.2 Control Variables

The selection of macroeconomic confounding variables in this study is informed by the Arbitrage Pricing Theory (APT) developed by Ross (1976). While this research does not directly test asset pricing models, the APT provides a theoretically grounded framework for identifying key systematic risk factors that influence broad market movements. These factors, including interest rates, inflation, exchange rates, and industrial production, are likely to affect market efficiency and liquidity, making them relevant confounders in the analysis of ETF impacts on market dynamics. By basing the variable selection on APT, a theoretically consistent and parsimonious approach to controlling for macroeconomic influences is ensured, even as the focus is on market microstructure outcomes rather than asset pricing directly.

Arbitrage Pricing Theory (APT) posits that the expected return of an asset can be explained by various set of various macroeconomic factors, which serve as systematic risk sources. The identification of these factors is crucial for the application of APT, as they facilitate an understanding of how different economic conditions influence asset prices. The APT is grounded in the principle of arbitrage, which suggests that if two assets yield the same return but are priced differently, an arbitrageur can exploit this price discrepancy to earn a risk-free profit. The theory asserts that in an efficient market, arbitrage opportunities will be quickly eliminated as investors act to correct the mispricing (Nyanga & Qutieshat, 2022). Therefore, the expected return on an asset should be proportional to its risk, as measured by its sensitivity to the identified factors. Accordingly, the APT is applied in this study to identify the complexities of market efficiency. For this study, these factors are utilised as control variables to accurately ascertain the effects of ETFs on market efficiency. The following macroeconomic factors have been selected based on prevailing literature.

Changes in interest rates represent a significant factor influencing asset prices. Elevated interest rates can result in increased borrowing costs, which may dampen consumer spending and business investment, thereby negatively impacting stock prices. Conversely, lower interest rates can stimulate economic activity and boost stock returns (Ayuba et al., 2018). APT incorporates interest rates as a critical determinant of expected returns, reflecting their pervasive influence on the economy.

Inflation is another key macroeconomic variable that influences purchasing power and investment returns. APT recognises that rising inflation can erode the real returns on investments, leading investors to demand higher returns as compensation for this risk (Kuntamalla & Maguluri, 2023; Messias & Carrasco-Gutierrez, 2022). Consequently, inflation rates are often included in empirical tests of APT to evaluate their impact on asset pricing. For assets exposed to international markets, exchange rates are essential in determining returns. Fluctuations in currency values can affect the profitability of multinational corporations and, consequently, their stock prices. APT models often incorporate exchange rates to account for the risks associated with currency movements (Siregar, 2019).

Industrial production is a significant macroeconomic factor frequently incorporated into the APT framework. It acts as an indicator of economic activity and is closely associated with corporate earnings and stock market performance. Industrial production measures the output of the industrial sector, which includes manufacturing, mining, and utilities. An increase in industrial production typically signals economic growth, potentially leading to higher corporate profits and, consequently, elevated stock prices.

This relationship is substantiated by empirical studies that have identified a significant correlation between industrial production and stock market returns (Chang et al., 2021; Hashmi & Chang, 2023). It is important to note that industrial production does not operate in isolation; it interacts with other macroeconomic variables, such as interest rates, inflation, and exchange rates. The combined effect of these factors can provide a more comprehensive understanding of stock price movements. For example, while industrial production may signal economic growth, rising interest rates could counterbalance this by increasing borrowing costs for companies, thereby affecting their profitability and stock prices (Vicente Cateia, 2021).

It is important to note that no universally agreed-upon set of macroeconomic factors adequately captures the systematic risk involved in asset pricing. However, the selected factors represent a significant portion of the literature that has been empirically validated to influence asset prices across various contexts.

The decision to limit confounding variables to those identified by APT as above is further justified by the significant overlaps between APT and market efficiency concepts. Both frameworks emphasise efficient information processing, arbitrage mechanisms, rational expectations, and equilibrium pricing (Kabašinskas & Šutienė, 2021). The APT factors represent key systematic risks that efficient markets should price, aligning with the core principles of market efficiency. This overlap allows for a focused examination of how ETF activity impacts the market's ability to efficiently process and price the most critical macroeconomic risks. Moreover, this approach maintains model parsimony while capturing the essential drivers of time-varying risk premia, a crucial element in assessing market-wide efficiency impacts (Bayram & Akat, 2019).

3.6.2.3 Dependent Variables

The bid-ask spreads are substituted with returns to achieve the objective of assessing the impact of ETFs on market efficiency, which provides direct insights into information asymmetry. Wider spreads indicate greater market frictions (asymmetry, transaction costs), while narrower spreads suggest the opposite. Thus, based on this substitution, the APT assumption posits that in an efficient market, significant information asymmetry should diminish over time, resulting in narrower spreads as informed and uninformed traders converge on the same information. If the spread does not narrow, it indicates that market frictions persist and that markets are inefficient. This method of price discovery also reveals the speed and accuracy with which prices adjust in response to new information. In efficient markets, spreads should tighten as price discovery occurs in reaction to new information.

The Abdi and Ronaldi (AR) spread estimator and the Efficient Discrete Generalised Estimator (EDGE) both capture distinct aspects of market dynamics differing in their focus and the range of market characteristics. The primary focus of the AR spread estimator is on transaction costs. This estimator decomposes the spread into its constituent parts by applying a regression-based approach. Typically, it captures short-term, trade-by-trade price dynamics by modelling the covariance between successive price changes to estimate the spread (Abdi and Ronaldi, 2017). By so doing, the AR specifically gives insights into market maker behaviour and how spreads are set in response to order flows (Goyenko et al., 2009).

In contrast, the EDGE is designed to capture a broader range of market efficiency measures due to its ability to handle discrete price changes that incorporate various market microstructure effects (Holden and Jacobsen, 2014). Thus, both short-term and longer-term market dynamics are represented that are indicators of general market quality and efficiency.

Specifically, this estimator models market efficiency elements such as price discovery efficiency, information asymmetry, and market impact costs.

The main differences between these estimators lie in scope, complexity, and applicability. While the AR estimator is more focused on the transaction costs, EDGE provides a more comprehensive view of market efficiency. EDGE is generally considered more complex and more robust to various market conditions. In terms of applicability, the AR estimator is more suitable for traditional, continuous markets, while EDGE can be particularly useful in markets with discrete pricing. Further description of the models is provided in section 3.3.2. By using both estimators, this study provides complementary insights into different aspects of market dynamics.

CHAPTER 4: ETF INTRODUCTION AND LIQUIDITY DYNAMICS

4.1 Introduction

In the preceding chapter, the selected proxies for liquidity were outlined, discussing their usefulness, drawbacks, and suitability for this study. This chapter addresses the first objective, which seeks to analyse the liquidity effects of introducing ETFs into the market. For this, the difference-in-differences (DiD) technique is applied as a suitable method of analysis. There are two important points for consideration to acquire a reliable estimation output with the DiD model. First, the treatment timing that causes estimation bias. It has already been determined that treatment timing is a factor for this study as ETFs were introduced to the markets at different times. This informs the application of the Goodman-Bacon (2021) decomposition model, which compensates for this bias in the 2×2 canonical DiD. The model specification is presented before the results.

We also consider the assumptions under which the model estimates would be reliable – the parallel-trends assumption. Marcus and Sant'Anna (2021) explain that any trade-offs between efficiency and strength of this assumption ought to be outlined. Thus, a discussion of the potential violations is provided. The need to adhere to the parallel-trends assumption is key to identifying and estimating causal parameters; this helps segue into the sample selection for analysis because the samples are based on parallel trends. The descriptive statistics of the samples selected of the treated and untreated are first presented. The empirical results are subsequently presented, followed by a discussion section.

4.2 Sample Selection

The population of the study consisted of all developing countries that had introduced ETFs that track a domestic index. The sample selection criteria included countries whose data were accessible for a sufficient period before and after the introduction of ETFs on their market. Having verified with Bloomberg database and Equity RT, the years 2000 to 2023, for purposes of this study, were deemed appropriate as a sample period due to the fact that most of the developing countries introduced ETFs during this period. The final sample, therefore, consisted of fourteen countries, nine of which introduced ETFs within the sample period and five that are control countries. The treated countries include Brazil, Bulgaria, Chile, Colombia, Greece, Philippines, Qatar and Russia. The control countries consist of Argentina, Czech Republic, Hungary, Kuwait and Peru.

4.3 Descriptive Statistics

Table 3 presents the descriptive statistics of the sample data for the four liquidity indicators introduced in Chapter 3. All variables exhibit positive skewness, indicating a right-tailed distribution. Moreover, these indicators have high absolute values of skewness, which suggests a significant degree of asymmetry. The elongated right tails indicate occasional periods of higher liquidity, presenting potential opportunities to manage trading risks. The data also demonstrate leptokurtic properties, which are commonly observed in financial data (Li et al., 2014; Premaratne, 2005). Furthermore, the Jarque-Bera statistic confirms the non-normality of the data ($p<0.01$). The peakedness of the liquidity value distribution implies a higher frequency of moderate levels of liquidity. However, the heavy tails indicate a higher likelihood of extreme liquidity values, which increases market risks due to the potential occurrence of low liquidity events and sensitivity to market shocks, particularly during periods of market stress. However, the positive skew indicates that while most values are lower, some high values are pulling the mean up.

Table 3: Descriptive Statistics of liquidity measures

	AR	CS	EDGE	ROLL
Mean	0.1318	0.0257	0.1223	0.1321
Median	0.0058	0.0029	0.0034	0.0088
Maximum	3.4307	0.9570	2.9359	3.6991
Minimum	0.0011	0.0010	0.0010	0.0013
Std. Dev.	0.4476	0.0901	0.4171	0.4585
Skewness	3.8214	5.0065	3.6646	4.0571
Kurtosis	17.6357	31.5540	15.9718	19.9171
Jarque-Bera	23308.60	78283.06	18979.78	30098.46
Probability	0.0000	0.0000	0.0000	0.0000
Observations	2052	2052	2052	2052

NB: A value of 0.01 corresponds to a spread of 1%. AR=Abdi & Ronaldo, CS=Corwin & Schultz high-low spread estimator, EDGE =Efficient Discrete Generalised Estimator, ROLL=Roll implicit effective spread estimator

Table 4 presents the descriptive statistics of the covariates compiled for all countries. The selection process for these covariates is discussed in Chapter 3. The variables include Broad Money (BM), Credit to the Private Sector (CP), Consumer Price Index (CPI), Foreign Direct

Investment (FDI), Government Expenditure (GE), Industrial Production (INDP), Interest Rate (INT), and Market Capitalisation (MC). The mean values range from -0.3910 for INDP to 59.2811 for CP, indicating substantial variation in the central tendencies across variables. Standard deviations reveal considerable dispersion, particularly in MC (32.5978) and CP (27.2011), suggesting high volatility in these sectors. Conversely, INDP exhibits the lowest standard deviation (2.5211), implying relatively stable industrial production levels.

Skewness measures indicate that most variables are positively skewed, with FDI displaying extreme positive skewness (5.4920). Only GE and INDP show negative skewness (-0.4388 and -3.5563, respectively). This asymmetry suggests that for most variables, there are more extreme positive values than negative ones. Kurtosis values exceed 3 for all variables except GE, indicating leptokurtic distributions with heavier tails than a normal distribution. FDI exhibits an exceptionally high kurtosis (50.5268), suggesting frequent extreme events in foreign direct investment flows. The Jarque-Bera test results, coupled with probability values of 0.0000 for all variables, strongly reject the null hypothesis of normal distribution. This non-normality is consistent with the observed skewness and kurtosis values.

FDI exhibits the most extreme characteristics, with the highest skewness and kurtosis, indicating highly volatile and potentially unpredictable investment patterns. INDP shows a notable negative skew (-3.5563) and high kurtosis (16.0922), suggesting occasional significant downturns in industrial production. GE exhibits the closest approximation to a normal distribution, with the lowest absolute skewness and kurtosis nearest to 3. INT and CPI display moderate positive skewness and kurtosis, reflecting the tendency for occasional spikes in interest rates and inflation.

Table 4: **Descriptives of Covariates**

	BM	CP	CPI	FDI	GE	INDP	INT	MC
Mean	11.1434	59.2811	4.5174	3.9816	17.0924	-0.3910	5.1047	49.6452
Median	9.6714	50.1747	3.3550	3.0274	17.9799	0.0903	3.7500	40.7253
Maximum	82.5883	139.0136	25.6112	106.4988	23.3230	2.5910	26.5000	157.7010
Minimum	-11.0922	16.8378	-3.9149	-41.0789	10.2926	-11.5299	0.0010	9.6053
Std. Dev.	8.6829	27.2011	4.2440	10.2542	3.1431	2.5211	4.9507	32.5978
Skewness	2.0639	1.0815	1.6618	5.4920	-0.4388	-3.5563	1.6083	0.8949
Kurtosis	11.9643	3.0995	6.5928	50.5268	2.0848	16.0922	5.7159	3.0804
Jarque-Bera	8327.608	400.8987	2048.128	203442.8	137.4828	18980.70	1515.289	274.4644
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	2052	2052	2052	2052	2052	2052	2052	2052

BM=Broad Money, CP=Credit to the Private Sector, CPI= Consumer Price Index, FDI=Foreign Direct Investment, GE=Government Expenditure, INDP=Industrial Production, INT= Interest Rate MC=Market Capitalisation

T-tests were applied as statistical analysis for significant differences between pre-ETF (pre-treatment) liquidity and post-ETF (post-treatment) liquidity in the markets. This is a preliminary step that helps indicate if there are further intricacies or patterns in the data to be revealed by more complex analysis tools. Log transformation was applied to address the non-normality and skewness of the spread estimators in order to obtain more reliable two-sample t-tests and improve their statistical power (Hammouri et al., 2020; O'Keeffe et al., 2017). This was also necessary to mitigate the effects of one country influencing the effect in one direction. For example, Brazil has a more active market compared to other countries, as illustrated in the means, pre- and post-treated, of Table 6. Table 5 presents the results of the full sample t-test. All four spreads show an increase in spreads, though the CS is insignificant. These represent increases of 13.68% of the ROLL, 21.49% of the EDGE and 14.34% of the AR.

Table 5: **Full Sample Pre and Post ETF Means of Liquidity**

	Pre-Treated Means	Post-treated means	Mean Diff	Pr(>|t|)	95% confidence	
AR	-4.7936	-4.6388	-0.1548	0.0419	-0.3039	-0.0057
CS	-5.5382	-5.5030	-0.0352	0.5742	-0.1578	0.0875
EDGE	-5.3450	-5.1030	-0.2420	0.0044	-0.4084	-0.0757
ROLL	-4.4681	-4.3210	-0.1471	0.0359	-0.2845	-0.0097

Table 6 presents a country-level t-test analysis to offer more detailed insights. Results of Brazil and Bulgaria indicate a reduction in spreads, although statistically insignificant across all estimators. Greece and Colombia show an increase in spreads across all estimators except for EDGE in the case of the latter. Philippines, Qatar and Russia indicate a reduction in spreads, although only significant for EDGE. Chile also shows a reduced spread post-treatment, significant for all except the ROLL estimator. While these results provide some understanding of the impact of ETF introduction, it is important to acknowledge the limitations of t-tests, which do not account for confounding variables and interaction effects. More sophisticated models can offer insights beyond what a t-test can provide. For instance, a Difference-in-Differences (DiD) analysis can identify treatment effects within specific subgroups or under specific conditions, which a simple t-test comparing means of groups might overlook. If the data include a temporal component, DiD analysis might reveal significant effects over time that may not be apparent in a static t-test. Furthermore, t-tests do not address the confounding effects of covariates, which can mask treatment effects that can be better captured using propensity score methods.

Table 6: **Country-level Two-Sample T-Tests**

Liquidity measure	AR			CS			EDGE			ROLL		
Mean	Pre	Post	Difference (p-value)	Pre	Post	Difference (p-value)	Pre	Post	Difference (p-value)	Pre	Post	Difference (p-value)
Brazil	1.4812	1.3845	0.0967 (0.3186)	0.2645	0.2487	-0.0158 (0.5657)	1.3782	1.3193	0.0589 (0.4958)	1.4748	1.3233	0.1515 (0.2022)
Bulgaria	0.0048	0.0045	0.0003 (0.3546)	0.0024	0.0023	0.0001 (0.4537)	0.0083	0.0076	0.0007 (0.3209)	0.0069	0.0067	0.0002 (0.7663)
Chile	0.0059	0.0046	0.0013 (0.0018)	0.0039	0.0026	0.0013 (0.0002)	0.0014	0.0018	-0.0004 (0.0022)	0.0086	0.0074	0.0012 (0.1215)
Colombia	0.0042	0.0056	-0.0014 (0.0035)	0.0024	0.0032	-0.0008 (0.0058)	0.0021	0.0020	-0.0001 (0.5598)	0.0065	0.0092	-0.0027 (0.0020)
Greece	0.0071	0.0120	-0.0049 (0.0000)	0.0037	0.0052	-0.0015 (0.0005)	0.0054	0.0077	-0.0018 (0.0000)	0.0097	0.0176	-0.0079 (0.0000)
Philippines	0.0066	0.0061	0.0005 (0.6353)	0.0040	0.0029	0.0011 (0.1662)	0.0046	0.0045	0.0001 (0.0004)	0.0094	0.0096	0.0002 (0.8864)
Qatar	0.0051	0.0049	0.0002 (0.6312)	0.0024	0.0026	-0.0002 (0.3998)	0.0041	0.0034	0.0007 (0.0545)	0.0071	0.0079	-0.0008 (0.2684)
Russia	0.0089	0.0079	0.0010 (0.3723)	0.0044	0.0031	0.0013 (0.0183)	0.0053	0.0073	-0.0020 (0.0966)	0.0131	0.0132	-0.0001 (0.9321)

4.4 The Parallel Trends Assumption

The assumption of parallel trends is a crucial concern for studies in the DiD literature. However, the application of parallel trends is often not realistic and does not hold empirically (Bilinski & Hatfield, 2018). Parallel trends assume that pre-intervention trends are similar for both the control and treated group (Ryan et al., 2019), and that, in the absence of intervention, the treated group's mean outcome would have evolved similarly to that of the control group. Oftentimes, the parallel trends assumption is demonstrated in a graph; however, the nature of this study poses some challenge to this. The staggered adoption of the treatment across eight countries introduces significant complexity in visualising parallel trends. The heterogeneity in treatment timing makes it challenging to construct a single, interpretable parallel trends graph that accurately represents the pre-treatment dynamics across all units (Athey & Imbens, 2022). Additionally, given the staggered adoption and the inclusion of multiple countries, the pre-treatment period can be defined in as many countries as there are included in the sample (Callaway & Sant'Anna, 2021). This complexity makes a single, clear parallel trends graph potentially misleading or uninformative. Sections 4.6.1 and 4.6.2 provide more details about the definition of the pre-treatment periods.

Roth *et al.* (2023) have identified two reasons why the parallel trends assumption may be violated in practice. One of those reasons is time-varying confounding effects such as macroeconomic shocks. Additionally, the parallel trends assumption can be sensitive to the chosen functional form of the outcome (Roth & Sant'Anna, 2023). Given that the violation of the parallel trends assumption is more likely than not in empirical research, numerous studies have proposed how this assumption can be relaxed while still allowing for reliable estimates of ATT (Ahlfeldt, 2018; Renson et al., 2023; Shin, 2022). More pertinent to this study is the argument advanced by Egami and Yamauchi (2023) that analysing multiple pre-treatment periods not only helps assess the validity of the parallel trends assumption but also improves estimation accuracy and allows for a more flexible interpretation of trends. This can be particularly beneficial in contexts where treatment effects are expected to evolve over time.

For this study, we considered the factors identified by Roth et al. (2023) that could lead to violations of parallel trends. The first factor is the inclusion of time-varying confounders in the Difference-in-Differences (DiD) model. However, a review of the literature suggests that the intuition of incorporating covariates into a DiD model is not as applicable as it is in a regression equation. Including confounders is likely to introduce bias after the treatment, particularly for those variables added post-intervention. This bias arises because the inclusion of a control variable that is likely affected by the intervention can distort the outcome, rendering the treatment ineffective (Zeldow & Hatfield, 2021).

To address the issue of estimation bias resulting from the inclusion of confounders in the DiD model, Zeldow and Hatfield (2021) propose a matching approach that involves matching pre-treatment outcomes to eliminate differences in covariates between groups, thereby eliminating non-parallel trends. There are three methods of matching. The first method is based on matching random error terms, where individual units of data are paired based on similar random errors, assuming that this adequately captures variability in treatment assignment. The advantage of this non-parametric matching method is that it does not rely on specific model assumptions such as distributional assumptions. However, random error terms are typically unobservable and difficult to estimate without additional assumptions, which can introduce bias in estimates. For instance, Lindner and McConnell (2019) demonstrated that matching based on random error terms leads to bias when a higher standard deviation causes short-term fluctuations that cannot be distinguished from structural outcomes through matching.

The literature also discusses matching based on conditional lagged outcomes of the comparison group. This approach involves matching treated units with control units based on the lagged outcomes of the control group. Lagged outcomes refer to past values of the outcome variable for the control group, which are used as a proxy for unobserved characteristics that may influence both treatment assignment and subsequent outcomes. This matching method relies on the assumption that lagged outcomes effectively capture the relevant unobserved characteristics of the treatment and control groups. Daw and Hatfield (2018) examined the effects of matching conditioned on lagged outcomes of comparison groups with the same trend and found that this results in the selection of a pre-trend control group with outcomes that eventually revert to the mean. Daw and Hatfield argue that due to this mean reversion effect, it may be better not to include conditional lagged outcomes. This sentiment is also echoed by Roth et al. (2023), who add that these covariates reduce the reliability of the decomposed regression parameter.

Propensity score matching (PSM) is a commonly utilised method for matching that estimates the propensity score, which is the predicted probability of receiving treatment based on observed covariates. PSM addresses selection bias by controlling for observed confounders and creates balanced comparison groups. PSM also serves as an alternative to the parallel trends assumption. Its advantage lies in its flexible matching algorithms, which allow for various types of applications determined by the study's criteria. However, PSM has a limitation in that it only accounts for observed confounders, and therefore, unobserved confounders may potentially influence treatment. To address this limitation, we draw a comprehensive list of confounders from the extensive research and documentation of the factors that influence market liquidity.

One of the key strengths of PSM is its effectiveness in eliminating systematic differences between treated and untreated subjects. Research indicates that PSM can reduce the standard mean differences (SMDs) of covariates more effectively than other methods, such as stratification or covariate adjustment alone (Austin, 2010; Wan, 2019). For instance, Austin (2011) highlights that PSM can significantly reduce bias in estimating treatment effects, making it a preferred choice for research. This balancing property is crucial, as it ensures that the groups being compared are similar in terms of observed characteristics, which is essential for valid causal inference. In contrast, matching random error terms does not adequately address the underlying confounding variables that may influence treatment assignment and outcomes. This method often fails to account for the systematic biases present in observational data, leading to potentially misleading conclusions (Desai et al., 2017).

Similarly, matching based on conditional lagged outcomes may not sufficiently control for time-varying confounders, which can introduce additional bias into the analysis. PSM, by focusing on the propensity score—which is the probability of treatment assignment based on observed covariates—provides a more robust framework for addressing these issues (Austin, 2014; Miyahara et al., 2021). Moreover, PSM allows for the incorporation of complex models that can include higher-order and interaction terms, enhancing the precision of the matching process (Abadie & Imbens, 2016). This flexibility is not typically available in simpler matching methods, which may limit their effectiveness in achieving balance across treatment groups. For example, studies have shown that PSM can achieve better covariate balance compared to conventional matching methods, thus leading to more reliable estimates of treatment effects (Zhang et al., 2020). The process of PSM conducted in this study is documented in the following section. The balance of covariates achieved through the PSM is demonstrated in Table 9, providing evidence of the comparability of the treatment and control units.

4.4.1 Propensity Score Matching

Despite the challenges associated with incorporating covariates in the DiD model, it is crucial to account for the influence of covariates on the treatment effect in order to mitigate any potential bias in the DiD estimate. Propensity score matching is a widely utilised analytical technique for estimating causal treatment effects. This approach is applicable when there are distinct groups of treated and untreated individuals, and its objective is to ensure comparability between the treatment and control groups used for subsequent analysis (Rosenbaum & Rubin, 1983). The propensity score represents the conditional probability of treatment assignment given a set of observed covariates.

Propensity score matching (PSM) involves four steps (Stuart, 2010), the first of which is determining the covariates to be used for analysis and achieving balance. In this study, the selected variables are those that have been empirically shown to influence market liquidity. Although numerous factors potentially affect market liquidity, this study focuses on macroeconomic variables due to their impact on market conditions and liquidity across the countries included in the panel. A more detailed discussion on the covariates is presented in Chapter 3.

Before conducting the balancing process, model tests were performed to validate the association between the covariates and the treatment variable, as well as between the liquidity variable and the covariates. To accomplish this, logistic regression was employed on the dataset, revealing significant relationships between “Treatment” and seven out of the eight covariates, as displayed in Table 7. As is customary in the literature, the logit model was utilised alongside the Propensity Score Matching (PSM) technique (Cushman & De Vita, 2017; Deuss, 2012). Additionally, a linear regression was executed to examine the relationship between the liquidity variables and the dependent variable. The outcomes are presented in Table 8, indicating seven of the eight variables were significant. In order to ensure comparability, only the variables that simultaneously significantly affected liquidity and treatment were balanced, while those that did not were disregarded in the analysis (Staffa & Zurakowski, 2018). This resulted in six covariates after dropping CPI per the logit model and FDI, per the linear regression.

Table 7: **Logit model of the influence of covariates on treatment**

	Marginal effects	Std. Error	z	Pr(>|z|)
BM	-0.0090	0.0011	-5.702	0.0000***
CP	0.0096	0.0007	15.764	0.0000***
CPI	-0.0010	0.0006	-0.293	0.7698
FDI	-0.0083	0.0015	-4.219	0.0000***
GE	-0.1804	0.0048	-7.594	0.0000***
INDP	0.0888	0.0050	3.8484	0.0000***
INT	0.0856	0.0023	4.816	0.0000***
MC	-0.0207	0.0004	-7.381	0.0000***

NB: ***, **, * indicates significance at 1%, 5% and 10% respectively.
BM=Broad Money, CP=Credit to the Private Sector, CPI= Consumer Price Index, FDI=Foreign Direct Investment, GE=Government Expenditure, INDP=Industrial Production, INT= Interest Rate MC=Market Capitalisation

Table 8: **Regression of the influence of covariates on liquidity**

	Liquidity			
	AR	**CS**	**EDGE**	**ROLL**
BM	-0.0044***	-0.0006***	-0.0039***	-0.00043***
	(0.0010)	(0.0002)	(0.0010)	(0.0012)
CP	-0.0009**	-0.0002**	-0.0007*	-0.0010*
	(0.0004)	(0.0000)	(0.0004)	(0.0004)
CPI	-0.0517***	-0.0091***	-0.0496***	-0.0504***
	(0.0027)	(0.0006)	(0.0025)	(0.0029)
FDI	0.0002	0.0000	0.0002	0.0002
	(0.0008)	(0.0002)	(0.0007)	(0.0080)
GE	0.0249***	0.0047***	0.0222***	0.0252***
	(0.0034)	(0.0007)	(0.0031)	(0.0036)
INDP	-0.0337***	-0.0061***	0.0315***	0.0325***
	(0.0033)	(0.0007)	(0.0031)	(0.0035)
INT	0.0779***	0.0134***	0.0740***	0.0763***
	(0.0025)	(0.0005)	(0.0023)	(0.0026)
MC	0.0014***	0.0003***	-0.0010***	0.0015***
	(0.0004)	(0.0000)	(0.0004)	(0.0004)

NB: ***, **, * indicate significance at 1%, 5% and 10% respectively.
BM=Broad Money, CP=Credit to the Private Sector, CPI= Consumer Price Index, FDI=Foreign Direct Investment, GE=Government Expenditure, INDP=Industrial Production, INT= Interest Rate MC=Market Capitalisation

Once the covariates were confirmed, we proceeded to the design phase of analysis, which involved selecting a matching method. To fulfil this purpose, the MatchIt package for R (Stuart et al., 2011) was implemented, which utilises a subset selection from the full sample to create a new sample that neutralises the effects of covariates, ensuring comparability between the treatment and control groups. Matchit is a toolset designed to implement PSM in

R. Propensity score matching offers the advantage of being nonparametric, as it does not rely on estimated model parameters as in the case of inverse probability weighting (IPW). In IPW, the weights estimated are directly related to the propensity score model, making it sensitive to the model's specification.

There are three classes of propensity score matching: distance matching, stratum matching and pure subset selection. Distance matching involves selecting units from the control group that pair with the treatment group based on the distance between units. When members of either the treated or control group are not matched, they are dropped from the sample. Stratum matching creates strata based on the unique values of covariates and assigns units with similar values to those strata. Any units assigned to a stratum that are not matched are dropped from the sample. The pure subset selection method creates subsets by ranking units in ascending order of their propensity scores. This ranked list is then divided into subsets such that treated and control groups are matched based on their ranking in the subset. It does not consider distance between units.

For purposes of this study, the distance matching class was selected due to the flexibility it allows when matching the sample by not constraining matching to strata or a subset. This allows for better matching across the entire sample and therefore better precision in finding matches with similar propensity scores. Additionally, because distance matching minimises the distance between the propensity scores of the treated and control groups by prioritising the smallest distance between matched pairs, it is potentially easier to achieve covariate balance between the treated and control groups.

The distance matching class of PSM comprises various matching techniques, including nearest neighbour matching, optimal matching, and optimal full matching. Nearest neighbour matching (NNM) is the most commonly used matching technique (Garrido et al., 2014). It involves matching the treated group with the closest eligible control unit, without prioritising any specific criteria (Harris & Horst, 2019). On the other hand, optimal matching also matches treated units with control units but aims to optimise the sum of pair distances in the matched sample. Optimal full matching (OFM), often referred to as full matching, creates subclasses that consist of at least one treated unit and one control unit or vice versa. It optimises the sum of within-subclass distances in the matched sample. The weights of the units are calculated based on subclass membership and used as propensity score weights. The selection of the matching method for this study primarily depended on its ability to achieve covariate balance. The target estimate and the sample size after matching were also taken into consideration. To assess suitability for further analysis, all four datasets were run through all the techniques, and the outputs were evaluated. In cases where balancing was not achieved for any of the covariates, the suggestion by Dehejia and Wahba (2002) was applied, which involves successively adding higher powers of the unbalanced covariate or including an adjusted functional form of the covariate until balance is achieved.

Assessing the effectiveness of covariate balance can be achieved through various statistical techniques. The SMD and VR provide a more comprehensive and standardised assessment of balance between treatment and control groups compared to simple mean comparisons. Covariate balances were assessed with the cobalt package (Greifer, 2022). The cobalt package allows for useful visualisation of covariate balances using various plots and complements the use of MatchIT, which was used for matching. One of the statistics commonly used for evaluating the sufficiency of covariate balancing after matching is the standard mean difference (SMD):

$$SMD = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt[2]{s_1^2 + s_2^2}} \tag{4.1}$$

$\bar{X}_1$ and $\bar{X}_2$ are the means of the treated and control groups, respectively and similarly, s_1^2 and s_2^2 are the sample variances. This standardisation facilitates a more intuitive interpretation of balance across diverse covariates. The guideline for a significant imbalance is an SMD with values greater than 0.1 (Stuart et al., 2013). Austin et al. (2021) recommend a SMD balance of between -0.1 and 0.1. Stuart et al. (2013) indicate that an SMD of 0.1 is generally considered a good standard for balance, while a threshold of 0.25 can also be acceptable in certain contexts, particularly when dealing with covariates that are inherently more difficult to balance. This flexibility acknowledges the practical challenges faced in achieving perfect balance, especially in observational studies. Wallace et al. (2024) discuss a sensitivity analysis where the balance tolerance for certain covariates with high levels of imbalance was set at SMD ≤ 0.25, while other covariates adhered to the more stringent SMD ≤ 0.1 threshold. This suggests that in cases where certain covariates are inherently more difficult to balance, a higher SMD threshold may be justified. Moreover, Munroe et al. (2023) utilised a calliper width of 0.2 standard deviations for matching, indicating that while an SMD < 0.1 is ideal, the use of a 0.2 calliper reflects a pragmatic approach in scenarios where achieving perfect balance is challenging. In addition, Zhang *et al.* (2020) highlight that while the goal is to minimise SMDs to below 0.1, they also recognise that some studies may accept higher thresholds depending on the context and the nature of the covariates being balanced. Cohen's original proposal that an SMD of 0.2 suggests a small effect size (Austin, 2009), provides further support for a higher SMD. Given the nature of covariates in this study being macro-economic variables that have complex interdependencies (Zaroomi et al., 2020) and are shaped by the unique cultural and institutional differences of each country (Arıkan et al., 2018), achieving balance is difficult. Hence, the threshold applied for what is an acceptable SMD is set at 0.2 for this study.

The variance ratio is another common statistic used to ascertain if covariates have achieved balance after PSM. The inclusion of the VR provides important information about the equality of variances between groups, which is not captured by mean comparisons alone. A VR of 1 indicates balance, and values of between 0.8 and 1.2 are generally accepted as the recommended limit in the literature (Rubin, 2001).

Table 9: **Balance of covariates before and after matching**

	Full Sample (unmatched)		Matched Sample	
	SMD	**VR**	**SMD**	**VR**
BM	-0.5398	0.1685	-0.0932	0.9626
CP	0.9410	2.4979	0.0784	0.8163
GE	-0.1476	0.8128	-0.1894	1.1485
INDP	-0.1016	2.6562	-0.0080	0.9025
INT	-0.1538	0.4456	-0.2050	1.2067
MC	0.3087	0.9593	0.1109	0.7687

Based on the criteria set for both the SMD and the VR, all covariates were successfully balanced. Thus, the mean likelihood for group assignment between control and treated is more directly comparable, and any bias has been significantly reduced. However, despite PSM, there is still bias that can arise from unobserved confounders such as geopolitical events that may not be captured in the data. Other biases could come from choice of matching techniques; however carefully considered they may have been. As such, one can only attain reasonable assurance that the PTA has been met from matching of covariates and ensuring balance between treatment and control groups. Having satisfied this criterion, further analysis is undertaken where the matched samples are applied directly in the DiD regressions.

4.5 Average Treatment Effect

To estimate the average treatment (ATE) effect, we use the matched data sample with balanced covariates and apply it for further statistical analysis. Table 10 presents the results of the canonical DiD of the form:

$$y_t = \beta_0 + \beta_1 Post + \beta_2 Treatment + \beta_3 Post \times Treatment + \gamma' X + \varepsilon_t \qquad (4.2)$$

where the covariates for each liquidity indicator are as identified in Table 7. The results indicate a significant increase in spread after the introduction of ETF in the market. Canonical DiD provides a baseline estimate of the average treatment effect, which can then be compared to the heterogeneous treatment effects identified in more complex models such as those used in Section 4.6. The canonical DiD offers the advantages of being able to control for unobserved confounding factors that are time invariant and allows for straightforward interpretation. Understanding the ATE provides context for why certain subgroups may experience different outcomes. This knowledge is essential for interpreting the results of heterogeneous treatment effect analyses, as it helps identify potential reasons for variation in responses (Fukugawa, 2023). Additionally, the canonical DiD analysis allows for the implementation of robustness checks that can validate the findings of heterogeneous treatment effects. By establishing a baseline, sensitivities to different specifications, or estimation techniques, can be analysed. The next sections present the results of other DiD models.

Table 10: **Average Treatment Effects of the DiD**

	Coefficient	Std. Error	z	Pr(>|z|)
AR	0.1397	0.0661	8.635	0.0000
CS	0.0281	0.0035	7.928	0.0000
EDGE	0.1399	0.0153	9.127	0.0000
ROLL	0.1280	0.0169	7.591	0.0000

For the next analyses, subsampling was undertaken for various reasons. Firstly, not all countries had data available for the full sample period from 2001 to 2023, which made it challenging to apply the Callaway and Sant'Anna analysis due to the requirement for a balanced panel. Accordingly, as a matter of pragmatism, the sample was divided into two sample periods of 2001-2015 and 2012-2023. These periods were carefully considered based on the dates of ETF inception in the countries. Second, PTA becomes increasingly difficult to justify over longer periods. In addition, the complexity of modelling long-term effects can introduce additional layers of uncertainty. Wang et al. (2021) noted that the long-term performance of policies or interventions can vary significantly across different contexts and time frames, complicating the interpretation of results.

Further considerations of subsampling were that it enables a more comprehensive exploration of the study period's economic and policy landscape. Major economic shocks or policy changes, such as the 2008 financial crisis or the COVID-19 pandemic, can significantly influence outcomes and potentially confound results. By creating subsamples that isolate these events, there is better control for their impacts and a more accurate assessment of the introduction of ETFs (Goodman-Bacon, 2021).

Other reasons for subsampling were to improve computational and estimation efficiency (Poudel & Bikdash, 2022), which improves robustness of results. This is especially important in econometric analyses where the presence of outliers or extreme values can skew results. Sabbaghi and Sabbaghi (2018) employed subsampling to control for sensitivity in econometric tests, allowing for more reliable conclusions about market efficiency. Subsampling allowed for sensitivity analysis where there was an overlap of sample periods to assess any impacts of time dependency or group influences on estimation results. This approach also allows for a more comprehensive examination of time-varying heterogeneity in treatment effects. The overlapping structure enables the analysis of how the same years (2012-2015) might yield different results when considered as part of distinct temporal contexts. This can reveal important insights about the dynamic nature of treatment effects and how they may be influenced by broader temporal trends or contexts (Goodman-Bacon, 2021).

In addition to sampling by periods, there was a need for further subsampling for purposes of controlling the number of units within the sample. Similar to the reasons advanced above, of chief consideration was the increased risk of the violation of PTA with numerous units. With a large number of units, it becomes more difficult to ensure that all units would have followed similar trends in the absence of treatment. This heterogeneity in trends can lead to biased estimates of the treatment effect (Abadie, 2005). Moreover, the presence of many units increases the likelihood of confounding factors that may not be adequately controlled for, potentially compromising the internal validity of the study (Lechner, 2011). The inclusion of numerous units can also complicate the interpretation of results. With a large and diverse set of units, treatment effects may vary substantially across different subgroups or contexts. This heterogeneity can make it challenging to derive clear, generalisable conclusions from the analysis (Bertrand et al., 2004). Furthermore, the risk of finding spurious correlations or statistically significant but practically insignificant effects increases with sample size, potentially leading to overinterpretation of results (Lin et al., 2013).

With consideration of all the above, there were three subsamples resulting in three panels for results. The first panel includes Brazil, Chile and Greece; Panel 2 includes Bulgaria, Philippines and Qatar; Panel 3 includes Colombia, Chile and Russia. In the next section, results are reported for all three panels.

4.6 Heterogeneous Treatment Timing Effect

The limitations of the canonical DiD approach were delineated in Chapter 3. Subsequently, alternative models are presented, commencing with the Goodman-Bacon analysis, followed by the Callaway and Sant'Anna model.

4.6.1 Goodman-Bacon Decomposition

Goodman-Bacon (2021) decomposes the weights of the subgroups based on three categories. The first weighting considered is identical to that of the canonical 2×2 DiD, where there are two groups, the treatment group (*j*) and untreated group (*U*) and two periods, the pre-treatment period and post-treatment period for *j* and *U*.

$$\hat{\beta}_{ju}^{2\times2} = \left(\bar{y}_j^{POST(j)} - \bar{y}_j^{PRE(j)}\right) - \left(\bar{y}_U^{POST(j)} - \bar{y}_U^{PRE(j)}\right) \tag{4.3}$$

The second decomposition considers if there were no untreated groups. In that case, the untreated group is considered to be the latter treated group (*l*) so that it is compared with an earlier treated group (*k*). Group *l* acts as a control during their pre-treatment period for Group *k*. The decomposition is thus:

$$\hat{\beta}_{kl}^{2\times2,k} = \left(\bar{y}_k^{MID(k,l)} - \bar{y}_k^{PRE(k)}\right) - \left(\bar{y}_l^{MID(k,l)} - \bar{y}_l^{PRE(k)}\right) \tag{4.4}$$

$MID(k,l)$ represents the time window where treatment status varies between the two groups. However, as the *l* group's treatment status changes to treated, Group *k* acts as the control so that:

$$\hat{\beta}_{kl}^{2\times2,l} = \left(\bar{y}_l^{POST(l)} - \bar{y}_l^{MID(k,l)}\right) - \left(\bar{y}_k^{POST(l)} - \bar{y}_l^{MID(k,l)}\right) \tag{4.5}$$

where average outcomes are compared between $POST(l)$ and $MID(k, l)$.

All the decomposed DiD estimators can be summarised in the following equation:

$$\beta^{DD} = \sum_{k \neq U} s_{kU}\, \widehat{\beta}_{kU}^{2\times2,l} + \sum_{k \neq U} \sum_{l > k} \left[s_{kl}^{k}\, \widehat{\beta}_{kl}^{2\times2,k} + s_{kl}^{l} \widehat{\beta}_{kl}^{2\times2,l} \right] \quad (4.6)$$

Goodman Bacon argued that the ATT of the TWFE constituted inappropriate comparisons in reference to the group "later vs earlier". In this set-up, the countries that introduced ETFs later are compared with those that introduced ETFs earlier, thus serving as a control. The 'early' group would have changing outcomes attributable to the treatment itself and therefore not valid to be used as a control because the early-treated group does not provide the correct counterfactual of how the subsequently treated group would look without treatment. Thus, the aggregated ATT would consist of invalid comparison groups. The study of the decomposition helps to identify how much of the TWFE ATT is attributable to these invalid comparisons. To further demonstrate this, the ATT in the context of the GBD is unpacked. In the context of the GBD, ATT is defined as:

$$ATT_k(\tau) = E\left[Y_{it}^{1} - Y_{it}^{0} \middle| k, t = \tau \right] \quad (4.7)$$

where k is the timing cohorts in a specific year τ. The ATT is the difference in outcomes of the treated units at time τ and the outcome of the units had they not received treatment. Equation 4.6 can be modified to define ATT over a time window W with T periods as follows:

$$ATT_k(W) = \frac{1}{T_W} \sum_{\tau \epsilon w} E\left[Y_{it}^{1} - Y_{it}^{0} \middle| k \right] \quad (4.8)$$

Accordingly, the GBD can be expressed as a combination of the variance-weighted average treatment effect (VWATT) on the treated, the variance-weighted common trend (VWCT) and the weighted sum of the changes in the treatment effects within each 2 × 2 DiD post period related to the timing (ΔATT).

$$p \lim_{n \to \infty} \beta^{DD} = VWATT + VWCT - \Delta ATT \quad (4.9)$$

This equation helps to understand the construction of the GBD and the underlying assumptions. In particular, the VWATT is a positively weighted average (derived from equation 4.6) of the three groups (the untreated, later treated and treated). The VWCT represents the source of bias of the TWFE. It represents the average difference in counterfactual trends across the various group pairs and over time, weighted per the decomposition. Essentially, the VWCT in equation 4.9 extends the common trends assumption into a staggered treatment assignment. The ΔATT captures the heterogeneity of treatment outcome of the subgroups over time. Figure 1 gives a visual assessment of the estimates of each comparison group and the associated weights. The same information is presented in Table 11.

4.6.2 Callaway and Sant'Anna

Callaway and Sant'Anna (2021) developed a DiD procedure that makes up for the shortcomings of the TWFE identified by numerous authors. They propose a three-step procedure that will allow for treatment effect heterogeneity and dynamic effects. The first step involves the identification of treatment-related disaggregated causal parameters denoted as:

$$ATT(g,t) = \mathbb{E}\left[Y_{i,t}(g) - Y_{i,t}(0) \middle| G_g = 1\right] \tag{4.10}$$

where $ATT(g,t)$ is the group-time average treatment effect. G_g denotes a binary variable equal to one if a group is first treated in period t. In this study, ATT(2005, 2010) would be the average treatment effect in 2010 for a country that first introduced ETFs in 2005. The second step summarises the measures of causal effects of the identified parameters. In this step, the $ATT(g,t)$ is identified by comparing the change in outcome of cohort g between periods $g-1$ and *t* (comparison between periods prior to 2005 and 2010) and the outcomes of the control group (not yet treated at time *t*). The model specifies two methods of comparisons with the control. The first is the comparison of the treated group with the not yet treated group. To apply the example further, that would mean comparing 2005 with another cohort that receives treatment in a later period, say 2008. The second option is comparison with a never-treated group. The group-time average treatment effect is estimated based on the average of the change in outcome of the different cohorts.

Callaway and Sant'Anna (2021) (C&S) also present an alternative to the GBD weighting of estimators that assigns higher weighting to the treated vs not-treated group. C&S estimates treatment effects by a non-parametric approach that assumes time-invariant covariates to calculate a group ATT by time relative to the treatment. Unlike other models, it takes a design-based approach to avoid bias from controlling for time-varying post-treatment confounding variables directly in the model (Griffin, 2023). This approach is a non-regression-based method, unlike the GBD and the DiD, and thus there is no 'forbidden' comparison group in the ATT defined thus:

$$ATT(g,t) = E\left[\left\{\frac{G_g}{E[G_g]} - \frac{\frac{{p_g}^{(X)C}}{1-{p_g}^{(X)}}}{E\left[\frac{{p_g}^{(X)C}}{1-{p_g}^{(X)}}\right]}\right\}(Y_t - Y_{g-1})\right]$$

[4.10]

Where p signifies the weights, the propensity scores normalised to 1. G and C are binary variables, treatment and control, respectively. The $ATT(g,t)$ is the average weighted difference between the treated and control group. In contrast to the GBD, the not yet treated group is dropped from weighting, assigning more weights to the control with similar characteristics (propensity scores) to the treated group and less to those with dissimilar scores. Thus, the C&S relies on the never-treated group as the control group, avoiding the GBD 'forbidden comparison' of the later-treated vs early-treated group. This difference in estimation procedure will help to understand the differences in estimates of the ATE of the DiD, the $ATT_k(\tau)$ of the GBD and the $ATT(g,t)$ of the C&S.

The Goodman-Bacon method decomposes the total effect of a variable into direct and indirect effects in a regression analysis. It shows the contribution of variables to the overall effect. The C&S, on the other hand, is used to estimate treatment effects in the presence of unobserved confounders that could affect the outcome, which helps in reducing bias in the estimator. By accounting for unobserved confounders, more robust and unbiased causal inference can be made compared to the GBD estimator. Additionally, the C&S method allows for the estimation of heterogeneous treatment effects, which can uncover potential non-linear relationships between the treatment (ETF introduction) and the outcome variables (liquidity measures). This is an important feature, as the previous results have suggested the possibility of non-linear or time-varying effects. The estimator can also capture dynamic treatment effects, meaning it can account for how the impact of ETF introduction may evolve over time. This could provide insights into the temporal dynamics of the relationship between ETF presence and market liquidity.

4.6.3 Results and Discussions

Having estimated the causal effect, this analysis reveals the effects of treatment timing. To that end, for each country, two compositions are considered. Firstly, the outcome comparison of the earlier treated with the later treated before treatment gives the composition effect. This captures the preexisting differences between the groups that could influence the outcome even without the treatment. Secondly, the interaction effect represents the differential impact of the treatment effect over time and reflects how the treatment effect varies between the groups. Table 9 summarises the composition and interaction effects of the panel.

Table 11: **Summary of Composition and Interaction Effects**

Component	**Cases**	**Liquidity**	**Mean. Coeff**		
			PANEL 1	**PANEL2**	**PANEL3**
Earlier vs Later	3	AR	0.1846	-0.5102	0.0881
		CS	0.2845	-0.1480	0.1300
		EDGE	0.1975	-0.3293	-0.8914
		ROLL	0.1883	-0.3078	0.2630
Later vs Earlier	3	AR	-0.2148	-0.3868	-0.1358
		CS	-0.1803	0.1585	-0.0758
		EDGE	-0.0241	-0.4837	0.1162
		ROLL	-0.2150	-0.1586	-0.1527
Treated vs Not	3	AR	0.1168	-0.0437	0.2104
		CS	0.2835	0.1636	-0.1657
		EDGE	0.6119	-0.3858	0.7065
		ROLL	0.1136	0.0758	0.2957

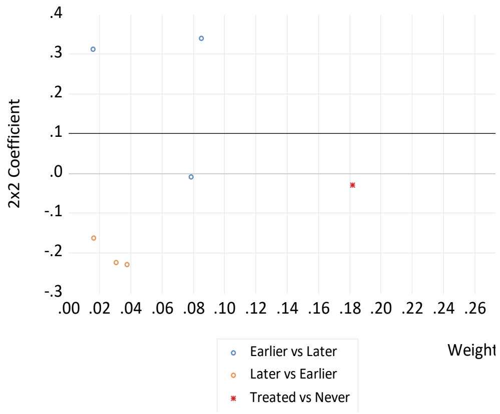
Panel 1 results consistently suggest that the introduction of ETFs is associated with an increase in spreads, ranging from about 20% to 33% for the early treated vs later treated. The treated vs. never treated comparison isolates the effect of ETF introduction by comparing units that received treatment to those that never received treatment during the study period. The treated vs not treated show a wide range of effects, from approximately 12% (0.1136 and 0.1168) to a substantial 84.4% (0.6119) increase in spreads. The EDGE is designed to be more robust to microstructure noise in high-frequency data. It attempts to separate the efficient price process from the noise component, which includes bid-ask bounce, discreteness of price changes, and other short-term deviations from the efficient price. The implication is that ETF introduction significantly altered the microstructure noise characteristics of the affected securities, and led to changes in how information is incorporated into prices and the EDGE captures these changes more acutely than other estimators.

The results of Panel 3 indicate an increase in spreads that is consistent for the AR (9.3% and 23.4% increases respectively) and ROLL (30.1% and 34.4% increases respectively) for earlier vs later group and the treated vs not treated. However, the CS and ROLL are inconsistent between the two groups, suggesting a difference in timing and overall treatment effect. The contradictory results might indicate non-linear effects or time-varying impacts of ETF introduction on market liquidity. Panel 2 also shows inconsistency in terms of timing and overall treatment effect; however, treatment timing is consistently negative. This again suggests that there may be non-linear and dynamic treatment effects of the introduction of ETFs to markets that require further investigation. The ATE of the canonical DiD masked these subtleties in results, showing only that there was an increase in spreads.

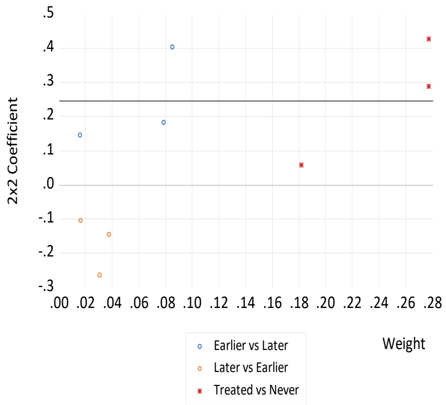
Table 10, indicating the coefficients of the different groups, reveals similarities across the groups. Figure 1 shows that the earlier vs later treated group has the least weight of the analysis compared to other groups. This can be attributed mostly to the number of countries that received treatment earlier on being less than those that introduced ETFs later during the period of assessment, which naturally causes lower weighting. The higher weighting in later groups suggests amplification of treatment effects over time. In other words, the reduction or increase in spreads accumulates overtime and therefore higher weights of the decomposition are allocated to the later periods. Additionally, the low weighting of the coefficient of the treated vs later-treated group suggests less stability and less precision in treatment effect. In general, an observation of Figure 1 reveals that the effects on each country vary. An exposition of the individual effects on countries is presented in the next sections.

Panel 1:

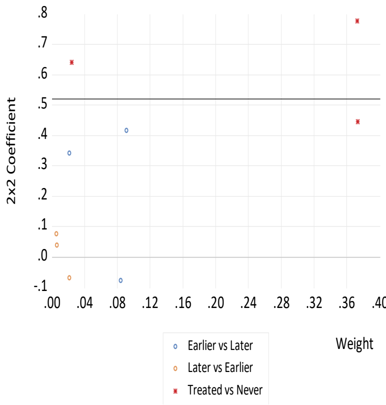
AR



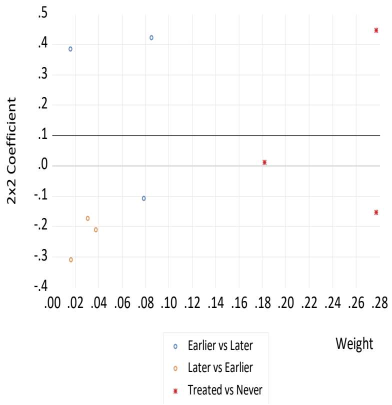
CS



EDGE

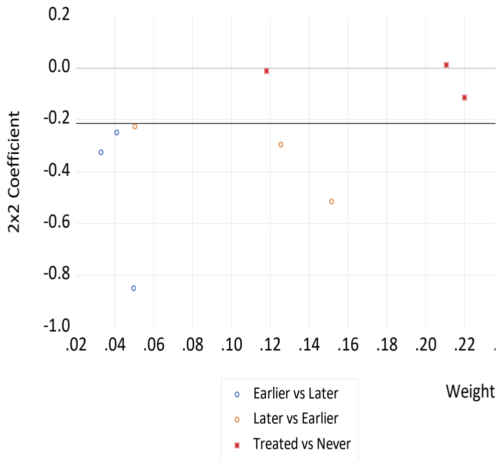


ROLL

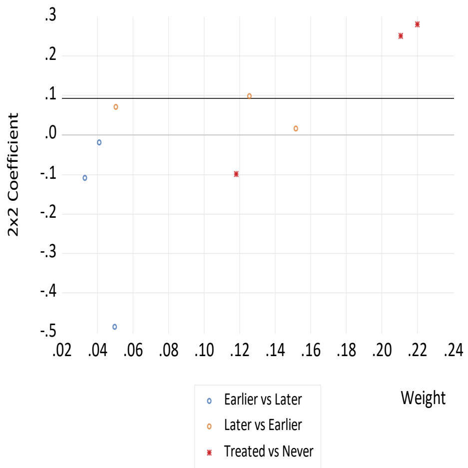


Panel 2:

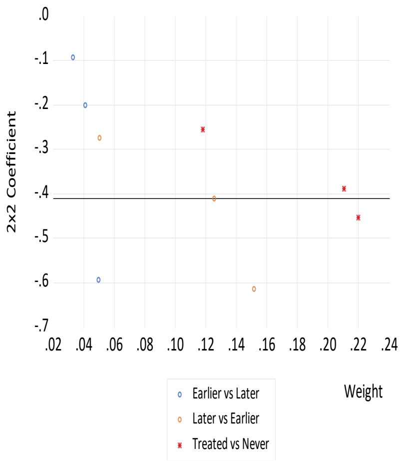
AR



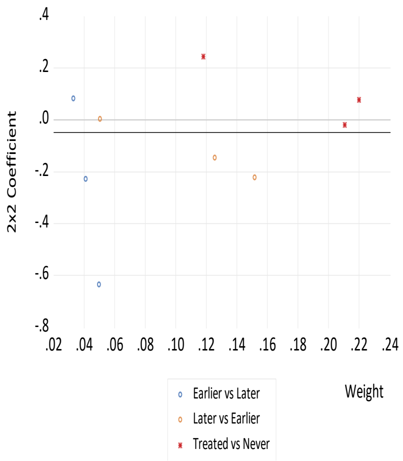
CS



EDGE



ROLL



Panel 3:

AR CS EDGE ROLL

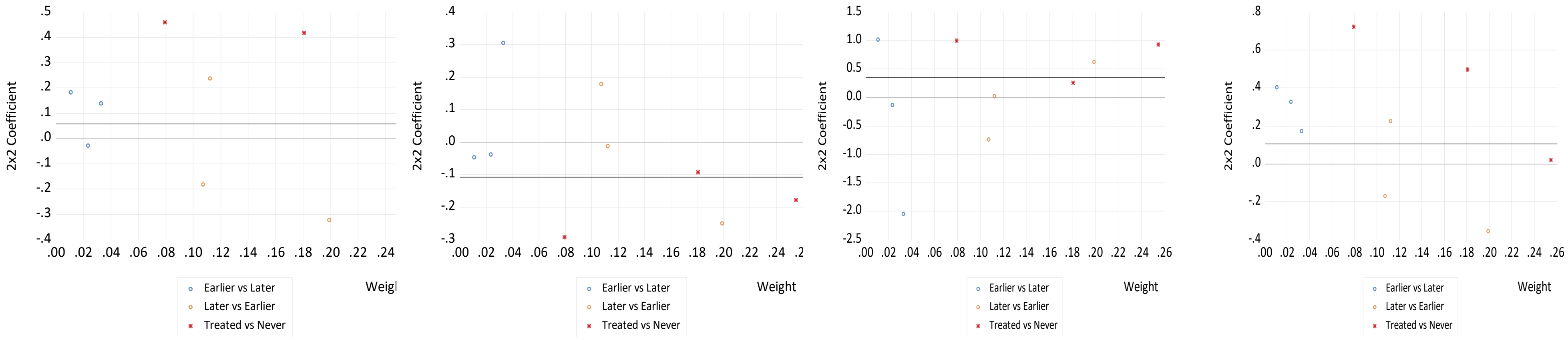


Figure 1. 2X2 DiD Decomposition.

The figure plots each 2×2 DiD component from the decomposition theorem against its weight. The blue and orange circles are the composition effects, which compare the outcomes of the earlier-treated group with those of the later-treated group and vice versa. The red circles are the interaction effects, that is, the treatment timing effects over time.

The ATT of Callaway and Sant'Anna are presented in Table 12.

Table 12: **Average Treatment Effect on the Treated**

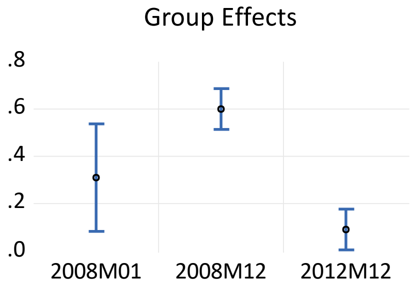
	AR	CS	EDGE	ROLL
Panel 1	0.3853***	0.5566***	-	0.3714***
	(0.1100)	(0.1917)		(0.0366)
Panel 2	-0.6238**	-0.4734**	-0.5082**	-0.0194
	(0.2626)	(0.2258)	(0.2184)	(0.1713)
Panel 3	0.1751	-0.0411***	0.0552	0.2241
	(1.0145)	(0.0115)	(0.1003)	(0.2567)

The results of Table 11 confirm those of Table 10 for all panels, although not all are statistically significant. The Panel 2 indicate results consistent with the findings of Saglam et al. (2019), who also observed an increase in liquidity associated with ETFs. Similarly, Agarwal *et al.* (2018) and Da and Shive (2018) found that ETF ownership significantly enhances the commonality in liquidity among the stocks held by ETFs, suggesting that arbitrage activities related to ETFs contribute to liquidity improvement (Ben-David et al., 2017). Similarly, liquidity commonality can inhibit market participants from diversifying their exposure to liquidity risks, which can exacerbate the liquidity problems as in the case of Panel 1 and Panel 3. Furthermore, the introduction of ETFs can lead to a migration of liquidity away from individual stocks to the ETF itself. Madhavan (2016) argues that this migration can result in decreased liquidity for the underlying securities, particularly if uninformed investors prefer trading ETFs over individual stocks to avoid trading against informed investors.

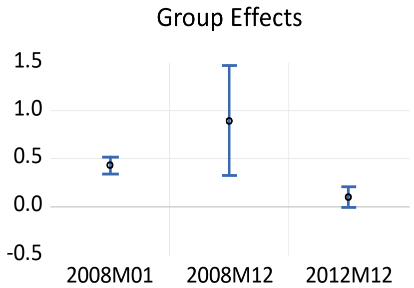
The C&S analysis allows researchers to estimate treatment effects for different groups based on their treatment status at different times (Goin & Riddell, 2023). The next section begins by discussing the heterogeneity of treatment effects and focuses on the group effects of the C&S analysis that may be masked by the ATT. The results of the group effects can be found in Figure 2.

PANEL 1

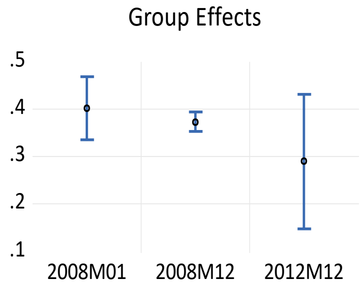
AR



CS

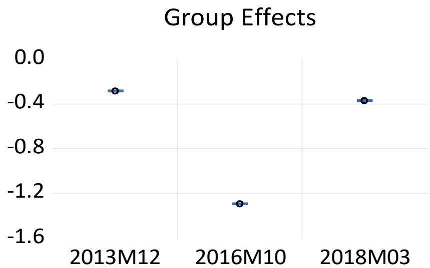


ROLL

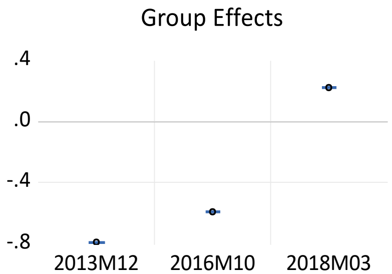


PANEL 2

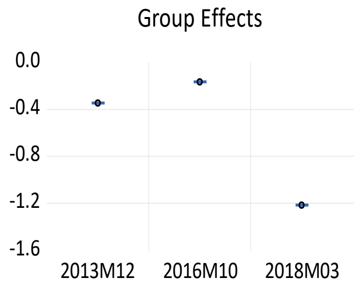
AR



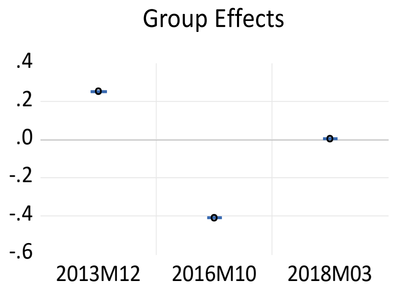
CS



EDGE



ROLL



PANEL 3:

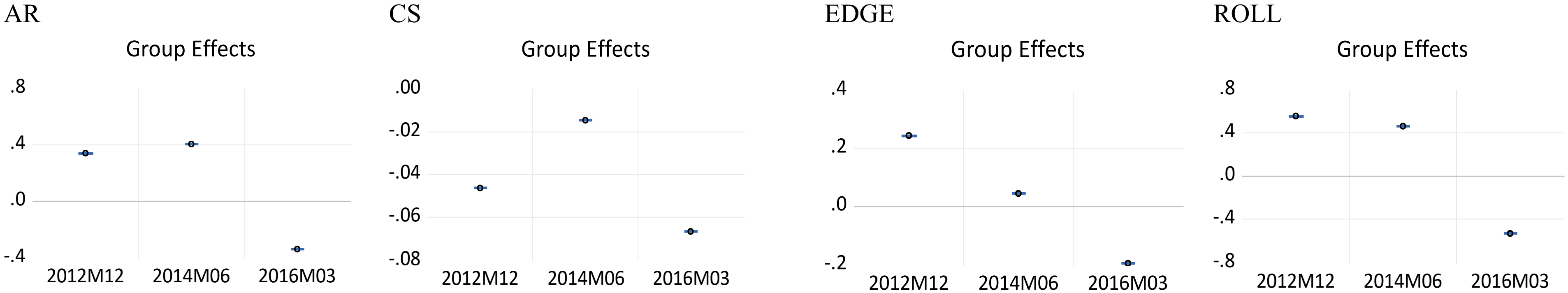


Figure 2. Group Effects.

NB: Each data point represents Philippines, Nigeria, Colombia, Egypt, Russia, Bulgaria and Qatar respectively.

Figure 2 confirms the presence of heterogeneous treatment effects among countries that have introduced ETFs at different points. The bars in the figure represent the confidence intervals (CIs), while the dots represent the mean effects of liquidity for each country. A shorter bar indicates a tighter range of possible values, which in turn suggests a more reliable estimate. Volatility plays a significant role in the construction and interpretation of confidence intervals. Higher volatility typically leads to wider CIs. This is because confidence intervals are constructed based on the standard error of the estimate, which is influenced by the variability of the underlying data (Gonçalves et al., 2014). This wider interval reflects the increased uncertainty about the true parameter being estimated. The results illustrate that the effects are sensitive to the spread estimator used. As such, it is useful to distil the results per estimator.

Panel 1 results indicate an increase in spreads according to the group effects for all spread estimators. The EDGE failed to converge, which resulted in NA values. This suggests that order processing costs and adverse selection costs as reflected by the ROLL and AR and CS, respectively, increased as a result of ETFs. Panel 2 and Panel 3 results indicate sensitivity to estimators and reveal heterogeneity in treatment outcomes that was masked by the ATT, which showed a reduction in spreads in general. The next section provides a country-by-country analysis of the C&S analysis.

Greece

The analysis of Greece's market response to ETF introduction reveals a consistent pattern of deterioration across multiple market quality indicators. The AR estimator shows a substantial increase, indicating a significant rise in adverse selection costs following the introduction of ETFs. The CS estimator exhibits the largest increase among the three measures. This substantial rise in the CS estimator points to a marked decrease in price efficiency within the Greek market post-ETF introduction. The magnitude of this effect may reflect the unique challenges faced by the Athens Stock Exchange, including limited liquidity and a relatively small number of actively traded stocks compared to other European markets. The Roll estimator also shows a considerable increase, indicating a rise in market friction and potentially higher transaction costs. The Greek market's apparent vulnerability to increased adverse selection, reduced price efficiency, and higher friction following ETF introduction may reflect broader structural issues, such as limited institutional investor participation and a high concentration of ownership among a few large domestic investors (Karanikolos & Kentikelenis, 2016).

Brazil

Brazil's market response to ETF introduction reveals a significant deterioration across all measured market quality indicators, with particularly pronounced effects on adverse selection costs and price efficiency. The AR estimator shows a substantial increase, indicating a marked rise in adverse selection costs following the introduction of ETFs. This finding is especially noteworthy in the context of Brazil's unique market structure, characterised by high ownership concentration and the prevalence of dual-class shares, which have historically been associated with information asymmetries (Leal et al., 2015). The considerable increase in adverse selection costs suggests that ETF introduction may have exacerbated existing informational disparities in the Brazilian market, potentially disadvantaging less informed investors.

The CS estimator exhibits the most dramatic increase among the three measures. This substantial rise points to a deterioration in price efficiency within the Brazilian market post-ETF introduction. The magnitude of this effect may reflect the Brazilian stock market’s relatively high volatility and sensitivity to both domestic political events and global commodity price fluctuations. The Roll estimator also shows a notable increase, indicating a rise in market friction and potentially higher transaction costs. While this increase is smaller compared to the other two estimators, it is still substantial and aligns with the overall trend of deteriorating market quality.

Philippines

The Philippines’ spreads decreased in case of the AR, CS and EDGE but increased for ROLL. While overall liquidity was improved, and adverse selection costs were reduced, the order processing costs increased. The reduction in adverse selection costs, as indicated by decreased AR and CS estimators, suggests that ETF introduction has improved the information environment. This phenomenon aligns with the theory that ETFs facilitate more efficient price discovery and reduce information asymmetry (Glosten et al., 2021). The improved informational efficiency may be attributed to ETFs attracting more informed traders or enabling more effective information dissemination across related securities (Ben-David et al., 2018). The decrease in the EDGE estimator points to an enhancement in overall market liquidity following ETF introduction. This finding is consistent with research suggesting that ETFs can increase trading activity and market depth (Madhavan, 2016). The improved liquidity may be a result of ETFs attracting new market participants or enabling more efficient risk transfer mechanisms, thereby contributing to a more robust trading environment.

Despite improvements in overall liquidity and information efficiency, the increase in the Roll estimator indicates higher order processing costs. This seemingly contradictory result suggests that while ETFs may enhance certain aspects of market quality, they may also introduce new complexities in trade execution (Hamm, 2014). The increased order processing costs could be attributed to higher operational demands on market makers, the need for more sophisticated order routing strategies, or liquidity fragmentation between ETFs and their underlying assets. The divergence between order processing costs and other spread components implies a fundamental change in market-making strategies. This shift suggests that market makers are adapting their approaches to account for the presence of ETFs, potentially incurring higher operational costs while benefiting from reduced information asymmetry risks.

This adaptation process aligns with theoretical models of market making in the presence of ETFs (Cespa & Foucault, 2014). The simultaneous reduction in adverse selection costs and increase in order processing costs may create novel arbitrage opportunities. This scenario aligns with theoretical predictions that financial innovations can lead to new forms of market inefficiencies while resolving others (Gromb & Vayanos, 2010). Sophisticated traders may develop strategies to exploit the divergence in spread components, potentially contributing to price discovery and market efficiency in the process.

Qatar

The EDGE estimator's significant decrease indicates a substantial reduction in overall market friction following ETF introduction. This finding aligns with the liquidity-enhancing role of ETFs observed in more developed markets (Madhavan, 2016). However, the magnitude of improvement suggests that the impact in Qatar may be more pronounced, potentially due to the market's emerging status and the relative novelty of ETFs in this context. The decrease in the AR estimator suggests a modest reduction in adverse selection costs. This improvement, while positive, is less dramatic than the overall liquidity enhancement. This pattern may indicate that while ETFs are improving information dissemination, the effect is tempered, possibly due to the unique information environment or investor composition in Qatar's market.

The increase in the CS estimator presents a counterintuitive result, as it suggests a potential increase in certain aspects of trading costs. This divergence from the AR estimator's trend could indicate increased volatility in daily high and low prices, which the CS estimator is particularly sensitive to (Corwin & Schultz, 2012) or a shift in intraday trading patterns that affects the CS estimator differently from other measures (Bleaney & Li, 2015). The Roll estimator's value of zero is particularly noteworthy. In the context of Qatar's market, this could imply an extremely efficient order processing mechanism, possibly due to technological advancements or market structure reforms coinciding with ETF introduction (Marszk & Lechman, 2019). The combination of significantly improved overall liquidity with negligible order processing costs suggests that ETF introduction in Qatar may have led to a restructuring of market-making activities. This could involve a shift towards more sophisticated, possibly algorithmic trading strategies that minimise explicit transaction costs (Chalamandaris & Antonopoulos, 2020).

Bulgaria

The results indicate a comprehensive improvement in market quality across various dimensions, suggesting that ETFs have had a significant positive impact on the Bulgarian financial market. This enhancement indicates that ETF introduction has positively affected multiple aspects of market microstructure and that these benefits are not limited to a single dimension of market quality. Additionally, there has likely been a structural change in how trading and information processing occur in the market (Bhojraj et al., 2020).

The AR estimator shows a significant decrease, indicating a substantial reduction in adverse selection costs. This suggests that ETF introduction has greatly improved information dissemination in the Bulgarian market, resulting in more efficient information incorporation into prices (Glosten et al., 2021). The CS estimator's decrease suggests an improvement in price efficiency, which could indicate reduced volatility in daily high and low prices and therefore more stable price formation processes. The EDGE estimator shows a modest decrease, indicating an improvement in overall market liquidity. While the change is less pronounced than in other measures, it still suggests a general enhancement in trading conditions and an improved market depth and resilience (Goyenko et al., 2009).

Panel 3

Colombia

The results from the spread estimators reveal a mixed effect on market quality, suggesting that the introduction of ETFs has had differential impacts across various aspects of trading and information processing in Colombia. The AR indicates a potential rise in adverse selection costs. This counterintuitive result suggests that the introduction of ETFs may have led to an increase in information asymmetry in the Colombian market, where evidence has shown a lack of information on the instruments in the market (Delgado-Domonkos & Zeng, 2023). This outcome could be attributed to institutional investors having gained an informational advantage through ETFs, potentially exacerbating the information gap with retail investors. Additionally, the relatively small size and concentrated nature of Colombia's stock market might amplify the impact of informed trading, leading to higher adverse selection costs.

Machuca Acevedo (2021) highlights the vulnerability of the Colombian stock market to illiquidity due to a limited number of shares for trading. Contrastingly, the substantial decrease in the Roll estimator points to a significant reduction in order processing costs. This improvement suggests that ETF introduction has enhanced the operational efficiency of trading in Colombia, possibly through increased competition among market makers or technological advancements in trading systems. The magnitude of this decrease is particularly noteworthy, indicating that ETFs have had a pronounced positive impact on the mechanics of trade execution in the Colombian market.

The negligible change in the CS estimator suggests that ETFs have had little impact on the daily price dynamics and volatility patterns in Colombia. This stability could reflect the resilience of Colombia's market structure or indicate that ETFs have not significantly altered the fundamental trading patterns of the market. The marginal increase in the EDGE estimator, while small, hints at a slight deterioration in overall market friction, which seems at odds with the improvement in order processing costs. The increase in adverse selection costs, coupled with improved order processing efficiency, could suggest a market in transition, where the benefits of new financial instruments are unevenly distributed across different aspects of market quality.

Russia

The analysis of the spread estimators reveals a consistent pattern of improvement across all the dimensions of market quality, suggesting that ETFs have had a largely positive impact on the Russian financial market's microstructure. The AR estimator shows a decrease, indicating a significant reduction in adverse selection costs. This improvement in information asymmetry is particularly noteworthy in the context of the Russian market, which has historically been characterised by concerns over transparency and insider trading. The decrease suggests that ETF introduction may have played a role in democratising information access, potentially by providing a more transparent and accessible investment vehicle that reduces the information advantage previously held by certain market participants.

The modest decrease in the CS estimator points to a slight improvement in daily price dynamics and volatility patterns, although political tensions, the effects of Covid-19, and sanctions on Russia have gradually eroded investor confidence (Mahlstein et al., 2022). As a result, the Russian stock market is characterised by extreme fluctuations and is highly volatile even by emerging market standards. While the change is not large, it is still positive and aligns with the overall trend of improvement. This modest enhancement in price efficiency could be attributed to the unique structure of the Russian market, where large state-owned enterprises and natural resource companies dominate the index. The introduction of ETFs might have helped in smoothing out some of the idiosyncratic volatility associated with these dominant firms, leading to more stable price formation processes.

The EDGE estimator's decrease indicates an improvement in overall market liquidity and friction. The improvement suggests that ETFs may have provided a new channel for capital flow, enhancing the market's ability to absorb trades without significant price impacts. Before 2016, when the first ETF was listed on the RTS exchange, Russian investors could only invest in the domestic index through a mutual fund (Tarassov, 2017). The substantial decrease in the Roll estimator points to a significant reduction in order processing costs. This improvement is especially noteworthy in the Russian context, where market infrastructure and trading systems have undergone significant modernisation efforts in recent years. The magnitude of this decrease suggests that ETF introduction may have catalysed or complemented these modernisation efforts, leading to more efficient trade execution and potentially attracting a broader range of market participants.

Chile

A sensitivity analysis was performed wherein Chile was included in both the first and third panels. When comparing the results of both panels, no contradiction is observed except in the case of the CS. That the results are consistent across both panels for three out of the four estimators suggests robustness and that the results are not just artefacts of a particular data sample. Across both panels, we observe a predominantly positive directionality in the estimators, indicating a general deterioration in market quality following ETF introduction.

The AR estimator shows positive values in both panels, suggesting an increase in adverse selection costs. Similarly, the ROLL estimator exhibits positive values in both panels, indicating an increase in market friction and higher transaction costs. The CS estimator, despite showing opposite signs in the two panels, demonstrates only minor variations. Though the third panel's CS is negative, it is only marginally so. The fact that the CS estimator remains close to zero in both panels suggests that the impact of ETF introduction on price efficiency, as measured by this estimator, is relatively small and stable. This stability across different panel compositions indicates a robust finding of minimal impact on price efficiency.

The group effects can be understood as both temporal effects for the introduction of treatment into the market, as previously discussed, and as indicators of group characteristics. In this context, group characteristics pertain to country-specific factors that may have impacted treatment outcomes. The subsequent section will delve into these group characteristics, as well as the individual effects of the GBD analysis. The effect of treatment timing allows us to understand if the timing itself changes the treatment's impact. Additionally, duration effects and temporal spillovers, such as changes in economic conditions and policies, are also considered.

4.7 Oaxaca-Blinder Decomposition Analysis

The Oaxaca-Blinder decomposition, established by Blinder (1973) and Oaxaca (1973), has been extensively utilised in economic and finance studies to analyse disparities across various contexts, particularly focusing on wage differentials and other socioeconomic inequalities. This method enables the disentanglement of the effects of different characteristics from the effects of discrimination or other unobserved factors. A prominent application of the Oaxaca-Blinder decomposition is in the analysis of wage gaps. For instance, Daudu employed this decomposition method to investigate the gender wage gap among farm workers in Nigeria, revealing the extent to which wage disparity could be attributed to differences in socioeconomic characteristics versus discrimination(Daudu et al., 2023). Although this method has primarily been applied to studies on discrimination, it can, in principle, be used to account for disparities in any continuous outcome between two groups.

The Blinder-Oaxaca decomposition seeks to quantify the extent to which the disparity in mean outcomes between two groups can be attributed to variations in their levels of explanatory variables, rather than differences in the magnitude of regression coefficients. Accordingly, it is applied in this study to identify the causes of disparities between the continuous outcomes of the two groups—pre-ETF and post-ETF liquidity. Specifically, we examine how much of the differences can be attributed to macroeconomic factors, such as how and to what extent mean market capitalisation influences liquidity pre- and post-ETF. Alternatively, we assess how much of the differences are attributable to the magnitude of regression coefficients, for example, whether market capitalisation leads to higher liquidity post-ETF compared to pre-ETF.

The Oaxaca-Blinder decomposition offers substantial complementary value to the analyses conducted using DiD, Goodman-Bacon decomposition, and Callaway and Sant'Anna methodologies. While these latter approaches excel in establishing causal inference and addressing heterogeneous treatment timing, the Oaxaca-Blinder decomposition provides a granular examination of group differences. This method decomposes outcome disparities into explained and unexplained components, facilitating a better understanding of the factors driving observed differences. Unlike DiD, which focuses on overall treatment effects, Oaxaca-Blinder scrutinises how variations in group characteristics contribute to outcome disparities, illuminating further the underlying mechanisms of treatment effects.

The Oaxaca-Blinder approach also complements DiD and related methods by analysing the impact of time-invariant factors and providing cross-sectional insights at specific time points. This can be especially valuable when considering the longitudinal focus of DiD-based analyses. Furthermore, it facilitates a more detailed heterogeneity analysis, uncovering subgroup effects that might be obscured in aggregate DiD results. From a policy perspective, the specific contributing factors identified through Oaxaca-Blinder decomposition can inform more targeted interventions.

4.7.1 Twofold Decomposition

The analysis begins with a twofold decomposition that gives broad insight into what the differences in liquidity outcomes result from observable characteristics or unobservable characteristics/structural differences between groups. To that end, the decomposition is estimated thus:

$$\Delta\bar{Y} = \underbrace{(\bar{X}_A - \bar{X}_B)'\hat{\beta}_R}_{\text{explained}} + \underbrace{\bar{X}'_A\left(\hat{\beta}_A - \hat{\beta}_R\right) + \bar{X}'_B\left(\hat{\beta}_R - \hat{\beta}_B\right)}_{\text{unexplained}} \tag{4.11}$$

$\bar{X}_A - \bar{X}_B$ represents the differences in mean outcomes of group A and group B, the pre-ETF liquidity and post-ETF liquidity. A regression model is run where liquidity is the outcome variable for each of the groups and the regressors are the explanatory variables. The difference between the mean outcomes of the regression coefficient explains the $\Delta\bar{Y}$. However, the twofold approach further decomposes the mean outcomes of the two groups with respect to a reference coefficient $\hat{\beta}_R$. The reference coefficient is used to standardise or anchor the estimation of the explained and unexplained components across the groups being compared. The reference coefficient is determined by either a pooled regression per Neumark (1988) or that of Jann (2008). The former regression model excludes the group indicator variable, that is, it assumes that there is a single relationship that applies to all groups without accounting for group-specific differences directly in the regression model. The latter includes the group indicator variable, which allows for group-specific intercepts and thus captures the unique effects of being in the pre-ETF period or the post-ETF period. The choice of reference coefficient stems from the expectation that group differences do in fact influence the outcome; thus, it is necessary to control for that directly in the model. Thus, the Jann (2008) reference coefficient is applied. The first part of the equation informs us of how much observed mean differences in market liquidity are explained by the covariates, and the second part of the equation tells us how much is unexplained. In other words, the second part helps identify unobserved confounders. The results for each country are presented in Table 13.

Table 13: Twofold Blinder-Oaxaca decomposition

	Brazil	**Bulgaria**	**Colombia**	**Chile**
Overall				
Group A	1.3782	0.0083	0.0021	0.0014
Group B	1.3194	0.0076	0.0020	0.0016
Diff	0.0589	0.0007	0.0001	-0.0002
Explained	0.1279	-0.0007	0.0005	0.0001
	(0.2358)	(0.0009)	(0.0006)	(0.0003)
Unexplained	-0.0690	0.0014	-0.0003	-0.0004
	(0.2416)	(0.0010)	(0.0005)	(0.0003)

	Greece	**Philippines**	**Russia**	**Qatar**
Overall				
Group A	0.0054	0.0046	0.0060	0.0041
Group B	0.0077	0.0045	0.0073	0.0034
Diff	-0.0023	0.0001	-0.0013	0.0007
Explained	-0.0006	-0.0033	-0.0022	-0.0002
	(0.0018)	(0.0016)	(0.0027)	(0.0012)
Unexplained	-0.0017	0.0034	0.0008	0.0009
	(0.0018)	(0.0018)	(0.0021)	(0.0011)

The 'overall' portion of Table 13 presents the mean spreads for Group A (pre-ETF), Group B (post-ETF), and the difference between the two groups. Consistent with previous analyses, the results indicate an increase in spreads for most countries. Additionally, the identified macroeconomic variables in Brazil, Colombia, and Chile exerted a negative influence on spreads. In Brazil and Colombia, the negative influence was greater than that of the unobservable characteristics, which, although positively affecting spreads, could not surpass the stronger impact of the observed covariates. Conversely, in Chile, the unobserved covariates compensated for the negative influence of the observed covariates, ultimately leading to an overall improvement in spreads. For Bulgaria, Greece, the Philippines, Russia, and Qatar, there was a positive influence of covariates on spreads. Thus, the macroeconomic conditions in these countries contribute to improved liquidity, notwithstanding the negative effects of unobserved confounders in all cases except Qatar, where the unobserved confounders had a positive influence. Nonetheless, Bulgaria, the Philippines, and Qatar experienced a net overall mean increase in spreads.

4.7.2 Threefold Decomposition

The threefold decomposition provides more detailed insights, offering a deeper understanding of how combined changes in characteristics and their effects contribute to liquidity differences. The threefold decomposition is expressed as:

$$\Delta\bar{Y} = \underbrace{(\bar{X}_A - \bar{X}_B)'\hat{\beta}_B}_{\text{endowments}} + \underbrace{\bar{X}'_B(\hat{\beta}_A - \hat{\beta}_B)}_{\text{coefficients}} + \underbrace{(\bar{X}_A - \bar{X}_B)'(\hat{\beta}_A - \hat{\beta}_B)}_{\text{interactions}} \tag{4.12}$$

The decomposition analyses the observed differences by breaking them down into three primary components: endowment, coefficient, and interaction. The endowment component quantifies the extent to which disparities in mean outcomes between two groups can be attributed to differences in the levels of observable characteristics. This component elucidates whether the differences arise from variations in what each group possesses or from comparisons of their fundamental characteristics. The coefficient component evaluates the degree to which the difference in outcomes is influenced by variations in the effects or "returns" associated with these characteristics between the two groups, often encompassing structural factors. This component frequently highlights structural barriers, efficiency differences, or biases, demonstrating how identical characteristics can result in disparate outcomes across different groups. The interaction term captures the simultaneous effects of differing characteristics and varying returns to those characteristics, reflecting the combined impact of disparities in both the levels and coefficients of the explanatory variables. Practically, if both the scale of market changes and their valuation differ before and after the introduction of ETFs, these combined effects are encapsulated within this term, providing insights into complex dynamics. Each of these three components can be distilled on a variable-by-variable basis. The results are presented in Table 14.

Table 14: Threefold decomposition analysis and variable-by-variable decomposition

	Brazil	**Bulgaria**	**Colombia**	**Chile**
Overall				
Group A	1.3782	0.0083	0.0021	0.0014
Group B	1.3194	0.0076	0.0020	0.0016
Diff	0.0589	0.0007	0.0002	-0.0002
Endowments	-3.2306	0.0079	-0.0066	-0.0024
	(0.5451)	(0.0133)	(0.0020)	(0.0007)
Coefficients	0.8892	0.0551	2.2177	0.0004
	(0.7912)	(0.0459)	(0.1760)	(0.0004)
Interactions	4.1787	-0.0623	-2.2109	0.0018
	(0.6026)	(0.0485)	(0.7761)	(0.0008)
Endowments				
INT	0.2735	0.0015	-0.0003	0.0000
	(0.8123)	(0.0009)	(0.0002)	(0.0000)
CP	-4.1895	0.0189	-0.0019	-0.0023
	(0.8576)	(0.0195)	(0.0015)	(0.0009)
GE	-0.0386	0.0036	-0.0006	-0.0006
	(0.0499)	(0.0019)	(0.0008)	(0.0008)
CPI	-0.0078	0.0004	0.0003	0.0001
	(0.1129)	(0.0013)	(0.0003)	(0.0000)
INDP	-0.2501	-0.0016	-0.0003	0.0008
	(0.4668)	(0.0030)	(0.0003)	(0.0005)
FDI	0.0854	-0.0017	0.0003	0.0002
	(0.1839)	(0.0011)	(0.0002)	(0.0001)
BM	0.6860	-0.0080	0.0005	-0.0004
	(0.7213)	(0.0031)	(0.0002)	(0.0002)
MC	0.2104	-0.0052	-0.0045	-0.00032
	(0.2530)	(0.0059)	(0.0013)	(0.0000)
Coefficients				
INT	-0.1968	0.0480	0.0018	0.0001
	(0.4536)	(0.0356)	(0.0118)	(0.0027)

CP	-12.5980	-0.1204	9.9797	-0.0191
	(0.9713)	(0.0949)	(1.5863)	(0.0055)
GE	-15.4703	0.1126	-6.5504	0.0081
	(1.0861)	(0.0879)	(0.4978)	(0.0052)
CPI	-0.2631	0.0022	0.0035	0.0008
	(0.7479)	(0.0029)	(0.0071)	(0.0003)
INDP	-0.0394	-0.0024	0.0016	0.0008
	(0.5619)	(0.0016)	(0.0021)	(0.0003)
FDI	0.6660	0.0046	9.0420	-0.0007
	(1.0251)	(0.0343)	(0.6795)	(0.0006)
BM	-2.3356	-0.0334	0.8707	0.0008
	(0.0510)	(0.0239)	(0.7544)	(0.0002)
MC	-2.3072	0.0229	4.1194	0.0027
	(1.8586)	(0.0306)	(0.0740)	(0.0008)
Interaction				
INT	-0.1211	-0.0467	-0.0005	-0.0000
	(0.8908)	(0.0346)	(0.0038)	(0.0000)
CP	5.4025	-0.0247	-6.8757	0.0043
	(0.0172)	(0.0198)	(0.6396)	(0.0013)
GE	0.0692	-0.0093	0.5395	-0.0015
	(0.0651)	(0.0070)	(0.9204)	(0.0010)
CPI	-0.0394	-0.0020	-0.0019	-0.0002
	(0.1159)	(0.0027)	(0.0038)	(0.0001)
INDP	0.04956	0.0057	-0.0034	-0.0013
	(0.7013)	(0.0036)	(0.0044)	(0.0006)
FDI	-0.1752	-0.0006	1.2427	-0.00016
	(0.2752)	(0.0047)	(0.8943)	(0.0002)
BM	-0.7969	0.0107	0.3468	0.0004
	(0.7179)	(0.0078)	(6.8075)	(0.0002)
MC	-0.2099	0.0045	2.5415	0.0003
	(0.2549)	(0.0060)	(0.9111)	(0.0001)

	Greece	**Philippines**	**Russia**	**Qatar**
Overall				
Group A	0.0054	0.0046	0.0060	0.0041
Group B	0.0077	0.0045	0.0073	0.0034
Diff	-0.0023	0.0001	-0.0013	0.0007
Endowments	0.0035	0.0010	-0.0580	0.0595
	(0.0075)	(0.0028)	(0.0274)	(0.0350)
Coefficients	-0.0069	8.5122	-0.0025	-0.0011
	(0.0037)	(0.52045)	(0.0038)	(0.0023)

Interactions	0.0011 (0.0083)	-8.5131 (0.5203)	0.0591 (0.0276)	-0.0577 (0.0350)
Endowments				
INT	0.0004 (0.0012)	0.0007 (0.0007)	0.0105 (0.0040)	0.0000 (0.0002)
CP	0.0033 (0.0048)	-0.0069 (0.0053)	-0.0678 (0.0231)	0.0317 (0.0192)
GE	0.0010 (0.0028)	0.0004 (0.0008)	0.0028 (0.0016)	-0.0072 (0.0057)
CPI	0.0003 (0.0010)	0.0001 (0.0002)	-0.0070 (0.0040)	0.0003 (0.0002)
INDP	-0.0033 (0.0023)	0.0001 (0.0004)	0.0318 (0.0109)	-
FDI	0.0002 (0.0002)	0.0023 (0.0024)	-0.0208 (0.0080)	0.0356 (0.0210)
BM	-0.0002 (0.0022)	0.0042 (0.0027)	-0.0097 (0.0087)	-0.0001 (0.0005)
MC	0.0019 (0.0035)	0.0000 (0.0005)	0.0022 (0.0020)	-0.0008 (0.0006)
Coefficients				
INT	0.0009 (0.0012)	0.0145 (0.0204)	-0.0146 (0.0087)	-0.0040 (0.0044)
CP	0.0302 (0.0253)	-5.8670 (0.5512)	-0.2155 (0.0761)	0.0674 (0.0440)
GE	-0.0927 (0.0862)	3.1263 (0.4855)	0.2397 (0.0907)	-0.1376 (0.0853)
CPI	0.0010 (0.0013)	-0.0051 (0.0201)	0.0072 (0.0044)	-0.0006 (0.0008)
INDP	-0.0007 (0.0011)	-0.0003 (0.0013)	0.0208 (0.0091)	-
FDI	0.0019 (0.0021)	6.5070 (0.7869)	0.0104 (0.0039)	0.0290 (0.0178)
BM	0.0011 (0.0018)	-5.4901 (0.9314)	0.0048 (0.0047)	-0.0002 (0.0004)
MC	-0.0013 (0.0025)	-5.9678 (0.8771)	-0.0487 (0.0229)	-0.0117 (0.0119)
Interaction				
INT	0.0010 (0.0014)	-0.0091 (0.0136)	-0.0072 (0.0044)	-0.0003 (0.0005)
CP	-0.0118 (0.0099)	5.5569 (0.1600)	0.0637 (0.0232)	-0.0298 (0.0195)

GE	0.0083 (0.0076)	-5.8543 (0.0781)	-0.0026 (0.0016)	0.0067 (0.0057)
CPI	0.0014 (0.0018)	0.0009 (0.0036)	0.0065	-0.0006 (0.0007)
INDP	0.0020 (0.0029)	0.00189 (0.0062)	-0.0291 (0.0126)	-
FDI	-0.0002 (0.0003)	-6.0120 (0.3949)	0.0209 (0.0081)	-0.0344 (0.0210)
BM	0.0023 (0.0035)	-4.3154 (0.4932)	0.0090 (0.0088)	-0.0003 (0.0006)
MC	-0.0019 (0.0038)	-1.8821 (0.8516)	-0.0021 (0.0020)	0.0008 (0.0009)

The results of the endowments component for Brazil, Colombia, Chile, and Russia indicate that the observable characteristics (macroeconomic variables) present in the pre-ETF period contributed to a reduction in the spread. This suggests that if the characteristics from the pre-ETF period remained effective post-ETF, they would generally lead to tighter spreads, indicating improved liquidity. However, the mentioned countries exhibit a positive coefficient, indicating that the impact of economic characteristics on spreads post-ETF is greater than it was pre-ETF for Brazil and Colombia. Essentially, these macroeconomic variables have a more pronounced and positive effect on widening spreads compared to their influence in the pre-ETF context. This implies that the introduction of ETFs may have altered the way these characteristics affect liquidity.

Conversely, Russia and Chile demonstrated lesser effects of macroeconomic characteristics post-ETF, resulting in an overall mean reduction in spreads. Bulgaria and the Philippines present similar findings, where their endowment effects widened spreads, and the post-ETF coefficient further amplified this effect, particularly in the Philippines, which experienced more pronounced effects post-ETF. Greece and Russia are the only countries where macroeconomic characteristics reduced spreads in the post-ETF period. The interaction effects for Brazil, Chile, Greece, and Russia indicate that the combined effects of changes in macroeconomic variable levels and their impacts contribute to widening spreads. For Brazil and Chile, the interaction effect reveals synergies post-ETF that adversely affected liquidity. In contrast, the interactions for Greece and Russia presented a counterfactual to liquidity in the post-ETF period. Bulgaria, Colombia, and the Philippines exhibit similar results, where the interaction effect helped mitigate the impact of widening spreads in the post-ETF period.

The following analysis examines the individual contributions of each variable to the three decompositions. A notable finding is the heterogeneous market characteristics regarding the effects of each variable on liquidity outcomes. This inconsistency in the directionality of effects underscores the differences in economic structures and their impact on how macroeconomic indicators influence liquidity. Despite the varying directionality, a discernible pattern emerges, indicating that certain variables serve as more significant influencers than others in each market. The analysis conducted reveals that two macroeconomic variables—government expenditure (GE) and credit to the private sector (CP)—have a considerable impact on market liquidity following the introduction of ETFs.

Fiscal policy variables often have a direct impact on economic activity. When the government increases its spending, it injects money into the economy, which can lead to immediate increases in demand for goods and services (Masnawaty et al., 2023). Access to credit is crucial for businesses and consumers, as it enables investment and consumption. When CP increases, businesses can finance expansion, and consumers can spend more, both of which contribute to economic growth. This is particularly relevant in developing economies, where access to credit can be a significant barrier to growth (Mertens & Ravn, 2012). However, fiscal policy variables can have varying effects, as is observed from Table 14, where in some countries the effects of the GE and CP were positive and in some negative (Hongzhong et al., 2023). Moreover, fiscal policy often works in conjunction with monetary policy to influence financial cycles, depending on whether it is pro-cyclical or counter-cyclical (Gafor & Mohammed, 2023). This interplay between fiscal and monetary policy can enhance the immediate effects of government expenditure and credit availability on the economy. In the post-ETF era, these interactions may be more quickly and fully priced into the market, affecting overall market liquidity.

All of these factors can relate to the post ETF periods through different mechanisms. Firstly, the creation/redemption mechanism of ETFs can amplify the effects of fiscal policy changes. As fiscal policies alter investor sentiment or sector outlooks, the resulting flows into or out of relevant ETFs can magnify liquidity effects beyond what might be observed in traditional securities markets. Secondly, the ETF ecosystem, with its many market participants and high-frequency trading, may facilitate faster and more efficient dissemination of fiscal policy information, leading to more immediate liquidity impacts. Finally, ETFs may enhance the 'expectation channel' of fiscal policy transmission. Anticipated fiscal policy changes can quickly affect ETF flows and market liquidity, even before the policies are implemented.

In the Philippines and Colombia, all macroeconomic indicators except industrial production and CPI post-ETF are generally highly influential. However, for most countries analysed, many macroeconomic variables are less influential on market liquidity after the introduction of ETFs. This is not unusual, as other studies have found some macroeconomic variables do not significantly influence some economic outcomes such as Basyariah et al. (2021), who found inflation to not affect Sukuk. Aithal et al. (2019) also noted that macroeconomic variables affect stock markets differently. This heterogenous effect can be attributed to the distinct economic structures and policies of each country(Khan et al., 2024).

The comparison of endowment effects with the coefficient component in the variable-by-variable analysis further reveals structural changes, as indicated by the variations in the directionality of the variables before and after the introduction of ETFs. This phenomenon may signify a fundamental shift in market dynamics prompted by the advent of ETFs. Structural breaks can arise from changes in economic policy (Eryigit et al., 2012), global events such as pandemics (Novák, 2018), and, perhaps most relevant to this discussion, shifts in market dynamics due to the introduction of new financial instruments. Such breaks can fundamentally alter the relationships among economic variables. For instance, You et al. (2017) found heterogeneous influences of economic variables on stock returns under different market conditions.

The observed disparities in the directional impact of macroeconomic variables in the periods preceding and following the introduction of ETFs warrant thorough examination. To clarify this issue, several key factors are considered. The proliferation of ETFs has led to a significant transformation in financial market architecture (Guzman et al., 2022). These instruments enhance accessibility to diverse asset classes and market segments (Liebi, 2020), potentially altering the transmission mechanisms of macroeconomic variables into market behaviour. Furthermore, the introduction of ETFs may have stimulated a shift in asset allocation strategies for both institutional and retail investors (Kaldor et al., 2021; Tang et al., 2021). This behavioural change could recalibrate how macroeconomic variables influence market movements. ETFs provide novel instruments for risk management and hedging (Guzman et al., 2022), potentially changing investors' responses to macroeconomic signals.

The findings challenge existing financial theories that assume a stable relationship between macroeconomic variables and market outcomes. Many economic theories, such as classical economic theory, posit that markets naturally return to equilibrium and that any deviations are temporary. Olokoyo et al. (2020) and Megaravalli and Sampagnaro (2018) affirm the self-correcting nature of macroeconomic variables following disequilibrium in capital market performance. However, market conditions can change, resulting in alterations to macroeconomic variables (Chen et al., 2024) that impact their influence on economic outcomes (You et al., 2017). Therefore, in the context of significant changes in the market environment, such as the introduction of ETFs, it is not uncommon to observe asymmetric effects on market outcomes (see, for example, Hoque et al., 2023; Mloyi & Vengesai, 2024; Zhao & Wang, 2022).

4.8 Conclusion

This chapter explored and analysed the effects of ETF introduction on the liquidity of markets for emerging countries. By adopting different methodologies and applying different indicators for the dependent variable, this study has revealed numerous insights into how ETFs affect market liquidity, contributing to the theoretical, methodological and empirical evidence in this area of research. The application of different methodologies revealed the market-specific factors and temporal effects as causes for ETF effects. While the average treatment effects of the canonical DiD indicated an increase in spreads, the Goodman Bacon decomposition and the C&S analyses revealed idiosyncrasies across countries further signified by the way each market was affected.

In general, this study indicated the varied effects of ETFs in emerging markets. Firstly, that the initial impact, positive or negative, diminishes or is exacerbated over time. Secondly, the liquidity effects are country-specific and the effects of ETFs on market liquidity vary based on market structures. The results of the study confirm Kyle (1985) and the Holden and Subrahmanyam (1992) models that suggest that the introduction of ETFs would usurp liquidity from the underlying index, while others confirm Jung & Shiller (2005) that the underlying index would be more active as a result of ETF introduction in the markets. The findings reveal a dynamic landscape, with some countries exhibiting positive effects while others show negative outcomes. Given that macroeconomic confounders were accounted for by PSM, and any other missed confounders addressed by the C&S, the heterogeneity was ascribed to institutional differences and policy environments of each country. The varied outcomes across countries underscore the importance of tailored policy approaches. Policymakers should consider local economic and institutional factors when designing interventions. The observed heterogeneity highlights the challenges in implementing uniform global policies and underscores the need for flexible, adaptable approaches in financial markets.

In order to explore further effects of ETFs, the Oaxaca blinder decomposition analysis was implemented. The results revealed that ETFs create structural breaks where the financial market architecture is changed. It was also found that as a matter of policy, government expenditure and credit to the private sector are the two policy aspects that ought to be closely monitored in order to stabilise markets and mitigate the adverse liquidity effects on markets post ETFs

In conclusion, while the findings reveal divergent effects across countries, this heterogeneity itself offers valuable insights. It underscores the complex interplay of factors shaping economic outcomes and highlights the need for nuanced, context-aware approaches in both theoretical development and policy formulation. Future research could explore the specific country-level characteristics that drive these divergent outcomes, potentially through in-depth case studies that explore the microeconomic aspects of financial markets.

CHAPTER 5: ETFs AND CROSS MARKET LIQUIDITY VOLATILITY

5.1 Introduction

In this chapter, the cross-market effects of liquidity are assessed between the ETF and index markets of nine countries. The dynamic conditional correlation generalised autoregressive conditional heteroskedastic (DCC-GARCH) and the time-varying parameter-vector autoregression (TVP-VAR) models are used. The DCC-GARCH model is used to capture the dynamic relationship between the ETF and index markets. It does this by modelling the changing relationships over time, especially during periods of market stress or instability. The TVP-VAR is then used to capture the time-varying nature of the relationship between the ETF liquidity and index liquidity, accounting for shifting dynamics and changing interdependencies.

Before the application of the aforementioned models, descriptives of the data are presented showing the liquidity of the ETF and that of the index of the sampled countries. The four liquidity measures as outlined in section 3.3.2 are applied in this chapter. Additionally, diagnostics tests are applied to check for the suitability of the data for further analysis. The data descriptives are followed by the DCC-GARCH analysis, then the TVP-VAR analysis.

5.2 Descriptive Statistics

Table 15 shows the descriptives of the daily AR liquidity estimator data. The descriptives of the other estimators are shown in Appendix B, Tables B1, B2 and B3 for the EDGE, ROLL and CS, respectively.

Table 15: Descriptive statistics

	Brazil		**Chile**		**Greece**	
	AR	ETFAR	AR	ETFAR	AR	ETFAR
Mean	0.006588	0.007077	0.004457	0.004997	0.007068	0.005418
Median	0.005993	0.006208	0.003567	0.004257	0.005821	0.002030
Maximum	0.050772	0.050276	0.031934	0.020516	0.032840	0.041982
Minimum	0.000183	3.72E-05	4.65E-05	5.82E-05	0.000189	0.000000
Std. Dev.	0.005106	0.005341	0.003604	0.003260	0.004991	0.007590
Skewness	4.984510	4.393903	3.032987	1.596368	1.942933	1.952200
Kurtosis	38.46728	32.67499	17.33966	6.729832	7.882152	7.540168
Jarque-Bera	111978.0***	79021.02***	20131.12	2001.737	3186.210	2934.335
ADF	-6.6403***	-6.7308***	-7.8867 ***	-9.2331***	-7.1419***	-4.7942***
Qk(10)	11885***	11443***	11345***	7716.8***	10883***	13737***
Sum	13.04406	14.01161	8.883373	9.959281	13.88218	10.64136
Sum Sq. Dev.	0.051594	0.056444	0.025873	0.021168	0.048892	0.113089

Observations	1980	1980	1993	1993	1964	1964

	Philippines		**South Africa**		**Taiwan**	
	AR	ETFAR	AR	ETFAR	AR	ETFAR
Mean	0.005499	0.005513	0.004745	0.006592	0.004187	0.004043
Median	0.004816	0.004792	0.004362	0.006297	0.003719	0.003825
Maximum	0.037065	0.025365	0.016418	0.024388	0.018480	0.015112
Minimum	0.000181	0.000142	0.000157	0.000102	6.19E-05	0.000150
Std. Dev.	0.004060	0.003352	0.002581	0.003270	0.002407	0.002203
Skewness	3.706283	1.248716	0.877123	0.921375	1.218101	1.075462
Kurtosis	25.53033	5.003008	3.917435	4.792226	5.067637	4.846797
Jarque-Bera	45661.28***	831.8940***	326.4256***	550.3748***	825.7497***	650.0029***
ADF	-7.7638***	-7.1735 ***	-8.0904***	-7.4675***	-8.3791***	-8.1254***
Qk(10)	10961***	10148***	7637.2***	9368.4***	6306.4***	5657.9***
Sum	10.71130	10.74027	9.484289	13.17708	8.126730	7.846526
Sum Sq. Dev.	0.032092	0.021873	0.013311	0.021370	0.011244	0.009419
Observations	1948	1948	1999	1999	1941	1941

	Thailand		**Qatar**	
	AR	ETFAR	AR	ETFAR
Mean	0.004154	0.003891	0.003716	0.008741
Median	0.003370	0.003222	0.003268	0.006768
Maximum	0.038497	0.032506	0.019244	0.035722
Minimum	4.73E-05	0.000126	0.000117	5.61E-05
Std. Dev.	0.003804	0.003127	0.002644	0.007344
Skewness	4.755374	3.984202	2.536886	1.464356
Kurtosis	33.50135	27.46212	13.03079	4.826062
Jarque-Bera	82726.26***	53640.73***	6228.487***	587.1552***
ADF	-5.7163***	-6.835***	-5.293***	-5.3518***
Qk(10)	12825***	11954***	5766.5***	3623.4***
Sum	8.079754	7.567498	4.395832	10.34011
Sum Sq. Dev.	0.028134	0.019009	0.008263	0.063752
Observations	1945	1945	1183	1183

Note: (1)A value of 0.01 corresponds to a spread of 1%. (2) AR=Abdi & Ronaldo bid-ask estimator. (3) AR denotes the index AR estimator, and ETFAR denotes the ETF AR bid-ask estimator. (4) Q_k represents Ljung-Box test. (5) ***denotes rejection of the null hypothesis at 1% significance level.

For further context, Figure 3 below graphs the AR estimator liquidity of the two assets for comparison. It can be observed that the liquidity of the two assets moves in tandem for the most part. Greece shows no liquidity measures for the years 2016 to late 2019. The Plots of the other estimators are presented in Appendix C, Figure C1, C2, and C3 for the EDGE, ROLL and CS, respectively.

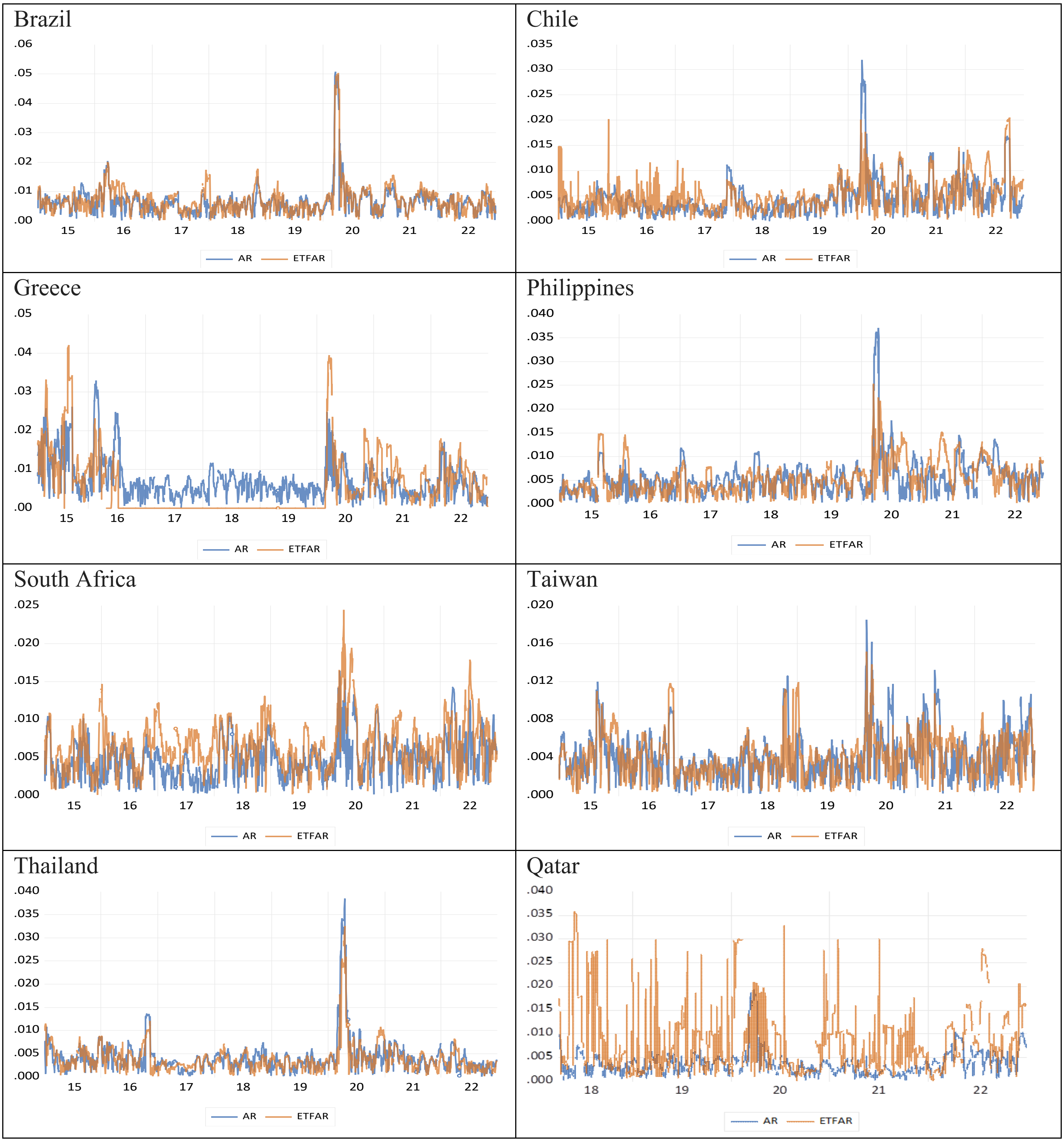


Figure 3. AR Plots of index and ETF

Table 16 presents the results of an independent samples t-test comparing the liquidities of the index and the ETF in each country. Based on the selection criteria of the ETF sample, which includes an 80% replication strategy and a passively managed fund, it is expected that there will be minimal to no difference in liquidity between the two assets. The results indicate that for most of the indicators, there is a significant difference in liquidity between the two assets for each country. However, the Roll indicator for Brazil, Greece, Taiwan and South Africa shows non-significance, suggesting that order processing costs across the assets are similar. Thus, one can conclude that both asset classes have comparable levels of operational efficiency in terms of trade execution, or that they share similar infrastructure. On the other hand, the Philippines and Thailand show similar adverse selection costs for both AR and CS for the former, and only CS for the latter. The similarities imply similarities in incorporation of information in both assets, though Thailand supports this only for intra-day liquidity.

It is also notable from Table 15 and Table 16, also observable in Figure 3 and Figures C1, C2 and C3 in Appendix C, that for Brazil, Chile, Qatar, Philippines and South Africa, the underlying market is more liquid than the ETF market. The significant difference in mean liquidity suggests that including both assets in a portfolio could offer diversification benefits, particularly to account for investor horizon heterogeneity (Khomyn et al., 2024). Broman and Shum (2018) suggested that more liquid assets attract short-term investors, whereas less liquid assets attract long-term investors. Whereas Greece and Taiwan's ETF markets are more liquid compared to the underlying index.

Table 16: **Independent Samples T test**

Country		Index liquidity	ETF Liquidity	Mean difference	t (df)	Pr(>|t|)
Brazil	AR	0.0066	0.0071	-0.0005	-2.9429 (3950)	0.0033
	EDGE	0.0008	0.0057	-0.0049	-44.093 (2049.7)	0.0000
	ROLL	0.0117	0.0121	-0.0004	-1.0783 (3955.6)	0.281
	CS	0.0024	0.0020	0.0004	7.5958 (3719.4)	0.0000
Chile	AR	0.0045	0.0050	-0.0005	-4.9593 (3944)	0.0000
	EDGE	0.0006	0.0032	-0.0026	-23.719 (2083.4)	0.0000
	ROLL	0.0081	0.0091	-0.001	-4.789 (3967.8)	0.0000
	CS	0.0020	0.0024	-0.0004	-6.7177 (3861.8)	0.0000
Greece	AR	0.0071	0.0054	0.0017	8.0503 (3393)	0.0000
	EDGE	0.0052	0.0132	-0.008	-16.958 (2048.2)	0.0000
	ROLL	0.0126	0.0127	-0.0001	-0.33969 (3923.4)	0.7341
	CS	0.0026	0.0010	0.0016	18.683 (3543.1)	0.0000
Philippines	AR	0.0055	0.0055	0.0000	-0.12468 (3759.2)	0.9008
	EDGE	0.0039	0.0051	-0.0012	-9.4003 (3852.3)	0.0000
	ROLL	0.0088	0.0080	0.0008	5.2165 (3711.2)	0.0000
	CS	0.0019	0.0020	-0.0001	-0.8669 (3860.3)	0.3861
South Africa	AR	0.0047	0.0066	-0.0019	-19.824 (3791.3)	0.0000
	EDGE	0.0002	0.0092	-0.009	-89.147 (2080.6)	0.0000
	ROLL	0.0088	0.0088	0.0000	-0.3030 (3892.3)	0.7619
	CS	0.0017	0.0025	-0.0008	-14.928 (3783)	0.0000
Taiwan	AR	0.0042	0.0040	0.0002	1.9488 (3850)	0.0514
	EDGE	0.0004	0.0032	-0.0028	-57.544 (2974.6)	0.0000

	ROLL	0.0075	0.0073	0.0002	1.3478 (3870.5)	0.1778
	CS	0.0019	0.0013	0.0006	11.92 (3368.8)	0.0000
Thailand	AR	0.0042	0.0039	0.0003	2.3586 (3747.6)	0.0184
	EDGE	0.0032	0.0040	-0.0008	-8.612 (3544.2)	0.0000
	ROLL	0.0071	0.0060	0.0011	5.1112 (3689)	0.0000
	CS	0.0013	0.0013	0.0000	-0.49372 (3850)	0.6215
Qatar	AR	0.0037	0.0088	-0.0051	-22.141 (1483.3)	0.0000
	EDGE	0.0026	0.0223	-0.0197	-34.409 (1196.6)	0.0000
	ROLL	0.0062	0.0097	-0.0035	-11.084 (1507.8)	0.0000
	CS	0.0015	0.0011	0.0004	6.7713 (2360.6)	0.0000

All data had a positive skew, indicating that the right tail of the distribution is longer than the left tail. Accordingly, the mean values ought to be interpreted with caution because the distributions are pulled towards higher values due to the presence of outliers in the right tail. Thus, the mean in such distributions will be greater than the median, as is the case as presented in Table 15. The positive skew of the data also suggests higher liquidity risk where there is a greater chance of extreme positive outcomes.

The kurtosis as implemented in the t series R package (Trapletti & Hornik, 2020), across the markets indicates a leptokurtic distribution with heavy tails and a sharp peak. For risk analysis purposes, a leptokurtic distribution signifies a greater probability of extreme events potentially leading to more volatility. The Jarque Bera test further confirmed the non-normality of the data. It tests the null hypothesis that the skewness and kurtosis of the dataset are both zero, indicating a normal distribution (Jarque & Bera, 1980). In all instances, the JB is highly significant at 1% level; therefore, the null hypothesis of normal distribution was rejected. In addition to the p value, the test statistic can be interpreted for the levels of non-normality. The JB follows a chi-square distribution with two degrees of freedom. A higher test statistic indicates a greater deviation from a normal distribution. It is observed from Table 14 that indeed the test statistic of the JB is not only significant but high for all data sets.

The Augmented Dickey Fuller (ADF) test, also implemented in the t series R package (Trapletti & Hornik, 2020), was applied to check for the stationarity of the data. Ensuring stationarity for the data set was necessary to allow for the use of the models applied for further analysis. Stationarity means that certain statistical properties such as the mean, variance and covariance remain constant over time and, as such, permits reliable and meaningful statistical modelling without the risk of underlying patterns or trends disrupting the analysis (Dickey & Fuller, 1979). Specifically, the DCC-GARCH model relies on the assumption of stable mean and variance over time in order to accurately model the conditional correlation between different time series. If the data are not stationary, the variance and covariance may change over time, which can lead to inaccurate estimation and prediction of conditional correlations. Similarly, the TVP-VAR models assume that the parameters of the vector autoregression change over time but still rely on the existence of stationary relationships between the variables to make meaningful inferences about the time-varying parameters. Just as with the JB, the test statistic and the p value are interpreted. The null hypothesis of non-stationarity of the series was rejected at 1% level of significance. The general rule for interpreting the test statistic for the ADF is that the more negative the value, the greater the indication of stationarity.

Further tests for the suitability of the data for further analysis were conducted using the Ljung-Box test. The Ljung-box test tests time series data for autocorrelation, helping to assess the goodness of fit of a model by examining the residuals (Ljung, 1978). The null hypothesis states that there is no autocorrelation, and for purposes of this study, this was rejected at 1% level for the data set. This suggests, along with a higher test statistic, that there is strong evidence of autocorrelation. The autocorrelation reveals that there is volatility clustering and that ARCH effects exist, indicating that the variance of the error term in the model is conditional on past observations, thus qualifying the use of GARCH.

The purpose of the next section of analysis is to provide a comprehensive understanding of the evolving dynamics between ETF liquidity and the liquidity of the underlying assets over time.

5.3 DCC-GARCH Analysis

The DCC model is estimated through maximum likelihood function in two steps due to the difficulty in estimating the correctly specified loglikelihood. The first step determines the univariate parameters of each series by substituting $\boldsymbol{R}_t$in the equation $\boldsymbol{H}_t = \boldsymbol{D}_t\boldsymbol{R}_t\boldsymbol{D}_t$ with the identifying matrix $\boldsymbol{In}$ being:

$$In\big(L(\theta)\big) = -\frac{1}{2}\sum_{t=1}^{T}(n\text{In}(2\pi) + ln\,(|\boldsymbol{H}_t|) + \boldsymbol{a}_t^T\boldsymbol{H}_t^{-1}\boldsymbol{a}_t)$$

$$= -\frac{1}{2}\sum_{t=1}^{T}(n\text{In}(2\pi) + ln\,(|\boldsymbol{D}_t\boldsymbol{R}_t\boldsymbol{D}_t|) + \boldsymbol{a}_t^T\boldsymbol{D}_t^{-1}\boldsymbol{R}_t^{-1}\boldsymbol{D}_t^{-1}\boldsymbol{a}_t)$$

$$= -\frac{1}{2}\sum_{t=1}^{T}(n\text{In}(2\pi) + 2ln\ (|\boldsymbol{D}_t|) + ln(|\boldsymbol{R}_t|) + \boldsymbol{a}_t^T\boldsymbol{D}_t^{-1}\boldsymbol{R}_t^{-1}\boldsymbol{D}_t^{-1}\boldsymbol{a}_t)$$

(5.1)

This results in the quasi-likelihood function:

$$\ln\ (L_1(\phi) = -\frac{1}{2}\sum_{t=1}^{T}(n\text{In}(2\pi) + 2\text{I}n\ (|\boldsymbol{D}_t|) + \text{In}(|\boldsymbol{I}_t|) + \boldsymbol{a}_t^T\boldsymbol{D}_t^{-1}\boldsymbol{I}_t^{-1}\boldsymbol{D}_t^{-1}\boldsymbol{a}_t)$$

$$= -\frac{1}{2}\sum_{t=1}^{T} n\text{In}(2\pi) + 2ln\ (|\boldsymbol{D}_t|) + \boldsymbol{a}_t^T\boldsymbol{D}_t^{-1}\boldsymbol{I}_t^{-1}\boldsymbol{D}_t^{-1}\boldsymbol{a}_t$$

$$= -\frac{1}{2}\sum_{t=1}^{T}\left(n\text{In}(2\pi) + \sum_{i=1}^{n}\left[\text{In}(h_{it}) + \frac{a_{it}^2}{h_{it}}\right]\right)$$

$$= \sum_{i=1}^{n}\left(-\frac{1}{2}\sum_{t=1}^{T}\left[\text{In}(h_{it}) + \frac{a_{it}^2}{h_{it}}\right] + \text{constant}\right)$$

(5.2)

From the quasi-likelihood function, the parameters ϕ of the univariate model are estimated as well as the conditional variance for each asset. In the second stage, the dcc a and b, which are the dynamic conditional correlation matrix terms, are estimated based on the standardised residuals obtained from the first stage ϕ parameters. The second stage is estimated thus:

$$\ln\bigl(L_2(\psi)\bigr) = -\frac{1}{2}\sum_{t=1}^{T}(n\ln(2\pi) + 2\ln\ (|\boldsymbol{D}_t|) + \ln\ (|\boldsymbol{R}_t|) + \boldsymbol{a}_t^T\boldsymbol{D}_t^{-1}\boldsymbol{R}_t^{-1}\boldsymbol{D}_t^{-1}\boldsymbol{a}_t)$$

$$= -\frac{1}{2}\sum_{t=1}^{T}(n\ln(2\pi) + 2\ln\ (|\boldsymbol{D}_t|) + \ln\ (|\boldsymbol{R}_t|) + \boldsymbol{\epsilon}_t^T\boldsymbol{R}_t^{-1}\boldsymbol{\epsilon}_t)$$

(5.3)

The DCC GARCH models must satisfy the assumption that the conditional correlation matrix is positive definite. Additionally, a and b as scalars must be larger than zero, but a+b<1.

For estimation, the GARCH (1,1) model was applied as per Hansen and Lunde (2005) Hansen and Lunde (2005) who found it to outperform more complex models. The DCC-GARCH was implemented with the rugarch and rmgarch packages in R (Ghalanos, 2012).

Table 17: **Estimated DCC parameters for all counties**

Parameters	AR	EDGE	ROLL	CS
		Brazil		
DCCα	0.3780***	0.2957***	0.3850***	0.4433***
	(0.0395)	(0.0499)	(0.0309)	(0.0459)
DCCβ	0.5695***	0.5534***	0.5630***	0.4845***
	(0.0507)	(0.0971)	(0.0374)	(0.0588)
		Chile		
DCCα	0.3023***	0.1035***	0.3982***	0.1176**
	(0.0183)	(0.0189)	(0.0436)	(0.0487)
DCCβ	0.6401***	0.7355***	0.5079***	0.8696***
	(0.0254)	(0.0513)	(0.0611)	(0.0571)
		Greece		
DCCα	0.3020***	0.5723***	0.2942***	0.11800***
	(0.0260)	(0.0890)	(0.0407)	(0.0140)
DCCβ	0.6218***	0.2628**	0.7001***	0.8086***
	(0.0355)	(0.1201)	(0.0444)	(0.0236)
		Philippines		
DCCα	N/A	0.5956***	0.4824***	0.4392***
		(0.0476)	(0.0406)	(0.0601)
DCCβ	N/A	0.2579***	0.4377***	0.4547***
		(0.0700)	(0.0534)	(0.0765)
		South Africa		
DCCα	0.5100***	0.2800***	0.4152***	0.4645***
	(0.0419)	(0.0568)	(0.0467)	(0.0383)
DCCβ	0.3669***	0.5175***	0.5190***	0.3437***
	(0.0577)	(0.1166)	(0.0603)	(0.0784)
		Taiwan		
DCCα	N/A	0.5954***	0.4218***	0.4969***
		(0.0761)	(0.0182)	(0.03789)
DCCβ	N/A	0.1701***	0.5310***	0.4266***
		(0.1047)	(0.0223)	(0.0514)
		Thailand		
DCCα	0.4898***	0.4648***	0.3973***	0.4598***
	(0.0387)	(0.0479)	(0.0301)	(0.0265)
DCCβ	0.3915***	0.3942***	0.5287***	0.4520***
	(0.0593)	(0.0720)	(0.0396)	(0.0369)

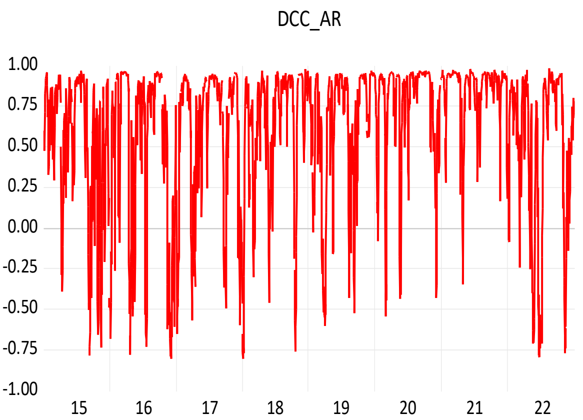
NB: ** and *** signify significance at 5% and 1% respectively. The Philippines and Taiwan AR DCC-GARCH model failed to converge.

Table 17 displays the parameter estimates for DCC-GARCH obtained from the pairwise analysis of ETF and Index liquidity. To obtain meaningful interpretations, the model needs to satisfy certain criteria. Firstly, it is necessary to confirm the presence of volatility clustering. Secondly, the sum of $\alpha + \beta$ should not exceed 1. In the latter case, the significance of DCC parameters confirms volatility clustering in most cases at a 1% level. Additionally, the sum of alpha and beta is confirmed to be less than 1 in all countries.

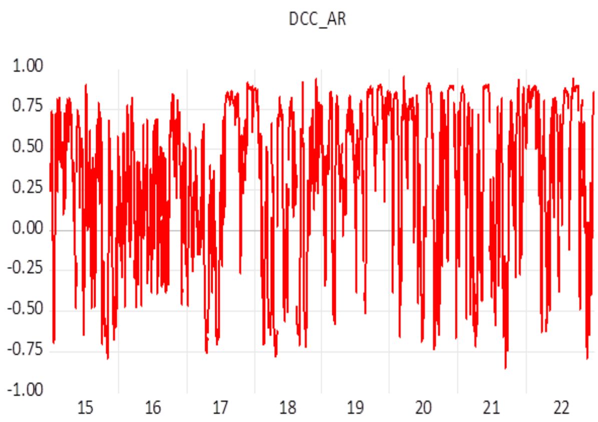
The parameters α + β in the model capture the effects of lagged standardised shocks and conditional correlations. Higher values of α indicate that the ARCH terms (the lagged squared residuals) have an increasing impact on the correlation. On the other hand, a higher β estimate indicates persistence of the conditional correlation. The alpha values reveal varying levels of correlation, with the majority of cases exhibiting moderate levels. Significant values of α and β indicate both short and long-term persistence for all four estimators.

Figure 4 presents the DCC pairwise correlation for each country using the AR estimator. During the period being assessed, it is observed that the correlations are mostly positive. However, there are periods with negative correlations as well. The DCC for all other estimators are shown in Appendix D, Figures D1 to D3, and they confirm the predominantly positive correlation relationship between the two assets.

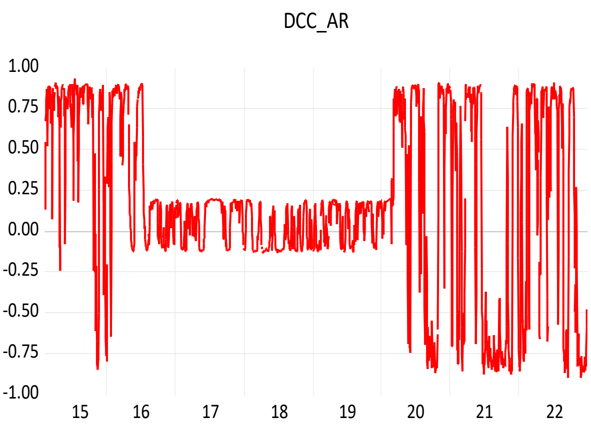
Brazil



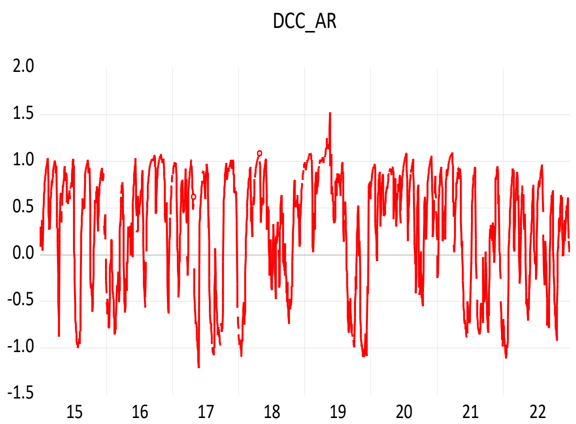
Chile



Greece



South Africa



Thailand

Qatar

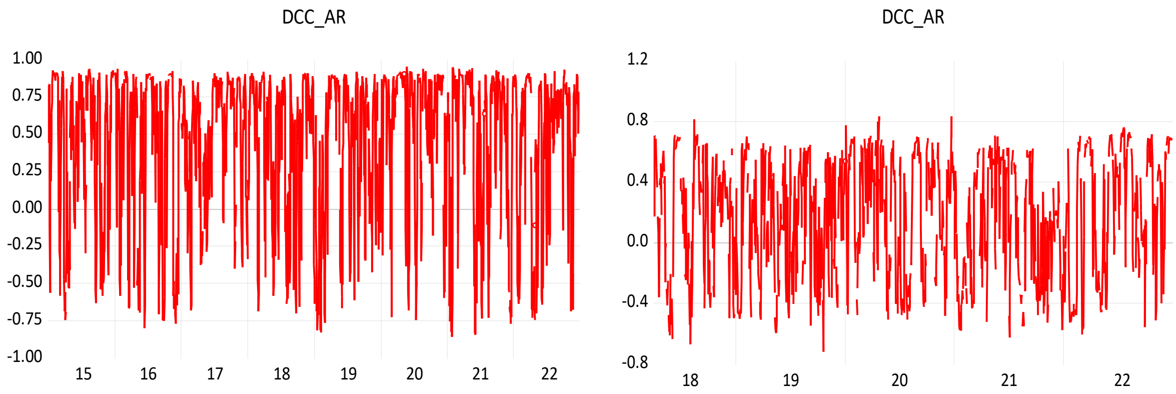


Figure 4. Dynamic correlation between ETF and Index liquidity

Table 18, Table 19, Table 20, and Table 21 present the descriptive statistics from the DCC-GARCH models for the AR, EDGE, ROLL, and CS estimators, offering better understanding of the correlation patterns. The four spread estimators yield consistent findings concerning cross-country variations in liquidity conditions. Brazil demonstrates the highest mean spreads across all four estimators. The spread data is marked by moderate to strong negative skewness across all countries and estimation methods, with the exception of the EDGE estimator, where South Africa, Chile, and Taiwan display positive skewness. This suggests a tendency for more frequent occurrences of wider bid-ask spreads. Notably, Brazil exhibits the most pronounced negative skewness, particularly in the ROLL and AR estimators, indicating an increased risk of extreme spread widening events in this market.

The kurtosis values of the spread distributions differ among countries and estimation methods, reflecting variations in the likelihood of extreme spread occurrences. Brazil showcases a leptokurtic distribution, with a high kurtosis value, signifying a greater probability of extreme spread events compared to a normal distribution, especially for the ROLL estimator. Conversely, South Africa and Thailand generally exhibit mesokurtic or platykurtic spread distributions, with kurtosis values near or below 3, suggesting a lower risk of extreme spread occurrences. The ROLL estimator displays the strongest average liquidity comovement, indicating a high degree of synchronicity in the challenges of executing trades across the markets. Brazil, South Africa, and Greece exhibit particularly high comovement in the ROLL estimator. In contrast, the EDGE estimator shows the lowest average liquidity comovement compared to the other spread estimators, implying that the price impact of the ETF and index markets is not closely linked. A more detailed exposition of the descriptives is presented in Appendix E for each of the four estimators (Table E1 to E4).

Table 18: **AR DCC Descriptives**

	Brazil	Chile	Greece	South Africa	Thailand	Qatar
Mean	0.6062	0.3139	0.1733	0.2943	0.4398	0.1736
Median	0.8075	0.4245	0.1535	0.4720	0.6454	0.2324
Maximum	0.9808	0.9515	0.9333	1.5172	0.9521	0.8319
Minimum	-0.8058	-0.8514	-0.8987	-1.2184	-0.8602	-0.7183
Std. Dev.	0.4456	0.4769	0.5202	0.6215	0.4936	0.3929
Skewness	-1.5223	-0.6132	-0.2350	-0.6553	-0.9961	-0.3114
Kurtosis	4.2863	2.1897	2.2435	2.2011	2.7161	1.7917
Jarque-Bera	901.2502	179.4212	64.9197	196.2244	328.1478	91.0813
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	1200.217	625.5780	340.4446	588.3603	855.4495	205.3815
Sum Sq. Dev.	392.9163	453.0991	531.1792	771.7155	473.5878	182.4747
Observations	1980	1993	1964	1999	1945	1183

Table 19: EDGE DCC Descriptives

	Brazil	Chile	Greece	Philippines	South Africa	Taiwan	Thailand	Qatar
Mean	0.139191	-0.083161	0.234157	0.147220	0.031919	0.044939	0.024295	0.162656
Median	0.299041	-0.145904	0.233951	0.367097	0.078841	0.034640	0.034771	0.342831
Maximum	0.909029	0.927033	0.965853	0.967502	0.947778	0.989099	0.926446	0.860128
Minimum	-0.883855	-0.623409	-0.868331	-0.887307	-1.003176	-0.815825	-0.907313	-0.883404
Std. Dev.	0.604588	0.331186	0.479452	0.626345	0.364675	0.322601	0.539929	0.582110
Skewness	-0.277472	0.344600	-0.449746	-0.284887	0.053844	0.183107	-0.033261	-0.343930
Kurtosis	1.436728	2.187159	2.494098	1.396239	3.312387	3.459635	1.517129	1.513892
Jarque-Bera	227.0219	94.31100	87.15440	235.1148	9.093969	27.93232	178.5617	132.1840
Probability	0.000000	0.000000	0.000000	0.000000	0.010599	0.000001	0.000000	0.000000
Sum	275.5979	-165.7400	459.8849	286.7845	63.80509	87.22730	47.25451	192.4224
Sum Sq. Dev.	723.3779	218.4911	451.2426	763.8243	265.7100	201.8984	566.7221	400.5236
Observations	1980	1993	1964	1948	1999	1941	1945	1183

Table 20: ROLL DCC Descriptives

	Brazil	Chile	Greece	Philippines	South Africa	Taiwan	Thailand	Qatar
Mean	0.830253	0.388706	0.607184	0.478995	0.657879	0.575410	0.481025	0.159872
Median	0.943059	0.573388	0.897282	0.716872	0.847222	0.776326	0.694190	0.191643
Maximum	0.996402	0.946302	1.058790	0.988489	0.981268	0.981002	0.975216	0.848832
Minimum	-0.771550	-0.788805	-0.906707	-0.863500	-0.829382	-0.901389	-0.782583	-0.819759
Std. Dev.	0.287320	0.482618	0.528677	0.522578	0.425562	0.464065	0.482209	0.365493
Skewness	-2.972307	-0.839188	-1.196388	-1.110800	-1.806713	-1.404432	-0.958571	-0.342265
Kurtosis	12.16647	2.412435	3.235530	2.872236	5.374228	3.908124	2.627060	2.121567
Jarque-Bera	9847.422	262.5924	473.0662	401.9236	1557.039	704.7776	309.1346	61.13280
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	1643.900	774.6909	1192.509	933.0827	1315.100	1116.871	935.5945	189.1284
Sum Sq. Dev.	163.3716	463.9760	548.6576	531.7027	361.8430	417.7906	452.0297	157.8979
Observations	1980	1993	1964	1948	1999	1941	1945	1183

Table 21: CS DCC Descriptives

	Brazil	Greece	South Africa	Taiwan	Thailand	Qatar
Mean	0.430663	0.189695	0.053592	0.393322	0.202890	0.148441
Median	0.546683	0.129637	0.064154	0.694362	0.350237	0.162654
Maximum	1.054383	0.897202	0.885474	0.976267	0.964915	0.875059
Minimum	-0.957961	-0.857121	-0.890215	-0.883913	-0.883063	-0.647188
Std. Dev.	0.470145	0.409169	0.507074	0.593197	0.595933	0.368113
Skewness	-0.871870	-0.083599	-0.064642	-0.800350	-0.356916	-0.127016
Kurtosis	2.973280	2.527565	1.576508	2.093703	1.625515	1.903447
Jarque-Bera	250.9106	20.55242	170.1684	273.6498	194.3999	62.45061
Probability	0.000000	0.000034	0.000000	0.000000	0.000000	0.000000
Sum	852.7134	372.5605	107.1304	763.4374	394.6212	175.6053
Sum Sq. Dev.	437.4303	328.6447	513.7346	682.6522	690.3845	160.1698
Observations	1980	1964	1999	1941	1945	1183

5.3.1 Copulas

This next section identifies and describes the best fit copula for the data.

5.3.1.1 Archimedean

Archimedean copulas are expressed as a specific generator function which is empirically favoured for convenience in its simple mathematical structure. As such, it allows for easy modelling and analysis of dependence between random variables (Ling et al., 2020). A copula C is Archimedean if it has the following form:

$$C(u_1, \ldots\ldots\ldots, u_d; \theta) = \psi^{-1}(\psi(u_1; \theta) + \cdots + \psi(u_d; \theta); \theta) \qquad (5.4)$$

ψ is the generator function satisfying the criteria that ψ is a continuous, strictly decreasing and convex function mapping [0, 1] onto [0, ∞] such that $\psi(1; \theta) = 0$ and θ is a parameter.

In financial applications, there is an empirically established evidence of strong lower tail dependence compared with upper tail dependence (Chikobvu & Jakata, 2023). This asymmetry makes the Archimedean copulas ideal, specifically, the Gumbel and Clayton copulas, which capture strong upper tail and strong lower tail dependence, respectively. Table 22 highlights and defines the characteristics of these two copulas.

5.3.1.2 Elliptical copula

An elliptical copula generalises the multivariate normal distribution such that they are used for studying symmetric distributions with fat or lighter tails (Frahm et al., 2003). A copula is elliptical if it satisfies this equation:

$$\phi_{X-\mu}(t) = \psi(t'\Sigma t) \qquad (5.5)$$

Where φ is the characteristic function of the copula and X is a random vector. μ is a location parameter, Σ is a non-negative definite matrix, and ψ is a scalar function. For this study, the Gaussian and Student's t copulas were used. The Gaussian copula has favourable analytical properties owing to its elliptical and symmetric characteristics. The Gaussian copula is fully determined by the correlation matrix. However, Gaussian copulas prove inadequate in effectively modelling tail dependencies as their tails are flat; hence, Gaussian copula captures symmetry or a lack of tail dependence. Due to its symmetry, the Gaussian copula assigns equal weight to both upside and downside scenarios. On the other hand, the student's T copula is able to model tail dependence. But like the Gaussian, it is symmetric as it treats positive and negative dependencies similarly. The characteristics of the Student's T copula are determined by its correlation matrix and the degrees of freedom. The degrees of freedom determine the heaviness of the tails of the copula (Zhi et al., 2021). Table 22 further defines the copulas.

Table 22: **Bivariate Copulas functions with generator functions**

Copula	**Bivariate copula (u, v**	**Generator**
Gumbel	$exp\left[-\left(\left(-log(u)\right)^{\theta} + (-log(v))^{\theta}\right)^{1/\theta}\right]$	$\left(-log(t)\right)^{\theta}$
Clayton	$\left[max\,\{u^{-\theta} + v^{-\theta} - 1; 0\}\right]^{-1/\theta}$	$\frac{1}{\theta}\left(t^{-\theta} - 1\right)$
Gaussian	$\Phi_{\rho}\left(\Phi^{-1}(u), \Phi^{-1}(v)\right)$	$\frac{1}{\sqrt{2\pi}}e^{-t/2}$
Student's t	$T_{\theta,v}[T_v^{-1}(u), T_v^{BV-1}(v)]$	$\frac{\Gamma\left(\frac{v+1}{2}\right)}{\Gamma\left(\frac{v}{2}\right)\sqrt{\pi v}}\left(1+\frac{t}{v}\right)^{-\frac{2+v}{2}}$

The choice of which copula to apply is generally an empirical one. Accordingly, all four copulas are fitted, and the best fit is selected based on three criteria, the Akaike Information

Criterion (AIC), Bayesian Information Criterion (BIC) and the Log-likelihood (LL) (Duarte & Ozaki, 2023). Both are used to compare models and help determine the best fitting model in terms of capturing dependency structure between the variables while balancing model complexity and goodness of fit. While there are other best fit measures for copula, the AIC and BIC are efficient (Nguyen-Huy et al., 2022). In particular, the AIC aims to find the model that best explains the data with the minimum number of parameters; as such, it avoids overfitting by penalising models with more parameters. The BIC imposes more penalty for added parameters so that it is more exacting than the AIC. Accordingly, the lower the AIC and BIC, the better the fit.

Both information criteria are used in conjunction with the LL that additionally, assesses how well the copula model explains the observed data. For the LL, the best fitting copula is the one that maximises the LL value. Robustness check of the fitted copulas is conducted by the application of the same copula fits and criteria to different data sets, i.e. the four different liquidity indicators. Table F1 provided in Appendix F presents the AIC, BIC and LL criteria for all data subsets. It shows that for most of the data subsets, the Gumbel copula is the best fit as confirmed by at least two of the data subsets. Other best fits include Student's T, the Gaussian and the Clayton copulas. Table 23 presents the results of the copulas analysis.

Table 23: **Estimation Results**

Country	Copula Type	Parameters θ	Kendall's Tau
Brazil	**Gumbel**		
	-EDGE	θ = 1.159	0.137
	-ROLL	θ = 3.003	0.667
	Student's T		
	-AR	rho.1 = 0.6949, df. = 3.0840	0.4869
	-CS	rho.1 = 0.4327, df. = 24.3939	0.2855
Chile	**Gumbel**		
	-AR	θ =1.463	0.3165
	-ROLL	θ = 1.593	0.3722
	-CS	θ = 1.478	0.3234
Greece	**Gumbel**		
	-AR	θ = 1.408	0.290
	-CS	θ = 1.377	0.274
	Clayton		
	-EDGE	θ = 0.5539	0.217
	Student's T		
	-ROLL	rho.1 = 0.8038, df = 1.2587	0.594
Philippines	**Gumbel**		
	-AR	θ = 1.347	0.258

	-EDGE -ROLL -CS	θ = 1.179 θ = 1.804 θ = 1.497	0.152 0.446 0.332
South Africa	**Gumbel** -AR -ROLL **Gaussian** -CS **Student's t** -EDGE	 θ = 1.383, θ = 2.496, 0.0644 rho.1 = 0.16 df = 30.21	 0.277 0.599 0.041 0.102
Taiwan	**Gumbel** -AR -EDGE -ROLL -CS	 θ = 1.483 θ = 1.041 θ = 2.105 θ = 1.75	 0.4104 0.0599 0.6075 0.5132
Thailand	**Gumbel** -AR -EDGE -ROLL -CS	 θ = 1.746 θ = 1.159 θ = 1.95 θ = 1.321	 0.5140 0.1902 0.5869 0.3115

Note: Kendall's tau (dependence coefficient) measures the strength of dependence between the two variables and ranges from -1to1. Only three liquidity measures are presented for Chile due to non-convergence of the copulas calculation. This can be due to several factors, however, based on Table 17, which indicates an average negative comovement between the liquidity of ETFs and the Index, it is likely due to a lack of dependence. In this instance, it is difficult for the model to converge when trying to fit a dependence structure that does not fit.

The ROLL and EDGE data subsets for Brazil suggest a best fit Gumbel copula which captures upper tail dependence. This implies a strong relationship between ETFs and the index when liquidity is diminished. The EDGE shows a 13.7% dependence coefficient, a weak positive rank correlation between extreme upper tail values of the ETF and index. However, the ROLL shows a moderate to strong positive rank correlation suggesting a more significant tendency for illiquidity of one asset to move in tandem with the illiquidity of the other. The AR and CS, which were best fitted for the student's t copula that captures dependence across the distribution, suggest that ETFs and the Index liquidity move together in general. Both the AR and CS indicate a moderate to strong positive rank correlation.

The data subsets produced conflicting results for Greece, with the best fit copula of Gumbel for the AR and CS datasets, and Clayton and Student's t copulas for the EDGE and ROLL, respectively. The AR and CS datasets exhibit moderate upper tail dependence, with percentages of 29% and 27% respectively. The Clayton copula indicates that the EDGE dataset has lower tail dependence, suggesting a 22% simultaneity of periods of increased liquidity. On the other hand, the ROLL dataset demonstrates strong tail dependence at 60%, which is supported by the low degree of freedom and suggests the presence of fat tails in the distribution.

South Africa's data subsets, similar to Greece and Brazil, indicate different copula fits for the data subsets. The AR and ROLL are best fit Gumbel and show moderate (28%) to high dependence (60%). The CS and EDGE were best fit for the Gaussian and Student's t but exhibited low dependence at 4% and 10% respectively.

The Southeast Asian countries display analogous findings, likely attributable to enhanced collective efforts that have improved market liquidity, such as economic development and integration initiatives. The rapid economic advancement and increasing integration of Southeast Asian economies have contributed to the expansion of their financial markets and capital flows, resulting in greater market liquidity in the region (Kakinuma, 2022). Many Southeast Asian nations possess similar macroeconomic characteristics, including stages of economic development, demographics, and monetary policies. These shared macroeconomic factors can exert a uniform influence on market liquidity across the region. Additionally, Southeast Asian countries exhibit common traits, such as emerging market status, robust economic growth, and vulnerability to global financial shocks, which may lead to correlated market liquidity trends (Kakinuma, 2022; Zhang, 2024). The growth of intra-regional trade and investment within Southeast Asia has further stimulated economic activity and market liquidity in the region (Fayaz & Kaur, 2022). Moreover, efforts to harmonise capital market standards and regulations among Southeast Asian countries have facilitated enhanced capital mobility and market integration, thereby contributing to similar liquidity patterns (Arsyad, 2015).

Firstly, they demonstrate that in extreme events, liquidity tends to decrease simultaneously in both assets. Secondly, the ROLL indicator shows a tendency towards high dependence, reaching up to 61% for Taiwan. The EDGE indicator exhibits the lowest dependence at 6% for Taiwan. The AR and CS indicate a moderate level of dependence between the variables. Chile also shows a Gumbel fit with similar moderate dependence coefficients for all data subsets.

For all data subsets, it is notable that the Roll estimator tends to have high dependence. This indicates high dependence of order processing costs between the two markets, particularly during times when costs are high as implied by the Gumbel fits. It suggests that factors affecting market makers' order processing costs (like trading volume, volatility, or market structure changes) tend to impact both the ETF and index markets similarly, especially during more challenging trading conditions. Greece's Roll was best fitted for a Student's T copulas, suggesting that the order processing costs tend to have a high dependence in both markets even when the costs are low.

Conversely, the EDGE exhibits the lowest dependence structure among all the estimators and generally low dependence across most countries. This indicates a relatively weak relationship between the price impact of the ETF and its underlying index, suggesting that changes in price impact for one are not strongly correlated with changes in the other. Consequently, the price impact behaviours in the ETF and index markets are largely independent of each other. The ETF and index markets may experience different liquidity conditions regarding price impact, where large trades in one market do not necessarily correspond to similar price movements in the other. This discrepancy could present opportunities for arbitrage or liquidity provision strategies that capitalise on these differences. The low dependence may imply that liquidity shocks in one market (in terms of price impact) are less likely to spill over to the other market. Despite the overall low dependence, the Gumbel copula, which best fits data from Brazil, the Philippines, Taiwan, and Thailand, suggests that any existing dependence is more pronounced in the upper tail. This indicates that during periods of exceptionally high price impact, there is a greater correlation between the ETF and index markets.

On the other hand, the best-fit copulas for South Africa and Greece EDGE were the Student's T and Clayton copulas, respectively. South Africa's EDGE exhibits a similarly low dependence structure; however, it employs a Student's T copula with a high degree of freedom (30.21). As the degrees of freedom increase, the Student's T copula approaches a Gaussian copula. This high value indicates relatively thin tails, suggesting that extreme co-movements are less likely. Consequently, the price impact behaviours of the ETF and index are largely independent. There is little evidence of strong tail dependence, implying that even in extreme market conditions, the price impact in one market is not strongly linked to the other. This could indicate resilience against contagion of liquidity shocks between the two markets. Greece demonstrates a stronger dependence structure, particularly when both markets experience low price impact (high liquidity) simultaneously, as suggested by the Clayton copula fit.

The AR and CS that represent adverse selection costs indicate moderate to high dependence, primarily represented by the Gumbel copula. This suggests a tendency for high correlation of adverse selection costs between ETF and Index liquidity when these costs are elevated. Similar dependence structures are observed for the AR and CS across all countries, except for South Africa, where the CS is best fitted by a Gaussian copula. Additionally, the CS indicates low dependence at only 4% versus 28% for the AR. This discrepancy suggests microstructure frictions, where the markets may be segmented or exhibit structural differences in informational flow, resulting in intraday prices that do not fully reflect available information.

5.4 TVP-VAR Analysis

The application of the TVP-VAR enables the identification of the contagion effect's source, unlike the DCC-GARCH. This is because the TVP-VAR accounts for time-varying parameters resulting from changes in economic conditions, allowing for the identification of additional characteristics in the data. The TVP-VAR was implemented based on the method developed by Antonakakis et al. (2020), utilising the connectedness approach package in R (Gabauer & Gabauer, 2022). The connectedness procedure provides five metrices represented as follows:

The GFEVD represents the variance share one variable has on others and is calculated as:

$$\tilde{\phi}_{ij,t}^{g}(J) = \frac{\sum_{t=1}^{J-1} \mathbf{\Psi}_{ij,t}^{2,g}}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} \mathbf{\Psi}_{ij,t}^{2,g}} \tag{5.6}$$

With the GFEVD, the total connectedness index is calculated as follows:

$$C_t^g(J) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\phi}_{ij,t}^{g}(J)}{\sum_{i,j=1}^{N} \tilde{\phi}_{ij,t}^{g}(J)} * 100 = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\phi}_{ij,t}^{g}(J)}{N} * 100 \tag{5.7}$$

The total directional connectedness to others, where variable i transmits its shock to variable j, is represented as

$$C_{i\rightarrow j,t}^{g}(J) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\phi}_{ji,t}^{g}(J)}{\sum_{j=1}^{N} \tilde{\phi}_{ji,t}^{g}(J)} * 100 \tag{5.8}$$

Then the total directional connectedness from others of variable j to variable i is calculated as follows:

$$C^{g}_{i\leftarrow j,t}(J) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\phi}^{g}_{ij,t}(J)}{\sum_{i=1}^{N} \tilde{\phi}^{g}_{ij,t}(J)} * 100 \tag{5.9}$$

Finally, the net total directional connectedness is calculated by subtracting the total directional connectedness to others from total directional connectedness from others.

$$C^{g}_{t}(J) = C^{g}_{i\rightarrow j,t}(J) - C^{g}_{i\leftarrow j,t}(J) \tag{5.10}$$

i, j represents the variables, index liquidity and ETF liquidity.

Table 24 presents the average connectedness measures of liquidity spillovers between the index and ETF markets for each country. These measures determine the transmission of liquidity shocks between the two markets. The TVP-VAR connectedness tables provide a comprehensive framework for analysing the dynamic interdependencies within the system of variables. Based on forecast error variance decompositions, these tables offer several key metrics for interpreting the results.

The Pairwise Connectedness is represented by the off-diagonal elements (i, j) in the table, indicating the percentage of forecast error variance of variable i attributable to shocks in variable j. These values quantify the bilateral relationships between variables, as outlined in Equation 5.7. The diagonal elements denote each variable's contribution to its own forecast error variance, reflecting the degree of self-influence relative to external factors.

The Total Directional Connectedness 'To Others' is calculated as shown in Equation 5.8, representing the row sum (excluding the diagonal element) for each variable. This metric indicates the cumulative impact of one variable on the other in the system, with higher values indicating that the variable is a significant transmitter of shocks. Conversely, the Total Directional Connectedness 'From Others' is computed as shown in Equation 5.9; this is the column sum (excluding the diagonal element) for each variable, representing the cumulative influence of all other variables on a specific variable. Higher values indicate greater susceptibility to external shocks. Given that there are only two variables in the analysis—index liquidity and ETF liquidity—the ‘To Others’ and ‘From Others’ measures mirror each other.

Net Directional Connectedness, as described in Equation 5.10, is derived by subtracting 'From Others' from 'To Others' for each variable. This metric determines whether a variable is a net transmitter (positive value) or net receiver (negative value) of shocks within the system. The Total Connectedness, an overall measure of system interconnectedness, is calculated per Equation 5.10 as the sum of all off-diagonal elements divided by the total sum of the matrix, expressed as a percentage. Values in the connectedness table are expressed as percentages, with higher values indicating stronger connections or influences.

In the following section, we will apply this interpretative framework to analyse the results of our TVP-VAR model, focusing on the changing patterns of connectedness among the variables in our study.

Table 24: Full sample volatility spillover tables

Brazil		Index liquidity	ETF liquidity	
Index liquidity	AR	72.92	27.08	
	EDGE	96.91	3.09	
	ROLL	59.16	40.84	
	CS	80.74	19.25	
ETF liquidity	AR	26.88	73.12	
	EDGE	5.27	94.37	
	ROLL	43.26	56.74	
	CS	18.95	81.05	
Directional to others	AR	26.88	27.08	
	EDGE	5.27	3.09	
	ROLL	43.26	40.84	
	CS	18.95	19.25	
Directional including own	AR	99.79	100.21	
	EDGE	102.18	97.82	
	ROLL	102.42	97.58	
	CS	99.70	100.30	
				Total spillover index
Net	AR	-0.21	0.21	26.98
	EDGE	2.18	-2.18	4.18
	ROLL	2.42	-2.42	42.05
	CS	-0.30	0.30	19.10

Chile		Index liquidity	ETF liquidity
Index liquidity	AR	88.48	11.52
	EDGE	96.59	3.41
	ROLL	89.51	10.49
	CS	85.65	14.35
ETF liquidity	AR	19.57	80.43
	EDGE	4.80	95.20
	ROLL	21.58	78.42
	CS	18.42	81.58
Directional to others	AR	19.57	11.52
	EDGE	4.80	3.41
	ROLL	21.58	10.49
	CS	18.42	14.35

Directional including own	AR	108.05	91.95	
	EDGE	101.38	98.62	
	ROLL	111.09	88.91	
	CS	104.47	95.93	
				Total spillover index
Net	AR	8.05	-8.05	15.54
	EDGE	1.38	-1.38	4.10
	ROLL	11.09	-11.09	16.04
	CS	4.07	-4.07	16.39

Greece		Index liquidity	ETF liquidity	
Index liquidity	AR	90.66	9.34	
	EDGE	96.69	3.31	
	ROLL	61.83	38.17	
	CS	90.52	9.48	
ETF liquidity	AR	7.14	92.86	
	EDGE	0.51	99.49	
	ROLL	34.11	65.89	
	CS	5.94	94.06	
Directional to others	AR	7.14	9.34	
	EDGE	0.51	3.31	
	ROLL	34.11	38.17	
	CS	5.94	9.48	
Directional including own	AR	97.80	102.20	
	EDGE	97.20	102.80	
	ROLL	95.94	104.06	
	CS	96.47	103.53	
				Total spillover index
Net	AR	-2.20	2.20	8.24
	EDGE	-2.80	2.80	1.91
	ROLL	-4.06	4.06	36.14
	CS	-3.53	3.53	7.71

Philippines		Index liquidity	ETF liquidity	
Index liquidity	AR	87.43	12.57	
	EDGE	94.32	5.68	
	ROLL	74.33	25.67	
	CS	80.24	19.76	
ETF liquidity	AR	12.45	87.55	
	EDGE	9.61	90.39	
	ROLL	24.56	75.44	
	CS	15.92	84.04	
Directional to others	AR	12.45	12.57	
	EDGE	9.61	5.68	
	ROLL	24.56	25.67	
	CS	15.92	19.76	
Directional including own	AR	99.88	100.12	
	EDGE	103.93	96.07	
	ROLL	98.99	101.11	
	CS	96.16	103.84	
				Total spillover index
Net	AR	-0.12	0.12	12.51
	EDGE	3.93	-3.93	7.65
	ROLL	-1.11	1.11	25.12
	CS	-3.84	3.84	17.84

South Africa		Index liquidity	ETF liquidity	
Index liquidity	AR	90.02	9.98	
	EDGE	97.26	2.74	
	ROLL	69.14	30.86	
	CS	94.93	5.07	
ETF liquidity	AR	9.40	90.69	
	EDGE	1.64	98.36	
	ROLL	38.47	61.53	
	CS	6.08	93.92	
Directional to others	AR	9.40	9.98	
	EDGE	1.64	2.74	
	ROLL	38.47	30.86	
	CS	6.08	5.07	
Directional including own	AR	99.41	100.59	
	EDGE	98.90	101.10	
	ROLL	107.62	92.38	
	CS	101.01	98.99	
				Total spillover index
Net	AR	-0.59	0.59	9.69
	EDGE	-1.10	1.10	2.19
	ROLL	7.62	-7.62	34.67
	CS	1.01	-1.01	5.58

Taiwan		Index liquidity	ETF liquidity	
Index liquidity	AR	78.89	21.11	
	EDGE	97.90	2.10	
	ROLL	67.68	32.32	
	CS	76.74	23.26	
ETF liquidity	AR	18.46	81.54	
	EDGE	2.96	97.04	
	ROLL	30.09	69.91	
	CS	26.91	73.09	
Directional to others	AR	18.46	21.11	
	EDGE	2.96	2.10	
	ROLL	30.09	32.32	
	CS	26.91	23.26	
Directional including own	AR	97.35	102.65	
	EDGE	100.87	99.13	
	ROLL	97.77	102.23	
	CS	103.65	96.35	
				Total spillover index
Net	AR	-2.65	2.65	19.78
	EDGE	0.87	-0.87	2.53
	ROLL	-2.23	2.23	31.21
	CS	3.65	-3.65	25.09

Thailand		Index liquidity	ETF liquidity
Index liquidity	AR	82.31	17.69
	EDGE	94.40	5.60
	ROLL	73.61	26.39
	CS	84.10	15.90
ETF liquidity	AR	22.03	77.97
	EDGE	7.58	92.42
	ROLL	28.45	71.55
	CS	12.79	87.21

Directional to others	AR	22.03	17.69	
	EDGE	7.58	5.60	
	ROLL	28.45	26.39	
	CS	12.79	15.90	
Directional including own	AR	104.33	95.67	
	EDGE	101.98	98.02	
	ROLL	102.07	97.93	
	CS	96.98	103.11	
				Total spillover index
Net	AR	4.33	-4.33	19.86
	EDGE	1.98	-1.98	6.59
	ROLL	2.07	-2.07	27.42
	CS	-3.11	3.11	14.35

Qatar		Index liquidity	ETF liquidity	
Index liquidity	AR	96.27	3.73	
	EDGE	97.61	2.39	
	ROLL	96.32	3.68	
	CS	96.80	3.20	
ETF liquidity	AR	4.14	95.68	
	EDGE	1.61	98.39	
	ROLL	4.49	95.51	
	CS	4.85	95.15	
Directional to others	AR	4.14	3.73	
	EDGE	1.61	2.39	
	ROLL	4.49	3.68	
	CS	4.85	3.20	
Directional including own	AR	100.41	99.59	
	EDGE	99.22	100.78	
	ROLL	100.81	99.19	
	CS	101.66	98.34	
				Total spillover index
Net	AR	0.41	-0.41	3.94
	EDGE	-0.78	0.78	2.00
	ROLL	0.81	-0.81	4.09
	CS	1.66	-1.66	4.03

The results indicate that there is generally a low level of net connectedness between the two markets. The direction of net connectedness appears to vary depending on the estimator used, as there are some contradictions for certain countries. However, for Chile, it is observed that the ETF received a net liquidity shock from the index market for all estimators, while Greece's ETF acted as a net conveyor of liquidity shock to the underlying index. Figure 3 illustrates the net directional connectedness, which demonstrates the mutual conveyance of liquidity shock between the two markets throughout the assessment period. This finding helps to explain the low level of net connectedness. Additionally, Figure 5 presents the connectedness of one market to the other, which indicates varying levels of connectedness, throughout the period of assessment.

The diagonal elements in the table indicate the self-influence of each variable on its own shock. Across all countries, each estimator demonstrates a significant contribution to its own forecast error variance for both assets. A high self-contribution implies that current liquidity conditions are strong indicators of future liquidity states. Liquidity can generate self-reinforcing cycles; for instance, high liquidity may attract more traders, further enhancing liquidity, while low liquidity can deter traders, thereby further diminishing liquidity (Cespa & Foucault, 2014). This phenomenon is commonly referred to as a liquidity spiral and is well-documented in the literature. It underscores that a substantial contribution to forecast error variance can signal the emergence of a liquidity spiral, wherein initial liquidity shocks lead to increased uncertainty and subsequent forecast errors (Schneider et al., 2018).

The 'directional connectedness to' elements in the table illustrates the liquidity shock transmissions between markets. A discernible trend is observed among all countries, except for Qatar, where the EDGE exhibits low spillover to other markets, while ROLL, AR, and CS demonstrate moderate spillover. This indicates that order processing costs and adverse selection costs present some liquidity risk; however, the net spillover effects remain low. The low net spillover suggests that, despite some correlation, there is not a significant overall interdependency between the two markets concerning transaction costs. Consequently, changes in transaction costs in one market do not substantially affect the overall liquidity conditions in the other market.

The combination of moderate risk and low net spillover may indicate asymmetric effects or offsetting factors between the markets. For instance, an increase in order processing costs in one market could lead some traders to shift to the other market, potentially enhancing liquidity there and mitigating the negative spillover. This scenario implies a degree of segmentation between the markets in terms of their responses to transaction cost fluctuations. While there exists sufficient connection for moderate risk transmission, the markets appear to operate somewhat independently in managing overall liquidity impacts.

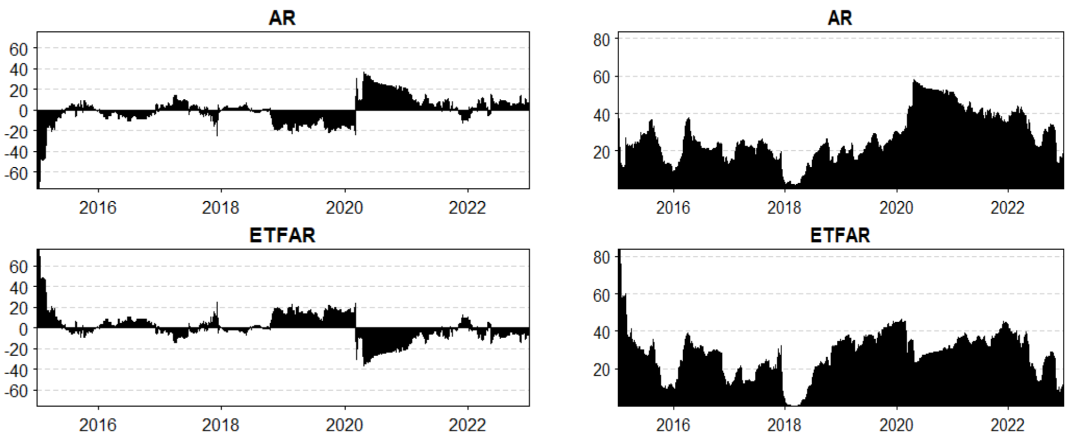
Further analysis of Figure 5 reveals the net spillover and directional connectedness over time. Appendix G, Figures G1 to G8 depict the net spillover and directional connectedness of the EDGE, ROLL and CS for each country. Two distinct changes in connectedness patterns are prevalent across the countries. The beginning of 2015 shows a high level of interconnectedness between ETF and index liquidity, reaching up to 70% in the case of

Brazil. Several economic events occurred during this period that could explain these findings. Notably, the Greek debt crisis came to a head in 2015, causing volatility in financial markets. Additionally, the crash of China's stock market occurred, with the Shanghai Stock Exchange Composite Index losing 30% within a month. Moreover, there was a significant global decline in oil prices, reaching their lowest levels since the 2008 financial crisis. Such market conditions affect market liquidity (Dunham & Garcia, 2021; Messaoud et al., 2023).

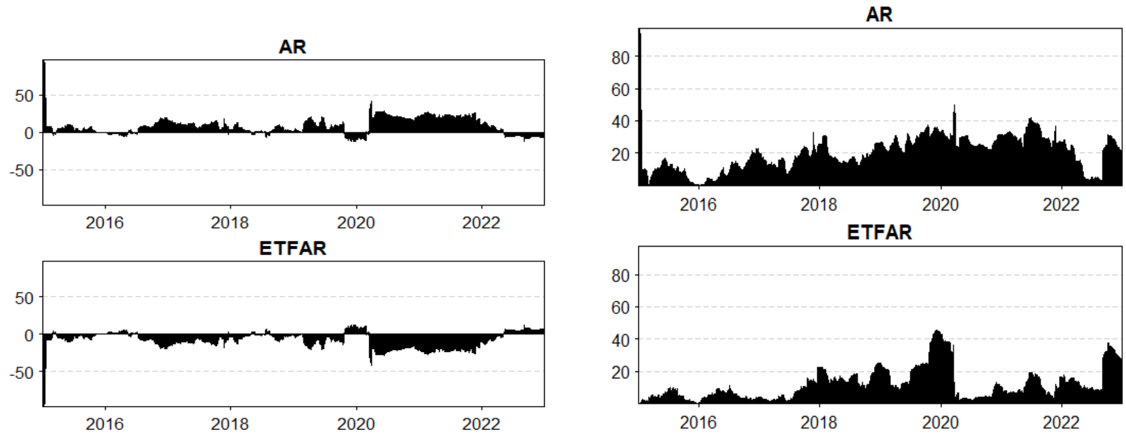
The second significant change occurred in 2020 when the COVID-19 pandemic hit. The policies implemented to contain the spread of the virus had economic impacts. Surprisingly, the impact on liquidity shocks was minimal and/or short-lived, barely registering in some countries. However, the effects on the interconnectedness of the ETF and index markets were more pronounced in 2015 compared to the COVID-19 pandemic in 2020.

A flight to quality, a phenomenon often observed during periods of economic stress (Ma et al., 2022), geopolitical turmoil (Mamun, 2021), and risk aversion (Baele et al., 2023). Firstly, an increase in liquidity shock transmission can be observed at certain times. Secondly, in some instances, transmission is reversed from one asset to the other. Further details specific to each country will be discussed in the section below.

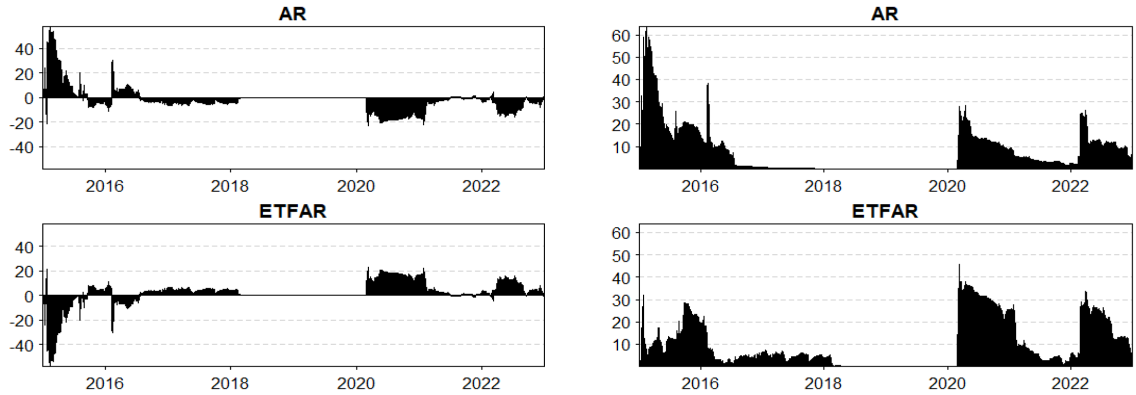
Brazil



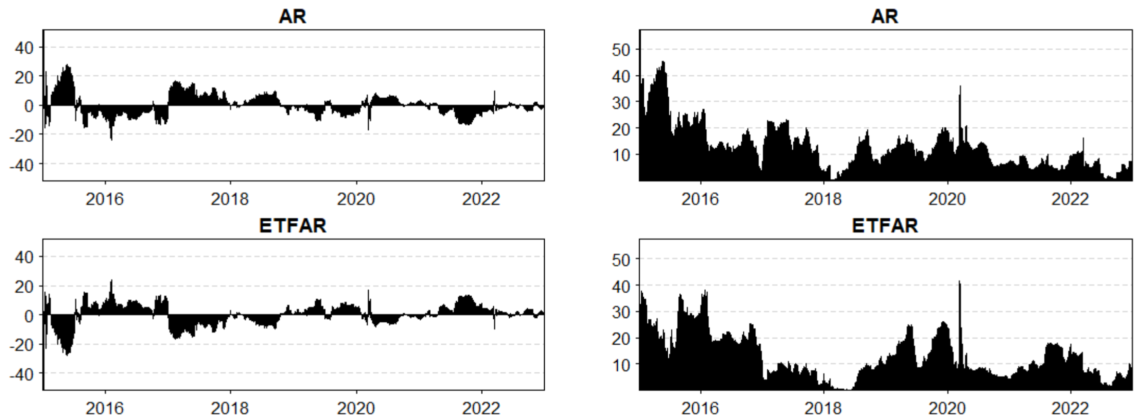
Chile



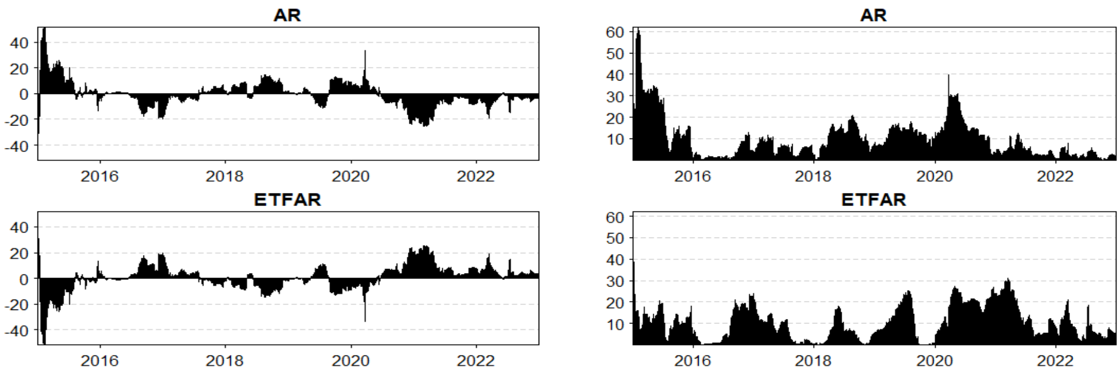
Greece



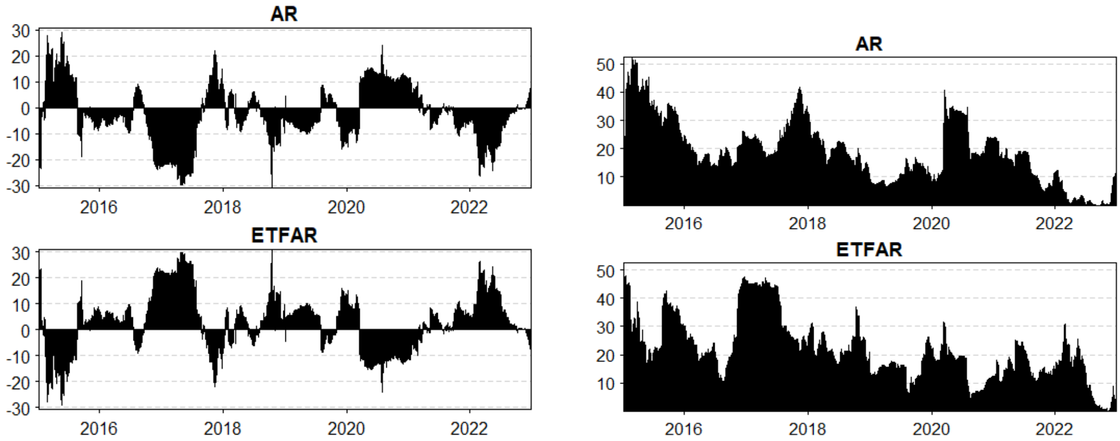
Philippines



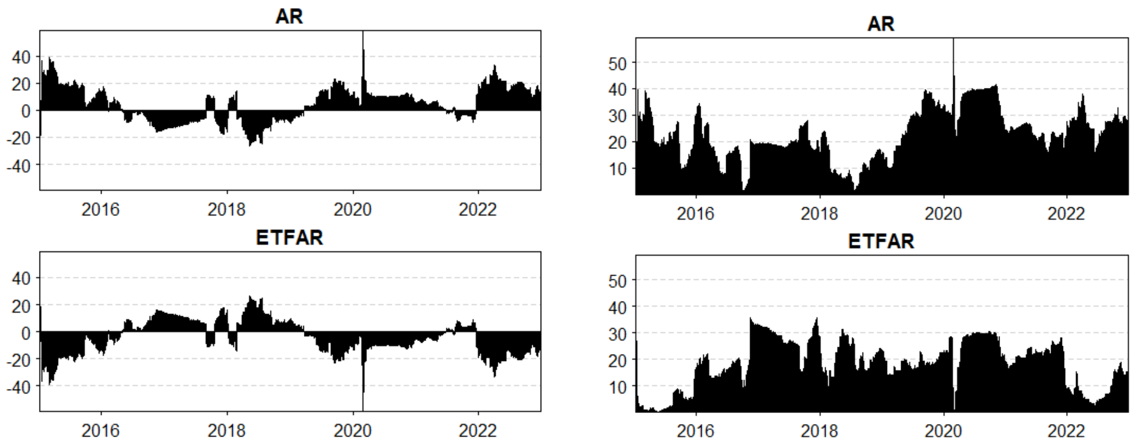
South Africa



Taiwan



Thailand



Qatar

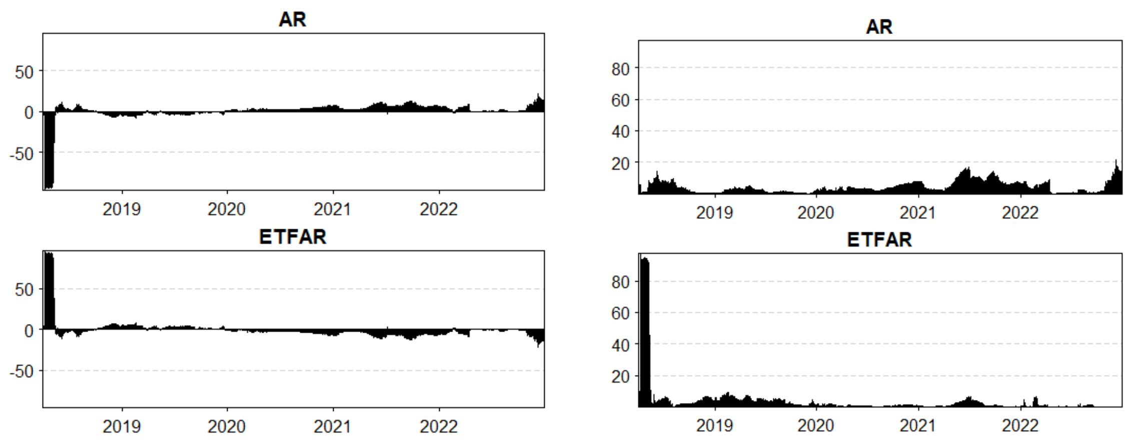


Figure 5. **Net total directional connectedness and Connectedness to**

5.4.1 Country Analysis
Brazil

Brazil exhibited the highest overall connectedness among all countries, with a moderate 26.98% for the AR indicator and 42.05% for the ROLL indicator. In terms of the AR indicator, the index market served as the primary receiver of liquidity shocks during the period under evaluation. Despite the moderate levels of total connectedness, the net connectedness is relatively low due to the similarity in directional connectedness between the ETF and index markets (27.08% and 26.88% respectively). However, there are three notable instances where liquidity transmission deviates from this pattern. These deviations can be observed in Figure 3, where there are sharp peaks in 2015 and early 2020. In 2015, the index market transmitted shocks to the ETF market, unlike in other periods. This peak coincided with a period of global volatility in international financial markets, resulting in overall market scepticism. The 2015 peak is evident in most countries. The effects of Covid-19 are also apparent, as there was a significant increase in liquidity shocks from the index market to the ETF market, which eventually subsided by 2022. The impact of 2018 is more clearly reflected in the ROLL and CS indicators, both of which indicate a sudden and fleeting increase in net connectedness. These three peaks demonstrate that during periods of market stress, the net connectedness between the two markets increases, suggesting a flight to liquidity from one asset to another. In other words, liquidity risk rises during market stress conditions. However, overall, the ETF market poses a low net risk.

Chile

In 2015 and late 2020, as previously mentioned, there was a period of global market volatility, resulting in higher-than-normal connectedness during that time. Total connectedness remained relatively low until 2018, when it increased and remained high (between 30% and 40%) until late 2020. This was the period when the Covid-19 pandemic occurred. However, unlike Brazil, the impact of Covid-19 on liquidity shock transmission was temporary and short-lived, according to the AR and EDGE estimators. Nevertheless, the ROLL and CS estimators indicate persistent liquidity connectedness extending into 2022. From late 2017 to early 2018, there was a significant increase in connectedness, although it did not affect the net directional connectedness between markets. It is important to note that Chile held its presidential elections in late 2017, which introduced potential uncertainty regarding policy direction and economic reforms under the new administration, thus influencing market sentiment and investor confidence. During this period, the Central Bank of Chile adjusted its monetary policy, which likely impacted market liquidity.

Greece

The Greek debt crisis was prominently observed at the beginning of 2015, with lasting effects throughout the year. The transmission of the AR estimator liquidity shock from the index to the ETF persisted for approximately half of 2015, after which the ETF became the primary transmitter of the shock for the remainder of the period. The opposite was true for the EDGE. From 2016 to 2020, there was minimal connectedness, which can be attributed to the ETF's lack of liquidity during that time. This lack of liquidity was depicted in Figure 1 when compared to the index, and further illustrated in Figure 2, which showed a period of low correlation followed by an increase in 2020. The effects of Covid seemed to have extended into 2021, after which the connectedness between the two markets significantly declined to low levels once again. It is important to note that Greece consistently faced ongoing challenges due to the debt crisis, which undoubtedly impacted the financial markets. Consequently, increased connectedness was observed during these significant periods of economic stress.

Philippines

The Philippines demonstrates a low level of connectivity between its ETF and index market, standing at 25.02%. Similar to other countries, the impact of the Covid-19 pandemic and the 2015 period is also evident. Throughout the assessment period, the transmission between the two markets remained relatively balanced, with 12.57% coming from the index and 12.45% from the ETF, resulting in a net connectedness of only 0.12%. Given its status as a significant trading partner and recipient of foreign direct investment from China, the Philippines' financial market would have been particularly affected by the China market crash in 2015. The relatively higher net connectedness at the beginning of 2015 indicates a brief flight to quality, suggesting that investors may have perceived the index as a safer investment compared to the ETF during that time. The effects of the Covid-19 pandemic are more pronounced in the ROLL and CS measures, with total connectedness decreasing for the former and increasing for the latter.

South Africa

There is a relatively low level of connectivity between the ETF market and the index, with the connection being less than 20% for most of the period, except for brief periods in 2015 and 2020. The impact of 2015 was more significant compared to that of 2020, with a connectivity index of up to 60% for the former and up to 40% for the latter. There were specific points during the period where no connectivity was observed between the two markets, particularly when using the EDGE estimator. In addition to the low level of overall connectivity, there is also limited directional connectivity from the index to ETF and vice versa (9.98% and 9.40% respectively). This suggests that there is little to no transmission of liquidity shocks between the two markets.

Taiwan

Taiwan shows a moderate level of directional connectedness. However, the overall connectedness between the two markets is low, which is similar to other countries. Additionally, the effects of both 2015 and 2020 are evident in Taiwan, as in other nations. Notably, in 2017, there was a significant divergence in spillover effects, as shown by the AR estimator.

Thailand

Thailand exhibits spillover effects of 19.86%. The impact of the Covid-19 pandemic was acute and transitory in 2020, affecting all estimators except for the CS. Both markets experience comparable spillovers, although the index market primarily functions as the main driver of liquidity spillover for all estimators, except for the CS estimator.

Qatar

The assessment period in Qatar extends from 2018 to 2023, which coincides with the introduction of the ETF in 2018. Overall, there is minimal observed liquidity spillover between Qatar's ETF market and index in terms of net, total, and cumulative effects. However, there were notable spillovers in 2018 immediately after the ETF's introduction, peaking at 60% (AR). This high spillover, however, was short-lived, and for the rest of the period, there was minimal spillover between the two markets. It is important to note that the estimators used in this analysis do not factor in the impact of Covid-19 or any other events that may potentially affect spillover activity during the assessment period.

5.5 Further Analysis

The risk analysis in general shows two prominent events per the TVP-VAR analysis, 2015, and 2020. As earlier mentioned, the events of 2015, that is, the Chinese stock market crash and the Brazilian recession, coincide with the most interconnected event of the assessed period. Interestingly, regardless of the magnitude of the pandemic, the events of 2015 far outweighed the pandemic. This can be attributed to government interventions specifically put in place to mitigate the effects of other policies aimed at minimising the spread of the virus. This was confirmed by John and Li (2021) in their study that found that government relief efforts reduced volatility. Ashraf (2020) also found that income support packages during the time of the pandemic had a positive impact on market return.

During the assessed period, there is a lack of a clear pattern of connectivity between the index and ETF. This suggests that the transmission of shocks between these two assets fluctuates significantly over time, possibly due to external influences and idiosyncratic events that impact each asset. A study by Kunjal et al. (2022) on the effects of country risk on volatility found that country risk has a minimal impact on ETFs because ETF investors minimise their exposure through various market timing activities. Meanwhile, Ikoku and Okany (2014) and Morema and Bonga-Bonga (2020) found that indexes are vulnerable to country risks. Consequently, investors and market participants may find it challenging to rely on historical relationships, making it difficult to gauge joint risk assessment and diversification strategies. On the other hand, the inconsistency in connectivity may indicate that the assets have the potential to adapt to changing market conditions independently, allowing for more flexible and resilient portfolio strategies. Furthermore, the variability in the relationship presents opportunities for active managers to capitalise on inefficiencies between the two markets. Thus, except for the Roll estimator, there is generally low net connectedness between the two markets. However, inspection of the spillover graphs indicates that some events can induce a heightened risk level where liquidity risk is elevated.

The copulas analysis of joint co-movement of the two markets reveals further insights about risks. As the TVP-VAR analysis showed some periods of elevated risk, the copulas reveal the dependence structure. The Gumbel copula was the best fit for most of the estimators for all countries showing extreme upper tail dependence. And per the earlier discussion, the ROLL metric showed high dependence compared to other estimators. The EDGE showed low dependence while the CS and AR revealed moderated dependence across all countries. This means that market risk is moderate (per the CS and AR estimators) during market events.

The results of the study further give insight into the trading behaviour of market participants. In the first place, the open-ended nature of ETFs makes it effective for arbitrage with the underlying index (Ben-David et al., 2017), and so the ETF and its underlying index often share an investor base (Kadiyala, 2022). While ETFs are better known for their attraction of retail investors, institutional investors have recognised and exploited the advantages that they provide for their needs, using them for portfolio rebalancing and tactical trading and hedging amongst others. It is these arbitrage or hedging strategies that are the mechanism for contagion of one asset market to the other (Boadu-Sebbe, 2022; Chen et al., 2024).

The upper tail risks suggest that trading activity in one asset causes illiquidity in the other asset. Support in the literature is found in Brogaard et al. (2023) where trading activity of the US ETF led to a decrease in liquidity of the underlying securities and an increase in volatility and co-movement conditioned on the replication strategy. Conversely, Box et al. (2021) found that contrary to prevailing thought, arbitrage trading does not relate to the underlying index liquidity of US ETFs. This study confirms both aspects for the emerging markets. The TVP-VAR and DCC GARCH analysis showed increased volatility spillover during periods of market stress but registers low market connectivity during normal periods similar to Box et al. (2021). The copula further shows that during high market stress, there is moderate to high risk of illiquidity co-movement, thus confirming Brogaard et al. (2023). Fiedor and Katsoulis

(2020) explain that the information linkages formed by arbitrage sensitise one asset to the demand shocks of the other asset, which consequently causes the illiquidity contagion when the information linkage is disrupted.

The findings of this study confirm that while ETFs are generally considered more liquid than other asset classes, they carry higher liquidity risk when markets are in distress. This phenomenon was made prominent by the flash crash of 2010, where equity ETFs invested in domestic securities (similar to this study's sample), experienced increased spreads more significantly. Liebi (2020) attributes this to decreased arbitrage activity when markets become volatile, which increases the potential for illiquidity during market stress conditions. Moise (2021) reiterates that when markets are distressed, assets trade away from fundamentals due to market frictions, thus impeding the efficient deployment of arbitrage capital. Further evidence by Thanakijsombat and Kongtoranin (2018) suggests that emerging market ETFs are more susceptible to downside risk during market downturns due to systemic risk posed by local market conditions and sentiments.

5.6 Conclusion

This chapter examined the cross-market effects of liquidity, thereby assessing the liquidity risk posed by ETFs to the underlying market and vice versa. The DCC-GARCH Copulas and TVP-VAR analyses were employed for this purpose, revealing various insights into the liquidity risk dynamics of ETFs and the underlying market.

Overall, the analyses indicated low net connectedness during the assessment period; however, temporal effects were observed during specific intervals. During these times, which coincide with periods of economic stress, heightened liquidity risk is prevalent. The analysis further demonstrated that order processing costs, as indicated by the ROLL metric, pose the greatest risk, while price impact, as indicated by the EDGE, poses the least risk. Furthermore, these risks tend to exacerbate illiquidity when they occur.

The findings of the study indicate that market participants should maintain heightened awareness of liquidity risk during periods of significant economic turmoil and adjust their trading strategies accordingly to mitigate this risk. Numerous regulatory implications arise primarily from the dynamic interconnectedness of the two assets. Firstly, regulators need to establish dynamic monitoring systems that can adapt to changing market conditions, particularly during times of economic stress. Additionally, there may be a need to reassess the design of circuit breakers and trading halts to account for the high upper tail dependence observed in spread estimators. Current circuit breakers may not adequately address the synchronised deterioration of liquidity in both ETFs and their underlying assets, suggesting that they should be designed to trigger based on joint movements rather than individual asset fluctuations. Furthermore, in addition to relying on price movements, circuit breakers should incorporate liquidity measures as triggering mechanisms. These circuit breakers may require dynamic thresholds that adjust according to prevailing market conditions and observed dependencies.

Various theoretical implications emerge from the findings of the study based on the liquidity funding model. The pronounced upper tail dependence observed in spread estimators is consistent with the funding liquidity model's prediction regarding liquidity spirals during periods of economic stress. When funding becomes scarce, it can simultaneously impact liquidity provision in both ETFs and their underlying assets, resulting in correlated spikes in illiquidity. The TVP-VAR analysis, which reveals increased connectedness during stress periods, aligns with the funding liquidity model's emphasis on the amplification of shocks during times of market distress.

The findings indicate a necessity to extend funding liquidity models to explicitly consider the interaction between ETFs and their underlying assets. These enhanced models should integrate the unique creation/redemption mechanism of ETFs and their interaction with funding constraints. Additionally, there is a need to refine theories of market making to account for the dual role of liquidity providers in both ETF and underlying asset markets, as well as the impact of funding constraints on their ability to provide liquidity across these interconnected markets. Furthermore, the results imply that funding liquidity models should be fundamental in assessing systemic risk, particularly in evaluating the potential for liquidity shocks to propagate between ETFs and underlying asset markets. The findings suggest that asset pricing models should include not only individual asset liquidity risk but also the systemic liquidity risk arising from the interconnectedness of ETFs and their underlying assets.

In conclusion, the study highlighted the importance of adaptiveness in managing liquidity risk to avoid propagating illiquidity cascades across markets.

CHAPTER 6: EVALUATING THE ETF-MARKET EFFICIENCY NEXUS

6.1 Introduction

This chapter provides an analysis of the effects of Exchange-Traded Funds (ETFs) on market efficiency, employing a robust methodological framework to capture the multifaceted nature of this relationship. The study of market efficiency, rooted in Fama's (1970) seminal work on the Efficient Market Hypothesis (EMH), has evolved to acknowledge the dynamic and adaptive nature of financial markets, as proposed by Lo's (2004) Adaptive Markets Hypothesis (AMH). Within this theoretical context, this research aims to elucidate how ETFs have influenced the efficiency of their respective markets. To address this question, three methodological approaches were employed: Variance Ratio (VR) tests, Autoregressive Distributed Lag (ARDL) models, and Granger causality analyses. Each of these methods offers unique insights into different aspects of market efficiency. This chapter is structured as follows: First, the theoretical underpinnings and practical applications of each method are presented, followed by analyses of each country. The analysis begins with the ARDL model, the baseline model, followed by the Granger causality analysis. The results are then synthesised along with the VR test to draw broader conclusions about the impact of ETFs on market efficiency.

6.2 Review of Theory

Having assessed and determined the impact that ETFs have on market liquidity, it is essential to probe further into a more comprehensive understanding of how ETFs affect market efficiency. To recap the findings of our first hypothesis, aggregated market liquidity improved (narrower spreads) after ETFs were introduced to the markets. However, heterogeneous effects showed varying effects on different countries. These findings strongly suggest that ETFs improved market efficiency (aggregated results). This assertion is based on Glosten and Milgrom (1985), who highlighted the tension between an efficient market and market frictions. Three points are underscored from their theory that links market liquidity to market efficiency, bid-ask spreads, the martingale properties of asset prices and risk neutrality of market makers. In the context of illiquidity, spreads indicate market frictions that occur because market makers need to be compensated for taking on inventory risk. The martingale properties of asset prices under risk neutrality suggest that expected return on all assets should be equal to the risk-free rate. In a perfect market, asset prices should follow a martingale process with no spread. However, market frictions exist, and market makers are not always risk neutral. The assumption of risk neutrality is often made in theory, allowing the martingale property of expectation to hold. Accordingly, in practice, short-term price movements may deviate from a pure martingale due to market frictions (spreads), but in the long term they can approximate a martingale.

The relationship between spreads and its implications for market efficiency has also been empirically established through various market microstructure tests. For example, Indriawan et al. (2019) found narrower bid/ask spreads coincided with lower pricing error variance and probability of informed trading. Similarly, Black (2022) found a widening of spreads as fewer informative trades were executed. Tsai and Dai (2020) applied the Glosten and Milgrom (1985) model explaining how information asymmetry links to spreads to determine the proportion of informed traders in the crypto market. There have been numerous studies applying the Kyle and Glosten, and Milgrom models to study market microstructure (see, for example, Goel et al., 2021; Vodret et al., 2022; Dalvi et al., 2023). Due to this empirically established link between spreads and market efficiency, economic experts routinely present bid/ask spreads as commonly accepted indicators of market efficiency (Bhole et al., 2020). Reference is further made to sections 2.2.1 and 2.3.2 of chapter 2 discussing the role of liquidity in the EMH and asset pricing.

Thus, having determined the effects of ETFs' introduction on spreads of the underlying securities, we study further the mechanisms through which liquidity is propagated into the market in line with the aforementioned and numerous other studies of market microstructure. Specifically, price discovery analysis, transaction costs, market quality and information efficiency analyses. These analyses offer insights into market efficiency from a microstructure perspective, which is more granular than traditional tests of market efficiency.

6.3. Estimation Procedure

6.3.1 Unit Root Test

The result of the Unit Root test is presented in Table 25. Variables integrated beyond the first difference, such as Chile's interest rate and Greece's CPI, were excluded from further analysis.

Table 25: Unit Root Test Results

		Brazil	Chile	Greece	Philippines	South Africa	Thailand
EDGE	I(0)	-6.0307 (1)***	-3.7974 (0)***	-5.8827 (0)***	-6.7453 (1)***	-8.4437(0)***	-4.1405(2)***
	I(1)	-9.3016 (1)***	-10.054 (1)***	-14.547 (0)***	-11.468(1)***	-11.228(1)***	-11.627(1)***
AR	I(0)	-6.2370 (1)***	-6.0535 (0)***	-5.4184 (0)***	-6.3136 (0)***	-7.4149(0)***	-5.6173(0)***
	I(1)	-8.4693 (3)***	-10.482 (1)***	-8.9769 (2)***	-12.148(1)***	-16.442(0)***	-11.469(1)***
INT	I(0)	-1.3679 (0)	-	-0.9017 (2)	-1.5247 (1)	-1.1793(1)	-1.1932(3)
	I(1)	-11.592 (0)***.	-	-17.385 (1)***	-7.4759(0)***	-5.5014(0)***	-3.7696(2)***
INP	I(0)	-4.7322 (1)***	-5.4300 (0)***	-1.0797 (2)	-3.2005 (0)**	-4.4632(0)	-2.7306(0)*
	I(1)	-9.7603 (0)***	-11.151 (1)***	-12.154 (1)***	-10.350(0)***	-9.9274(1)***	-9.6110(0)***
EXR	I(0)	-1.8283 (0)	-1.1127 (1)	0.5031 (0)	-2.0559 (0)	-1.9205(0)	-1.9824(0)
	I(1)	-9.6664 (0)***	-14.047 (0)***	-8.7902 (0)***	-12.083(0)***	-11.181(0)***	11.209(0)***
CPI	I(0)	0.5670 (1)	1.0755 (2)	-	1.7693 (1)	1.6728(2)	0.0088(0)
	I(1)	-5.3310 (0)***	-3.3809 (1)**	-	-6.8996(0)***	-8.1299(1)***	-8.1144(0)***
ETV	I(0)	-3.3230 (0)**	-3.4356 (1)***	-9.0842 (0)***	-8.0299 (0)***	-2.7597(2)***	-4.1112(1)***
	I(1)	-12.374 (0)***	-17.026 (0)***	-3.3818 (10)**	-11.285(1)***	-13.156(1)***	-18.076(0)***

Note: EDGE and AR are the dependent variables. INT=interest rate INP=industrial production, EXR=exchange rate, CPI=consumer price index, ETV= ETF volume. ** and *** indicate significance at 5% and 1% respectively. The INT of Chile and the CPI of Greece were integrated >I (1); thus, they were not included in the models.

6.3.2 Model Estimation

The generalised ARDL model is specified as follows:

$$Y_t = \gamma_{oi} + \sum_{i=1}^{p} \delta_i Y_{t-1} + \sum_{i=0}^{q} \beta'_i X_{t-i} + \varepsilon_{it} \tag{6.1}$$

Where Y_t is the dependent variable and Y_{t-1} is the lagged dependent variable that is an explanatory variable. X_t represents the regressors in the model that are current and lagged. p

and q are the optimal lagged order values of the dependent and independent variables, respectively. δ and β are coefficients and ε_{it} is the white noise error term.

An extension of the ARDL model, the Nonlinear Autoregressive Distributed Lag (NARDL), facilitates the analysis of asymmetric effects between variables, which is particularly relevant in economic contexts where positive and negative shocks may yield different impacts (Fousekis et al., 2016; Khan, 2023). NARDL is a statistical model that integrates autoregressive and distributed lag components while accommodating nonlinear relationships among variables. Proposed by Greenwood-Nimmo et al. (2011), it aims to capture the asymmetries in the effects of independent variables on a dependent variable (Emir et al., 2024). Unlike the linear ARDL model, which assumes symmetric effects, NARDL allows for differentiation between the impacts of positive and negative changes in the independent variables. The NARDL model decomposes the independent variables into their positive and negative components, thereby enabling separate estimation of their effects.

Empirical evidence indicates that asymmetric relationships are plausible for this study. For instance, Long and Liang (2018) found that CPI inflation exhibited an asymmetric relationship with crude oil prices. Similarly, Eregha (2022) identified asymmetry in exchange rates within their study and applied the NARDL model. Asymmetrical relationships have also been empirically observed between interest rates and other variables, including pass-through effects (Puah et al., 2017), inflation (Ali & Nasir, 2023), exchange rates (Karamelikli & Karimi, 2022), and economic growth (Elsamadisy et al., 2014). Additionally, Kaya and Soybilgen (2019) analysed the effects of industrial production, interest rates, and exchange rates on Turkish stock prices using the NARDL model. Their findings suggested that increases in industrial production had a more substantial positive impact on stock prices compared to the negative impact of declines in industrial production. Therefore, based on the documented literature, this study aims to test for asymmetric relationships among variables and appropriately apply the ARDL and NARDL models.

The Conditional Error Correction Model of interest is expressed as:

$$
\begin{aligned}
\Delta Sprd = {} & \emptyset_{sprd}(Sprd)_{t-1} + \emptyset_{INT}^{+}\ln(INT)_{t-1}^{+} + \emptyset_{INT}^{-}\ln(INT)_{t-1}^{-} + \emptyset_{CPI}^{+}\ln(CPI)_{t-1}^{+} \\
& + \emptyset_{CPI}^{-}\ln(CPI)_{t-1}^{-} + \emptyset_{EXR}^{+}\ln(EXR)_{t-1}^{+} + \emptyset_{EXR}^{-}\ln(EXR)_{t-1}^{-} + \emptyset_{INP}^{+}\ln(INP)_{t-1}^{+} \\
& + \emptyset_{INP}^{-}\ln(INP)_{t-1}^{-} + \emptyset_{ETV}^{+}\ln(ETV)_{t-1}^{+} + \emptyset_{ETV}^{-}\ln(ETV)_{t-1}^{-} \\
& + \sum_{J=1}^{P-1}\gamma Sprd_{j}\Delta(Sprd)_{t-j} + \sum_{k_1=1}^{q_1-1}(\gamma_{INT,k_1+}^{+}\Delta\ln(INT)_{t-k_1}^{+} + \gamma_{INT,k_1+}^{-}\Delta\ln(INT)_{t-k_1}^{-} \\
& + \sum_{k_2=1}^{q_2-1}\left(\gamma_{CPI,k_2+}^{+}\Delta\ln(CPI)_{t-k_2}^{+} + \gamma_{CPI,k_2+}^{-}\Delta\ln(CPI)_{t-k_2}^{-}\right) \\
& + \sum_{k_3=1}^{q_3-1}\left(\gamma_{EXR,k_3+}^{+}\Delta\ln(EXR)_{t-k_3}^{+} + \gamma_{EXR,k_3+}^{-}\Delta\ln(EXR)_{t-k_3}^{-}\right) \\
& + \sum_{k_4=1}^{q_4-1}\left(\gamma_{INP,k_4+}^{+}\Delta\ln(INP)_{t-k_4}^{+} + \gamma_{INP,k_4+}^{-}\Delta\ln(INP)_{t-k_4}^{-}\right) \\
& + \sum_{k_5=1}^{q_5-1}\left(\gamma_{ETV,k_5+}^{+}\Delta\ln(ETV)_{t-k_5}^{+} + \gamma_{ETV,k_5+}^{-}\Delta\ln(ETV)_{t-k_5}^{-}\right) + \alpha_O + \alpha_1 t \\
& + \sum_{i=1}^{11}\delta_i m_i + \varepsilon_t
\end{aligned}
\tag{6.3}
$$

In this model, *Sprd* is represented as an autoregressive process of order p, *while INT, CPI, EXR, INP*, and *ETV* are asymmetric distributed lag variables with orders q1, q2, q3, q4, and q5, respectively. The initial segment of the equation accounts for long-run (cointegrating) relationships in levels. It incorporates the decomposition of the explanatory variables into their positive and negative partial sums, a key feature that distinguishes NARDL from standard ARDL models. The subsequent section of the model addresses the short-run (adjusting) relationship in differences, emphasising the immediate or short-term effects of variations in the explanatory variables on the dependent variable. This part includes an error correction term that consists of the lagged differences of both dependent and independent variables, capturing the dynamic adjustment process that reflects the speed of return to long-run equilibrium following a deviation.

Lastly, the model encapsulates the deterministic dynamics that are non-stochastic and evolve in a predetermined manner over time, capturing the effect of the constant trend. Additionally, the model incorporates monthly dummy variables to account for regular, periodic fluctuations in the data, particularly in the presence of seasonal components. ε_t represents an error term or white noise which should be serially independent, homoscedastic and normally distributed (i.i.d.) for the models to be viable. Thus, all models are validated against this criterion and reported along with the main results. Log transformations were necessary to stabilise the models and achieve the i.i.d. properties of the models. Plots for the CUSUM and CUSUM of squares test are presented in Appendix H.

6.3.3 Variables Asymmetry Test

A general-to-specific procedure was employed to derive the final models. The analysis began with the estimation of the initial model, under the assumption that all independent variables exhibited asymmetry, with the aim of validating this asymmetry. Following the model estimation, symmetry tests were conducted, where the null hypothesis posited that the coefficients were symmetric. Variables for which the results did not reject the null hypothesis were subsequently incorporated as linear variables in the model. This iterative process culminated in the final validation of asymmetric variables, as presented in Table 26. In certain instances, some variables exhibited partial symmetry and were included in either the cointegrating or adjusting dynamics. The final models were adjusted accordingly to ensure that asymmetries and partial asymmetries were appropriately accounted for within a NARDL framework. In cases where no asymmetries were detected, the standard ARDL model was employed.

Table 26: NARDL Model Asymmetry Results

Country	**Variable**	**Test statistic:**	
		EDGE	AR
Brazil	Log(INT)	-	10.2190***
Chile			
long-run	Log (CPI)	-	6.8561***
	Log (ETV)	-	13.2094***
	Log (INP)	-	4.2375**
Philippines			
long-run	Log (EXR)	12.1397***	_-
	Log (INT)	12.6029***	-
South Africa			
joint	Log (EXR)	5.6402**	-
	Log (INP)	9.5351***	-
long-run	Log (INT)	6.4922***	-
	Log (EXR)	-	5.5057**
	Log (INP)	-	5.6496**
	Log (INT)	-	4.9078**
Thailand			
joint	Log (CPI)	15.4772***	-

long-run	Log (EXR)	12.7447***	-

6.3.4 Bounds test

The next stage of the analysis involves a bounds test performed per Pesaran et al. (2001), who suggested tests that are robust to different integration orders of the variables. The following hypothesis is tested in the bound testing

$$H_0: \{\emptyset, \lambda_1 \dots \dots \dots \dots \lambda_k\} = 0$$

$$H_1: \{\emptyset, \lambda_1 \dots \dots \dots \dots \lambda_k\} \neq 0$$

The bounds test is conducted as an F-test for the significance of the cointegrating relationship within the conditional ARDL model. Its objective is to ascertain the existence of a long-run equilibrium relationship among the variables, irrespective of whether they are I(0), I(1), or mutually cointegrated. This approach addresses the limitations of traditional cointegration tests, which necessitate that all variables be integrated of the same order. The test statistic is then compared to the asymptotic critical values; if it exceeds the critical value, the null hypothesis is rejected, thereby validating the conclusion of cointegration among the variables. Conversely, if the test statistic is below the lower critical value, we fail to reject the null hypothesis and conclude that no cointegration exists. If the test statistic falls between the lower and upper critical values, the results are deemed inconclusive.

Upon rejection of the null hypothesis, the t-bounds test is performed to provide an alternative assessment of the existence of a long-run relationship. This test focuses on the coefficient of the lagged dependent variable in the error correction form of the ARDL model. Unlike the F-bounds test, the t-bounds test is based on a single parameter rather than joint significance; however, similar to the F-bounds test, it compares the calculated t-statistic against two sets of critical values (lower and upper bounds) to determine the presence of cointegration. Employing both tests ensures robust conclusions regarding the existence of long-run relationships within ARDL models.

After rejecting the null hypothesis of no cointegration, a further Wald test is conducted to confirm that the cointegrating relationship identified by the F-bound and t-bound tests is not degenerate. This degeneracy may occur when the long-run relationship between variables is trivial despite the bounds test indicating cointegration. The Wald test assesses the joint significance of the coefficients of the variables in levels, with the null hypothesis positing that the coefficients are jointly equal to zero. In addition to serving as an additional robustness check, the Wald test facilitates proper model specification by confirming the relevance of the variables included in the model. A significant Wald test result leads to the rejection of the null hypothesis of no cointegration, whereas an insignificant result suggests that the coefficients are jointly insignificant, thereby discrediting the existence of a long-run relationship. Table 27 presents the results of the Bounds and Wald tests. Because the Wald test was performed to validate the results of the F and t-bound tests, where no cointegration was established, no further testing was necessary.

Table 27: Bounds and Wald Test

Country	Test statistic	EDGE			AR		
		Value	I(0)	I(1)	Value	I(0)	I(1)
Brazil	F-stat	8.5679	3.410	4.680	8.4258	3.410	4.680
	t-stat	-6.9822	-3.430	-4.790	-5.9624	-3.430	-4.790
	Wald	2.8699***			6.8229***		
Chile	F-stat	1.5187	5.150	6.360	9.7424	2.960	4.260
	t-stat	-1.8494	-3.430	-4.100	-8.5664	-3.430	-5.190
	Wald	-			5.9974***		
Greece	F-stat	5.9995	3.740	5.060	9.9692	3.740	5.060
	t-stat	-5.3148	-3.430	-4.600	-6.8976	-3.430	-4.600
	Wald	1.8201			1.7947		
Philippines	F-stat	5.6922	3.150	4.430	10.9364	3.740	5.060
	t-stat	-3.3341	-3.430	-4.990	-6.6205	-3.430	-4.600
	Wald	4.1918***			2.3226**		
SA	F-stat	3.2989	2.960	4.260	5.1587	2.960	4.260
	t-stat	-2.9428	-3.430	-5.190	-6.2389	-3.430	-5.190
	Wald	-			2.6135**		
Thailand	F-stat	8.8062	2.960	4.260	10.4854	3.410	4.680
	t-stat	-7.3229	-3.430	-5.190	-7.6084	-3.430	-4.790
	Wald	5.7850***			4.3559***		

Note: I(0) and I(1) indicate the lower and upper bound critical values. ** and *** indicate significance at 5% and 1% respectively.

Results from the analysis indicate cointegration for Brazil, Philippines and Thailand for both dependent variables. This was confirmed by the F-bound and T-bound tests and the Wald test indicating that cointegration was not degenerate. The results for Greece show that while the F-bound and t-bound tests suggest cointegration, the Wald calls the cointegration in question and thus conclusion is that while there is evidence of a long run relationship, that relationship is degenerate for both dependent variables. For South Africa, the F-bound test is inconclusive as it falls between the lower and upper critical values, and the t-bound test is less ambiguous, with an outright failure to reject the null hypothesis. However, for the AR dependent variable, all tests suggest cointegration with the Wald at 5% significance.

Further analysis is undertaken based on all the above tests. Where no cointegration was established, only the short run models are estimated. The next section presents and discusses the results of each country.

6.4 ARDL/NARDL Country Analysis

Brazil

Table 28: Brazil- AR and EDGE Results

Long-run Conditional Error Correction Model (AR)

Variable	Coefficient	T-statistic
LAR_1	-1.1247	-5.9624***
LEXR	1.2318	2.4588**
$LCPI_1$	-2.6957	-3.8051***
LINP	-1.9152	-2.1347**
$LINT_1$	0.0675	0.6598
$LETV_1$	0.2871	1.0469

Short-run Error Correction Model (AR)

Variable	Coefficient	T-statistic
ΔLAR_1	0.1290	1.1134
ΔLAR_2	-0.1875	-2.1479**
$\Delta LCPI$	-14.3526	-1.8871*
$\Delta LETV$	0.5402	4.4515***
$\Delta LETV_1$	0.5356	3.8454***
$\Delta LETV_2$	0.2724	2.0571**
$\Delta LETV_3$	0.3440	2.7784***
$\Delta LINT\_POS$	-0.8457	-2.5898**
$\Delta LINT\_NEG$	0.7438	1.9486**
$\Delta LINT\_POS_1$	-0.0336	-0.0915
$\Delta LINT\_NEG_1$	1.0480	2.7214***
$\Delta LINT\_POS_2$	0.1539	0.4101
$\Delta LINT\_NEG_2$	0.6509	1.8936*
ECM	-1.1247	-7.3496***
Diagnostics		
Breusch-Godfrey LM	0.1841 (0.9459)	

Breusch-Pagan Godfrey	0.9140 (0.5976)
Jarque-Bera	0.9281
CUSUM	Stable
CUSUM of Squares	Stable

Lon-run Conditional Error Correction Model (EDGE)

Variable	**Coefficient**	**T-statistic**
$LEDGE_1$	-0.7106	-6.9822***
$LINT_1$	0.2231	2.5415***
$LINP_1$	-1.5708	-1.3968
$LEXR_1$	-0.1869	-0.3381
LCPI	-1.9771	-3.4093***
$LETV_1$	0.4439	1.9332*

Short-run Error Correction Model (EDGE)

Variable	**Coefficient**	**T-statistic**
$\Delta LEDGE_1$	0.2672	2.9110***
ΔLINT	-0.3460	-1.3046
ΔLINP	-0.1586	-0.1396
ΔLEXR	1.0920	1.2590
$\Delta LEXR_1$	1.5497	1.8528*
ΔLETV	0.7946	5.1142***
ECM	-0.7106	-7.3853***
Diagnostics		
Breusch-Godfrey LM	0.8236 (0.4425)	
Breusch-Pagan Godfrey	0.8165 (0.7019)	
Jarque-Bera	2.2582 (0.3233)	
CUSUM	Stable	
CUSUM of Squares	Stable	

NB: LAR, LEDGE, LEXR, LCPI, LINP, LINT, LETV denote the logarithms of AR and EDGE estimators, exchange rate, consumer price index, industrial production, interest rate, EFT trading volume.
2. All variables are in logarithmic form to address potential non-linearity and to interpret coefficients as elasticities.
3. Δ denotes the first difference of the variable.
4. ECM represents the error correction term.
5. POS and NEG subscripts indicate positive and negative changes in the variables, respectively.
6. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
7. Breusch-Godfrey LM test for serial correlation; Breusch-Pagan-Godfrey test for heteroskedasticity; Jarque-Bera test for normality of residuals.
8. p-values are reported in parentheses for the diagnostic tests.

ETV is not significant in the long run and only marginally significant for the EDGE. The short-run dynamic captures more persistence of the ETV, where for both spread estimators, they are significant at all levels. The AR indicates that a 1% increase in ETV results in a spread increase of 0.54% which diminishes up to 0.34% in the subsequent three months. The EDGE indicates a 0.79% increase from a 1% increase in ETV. In the long run, the model reveals a significant adjustment process towards equilibrium, with the ECT significant at all levels. This indicates a relatively rapid speed of adjustment, suggesting that about 71% and 114% of any disequilibrium is corrected within one month for the AR and EDGE models, respectively.

In the short term, the persistent positive influence of ETV suggests that increased ETF trading activities are associated with wider spreads, potentially indicating a temporary reduction in market efficiency. This short-run effect may be attributed to the complex mechanics of ETF creation/redemption processes and associated arbitrage activities, which could temporarily increase trading frictions. These short-run dynamics may temporarily alter the market microstructure, affecting both transaction costs (as measured by AR) and price impact (reflected in EDGE). However, the lack of long-run persistence of transaction costs for the AR implies that markets eventually absorb and adjust to these ETF-induced liquidity shocks. Thus, any initial widening of spreads due to increased ETF activity is transitory, with markets demonstrating resilience and efficiency in the longer term.

In terms of the EDGE, the analysis indicates significant persistence in both short-run and long-run coefficients, with the latter exhibiting a coefficient of 0.44, significant at the 10% level. The long-term effect implies that the influence of ETF trading on market efficiency extends beyond transitory shocks, indicating a more structural change in market dynamics. The positive long-run coefficient suggests that increased ETF activity is associated with wider spreads over time, which is interpreted as a persistent reduction in market efficiency. The coexistence of short-run and long-run impacts underscores the complex role of ETFs in shaping market efficiency. It implies that while markets may partially adjust to ETF-induced liquidity changes, there remains a residual effect that persists over longer horizons. This persistence could be attributed to factors such as changed information dynamics, altered trading behaviours of market participants, or shifts in the underlying market structure due to the growing prominence of ETFs.

Philippines

Table 29: Philippines- AR and EDGE Results

Long-run Conditional Error Correction Model (AR)

Variable	Coefficient	T-statistic
$LIAR_1$	-0.7195	-6.6205***
LEXR	2.2420	2.1168**
LINT	-0.1327	-1.3968
$LINP_1$	-0.0603	-0.4393
LETV	0.1351	1.7204*

Short-run Error Correction Model (AR)

Variable	Coefficient	T-statistic
ΔLINP	-0.4788	2.7390***
ECT	-0.7195	-7.5591***
Diagnostics		
Breusch-Godfrey LM	0.7567 (0.3867)	
Breusch-Pagan Godfrey	1.3161 (0.2014)	
Jarque-Bera	1.6841 (0.4308)	
CUSUM	Stable	
CUSUM of Squares	Stable	

Lon-run Conditional Error Correction Model (EDGE)

Variable	Coefficient	T-statistic
$LEDGE_1$	-0.4426	-3.3341***
LINP	0.0224	0.1409
$LETV_1$	0.4103	3.9333***
LEXR_POS	2.1755	1.5109
LEXR_NEG	-7.5913	-2.6552***
$LINT\_POS_1$	-0.3221	-2.3230**
$LINT\_NEG_1$	0.6185	3.2369**

Short-run Error Correction Model (EDGE)

Variable	Coefficient	T-statistic
$\Delta LEDGE_1$	-0.0950	-1.1419
$\Delta LEDGE_2$	-0.2145	-2.5202***
ΔLETV	0.2181	3.1438***
ΔLINT	0.3757	1.3134
$\Delta LINT_1$	0.3810	1.3291
$\Delta LINT_2$	0.8301	2.8653**
ECT	-0.4426	-6.5447***
Diagnostics		

Breusch-Godfrey LM	2.080 (0.1098)
Breusch-Pagan Godfrey	1.6614 (0.0485)
Jarque-Bera	0.4824 (0.7857)
CUSUM	Stable
CUSUM of Squares	Stable

NB: LAR, LEDGE, LEXR, LCPI, LINP, LINT, LETV denote the logarithms of AR and EDGE estimators, exchange rate, consumer price index, industrial production, interest rate, EFT trading volume.
2. All variables are in logarithmic form to address potential non-linearity and to interpret coefficients as elasticities.
3. Δ denotes the first difference of the variable.
4. ECM represents the error correction term.
5. POS and NEG subscripts indicate positive and negative changes in the variables, respectively.
6. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
7. Breusch-Godfrey LM test for serial correlation; Breusch-Pagan-Godfrey test for heteroskedasticity; Jarque-Bera test for normality of residuals.
8. p-values are reported in parentheses for the diagnostic tests.

The AR estimator indicates a long run equilibrium dominance with little, short-term dynamics evidenced by the presence of only one independent variable in the short run model. Industrial production has an immediate impact on the AR that does not persist as opposed to the other variables whose impact registers over a more extended period of time. Despite this, there is a relatively rapid adjustment to long run equilibrium at 72%. ETV has a 0.14% long run effect on the AR from a 1% increase, which is marginally significant at 10%, a subtle but lasting influence on transaction costs. While not immediately impacting spread, the cumulative effect of increased ETF activity gradually widens spreads, potentially due to changes in market maker behaviour or order flow dynamics. This suggests that the impact of ETFs on basic transaction costs unfolds slowly, possibly as market participants adjust their strategies over time.

Both the long-run and short-run coefficients of ETV are positive and significant at the 1% level, with values of 0.41 and 0.22, respectively. These positive coefficients suggest that increases in ETF trading volume are associated with a deterioration in market efficiency, both in the immediate term and over a longer horizon. The short-run significance suggests that increased ETF activity quickly affects price discovery processes, information asymmetry, or market impact costs. The larger magnitude of the long-run coefficient (0.41) compared to the short-run coefficient (0.22) implies that the negative impact of ETF trading on market microstructure intensifies over time. In the short run, the 0.22 coefficient indicates that ETF volume has an immediate adverse effect on market efficiency, possibly due to increased noise trading or temporary liquidity pressures. The larger long-run coefficient of 0.41, associated with the first lag of ETV, suggests a more pronounced and persistent negative impact on market microstructure. This comprehensive deterioration in market quality metrics implies that ETFs might be introducing complexities or frictions into the market that affect both immediate trading conditions and long-term market structure. So, while ETFs contribute to immediate declines in market quality, their full detrimental impact on market microstructure becomes more substantial over an extended period.

While the basic transaction cost measure (AR) shows only long-term effects, the broader efficiency measure (EDGE) captures both immediate and lasting impacts. This suggests that ETFs may have a more immediate influence on complex market dynamics such as price discovery and information efficiency, while their effect on simple transactions costs takes longer to manifest. The positive coefficients for both estimators indicate that increased ETF activity generally leads to a deterioration in market quality, but through different mechanisms and over different time frames.

Thailand

Table 30:**Thailand- AR and EDGE Results**

Long-run Conditional Error Correction Model (AR)

Variables	**Coefficient**	**T-statistic**
$LIAR_1$	-0.7909	-7.6084***
$LCPI_1$	-0.5013	-0.3321
$LINT_1$	-0.0318	-0.3906
$LEXR_1$	1.5273	1.7228*
LINP	0.0659	0.0732
$LETV_1$	0.5060	3.2060***

Short-run Error Correction Model (AR)

Variables	**Coefficient**	**T-statistic**
ΔLCPI	-16.2850	-2.3146**
ΔLINT	-0.8956	-2.0623**
$\Delta LINT_1$	-1.4513	-3.3483***
$\Delta LINT_2$	-0.7911	-1.7355*
ΔLEXR	4.6141	2.1561**
ΔLETV	0.2253	2.4533**
ECT	-0.7909	-8.1729***
Diagnostics		
Breusch-Godfrey LM	0.2640 (0.8511)	
Breusch-Pagan Godfrey	0.8040 (0.7169)	
Jarque-Bera	0.5779 (0.7491)	
CUSUM	Stable	

CUSUM of Squares	Stable

Lon-run Conditional Error Correction Model (EDGE)

Variables	Coefficient	T-statistic
LEDGE $_1$	-0.9778	-7.3229***
LINP $_1$	0.8993	0.7785
LINT $_1$	-1.0069	-4.4378***
LETV $_1$	0.7493	3.1966***
LCPI_POS $_1$	0.1779	0.0365
LCPI_NEG $_1$	70.9954	4.7669***
LEXR_POS	9.6069	3.4222***
LEXR_NEG	-3.4075	-2.7409***

Short-run Error Correction Model (EDGE)

Variables	Coefficient	T-statistic
ΔLEDGE$_1$	0.1594	1.7325 *
ΔLINP	-0.2070	-0.1575
ΔLINP$_1$	1.4965	1.0814
ΔLINP$_2$	2.1973	1.5133
ΔLINP$_3$	3.2115	2.3325**
ΔLINT	-1.9062	-4.7041***
ΔLETV	-0.0779	-0.6965
ΔLETV$_1$	-0.5156	-3.2481***
ΔLETV$_2$	-0.5879	-4.1447***
ΔLETV$_3$	-0.3002	-2.5994***
ΔLCPI_POS	38.4771	3.2521***
ΔLCPI_NEG	-62.2628	-4.4213***
ΔLCPI_POS$_1$	7.6692	0.6253
ΔLCPI_NEG$_1$	-68.9934	-3.8160***
ΔLCPI_POS$_2$	6.7116	0.6041
ΔLCPI_NEG$_2$	-49.2694	-2.8842***
ΔLCPI_POS$_3$	-4.1176	-0.3678
ΔLCPI_NEG$_3$	-59.4128	-3.8669***
ECT	-0.9778	-8.8338***
Diagnostics		
Breusch-Godfrey LM	0.5916 (0.6700)	
Breusch-Pagan Godfrey	0.9127 (0.6118)	
Jarque-Bera	0.5761 (0.7497)	
CUSUM	Stable	
CUSUM of Squares	Stable	

NB: LAR, LEDGE, LEXR, LCPI, LINP, LINT, LETV denote the logarithms of AR and EDGE estimators, exchange rate, consumer price index, industrial production, interest rate, EFT trading volume.
2. All variables are in logarithmic form to address potential non-linearity and to interpret coefficients as elasticities.
3. Δ denotes the first difference of the variable.
4. ECM represents the error correction term.
5. POS and NEG subscripts indicate positive and negative changes in the variables, respectively.
6. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

7. Breusch-Godfrey LM test for serial correlation; Breusch-Pagan-Godfrey test for heteroskedasticity; Jarque-Bera test for normality of residuals.
8. p-values are reported in parentheses for the diagnostic tests.

Firstly, consider the AR estimator. The results indicate a positive and statistically significant relationship between ETV and transaction costs in both the long run and short run. Specifically, the long-run coefficient of 0.51 suggests that a 1% increase in ETV is associated with a 0.51% deterioration in the bid-ask spread over the long term. The short-run coefficient of 0.23 points to a more immediate 0.23% widening of the spread in response to a 1% rise in ETV. These positive coefficients imply that increased ETF trading activity is linked to higher transaction costs for market participants, potentially due to factors such as greater order flow imbalances, reduced liquidity provision by market makers, or heightened adverse selection risks.

The impact on the EDGE is even more pronounced, with ETV exhibiting positive and significant effects across multiple lags. The long-run coefficient of 0.75 suggests that a 1% increase in ETV leads to a substantial 0.75% decline in overall market efficiency in the long run. Interestingly, the short-run effects are also statistically significant, with coefficients of 0.52, 0.59, and 0.30 for the first, second, and third lags of ETV, respectively. This indicates that ETF trading volume has an immediate, as well as a persistent, adverse impact on a broader set of market quality metrics captured by the EDGE estimator, including price discovery, information asymmetry, and market impact costs.

While both measures point to a deterioration in market quality associated with increased ETV, the EDGE results suggest that the negative effects extend beyond just transaction costs, also manifesting in reduced overall market efficiency. The more immediate and long-term impact on EDGE compared to the AR estimator underscores that ETFs may be introducing complexities and frictions that go beyond traditional spread-based measures, potentially altering price discovery mechanisms, information flows, and other fundamental market dynamics.

South Africa

Table 31:South Africa- AR and EDGE Results

Long-run Conditional Error Correction Model (AR)

Variables	**Coefficient**	**T-statistic**
LAR_1	-1.0357	-6.2389***
$LETV_1$	0.5101	2.3766**
LINP_POS	1.9436	1.7509*
LINP_NEG	-1.7967	-2.1896**
LINT_POS	-1.3173	-2.5486***
LINT_NEG	3.4391	2.0612**
$LEXR\_POS_1$	0.0688	0.1037
$LEXR\_NEG_1$	-0.9113	-1.2155

Short-run Error Correction Model (AR)

Variables	**Coefficient**	**T-statistic**
ΔLAR_1	0.2824	2.0922**
ΔLAR_2	0.3609	3.1974***
ΔLAR_3	0.2198	2.2998**
ΔLETV	0.3652	3.4473***
$\Delta LETV_1$	-0.1179	-0.9391
$\Delta LETV_2$	-0.0266	-0.2214
$\Delta LETV_3$	-0.2797	-2.7260***
ΔLEXR	1.1771	1.3067
ECT	-1.0357	-6.7135***
Diagnostics		
Breusch-Godfrey LM	0.6706 (0.6145)	
Breusch-Pagan Godfrey	1.0872 (0.3765)	
Jarque-Bera	0.4240 (0.8090)	
CUSUM	Stable	
CUSUM of Squares	Stable	

Short-run Model (EDGE)

Variables	**Coefficient**	**T-statistic**
$\Delta LEDGE_1$	-0.1278	-1.3344
$\Delta LEDGE_2$	-0.2897	-2.9682***
ΔLINT	32.2028	1.8289*
ΔLINP_POS	-21.0918	-0.4635
ΔLINP_NEG	-20.3536	-2.0228**
$\Delta LINP\_POS_1$	-92.4434	-2.0328**
$\Delta LINP\_NEG_1$	-191.0720	-4.7612***
$\Delta LINP\_POS_2$	1.1925	0.0321
$\Delta LINP\_NEG_2$	-145.0276	-4.1766***
$\Delta LINP\_POS_3$	72.1041	2.7977***

ΔLINP_NEG$_3$	-74.9248	-2.5863***
ΔLEXR_POS	15.7448	0.7275
ΔLEXR_NEG	6.0996	0.1988
ΔLEXR_POS$_1$	-50.0978	-2.0936**
ΔLEXR_NEG$_1$	-0.6432	-0.0223
ΔLEXR_POS$_2$	-75.2978	-2.9369***
ΔLEXR_NEG$_2$	94.0773	3.0798***
Diagnostics		
Breusch-Godfrey LM	0.2513 (0.9078)	
Breusch-Pagan Godfrey	1.042 (0.4333)	
Jarque-Bera	3.5450 (0.1699)	
CUSUM	Stable	
CUSUM of Squares	Stable	

NB: LAR, LEDGE, LEXR, LCPI, LINP, LINT, LETV denote the logarithms of AR and EDGE estimators, exchange rate, consumer price index, industrial production, interest rate, EFT trading volume.
2. All variables are in logarithmic form to address potential non-linearity and to interpret coefficients as elasticities.
3. Δ denotes the first difference of the variable.
4. ECM represents the error correction term.
5. POS and NEG subscripts indicate positive and negative changes in the variables, respectively.
6. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
7. Breusch-Godfrey LM test for serial correlation; Breusch-Pagan-Godfrey test for heteroskedasticity; Jarque-Bera test for normality of residuals.
8. p-values are reported in parentheses for the diagnostic tests.

In the long run, the results indicate a statistically significant positive relationship between ETV and transaction costs, as captured by the AR spread measure. Specifically, the coefficient of 0.51 on the first lag of ETV suggests that a 1% increase in ETF trading volume is associated with a 0.51% deterioration in the bid-ask spread over the long term. This implies that heightened ETF activity exerts a persistent upward pressure on basic trading costs for market participants, potentially due to factors such as reduced liquidity provision, order flow imbalances, or heightened adverse selection risks.

In the short-run, the contemporaneous effect of ETV on AR is positive and significant, with a coefficient of 0.37 indicating a 0.37% increase in spreads. The first lag of ETV shows a negative coefficient of -0.12, suggesting a potential transitory improvement in spreads. However, this effect is not statistically significant. In contrast, the third lag of ETV exhibits a significant negative coefficient of -0.28, implying that the adverse impact of ETV on transaction costs may dissipate over time.

The long-run findings point to a persistent deterioration in transaction costs, the short-run dynamics suggest that the immediate impact of ETV may be followed by a partial reversal or offsetting effects. This could reflect the interplay of various market mechanisms, such as liquidity adjustments, changes in trading strategies, or the gradual incorporation of information into prices.

While the analysis of the AR spread measure revealed a persistent long-run deterioration in transaction costs associated with increased ETV, the EDGE estimator results present a markedly different picture. For the EDGE estimator, which captures a broader set of market efficiency and quality metrics, the analysis indicates no evidence of cointegration between ETV and the dependent variable. This suggests that there is no long-run equilibrium relationship between these variables, implying that the impact of ETV on overall market efficiency may not be as stable or predictable as its effect on more narrowly defined transaction costs. Furthermore, the short-run dynamics analysis for the EDGE model shows that ETV does not feature as a significant explanatory variable. This contrasts with the significant short-run effects observed for the AR estimator, where ETV had both positive and negative impacts on bid-ask spreads at different lags.

These findings suggest that while ETF trading may have a clear and persistent influence on basic transaction costs, as evidenced by the AR results, its impact on the broader market efficiency landscape, as captured by the EDGE estimator, is less pronounced or more complex. The effects of ETV on market quality metrics such as price discovery, information asymmetry, and market impact costs may be either more indirect or dependent on the interplay of other market dynamics that are not adequately captured by the EDGE model.

Greece

Table 32: **Greece- AR and EDGE Results**

Short-run Model (AR)

Variable	**Coefficient**	**T-statistic**
ΔINT	0.0307	0.6256
ΔINT_1	0.1739	3.1555***
ΔINT_2	0.0724	1.3976
ΔETV	0.0000	1.7974*
ΔETV_1	-0.0000	-3.0889***

Diagnostics		
Breusch-Godfrey LM	0.3801 (0.7676)	
Breusch-Pagan Godfrey	0.7163 (0.8047)	
Jarque-Bera	2.1155 (0.3472)	
CUSUM	Stable	
CUSUM of Squares	Stable	

Short-run Model (EDGE)

Variable	Coefficient	T-statistic
ΔINT	-0.0031	-0.0658
ΔINT_1	0.1115	2.4686**
ΔINP	0.0000	1.4081
ΔINP_1	0.0000	2.2983**
Diagnostics		
Breusch-Godfrey LM	0.3373 (0.7147)	
Breusch-Pagan Godfrey	0.9433 (0.5364)	
Jarque-Bera	0.7590 (0.6842)	
CUSUM	Stable	
CUSUM of Squares	Stable	

NB: LAR, LEDGE, LEXR, LCPI, LINP, LINT, LETV denotes the logarithms of AR and EDGE estimators, exchange rate, consumer price index, industrial production, interest rate, EFT trading volume.
2. All variables are in logarithmic form to address potential non-linearity and to interpret coefficients as elasticities.
3. Δ denotes the first difference of the variable.
4. ECM represents the error correction term.
5. POS and NEG subscripts indicate positive and negative changes in the variables, respectively.
6. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
7. Breusch-Godfrey LM test for serial correlation; Breusch-Pagan-Godfrey test for heteroskedasticity; Jarque-Bera test for normality of residuals.
8. p-values are reported in parentheses for the diagnostic tests.

The absence of cointegration suggests that there is no long-run equilibrium relationship between ETV and transaction costs, as measured by the AR. However, the coefficient on the contemporaneous ETV term is positive and significant at the 10% level, indicating a small but immediate increase in spreads associated with higher ETF trading activity. This effect is relatively modest, with a coefficient of just 0.00000747, implying that a 1% increase in ETV would lead to a 0.0000747% widening of the bid-ask spread. However, first lag of ETV exhibits a negative and statistically significant (at the 1% level) coefficient of -0.0000127. This suggests that the adverse impact of ETV on transaction costs may be partially offset or even reversed in the short run. These findings suggest that the influence of ETV on basic trading costs is relatively smaller and transitory than a simple linear relationship would imply.

On the other hand, the EDGE analysis again indicates the absence of cointegration. Furthermore, the short-run model shows that ETV does not feature as a significant explanatory variable for the EDGE measure. This suggests that ETF trading activity may not have a direct or immediate impact on the overall efficiency and information dynamics of the market, as captured by the EDGE estimator. While ETV may have modest and mixed short-run effects on basic transaction costs, its influence on the broader efficiency and quality of the market appears to be more muted or indirect.

Chile

Table 33: Chile- AR and EDGE Results

Long-run Conditional Error Correction Model (AR)

Variable	Coefficient	T-statistic
LAR_1	-0.8464	-8.5664***
$LEXR_1$	1.4548	1.1746
$LCPI\_POS_1$	6.6347	2.7171***
$LCPI\_NEG_1$	-126.5746	-2.5449***
LINP_POS	-1.0727	-0.4506
LINP_NEG	-6.7676	-2.7450***
$LETV\_POS_1$	0.0604	0.8550
$LETV\_NEG_1$	0.3604	3.5182***

Short-run Error Correction Model (AR)

Variable	Coefficient	T-statistic
ΔLEXR	1.9402	1.6642*
$\Delta LEXR_1$	1.8310	1.4241
$\Delta LEXR_2$	2.9402	2.2848**
$\Delta LEXR_3$	4.8096	4.0891***
ΔLCPI	-22.8892	-2.4593***
ΔLETV	0.0848	1.6239
ECT	-0.8464	-9.2159***
Diagnostics		
Breusch-Godfrey LM	0.6976 (0.5960)	
Breusch-Pagan Godfrey	1.0239 (0.4489)	
Jarque-Bera	0.0966 (0.9529)	
CUSUM	Stable	
CUSUM of Squares	Stable	

Short-run Error Correction Model (EDGE)

Variable	Coefficient	T-statistic

$\Delta SEDGE_1$	-0.2440	-2.2663**
$\Delta SEDGE_2$	-0.1680	-1.5804
$\Delta SINP$	0.0000	-0.5943
$\Delta SINP_1$	0.0000	-2.1524**
$\Delta SETV$	0.0000	1.1471
$\Delta SETV_1$	0.0000	2.2678**
Diagnostics		
Breusch-Godfrey LM	0.8172 (0.6865)	
Breusch-Pagan Godfrey	1.1996 (0.3065)	
Jarque-Bera	5.6706 (0.0587)	
CUSUM	Stable	
CUSUM of Squares	Stable	

NB: LAR, LEDGE, LEXR, LCPI, LINP, LINT, LETV denote the logarithms of AR and EDGE estimators, exchange rate, consumer price index, industrial production, interest rate, EFT trading volume.
2. All variables are in logarithmic form to address potential non-linearity and to interpret coefficients as elasticities.
3. Δ denotes the first difference of the variable.
4. ECM represents the error correction term.
5. POS and NEG subscripts indicate positive and negative changes in the variables, respectively.
6. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
7. Breusch-Godfrey LM test for serial correlation; Breusch-Pagan-Godfrey test for heteroskedasticity; Jarque-Bera test for normality of residuals.
8. p-values are reported in parentheses for the diagnostic tests.

In the short run, the model indicates a positive coefficient of 0.0848 for ETV. However, this coefficient is statistically insignificant, suggesting that immediate changes in ETF trading volume do not have a reliable impact on bid-ask spreads. This finding implies that the market's liquidity provision and price formation processes may be resilient to short-term fluctuations in ETF trading activity. The long-run dynamics, however, reveal a more complex and asymmetric relationship between ETV and market microstructure. The model distinguishes between positive and negative changes in ETV, both lagged by one period, to capture potential non-linear effects.

For positive changes in ETV, the long-run coefficient is 0.0604. While this suggests a slight widening of spreads in response to increases in ETF trading volume, the coefficient is statistically insignificant. This indicates that positive shocks to ETF trading activity do not have a reliable long-term impact on transaction costs. Conversely, for negative changes in ETV, the long-run coefficient is 0.3604 and is statistically significant at the 1% level. This finding implies that decreases in ETF trading volume are associated with a substantial widening of bid-ask spreads over the long run.

The insignificant effect of positive changes in ETV suggests that markets may have developed mechanisms to absorb increases in ETF trading activity without significantly impacting transaction costs. This could be attributed to improved liquidity provision, enhanced price discovery processes, or the market's ability to efficiently incorporate information from increased ETF trading. Moreover, the significant and positive coefficient for negative changes in ETV indicates that reductions in ETF trading volume have a detrimental effect on market quality. This finding implies that ETFs may play a crucial role in maintaining market liquidity and efficiency. When ETF trading activity declines, it leads to reduced liquidity, increased information asymmetry, or decreased market participation, all of which could contribute to wider bid-ask spreads.

These results suggest that while increases in ETF activity may not necessarily improve market quality, decreases in ETF trading lead to a deterioration in market conditions. This asymmetry highlights the importance of maintaining a certain level of ETF trading activity to support market liquidity and efficiency.

6.5 Granger Causality

The previous analysis gave insight into the arbitrage mechanism between ETF activity and market efficiency, specifically, the speed and magnitude of the adjustments. The next analysis focuses on the price discovery process and the lead-lag relationships between ETF returns and index returns.

Granger causality is a statistical hypothesis test that determines whether one time series can predict another. In the context of market efficiency, Granger causality tests are instrumental in understanding the dynamic relationships between ETF returns and Index returns. The presence of Granger causality can indicate the degree of market efficiency, as it reflects the extent to which information is rapidly incorporated into asset prices; that is, the price discovery mechanism. The EMH posits that asset prices should reflect all available information if it is efficient. Therefore, there should be no predictive power between the ETF and the underlying index. Conversely, if one variable Granger-causes another, it suggests that information flows between them, indicating potential inefficiencies. For the pairwise Granger causality test, the following hypothesis is tested:

H_0= there is no granger causality

H_1= null hypothesis is not true

The decision criteria applied rejects the null hypothesis if the p-value of the f-statistic is ≤0.05. Granger causality is formulated based on a linear regression stochastic process (Granger, 1969). The bivariate model with X_1 and X_2 representing index returns and ETF returns, respectively, is illustrated thus:

$$X_1(t) = \sum_{j=1}^{p} A_{11,j} X_1(t-j) + \sum_{j=1}^{p} A_{12,j} X_2(t-j) + E_1(t) \tag{6.3}$$

$$X_2(t) = \sum_{j=1}^{p} A_{21,j} X_1(t-j) + \sum_{j=1}^{p} A_{22,j} X_2(t-j) + E_2(t) \tag{6.4}$$

p represents the model's maximum number of lagged observations. A is a matrix of coefficients that illustrates the contributions of each lagged observation to the predicted values of X_1 and X_2. E_1 and E_2 denote the prediction errors. Granger causality exists if including either index returns or ETF returns in either equation reduces the variance of the prediction error. In other words, ETF returns Granger cause index returns if the coefficients in A_{12} are jointly significantly different from zero

Table 34 presents 14 lags of the Granger causality between the returns of ETF and the index. The rationale for including multiple lags stems from the inherent time-dependent nature of economic and financial data, where past values can influence current outcomes over varying time frames(Alvarez-Socorro et al., 2023). Presenting multiple time lags accounts for the delayed effects that one variable may have on another. Economic processes often do not react instantaneously; instead, they exhibit time lags due to factors such as information dissemination, decision-making processes, and market adjustments. Due to these delays, information is incorporated across lags rather than a single maximal lag (Costa et al., 2022). By including multiple lags, these delayed effects are captured for more robust conclusions about causal relationships. Additionally, in the context of market dynamics, Tang et al. (2019) emphasise how observing multiple lags can inform trading strategies and risk management. Multiple lags allow investors to exploit predictive relationships that may exist over time.

Table 34: Granger Causality Results

	Brazil		Chile		Philippines		South Africa		Taiwan		Thailand		Greece	
Lags	IE	EI	IE	EI	IE	EI	IE	EI	IE	EI	IE	EI	IE	EI
1	0.0398	9.5170***	166.139***	1.5701	46.0353***	1.1928	56.5901***	2.76842*	12.8541***	1.1035	39.3510***	1.6928	18.0615***	0.2480
2	0.2045	6.1475***	98.8182***	0.9265	29.5925***	1.0556	37.5920***	1.8542	6.4432***	0.8288	32.5511***	1.7245	11.9918***	0.4727
3	0.7724	4.2117***	69.0756***	0.3921	23.4357***	0.8745	41.8291***	6.9771***	4.4392***	1.0199	24.1139***	3.2112**	9.0463***	22.8836***
4	0.9805	3.5831***	53.5173***	0.1939	20.9725***	0.8786	34.3274***	5.5231***	**3.2639*****	**0.8137**	17.9010***	2.6001**	6.8682***	16.3881***
5	0.7380	3.0434***	42.9433***	0.6123	**16.8077*****	**0.5613**	33.5726***	8.6980***	2.6145**	0.6715	15.6188***	1.9287*	6.3562***	14.6052***
6	0.9627	3.0805***	35.7568***	0.6715	13.9003***	0.5464	28.3510***	7.1414***	2.3180**	0.7121	13.5064***	1.7347*	6.8107***	12.5683***
7	1.2843	2.6481***	31.3878***	0.6832	12.0496***	0.5886	26.3475***	5.9430***	2.5644***	0.8335	11.4812***	1.5242	**5.8426*****	**11.2209*****
8	1.2567	2.3222**	27.3683***	0.7401	10.7057***	0.4864	22.7408***	4.9069***	2.3048**	0.9616	10.4989***	1.4506	5.1360***	9.8661***
9	1.0876	2.0379**	24.4866***	0.7425	9.4590***	0.5086	20.0137***	4.3901***	2.0552**	0.8554	9.7738***	1.6802*	4.8232***	9.0953***
10	1.3461	1.8956**	23.4031***	1.2069	8.6825***	0.5509	**17.7924*****	**4.0255*****	1.8618**	0.7568	8.8624***	1.6951*	4.4249***	8.3507***
11	1.2566	1.7130*	21.1563***	1.0923	7.8759***	0.4817	16.2678***	3.6879***	1.6667*	0.7098	8.3344***	1.5972*	4.0792***	7.735***
12	**2.0704****	**2.2224*****	**19.7412*****	**0.9369**	7.2514***	0.4628	14.9525***	3.4316***	1.5372*	0.6687	7.7015***	1.4656	3.8342***	7.0708***
13	1.9520**	2.0110**	0.4402***	1.0081	7.2460***	1.0683	13.9137***	3.2098***	1.4150	0.6216	**7.2934*****	**1.5785***	3.5548***	6.5120***
14	1.7944**	1.8630**	17.1344***	0.9711	6.8771***	0.9975	12.8737***	2.9849***	1.2971	0.5679	6.4758***	1.4360	3.2992***	6.1554***
21	1.5836**	1.5255*	11.5344***	0.8906	4.80775***	0.8739	8.7156***	2.2826***	1.2767	0.8982	5.6831***	2.1995***	2.6815***	4.3135***

Nb: IE indicates Index to ETF causality and EI indicates ETF to Index causality. In bold is the optimal lag selection per the AIC and HQ information criterion.

The results of Brazil indicate that ETF returns granger cause index returns up to 14 lags whereas the index returns granger causes ETF returns from the twelfth lag. In the short term, this suggests that ETF returns contain predictive information about future index returns. It implies that the ETF market incorporates information faster than the underlying index. ETFs appear to play a significant role in price discovery, potentially leading the price formation process. This could be due to ETFs being more accessible to a wider range of investors or having lower transaction costs. The difference in short-term and long-term Granger causality patterns suggests complex dynamics between ETFs and indices. Index returns Granger cause ETF returns only from lag 12 onwards, indicating a delayed feedback effect from the index to the ETF. It suggests that while ETFs lead in the short term, there's a longer-term adjustment process where the index influences ETF pricing. The 12-lag delay implies about 2-3 weeks of trading days before this effect becomes significant.

In the case of the Philippines and Taiwan, the index returns granger causes the ETF returns, which suggests that information is incorporated into the index faster than into the ETF. Unlike Brazil, there is no bidirectional causation, which suggests microstructural differences between the ETF and Index that do not reconcile in the short term. For example, the index is more liquid than the ETF, making it easier to trade than the ETF that could have higher transaction costs or management fees. It is possible, given that ETFs are a relatively new asset class, that they are not yet popular in these countries and so investors prefer to trade the index. The general analysis leads to the conclusion that ETFs do not increase market efficiency because it would be expected that there is no granger causality between the two assets or that the ETF would lead the index. However, price discovery happens in the index rather than the ETF. Taiwan indicates index leading the ETF up to twelve lags, suggesting a short-term predictive relationship. The twelve-day lag approximates a two-week trading period, suggesting that it is the length of time it takes for the arbitrage mechanism to kick in. Alternatively, it could relate to the short-term market frictions that correct in the long term.

There is a bidirectional granger causality for South Africa and Greece that persists into the long term. Bidirectional Granger causality between index returns and ETF returns implies a complex, interdependent relationship where both markets significantly influence each other. This suggests a sophisticated information flow and price discovery process occurring simultaneously in both markets, indicating a high degree of market integration and efficiency. It reflects active arbitrage and a dynamic feedback loop between the two, where neither consistently leads the other. This relationship complicates modelling and trading strategies, as it requires considering mutual influences and potential feedback effects. The bidirectional nature may also contribute to market volatility and has implications for regulatory approaches. It suggests that investors are actively using information from both markets, leading to a more intricate market structure where both the index and ETF play equally important roles in price formation.

Thailand reveals a pattern where the index consistently granger causes ETF returns, while ETFs only granger cause the index at inconsistent lags, showing a complex and asymmetric relationship between these markets. This suggests that while the index generally leads in price discovery and information processing, ETFs occasionally play a significant role in influencing market dynamics. The consistent index-to-ETF causality indicates that the index remains the primary reference point for market movements. However, the sporadic ETF-to-index causality implies that ETFs sometimes capture unique market information or sentiment not immediately reflected in the index. This asymmetric relationship points to an evolving market structure where ETFs are growing in importance, albeit not uniformly.

6.6 Variance Ratio Test

The variance ratio (VR) is a statistical measure used to test the random walk hypothesis (RWH) in financial markets. The RWH posits that asset prices evolve according to a random process, implying that future price movements are independent of past movements and cannot be predicted based on historical data. The variance ratio test assesses whether the observed variance of returns over multiple periods is consistent with the variance expected under a random walk. Specifically, it tests whether a time series, $x_t = y_t - y_{t-1}$, is i.i.d or follows a martingale difference sequence.

The variance ratio is defined as the ratio of the variance of returns over a longer time horizon (k periods) to the variance of returns over a single period. Mathematically, it can be expressed as:

$$V(k) = \frac{Var(x_t + x_{t-1} + \cdots + x_{t-k+1})/k}{Var(x_t)}$$

$$= \frac{Var(y_t - y_{t-k})/k}{Var(y_t - y_{t-1})} = 1 + 2\sum_{i=1}^{k-1}\left(\frac{(k-i)}{k}\right)\rho_i \qquad (6.5)$$

The variance ratio V(k) can be expressed as a weighted sum of the first (k - 1) autocorrelation coefficients of the time series. The weights assigned to each autocorrelation coefficient decrease linearly as the lag increases. This formulation provides an alternative interpretation of the variance ratio test, linking it directly to the autocorrelation structure of the time series under examination. $\left(\frac{(k-i)}{k}\right)$ are the linearly declining weights. ρ_i represents the i^{th} order autocorrelation coefficient. The fundamental principle underlying the variance ratio test is rooted in a key property of uncorrelated time series, particularly those adhering to the random walk hypothesis. For a series of returns that exhibit no serial correlation, the variance of k-period returns should scale linearly with the time horizon k. Specifically, the variance of the sum of k consecutive one-period returns should be exactly k times the variance of a single-period return. Under the null hypothesis of uncorrelated returns, V(k) should equal unity for all values of k. Any significant deviation of V(k) from 1 suggests the presence of serial correlation in the return series, thereby challenging the random walk hypothesis.

Various steps were taken to ensure robustness of the analysis. Certain parameters were specified for analysing the stochastic properties of the data. Firstly, by utilising returns data instead of price levels, the analysis addresses the inherent non-stationarity often present in financial time series, thereby aligning with the stationarity assumption underlying the variance ratio test. This approach facilitates a more direct examination of asset return behaviour, which is typically of greater interest in financial economics than raw price movements. Furthermore, heteroskedasticity-robust standard error estimates were incorporated to account for the volatility clustering tendency of financial data. This adjustment enhances the reliability of test statistics and p-values, thereby mitigating the risk of Type I errors in the presence of time-varying volatility.

The allowance for drift through a data demeaning approach to modelling financial returns recognises the potential for a non-zero drift term in the random walk model. This specification evaluates random walk behaviour around a potentially non-zero mean, providing a less restrictive and more realistic representation of financial market dynamics. The application of unbiased variance estimators further enhances the analysis by correcting for small-sample bias, thereby improving the accuracy of variance ratio estimates, particularly in situations where the sample size may be insufficient to rely on asymptotic properties.

These methodological choices collectively contribute to a more robust and economically relevant analysis. The results derived from this approach are likely to be more resilient to common statistical issues in financial time series analysis, such as heteroskedasticity and small sample biases. This enhanced robustness increases the confidence in the findings and their implications for market efficiency. The interpretation of results should focus on detecting predictable patterns in returns that deviate from the expectations under a random walk with drift hypothesis. Any significant deviations identified through this method are less likely to be attributable to statistical artefacts, given the conservative nature of the heteroskedasticity-robust inference.

Table 35: Variance Ratio Results

	lags	Brazil	Chile	Greece	Philippine
Pre-ETF	5	0.2031***	0.2430***	0.2290***	0.2387***
	10	0.0982***	0.1219***	0.1139***	0.1348***
	15	0.0664***	0.0781***	0.0737***	0.1196***
	21	0.0484***	0.0576***	0.0571***	0.1227***
Post-ETF	5	0.1833***	0.2129***	0.2126***	0.2141***
	10	0.0910***	0.1151***	0.1058***	0.1021***
	15	0.0618***	0.0760***	0.0686***	0.0671***
	21	0.0444***	0.0532***	0.0494***	0.0492***

Results of the VR test indicate significance at all levels and all lags for all countries, suggesting reliability. All variance ratio values are less than 1, indicating mean-reverting behaviour in both periods. The variance ratios decrease as the lag increases in both periods, which is a typical pattern. The next section provides more specific observations for each country and, where necessary, with added context of previous results.

Brazil

VR results indicate stronger mean reversion post ETF at all lags in the short term. This mean reversion effect is stronger at shorter lags and decreases at longer lags. Both pre-ETF and post-ETF periods show significant deviations from the random walk hypothesis, indicating market inefficiency in both periods. The consistently lower VRs in the post-ETF period suggest that the introduction of ETFs has increased the strength of mean reversion in the Brazilian market and thus decreased market efficiency post-ETF, as efficient markets should exhibit more random walk-like behaviour. The effect appears to be more pronounced at shorter lags (5 and 10) and diminishes somewhat at longer lags (15 and 21), suggesting that the impact of ETFs might be stronger on short-term price dynamics.

The persistence of low variance ratios at higher lags in both periods indicates that there might be longer-term inefficiencies in the Brazilian market that were not significantly altered by the introduction of ETFs. This coincides with the cointegration results that indicated non-significance of ETF activity on market efficiency for AR and marginal significance for the EDGE. Additionally, similar to the VR results, the cointegration results indicated quick adjustment to ETF shocks. In the VR results, by 21 days, market efficiency is similar, just as the ARDL indicated that within one month (approx. 21 days of trading) 71% of any disequilibrium is corrected. The increased short-term inefficiency could be due to the ETF leading the price discovery process (per the granger causality results above), causing short-term overshooting or undershooting, resulting in mean reversion. In other words, the easier tradability of ETFs might be allowing for overreaction to new information in the short term, leading to the observed mean reversion. So, while ETFs seem to enhance information flow (as per Granger causality), they also appear to introduce or exacerbate some short-term inefficiencies (as per VR test)

Chile

VR results for Chile are similar to those of Brazil in that there is a stronger mean reversion tendency post-ETF that is strongest up to two weeks of trading. However, while these results are similar to Brazil, the granger causality and ARDL results suggest a different mechanism through which ETFs decrease market efficiency. Firstly, in the case of Chile, the index returns lead the price discovery process rather than the ETF. Secondly, the cointegration results revealed that decreases in ETF activity resulted in wider spreads. The combined results of the analysis suggest that while ETFs do not lead the price discovery process, they do impact market efficiency through liquidity provision in the long term. This suggests that in Chile, ETFs may be more important for their role in liquidity provision than for price discovery. ETFs in Chile are primarily used by investors for passive exposure or liquidity management rather than active trading or arbitrage.

The lack of bidirectional causality between ETFs and the underlying index implies that ETF trading does not significantly contribute to price discovery or exploiting short-term arbitrage opportunities. This is consistent with a market where ETFs are not primarily used for active trading strategies. The VR indicating a decrease in market efficiency, coupled with the small yet significant impact of ETF activity on spreads in the short run ARDL, may represent a small subset of more active ETF traders or institutional investors engaging in rebalancing activities. The small short-term impact could also indicate that while ETF activity does influence spreads, the market has sufficient depth to absorb most of this activity without significant price impacts. This would be consistent with ETFs being used more for liquidity management than for speculative trading.

Philippines

The results for the Philippines are similar to those of Chile in terms of VR trend, indicating more mean reversion post-ETF and the unidirectional granger causality from index to ETF. However, the ARDL results indicate positive and significant effect of ETF activity on spreads in the short run and the long run. Accordingly, similar conclusions are drawn about the effects of ETF on market efficiency. Short run effects of the VR indicate reduced efficiency in line with the ARDL results, which also shows that ETF activity is associated with wider spreads. The short-term effects of ETF activity are more pronounced compared to Chile, suggesting that ETFs in the Philippines have a greater price impact in the short term than Chile.

The integrated findings reveal, similar to Chile, that ETFs are used for passive exposure or liquidity management rather than active trading, with the exception that in the short term, there are more active ETF traders than in Chile, which still does not contribute to the price discovery process. The dominance of passive exposure and liquidity management in the use of ETFs suggests that the Philippine market may not yet be characterised by a high degree of informational efficiency. The absence of active trading and arbitrage activities indicates that price discovery is not being significantly enhanced through ETF trading.

Greece

Post ETF VR test indicates a further departure from the random walk hypothesis compared to the pre-ETF period. The lack of cointegration and the minimal impact in the short run of the ARDL reiterates the lack of impact of ETF activity on market efficiency. Thus, based on the VR and ARDL, ETFs have not significantly altered market efficiency. However, the granger causality results indicate an integration of ETFs in the price formation process, suggesting a market in transition, adapting to the financial instrument that is yet to have a structural impact on the markets.

6.7 Conclusion

This study on the impact of ETFs on market efficiency across multiple countries has yielded valuable insights into the complex dynamics of financial markets in the face of innovation. By employing a multi-faceted methodological approach, including VR tests, ARDL/NARDL models, and Granger causality analyses, a varied landscape of ETF effects on market efficiency is uncovered that underscores the importance of context-specific analysis.

The application of these diverse methodological tools has helped in capturing different aspects of market efficiency. The VR test provided important understanding into the random walk behaviour of asset prices, a fundamental aspect of weak-form market efficiency. This test's ability to detect mean reversion or momentum in price series showcased how ETF introduction has altered the statistical properties of asset returns. The ARDL model, with its capacity to distinguish between short-run and long-run effects, allowed for a multifacted examination of the relationship between ETF activity and market efficiency. This approach revealed both immediate impacts and longer-term equilibrium relationships, providing a more comprehensive view of ETF influence on market microstructure. Granger causality tests complemented these analyses by elucidating the directional relationships between ETFs and underlying indices, offering insights into the evolving nature of price discovery processes across different markets.

Empirically, our findings reveal a heterogeneous impact of ETFs on market efficiency across different countries. While some markets showed signs of improved efficiency post-ETF introduction, others exhibited more complex patterns, including increased mean reversion and evolving causality relationships. This heterogeneity underscores the importance of considering market-specific factors, such as regulatory environments, market maturity, and investor composition, in assessing the impact of financial innovations.

Theoretically, the results contribute to the ongoing debate on the nature of market efficiency. The varied outcomes observed across different markets align more closely with the Adaptive Markets Hypothesis (AMH) proposed by Andrew Lo than with the traditional Efficient Market Hypothesis (EMH). The AMH framework provides a more flexible interpretation of our findings, allowing for periods of apparent inefficiency as markets adapt to new financial instruments. This perspective suggests that market efficiency is not a binary state but a dynamic process that evolves as market participants learn and adapt to new information and trading mechanisms.

From a policy perspective, the findings have significant implications for regulators and policymakers. The varied impact of ETFs across different markets suggests that a one-size-fits-all approach to ETF regulation may be inappropriate. Instead, policymakers should consider market-specific characteristics when designing regulatory frameworks for ETFs. Moreover, the potential for ETFs to temporarily disrupt established efficiency patterns highlights the need for vigilant monitoring of market dynamics following the introduction of new financial instruments.

Practically, this research provides valuable insights for investors and market participants. The evolving nature of price discovery processes and the potential for short-term inefficiencies following ETF introduction suggest opportunities for informed traders. However, the gradual integration of ETFs into market processes also indicates that such opportunities may be transient, underscoring the need for adaptive trading strategies.

Looking forward, several avenues for future research emerge from this study. First, longer-term analyses of markets that have introduced ETFs could provide insights into whether the observed effects are transitional or represent a new equilibrium state. Second, comparative studies across a broader range of markets, including both developed and emerging economies, could help identify the market characteristics that influence the impact of ETFs on efficiency. Third, investigation into the role of specific ETF features (e.g., leveraged or inverse ETFs) on market efficiency could offer more granular insights. Finally, exploring the interaction between ETFs and other financial innovations, such as high-frequency trading or algorithmic trading, could provide a more comprehensive understanding of how modern financial markets evolve.

In conclusion, this study has demonstrated the complex impact of ETFs on market efficiency across different countries. The findings not only contribute to the academic discourse on market efficiency but also offer practical insights for policymakers and market participants navigating the evolving landscape of modern financial markets. As financial innovation continues to reshape global markets, continued research in this vein will be fundamental for understanding and adapting to the changing nature of market efficiency.

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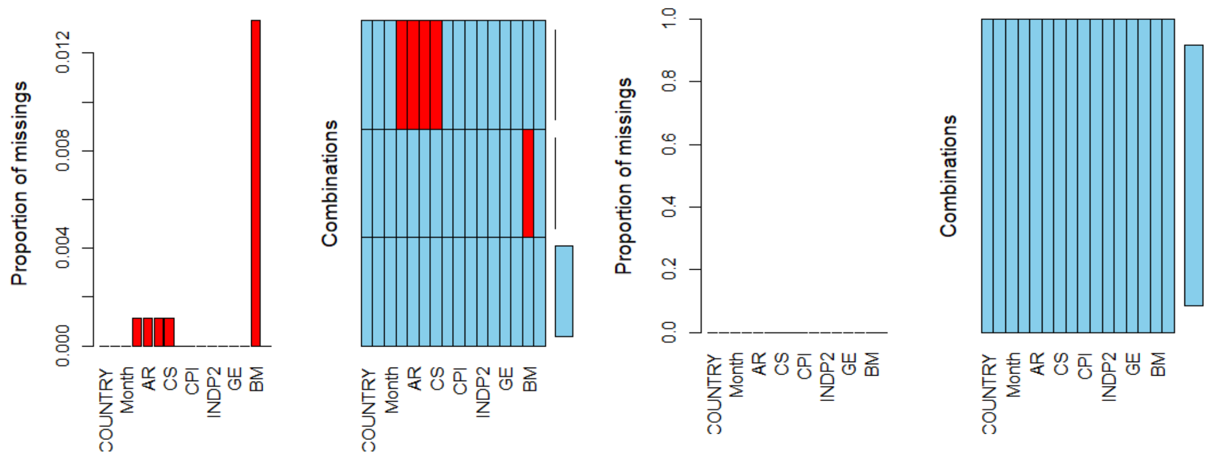
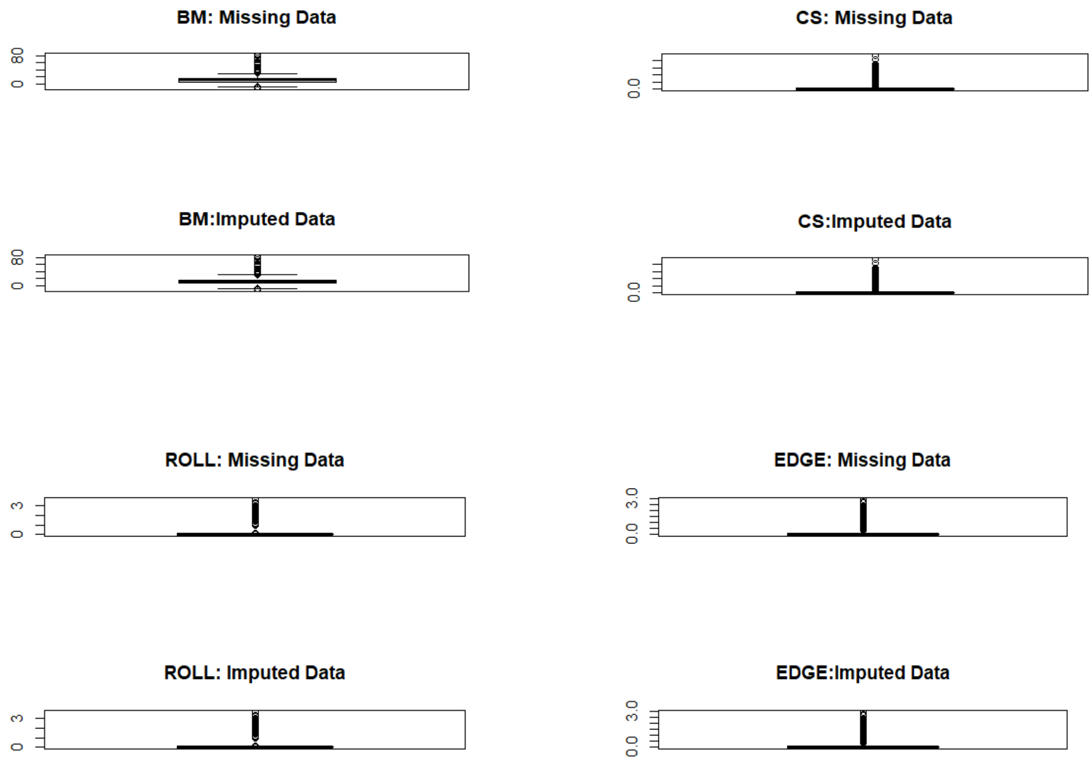
APPENDICES

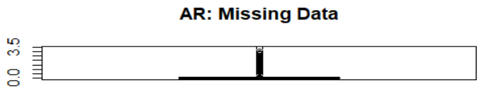
Appendix A: Imputation of Missing Variables

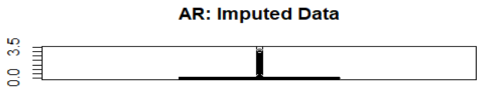
Appendix A.1: Missing Variables



Appendix A.2 Box Plots of Missing vs Imputed Variables







Appendix A.3 T-test for Imputed Variables

	Missing data	Imputed data	Mean Diff	Pr(>|t|)	95% confidence	
BM	13.1697	13.4968	-0.3271	0.5275	-1.3425	0.6882
CS	0.0540	0.0539	0.0001	0.9923	-0.0120	0.01212
ROLL	0.2891	0.2889	0.0002	0.9923	-0.0607	0.0613
EDGE	0.2731	0.2728	0.0003	0.9918	-0.0549	0.0555
AR	0.2927	0.2924	0.0003	0.9917	-0.0589	0.0596

Appendix B: Descriptives Statistics of Spread Estimators of Index and ETF
Table B1: EDGE Index and ETF

	Brazil		**Chile**		**Greece**	
	EDGE	ETFEDGE	EDGE	ETFEDGE	EDGE	ETFEDGE
Mean	0.000805	0.005718	0.000611	0.003240	0.005172	0.013238
Median	0.000695	0.004772	0.000377	0.001375	0.004539	0.005330
Maximum	0.005994	0.046648	0.003725	0.038507	0.015517	0.176296
Minimum	4.64E-05	0.000102	1.22E-12	1.81E-12	0.000234	0.000000
Std. Dev.	0.000657	0.004914	0.000741	0.004891	0.003074	0.020853
Skewness	4.261631	4.932250	1.308376	3.892357	0.979738	2.638416
Kurtosis	29.84953	37.92563	4.372746	24.54520	3.526635	12.05002
Jarque-Bera	65467.31***	108661.4***	725.1052	43580.06	336.8991	8981.030
ADF	-5.9655***	-7.6165***	-6.0934***	-7.2535***	-6.8764***	-6.4325***
Qk(10)	15189***	11160***	13997***	12014***	11829***	12546***
Sum	1.593801	11.32138	1.218549	6.456713	10.15750	25.99909
Sum Sq. Dev.	0.000854	0.047792	0.001094	0.047654	0.018543	0.853632
Observations	1980	1980	1993	1993	1964	1964

	Philippines		**South Africa**		**Taiwan**	
	EDGE	ETFEDGE	EDGE	ETFEDGE	EDGE	ETFEDGE

Mean	0.003889	0.005074	0.000173	0.009249	0.000425	0.003207
Median	0.003253	0.004277	0.000000	0.008534	0.000000	0.002862
Maximum	0.042639	0.032861	0.006366	0.025260	0.006201	0.011482
Minimum	0.000116	0.000114	0.000000	0.000190	0.000000	5.90E-05
Std. Dev.	0.004132	0.003723	0.000648	0.004506	0.001008	0.001876
Skewness	6.513164	2.141438	6.839940	0.588493	3.055985	1.090050
Kurtosis	55.79314	9.498723	56.19945	2.924084	13.30655	4.323053
Jarque-Bera	239993.7	4916.787	251317.7	115.8638	11612.12	525.9544
ADF	-7.5326***	-6.6392***	-8.6996***	-7.8736***	-9.0888***	-7.0332***
Qk(10)	12362***	13555***	12643***	13224***	9016.4***	7310.4***
Sum	7.575691	9.883292	0.345526	18.48945	0.825475	6.224248
Sum Sq. Dev.	0.033248	0.026982	0.000838	0.040565	0.001972	0.006826
Observations	1948	1948	1999	1999	1941	1941

	Thailand		Qatar	
	EDGE	ETFEDGE	EDGE	ETFEDGE
Mean	0.003193	0.004034	0.002558	0.022271
Median	0.002524	0.003560	0.002367	0.013301
Maximum	0.036979	0.018340	0.013359	0.090246
Minimum	7.65E-05	0.000112	0.000158	0.000377
Std. Dev.	0.003488	0.002527	0.001543	0.019645
Skewness	5.883209	1.950910	2.159955	0.981015
Kurtosis	46.05679	8.552153	11.82701	3.044637
Jarque-Bera	161462.2	3732.018	4760.480	189.8497
ADF	-6.1449***	-8.4569***		
Qk(10)	13763***	8530.9***	4907.4***	5766.5***
Sum	6.209797	7.845674	3.025936	26.34694
Sum Sq. Dev.	0.023647	0.012416	0.002816	0.456153
Observations	1945	1945	1183	1183

Table B2: ROLL Index and ETF

	Brazil		Chile		Greece	
	ROLL	ETFROLL	ROLL	ETFROLL	ROLL	ETFROLL
Mean	0.011726	0.012105	0.008068	0.009084	0.012550	0.012656
Median	0.010266	0.010547	0.006782	0.007441	0.010207	0.010266
Maximum	0.120669	0.114698	0.069694	0.051415	0.068307	0.073796
Minimum	0.000139	0.000269	0.000172	0.000175	0.000292	0.000000
Std. Dev.	0.011195	0.010925	0.006912	0.006483	0.009841	0.009593
Skewness	6.586899	6.050417	3.768944	1.900526	2.166874	1.693763

Kurtosis	58.06381	51.72131	26.25189	8.718065	8.655283	7.159288
Jarque-Bera	264459.7***	207916.2***	49614.92***	3914.939***	4154.155***	2354.755***
ADF	-8.1933***	-7.6573***	-7.1439***	-7.9419***	-7.0353***	-6.4517***
Qk(10)	11347***	11668***	11421***	8494.5***	10452***	9479.3***
Sum	23.21680	23.96733	16.07872	18.10471	24.64876	24.85566
Sum Sq. Dev.	0.248018	0.236210	0.095160	0.083721	0.190115	0.180653
Observations	1980	1980	1993	1993	1964	1964

	Philippines		**South Africa**		**Taiwan**	
	ROLL	ETFROLL	ROLL	ETFROLL	ROLL	ETFROLL
Mean	0.008841	0.007976	0.008788	0.008840	0.007461	0.007254
Median	0.008042	0.007221	0.007516	0.008060	0.006637	0.006394
Maximum	0.059900	0.043673	0.054857	0.047596	0.042328	0.045209
Minimum	0.000160	0.000270	0.000164	0.000267	9.47E-06	0.000212
Std. Dev.	0.005725	0.004568	0.005828	0.004943	0.004645	0.004882
Skewness	3.071820	1.999665	2.552493	1.474514	1.809102	2.264394
Kurtosis	20.27797	12.39800	14.75768	8.567170	9.093768	11.46213
Jarque-Bera	27294.13***	8467.061***	13685.14***	3305.858***	4061.980***	7450.003***
ADF	-6.4388***	-7.2623***	-7.0776***	-7.36***	-8.1249***	-7.6198***
Qk(10)	9235.6***	6496.7***	7425.6***	8446.4***	6336.7***	5768.5***
Sum	17.22296	15.53674	17.56684	17.67039	14.48100	14.08084
Sum Sq. Dev.	0.063807	0.040631	0.067874	0.048823	0.041861	0.046233
Observations	1948	1948	1999	1999	1941	1941

	Thailand		**Qatar**	
	ROLL	ETFROLL	ROLL	ETFROLL
Mean	0.007088	0.006006	0.006233	0.009678
Median	0.005428	0.004872	0.005419	0.006563
Maximum	0.069201	0.054724	0.028077	0.053010
Minimum	0.000219	5.37E-05	0.000196	0.000219
Std. Dev.	0.007324	0.005781	0.003752	0.010009
Skewness	4.777012	4.903212	1.300285	2.521122
Kurtosis	32.61333	35.55027	5.548180	9.215839
Jarque-Bera	78466.85	93658.71	653.4194	3157.668
ADF	-6.0841***	-6.2943***	-5.3083***	-5.6534***
Qk(10)	14170***	12562***	5197.5***	3667***
Sum	13.78576	11.68262	7.374228	11.44946
Sum Sq. Dev.	0.104264	0.064960	0.016643	0.118414
Observations	1945	1945	1183	1183

Table B3: CS Index and ETF

	Brazil		Chile		Greece	
	CS	ETFCS	CS	ETFCS	CS	ETFCS
Mean	0.002426	0.002006	0.001956	0.002378	0.002625	0.001009
Median	0.001998	0.001646	0.001436	0.001944	0.001710	5.78E-05
Maximum	0.015389	0.009345	0.011781	0.016685	0.022373	0.018415
Minimum	1.14E-06	4.65E-08	9.57E-07	1.21E-06	3.54E-07	0.000000
Std. Dev.	0.001950	0.001505	0.001794	0.002148	0.003124	0.002220
Skewness	1.585112	0.994880	1.590390	2.446165	2.992499	4.200639
Kurtosis	7.256988	3.930863	5.988812	12.62242	14.11397	25.16613
Jarque-Bera	2324.212***	398.1162***	1581.974***	9676.496***	13039.37***	45983.68***
ADF	-8.0118***	-8.8255***	-7.0817***	-6.6735***	-7.2046***	-7.3789***
Qk(10)	7240.1***	6107.5***	10990***	9050.5***	12494***	12725***
Sum	4.804210	3.971515	3.899130	4.738463	5.154869	1.981518
Sum Sq. Dev.	0.007527	0.004485	0.006414	0.009189	0.019157	0.009678
Observations	1980	1980	1993	1993	1964	1964

	Philippines		South Africa		Taiwan	
	CS	ETFCS	CS	ETFCS	CS	ETFCS
Mean	0.001916	0.001981	0.001677	0.002533	0.001934	0.001343
Median	0.001380	0.001374	0.001230	0.002059	0.001480	0.001008
Maximum	0.024150	0.016568	0.012125	0.012470	0.013915	0.007931
Minimum	1.04E-06	3.30E-07	1.87E-07	3.93E-06	1.15E-06	7.61E-07
Std. Dev.	0.002444	0.002226	0.001583	0.002017	0.001823	0.001208
Skewness	5.078065	3.103853	2.129127	1.472446	1.897001	1.594621
Kurtosis	37.38876	15.93503	9.869368	5.712791	8.041898	5.941521
Jarque-Bera	104358.7***	16708.21***	5440.690***	1335.301***	3220.053***	1522.376***
ADF	-6.8235***	-6.2068***	-8.5455***	-8.9237***	-7.8116***	-7.0322***
Qk(10)	13685***	13629***	8446.4***	10353***	10448***	8414.9***
Sum	3.732012	3.858489	3.351722	5.063105	3.754841	2.606331
Sum Sq. Dev.	0.011631	0.009643	0.005010	0.008127	0.006447	0.002832
Observations	1948	1948	1999	1999	1941	1941

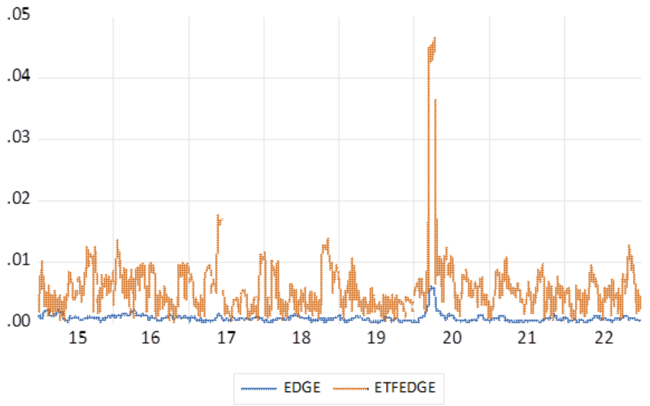
	Thailand		Qatar	
	CS	ETFCS	CS	ETFCS
Mean	0.001322	0.001340	0.001463	0.001051
Median	0.001084	0.000972	0.000997	0.000419
Maximum	0.008935	0.006158	0.008791	0.009885
Minimum	2.14E-07	3.30E-06	5.05E-07	3.63E-19
Std. Dev.	0.001080	0.001193	0.001449	0.001505
Skewness	1.534884	1.235913	1.847370	2.667389

Kurtosis	6.545755	4.088731	7.112285	11.71402
Jarque-Bera	1782.581***	591.2198***	1506.452***	5145.750***
ADF	-7.5934***	-6.5935***	-5.8246***	-5.7372***
Qk(10)	7743***	9401.6***	6195.7***	3401.6***
Sum	2.572144	2.607173	1.730379	1.243706
Sum Sq. Dev.	0.002266	0.002766	0.002483	0.002679
Observations	1945	1945	1183	1183

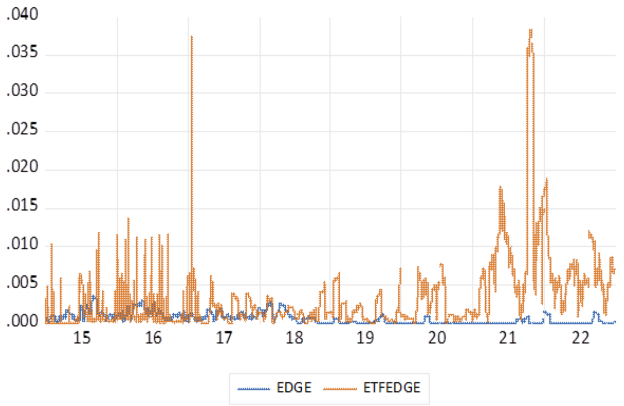
Appendix C: Plots of Index and ETF

Figure C1: EDGE Plots of Index and ETF

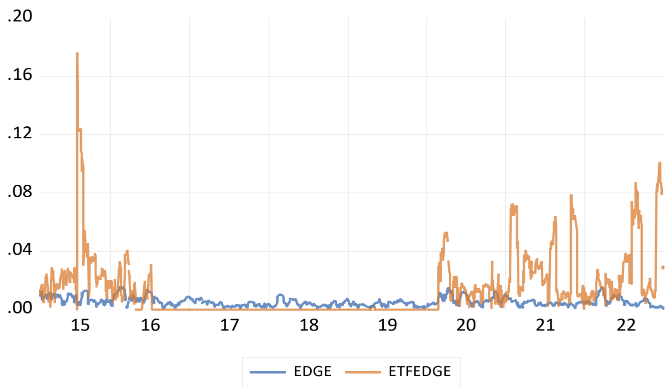
Brazil



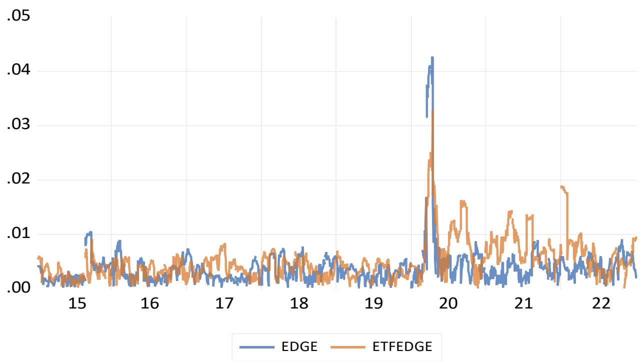
Chile



Greece

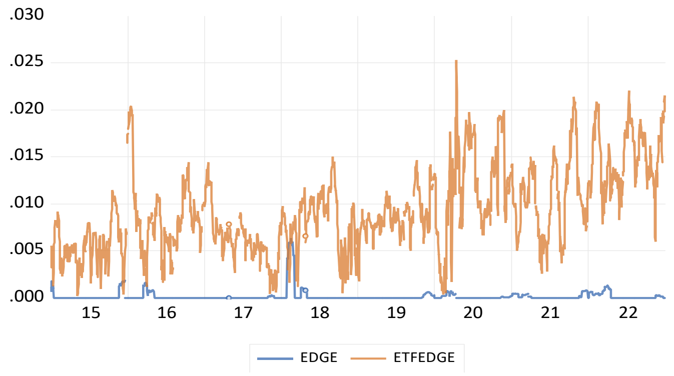


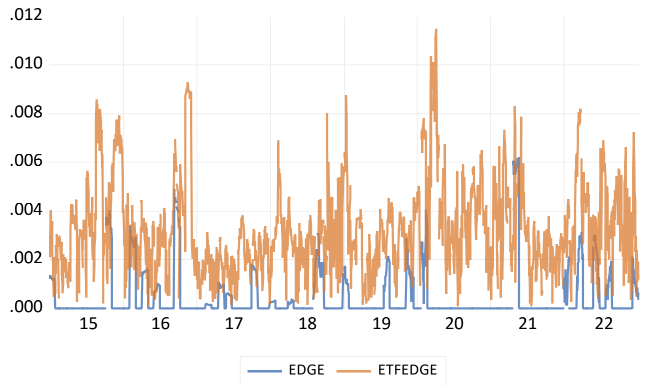
Philippines



South Africa

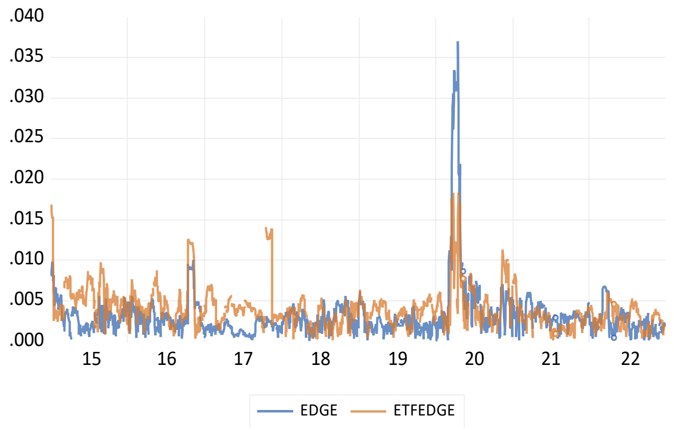
Taiwan





Thailand

Qatar



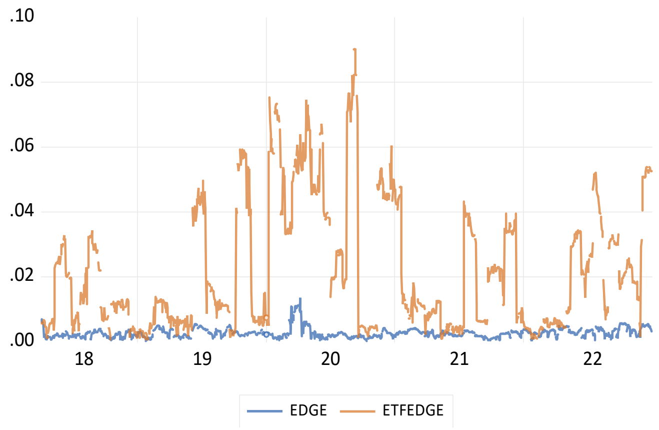
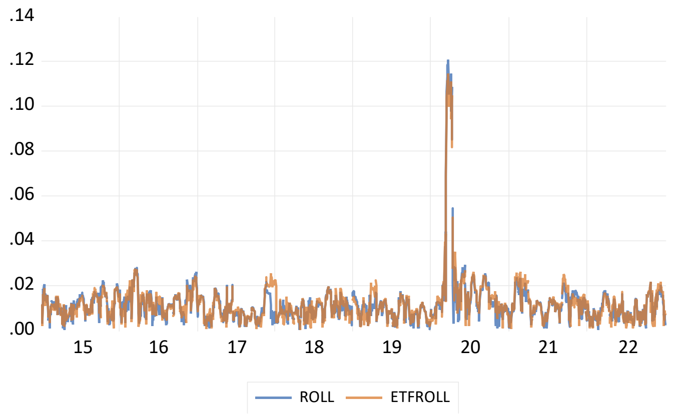
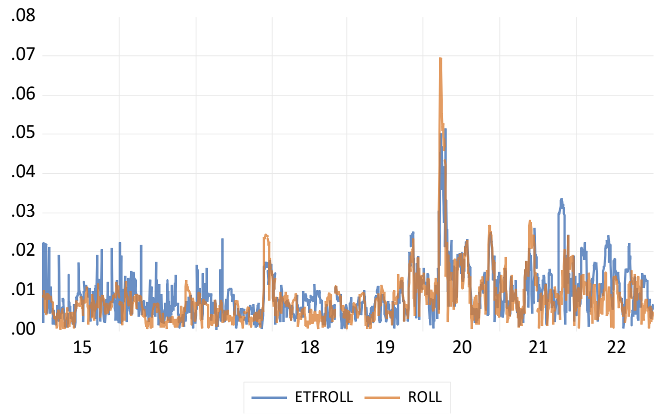


Figure C2: ROLL Plots of Index and ETF

Brazil

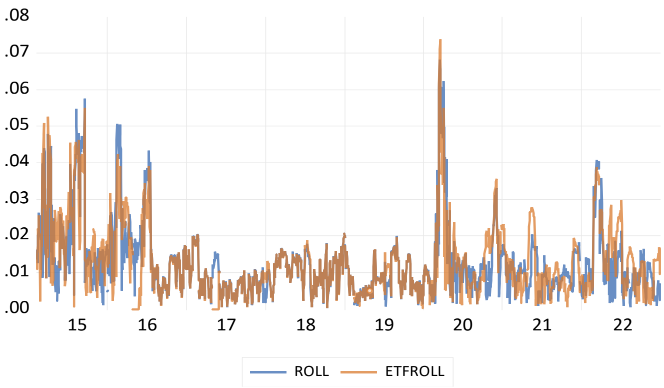
Chile

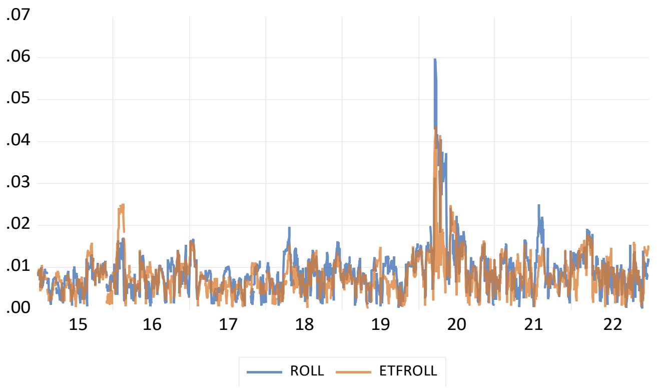




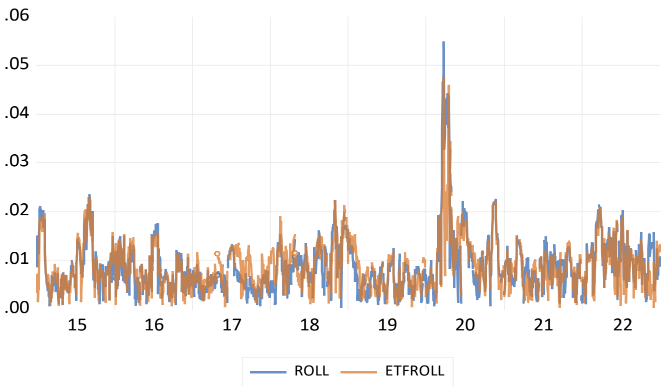
Greece

Philippines

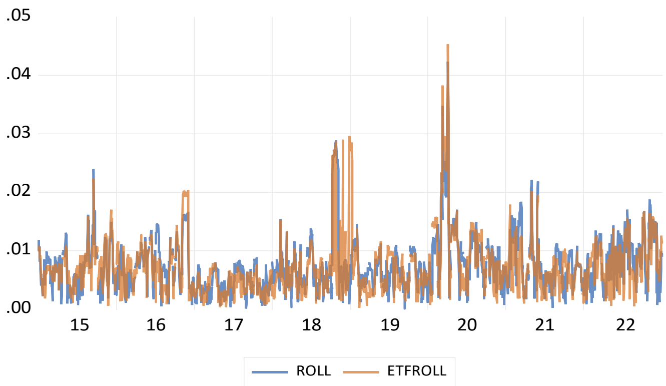




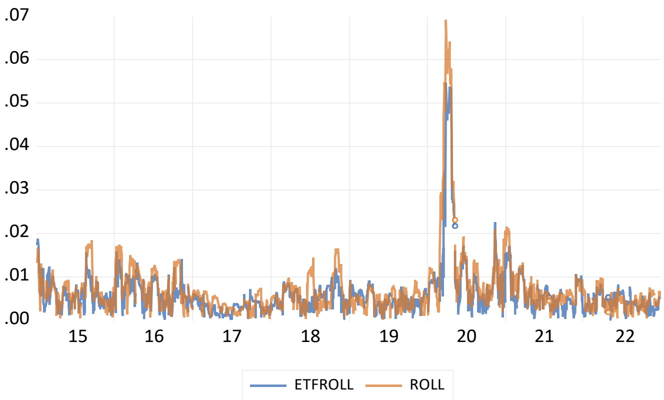
South Africa



Taiwan



Thailand



Qatar

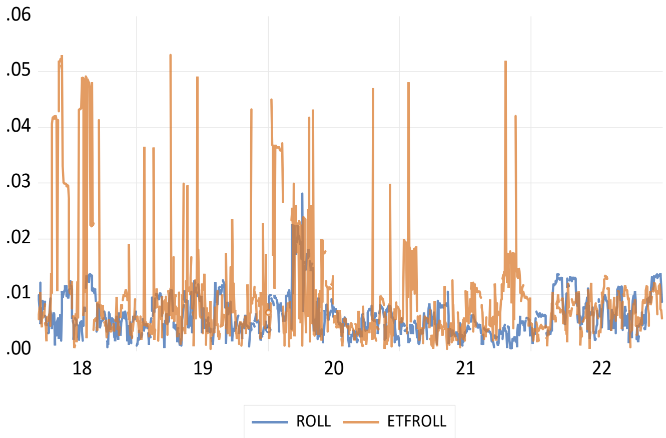
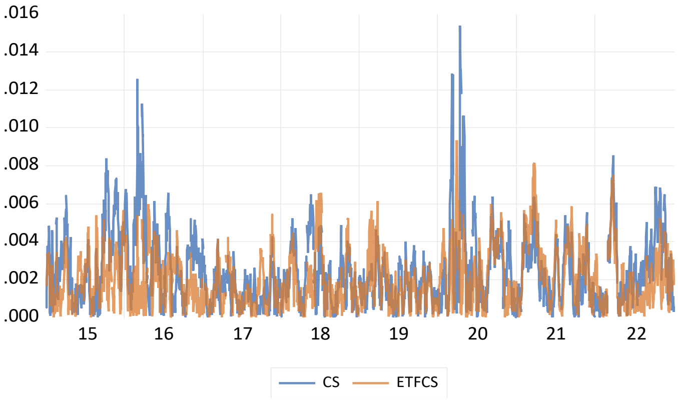
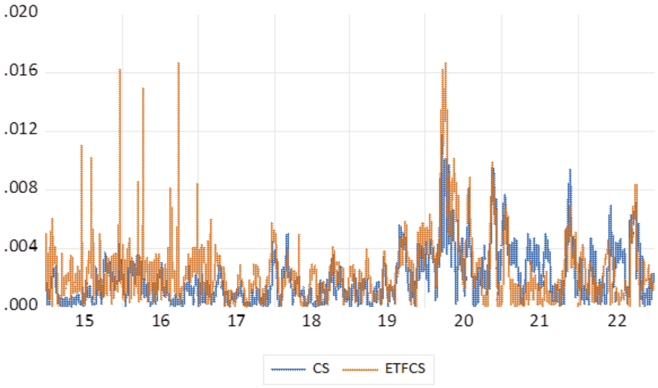


Figure C3: CS Plots of Index and EDGE

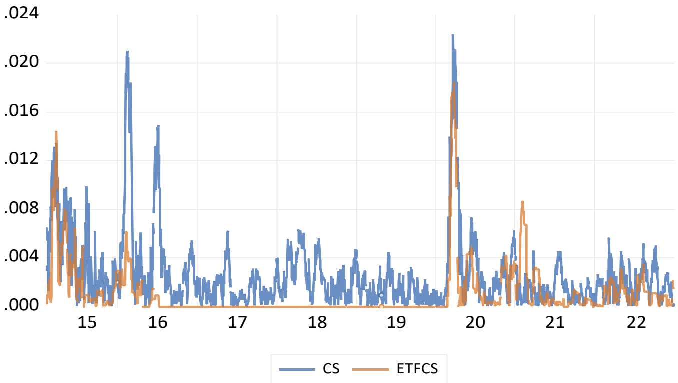
Brazil



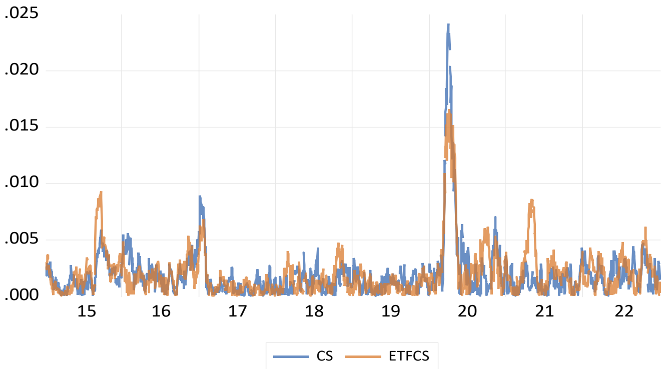
Chile



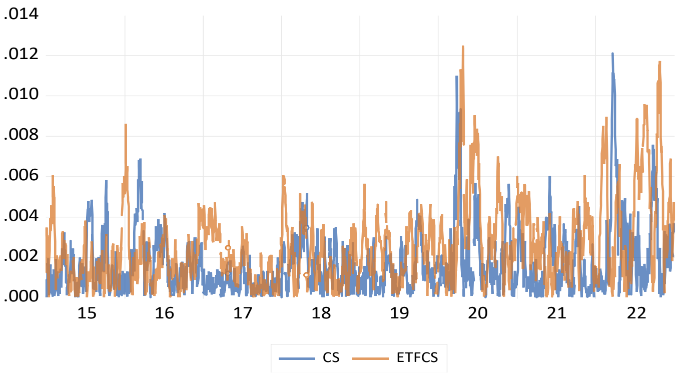
Greece



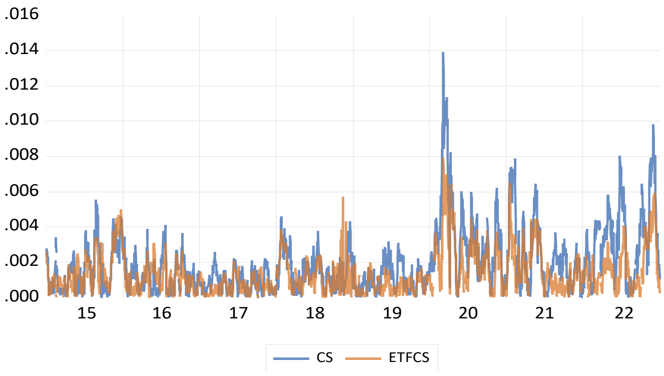
Philippines



South Africa

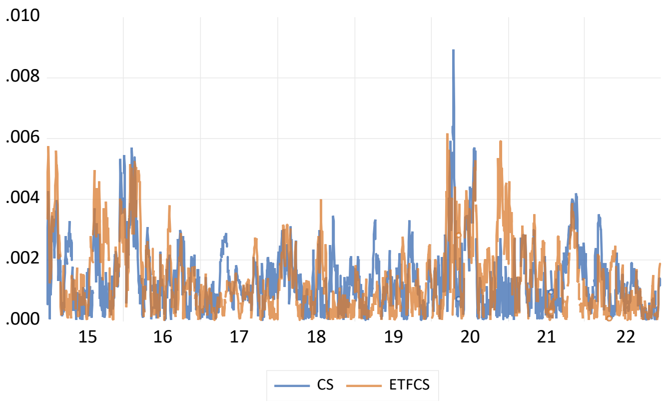


Taiwan



Thailand

Qatar


.010
.008
.006
.004
.002
.000
15
16
17
18
19
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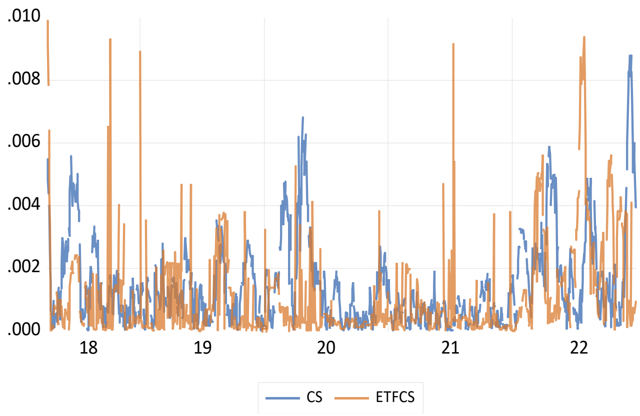
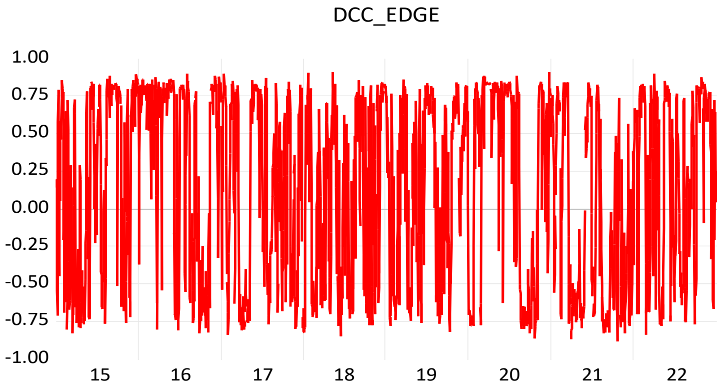
21
22
CS
ETFCS

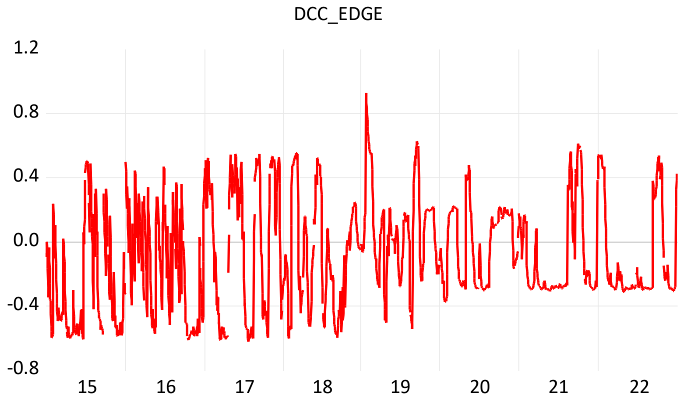

.010
.008
.006
.004
.002
.000
18
19
20
21
22
CS
ETFCS

Appendix D: DCC-GARCH Plots

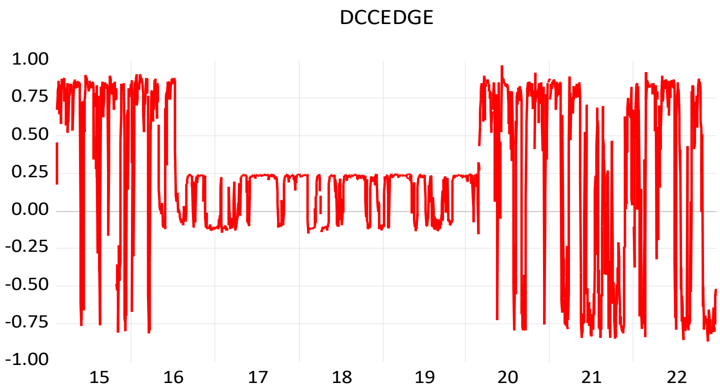
Brazil



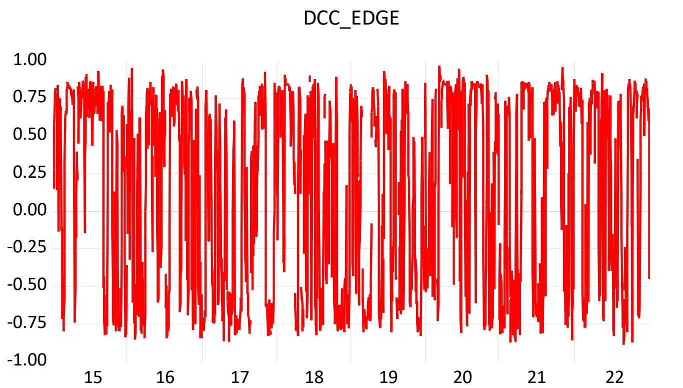
Chile



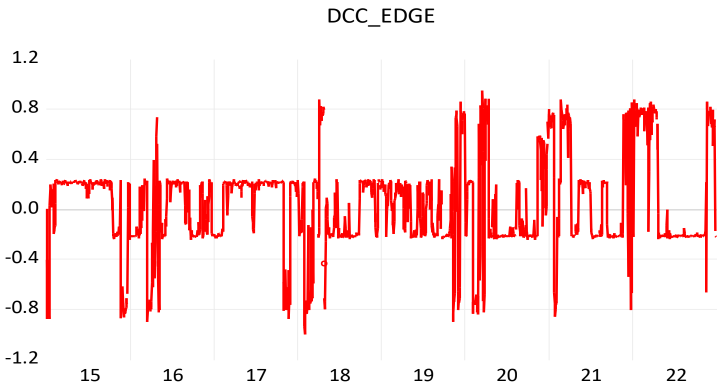
Greece



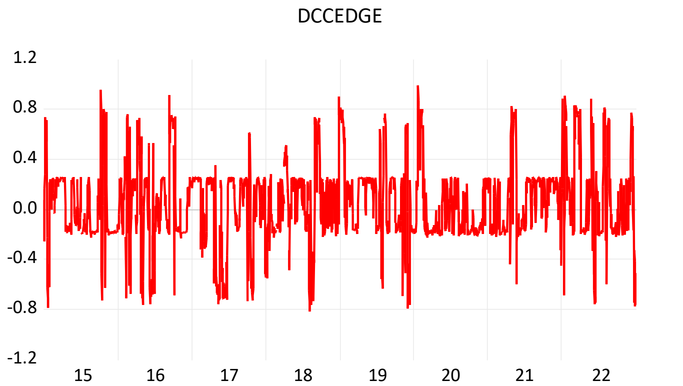
Philippines



South Africa



Taiwan



Thailand

Qatar

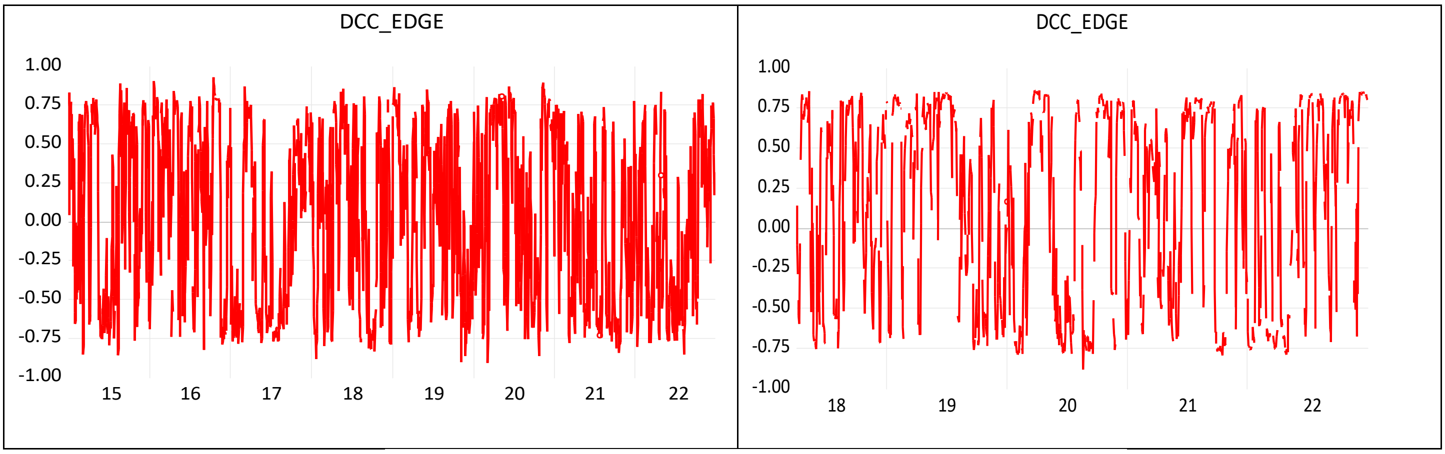
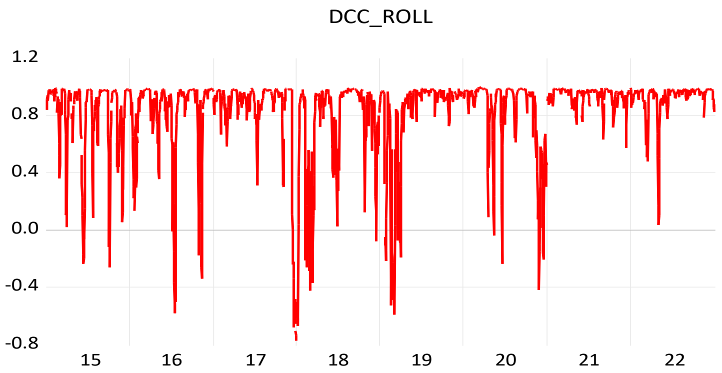
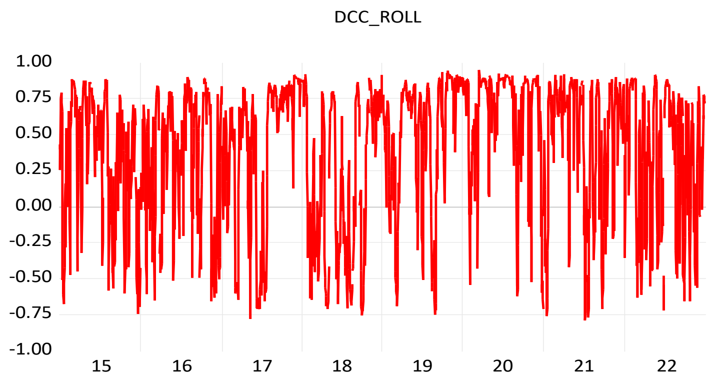


Figure D1. EDGE Dynamic correlation between ETF and Index liquidity

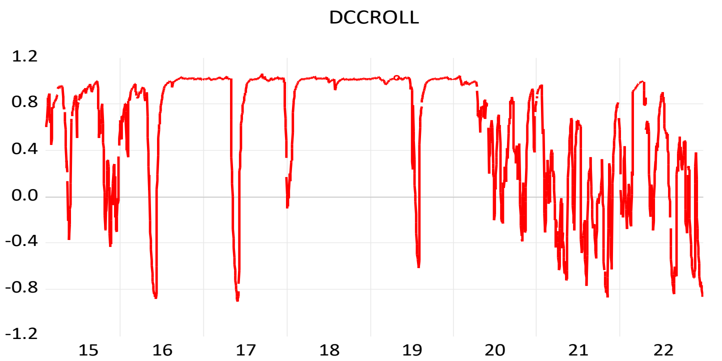
Brazil



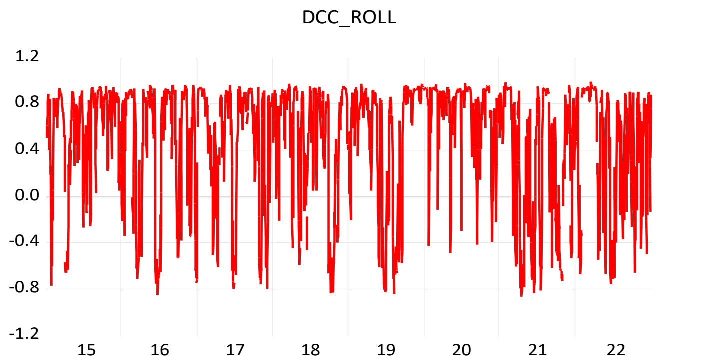
Chile



Greece



Philippines



South Africa

Taiwan

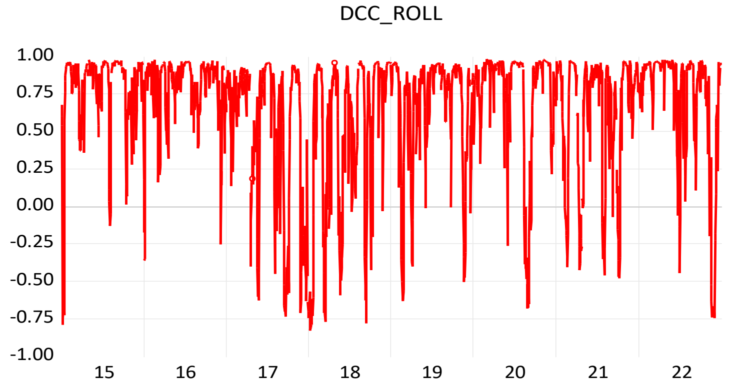
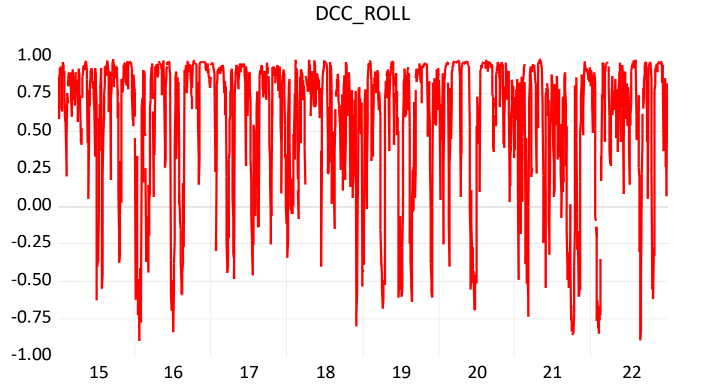
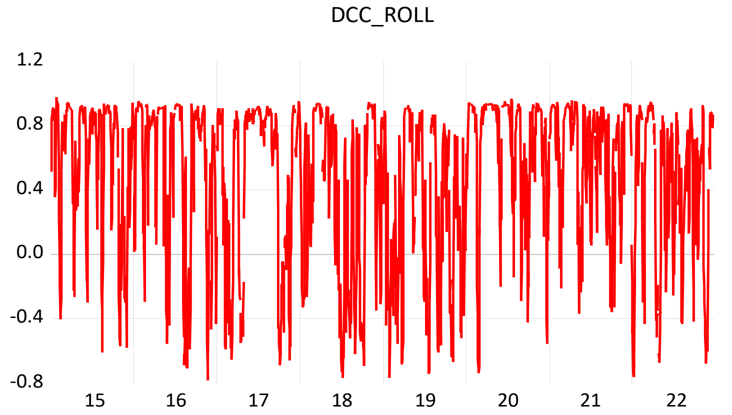
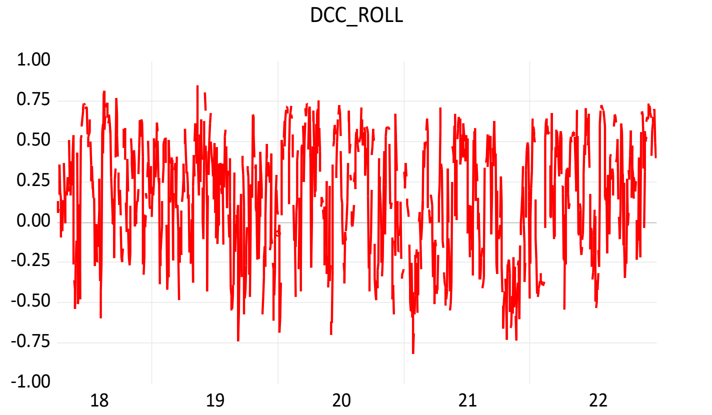
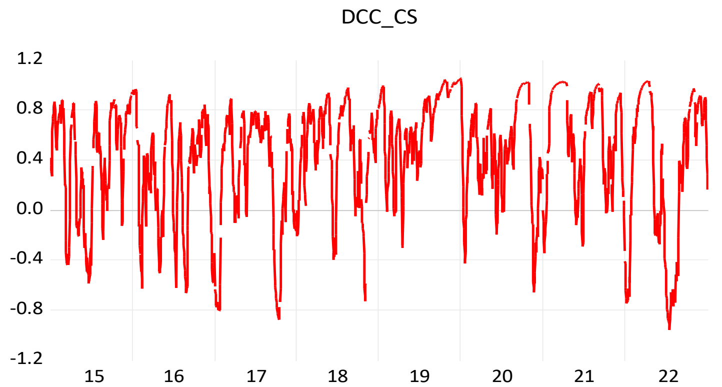
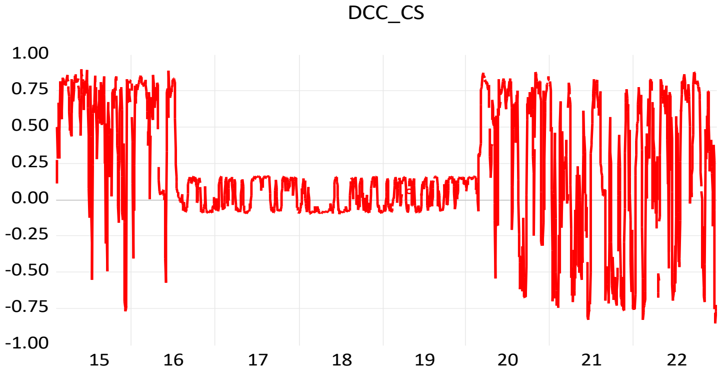
	
Thailand 	Qatar 

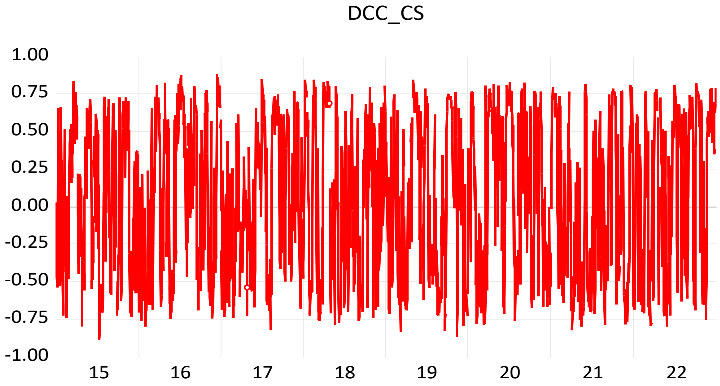
Figure D2. ROLL Dynamic correlation between ETF and Index liquidity

Brazil 	Chile Non-converged
Greece	Philippines

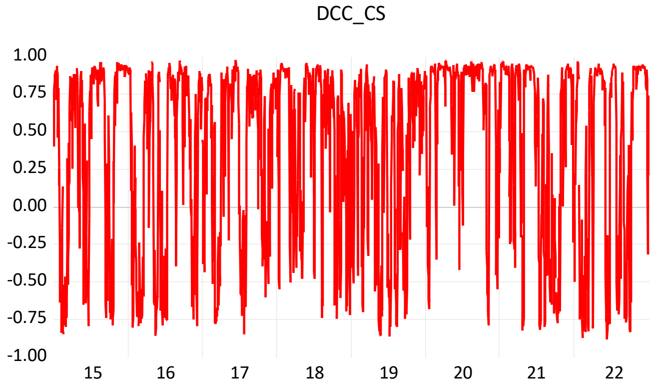


Non-converged

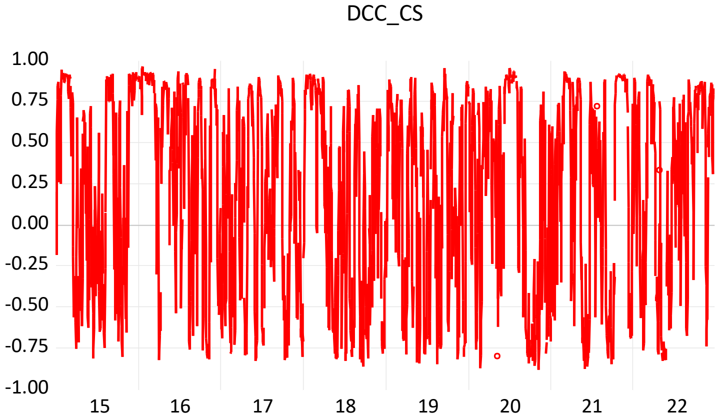
South Africa



Taiwan



Thailand



Qatar

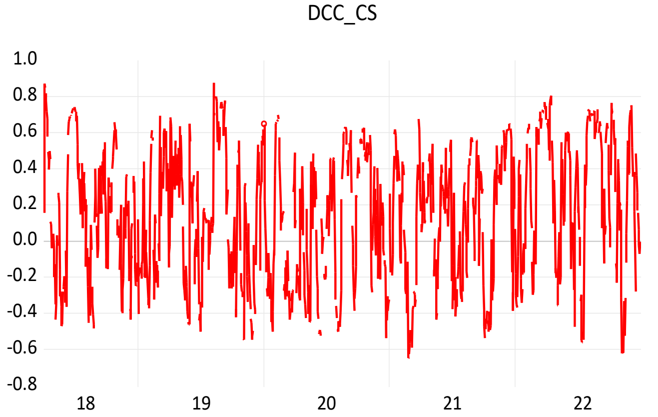


Figure D3. CS Dynamic correlation between ETF and Index liquidity

Appendix E: DCC Descriptive Statistics

Table E1: AR DCC Descriptives

	Brazil	Chile	Greece	South Africa	Thailand	Qatar
Mean	0.6062	0.3139	0.1733	0.2943	0.4398	0.1736
Median	0.8075	0.4245	0.1535	0.4720	0.6454	0.2324
Maximum	0.9808	0.9515	0.9333	1.5172	0.9521	0.8319
Minimum	-0.8058	-0.8514	-0.8987	-1.2184	-0.8602	-0.7183
Std. Dev.	0.4456	0.4769	0.5202	0.6215	0.4936	0.3929
Skewness	-1.5223	-0.6132	-0.2350	-0.6553	-0.9961	-0.3114
Kurtosis	4.2863	2.1897	2.2435	2.2011	2.7161	1.7917
Jarque-Bera	901.2502	179.4212	64.9197	196.2244	328.1478	91.0813
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	1200.217	625.5780	340.4446	588.3603	855.4495	205.3815
Sum Sq. Dev.	392.9163	453.0991	531.1792	771.7155	473.5878	182.4747
Observations	1980	1993	1964	1999	1945	1183

The mean values for all countries are positive, with Brazil having the highest correlation coefficient, while Greece and Qatar exhibit relatively low mean correlations. The negative skewness observed in all countries suggests that majority of data points are concentrated on the right side of the distribution, with a few smaller values on the left side serving as outliers. These outliers on the lower end of the distribution tend to pull the mean in that direction. Notably, Brazil stands out as the only DCC with leptokurtic characteristics, indicated by a kurtosis value above three, which implies a sharp peak in the data and heavier tails. In contrast, the other countries display almost mesokurtic properties, with lighter tails and a flatter distribution. Qatar, in particular, exhibits a platykurtic distribution, characterised by lighter tails and a flatter shape compared to a normal distribution.

Table E2: EDGE DCC Descriptives

	Brazil	Chile	Greece	Philippines	South Africa	Taiwan	Thailand	Qatar
Mean	0.139191	-0.083161	0.234157	0.147220	0.031919	0.044939	0.024295	0.162656
Median	0.299041	-0.145904	0.233951	0.367097	0.078841	0.034640	0.034771	0.342831
Maximum	0.909029	0.927033	0.965853	0.967502	0.947778	0.989099	0.926446	0.860128
Minimum	-0.883855	-0.623409	-0.868331	-0.887307	-1.003176	-0.815825	-0.907313	-0.883404
Std. Dev.	0.604588	0.331186	0.479452	0.626345	0.364675	0.322601	0.539929	0.582110
Skewness	-0.277472	0.344600	-0.449746	-0.284887	0.053844	0.183107	-0.033261	-0.343930
Kurtosis	1.436728	2.187159	2.494098	1.396239	3.312387	3.459635	1.517129	1.513892
Jarque-Bera	227.0219	94.31100	87.15440	235.1148	9.093969	27.93232	178.5617	132.1840
Probability	0.000000	0.000000	0.000000	0.000000	0.010599	0.000001	0.000000	0.000000

Sum	275.5979	-165.7400	459.8849	286.7845	63.80509	87.22730	47.25451	192.4224
Sum Sq. Dev.	723.3779	218.4911	451.2426	763.8243	265.7100	201.8984	566.7221	400.5236
Observations	1980	1993	1964	1948	1999	1941	1945	1183

The analysis reveals substantial heterogeneity in liquidity comovement across the sample countries. Greece exhibits the strongest average comovement (mean correlation: 0.234157), followed by Qatar (0.162656) and the Philippines (0.147220). In contrast, Thailand (0.024295) and South Africa (0.031919) show the weakest average comovement. The stability of liquidity relationships varies significantly across countries. The Philippines demonstrates the highest variability (standard deviation: 0.626345), followed closely by Brazil (0.604588). Conversely, Taiwan exhibits the most stable relationship (standard deviation: 0.322601). Most countries display negative skewness in their correlation distributions, with Greece showing the most pronounced negative skewness (-0.449746). This suggests a tendency for occasional periods of substantially weaker comovement. Chile stands out with positive skewness (0.344600), indicating occasional stronger positive comovements. South Africa and Taiwan exhibit higher kurtosis (3.312387 and 3.459635 respectively), suggesting more frequent extreme comovements. In contrast, Brazil and the Philippines show lower kurtosis (1.436728 and 1.396239), indicating fewer extreme comovements.

Table E3: ROLL DCC Descriptives

	Brazil	Chile	Greece	Philippines	South Africa	Taiwan	Thailand	Qatar
Mean	0.830253	0.388706	0.607184	0.478995	0.657879	0.575410	0.481025	0.159872
Median	0.943059	0.573388	0.897282	0.716872	0.847222	0.776326	0.694190	0.191643
Maximum	0.996402	0.946302	1.058790	0.988489	0.981268	0.981002	0.975216	0.848832
Minimum	-0.771550	-0.788805	-0.906707	-0.863500	-0.829382	-0.901389	-0.782583	-0.819759
Std. Dev.	0.287320	0.482618	0.528677	0.522578	0.425562	0.464065	0.482209	0.365493
Skewness	-2.972307	-0.839188	-1.196388	-1.110800	-1.806713	-1.404432	-0.958571	-0.342265
Kurtosis	12.16647	2.412435	3.235530	2.872236	5.374228	3.908124	2.627060	2.121567
Jarque-Bera	9847.422	262.5924	473.0662	401.9236	1557.039	704.7776	309.1346	61.13280
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	1643.900	774.6909	1192.509	933.0827	1315.100	1116.871	935.5945	189.1284
Sum Sq. Dev.	163.3716	463.9760	548.6576	531.7027	361.8430	417.7906	452.0297	157.8979
Observations	1980	1993	1964	1948	1999	1941	1945	1183

The ROLL estimator reveals significant cross-country variations in liquidity conditions. Brazil exhibits the highest mean spread (0.830253), while Qatar has the lowest (0.159872).

Countries also differ in terms of spread variability, with the Philippines and Greece showing the highest standard deviations (0.522578 and 0.528677, respectively). The descriptives reveal strong negative skewness across all countries, indicating a tendency for more frequent occurrences of wider bid-ask spreads. Brazil stands out with the most pronounced negative skewness (-2.972307) and the highest kurtosis (12.16647), suggesting a heightened risk of extreme spread widening events. Greece exhibits the strongest average comovement, followed by Qatar and the Philippines. In contrast, Thailand and South Africa show the weakest average comovement. The stability of liquidity relationships also varies significantly across countries. The Philippines demonstrates the highest variability in liquidity comovement, while Taiwan exhibits the most stable relationship.

Table E4: CS DCC Descriptives

	Brazil	Greece	South Africa	Taiwan	Thailand	Qatar
Mean	0.430663	0.189695	0.053592	0.393322	0.202890	0.148441
Median	0.546683	0.129637	0.064154	0.694362	0.350237	0.162654
Maximum	1.054383	0.897202	0.885474	0.976267	0.964915	0.875059
Minimum	-0.957961	-0.857121	-0.890215	-0.883913	-0.883063	-0.647188
Std. Dev.	0.470145	0.409169	0.507074	0.593197	0.595933	0.368113
Skewness	-0.871870	-0.083599	-0.064642	-0.800350	-0.356916	-0.127016
Kurtosis	2.973280	2.527565	1.576508	2.093703	1.625515	1.903447
Jarque-Bera	250.9106	20.55242	170.1684	273.6498	194.3999	62.45061
Probability	0.000000	0.000034	0.000000	0.000000	0.000000	0.000000
Sum	852.7134	372.5605	107.1304	763.4374	394.6212	175.6053
Sum Sq. Dev.	437.4303	328.6447	513.7346	682.6522	690.3845	160.1698
Observations	1980	1964	1999	1941	1945	1183

The spread estimator reveals significant cross-country variations in liquidity conditions. Brazil exhibits the highest mean spread (0.430663), while Qatar has the lowest (0.148441). Countries also differ in terms of spread variability, with Thailand and Taiwan showing the highest standard deviations (0.595933 and 0.593197, respectively). The spread data is characterized by moderate negative skewness across all countries, indicating a tendency for more frequent occurrences of wider bid-ask spreads. Brazil stands out with the most pronounced negative skewness (-0.871870), but the kurtosis values are relatively low, suggesting a less extreme distribution of spread occurrences. Brazil exhibits the highest average DCC (0.430663), followed by Taiwan (0.393322) and Greece (0.189695). In contrast, South Africa and Thailand show the lowest average DCC (0.053592 and 0.202890, respectively), indicating weaker liquidity comovement. Thailand and Taiwan demonstrate the highest variability in DCC, as indicated by their high standard deviations (0.595933 and 0.593197, respectively). Brazil and Qatar, on the other hand, exhibit the most consistent liquidity comovement, with lower DCC standard deviations.

Appendix F: COPULAS Information Criteria

Table F1: Information Criteria for the estimated copulas

Country	Copula	AIC				BIC				LL			
		AR	**EDGE**	**ROLL**	**CS**	**AR**	**EDGE**	**ROLL**	**CS**	**AR**	**EDGE**	**ROLL**	**CS**
Brazil	Gumbel	-1257.148	**-131.4734**	-2663.241	**-396.4939**	**-1251.557**	**-125.8825**	-2657.65	**-390.903**	629.6	**66.74**	1333	**199.2**
	Clayton	-263.4616	14.5851	-528.8864	-0.1109	-257.8707	20.1760	-523.2956	5.4800	132.7	-6.293	265.4	1.055
	Gaussian	-995.3241	-86.9411	-2127.075	-386.2449	-989.7333	-81.3502	-2121.484	-380.6541	498.7	44.47	1065	194.1
	Student's t	**-1258.881**	-88.5818	**-2857.717**	-384.6172	-1247.699	-77.4001	**-2846.535**	-373.4355	**631.4**	46.29	**1431**	194.3
Chile	Gumbel	**-590.2112**	2.0000	**-819.637**	**-649.286**	**-584.6138**	7.5974	**-814.0396**	**-643.6886**	**296.1**	-	**410.8**	**325.6**
	Clayton	41.6989	1.9826	22.8444	14.35163	47.29625	7.5800	28.44175	19.94903	-19.85	0.00871	-10.42	-6.176
	Gaussian	-417.4627	-0.4522	-641.4158	-415.9189	-411.8653	5.1452	-635.8184	-410.3205	209.7	1.226	321.7	209
	Student's t	-455.8322	1.6055	-656.2035	-498.6627	-444.6374	12.8003	-645.0087	-487.4679	229.9	1.197	330.1	251.3
Greece	Gumbel	**-464.0986**	-77.0906	-1673.222	**-446.4682**	**-458.5159**	-71.5079	-1667.639	**-440.8854**	**233**	39.55	837.6	**224.2**
	Clayton	-97.0823	**-143.1579**	-319.3929	-76.15204	-91.4996	**-137.5751**	-313.8102	-70.5693	49.54	**72.58**	160.7	39.08
	Gaussian	-399.5989	-122.9169	-1122.822	-306.1591	-394.0162	-117.3342	-1117.239	-300.5764	200.8	62.46	562.4	154.1
	Student's t	-398.5373	-136.4379	**-2016.451**	-378.2118	-387.3718	-125.2724	**-2005.286**	-367.0464	201.3	70.22	**1010**	191.1
Philippine s	Gumbel	**-368.1857**	**-176.3356**	**-1114.143**	**-665.5357**	**-362.6111**	**-170.7611**	**-1108.568**	**-659.9628**	**185.1**	**89.17**	**558.1**	**333.8**
	Clayton	33.0447	-46.7030	-169.7087	-29.63016	38.6923	-41.1284	-164.1341	-24.0556	-15.52	24.35	85.85	15.82
	Gaussian	-284.7208	-121.9792	-935.0669	-462.627	-279.1462	-116.4046	-929.4923	-457.0524	143.4	61.99	468.5	232.3
	Student's t	-305.8925	-143.8445	-991.7144	-514.0955	-294.7434	-132.6954	-980.5653	-502.9464	154.9	73.92	497.9	259
South Africa	Gumbel	**-440.8482**	-25.61404	**-2177.386**	-	**-435.2478**	-20.0136	-217.785	-	**221.4**	13.81	**1090**	-
	Clayton	-4.9623	16.79104	233.0343	3.0114	0.6381	22.3914	238.6347	8.6118	3.481	-7.396	-115.5	-0.5057
	Gaussian	-334.2588	-39.2520	-1612.27	**-6.1975**	-328.6584	**-33.6516**	-1606.67	**-0.5971**	168.1	20.63	807.1	**4.099**
	Student's t	-360.5964	**-39.4096**	-1825.905	-	-349.3956	-28.2088	**-1814.704**	**-**	182.3	**21.7**	915	**-**
Taiwan	Gumbel	**-588.0645**	**-7.9071**	**-1542.287**	**-1067.338**	**-582.4963**	**-2.3362**	**-1536.716**	**-1061.767**	**295**	**4.954**	**772.1**	**534.7**
	Clayton	9.0233	1.0641	70.0395	63.9737	14.5943	6.6351	75.6105	69.5447	-3.512	0.4679	-34.02	-30.99
	Gaussian	-473.7656	-7.7411	-1119.497	-782.7376	-468.1946	-2.1702	-1113.926	-777.1666	237.9	4.871	560.7	392.4
	Student's t	-502.0453	-5.5569	-1347.933	-839.6228	-490.9034	5.5850	-1336.791	-828.4809	253	4.778err	676	421.8

Thailand	Gumbel	**-1037.932**	**-160.0931**	**-1386.226**	**-354.8119**	**-1032.359**	**-154.52**	**-1380.653**	**-349.2389**	**520**	**81.05**	**694.1**	**178.4**
	Clayton	33.43315	29.6569	131.3091	26.6939	39.0062	35.2299	136.8822	32.2669	-15.72	-13.83	-64.65	-12.35
	Gaussian	-712.6862	-58.4127	-1022.297	-253.5818	-707.1132	-52.8397	-1016.724	-248.0087	357.3	30.21	512.1	127.8
	Student's t	-854.2097	-70.0754	-1086.296	-256.6173	-843.0636	-58.9294	-1075.15	-245.4712	429.1	37.04	545.1	130.3

Appendix G: TVP-VAR ANALYSIS

Brazil

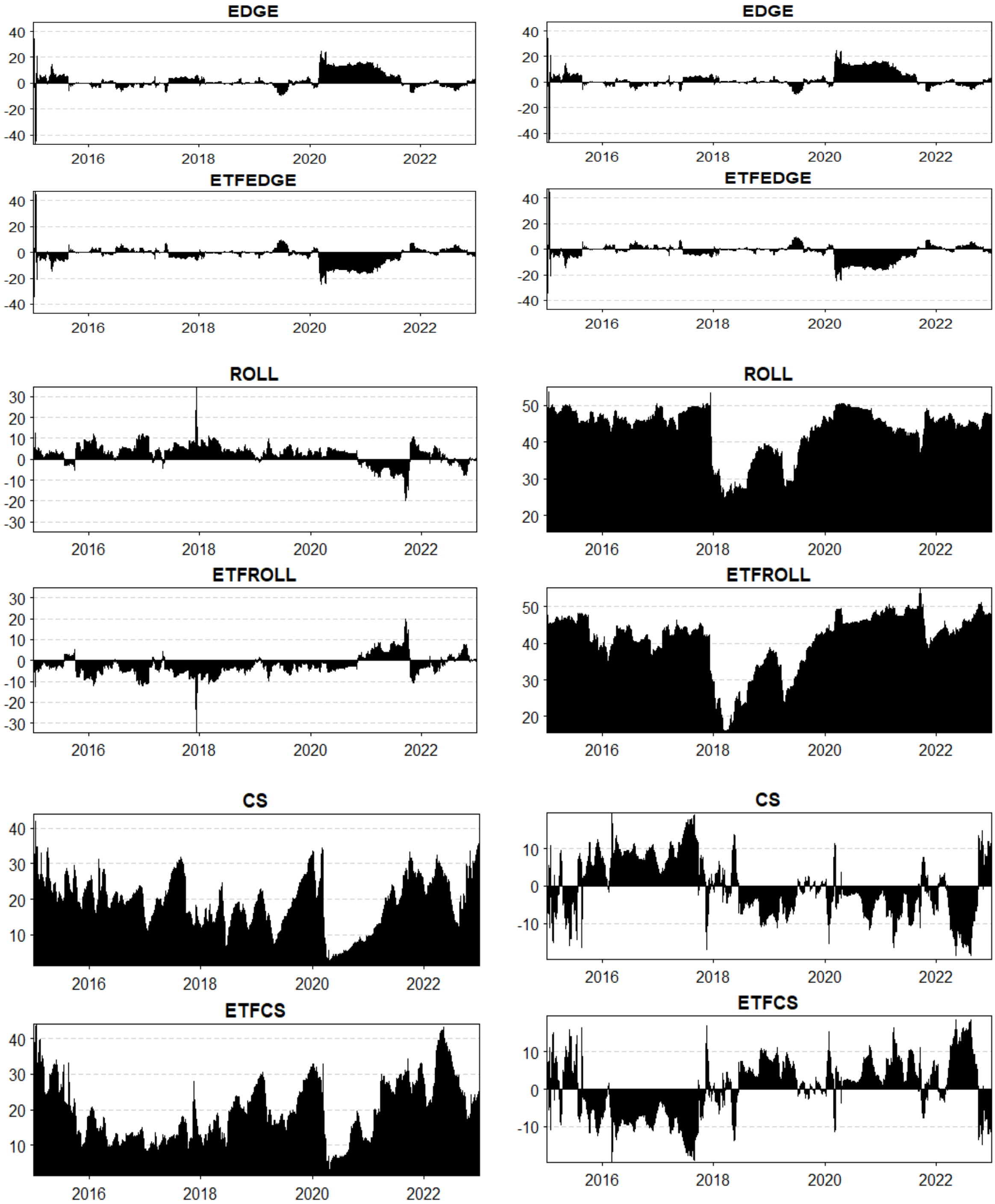


Figure G1. **Brazil Net total directional connectedness and Connectedness to**

Chile

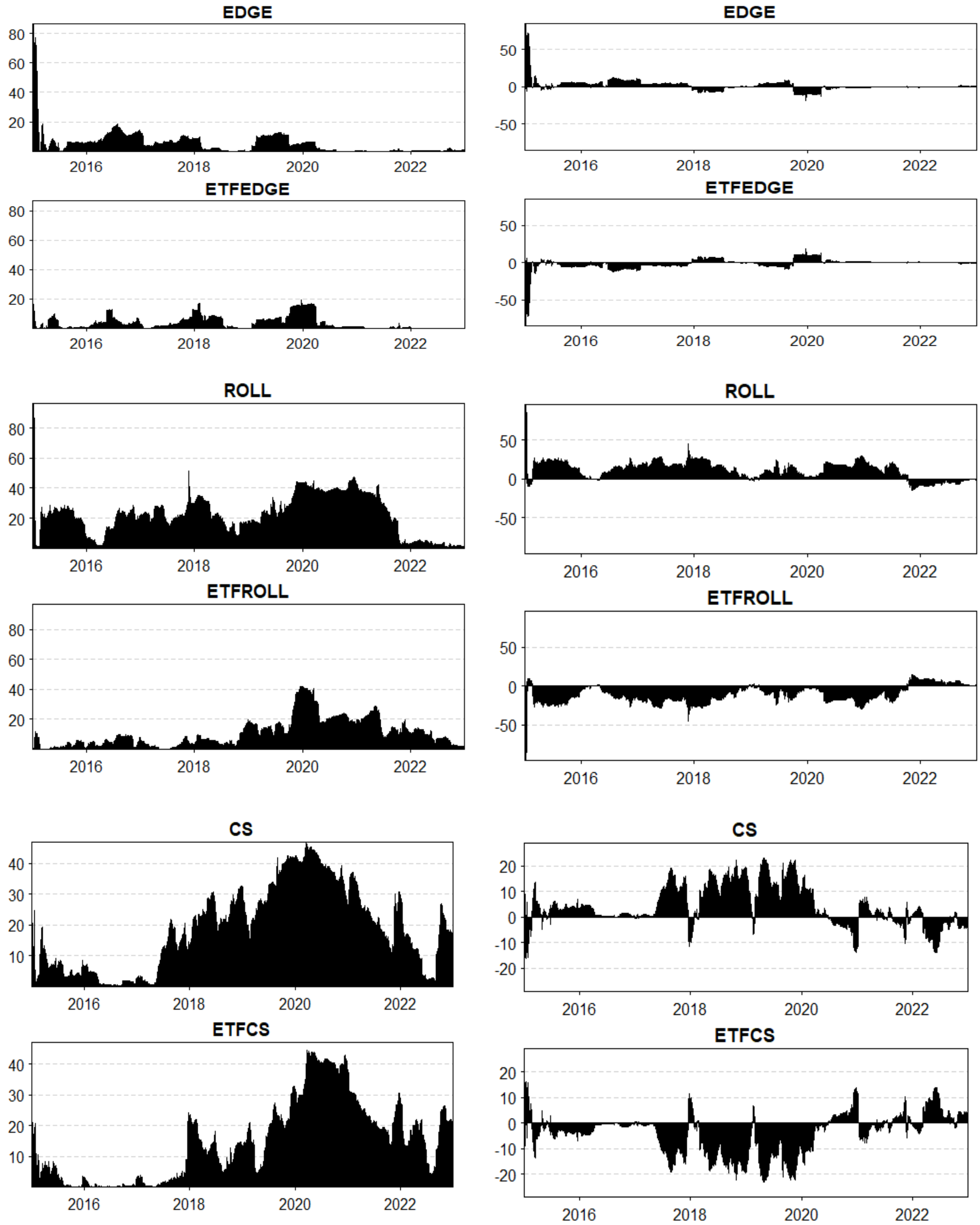


Figure G2. **Chile Net total directional connectedness and Connectedness to**

Greece

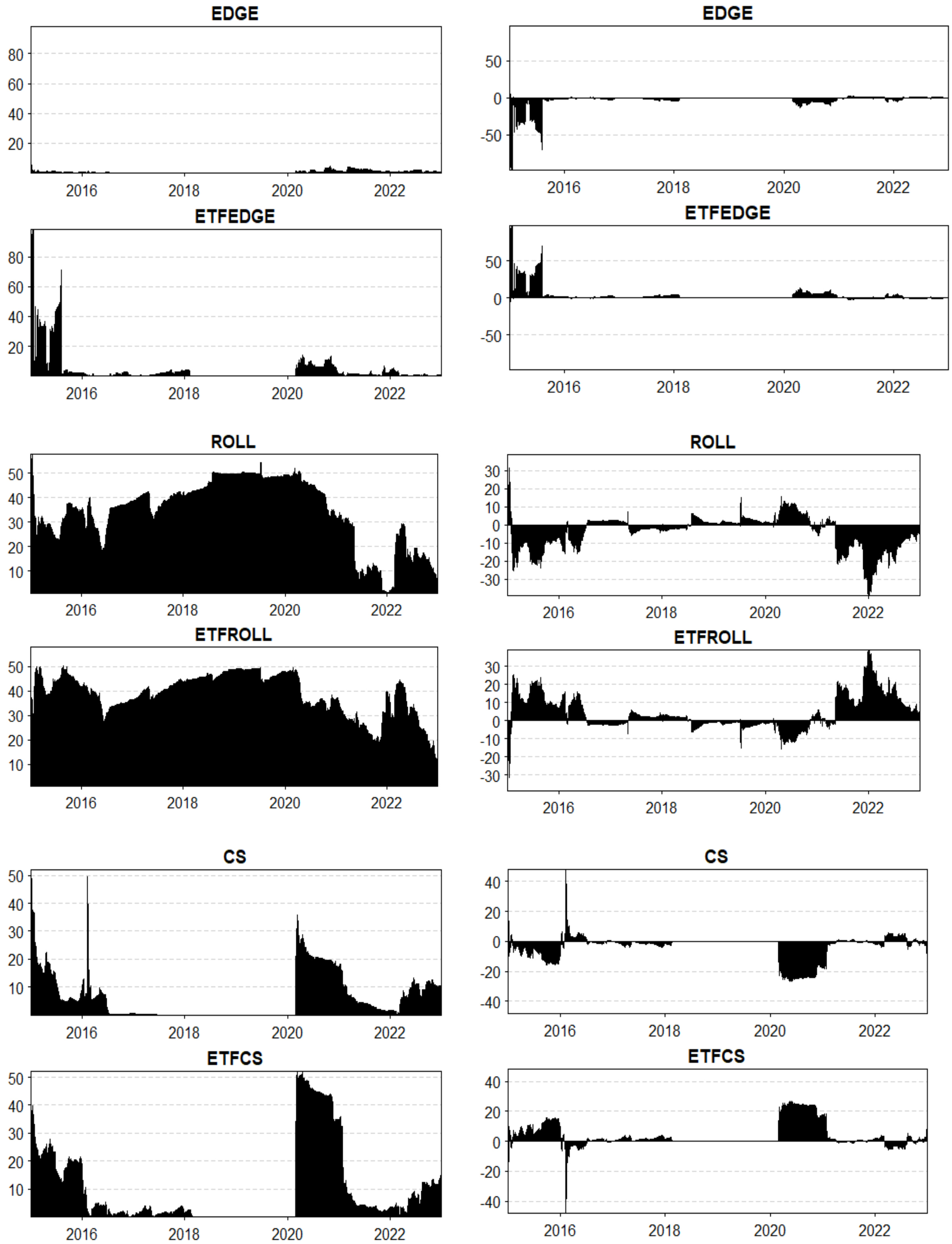


Figure G3. **Greece Net total directional connectedness and Connectedness to**

Philippines

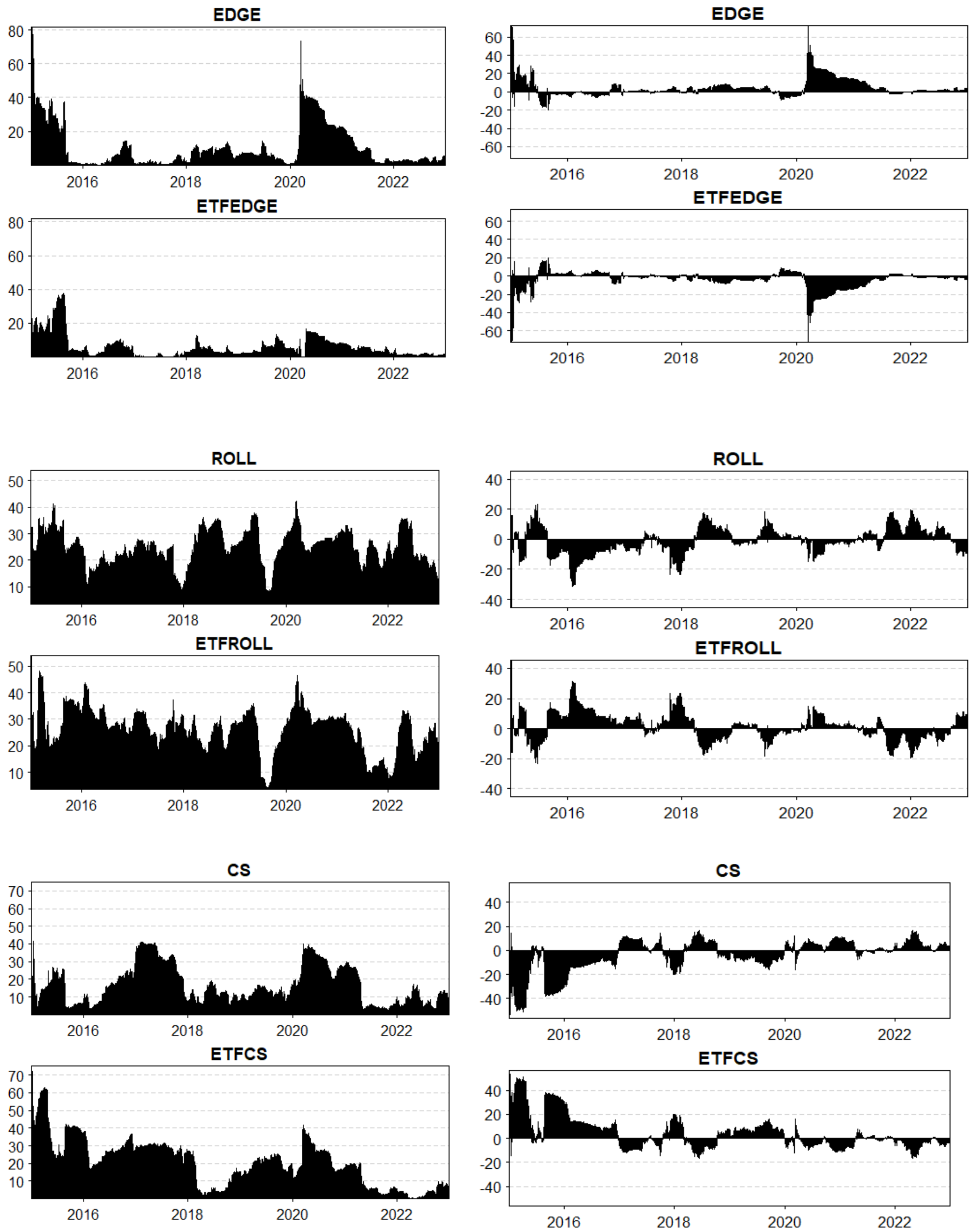


Figure G4. **Philippines Net total directional connectedness and Connectedness to**

South Africa

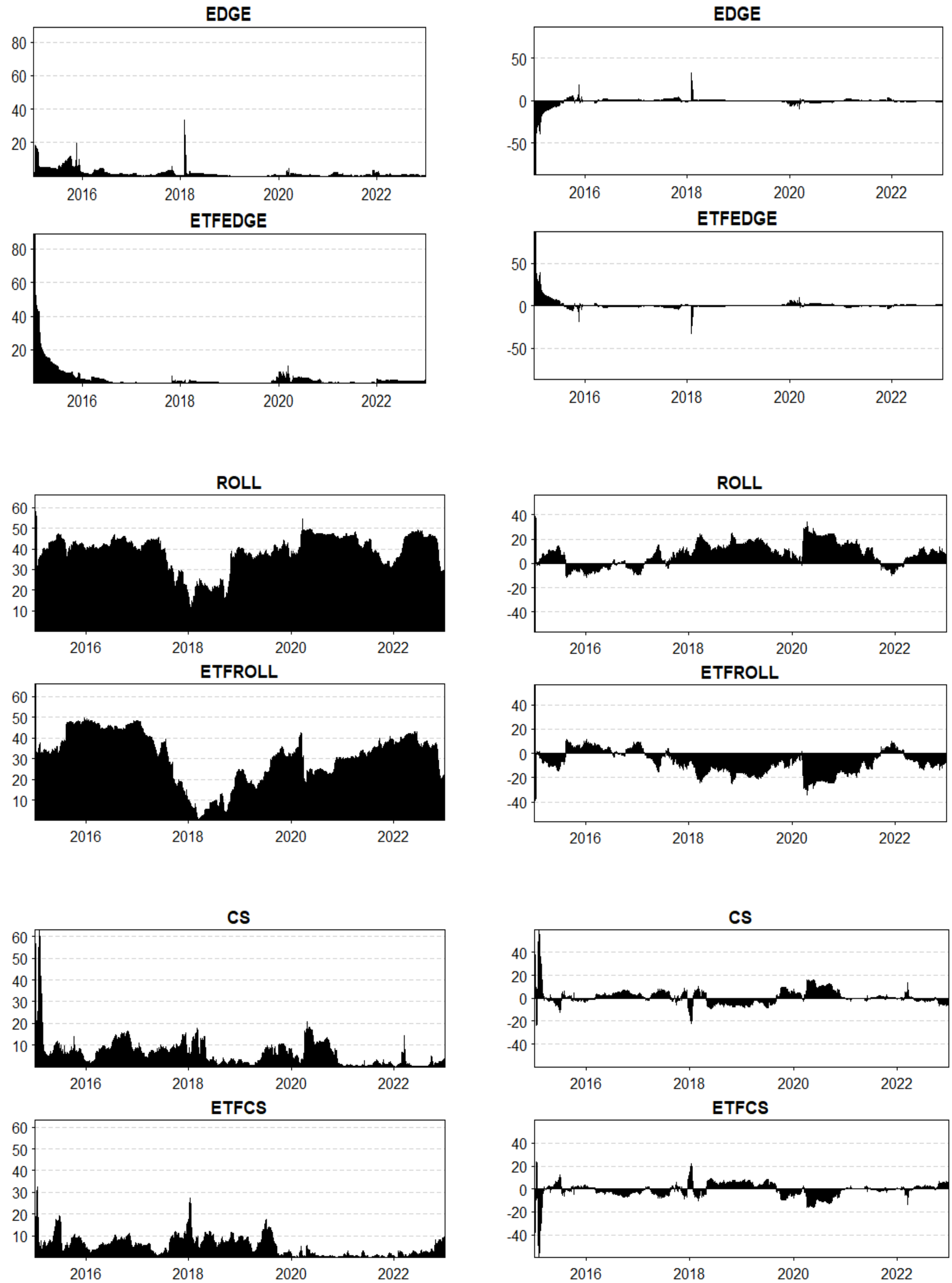


Figure G5. **South Africa Net total directional connectedness and Connectedness to**

Taiwan

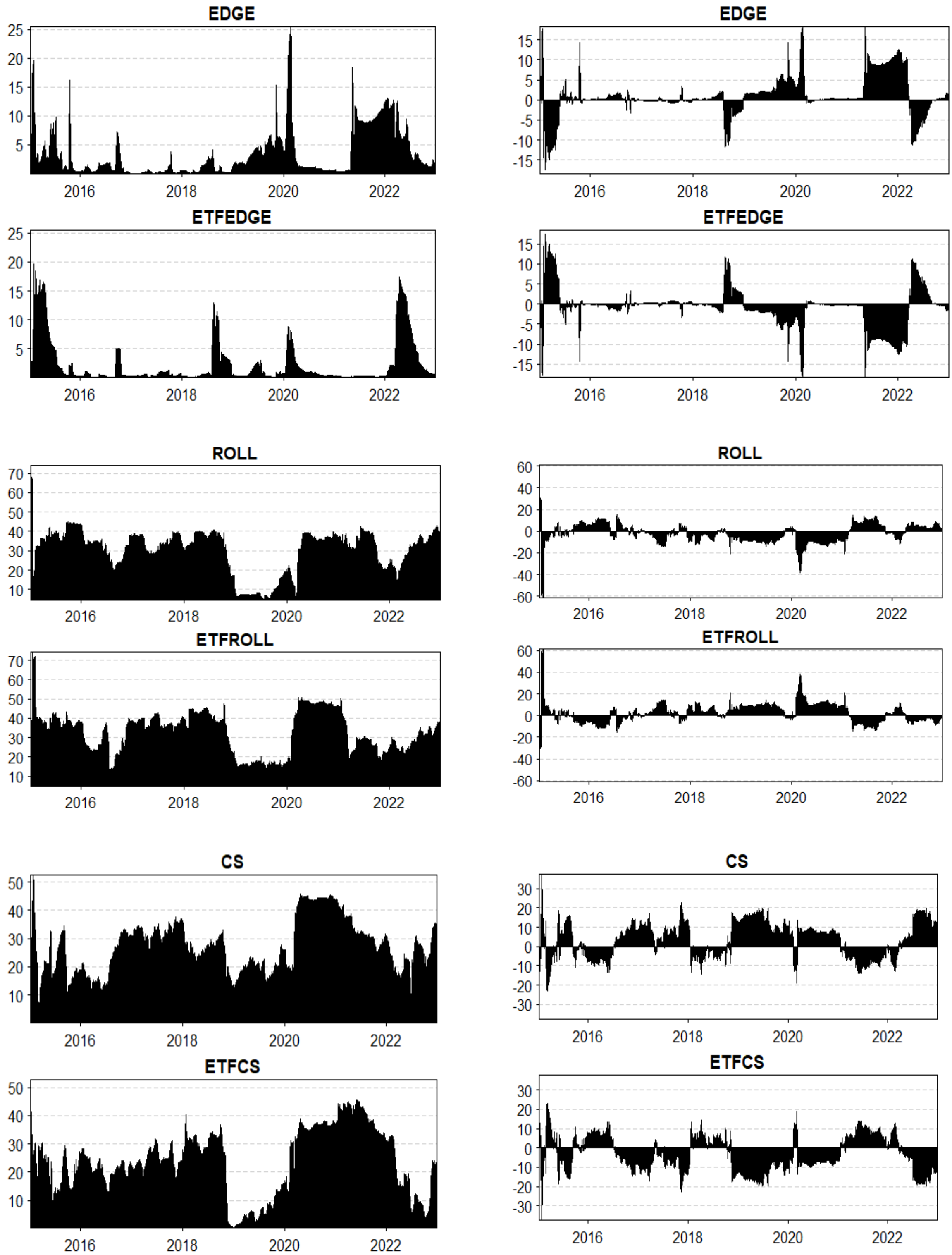


Figure G6. Taiwan Net total directional connectedness and Connectedness to

Thailand

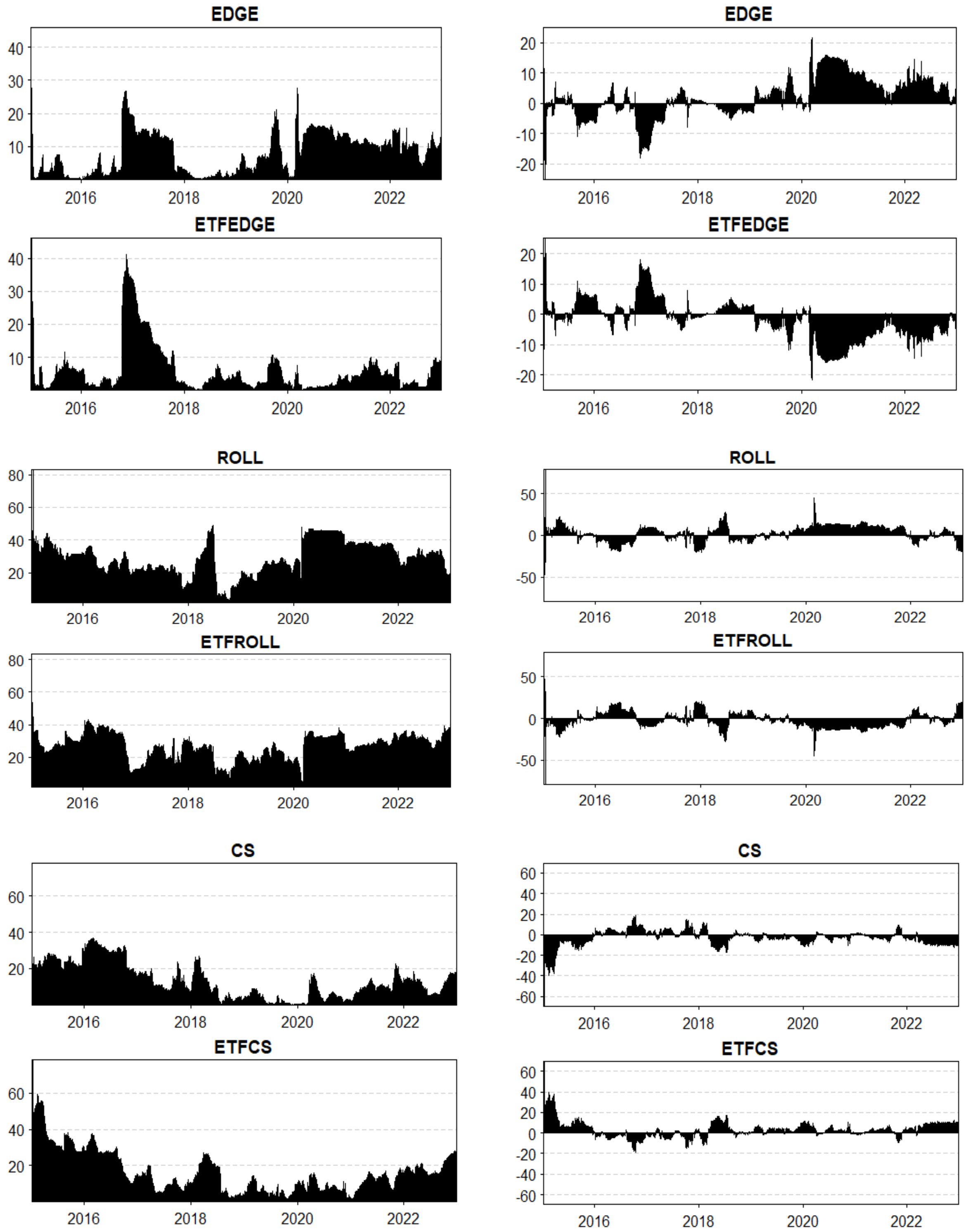


Figure G7. **Thailand Net total directional connectedness and Connectedness to**

Qatar

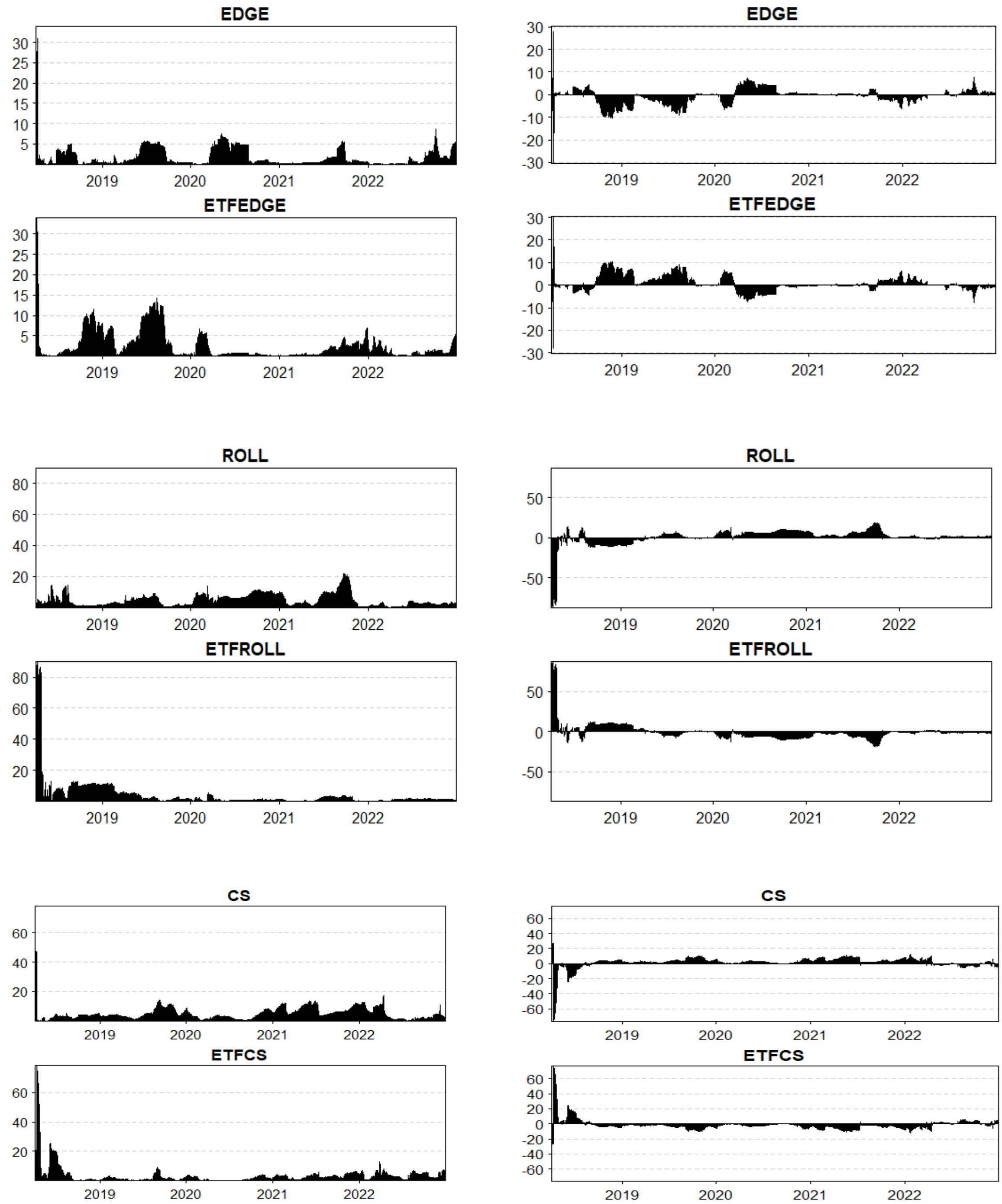
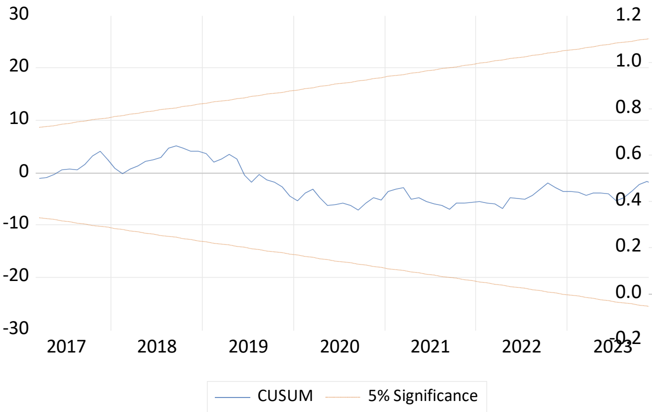


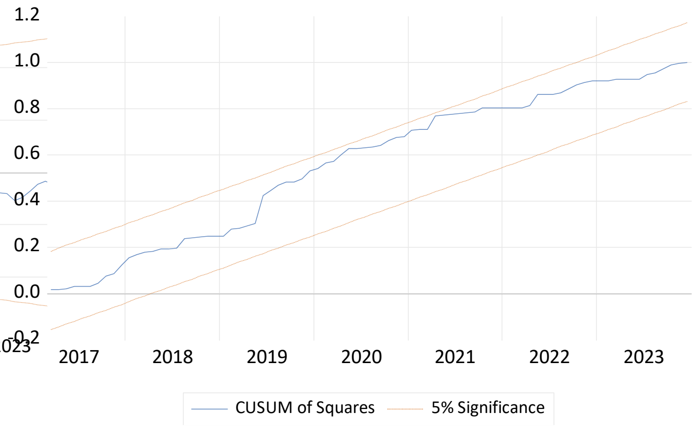
Figure G8. **Qatar Net total directional connectedness and Connectedness to**

Appendix H: Stability Diagnostics

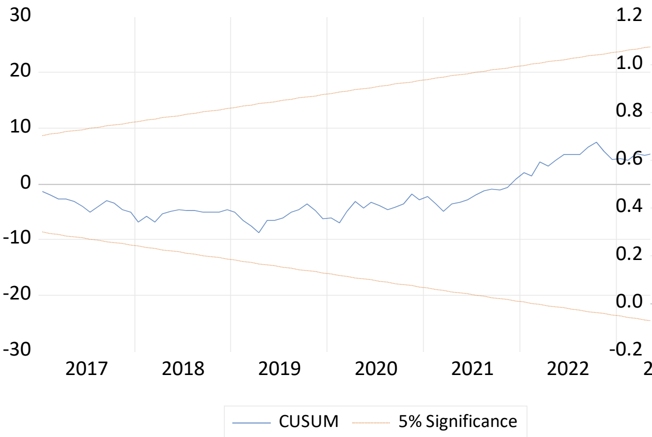
EDGE MODELS

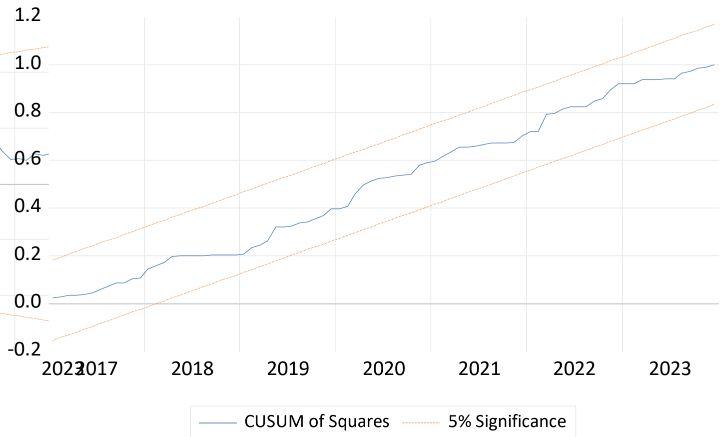
BRAZIL



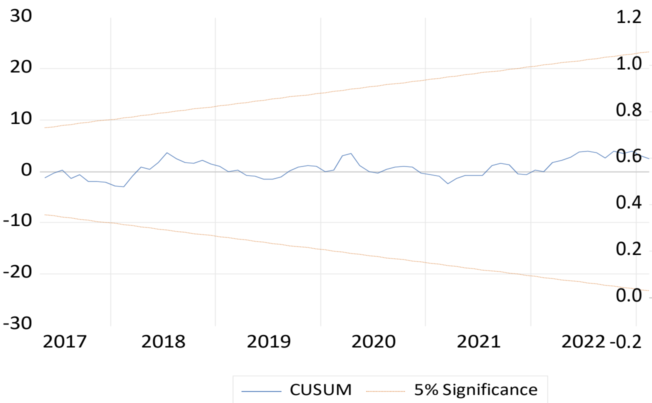


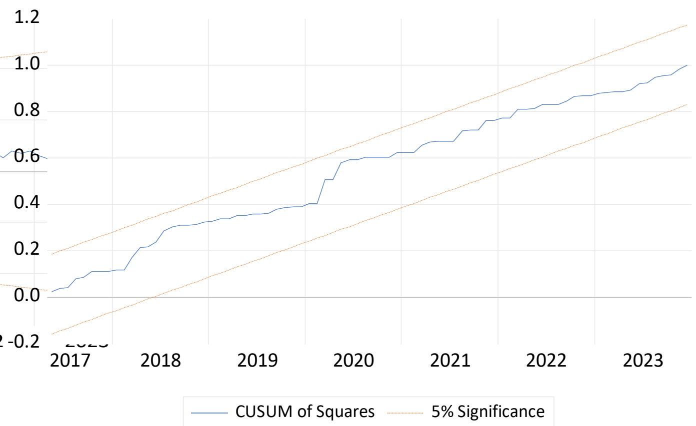
GREECE



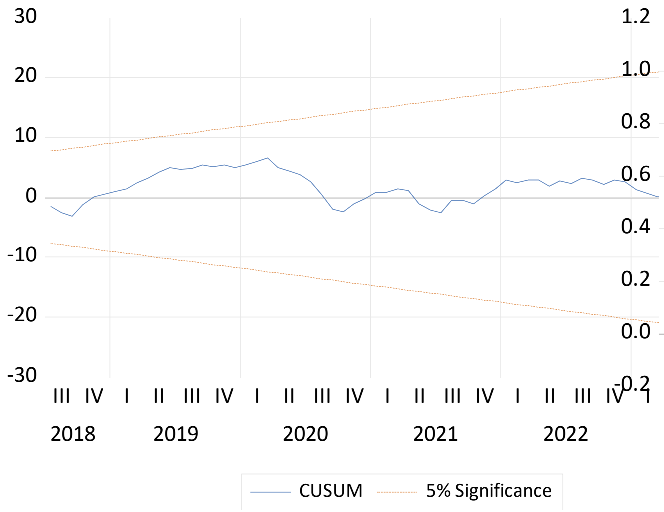


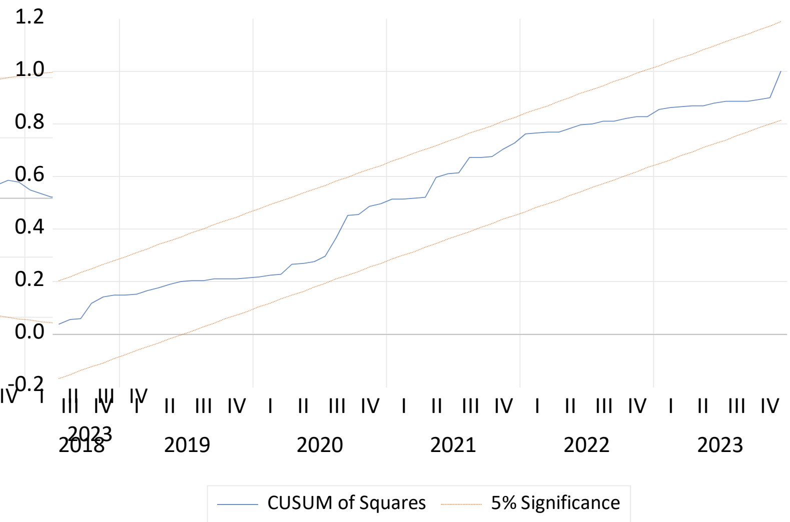
PHILIPPINES



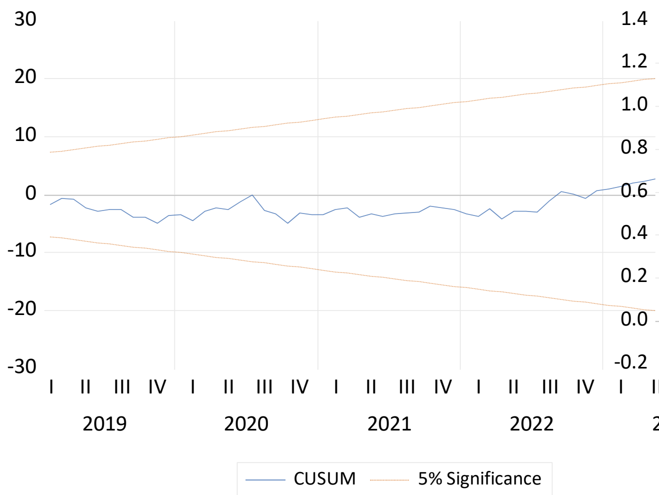


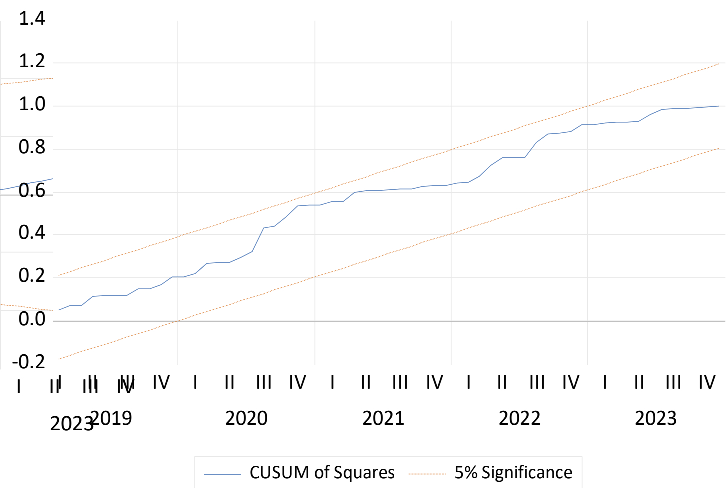
SOUTH AFRICA



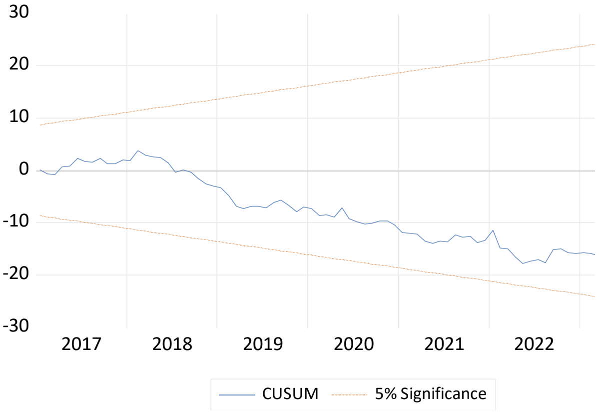


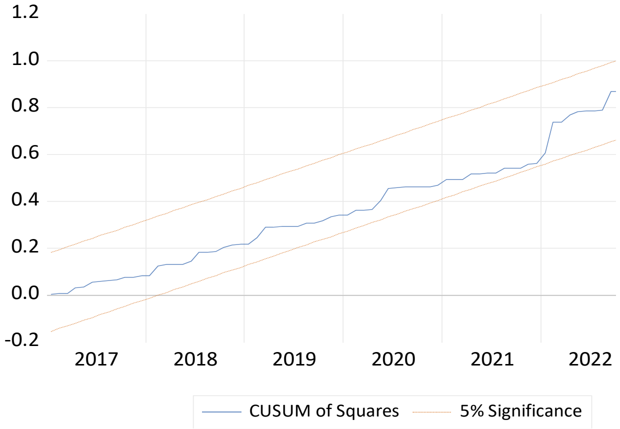
THAILAND





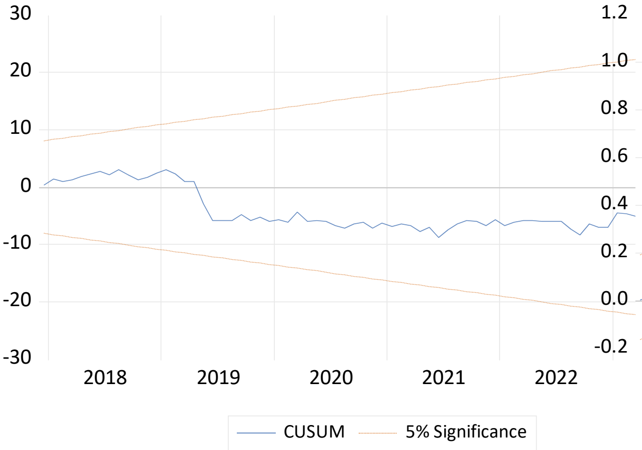
CHILE

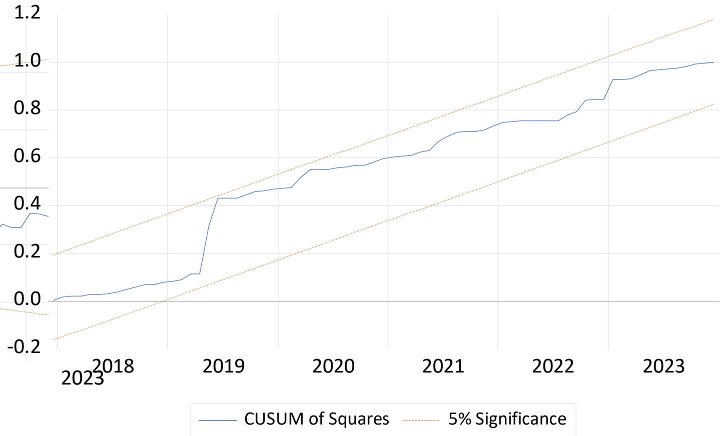




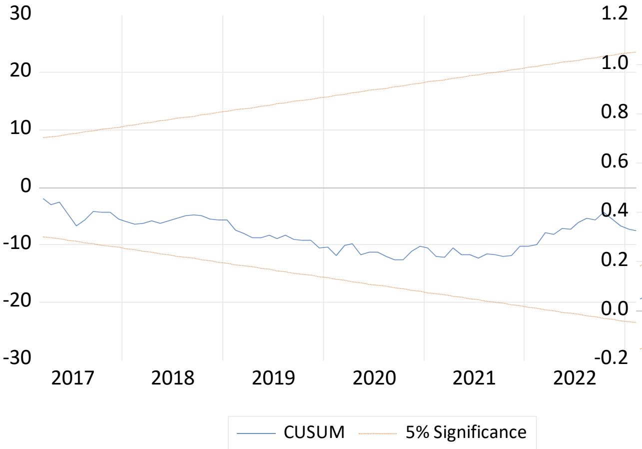
AR MODELS

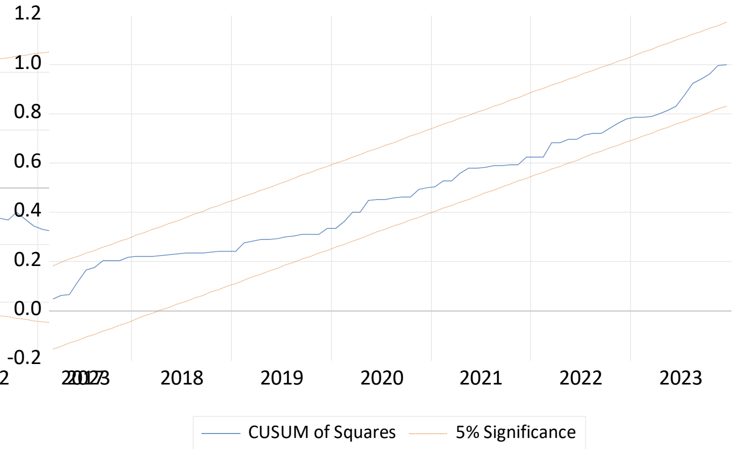
BRAZIL



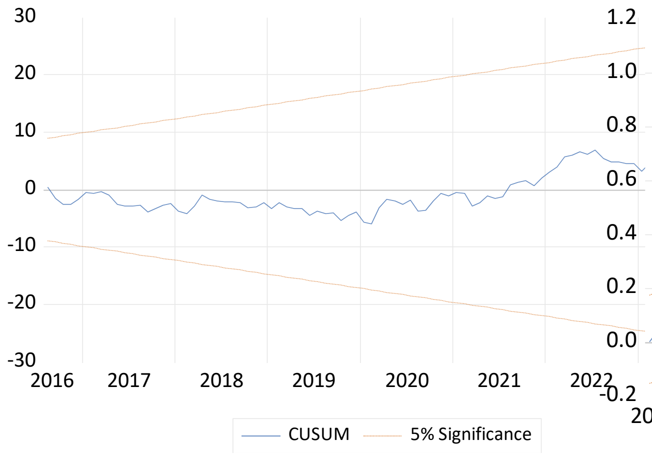


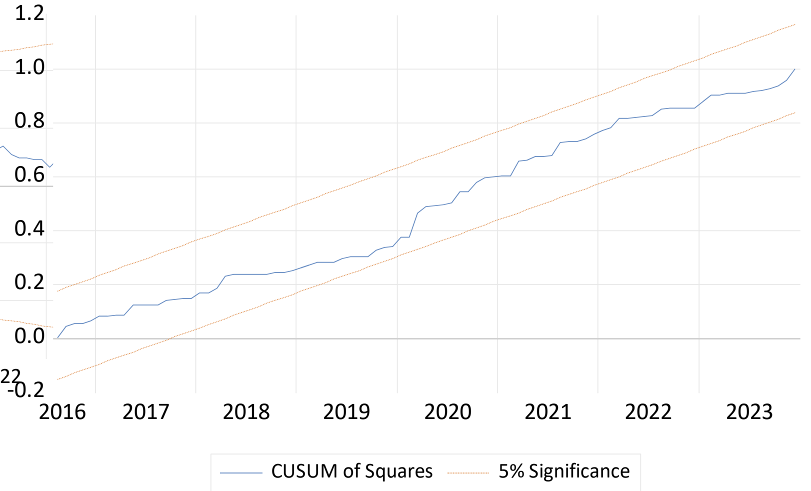
GREECE



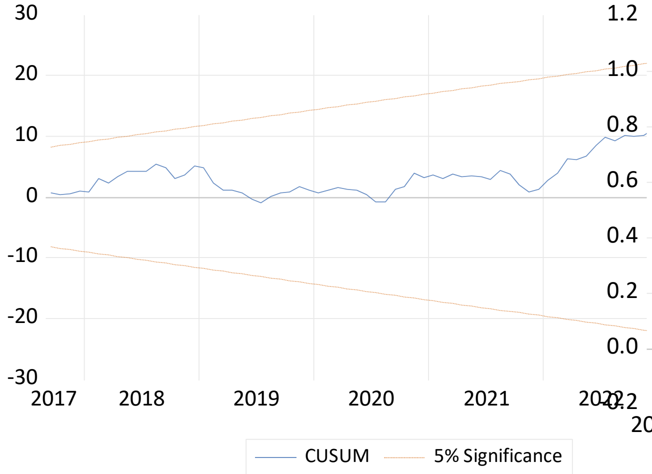


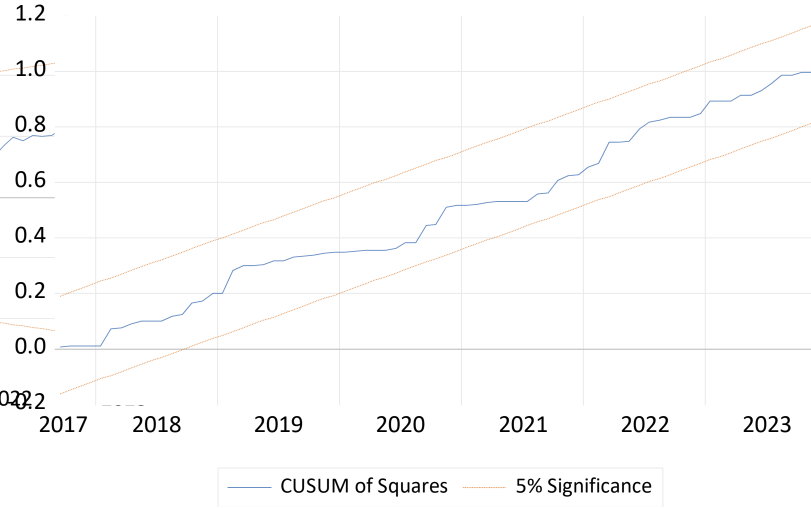
PHILIPPINES



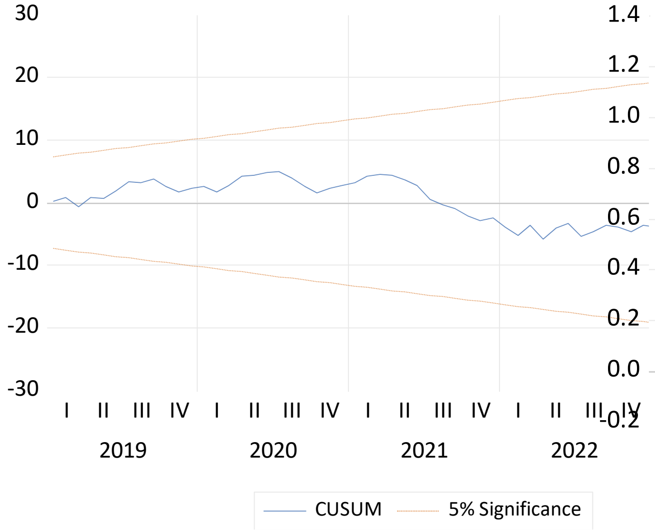


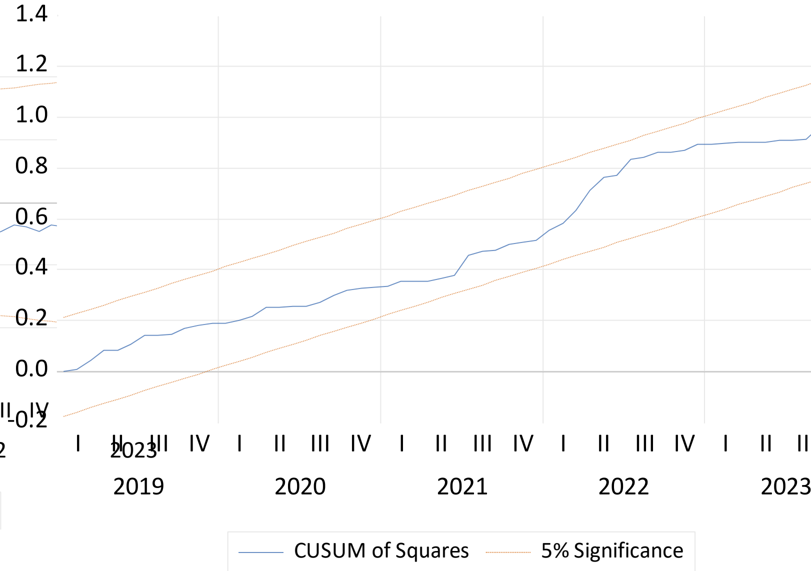
SOUTH AFRICA





THAILAND





CHILE