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Ph.D. THESIS

Ayşe Nur ŞAHİNLER

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ANKARA YILDIRIM BEYAZIT UNIVERSITY

GRADUATE SCHOOL OF SOCIAL SCIENCES

ESSAYS ON EFFICIENCY OF GREEN BOND MARKERTS

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APPROVAL PAGE

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I certify that this dissertation fulfills all the requirements to be deemed a doctoral thesis at Ankara Yıldırım Beyazıt University, Institute of Social Sciences, Department of Economics.

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Director of the Institute of Social Sciences

PLAGIARISM STATEMENT

I hereby declare that all information in this dissertation has been obtained and presented by academic rules and ethical conduct. I also declare that, as required bythese rules and conduct, I have fully cited and referenced all material and results that are not original to this work; otherwise, I accept all legal responsibility.

16.07.2024

Ayşe Nur Şahinler

To my dear family

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ABSTRACT

Essays on Efficiency of Green Bond Markets

This thesis consists of three main studies examining the efficiency of green bonds in weak-form and semi-strong-form of the efficient market hypothesis. The first study evaluates the weak-form efficiency of green bond markets using daily, weekly, and monthly data, investigating whether the market exhibits a random walk through different unit root tests. The second study investigates its relationship with various financial markets using daily data and analyzes these relationships econometrically employing methods such as causality in mean proposed by Hong (2001), causality in risk proposed by Hong (2009), and DCC GARCH models. The third study investigates the response of green bond prices to various uncertainties indices using monthly data, focusing on the effects of climate policy, economic policy and monetary policy uncertainty indices using the Bootstrap Fourier ARDL methodology.

Keywords: Green Bonds, Market Efficiency, Nonlinear Models, DCC GARCH Models, Causality in Mean, Causality in Risk, Fourier ARDL

ÖZET

Yeşil Tahvil Piyasalarının Etkinliği Üzerine Makaleler

Bu tez, yeşil tahvillerin etkin piyasa hipotezinin zayıf ve yarı güçlü formalarında sergiledikleri etkinliği inceleyen üç ana çalışmadan oluşmaktadır. İlk çalışma, günlük, haftalık ve aylık veriler kullanılarak yeşil tahvil piyasalarının zayıf formda etkinliğini değerlendirmekte ve farklı birim kök testleriyle piyasanın rassal bir yürüyüş sergileyip sergilemediğini araştırmaktadır. İkinci bölümde ise günlük veriler üzerinden farklı finansal piyasalarla olan ilişkisi yarı güçlü formda incelenmektedir. Hong (2001) tarafından önerilen ortalamada nedensellik, Hong (2009) tarafından önerilen riskte nedensellik yöntemleri ve çoklu GARCH modelleri kullanılarak bu ilişkiler ekonometrik olarak analiz edilmektedir. Üçüncü bölümde ise yeşil tahvil fiyatlarının çeşitli belirsizliklere olan tepkisi aylık verilerle ölçülmektedir. Bu bölümde, iklim politikası, ekonomi politika ve para politikası belirsizlik endekslerinin etkileri Bootstrap Fourier ARDL metodolojisi kullanılarak incelenmektedir.

Anahtar Kelimeler: Yeşil Tahviller, Etkin Piyasa, Doğrusal Olmayan Modeller, DCC GARCH Modeller, Ortalamada Nedensellik, Riskte Nedensellik, Fourier ARDL

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LIST OF ABBREVIATIONS

ADF	: Augmented Dickey Fuller
ALIDE	: Latin American Association of Development Financing Institutions
ARCH	: Autoregressive Conditional Heteroskedasticity
ARDL	: Auto Regressive Distributed Lag
CBI	: Climate Bond Initiative
CFF	: Cross-correlation Function
CPU	: Climate Policy Uncertainty
DCC	: Dynamic Conditional Correlation
ECM	: Error Correction Model
EMH	: Efficient Market Hypothesis
EPU	: Economy Policy Uncertainty
ESTAR	: Exponential Smooth Transition Autoregressive
FOMC	: Federal Open Market Committee
ICSS	: Iterated Cumulative sums of Squares
KPSS	: Kwiatkowski-Phillips-Schmidt-Shin
LST	: Logistic Smooth Transition
LSTAR	: Logistic Smooth Transition Autoregressive
MPU	: Monetary Policy Uncertainty
OLS	: Ordinary Least Square
PP	: Phillips Perron
RALS	: Residual Augmented Least Squares
SQP	: Sequential Quadratic Programming
QARDL	: Quantile Autoregressive Distributed Lag
VaR	: Value at Risk

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1. INTRODUCTION

Climate change is one of the most challenging issues faced globally today (Ahiduzzaman & Islam, 2011:4660). Greenhouse gases such as carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), and carbon monoxide (CO), emitted into the atmosphere as a result of burning fossil fuels, adversely affect our climate by causing rising sea levels and threatening the survival of both human civilization and the surrounding ecosystems. In this context, climate change has significant adverse impacts on water resources, food security, hydroelectric power, and human health (Sathiendrakumar, 2003:1234). Climate change not only affects the environment but also poses threats to economic and social development, making it more challenging to achieve sustainable development goals.

The concept of sustainable development has gained significant importance. The Report of the World Commission on Environment and Development (WCED), in 1987, defined sustainable development as "*development that meets the needs of the present without compromising the ability of future generations to meet their own needs*" (WCED, 1987:41). Achieving sustainable development is not possible without addressing climate change; therefore, the use of renewable energy sources to reduce greenhouse gas emissions in energy production and consumption is importance. Investments in renewable energy sources are a fundamental necessity to achieve sustainable development goals.

Governments require suitable and reliable sources of financing to fulfill their commitments to keep the global average temperature rise below 2°C compared to pre-industrial levels, as outlined in the 2015 Paris Agreement. According to a report published by the Climate Bonds Initiative (CBI) in September 2023, approximately $200 trillion in climate finance is needed, with an annual requirement of $6.2 trillion by 2030 and $7.3 trillion by 2050. Among the areas where this financing is most needed are the transportation sector, energy systems, improving energy efficiency in buildings, decarbonizing industrial processes, and developing clean energy storage solutions. The transportation sector accounts for 50% of the total requirement, requiring at least $3.2 trillion annually by 2050. Energy

systems constitute 32% of the total requirement, necessitating a minimum of $2.1 trillion annually. Additionally, annual funding of $731 billion is needed for improving energy efficiency in buildings, $320.2 billion for decarbonizing industrial processes, $251.3 billion for developing clean energy storage solutions, and $145.3 billion for carbon capture, utilization, and storage (CCUS) technologies.

In this context, the role of green bonds becomes even more crucial. Green bonds play a critical role in addressing these financing needs, with a particular emphasis on increasing investments in renewable energy projects (Sobik, 2023:58). Prioritizing investments in transportation and energy systems is seen as essential for sustainable economic transformation. Investors are encouraged to adapt their business models not only to create financial value but also to generate social and environmental values. In this regard, green bonds emerge as an important source of financing to support both sustainable development and the fight against climate change. Consequently, increasing investments in renewable energy projects can be a significant step towards combating climate change and achieving sustainable development goals.

While green bonds are known as investments supporting environmentally friendly initiatives, how can investors ensure that these bonds are indeed directed towards eco-friendly projects and not merely subjected to "greenwashing"? (Ehlers and Packers, 2017:89). Some analysts fear that in a market without strict standards, green bonds could completely undermine investor confidence as a debt instrument. Investors committed to financing climate change mitigation and adaptation may lack trust in whether green-labeled bonds are truly allocated to environmentally friendly projects. Consequently, they might have to conduct costly preliminary research to analyze the climate impacts of individual issuances. This could lead to a reduction in private investor interest at a critical time for achieving the necessary climate mitigation to stay below the 2°C (Bishop, 2019:379-380). To ensure that investments indeed go to environmentally beneficial projects, investors can refer to external review reports from organizations such as CICERO and Sustainalytics. Additionally, reports from agencies like Barclays, Moody's, or S&P, which assess the ratings of green bonds, can be consulted. Furthermore, various non-profit and independent organizations have begun offering green label certifications that signify adherence to specific green criteria. This helps align the incentives of those interested in investing in these bonds

and simplifies the task for asset managers in meeting these preferences. (Ehlers and Packers, 2017:89).

Green bonds typically provide financing for environmental projects such as renewable energy, energy efficiency, clean water, and waste management. These projects aim to reduce carbon emissions and promote the sustainable use of natural resources. Additionally, the evaluation and pricing processes of green bonds can be compared to fixed-income instruments like corporate and government bonds (Liu et al., 2021). This market has emerged as one of the fastest-growing segments of international capital markets, driven by investor interest in environmental risks and the impact of the 2015 Paris Agreement. The Paris Agreement involved commitments from numerous countries to transition to a climate-resilient economy (Reboredo, 2018). According to CBI reports (2019, 2020, 2023), the green bond issuance initiated by the European Investment Bank in 2007 surpassed a total of $754 billion by 2019, with $258.9 billion of this amount being issued solely in 2019. During this period, the United States took the lead in green bond issuance, followed by China and France. With the onset of the Covid-19 pandemic, green bond issuance in the first half of 2020 dropped below half of the 2019 levels. However, this decline was not observed in Latin America due to continuous sovereign issuance from Chile. Globally, green bond issuance from Europe holds a significant share, representing more than 55% of the global total for the first time. This indicates an increase in Europe's share despite an overall decrease in issuances. As of September 2023, cumulative green bond issuance has exceeded $2.5 trillion. In terms of countries leading in green bond issuance, Germany holds the top position during this period.

The main objective of this thesis is to examine the efficiency of the green bond market. In pursuit of this objective, the first section will test the efficiency of the weak form of the green bond market using various unit root tests. Firstly, traditional unit root tests will be applied. Subsequently, Fourier-based unit root tests that consider structural breaks, nonlinear unit root tests, and finally tests considering non-normal errors will be employed.

In the second section, the correlation between the green bond market and various financial markets will be examined. In this context, its relationship with three different markets will be addressed. Firstly, its connection with traditional bonds, which are also part of the fixed-income asset class, will be reviewed. Secondly, the association with clean

energy stocks, directly linked to the projects supported by green bonds, will be analyzed. Additionally, the relationship with energy commodities, which do not share the same common objective, will be explored. The aim is to test these relationships in terms of causality in mean proposed by Hong (2001), causality in risk proposed by Hong (2009). Moreover, the focus will be on how these correlations change over time, especially examining how correlation evolves over time using different DCC GARCH models.

In the third chapter, the effects of economic policy uncertainty, climate policy uncertainty, and monetary policy uncertainty on the green bond markets in the short and long term will be investigated. This analysis will consider both sharp and smooth structural breaks caused by crises such as the European debt crisis and the COVID-19 pandemic. Fourier-based ARDL models will be used as the primary tool for this analysis, allowing for a detailed examination of the sensitivity and responses of green bond markets to various uncertainty factors. This approach aims to provide a comprehensive understanding of how green bond markets behave during crisis periods and the extent to which they are affected by different factors.

2. WEAK-FORM MARKET EFFICIENCY: EVIDENCE FROM THE GREEN BOND MARKET

2.1. Introduction

The primary function of the capital market is to achieve the distribution of ownership of the capital resources that are available to the economy. In a market environment that is functioning at its best, prices function as accurate indications for the distribution of resources; that is, firms and investors operate under the assumption that security prices fully reflect all available information. Such a market, where prices always fully incorporate available information, is referred to as an efficient market (Fama, 1970:383).

The Efficient market gained attention through Eugene Fama's 1970 study, but its origins can be traced back to the early 1900s. Louis Bachelier (1900) postulated that the prices of assets traded in an ideal market should exhibit random fluctuations. Based on this statement, he deduced, albeit in an informal manner, the Brownian motion mechanism. Bachelier's research proposed that prices exhibit random movements, and that any relevant information is rapidly incorporated into prices (Taylor, 1975:245)

Fama (1970) has also discussed market conditions that could facilitate or hinder the efficient adjustment of prices to information. These conditions include the absence of transaction costs in securities trading, the costless availability of all existing information to all market participants, and a consensus among participants on the impact of current information on current prices and future price distributions of each security. In such an ideal market, the price of a security fully reflects all available information, thereby ensuring market efficiency. However, the concept of efficiency for financial markets is classified in three different ways. Firstly, operational efficiency is achieved when the transfer cost of financial funds is reasonable. This is determined by a high number of participants in the market and mechanisms that contribute to ensuring equilibrium prices. In terms of operational efficiency, market participants can trade actively due to lower transaction costs. This indicates that the market operates efficiently, and the trading costs for participants are minimized. As a result, market participants can engage in more transactions, thereby

increasing market liquidity. (Birău, 2011; Seo and Chai, 2013). Secondly, allocative efficiency is achieved when the prices of securities are set in a way that equalizes the risk-adjusted rates of return across all securities. This means that securities with the same level of risk will offer the same expected return. In a market that is allocational efficient, savings are optimally allocated to productive investments, ensuring that resources are used in the most effective manner. This optimal allocation benefits all participants in the market, as it leads to an efficient distribution of resources, maximizing overall economic welfare (Emerson et al., 1997:76). Lastly, for a market to be defined as "informationally efficient," all investors must have access to accurate and complete information simultaneously, and information about all firms must be obtainable by all market participants (Duman-Atan and Özdemir, 2009:34). This condition is referred to as informational efficiency and is commonly known as market efficiency in academic literature.

Fama (1970) describes this informational efficiency market in three different forms: weak form, semi-strong form, and strong form. These forms depend on the information sets available to investors under the efficient market hypothesis. The weak form market efficiency is based on the assumption that investors cannot achieve abnormal returns using past price changes because, in a weak form efficient market, past prices do not provide any information about future prices. This is because prices follow a random walk, meaning past performance is not a reliable indicator of future performance (Balaban, 1995:44). Many researchers and academics have investigated weak form market efficiency using various econometric methods. Among the most commonly used methods in the literature are the autocorrelation test, runs test, variance ratio test, unit root tests, long memory models, and others.

The semi-strong form of market efficiency hypothesis states that, in addition to past prices, all publicly available information is fully reflected in asset prices. This includes fundamental data such as the firm's product line, earnings forecasts, dividends, stock split announcements, quality of management, balance sheet composition, patents held, accounting practices, and other economic or political events (Clarke et al., 2001; Adali, 2006; Naseer and Tariq, 2015). In a semi-strong form efficient market, prices adjust immediately and accurately to incorporate all such information as soon as it becomes available. Basically, the semi-strong form of the market efficiency theorem supports the idea that there is no lag effect in the spread of public information. When a company makes an

announcement, investors across the country evaluate the information at the same pace (Hirt and Block, 2011:239). To test the existence of semi-strong form efficiency, announcements made by companies are often examined using event study methodology (Jones and Bacon, 2007; Hussin et al., 2010; Bacon and Cagigas, 2022), while cointegration and causality analyses have frequently been employed to assess the presence of macroeconomic and other variable information (Beck, 1994; Liu et al., 1997, Taş and Tokmakçıoğlu, 2010).

The strong-form market efficiency posits that stock prices reflect all information, both public and private. In this form of market efficiency, insiders such as managers and employees cannot consistently achieve abnormal returns using their private information. Testing for strong-form efficiency is more challenging compared to the other two forms. This difficulty arises because it often requires examining the investment accounts of firm insiders or managers. Another method of testing involves checking whether mutual funds achieve abnormal returns. However, while this may be necessary to reject strong-form efficiency, it is not sufficient on its own (Karan, 2022).

According to these three hypotheses, prices can always be regarded as optimal estimates of fundamental value (Shiller, 1999:1307). An efficient market, in turn, is assumed to exhibit many characteristics of perfectly competitive markets. These characteristics include a large number of participants, none of whom possess a significant share to influence the market. Information regarding securities is accessible at a relatively low cost, and economic, political, and social changes are immediately reflected in market prices. Furthermore, these markets demonstrate high liquidity and low transaction costs, enabling security prices to swiftly adapt to overall changes. Additionally, the institutional framework of the market is highly developed, and regulatory measures ensure the stable functioning of the markets. In an efficient market, investors are also assumed to act rationally, making decisions based on all available information (Hatipoğlu, 1999:10-11).

Although numerous results supporting the efficient market hypothesis (EMH) have been found over the past few decades, the finance literature has accumulated a substantial number of observations against market efficiency (Shiller, 1999:1307). These observations include price anomalies such as the Monday effect, January effect, and small firm effect, etc. (Gibbons and Hess, 1981; Washer et al., 2011; Chen et al., 2011); downward-sloping demand, where the demand curve slopes downward in an unexpected manner (Stout, 2003);

excessive volatility, where market prices fluctuate unnecessarily and excessively (Fakhry and Richter, 2015; Tang et al., 2020); delayed information response, where markets do not immediately react to new information, and this information is slowly reflected in prices (Ramesh and Rajumesh, 2014); and consistently superior traders, where some investors consistently outperform others, indicating that the market is not entirely random and that certain individuals have superior knowledge or strategies (Coval et al., 2021). These findings challenge the efficient market hypothesis and suggest that markets are not always efficient (Stout, 2005:12). These observations also suggest that the principles of rational behavior underlying the EMH may not be entirely correct and that it is necessary to consider other models of human behavior studied in the social sciences.

EMH assumes that people act rationally. However, certain cognitive biases and psychological factors contribute to this inefficiency, including overconfidence, personal judgment, overreaction, self-esteem, optimism or pessimism from rumors, and expectations about the future (Naseer and Tariq, 2015:1). These biases and psychological tendencies can cause asset prices to deviate from their true values, leading to market inefficiency. For example, according to Karan (2022), the negative effect observed in stocks on Mondays could be attributed to factors such as the Monday syndrome, the settlement process effect, or the tendency for bad news to be released on Mondays.

Despite the views developed against the Efficient Market Hypothesis (EMH), its proponents argue that markets can still be efficient even if individuals are not rational and anomalies exist. According to Malkiel (2003), anomalies are generally not large enough to outweigh the transaction costs incurred by investors. Furthermore, it is suggested that when prices deviate from their true value, they will be driven back to their true value by arbitrageurs seeking profit opportunities. This perspective posits that while irrational behavior and anomalies may occur in the short term, long-term market efficiency can be maintained through the actions of arbitrageurs. However, contrary to what proponents of the Efficient Market Hypothesis (EMH) suggest, when prices deviate from their true values, such as when they fall below intrinsic value, they may not revert to their previous levels through the actions of arbitrageurs. As Barberis and Thaler (2003) state, various factors, including the presence of irrational individuals (noise traders) and significant implementation costs (such as bid-ask spreads, commissions, and price impact), can prevent this correction. Noise traders can drive prices further down instead of correcting them, and

the associated costs can make exploiting mispricing less attractive. Shiller (1984) and Summers (1986) argue that while noise traders may influence prices to drop further, their overall impact on returns is minimal. However, Barberis and Thaler (2003) argue that arbitrageurs are risk-averse, and the risks involved can be systematic, meaning they cannot be entirely eliminated. Consequently, a single investor, even if taking a large position, may not be able to correct the mispricing. Similarly, many investors taking small positions may also fail to correct the mispricing, leading to market inefficiency. One of the criticisms against the Efficient Market Hypothesis (EMH) revolves around the assumption that the costs of obtaining information are very low. However, Grossman and Stiglitz (1980) argue that the costs of acquiring information can be significant, making it challenging for a perfectly efficient market to exist.

There is considerable research on markets like stock within the framework of weak-form efficient market hypothesis. However, studies on green bonds are notably limited and none of these studies have analyzed the market's efficiency by examining whether the series follows a random walk using unit root tests. Hence, this study seeks to enhance the existing body of knowledge by assessing the weak form efficiency of the green bond market through the application of various unit root tests that consider different aspects. This research aims to provide a thorough investigation of market efficiency by utilizing advanced unit root tests. For example, the Dickey-Fuller unit root test, along with other traditional unit root tests based on it, faces significant criticism for being weak in rejecting the null hypothesis of a unit root (Hepsağ and Akçalı, 2015:78). This situation can lead to the conclusion that a time series, which is actually stationary, possesses a unit root. Consequently, using traditional unit root tests to test the weak form of market efficiency can result in the incorrect conclusion that a stock market, which is not weak form efficient, appears to be weak form efficient. Furthermore, a common feature of the existing empirical evidence on the efficiency of emerging markets is that potential nonlinearities in the conditional mean of the series have not been taken into account (Hasanov and Omay, 2007). The proposed study aims to address these gaps by comprehensively analyzing the efficiency of green bond markets. This will be achieved by employing nonlinear unit root tests and approaches that account for non-normal errors, in addition to tests that consider structural breaks and smooth transitions. These methods will provide a more accurate understanding of how green bond markets respond to market shocks and other external influences, thereby making significant and innovative contributions to the literature.

2.2. Literature Review

A significant body of literature has focused on weak-form market efficiency, particularly in the context of stock markets. Researchers have employed various econometric methods to investigate this phenomenon. For instance, some studies have utilized the runs test to examine market efficiency in different markets. Sharma and Kennedy (1977) for the Bombay Stock Exchange, Dickinson and Muragu (1994) for the Nairobi Stock Exchange, Urrutia (1995) for Latin American stock exchanges, Andor et al. (1999) for the Hungarian Stock Exchange, Gupta and Gedam (2014) for the Indian Stock Market analyzed. These studies generally found markets to be efficient using the runs test. Conversely, other researchers have found evidence of inefficiency using the same method. Bekçioğlu and Ada (1985), as well as Taş and Dursunoğlu (2005), analyzed the Turkish IMKB stock market, while Cornelis (2004) examined East Asian markets and found them to be inefficient.

Studies employing the variance ratio test have also produced mixed results across different stock markets. Huang (1995) found East Asian markets to be efficient, as did Grieb and Reyes (1999) for Brazil and Mexico, Ojah and Karemera (1999) for Latin American emerging equity markets, Chun (2000) and Gilmore and McManus (2003) for Hungary, the Czech Republic, and Poland, and Lagoarde-Segot and Lucey (2008) along with Al-Khazali et al. (2007) for MENA countries, Mobarek ve Fiorante (2014) for Bric countries. However, Urrutia (1995) for Latin American countries, Arlt and Arltová (2000) for the Czech Stock Exchange, Hamid et al., (2017) for Asia-Pasific markets reported inefficiency.

Additionally, some studies have used unit root tests to assess market efficiency. Hasanov and Omay (2007) analyzed transition economies such as Bulgaria, Hungary, the Czech Republic, and Slovakia, finding these markets to be efficient. Narayan and Narayan (2007) confirmed efficiency for G7 countries, Murthy et al. (2011) for U.S. stock markets, Chaffai and Medhioub (2012) for emerging markets like Egypt, Morocco, Jordan, and Tunisia, and Ryaly et al. (2014) for Asian stock markets. However, other studies, such as Narayan (2008) for G7 countries, Tiwari and Kyophilavong (2014) for BRICS countries excluding Russia, and Turguttopbaş and Omay (2023) for emerging markets including Brazil, China, Russia, Türkiye, and South Africa, found these markets to be inefficient.

While most of the literature has focused on examining the weak-form efficiency of stock markets, significant studies also investigate the efficiency of bond markets. One notable example is the work of Afonso and Teixeira (1999), which explores the weak-form efficiency of government bond markets in the Eurozone. Specifically, their study examines the bond markets of ten countries: Portugal, Spain, France, Italy, Belgium, Germany, the Netherlands, Luxembourg, Austria, Ireland, and Finland. They employ several econometric tests to analyze bond market efficiency, including the ARCH test, the Hinich bispectrum test, the Lyapunov exponent test, and the BDS statistic. Their findings indicate that 10-year government bonds exhibit nonlinear dependencies and suggest that bond returns possess a certain degree of predictability.

Babu (2017) examined the efficiency of the Indian bond market using daily and weekly data spanning from January 3, 2011, to December 30, 2016. Employing the variance ratio test to assess market efficiency, findings indicate a rejection of the random walk hypothesis. This result suggests that the Indian bond market is not weak-form efficient. Consequently, the author concludes that investors have the potential to achieve abnormal returns through speculation, as the market does not fully reflect all available information.

Omran and Semenkova (2019) investigated the efficiency of Russia's corporate and government bond markets using the GARCH (1,1) model. The study analyzed daily data from June 4, 2013, to November 30, 2018. Their findings indicate that neither the corporate nor government bonds in Russia exhibit weak-form market efficiency. The total sum of the GARCH parameters being close to one suggests a high persistence of volatility clusters in both markets. This implies that past volatility significantly influences future volatility, indicating the presence of predictable patterns and inefficiencies within these bond markets.

Liu (2013) examined the weak-form efficiency of South Africa's bond market, focusing on government bonds, corporate bonds, and the All Bond Index, which represents the average performance of all bonds. The study used different time periods for each bond type: July 2009 to May 2012 for government bonds, July 2010 to May 2012 for corporate bonds, and January 2014 to October 2012 for the All Bond Index. Employing daily data and a time-varying parameter approach, Liu (2013) found that South Africa's bond market is efficient.

Guduza and Phiri (2017) also focused on South Africa's stock and bond markets using monthly data from 2002 to 2016, a period that includes the 2008 financial crisis. They employed both individual unit root tests (ADF, PP, and KPSS) and panel unit root tests (Maddala and Wu, 1999; Hadri, 2000; Levin et al., 2002; Im, Pesaran, and Shin, 2003). To account for the impact of the financial crisis, they divided the dataset into two sub-samples. Their analysis showed no evidence of unit roots in the return series for either the full period or the sub-samples, suggesting market efficiency.

Mutize and Gossel (2020) expanded the scope to include stock and bond markets in 19 African countries. They used the Ljung-Box Q ACF test, runs test, and variance ratio test. While the autocorrelation test suggested market efficiency for both markets, the runs test indicated inefficiency in both. The variance ratio test found the bond market to be inefficient while the stock market was efficient. The authors concluded that bond markets are generally less efficient and less competitive than stock markets.

Muzhoba (2021) conducted a comparative analysis of the weak-form efficiency of bond markets in developed and emerging economies. This study used the Botswana aggregate bond index as a representative of an emerging market and the Bloomberg Barclays Capital Global Aggregate Bond Index as a proxy for developed markets. The methodological approach included applying GARCH, ARFIMA, and HYGARCH models to assess market efficiency. The findings revealed that while short-term memory dynamics were present in the global index, indicating some predictability over a short horizon, long-term dependence was more pronounced in the Botswana market. This suggests that the Botswana bond market exhibits significant long-term dependencies, which are less common in the more developed and sophisticated global bond markets. According to the author, these results indicate that global indices represent more efficient markets. In contrast, the Botswana market's inefficiencies are likely due to liquidity constraints and other market frictions typical of smaller, less developed financial markets. Consequently, the lack of liquidity and market sophistication in Botswana affects its market efficiency, making it more predictable over the long term compared to the global index.

Research on bond markets has been relatively limited. Specifically, there are few studies investigating the efficiency of green bond markets. To our knowledge, the pioneering work in this area was conducted by Karginova-Gubinova et al. (2020). This study aimed to

determine whether the green bond market is inefficient by examining calendar effects using the Breusch-Godfrey LM test. The authors analyzed data from July 31, 2014, to the end of 2018, focusing on calendar effects such as the "day of the week effect" (the Monday effect), the "weekend effect" (Friday effect), and the "January effect." To test for the first two effects, they compared the average daily change of the green bond index for each day of the week with the overall average daily change and calculated the proportion of days when the index increased or decreased. This method allowed them to analyze whether the index behaved differently on specific days of the week. For the January effect, they calculated the monthly growth of the index and ranked January among all months for each year to see if January returns were significantly different from those of other months. The results indicated significant autocorrelation in the series, while no substantial day-of-the-week or weekend effects were observed. However, it was found that Monday returns were generally higher compared to other days, suggesting potential inefficiencies in the green bond market. In conclusion, the findings of Karginova-Gubinova et al. (2020) imply that the green bond market may not be efficient, as evidenced by the significant autocorrelation and the higher returns observed on Mondays.

Pham (2016) examined the green bond market using the S&P Green Bond Index and the S&P Green Project Index, employing a GARCH (1,1) model for the period from April 30, 2010, to April 29, 2015. The study found that the sum of alpha and beta parameters being close to one suggests persistent volatility and prolonged responses to shocks in the green bond market. Consequently, it can be inferred that the market is not efficient.

Adekoya et al. (2021) investigated the efficiency of the S&P Green Bond Select Price Index and the S&P Green Bond Price Index returns using a GARCH (1,1) model. The authors obtained results similar to those of Pham (2016) for the period spanning November 28, 2008, to September 23, 2020, indicating persistent volatility and prolonged responses to shocks in the green bond market. Additionally, the authors re-applied the GARCH (1,1) model for two specific periods: the financial crisis period from November 28, 2008, to March 6, 2009, and the health crisis period from January 1, 2020, to September 23, 2020. They found that during the COVID-19 period, volatility shocks remained persistent, whereas, during the financial crisis period, the green bond market exhibited mean-reverting behavior. This suggests that during the COVID-19 period, the green bond market continued to

experience persistent volatility shocks, while during the financial crisis period, it showed a tendency to revert to its mean behavior.

Naeem et al. (2021) examined the efficiency of green bonds and compared them with traditional bonds, both before and after the COVID-19 period, using the asymmetric multifractal detrended fluctuation method. They assessed how the returns of Solactive, S&P, and Bloomberg Barclay MSCI green bonds and traditional bonds responded to different market conditions (bullish and bearish). During the period from November 3, 2014, to September 3, 2020, the authors found that multifractality was lower in the traditional bond market, indicating higher efficiency in these markets, while green bond markets were more influenced by downward market trends, suggesting greater efficiency. Additionally, during the COVID-19 pandemic period, although efficiency decreased in both markets, it decreased more in the traditional bond market.

In general, findings regarding weak-form market efficiency for stock markets vary depending on the market and the methodology used. For instance, in studies conducted on G7 countries, tests that do not account for structural breaks typically find markets to be efficient, whereas those that do consider structural breaks indicate market inefficiency. Studies on bond markets generally suggest market inefficiency, with this inefficiency being more pronounced in developing countries' markets. Additionally, four studies on the green bond market using different econometric methods all indicate that the market is not weak-form efficient.

2.2.1 Anomalies

Fama (1976) highlighted that all methods used to test market efficiency assume that the market is in equilibrium. This implies that market participants form fair prices based on available information and expectations, and prices generally align closely with expected values. Therefore, it is assumed that expected returns are constant within a certain model, and actual returns are adjusted based on these expected returns. However, empirical studies in the literature suggest that this assumption may vary in certain cases, especially regarding variations in returns based on days of the week or month effects.

One such study was conducted by Gibbons and Hess (1981), who analyzed the period from November 29, 1974, to December 28, 1978, using assets such as the S&P 500 and treasury bills. In their study, the most evident indication of daily seasonality was observed, particularly strong and persistent negative average returns on Mondays for stocks and below-average returns on Mondays for treasury bills. Consequently, it can be inferred that, contrary to Fama's (1976) assertion, there is not a single equilibrium condition.

Flannery and Protopadakis (1988) conducted research on intra-week seasonality for eleven different assets between 1976 and 1984. The authors revealed distinct seasonal patterns between stocks and Treasury bonds. For instance, while stock returns are higher on Wednesdays and Fridays, Treasury bond returns peak on Thursdays. Additionally, they discovered that while there is a negative return on Mondays for all assets, this negative trend intensifies on Mondays as the maturity of Treasury bonds lengthens. The authors attributed this phenomenon to the weekly fluctuations in market discount rates and suggested that the increasing maturity premiums over the weekend could explain this trend. According to the authors, these findings indicate that intra-week seasonality exhibits different performances depending on the asset types, potentially impacting investment strategies.

Nippani and Arize (2008) examined anomalies in three different bond markets (Dow Jones Bond Average, Industrial Bond Average, and Utility Bond Average) in the US market for the period from January 1, 1982, to April 5, 2002. The authors investigated the day-of-week effect by employing various models. For instance, they adopted Connolly's (1989) model, which includes only a dummy variable for Mondays in the regression and found no significant Monday effect. However, when they applied French's (1980) model, which substitutes the dummy variable representing Monday with dummy variables for other days, they observed that Monday returns were considerably lower compared to other days. Additionally, the authors examined the January effect and found its impact on the returns of the three bonds.

In contrast to the three studies mentioned earlier, Jordan and Jordan (1991) demonstrated that there was no day-of-the-week effect on the Dow Jones Composite Bond Average index. However, they found that this index exhibited turn-of-the-year effects, January effects, and week-of-the-month effects. Each of these recognized seasonal effects

was investigated individually using a one-way analysis of variance to determine their presence or absence in the bond market.

Studies examining the day-of-the-week effect on bonds exist not only in the American market but also in other countries. One such study is conducted by Khanthavit (2016), focusing on Thai government bonds. Similar to the findings of Jordan and Jordan (1991), Khanthavit found a reverse day-of-the-week effect. For the period spanning from 2001 to 2015, they noted that Monday returns were positive for 1- and 3-month bonds, while for 3-month and longer-term bonds, the positive effect was more prominent on Thursdays and Fridays.

Bespalco (2009) expanded the scope by including a wider range of countries (Ukraine, Türkiye, Mexico, Brazil, Philippines, Bulgaria, and Russia) and examined anomalies in both stock and government bonds. While no Monday effect was observed for bonds, a Tuesday effect was found in countries other than Bulgaria and Brazil. However, no day effect was observed in stock markets. According to the authors, these results suggest that stock markets are more efficient than bond markets.

Unlike previous studies investigating the day-of-the-week effect, Washer et al. (2011) examined the day effect on Canadian treasury bills using both parametric (t-test) and non-parametric (Wilcoxon signed rank test) methods for the period from 1980 to 2009. They found a negative Monday effect for the entire period, which turned insignificant but remained negative between 1990 and 2000 and then became positive after 2000. This observation suggests that the day effect across periods did not follow a stable pattern.

Compton et al. (2013) investigated calendar anomalies in the Russian stock and bond markets and compared them with the American S&P 500 and Dow Jones Corporate Bond Index markets. They used data from 2003 to 2008 for bond markets and from 1998 to 2008 for stock markets. While both January and day-of-the-week effects were observed in the bond markets during these periods, only the day-of-the-week effect was observed for US corporate bonds. However, neither of these effects was found in either country's stock markets. These results suggest that stock markets are more efficient, and on a country level, the US market appears to be more efficient.

Some studies have focused solely on January anomalies. One such study is conducted by Schneeweis and Woolridge (1979). The authors investigated the seasonality effect for corporate, public utility, municipal, and treasury bond data using autocorrelation tests, variance tests, and the non-parametric Kruskal-Wallis test. The results indicated a January effect in bond returns, except for treasury bonds, with higher returns observed in January compared to other months. Clayton et al. (1989) examined the January effect on government bonds based on their maturity structures. They emphasized that as the maturity structure increases, the returns obtained in January turn negative. Compton and Kunkel (2000) conducted a study on the CREF Stock and the CREF Bond markets, where they did not find any January effect or day-of-the-weekend effect. However, they did find that the Monday effect, indicating higher returns on Mondays compared to other days, was present in their analysis. Greer (2015) focused on the municipal bond market and, similar to the study by Stark et al. (2006), observed negative returns in January using the Box-Jenkins method of identifying a seasonally adjusted ARIMA method. On the other hand, Chen et al. (2011) conducted a study on municipal bonds and observed positive returns in January using the GMM method.

Smith (2002) conducted a study to test for seasonality in various government bond markets of major industrial countries for the period from February 1985 through March 1999. Statistically significant January effects were found in the government bond markets of the United States, the United Kingdom, Germany, France, and Canada when measured in local currencies. Similar results were obtained for excess returns measured in US dollars for the same markets, except for Canada, which stood out as an exception by not exhibiting a January effect when measured in US dollars. Additionally, the authors applied the Wilcoxon rank test, a non-parametric test, and obtained different results. Non-parametric tests failed to detect the January effect regardless of the measurement unit used. However, this was an exception for the French government bond market when measured in local currency, where the January effect was observed. Another finding of the study was that during the 1987 October crisis, investors tended to turn to bonds, particularly Canadian bonds.

In summary, various studies question the assumption of market efficiency by investigating anomalies. While some, like Gibbons and Hess (1981), find differences in asset prices depending on the days of the week, others (Flannery and Protopadakis, 1988; Jordan and Jordan, 1991) challenge the existence of such effects. Additionally, studies such as those

by Nippani and Arize (2008) demonstrate distinct day effects across different financial instruments. These diverse findings contribute to our understanding of market efficiency.

2.3. Econometric Methodology and Data

2.3.1. Econometric Methodology

In this section, a brief overview of the theoretical foundations of unit root tests to be applied in determining whether markets are weak-form efficient is provided. In this context, traditional unit root tests are first examined, followed by Fourier-based unit root tests that consider structural breaks, tests assessing linearity in series, and finally, tests addressing non-normality in error terms.

2.3.1.1. Unit Root (Stationarity) Tests

A fundamental requirement is that the series used must be stationary in studies utilizing time series data. However, many economic time series exhibit non-stationary behavior. In such cases, assuming the series to be stationary without proper examination can lead to incorrect results. Econometric studies conducted over the last 30 years have particularly focused on this issue. The concept of stationarity in time series analysis is assessed through unit root tests.

2.3.1.1.1. Linear Unit Root Tests

2.3.1.1.1.1. Augmented Dickey-Fuller

The distinction between the Augmented Dickey-Fuller (ADF) stationary test of Dickey and Fuller (1981) and the Dickey and Fuller (1979) stationary test lies in addressing the autocorrelation issue by incorporating lagged variables of the dependent variable into the model. Equations 2.1 and 2.2 illustrate the regression models for the ADF unit root test applied to the three variables in the analysis.

$$\Delta y_t = \alpha_0 + \alpha_1 y_{t-1} + \sum_{i=1}^{p} \alpha_i y_{t-1} + u_t \quad (2.1)$$

$$\Delta y_t = \alpha_0 + \alpha t + \alpha_1 y_{t-1} + \sum_{i=1}^{p} \alpha_i y_{t-1} + u_t \quad (2.2)$$

Where, α_0 represents the intercept term, α_1 and α_i denote the coefficients, t is the trend, p denotes the optimal lag length determined by different information criteria, u_t represents the error term. The hypotheses are presented as follows:

H_0: (The series is non-stationary).

H_1: (The series is stationary).

If the computed statistic value is greater in absolute value than the critical values from the Dickey and Fuller (1981) study, the null hypothesis of "the series is non-stationary" is rejected.

2.3.1.1.1.2. Phillips and Perron (1988)

The stationarity test developed by Phillips and Perron (1988) is a transformed version of the ADF test. This transformation asymptotically removes the dependency of the variables. In the PP stationarity test, regression equations are not used as in the ADF test. Instead, a transformation is applied to compute the test statistic. In studies, three different types of equations are used:

1. Equation not including an intercept term and an intercept and trend term,
2. Equation including an intercept term,
3. Equation including an intercept and trend term,

The Phillips-Perron (PP) test is widely used in econometric analysis as an important method to assess the presence of unit roots and stationarity properties of time series. Equations 2.3 and 2.4 represent the PP equations.

$$y_t = \alpha_0^* + \alpha_0^* y_{t-1} + \varepsilon_t \quad (2.3)$$

$$y_t = \tilde{\alpha}_0 + \tilde{\alpha}_0 y_{t-1} + \tilde{\alpha}_2 (t - {}^{T}/_{2} + \varepsilon_t) \quad (2.4)$$

where T represents the number of observations and ε_t denotes the error term. The Z-test method proposed by Phillips-Perron (1988) is advantageous and more robust than other tests in time series models when the mean components are positively trending. However, if the mean components are negatively trending, its usage is not recommended as it can lead to dimensional skewness (Phillips and Perron, 1988: 337). The hypotheses of the Phillips-Perron stationarity test are as follows:

H_0: (The series is non-stationary).

H_1: (The series is stationary).

If the computed Z-statistic value is greater in absolute value than the critical value, the null hypothesis is rejected.

2.3.1.1.2. Fourier Unit Root Tests

The Fourier approach stands out for its ability to capture the behavior of a deterministic function that does not have a specific form. This method can successfully capture the behavior of a deterministic function regardless of whether the function is periodic or not. Additionally, this approach performs better than dummy variable methods irrespective of whether the breaks are instantaneous or smooth. By avoiding the issues of selecting the dates, number, and form of breaks, the Fourier approach provides a significant advantage in overcoming such challenges. Due to these features, the Fourier approach is considered a more flexible and reliable tool when examining structural breaks in economic and financial time series. By accurately modeling the nature of breaks, the Fourier approach has the potential to enhance the accuracy and reliability of economic analyses (Omay, 2015:123).

2.3.1.1.2.1. Beckers, Enders, and Lee (2006)

The Fourier version of the traditional KPSS test was developed by Beckers et al. (2006). The stationarity test is characterized by a null hypothesis that asserts the presence of stationarity in the time series. The following models are estimated using the Ordinary Least Squares (OLS) method in the first stage of the process, which is necessary in order to apply the test. After that, the residuals of the models are obtained:

$$y_t = \beta_0 + \beta_1 \sin\left(\frac{2\pi kt}{T}\right) + \beta_2 \cos\left(\frac{2\pi kt}{T}\right) + \varepsilon_t \quad (2.5)$$

$$y_t = \beta_0 + \alpha_t + \beta_1 \sin\left(\frac{2\pi kt}{T}\right) + \beta_2 \cos\left(\frac{2\pi kt}{T}\right) + \varepsilon_t \quad (2.6)$$

Equations 2.5 and 2.6 represent models with different terms; the first one is a constant term model, and the second one is a constant and trend model. It is used k ($k = 1,2,\dots,5$) for the number of frequencies, t for the deterministic trend term, and T for the sample size. In the initial step of the process, an appropriate frequency is chosen, and the residuals that have been collected from the regression are obtained. These residuals are applied to the KPSS test in the second step of processing.

$$\tau_\mu(k) \; or \; \tau_\tau(k) = \frac{1}{T^2} \frac{\sum_{t=1}^{T} t(k)^2}{\tilde{\sigma}^2} \quad (2.7)$$

where $\tau_\mu(k)$ and $\tau_\tau(k)$ represent the test statistic for the model with constant term and the model with constant and trend terms. In addition, the numerator represents the squared residuals, and the denominator represents the long-run variance, where T denotes the number of observations. If this test statistic is lower than the critical values obtained by Beckers et al. (2006), then the null hypothesis that the series is stationary cannot be rejected. Once the series is determined to be stationary, the trigonometric terms of the Fourier functions are examined for their significance. The test used for this is an F-test, as described below.

$$F(\hat{k}) = \left(\frac{\frac{SSR_0 - SSR_1(k)}{2}}{\frac{SSR_1(k)}{T-q}} \right) \quad (2.8)$$

where SSR_0 represents the sum of squared residuals obtained without using trigonometric terms, $SSR_1(k)$ represents the sum of squared residuals obtained from Equation (2.5) or Equation (2.6). T is the sample size, and q is the number of parameters in the unrestricted model. The null hypothesis ($H_0: \beta_1 = \beta_2 = 0$) suggests that the Fourier terms are not statistically significant, while the alternative hypothesis ($H_1: \beta_1 \neq \beta_2 \neq 0$) indicates that the Fourier terms are statistically significant. If the F-test statistic is greater

than the critical values obtained by Beckers et al. (2006), the null hypothesis is rejected. Thus, it suggests that the trigonometric terms are statistically significant.

2.3.1.1.2.2. Christopoulos and Leon Ledesma (2010)

Finding the right model definition is one of the biggest problems with unit root tests. Enders and Granger (1998) demonstrated that traditional unit root tests had lower power in the presence of misspecified dynamics. According to Perron (1989), when structural breaks are ignored in traditional unit root tests, they are biased toward not rejecting. In this context, Christopoulos and Leon Ledesma (2010) suggested Fourier unit root tests with smooth breaks to detect unknown structural breaks in time series. In addition, they added structural breaks and nonlinear forms to the unit root models. The structure of the model is described below.

$$y_t = \theta(t) + \varepsilon_t \tag{2.9}$$

where $\theta(t)$ is a time-varying deterministic component and ε_t is a random variable with a distribution $N(0, \sigma)$. The following Fourier functions are used for $\theta(t)$:

$$\theta(t) = \theta_0 + \sum_{k=1}^{G} \theta_1^k \sin(\frac{2\pi kt}{T}) + \sum_{k=1}^{G} \theta_2^k \cos(\frac{2\pi kt}{T}) \tag{2.10}$$

It is used k ($k = 1,2,\dots,5$) for frequency count, t for time term, and T for sample size. k is usually unknown; thus, an equality is estimated for each integer number between 1 and 5. Then, the value with the lowest sum of squared errors is chosen. Under the null hypothesis $H_0: \theta_1 = \theta_2 = 0$, the significance of the Fourier terms is tested using the F-statistic. The procedure for generating the data in Equation 2.11 consists of two stages:

$$y_t = \theta_0 + \theta_1 \sin\left(\frac{2\pi kt}{T}\right) + \theta_2 \cos\left(\frac{2\pi kt}{T}\right) + \varepsilon_t \tag{2.11}$$

The Ordinary Least Squares (OLS) residuals in Equation (2.12) are derived in the second stage of the test:

$$\hat{\varepsilon}_t = y_t - (\hat{\theta}_0 + \hat{\theta}_1 \sin(\frac{2\pi \hat{k} t}{t}) + \hat{\theta}_2 \cos(\frac{2\pi \hat{k} t}{t})) \quad (2.12)$$

The residuals from Equation 2.12 are unit root tested. The authors proposed the following model as the linear form for the unit root test. FADF represents the classic ADF regression.

$$\Delta\varepsilon_t = \beta_1 \varepsilon_{t-1} + \sum_{j=1}^{p} \alpha_j \Delta\varepsilon_{t-j} + e_t \quad (2.13)$$

The authors have proposed the following model for the nonlinear form. This test, called the FKSS unit root test, is built on the Exponential Smooth Transition Autoregressive (ESTAR) process.

$$\Delta\varepsilon_t = \emptyset_1 \varepsilon_{t-1}^3 + \sum_{j=1}^{p} \beta_j \Delta\varepsilon_{t-j} + e_t \quad (2.14)$$

In the second step, the ADF / (KSS) test is applied to the residuals shown in Equation 2.13/ (in Equation 2.14). In this context, the null hypothesis indicates the presence of a unit root, while the alternative hypothesis suggests stationarity. If the series is determined to be stationary, then it is necessary to test whether the coefficients of the trigonometric terms in the regression are statistically significant. If a unit root is found, no further testing is required. However, if the series is found to be stationary, it is important to assess the statistical significance of the Fourier terms using an F-test. If the trigonometric terms are not statistically significant, the classical ADF test can be applied.

2.3.1.1.2.3. Enders and Lee (2012)

Enders and Lee (2012) extended Dickey and Fuller (1979) unit root test by using Fourier functions as deterministic terms. In their work, Equation 2.15 describes the regression model with a deterministic term ($\alpha(t)$) that is a time-dependent function.

$$y_t = \alpha(t) + \rho y_{t-1} + \gamma t + \varepsilon_t \quad (2.15)$$

Where $\alpha(t)$ is deterministic term and ε_t is a stationary disturbance with variance σ_ε^2. The hypothesis being tested is the absence of a unit root ($\rho = 1$). If the structure of $\alpha(t)$ is

unknown, it can lead to biased test results for the null hypothesis. To overcome this challenge, it is suggested that the unknown functional structure of $\alpha(t)$ can be expressed using Fourier terms, as illustrated in Equation 2.16.

$$\alpha(t) = \alpha_0 + \sum_{k=1}^{n} \alpha_k (sin \frac{2\pi kt}{T}) + \sum_{k=1}^{n} \beta_k \, (cos \frac{2\pi kt}{T}); \qquad n \leq T/2 \tag{2.16}$$

Equation (2.15) denotes n as the number of frequencies, T as the number of observations, and k as the frequency number. When $\alpha_1 = \beta_1 = \cdots = \alpha_n = \beta_n = 0$, it signifies that the process is linear, and it is necessary to use a conventional unit root test. Alternatively, in the presence of a structural break or a non-linear trend in the series, there will be at least one Fourier frequency involved in the process of generating the data (Enders and Lee, 2012:197).

Equation 2.16, when viewed as a regression equation, faces challenges with a large number of frequencies n. This necessitates including numerous frequency components, potentially leading to overfitting, especially in datasets with limited observations. To address this, rather than specifying a specific form for $\alpha(t)$, it is more effective to select appropriate frequencies. Assuming a single frequency, as in Equation 2.17, the test equation becomes more parsimonious, aiding interpretation and generalization in regression analysis. Frequency selection is crucial for reliable unit root testing, particularly with limited sample sizes (Enders and Lee, 2012:197). Considering the testing regression with a single frequency k like Equation 2.17

$$\Delta y_t = \rho y_{t-1} + c_1 + c_2 t + c_3 \sin\left(\frac{2\pi kt}{T}\right) + c_4 \cos\left(\frac{2\pi kt}{T}\right) + \varepsilon_t \tag{2.17}$$

The test result from testing the null hypothesis $\rho = 0$ is shown by τ_{DF_t} in Equation 2.17. There is no need for a different asymptotic distribution for this test because the asymptotic properties of the DF version tests are the same as those of the LM version tests. Another important thing about this test is that the critical values are only influenced by the frequency number k and the sample size T. Fourier terms and other deterministic terms don't change them. The right frequency number k for Equation 2.17 can be estimated using the two-step process shown below.

Step 1: Estimate Equation 2.17 for all integer values of k that are between 1 and 5. The value of $\hat{k}$ is obtained via the regression that has the smallest sum of squared residuals. If there is a serial correlation between the residuals, then modify Equation 2.17 by adding the lagged values of Δy_t

Step 2: For the determination of non-linear form existence, the classic F test is utilized. This requires testing null hypothesis ($c_3 = c_4 = 0$). If the null hypothesis cannot be rejected, it can be concluded that the data generation process is influenced by frequency. Otherwise, the data generation process will be the same as the traditional Dickey-Fuller (DF) process. At this point, the authors recommend the DF test.

2.3.1.1.2.4. Omay (2015)

Omay (2015) introduced a new ADF unit root test, which incorporates fractional frequencies of Fourier terms, adding to the literature. The author has demonstrated that the fractional FADF unit root test, utilizing Fourier expansion, can yield better results in cases where deterministic components are unknown. The ADF test is written in the form that is shown in Equation 2.18 below.

$$y_t = d(t) + \gamma_1 y_{t-1} + \delta t + \varepsilon_t \tag{2.18}$$

Where $d(t)$ shows a deterministic component, and it is described below:

$$d(t) = \beta_0 + \alpha_k \sin\left(\frac{2\pi kt}{T}\right) + \beta_k \cos\left(\frac{2\pi kt}{T}\right) \tag{2.19}$$

Where $d(t)$ represents the deterministic function of t. k shows the fractional frequency, which is defined to range between 0.1 and 2. In this test, analyzing the significance of trigonometric terms is first conducted. If these trigonometric terms are statistically significant, it is suggested that Omay (2015) can be employed to examine the presence of unit roots. The testable regression is depicted below:

$$\Delta y_t = \rho y_{t-1} + a_1 + a_2 t + a_3 \sin\left(\frac{2\pi k^{fr} t}{T}\right) + a_4 \cos\left(\frac{2\pi k^{fr} t}{T}\right) + e_t \tag{2.20}$$

Equation 2.20 with a single frequency within the range of $0.1 \leq k^{fr} \leq 2$ is conducted. The significance of the trigonometric terms is tested using the following F-statistic formula:

$$F(\hat{k}) = \left(\frac{\frac{SSR_0 - SSR_1(k)}{2}}{\frac{SSR_1(k)}{T-q}} \right) \tag{2.21}$$

$H_0: a_1 = a_2 = 0$ implies no statistical significance in fractional Fourier terms, while $H_1: a_1 \neq a_2 \neq 0$ indicates statistical significance in fractional Fourier terms. The null hypothesis is rejected if the F-test statistic is higher than the critical values determined by Omay (2015). This indicates that the trigonometric terms have a statistically significant implication. Consequently, we can use this unit root test results. In the contrary case, if fractional Fourier terms are not statistically significant, we cannot use this test, and it can revert to either the DF or ADF unit root test.

2.3.1.1.2.5. Shahbaz, Omay, and Roubaud (2018)

A series may have breaks that are both sharp and smooth at the same time. In response to this gap in the literature, Shahbaz et al. (2018) constructed a new test (shortly SOR test) that takes breaks into account and evaluates them as both smooth and sharp. In their paper, the authors say that predictions are biased and ambiguous when dynamics such as structural breaks and nonlinearity are ignored.

The logistic smooth transition autoregressive (LSTAR) model, which was developed by Leybourne et al. (1998), provides a framework for the unit root test that is used in the SOR (2018) test. The SOR test is also a two-step process. In the first step of the process, the deterministic component of the model is estimated by employing a genetic algorithm together with a constrained nonlinear performance optimization method.

$$Model\ A: \hat{\varepsilon}_t = S\&P_t - \hat{\beta}_1 - \hat{\beta}_2 F_t(\hat{\gamma}, \hat{\tau}) \tag{2.22}$$

$$Model\ B: \hat{\varepsilon}_t = S\&P_t - \hat{\beta}_1 - \hat{\alpha}_1 t - \hat{\beta}_2 F_t(\hat{\gamma}, \hat{\tau}) \tag{2.23}$$

$$Model\ A: \hat{\varepsilon}_t = S\&P_t - \hat{\beta}_1 - \hat{\alpha}_1 t - \hat{\beta}_2 F_t(\hat{\gamma}, \widehat{\tau}) - \hat{\beta}_2 F_t(\hat{\gamma}, \hat{\tau})\text{t} \tag{2.24}$$

Model A tests for structural breaks in the intercept term, Model B tests for structural breaks in the trend term, and Model C tests for structural breaks in both the intercept and trend terms. In the second stage, the t-statistic proposed by Enders and Lee (2012) is calculated in the following OLS estimation:

$$\hat{\varepsilon}_t = d(t) + \theta_1 \hat{\varepsilon}_{t-1} + u_t \tag{2.25}$$

Where $d(t)$ shows a deterministic component, and it is described as below

$$d(t) = \beta_0 + \sum_{k=1}^{n} \beta_k \sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \alpha_k \cos\left(\frac{2\pi kt}{T}\right), n \leq \frac{T}{2} \tag{2.26}$$

Where T represents the number of observations, n approximates the cumulative frequency, and k is a certain frequency. Finally, the testable regression is below:

$$\Delta\hat{\varepsilon}_t = \beta_0 + \sum_{k=1}^{n} \beta_k \sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \alpha_k \cos\left(\frac{2\pi kt}{T}\right) + \theta_1 \hat{\varepsilon}_{t-1} + \sum_{i=1}^{p} \varphi_k \Delta\hat{\varepsilon}_{t-1} + u_t \tag{2.27}$$

To account for the stationary dynamics in $\hat{\varepsilon}_t$, it is commonly observed that increasing the lag order of the dependent variables. Therefore, the Enders and Lee (2012) test statistic is used as $s\tau_\alpha$ in Model A, $s\tau_{\alpha(\beta)}$ in Model B, and $s\tau_{\alpha,\beta}$ in Model C. The null hypothesis of the SOR test expressed that a unit root exists in the data, while the alternative hypothesis reports that the series is nonlinear stationary.

2.3.1.1.3. Nonlinear Unit Root Tests

Policy changes, financial crises, disasters, and other similar events have a substantial impact on both economic and financial data. Conventional unit root tests do not take into consideration the impacts of these factors. However, unit root tests introduced by Perron (1998) and Zivot and Andrews (2002) consider these effects by allowing for a sudden structural change in the series. Nevertheless, Leybourne et al. (1998) argue that it is not necessarily accurate to assume that fundamental changes in economic time series usually happen suddenly. The behavior of numerous individuals frequently exerts an effect on

economic changes, and it is hard to expect simultaneous reactions from all persons. Certain individuals may exhibit quick reactions, but others may display a slow response. Thus, a smooth transition model is more effective in capturing structural changes in economic series. Nonlinear unit root tests are valuable in this context because they enable the examination of sudden and smooth transitions between different regimes in the series, allowing for a more flexible and realistic analysis.

2.3.1.1.3.1. ESTAR Type Unit Root Tests

The assumption of a smooth transition between regimes is made by several nonlinear unit root tests rather than a sharp transition. Some of these tests are based on models in which regime shifts take place gradually and exponentially over time. These models are referred to as Exponential Smooth Transition Autoregressive (ESTAR) models. Kapetanios et al. (2003), Sollis (2009), and Kruse (2008) are some examples of tests that use ESTAR models.

2.3.1.1.3.1.1. Kapetanios, Shin, and Snell (2003)

Kapetanios et al. (KSS, 2003) expanded upon the conventional ADF unit root test by proposing a framework that models structural shifts in the series as exponential and gradual rather than sharp. Introducing an alternative unit root test, they specifically targeted linear non-stationary processes, notably the ESTAR type, which assumes changes to be exponential and gradual rather than linear.

$$y_t = \beta y_{t-1} + \vartheta y_{t-1} F(\theta; y_{t-d}) + \varepsilon_t \tag{2.28}$$

Where $\varepsilon_t \; iid(0, \sigma^2)$ and β and ϑ are unknown parameters. The exponential transition function is expressed as follows: $F(\theta; y_{t-1}) = 1 - exp\{-\theta(y_{t-d} - c)^2\}$. d is the delay parameter and bigger than zero and c is zero. Therofore, the ESTAR model can be displayed below:

$$\Delta y_t = \beta y_{t-1} + \vartheta y_{t-1}(1 - exp\{-\theta y_{t-d}^2\}) + \varepsilon_t \tag{2.29}$$

$H_0: \theta = 0$ (The series is non-stationary).

$H_1: \theta > 0$ (The series is non-stationary).

In accordance with this Equation 2.29, it is not possible to directly test this null hypothesis because the ϑ parameter is not defined under the null hypothesis. Therefore, the authors have reformulated the above KSS Equation 2.29 by computing a first order Taylor approximation. The new equation can be expressed as follows:

$$\Delta y_t = \delta y_{t-1}^3 + \varepsilon_t \tag{2.30}$$

$H_0: \delta = 0$ (There is a unit root)
$H_1: \delta > 0$ (There is non-linear stationarity)

The test statistic for Equation 2.30 is $t_{NL} = \frac{\hat{\delta}}{std.dev(\hat{\delta})}$. Here, $\hat{\delta}$ denotes OLS estimate of δ, while $std.dev.(\hat{\delta})$ represents the standard error of δ. However, the authors calculated critical values via simulations since t's asymptotic distribution is not normal.

2.3.1.1.3.1.2. Sollis (2009)

Sollis (2009) modified the KSS unit root test to determine the asymmetric adjustment of shocks in time series data. This method is recognized in the literature as the "Asymmetric ESTAR-type unit root." It provides an effective tool for identifying asymmetric nonlinear adjustment in series data.

$$\Delta y_t = G(\gamma_1, y_{t-1})\{S_t(\gamma_2, y_{t-1})\rho_1 + (1 - S_t(\gamma_2, y_{t-1}))\rho_2\}y_{t-1} + \sum_{i=1}^{k} k_i \Delta y_{t-i} + \varepsilon_t \tag{2.31}$$

$$G(\gamma_1, y_{t-1}) = 1 - exp(-\gamma_1(y_{t-1}^2)) \qquad \gamma_1 \geq 0 \tag{2.32}$$

$$S_t(\gamma_2, y_{t-1}) = \{1 + exp(-\gamma_2 y_{t-1})\}^{-1} \qquad \gamma_2 \geq 0 \tag{2.33}$$

In the case when the mean is zero, we can test the hypothesis of a unit root versus the alternative hypothesis of globally stationary symmetric or asymmetric ESTAR nonlinearity

with the unit root central regime. This testing approach involves evaluating the null hypothesis $H_0: \gamma_1 = 0$ in Equation 2.31 Unfortunately, there are γ_2, ρ_1 and $\rho_2$that cannot be determined within this null hypothesis (Sollis, 2009:120).

In Equation 2.31, the author has assumed that k is equal to zero. $G(\gamma_1, y_{t-1})$ in Equation 2.31 has been substituted with a first-order Taylor expansion centered around the value of γ_1 equal to zero. To test for the presence of a unit root, the following Equation 2.34 are obtained, where all parameters are defined as:

$$\Delta y_t = \rho_1 \gamma_1 y_{t-1}^3 S_t(\gamma_2, y_{t-1}) + \rho_2 \gamma_1 y_{t-1}^3 \big(1 - S_t(\gamma_2, y_{t-1})\big) + \eta_t \quad (2.34)$$

Where η_t equals the summation of ε_t and R_t. R_t represents the residual term resulting from the first-order Taylor expansion. However, under null hypothesis ($H_0: \gamma_1 = 0$), the parameters of γ_2, ρ_1, and ρ_2 cannot be determined. In this case, the author employs the Taylor expansion once again using the logistic function. It is replaced $S_t(\gamma_2, y_{t-1})$ with $S_t^*(\gamma_2, y_{t-1})$=$S_t(\gamma_2, y_{t-1})$-0.5. The new equation can be expressed as follows:

$$\Delta y_t = \rho_1^* \gamma_1 y_{t-1}^3 S_t^*(\gamma_2, y_{t-1}) + \rho_2^* \gamma_1 y_{t-1}^3 \big(1 - S_t^*(\gamma_2, y_{t-1})\big) + \eta_t \quad (2.35)$$

Where ρ_1^* and $\rho_2^*$are linear functions that are derived from ρ_1 and ρ_2. Both Equation 2.34 and Equation 2.35 allow for the same pattern of nonlinearity to be present. When a Taylor expansion of $S_t^*(\gamma_2, y_{t-1})$ is performed in Equation 2.35 around the point where γ_2 equals zero, the model shown in Equation 2.36 is obtained:

$$\Delta y_t = a(\rho_2^* - \rho_1^*)\gamma_1 \gamma_2 y_{t-1}^4 + \rho_2^* \gamma_1 y_{t-1}^3 + \eta_t \quad (2.36)$$

Where the value of a is equal to 1/4. It can be rewritten as:

$$\Delta y_t = \phi_1 y_{t-1}^3 + \phi_2 y_{t-1}^4 + \eta_t \quad (2.37)$$

Where $\phi_1 = \rho_1^* \gamma_1$ and $\phi_2 = a(\rho_2^* - \rho_1^*)\gamma_1 \gamma_2$.

In the presence of autocorrelation in Equation 1.37, it can be expanded and rewritten as follows:

$$\Delta y_t = \phi_1 y_{t-1}^3 + \phi_2 y_{t-1}^4 + \sum_{i=1}^{k} k_i \, \Delta y_{t-i} + \eta_t \tag{2.38}$$

Thus, the null hypothesis expressed in Equation 2.31 as $H_0: \gamma_1 = 0$ is represented as $H_0: \phi_1 = \phi_2 = 0$. While this hypothesis indicates non-stationarity, the alternative hypothesis signifies symmetric or asymmetric ESTAR stationarity. If the null hypothesis is rejected, the decision regarding whether the series is symmetric or asymmetric ESTAR stationary is determined by testing the hypothesis $H_0: \phi_2 = 0$ against the alternative $H_1: \phi_2 \neq 0$. Here, the null hypothesis indicates symmetric ESTAR stationarity, while the alternative hypothesis indicates asymmetric ESTAR stationarity. To test the null hypothesis expressed in Equation 2.37, the *F* critical values provided in Sollis (2009) should be used instead of traditional *F* critical values.

2.3.1.1.3.1.3. Kruse (2011)

In the KSS (2003) unit root test, the assumption $c = 0$ is made in Equation 2.28. Kruse (2011) eliminated this assumption and proposed a model shown in Equation 2.39 under the assumption of $c \neq 0$.

$$\Delta y_t = \phi y_{t-1}(1 - exp\{-\gamma(y_{t-1} - c)^2\}) + \varepsilon_t \tag{2.39}$$

As in the KSS (2003) unit root test, Kruse (2011) applied a first-order Taylor expansion to Equation 2.39, resulting in Equation 2.40, which allows for the direct testing of the unit root hypothesis.

$$\Delta y_t = \beta_1 y_{t-1}^3 + \beta_2 y_{t-1}^2 + \beta_3 y_{t-1} + u_t \tag{2.40}$$

The author assumes $\beta_3 = 0$ to increase the power of the test. Consequently, the new equation is expressed as follows.

$$\Delta y_t = \beta_1 y_{t-1}^3 + \beta_2 y_{t-1}^2 + u_t \tag{2.41}$$

For the Kruse (2011) unit root test in Equation 2.41, the null hypothesis ($\beta_1 = \beta_2 = 0$) indicates the presence of a unit root, while the alternative hypothesis ($\beta_1 < 0, \beta_2 \neq 0$) signifies nonlinear ESTAR stationarity. In the alternative hypothesis, the parameter β_1 is subject to a one-sided test, while the parameter β_2 is subject to a two-sided test, making it impossible to use the F test. To address this issue, the author employs the method proposed by Adabir and Distaso (2007), which orthogonalizes the one-sided parameter with respect to the two-sided parameter. This allows for the calculation of a modified Wald test statistic. The calculation of this statistic is illustrated in Equation 2.42.

$$\tau = \left(\hat{\mathrm{v}}_{22} - \frac{\hat{\mathrm{v}}_{21}^2}{\hat{\mathrm{v}}_{11}}\right)^{-1} \left(\hat{\beta}_2 - \hat{\beta}_1 \frac{\hat{\mathrm{v}}_{21}}{\hat{\mathrm{v}}_{11}}\right)^2 + 1\left(\hat{\beta}_1 < 0\right) \frac{\hat{\beta}_1^2}{\hat{\mathrm{v}}_{11}} \tag{2.42}$$

An easier method to present this statistic is

$$\tau = t_{\beta_2^{\perp}=0}^2 + 1(\hat{\beta}_1 < 0) t_{\beta_1=0}^2 \tag{2.43}$$

The first term is equal to the square of the t-statistic for the $\beta_2^{\perp} \equiv \beta_2 - \beta_1 v_{21}/v_{11} = 0$ with $\beta_2^{\perp}$ being orthogonal to β_1 (Kruse, 2011:76). t_{β_1} and $t_{\beta_2^{\perp}}$ are calculated as follow:

$$t_{\beta_1=0} = \frac{\sum_{t=1}^T y_{t-1}^4 \sum_{t=1}^T y_{t-1}^3 \Delta y_t - \sum_{t=1}^T y_{t-1}^2 \Delta y_t \sum_{t=1}^T y_{t-1}^5}{\sqrt{\hat{\sigma}^2 \left(\left(\sum_{t=1}^T y_{t-1}^4\right)^2 \sum_{t=1}^T y_{t-1}^6 - \sum_{t=1}^T y_{t-1}^4 \left(\sum_{t=1}^T y_{t-1}^5\right)^2 \right)}} \tag{2.44}$$

$$t_{\beta_2^{\perp}=0} = \frac{\sum_{t=1}^T y_{t-1}^2 \Delta y_t \left(\left(\sum_{t=1}^T y_{t-1}^4\right)^{3/2} \sum_{t=1}^T y_{t-1}^6 - \left(\sum_{t=1}^T y_{t-1}^4\right)^{1/2} \left(\sum_{t=1}^T y_{t-1}^5\right)^2 \right)}{\hat{\sigma} \left(\left(\sum_{t=1}^T y_{t-1}^4\right)^2 \sum_{t=1}^T y_{t-1}^6 - \sum_{t=1}^T y_{t-1}^4 \left(\sum_{t=1}^T y_{t-1}^5\right)^2 \right)} \tag{2.45}$$

2.3.1.1.3.1.4. Omay and Yıldırım (2014)

Omay and Yıldırım (2014) proposed a new unit root test (hereafter, OY test) by combining the KSS (2003) and LNV (1998) tests. Similar to the LNV (1998) test, this test also examines three different equations, namely Model A, B, and C. These models are as follows:

$$y_t = \alpha + \alpha_2 S_t(\gamma, \tau) + \varepsilon_t \quad (2.46)$$

$$y_t = \alpha + \beta_1 t + \alpha_2 S_t(\gamma, \tau) + \varepsilon_t \quad (2.47)$$

$$y_t = \alpha + \beta_1 t + \alpha_2 S_t(\gamma, \tau) + \beta_2 t S_t(\gamma, \tau) + \varepsilon_t \quad (2.48)$$

Where y_t is a function that represents a changing trend with a smooth transition on the time domain $t = 1,2, \ldots, T$. ε_t represents a zero mean $I(0)$ process and and $S_t(\gamma, \tau)$ represents the following the logistic smooth transition (LST) function, which is based on a sample size of T and N.

$$S_t(\gamma, \tau) = \{1 + exp[-\gamma(1 - \tau T)]\}^{-1}, \quad \gamma > 0 \quad (2.49)$$

In this modeling approach, structural change is depicted as a smooth transition between different regimes rather than a sudden break, as suggested by Leybourne et al. (1996). The transition function, $S_t(\gamma, \tau)$, is a continuous function bounded between 0 and 1. Hence, the Smooth Transition Autoregressive (STAR) model serves as a regime-switching model allowing for two regimes associated with extreme values of the transition function, $S_t(\gamma, \tau) = 0$ and $S_t(\gamma, \tau) = 1$, with a gradual transition between them. The parameter γ governs the transition speed, determining the smoothness of the regime shift. Two regimes are linked to large and small values of the transition variable $s_t = t$ relative to the threshold $c = \tau$. For high γ values, $S_t(\gamma, \tau)$ rapidly spans the (0,1) interval, and as γ approaches $+\infty$, it transitions instantaneously from 0 to 1 at $t = \tau T$. Assuming ε_t is a zero-mean stationary process in I(0), in Equation 2.46, y_t is stationary around a mean shifting from an initial value α_1 to a final value $\alpha_1 + \alpha_2$. Leybourne et al. (1996) detail similar conditions for Equation 2.47 and 2.48. This specification encompasses gradual structural changes alongside the no-change and instantaneous change scenarios (Omay and Yıldırım, 2014:2).

Based on Equations 2.46, 2.47, and 2.48, it is established unit root testing hypotheses:

H_0: (The series is linear non-stationary).

H_a: (The series is nonlinear and stationary around smoothly changing trend and intercept)

Step 1: It is calculated test statistics in two steps, following Leybourne et al. (1996):

Model A: $\hat{\varepsilon}_t = y_t - \hat{\alpha}_1 - \hat{\alpha}_2 S_t(\gamma, \tau)$ (2.50)

Model B: $\hat{\varepsilon}_t = y_t - \hat{\alpha}_1 - \hat{\beta}_1 t - \hat{\alpha}_2 S_t(\gamma, \tau)$ (2.51)

Model C: $\hat{\varepsilon}_t = y_t - \hat{\alpha}_1 - \hat{\beta}_1 t - \hat{\alpha}_2 S_t(\gamma, \tau) - \hat{\beta}_2 t S_t(\gamma, \tau)$ (2.52)

Step 2: The KSS test statistic is computed, which is the t-ratio associated with the estimated coefficient ($\hat{\rho}_i$) in OLS regression.

$$\Delta\hat{\varepsilon}_t = \hat{\rho}\hat{\varepsilon}_t^{\,3} + \sum_{j=1}^{k} \hat{\delta}_j \Delta\hat{\varepsilon}_{t-j} + \hat{\eta}_t \quad (2.53)$$

Models 1, 2, and 3 use t statistics for $\hat{\rho}_i$as $\bar{t}_{br1}$, $\bar{t}_{br2}$, and $\bar{t}_{br3}$, respectively.

$H_0: \rho = 0 \;\; for\ all\ i$ (The series is linear non-stationary).

$H_1: \rho < 0\ for\ some\ i$ (The series is stationary arounds nonlinear trend and/ or intercept)

2.3.1.1.3.1.5. Çorakçı, Emirmahmutoğlu, and Omay (2017)

The flexible Fourier form has been demonstrated by Çorakçı et al. (2017) (hereafter, CEO) to be incapable of providing a constant mean for series under temporary structural breaks. They have stated that the exponential smooth transition function is more appropriate for a temporary structural break. The smooth transition function guarantees that the required conditions are met by maintaining a consistent and identical average at both ends of the temporary breaks. The test procedure is as follows:

Model A: $y_t = \alpha_1 + \alpha_2 F_t(\gamma, \tau) + \varepsilon_t$ (2.54)

Model B: $y_t = \alpha_1 + \beta_1 t + \alpha_2 F_t(\gamma, \tau) + \varepsilon_t$ (2.55)

Model C: $y_t = \alpha_1 + \beta_1 t + \alpha_2 F_t(\gamma, \tau) + \beta_2 F_t(\gamma, \tau) t + \varepsilon_t$ (2.56)

Where y_t is a function that represents a changing trend with a smooth transition. ε_t represents a zero mean $I(0)$ process, and $F_t(\gamma, \tau)$ represents the following exponential smooth transition (EST) function, which is derived using a sample size of T:

$$F_t(\gamma, \tau) = 1 - exp[-\gamma(1-\tau)^2], \quad \gamma > 0 \tag{2.57}$$

This modeling technique represents structural change as a smooth transition between multiple regimes rather than a sudden structural break. The absence of sharp changes at a specific point and, instead, the occurrence of a smooth and continuous transition between changing conditions is implied.

The hypotheses for unit root testing, based on models A, B, and C, are established as follows:

H_0: $Unit\ Root$ (The series is linear nonstationary)

H_1: Nonlinear Stationary (The series is stationary arounds smoothly changing trend and intercept)

The proposed test statistics in Leybourne et al. (1998) are calculated by a two-stage process:

Step 1: By employing the Sequential Quadratic Programming (SQP) algorithm technique for restricted nonlinear optimization, we only estimate the deterministic component of the preferred model and calculate its residuals. Formulate the hypotheses for conducting unit root testing using model A, model B, and model C as outlined below:

Model A: $\hat{\varepsilon}_t = y_t - \hat{\alpha}_1 - \hat{\alpha}_2 F_t(\hat{\gamma}, \hat{\tau})$ (2.58)

Model B: $\hat{\varepsilon}_t = y_t - \hat{\alpha}_1 - \hat{\beta}_1 t - \hat{\alpha}_2 F_t(\hat{\gamma}, \hat{\tau})$ (2.59)

Model C: $\hat{\varepsilon}_t = y_t - \hat{\alpha}_1 - \hat{\beta}_1 t - \hat{\alpha}_2 F_t(\hat{\gamma}, \hat{\tau}) - \hat{\beta}_2 F_t(\hat{\gamma}, \hat{\tau}) t$ (2.60)

Step 2: Calculate the ADF statistic, which is the t-ratio associated with the estimated coefficient ($\hat{\rho}$) in OLS regression.

$$\Delta\hat{\varepsilon}_t = \rho\hat{\varepsilon}_{t-1} + \sum_{j=1}^{p} \delta_j \Delta\hat{\varepsilon}_{t-j} + u_t \quad (2.61)$$

Models A, B, and C use t statistics for $\hat{\rho}$ as $\tilde{s}_\alpha$, $\tilde{s}_{\alpha(\beta)}$, and $\tilde{s}_{\alpha\beta}$, respectively.

$H_0: \rho = 0$ (The series is linear nonstationary)
$H_1: \rho < 0$ (The series is stationary arounds nonlinear trend and/or intercept)

2.3.1.1.3.1.6. Omay, Emirmahmutoğlu, and Hasanov (2018)

Omay et al. (2018) developed a new unit root test (hereafter, OEH test) that allows for gradual structural breaks and asymmetric adjustments to disequilibria. Their Monte-Carlo simulations on small samples demonstrated that this test performs well. The data generation process for this test is as follows:

$$y_t = \emptyset(t) + u_t \quad (2.62)$$

Where $\emptyset(t)$ is the deterministic nonlinear function and u_t is the deviations from the trend. Equation 2.62 allows for a deterministic trend function under both the null and alternative hypotheses without introducing any parameters. The authors examine two common trend function specifications, a logistic transition function, and a Fourier function, to model the deterministic component. Firstly, it is considered a logistic trend function given in Equations 2.63, 2.64, and 2.65.

Model 1: $\emptyset(t) = \alpha_1 + \alpha_2 S_t(\gamma, \tau) + u_t$ (2.63)

Mode1 2: $\emptyset(t) = \alpha_1 + \beta_1 t + \alpha_2 S_t(\gamma, \tau) + u_t$ (2.64)

Mode1 3: $\emptyset(t) = \alpha_1 + \beta_1 t + \alpha_2 S_t(\gamma, \tau) + u_t$ (2.65)

Where $S_t(\gamma, \tau)$ is the logistic smooth transition function over sample of T and a continuous function between 0 and 1:

$$S_t(\gamma, \tau) = \{1 + exp[-\gamma(1 - \tau T)]\}^{-1}, \quad \gamma > 0 \tag{2.66}$$

Where γ is smoothness parameters and τ is location parameters. When γ takes small values, the trastion between two regimes occurs very slowly. If γ takes 0, $S_t(\gamma, \tau)$ transition function will be 0.5 for all values of t. However, if γ takes very large values, $S_t(\gamma, \tau)$ will approach a heaviside step function and the change from one regime to the other regime will become almost instantaneous at time $t = \tau T$. Equation 2.63 specifies no trend, but the mean shifts from α_1 to $\alpha_1 + \alpha_2$. While Equation 2.64 allows for a break only in the mean, the slope is considered to be constant. Finally, Equation 2.65 shows the mean of the nonlinear attractor gradually changing from α_1 to t, $\alpha_1 + \alpha_2$, while the slope changes from $\beta_1$to $\beta_1 + \beta_2$ at time $t = \tau T$ (Omay et al., 2018:1293). As the authors explain, series can be subject to multiple breaks, and allowing for only a single break may lead to incorrect results. In this context, they have also considered Fourier functions.

$$\text{Model 4: } \emptyset(t) = a_0 + \delta t + \sum_{k=1}^{n} \alpha_k \sin\left(\frac{2\pi k t}{T}\right) + \sum_{k=1}^{n} b_k \cos\left(\frac{2\pi k t}{T}\right) + u_t \,; n < \frac{T}{2} \tag{2.67}$$

where n represents the number of cumulative frequencies, while k represents the frequency chosen for the approximation. The parameters α_i and b_i quantify the amplitude and displacement of the sinusoidal components of the trend function. Given sufficiently weak conditions, a sufficiently long Fourier series in Equation 2.67 can approximate any function with an unknown number and forms of breaks to any desired level of accuracy (Omay et al., 2018:1293).

They made an assumption that the rate at which the deviations u_t are adjusted in order to fit the nonlinear trend function given in Equation 2.62 is dependent not only on the magnitude of the disequilibrium but also on the sign of the disequilibrium. To be more specific, they modeled the adjustment towards equilibrium by employing asymmetric ESTAR (AESTAR) nonlinearity, similar to that proposed by Sollis (2009). The AESTAR model for deviations from equilibrium is as follows:

$$\Delta u_t = G_t(\theta_1, u_{t-1})\{F_t(\theta_2, u_{t-1})\rho_1 + (1 - F_t(\theta_2, u_{t-1})\rho_2\}u_{t-1} + \varepsilon_t \quad (2.68)$$

$$G_t(\theta_1, u_{t-1}) = 1 - \exp\left(-\theta_1(u_{t-1}^2)\right), \theta_1 > 0 \quad (2.69)$$

$$F_t(\theta_2, u_{t-1}) = (1 + \exp\,(\theta_2 u_{t-1})^{-1}, \theta_2 > 0 \quad (2.70)$$

Where $\varepsilon_t \sim i.i.d(0, \sigma^2)$

The logistic transition function $F_t(\theta_2, u_{t-1})$ seems like the $S_t(\gamma, \tau)$ function, which controls the gradual change in series mean and/or trend. Since u_t is a zero-mean variable, the $F_t(\theta_2, u_{t-1})$ function's two regimes are dictated by positive and negative realizations of the disequilibrium u_t. The exponential transition function $G_t(\theta_1, u_{t-1})$ is symmetrically U-shaped and bounded between 0 and 1. Small and large absolute values of the disequilibrium u_t establish the regimes associated with the $G_t(\theta_1, u_{t-1})$ function, regardless of the sign of deviation from equilibrium (Omay et al., 2018:1294).

It is established hypotheses as follow:

$H_0: \theta_1 = 0$
$H_1: \theta_1 > 0$

However, testing the null hypothesis directly is not practical due to undetermined parameters. Following KSS (2003) and Sollis (2009) they replaced the transition functions by Taylor series, and they obtained:

$$\Delta u_t = \varphi_1 u_{t-1}^3 + \varphi_2 u_{t-1}^4 + \vartheta_t \quad (2.71)$$

Where $\varphi_1 = \theta_1\rho_2$, $\varphi_2 = \frac{1}{4}\theta_1\theta_2(\rho_1 - \rho_2)$. Now, the null hypothesis $H_0: \theta_1 = 0$ will become as follow:

$H_0: \varphi_1 = \varphi_2 = 0$

2.3.1.1.3.1.7. Ranjbar, Chang, Elmi, and Lee (2018)

Ranjbar et al. (2018) constructed a new unit root test that allows smooth deterministic component breaks and asymmetric nonlinear modifications extending the Sollis (2009). The data generation process for this test is as follows:

$$y_t = a(t) + \varepsilon_t \tag{2.72}$$

where $a(t) = Z_t\lambda + \sum_{k=1}^{n}\gamma_{1,k}\sin\left(\frac{2\pi kt}{T}\right) + + \sum_{k=1}^{n}\gamma_{2,k}cos\left(\frac{2\pi kt}{T}\right)$. $a(t)$ is a deterministic component that changes over time. Gallant's (1981) Fourier approximation method was used to achieve a global approach from smooth transitions and independent of an unknown number and incorporate breaks into deterministic components. The variables k, t, and T represent the number of frequencies, the trend term, and the sample size in the Fourier function, respectively. Z represents deterministic terms like constant and trend terms. $\gamma = [\gamma_1, \gamma_2]'$ is the displacement of the frequency component. According to the authors, the restriction of $n = 1$ is deemed reasonable as the joint hypothesis for a single frequency has been rejected, alongside the hypothesis of time invariance. Similarly, Enders and Lee (2012) observed that imposing the restriction $n = 1$ is beneficial for preserving degrees of freedom and preventing the risk of overfitting. Equation 2.72 can be rewritten as follows:

$$y_t = Z_t\lambda + \gamma_1\sin\left(\frac{2\pi kt}{T}\right) + \gamma_2 cos\left(\frac{2\pi kt}{T}\right) + \varepsilon_t \tag{2.73}$$

The authors followed the approach of Christopoulos and Leon-Ledesma (2010) to test the validity of the null hypothesis ($H_0: \varepsilon_t = v_t,\ v_t = v_{t-1} + u_t$). They computed statistics in three steps for the constant model and the model including both constant and trend components.

Step 1: In order to estimate Equation 2.73, it is first determined all integer values of k that ranges between 1 and 5. Then the regression with the minimum sum of squared residuals is utilized to determine the value of k^*.

Step 2: The presence of a unit root in the OLS residuals obtained from Equation 2.74 is examined using the AESTAR model. The AESTAR model integrates the exponential function and logistic function.

$$\hat{\varepsilon}_t = y_t + \hat{a}(t) \tag{2.74}$$

Where $\hat{a}(t) = Z_t\hat{\lambda} + \hat{\gamma}_1 \sin\left(\frac{2\pi k^* t}{T}\right) + \hat{\gamma}_2 cos\left(\frac{2\pi k^* t}{T}\right)$. In this model, an assumption is posited wherein the $\hat{\varepsilon}_{t-1}$ variable serves as a transitional variable. The authors constructed a model as shown Equation 2.75 utilizing the Taylor series, following the research conducted by Sollis (2009).

$$\Delta\hat{\varepsilon}_t = \psi_1\hat{\varepsilon}_{t-1}^3 + \psi_2\hat{\varepsilon}_{t-1}^4 + \sum_{i=1}^{l} l_i\Delta\hat{\varepsilon}_{t-i} + v_t \tag{2.75}$$

The null hypothesis is formulated as $\psi_1 = \psi_2 = 0$. While this hypothesis indicates non-stationarity, the alternative hypothesis signifies symmetric or asymmetric ESTAR stationarity. If the null hypothesis is rejected, the decision regarding whether the series is symmetric or asymmetric ESTAR stationary is determined by testing the hypothesis $H_0: \psi_2 = 0$ against the alternative $H_1: \psi_2 \neq 0$. Here, the null hypothesis indicates symmetric ESTAR stationarity, while the alternative hypothesis indicates asymmetric ESTAR stationarity. The F-test is used to test the null hypothesis.

Step 3: After rejecting the null hypothesis of a unit root in the second step, it is proceeded to test for the absence of the nonlinear component in Equation 2.73. Based on the study conducted by Beckers et al. in 2006, the F-test statistic is computed.

2.3.1.1.3.1.8. Güriş (2019)

Güriş (2019) proposed a new test by modeling structural breaks using a Fourier function and nonlinear adjustments using the exponential smooth transition autoregressive (ESTAR) model, as suggested by Kruse (2011). In the first stage of the proposed test, structural breaks of unknown forms and numbers were modeled using the Fourier function, as described by Christopoulos and León-Ledesma (2010). In the second stage, the Kruse (2011) test was used to assess the unit root presence.

Step 1: specify the nonlinear deterministic component following Equation 2.74

$$y_t = a_0 + a_1 \sin\left(\frac{2\pi kt}{T}\right) + a_2 \cos\left(\frac{2\pi kt}{T}\right) + v_t \quad (2.76)$$

Where k is optimal frequency and $1 \leq k \leq 5$.

Step 2: The error terms are obtained from Equation 2.76.

$$v_t = y_t - a_0 - a_1 \sin\left(\frac{2\pi k^* t}{t}\right) - a_2 \cos\left(\frac{2\pi k^* t}{t}\right) \quad (2.77)$$

Step 3: the error terms are derived from the Equation 2.77 and applied Kruse (2011) test procedure. Equation 2.78 is obtained.

$$\Delta v_t = \delta_1 y_{t-1}^3 + \delta_2 y_{t-1}^2 + \sum_{i=1}^{k} \varphi_i \Delta v_{t-i} + \varepsilon_t \quad (2.78)$$

The null hypothesis is H_0: $a1 = a2 = 0$ and the alternative hypothesis is H_1: $a1 \neq a2 \neq 0$, which indicates that the variable is stationary. To perform this test, the F test is used. If the F test results in the rejection of the null hypothesis, it indicates that the variable is stationary around a deterministic function with a break. In other words, the time series data has a stable structure around a certain trend or break point.

2.3.1.1.3.1.9. Omay, Shahbaz, and Hasanov (2020)

Omay et al. (2020) (hereafter, OSH) argued that Fourier series are not suitable for modeling the deterministic component and contradict economic theory. Instead, they used an exponential smooth transition function. They examined mean reversion using both symmetric and asymmetric ESTAR-type nonlinear models. To model the temporary gradual structural changes in the deterministic components of the series, gradually changing trend functions were followed:

Model A: $y_t = \alpha_1 + \alpha_2 S_t(\gamma, \tau) + u_t$ (2.79)

Model B: $y_t = \alpha_1 + \beta_1 t + \alpha_2 S_t(\gamma, \tau) + u_t$ (2.80)

Model C: $y_t = \alpha_1 + \beta_1 t + \alpha_2 S_t(\gamma, \tau) + \beta_2 t S_t(\gamma, \tau) + u_t$ (2.81)

Where u_t represents trend deviations and τ represents exponential smooth transition over T sample:

$$S_t(\gamma, \tau) = \{1 + exp[-\gamma(1 - \tau T)]\}^{-1}, \quad \gamma > 0 \tag{2.82}$$

The transition function $S_t(\gamma, \tau)$ is a continuous function that is bound within the range of 0 to 1 and is symmetric around zero. The parameter γ is responsible for determining the smoothness of transition, while the rate of structural change increases as γ increases. The parameter τ dictates the timing of the transition midpoint, determining when the transition function $S_t(\gamma, \tau)$ switches from one regime to another. Specifically, τ parameter determines the transition midpoint as $S_t(\gamma, \tau) = 0$ when $t = \tau T$, and $S_t(\gamma, \tau) = 1$ both for when $t < \tau T$ and $t > \tau T$. These characteristics indicate that the structural changes in the series' deterministic components are temporary. Model A in Equation 2.79 is suitable for capturing temporary breaks in the mean of the non-trending series. In particular, when $S_t(\gamma, \tau) = 1$, Model A reduces to $y_t = \alpha_1 + \alpha_2 + u_t$. Conversely, when $S_t(\gamma, \tau) = 0$, the model simplifies to $y_t = \alpha + u_t$, signifying a gradual shift in the series' mean from an initial value of $\alpha_1 + \alpha_2$ to α_1 around $t = \tau T$, before reverting back to $\alpha_1 + \alpha_2$ when $t > \tau T$. Model B, as presented in Equation 2.80, accommodates a temporary break solely in the series' mean, while maintaining a constant slope (at β_1) throughout the observation period. Conversely, Model C, expressed in Equation 2.81, allows for simultaneous temporary shifts in both the mean and trend of the series. In this model, the slope transitions from its initial value of $\beta_1 + \beta_2$ to β_1, before returning to $\beta_1 + \beta_2$. It's important to note that changes in the trend coincide with variations in the series' mean. Finally, the magnitudes of parameters of α_1 and α_2 (β_1 and β_2) determine the extent of alterations in the mean (trend) of the series (Omay et al., 2020:3840-3841).

The speed of deviation correction towards the nonlinear trend function relies on the sign and size of disequilibrium. The nonlinear dynamics are modeled using the AESTAR model, as below:

$$\Delta u_t = G_t(\theta_1, u_{t-1})\{F_t(\theta_2, u_{t-1})\rho_1 + (1 - F_t(\theta_2, u_{t-1})\rho_2\}u_{t-1} + \epsilon_t \tag{2.83}$$

$$G_t(\theta_1, u_{t-1}) = 1 - \exp\left(-\theta_1(u_{t-1}^2)\right), \theta_1 > 0 \quad (2.84)$$

$$F_t(\theta_2, u_{t-1}) = (1 + \exp\,(\theta_2 u_{t-1})^{-1}, \theta_2 > 0 \quad (2.85)$$

Where $\varepsilon_t \sim i.i.d(0, \sigma^2)$

The exponential transition function $G_t(\theta_1, u_{t-1})$ seems like the $S_t(\gamma, \tau)$ function, which controls the gradual change in series mean and/or trend. The $G_t(\theta_1, u_{t-1})$ function delineates regimes based on the magnitude of the disequilibrium. The $F_t(\theta_2, u_{t-1})$ is a continuous function bounded between 0 and 1; u_t is a zero-mean variable. Positive and negative realizations of the disequilibrium u_{t-1} determines the two regimes associated with the $F_t(\theta_2, u_{t-1})$ function. The transition speed of $F_t(\theta_2, u_{t-1})$ is regulated by θ_2, with slower transitions for smaller θ_2 values, gradually becoming sharp as θ_2 approaches infinity. When θ_2 tends to zero, $F_t(\theta_2, u_{t-1})$ converges to 0.5, and thus the symmetric ESTAR model initially proposed by KSS (2003) (Omay et al., 2020: 3482).

The AESTAR model suggests that to observe nonlinear dynamics, u_{t-1} moves from 0 to $-\infty$. As $u_{t-1} \to -\infty$, the logistic function $F_t(\theta_2, u_{t-1})$ approaches 0. Consequently, Equation 2.83 transforms as follows:

$$\Delta u_t = G_t(\theta_1, u_{t-1})\rho_2 u_{t-1} + \epsilon_t \quad (2.86)$$

In this case transition is written as:

$$\Delta u_t = \epsilon_t \quad (2.87)$$

To the outer regime is written as:

$$\Delta u_t = \rho_2 u_{t-1} + \epsilon_t \quad (2.88)$$

As the $G_t(\theta_1, u_{t-1})$ moves from 0 to 1 as $u_{t-1} \to -\infty$. On the other hand, $F_t(\theta_2, u_{t-1}) \to 1$ as $u_{t-1} \to +\infty$. Equation 2.83 collapses to the following form as the deviations from the equilibrium increase from zero to positive infinity:

$$\Delta u_t = G_t(\theta_1, u_{t-1})\rho_1 u_{t-1} + \epsilon_t \quad (2.89)$$

In this case transition is written as:

$$\Delta u_t = \epsilon_t \quad (2.90)$$

To the outer regime is written as:

$$\Delta u_t = \rho_1 u_{t-1} + \epsilon_t \quad (2.91)$$

As the $G_t(\theta_1, u_{t-1})$ moves from 0 to 1 as $u_{t-1} \rightarrow +\infty$. The global stationarity of the AESTAR process given above requires that $\rho_1$and $\rho_2$is smaller than 0 and $\theta_1$is bigger than 0. When $\rho_1 \neq \rho_2$, positive and negative deviations will revert to equilibrium at varying speeds. This means that the adjustment to the nonlinear attractor is influenced by both the direction and the size of the deviation. Alternatively, if ρ_1 equals ρ_2, the AESTAR model reduces to a symmetric ESTAR adjustment toward equilibrium. In this scenario, the adjustment is based solely on the magnitude of the deviations, irrespective of their direction. When equilibrium adjustment depends only on the size of the deviations and not their direction, the process can be modeled as follows:

$$\Delta u_t = G_t(\theta_1, u_{t-1})\rho u_{t-1} + \epsilon_t \quad (2.92)$$

The null hypothesis of a unit root can be formally tested against the alternative of ESTAR or AESTAR-type stationarity by evaluating the following null hypothesis:

H_0: $\theta_1 = 0$

H_1: $\theta_1 > 0$

However, testing the null hypothesis directly is not practical due to undetermined parameters (ρ_1, ρ_2, and θ_2). Following Luukkonen et al. (1988), the authors replaced the transition functions by using the Taylor series and they obtained the following:

$$\Delta u_t = \varphi_1 u_{t-1}^3 + \varphi_2 u_{t-1}^4 + \sum_{j=1}^{p} \delta_j \Delta u_{t-j} + \vartheta_t \quad (2.93)$$

Where $\varphi_1 = \theta_1\rho_2$, $\varphi_2 = \frac{1}{4}\theta_1\theta_2(\rho_1 - \rho_2)$. Now, the null hypothesis H_0: $\theta_1 = 0$ will become as follow:

H_0: $\varphi_1 = \varphi_2 = 0$

To derive the auxiliary regression for the symmetric ESTAR model, replace the exponential transition function in Equation 2.92 with a Taylor series approximation and account for residual autocorrelation:

$$\Delta u_t = \varphi_1 u_{t-1}^3 + \sum_{j=1}^{p} \delta_j \Delta u_{t-j} + \vartheta_t \quad (2.94)$$

To test the null hypothesis of unit root against ESTAR stationary, use Equation 2.94 to test H_0: $\varphi = 0$. Hypotheses can be examined using a two-step process as outlined by LNV (1998).

Step 1:

Model A: $\hat{u}_t = y_t - \hat{\alpha}_1 - \hat{\alpha}_2 S_t(\hat{\gamma}, \hat{\tau})$ (2.95)

Model B: $\hat{u}_t = y_t - \hat{\alpha}_1 - \hat{\beta}_1 t - \hat{\alpha}_2 S_t(\hat{\gamma}, \hat{\tau})$ (2.96)

Model C: $\hat{u}_t = y_t - \hat{\alpha}_1 - \hat{\beta}_1 t - \hat{\alpha}_2 S_t(\hat{\gamma}, \hat{\tau}) - \hat{\beta}_2 t S_t(\hat{\gamma}, \hat{\tau})$ (2.97)

Step 2: Using the residuals $\hat{u}_t$ obtained from step 1, calculate the F-statistic to test the null hypothesis H_0: $\varphi_1 = \varphi_2 = 0$ in the OLS regression given by:

$$\Delta\hat{u}_t = \hat{\varphi}_1 \hat{u}_{t-1}^3 + \hat{\varphi}_2 \hat{u}_{t-1}^4 + \sum_{j=1}^{p} \hat{\delta}_j \Delta\hat{u}_{t-j} + \vartheta_t \quad (2.98)$$

Regarding AESTAR-type stationarity and OLS regression t-statistic linked with $\hat{\varphi}$

$$\Delta\hat{u}_t = \hat{\varphi}_1 \hat{u}_{t-1}^3 + \sum_{j=1}^{p} \hat{\delta}_j \Delta\hat{u}_{t-j} + \vartheta_t \quad (2.99)$$

Equation 2.99 is for the ESTAR type stationary.

Test statistics are denoted as $F_{AE\alpha}(t_{E\alpha})$ for Model A, $F_{AE\beta}(t_{E\beta})$ for Model B, and $F_{AE\alpha\beta}(t_{E\alpha\beta})$ for Model C, for AESTAR (ESTAR)-type stationarity.

2.3.1.1.3.2. LSTAR Type Unit Root Tests

Unit root tests, such as the LNV, Pascalau, and Sor tests, make the assumption that regime shifts are smooth and that the transition function between regimes follows a logistic function rather than an exponential one.

2.3.1.1.3.2.1. Leybourne, Newbold, and Vougas (1998, LNV)

One of the STAR type unit root tests based on a logistic function, proposed by Leybourne et al. (1998, LNV), is expressed through three distinct equations.

$$Model\ A\colon\ y_t = \alpha_1 + \alpha_2 S_t(\gamma,\tau) + v_t \tag{2.100}$$

$$Model\ B\colon\ y_t = \alpha_1 + \beta_1 t + \alpha_2 S_t(\gamma,\tau) + v_t \tag{2.101}$$

$$Model\ C\colon y_t = \alpha_1 + \beta_1 t + \alpha_2 S_t(\gamma,\tau) + \beta_2 t S_t(\gamma,\tau) + v_t \tag{2.102}$$

$S_t(\gamma,\tau)$shows the logistic smooth transition function. This function is represented as follow:

$$S_t(\gamma,\tau) = [1 + exp\{-\gamma(t-\tau T)\}]^{-1} \qquad \gamma > 0 \tag{2.103}$$

v_t represents a process with a zero-mean I(0) process. The parameter τ determines the location of the smooth structural break, while γ shows the transition speed between two regimes. T denotes the total number of observations, and t represents the deterministic trend in the logistic function. The null and alternative hypotheses are presented below.

$$H_0\colon y_t = \mu_t, \mu_t = \mu_{t-1} + \varepsilon_t, \mu_0 = \psi$$

$H_1: Model\ A, Model\ B, Model\ C$

or

$H_0: y_t = \mu_t, \mu_t = K + \mu_{t-1} + \varepsilon_t, \mu_0 = \psi$
$H_1: Model\ B\ or\ Model\ C$

It is assumed that both v_t and ε_t are stationary processes with zero mean. In the application of the LNV nonlinear unit root test, a two-stage process is employed. In the first stage, certain models are estimated, and in the second stage, tests are conducted on the residuals obtained from these estimations. In this process, a nonlinear least squares (NLS) algorithm is preferred. The reason for choosing this method is that the test equations are expressed with nonlinear logistic functions, and the parameters in these functions are not linear. The first stage proceeds as follows:

$$Model\ A: \hat{v}_t = y_t - \hat{\alpha}_1 - \hat{\alpha}_2 S_t(\hat{\gamma}, \hat{\tau}) \quad (2.104)$$

$$Model\ B: \hat{v}_t = y_t - \hat{\alpha}_1 t - \hat{\beta}_1 - \hat{\alpha}_2 S_t(\hat{\gamma}, \hat{\tau}) \quad (2.105)$$

$$Model\ C: \hat{v}_t = y_t - \hat{\alpha}_1 t - \hat{\beta}_1 - \hat{\alpha}_2 S_t(\hat{\gamma}, \hat{\tau}) - \hat{\beta}_2 t S_t(\hat{\gamma}, \hat{\tau}) \quad (2.106)$$

In the second stage, an ADF-type unit root test is applied to the residuals that were generated from Model A, Model B, and Model C. This is demonstrated in Equation 2.107, which details the procedure.

$$\hat{v}_t = \hat{\rho}\hat{v}_{t-1} + \sum_{i=1}^{k} \hat{\delta}_i \Delta \hat{v}_{t-i} + \hat{\eta}_t \quad (2.107)$$

In the implementation of this test, critical values were specially calculated by Leybourne et al. (1998).

2.3.1.1.3.2.2. Pascalau (2007)

Pascalau (2007) follows the studies of Teräsvirta (1994) and Kapetanios et al. (2003). Similar to Teräsvirta (1994), it employs a third-order Taylor series approximation for the logistic STAR component. Generally, it has the representation given in Equation 2.108 for the first-order univariate smooth transition autoregressive (STAR) model.

$$y_t = \alpha y_{t-1} + \beta y_{t-1} G(\theta; y_{t-d}; c) + \epsilon_t, t = 1, \ldots, T \quad (2.108)$$

Where $G(\theta; y_{t-d})$,α, and β show the logistic function, unknown parameters, respectively.

$$G(\theta; y_{t-d}) = [1 + exp\{-\theta(y_{t-d} - c)\}]^{-1} \quad (2.109)$$

In the logistic function shown in Equation 2.109, c represents the threshold value, and θ represents the slope parameter. Here, it is assumed that $\theta > 0$ and $d \geq 1$. A limited function of the transition variable y_{t-d} is continuous everywhere in parameter space as the transition function. $G(\theta; y_{t-d}; c)$has a monotonically increasing structure when $|y_{t-d} - c|$ is large and when y_{t-d} is smaller than c. $y_t$is efficiently constructed by the linear model, which is as follows:

$$y_t = \alpha y_{t-1} + \epsilon_t, t = 1, \ldots, T \quad (2.110)$$

If $|y_{t-d} - c|$ is large and $y_{t-d} > c$, y_t, then it is written as in Equation 2.111

$$y_t = (\alpha + \beta) y_{t-1} + \epsilon_t, t = 1, \ldots, T \quad (2.111)$$

By referring to the relationship in Equation 2.110 as the low regime and the relationship in Equation 2.111 as the high regime, it is possible to observe that the parameters α and $\beta G(\theta; y_{t-d}; c)$ have a monotonic change as a function of y_{t-d}, ranging from α to $\alpha + \beta$ on the continuous.

The LSTAR model of order one delineates the asymmetric behavior of processes, where the dynamic properties differ between expansions and recessions. This model characterizes scenarios where the transition from one regime to another is smooth over time. By utilizing Equation 2.109 within Equation 2.108, one derives the logistic Smooth Transition Autoregressive (LSTAR) model (Pascalau, 2007:4). The logistic Smooth Transition Autoregressive (LSTAR) model is expressed as follows.

$$y_t = \alpha y_{t-1} + \beta y_{t-1}[1 + exp\{-\theta(y_{t-d} - c)\}]^{-1} + \epsilon_t \quad (2.112)$$

Following the approach of Kapetanios et al. (2003), Equation 2.112 is being reparameterized as:

$$\Delta y_t = \delta y_{t-1} + \beta y_{t-1}[1 + exp\{-\theta(y_{t-d} - c)\}]^{-1} + \epsilon_t \quad (2.113)$$

Using Equation 2.113, null hypothesis will be $H_0: \delta = \theta = \beta = 0$ and alternative hypothesis will be $H_1: \delta + \beta < 0$, ve $\theta > 0$.

When the alternative hypothesis of a standard ADF test is stationary but nonlinear, it is expected to lose power. However, this testing approach has been criticized by Davies (1987). This criticism arises because the parameters β and θ are not well-defined under the null hypothesis (i.e., when $\beta = 0$, θ can take any value, and when $\theta = 0$, $\beta = 0$, δ cannot be distinguished) (Pascalau, 2007:5). Under the assumption of $\delta = 0$, Equation 2.114 is obtained.

$$\Delta y_t = \beta y_{t-1}[1 + exp\{-\theta(y_{t-1} - c)\}]^{-1} + \epsilon_t \quad (2.114)$$

Using Equation 2.114, null hypothesis will be $H_0: \theta = \beta = 0$ and alternative hypothesis will be $H_1: \beta < 0$, ve $\theta > 0$. Following Teräsvirta (1994), the test equation 2.115 is obtained by applying the third-order Taylor expansion to Equation 2.115.

$$\Delta y_t = \gamma_1 y_{t-1}^2 + \gamma_2 y_{t-1}^3 + \gamma_3 y_{t-1}^4 + \epsilon_t \quad (2.115)$$

Using Equation 2.115, the null hypothesis and the alternative hypothesis can be written as follows:

$H_0: = \gamma_1 = \gamma_2 = \gamma_3 = 0$ (The series is non-stationary).
$H_1: \gamma_1 \neq \gamma_2 \neq \gamma_3 \neq 0$ (The series is nonlinear stationary).

In many economic and financial applications of the LSTAR function, there exist prior theoretical arguments for constraining the threshold parameter c to be zero (Pascalau, 2007:6). In such cases, the following restricted regression is obtained:

$$\Delta y_t = \gamma_1 y_{t-1}^2 + \gamma_3 y_{t-1}^4 + \epsilon_t \quad (2.116)$$

The $\bar{F}_{NL}$ test statistic is then utilized in order to conduct the following hypothesis test:

$H_0: = \gamma_1 = \gamma_2 = \gamma_3 = 0$ (The series is non-stationary).
$H_1: \gamma_1 \neq \gamma_2 \neq \gamma_3 \neq 0$ (The series is nonlinear stationary).

2.3.1.1.4. RALS Unit Root Tests

An increase in the effectiveness of conventional unit root testing can be achieved by taking into account non-normal errors. It has been observed that the information that is contained in errors of this nature contributes to the effectiveness of the recently proposed experiments on unit roots. The literature, on the other hand, makes notice of the fact that this information is frequently neglected, despite the fact that conventional tests can produce reliable outcomes even when errors that are not usual are ignored. If used properly, non-normal error data can be useful. This highlights the significance of non-normal errors as a crucial resource for augmenting the power of unit root tests. Consequently, the effective utilization of information from non-normal errors emerges as a pertinent research area (Im et al., 2014:315-316).

2.3.1.1.4.1. Im, Lee, and Tieslau (2014)

The presence of series that do not exhibit a normal distribution is quite common in financial time series. Compared to a normal distribution, the distribution of financial time series often demonstrates leptokurtic distributions. Various reasons can lead to such distributions, and sometimes, distinguishing these differences from certain nonlinear patterns can be challenging. For instance, some financial variables may have asymmetric distributions arising from an asymmetric relationship within the data. Additionally, some economic time series variables may exhibit a mixture of different distributions, often modeled as regime transition models (Im et al., 2014; Yilanci et al., 2019; Hepsağ, 2022).

Im et al. (2014) introduced a new test that does not rely on a specific density function or functional form. Instead, it utilizes information on the non-normality found in the higher moments of residuals from the regression being tested. Specifically, it adopts a simple two-step procedure based on the residual augmented least squares (RALS) methodology. The RALS-ADF unit root test uses a two-step estimation approach to determine the value of the unit root. In the first stage, the traditional ADF test regressions that represent stationary with a constant term (Equation 2.117) or with both a constant and trend term (Equation 2.118) are estimated using the traditional least squares method. This results in the generation of residual series for these test regressions.

$$\Delta y_t = \mu + \delta y_{t-1} + \sum_{i=1}^{k} \alpha_i \Delta y_{t-i} + \varepsilon_t \tag{2.117}$$

$$\Delta y_t = \mu + \beta t + \delta y_{t-1} + \sum_{i=1}^{k} \alpha_i \Delta y_{t-i} + \varepsilon_t \tag{2.118}$$

After estimating Equations 2.117 and 2.118, residuals are obtained, and these residuals are utilized in the second stage of the RALS-ADF unit root test. At this point, non-normality information is taken into account by obtaining the second moments ($m_2 = \frac{\sum_{t=1}^{T} \hat{\varepsilon}_t^2}{T}$) and third moments ($m_3 = \frac{\sum_{t=1}^{T} \hat{\varepsilon}_t^3}{T}$) of the residuals. Then, the variables defined as the extended variables with residuals, denoted as $\widehat{w}_{2t}$ and $\widehat{w}_{3t}$, are computed as shown in Equations 2.119 and 2.120.

$$\widehat{w}_{2t} = \hat{\varepsilon}_t^2 - m_2 \tag{2.119}$$

$$\widehat{w}_{3t} = \hat{\varepsilon}_t^3 - m_3 - 3m_2\hat{\varepsilon}_t \quad (2.120)$$

Equation 2.119 derives $\widehat{w}_{2t}$ using squared residuals and their second moments, while Equation 2.120 obtains $\widehat{w}_{3t}$ by considering squared and cubed residuals along with their second and third moments. In the second stage, these extended variables are added to traditional ADF test regressions (Equations 2.117 and 2.118) to form the RALS-ADF test regression:

$$\Delta y_t = \mu + \delta y_{t-1} + \sum_{i=1}^{k} \alpha_i \Delta y_{t-i} + \gamma_2 \widehat{w}_{2t} + \gamma_3 \widehat{w}_{3t} + u_t \quad (2.121)$$

$$\Delta y_t = \mu + \beta t + \delta y_{t-1} + \sum_{i=1}^{k} \alpha_i \Delta y_{t-i} + \gamma_2 \widehat{w}_{2t} + \gamma_3 \widehat{w}_{3t} + \varepsilon_t \quad (2.122)$$

The test statistics are computed as follows:

$$\tau_{RALS-ADF} = \rho\tau_{ADF} + \sqrt{1-\rho^2}Z \quad (2.123)$$

Where the parameter $\rho^2$is estimated as $\hat{\rho}^2 = \hat{\sigma}_u^2/\hat{\sigma}_\varepsilon^2$. $\hat{\sigma}_u^2$ is the variance of the error terms obtained from the RALS-ADF regression, and $\hat{\sigma}_\varepsilon^2$ is the variance of the error terms obtained from the traditional ADF regression. The authors have derived critical values for the $\tau_{RALS-ADF}$ test statistic ranging from 0.1 to 0.9 for $\hat{\rho}^2$. Z is a random variable with zero mean and constant variance. The hypotheses for unit root testing as follow:

H_0: $\delta = 0$ (The series is non-stationary).
H_1: $\delta < 0$ (The series is stationary).

2.3.1.1.4.2. Meng et al. (2014)

Expanding on the work of Im et al. (2014), Meng et al. (2014) proposed the Lagrange Multiplier (LM) version of RALS unit root tests. Briefly, these can be referred to as RALS-LM tests. The authors have presented different RALS-LM tests, including the trend-stationary, one-break, and two-break tests.

The first RALS-LM unit root test is an extension of the LM test developed by Schmidt and Phillips (1992), which does not take into account structural breaks. This test follows a 2-step estimation process. In the first stage, the regression of the traditional LM test is applied to the usual least squares estimation procedure, and the residual series of this test regression is obtained:

$$\Delta y_t = \delta' z_t + y_t \tag{2.124}$$

$$\Delta y_t = \delta' \Delta z_t + \phi y_{t-1} + \sum_{i=1}^{k} \alpha_i \Delta y_{t-i} + \varepsilon_t \tag{2.125}$$

Where $z_t = [1, t]$ is a deterministic component indicating the constant term and trend. The residuals obtained from Equations 2.124 and 2.125, representing the traditional LM test versions, are used to calculate the second moments ($m_2 = \frac{\sum_{t=1}^{T} \hat{\varepsilon}_t^2}{T}$) and third moments ($m_3 = \frac{\sum_{t=1}^{T} \hat{\varepsilon}_t^3}{T}$). Using the second and third moments, the following equations are derived:

$$\widehat{w}_{2t} = \hat{\varepsilon}_t^2 - m_2 \tag{2.126}$$

$$\widehat{w}_{3t} = \hat{\varepsilon}_t^3 - m_3 - 3m_2\hat{\varepsilon}_t \tag{2.127}$$

In the second step of the test, the extended variables $\widehat{w}_{2t}$ and $\widehat{w}_{3t}$, along with the residuals, are added to the traditional LM test regressions that are given in Equations 2.124 and 2.125. This results in the formation of the test regression for RALS-LM.

$$\Delta y_t = \delta' \Delta z_t + \phi y_{t-1} + \sum_{i=1}^{k} \alpha_i \Delta y_{t-i} + \gamma_2 \widehat{w}_{2t} + \gamma_3 \widehat{w}_{3t} + u_t \tag{2.128}$$

The test statistic for the RALS-LM regression without breakpoints, as depicted in Equation 2.128, is calculated as follows:

$$\tau_{RALS-LM} = \rho \tau_{LM} + \sqrt{1 - \rho^2} Z \tag{2.129}$$

The parameter ρ^2 is estimated as $\hat{\rho}^2 = \hat{\sigma}_u^2/\hat{\sigma}_\varepsilon^2$. Here, $\hat{\sigma}_u^2$ represents the variance of the error terms obtained from the RALS-LM regression, while $\hat{\sigma}_\varepsilon^2$ denotes the variance of the error terms obtained from the traditional LM regression. Critical values for the $\tau_{RALS-LM}$ test statistic ranges from 0.1 to 0.9 for ρ^2. Z is a random variable with a mean of zero and constant variance.

In the study conducted by Meng et al. (2014), the deterministic component $z_t = [1, t]$, which includes only a constant and trend, is restructured to allow for one and two break points. This restructuring enables the model to account for breakpoints within the series. When there is a single break in the constant, the model is expressed as $z_t = [1, t, D_{1t}]$, and when there are two breaks in the constant, it is defined as $z_t = [1, t, D_{1t}, D_{2t}]$. These extended models follow the same testing procedures as the model without breaks. At this point the authors aim to assess the presence of deterministic components more accurately by considering the break points.

2.3.1.1.4.3. Meng et al. (2017)

Meng et al. (2014) proposed a unit root test allowing for breaks only in the constant term. However, in a subsequent study, Meng et al. (2017) introduced a new test that permits breaks in both the trend and the constant term. This new test extends the LM unit root test developed by Lee and Strazicich (2003), which considers one and/or two structural breaks in the constant term and deterministic trend by incorporating residual adjustments. The test proposed by Meng et al. (2017) consists of two stages. In the first stage, following the LM principle proposed by Lee and Strazicich (2003), the unit root test statistic is then obtained from the regression:

$$\Delta y_t = \beta' z_t + y_t \tag{2.130}$$

$$\Delta y_t = \beta^{'} \Delta z_t + \theta y_{t-1} + \sum_{i=1}^{k} \alpha_i \Delta y_{t-i} + \varepsilon_t \tag{2.131}$$

where $z_t = [1, t, D_{1t}, DT_{1t}]^{'}$, the vector includes a constant, a trend, and the dummy variables D_{1t} and DT_{1t}, which denote the positions of the level and trend breaks, respectively. For the residuals obtained from Equation 2.131, the second moments ($m_2 =$

$\frac{\sum_{t=1}^{T}\hat{\varepsilon}_t^2}{T}$) and third moments ($m_3 = \frac{\sum_{t=1}^{T}\hat{\varepsilon}_t^3}{T}$) are computed. These computed moments are then used to augment the following equations 2.132 and 2.133 with residuals:

$$\widehat{w}_{2t} = \hat{\varepsilon}_t^2 - m_2 \tag{2.132}$$

$$\widehat{w}_{3t} = \hat{\varepsilon}_t^3 - m_3 - 3m_2\hat{\varepsilon}_t \tag{2.133}$$

In the second stage of the test, the variables augmented with residuals $\widehat{w}_{2t}$and $\widehat{w}_{3t}$are incorporated into the classical LM test regressions, as specified in Equations 2.132 and 2.133. This incorporation constructs the test regression as shown in Equation 2.134 for the RALS-LM procedure, which allows for one break in both the level and the trend.

$$\Delta y_t = \beta^{'}\Delta z_t + \theta y_{t-1} + \sum_{i=1}^{k}\alpha_i\Delta y_{t-i} + \delta_2\widehat{w}_{2t} + \delta_3\widehat{w}_{3t} + u_t \tag{2.134}$$

The test statistic for the RALS-LM regression with one breakpoint in both the level and the trend, as depicted in Equation 2.128, is calculated as follows:

$$\tau_{RALS-LM} = \rho\tau_{LM} + \sqrt{1-\rho^2}Z \tag{2.135}$$

The hypotheses for this test are given as follows:

H_0: $\theta = 0$ (The series is non-stationary under one breakpoint in both the level and the trend)

H_1: $\theta < 0$ ((The series is stationary under one breakpoint in both the level and the trend)

This test procedure is applicable within a model allowing for two breaks in both the constant and trend. The deterministic part allowing for two breaks is expressed as $[1, t, D_{1t}, D_{2t}, DT_{1t}, DT_{2t}\,]^{'}$.

2.3.2. Data

In this chapter, daily data was used for the period from November 28, 2008, to February 15, 2008, for S&P green bonds, and from January 3, 2012, to February 13, 2024, for Solactive green bonds[1]. Various unit root tests were applied to the logarithmic forms of the price series.

2.4. Empirical Results

First, the PP test and the ADF test, two common linear unit root tests, are applied to the series. The results of these tests are presented in Table 2.1. The ADF test result for the S&P green bond price indicates that the test statistic value for the constant model is -1.048, while the test statistic value for the constant and trend model is -2.542. Both model test statistic values are lower than the critical values. The null hypothesis of the series containing a unit root was not rejected. Therefore, it is concluded that the S&P series exhibits a unit root. Similarly, in the ADF test for Solactive, the null hypothesis cannot be rejected because the critical value in both the constant and the constant and trend models is smaller than the critical values in absolute value. It has been determined that Solactive exhibits a unit root.

According to the results of both the ADF and PP tests, the S&P and Solactive green bond prices contain a unit root, indicating that they follow a random walk process. Consequently, the findings from these linear unit root tests suggest that these two green bond assets exhibit characteristics of an efficient market.

[1] As suggested by De Bond and Thaler (1987), monthly and weekly data were also utilized to overcome specific measurement problems. When daily data is used, certain issues can arise in both risk and return calculations. The most common problems include the “bid-ask spread” effect and the consequences of infrequent trading. The bid-ask spread can make it challenging to determine the true market value of an asset, while infrequent trading may result in price changes not being accurately reflected, leading to misleading signals. Using monthly data helps minimize errors stemming from these daily fluctuations and allows for more stable and reliable analyses. Therefore, the preference for monthly data enhances the accuracy and reliability of the research. In this section, unit root tests were also conducted using monthly and weekly data. The results of these are included in the Appendix.

Table 2.1. Linear Unit Root Test Results

Daily Data				
Tests	***ADF***		***PP***	
Models	Constant	Constant and Trend	Constant	Constant and Trend
S&P	-1.048	-2.543	-1.034	-2.534
Solactive	-1.562	-1.528	-1.626	-1.587

Table 2.2 summarizes the outcomes of the different Fourier-based unit root test results[2]. The results obtained from the Becker-Enders-Lee (2006) Fourier KPSS test's stationary model, the S&P and Solactive price series, are not found to be stationary at the 1%, 5%, and 10% significance level for the constant model and the constant and trend model[3].

According to the Fourier ADF test results proposed by Christopoulos-León-Ledesma (2010), the test statistics for S&P that are computed in models that include a constant are less than the critical values that correspond to them. This suggests that S&P contains a unit root. But in the constant and trend model, S&P is stationary at the 10% level. For the Solactive index, the test statistics calculated for both the model with a constant and the model with a constant and a trend are smaller than the critical values. Therefore, the Solactive green bond price contains a unit root.

The results of the Fourier KSS test indicate that both price series contain a unit root in both the model with a constant and the model with both a constant and a trend.

In the context of the Enders and Lee (2012) and Omay (2015) tests, the significance of the Fourier terms is first assessed. The trigonometric terms are evaluated to determine their relevance in the model. If these terms are found to be significant, the unit root test statistic values of the series are then compared with the critical values from the table. Upon examining the F-test statistic values for both tests, it is evident that they are not significant in all models, as the test statistic values are smaller than the critical values from the table.

[2] Graphs related to the unit root tests, including Fourier unit roots and nonlinear unit roots, are presented in the appendix.
[3] The critical values for unit root tests are provided in Appendix A.

Within the scope of this study, the SOR unit root test models A, B, and C, proposed by Shahbaz et al. (2019), were applied to the entire dataset. According to the results, it is observed that the test statistics for the level of the series in models A and B are higher than the critical values at the 5% significance level for both green bond series. This indicates that S&P does not contain a unit root. On the other hand, the test statistics Solactive in Models A, B, and Model C are smaller than the critical values at the 1%, 5%, and 10% significance levels. Consequently, the null hypothesis cannot be rejected, suggesting that the price of the Solactive index is not stationary.

When comparing the results, we observe different outcomes. The Fourier KPSS and KSS test indicate that both price series and models are not stationary, these tests imply that the markets are efficient, and prices follow a random walk process. Additionally, the Fourier ADF test results and SOR test results are mixed. Specifically, for the Solactive index, both models exhibit a unit root, indicating non-stationarity. However, for the S&P Green Bond index, the series is found to be stationary in model A and B values at the 5%, and 10% significance levels.

Table 2.2. Fourier Unit Root Test Results

Test	**Becker et al. (2006)**					
Models	Constant			Constant and Trend		
	Test Statistics	k	F Statistics	Test Statistics	k	F Statistics
S&P Green	184.8	2	1178.57	18.8	2	5757.4
Solactive	34.92	2	905.7	16.36	2	687.4
Test	**Christopoulos and Leon-Ledesma (2010, ADF)**					
Models	Constant			Constant and Trend		
	Test Statistics	k	F Statistics	Test Statistics	k	F Statistics
S&P Green	-1.8253	2	1178.57	-3.752*	2	2623.14***
Solactive	-2.1129	2	769.49	-2.852	2	927.24
Test	**Christopoulos and Leon-Ledesma (2010, KSS)**					
Models	Constant			Constant and Trend		
	Test Statistics	k	F Statistics	Test Statistics	k	F Statistics
S&P Green	-2.8689	2	1178.57	-3.3204	2	2623.14

Solactive	-2.7534	2	769.49	-3.144	2	927.24
Test	**Enders and Lee (2012)**					
Models	Constant			Constant and Trend		
	Test Statistics	k	F Statistics	Test Statistics	k	F Statistics
S&P Green	-1.824	2	3.321	-3.751	2	4.735
Solactive	-1.976	2	5.079	-1.921	2	4.751
Test	**Omay (2015)**					
Models	Constant			Constant and Trend		
	Test Statistics	k	F Statistics	Test Statistics	k	F Statistics
S&P Green	-2.7788	0.1	4.425	-2.8454	0.1	0.882
Solactive	-1.927	0.1	0.4702	-2.405	0.2	1.066
Test	**SOR (2018)**					
Models	Model A		Model B		Model C	
S&P Green	-4.475** (1)		-4.483** (2)		-4.559 (2)	
Solactive	-3.158 (1)		-3.353 (1)		-3.352 (1)	

Note: *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

Table 2.3 summarizes the outcomes of the different ESTAR type nonlinear unit root test results. Based on the results of the nonlinear unit root test developed by KSS (2003), tests were conducted to examine three different cases for the S&P price index: raw data (case 1), demeaned data (case 2), and detrended data (case 3). For cases 1 and 2, the test statistics obtained are smaller in absolute value than the critical values from the table. This indicates that the null hypothesis cannot be rejected in both cases, implying that the S&P index series contains a unit root. In contrast, for case 3, the test statistic is greater than the critical value at the 5% significance level. This result leads to the rejection of the null hypothesis, indicating that the S&P index series is stationary in the detrended case. For the Solactive Green Bond price, the test statistics for all three cases are smaller in absolute value than the critical values. Consequently, the null hypothesis cannot be rejected, indicating that the series exhibits a random walk process.

The results of the Asymmetric ESTAR unit root test proposed by Sollis (2009) are similar to those of the KSS test. For the S&P Green Bond price series in both case 1 and case

2, the test statistics are smaller than the critical values, indicating that the series has a unit root. However, for case 3, the test statistic is greater than the critical value at the 5% significance level, leading to the rejection of the null hypothesis. This indicates that the series is stationary after detrending. A key difference between the KSS and Sollis tests is how they handle mean reversion. The KSS test assumes that positive and negative shocks have the same effect on mean reversion, while the Sollis test allows for the possibility of asymmetry in these shocks. In case 3, where the series is found to be stationary, it is also tested whether the mean reversion is symmetric or asymmetric. To determine this, the cubic term of y is examined to see if it is positive or negative. If the coefficient is positive, it is not possible to determine whether the mean reversion is symmetric or asymmetric. However, if the coefficient is negative, the F-test can be used to make this determination. For the S&P Green Bond price series, the cubic term coefficient is negative (-0.166). An F-test is then conducted, yielding an F-statistic value of 1.07. Since this value does not lead to the rejection of the null hypothesis, it can be concluded that the mean reversion process is symmetric. The Solactive Green Bond price series exhibits a unit root in all three cases. This finding indicates that the series is non-stationary and follows a random walk.

Similarly, Kruse (2011) confirms that the Solactive Green Bond price series has a unit root for all three cases. For the S&P price index, this test also aligns with the results from the Sollis (2009) and KSS tests. In cases 1 and 2, the series is found to have a unit root, indicating non-stationarity. However, in case 3, where the series is detrended, the test statistic exceeds the critical value at the 10% significance level, leading to the rejection of the null hypothesis. This indicates that the S&P index series is stationary in the detrended case.

In the study conducted by OY (2014), a method referred to as a Hybrid test is employed, where the LNV (1998) model is utilized in the first stage, followed by the application of the KSS test procedure. According to the findings of this unit root test, unlike the other three tests, the S&P variable is found to be stationary at the one percent significance level across all three models. Similarly, for the Solactive green bond, in Models B and C, stationarity is detected at the one percent significance level. Non-linear and stationary interpretations are made for the series found to be stationary.

Omay et al. (2018) present two different tests, namely OEHa and OEHb. OEHa is based on the Asymmetric ESTAR unit root test relying on a logistic function, while OEHb is based on the AESTAR unit root test relying on a Fourier function. The results of the OEHa test indicate that in Model A, the S&P green bond price, with a break in mean without a trend, is significantly bigger than critical values. This leads to the rejection of the null hypothesis and implies a stationary, ESTAR-type nonlinear situation. In Model B, with a break only in the mean but not in the trend, and in Model C, with breaks in both mean and trend, the null hypothesis is rejected at the 1% significance level. Conversely, Solactive is found to have a unit root in all models. The results of the OEHb test indicate that both green bond series have unit roots.

According to the unit root test results suggested by Ranjbar et al. (2018), also known as Fourier Solis, for S&P, the test statistic value in the constant model is smaller than the critical values; hence the null hypothesis cannot be rejected, implying the presence of a unit root. However, in the constant and trend model, the test statistic at the ten percent significance level is greater than the critical value, leading to the rejection of the presence of a unit root. Consequently, it can be stated that the series is stationary for this model. As for Solactive green bonds, the test statistic values are smaller than the critical value in both models, indicating the presence of a unit root.

According to Güriş (2019), also known as the Fourier-Kruse test, the findings indicate that the Solactive green bond price series contains a unit root both in the constant model and in the model with constant and trend. However, S&P only exhibits a unit root in the model with a constant. The model with constant and trend components at a ten percent significance level rejects the null hypothesis and indicates the stationarity of S&P green bonds.

Lastly, the test procedure proposed by Omay et al. (2020) permits smooth transitions in deterministic components and accommodates non-linear models using an ESTAR function. According to the test results, OSH is found to be stationary at the one percent significance level in both models B and C for S&P and Solactive.

In general, when examining the unit root test results of the ESTAR-type nonlinear models, it is observed that the price of S&P green bonds is stationary, whereas the price of Solactive green bonds is found to have a unit root, except for the OSH and OY tests.

Table 2.3. ESTAR Type Unit Root Test Results

Tests	**KSS**			**Sollis**		
Models	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3
S&P Green	-0.5539	-0.9946	-3.7509**	0.7244	0.8013	7.4457**
Solactive	-0.0731	-2.1948	-2.2406	1.2391	3.1660	3.0789
Tests	**Kruse**			**OY**		
Models	Case 1	Case 2	Case 3	Model A	Model B	Model C
S&P Green	1.4020	7.0677	11.4164*	-6.686***	-6.204***	-6.201***
Solactive	2.5449	5.9389	5.5471	-2.357	-6.606***	-6.654***
Tests	**CEO**			**OEH_a**		
Models	Model A	Model B	Model C	Model A	Model B	Model C
S&P Green	-3.551	-5.430***	-5.427**	9.358**	15.555***	15.476***
Solactive	-3.518	-3.457	-3.518	4.190	5.585	4.966
Tests	**OEH_b**			**Ranjbar et al.**		
Models	Constant		Constant and Trend	Constant		Constant and Trend
S&P Green	-2.106		-3.858	2.621		7.780*
Solactive	-2.434		-2.679	3.627		3.505
	Güriş			**OSH**		
	Constant		Constant and Trend	Model A	Model B	Model C
S&P Green	9.40		14.983*	-0.856	-5.772***	-5.773***
Solactive	7.867		7.413	-1.812	-5.759***	-5.762***

Note: *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively

Table 2.4 displays the results of unit root tests based on the logistic function. The LNV (1998) nonlinear unit root test is listed as Model A, Model B, and Model C. Model A indicates a constant smooth break, Model B shows a constant break in the presence of a deterministic trend, and Model C indicates both a constant and deterministic trend break. In all three models, the test statistic value for both green bond price series is smaller than the critical values. This indicates that the null hypothesis of the presence of a unit root cannot be rejected. Therefore, both series follow a random walk process according to this unit root result.

According to the unit root test results by Pascalau (2007), Case 1, Case 2, and Case 3 represent raw data, demeaned data, and detrended data, respectively. For Solactive, the test statistic value in all three models is smaller than the critical values. Hence, the null hypothesis cannot be rejected, indicating that the series contains a unit root. On the other hand, for S&P, although a unit root is found in Case 1, it is observed that the Case 2 and Case 3 models are stationary at a 5% significance level.

The overall conclusions drawn from these two models indicate that the Solactive green bond price series contains a unit root; however, different results are obtained for S&P. While the LNV test detects the presence of a unit root, Pascalau unit root test analysis suggests stationarity in the series.

Table 2.4. LSTAR Type Unit Root Test Results

		LNV	
	Model A	Model B	Model C
S&P	-0.952	-1.966	-1.894
Solactive	-1.483	-1.686	-3.997
		Pascalau	
	Case 1	Case 2	Case 3
S&P	0.7127	3.6414**	5.0584***
Solactive	1.2558	1.6805	1.9352

Note: ** represents a significance level of 5%

Table 2.5 displays the results of the Rals unit root tests without structural breaks, taking into account the non-normality of error terms. According to the RALS-ADF and RALS-LM

test results, the test statistic values obtained for the S&P and Solactive green bond prices are smaller than the respective critical values. Therefore, it is concluded that the series exhibit non-stationarity and contain a unit root.

Table 2.5. RALS Unit Root Test Results without Structural Breaks

Tests	**RALS ADF**				**RALS LM**	
Models	Constant		Constant and Trend		Constant	
	Test Stat	rho	Test Stat	rho	Test Stat	rho
S&P	0.829	-1.210	-2.840	0.822	-2.772	0.860
Solactive	-2.046	0.816	-2.018	0.816	-0.409	0.809

Meng et al. (2014) propose models allowing for one and two structural breaks in unit root tests, taking into account non-normality in the error terms. Conversely, Meng et al. (2017) suggest unit root tests permitting one and two breaks in both intercept and trend terms while also considering non-normality in the error terms. The results of these tests are presented in Table 2.6. Additionally, these results will be compared with the Lee-Strazicich unit root test results, which do not consider normal distribution but include structural breaks. The Lee-Strazicich unit root test indicates that both green bond price series contain unit roots. Furthermore, the Jarque-Bera test statistics show that the error terms from these unit root tests are not normally distributed. Similarly, the RALS LM unit root test, accounting for nonnormality, indicates that the S&P green bond price series contains unit roots when allowing for a level break. On the other hand, the RALS LM unit root test, which allows for a structural break in a trend break, shows that the S&P is stationary at the one percent significance level. Lastly, for the Solactive green bond series, test statistics under both a level and a trend break are smaller than the critical value, indicating that the null hypothesis cannot be rejected, and thus, the series contain unit roots. According to the results of the two-break unit root tests, the Lee-Strazicich unit root test identifies both green bond price series as exhibiting unit root processes across all models. However, the RALS LM unit root test, with both level and trend breaks, suggests that the S&P green bond price is stationary. Conversely, it indicates that the Solactive green bond market is characterized by unit root behavior.

Tablo 2.6 RALS Unit Test Results with Structural Breaks

	ONE BREAK											
	Lee-Strazicich						RALS LM					
	Constant			Constant and Trend			Constant			Constant and Trend		
	Test Statistics	Date	Prob (JB)	Test Statistics	Date	Prob (JB)	Test Statistics	rho	Date	Test Statistics	rho	Date
S&P	-1.994	2011:09:26	0.000	-2.8418	2022:04:19	0.000	-0.348	0.872	2011:09:20	-5.502***	0.853*	2011:11:20
Solactive	-2.811	2013:06:03	0.000	-3.0570	2021:06:10	0.000	-2.266	0.891	2015:08:20	-2.111	0.897	2022:07:00
	TWO BREAKS											
	Lee-Strazicich						RALS LM					
	Constant			Constant and Trend			Constant			Constant and Trend		
	Test Statistics	Date	Prob (JB)	Test Statistics	Test Statistics	Prob (JB)	Test Statistics	rho	Date	Test Statistics	rho	Date
S&P	-3.124	2022:01:13	0.000	-3.531	2015:03:05 2022:01:13	0.000	-3.852***	0.917	2015:07:2 2015:08:2	-8.570***	0.8262	2011:09:01 2011:10:01
Solactive	-2.863	2013:06:03 2020:03:17	0.000	-3.3867	2013:04:24 2020:12:30	0.000	-0.873	0.81	2020:03:10 2022:04:21	-3.433	0.9	2022:03:1 2022:09:0

Note: * and *** represent significance levels of 10% and 1%, respectively

2.5. Conclusion

The capital market facilitates the fair distribution of economic resources. Therefore, green bond markets aim to provide effective capital intermediation between investors and green or climate-related projects that contribute to reducing carbon emissions. The rise of green bonds has gained momentum in parallel with increasing efforts towards environmental sustainability. Particularly, the signing of the 2015 Paris Agreement has led to increased international commitments to reducing carbon emissions and combating climate change. This agreement further emphasized the importance and impact of green bonds, as they became significant instruments for investors contributing to the goals of the agreement by investing in climate-friendly projects.

The efficiency of green bond markets should be evaluated within the framework of the Efficient Market Hypothesis (EMH) as defined by Eugene Fama's seminal work in 1970. EMH posits that market prices accurately reflect all available information. Therefore, understanding whether price movements in the green bond market fully reflect environmental factors and other relevant information is crucial for testing the validity of EMH. If green bond markets accurately price environmental factors and sustainability-related information, this can support the accuracy of EMH. However, situations such as market prices not moving according to expected information or information being inadequately or incorrectly priced can raise questions about the limits of EMH and the efficiency of green bond markets. Hence, analyzing green bond markets is important not only for understanding the theoretical framework of EMH but also for assessing the practical efficiency of the market.

This section evaluates the efficiency of green bond markets within the framework of the Efficient Market Hypothesis (EMH) outlined in Eugene Fama's 1970 study. EMH is examined in three different categories: weak form, semi-strong form, and strong form. Weak form efficiency relies on the assumption that past prices do not provide information about future prices, suggesting that past performance is random. Semi-strong form efficiency suggests that all publicly available information is accurately and immediately reflected in asset prices. This implies that market prices adjust promptly and accurately to this information. Strong form efficiency argues that all private information is already reflected in prices, making it impossible for insiders to consistently achieve abnormal returns. This

section focuses on weak form efficiency and applies various unit root tests to assess whether the market behaves weak form efficiently.

This study is significant because existing research indicates a limited examination of green bond markets from the perspective of the Efficient Market Hypothesis (EMH), and none of these studies, to the best of our knowledge, have analyzed whether the series of green bond markets follows a random walk using unit root tests. Therefore, this study aims to contribute to the literature by expanding existing knowledge and assessing the weak form efficiency of the green bond market using various unit root tests that consider different aspects. Additionally, Enders and Granger (1998) state that traditional unit root tests have lower power in the presence of misspecified dynamics. Hence, evaluating weak form market efficiency using traditional unit root tests can lead to incorrect conclusions about market efficiency. Moreover, neglecting conditional nonlinearities in the mean of the series is a common feature in existing studies on the efficiency of emerging markets. This study aims to address these gaps by comprehensively analyzing the efficiency of green bond markets, employing nonlinear unit root tests, methods considering non-normal distributions, and tests accounting for structural breaks. These approaches will provide a more accurate understanding of how green bond markets respond to market shocks and external influences, making significant and innovative contributions to academic literature.

Four different groups of unit root tests were applied in this study. These tests include traditional tests such as ADF and PP, tests that consider structural breaks in the smooth form: Fourier KPSS, Fourier ADF, Fourier KSS, Flexible Fourier ADF, Fractional Frequency Flexible Fourier ADF, unit root tests that examine both sharp and smooth breaks: SOR, unit root test based on nonlinear structure: KSS, Sollis, Kruse, OY, CEO, OEH, OSH, LNV, and finally, unit root tests that consider non-normal errors and account for sharp breaks, known as the RALS unit root tests.

According to the results, none of the unit root tests that do not consider structural breaks could find stationary behavior for either the S&P green bond price or the Solactive green bond price. On the other hand, among the tests that consider smooth breaks, Fourier-type unit root tests, found the series to be unit root processes for the Solactive variable. Conversely, for the S&P Green Bond Index, Fourier ADF, and SOR tests found the series to be stationary, while the remaining tests found them to be unit root processes. The majority

of nonlinear unit root tests found the S&P to be stationary, with the exceptions being the OEHb and LNV tests. Those not rejecting stationarity at a ten percent significance level were the Güriş and Kruse tests. Sharp structural break unit root tests found both green bond prices to be unit root processes under one break and two breaks, while tests considering non-normal error found the S&P Green Bond Index to be stationary, while the Solactive was found to be unit root. Overall, when considering these results, it can be inferred that both series follow a random process in their deterministic structure when nonlinearity or breaks are not considered. However, the S&P green bond price can exhibit stationary behavior when these characteristics are taken into account, whereas the Solactive green bond price, except for three tests (OY, and OSH), displays unit root behavior. Based on these results, it can be concluded that the S&P series does not follow a random process, while the Solactive green bond price may follow a random process. Within the framework of the Efficient Market Hypothesis, it can be inferred that the S&P is not weak form efficient, whereas the Solactive green bond price may be weak form efficient.

When the obtained results are evaluated collectively, several conclusions can be drawn. Firstly, the analyses suggest that the S&P green bond series does not exhibit random behavior, indicating a departure from weak form efficiency within the framework of the Efficient Market Hypothesis (EMH). Conversely, the Solactive green bond price appears to demonstrate characteristics aligned with weak form efficiency, except for a few exceptions. These findings imply that the S&P green bond market may not fully reflect all available information in its pricing dynamics, potentially providing opportunities for investors to achieve abnormal returns based on historical price patterns. In contrast, the Solactive green bond market seems to promptly and accurately incorporate new information into its prices, supporting the notion of market efficiency to a greater extent.

Analyses of the green bond markets using daily, weekly, and monthly data across different frequencies reveal consistent results. The stationary nature of S&P green bond prices suggests a potentially inefficient market where prices do not fully reflect all available information. In contrast, Solactive green bond prices exhibit unit root characteristics, suggesting that they follow a random walk process and thus align with an efficient market hypothesis, where prices incorporate all current information, and future movements are unpredictable. According to Bond and Thaler (1985), common market anomalies such as the bid-ask spread, and the impact of infrequent trading can obscure true asset values and distort

price signals. Therefore, they suggested that using monthly data is more appropriate. However, green bonds do not seem to have a significant effect.

The S&P Green Bond Index is generally stationary, indicating an inefficient market structure. In contrast, the Solactive Green Bond Index exhibits a random walk, suggesting an efficient market. Although both green bond indices are issued with the goal of supporting sustainability and environmentally friendly projects, the different outcomes from the applied tests might stem from methodological differences. When examining the methodological differences, S&P green bonds offer a wide variety of coupon types, including fixed, zero, step-up, fixed to float, and floaters, while Solactive green bonds are limited to fixed coupons (Climate Bonds Initiative, 2015; Ehler and Packer, 2016). Research by Nanayakkara and Colombage (2021) indicates that investors tend to prefer fixed-coupon green bonds, enhancing market liquidity and efficiency as demand increases. Moreover, S&P green bonds are issued in any country and in any currency worldwide, whereas Solactive bonds are restricted to issuance in USD and EUR (Latin American Association of Development Financing Institutions [ALIDE], 2019). This broader currency diversity exposes S&P bonds to higher foreign exchange risk, potentially increasing market uncertainty and decreasing efficiency. Solactive green bond's limited currency issuance can provide a more predictable and manageable risk profile for investors, supporting market efficiency. Both types of bonds lack hedging indices against foreign currencies, unlike indices such as Barclays MSCI and BofA Merrill Lynch, which means they do not offer protection against currency risk. The issuance of S&P green bonds in various currencies could lead to greater vulnerability to exchange rate fluctuations, further complicating market dynamics and efficiency.

3. RELATIONSHIP BETWEEN GREEN BONDS AND FINANCIAL AND ENVIRONMENTAL VARIABLES

3.1. Introduction

Sustainable development, environmentally friendly growth, and equitable economic development are the goals of modern global efforts (Duran et al., 2015). Achieving these goals will require cutting carbon emissions and stopping the increase in temperatures (Edenhofer et al., 2014). In this context, a variety of low-carbon investment strategies have been developed as key tools in addressing climate and emission issues (Madaleno et al., 2022, Wang et al., 2022). For instance, investments in renewable energy sources are noted not only for their positive impacts on economic growth but also for their significant contributions to reducing carbon emissions and promoting a sustainable development which defined it as development that meets present needs without compromising future needs (WCED, 1987; Salim and Rafiq, 2012; Bhattacharya, 2020). However, transitioning to a low-carbon economy and financing the necessary transformation projects require a significant amount of capital. In this regard, Alamgir and Cheng (2023) emphasizes the potential of green bonds to mobilize financial resources for environmentally beneficial projects and thereby play a crucial role in combating climate change.

Green bonds not only offer funding for investment projects that have positive impacts on the climate and environment, such as lowering carbon emissions, but they are also evaluated and priced in a manner comparable to fixed-income instruments like corporate and government bonds (Liu et al., 2021). This market has become one of the fastest-growing segments of international capital markets as a result of investor interest in environmental risks and the 2015 Paris Agreement, which included the commitment of numerous countries to transition to a climate-resilient economy (Reboredo, 2018). Reports show that green bonds had an unprecedented growth in 2020, and in 2021, it expanded by 75%, reaching a total value of $1.6 trillion (European Parliament, 2023). This amount has surpassed $2.5 trillion as of September 2023 (Climate Bond Initiative, 2023). Since their introduction in 2007, this significant expansion of green bonds has prompted investigations into their potential as a means of diversifying portfolios, like other financial instruments. Understanding the

interconnectedness between green bonds and various financial instruments has become significant in this context. As Longin and Solnik (1995) highlighted, the correlation matrix of international asset returns is particularly significant. Because this correlation matrix can be used to understand the relationships between the returns of different assets, which can help investors better manage their risks and returns. Therefore, with the increasing interest in sustainable investment products, it is crucial to determine whether green bonds can be considered a viable portfolio tool for investors.

In academic literature, there is significant interest in the correlation relationship between financial assets. Particularly, attention has been focused on the dynamics of relationships among emerging stock markets and the factors influencing these connections (Koch and Koch, 1991; Longin and Solnik, 1995; Fleming et al., 1998, Chen et al., 2002; Onnela et al., 2003; Cappiello et al., 2006; Choi et al., 2010). There is also evidence in the literature that shows these linkages between international markets change over time and are also affected by market conditions. For instance, Longin and Solnik (1995, 2001), in their analyses of the financial markets of developed countries, do not support an increase in correlation during bull markets but rather during bear markets. These results are also supported by several studies (Erb et al., 1994; Ang and Bekaert, 2002; Ang and Bekaert, 2004; Phylaktis and Xia, 2009).

A further important point concerning the relationship between markets is whether markets affect each other only during crisis periods or also under normal market conditions. Forbis and Rigobon (2002) have distinguished between two scenarios by employing the concepts of “contagion” and “interconnectedness” to determine whether market interactions occur solely during crisis periods or also during normal times. The term “Contagion” refers to a substantial rise in correlation between different markets following a shock to a single country or a group of countries. The term “interconnectedness” refers to the situation where two markets exhibit strong comovement during stable periods, and this comovement persists even after a shock to one market. According to these definitions, if two markets exhibit a high degree of co-movement during stable periods, contagion does not occur if markets continue to be highly correlated after a shock to one market.

Masson (1998) also defined contagion and categorized it into three distinct types: monsoonal effects, spillover effects, and pure contagion effects. Monsoonal effects are

described as contagions arising from common causes, where countries with similar economic fundamentals or facing common external shocks tend to exhibit similar responses to events such as financial crises or other economic issues. Spillovers explain how a crisis in one country can affect other emerging markets through trade, economic activity, or competition. Pure contagion, on the other hand, occurs when the spread of a crisis from one country to another cannot be attributed to macroeconomic factors but rather stems from changes in the interpretation given to existing information and shifts in market sentiment. The first two channels can be characterized as crises driven by fundamental factors. This categorization arises from the observation that the countries affected by these crises typically share certain macroeconomic fundamentals. Consequently, the transmission of financial crises across these countries is primarily attributed to their interdependence rather than being solely ascribed to contagion effects (Tai, 2003:958). In this context, the spread of the crisis from one country to another is rooted in the shared economic characteristics among these countries and, therefore, should be regarded not merely as a contagion event but rather because of interdependence between markets. The third definition of contagion, termed as pure contagion, has similarly been described by Pretorius (2002), wherein contagion between markets is not explicable by macroeconomic factors. According to Edward (2000), contagion occurs when the extent and magnitude of a crisis in one country affect the economic conditions of other countries beyond the expectations of market participants.

The findings in academic literature regarding whether financial crises lead to contagion among markets are mixed. Some studies argue that there is no contagion, only interdependence (Forbes and Rigobon, 2002; Wilson and Zurbruegg, 2004; Ismailescu and Kazemi, 2011; Davidson, 2020). Others acknowledge the significance of interdependence but have found some evidence of contagion during crisis periods (Baur and Fry, 2009; Morales and Andreosso-O'callaghan, 2012). Conversely, some studies have identified a contagion effect (Favero and Giavazzi, 2000; Bodart and Candelon, 2009; Marçal et al., 2011; Boubaker et al., 2016).

A growing interconnectedness and interdependence among global financial markets are potentially influenced by factors such as advancements in technology, the liberalization of financial systems, and the expansion of international trade and investment. These linkages between financial assets can be understood as a mechanism for the transfer of information, wherein developments in one market quickly transmit to and influence others. The Efficient

Market Hypothesis (EMH) posits that asset prices fully reflect all available information and adjust rapidly to new information. However, deviations from expected price adjustments, whether too slow or too rapid, can present opportunities for certain investors to gain advantages over others, thereby challenging the notion of market efficiency. If prices exhibit non-random movements and become predictable, it undermines the validity of the EMH (Taş and Tokmakçıoğlu, 2010:286). Particularly in cases of excessive volatility or sudden price movements, it can be observed that market prices do not fully reflect all available information or that prices do not adjust rapidly enough to reach an appropriate level.

Providing investors within a country with a broader range of investment opportunities in international financial markets can facilitate risk diversification and lead to more effective portfolio management, aiming to avoid domestic systemic risk. However, high levels of integration can also result in the rapid transmission of shocks between markets, exacerbating systemic risk. As stated by Schinasi and Simit (2000), an adverse shock in one asset may lead to reductions in positions in other risky assets, with this effect being more determinant for leveraged investors. This is because a loss in a specific asset can prompt leveraged investors to decrease their risky positions across all markets.

According to Markowitz (1959), the founder of Modern Portfolio Theory, it is essential for a portfolio to consist of securities with low levels of correlation to reduce risk effectively. A portfolio consisting of securities whose returns move in near unison offers little more protection than the uncertain return of a single security. Typically, we anticipate that returns on a security will exhibit higher correlation with those of other securities within the same industry. Factors such as business relationships among companies, serving the same geographical area, common reliance on military expenditure, construction activity, or weather dependency, tend to increase the tendency for certain returns to move together.

This study makes notable contributions to the current body of research by investigating the correlation between the green bond market and different financial markets. Existing literature has typically focused narrowly on the relationship between the green bond market and different financial markets, such as energy commodities, and only a few studies have examined subsets of this relationship. Our aim is to investigate this relationship more comprehensively across different markets. Moreover, the current body of research has predominantly focused on investigating causality in terms of the mean, or first moment, of

the variables. This means that most studies have been concerned with how one variable's average level influences another's, rather than exploring higher moments such as variance or other aspects of their distributions. However, as highlighted by Gębka and Serwa (2007) and Cevik et al. (2020), the first-generation causality-in-variance tests introduced by Cheung and Ng (1996) are considered ineffective due to their approach of treating all cross-correlations equally. This method does not account for the fact that cross-correlation between returns typically diminishes and approaches zero as the lag length increases. As a result, these tests may fail to capture the true nature of the relationships between variables over different time lags. Therefore, in this study, we employ Hong's (2001) causality-in-mean test. Additionally, according to the efficient market hypothesis, public information gets reflected in asset prices without delay, providing insights into interactions between markets at lagged values. Another significant consideration is that research examining the correlation between green bonds and other financial markets has mostly ignored the influence of structural breaks in variance. Nonetheless, structural breaks in variance can create size distortions in causality-in-mean tests. Hence, it is utilized the variance test for structural breaks constructed by Sansó et al. (2004) to examine the influence of these breaks on the causality-in-mean test, using the approach described by Hong (2001) in this chapter. Finally, to better understand the dynamic relationship between the green bond market and various financial markets, we utilize multivariate GARCH models. This enables us to analyze how the volatility spillover effect between variables fluctuates during periods of stability and financial turmoil.

3.2. Literature Review

3.2.1. Traditional Financial Markets and Green Bonds

The increasing importance of the green bond market has led to a more detailed examination of its relationships with other financial markets. In this context, the first study conducted by Pham (2016) addressed the relationship between Green Bonds and the Aggregate US bond market, analyzing how this relationship evolved over time. Using data from the period 2010-2015, the study employed both single and multiple GARCH models to assess this relationship. Empirical findings indicate a time-varying volatility spillover between Green Bonds and the aggregate bond market. This suggests that the Green Bond

market may exhibit greater or lesser volatility compared to the aggregate bond market during certain periods.

Reboredo (2018) extended the study conducted by Pham (2016) by examining the relationship of green bond markets with various financial markets, using the Barclays MSCI Green Bond Index as an indicator of the green bond markets. In this context, Reboredo analyzed the impact of fixed-income markets (Barclays Global Aggregate Corporate Index and Bloomberg Barclays Global Treasury Total Return Index), stock markets (the MSCI World Index), and energy markets (the S&P GSCI Energy Spot CME Index) on green bonds. Employing the copula function, the author investigated the interdependence among markets using daily data from 2014 to 2017 and demonstrated a strong relationship between green bonds and bond markets while indicating a weak relationship with stock markets.

Reboredo and Ugolini (2020) replicated the study using the same dataset covering the period from 2014 to 2019, employing structural VAR analysis, and their findings corroborated those of Reboredo (2018). Reboredo et al. (2020) not only focused on the US market but also considered European markets. Utilizing wavelet-based methods and VAR models, they identified a strong relationship between green bonds and treasury bonds as well as corporate bonds in both short and long terms. However, they found a weak relationship between green bonds and stock markets, as well as high-yield corporate bonds. These findings are consistent with previous studies.

A study conducted by Wang et al. (2020) emphasized the relationship between stock markets and green bond markets, particularly in China, and found a positive and strong relationship for the period 2016-2019. Hammoudeh (2020) investigated solely the US 10-year treasury bond from traditional markets and applied the time-varying causality method constructed by Shi et al. (2018, 2020) to examine green bonds. Their analysis from July 30, 2014, to February 10, 2020, generally revealed a significant causality running from treasury bonds to green bonds since the end of 2016, whereas green bonds showed no causal effect on traditional bond indices throughout the study period.

Unlike other studies, Park et al. (2020) attempted to explain the effects of the S&P 500 index as an indicator of the stock market on green bond markets using daily data and multiple GARCH models for the period 2010-2020. According to the findings obtained by

the authors, the S&P Green Bond Select Index, as an indicator of green bond markets, exhibited asymmetric properties, being more sensitive to positive shocks. Despite the presence of volatility spillover effects between the two markets, it was also found that these markets did not respond significantly to negative shocks.

Pham (2021) investigated the impact of green equities on green bonds, alongside examining their relationship with treasury and corporate bonds. Utilizing frequency connectedness and cross-quantilogram methods, the study emphasized that the influence of these two traditional assets is significantly greater on green bonds.

In the study conducted by Nguyen et al. (2021), daily data from 2008 to 2019 was analyzed for the S&P Green Bond market, incorporating both the S&P 500 and the MSCI World Index as indicators of the stock market and utilizing the Barclays Bloomberg Global Treasury Index as a benchmark for traditional bond indicators. Employing wavelet correlation analysis, the research aimed to identify the correlation between different financial assets and green bonds. The findings revealed that while stock markets exhibited the lowest correlation with green bonds, treasury bonds demonstrated the highest correlation. This suggests that green bonds are generally less influenced by stock markets and more closely connected with traditional bond markets.

Similar to the research conducted by Wang et al. (2020), Gao et al. (2021) investigated the relationship between green bonds and financial markets in China by employing several asymmetric GARCH models for the time period of 2015-2020. The researchers conducted a more comprehensive study by including various markets such as forex markets, corporate bonds, government bonds, and the industrial and materials sector. While a strong correlation was found between the green bond market and traditional bond markets, a weak correlation was observed between Forex and money markets and green bonds. The authors also emphasized that the transfer of risk between green bonds and other financial markets occurs more during unexpected market conditions. While a bidirectional relationship was observed between green bonds and traditional bonds, it was noted that there is a unidirectional transfer from the stock market to green bonds.

Adopting a different perspective, Rizvi et al. (2022) investigated whether green bonds, Islamic equities, and conventional bonds exhibited safe-haven properties similar to

gold over a five-year period from 2017 to 2022. Using the quantile VAR analysis method, the study found that Solactive green bonds and Islamic equities only acted as safe havens during normal market conditions. However, assets such as US Treasury bonds, cryptocurrencies, and Gold-Silver emerged as safe-haven assets during bearish market periods or periods of extreme volatility.

Wei et al. (2023) examined the effects of S&P green bonds using the S&P 500 for the U.S. and STOXX 600 for Europe as indicators of the stock market, the 10-year U.S. Treasury bond index for the traditional bond market, and ICE EUA futures prices for the carbon market. The authors applied Granger causality analysis along with Diebold and Yılmaz's (2009, 2012, 2014) econometric methodology for the period from April 16, 2013, to March 10, 2021. According to the Granger causality results, there is bidirectional causality between green bonds and all variables except for the European stock market, where there is a unidirectional causality from the stock market to green bonds. The spillover analysis indicated that treasury bonds are the main contributors to changes in green bonds. Stock markets, particularly during economic turmoil, have a significant spillover effect on green bonds. Additionally, the European stock market also has a direct spillover effect on the green bond market.

When the results of all studies in the literature are combined, the general finding is that green bonds have a considerable impact on markets within the same fixed income group. This conclusion is consistent regardless of different time periods, various econometric methods employed, or different regions under investigation. However, However, studies yield mixed results concerning the relationship between the stock market and the green bond market. Initial studies in the literature suggest a weak correlation, while subsequent research provides evidence of a strong relationship between them.

3.2.2. Clean Energy Markets and Green Bonds

While the research on other markets and green bonds takes a big place in the limited literature, only a few studies have examined the relationship between green bonds and the clean energy market. According to the studies, there is a positive relationship tendency between green bonds and clean energy. A summary of the literature can be represented as follows:

Hammoudeh et al. (2020) applied a time-varying causality test to examine the relationship between green bonds and other assets for the period spanning from 2014 to 2020. The study shows that there is a unidirectional relationship between clean energy and green bonds, and causality is limited. Nguyen et al. (2021) used wavelet analysis to investigate the relationship between green bonds and other financial markets in which they employed daily data for the period of 11 years between 2008 and 2019. They found a two-way high correlation between green bonds and clean energy. Hung (2021) conducted a quantile-on-quantile regression and Granger causality in quantiles approaches to investigate the relationship between green bonds and other conventional assets, such as the clean energy index for the period of 2013 and 2019. The study showed that clean energy is significantly associated with green bonds in the long-term quantiles. Ferrer et al. (2021) analyzed the time-frequency connectedness across the global green bonds and several financial and energy markets. They conduct the analysis for the period of 2014 and 2019 with 1348 daily observations in it. The results of this study showed that there is a significant relationship between clean energy and green bonds.

The study conducted by Liu et al. (2021) represents the first empirical investigation into the relationship between the green bond market and clean energy markets, both on a sectoral and global basis. The study, covering the period from 2011 to 2020, employed Copula analysis. The authors included three global and three sub-sector indices as representations of the clean energy market. Among the global indices were the Wilder Hill Clean Energy Index, the S&P Global Clean Energy Index, and the European Renewable Energy Index. The sub-sector indices comprised the ISE Global Wind Energy Index, the MAC Global Solar Energy Stock Index, and the S&P Renewable Energy and Clean Technology Index. The findings of the study reveal temporal, mean, and positive tail dependence between green bonds and sectoral clean energy stock markets. Additionally, the study identified an asymmetric risk transfer mechanism, with downward risk spreading more pronounced in the green bond market.

Like Liu et al. (2021), Pham (2021) concentrated on the impacts of different green equity markets on green bonds. Several different green equities, such as clean energy, green building, green transportation, and water, were included. The findings of the spillover analysis indicate that the influence of green equities on green bonds is not particularly significant. The cross-quantilogram directional spillover analysis, on the other hand, showed

that green equities have a positive impact on green bonds. Specifically, it was observed that green finance markets, such as clean energy and water, have a more significant effect on green bonds. Additionally, it was found that the impact of green finance markets on green bonds is lower in median quantiles but increases in extreme quantiles. These findings indicate that green finance markets may play a significant role in the performance of green bonds.

Yan et al. (2022) only used the Wilderhill Clean Energy Index to examine the correlation between clean energy equities and S&P green bonds. The results of the quantile ARDL indicate that although Wilderhill clean energy equities have positive effects in low and medium quantiles, they do not have any effect in high quantiles over the long term. On the other hand, it has been noted that they have a positive effect in almost all quantiles in the short run.

Chatziantoniou et al. (2022) investigated the impact of not only clean energy but also environmental and sustainability indexes on green bonds. In this context, the authors examined the dynamic integration and return transmission among four prominent environmental finance indices: the MSCI Global Environment Index, the Dow Jones Sustainability Index, the S&P Global Clean Energy Index, and the S&P Green Bond Index. The researchers analyzed the period from November 28, 2008, to September 23, 2020. They employed a quantitative frequency connectivity approach to establish a methodological framework. The findings suggest that while the green bond market and clean energy market appear to be both short and long-term net shock receivers, the MSCI Global Environment and Dow Jones Sustainability Indices are positioned as short and long-term shock transmitters.

One last recent study is Şahinler's (2022) study, which has covered the volatility spillover between green bonds and clean energy markets utilizing the Hafner and Herwatz time-varying causality test approach to get a better understanding of the sub-periods spillover changing. The empirical findings showed that the clean energy market dominates the green bond market.

Tiwari (2022) examined global and sectoral clean energy sources alongside the green bond market for the period spanning from January 4, 2015, to September 22, 2020.

Econometric methods such as TVP-VAR were employed in the study. The results revealed that the S&P clean energy index dominated all other markets included in the analysis, yet the spillover effects of all indices remained below two.

Similarly, Chai et al. (2022) used a time-varying parameter vector autoregression model (TVP-VAR) to analyze the connectedness between green bonds, clean energy, and stock prices during the period of pre- and during the COVID-19 pandemic. Their result indicated the positive impact of clean energy on green bonds and green bonds' positive influence on clean energy in the short and long term.

Şahinler et al. (2024) also conducted a similar study. In this study, various indices, such as the S&P clean energy index, Nasdaq, and WilderHill Global Indexes, were evaluated. Additionally, sectoral analysis included solar, water, and buildings. Findings from the period of 2008 to 2022 indicated that the highest spillover in terms of returns was from clean energy (6.42%), followed by the building stock index (4.49%). However, the highest spillover in terms of volatility was still observed in the S&P global clean energy index (12.16%).

To summarize, the research consistently demonstrates a positive correlation between green bonds and the clean energy market. Nevertheless, a number of studies, including Liu et al. (2021) and Pham (2021), suggest that this correlation becomes more apparent during extreme market conditions. Yan et al. (2022) distinguishes between short-term and long-term effects, indicating that the effect is stronger in the short term and tends to decrease over a longer period. Lastly, when comparing the effects of sub-sectors and global clean energy sectors on green bonds, it has been observed that global clean energy indices have a greater impact on green bonds.

3.3.3. Energy Commodities and Green Bonds

The first studies focused on the relationship between green bonds and energy commodities, often utilizing the S&P GSCI Energy Spot Index as an indicator of the energy market. Reboredo et al. (2018) used a copula model to examine the relationship between the Barclays MSCI Green Bond Index and energy prices for the period 2014-2017, finding a weak relationship. Similarly, Reboredo and Ugolini (2020) revisited these indices using a

structural VAR method for the period 2014-2019, yielding findings consistent with Reboredo (2018). Employing a different econometric approach, Nguyen et al. (2021) used wavelet correlation analysis to reach a similar conclusion regarding the relationship between the S&P Green Bond and S&P GSCI Energy Spot Indices for the period 2008-2019.

In contrast, Ferrer et al. (2021) used Brent crude oil price as an indicator of the energy market, employing the connectedness method developed by Diebold and Yilmaz (2012, 2014) and Baruník and Křehlík (2018). Their study found a relationship between Brent crude oil and green bonds only for a period of less than one week. Similarly, Arif et al. (2022) used Brent crude oil and the cross-quantilogram approach to find a weak relationship between these two assets for the period 2008-2021.

Tsagkanos et al. (2022) used a Value at Risk (VaR) based copula approach that considers asymmetrical tail distributions to look at the asymmetric risk spillover between green bonds and commodities like metal, soft, and energy commodities. Their findings indicate that the impact of commodities such as oil and heating oil on green bonds is minimal, while the strongest effect emanates from gold. Specifically, the influence of commodities like WTI crude oil, silver, copper, and wheat on green bonds was examined, with the determination that their impact is relatively weak.

Saeed et al. (2020) focused on examining the relationship between green bonds and dirty energy assets, including crude oil and the iShares U.S. Oil & Gas Exploration & Production ETF (IEO), using the corrected Dynamic Conditional Correlation (DCC) method. Their analysis covering the period from 2012 to 2019 revealed a weak correlation between these assets.

Huynh (2020) examined the influence of various equity indices and commodities on the Nasdaq Artificial Intelligence (AI) index, including crude oil, gold, the VIX, MSCI World. Their study utilized volatility spillover analysis and focused on green bonds, covering a period of approximately three years from December 19, 2017, to January 16, 2020. Among their findings, for short-term effects (1 to 5 days), the MSCI US equity index showed the most significant impact on S&P green bonds, with a volatility of 13.68, while gold exhibited a volatility of 4.12.

Doğan et al. (2023) conducted a comprehensive investigation into the relationship between the oil market and the green bond index, revealing significant two-way Granger causality findings between risks across different quantiles. In this analysis, nonparametric testing methods proposed by Jeong et al. (2012), Baruník and Kley (2015), and Han et al. (2016) were utilized. The results demonstrated that changes in oil market prices can predict fluctuations in green bond prices and that reverse causality exists. Additionally, a negative relationship was identified between the oil and green bond markets, particularly in the middle quantiles. These findings support the potential for green bonds to serve as safe havens during turbulent periods.

Su et al. (2023) also focused on only the link between oil prices and green bond markets, utilizing monthly data from 2011 to 2021. They employed wavelet transformation methodology and quantile-on-quantile techniques. The results indicated that in the short term, oil prices positively impact green bonds, whereas this effect turns negative in the medium and long terms. Additionally, the authors found that green bonds positively influence oil prices across all quantiles.

Lee et al. (2021) focused on how oil prices affected green bonds using monthly data from 2013 to 2019. In contrast to many studies, the authors used the Barclays MSCI green bond index as a proxy for green bonds. According to quantile cointegration analysis, no long-term relationship was found between oil and green bonds. For causality analysis, the authors employed the Granger-causality quantile analysis proposed by Troster (2018). While traditional Granger causality analysis did not reveal any causality, quantile-based causality analysis indicated a causality from oil to green bonds in the low and medium quantiles, persisting across the first, second, and third lags, suggesting a lead-lag effect. Similarly, causality from green bonds to oil was also observed, indicating bidirectional causality. Lee et al. (2022) repeated their investigation using a different econometric tool, namely the structural VAR model, for the period 2010-2021. Their findings indicate that green bond returns reduce when there is an unexpectedly positive oil shock.

In contrast to previously conducted academic research, Kanamura (2020) investigated the impact that the prices of West Texas Intermediate (WTI) and Brent crude oil have on various green bond indices. These indices include Bloomberg Barclays MSCI, S&P, and Solactive. The study examined this relationship using daily data covering the

period from 2014 to 2018. The researcher analyzed the relationship between green bonds and various oil prices using correlation model parameters. The findings revealed a generally positive relationship between Bloomberg Barclays and WTI crude oil that varied over time, although the positive correlation coefficients were typically below 0.2. This was also the case for the S&P green bond index. However, the relationship with the Solactive green bond index was generally found to be negative over time. When examining the correlations between Brent crude oil and green bonds, similar results to those obtained with WTI were observed.

Xiang and Cao (2023) examined the effects of crude oil as well as other natural resources, such as natural gas and coal, on S&P green bonds. He applied the quantile ARDL method over the period 2010-2021. According to the findings, while crude oil has a positive effect on green bonds across all quantiles, natural gas, and coal have no significant effect on green bonds in the low quantiles; however, they exhibit a negative effect in the medium and high quantiles. In the short term, alongside crude oil, natural gas has a positive effect on green bonds in the short quantiles, followed by a negative effect. Coal, on the other hand, positively influences green bond prices across all quantiles. Yan et al. (2022) similarly employed the Quantile ARDL method, but unlike the study by Xiang and Cao (2023), they found only a negative effect in the low and medium quantiles in both the long and short terms. However, they observed that in high quantiles, there was no impact of oil prices on S&P green bonds. The authors investigated the same period as Xiang and Cao (2023), which is from 2010 to 2021, but they utilized oil and gold prices specific to Türkiye.

Mezghani et al. (2023) focused on both the Chinese and international markets to examine the impact of Brent crude oil on green bonds. Frequency Connectedness Analysis was employed in the study. The sample period was selected from 2018 to 2021, divided into two periods: pre-COVID and post-COVID. Brent exhibited the least spillover effect on S&P green bonds during the pre-COVID period. For both pre- and post-COVID periods, Chinese green bonds showed the least spillover effect from Brent, following S&P green bonds. While Brent had the lowest spillover effect on S&P green bonds during the pre-COVID period, it rose to the second lowest spillover effect among financial assets in the post-COVID period. Thus, it can be inferred that the spillover effect of Brent on S&P increased post-COVID. In the long term, Chinese green bonds receive much lower spillover effects from Brent compared to S&P green bonds.

Su et al. (2022) and Wang et al. (2023) only focused on China's green bond market and its relationship with energy commodities. While Su et al. (2022) utilized the CSI Energy Futures Composite Index as an indicator of the energy market, Wang et al. (2023) only considered crude oil as an energy commodity. Su et al. (2022) employed the spillover method proposed by Baruník and Křehlík (2018) and Diebold and Yilmaz (2012), along with the VAR for VaR (MVMQ-CAViaR) model suggested by White et al. (2015). According to the findings from the period 2012-2020, energy commodities consistently emerged as the major information contributors for green bonds. On the other hand, Wang et al. (2023) used the quantile ARDL method and time-varying method. They found that the impact of oil prices on green bonds is significant and positive across all quantiles in the long term, while it is insignificant in the short term for low quantiles and significant and negative for high quantiles. Thus, the authors demonstrate the asymmetric effect of oil prices in both short and long terms. According to time-varying results, the effect of oil prices on green bonds is positive and significant at the 5% level across the 0.25, 0.50, and 0.75 quantiles in the full sample. However, the rolling estimates sharply decline in the year 2016, losing their significance.

Generally speaking, the investigations that have been conducted on the connection between oil prices and green bonds have revealed that it is a weak and unclear relationship. Most research shows that oil prices have little or no effect on green bonds, depending on market conditions and periods. Rising oil prices may have a short-term favorable influence on green bonds (Su et al., 2023; Xiang and Cao, 2023), but others suggest a long-term negative or insignificant link (Yan, 2022; Reboredo, 2018; Saeed, 2020).

3.3. Econometric Methodology and Data

3.3.1. Econometric Methodology

This study conducts causality analyses for both mean and risk using GARCH models, which utilize the second moments of return series. Consequently, the purpose of this chapter is to present the various GARCH models that were utilized in the analysis.

3.3.1.1. Univariate GARCH Models

3.3.1.1.1. GARCH

Bollerslev (1986) proposed the Generalized ARCH (GARCH) model as the extension of Engle's (1982) Autoregressive Conditional Heteroskedasticity (ARCH) model. Bollerslev (1986) expanded the model by incorporating more historical information and flexible lag structures. In the GARCH (p, q) model, the ARCH component is modeled with p lags, while the GARCH component is modeled with q lags. This allows the GARCH model to account for not only the volatility but also the lagged conditional variances, providing a more accurate representation of financial volatility. The GARCH (p, q) model can be expressed by the following Equation 3.2:

$$\varepsilon_t|\psi_{t-1} \sim N(0,\ h_t) \tag{3.1}$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} = \alpha_0 + A(L)\varepsilon_t^2 + B(L)h_t \tag{3.2}$$

where, h_t represents the conditional variance, α_0 is the constant term, α_i are the ARCH parameters, ε_{t-i}^2 are the lagged squared residuals and β_j are the GARCH parameters. Additionally, the following conditions must be satisfied:

$$p \geq 0\ , q > 0 \tag{3.3}$$

$$\alpha_0 > 0, \alpha_i \geq 0, i = 1, \ldots, q \tag{3.4}$$

$$\beta_i \geq 0, i = 1, \ldots, p \tag{3.5}$$

$$\alpha_i + \beta_i < 1 \tag{3.6}$$

Specifically, when p = 0, the process reduces to an ARCH(q) process. In this case, the conditional variance is determined solely as a linear function of past sample variances. Similarly, when p = q = 0, ε_t is simply white noise, meaning it contains no predictable pattern or structure. In the ARCH process, the conditional variance is expressed only as a linear

function of past sample variances, while the GARCH (p, q) process allows for the inclusion of lagged conditional variances (Bollerslev, 1986: 309).

GARCH is a popular approach for modeling volatility in financial markets, and there are various enhanced versions of this model. Alongside the general structure of the GARCH model, derivative versions such as EGARCH, GJR GARCH (TGARCH), and APARCH have been developed to more effectively capture the complex and dynamic features of volatility. EGARCH models asymmetric volatility responses, GJR GARCH captures threshold volatility effects, and APARCH addresses different volatility regimes. Models like FIGARCH and HYGARCH, which represent long memory, model the relationship between volatility and its past more flexibly. Meanwhile, FIEGARCH and FIAPARCH combine asymmetry and long memory interactions, offering a broader analytical perspective. These enhanced GARCH models allow for a more successful handling of the complex volatility dynamics, particularly for financial assets with high volatility.

3.3.1.1.2. EGARCH

GARCH models offer suitable fits for exchange-rate dynamics, but they often struggle to effectively model the volatility of stock returns. Despite the solutions presented by these simple parameterizations, ARCH and GARCH models have limitations in capturing the full complexity and dynamics of financial data. Specifically, GARCH models assume a symmetric response between volatility and returns, which leads them to overlook the "leverage effect" in stock returns. As a result, GARCH models could not account for the leverage effect (Schmitt, 1996:2). To address this limitation and to model asymmetric variance effects, Nelson (1991) proposed the Exponential GARCH (EGARCH) model. The conditional variance Equation 3.7 can be formulated in several ways, and one of the possible specifications is provided by Brooks (2019).

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left(\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right) \quad (3.7)$$

The EGARCH model offers several key advantages over the standard GARCH specification. Firstly, due to the logarithmic modeling of the conditional variance as $\ln(\sigma_t^2)$,

the conditional variance remains positive even if the parameters are negative. This ensures that the model parameters naturally remain positive, preserving the mathematical integrity of the model without the need for artificial constraints. Secondly, the EGARCH model allows for asymmetric effects through the γ parameter. If the relationship between volatility and returns is negative, the γ parameter also takes a negative value, capturing the model's ability to respond differently when volatility increases. These asymmetric effects can more accurately reflect the realities observed in financial markets (Brooks, 2019:523)

$\gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}}$ and $\alpha \left(\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right)$ in the EGARCH model are designed to quantify the sign and magnitude effects, respectively.

The negative γ parameter indicates that negative shocks have a stronger effect on conditional volatility compared to positive shocks. This feature of the EGARCH model effectively captures the market's varying reactions to upward and downward movements, providing a more insightful view of market volatility.

3.3.1.1.3 APARCH

In the GARCH model, the conditional variance is a linear function of lagged squared returns. Ding et al. (1993) introduced the Asymmetric Power ARCH (APARCH) model, which includes the Box-Cox power transformation of conditional standard deviation along with asymmetric effects. This model combines different GARCH models, offering a more effective way to model the complexity of financial data.

$$s_t^{\delta} = \alpha_0 + \sum_{i=1}^{p} \alpha_i (|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i})^{\delta} + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^{\delta} \quad (3.8)$$

For this model $\alpha_0 > 0, \delta \geq 0, \alpha_i \geq 0, i = 1, \dots, p, -1 < \gamma_i < 1, \beta_j \geq 0, j = 1, \dots, q$

The parameters α_i and β_j in the model represent GARCH parameters, while γ denotes the leverage effect and δ represents the power parameter. In contrast to the EGARCH model, the presence of a leverage effect requires γ to be positive.

3.1.1.1.4. IGARCH

A widely recognized empirical observation regarding financial markets is the notable level of persistence in stock price volatility. The conventional GARCH framework frequently shows evidence that the conditional volatility process is extremely persistent and potentially not covariance stationary (Caporale et al., 2003:765). Engle and Bollerslev (1986) proposed the Integrated GARCH (IGARCH) model to address this issue. IGARCH is defined as:

$$\sigma^2 = \omega + \sum_i^p \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 \quad (3.9)$$

In this formula, σ^2 represents the conditional variance, ω denotes the constant term, ε signifies the error term, and α_i and $\beta_j$denote the ARCH and GARCH parameters, respectively. In the IGARCH model, the restriction on the total variance imposes that the sum of coefficients equals 1.

3.3.1.1.5. GJR-GARCH

The EGARCH (Exponential GARCH) model emphasizes the importance of asymmetry when modeling financial volatility. In this model, the natural logarithm of the conditional variance is expressed as a nonlinear autoregressive moving average (ARMA) model, along with a term that captures asymmetry based on the sign of past returns. This approach acknowledges that the effects on volatility can vary depending on the direction of price movements. The EGARCH model generally deals with asymmetric effects (Medeiros and Veiga, 2009:118). In the GJR GARCH model proposed by Glosten et al. (1993), asymmetric effects are specifically addressed, particularly in relation to the sign of past returns. In the GJR GARCH model, the authors recognize that the effects of positive and negative returns in the past may differ and that these effects may vary in their impact on conditional variance. Thus, the GJR model presents a framework where the dynamics of conditional variance can change based on the sign of past returns. This approach specifically tackles asymmetric effects and provides a more detailed explanation of the nature of price movements in financial markets. The GJR GARCH model is expressed as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_t^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \gamma_i I_{t-i} \varepsilon_{t-i}^2 \quad (3.10)$$

If $\varepsilon_{t-i} < 0$, then I_{t-i} takes the value of 1. However, if $\varepsilon_{t-i} > 0$, then I_{t-i} takes the value of 0.

Where if $\varepsilon_{t-i} < 0$, I_{t-i} takes 1. If, $\varepsilon_{t-i} > 0$, I_{t-i} takes 0. The condition for non-negativity requires $\alpha_i > 0, \beta_j > 0$ and $\alpha_i + \gamma_i > 0$. In addition to providing stationarity conditions, Ling and McAleer (2002) also specify the conditions of existence in the second and fourth moments of the GJR. The second-moment condition for the asymmetric GJR GARCH (1,1) model, which may be easily verified, is expressed as follows:

$$\beta + \alpha + \frac{1}{2}\omega < 1 \quad (3.11)$$

For the asymmetric GJR-GARCH (1,1) model, the fourth-moment condition is specified as follows:

$$\beta^2 + 2\alpha\beta + 3\alpha^2 + \beta\omega + 3\alpha\omega + \frac{3}{2}\omega^2 < 1 \quad (3.12)$$

The parameter "γ" represents asymmetry effects, indicating how positive and negative shocks affect conditional volatility differently in the GJR GARCH. More precisely, when $\gamma > 0$, it shows the existence of a leverage effect, meaning that negative shocks have a stronger impact on volatility than positive shocks.

3.3.1.1.6. FIGARCH

Recent research findings indicate a departure from the traditional exponential decay pattern in the persistence of shocks to volatility. Instead of following an exponential decay, these shocks exhibit a slow hyperbolic decay rate, a phenomenon referred to as "long memory" (Yıldırım et al., 2020: 5). Fractionally Integrated GARCH (FIGARCH) model proposed by Baillie et al. (1996) indicates that the model implies a slow hyperbolic decay rate for lagged squared innovations in the conditional variance function. In other words, the impact of past volatility shocks on future conditional variance predictions diminishes over time, but this decrease is very gradual. However, despite this diminishing effect over time, the influence of volatility shocks on future conditional variance predictions eventually

approaches zero. This property is shared with weakly stationary GARCH processes. Therefore, the FIGARCH model exhibits a long-lasting effect on volatility, albeit with a gradual decline over time, resembling the behavior of weakly stationary GARCH processes (Baillie et al., 1996:5). Baillie et al. (1996), often referred to as BBM, introduced the Fractionally Integrated GARCH (FIGARCH) model by replacing the first difference operator in the equation by $(1-L)^2$.

$$\sigma_t^2 = \omega[1-\beta(L)]^{-1} + \{1 - [1-\beta(L)]^{-1}\varphi(L)(1-L)^d\}\varepsilon_t^2 \quad (3.13)$$

$$\sigma_t^2 = \omega^* + \lambda(L) \quad (3.14)$$

Where $\omega^* is\ \omega[1-\beta(L)]^{-1}$ and $\lambda(L) = \lambda_1 L + \lambda_2 L^2 + \cdots$. For the FIGARCH $(1, d, 1)$ model, the parameter d needs to satisfy the condition 0 < d < 1. It can be demonstrated that ensuring $\omega > 0$, $\beta - d \leq \varphi \leq \frac{2-d}{3}$ and $d\left(\varphi - \frac{1-d}{2}\right) \leq \beta(\varphi - \beta + d)$ are adequate to guarantee the positivity of the conditional variance for all instances denoted as t. Notably, if d equals 0, the model reverts to a standard GARCH model, while if d equals 1, it transforms into an Integrated GARCH (IGARCH) model.

3.3.1.1.7. FIEGARCH

When it comes to the analysis of financial volatility, there are tests that take into consideration both long-term memory (also known as long memory) and asymmetry. Bollerslev and Mikkelsen (1996) emphasized the importance of a model in their proposed Fractal Integrated Exponential GARCH (FIEGARCH) model, which accounts for long-range dependencies in financial markets and the differing responses of price movements to positive and negative news. Thanks to its fractal structure, the model can better capture long-memory observed in financial datasets. Additionally, by considering the effects of asymmetry, it can model the different impacts of positive and negative movements on volatility. The FIEGARCH (p, d, q) model can be expressed as follows:

$$\ln(\sigma_t^2) = \omega + \varphi(L)^{-1}(1-L)^{-d}[1+\vartheta(L)]g(z_{t-1}) \quad (3.15)$$

The FIEGARCH (p, d, q) model combines the traditional EGARCH model (d = 0) with the IEGARCH model (d = 1), providing a versatile tool for understanding volatility. Similar to the ARFIMA class models for the conditional mean, $\ln(\sigma_t^2)$ exhibits covariance stationarity and invertibility when the parameter d ranges between -0.5 and 0.5. Nevertheless, disturbances to the optimal forecasts of future $\ln(\sigma_t^2)$ values diminish for all d values less than 1. It is notable that, unlike the FIGARCH approach, the parameters of the FIEGARCH model aren't required to meet any non-negativity constraints for the model to remain well-defined (Bollerslev and Mikkelsen, 1996:160).

3.3.1.1.8. FIAPARCH

Tse (1998) introduced the Fractal Integrated Absolute Power ARCH (FIAPARCH) model as an extension of the Asymmetric Power ARCH (APARCH) model, aiming to incorporate both long memory and asymmetric effects in financial volatility modeling. By utilizing absolute values of past price changes, this model enhances its ability to capture long-term dependencies in financial data while also accommodating variations between positive and negative returns. The FIAPARCH (p, d, q) model can be expressed as follows:

$$\sigma_t^{\delta} = \omega + \{1 - [1 - \beta(L)]^{-1}\varphi(L)(1 - L)^{d}\}(|\varepsilon_t| - \gamma\varepsilon_t) \quad (3.16)$$

$\gamma, \delta \; and \; d$ represent respectively the asymmetry, power, and long memory parameters of the model. The long memory parameter d is in the range of $0 < d < 1$, it can be said that the conditional variance series exhibits long memory. Positive shocks will have a greater impact on volatility than negative shocks if γ is greater than zero. On the other hand, when the value of γ is less than one, positive shocks will have a greater impact on the volatility than negative shocks (Tse, 1998: 50).

3.3.1.2. Multivariate GARCH Models

A two-step estimation approach is used, followed by Engle's (2002) dynamic conditional correlation (DCC) model and Tse and Tsui's (2002) time-varying correlation model. The initial step includes estimating the univariate GARCH model. In the second step, the estimation results serve as input for estimating the correlation parameters.

$$H_t = D_t R_t D_t \tag{3.17}$$

The matrix R_t is specified as:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{3.18}$$

$$Q_t = (1 - \sum_{m=1}^{M} \alpha_m - \sum_{m=1}^{M} \beta_m)Q + \sum_{m=1}^{M} \alpha_m (u_{t-m} u'_{t-m}) + \sum_{m=1}^{M} \beta_m Q_{t-n} \tag{3.19}$$

Where Q_t is a symmetric positive definitive conditional variances covariances matrix. $Q = E[u_t u'_t]$, α_m and β_m are scalars such that $\sum_{m=1}^{M} \alpha_m + \sum_{m=1}^{M} \beta_m < 1$. $u_t \sim U(0, R_t)$ is a $N\,x1$ vector of residuals standardized by their conditional standard deviations with typical element $u_{it} = \frac{\varepsilon_{it}}{\sqrt{h_{ii,t}}}$ which derived from the estimation of univariate GARCH volatility models.

Q_t^* is a diagonal matrix composed of the elements of Q_t. This means that the elements of Q_t^* will only be present on the diagonal, reflecting the correlation structure of Q_t in a simplified form. Q_t^* is as follows:

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11,t}} & 0 & 0 & \vdots \\ 0 & \sqrt{q_{22,t}} & 0 & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \sqrt{q_{NN,t}} \end{bmatrix} \tag{3.20}$$

So that $Q_t^* = [q_{ii,t}^*] = [\sqrt{q_{ii,t}}]$ is a diagonal matrix where each diagonal element is the square root of the corresponding diagonal element of Q_t. The typical element of R_t will be of the form Engle and Sheppard (2001) established that the positive definiteness of Q_t implies the positive definiteness of R_t, confirming R_t as a valid correlation matrix. They proposed substituting the unconditional variance-covariance matrix of standardized residuals for $\bar{Q}$ during parameter estimation, aligning with different univariate GARCH models. $\bar{Q}$ is as follows:

$$\bar{Q} = \frac{1}{T}\sum_{t=1}^{T} u_t\, u_t' \tag{3.21}$$

Ultimately, it can be expressed the dynamic conditional correlation as:

$$p_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \tag{3.22}$$

Aielli (2013) raises concerns regarding the feasibility and reliability of the Dynamic Conditional Correlation (DCC) model, particularly casting doubt on the empirical underpinnings of the location correlation parameter estimation in its second step. Consequently, he advocates for a paradigm shift by proposing a reformulation of the DCC correlation process within a linear multivariate Generalized Autoregressive Conditional Heteroscedasticity (MGARCH) framework, leading to the development of the corrected DCC model. He expands on these findings by presenting new theoretical and empirical insights. Specifically, the study demonstrates potential inconsistencies in the second step of the DCC estimator and highlights the risk of drawing erroneous conclusions from the conventional interpretation of dynamic correlation parameters. Aielli (2013) proposes the use of a consistent estimator for dynamic correlations, referred to as the corrected DCC (cDCC), as a solution to address this issue. The cDCC model can be formulated as follows:

$$\begin{aligned} Q_t = {} & (1 - \textstyle\sum_{m=1}^{M} \alpha_m - \sum_{m=1}^{M} \beta_m)Q + \\ & \textstyle\sum_{m=1}^{M} \alpha_m \left(Q_{t-n}^{*1/2} u_{t-m} u_{t-m}' Q_{t-}^{*1/2}\right) + \sum_{m=1}^{M} \beta_m Q_{t-n} \end{aligned} \tag{3.23}$$

Then, the correlation can be represented as follows:

$$p_{ij,t} = \frac{w_{ij,t-1} + \alpha_{i,t-1} u_{j,t-1} + \beta \rho_{ij,t-1}}{\sqrt{\{w_{ii,t-1} + \alpha u_{i,t-1}^2 + \beta \rho_{ii,t-1}\}\{w_{jj,t-1}\} + \alpha u_{j,t-1}^2 + \beta \rho_{jj,t-1}}} \tag{3.24}$$

where $w_{ij,t} \equiv \frac{(1 - \sum_{m=1}^{M} \alpha_m - \sum_{m=1}^{M} \beta_m) q_{ij}}{\sqrt{q_{ii,t} q_{jj,t}}}$ (Erarslan, 2016: 2066).

Financial market interactions are better understood through asymmetric links. In this context, the model proposed by Cappiello et al. (2006) provides a strategy that allows for asymmetry in correlation changes over time. This model effectively considers the

interrelationships between variables in financial markets by incorporating series-specific news impacts and adjustment factors. The correlation structure that changes over time is defined as follows:

$$Q_t = (1 - \sum_{m=1}^{M} \alpha_m - \sum_{m=1}^{M} \beta_m)Q - \sum_{k=1}^{K} \tau_k \bar{N} + \sum_{m=1}^{M} \alpha_m (u_{t-m} u'_{t-m}) + \sum_{m=1}^{M} \beta_m Q_{t-n} + \sum_{k=1}^{K} \tau_k (n_t n'_{t-k}) + \sum_{m=1}^{M} \beta_m Q_{t-n} \quad (3.25)$$

Where u_t and Q are exactly as in the DCC case. $n_t = I_{[u_t<0]} \odot u_t$, with $I_{[u_t<0]}$ being a $kx1$ indicator function, which takes on the value 1 when $u_t < 0$ and 0 otherwise. $\bar{N} = E[n_t n'_t]$ is the unconditional covariance matrix of n_t and is estimated using the sample analog $T^{-1} \sum_{t=1}^{T} n_t n'_t$. When both indicators are equal to one, or when both returns happen to be negative (jointly bad news), the term $n_{i,t} n_{j,t}$ will not be zero. Hence, the asymmetry indicates a greater correlation coefficient following the simultaneous occurrence of negative events compared to positive events (Gjika and Horváth, 2013:59).

3.3.1.3. Causality in Mean

Cheung and Ng (1996) suggest a two-step method for establishing causality in the variance test. The initial step involves estimating univariate time-series models that consider changes over time in both conditional means and conditional variances. The second step involves constructing a series of squared residuals that have been normalized by conditional variances. The null hypothesis that there is no causation in variance is subsequently examined by employing the cross-correlation function (CCF) of the squared-standardized residuals.

Consider the time series X_t and Y_t which are both stationary and ergodic. Let $I_t$and J_t represent two information sets defined by $I_t = \{X_{t-j}, J \geq 0\}$ and $J_t = \{X_{t-j}, Y_{t-j}, J \geq 0\}$, respectively. In order for Y_t to be the cause of X_{t+1} in variance.

$$E\{(X_{t+1} - \mu_{x,t+1})^2 | I_t\} \neq E\{(X_{t+1} - \mu_{x,t+1})^2 | J_t\} \quad (3.26)$$

where $\mu_{x,t+1}$represents the mean of X_{t+1}conditioned on I_t. In order for instantaneous causality to arise in the variance between the $X_t$and Y_t variables.

$$E\{(X_{t+1} - \mu_{x,t+1})^2 | J_t\} \neq E\{(X_{t+1} - \mu_{x,t+1})^2 | J_t + Y_t\} \quad (3.27)$$

As with causality in mean, the concepts stated in relations (3.28) and (3.29) are too broad to be empirically tested. Thus, in order to use the general causality idea in the application, additional structure is needed. Let us say that $X_t$and Y_t may be expressed as;

$$Y_t = \mu_{y,t} + (h_{y,t}\varsigma_t)^{\frac{1}{2}} \quad (3.28)$$

$$X_t = \mu_{X,t} + (h_{X,t}\varepsilon_t)^{\frac{1}{2}} \quad (3.29)$$

$\{\varsigma_t\}$and $\{\varepsilon_t\}$ are two independent white noise processes having a mean of zero and a variance of one. Their conditional means and variances are shown below:

$$\mu_{z,t} = \sum_{i=0}^{\infty} \varphi_{z,i}(\theta_{z,\mu}) Z_{t-i} \quad (3.30)$$

$$h_{z,t} = \varphi_{z,0} \sum_{i=0}^{\infty} \varphi_{z,i}(\theta_{z,h})\{(Z_{t-i} - \mu_{z,0})^2 - \varphi_{z,0}\} \quad (3.31)$$

$\theta_{z,w}$is a $p_{z,w} \times 1$-dimensional parameter vector. $W = \mu, h$; $\phi_{z,i}(\theta_{z,\mu})$ and $\varphi_{z,i}(\theta_{z,h})$ are functions of $\theta_{z,\mu}$ and$\theta_{z,h}$; and $Z = X, Y$ that are uniquely defined. The squared standardized residuals for the $X_t$and $Y_t$variables are as follows:

$$U_t = \{(X_t - \mu_{x,t})^2 / h_{x,t}\} = \varepsilon_t^2 \quad (3.32)$$

$$V_t = \{(Y_t - \mu_{y,t})^2 / h_{y,t}\} = \varsigma_t^2 \quad (3.33)$$

where the standardized residuals are $\{\varsigma_t\}$ and $\{\varepsilon_t\}$. $r_{UV}(k)$ and $r_{\varepsilon\varsigma}(k)$ are the sample cross-correlation of the squared standardized residual series and the sample cross-correlation of the standardized residual series at lag k, respectively. Test statistics can be calculated to determine causality in mean as follows:

Causality in mean test = $T^{\frac{1}{2}} x r_{\varepsilon\varsigma}(k)$

3.3.1.4 Hong (2001)

Cheung and Ng's (1996) test is identical to one that uses a uniform weighting basis since they give each lag the same amount of weight. When compared to uniform weighing, non-uniform weighting frequently provides more power. Hong (2001) used a non-uniform kernel weighting mechanism to modify the Cheung and Ng test statistics.

Hong (2001) uses the modified Q-statistic, which is defined as follows, to test the causality link:

$$Q_1 = \frac{\left\{T\sum_{j=1}^{T-1} k^2(\frac{j}{M})\hat{p}_{UV}^2(j) - C_{1T}(k)\right\}}{\{2D_{1T}(k)\}^{0.5}} \tag{3.34}$$

Where $\hat{p}_{uv}(j)$is the j-th lag sample cross-correlation between $\hat{u}_t$and $\hat{v}_t$which is defined as:

$$\hat{p}_{uv}(j) = \left\{\hat{C}_{uu}(0)\hat{C}_{vv}(0)\right\}^{-0.5}\hat{C}_{uv}(j) \tag{3.35}$$

The sample covariance function is defined as:

$$\hat{C}_{uv}(j) = \begin{cases} \frac{1}{T}\sum_{t=j+1}^{T}\hat{u}_t\hat{v}_{t-j}, j > 0, \\ \frac{1}{T}\sum_{t=-j+1}^{T}\hat{u}_{t+j}\hat{v}_t, j < 0, \end{cases} \tag{3.36}$$

$$\hat{C}_{uu}(0) = \frac{1}{T}\sum_{t=1}^{T}\hat{u}_t^2, \quad \hat{C}_{vv}(0) = \frac{1}{T}\sum_{t=1}^{T}\hat{v}_t^2, \tag{3.37}$$

In equation 3.34, $k(\frac{j}{M})$ is a weighting function, and M is a positive integer. The following is written for Bartlett and Daniel[4], respectively:

[4] Bartlett and Daniel are a weighting functions method to account for changing effect of causality. The Bartlett weighting function focuses on past correlations, while the Daniel weighting function focuses on current periods (Hong, 2001).

$$\mathrm{k}\left(\frac{\mathrm{j}}{\mathrm{M}}\right) = \begin{cases} 1 - \left|\frac{j}{M+1}\right|, \left|\frac{j}{M+1}\right| \leq 1, \\ 0, otherwise \end{cases} \quad (3.38)$$

$$\mathrm{k}\left(\frac{\mathrm{j}}{\mathrm{M}}\right) = \frac{\sin\left(\pi\frac{j}{M+1}\right)}{\pi\frac{j}{M+1}}, -\infty < \left|\frac{j}{M}\right| < \infty \quad (3.39)$$

And where $C_{1T}(k)$ and $D_{1T}(k)$ in equation 3.34 are approximately the mean and variance. They can be shown as:

$$C_{1T}(k) = \sum_{j=1}^{T-1}\left(1 - \frac{j}{T}\right)k^2\left(\frac{j}{M}\right), \quad (3.40)$$

$$D_{1T}(k) = \sum_{j=1}^{T-1}\left(1 - \frac{j}{T}\right)\left\{1 - \frac{(j+1)}{T}\right\}k^4\left(\frac{j}{M}\right) \quad (3.41)$$

Hong (2001) offers the following summary of the testing processes:

- Estimate univariate GARCH(p, q) models for $\{\hat{\varepsilon}_{1t}\}$ and$\{\hat{\varepsilon}_{2t}\}$, respectively, and store the conditional variance estimators.

- Calculate the sample cross-correlation function $\hat{p}_{uv}(j)$ between the centered squared standardized residuals $\left\{\hat{u}_t = \frac{\hat{\varepsilon}_{1t}^2}{\hat{h}_{1t}} - 1\right\}$ and $\left\{\hat{v}_t = \frac{\hat{\varepsilon}_{2t}^2}{\hat{h}_{2t}} - 1\right\}$

- Select a weighting function $k(.)$ and an integer M, then compute $C_{1T}(k)$ and $D_{1T}(k)$

- Calculate the test statistic Q_1 and compare it to the appropriate upper-tailed critical value of $N(0; 1)$ If Q_1 exceeds the critical value, the null hypothesis H_0 (no causality) is rejected. H_0 is not rejected otherwise.

3.3.1.5. Causality in Risk

When one market has a substantial downside risk, this risk could spread to another market. Understanding risk spillovers across financial markets is crucial not just for policy implications but also for risk management and asset allocation (Liu, 2014:39). Hong et al.

(2009) construct econometric tools based on a Granger causality in risk that focuses on the co-movements between the tails of the two distributions and present a class of kernel-based tests to identify whether a high downside risk in one market would Granger-cause a large downside risk in another market. According to the authors, value at risk (VaR) estimation is a critical step in applying causality in risk procedures. Because VaR can be quickly estimated by the majority of common risk management software, this is quite straightforward for practitioners in the real financial market. Furthermore, VaR can be adjusted at any level, not just the typically used 1% or 5%. VaR is defined as the loss over the time horizon τ that is not surpassed with probability $1-\alpha$ for a given time horizon τ and confidence level $1-\alpha$, where $\alpha \in (0,1)$. The negative quantile of the conditional probability distribution of a time series Y_t (such as portfolio return) is known as VaR, which is represented by the symbol $V_t = V(I_{t-1}, \alpha)$. VaR satisfies the following equation:

$$P(Y_t < -V_t | I_{t-1}) = \alpha \tag{3.42}$$

Where $I_{t-1} \equiv \{Y_{t-1}, Y_{t-2}, \dots\}$ the information set that was accessible at time $t-1$. The left tail probability in equation 3.42 is commonly referred to as the shortfall probability in financial risk management. In practice, 10%, 5%, or 1% are often employed levels for α.

The null hypothesis and its alternative hypothesis of Granger causality in risk are as follows:

$$H_0 = P(Y_{1t} < -V_{1t} \big| I_{1(t-1)} = P(Y_{1t} < -V_{1t} | I_{t-1}) \tag{3.43}$$

$$H_1 = P(Y_{1t} < -V_{1t} \big| I_{1(t-1)} \neq P(Y_{1t} < -V_{1t} | I_{t-1}) \tag{3.44}$$

Where $I_{t-1} \equiv (I_{1(t-1)}, I_{2(t-1)})$, $I_{1(t-1)} = \{Y_{1(t-1)}, ., Y_{11}\}$, $I_{2(t-1)} = \{Y_{2(t-1)}, ., Y_{21}\}$ are the information sets available at time $t-1$ for two time series, respectively. Assume $\{\hat{z}_{1t}\}$and $\hat{z}_{2t}$ are two estimated series of risk indicators for two separate markets. The sample cross-covariance function between them:

$$\hat{C}(j) \equiv \begin{cases} \frac{1}{T}\sum_{t=1+j}^{T}(\hat{Z}_{1t} - \hat{\alpha}_1)(\hat{Z}_{2(t-j)} - \hat{\alpha}_2), & 0 \le j \le T-1 \\ \frac{1}{T}\sum_{t=1-j}^{T}(\hat{Z}_{1(t+j)} - \hat{\alpha}_1)(\hat{Z}_{2t} - \hat{\alpha}_2), & 1-T \le j < T-1 \end{cases} \quad (3.45)$$

where $\hat{\alpha}_1 \equiv \frac{1}{T}\sum_{t=1}^{T}\hat{Z}_{1t}$between $\{\hat{Z}_{1t}\}$ and $\{\hat{Z}_{2t}\}$, the sample cross-correlation function will be $\hat{p}(j) \equiv \frac{\hat{C}(j)}{\hat{S}_1\hat{S}_2}$, $j = 0, \pm 1, \dots, \pm(T-1)$ where $\hat{S}_1^2 = \hat{\alpha}_1(1-\hat{\alpha}_1)$ is the sample variance of $\{\hat{Z}_{1t}\}$

The test statistic for evaluating the one-way Granger causality in risk is

$$Q_1(M) \equiv \frac{T\sum_{j=1}^{T-1}k^2\left(\frac{j}{M}\right)\hat{\rho}^2(j) - C_{1T}(M)}{\sqrt{D_{1T}(M)}} \quad (3.46)$$

where the standardization and centering constants are:

$$C_{1T}(M) = \sum_{j=1}^{T-1}(1-\frac{j}{T})k^2(\frac{j}{M}) \quad (3.47)$$

$$D_{1T}(M) = 2\sum_{j=1}^{T-1}(1-\frac{j}{T})(1-\frac{j+1}{T})k^4(\frac{j}{M}) \quad (3.48)$$

where M is a specified lag level, and k is a kernel function $k(\frac{j}{M})$. The authors use the Daniell kernel $k(\frac{j}{M})$ which has a reasonable size and power versus several alternatives.

3.3.2. Data

The focus of this chapter is the relationship between the green bond market and other financial markets. In this context, alongside conventional financial market benchmarks such as the S&P US Aggregate Bond Index, the US 10-year Treasury Bond Index, and the MSCI World Index, data related to environmentally sensitive clean energy markets such as the Wilder Hill Clean Energy Index, S&P Global Clean Energy Index, European Renewable Energy Index, energy-related commodities such as natural gas, heating, crude oil, brent oil,

and biofuel will be examined for their correlations[5]. The daily range data of these indices is obtained using Thompson Reuters Eikon from November 2008 to July 2023. We calculated the daily price returns of the variables as follows:

$$R_t = (lnP_t - lnP_{t-1}) * 100 \quad (3.49)$$

Table 3.1. Descriptive Statistics

	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	J-B
Green (US)	0.00425	0	6.815	-3.782	0.519	0.844	20.14	47143.69
Green (Euro)	-0.00081	0.000761	2.787	-2.487	0.361	-0.169	9.084	5899.218
Treasury	0.002392	0	3.472	-2.478	0.420	0.157	6.377	1827.758
Aggregate	-0.00089	0	2.014	-1.520	0.245	-0.039	7.245	2864.35
Stock	0.03167	0.061011	8.406	-10.44	1.013	-0.778	14.35	20858.79
Wilderhill	0.000399	0	13.50	-15.63	2.202	-0.326	7.311	3020.578
Renewable	0.020343	0	42.21	-41.62	2.260	-0.373	105.2	1661915
Clean	-0.00061	0.043228	11.79	-12.8	1.663	-0.296	9.607	6992.312
Carbon	0.05086	0	21..06	-44.65	3.06	-0.90	19.05	41102.8
Energy	0.007488	0.043208	17.386	-30.17	2.172	-1.009	22.110	58672.51
Natural Gas	-0.02396	0	17.129	-19.18	3.096	-0.057	6.023	1454.282
Crude	0.008625	0.027936	43.790	-56.86	2.814	-1.712	73.59	793534.5
Brent	0.009525	0.026227	19.079	-26.82	2.258	-0.677	16.44	28990.06
Biofuel	0.01297	0	5.648	-8.277	1.261	-0.172	5.116	730.6785
Gasoil	0.009021	0	11.514	-16.29	2.054	-0.343	9.083	5953.785
Heating	0.010678	0.005418	10.953	-24.27	2.103	-0.641	12.94	15987.45

The data in Table 3.1 provides various statistical measures to evaluate the performance of different financial asset classes and subcategories. Asset classes with higher risk, such as stocks, typically have the potential for higher average returns. Stocks exhibit an average return of 3.167%, suggesting the possibility of a higher return. In contrast, asset types with lesser risk, such as government bonds, generally have a lower average rate of return. Government bonds exhibit an average return of 0.2392%. Likewise, asset categories

[5] Since carbon and renewable energy are denominated in euros, while other variables are denominated in US dollars, tables and graphs were created according to currency for analyzing their relationships with green bonds.

that represent different industrial sectors, such as energy commodities, display diverse average return values. For example, the average return for natural gas is negative and -0.2.396%. Biofuel and heating are positive and 0.1297% and 1.1067%, respectively. These comparisons serve as a reference for investors in creating asset allocations that are customized to their risk-return preferences and investing strategies.

Investors can also obtain essential information by comparing the minimum, maximum, and standard deviation values of various financial assets in Table 3.1. Compared to riskier assets, less risky assets have smaller ranges between their minimum and maximum values. (Brealey et al., 2014; Bodie et al., 2014). For example, asset classes with low risk, such as Treasury bonds, have narrower ranges for both minimum and maximum values. The minimum value for this asset class is -2.478, while the largest value is 3.472. When it is looked at the green bond market, the maximum return for Green (US) is 6.815, whereas the minimum return is -3.782. Similarly, the maximum return for Green (Euro) is 2.787, while the minimum return is -2.487. Although the average returns on these green energy-based assets are negative, their variabilities are different. Asset types with higher risk, such as stocks, have wider ranges. As an illustration, in the case of stocks, the lowest value is -10.44, while the highest value is 8.406. Asset classes exhibit notable variations in standard deviation levels. Asset classes with lesser risk typically exhibit lower standard deviation values, whereas asset classes with higher risk tend to have larger standard deviation values. Treasury bonds exhibit a standard deviation of 0.420, while stocks demonstrate a standard deviation of 1.013. Furthermore, it is crucial to take into account asset classes that represent energy markets. These assets generally have a moderate level of risk and show a wide range of minimum-maximum values and moderate standard deviation values across various energy kinds and derivatives. These comparisons offer investors significant information in creating asset allocations that are in line with their risk-return preferences and investing strategies.

The return distributions of most variables exhibit noteworthy characteristics in terms of skewness and kurtosis. The S&P Green Bond Series stands out as it exhibits positive skewness, suggesting a distribution that is skewed to the right. This contrasts with the other series in the table. As an example, the Green (US) data has a skewness of 0.844, whereas the Green (Euro) data has a skewness of -0.169. This indicates that the distribution is left-skewed, meaning that most of the observations are greater than the average value. Furthermore, all series have kurtosis values greater than three, such as 20.14 for Green (US)

and 105.2 for Renewable, which suggests the presence of fat-tail distributions and implies heterogeneous variability within the data. Furthermore, the Jarque-Bera (JB) test results, with statistics like 47143.69 for Green (US) and 793534.5 for Crude, align with the statement, rejecting the null hypothesis of normality for all series at a significance level of 1%, providing further evidence that none of the examined series follows a normal distribution.

Table 3.2 displays the correlation matrix. To evaluate the connections that exist between the many different types of financial assets, this correlation matrix has been utilized. Positive correlation coefficients show a direct and positive association between two assets, while negative correlation coefficients suggest an inverse and negative relationship. For example, the correlation coefficient between “Green” and “Stock” is 0.44, between “Green” and “Treasury” is 0.12, and between “Green” and “Aggregate” is 0.16. The data indicate a moderate positive correlation between the green bond market and other asset classes. Nevertheless, more robust connections have been identified between the “Green” series and specific asset classes. The correlation coefficient between the terms “Green” and “Clean” is 0.41, whereas the correlation coefficient between “Green” and “Renewable” is 0.17. The results suggest a notably robust correlation between the “Green” series and asset classes that are focused on the environment, such as “Clean” and “Renewable.” These insights can assist investors in comprehending the correlations between green bonds and different financial asset types. However, it is crucial to consider additional elements in investment decisions, in addition to the correlation matrix, as correlations can vary over time, and forecasting future performance may not always be simple.

Table 3.2. Correlation Matrix

	Green	Stock	Treasury	Aggregate	Clean	Renewable	Wilderhill	Carbon	Energy	Crude	Gasoil	Brent	Biofuel	Heating	Natural
Green	1														
Stock	0.44	1													
Treasury	0.12	-0.30	1												
Aggregate	0.16	-0.20	0.96	1											
Clean	0.41	0.74	-0.19	-0.12	1										
Renewable	0.17	0.40	-0.10	-0.05	0.59	1									
Wilderhill	0.24	0.73	0.22	0.15	0.81	0.49	1								
Carbon	0.03	0.07	0.05	0.03	0.06	0.04	0.04	1							
Energy	0.16	0.41	0.21	0.18	0.33	0.19	0.33	0.03	1						
Crude	0.14	0.36	-0.19	-0.16	0.29	0.17	0.30	0.03	0.95	1					
Gasoil	0.18	0.36	0.16	-0.12	0.31	0.20	0.26	0.06	0.74	0.63	1				
Brent	0.15	0.40	0.21	0.18	0.33	0.18	0.32	0.03	0.97	0.90	0.71	1			
Biofuel	0.18	0.25	0.10	0.08	0.22	0.12	0.19	0.05	0.34	0.31	0.27	0.34	1		
Heating	0.14	0.37	0.18	0.16	0.31	0.17	0.30	0.03	0.90	0.80	0.77	0.90	0.33	1	
Natural	0.03	0.09	-0.04	-0.03	0.07	0.05	0.08	0.01	0.22	0.11	0.11	0.13	0.11	0.16	1

3.4. Empirical Results

The graph of green bonds and other financial markets is presented in Figures 3.1.a and 3.1.b. There is a gradual decrease in green bonds between 2014 and mid-2016. Before 2014, green bonds fluctuated at high levels and peaked at the rate of 125 USD in mid-2011 because of the Eurozone debt crisis. The crisis peaked between 2010 and 2012. After 2015, the fluctuations in green bonds are between rates of 97 USD and 107 USD. With the 2008 financial crisis, Aggregate and treasury prices increase. After 2013, they dropped gradually and then rose. Aggregate bonds decreased sharply to about 105 USD due to the shock of the COVID-19 pandemic, and then the index increased for a while, but in mid-2020, showed a downward trend. Aggregate bonds and green bonds also show a very similar pattern. Observe that the carbon allowance is rather stable at the beginning of the sample. After 2017, the carbon allowance price showed small fluctuations compared to the beginning of the sample period. It started to climb high levels and plummeted to $120 due to a combination of policy decisions and larger economic factors, including a shortage of allowances and an increase in coal and natural gas prices. It appears from the data that the Wilderhill, Clean, Renewable, and Carbon prices all follow the same patterns. Although the price range for green bonds varies between 95 and 120, it can be observed that the range of fluctuations for other assets is wider. These findings indicate that the green bond market has a more stable pattern of development in comparison to other clean assets and is characterized by less significant fluctuations in prices. Examining the changes in green and energy commodities over time reveals certain trends. Specifically, from 2015 and earlier, there was a similar trend found in commodities such as the green bond, Gas oil, Brent, crude, energy, and heating prices. However, starting from 2015 and especially during the COVID-19 pandemic period, differences in the fluctuations among these commodities have been observed. In the post-COVID-19 period, a reverse relationship between energy prices and green bond prices is observed.

Figure 3.2 illustrates a graphical representation of each return series. The graphs vividly depict the dynamic nature of the return series, characterized by the presence of extreme values. Moreover, there is an observable clustering of returns over time, indicative of potential time series dependence, which is reminiscent of the Autoregressive Conditional Heteroskedasticity (ARCH) process proposed by Engle in 1982. Consequently, truncation becomes necessary for accurate estimation of parameters in the Generalized Autoregressive Conditional

Heteroskedasticity (GARCH) model. Without truncation, the estimated GARCH parameters may fail to satisfy the essential requirements of positivity and stability for the GARCH process, as highlighted in the study by Öztek and Öcal (2016).

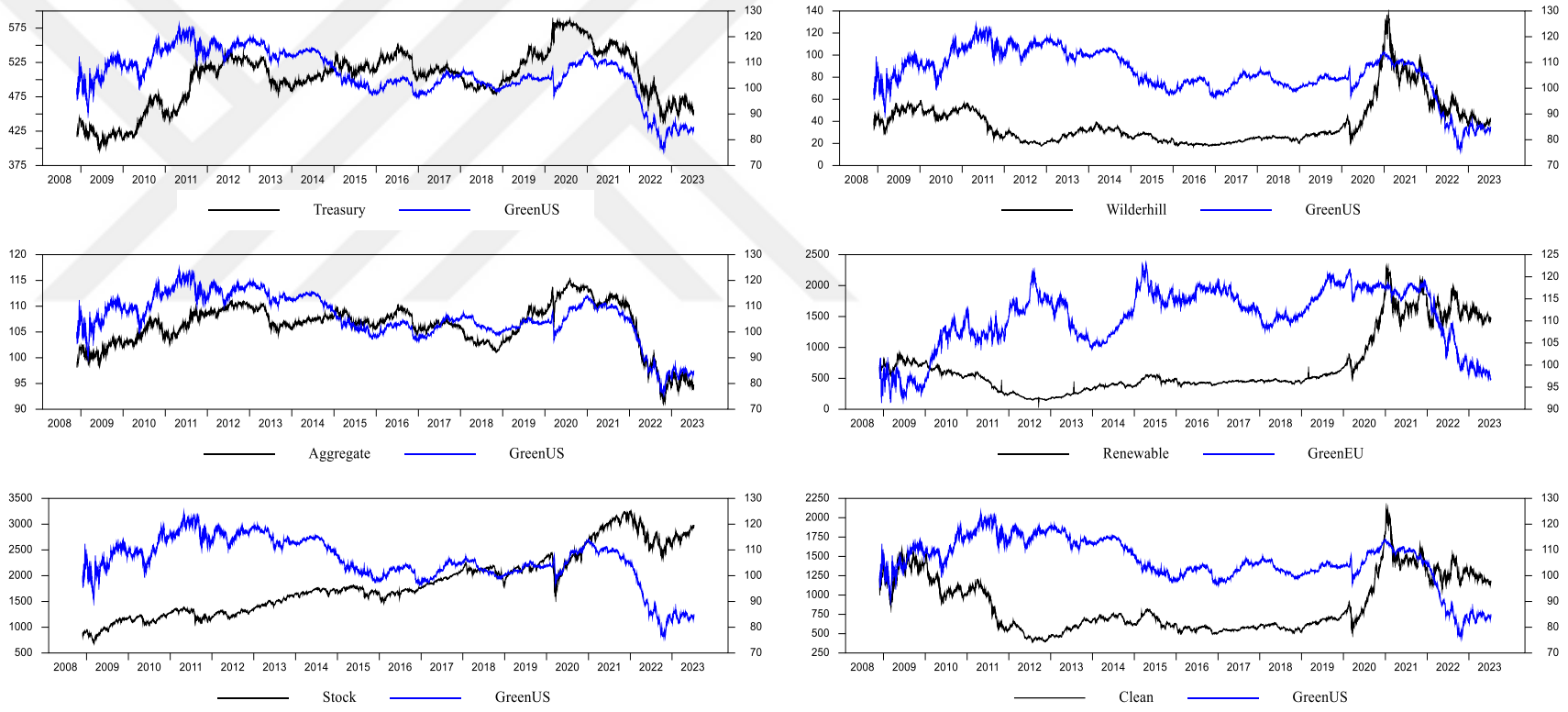


Figure 3.1.a. Time Graph of Green Bond and Other Financial Market Prices

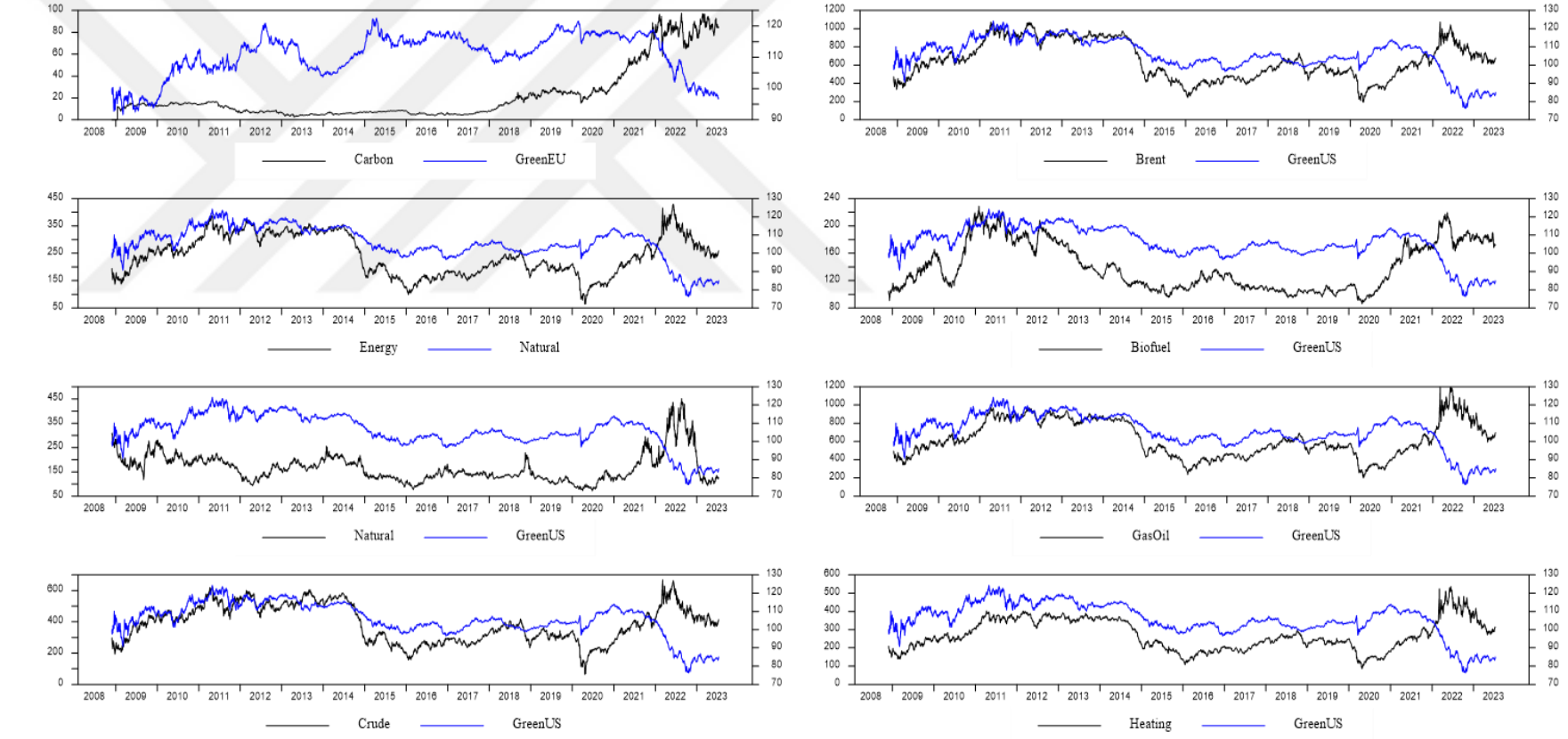


Figure 3.1.b. Time Graph of Green Bond and Other Financial Market Prices

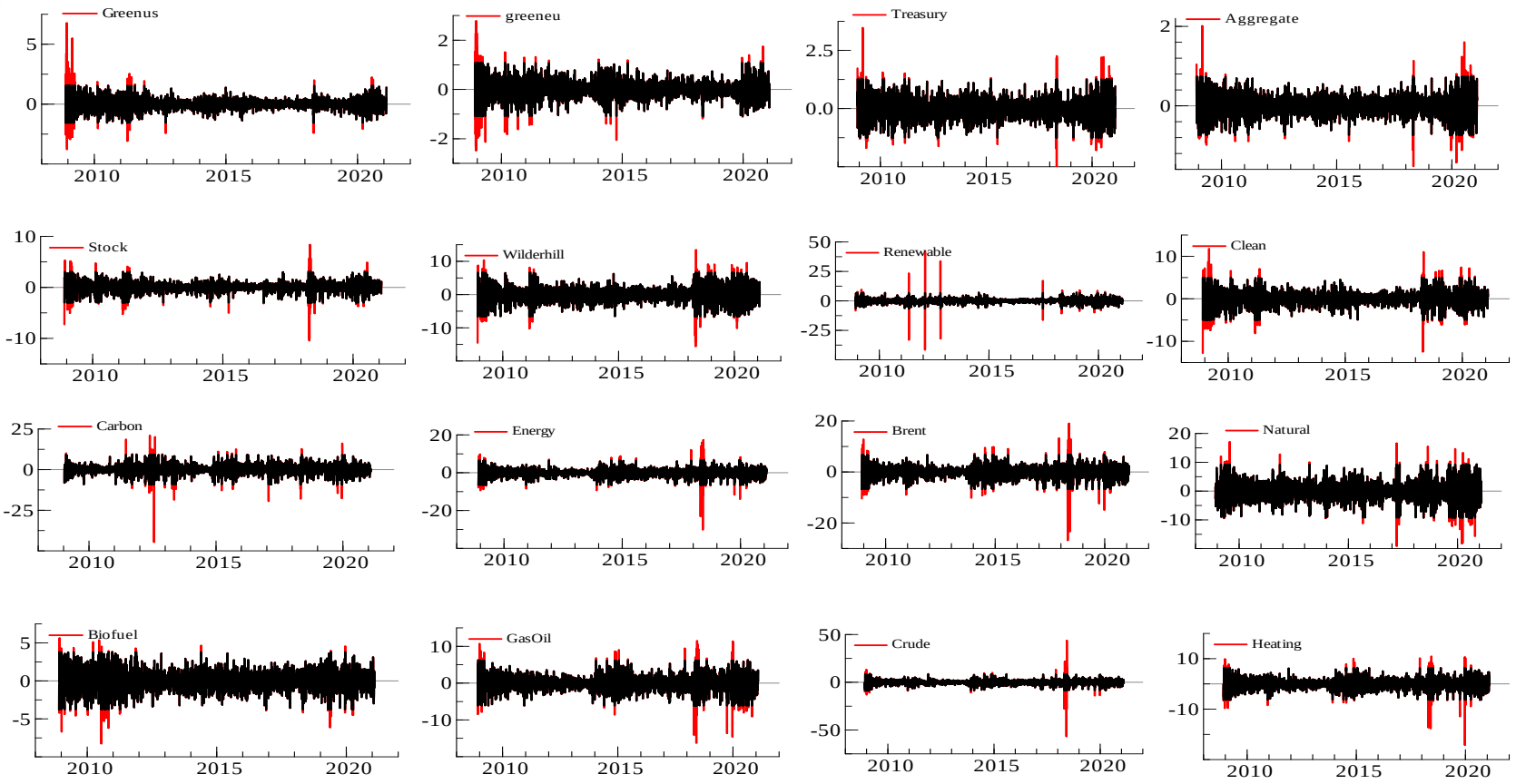


Figure 3.2. Time Graph of Return Series.

Note: The Red line represents the return series with the outlier included, while the black line shows the return series without the outlier included

The detection of structural shifts in unconditional variance can significantly affect estimated GARCH models, necessitating robust detection methods. Inclan and Tiao (1994) introduced an approach utilizing an iterated cumulative sums of squares (ICSS) algorithm to identify multiple breaks in unconditional volatility. However, Sansó et al. (2004) highlighted limitations in the original test, particularly its oversight of fourth-moment properties and its inadequacy for financial time series due to disregarding conditional heteroscedasticity. To address these concerns, Sansó et al. (2004) modified the ICSS algorithm, incorporating adjustments to account for conditional heteroscedasticity and ensuring consideration of fourth-moment properties. By employing this modified algorithm and integrating dummy variables to accommodate multiple structural breaks in conditional volatility, a comprehensive analysis of volatility dynamics can be achieved.

For instance, in Table 3.3, the outcomes of this modified algorithm reveal significant insights across various assets. Specifically, the assets Green (US), Treasury, Aggregate, Renewable, and Natural Gas exhibit three sudden change points each, while Green (Euro), Stock, and Energy assets display six regime shifts in variance. Additionally, the Gas oil asset shows the highest number of breaks with 13, followed by Clean return series with 10 breaks, forming a notable contrast. There are no breaks observed in the Carbon return series.

These structural shifts in unconditional variance are crucial in understanding the dynamics of financial markets. The global financial crisis of 2008-2009, for example, represents a significant breakpoint, characterized by substantial declines in stock prices and risky asset values, followed by efforts toward economic recovery. Similarly, the European debt crisis in 2012 marked a turning point with heightened uncertainty, leading to decreased demand for risky assets. In the latter half of the 2010s, the growth observed in the renewable energy sector emerged as a breakpoint, driven by increased investments in clean energy. Finally, the COVID-19 pandemic and subsequent economic lockdowns served as major breakpoints in financial markets in 2020, resulting in significant market declines followed by government stimulus measures and recovery efforts. These breakpoints play a pivotal role in influencing changes in financial asset prices and shaping investor behavior.

Table 3.3. Break Points for Unconditional Variance

Series	Breaks	Dates of Breaks						
Green (US)	3	24.04.2009	8.10.2012	31.12.2021				
Green (Euro)	6	27.04.2009	11.07.2013	14.01.2015	03.09.2015	20.07.2017	26.01.2022	
Stock	6	09.04.2009	03.08.2012	09.11.2020	17.01.2022	11.11.2022	22.03.2023	
Treasury	3	13.08.2009	06.04.2012	03.11.2021				
Aggregate	3	24.08.2009	28.12.2011	03.11.2021				
Wilderhill	4	16.07.2009	03.09.2010	02.03.2016	13.12.2018	18.02.2020		
Clean	10	09.04.2009	06.03.2012	27.06.2013	26.05.2015	11.11.2016	01.02.2018	18.02.2020
		31.03.2021	20.01.2022	10.11.2022				
Renewable	3	05.08.2009	26.02.2016	06.02.2020				
Carbon	0							
Energy	6	02.04.2009	16.11.2009	03.08.2012	27.11.2014	01.12.2016	12.11.2018	
Natural Gas	3	02.07.2010	23.11.2017	25.08.2021				
Gas Oil	13	20.04.2009	24.11.2009	03.08.2010	26.07.2012	01.04.2013	03.07.2013	28.10.2014
		30.11.2015	12.04.2016	19.12.2016	31.10.2018	21.03.2022	07.02.2023	
Biofuel	3	23.05.2011	28.09.2012	05.03.2020				
Brent	4	02.04.2009	09.11.2009	23.07.2012	05.03.2020			
Crude	3	02.04.2009	03.08.2012	27.11.2014				
Heating	10	02.04.2009	16.11.2009	05.01.2012	20.11.2012	27.11.2014	01.12.2016	06.11.2018
		05.03.2020	16.06.2020	25.02.2022				

The GARCH model was formulated with the underlying assumption that financial time series conform to a Normal (Gaussian) distribution (Feng and Shi, 2017:3). However, price changes observed in financial markets often deviate from the normal distribution. In such cases, using the Student-t distribution, which has fat tails, may be more appropriate. Fat tails better reflect the probability of unexpected and extreme events. Therefore, in such situations, the Student-t distribution is preferred for more accurate financial data modeling. Consequently, many studies have found that the Student-t distribution performs better than

the normal distribution in modeling financial data with fat tails (Bollerslev, 1987; Baillie and Bollerslev, 2002; Cheong, 2008; Chkili et al., 2012). We estimate 10 different ARMA-GARCH (p, q) models for the return series before including structural breaks in the variance. Since the series are not normally distributed, we use t-distribution for the GARCH models. Accounting for structural breaks can also enhance the forecasting capabilities of the model and provide a more accurate reflection of the true nature of the series.

Determining the most suitable ARMA structure involved estimating various ARMA models and selecting the best-fitting model using the Akaike Information Criterion (AIC). According to the results, different ARMA structures were identified for various asset classes. For instance, ARMA (3,3) was deemed most appropriate for Green (US); ARMA (4,4) for Green (Euro); ARMA (5,4) for treasury; ARMA (1,0) for Aggregate; ARMA (3,2) for Stock; ARMA(4,2) for Clean, Renewable, Wilderhill, and Energy; ARMA (4,4) for Heating; ARMA(3,3) for Gas Oil; ARMA (4,5) for Crude; ARMA(2,2) for Natural Gas; ARMA(0,0) for Brent; ARMA (2,5) for Biofuel. Ten different GARCH models were estimated for each asset class, and the best model was determined based on the AIC[6]. The performance of these models was examined under scenarios including and excluding structural breaks. The final appropriate GARCH models and their results are summarized in Table 3.4.

For Green (US), the IGARCH model, and for Green (Euro), the FIAPARCH model was selected as the most suitable. For Treasury, Aggregate, and Biofuel, the GARCH model was preferred, while for Clean, Renewable, Wilderhill, Carbon, Natural Gas, Heating, Energy, and Crude, the FIAPARCH model was chosen. Gas oil, Stock, Brent were modeled using FIEGARCH.

According to the results, the findings indicate that all GARCH (β) parameters are statistically significant at the 1% level in all estimated models. Specifically, for Aggregate, Treasury, Green (US), Natural Gas, and Biofuel, this parameter exceeds 0.9. This finding suggests a high degree of persistence in volatility. In other words, it implies that once a volatility shock occurs, its effect does not rapidly dissipate; instead, volatility remains influenced over the long term. Such findings underscore the notion that uncertainties in financial markets exert long-lasting and enduring effects.

[6] Comparisons of the information criteria for all univariate GARCH models are presented in the appendix B.

In the assessment of stability criteria for the GARCH models estimated for Aggregate, Treasury, and Gas Oil, it was observed that the parameters ω, α, and β are statistically significant. Additionally, all coefficients in the variance equation are positive, and the sum of α and β is less than one. These findings indicate the stability of the model and suggest that future predictions could be reliable. In the evaluation of GARCH models, the Box-Pierce test was used to analyze autocorrelation, and the results supported the hypothesis of no autocorrelation in the models. These data indicate that the residuals of the model demonstrate both independence and randomness. Based on the evaluation using the AIC, it is evident that the GARCH model, which includes breakpoints, provides a better fit than the model that does not include breakpoints.

For three different financial series - Brent, Stock, and Gas Oil - analyzed using the FIEGARCH model, the γ parameter was observed to be statistically significant and negative at a 1% significance level. This indicates the presence of a leverage effect, implying that in the market, bad news tends to increase volatility more than good news. Additionally, analyses have shown that models with breakpoints are more suitable compared to traditional ones, and no autocorrelation issues were detected in the variances. The parameter d in the model represents long memory. When the d value is less than 0.5, autocorrelation exhibits a decreasing trend over time. However, if autocorrelation exceeds 0.5, correlations decrease very slowly. In the model where breaks are not considered for Brent, the parameter is 0.751, while it decreases to 0.57 when breaks are included. Thus, including breaks reduces long-term memory in volatility for Brent. Even when breaks are considered for Brent, the decrease in the d parameter is much smaller, and it remains above 0.7 in both cases. This indicates that autocorrelations decrease very slowly in volatility and exhibit long memory. For Stock, the d parameter is relatively lower compared to the other two series and is approximately 0.5. Furthermore, studies have demonstrated that models with breakpoints are more appropriate in comparison to models without breakpoints, and there were no indications of autocorrelation problems in the variances.

The returns of other financial assets, except for silver, were estimated using the FIAPARCH model. In this model, the γ parameter, which represents the leverage effect indicating asymmetric impact, is expected to take a positive value. The γ parameter for all series except Natural Gas is statistically significant and positive at a 1% significance level.

This suggests that for these series, the volatility increases more in response to negative shocks compared to positive shocks. However, for Natural Gas, the γ parameter value is positive and statistically significant at a 1% significance level. Consequently, it is observed that positive shocks increase volatility more than negative shocks. The parameter d, indicating long memory, is below 0.5 for all series except Natural Gas. For Natural Gas, this value is above 0.9 in both models with and without dummy. Therefore, it can be said that natural gas exhibits long memory in volatility. When examining autocorrelation results, it is observed that there is no autocorrelation in the variances of the series except for Natural gas and Wilderhill. However, autocorrelation is only observed at a significance level of 1% in these two series.

Finally, the APARCH-GARCH model has been employed for Silver. The γ parameter, indicating an asymmetric effect, has been found to take a negative value and is statistically significant. Consequently, it suggests that positive shocks increase volatility more than negative shocks. For the model including breaks, the parameter d is calculated as 0.951, whereas for the model without breaks, it is 0.961. It can be stated that Silver exhibits a long memory in volatility for both models. Additionally, no autocorrelation issue has been observed in the series.

Table 3.4. Estimated GARCH Results

		ω	α	β	d	γ	δ	$Q(50)$	$Qs(50)$	AIC
Green (US)	Without	0.0003 (0.01)	0.050 (0.00)					(0.196)	(0.482)	0.874
	With	0.002 (0.02)	0.054 (0.00)					(0.202)	(0.527)	0.871
Green (Euro)	Without	0.631 (0.057)	0.306 (0.00)	0.678 (0.00)	0.498 (0.00)	0.113 (0.00)	1.664 (0.00)	(0.154)	(0.133)	0.392
	With	0.702 (0.00)	0.327 (0.00)	0.560 (0.00)	0.332 (0.00)	0.196 (0.012)	1.176 (0.00)	80.148)	(0.295)	0.378
Stock	Without	-0.338 (0.376)	0.009 (0.974)	0.628 (0.00)	0.554 (0.00)	-0.144 (0.00)	0.154 (0.00)	(0.061)	(0.363)	0.280
	With	0.358 (0.178)	-0.106 (0.647)	0.712 (0.00)	0.501 (0.00)	-0.149 (0.00)	0.148 (0.00)	(0.025)	(0.434)	0.274
Aggregate	Without	0.003 (0.00)	0.05 (0.00)	0.93 (0.00)				(0.404)	(0.894)	-0.2933
	With	0.004 (0.00)	0.057 (0.00)	0.93 (0.00)				(0.379)	(0.912)	-0.2937
Treasury	Without	0.001 (0.014)	0.051 (0.00)	0.942 (0.00)				(0.653)	(0.490)	0.860
	With	0.016 (0011)	0.055 (0.00)	0.902 (0.00)				(0.665)	(0.390)	0.852

		ω	α	β	d	γ	δ	$Q(50)$	$Qs(50)$	AIC
Clean	Without	6.339 (0.00)	0.192 (0.00)	0.620 (0.00)	0.511 (0.00)	0.190 (0.00)	1.736 (0.00)	(0.238)	(0.249)	3.722
	With	5.217 (0.00)	0.193 (0.00)	0.513 (0.00)	0.392 (0.00)	0.237 (0.00)	1.499 (0.00)	(0.272)	(0.439)	3.713
Energy	Without	-0.033 (0.534)	0.279 (0.00)	0.505 (0.00)	0.290 (0.00)	0.392 (0.00)	2.02 (0.00)	(0.728)	(0.266)	3.8747
	With	0.410 (0.00)	0.264 (0.00)	0.499 (0.00)	0.298 (0.00)	0.675 (0.00)	1.21 (0.00)	(0.691)	(0.136	3.869
Carbon	Without	1.683 (0.433)	0.085 (0.427)	0.409 (0.00)	0.4095 (0.00)	0.139 (0.00)	2.182 (0.00)	(0.064)	(0.990)	4.671
	With									
Wilderhill	Without	0.04 (0.468)	0.193 (0.00)	0.481 (0.00)	0.336 (0.00)	0.196 (0.00)	2.135 (0.00)	(0.544)	(0.551)	4.04
	With	0.721 (0.00)	0.102 (0.322)	0.328 (0.02)	0.284 (0.00)	0.41 (0.00)	1.349 (0.00)	(0.363)	(0.012)	4.037
Renewable	Without	5.472 (0.03)	0.282 (0.00)	0.596 (0.00)	0.439 (0.00)	0.193 (0.00)	1.802 (0.00)	(0.07)	(0.267)	3.6439
	With	4.547 (0.02)	0.289 (0.00)	0.572 (0.00)	0.405 (0.00)	0.212 (0.00)	1.803 (0.00)	(0.07)	(0.258)	3.6418
Crude	Without	0.019 (0.773)	0.291 (0.00)	0.545 (0.00)	0.326 (0.00)	0.420 (0.00)	1.883 (0.00)	(0.818)	(0.454)	4.189
	With	0.192 (0.00)	0.285 (0.00)	0.592 (0.00)	0.383 (0.00)	0.497 (0.00)	1.545 (0.00)	(0.834)	(0.395)	4.188
N.Gas	Without	0.05 (0.00)	-0.06 (0.00)	0.919 (0.00)	0.983 (0.00)	-0.075 (0.100)	1.846 (0.00)	(0.584)	(0.016)	4.8285
	With	0.051 (0.00)	-0.05 (0.248)	0.916 (0.00)	0.971 (0.00)	-0.076 (0.099)	1.819 (0.00)	(0.705)	(0.012)	4.8281
Gas	without	1.833 80.00)	-0.535 (0.182)	0.706 (0.00)	0.751 (0.00)	-0.069 (0.00)	0.120 (0.00)	(0.715)	(0.053)	3.841
	With	1.735 (0.00)	-0.279 (0.483)	0.729 (0.00)	0.575 (0.00)	-0.057 (0.00)	0.098 (0.00)	(0.663)	(0.160)	3.833
Biofuel	without	0.011 (0.00)	0.045 (0.00)	0.94 (0.00)				(0.922)	(0.443)	3.122
	With	0.106 (0.00)	0.042 (0.00)	0.92 (0.00)				(0.942)	(0.339)	3.117
Brent	Without	1.880 (0.00)	0.902 (0.00)	-0.713 (0.00)	0.768 (0.00)	-0.109 (0.00)	0.174 (0.00)	(0.824)	(0.461)	3.989
	With	1.147 (0.00)	0.866 (0.00)	-0.645 (0.02)	0.756 (0.00)	-0.100 (0.00)	0.171 (0.00)	(0.787)	(0.553)	3.987
Heating	Without	0.014 (0.797)	0.255 (0.00)	0.482 (0.00)	0.299 (0.00)	0.328 (0.00)	2.06 (0.00)	(0.633)	(0.09)	3.9026
	With	0.603 (0.00)	0.171 (0.195)	0.362 (0.00)	0.251 (0.02)	0.680 (0.00)	0.97 (0.00)	(0.598)	(0.110)	3.893

Q() and $Q_s()$ show the Box-Pierce test for standardized residuals and the Box-Pierce test for squared standardized residuals, respectively. Numbers in parentheses represent significance levels. “with” demonstrates the inclusion of structural breaks by adding a dummy, while “without” shows the variance equation without adding a dummy.

In the study, the causality test proposed by Hong (2001) was employed to examine whether there exists a transmission effect in terms of returns between green bonds and other financial markets. Prior to conducting the Hong (2001) test, an appropriate GARCH model

was determined for all the return series included in the study. By comparing models that account for and do not account for variance breaks, the most suitable model was selected based on the Akaike Information Criterion (AIC). Subsequently, the statistical values of the standardized errors derived from the selected GARCH models were computed, and the causality outcomes were presented in Table 3.5.

Table 3.5 illustrates the causal relationship in mean between green bonds and various financial markets. The null hypothesis of no causality from the Aggregate, Treasury, Clean, Wilderhill, Biofuel to the green bond market is rejected. On the other hand, the null hypothesis of no causality from the green bond market to these markets cannot be rejected. This suggests a unidirectional causality from the Aggregate, Treasury, Clean, Wilderhill, and Biofuel to the green bond market. However, the results of the causality analysis indicate that there is no causality between the series at the first lag. This unidirectional causality is only valid at lags 2, 3, 4, and 5[7].

A unidirectional causality relationship has also been identified from the Heating, Brent, and Natural Gas markets to green bonds. However, this relationship occurs at different lag lengths and various levels of statistical significance. For instance, the hypothesis of no causality from the Heating market to green bonds is rejected at a 5% significance level, while the hypothesis of no causality from the Brent market to green bonds can only be rejected at a 10% significance level. For Natural Gas, this relationship is rejected at a one percent significance level.

When examining the causal relationships between energy, carbon, crude oil, and green bonds, there is no causality from green bonds to other markets at any lag. Similarly, there is no causality from energy, carbon, and crude oil to green bonds at any lag either. Consequently, it can be concluded that there is no causality among these variables.

In the context of causality between Renewable and green bonds, there is no causality found from Renewable to green bonds at any lag. However, there is a causality observed from green bonds to Renewable starting from the 2nd lag with a significance level of one percent. Similarly, in the case of Gas Oil and green bonds, there is no causality found from

[7] Since daily data was used, M was selected up to five lags.

Gas Oil to green bonds at any lag. However, there is a one percent significance level causality observed from green bonds to Gas Oil only for the first lag. There is no causality relationship between the two variables for other lags.

Table 3.5. The Results of Causality in Mean

Causality Direction	M-1	M-2	M-3	M-4	M-5
Stock→ Green	-0.249	16.869***	16.374***	14.757***	13.412***
	(0.598)	(0.000)	(0.000)	(0.000)	(0.000)
Green → Stock	-1.053	0.614	1.015	1.312*	1.326*
	(0.854)	(0.269)	(0.155)	(0.095)	(0.092)
Aggregate→ Green	0.470	30.121***	29.935***	28.023***	25.764***
	(0.319)	(0.000)	(0.000)	(0.000)	(0.000)
Green → Aggregate	-1.239	0.361	0.357	0.026	0.152
	(0.892)	(0.359)	(0.360)	(0.490)	(0.440)
Treasury→ Green	0.593	26.561***	26.222***	24.357***	22.271***
	(0.277)	(0.000)	(0.000)	(0.000)	(0.000)
Green → Treasury	-1.273	-0.741	-0.709	-0.938	-0.785
	(0.899)	(0.771)	(0.761)	(0.826)	(0.784)
Clean → Green	-1.724	9.007***	9.379***	9.151***	8.659***
	(0.958)	(0.000)	(0.000)	(0.000)	(0.000)
Green → Clean	-0.918	-0.612	-0.543	-0.566	-0.526
	(0.821)	(0.73)	(0.706)	(0.714)	(0.7)
Energy → Green	1.97	-0.167	-0.223	-0.39	-0.444
	(0.024)	(0.566)	(0.588)	(0.652)	(0.672)
Green→ Energy	-0.422	-0.709	-0.781	-0.854	-0.778
	(0.664)	(0.761)	(0.783)	(0.804)	(0.782)
Carbon→ Green	1.146	-0.553	-0.625	-0.585	-0.738
	(0.126)	(0.71)	(0.734)	(0.721)	(0.77)
Green → Carbon	-0.076	-0.659	-0.706	-0.592	-0.616
	(0.53)	(0.745)	(0.76)	(0.723)	(0.731)
Wilderhill→ Green	-0.775	16.432***	16.14***	15.211***	14.16***
	(0.781)	(0.000)	(0.000)	(0.000)	(0.000)
Green → Wilderhill	-0.645	-0.117	0.473	0.965	1.217
	(0.741)	(0.547)	(0.318)	(0.167)	(0.112)
Renewable→ Green	-1.898	1.157	0.841	0.804	0.691
	(0.971)	(0.124)	(0.2)	(0.211)	(0.245)
Green → Renewable	1.364	6.5***	6.261***	5.64***	5.168***
	(0.086)	(0.000)	(0.000)	(0.000)	(0.000)
Crude → Green	0.59	-0.072	-0.058	-0.159	-0.194
	(0.278)	(0.529)	(0.523)	(0.563)	(0.577)
Green → Crude	0.142	-0.645	-0.767	-0.832	-0.761
	(0.444)	(0.741)	(0.778)	(0.797)	(0.777)

Causality Direction	M-1	M-2	M-3	M-4	M-5
N.Gas → Green	2.539***	-0.054	-0.157	-0.146	-0.278
	(0.006)	(0.521)	(0.562)	(0.558)	(0.61)
Green → N.Gas	-1.011	-0.632	-0.716	-0.903	-0.933
	(0.844)	(0.736)	(0.763)	(0.817)	(0.825)
Gas → Green	1.114	0.833	0.754	0.578	0.361
	(0.133)	(0.203)	(0.225)	(0.281)	(0.359)
Green → Gas	2.817***	-0.707	-0.816	-0.959	-1.078
	(0.002)	(0.76)	(0.793)	(0.831)	(0.86)
Biofuel → Green	-0.495	3.393***	3.188***	2.704***	2.462***
	(0.69)	(0.000)	(0.001)	(0.003)	(0.007)
Green → Biofuel	-0.227	0.58	0.417	0.207	-0.05
	(0.59)	(0.281)	(0.338)	(0.418)	(0.52)
Brent → Green	1.414*	-0.644	-0.59	-0.654	-0.638
	(0.079)	(0.74)	(0.722)	(0.743)	(0.738)
Green → Brent	-0.044	-0.691	-0.768	-0.791	-0.67
	(0.517)	(0.755)	(0.779)	(0.785)	(0.749)
Heating → Green	2.148**	-0.67	-0.535	-0.739	-0.617
	(0.016)	(0.749)	(0.704)	(0.77)	(0.731)
Green → Heating	0.207	-0.511	-0.583	-0.41	-0.154
	(0.418)	(0.695)	(0.72)	(0.659)	(0.561)

Note: *, **, and *** represent causal relationships with significance levels of 10%, 5%, and 1%, respectively.

According to Hong (2009), volatility measures two types of risk but fails to capture heavy tails due to jumps. Therefore, the possibility of risk contagion between the green bond and different financial markets is also being examined. The analysis begins with calculating VaR using GARCH models for both green bonds and other return series. While a generally accepted risk level of 95% is used to assess upside risk in VaR calculation, a 5% risk level is employed for downside risk in VaR calculation in this study. This approach ensures a thorough consideration of risks in both directions.

After identifying the days when the return series exceeded VaR values at different risk levels, these days were assigned a value of 1 and other days a value of 0. Consequently, the return series were converted into binary variables. The results report the Daniel kernel weighting-based test statistics for downside risk spillover. According to Table 3.6, there is causality from traditional bonds to green bonds at the one percent significance level at the last four lags, while no causality is observed from the green bond market to Aggregate and Treasury. When examining the causality between the stock market and green bonds,

causality from Stock to green bonds is observed at the 2nd, 3rd, and 4th lags, whereas no causality from green bonds to Stock is evident.

According to the downside risk analysis results between the green bond market and energy commodities, excluding Natural Gas and Gas Oil, no causality was observed from green bonds to energy commodities or vice versa at any lag. Regarding the causality between Natural Gas and the green bond market, a causality at a five percent significance level was found from Natural Gas to green bonds only in the first lag, while no causality was identified from green bonds to Natural Gas. Consequently, no causality relationship was observed between the two variables for the last four lags, but a unidirectional causality was evident in the first lag. As for the results between Gas Oil and the green bond market, a causality at a ten percent significance level was detected from Gas Oil to the green bond market only in the last two lags. However, causality was observed only during these two lag periods.

When examining the causality results with clean and renewable energy sources, it is found that there is a downside risk at the one percent significance level from Clean and Wilderhill to green bonds in the last four lags, while there is no causality from green bonds to Clean and Wilderhill. However, there is a unidirectional causality at the one percent significance level from green bonds to Renewable in the first lag. Lastly, there is a unidirectional causality at the first lag between Carbon and the green bond market, with the direction of causality being from green.

Table 3.6. Causality in Risk (0.05)

Causality Direction	M-1	M-2	M-3	M-4	M-5
Stock→ Green	1.263	1.816**	1.552*	1.282*	1.18
	(0.103)	(0.035)	(0.06)	(0.1)	(0.119)
Green → Stock	-2.017	-0.505	-0.608	-0.807	-0.712
	(0.978)	(0.693)	(0.728)	(0.79)	(0.762)
Aggregate→ Green	0.362	11.889***	11.51***	10.344***	9.47***
	(0.359)	(0.000)	(0.000)	(0.000)	(0.000)
Green → Aggregate	0.001	-0.665	-0.396	-0.135	-0.138
	(0.499)	(0.747)	(0.654)	(0.554)	(0.555)
Treasury→ Green	-1.315	16.134***	15.703***	14.151***	12.794***
	(0.906)	(0.000)	(0.000)	(0.000)	(0.000)

Causality Direction	M-1	M-2	M-3	M-4	M-5
Green → Treasury	0.38	-0.702	-0.645	-0.527	-0.503
	(0.352)	(0.759)	(0.741)	(0.701)	(0.693)
Clean → Green	0.452	9.824***	9.531***	8.68***	7.702***
	(0.326)	(0.000)	(0.000)	(0.000)	(0.000)
Green → Clean	-0.584	-0.816	-0.315	-0.028	0.116
	(0.721)	(0.793)	(0.624)	(0.511)	(0.454)
Energy → Green	0.565	-0.763	0.138	0.974	1.287
	(0.286)	(0.777)	(0.445)	(0.165)	(0.099)
Green→ Energy	-1.224	-0.589	-0.763	-0.795	-0.522
	(0.89)	(0.722)	(0.777)	(0.787)	(0.699)
Carbon→ Green	-1.655	0.295	0.317	0.352	0.36
	(0.951)	(0.384)	(0.376)	(0.362)	(0.359)
Green → Carbon	3.552***	-0.533	-0.5	-0.124	0.235
	(0.000)	(0.703)	(0.691)	(0.549)	(0.407)
Wilderhill→ Green	0.282	9.874***	9.588***	8.486***	7.659***
	(0.389)	(0.000)	(0.000)	(0.000)	(0.000)
Green → Wilderhill	-1.353	-0.808	-0.687	-0.95	-0.899
	(0.912)	(0.791)	(0.754)	(0.829)	(0.816)
Renewable→ Green	-1.46	0.286	0.306	0.34	0.345
	(0.928)	(0.387)	(0.38)	(0.367)	(0.365)
Green → Renewable	3.527***	-0.535	-0.503	-0.131	0.224
	(0.000)	(0.704)	(0.693)	(0.552)	(0.411)
Crude → Green	-0.488	-0.609	-0.331	-0.129	-0.087
	(0.687)	(0.729)	(0.63)	(0.551)	(0.535)
Green → Crude	-0.295	-0.674	-0.788	-0.718	-0.612
	(0.616)	(0.75)	(0.785)	(0.764)	(0.73)
N.Gas → Green	1.891**	-0.625	-0.729	-0.895	-0.98
	(0.029)	(0.734)	(0.767)	(0.815)	(0.836)
Green → N.Gas	1.171	-0.745	-0.871	-0.938	-0.969
	(0.121)	(0.772)	(0.808)	(0.826)	(0.834)
Gas → Green	-1.816	0.2	0.829	1.32*	1.433*
	(0.965)	(0.421)	(0.204)	(0.093)	(0.076)
Green → Gas	-1.273	-0.565	-0.628	-0.619	-0.656
	(0.899)	(0.714)	(0.735)	(0.732)	(0.744)
Biofuel → Green	1.002	0.91	0.771	0.693	0.59
	(0.158)	(0.181)	(0.22)	(0.244)	(0.277)
Green → Biofuel	0.612	-0.114	-0.327	-0.376	-0.466
	(0.27)	(0.545)	(0.628)	(0.647)	(0.68)

Causality Direction	M-1	M-2	M-3	M-4	M-5
Brent → Green	-1.413	-0.337	0.083	0.424	0.467
	(0.921)	(0.632)	(0.467)	(0.336)	(0.32)
Green → Brent	0.076	-0.712	-0.886	-0.964	-0.972
	(0.47)	(0.762)	(0.812)	(0.833)	(0.834)
Heating → Green	-0.561	-0.756	-0.307	0.108	0.205
	(0.712)	(0.775)	(0.621)	(0.457)	(0.419)
Green → Heating	-2.228	-0.778	-0.613	-0.615	-0.556
	(0.987)	(0.782)	(0.73)	(0.731)	(0.711)

Note: *, **, and *** represent causal relationships with significance levels of 10%, 5%, and 1%, respectively.

The results of the Daniel kernel weighting-based test statistics for upside risk spillover are presented in Table 3.7. According to the results, there is a bidirectional causality at the one percent significance level between Aggregate and green bonds in the last four lags, while the causality in the upside risk between Stock and green bonds exhibits bidirectionality only at a five percent significance level in the last two lags. No causality is observed between Clean, Carbon, Energy, Crude, Heating, and green bonds, whereas there is causality from Wilderhill, Natural Gas, Biofuel, and Brent to green bonds. This unidirectional causality varies in significance levels and across different lags. For instance, Biofuel, Brent, and Natural Gas show unidirectional causality to green bonds at a five percent significance level only in the first lag. Finally, there is a unidirectional causality relationship at a one percent significance level from green bonds to Wilderhill and Renewable in the first lag.

Table 3.7. Causality in Risk (0.95)

Causality Direction	M-1	M-2	M-3	M-4	M-5
Stock→ Green	-2.326	1.618*	1.858**	1.89**	1.694**
	(0.99)	(0.053)	(0.032)	(0.029)	(0.045)
Green → Stock	-1.59	-0.507	0.685	1.805**	2.363***
	(0.944)	(0.694)	(0.247)	(0.036)	(0.009)
Aggregate→ Green	1.117	16.388***	15.984***	14.827***	13.538***
	(0.132)	(0.000)	(0.000)	(0.000)	(0.000)
Green → Aggregate	-0.924	3.136***	2.514***	2.484***	2.761***
	(0.822)	(0.001)	(0.006)	(0.006)	(0.003)
Treasury→ Green	-0.344	16.751***	16.311***	15.762***	15.163***
	(0.635)	(0.00)	(0.000)	(0.000)	(0.000)

Causality Direction	M-1	M-2	M-3	M-4	M-5
Green → Treasury	0.097	2.973***	2.597***	2.342***	2.323***
	(0.461)	(0.001)	(0.005)	(0.01)	(0.01)
Clean → Green	-2.252	0.791	0.759	0.587	0.452
	(0.988)	(0.215)	(0.224)	(0.279)	(0.326)
Green → Clean	1.154	-0.736	-0.881	-0.921	-0.97
	(0.124)	(0.769)	(0.811)	(0.821)	(0.834)
Energy → Green	1.433*	-0.138	-0.121	0.035	0.131
	(0.076)	(0.555)	(0.548)	(0.486)	(0.448)
Green→ Energy	-2.449	-0.715	-0.709	-0.758	-0.937
	(0.993)	(0.763)	(0.761)	(0.776)	(0.826)
Carbon→ Green	-1.41	-0.459	-0.203	0.059	0.228
	(0.921)	(0.677)	(0.58)	(0.476)	(0.41)
Green → Carbon	0.376	0.281	0.421	0.635	0.714
	(0.354)	(0.389)	(0.337)	(0.263)	(0.238)
Wilderhill→ Green	-2.518	1.697**	1.79**	1.858**	1.882**
	(0.994)	(0.045)	(0.037)	(0.032)	(0.03)
Green → Wilderhill	2.937***	-0.501	-0.391	-0.515	-0.311
	(0.002)	(0.692)	(0.652)	(0.697)	(0.622)
Renewable→ Green	-3.851	-0.728	-0.807	-0.924	-0.922
	(1.00)	(0.767)	(0.79)	(0.822)	(0.822)
Green → Renewable	3.419***	-0.549	-0.683	-0.756	-0.717
	(0.000)	(0.708)	(0.753)	(0.775)	(0.763)
Crude → Green	0.961	-0.515	-0.544	-0.554	-0.574
	(0.168)	(0.697)	(0.707)	(0.71)	(0.717)
Green → Crude	-2.271	-0.763	-0.828	-0.94	-1.105
	(0.988)	(0.777)	(0.796)	(0.826)	(0.865)
N.Gas → Green	2.056**	0.472	0.075	0.108	0.235
	(0.02)	(0.318)	(0.47)	(0.457)	(0.407)
Green → N.Gas	-1.185	-0.071	0.171	0.34	0.602
	(0.882)	(0.528)	(0.432)	(0.367)	(0.274)
Gas → Green	1.092	1.808**	1.837**	1.753**	1.703**
	(0.137)	(0.035)	(0.033)	(0.04)	(0.044)
Green → Gas	-0.436	-0.231	-0.372	-0.555	-0.724
	(0.669)	(0.591)	(0.645)	(0.71)	(0.765)
Biofuel → Green	2.44**	-0.759	-0.25	0.061	0.249
	(0.007)	(0.776)	(0.599)	(0.476)	(0.402)
Green → Biofuel	0.602	-0.272	-0.297	-0.384	-0.473
	(0.274)	(0.607)	(0.617)	(0.649)	(0.682)

Causality Direction	M-1	M-2	M-3	M-4	M-5
Brent → Green	2.419***	-0.016	-0.415	0.195	0.811
	(0.008)	(0.507)	(0.661)	(0.423)	(0.209)
Green → Brent	-2.432	-0.398	-0.094	0.458	0.707
	(0.993)	(0.655)	(0.538)	(0.323)	(0.24)
Heating → Green	0.216	-0.322	-0.312	0.212	0.496
	(0.415)	(0.626)	(0.623)	(0.416)	(0.31)
Green → Heating	-0.345	-0.615	0.387	1.179	1.422
	(0.635)	(0.731)	(0.35)	(0.119)	(0.077)

Note: *, **, and *** represent causal relationships with significance levels of 10%, 5%, and 1%, respectively.

Before estimating a DCC(1,1)-GARCH(1,1) model, time series have to be filtered to ensure zero expected (mean) value of the time series. A bivariate Vector Autoregressive (VAR) model for the return series is used to initially remove potential linear structure between pairs of financial indices returns (Dajcman and Festic, 2012; Pham, 2016; Hepsağ and Akçalı, 2016; Mighri and Alsaggaf, 2019). Following the study conducted by Reberedo and Ugoloni (2020), we use the Structural VAR (SVAR) model. Then, the residuals of the VAR model are used as inputs for the DCC-GARCH model.

The appropriate lag of the explanatory variables is an important part of designing a VAR model. There are many criteria that can be applied. AIC (Akaike Information Criterion), BIC (Bayesian information criteria), SIC (Schwarz Information Criterion), and HQC (Hannan-Quinn Criterion) are the most utilized in the empirical literature. According to the AIC, a SVAR model with lag structures of one for Green-Clean, Green-Wilderhill, Green-Renewable, Green-Energy, Green-Biofuel, Green-Brent, Green-Crude, Green-Gas Oil, Green-Natural Gas, and Green-Heating, four for Green-Treasury-Aggregate and Green-Stock, and six for Green-Carbon was selected.

Table 3.8 shows the estimation result of the FIGARCH- asymmetric corrected DCC model. The first, second, and third parts indicate GARCH (1,1) parameters for the green bond, the aggregate bond, and DCC, respectively. The ARCH parameter α represents the short-run volatility effect (the persistence of standardized residuals from the previous period). For both series, this coefficient is positive and statistically significant at the one percent significance level. The values for green bonds and aggregate bonds, which are 0.262

and 0.28, respectively, indicate that the impact of past price shocks on current volatility remains significant but lower. β is the GARCH parameter, which depicts the shock's persistent effect on the conditional variances. The β values indicate that volatility tends to persist during periods of high past volatility. According to the observed data, the parameter d represents the presence of long memory in a time series. This parameter takes a value ranging from 0 to 1 and represents the extent to which volatility in the series is influenced by previous values over an extended period of time. The calculated value of d is determined to be 0.446 and 0.381 for green bonds and aggregate bonds, respectively. This outcome suggests the existence of long-term memory in the series. Moreover, when the value of the d parameter is less than 0.5, it may be concluded that autocorrelations decline more rapidly in comparison to values that are greater than 0.5.

Upon examining the DCC parameters, it is evident that both the $Alpha$ and $Beta$ parameters are statistically significant at a one percent significance level. In the model, the derived $alpha$ value is 0.027, while the $beta$ value is 0.97. A low $alpha$ parameter value suggests limited short-term correlation effects, while a high $beta$ value indicates strong long-term correlations. This implies that historical periods have a greater influence on current correlations, reflecting the continuous evolution of relationships between financial assets. The $gamma$ parameter is negative and statistically significant. This suggests that negative information shocks tend to decrease the conditional correlation between green bonds and aggregate bonds.

Table 3.8. FIGARCH- Asymmetric cDCC Results for Green-Aggregate

Parameter estimates for the Green Bond Market Index					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
ω	0.015***	0.005	0.005	0.278	0.287
d	0.446***	0.050	0.000		
α	0.262***	0.047	0.000		
β	0.647***	0.065	0.000		
Parameter estimates for the benchmark Aggregate market					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
ω	0.030**	0.012	0.012	0.255	0.959
d	0.381***	0.049	0.000		
α	0.280***	0.061	0.005		
β	0.590***	0.079	0.000		
Estimates for the conditional correlation parameters					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
alpha	0.022***	0.004	0.000	0.03	0.001
beta	0.976***	0.004	0.000		
gamma	-0.002*	0.001	0.089		

Note: *, **, and *** represent causal relationships with significance levels of 10%, 5%, and 1%, respectively.

Table 3.9 shows the estimation result of the GARCH-corrected DCC model for green bonds and treasury bonds. Very low values of α indicate that the impact of past volatility shocks on current volatility is weak, while β coefficients above 0.90 indicate that the effect of a shock on volatility is persistent. The DCC parameters reveal that both Alpha and Beta parameters are statistically significant. The estimated alpha value is 0.026, while the beta value is 0.97. This implies that past periods exert a greater influence on current correlations.

Table 3.9. GARCH- cDCC Results for Green-Treasury

Parameter estimates for the Green Bond Market Index					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
ω	0.003***	0.001	0.005	0.232	0.516
α	0.051***	0.006	0.000		
β	0.946***	0.007	0.000		
Parameter estimates for the benchmark Treasury market					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
ω	0.009**	0.003	0.035	0.516	0.725
α	0.054***	0.001	0.000		
β	0.936***	0.012	0.000		
Estimates for the conditional correlation parameters					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
$alpha$	0.026***	0.004	0.000	0.051	0.00
$beta$	0.970***	0.004	0.000		

Note: *, **, and *** represent causal relationships with significance levels of 10%, 5%, and 1%, respectively.

Table 3.10 presents the estimation results of the FIAPARCH-GARCH-DCC model for Green-Stock. For green bonds, the constant parameter in the FIAPARCH equation is only significant at the ten percent level. "d" "α," "β," and "δ," are significant at the one percent level, while the parameter "γ" indicating asymmetric effects is statistically insignificant. In the model, the α parameter determines the persistence of past shocks on current volatility, while the β parameter describes the persistence of volatility clustering. For instance, the α parameter for green bonds is 0.35, indicating that the impact of past price shocks on current volatility is still significant but lower. β value is 0.68, suggesting a tendency for volatility to continue during periods of high previous volatility. This combination of values indicates that while the effect of past price shocks on current volatility remains significant, it diminishes over time, with a tendency for volatility to persist during high volatility periods. The parameter "d" investigates the presence of long memory in return series. For the green bond return series, the parameter d is 0.441, indicating the presence of long memory, albeit weak. The parameter "γ" indicates asymmetric effects in the series. While taking a positive value, this coefficient signifies the presence of leverage effect, yet it is not statistically significant.

When examining the results for Stock in the FIAPARCH model, the constant parameter in the variance equation, denoted as ω, is significant at the five and ten percent levels, while all other parameters are significant at the one, five, and ten percent levels. α value is even lower compared to green bonds, standing at 0.164, indicating a much lower impact of past shocks on the present. β value is 0.397, indicating a lower persistence of volatility in comparison. The parameter "d" is 0.339, suggesting weak long memory. The γ parameter indicating asymmetric effects is positive. While indicating the presence of a leverage effect, this positive value is not statistically significant.

When looking at the DCC parameters, both $alpha$ and $beta$ parameters are significant at the one percent level, with values of 0.032 and 0.964, respectively. A low value for the $alpha$ parameter implies that the consequences of short-term correlations are limited, whereas a high $beta$ value shows that there are strong connections over the long run. It can be deduced from this that previous periods exhibit a greater effect on the correlations that exist currently, which reflects the consistently improving connections that exist between financial assets.

Table 3.10. FIAPARCH-GARCH-DCC Results for Green-Stock

Parameter estimates for the Green Bond Market Index					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
ω	0.013*	0.006	0.058	0.187	0.176
d	0.441***	0.066	0.000		
α	0.313***	0.054	0.000		
β	0.681***	0.065	0.000		
γ	0.074	0.059	0.214		
δ	1.977***	0.118	0.000		
Parameter estimates for the benchmark Stock market					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
ω	0.067**	0.032	0.035	0.044	0.950
d	0.339***	0.069	0.000		
α	0.164***	0.059	0.005		
β	0.397***	0.085	0.000		
γ	0.683***	0.139	0.000		
δ	1.433***	0.193	0.000		
Estimates for the conditional correlation parameters					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
$alpha$	0.032***	0.005	0.000	0.106	0.130
$beta$	0.964***	0.007	0.000		

Note: *, **, and *** represent causal relationships with significance levels of 10%, 5%, and 1%, respectively.

Table 3.11 presents the estimation results of the FIGARCH- Asymmetric DCC model for Green-Clean. For green bonds, the constant parameter in the FIGARCH model is significant at the five percent level, while the "d," "α," and "β" parameters are significant at the one percent level. The α parameter for green bonds is calculated as 0.254, indicating a low impact of past price shocks on current volatility. The β value is 0.636, suggesting a tendency for volatility to persist during previous volatility periods. The parameter "d" is determined as 0.436 for the green bond return series, indicating the presence of weak long memory.

When examining the results for Clean in the FIGARCH model, all parameters in the variance equation are significant at the one percent level. The α value, calculated as 0.318, is higher compared to green bonds, indicating a relatively higher impact of past shocks on the present. The β value is 0.597, indicating a lower persistence of volatility. The parameter "d" is calculated as 0.411, indicating weak long memory.

Considered individually, the DCC parameters $alpha$ (with a value of 0.018), $beta$ (with a value of 0.972), and $gamma$ (with a value of 0.010) all exhibit significance at the 1% level. A low value for the $alpha$ parameter suggests limited consequences of short-term correlations, while a high $beta$ value indicates strong connections over the long run. The $gamma$ parameter is positive and statistically significant. This suggests that the conditional correlations exhibit an asymmetry property, where negative and positive information shocks affect the correlations between assets at different levels. In summary, the occurrence of negative information shocks increases the conditional correlation between asset returns (Çelik et al., 2022:12). When bad news hits financial markets, the conditional correlation between the Green and the Clean volatility index increases more than in the case of good news.

Table 3.11. FIGARCH- Asymmetric DCC Results for Green-Clean

Parameter estimates for the Green Bond Market Index					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
ω	0.014**	0.005	0.011	0.134	0.361
d	0.436***	0.052	0.000		
α	0.254***	0.054	0.000		
β	0.636***	0.071	0.000		
Parameter estimates for the benchmark Clean Energy market					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
ω	0.025***	0.009	0.007	0.784	0.760
d	0.411***	0.060	0.000		
α	0.318***	0.060	0.000		
β	0.597***	0.078	0.000		
Estimates for the conditional correlation parameters					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
$alpha$	0.018***	0.004	0.000	0.452	0.058
$beta$	0.972***	0.006	0.000		
$gamma$	0.010**	0.004	0.017		

Note: *, **, and *** represent causal relationships with significance levels of 10%, 5%, and 1%, respectively.

A summary of the estimation results obtained from the FIAPARCH- asymmetrically corrected DCC model for Green-Energy is provided in Table 3.12. In the case of green bonds, the constant parameter in the FIAPARCH equation is only significant at the ten percent level. The parameter "γ" is statistically insignificant, but "α," "β," and "δ" are significant at the one percent level. The "α" parameter for green bonds is calculated as 0.042,

indicating a very low effect of past price shocks on current volatility. The "β" value is 0.950, suggesting a tendency for volatility to persist during previous volatility periods. In the case of Energy, "ω" and "δ" are significant at ten percent levels, while all other parameters are significant at the one percent levels. The "α" value, calculated as 0.067, indicates a lower effect of past shocks on the present. The β value is 0.93, indicating a higher persistence of volatility.

Individually considered, the DCC parameters alpha, beta, and gamma, with respective values of 0.009, 0.983, and 0.06. A low $alpha$ value suggests limited short-term correlation consequences, while a high $beta$ value indicates robust long-term connections. The positive and statistically significant gamma parameter implies an asymmetry in conditional correlations; Thus, negative information shocks increase asset return conditional correlation. When financial markets face adverse news, the conditional correlation between the Green and Energy volatility index increases more than in times of positive news.

Table 3.12. FIAPARCH-GARCH- Asymmetric cDCC Results for Green-Energy

Parameter estimates for the Green Bond Market Index

	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
ω	0.002**	0.001	0.032	0.341	0.345
α	0.042***	0.011	0.000		
β	0.950***	0.008	0.0000		
γ	0.065	0.056	0.2525		
δ	2.161***	0.338	0.000		

Parameter estimates for the benchmark Energy market

	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
ω	0.008*	0.003	0.085	0.885	0.547
α	0.067***	0.010	0.000		
β	0.930***	0.087	0.000		
γ	0.343***	0.087	0.000		
δ	1.555*	0.003	0.085		

Estimates for the conditional correlation parameters

	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
$alpha$	0.009**	0.003	0.017	0.401	0.216
$beta$	0.983***	0.005	0.000		
$gamma$	0.006*	0.003	0.061		

Note: *, **, and *** represent causal relationships with significance levels of 10%, 5%, and 1%, respectively.

Table 3.13 presents the estimation results of the FIGARCH-cDCC model for Green-Carbon. the constant parameter in the FIGARCH model for Green is significant at the five percent level, while parameters "d," "α," and "β" are significant at the one percent level. The calculated α parameter for green bonds is 0.245, indicating a modest impact of past price shocks on current volatility. The β value of 0.671 suggests a tendency for volatility to persist during previous volatile periods, while the parameter "d" is found to be 0.542, indicating long memory. Conversely, for Carbon, all parameters in the variance equation are significant at the one percent level. The α value of 0.360 signifies a lower impact of past shocks on the present. Meanwhile, the β value is 0.593, implying lower persistence of volatility, with the parameter "d" calculated as 0.360, indicating weak long memory. After looking at the DCC parameters, the $beta$ coefficient (with a value of 0.957) and the $alpha$ coefficient (with a value of 0.039) are both significant at the 1% level. The low value of the $alpha$ parameter shows that the short-term correlation influence is limited; however, the high $beta$ value indicates that the long-term linkages exist for a longer period.

Table 3.13. FIGARCH-cDCC Results for Green-Carbon

Parameter estimates for the Green Bond Market Index					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
ω	0.003**	0.001	0.018	0.003	0.962
d	0.542***	0.063	0.000		
α	0.245***	0.061	0.000		
β	0.671***	0.079	0.000		
Parameter estimates for the benchmark Carbon market					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
ω	0.034***	0.013	0.009	0.322	0.917
d	0.356***	0.046	0.000		
α	0.360***	0.086	0.000		
β	0.593***	0.090	0.000		
Estimates for the conditional correlation parameters					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
$alpha$	0.039***	0.005	0.000	0.003	0.664
$beta$	0.957***	0.006	0.000		

Note: *, **, and *** represent causal relationships with significance levels of 10%, 5%, and 1%, respectively.

The results of the FIAPARCH GARCH asymmetrically corrected DCC model estimation for Green-Willderhill are presented in Table 3.14. According to the findings, while the asymmetry parameter is statistically insignificant for Green, it is significant and

has a positive coefficient for Willderhill. This indicates Negative shocks increase volatility further. The long memory parameter is statistically significant for both assets and is less than 0.5, suggesting a tendency for the series to revert to the mean while still exhibiting long memory.

The DCC parameters, $alpha$, $beta$, and $gamma$, are statistically significant. $Alpha$ has a very small coefficient of 0.015, while $beta$ has a very high coefficient of 0.972. Finally, although the $gamma$ parameter is positive, its effect is very small. While negative shocks are expected to increase conditional correlation, this effect remains relatively weak.

Table 3.14. FIAPARCH-GARCH Asymmetric CDCC Results for Green-Wilderhill

Parameter estimates for the Green Bond Market Index

	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
ω	0.013*	0.007	0.065	0.178	0.539
d	0.429***	0.064	0.000		
α	0.287***	0.060	0.000		
β	0.653**	0.073	0.000		
γ	0.068	0.056	0.229		
δ	1.995***	0.126	0.000		

Parameter estimates for the benchmark Wilderhill Clean Energy Market

	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
ω	0.010	0.014	0.449	0.763	0.348
d	0.310***	0.054	0.000		
α	0.297***	0.073	0.000		
β	0.521***	0.086	0.000		
γ	0.135***	0.052	0.010		
δ	2.234***	0.167	0.000		

Estimates for the conditional correlation parameters

	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
$alpha$	0.015***	0.004	0.000	0.098	0.139
$beta$	0.972***	0.006	0.000		
$gamma$	0.009**	0.004	0.029		

Note: *, **, and *** represent causal relationships with significance levels of 10%, 5%, and 1%, respectively.

The estimation for Green-Renewable employs the FIAPARCH GARCH asymmetrically corrected DCC model, with the results displayed in Table 3.15. The analysis reveals that while the asymmetry parameter remains statistically insignificant for Green, it holds significance for Renewable, characterized by a positive coefficient. Consequently,

negative shocks exacerbate volatility. Both assets exhibit statistically significant long memory parameters, each less than 0.5, indicating a propensity for mean reversion despite the presence of long memory.

Moreover, the DCC parameters—$alpha$, $beta$, and $gamma$—are statistically significant. Notably, $alpha$ and $gamma$ parameters exhibit relatively higher values compared to Green-Renewable. The $beta$ parameter remains high, with a coefficient of 0.916. These findings suggest a notable influence of past periods on current correlations, further emphasizing the persistence of interconnections within the financial assets' dynamics.

Table 3.15. FIAPARCH-GARCH Asymmetric cDCC Results for Gren-Renewable

Parameter estimates for the Green Bond Market Index

	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
ω	0.014	0.017	0.399	0.206	0.104
d	0.254***	0.061	0.000		
α	0.268***	0.092	0.003		
β	0.431***	0.110	0.000		
γ	0.090*	0.049	0.064		
δ	2.331***	0.206	0.000		

Parameter estimates for the benchmark Renewable Energy Index

	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
ω	0.017	0.018	0.340	0.026	0.947
d	0.321***	0.064	0.000		
α	0.408***	0.113	0.000		
β	0.607***	0.122	0.000		
γ	0.068	0.054	0.210		
δ	2.151***	0.189	0.000		

Estimates for the conditional correlation parameters

	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
$alpha$	0.021**	0.009	0.023	0.311	0.268
$beta$	0.916***	0.046	0.000		
$gamma$	0.025*	0.014	0.082		

Note: *, **, and *** represent causal relationships with significance levels of 10%, 5%, and 1%, respectively.

The estimation for Green-Crude employs the APARCH GARCH corrected DCC model, with the results outlined in Table 3.16. Analysis reveals that while the asymmetry parameter remains statistically insignificant for Green, it holds significance for Crude, with

a coefficient of 0.345. Consequently, negative shocks accelerate volatility. Notably, the β parameter for both return series is statistically significant at the 1% level, with values exceeding 0.9 for both Green and Crude. This suggests a persistent influence of shocks on volatility, indicating that the persistence of volatility clustering is very high.

Furthermore, the DCC parameters—$alpha$ and $beta$—are statistically significant. Alpha exhibits a coefficient of 0.016, while beta is at 0.975. These findings suggest a substantial impact of previous periods on current correlations, highlighting a persistent and significant relationship between the assets' dynamics.

Table 3.16. APARCH-GARCH-cDCC Results for Green-Crude

Parameter estimates for the Green Bond Market Index					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
ω	0.002**	0.001	0.034	0.337	0.393
α	0.042***	0.011	0.000		
β	0.951***	0.008	0.000		
γ	0.066	0.057	0.245		
δ	2.167***	0.343	0.000		
Parameter estimates for the benchmark Crude oil market					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
ω	0.011***	0.003	0.001	0.943	0.789
α	0.072***	0.011	0.000		
β	0.919***	0.012	0.000		
γ	0.345***	0.096	0.000		
δ	1.675***	0.248	0.000		
Estimates for the conditional correlation parameters					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
$alpha$	0.016***	0.005	0.001	0.381	0.186
$beta$	0.975***	0.010	0.000		

Note: *, **, and *** represent causal relationships with significance levels of 10%, 5%, and 1%, respectively.

The APARCH GARCH corrected DCC model is also utilized in the estimation process for Green-Natural Gas, and the findings are presented in Table 3.17. For Natural Gas, the asymmetry parameter is statistically significant with a coefficient of -0.020, but not for Green. Considering this, it appears that positive shocks significantly increase the volatility of the crude market. Therefore, it can be said that there is no leverage effect for Natural Gas. Additionally, the β parameter for both return series is statistically significant at

the 1% level, with values exceeding 0.9 for both Green and Natural Gas. This implies a high degree of volatility clustering, indicating periods of high volatility followed by periods of low volatility in financial markets. Furthermore, In the estimation of the DCC model, the alpha parameter with 0.001 is found to be statistically significant, while the beta parameter with 0.007 is found to be statistically insignificant. The fact that the alpha parameter takes a small value, and the beta parameter is insignificant in the DCC model estimation indicates that there is limited short-term correlation impact and a weak relationship between the dynamics of the assets in the correlation modeling.

Table 3.17. APARCH-GARCH-cDCC Results for Green-Natural Gas

Parameter estimates for the Green Bond Market Index					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
ω	0.002***	0.001	0.006	0.320	0.458
α	0.041***	0.009	0.000		
β	0.949***	0.007	0.000		
γ	0.010	0.009	0.272		
Parameter estimates for the benchmark Natural Gas oil market					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
ω	0.007***	0.002	0.000	0.743	0.004
α	0.069***	0.008	0.000		
β	0.934***	0.006	0.000		
γ	-0.020*	0.010	0.056		
Estimates for the conditional correlation parameters					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
$alpha$	0.001***	0.016	0.000	0.356	0.058
$beta$	0.007	1.468	0.996		

Note: *, **, and *** represent causal relationships with significance levels of 10%, 5%, and 1%, respectively.

The FIAPARCH GARCH asymmetry-corrected DCC model is used for the Green-Gas Oil estimation, and the results are shown in Table 18. Even though the asymmetry parameter continues to be statistically insignificant for Green, the study reveals that it is significant for Gas Oil, which is defined by a positive coefficient. Consequently, negative shocks significantly increase volatility. Although long memory is present, both assets show a tendency for mean reversion due to their statistically significant long memory parameters, which are both smaller than 0.5. DCC parameters $alpha$, $beta$, and $gamma$ are statistically significant. While $beta$ has a coefficient that is quite high at 0.982, the coefficient for alpha

is only 0.01, which is a very low value. Finally, while the gamma value is positive, its effect is very small.

Table 3.18. APARCH-GARCH Asymmetric CDCC Results for Green-Gas Oil

Parameter estimates for the Green Bond Market Index					
	Coefficient	Std. Error	t-prob	Q(50)	$Q_S(50)$
ω	0.002**	0.001	0.025	0.426	0.507
α	0.042***	0.010	0.000		
β	0.950***	0.008	0.000		
γ	0.065	0.056	0.252		
δ	2.178***	0.311	0.000		
Parameter estimates for the benchmark Aggregate bond market					
	Coefficient	Std. Error	t-prob	Q(50)	$Q_S(50)$
ω	0.001	0.001	0.243	0.893	0.223
α	0.030**	0.013	0.025		
β	0.958***	0.009	0.000		
γ	0.319***	0.083	0.000		
δ	2.296***	0.446	0.000		
Estimates for the conditional correlation parameters					
	Coefficient	Std. Error	t-prob	Q(50)	$Q_S(50)$
$alpha$	0.010***	0.003	0.001	0.702	0.399
$beta$	0.982***	0.003	0.000		
$gamma$	0.010***	0.003	0.003		

Note: *, **, and *** represent causal relationships with significance levels of 10%, 5%, and 1%, respectively.

Table 3.19 displays the estimation results of the IGARCH- DCC model for Green - Biofuel. All parameters are statistically significant for both series. The $alpha$ parameter, which measures the persistence of shocks, is notably low for both series. Upon examining the DCC parameters, it is evident that both the $alpha$ and $beta$ parameters are statistically significant at the one percent significance level. In the model, the $alpha$ value is 0.021, while the $beta$ value is 0.821. A low $alpha$ parameter value suggests limited short-term correlation effects, while a high $beta$ value indicates strong long-term correlations. This implies that historical periods have a greater influence on current correlations, reflecting the continuous evolution of relationships between financial assets.

Table 3.19. IGARCH-DCC Results for Green-Biofuel

Parameter estimates for the Green Bond Market Index					
	Coefficient	Std. Error	t-prob	Q(50)	$Q_S(50)$
ω	0.001**	0.007	0.010	0.326	0.390
α	0.051***	0.007	0.000		
Parameter estimates for the benchmark Biofuel					
	Coefficient	Std. Error	t-prob	Q(50)	$Q_S(50)$
ω	0.003**	0.001	0.014	0.868	0.617
α	0.048***	0.007	0.000		
Estimates for the conditional correlation parameters					
	Coefficient	Std. Error	t-prob	Q(50)	$Q_S(50)$
alpha	0.021*	0.011	0.070	0.731	0.163
beta	0.821***	0.144	0.000		

Note: *, **, and *** represent causal relationships with significance levels of 10%, 5%, and 1%, respectively.

The FIAPARCH-GARCH-DCC model is estimated for Green-Brent, and the results are presented in Table 3.20. For Green bonds, all parameters except the asymmetry parameter are statistically significant. In contrast, for Brent, all parameters in the variance equation are significant except for the constant parameter. The parameter "d" indicating long memory is higher for Green, implying a slower decay over time compared to Brent, where this value is lower, suggesting a quicker decay despite having long memory. This indicates that while Brent exhibits long memory, it dissipates more rapidly over time compared to Green. The asymmetry parameter for Brent reflects the leverage effect. Both DCC parameters are statistically significant, with the $alpha$ parameter being very low and the $beta$ parameter being quite high in this model estimation.

Table 3.20. FIAPARCH-GARCH-DCC Results for Green-Brent

Parameter estimates for the Green Bond Market Index					
	Coefficient	Std. Error	t-prob	Q(50)	$Q_S(50)$
ω	3.505***	1.362	0.010	0.228	0.204
d	0.553***	0.058	0.000		
α	0.242***	0.039	0.000		
β	0.734***	0.058	0.000		
γ	0.066	0.058	0.258		
δ	1.689***	0.140	0.000		
Parameter estimates for the benchmark Brent oil market					
	Coefficient	Std. Error	t-prob	Q(50)	$Q_S(50)$
ω	0.358	0.499	0.473	0.836	0.670
d	0.341***	0.074	0.000		
α	0.276***	0.100	0.006		
β	0.527***	0.139	0.002		
γ	0.314***	0.083	0.002		
δ	1.931***	0.209	0.000		
Estimates for the conditional correlation parameters					
	Coefficient	Std. Error	t-prob	Q(50)	$Q_S(50)$
alpha	0.016***	0.005	0.002	0.215	0.098
beta	0.976***	0.010	0.000		

Note: *, **, and *** represent causal relationships with significance levels of 10%, 5%, and 1%, respectively.

The APARCH-GARCH corrected DCC model has been identified as the most suitable model for capturing the dynamic relationship between Heating and Green, with the results presented in Table 3.21. Similar to other models, the parameter indicating asymmetric effects is statistically insignificant for Green, suggesting no significant asymmetry in the series. However, α parameter is statistically significant but has a small coefficient of 0.042, indicating low persistence of shocks for Green in this model. Conversely, β coefficient, indicating the persistence of volatility clustering, is above 0.9, suggesting high persistence of volatility clustering. For Heating, all parameters are statistically significant. The α coefficient is 0.071, indicating low persistence of shocks, while β coefficient is 0.926, indicating volatility clustering. Additionally, the asymmetry parameter is positive at 0.310, indicating the presence of a leverage effect in the series. Moreover, the DCC parameters are statistically significant, with the $alpha$ parameter being low at 0.01 and the $gamma$ parameter being high at 0.98.

Table 3.21. APARCH-GARCH-cDCC Results for Green-Heating

Parameter estimates for the Green Bond Market Index					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
ω	0.005^{**}	0.001	0.033	0.335	0.336
α	0.042^{***}	0.011	0.000		
β	0.950^{***}	0.008	0.000		
γ	0.064	0.056	0.257		
δ	2.170^{***}	0.338	0.000		
Parameter estimates for the benchmark Heating					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
ω	0.009^{***}	0.003	0.003	0.840	0.295
α	0.071^{***}	0.011	0.000		
β	0.926^{***}	0.011	0.000		
γ	0.310^{***}	0.069	0.000		
δ	1.536^{***}	0.208	0.000		
Estimates for the conditional correlation parameters					
	Coefficient	Std. Error	t-prob	$Q(50)$	$Q_S(50)$
alpha	0.010^{***}	0.003	0.009	0.290	0.089
beta	0.983^{***}	0.007	0.000		

Note: *, **, and *** represent causal relationships with significance levels of 10%, 5%, and 1%, respectively.

Figures 3.3.a and 3.3.b illustrate the DCC-GARCH model's time-varying conditional correlations. DCCs between green bond and aggregate bond switch in sign and cover a value range between -0.5 and 0.75. Correlation is negative in 2009-2011s. This negative correlation provides an opportunity for portfolio diversification. After 2011, the correlation between them turns positive. This means that portfolio diversification between green bond and aggregate bond disappear. The positive correlation increases over time and peaks at the beginning of the COVID-19 period. DCCs between green bond and treasury bond has similar pattern compared to green-aggregate. The correlation between green bonds and treasury bonds exhibits a change in direction and spans a value range from -0.64 to 0.70.

The correlation of green bonds with Stock, Wilderhill, and Clean tends to vary over time, often aligning with increases or decreases in these indices. For instance, the correlation with Stock typically ranges between 0.506 and -0.660, while with Clean, it fluctuates between 0.401 and -0.453. The correlation with Wilderhill usually changes between 0.346 and -0.393. Notably, between 2009 and 2013, these correlations were generally positive but not significantly high. However, they turned negative until around 2020, after which they mostly returned to positive territory. This suggests that green bonds are sensitive to various

factors that can change over time. When examining the correlation between Green and Renewable, generally low correlations are observed, but in certain periods, this relationship exhibits significant increases. Particularly notable are the increases observed around the year 2016 and during the onset of the COVID-19 pandemic. Focusing on the relationship between Energy and Green, during the period between 2009 and 2014, the correlation between Energy and Green tends to be positive, while concurrently, the correlation between Carbon and Green tends to be negative. However, post-2016, and especially since the onset of the COVID-19 pandemic, while the correlation between Green and Energy generally tends to become negative, the relationship between Carbon and Green shifts towards a positive correlation, showing an increase.

When examining the correlation between energy commodities other than biofuels and natural gas with Green, it is observed that prior to 2013, these correlations generally showed positive values, whereas in subsequent periods, these correlations turned negative or approached zero.

For the period 2008-2023, correlations between green energy and commodities like biofuels typically fluctuated within a lower range, typically between 0.1 and -0.1. This indicates that these commodities could potentially serve as good tools for portfolio diversification. The correlation between natural gas and Green is even smaller, fluctuating between -0.05 and 0.05. This suggests that natural gas, like Biofuel, could be a good diversification tool for portfolios. Lastly, the correlations of green energy with other commodities such as gold and silver, initially negative, turned positive from the mid-2011s and continued until the end of 2021. Towards the end of 2021, this correlation turned negative again.

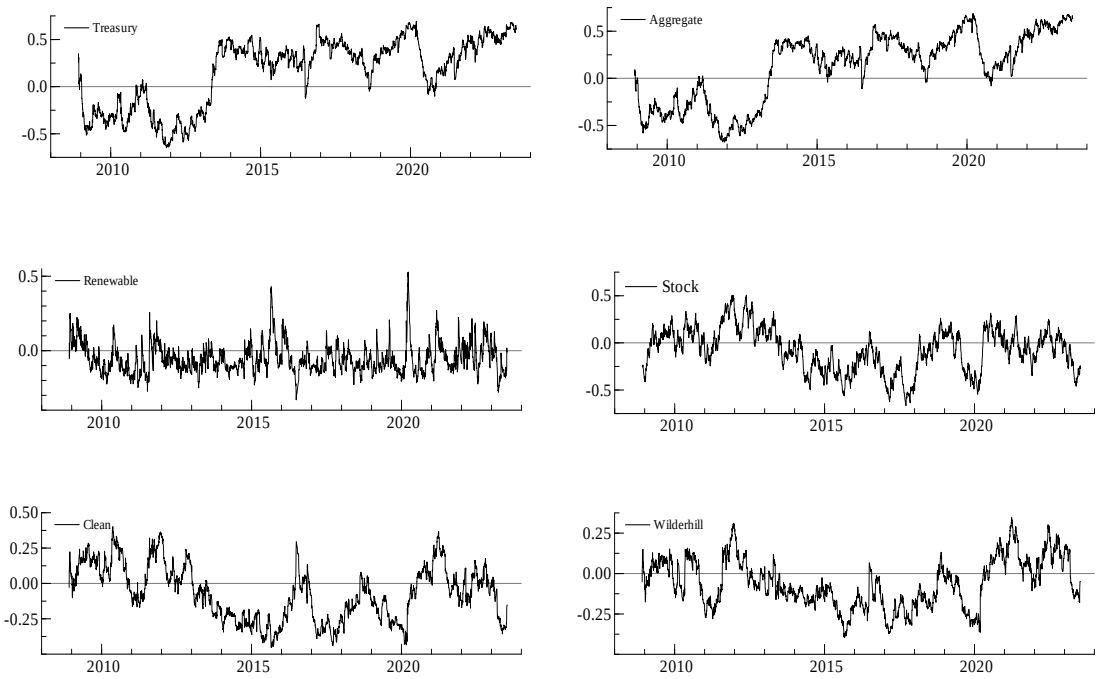


Figure 3.3.a. Time Graph of Correlation

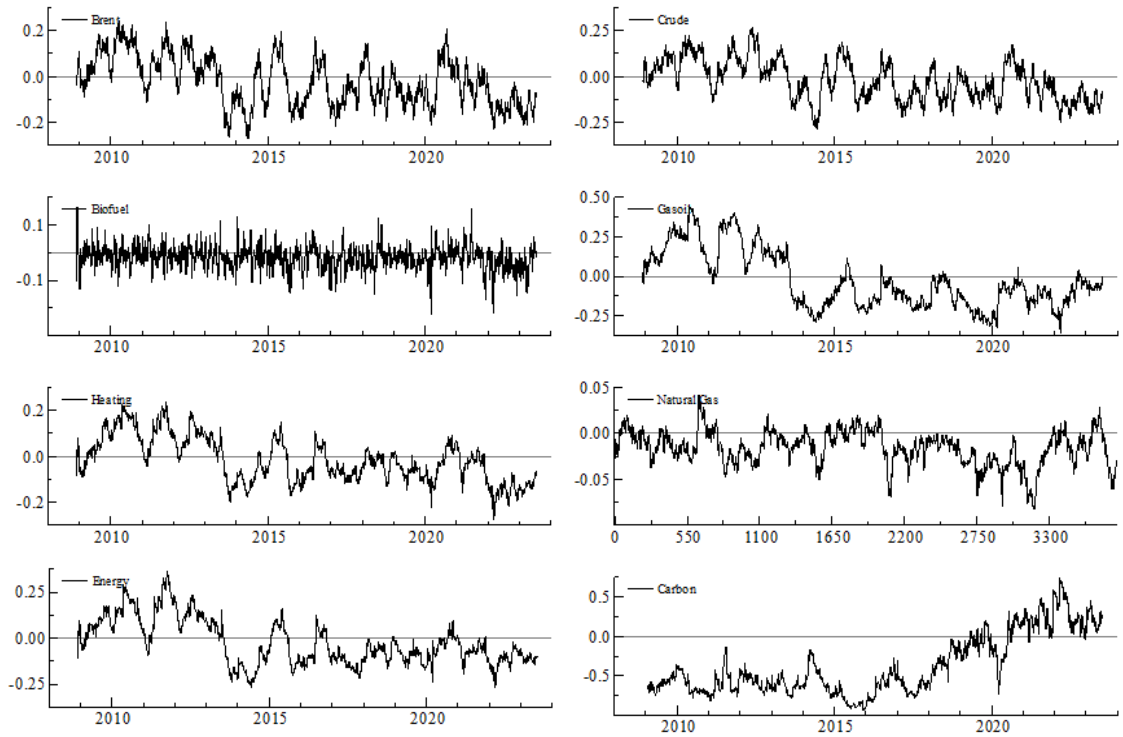


Figure 3.3.b. Time Graph of Correlation

2.5. Conclusion

The significant increase in the issuance of green bonds, which symbolizes the shift towards a more environmentally friendly economy, highlights the growing acknowledgment of the crucial role of sustainable finance in tackling worldwide concerns. The green bond market has exceeded the $2 trillion threshold by September 2022, indicating strong investor confidence in sustainable investments as a strategy to address climate change. This emerging sector not only offers new prospects for market participants but also corresponds with the objectives of sustainable development and fair economic growth. Nevertheless, as demonstrated by the literature, comprehending the relationship between green bonds and other financial assets is crucial for making well-informed investment choices. Research investigating the interactions between developing stock markets and the factors that drive these connections demonstrates a complex interplay influenced by different market situations. Furthermore, the differentiation between dependency and contagion in financial markets continues to be a topic of discussion, as conflicting results indicate the necessity for additional investigation. Although diversifying investments across worldwide financial markets can help reduce the danger of a financial crisis within a single country, increased integration also presents difficulties, such as the quick spread of negative impacts from one market to another. Therefore, the implementation of Modern Portfolio Theory principles in effective portfolio management highlights the significance of choosing stocks with little correlation to efficiently mitigate risk. As investors incorporate climate change risks into their portfolios, the importance of sustainable investment products such as green bonds is expected to continue growing. This will shape the future of finance towards a more environmentally sensitive approach.

Studies indicate a strong relationship between green bonds and traditional bond markets, typically characterized as unidirectional, flowing from traditional bond markets towards green bond markets (Pham, 2016; Reboredo, 2018; Reboredo and Ugolini, 2020; Pham, 2021; Gao et al., 2021). However, findings concerning stock markets vary regionally and depend on the index used. For instance, studies utilizing indicators such as the MSCI World Index suggest a weak relationship between green bonds and stock markets (Reboredo 2018; Reboredo and Ugolini 2020), whereas research focusing on specific markets like China or employing indices such as the S&P 500 reveal a strong and positive correlation between green bonds and equity markets Wang et., 2020; Park et al., 2020).

Studies have also suggested a strong relationship between different clean energy sources and green bonds (Nguyen, 2021; Hung, 2021; Ferrer et al., 2021; Pham, 2021). Both sectoral and global clean energy stocks have been shown to have a dominant impact on green bonds, particularly in global-based indices (Liu et al., 2021; Şahinler et al., 2021). Nevertheless, there is no uniform agreement on energy-related studies. Initial studies often utilized general indicators such as the MSCI Energy Index and Brent Oil and indicated a weak correlation with green bonds (Reboredo, 2018; Saeed et al., 2020; Ferrer et al., 2021; Arif et al., 2021). Studies conducted in different countries and subcategories have mixed results (Kanamura, 2020; Doğan et al., 2023; Su et al., 2023; Xiang and Cao, 2023; Su et al., 2022).

In this paper, we investigate interconnectedness between the green bond market, represented by the S&P Dow Jones GB Index, and traditional financial market benchmarks such as the S&P US Aggregate Bond Index, the US 10-year Treasury bond index, and the MSCI World Index, we analyze data concerning environmentally friendly clean energy markets such as the Wilder Hill Clean Energy Index, S&P Global Clean Energy, European Renewable Energy Index, as well as energy-related commodities including natural gas, heating, WTI crude oil, brent oil, and biofuel.

As Forbes and Rigobon (2002) pointed out, contagion and interconnectedness are different concepts. Contagion refers to a significant increase in the correlation between financial assets during periods of crisis, while interconnectedness describes a situation where the relationship between financial assets is strong not only during crisis periods but also under normal market conditions. To investigate the presence of contagion effects, left-tail distribution analysis is an important tool as it shows whether markets influence each other in situations of downside risk. Thus, this analysis helps us identify the existence of contagion effects between markets. Such research attempts may help investors and financial institutions in making more informed decisions. Furthermore, the computation of downward risk is conducted by utilizing value at risk (VaR) values determined within a 5% confidence interval. This methodology enables us to examine the impact of an unexpected loss of one asset on another asset, so offering empirical support for the presence of contagion effects. The results of Hong's (2009) causality in risk analysis indicate that the green bond market does not have an influence on other markets. However, other markets such as treasury bonds,

aggregated bonds, Clean and Wilderhill energy stocks unidirectionally affect the green bond market. As a result, when unexpected losses happen in these markets, there is also a delayed impact on the green bond market. However, there is no observed causal relationship in terms of risk between Renewable, Carbon, Energy, WTI Crude oil, Natural Gas, Gas oil, Biofuel, Brent, Heating, and green bonds. Finally, there exists a unidirectional causality in terms of risk between the stock market and the green bond market. This causality is directed from the stock market to the green bond market. However, it is important to note that causality is not present in all lagged periods, and even when it is present, its causality in risk effect is not particularly strong.

In this study, the dynamic relationships between green bonds and other financial assets were investigated using a causality test in terms of upside risk. In this context, VaR values were calculated using a 95% confidence interval. This method aims to observe how an unexpected gain in one asset affects another. The findings reveal bidirectional lagged causality between green bonds, treasury bonds, and aggregated bonds, whereas Wilderhill unidirectionally affects green bonds. No causality relationship was observed with other variables. Furthermore, the relationship between the stock market and the green bond market is unidirectional, with the impact being stronger on green bonds in lagged values when compared to downside risk.

The findings suggest that, in general, there is no causality in returns and risks between energy commodities and green bonds, and the correlation between these assets remains quite low. On the other hand, causality analyses conducted from the perspective of traditional bonds indicate that green bonds are significantly affected by traditional bonds, with the relationship initially being negative but turning positive, particularly after the Paris Agreement, and increasing during the COVID period. Although studies like those by Pham (2021) and Huynh (2022) have identified contagion effects during the COVID period, the results obtained in this study indicate a stronger link primarily between green bonds, treasury bonds, aggregated bonds, and clean energy stocks. While downward causality and DCC results suggest the presence of contagion effects, indicating that adverse movements in other financial assets negatively affect green bonds, the presence of causality in returns and upward risks suggests a general interdependence between the two assets. This interdependence is valid not only during crisis periods but also under general market conditions. When there is causality in both downside risk and returns/upward risk, it implies

both contagion effects and a general interdependence between the two assets. The discrepancy between the findings of DCC-GARCH and causality analysis is attributed to the computational complexity of multivariate GARCH models. In contrast, univariate GARCH models are more flexible and better able to capture the unique structure of assets. In DCC GARCH models, assets are forced into the same GARCH process, implying the use of the same parameters that affect the volatility of each variable. However, single GARCH models allow for the individual modeling of volatility for each variable. This enables the straightforward selection of the GARCH model that best reflects the volatility of each variable. Hence, the standardized errors obtained from single GARCH models can be used to achieve stronger results in causality analysis. In conclusion, it can be said that green bonds exhibit an interdependency with traditional bonds and clean energy stocks.

According to the Efficient Market Hypothesis, if a market is not fully efficient and does not reflect all available information completely and instantly in the prices, investors may find opportunities to earn above-normal returns. When evaluated in terms of the efficient market hypothesis, the findings indicate that excessive gains or losses in assets such as treasury bonds, aggregated bonds, or clean energy stocks are reflected with a delay in green bonds. This can allow investors to earn more returns than expected. Therefore, it can be argued that the green bond market is not efficient, and investors can achieve higher returns than expected by following the movements of other financial assets. The efficient market hypothesis of the green bond market can also be assessed using a univariate GARCH model. Typically, the efficient market hypothesis is examined with long-memory GARCH models. For example, in GARCH models incorporating long memory, such as FIGARCH, when the parameter d representing long-term dependence equals 1, it signifies that past volatility influences current volatility, indicating long-term efficiency and transforming the model into IGARCH. Therefore, a conclusion can be drawn that the green bond market is not weak-form efficient. This result indicates that the volatility of green bonds is influenced by their past values and, consequently, exhibits a predictable pattern.

When evaluated from a portfolio perspective, the green bond market exhibits a tight relationship with treasury bonds and aggregated bonds, which belong to the same asset class and offer fixed returns. Similarly, clean energy stocks serve similar purposes and are closely related to green bonds. The benefits of diversity for investors are decreasing due to the substantial impact that these assets have on green bonds. However, there is not as strong a

relationship between dirty energy and green bonds. In this context, green bonds and energy commodities enhance the diversification benefits for investors. Additionally, they provide investors with a hedge against adverse price movements in energy commodities.

Salim and Rafiq (2012) and Bhattacharya et al. (2017) emphasize the significant role of clean energy not only in promoting economic growth but also in reducing carbon emissions, which contribute to environmental issues. These findings suggest that supporting the clean energy sector through incentives can be beneficial for governments. Moreover, this study demonstrates that the green bond market is influenced by clean energy markets. Supporting clean energy markets will also contribute to the green bond markets. Although the popularity and growth of green bonds have increased over time, they can still be considered nascent compared to traditional bonds. Therefore, because of this, government supporting for clean energy can help the green bond market grow even more.

4. THE EFFECTS OF UNCERTAINTY ON THE GREEN BOND MARKET

4.1. Introduction

Financial markets are sensitive to being influenced by a wide range of factors, including social and political events, as well as domestic and international economic situations (Yeap and Gan, 2017:79). Other factors that can influence the movements of stocks and other financial markets include, but are not limited to, the policies of central banks, the performance of companies, global trade connections, natural disasters, developments in technology, and even the attitudes of society. Each decision made by financial actors will subject them to the risks and uncertainties that result from these factors. Decision-makers in uncertainty often struggle to define problems, capture data, and synthesize knowledge to establish decision-making rules (Pompian, 2006:29).

Uncertainty was defined by Knight in his 1921 book "Risk, Uncertainty, and Profit" as the state in which investors are unable to predict potential outcomes because of a lack of information (i.e., the information is not available at any cost) (Aharoni, 2015:12). The author has also made a differentiation between risk and uncertainty by calling measurable uncertainties "risk" and unmeasurable uncertainties "uncertainty." Using the Knightian distinction, Runde (1998) provided the following definitions of risk and uncertainty in this context: in risk situations, the decision-maker assigns probabilities to events based on "known chances," which are numerical proportions. In uncertain situations, the decision-maker cannot compute the chances and assign probabilities to events.

Fischer (1970) also distinguished between risk and uncertainty as follows: risky situations involve a known probability distribution and an uncontrollable random event. One example of a risky activity is to flip a fair coin, which has a probability of 0.5 percent of landing on the heads side. Conversely, uncertainty emerges when the probability distribution associated with the uncontrollable random event remains unknown.

Uncertainty is naturally unobservable; however, it is possible to build proxies to evaluate, at the very least, the changes that it undergoes over time (Makarova, 2014;

2). Researchers have used a variety of different measures of uncertainty. For example, the standard deviation of stock prices and returns is a common and well-accepted measurement that has been around for a long time (Lipe, 1990; Imhoff and Lobo, 1992; Kacker and Jones, 2003; Loughlin and Cohen, 2004). The Chicago Board Options Exchange Volatility Index (VIX), derived from the Chicago Board Options Exchange, has long served as a proxy for equity market uncertainties (Connolly et al., 2005; Bloom, 2009; Bekaert et al., 2013; Sarwar and Khan, 2017; Al-Yahyaee et al., 2019; Istiak and Serletis, 2020; Lin and Su, 2022). Stock market volatility has also been used as a measure of uncertainty (Leahy and Whited, 1996; Bloom et al., 2007; Bloom, 2009; Panousi and Papanikolaou, 2012; Kang et al., 2014; Meinen and Röhe, 2017; Aastveit et al., 2017). However, common indicators may not accurately reflect the conventional uncertainty. For example, the VIX may not be suitable as a uniform indicator because of the differences in liquidity and depth in the market. Even if there is no change in the level of uncertainty, different stocks may react differently to common risk factors, which can cause their returns to fluctuate. Likewise, even if there is no change in the level of economic volatility, situations such as changes in leverage and/or adjustments in risk aversion by investors may cause the volatility of financial markets to increase or decrease.

In recent years, there has been an increase in the number of unique indices made to quantify uncertainty. Jurado et al. (2015) constructed and presented new indicators to measure the degree of macroeconomic uncertainty. A total of 132 macroeconomic series and 147 financial time series were utilized in the construction of this uncertainty index. Their technique provides a holistic perspective on the complexities of the uncertainty dynamics within a larger economic landscape.

Baker et al. (2016) have collected and maintained an up-to-date dataset covering the years 1985 through the present to create an Economic Policy Uncertainty (EPU) index based on the frequency of newspaper coverage. The EPU index uses newspaper archives to understand the complex interactions between policy decisions, market sentiments, and economic trends. As such, it helps policymakers, investors, and researchers understand and cope with uncertainty in economic decision-making and market behavior. Baker et al. (2016) have also expanded their research by utilizing the Access World Database to develop several subcategory uncertainty indices. These indices consider many different aspects, including monetary policy, fiscal policy, government expenditures, taxation, healthcare, and

regulation. Their methodology provides a thorough framework for comprehending and quantifying uncertainty across various policy domains by combining data. With the help of this multifaceted analysis, it is possible to conduct a more in-depth investigation into the connections that exist between policy decisions, regulatory frameworks, and economic outcomes. These subcategory indices can help policymakers, economists, and analysts understand the uncertainty dynamics in specific policy contexts and make better decisions.

Manela and Moreira (2017) used Wall Street Journal (WSJ) articles to create a text-based uncertainty index (NVIX) covering 1890–2016. This index, which was generated from the textual analysis of articles published in the Wall Street Journal, offers a complete view of the dynamics of uncertainty over nearly a century. It also provides insights into the development of economic and financial sentiments during this period.

In recent years, there has been a noticeable increase in the frequency of extreme weather phenomena and abnormal climate events, as well as an increase in their severity. These include global warming, sea-level rise, cyclone intensification, and forest fires. Not only do these challenges pose significant threats to energy systems, but they also pose threats to human assets and threaten their safety and lives (Sussman and Freed, 2008; Morales, 2015). Meteorological factors and climate policies play an important role in shaping the evolving energy landscape. These factors have a direct effect on the current state of traditional energy sources as well as the future prospects of green markets (Ren et al., 2023a: 1). Within this context, Gavriilidis (2021) developed a new index to measure the uncertainties associated with climate policy based on news from major US newspapers. According to the author, The Climate Policy Uncertainty (CPU) index seems to be able to effectively capture significant events and fluctuations that are relevant to climate policy and related developments.

Other indices have emerged in the literature to capture various dimensions of uncertainty across various areas from different perspectives. For instance, Baker et al. (2021) presented the Twitter-based Economic Policy Uncertainty Index, which makes use of data from Twitter in order to measure changes in economic policy uncertainty. Dank et al. (2023) developed an Energy Uncertainty Index to evaluate the uncertainties that naturally connect with the energy industry. Caldara and Iacoviello (2022) proposed an index called the GPR index to quantify the uncertainties caused by geopolitical events and tensions. Ahir et al.

(2022) presented the World Uncertainty Index, which offers insights into global uncertainties that have an impact on the stability of the economy and financial system. Additionally, Abiad and Qureshi (2023) developed the News-Based Oil Price Uncertainty Index, which was intended to capture the uncertainties associated with oil prices based on the coverage provided by newspapers.

Researchers have noticed that during times of increased uncertainty, firms tend to lower their investments (Bernanke, 1983; Leahy and Whited, 1996; Guiso and Parigi, 1999; Bloom et al., 2007; Gulen and Ion, 2016), savings tend to increase (Sandmo, 1970; Caballero, 1990), consumption decreases (Mason and Wright, 2001), exchange rate volatility (Krol, 2014; Chen et al., 2020; Bush and Noria,2021), and financial market volatility tends to increase (Chinzara, 2011; Chau et al., 2014; Ma et al., 2022). This demonstrates that uncertainty has a broad impact on economic actors and can result in considerable changes in various economic indicators.

Ilmanen (2003) stated that when dealing with risks, uncertainties, and overall economic conditions, stocks and bonds react in different ways. At times, they move in opposite directions, while at other times, they move together in response to specific factors. For example, economic growth boosts stock prices but hurts bond prices. On the other hand, periods of increased market volatility, such as during episodes of flight-to-quality behavior, have a tendency to be detrimental to stocks while being beneficial to bonds. Conversely, bond and stock prices are affected similarly by monetary policy uncertainty. When this is taken into consideration, an important question arises regarding whether or not the efficiency of the stock market is significantly impacted by economic uncertainty (Yeap and Gan, 2017).

This chapter examines the effects of various uncertainty indices—economic policy uncertainty, climate policy uncertainty, and monetary policy uncertainty—on the green bond market within the framework of the Efficient Market Hypothesis (EMH). In the semi-strong form of the EMH, which was described by Fama (1970), it is suggested that the market reflects all information that is available. This suggests that prices adjust quickly in order to incorporate new information, which makes it difficult for investors to consistently outperform the market based on information that is readily available to the public.

Despite growing interest in the relationship between the green bond market and other financial markets, the impact of uncertainty, particularly in climate policy, on the green bond market is still not well studied. The significance of this study lies in its examination of green bonds and uncertainty within the framework of market efficiency using an econometric methodology based on the bootstrap Fourier ARDL method. It is important to note that there has been an absence of previous research that has undertaken the investigation of this intersection using such a methodology.

4.2. Literature Review

4.2.1. Economic Policy Uncertainty

The general stability of the world economy has been put to many tests over the past century. The absence of peace in the global economy can be traced back to various historical events, such as the Great Depression of 1929-1939, the OPEC Oil Price Shock of 1973, the Asian Crisis of 1997 (Gyamerah and Asare, 2024), the global financial crisis in 2008, the European sovereign debt crisis in late 2009 (Dong et al., 2023), the trade friction between the United States and China, the COVID-19 pandemic (Wei et al., 2024), and the Russian invasion of Ukraine in 2022 (Tang et al., 2023). These ongoing instabilities give rise to the idea of economic policy uncertainty associated with spikes in trade, fiscal, and regulatory policies; thus, it has become the focus of existing studies.

The effects of economic policy uncertainty on energy markets (Yang, 2019; Shafiullah et al., 2021; Borozan and Borozan, 2022; Wang et al., 2023; Gong et al., 2024), effects on stock markets (Wu et al., 2016; Tsai, 2017; Phan et al., 2018; Lean et al., 2024), effects on bond markets (Jiang and Tong, 2016; Loannidis and Ka, 2021; Benlagha and Hemrit, 2022), effects on economic growth (Aisen and Veiga, 2013; Junttila and Vataja, 2018; Wen et al., 2022), its effects on trade (Krol, 2018; Wei, 2019), and its effects on many other economic and financial indicators have attracted increasing attention.

The study by Haq et al. (2021) is the first to look into whether the green bond market acts as a safe haven and a hedge against economic policy uncertainty. This research was undertaken by the authors in three distinct markets: China, the United States, and the United Kingdom. The DCC-GARCH econometric approach was employed for the time frame

spanning March 11, 2014, to September 29, 2020. Based on the findings, it can be observed that green bond returns exhibit a more effective hedging characteristic in relation to the UK EPU and China EPU. However, this effect has not been observed in the United States. During the COVID-19 time, green bond markets served as a safe haven for investors in response to the US EPU and the UK EPU. However, this assertion does not hold for the Chinese EPU. In the end, the authors stated that the benefit of acting as a hedge dominates the benefit of providing a safe haven by comparing the two features. Similar to Haq et al. (2021), Dong et al. (2023) utilized multivariate GARCH models; however, in this particular study, the authors examined the performance of conventional bonds with green bonds under economic policy uncertainty. This is the first study to assess the performance of conventional and green bonds using the DCC-Midas-X approach. The study shows that the green bond market outperforms traditional bond markets in terms of safe-haven attributes during times of high uncertainty. Furthermore, the findings of the dynamic correlation analysis indicate that green bonds have better hedging potential than conventional bonds.

Pham and Nguyen (2022) examined the impact of economic policy uncertainties on four distinct green bond markets: the Solactive Green Bond, S&P Green Bond, Bloomberg Barclays MSCI Euro, and the USD Green Bond Index. The study utilized the Markov Switching Regression and TVP-VAR model to analyze data from October 13, 2014, to November 4, 2020. During times of increased uncertainty, Solactive and Barclays' MSCI Euro green bond returns are positively impacted; however, the impact on the other two green bond markets is negligible. As per the authors, this is due to the fact that the first two green bonds are primarily denominated in euros. The impacts of times characterized by low uncertainty are minimal or negligible. Nevertheless, it exerts a positive impact on the return of S&P green bonds.

Syed et al. (2022) employed the nonlinear ARDL econometric technique to examine the presence of an asymmetric relationship between the EPU index and the green bond market during the period of December 2016-October 2021. Based on the findings, an increase in uncertainty for both the long- and short-term leads to a fall in the return of green bonds. Conversely, a decrease in uncertainty results in an increase in the returns of green bonds. Furthermore, the researchers concluded that the significance of the long-term effects surpasses that of the short-term effects.

In order to investigate the impact of uncertainty on green bond prices, Wang et al. (2022) employed the Time-varying Granger Causality test, which was proposed by Shi et al. (2018, 2020). This study employed three distinct algorithms: forward expanding, recursive evolving, and rolling windows. The recursive evolving algorithm method revealed a causal relationship from EPU to the price of green bonds in early 2020. Based on the outcomes obtained using the other two algorithms, the time-varying causality from EPU to green bond prices is less obvious. Upon examining the causality outcomes from green bonds to the EPU index, the forward-expanding algorithm failed to identify any causality. However, the other two algorithms detected a causal relationship towards EPU starting from the start of 2020.

The study conducted by Wei et al. (2024) examined the correlation between economic policy uncertainty and the green bond market, both in the short and long terms. This investigation was conducted within the context of efficient market theory. The research conducted by the authors focused on examining the response of the green bond market to economic policy uncertainty across various market conditions, employing the Quantile ARDL approach. The analysis of daily data spanning April 2014 - March 2021 revealed a strong correlation between economic policy uncertainty and the efficiency of the green bond market, both in the short term and long term. Nevertheless, empirical evidence has demonstrated that the observed positive impact is based on quantiles, with a greater impact observed in the lower and middle quantiles, while effectiveness diminishes in the higher quantiles.

According to Lin and Su (2023), a significant challenge in the analysis of green bond markets is the potential variability observed across various countries. Wang et al. (2023) examined the impact of EPU on the Chinese green bond market using the QARDL approach. The study revealed that a negative impact was first found in the short term, particularly at higher quantiles. However, over the long run, this impact transitioned to a positive impact across almost all quantiles. The study conducted by Tang et al. (2023) investigated the impact of the EPU index on the green bond market through the utilization of the nonlinear succession approach. The findings of the study revealed that higher uncertainty in both the short and long term exerts a detrimental influence on the return of green bonds. In contrast to the research conducted by Tang et al. (2023) and Wang et al. (2023), the study conducted by Gyamerah et al. (2024) revealed that both positive and negative shocks in the EPU have positive effects on the long-term green bond return. The analysis was performed by utilizing

the S&P green bond return together with the global EPU index, which was produced by Baker et al. (2016). However, Wang et al. employed the EPU index specifically designed for China, while Tang et al. utilized the index specifically established for the United States.

The study conducted by Long et al. (2022) investigated the impact of EPU on three distinct markets: the Chinese, US, and European green bond markets. The researchers employed a quantile VAR model for their analysis. Extreme conditions have been demonstrated to result in greater spillover effects than normal conditions. The US green bond return is the source of spillover in all quantiles, whereas the Chinese green bond is the recipient. In the European green bond market, the dynamics of receivers or transmitters change more depending on time. Only for the US and China, Lin and Su's (2023) investigation focused on the impact of EPU on green bond return and volatility. The authors distinguished themselves from other studies by selecting the Bloomberg Barclays MSCI US Green Bond Index, specifically for the US. The cross-quantilogram method and causality in the quantile method were employed in their study. They demonstrated that the return of US green bonds is positively influenced by EPU, but only during periods of bull market conditions. Additionally, its effect on green bond volatility is observed only in a limited few extreme case. According to the authors, the effects of VIX and OVX, which are included in the analysis, have a greater impact on the US green bond market than EPU. When uncertainties decrease in China, this positive effect on the green bond market turns negative as uncertainty increases. At the same time, volatility increases as uncertainty increases in low quantiles, but a sudden change in CPU turns the movement negative. China's green bonds exhibit a higher degree of sensitivity to extreme uncertainty.

Wang (2024) only investigated the effects of EPU on the green bond market in China. The author observed that the relationship between the green bond market and EPU varied in different quantiles and frequencies. He initially obtained short-term, medium-term, and long-term frequencies using wavelet transformation for two variables and then used Sim and Zhou's quantile on the quantile regression approach for these frequencies. Although the impact of EPU on the green bond market is negligible across all quantiles in the short run, the connection between green bonds and EPU becomes positive in the long run, particularly in extreme quantiles. In the long run, EPU has a negative effect on the short and medium frequencies of green bonds in almost all quantiles but has a positive impact on the long-term

frequency value. In summary, the author has demonstrated that the impact of economic policy uncertainty on green bonds can vary across different frequencies and quantiles.

The cross-quantilogram method was employed by Su et al. (2023) to examine the relationship between green bonds and green equities. The analysis undertaken for China involved the selection of the CUFE-CNI High-Grade Green Bond Total Return Index, which held the distinction of being the first index in the market. They indicated that under severe market conditions, there exists a higher degree of integration between these two markets compared to normal market situations. Furthermore, it demonstrates that the exchange of information between these two markets is ineffective.

In summary, the green bond market tends to serve as a shelter and protection tool against rising economic policy uncertainties. Based on research findings, green bonds exhibit a greater capacity to protect investors from economic policy uncertainty, specifically in the United Kingdom and China. However, this effect is comparatively weaker in the United States. This may be due to the different characteristics of the countries or regions and the currencies upon which the bonds are denominated. The results show that while green bonds have both a hedge and a safe-haven feature, the hedge characteristic has been shown to be more prominent. These studies also suggest that the green bond market outperforms traditional bond markets against economic policy uncertainty, and dynamic correlation analysis suggests that green bonds have better hedging potential than traditional bonds.

4.2.2. Climate Policy Uncertainty

Sustainability, environmental friendliness, and inclusive growth initiatives have created concerns about how to fund such activities. Within this framework, financial instruments such as sustainable bonds or green bonds, which support these efforts, can be issued to finance activities that provide environmental benefits. Over the past few years, alongside the emergence of green bonds, the impact of environmental issues and related regulations on the pricing of green bonds has become a topic of increasing research interest in academic literature. One of the pioneering studies that has been undertaken to investigate the impact of climate policy and the uncertainty that is linked with it on green bonds is the study that was carried out by Tian et al. (2022). They use the asymmetric ARDL method to investigate how uncertainty in climate policy affects green bonds. In addition, they

investigated the impact of a variety of risk and uncertainty indices, including geopolitical risk, volatility of crude oil, and infectious diseases, on green bonds. The US, Europe, and China were the three distinct markets analyzed in this study. In the short term, a decrease in infections and climate policy uncertainty led to an increase in green bond prices in China. It was also found that there was a negative link between the uncertainty of climate policy and the prices of green bonds across all markets in the long run. In this context, rising climate policy uncertainty has a negative impact on green bond prices, which is especially apparent in Europe. The study also found that the volatility of crude oil had a positive effect on the prices of green bonds in all three markets. In contrast, geopolitical risk did not have a significant impact on green bonds in China. This effect was found to be significantly larger in Europe compared to the United States.

Bouri et al. (2022) investigated the effects of climate policy uncertainty using iShares exchange-traded funds (ETFs) as proxies for green assets rather than concentrating specifically on green bonds. Indicators of environmentally friendly assets were utilized, including the iShares Global Energy ETF and iShares US Energy indices. The time period ranges from July 2008 to March 2021. The green-to-brown stock ratio was the dependent variable. To indicate climate policy uncertainty, they used Gavriililidis' (2021) climate policy uncertainty index. According to the findings, the ratio of green assets to brown assets has tended to increase during times of increased uncertainty and crisis, which indicates that there is a positive relationship between the two types of assets. In light of these findings, it appears that the market for green assets may be significantly influenced by climate policy uncertainty.

Husain et al. (2022) investigated the transfer of climate policy uncertainty risk to global green financial instruments using the cross-quantilogram approach developed by Han et al. (2016). The findings obtained from data covering the period from July 2014 to March 2021 suggest that green equity returns are more sensitive to increases and decreases in climate policy uncertainty compared to green bond returns in the medium term. However, in the long run, risk is transferred to both green equity and green bond returns. According to the authors, this allows both markets to exhibit high portfolio performance in the long-run.

Silva et al. (2022) took a different approach than previous research, comparing the performance of green bonds to traditional bonds under climate policy uncertainty. In this

study, the authors examined the return performance of green bonds as sustainable financial assets in the context of climate policy uncertainty. They applied the econometric method of the multi-factor model proposed by Elton et al. (1995), covering the period from January 2015 to March 2021. According to the results, during periods of low uncertainty, green bond returns exhibit a lower performance. Conversely, during periods of increased uncertainty, green bond returns outperform the black and traditional bond returns.

Ren et al. (2023a) used a time-varying Granger causality test to investigate the relationship between climate policy uncertainty and green bonds. In addition to green bonds, they also included indicators of the green market, such as carbon trading and clean energy. Their study covered March 2011 to December 2021 for clean energy and green bonds and August 2009 to December 2021 for carbon trading. The causality analysis revealed no causal relationship between green bonds and climate policy uncertainty in either direction over the entire period. However, using the time-varying Granger causality test, they found that green bonds affected climate policy uncertainty, especially during 2017. On the other hand, a Granger causality was discovered between climate policy uncertainty and green bonds in 2014 and 2018.

Ren et al. (2023b) reexamined climate policy uncertainty and the green bond market from October 2011 to March 2021 using Quantile ARDL rather than time-varying Granger causality analysis. They used the climate policy uncertainty index suggested by Gavriilidis (2021) to indicate climate policy uncertainty. In their analysis, the authors included futures prices of crude oil and five-year treasury bond yields. Based on the results obtained from the Quantile ARDL analysis, it was observed that climate policy uncertainty did not have a notable effect on green bond returns in the short term across all quantiles. Yet, in the long term, especially at higher quantiles, uncertainty in climate policy had a positive effect on green bond returns. In addition, they revealed that crude oil prices always influenced green bond returns positively, suggesting that rising oil prices could lead to higher returns on green bonds. On the other hand, it was noted that treasury bond yields had a negative effect on green bond returns, suggesting that increased treasury bond yields could result in decreased returns on green bonds.

Following a methodology similar to that of Ren et al. (2023), Wang et al. (2023) initially quantile-segmented the series. They then used the spillover technique developed by

Diebold and Yılmaz (2012) and Diebold and Yılmaz (2014) as the econometric method. The period from September 2012 to August 2022 was used to investigate the connection between the green bond market, prices of carbon emission trading, prices of energy, and uncertainty of climate policy. According to the findings, there is a significant connection between the variables. However, pairwise analysis of green bonds and climate policy uncertainty in high quantiles shows that they were receivers from 2017 to 2019 but transmitters in 2019 and 2021. According to Su et al. (2024), who employed a wavelet econometric approach based on quantile on quantile, climate policy uncertainty has a negative and time-varying effect on the green bond market. In the long run, this phenomenon can have either a positive or negative impact, with the determining factor being how the market is performing. In the event of a bear market in an economy, CPU has an adverse effect on the green bond market. In the event of a bullish market, CPU has an adverse effect on green bonds.

Several researchers, including Yu et al. (2023) and Raza et al. (2024), investigated the impact that climate policy uncertainty has on the volatility of the green bond market. In their study, Yu et al. (2023) utilized the TVP VAR econometric method to investigate the impact of climate policy uncertainty on the volatility of China's green bond market. On the other hand, Raza et al. (2024) applied the GARCH MIDAS method to investigate the impact of climate policy uncertainty on the volatility of the S&P global green bond market. Both studies used the climate policy uncertainty index constructed by Gavriilidis in 2021. The results of these studies show that the green bond market becomes more volatile when there is more uncertainty about climate policy.

4.2.3. Monetary Policy Uncertainty

The effects of unexpected monetary policy decisions on bond prices are extensively studied in financial markets. Particularly, significant monetary policy tools such as central banks adjusting interest rates, forward guidance policies and large-scale asset purchases can cause notable price fluctuations in the bond market (Jiang and Tong, 2016:2). These changes are crucial for both bond investors and policymakers because fluctuations in bond prices can impact not only key economic indicators like economic growth and inflation but also international bond markets and market risk perceptions (Gürkaynak et al., 2004; Rigobon and Sack, 2004; Andersen et al., 2007; Basistha and Kurov, 2008; Bredin et al., 2010; Gertler and Karadi, 2015; Gali and Gambetti, 2015; Paul, 2020, Gürkaynak et al., 2021). Jiang and

Tong (2005) demonstrated that when uncertainty rises, the excess returns and risk premium of treasury bonds also increase, using the MPU index created by Baker et al. (2016). Tillman (2020) highlighted in his study that the yield of treasury bonds exhibits different growth rates during periods of differing levels of uncertainty. The yield on treasury bonds tends to be lower during periods of high MPU, as indicated by the index developed by Husted et al. (2016). As per the author's statement, monetary policy uncertainty refers to the uncertainty in future short rates. Consequently, investors expect reduced term premiums for long-term securities. Lakdawala et al. (2021), along with the other two studies, showed that an increase in uncertainty has a positive effect on treasury bond yields. In contrast to previous studies, the authors employed the market-based monetary policy uncertainty index developed by Bauer et al. (2022). Several studies have specifically examined the impact of uncertainty on volatility rather than its effect on bond yield. Arnold and Vrugt (2010) utilized interest rates as a proxy of monetary policy uncertainty, whereas Huang et al. (2008) considered variables like money supply, Federal funds rate, and nonborrowed reserves. Both studies found that when uncertainty rises, the volatility of treasury bonds also rises.

Academic literature includes research that analyzes the impacts of monetary policy shocks using event studies. Rigobon and Sack (2004) utilized the 6-month monetary policy statement presented to Congress and the observed increases in the variance of policy shocks during FOMC meetings to quantify the impact of monetary policy shocks. The findings indicate a positive correlation between monetary shocks and an increase in government bond yields in the United States. Andersen et al. (2007) investigated the impact of monetary shocks on the foreign currency market, stock market, and bond market in three distinct markets: the United Kingdom, the United States, and Germany. Research has revealed that shocks have a greater impact on the bond market than on the other two markets. Conversely, Kubota and Shintani (2022) conducted their research focusing only on Japan. The authors demonstrate that an unanticipated contractionary monetary policy has a positive effect on government bond yields. To assess the impact of monetary shocks, the researchers utilized changes in 10-year government bonds and 3-month Euroyen futures prices after the release of monetary policy meeting press statements.

Tu et al. (2020) investigated the variables influencing the growth of the green bond market in Vietnam by the utilization of a multi-criteria decision-making approach, specifically the analytical hierarchy process method. The factors influencing green bonds

were categorized into four primary groups, each of which contained subgroups. Economic factors include monetary policy, fiscal policy, economic stability, exchange rates, interest rates, and inflation rates. Political factors consist of state support, political stability, and state support. Infrastructural factors involve international cooperation in green bonds, legal framework, and limited application to international standards and institutional infrastructure. Lastly, sociocultural factors encompass social support, high education level, and social-environmental linkage. The findings indicate that economic criteria and infrastructural factors hold greater significance in the green bond market. Within the subcategories, it was determined that the legislative framework holds the most significance, followed by monetary policy and interest rates as the second- and third-most important elements, respectively.

Kocaarslan (2021) stated that the existing literature lacks any direct investigation into the impact of macroeconomic issues on the green bond market. The author conducted an analysis of the impact of business cycles (specifically, the term spread and default spread), financial stress (measured by the TED spread, which is the difference between 3-month LIBOR and Treasury Bill rates), monetary conditions (represented by the federal funds rate), and global market uncertainty on the green bond market. The investigation focused on the period from August 1, 2014, to October 19, 2019, using the DCC-GARCH model constructed by Engle (2002) and the ARDL econometric approach developed by Pesaran et al. (2001). In addition, this study conducted a comparison of the green bond, energy, and stock markets. Research has shown that interest rates, as a monetary indicator, have a negative impact on bond prices to a limited degree. However, they have a positive effect on the stock and energy markets, also to a limited degree. The appreciation or depreciation of the US dollar is the primary determinant of the three markets' performance. When the value of the dollar rises significantly, it has a negative impact on the prices of energy commodities and stocks while simultaneously increasing the price of green bonds.

Lin and Su (2022) are the pioneering researchers who have investigated the rationale behind the issuance preferences of green bonds and conventional bonds in China. Factors that influence preferences can be categorized into three broad groups. The features include macro and market factors, issuer characteristics, and bond properties. The researchers utilized logit and probit models and fuzzy-set qualitative comparative analysis to perform their study from January 1, 2016, to June 30, 2021. M2 money supply served as an indicator for assessing monetary policy. Of all macro and market features, money supply has the most

significant influence. According to Foley-Fisher et al. (2016), monetary policy can affect firms' financing constraints. When a tight monetary policy is implemented, it becomes more difficult for companies to obtain financing through traditional methods. As a result, there may be an increase in the demand for green bonds. Lin and Su (2022) indicated that changes in monetary policy have a detrimental impact on the decision-making process for selecting corporate bonds. Furthermore, an expansionary monetary policy reduces the demand for green bonds.

Dafermos et al. (2018) investigated the impact of climate change on financial stability and highlighted the potential benefits of implementing a green corporate quantitative easing program in monetary policy. This program would not only help mitigate global warming but also decrease the risk of financial instability resulting from climate change. As to the author's analysis, climate change has the potential to diminish corporations' profitability and deteriorate their financial circumstances. This has an impact on the confidence of investors and could result in a rise in the preference for liquidity. They utilized the stock-flow-fund ecological macroeconomic model established by Dafermos et al. (2017) for their investigation. The implementation of a green quantitative easing policy leads to an increase in the price of green corporate bonds, resulting in a decrease in the yield of green bonds. This scenario presents enterprises with reduced borrowing options and hence encourages higher levels of investment. Ferrari and Landi (2024) employ a Dynamic Stochastic General Equilibrium (DSGE) Model. Given the assumption that green bonds and traditional bonds are not perfect substitutes, the authors propose that the central bank should introduce green quantitative easing. This would result in a decrease in the interest rates paid on green bonds and an increase in interest rates on traditional bonds. Consequently, companies would be incentivized to redirect their investments towards low-carbon initiatives.

4.3. Econometric Methodology and Data

4.3.1. Econometric Methodology

In this section, the econometric methodology includes the Bootstrap Fourier ARDL model and causality tests. As unit root tests are discussed in the second chapter, methodology will not be mentioned here again.

4.3.1.1. Bootstrap Fourier ARDL

The autoregressive distributed lag (ARDL) test is widely employed by researchers as a well-known cointegration technique (Pesaran and Shin, 1995; Pesaran et al., 2001). This test allows for the examination of variables, both in their first differences and levels. However, it is important to note that the dependent variable should be integrated at the first difference level, whereas the independent variables should not exceed an integration order of two. To investigate the effect of different uncertainties on the green bond price, we use the following model:

$$GR_t = \alpha_0 + \alpha_1 EPU_t + \alpha_2 CPU_t + \alpha_3 MPU_t + \varepsilon_t \quad (4.1)$$

where GR, EPU, CPU, and MPU stand for green bond, economic policy uncertainty, climate policy uncertainty, and monetary policy uncertainty, respectively. By employing the ARDL bounds test, we can ascertain the validity of the relationship outlined in Equation 4.1. This equation can then be reformulated into an error-correction representation, facilitating a more nuanced analysis of the dynamics involved.

$$GR_t = \beta_0 + \beta_1 GR_{t-1} + \beta_2 EPU_{t-1} + \beta_3 CPU_{t-1} + \beta_4 MPU_{t-1} + \sum_{i=1}^{p-1} \varphi_i' \Delta GR_{t-1} + \sum_{i=1}^{p-1} \varphi_i' \Delta EPU_{t-1} + \sum_{i=1}^{p-1} \varphi_i' \Delta CPU_{t-1} + \sum_{i=1}^{p-1} \varphi_i' \Delta MPU_{t-1} + e_t \quad (4.2)$$

Regarding the following hypotheses, the F-test or t-test is required for the cointegration test, as stated by Pesaran et al. (2001):

$$H_{0All} = \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0 \quad (4.3)$$

$$H_{0DV} = \beta_1 = 0 \quad (4.4)$$

If null hypotheses (4.3) and (4.4) are rejected, it signifies the presence of a long-term equilibrium between the explanatory factors and those being explained. Within the ARDL model, the F_A test is employed to assess the appropriate lag length for both the dependent and independent variables simultaneously. Conversely, the t-test is specifically employed to

assess the lag length of the dependent variable. When the calculated F_A and t statistics exceed the upper critical value, it leads to the rejection of the null hypothesis. In addition to the F-test and t-test proposed by Pesaran et al. (2001) for cointegration analysis, McNown et al. (2018) recommended incorporating an F_B test. By employing the bootstrap ARDL method, McNown et al. (2018) enhanced the ARDL bounds test, initially developed by Pesaran et al. (2001). This enhancement enabled them to distinguish between three distinct scenarios: cointegration, non-cointegration, and degeneration. They defined the degeneration cases as follows:

Case 1: Cointegration arises when F_A, F_B and t are significant.

Case 2: No-cointegration arises when all statistics are insignificant.

Case 3: Degenerate 1 arises when F_B is insignificant but F_A and t are significant.

Case 4: Degenerate 2 arises when t is insignificant but F_A and F_B are significant.

In the study by Pesaran et al. (2001), critical values for the F_A and t-tests were tabulated and computed for both the lower bound, I(0), and the upper bound, I(1). When the test results fall within these bounds, determining the cointegration becomes challenging. However, McNown et al. (2018) addressed this issue by utilizing bootstrap simulations to calculate the critical values for all three tests, thus eliminating indecision. Furthermore, McNown et al. (2018) demonstrated that bootstrap testing surpasses asymptotic tests in traditional ARDL testing in terms of power and size. The reliability of a model can be affected by structural changes in time series data. Hence, researchers often account for the presence of structural breaks and employ various methodologies. Gallant and Souza (1991) showed that a limited number of low-frequency components in the Fourier approximation can effectively represent an unknown number of sharp and smooth structural breaks. Building on this, Yilanci et al. (2020) adapted the Bootstrap ARDL method proposed by McNown et al. (2018) to incorporate a smooth break using the Fourier function. By integrating the Fourier terms into Equation 4.5, it assumes the following form:

$$GR_t = \beta_0 + \gamma_1 sin\left(\frac{2\pi kt}{t}\right) + \gamma_1 cos\left(\frac{2\pi kt}{t}\right) + \beta_1 GR_{t-1} + \beta_2 EPU_{t-1} + \beta_3 CPU_{t-1} + \beta_4 MPU_{t-1} + \sum_{i=1}^{p-1} \varphi_i' \Delta GR_{t-1} + \sum_{i=1}^{p-1} \varphi_i' \Delta EPU_{t-1} + \sum_{i=1}^{p-1} \varphi_i' \Delta CPU_{t-1} + \sum_{i=1}^{p-1} \varphi_i' \Delta MPU_{t-1} + e_t \quad (4.5)$$

Bootstrap simulation is employed to derive the critical values for F_A, F_B, and t. To determine the presence of a cointegration relationship between variables, the computed test statistic values must surpass the absolute value of the bootstrap critical values.

4.3.1.2. Granger Causality based on ECM

The efficient market hypothesis for the green bond market, whether green bond markets are effective under uncertainty in the short term, was investigated using the Granger causality test based on The Error Correction Model. ECM is employed to correct the disequilibrium and examine the causal relationship in the cointegrated variable for both the short- and long-term periods.

$$\Delta S\&P = \beta_0 + \sum_{i=1}^{q} \alpha_{2i} \Delta EPU_{t-1} + \sum_{i=1}^{q} \alpha_{3i} \Delta CPU_{t-1} + \sum_{i=1}^{q} \alpha_{1i} \Delta MPU_{t-1} + \theta_1 ECT_{t-1} + \epsilon_{1t} \quad (4.6)$$

$$\Delta Solactive = \partial_0 + \sum_{i=1}^{q} \emptyset_{1i} \Delta Solactive_{t-1} + \sum_{i=1}^{p} \emptyset_{2i} \Delta EPU_{t-1} + \sum_{i=1}^{q} \emptyset_{3i} \Delta CPU_{t-1} + \sum_{i=1}^{q} \emptyset_{1i} \Delta MPU_{t-1} + \theta_2 ECT_{t-1} + \epsilon_{1t} \quad (4.7)$$

Once a long-term relationship is identified, the variables can be subjected to a Granger causality test using the short-term equations (4.6 and 4.7). The hypotheses to be established are as follows:

H_0: $\alpha_{2i} = 0$; $\emptyset_{2i} = 0$ (There is no causality from EPU to S&P and from EPU to Solactive in the short run)

H_1: $\alpha_{2i} \neq 0$; $\emptyset_{2i} \neq 0$ (There is causality from EPU to S&P and from EPU to Solactive in the short run)

H_0: $\alpha_{3i} = 0$; $\emptyset_{3i} = 0$ (There is no causality from CPU to S&P and from CPU to Solactive in the short run)

H_1: $\alpha_{3i} \neq 0$; $\emptyset_{3i} \neq 0$ (There is causality from CPU to S&P and from CPU to Solactive in the short run)

H_0: $\alpha_{4i} = 0$; $\emptyset_{4i} = 0$ (There is no causality from MPU to S&P and from MPU to Solactive in the short run)

H_1: $\alpha_{4i} \neq 0$; $\emptyset_{4i} \neq 0$ (There is causality from MPU to S&P and from MPU to Solactive in the short run)

One of the methods used to determine the presence of a causality relationship between variables and green bonds in the long term is to test whether the error correction term coefficient is equal to zero. The hypotheses to be established are as follows:

H_0: $\theta_1 = 0$; $\theta_2 = 0 = 0$ (There is no causality from EPU, CPU and MPU to S&P and from EPU, CPU and MPU to Solactive in the long run)

H_1: $\theta_1 \neq 0$; $\theta_2 \neq 0$ (There is causality from EPU, CPU and MPU to S&P and from MPU to Solactive in the long run)

4.3.1.3. Time Varying Granger Causality Test

We have also applied the rolling window approach Granger causality test based on the modified bootstrap developed by Balcılar et al. (2010) to examine the effects of structural changes between green bonds and CPU, EPU, and MPU. Structural changes can lead to alterations in the parameters and causality patterns over time. To address these issues and account for the non-constancy of the parameters, we conducted a bootstrap causality test for rolling window sub-samples at t=τ-l+1, τ-l,…,τ, τ=l, l+1, …, T as specified in Equations 4.8, 4.9, and 4.10, where l denotes the size of the rolling window.

$$S\&P_{1t} = \beta_{10} + \beta_{11}(L)S\&P_{1t} + \beta_{12}(L)EPU_{2t} + \varepsilon_{1t} \quad (4.8)$$

$$S\&P_{2t} = \phi_{10} + \phi_{11}(L)S\&P_{1t} + \phi_{12}(L)CPU_{2t} + \varepsilon_{2t} \quad (4.9)$$

$$S\&P_{3t} = \alpha_{10} + \alpha_{11}(L)S\&P_{1t} + \alpha_{12}(L)MPU_{2t} + \varepsilon_{3t} \quad (4.10)$$

Where $\beta_{ij}(L) = \sum_{k=1}^{p} \beta_{ij,k} L^k$, $i, j = 1,2$ and L is the lag operator defined as $L^k x_t = x_{t-k}$. The hypotheses to be established are as follows:

The hypotheses to be established are as follows:

H_0: $\beta_{12,1} = \beta_{12,2} = \beta_{12,p} = 0$ (There is no causality from EPU to S&P)

H_0: $\beta_{12,1} \neq \beta_{12,2} \neq \beta_{12,p} \neq 0$ (There is causality from EPU to S&P)

H_0: $\phi_{12,1} = \phi_{12,2} = \phi_{12,p} = 0$ (There is no causality from CPU to S&P)

H_0: $\phi_{12,1} \neq \phi_{12,2} \neq \phi_{12,p} \neq 0$ (There is causality from CPU to S&P)

H_0: $\alpha_{12,1} = \alpha_{12,2} = \alpha_{12,p} = 0$ (There is no causality from MPU to S&P)

H_0: $\alpha_{12,1} \neq \alpha_{12,2} \neq \alpha_{12,p} \neq 0$ (There is causality from MPU to S&P)

4.3.2. Data

Our main objective in this chapter is to investigate the effects of different uncertainty indices on green bond prices. The S&P Green Bond price index and the Solactive Green Bond price index started in November 2008 and January 2012, respectively, so different periods were selected for the two different green bond series. We analyze the pattern of the green bond price and its altering features based on economic policy uncertainty, climate, and macroeconomic risk profiles. We use a modified ARDL cointegration test with a Fourier function in order to test this link.

In this paper, we use a data set of monthly observations for the worldwide green bond market with the S&P Dow Jones GB Index (S&P), the Solactive Green Bond Index (Solactive), the economic policy uncertainty index (EPU), the climate policy uncertainty (CPU), the macroeconomic policy uncertainty (MPU). To correct for potential heteroscedasticity and dimensional differences between series, all original data were processed by taking natural logarithms (Li et al., 2016).

To assess policy-related economic uncertainty, Baker et al. (2016) created an index using EPU reports from 10 major newspapers (Wall Street Journal, Dallas Morning News, USA Today, Chicago Tribune, Miami Herald, Washington Post, Boston Globe, Los Angeles Times, San Francisco Chronicle, and Houston Chronicle). They have conducted a search within the digital archives of each publication using the following keywords: uncertain or uncertainty; economic or economy; and one or more of the following terms: deficit, congress, Federal Reserve, legislation, White House, or regulation.

Gavriilidis (2021) has constructed the Climate Policy Uncertainty index by following the methodology described in the research carried out by Baker et al. (2016). The authors searched eight prominent US newspapers for articles containing uncertainty, climate change, climate risk, greenhouse gas emissions, CO2 emissions, global warming, climate change, green energy, renewable energy, and so on. Additionally, Baker et al. (2016) have generated data that includes a number of sub-indices, such as MPU. The Access World News database, which contains more than 2,000 newspapers from the United States, was used to construct these indices. Every sub-index necessitates the utilization of our economic, uncertainty, and policy terms, in addition to a collection of categorical policy terms.

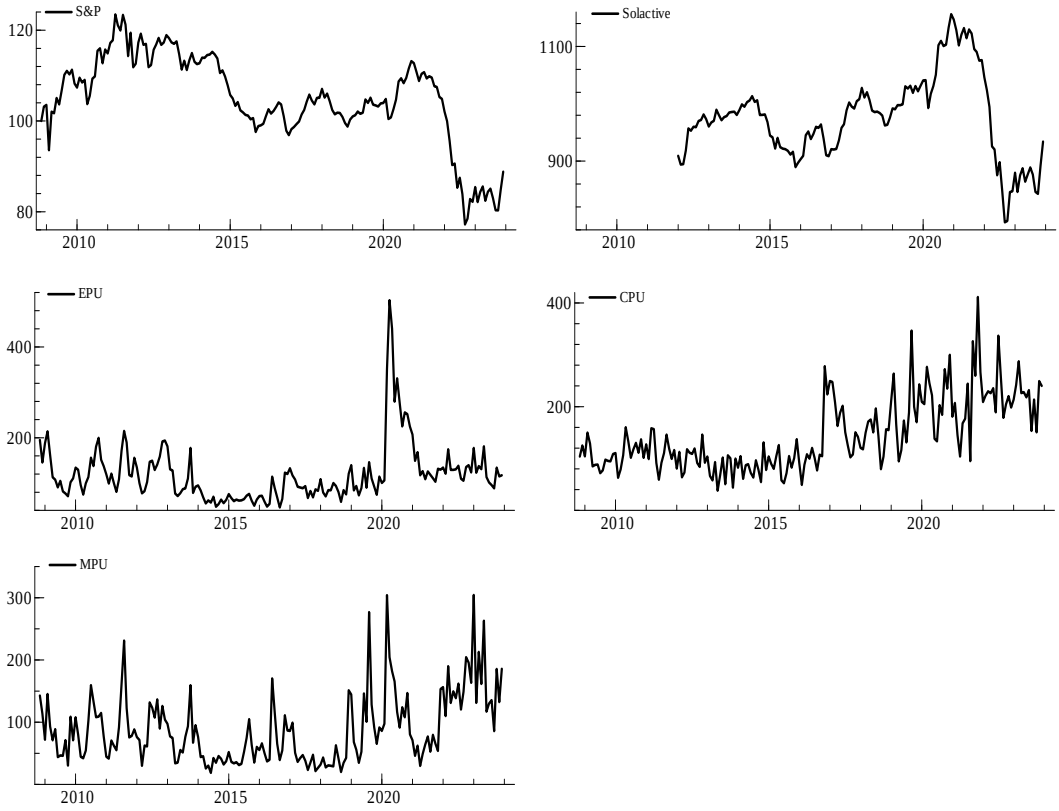


Figure 4.1. Time series graph of variables

Before we discuss the inferences from the analysis, it is better to mention some of the general observations related to the data properties. Figure 4.1 plots S&P, Solactive, EPU, MPU, and CPU. The S&P green bond pricing began in December 2008, whereas the Solactive green bond began in January 2012. The S&P index has fluctuated over the years, with its lowest price reaching 77.2 and its highest price reaching 123.5 between the period

of December 2008 and December 2023. The green bond market grew continuously until 2011, ending at its peak price this year. The S&P index, which has been in a declining trend since 2014, had modest declines throughout the period of the Covid-19 pandemic. However, it has once again begun to rise. In early 2022, the Federal Reserve started a rise in interest rates. The interest rate rose by 0.75 percentage points for four successive months, beginning in June, resulting in the S&P green bond price reaching its lowest point in September. Although the same trend is observed in the Solactive green bond price compared to S&P, the magnitude of its fluctuations is greater than that of S&P. A significant shift in the level of uncertainty around monetary policy was seen during the period spanning from 2009 to 2023. Unconventional monetary policies were adopted in response to the financial crisis, and specific events between 2008 and 2015 caused sudden increases in the uncertainty surrounding both monetary and economic policies. Examples that might be highlighted include the worsening of the European debt crisis in 2011 and the shutdown incident in October 2013 (Baker et al., 2016). The Brexit referendum in June and the presidential elections in November were identified as key factors contributing to the increase in monetary policy uncertainty and subsequent changes in 2016. The beginning of the pandemic marked the highest level of uncertainty within the historical framework under consideration. The uncertainty in economic policy also increased significantly at the beginning of the pandemic. Nevertheless, the considerable increase in inflation following 2022, coupled with the Federal Reserve's unexpected tightening of monetary policy, has once again increased the level of uncertainty related to monetary policy (Lastauskas and Nguyen, 2024:2). The changing levels of uncertainty regarding the climate policy remained stable until 2017. However, Trump, who won the election and became president on November 8, 2016, said that the US would leave the Paris Agreement. The withdrawal of the United States from the Paris Agreement in 2017 resulted in a significant increase in uncertainty regarding climate policy. This event had a detrimental impact on the advancement of long-term objectives and international cooperation about climate change. Because the United States has reduced its climate change budget and stopped donations to multinational environmental funds (Zhang et al., 2017; 213). With the outbreak of the pandemic, climate policy uncertainty increased again. The postponement of the United Nations Climate Change Conference serves as a clear illustration of the significant influence of COVID-19 on the uncertainty surrounding climate policy (Raza et al., 2024:8). The 2022 Russian invasion of Ukraine raised vulnerability to climate change, hampered efforts to reduce carbon emissions, and hindered collaborative

climate initiatives. This has also resulted in increased uncertainty about climate policy (Brown et al., 2023).

Table 4.1. Descriptive statistics

	S&P	Solactive	EPU	CPU	MPU
Mean	105.02	975.62	119.75	145.40	89.02
Median	105.01	979.08	108.15	122.83	75.18
Maximum	123.49	1156.21	503.01	411.29	304.29
Minimum	77.22	793.3	46.39	38.09	18.68
Std. Dev.	9.84	73.62	63.43	69.03	55.84
Skewness	-0.79	0.24	2.69	0.95	1.33
Kurtosis	3.44	3.05	13.76	3.60	5.05
Jarque-Bera	20.25	1.437	1098.29	30.20	85.62
Probability	0.00	0.00	0.00	0.00	0.00
Observations	182.00	144	182.00	182.00	182.00

Table 4.1 displays the descriptive statistics for the five indices. When comparing the variability of the green bond indices to the uncertainty indices, we observe that the variability of the two green bond markets, particularly S&P, is lower. The climate policy uncertainty index exhibits the highest variability, with a standard deviation of 69. Except for the S&P green bond, all series have positive skewness, indicating that they are skewed to the right. The right-skewness of the series indicates that most observations have values lower than the mean. The S&P series is skewed to the left because of its negative values. Consequently, the majority of observations in the series have values that exceed the average. Since the kurtosis values exceed three, it indicates that all series in our sample have fat-tail distributions. This means the variability of the series is not homogeneous. The Jarque-Bera (JB) test indicates a rejection of the null hypothesis of normality with a significance level of 1%. This test provides evidence that none of the series being examined follows a normal distribution.

Table 4.2. Correlation matrix

	S&P	*Solactive*	*EPU*	*CPU*	*MPU*
S&P	1	0.643	-0.01	-0.496	-0.345
Solactive	0.643	1	0.253	0.081	-0.210
EPU	-0.01	0.253	1	0.516	0.705
CPU	-0.496	0.081	0.516	1	0.498
MPU	-0.345	-0.210	0.705	0.498	1

Table 4.2 displays the correlation matrix. The correlation between the prices of S&P green bonds and Solactive green bonds is positive at around 0.64. The S&P and economic policy uncertainty exhibit a negative correlation of -0.01, representing the lowest value. The S&P and climate policy uncertainty have a negative correlation of -0.496, which is the strongest seen. With regard to the price of the Solactive green bond, there is a positive correlation with both the EPU and the CPU; however, the correlation with the MPU is negative and -0.21. When the correlation between the uncertainty indices is examined, it is demonstrated that all three indices have positive effects on one another.

4.4. Empirical Results

In this chapter, we first apply the Phillips-Perron (PP) test and the Augmented Dickey-Fuller (ADF) test, two common unit root tests, to the series. The results of these tests are presented in Table 4.3. The ADF test result for the S&P index indicates that the test statistic value for the constant model is -1.905, while the test statistic value for the constant and trend model is -3.088. Both model test statistic values are lower than the critical values. When we look at the probability values, we can see that they are greater than 10%. The null hypothesis of the series containing a unit root was not rejected. Therefore, it is concluded that the S&P series exhibits a unit root at level. When the difference in the S&P series is taken, and the ADF test is applied again, the null hypothesis is rejected at the five percent level in the constant model and at the 10 percent level in the constant and trend model. Therefore, it can be concluded that the series is stationary to the first degree. Similarly, in the ADF test for Solactive, the null hypothesis cannot be rejected because the critical value in both the constant and the constant and trend models is lower than the critical values in absolute value. It has been determined that Solactive exhibits a unit root at the same

level. When the Augmented Dickey-Fuller (ADF) test is reapplied by calculating the difference of the series, the critical values at the 1 percent significance level in the model with both models are greater than the critical values in the table when considering absolute values. Thus, it may be concluded that the series is a first-order stationary process. Upon evaluating the CPU index findings, we observe that the test statistic for the constant model of the ADF unit root test is smaller in absolute value compared to the critical values. Thus, the series has a unit root. Using the constant and trend model, the index test statistic at the 1% significance level is larger than the critical values. Therefore, it is stated that the series is stationary at the level. According to the results of the last two uncertainty indices (EPU and MPU), the null hypothesis is rejected at the 1 percent significance level for both the model with constant and the model with constant and trend. Therefore, it is found that both series are stationary at level.

The PP test results for the S&P indicate that the test statistic values are less than the critical values in absolute terms for both models. Thus, the null hypothesis cannot be rejected, indicating the presence of a unit root at the level. After taking the difference in the S&P series and applying the PP test, it is found that the null hypothesis is rejected at the 1 percent significance level in both models. This indicates that the series is considered to be stationary of degree 1. Similarly, in the case of the Solactive price series, the null hypothesis cannot be rejected, as the critical value in both the constant and trend models of the PP test is lower than the table values in absolute value. Therefore, Solactive has a unit root. When the PP test is applied again to the first difference of the series, it is seen that it is constant and stationary at the 1 percent level in the trend model. All uncertainty indices reject the null hypothesis at the 1% significance level for both models. Thus, it can be concluded that all of these indices exhibit stationarity at the level.

Table 4.3. ADF and PP unit root test results

Variables	*Level*			
	ADF		*PP*	
	Constant	*Constant & Trend*	*Constant*	*Constant & Trend*
GR	-1.905 (0.329)	-3.088 (0.112)	-1.201 (0.673)	-2.587 (-4.009)
Solactive	-1.726 (0.416)	-1.694 (0.749)	-2.052 (0.264)	-2.004 (0.593)
EPU	-4.313*** (0.000)	-4.398*** (0.002)	-4.133*** (0.001)	-4.217 (0.005)
CPU	-0.885 (0.790)	-4.762*** (0.000)	-5.360*** (0.000)	-8.118 (0.000)
MPU	-2.914** (0.045)	-5.694*** (0.000)	-5.187*** (0.000)	-5.585 (0.000)
Variables	*First Differences*			
	ADF		*PP*	
	Constant	*Constant & Trend*	*Constant*	*Constant & Trend*
GR	-3.30** (0.016)	-3.421* (0.051)	-14.62*** (0.000)	-14.66*** (0.000)
Solactive	-10.14*** (0.000)	-10.154*** (0.000)	-10.19*** (0.000)	-10.16*** (0.000)
EPU	-10.28*** (0.000)	-10.27*** (0.000)	-19.93*** (0.000)	-19.98*** (0.000)
CPU	-5.91*** (0.000)	-5.90*** (0.000)	-50.23*** (0.000)	-56.45*** (0.000)
MPU	-9.81*** (0.000)	-9.82*** (0.000)	-34.72*** (0.000)	-54.71*** (0.000)

Note: *, **, and *** represent causal relationships with significance levels of 10%, 5%, and 1%, respectively.

Table 4.4 summarizes the outcomes of the different Fourier-based unit root test results. According to the Fourier ADF test results proposed by Christopoulos-León-Ledesma (2010), the test statistics for S&P that are computed in models that include a constant, as well as models that include a constant and trend, are less than the critical values[1] that correspond to them. This suggests that S&P contains a unit root. Similarly, Solactive has the same result. The reason is that all critical values, including 1%, 5%, and 10%, are higher in absolute value than the test statistic. Consequently, the null hypothesis remains unchallenged, indicating the presence of a unit root in the series. As a result, the null hypothesis is not rejected, indicating that the series contains a unit root. Examining the results of EPU, CPU, and MPU subjected to Fourier-based unit root tests reveals that the calculated test statistics for both the constant and constant and trend models are greater than the critical values, indicating that they are stationary at the level. Due to the stationarity of the series, the significance of the Fourier terms should be tested using the F-test. Since

the F-test statistic is greater than the critical values at the 1% level, the null hypothesis is rejected. Hence, it can be concluded that the trigonometric terms are statistically significant.

Table 4.4. Unit root test basic on Fourier term results

Christopoulos- León-Ledesma (2010) Fourier ADF (Constant Model)					
Variables	GR	Solactive	EPU	CPU	MPU
Test statistics	-1.767	-2.037	-4.922***	-6.681***	-5.393***
Frequency	2	2	1	1	1
Lags	1	0	1	1	1
$F_m(k)$ statistics	52.154	39.349	39.947***	99.791***	34.238***
Christopoulos- León-Ledesma (2010) Fourier ADF (Constant and Trend Model)					
Variables	GR	Solactive	EPU	CPU	MPU
Test statistics	-3.128	-2.083	-4.942***	-7.433***	-5.828***
Frequency	2	2	1	1	1
Lags	1	0	1	1	1
$F_m(k)$ statistics	119.358	45.719	37.939	28.972	36.378
Christopoulos- León-Ledesma (2010) Fourier KSS (Constant Model)					
Variables	$S\&P$	Solactive	EPU	CPU	MPU
Test statistics	-2.165	-2.468	-2.148	-4.278***	-5.438***
Frequency	2	2	1	1	1
Lags	1	0	1	1	1
$F_m(k)$ statistics	52.154	39.349	39.947	99.791	48.932
Christopoulos- León-Ledesma (2010) Fourier KSS (Constant and Trend Model)					
Variables	$S\&P$	Solactive	EPU	CPU	MPU
Test statistics	-3.537	-2.842	-2.186	-4.537**	-4.774***
Frequency	2	2	1	1	1
Lags	1	0	1	1	1
$F_m(k)$ statistics	119.358	45.719	37.939	28.972	36.378
Becker-Enders-Lee (2006) Fourier KPSS (Constant)					
Variables	$S\&P$	Solactive	EPU	CPU	MPU
Test statistics	8.07	1.547	0.061***	0.248*	0.142**
Frequency	2	2	1	1	1
$F_m(k)$ statistics	52.154	39.349	39.947	99.791	34.238

Becker-Enders-Lee (2006) Fourier KPSS (Constant and Trend)					
Variables	*S&P*	Solactive	*EPU*	*EPU*	*MPU*
Test statistics	0.919	0.736	0.056*	0.042***	0.028***
Frequency	2	2	1	1	1
$F_m(k)$ statistics	119.35	45.719	37.939	28.972	36.378

Note: *and *** represent causal relationships with significance levels of 10% and 1%, respectively.

Within the scope of this study, the SOR unit root test models A, B, and C, proposed by Shahbaz et al. (2019), were applied to the entire dataset. Table 4.5 displays the findings from the relevant unit root tests. According to the data in Table 4.5, it is observed that the test statistics for the level of the series in models A, B, and C are smaller than the critical values based on the values obtained for both green bond series. This indicates that they contain a unit root at the level. Furthermore, the test statistics for the CPU, MPU, and EPU variables in Models A, B, and Model C are greater than the critical values at the 1% significance level. Consequently, the null hypothesis is rejected, suggesting that the level values of these series are stationary.

The SOR test distinguishes itself from alternative tests by accounting for both sharp and smooth breaks within the model. In spite of the fact that the results of other tests are inconsistent, with the exception of the green bond series, this study highlights noteworthy findings in model A: for economic policy uncertainty, there is one sharp break and two smooth breaks; for climate policy uncertainty, monetary policy uncertainty, there is one sharp break and one smooth break each, which indicates that there is a stationary process in each uncertainty index at the level. This intricate data structure poses challenges for simple unit root test procedures to capture adequately. Consequently, it suggests that tests failing to consider the broader data structure may result in misidentified models, potentially yielding misleading findings (Shahbaz et al., 2019)

Table 4.5. SOR unit root test results

Models	*Model A*		*Model B*		*Model C*	
Variables	*Test Statistic*	*Frequency*	*Test Statistic*	*Frequency*	*Test Statistic*	*Frequency*
S&P	-3.559	1	-3.218	2	-3.417	2
Solactive	-3.404	1	-3.664	1	-3.765	1
EPU	-5.749***	2	-5.796***	2	-6.287***	2
CPU	-7.869***	1	-7.772***	6	-8.879***	3
MPU	-4.483***	1	-5.853***	7	-5.973***	7

Note: *** represents a causal relationship with a significance level of 1%.

The different results of unit root tests indicate that S&P and Solactive are non-stationary at the I(0) level but become stationary at the I(1) level when conventional unit root tests are applied to the relationship between green bonds and various uncertainty indices. The results of the other series that were included in the analysis vary depending on the unit root test that was performed; nonetheless, when they were differentiated, they were all determined to be stationary. Due to the varying degrees of cointegration among the series, the ARDL cointegration approach has been preferred to determine the existence of long-term relationships. Structural breaks have also been considered by incorporating sharp and smooth breaks into the ARDL model. This way, the aim is to determine the most effective methodology.

Table 4.6. Bootstrap Fourier ARDL results for S&P

Dependent: S&P	*k*	*AIC*	*LAGS*
Model: $F_1(GB, EPU, CPU, MPU)$	*2*	*-4.599*	*(1, 1, 4, 0)*
	Bootstrap Critical Values		
F_A = 4.796**	*0.9*	*0.95*	*0.99*
	3.951	4.597	6.483
	Bootstrap Critical Values		
t = -3.38*	*0.9*	*0.95*	*0.99*
	-3.31	-3.64	-4.36
	Bootstrap Critical Values		
F_B = 5.448**	*0.9*	*0.95*	*0.99*
	3.789	4.517	6.326

Note: * and ** represent causal relationships with significance levels of 10% and 5%, respectively.

The results of the cointegration tests are presented in Tables 4.6 and 4.7. In the first model, a cointegration relationship has been found between the dependent variable, which comprises two different green bonds, and the independent variables, which are economic policy uncertainty, climate policy uncertainty, and monetary policy uncertainty.

The first model considers the S&P as the dependent variable, whereas the independent variables are EPU, CPU, and MPU. The F_A test statistic with a value of 4.79, which is used to evaluate the significance of all variables in the model, is significant at the 5% level; the t statistic with a value of -3.38, which tests the significance of only the dependent variable, is significant at the 10% level; and the F_B statistic with a value of 5.44, which checks the significance of only the independent variables, is significant at the 5% level. These results demonstrate the existence of a long-term link between CPU, MPU, EPU, and S&P.

In our second model, the Solactive variable is the dependent variable, while the EPU, CPU, and MPU variables are independent variables. The Fa test statistic for all variables in the model is significant at the 5% level, the t statistic for only the dependent variable is significant at the 1% level, and the F_B statistic for only the independent variables is significant at the 5% level. These results demonstrate that there is a long-term link between CPU, MPU, EPU, and Solactive.

Table 4.7. Bootstrap Fourier ARDL results for Solactive

Dependent: Solactive	*k*	*AIC*	*LAGS*
$F_1(GB, EPU, CPU, MPU)$	*5*	*-5.033*	*(1,1,2,0)*
	Boostrap Critical Values		
F_A = 5.190***	*0.9*	*0.95*	*0.99*
	3.212	3.783	5.159
	Boostrap Critical Values		
t = -3.819**	*0.9*	*0.95*	*0.99*
	-2.891	-3.277	-3.850
	Boostrap Critical Values		
F_B = 5.257***	*0.9*	*0.95*	*0.99*
	3.058	3.728	5.244

Note: * and ** represent causal relationships with significance levels of 10% and 5%, respectively.

Table 4.8. Bootstrap Fourier ARDL long-term results for Solactive and S&P

Variables	Dependent: Solactive	Dependent: S&P
Constant	6.459***	4.919***
	(0.000)	(0.000)
EPU	0.277***	0.222***
	(0.000)	(0.001)
CPU	-0.088*	-0.219***
	(0.072)	(0.000)
MPU	-0.098***	-0.066*
	(0.000)	(0.055)

Note: * and *** represent causal relationships with significance levels of 10% and 1%, respectively. The numbers in parenthesis represent probability values.

The results presented in Table 4.8 are derived from the bootstrap Fourier ARDL estimation. The first column displays the variables included in the model, while the second column presents the long-term coefficients and probability values that indicate the influence of changes in economic, climate, and monetary policy uncertainties on S&P. The second column displays the coefficients and probability values of the independent variables, indicating their impact on Solactive.

The economic policy uncertainty index for S&P is statistically significant at the 1% level. Based on this finding, a 1 % rise in economic policy uncertainty will result in a 0.22 percent increase in the price of S&P green bonds. Climate policy uncertainty has a negative and statistically significant impact on S&P at the one percent level. In this context, a one percent increase in climate policy uncertainty will result in a 0.219 percent fall in the price of S&P green bonds. When compared to the other independent factors, the uncertainty in monetary policy has a small effect. MPU, which exhibits statistical significance at the 10 percent level, has a negative effect on S&P. Based on these findings, a 1 percent increase in the uncertainty surrounding monetary policy will lead to a 0.066 percent fall in the price of the S&P green bond index.

The economic policy uncertainty index for Solactive exhibits a statistically significant relationship at the 1 percent level, with a positive coefficient. Within this framework, a 1 percent rise in economic policy uncertainty will result in a 0.277 percent increase in the price of the Solactive green bond. There is a statistically significant negative impact of climate policy uncertainty on Solactive, with a significance level of 1 percent.

Based on these findings, a 1 percent rise in CPU will result in a 0.088 percent decline in the price of the Solactive green bond. The statistical significance of monetary policy uncertainty at the 1 percent level indicates that it has a negative impact on Solactive. This indicates that a 1% increase in monetary policy uncertainty will lower S&P by 0.098 percent.

Based on the diagnostic results of the Bootstrap ARDL analysis (see Appendix C), it is determined that there is no autocorrelation or heteroskedasticity issues for the S&P index. Regarding stability diagnosis, the results indicate that CUSUM and CUSUM square are stable. According to the Ramsey Reset test results, the null hypothesis indicating that the model is correctly specified in terms of functionality cannot be rejected. Thus, it can be said that the model is correctly specified in terms of functionality. However, for the Solactive green bond, a heteroskedasticity issue is identified. To address this problem, Newey-West robust estimators have been employed.

We employed the FMOLS, DOLS, and CCR estimators to verify the consistency of the bootstrap Fourier ARDL long-run estimation. Table 4.9 shows the results of these methods. The impact of economic policy uncertainty on all three forecasting approaches for S&P is both statistically significant and positive. Their coefficients are roughly 0.20. When uncertainty increases by one percent, the price of S&P will rise by 0.20 percent. The outcomes of these three robust estimation techniques support the estimated outcome derived from bootstrap Fourier ARDL. The same outcome is valid for climate policy uncertainty. The CPU coefficient is negative and statistically significant at the 1% level for all techniques. Since their coefficients are so close to one another, the S&P price would decrease by roughly 0.15 for every 1% rise in CPU. Finally, the CPU coefficient for all three techniques is negative and significant at the 1% level. A rise in uncertainty would result in a decrease in the S&P price by almost 12 percent.

In the results for Solactive, the impact of economic policy uncertainty is statistically significant and positive. The EPU coefficient in all three approaches is 0.17. When uncertainty increases by one percent, the price of the S&P will increase by 0.20 percent. The results of the strong long-term prediction methods show that the CPU coefficient is positive but not statistically significant. The coefficients of MPU are negative and statistically significant at the one percent level. Bootstrap Fourier ARDL results are validated by all variables for Solactive, with the exception of CPU.

Table 4.9. FMOLS, DOLS and CCR long-term results

FMOLS		
Variables	Dependent: S&P	Dependent: Solactive
Constant	4.969*** (0.000)	6.542*** (0.000)
EPU	0.198*** (0.000)	0.172*** (0.000)
CPU	-0.149*** (0.000)	0.012 (0.573)
MPU	-0.121*** (0.000)	-0.122*** (0.000)
DOLS		
Constant	4.978*** (0.000)	6.553*** (0.000)
EPU	0.200*** (0.000)	0.173*** (0.000)
CPU	-0.156*** (0.000)	0.011 (0.618)
MPU	-0.117*** (0.000)	-0.124*** (0.000)
CCR		
Constant	4.974*** (0.000)	6.540*** (0.000)
EPU	0.201*** (0.000)	0.172*** (0.000)
CPU	-0.152*** (0.000)	0.014 (0.562)
MPU	-0.122*** (0.000)	-0.124*** (0.000)

Note: *** represents a causal relationship with a significance level of 1%. The numbers in parenthesis represent probability values.

Table 4.10. Granger causality test results based on ECM

Dependent variable	Short-run			Long-run
	EPU	CPU	MPU	ECT_{t-1}
S&P	0.954 (0.341)	4.053*** (0.003)	0.265 (0.606)	37.859*** (0.00)
Solactive	1.272 (0.261)	1.079 (0.342)	1.792 (0.182)	31.129*** (0.000)

Note: *** represents a causal relationship with a significance level of 1%. The numbers in parenthesis represent probability values.

Table 4.10 the Wald statistics values for the lagged explanatory uncertainty variables of the ECM. These results indicate whether economic policy, climate policy, and monetary policy uncertainty have a short-term causal effect on the price of S&P (Solactive) green bonds. A further point to consider is that there are Wald statistic results that demonstrate long-term causation between all uncertainty indices and the green bond through the ECT coefficient. Starting with the short-term effects of economic policy uncertainty, the F-statistic for EPU has no statistical significance for S&P. Therefore, there is no causality from EPU to S&P in the short-run. Another uncertainty indicator, the causality results of climate policy uncertainty on S&P, shows that the F statistical value is significant at the five percent significance level. Thus, it may be concluded that there is a short-term causality from EPU to S&P. Lastly, we observe that the F-statistic value is not significant when we examine the causality results from MPU to S&P. Therefore, there is no causality from EPU to S&P in the short-run. To determine if there is a causal association between all uncertainty indices and the long-term price of S&P green bonds, the significance of the ECT coefficient is assessed using the Wald t-statistic. Based on the findings, the Wald t-statistic exhibits statistical significance at the one percent significance level. From this context, it is possible to conclude that the independent variables have a long-term causal effect on S&P.

When we examine the short-term causality results from CPU, MPU, and EPU to the price of the Solactive green bond, we observe that none of the Wald statistics are significant. Within this framework, it is stated that there is no short-term causal relationship from CPU to Solactive, from EPU to Solactive, and from MPU to Solactive. On the other hand, when we consider the long run, we can assert that there is a causal relationship going in the direction of Solactive among all of the variables.

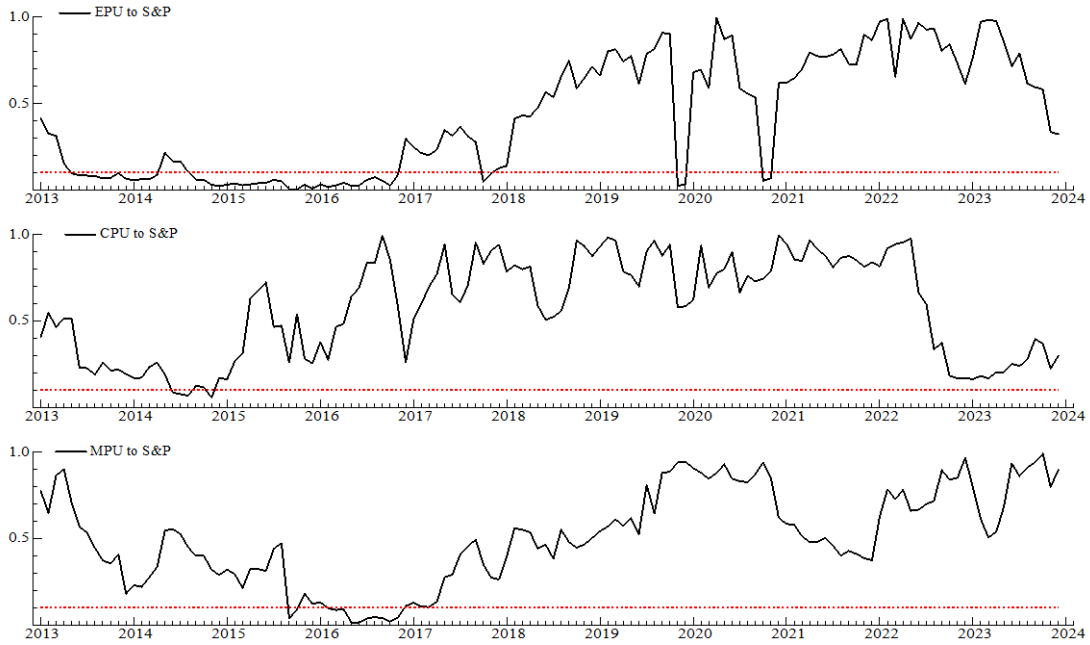


Figure 4.2. Time varying causality for S&P

Note: The red line indicates 10% critical values.

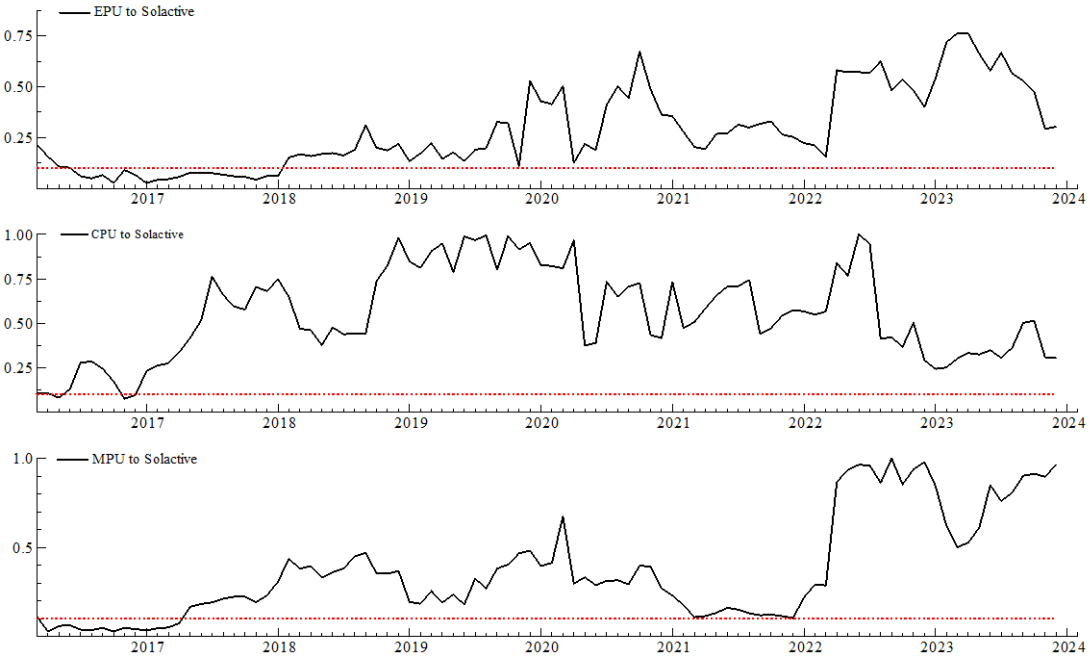


Figure 4.3. Time varying causality for Solactive

Note: The red line indicates 10% critical values.

It is possible to determine the presence of causality over the entire time span, as well as conduct a Granger causality test for each of the time intervals. The second and third figures show time-varying causality results. The government shutdown in October 2013, the Brexit referendum, and the 2016 presidential elections resulted in variations in economic policy uncertainty over these timeframes. During this time period, a clear relationship can be shown between economic policy uncertainty and the performance of the S&P (Solactive) index. During the initial stages of the Covid-19 pandemic, there was a high level of uncertainty in economic policy. It was during this time that a causal relationship was observed between Economic Policy Uncertainty (EPU) and the performance of the S&P (Solactive) index. Ultimately, it was once again determined that there was a direct relationship between Economic Policy Uncertainty (EPU) and the performance of the S&P index during the presidential elections at the end of 2020. When we look at the results of the time-dependent causality analysis from climate policy to S&P (Solactive), it is observed that there is an unclear causality at the ten percent significance level from CPU to S&P (Solactive) in mid-2014. This year, the level of uncertainty in climate policy is relatively stable and low. The Federal Reserve's initial hike in interest rates in late 2015, following the 2008 financial crisis, along with the previously stated occurrences of Brexit and the presidential elections in 2016, align with the timeframe in which there is a causal relationship from the Monetary Policy Uncertainty (MPU) to the Standard & Poor's (S&P) index.

4.5. Conclusion

Financial markets are influenced by various factors, such as social and political events, economic situations, central bank policies, company performance, global trade connections, natural disasters, technological developments, and societal attitudes. Decision-makers in uncertainty often struggle to define problems, capture data, and synthesize knowledge to establish decision-making rules. Researchers have used various measures of uncertainty, such as the standard deviation of stock returns and stock market volatility. However, these indicators may not accurately reflect conventional uncertainty due to differences in liquidity and depth in the market. In recent years, there has been an increase in the number of unique indices made to quantify uncertainty, such as the economy policy uncertainty index constructed by Baker et al. (2016), a text-based uncertainty index created by Manela and Moreira (2017), climate policy uncertainty index developed by Gavriilidis (2021), etc. Researchers have noted that, in periods of heightened uncertainty, companies

tend to reduce their investments, increase their savings, decrease their consumption, notice an increase in exchange rate volatility, and observe an increase in financial market volatility.

Fluctuations in financial markets and the factors affecting them can be explained within the efficient market framework developed by Fama (1970). Market efficiency implies that all available information in a market is completely represented in stock prices. Although this concept has its roots in the nineteenth century, it was not formally established until 1970 by Fama. All participants have full information, and no investor controls prices in an efficient market. Investors exhibit rational behavior by reacting correctly to new information and are not likely to make excessive profits in such a market.

Studies on the efficiency of the green bond market under uncertainty are quite limited. The majority of research conducted on the green bond market, which has had substantial advancements over the past 15 years, has primarily concentrated on establishing the correlation between these bonds and other financial markets, as well as assessing their potential as a portfolio instrument. Despite recent research efforts, studies investigating the effect of uncertainty on the returns of green bonds remain insufficient. In this context, the purpose of this study is to explain how the efficiency of the green bond market is affected by climate policy, monetary policy, and economic policy uncertainty by employing econometric methodologies in both the short- and long-term.

Green bond markets are still classified as emerging markets compared to conventional bond markets. However, its popularity has increased even more as a result of the rapid growth of this market, its long-term sustainability and environmental friendliness, and its perception as an alternative investment choice for risk-averse investors. Our analysis included the prices of S&P green bonds and Solactive green bonds. S&P green bond prices were initiated in November 2008, while the Solactive green bond pricing began in January 2012. As a result, this research was conducted over two distinct periods. Studies have relatively explored the effects of economic policies on green bonds. However, the impacts of climate policies and monetary policies on green bond markets remain insufficiently examined. This study presents an opportunity to understand the relationships between green bonds and monetary and climate policies and their economic implications. Moreover, this study contributes to the advancement of econometric methodology and offers a more comprehensive understanding of the economic and financial impacts of green bonds. This

constitutes a significant step towards making more effective and informed decisions in sustainable finance and climate policy. Therefore, the literature has been expanded by methodological advancements. The ARDL cointegration approach is chosen to determine the presence of long-term associations due to the different levels of cointegration among the series. The inclusion of sudden and gradual changes in the ARDL model has also taken into account structural fractures. This way, the aim is to determine the most efficient process. Furthermore, the efficiency of the short-term green bond market in specific periods was examined using both the ECM-based Granger causality test and time-varying Granger causality tests.

From a financial and economic perspective, countries becoming more integrated with each other, recent conflicts in trade between China and the US, uncertainties caused by the COVID-19 pandemic, and governments' unclear tax, expenditure, and other regulatory practices have led to fluctuations and sudden rises in economic policy uncertainties. Within the portfolio framework, investors prefer to hold more stable assets, such as bonds, alongside tangible assets, such as gold, to protect themselves and diversify risk. In this context, the results of the analysis found a positive relationship between both S&P and Solactive green bond prices and economic policy uncertainty. In the face of increasing economic policy uncertainties, investors demonstrate that they can use green bonds as a hedge. This finding is supported by the results of studies such as Syed et al. (2022), Tang et al. (2023), and Wang et al. (2023). Additionally, studies during the COVID-19 period by Haq et al. (2021) and Dong et al. (2023) highlighted the role of green bonds as a safe haven. While our findings support this conclusion for S&P green bonds, Solactive green bonds do not exhibit this characteristic.

The impact of climate policy uncertainty included in the analysis is negative on green bonds. An increase in climate policy uncertainty or negative news related to climate policy changes will lead to an increase in the costs of new green investment projects and discourage environmentally friendly investments. On the other hand, due to undermining market participants' confidence, a decrease in demand for green bond purchases and subsequent selling by investors will result in a decrease in prices. Both short-term causality tests and long-term coefficients obtained from ARDL indicate that investors respond to climate policy uncertainties both in the short and long term. This finding is supported by the studies of Tian et al. (2022) and Silva et al. (2022).

Bond market participants should also be concerned about monetary policy uncertainty because it is directly related to uncertainty in future returns and bond prices. Therefore, diversifying this uncertainty driven by policy is not entirely possible. Bond holders also demand an additional risk premium to bear this policy uncertainty. This, in turn, will cause the price of green bonds to decrease, similar to other types of bonds. The negative effect of monetary policy uncertainty on green bond prices is supported by the literature, as seen in the studies of Kocaarslan (2021) and Lin and Su (2022).

Whether a market is semi-strong form efficient can also be tested through a cointegration analysis. If there is no cointegration between the series, the efficient market hypothesis holds. However, if it is determined that the series are cointegrated, then the efficient market hypothesis does not hold, meaning forecasting one based on the other violates one of the assumptions of the efficient market hypothesis. Bootstrap Fourier ARDL cointegration results indicate that green bonds are cointegrated with the uncertainty indices in the long term. In this context, we can say that green bonds are not semi-strong form efficient. Additionally, the results of causality analysis based on ECM also indicate whether green bonds are semi-strong-form efficient in the short term. If there is causality from uncertainty to green bond prices, it can be said that the market is not efficient in the short term. The results of the analysis only show that the S&P green bond market is not efficient when considering climate policy uncertainty. Ultimately, climate policy uncertainty has a significant impact on green bond prices both in the short and long term. Overall, as also noted by Wang (2023), financial markets are more efficient in the short term than in the long term. Bootstrap Fourier ARDL cointegration analysis shows that the green bond market is not efficient under long-term uncertainty, while short-term causality analysis shows that the market is not efficient only when evaluating climate policy uncertainty. Some studies on uncertainties and the green bond market (Syed, 2022; Wei et al., 2024; Lin and Su, 2023; Wang et al., 2024) also support this finding.

The obtained analyses indicate that markets are not efficient during certain periods of time, contrary to the short-term causality analysis. While these findings present various results emphasizing the diversification and hedging properties of green bonds against economic policy uncertainty, they also demonstrate the negative effects of climate policy uncertainty and monetary policy uncertainty on green bond prices. Based on the first conclusion, investors may be advised to include green bonds in their portfolios as a risk

diversification tool, whereas based on the second conclusion, given the long-term negative effects of climate and monetary policy uncertainties, investors may need to be more cautious when investing in green bonds. It is emphasized that during periods of high uncertainty, investors should exercise more caution when investing in green bonds, as the detrimental impact of Economic Policy Uncertainty (EPU) on green bonds becomes even more pronounced in the long run.

Green bonds are known not only as an alternative instrument against economic policy uncertainties but also as environmentally friendly markets. Increased carbon emissions, global warming, and crises related to non-renewable energy sources have highlighted alternative clean and renewable energy sources, thus increasing the importance of green bonds in this context. Policymakers can enhance the efficiency of the green bond market by increasing transparency through the implementation of climate policies and monetary policies. Climate change has the potential to reduce profitability and worsen the financial status of companies. This situation can affect investor confidence and lead to an increase in liquidity preference. As mentioned in the study by Dafermos et al. (2018), the implementation of a quantitative expansion program for green corporate initiatives by authorities to combat climate change can not only help reduce global warming but also mitigate the adverse effects on green bonds.

5. CONCLUSION

This study focuses on examining the efficiency of green bond markets. The study is composed of three main sections, with the initial focus on investigating whether green bonds exhibit weak-form efficiency. In this context, the S&P Dow Jones Green Bond Index and the Solactive Green Bond Index have been utilized. These indices have different inception dates, and to obtain the longest possible study period, the analysis has been based on the earliest available start date and the latest end date. Daily data covering the periods from November 28, 2008, to February 15, 2024, for the S&P Green Bond Index, and from January 3, 2012, to February 13, 2024, for the Solactive Green Bond Index have been used. To determine the weak-form efficiency, unit root tests have been conducted in four different categories to examine whether the series follow a random walk.

Traditional unit root tests, such as the ADF and PP tests, Fourier unit root tests that account for structural smooth breaks (Fourier ADF, Fourier KSS, Fourier KPSS, flexible Fourier, fractional flexible Fourier), tests that allow for both sharp and smooth breaks (like the SOR test), tests that consider nonlinear structures such as KSS, Sollis, Kruse, OY, CEO, OEH, OSH, LNV and RALS unit root tests that account for non-normal error, have all been applied. The traditional unit root tests failed to reject the presence of a unit root for both green bonds, suggesting that the series exhibit random walks according to these tests. However, when structural breaks with smooth breaks are considered, the Fourier ADF test found only the S&P green bond market to be stationary. The other Fourier unit root tests indicated the presence of unit roots in the series.

According to the results of nonlinear unit root tests, the KSS, Sollis, Kruse, CEO, OEHa, Ranjbar et al. (2018), and Güriş (2019) tests suggest that the S&P green bond price is stationary in different models, while the Solactive green bond price is still following a random walk process. Additionally, Omay and Yıldırım (2014) and Omay, Shahbaz and Hasanov (2020) tests indicate that both series are stationary, whereas the LNV test shows that both series follow a random walk process. When compared to the results of linear unit root tests that account for smooth structural breaks, nonlinear unit root tests largely determine that the S&P green bond is stationary. This finding underscores that the series is nonlinear in nature and highlights the importance of using tests that are suitable for the

series' structure. Among the nonlinear tests, the OY and OSH tests, which indicate that both green bonds are stationary, are found to be more successful. The OY test combines the LNV-KSS nonlinear unit root tests, while the OSH test integrates the LNV-Sollis nonlinear unit root tests, demonstrating a higher presence of structural breaks.

There are very few studies that examine whether green bonds are weak-form efficient. The results obtained from studies examining market efficiency based on S&P green bond prices are consistent with the finding that this series does not possess an efficient market structure.

In the second part of this study, the relationship between green bonds and other financial assets was examined, with a particular focus on whether correlations increase during crisis periods and whether there is a contagion effect. Additionally, the potential use of green bonds as a portfolio diversification tool was explored. To this end, analyses were conducted on the second moments of the series rather than the first moments. Appropriate univariate GARCH models were selected for each financial asset, and models allowing for sharp breaks were added to evaluate the impact of structural breaks. It was found that GARCH models with structural breaks performed better.

Using standardized errors and Value at Risk (VaR) risk values obtained from GARCH models, causality in mean and causality in risk tests (downside risk and upside risk) were applied. The findings from these tests indicated that traditional bonds and clean energy stock markets have causal effects on green bonds in both returns and in downside and upside risks. However, no relationship was found between energy commodities and green bonds.

According to the definition of the contagion effect, the relationship between assets is only observed during crisis periods, whereas in normal periods, this relationship is either very weak or nonexistent. For crisis periods, causality results in downside risk can be used to examine the contagion effect, while the overall dependency can be understood through a general assessment of causality in returns, downside, and upside risks. The unidirectional influence of traditional bonds and clean energy stocks on green bonds in all three tests suggests that green bonds are dependent on these markets. The absence of a relationship with energy stocks indicates that there is neither contagion nor dependency between the series.

From the perspective of the Efficient Market Hypothesis (EMH), the S&P green bond market is found to price information from traditional bonds and clean energy stocks with a delay. According to the semi-strong form of the EMH, markets should instantaneously price all publicly available information and macroeconomic variables. However, the green bond market prices the effects of traditional bonds and clean energy stocks with a lag, indicating that the market is not efficient in the semi-strong form.

In addition to causality analyses, multivariate GARCH models were also applied, and the results regarding energy commodities supported the findings of the causality analyses. According to the results from DCC (Dynamic Conditional Correlation) GARCH models, the correlation between green bonds and energy commodities was found to be negligible. For other markets, a dependency structure similar to the results of the causality analyses was observed. A drawback of the DCC GARCH models is that they subject all financial assets to the same GARCH process. In contrast, the causality analyses selected the most appropriate GARCH model for each series.

In the third part, the effects of uncertainties on the efficiency of green bonds are examined. The study investigates the impact of climate policy uncertainty, monetary policy uncertainty, and economic policy uncertainty using monthly data. The long-term effects of these uncertainty indices on green bonds indicate that the market is not semi-strong efficient. Additionally, while monetary and climate policy uncertainties negatively affect green bond prices, economic policy uncertainty has a positive impact. In the short term, no impact is observed on the Solactive green bond index, while the S&P green bond index is affected by climate policy uncertainty even in the short term.

Although both green bond markets are not affected by monetary and economic policy uncertainties in the short term, these uncertainties undermine market efficiency in the long term. According to Wei et al. (2022), green bonds, as sustainable financial instruments with social responsibility, are typically preferred for long-term investments. In the short term, speculative trading has little impact on the green bond market, and adjustments occur more slowly. Therefore, green bonds can be considered more efficient in the short term.

However, while the S&P green bond market is influenced by climate policy uncertainty in the short term, the Solactive green bond market is not. This difference may

stem from their criteria. Solactive adheres only to the Climate Bonds Taxonomy, whereas S&P includes both this criterion and unlabelled climate project bonds. This indicates that Solactive makes a stricter selection, including only bonds deemed definitively "green," which may provide clearer information to investors. Moreover, the lack of a standardized definition for green bonds complicates understanding these emerging markets. The Climate Bonds Initiative (CBI) aims to provide clear criteria for green bonds and certify compliance through approved verifiers. For example, CBI defines emission performance criteria for buildings to qualify for green bond issuance.

From the Efficient Market Hypothesis (EMH) perspective, the response of green bond markets to policy uncertainties suggests a deviation from semi-strong form efficiency in the long term. Solactive's strict selection criteria may result in better short-term efficiency compared to S&P's broader inclusion criteria. This difference reflects how quickly and significantly markets react to new information.

When evaluating the weak form and semi-strong form efficiency of green bond markets, it is evident that these markets are not efficient. According to the Efficient Market Hypothesis (EMH), it should not be possible to achieve abnormal returns using past prices or other available information, rendering technical analyses useless. However, findings indicate that technical analysis can be employed for predictions in green bond markets. Understanding the characteristics of these markets is crucial for accurate forecasting. Linear models have shown poor performance in capturing the market structure compared to non-linear models, highlighting the inefficiency of green bond markets and challenging the EMH.

According to Naeem et al. (2021), one possible explanation for the lower efficiency of green bonds is that the green bond market is still in its infancy, making it more unstable and prone to complex nonlinear dynamics compared to the regular bond market. The Climate Bond Initiative's September 2023 report indicates that approximately $200 trillion in climate finance is needed by 2050, with annual requirements of $6.2 trillion by 2030 and $7.3 trillion by 2050. However, the cumulative total of green bonds issued since 2007 has only reached about $3 trillion, highlighting the nascent stage of this market. Additionally, the methodologies adopted by S&P and Solactive show differences that could affect the efficiency of these two markets. Furthermore, the policies adopted by countries and regions are also significant. While Europe takes more consistent steps in climate policies, the U.S.

has seen variations in its climate policies over time, which could impact the efficiency of the green bond market.

When evaluating the impact on portfolios, it is evident that traditional bonds and clean energy stocks influence green bonds under all market conditions. The delayed and unidirectional impact of both traditional bonds and clean energy stocks on green bonds allows investors to optimize their risk management and return potential. Investors looking to hedge against potential declines in green bond prices can take short positions, profiting from any decrease in value (Liu et al., 2021). Conversely, those expecting an increase in green bond values can take long positions to benefit from their rise. The low correlation with energy commodities implies that investors can use these assets to diversify their portfolios. An investor holding energy commodities can hedge against potential declines in these assets by incorporating green bonds. This strategy offers the opportunity to balance risks and enhance return potential by leveraging different asset classes within a portfolio.

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6. APPENDICES

6.1. Appendix A

Table 6.1.1. Traditional Unit Root Test Results

Panel A: Daily Data				
Tests	**ADF**		**PP**	
Models	Constant	Constant and Trend	Constant	Constant and Trend
S&P Green	-1.048	-2.543	-1.034	-2.534
Solactive	-1.562	-1.528	-1.626	-1.587
Panel B: Weekly Data				
Tests	**ADF**		**PP**	
Models	Constant	Constant and Trend	Constant	Constant and Trend
S&P Green	-0.963	-2.471	-0.963	-2.504
Solactive	-1.546	-1.523	-1.802	-1.770
Panel C: Monthly Data				
Tests	**ADF**		**PP**	
Models	Constant	Constant and Trend	Constant	Constant and Trend
S&P Green	-1.905	-3.088	-1.201	-2.587
Solactive	-1.726	-1.699	-2.052	-2.004

Table 6.1.2. Fourier Unit Root Test Results

Weekly Data						
Tests	Becker et al. (2006) Fourier KPSS					
	Constant			Constant and Trend		
	Test Statistics	k	F Statistics	Test Statistics	k	F Statistics
S&P Green	34.8	2	1178.57	3.64	2	5757.4
Solactive	6.94	2	905.7	3.34	2	687.4
Tests	Christopoulos and Leon-Ledesma (2010) Fourier ADF					
	Constant			Constant and Trend		
	Test Statistics	k	F Statistics	Test Statistics	k	F Statistics
S&P Green	-1.8253	2	1178.57	-3.752*	2	2623.14***
Solactive	-2.1129	2	769.49	-2.852	2	927.24

Christopoulos and Leon-Ledesma (2010) Fourier KSS						
Models	Constant			Constant and Trend		
	Test Statistics	k	F Statistics	Test Statistics	k	F Statistics
S&P Green	-2.8689	2	1178.57	-3.3204	2	2623.14
Solactive	-2.7534	2	769.49	-3.144	2	927.24

Enders and Lee (2012) Flexible Fourier ADF						
	Constant			Constant and Trend		
	Test Statistics	k	F Statistics	Test Statistics	k	F Statistics
S&P Green	-1.824	2	3.321	-3.751	2	4.735
Solactive	-1.976	2	5.079	-1.921	2	4.751

Omay (2015)						
	Constant			Constant and Trend		
	Test Statistics	k	F Statistics	Test Statistics	k	F Statistics
S&P Green	-2.7788	0.1	4.425	-2.8454	0.1	0.882
Solactive	-1.927	0.1	0.4702	-2.405	0.2	1.066

SOR (2018)			
	Model A	Model B	Model C
S&P Green	-4.475** (1)	-4.483** (2)	-4.559* (2)
Solactive	-3.158(1)	-3.353(1)	-3.352(1)

Monthly Data

Becker et al. (2006) Fourier KPSS						
	Constant			Constant and Trend		
	Test Statistics	k	F Statistics	Test Statistics	k	F Statistics
	8.07	2	52.154	0.919	2	119.35
	1.5479	2	39.349	0.736	2	45.719

Christopoulos and Leon-Ledesma (2010) Fourier ADF						
	Constant			Constant and Trend		
	Test Statistics	k	F Statistics	Test Statistics	k	F Statistics
	-2.037	2	52.154	-3.128	2	119.358
	-1.767	2	39.349	-2.083	2	45.719

Christopoulos and Leon-Ledesma (2010) Fourier KSS						
	Constant			Constant and Trend		
	Test Statistics	k	F Statistics	Test Statistics	k	F Statistics
	-2.165	2	52.154	-3.537	2	119.358

-2.468	2	39.349	-2.842	2	45.719

Enders and Lee (2012) Flexible Fourier ADF

Constant			Constant and Trend		
Test Statistics	k	F Statistics	Test Statistics	k	F Statistics
-3.100	2	4.452	-1.740	2	3.90
-1.824	3	4.391	-1.869	3	4.678

Omay (2015)

Constant			Constant and Trend		
Test Statistics	k	F Statistics	Test Statistics	k	F Statistics
-2.318	0.10	2.881	-2.340	0.2	0.285
-1.755	0.1	0.371	-2.052	0.2	0.703

SOR (2018)

Model A	Model B	Model C
-3.559	-3.218	-3.417
-3.404	-3.664	-3.765

Table 6.1.3. ESTAR Type Unit root Test Results

Weekly Data						
Tests	**KSS**			**Sollis**		
Models	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3
S&P Green	-0.5652	-1.1576	-3.7410**	0.6294	0.8073	7.8247**
Solactive	-0.0463	-2.0214	-2.0286	1.1175	2.5665	2.5179
Tests	**Kruse**			**OY (2014)**		
Models	Case 1	Case 2	Case 3	Model A	Model B	Model C
S&P Green	1.2323	5.0575	13.9777**	-10.639***	-11.796***	-11.830***
Solactive	2.2866	4.7044	4.5906	-2.129	-4.654**	-3.622
Tests	**CEO (2017)**			**OEHa (2018)**		
Models	Model A	Model B	Model C	Model A	Model B	Model C
S&P Green	-2.332	-5.036***	-5.039**	13.032***	14.864***	14.562***
Solactive	-2.320	-2.409	-2.408	3.605	4.819	4.045
Tests	**OHEb(2018)**			**Ranjbar et al.(2018)**		
Models	Constant	Constant and Trend		Constant	Constant and Trend	
S&P Green	-2.106	-3.858		2.621	7.780**	
Solactive	-2.434	-2.679		3.627	3.505	
Tests	**Güriş (2019)**			**OSH (2020)**		
Models	Constant	Constant and Trend		Model A	Model B	Model C
S&P Green	9.40	14.983*		-2.279	-11.477***	-11.511***
Solactive	7.867	7.413		-2.667	-5.644***	-5.639***

Monthly Data						
Tests	**KSS**			**Sollis**		
Models	Case 1	Case 2	Case 3	Case 2	Case 1	Case 2
S&P Green	-0.5885	-1.9764	-4.4779***	1.44357	2.0061	10.584***
Solactive	-0.0755	-2.3607	-2.3700	1.2378	4.7074**	4.6724
Tests	**Kruse**			**OY (2014)**		
Models	Case 1	Case 2	Case 3	Case 2	Case 1	Case 2
S&P Green	2.9278	10.0334*	20.026***	-5.230***	-6.493***	-6.491***
Solactive	2.5426	8.9707*	8.8714	-2.991	-3.546	-3.094
Tests	**Corakcı et al. (2017)**			**OEHa (2018)**		
Models	Model A	Model B	Model A	Model B	Model A	Model B
S&P Green	-2.395	-3.272	-3.300	6.756	8.389	10.630**
Solactive	-3.676	-2.899	-2.917	2.654	2.858	2.586
Tests	**OHEb(2018)**			**Ranjbar et al.(2018)**		
Models	Constant	Constant and Trend		Constant	Constant and Trend	
S&P Green	-2.165	-3.537		2.385	6.668	
Solactive	-2.829	-3.270		3.911	4.169	
Tests	**Güriş (2019)**			**OSH (2020)**		
Models	Constant	Constant and Trend		Constant	Constant and Trend	Constant
S&P Green	7.595	12.583		-3.802	-6.524	-6.965
Solactive	8.253	8.606		-3.108	-5.905	-5.917

Table 6.1.4 . LSTAR Type Unit root Test Results

Weekly Data			
Test		**LNV (1998)**	
Models	Model A	Model B	Model C
S&P	-2.205	-2.620	-2.510
Solactive	-1.435	-2.286	-2.021
Test		**Pascalau**	
Models	Case 1	Case 2	Case 3
S&P	0.6228	2.9982*	9.2083***
Solactive	1.1304	1.5348	1.6717
Monthly Data			
Test		**LNV (1998)**	
Models	Model A	Model B	Model C
S&P	-2.301	-2.780	-2.640
Solactive	-1.523	-2.197	-2.231
Test		**Pascalau**	
Models	Case 1	Case 2	Case 3
S&P	1.4541	7.7492***	4.9288***
Solactive	1.2545	1.6728	1.7801

Table 6.1.5. Rals Unit Root Test Without Structural Breaks

Weekly Data						
Tests	**RALS ADF**				**RALS LM**	
Models	Constant		Constant and Trend		Constant	
	Test Stat	rho	Test Stat	rho	Test Stat	rho
S&P Green	-1.186	0.768	-2.801	0.765	-1.413	0.785
Solactive	-1.633	0.821	-1.612	0.816	-0.469	0.822
Monthly Data						
Tests	**RALS ADF**				**RALS LM**	
Models	Constant		Constant and Trend		Constant	
	Test Stat	rho	Test Stat	rho	Test Stat	rho
S&P Green	-1.136	0.805	-2.415	0.795	-3.58	0.87
Solactive	-1.828	0.789	-1.795	0.793	-0.399	0.839

Table 6.1.6. Rals Unit Root Test with Structural Breaks

Weekly Data

ONE BREAK

	Lee-Strazicich						RALS LM					
	Constant			Constant and Trend			Constant			Constant and Trend		
	Test Statistics	Date	Prob (JB)	Test Statistics	Date	Prob (JB)	Test Statistics	rho	Date	Test Statistics	rho	Date
S&P Green	-2.361	2011:10:21	0.000	-3.755	2022:05:27	0.000	-1.1089	0.828	2020:03:10	-3.499*	0.7904	2011:11:20
Solactive	-2.448	2022:09:16	0.000	-3.283	2022:02:11	0.000	-1.319	0.837	2020:03:1	-3.831**	0.807	2022:03:2

TWO BREAKS

	Lee-Strazicich						RALS LM					
	Constant			Constant and Trend			Constant			Constant and Trend		
	Test Statistics	Date	Prob (JB)	Test Statistics	Test Statistics	Prob (JB)	Test Statistics	rho	date	Test Statistics	rho	Date
S&P Green	-2.435	2011:10:21 2022:06:03	0.000	-4.325	2015:02:27 2022:01:14	0.000	-3.499**	0.790	2011:11:20	-6.057***	0.817	2020:03:2 2020:03:20
Solactive	-2.614	2020:03:13 2022:09:16	0.000	-4.090	2020:03:20 2022:05:20	0.000	-7.13***	0.861	2020:03:0 2020:03:20	-6.518***	0.892	2020:02:2 2020:03:20

Monthly Data

ONE BREAK

Lee-Strazicich Unit Root Test						RALS LM Unit Root Test					
Constant			Constant and Trend			Constant			Constant and Trend		
Test Statistics	Date	Prob (JB)	Test Statistics	Date	Prob (JB)	Test Statistics	rho	Date	Test Statistics	rho	Date
-2.758	2011:08	0.000	-3.545	2011:08	0.00	-0.107	0.92	2011:03	-5.219**	0.85	2022:02
-3.415*	2013.04	0.000	-4.827***	2020:02	0.000	1.595	0.87	2022:03	3.836	0.917	2022:02

TWO BREAKS

Lee-Strazicich						RALS LM					
Constant			Constant and Trend			Constant			Constant and Trend		
Test Statistics	Date	Prob (JB)	Test Statistics	Date	Prob (JB)	Test Statistics	rho	Date	Test Statistics	rho	Date
-3.575*	2012:08 2022:06	0.000	-4.634	2015:02 2021:11	0.000	-2.189	0.899	2011:03 2022:05	-6.013***	0.86	2012:02
-4.60***	2020:01 2022:01	0.000	-5.897**	2015:11 2022:01	0.00	4.255	0.89	2022:03 2022:09	-0.904	0.87	2021:11 2022:08

Table 6.2.1. Critical Values for Fourier KPSS, ADF, and KSS

		Fourier KPSS		*Fourier ADF*		*Fourier KSS*	
Frequency		*Constant*	*Constant and Trend*	*Constant*	*Constant and Trend*	*Constant*	*Constant and Trend*
	1%	0.270	0.0718	-4.40	-4.86	-4.19	-4.63
1	5%	0.1704	0.0538	-3.78	-4.30	-3.64	-4.10
	10%	0.129	0.0461	-3.46	-4.02	-3.32	-3.81
	1%	0.6526	0.1959	-3.87	-4.64	-3.82	-4.43
2	5%	0.4047	0.1275	-3.27	-4.02	-3.28	-3.82
	10%	0.3050	0.0994	-2.93	-3.69	-2.99	-3.53

Table 6.2.2. Critical Values for Enders and Lee (2012)

		Flexible Fourier ADF	
		Constant	*Constant and Trend*
k=1	1%	-4.31	-4.80
	5%	-3.75	-4.27
	10%	-3.45	-4.00
k=2	1%	-3.89	-4.58
	5%	-3.25	-3.98
	10%	-2.90	-3.67

Table 6.2.3. Critical Values for Omay (2015)

		Fractional Frequency Flexible Fourier Adf	
		Constant	*Constant and Trend*
0.1	1%	-4.26	-4.80
	5%	-3.68	-4.28
	10%	-3.38	-4.00
0.2	1%	-4.21	-4.80
	5%	-3.62	-4.27
	10%	-3.30	-4.00

Table 6.2.4. Critical Values for SOR Test

		Model A	*Model B*	*Model C*
	1%	-4.807	-5.129	-5.345
k=1	5%	-4.281	-4.513	-4.810
	10%	-4.007	-4.273	-4.518
	1%	-4.997	-5.227	-5.563
k=2	5%	-4.480	-4.711	-5.020
	10%	-4.192	-4.436	-4.704

Table 6.2.5 Critical Values for ESTAR Type Nonlinear Unit Root Tests

		KSS			***Sollis***		
		Case 1	*Case* 2	*Case* 3	*Case* 1	*Case* 2	*Case* 3
	1%	-2.82	-3.48	-3.93	4.241	6.236	8.344
	5%	-2.22	-2.93	-3.40	2.205	4.557	6.292
	10%	-1.92	-2.66	-3.13	1.837	3.725	5.372
		Kruse			***OY***		
		Case 1	*Case* 2	*Case* 3	*Model A*	*Model B*	*Model C*
	1%	13.15	13.75	17.10	-4.412	-4.757	-4.969
	5%	9.53	10.17	12.82	-3.801	-4.180	-4.370
	10%	7.85	8.60	11.10	-3.489	-3.879	-4.053
		Çorakcı et al.			***OHEa* (2018)**		
		Model A	*Model B*	*Model C*	*Model A*	*Model B*	*Model C*
	1%	-4.810	-5.328	-5.592	10.00	12.16	13.22
	5%	-4.271	-4.766	-5.036	8.09	9.60	10.52
	10%	-3.976	-4.494	-4.738	6.95	8.39	9.13
		***OEHb* (2018)**			***Ranjbar et al.* (2018)**		
Frequency		*Constant*	*Constant and Trend*		*Constant*	*Constant and Trend*	
	1%	9.92	11.16		9.768	11.832	
k=1	5%	7.64	8.66		7.48	9.346	
	10%	6.59	7.51		6.427	8.161	
	1%	8.62	10.39		8.324	10.691	
k=2	5%	6.34	7.91		6.193	8.24	
	10%	5.30	6.70		5.204	7.097	

		***Güriş* (2019)**	
		Constant	*Constant and Trend*
k=1	1%	19.56	23.26
	5%	14.86	18.14
	10%	12.7	15.08
k=2	1%	16.36	20.4
	5%	12.01	16.08
	10%	9.92	13.64

	***OSH* (2020)**		
	Model A	*Model B*	*Model C*
1%	-4.379	-4.694	-4.361
5%	-3.738	-4.116	-3.671
10%	-3.409	-3.780	-3.344

Table 6.2.6 Critical Values for LNV Nonlinear Unit Root Tests

	LNV		
	Model A	*Model B*	*Model C*
1%	-4.685	-5.141	-5.420
5%	-4.103	-4.565	-4.825
10%	-3.797	-4.277	-4.552

Table 6.2.7. Critical Values for RALS Unit Root Tests

The number of breaks		***Constant* (*Meng et al.*, 2014)**		***Constant* & *Trend* (*Meng et al.*, 2017)**		***Constant With No Breaks***	
Breaks	rho	0.8	0.9	0.8	0.9	0.8	0.9
1	1%	-3.504	-3.536	-4.049	-4.114	-3.51	-3.538
	5%	-2.948	-2.993	-3.516	-3.594	-2.947	-2.990
	10%	-2.667	-2.715	-3.245	-3.325	-2.667	-2.715
2	1%	-3.510	-3.544	-4.496	-4.592		
	5%	-2.950	-2.990	-3.982	-4.079		
	10%	-2.665	-2.715	-3.703	-3.811		

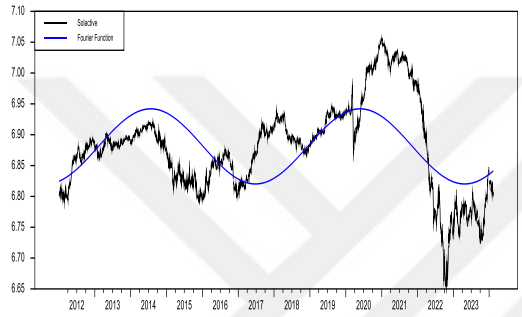
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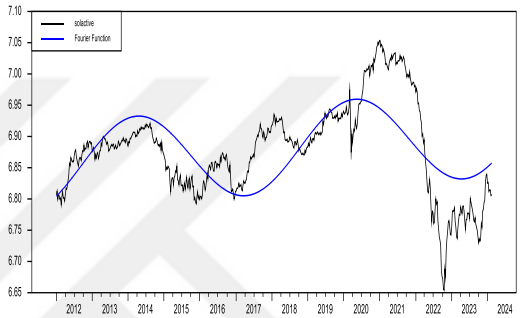
S&P Green Bond





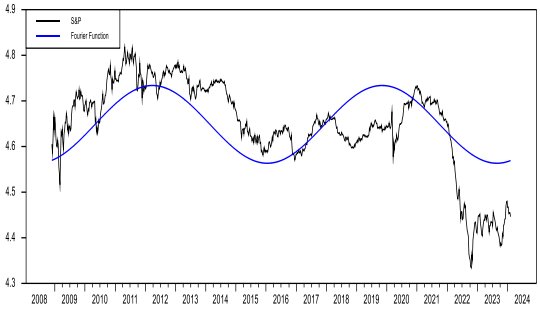
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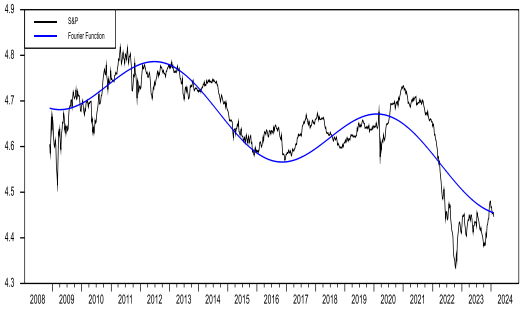




Weekly Data

S&P Green Bond





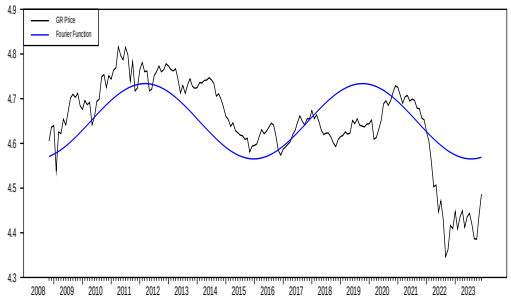
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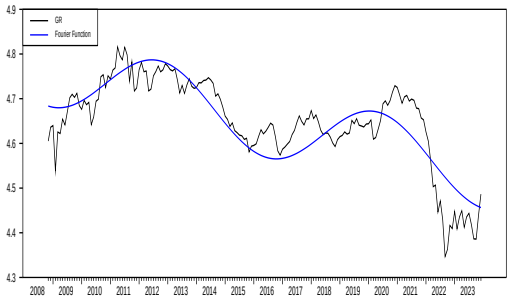




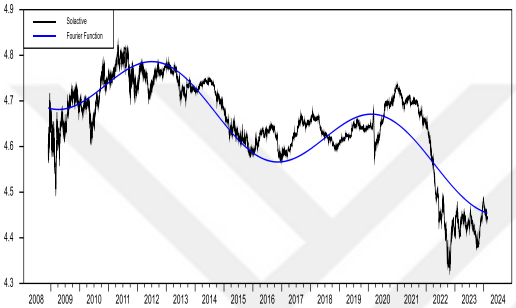
Monthly Data

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Solactive Green Bond



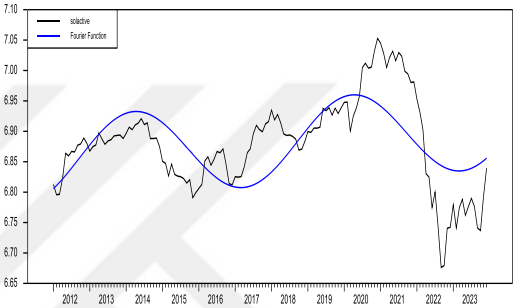
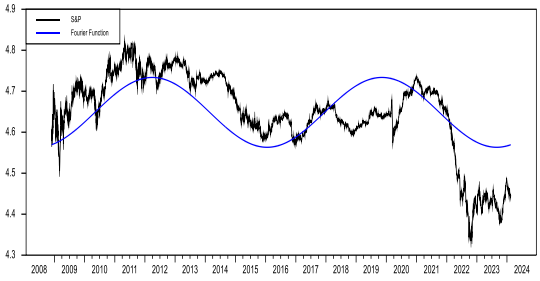
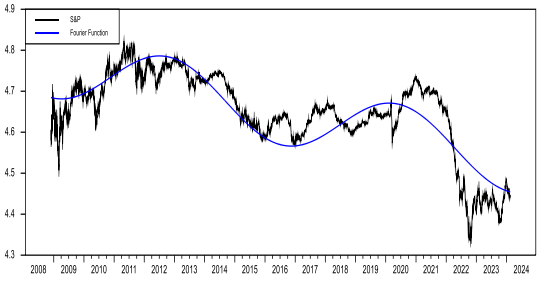


Figure 6A.1. Beckers Enders Lee (2006) Test

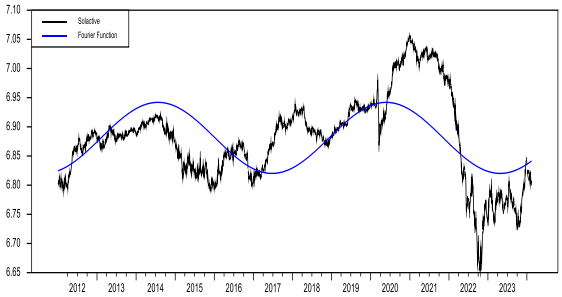
Daily Data

S&P Green Bond





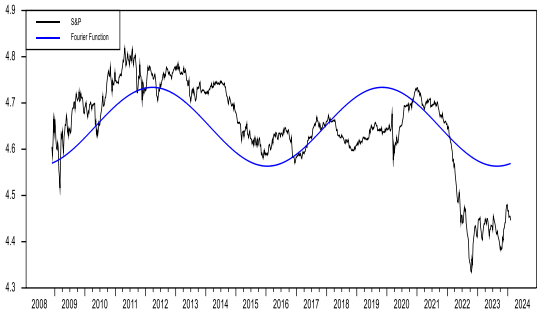
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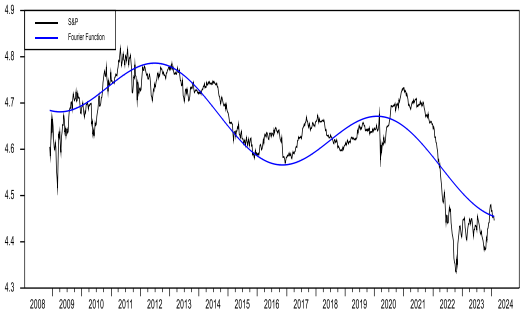




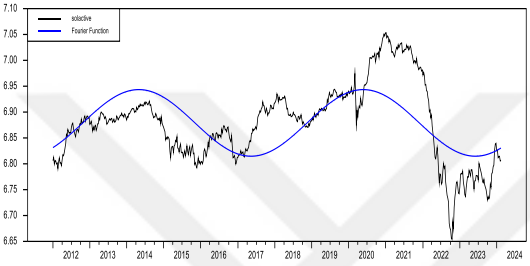
Weekly Data

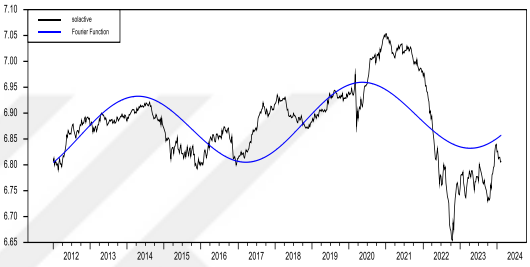
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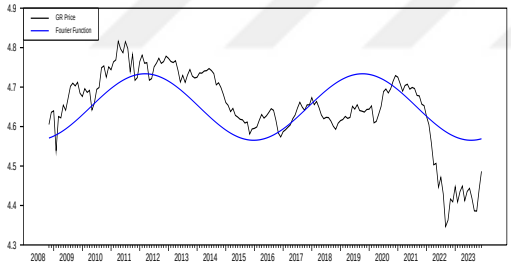
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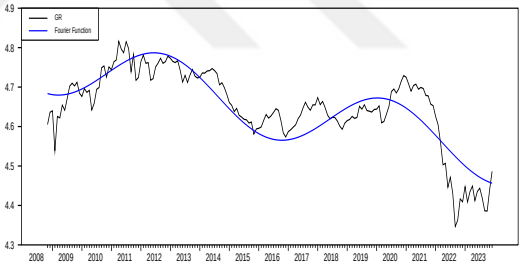




Monthly Data

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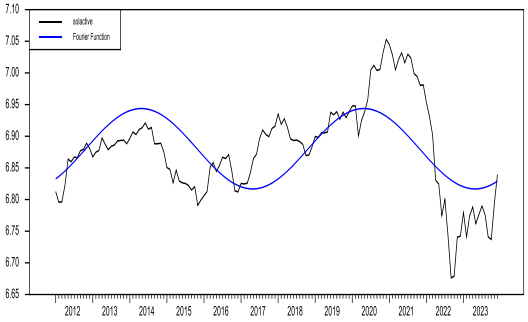


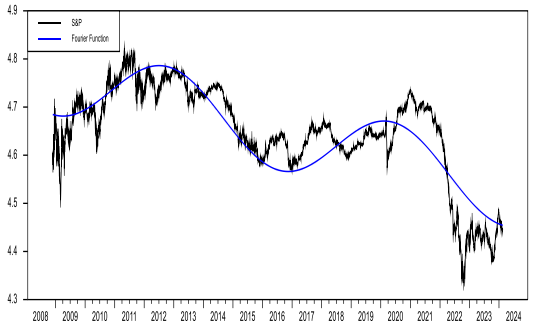


Figure 6A.2. Christopoulos and Leon-Ledesma (2010) Fourier ADF Test

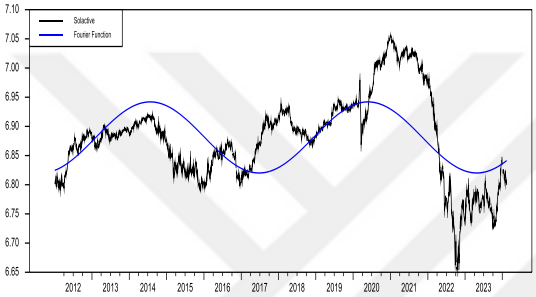
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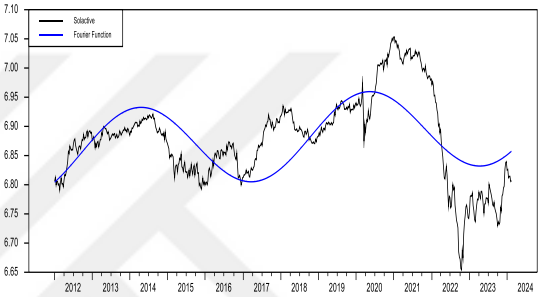
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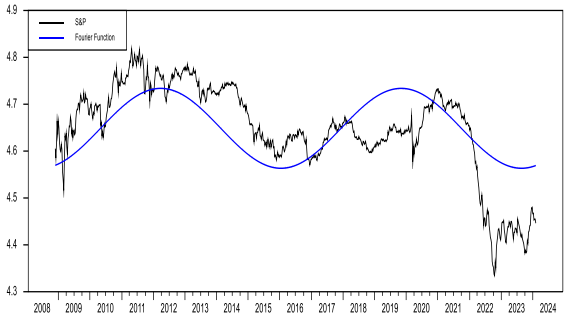
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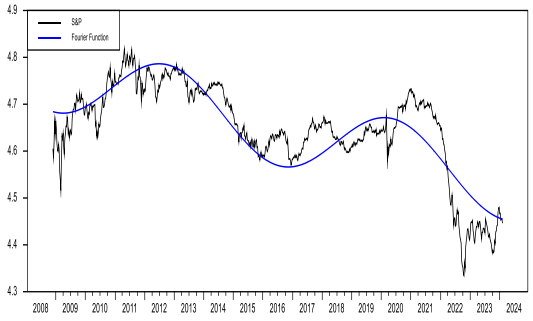




Weekly Data

S&P Green Bond





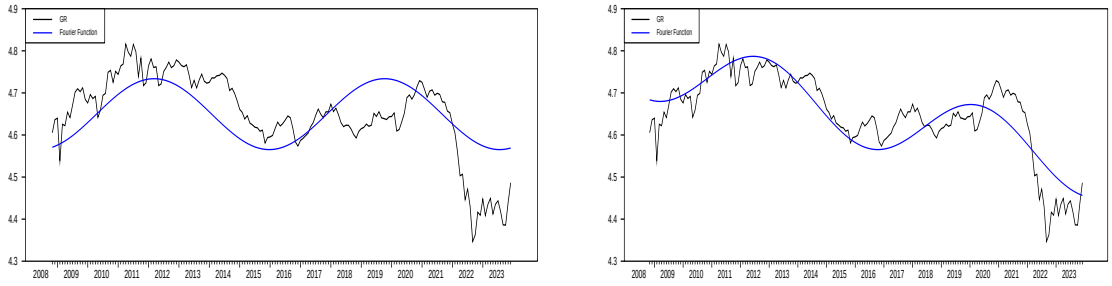
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Monthly Data

S&P Green Bond



Solactive

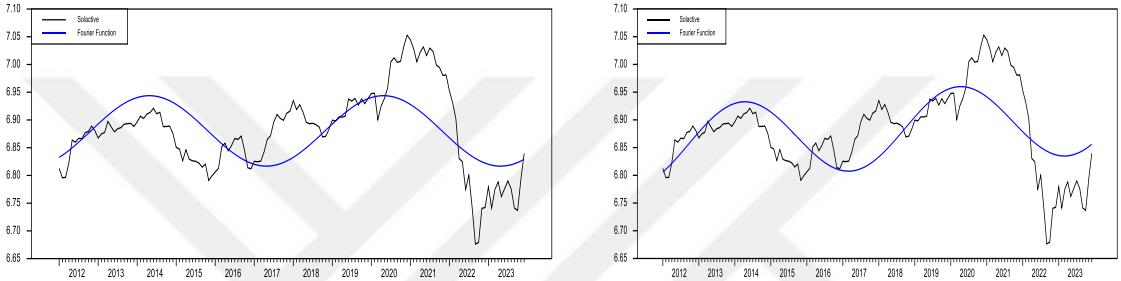
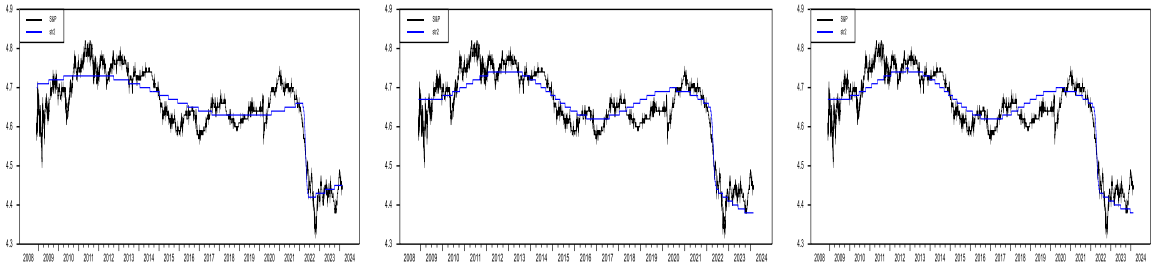


Figure 6A.3. Christopoulos and Leon-Ledesma (2010) Fourier KSS Test

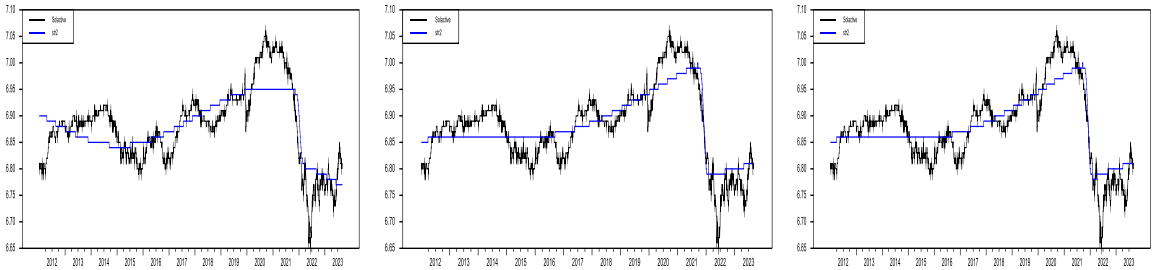
Daily Data

Model A | Model B | Model C

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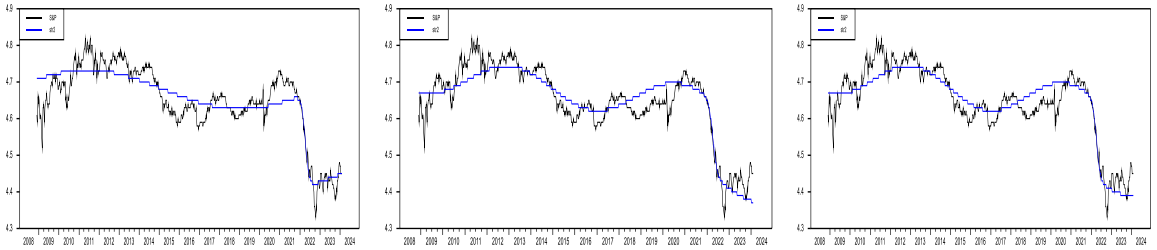


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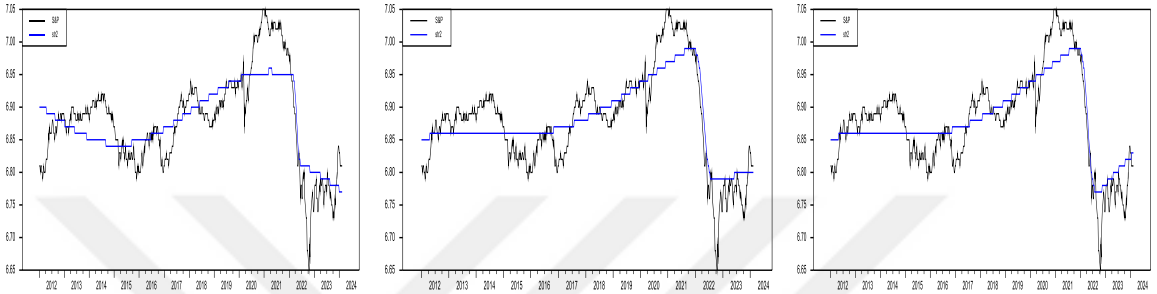


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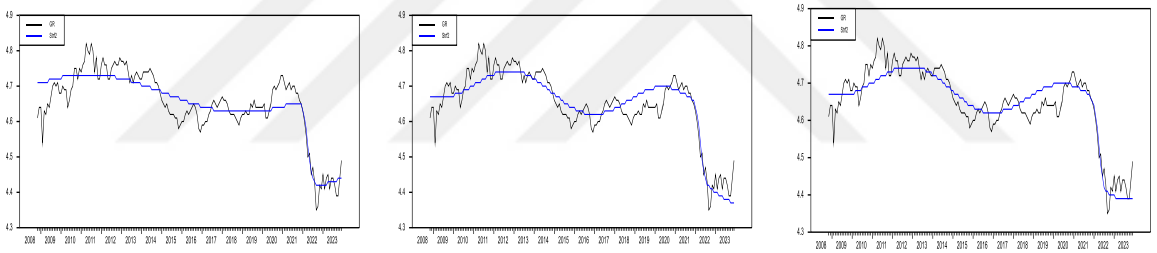


Solactive Green Bond



Monthly Data

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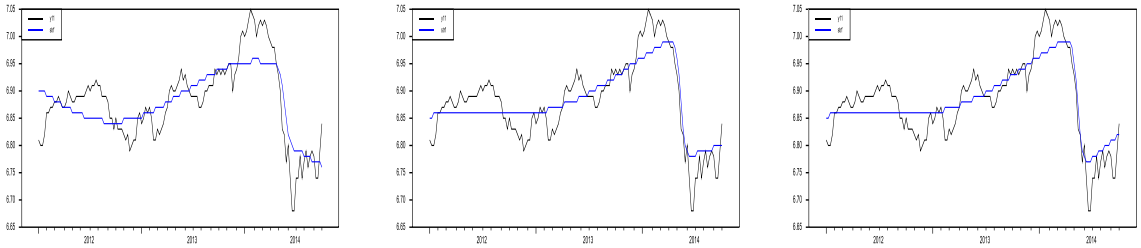
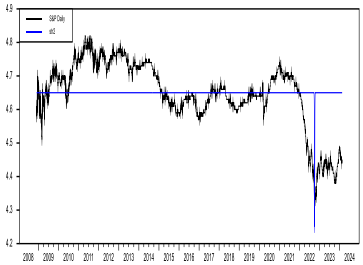


Figure 6A.4. SOR Test

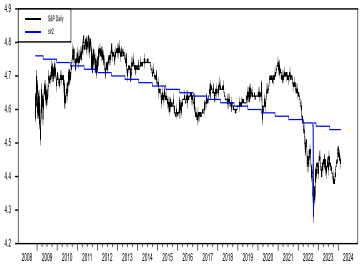
Daily Data

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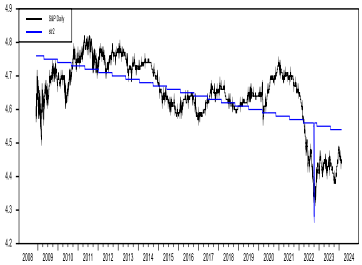
Model A



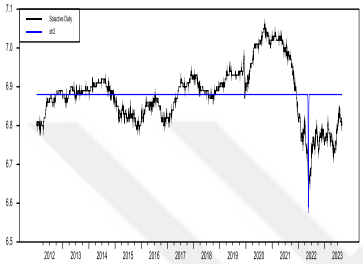
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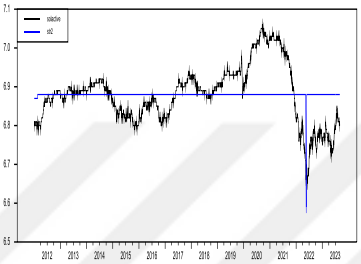


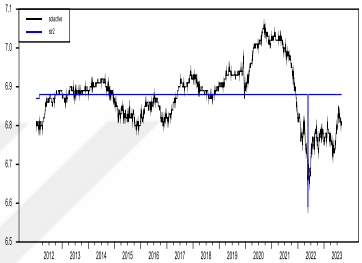
Model C



Solactive Green Bond

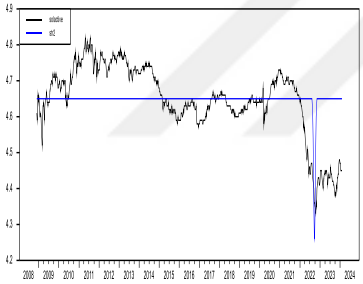


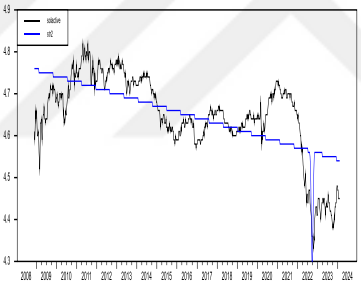


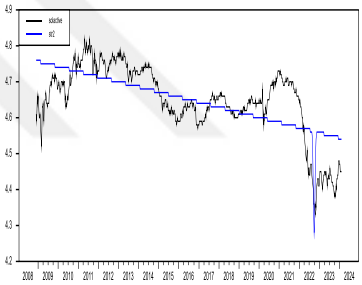


Weekly data

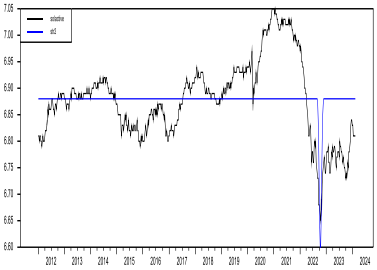
S&P Green Bond

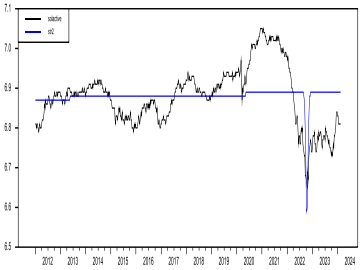


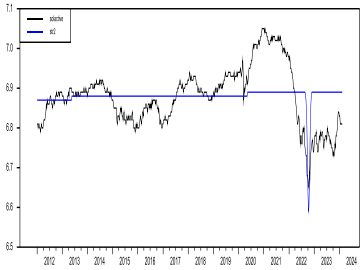




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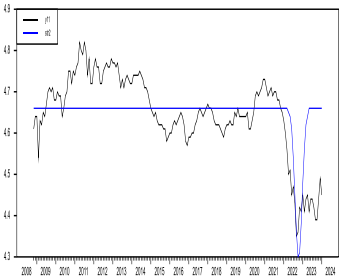


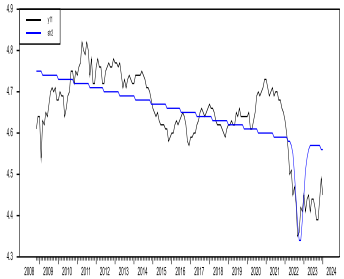


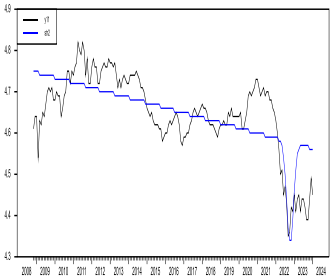


Monthly Data

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Solactive Green Bond

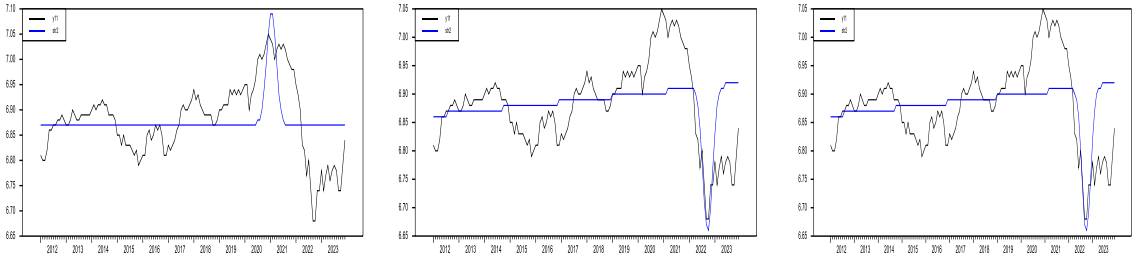
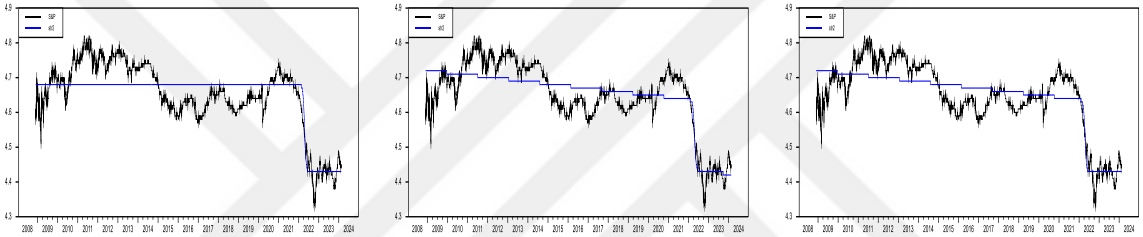


Figure 6A.5. CEO Test

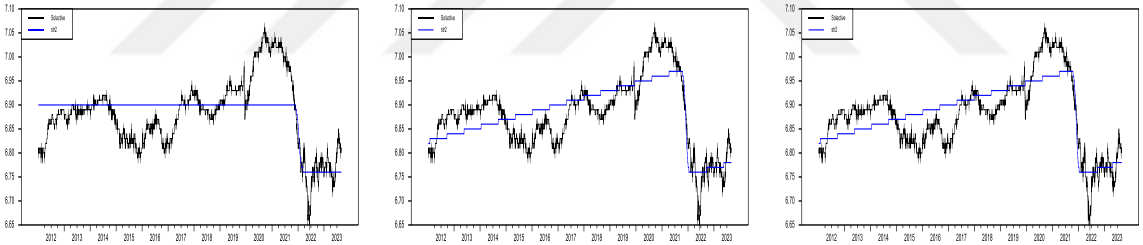
Daily Data

Model A **Model B** **Model C**

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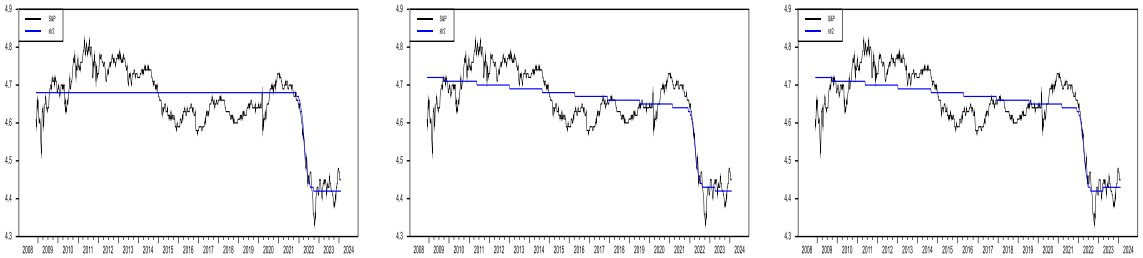


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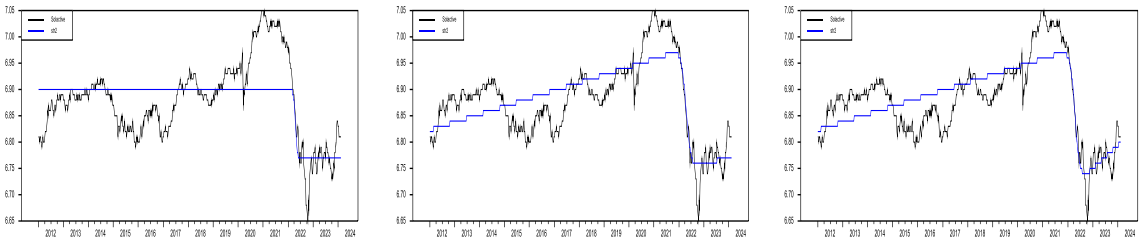


Weekly Data

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Solactive Green Bond



Monthly Data

S&P Green Bond



Solactive Green Bond

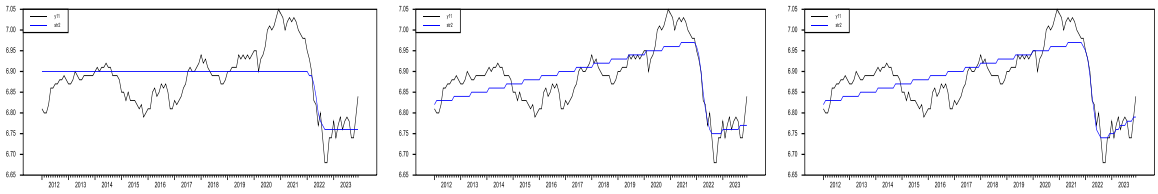


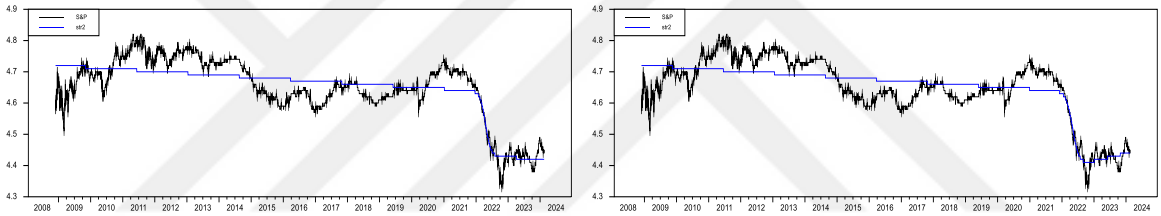
Figure 6A.6 OY Test

Daily Data

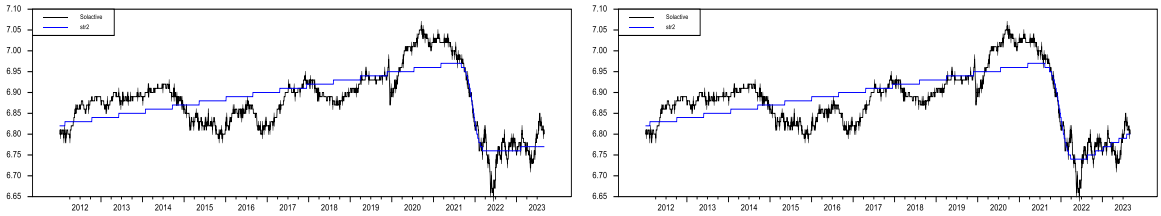
Model B

Model C

S&P Green Bond

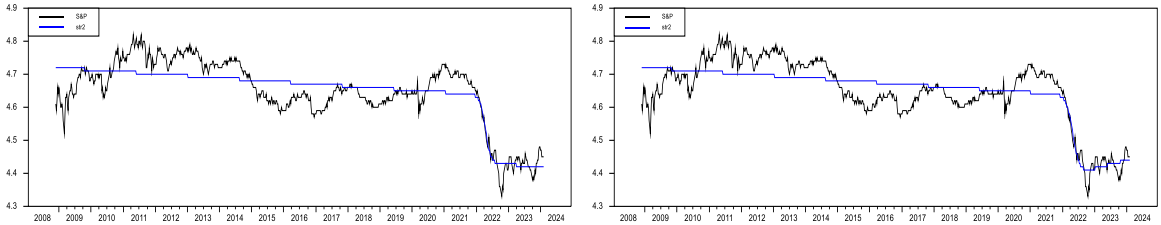


Solactive Green Bond

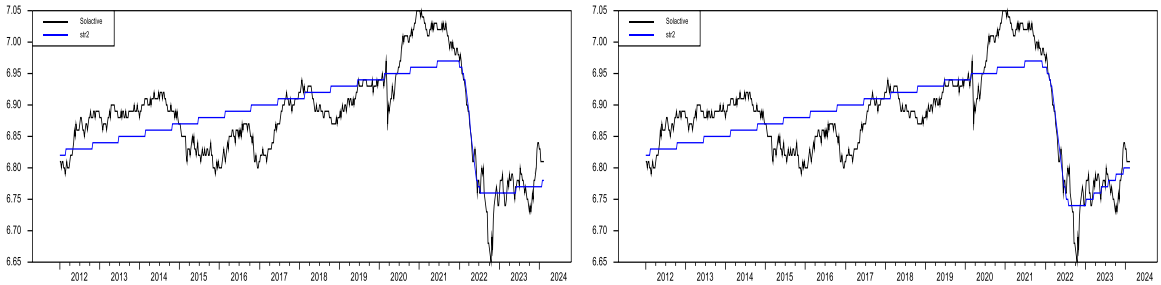


Weekly Data

S&P Green Bond

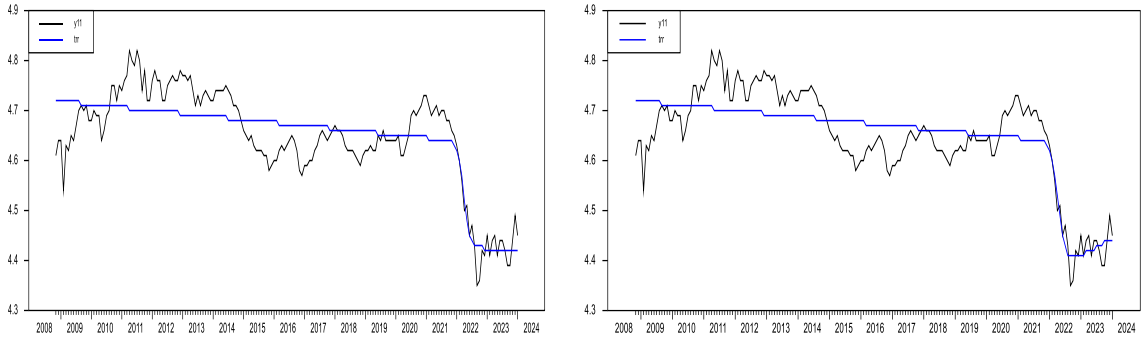


Solactive Green Bond



Monthly Data

S&P Green Bond



Solactive Green Bond

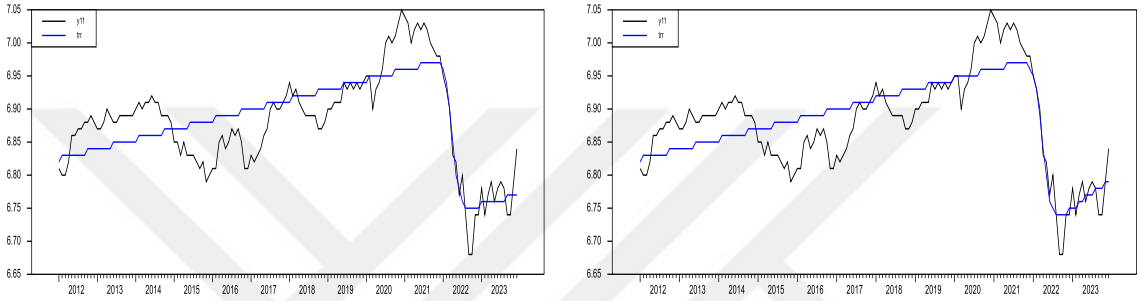


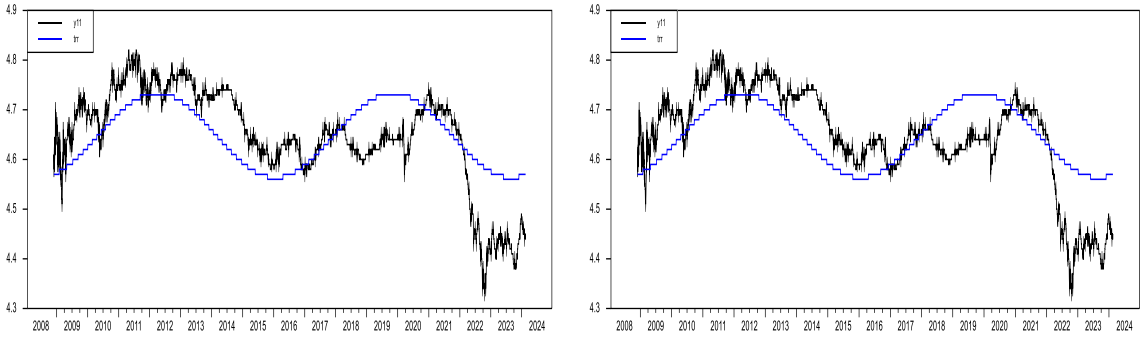
Figure 6A.7. OHEa Test

Daily Data

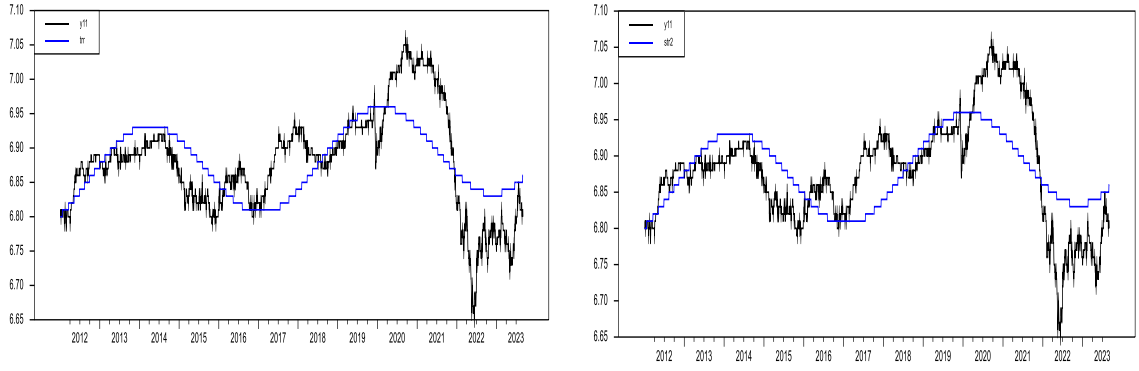
Model B

Model C

S&P Green Bond

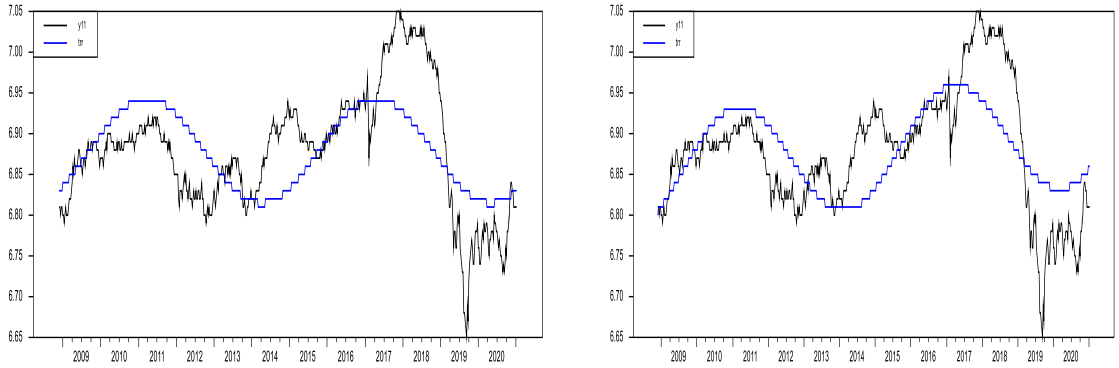


Solactive Green Bond

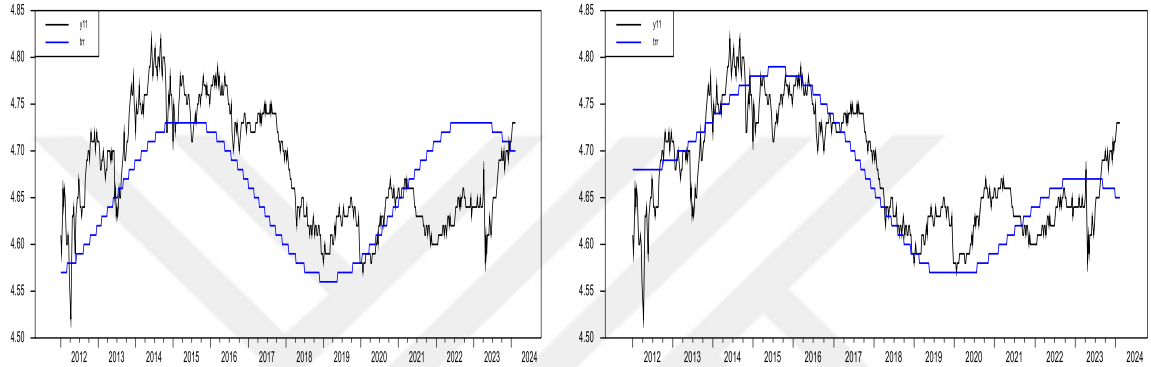


Weekly Data

S&P Green Bond

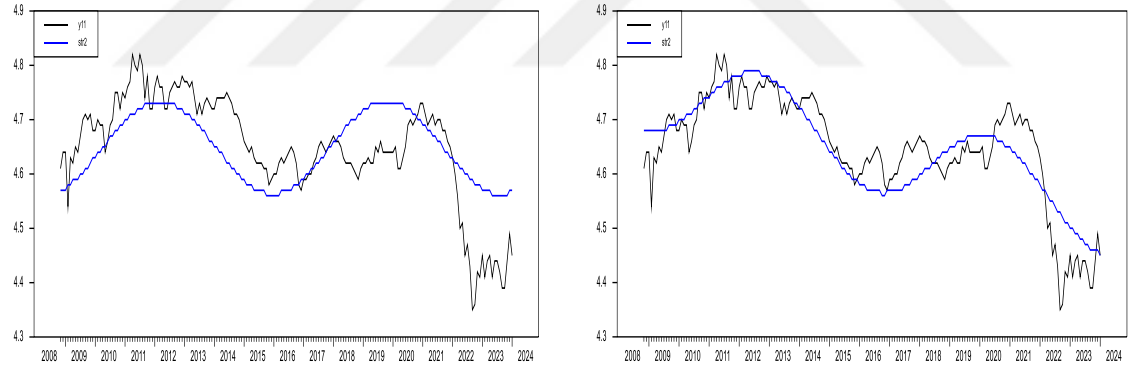


Solactive Green Bond



Monthly Data

S&P Green Bond



Solactive Green Bond

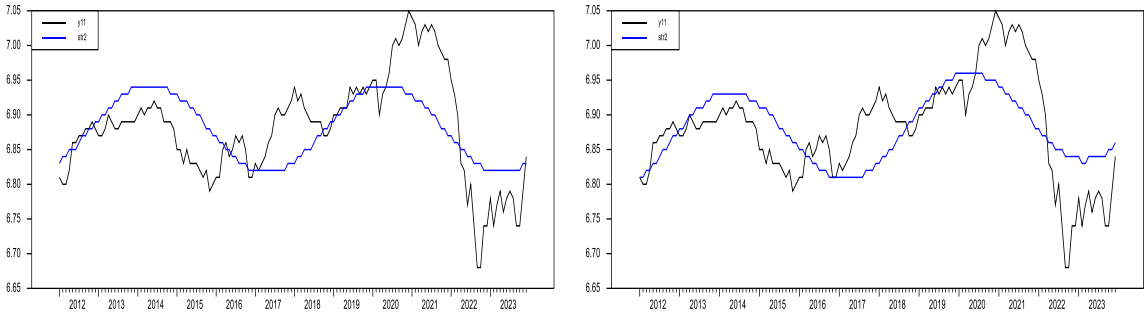
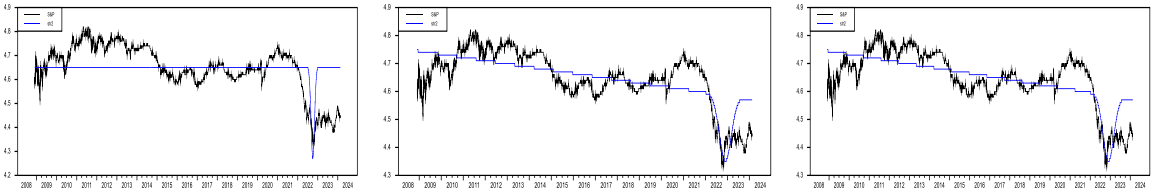


Figure 6A.8. OEHb Test

Daily Data

Model A | Model B | Model C

S&P Green Bond

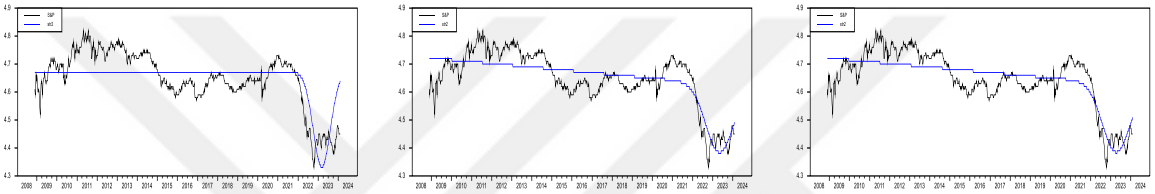


Solactive Green Bond

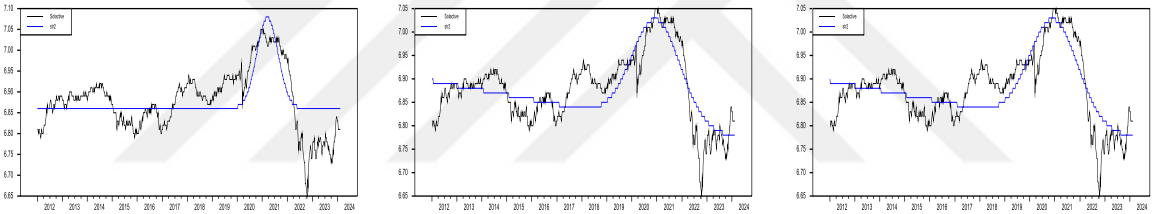


Weekly Data

S&P Green Bond

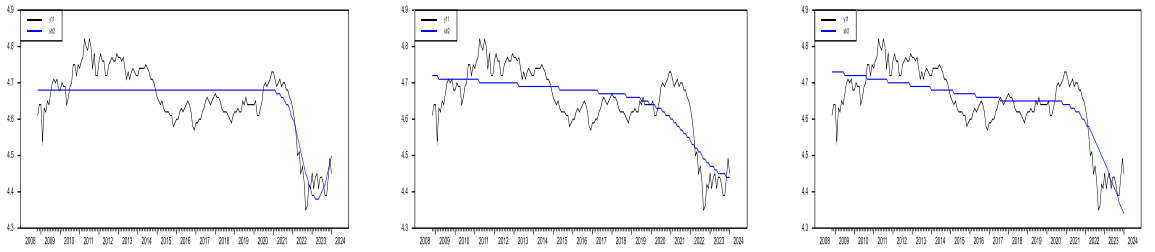


Solactive Green Bond



Monthly Data

S&P Green Bond



Solactive Green Bond

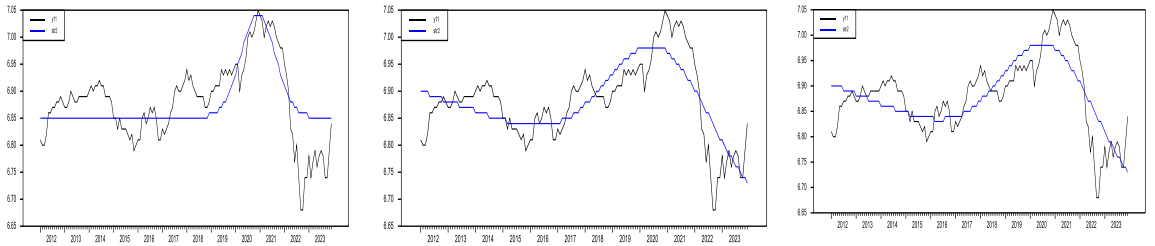


Figure 6A.9. OSH Test

7.2. Appendix B

Green (US)

	GARCH	EGARCH	GJR	APARCH	IGARCH	FIGARCH BBM	FIGARCH CHUNG	FIEGARCH	FIAPARCH BBM	FIAPARCH CHUNG	HYGARCH
AIC	0.8767	*	*	*	**0.8743**	0.879	*	X	0.8777	*	0.8782
BIC	0.8947	*	*	*	**0.8906**	0.8989	*	X	0.9000	*	0.8995
HQ	0.8831	*	*	*	**0.8801**	08862	*	X	0.8859	*	0.8858
Log-Likelihood	-1660.5	*	*	*	-1656.85	-1664.3	*	X	-1659.44	*	-1661.37

Green (EURO)

	GARCH	EGARCH	GJR	APARCH	IGARCH	FIGARCH BBM	FIGARCH CHUNG	FIEGARCH	FIAPARCH BBM	FIAPARCH CHUNG	HYGARCH
AIC	0.3972	*	-	0.3974	0.3971	0.394	-	X	*	**0.392**	0.394
BIC	0.418	*	-	0.422	**0.416**	0.417	-	X	*	0.418	0.418
HQ	0.4047	*	-	0.406	0.404	**0.402**	-	X	*	**0.402**	**0.402**
Log-Likelihood	-744.3	*	-	-742.8	-745.1	-737.6	-	X	*	-732.7	-736.2

Stock

	GARCH	EGARCH	GJR	APARCH	IGARCH	FIGARCH BBM	FIGARCH CHUNG	FIEGARCH	FIAPARCH BBM	FIAPARCH CHUNG	HYGARCH
AIC	2.318	2.286	-	2.285	2.317	2.310	2.309	**2.280**	*	*	2.301
BIC	2.334	2.306	-	2.304	2.332	2.328	2.327	**2.301**	*	*	2.330
HQ	2.323	2.293	-	2.292	2.322	2.317	2.315	**2.287**	*	*	2.310
Log-Likelihood	-4409.3	-4347.8	-	-4344.7	-4409.3	-4394.4	-4391.7	-4334.0	*	*	-4392.9

Aggregate

	GARCH	EGARCH	GJR	APARCH	IGARCH	FIGARCH BBM	FIGARCH CHUNG	FIEGARCH	FIAPARCH BBM	FIAPARCH CHUNG	HYGARCH
AIC	**-0.293**	-0.285	-0.292	*	*	-0.292	-	-0.287	-0.291	-0.292	-0.292
BIC	**-0.283**	-0.272	-0.281	*	*****	-0.281	-	-0.273	-0.277	-0.278	-0.279
HQ	**-0.289**	-0.271	-0.288	*	*****	-0.288	-	-0.282	-0.286	-0.287	-0.287
Log-Likelihood	565.24	553.06	565.35	*	*	565.17	-	557.74	565.46	567.14	565.24

Treasury

	GARCH	EGARCH	GJR	APARCH	IGARCH	FIGARCH BBM	FIGARCH CHUNG	FIEGARCH	FIAPARCH BBM	FIAPARCH CHUNG	HYGARCH
AIC	**0.860**	0.866	0.861	0.865	0.861	0.861	-	*	0.862	0.861	0.865
BIC	0.883	0.892	0.885	0.891	**0.882**	0.885	-	*	0.889	0.889	0.891
HQ	0.868	0.875	0.869	0.874	**0.868**	0.870	-	*	0.872	0.871	0.874
Log-Likelihood	-0.1626	-0.1635	-1626.6	-1634	-1628.5	-1727	-	*	-1626.6	-1625.5	-1634.3

Carbon

	GARCH	EGARCH	GJR	APARCH	IGARCH	FIGARCH BBM	FIGARCH CHUNG	FIEGARCH	FIAPARCH BBM	FIAPARCH CHUNG	HYGARCH
AIC	4.6772	4.6794	-	-	4.6766	4.6770	--	4.6780	4.6744	**4.6718**	4.685
BIC	4.7019	4.7074	-	-	**4.6997**	4.7034	-	4.7077	4.7042	4.7015	4.7108
HQ	4.6860	4.6894	-	-	4.6848	4.6864	-	4.6885	4.6850	**4.6824**	4.691
Log-Likelihood	-8820.2	-8822.4	-	-	-8820.2	-8819.01	-	-8818.8	-8812.1	-8807.1	-8821.3

Energy

	GARCH	EGARCH	GJR	APARCH	IGARCH	FIGARCH BBM	FIGARCH CHUNG	FIEGARCH	FIAPARCH BBM	FIAPARCH CHUNG	HYGARCH
AIC	3.885	3.879	-	3.883	3.885	3.885	-	X	3.8747	3.877	3.890
BIC	3.907	3.904	-	3.907	3.904	3.908	-	X	3.900	3.903	3.915
HQ	3.893	3.888	-	3.891	3.892	3.893	-	X	3.884	3.886	3.890
Log-Likelihood	-7395.2	-7381.0	-	-7388	-7395.2	-7393.2	-	X	-7371	-7375	-7403

Clean

	GARCH	EGARCH	GJR	APARCH	IGARCH	FIGARCH BBM	FIGARCH CHUNG	FIEGARCH	FIAPARCH BBM	FIAPARCH CHUNG	HYGARCH
AIC	-	*	-	3.777	3.379	3.376	-	*	3.372	**3.722**	3.376
BIC	-	*	-	3.999	3.396	3.383	-	*	3.395	**3.397**	3.397
HQ	-	*	-	3.385	3.385	3.395	-	*	3.380	**3.380**	3.383
Log-Likelihood	-	*	-	-6426.55	-6433.81	-6424.46	-	*	-6415.5	-6415.3	-6423.3

Wilderhill

	GARCH	EGARCH	GJR	APARCH	IGARCH	FIGARCH BBM	FIGARCH CHUNG	FIEGARCH	FIAPARCH BBM	FIAPARCH CHUNG	HYGARCH
AIC	4.047	4.054	-	4.041	4.044	4.046	-	*	**4.040**	4.042	4.046
BIC	4.065	4.075	-	4.062	4.063	4.065	-	*	4.063	4.065	4.067
HQ	4.053	4.062	-	4.049	4.048	4.053	-	*	**4.048**	4.051	4.053
Log-Likelihood	-7704.6	-7716.9	-	-7692.1	-7701	-7701	-	*	-7688	-7693	-7700

Renewable

	GARCH	EGARCH	GJR	APARCH	IGARCH	FIGARCH BBM	FIGARCH CHUNG	FIEGARCH	FIAPARCH BBM	FIAPARCH CHUNG	HYGARCH
AIC	3.651	*	-	3.647	3.651	3.6472	-	*	3.6443	3.6439	3.646
BIC	3.669	*	-	3.669	3.667	3.666	-	*	3.6672	3.666	3.667
HQ	3.657	*	-	3.655	3.657	3.654	-	*	3.6525	3.6520	3.653
Log-Likelihood	-6950.74	*	-	-6941.47	-6951.1	-6941.44	-	*	-6933.97	-6933.15	-6938.7

Crude

	GARCH	EGARCH	GJR	APARCH	IGARCH	FIGARCH BBM	FIGARCH CHUNG	FIEGARCH	FIAPARCH BBM	FIAPARCH CHUNG	HYGARCH
AIC	4.206	*	-	4.196	4.200	4.200	-	X	**4.189**	4.190	4.200
BIC	4.229	*	-	4.222	**4.221**	4.224	-	X	4.217	4.218	4.226
HQ	4.214	*	-	4205	4.208	4.209	-	X	**4.199**	4.200	4.209
Log-Likelihood	-8004.9	*	-	-7983.8	-7995.1	-7992.9	-	X	-7970.8	-7972.6	-7992.3

Brent

	GARCH	EGARCH	GJR	APARCH	IGARCH	FIGARCH BBM	FIGARCH CHUNG	FIEGARCH	FIAPARCH BBM	FIAPARCH CHUNG	HYGARCH
AIC	4.004	4.002	-	3.996	4.003	4.002	-	**3.989**	3.992	3.993	4.002
BIC	4.012	4.014	-	4.007	4.010	4.012	-	**4.002**	4.005	4.006	4.013
HQ	4.007	4.006	-	4.000	4.006	4.006	-	**3.993**	3.996	3.998	4.006
Log-Likelihood	-7629	-7624.1	-	-7612.2	-7624.2	-7624.8	-	-7597.09	-7602.9	-7606.1	-7623.0

Natural Gas

	GARCH	EGARCH	GJR	APARCH	IGARCH	FIGARCH BBM	FIGARCH CHUNG	FIEGARCH	FIAPARCH BBM	FIAPARCH CHUNG	HYGARCH
AIC	4.831	*	4.830	4.830	4.831	-	-	X	4.828	4.830	X
BIC	4.845	*	4.846	4.848	4.844	-	-	X	4.848	4.850	X
HQ	4.836	*	4.836	4.836	4.836	-	-	X	4.835	4.837	X
Log-Likelihood	-9201.5	*	-9198.7	-9198.1	-9203.1		-	X	-9193.3	-9298.08	X

Gas Oil

	GARCH	EGARCH	GJR	APARCH	IGARCH	FIGARCH BBM	FIGARCH CHUNG	FIEGARCH	FIAPARCH BBM	FIAPARCH CHUNG	HYGARCH
AIC	3.853	*	-	3.845	3.852	3.853	--	3.841	*	3.848	3.853
BIC	3.871	*	-	3.866	3.868	3.873	-	3.864	*	3.871	3.874
HQ	3.859	*	-	3.852	3.858	3.860	-	3.849	*	3.856	3.860
Log-Likelihood	-7334	*	-	-7318.0	-7334.7	-7334.8	-	-7310.2	*	-7323.2	-7333.4

Biofuel

	GARCH	EGARCH	GJR	APARCH	IGARCH	FIGARCH BBM	FIGARCH CHUNG	FIEGARCH	FIAPARCH BBM	FIAPARCH CHUNG	HYGARCH
AIC	**3.122**	*	3.123	3.123	3.123	3.125	-	*	3.126	3.123	3.126
BIC	3.142	*	3.144	3.146	**3.141**	3.147	-	*	3.149	3.148	3149
HQ	**3.129**	*	3.130	3.131	3.130	3.133	-	*	3.134	3.132	3.134
Log-Likelihood	-5941.8	*	-5941.3	-5941.2	-5944.4	-5946.1	-	*	-5945.6	-5940.1	-5946.1

Heating

	GARCH	EGARCH	GJR	APARCH	IGARCH	FIGARCH BBM	FIGARCH CHUNG	FIEGARCH	FIAPARCH BBM	FIAPARCH CHUNG	HYGARCH
AIC	3.913	*	-	3.905	3.913	3.911	-	X	**3.902**	3.903	3.911
BIC	3.934	*	-	3.929	3.933	3.934	-	X	**3.928**	3.930	3.935
HQ	3.921	*	-	3.913	3.920	3.919	-	X	**3.911**	3.913	3.919
Log-Likelihood	-7448	*	-	-7429.9	-7448	-7443	-	X	-7424.4	-7426.9	-7441.6

"*"shows no converge problem. "–" indicates that constraint for the GARCH model is not observed. Lastly, "X" indicates the GARCH parameter(s) or/and the parameters showing the asymmetric effect are not significant.

7.3. Appendix C

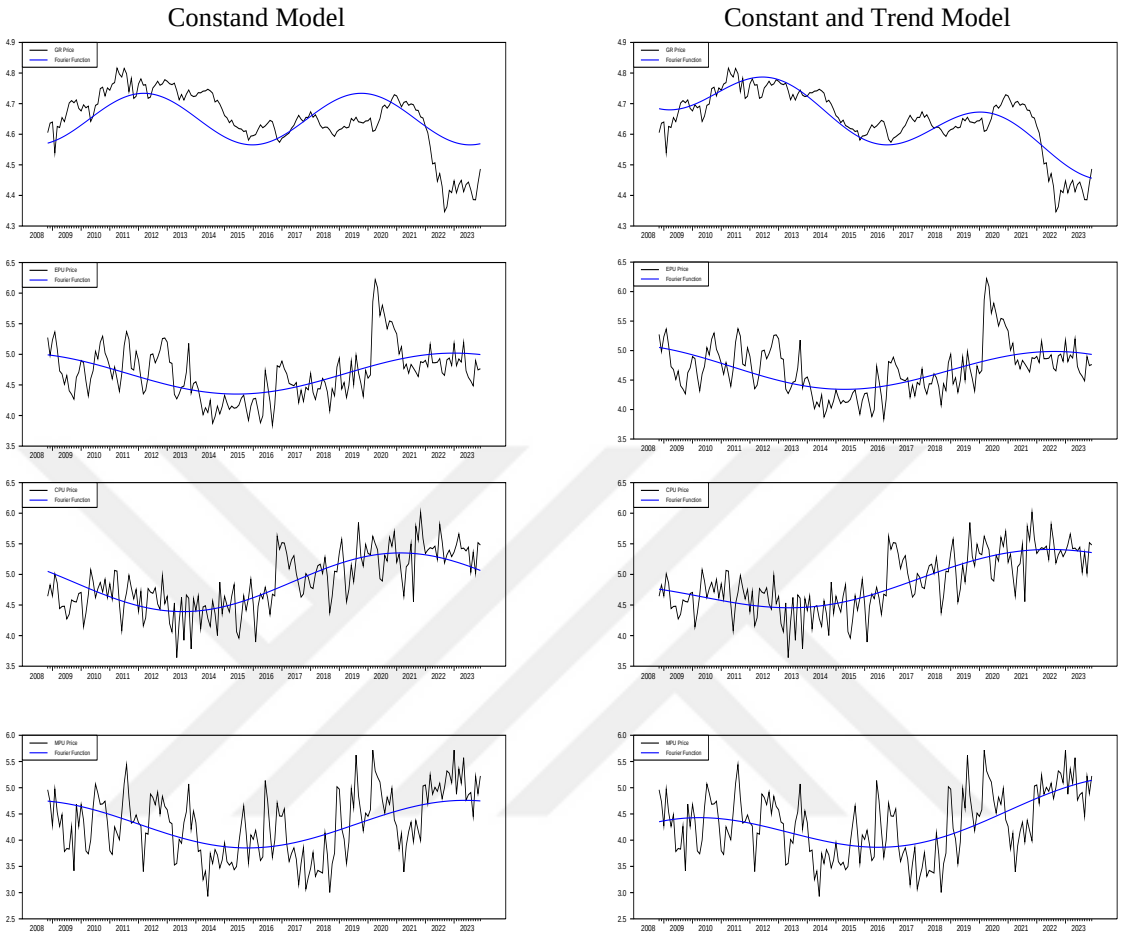


Figure 7.5. Fourier KPSS Test

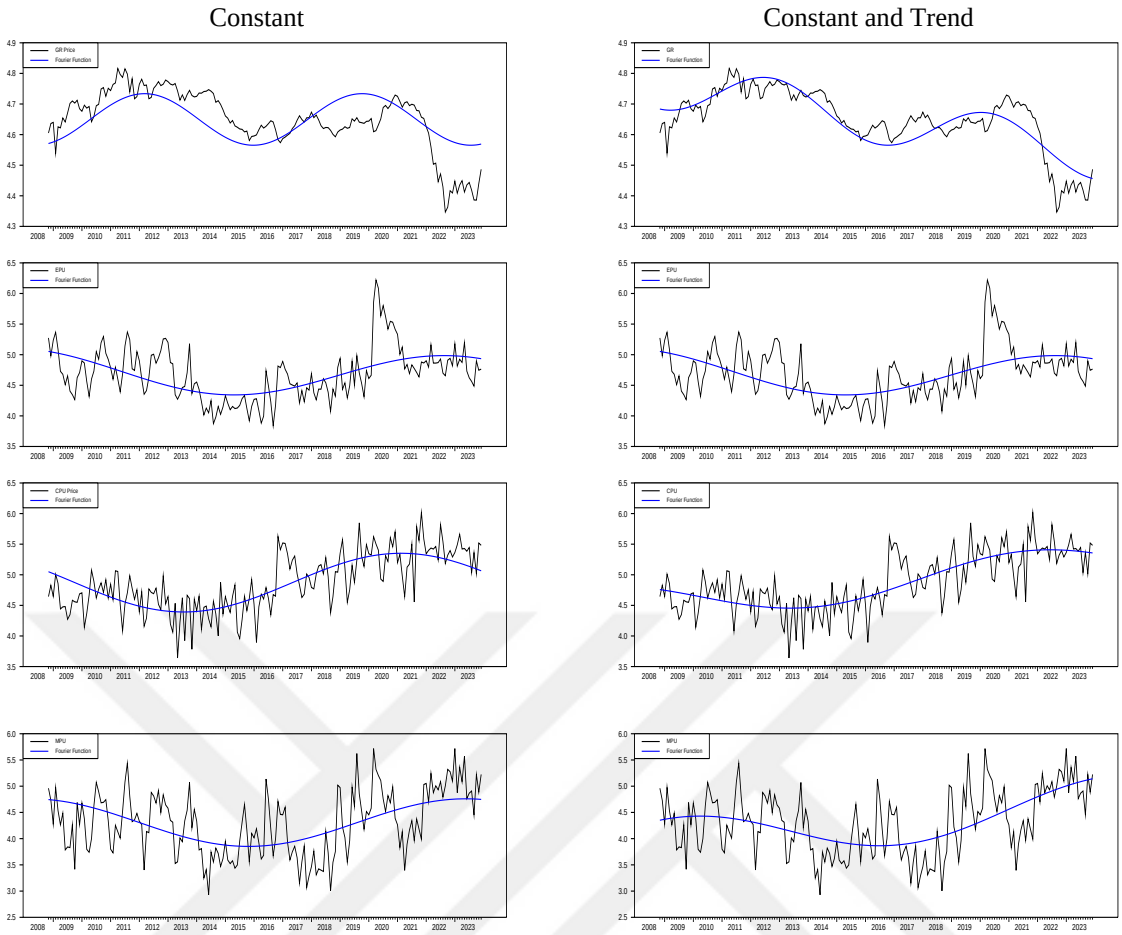


Figure 7.6. Fourier ADF Test

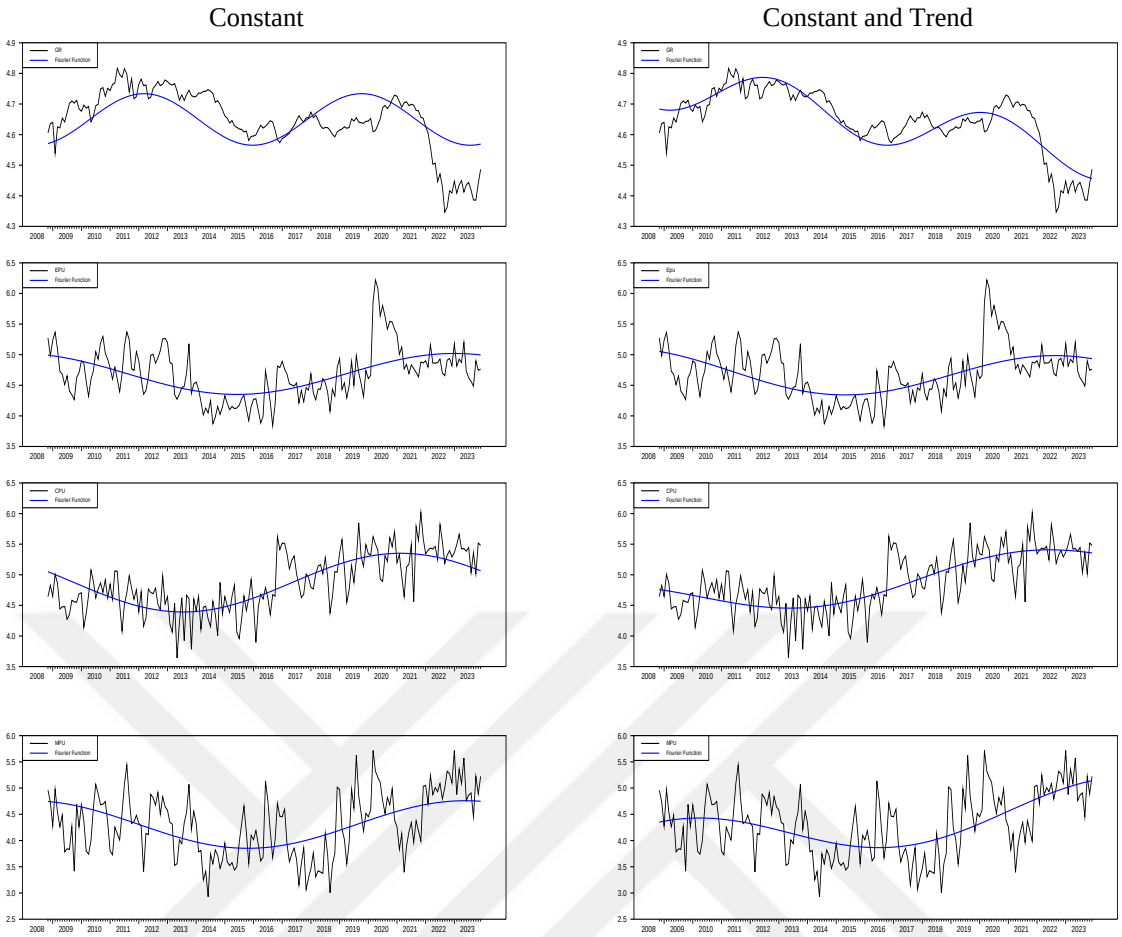


Figure 7.7. Fourier KSS Test

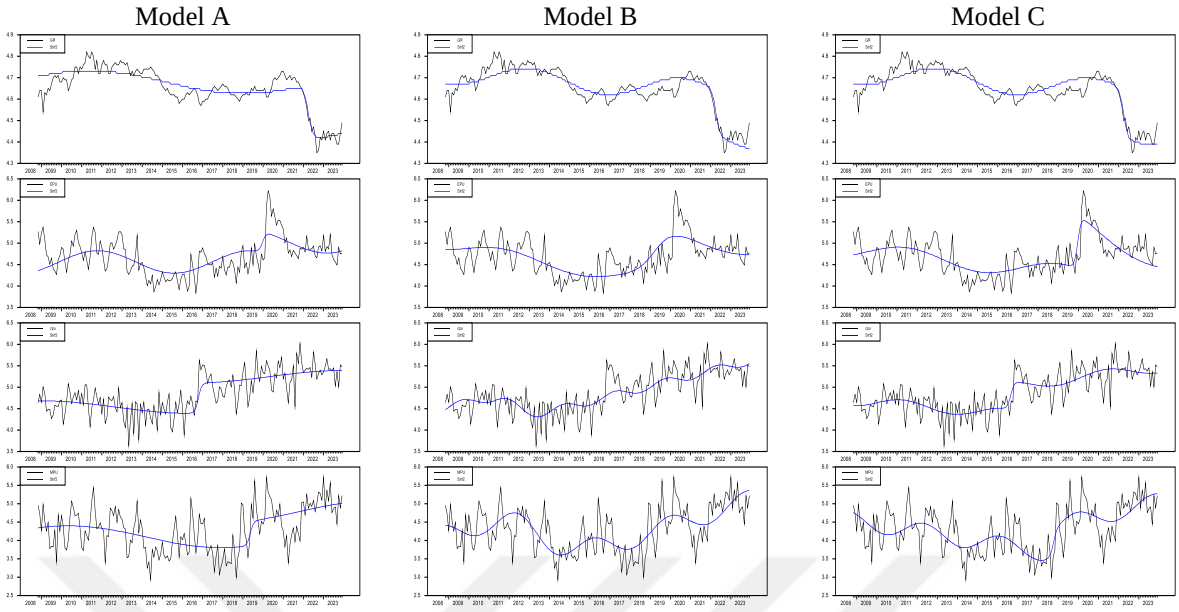


Figure 7.8. SOR Test

Table 7.5. **Fourier Bootstrap ARDL Diagnostic test results**

		S&P			
	Test statistics	*Prob*	*Tests*	*Test statisticts*	*Prob*
@SIN	0.006***	(0.008)	$BG-LM$	0.918	0.470
@COS	-0.002	(0.446)	Breusch-Pagan-Godfrey	1.477	0.137
Dummy1	08.2021***	(0.000)	Ramsey-Reset	0.898	0.344
		Solactive			
@SIN	-0.001	0.545	$BG-LM$	0.308	0.907
@COS	0.005**	0.046	Breusch-Pagan-Godfrey	4.68***	0.000
Dummy1	04.2022***	0.000	Ramsey-Reset	0.321	0.571

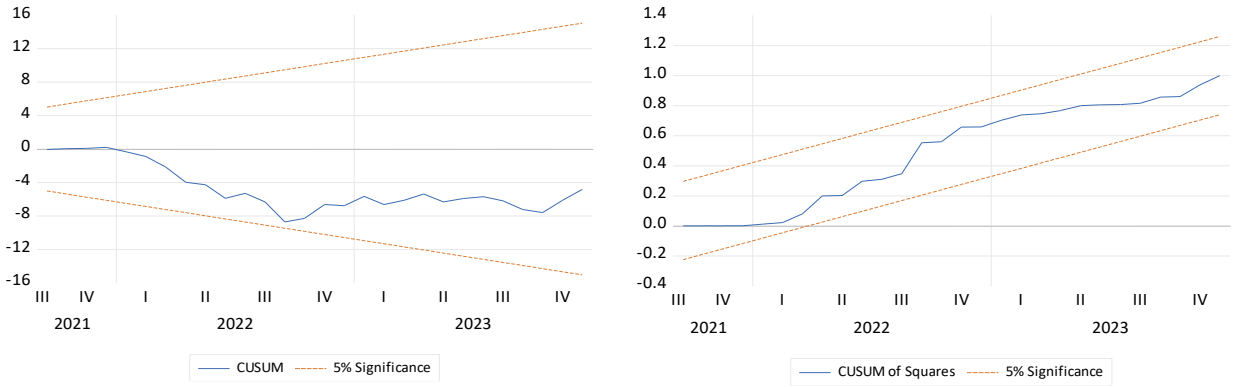


Figure 7.9. CUSUM and CUSUMsq graphs for S&P

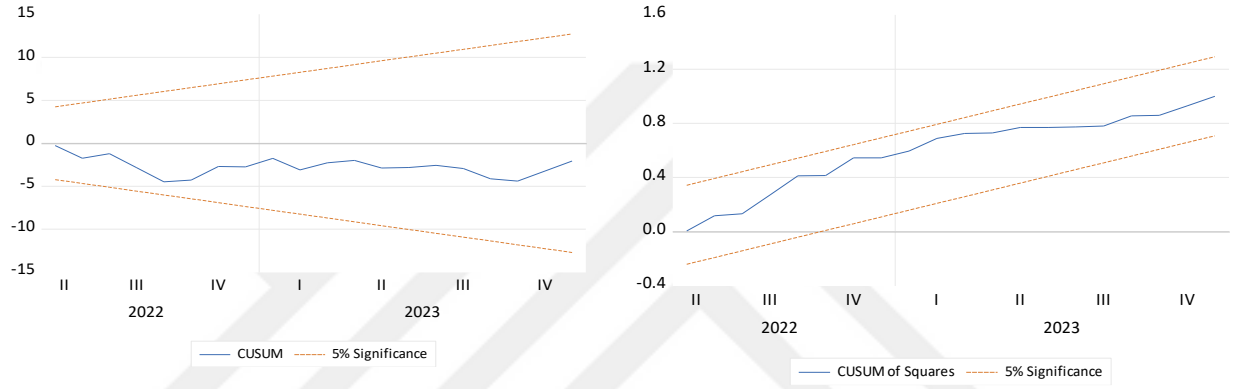


Figure 7.10. CUSUM and CUSUMsq graphs for Solactive