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Master Thesis U.S.E.

"Diversifier, Hedge, or Safe Haven? An Empirical Investigation of the Co-Movement between Green Bonds and Other Financial Instruments."

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Abstract

This thesis presents a comprehensive analysis of the diversification benefits offered by green bonds through an examination of their co-movement with other financial instruments. The study covers a sample period spanning from February 5, 2016, to March 10, 2023. By employing a Markov-switching VAR model with time-varying transition probabilities, we effectively capture the regime-specific correlations between the green bond index and various financial indices. Our findings robustly challenge the prevailing notion that green bonds serve as hedges or safe havens for other financial markets. However, we do observe significant diversification benefits of green bonds in relation to the commodity, oil & gas, global stock, low-carbon, and carbon markets. These results underscore the potential of green bonds as an effective tool for portfolio diversification.

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Contents

1 Introduction

Green bonds are fixed-income assets similar to conventional corporate and government bonds in terms of pricing and rating (Reboredo, 2018). However, their distinctive feature is that their proceeds are earmarked for environmentally beneficial projects. The green bond market began in 2007 when the European Investment Bank (EIB) issued the Climate Awareness Bond (CAB), a new fixed-income instrument aimed at financing projects with environmental benefits (Cortellini and Panetta, 2021).

Initially, the green bond market was mainly driven by supranational issuers like the EIB and the World Bank due to the lack of a common definition and framework for the instrument (Cortellini and Panetta, 2021). However, the introduction of the Green Bonds Principles (GBP) in 2014 provided guidelines and non-prescriptive recommendations for best practices in the market, leading to a surge in green bond issuances to 36.6 billion USD, more than triple that of 2013 (Cortellini and Panetta, 2021). The GBP became an internationally recognized standard for green bond issuance, allowing both government and private institutions to enter the market and providing investors with a way to assess the reliability and "greenness" of the issuer and bond, respectively. Moreover, the Paris Climate Agreement of 2015 provided a significant boost to the green bond market (Cortellini and Panetta, 2021). It was the first legally binding global climate deal in which 195 countries expressed their commitment to reduce global warming. The deal provided a strong incentive for financing climate-friendly projects through green finance. Overall, the GBP and Paris Agreement have played critical roles in the development of the green bond market, which has become an increasingly important tool for financing sustainable projects and combating climate change.

Green bonds have emerged as a crucial source of capital to finance sustainable projects aimed at reducing carbon dioxide emissions and achieving sustainability goals (Bhutta et al., 2022). However, according to the European Commission, Europe is facing an annual investment shortfall of €179 billion to meet the Paris Agreement targets by 2030 (Cortellini and Panetta, 2021). Therefore, there is an increasing need to rapidly develop the green bond market, which has gained the attention of policy makers, scholars, and academics. As noted by (Cortellini and Panetta, 2021)., the empirical literature highlights certain trends, such as the "Greenium," which refers to green bonds being priced at a lower interest rate, as well as connectedness with other financial instruments, supply-side analysis, stock reactions, and market performance analysis (Febi et al., 2018); (Reboredo, 2018); (Lebelle et al., 2020); (Barua and Chiesa, 2019).

Although environmentally conscious investors have historically displayed demand for green bonds, there is now increasing interest from more conventional investors around the globe (Nguyen et al., 2021). This interest has been sparked by the belief that green bonds could potentially deliver financial benefits by providing investors with an opportunity to diversify their portfolios (Naeem et al., 2021a). (Naeem et al., 2021b). Despite the growing research on green bonds' connection to other financial instruments, little is known about the role of green bonds in an investment portfolio (Nguyen et al., 2021).

This thesis aims to investigate the connectedness of green bonds with other financial instruments, particularly their effectiveness as diversifier, hedge, or safe haven against several types of market risk. Previous research suggests that green bonds serve as a hedge and safe haven for the stock, energy, commodity, and high-yield treasury bond market (Reboredo, 2018; Reboredo and Ugolini, 2020; Naeem et al., 2021b; Nguyen et al., 2021; Han and Li, 2022; Arif et al., 2022; Yadav et al., 2023). Furthermore, the green bond market is identified as a hedge and safe haven for the carbon market (Jin et al., 2020; Yadav et al., 2023). Moreover, the green bond market has sizeable diversification benefits on the low-carbon stock market (Reboredo et al., 2022). Additionally, the green bond market is considered not only a diversifier and hedge, but also a safe haven for the stock and (energy) commodity market (Arif et al., 2022; Martiradonna et al., 2023). Prior research also highlights the importance of macroeconomic circumstances on the return connectedness between green bonds and other financial instruments (Broadstock and Cheng, 2019; Saeed et al., 2021; Lee et al., 2021). Others emphasize the need for further research on the hedge and safe haven properties of green bonds and their role in crises (Naeem et al., 2021b,0). Based on these findings we have formulated the following research question:

RQ: *"Do green bonds exhibit diversifier, hedge, or safe haven properties with respect to other financial instruments?"*

Our study aims to examine the co-movement between the green bond index and 7 other market indices from February 5, 2016, to March 10, 2023. We use a time-varying transition probability (TVTP) specification of a two-state Markov-switching vector autoregression (MS-VAR) model to identify crisis periods endogenously in terms of volatility. We leverage the COVID-19 pandemic, Ukraine-Russia war, and the 2022 bear market to assess the safe-haven properties of green bonds.

This thesis makes several contributions to the existing literature. First, by exploring the co-movement between green bond and other financial markets, this study offers essential information for investors as it demonstrates how the green bond market is impacted by oscillations in other financial markets (Reboredo, 2018). Moreover, demonstrating the effectiveness of the green bond as a diversifier, hedge, or safe haven is likely to stimulate the demand from both investors concerned with environmental, social, and governance (ESG) matters and conventional investors, thereby increasing the demand for being green. This, in turn, could significantly benefit society, as the growth in sustainable finance could improve our chances of achieving the sustainability goals set by the Paris Agreement. Second, this study analyses an extended sample with respect to prior studies, providing more comprehensive insights into the potential benefits of green bonds Finally, as previous research on this topic has primarily examined bullish periods, investigating the recent bearish period characterized by pronounced market volatility and a prolonged decline in stock market returns could provide valuable insights into the diversification benefits of green bonds.

Based on our TVTP MS-VAR Model estimations, our study challenges the notion that the green bond serves as a hedge or safe haven for any of the financial markets considered. The regime-specific correlations reveal a positive co-movement between the green bond and all other indices, indicating significant diversification benefits in both non-crisis and crisis periods, albeit to a lesser extent during crises.

The remainder of this thesis is organized as follows: Section 2 serves as an introduction, covering key concepts and definitions pertinent to our study. It also includes an extensive literature review exploring the linkages between green bonds and financial assets. Additionally, this section provides contextual information on the recent crisis periods encompassed in our sample. Section 3 presents the theoretical framework, building upon the insights gleaned from Section 2. Section 4 provides a comprehensive description of our data, preliminary data analysis, and the econometric methodology employed. In Section 5, we present the empirical results obtained from our linear VAR and TVTP MS-VAR model estimations, along with a detailed interpretation of their implications. Finally, Section 6 encompasses the discussion and conclusion, summarizing the key findings and offering concluding remarks on our study.

2 Literature Review

2.1 Diversifier, Hedge, or Safe Haven?

The publication of the article "Portfolio Selection" by Harry Markowitz in 1952, gave birth to what is now known as modern portfolio theory (MPT) (Fabozzi et al., 2002). With time, MPT grew in popularity and greatly influenced the practice of portfolio management. Although it was already considered common sense not to put all your eggs in one basket, MPT quantified the benefits of diversification by introducing the statistical notion of correlation (Fabozzi et al., 2002). The basic idea behind this, is that is not a good investment strategy to put all you money in investments whose returns are highly correlated, as it is very likely they will go broke at the same time. Therefore, investors seek for ways to diversify their portfolio and limit their exposure to financial risks.

The rapid expansion of financial markets in recent decades has resulted in an elevated level of risk in the financial system (Baur and Lucey, 2010). Consequently, investors are increasingly seeking ways to limit their exposure to financial risks. Based on the definitions provided by Baur and Lucey (2010). we can distinguish between three types of financial instruments that investors can use to achieve this goal. First, a diversifier is an asset that is positively, but not perfectly correlated, with another asset on average. Second, a hedge is an asset that is uncorrelated or negatively correlated with another asset on average. Finally, a safe haven is an asset that is uncorrelated or negatively correlated with another asset in times or market turmoil. The specific property of a safe haven asset does not force the correlation to be non-positive on average, but only during extreme market conditions (Baur and Lucey, 2010).

The 2020 stock market crash triggered by the COVID-19 pandemic has renewed the interest in safe haven assets as it demonstrated that diversification benefits across asset classes decrease during times of high volatility in financial markets (Arif et al., 2022). Research indicates that various financial assets, such as gold, long-term treasury bonds, currencies, and crypto-currencies, have been utilized as effective hedge and safe haven assets (Baur and Lucey, 2010; Baur and McDermott, 2016; Flavin et al., 2014; Urquhart and Zhang, 2019).

The green bond possesses a unique combination of financial resources and environmental protection, making it a valuable component of a well-diversified portfolio (Le et al., 2021). Given their stability and sustainability as long-term investments, green bonds are likely to be included in diversified portfolios. Recent evidence shows that green bonds hold significant diversification benefits for financial markets (Arif et al., 2022) Additionally, previous studies have also highlighted that, unlike equity, the volatility of green bonds exhibits an asymmetric response to positive return shocks (Le et al., 2021). This implies that green bonds may behave differently from equities in certain market conditions. This asymmetry in response to positive return shocks can potentially contribute to the diversification of an investment portfolio, offering investors an additional risk management tool. As investors become more interested in the portfolio diversification benefits, they are increasingly embracing green bonds as an alternative to traditional bonds (Naeem et al., 2021a). This growing demand has become evident from the rising connectedness between green bonds and other financial assets.

Due to the diversification benefits of green bonds, they may also be effective for hedging and safe haven purposes (Arif et al., 2022). Flavin and Sheenan (2023) identify three main reasons to support this hypothesis. First, the pricing of climate and carbon risks in financial markets makes green bonds a potential safe haven asset for equities. Second, green bond prices are influenced by both economic and ESG factors, indicating that investors appreciate the environmental benefits that green bonds aim to achieve. Finally, the preference of investors for green assets may lead to a sustained increase in prices, potentially resulting in longer-term holdings of green bonds and less price volatility during periods of crisis.

The following section aims to provide a clear and chronological overview of the studies that have explored the diversification benefits of green bonds by examining their co-movement with other financial assets.

2.2 Green Bonds' Connectedness with Financial Assets

Although there has been a growing body of research on green bonds in recent years, only a limited number of studies have explored the potential diversification benefits of green bonds in relation to other asset classes (Nguyen et al., 2021; Bhutta et al., 2022) However, given that investors' portfolio strategies are influenced by the connectedness among financial assets, it is crucial for market participants to comprehend the framework of connectedness between green bonds and other financial assets over time (Le et al., 2021).

Reboredo (2018) analyses the co-movement between the green bond and financial markets from October 2014 to August 2017 finding that the green bond market weakly co-moves with stock and commodity markets. The dependence between the green bond and financial markets varies across markets and over time, with important implications for potential diversification benefits and price spillovers between the markets. To assess the diversification benefits of green bonds, Reboredo (2018) uses the conditional diversification benefit (CDB) measure, which he observes to remain relatively stable over the sample period, with the exception of the stock market. He finds that green bonds have a considerable CDB on stocks and strong diversification effects on commodity markets, particularly at the lower tail of the distribution. Regarding price spillovers, Reboredo (2018) he finds that stock markets could be useful to green bond investors in terms of extreme risk management, as there is evidence of both upward and downward price spillovers. However, for the commodity markets, he finds limited evidence of price spillovers. Overall, his findings highlight the potential diversification benefits of green bonds for investors, particularly in relation to stocks and commodity stocks, and the importance of considering the dynamics of co-movement and price spillovers between the green bond market and other financial markets.

Broadstock and Cheng (2019) analyze the dynamic relationship between green and conventional or "black" bond price benchmarks in the US market using daily data from November 2008 to July 2018. Their study identifies various factors that influence the correlation patterns between these two markets. They find that the strength of the connection between green and black bonds is affected by changes in financial market volatility, economic policy uncertainty, daily economic activity, oil prices, and positive and negative news-based sentiment towards green bonds. Their findings suggest that the relationship between green and black bonds is complex and subject to a range of external factors that impact both markets. The authors also suggest that future research should explore the role of individual determinants in driving the growth of the green bond market. This could help identify key drivers of green bond demand and inform the development of more effective policies and regulations to support the expansion of this market. Overall, the study highlights the importance of understanding the dynamic relationship between green and black bonds, as well as the broader market and economic factors that influence their performance.

Reboredo and Ugolini (2020) examine the price connectedness between the green bond and financial markets over the period of October 2014 to June 2019. In this research, a structural vector-autoregressive (VAR) model and Monte Carlo simulations are used to assess the direct and indirect impact of financial shocks across the markets. Their empirical results support the findings of their prior research as they reveal that the green bond market is closely linked to the fixed-income and currency markets, receiving sizeable price spillovers from those markets, and transmitting negligible reverse effects. They also show that, in contrast, the green bond market is weakly tied to the stock and commodity markets.

Jin et al. (2020) investigate the effectiveness of various hedging instruments for carbon market risk by examining the relationship between the returns of carbon futures of the European Union Emission Trading Scheme (EU ETS) and the returns of four major market indices, namely the VIX index, the commodity index, the energy index, and the green bond index. They analyze the period from December 2008 to August 2018, which they divide into two sub-periods. The first sub-period covers the relatively volatile period of the 2008 Great Financial Crisis (GFC), the 2010 EU debt crisis, and the drastic decline in the price of European Union Carbon Emission Allowances (EUA) from 2012 to 2013. The second sub-period covers the relatively tranquil period from April 2013 to August 2018. Using various extensions of the GARCH model, they find that the green bond index is the best hedge for carbon futures among the four indices, and it performs well even during the crisis period, which contrasts with the other indices' performance.

Hammoudeh et al. (2020) examine the time-varying causal relationship between green bonds and other assets from July 2014 to February 2020. They use a novel time-varying Granger-causality test based on an evolving algorithm to bridge a gap in the existing literature. They find significant causality running from the US 10-year treasury bond index to green bonds starting from the end of 2016 until the end of the sample period. Additionally, they observe a causal relationship between CO2 emission allowances price and green bonds from the beginning of their sample period to the end of 2015. Furthermore, they find only limited causality running from the clean energy index to the green bond index and no significant causality running from green bonds to all other assets. Their findings suggest that changes or fluctuations in the green bond market do not cause corresponding changes or fluctuations in other financial markets.

Saeed et al. (2021) investigate the determinants of extreme return connectedness between clean/green and dirty energy investments in the US. They use a quantile VAR model to study a sample of US firms at the daily frequency over the period January 2012 to November 2019. Their findings reveal that the return connectedness across clean energy stocks, green bonds, crude oil, and energy exchange traded fund (ETF) is larger at both left and right tails, and that return connectedness differs between periods of extreme negative returns, suggesting asymmetric behavior. Moreover, they show that macroeconomic conditions play a crucial role in driving the return connectedness between clean/green and dirty energy investments.

Lee et al. (2021) investigate the causal relationship between oil price, geopolitical risks, and green bonds in the US market over the period from December 2013 to January 2019. They employ the Granger-causality in quantile analysis and observe a unidirectional Granger-causality from geopolitical risk to oil price at extreme quantiles. They find a bi- directional causality between oil price and the green bond index for the lower quantiles, and causality from geopolitical risk to the green bond index in the lower quantiles of the distribution. The study highlights the importance of macroeconomic conditions in understanding green bond market dynamics. Their findings imply the explanatory power of oil price or geopolitical risk is heterogeneous in different market conditions and states that only the lower negative oil price changes or geopolitical risk changes lead to changes in the green bond index.

The study by Naeem et al. (2021b) focuses on exploring the asymmetric relationship between green bonds and commodities using a cross-quantilogram approach. They examine a global sample from December 2008 to December 2019 and find that incorporating green bonds into commodity portfolios provides hedging and diversification benefits. The results show that green bonds offer the strongest hedging benefits against the fluctuations of natural gas, certain industrial metals, and agricultural commodities. Naeem et al. (2021b) recommend the use of green bonds as a hedging instrument in the longer term rather than the short term. Furthermore, they suggest further investigation of the hedge and safe haven properties of green bonds in different frameworks as a future research avenue. Overall, the study contributes to the literature on the use of green bonds as an effective hedging tool against commodity market risk.

Naeem et al. (2021a) also investigate the impact of COVID-19 on the time frequency connectedness between green bonds and other financial assets. They claim that their study completes the prior literature on connectedness of green bonds with other financial assets (Reboredo, 2018; Reboredo and Ugolini, 2020; Jin et al., 2020; Saeed et al., 2021) Their sample consists of daily observations over the period May 2013 to August 2020. Using the methodology of Diebold and Yilmaz (2012) and Baruník and Křehlík (2018), they find that financial assets have a heterogeneous relationship with green bonds. Their frequency analysis unveils that the connectedness is more pronounced in the short-run than in the long-run. Finally, their empirical results point out that the role of green bonds in a crisis should not be ignored, as it can be an effective hedge for some assets, while a contagion amplifier for other assets. The authors suggest that for future research, investigating which specific macroeconomic variables drive the return connectedness of green bonds with these selected assets constitutes a relevant research idea, particularly within the context of the COVID pandemic.

Nguyen et al. (2021) contributes to the literature by investigating the connnectedness between green bonds and other asset markets using the rolling window wavelet correlation approach. The analysis covers daily data from December 2008 to December 2019 and reveals that the correlation between green bonds and other asset markets emerged and peaked after the GFC. The study also demonstrates the diversification benefit of green bonds due to their low or negative correlation with stocks and commodities, suggesting their potential role as a safe haven asset. In contrast, co-movement between stocks, commodities, and clean energy is found to be relatively high, emphasizing the need for investors to diversify their portfolios to mitigate risk. The findings of this study are relevant for investors seeking to optimize their portfolio allocation and risk management strategies.

Reboredo et al. (2022) explore the extent to which green bonds could de-risk investments in low-carbon assets. To do so, they use a sample consisting of Chinese, European, and US markets for the period 2016 to 2020. They determine the hedging and de-risking abilities of green bonds by the dependence structure between green bonds and low-carbon stocks. This dependence structure is characterized by their joint returns distribution. Additionally, they use a measure of Expected Shortfall (ES) to examine how green-bond returns behave in response to abrupt changes in value in low-carbon stock returns and vice versa. Their findings indicate that green bond and low-carbon stock returns move in opposite directions or independently. Lastly, the authors conclude that green bonds have sizeable diversification benefits when they are included low-carbon investment portfolios. This findings is particularly valuable for climate-aware investors as they can hedge portfolio risk solely by using green financial instruments that are consistent with their environmental stance.

Han and Li (2022) provide valuable insights into the role of green bonds in asset allocation. They use the dynamic R-vine copula-based mean-CVAR approach to analyze the connectedness between assets in the entire portfolio for the period December 2013 to March 2021. The study's results demonstrate that portfolios including green bonds outperform portfolios including conventional bonds in terms of risk-adjusted returns in both European and U.S. markets. This finding suggests that investors can benefit from including green bonds in their portfolio allocation strategy. The authors' analysis of the sources of this outperformance, specifically the increase in the return and the decrease in the volatility of green bonds, provides additional insights into the factors driving the performance of green bonds as an asset class. Overall, this study highlights the potential benefits of incorporating green bonds into a diversified investment portfolio.

Arif et al. (2022) investigate the hedging and safe haven potential of green bonds for conventional equity, fixed income, and forex investments from 2010 to 2021 using the cross-quantilogram approach. Their results demonstrate that the green bond index can function as a diversifying asset for medium- and long-term equity investors and a hedging and safe-haven instrument for currency and commodity investments. However, during the COVID-19 pandemic period, the green bond index did not provide any safe-haven opportunities during the market contagion, as indicated by an enhanced lead-lag association between the green bond index and conventional investments on the short- and medium-term.

Yadav et al. (2023) investigate the diversification opportunities of green bonds during the COVID-19 pandemic and their connectedness with energy, crypto, and carbon markets. Similar to Naeem et al. (2021a), they apply Diebold and Yilmaz (2012), Baruník and Křehlík (2018), and wavelet coherence econometric techniques to a global sample spanning from October 2015 to December 2021. They report that the overall diversification benefits of green bonds with energy stocks, bitcoin, and the carbon market are more pronounced in the short-run than in the medium and long-run.

Similarly, Martiradonna et al. (2023) investigate the role of green bonds as a novel strategic asset class. Specifically, they analyze green bond diversification benefits, their co- movements with the several global markets, and the corresponding implications for portfolio implications. Using a sample composed of daily observations from October 2014 to June 2021, they find that both the Bloomberg Barclays MSCI Green Bond Index and the Solactive Green Bond Index show significantly positive conditional correlation with the corporate bond market throughout the entire period. Although both indices do not appear to be useful for diversification in the corporate bond market, their lower volatility does make them an appealing asset class for conservative investors. More notably, they find that the Solactive Green Bond Index negatively co-moves with all other sectors in the analysis: the global stock market, the energy commodity index, the airline industry, the healthcare sector, and the IT index. This finding applies for all periods considered in the analysis, also the pre-pandemic and pandemic period. However, the Bloomberg Barclays MSCI Green Bond Index does not seem to possess this property as it positively co-moves with the other sectors. Consequently, the Solactive Green Bond Index appears to provide better diversification opportunities for investors in these sectors.

While there is already a significant body of literature demonstrating the potential diversification benefits of green bonds in relation to other financial assets, many of these studies have primarily focused on analyzing green bonds' diversification benefits in bullish market conditions (Reboredo, 2018; Broadstock and Cheng, 2019; Reboredo and Ugolini, 2020; Hammoudeh et al., 2020; Saeed et al., 2021; Lee et al., 2021; Naeem et al., 2021b). Some studies have also included the volatile period of the Great Financial Crisis (GFC) in their sample (Naeem et al., 2021b; Nguyen et al., 2021; Jin et al., 2020). More recently, researchers have explored the connectedness of green bonds with other financial assets during the COVID-19 period (Han and Li, 2022; Arif et al., 2022; Yadav et al., 2023; Martiradonna et al., 2023; Naeem et al., 2021a). Although these studies highlight the potential diversification benefits of green bonds, it remains unclear whether green bonds can serve as a hedge and/or safe haven in relation to other financial assets (Arif et al., 2022; Martiradonna et al., 2023). Therefore, it is essential to conduct further investigations to explore the role of green bonds in an investment portfolio, particularly during times of crises.

2.3 Crises and Financial Contagion

As we focus specifically on the role of green bonds as safe haven assets, our research aims to examine the co-movement between green bonds and other financial assets during several crisis periods defined by declining stock market returns and increased volatility. Therefore, it is crucial to comprehend the factors that contributed to the decline in stock market returns during this period.

Recent literature, including Naeem et al. (2021a), highlights several reasons for the decline in stock market returns during the COVID-19 Pandemic, such as heightened uncertainty and fear, negative investor sentiment, and systematic risks. Furthermore, the COVID-19 pandemic exacerbated stock market volatility, leading to significant decreases in returns (Naeem et al., 2021a). The impact of COVID-19 extended beyond the stock market, profoundly affecting the oil market as well. As emphasized by Ready (2018), a strong correlation exists between the stock market and the oil market. Consequently, the substantial decline in global oil prices since the onset of the COVID-19 pandemic has had a significant negative impact on the stock market (Naeem et al., 2021a). This is particularly relevant for the green bond market since the price of oil is linked to the demand for environmentally friendly investments (Broadstock and Cheng, 2019). Lower oil prices lead to increased demand for oil and, consequently, alter the demand for socially responsible investments through green bonds. Similarly, investors are incentivized to switch from green bonds to more traditional assets when financial markets experience heightened instability (Broadstock and Cheng, 2019). Moreover, the exposure of clear weaknesses in the real economy and the ongoing rise in economic policy uncertainty (EPU) caused by the COVID-19 pandemic continue to significantly influence investment activity, providing an incentive for investors to re-evaluate their investment strategies (Haq et al., 2021).

Our sample period also encompasses the Ukraine-Russia war, an event that carries global economic implications, such as heightened inflation, reduced household consumption resulting from increased prices of commodities like oil, gas, wheat, and minerals. It also entails supply chain disruptions, heightened uncertainty, obstacles to economic growth, decreased investment, and increased global stock market volatility (Mbah and Wasum, 2022). The impact on Europe is particularly significant, as both Ukraine and Russia are major exporters to the region. Notably, on 24 February 2022, when Russia initiated its invasion of Ukraine, the global stock market witnessed a substantial decline in returns. However, this downturn proved to be short-lived as the impact gradually diminished over the course of three to four weeks following the invasion. This indicates a rapid rebound in global stock markets following the unexpected Russian invasion, as noted in studies by Boungou and Yatié (2022) and Deng et al. (2022). According to research conducted by Deng et al. (2022), stocks that were more exposed to regulatory risks associated with the shift to a low-carbon economy exhibited better performance during the lead-up to the invasion and in the subsequent weeks. This effect was particularly pronounced in the United States. In Europe, stocks with opportunities in the low-carbon transition benefited as market participants anticipated stronger policy responses aimed at supporting the shift to renewable energy. This was driven by Europe's significant reliance on Russian oil and gas, prompting expectations of greater emphasis on renewable energy sources (Deng et al., 2022).

Together, the repercussions of the COVID-19 pandemic and the Ukraine-Russia war triggered a bear market that officially commenced on June 13, 2022, when MSCI's global index plummeted by 21% from its peak in late 2021 (Maki, 2022). As inflation surged, leading to a tightening of monetary policy worldwide, traders' outlook on global economic growth declined, subsequently raising concerns about an impending recession. In general, a bear market refers to a period in the stock market characterized by a sustained decline in stock returns, heightened volatility, and increased correlations across the global stock market (Maheu and McCurdy, 2000; Campbell et al., 2002).

As we investigate the co-movement between green bonds and other financial assets during two crisis periods and a bear market, it is crucial to grasp the concept of contagion in financial markets. Following the definition proposed by Longstaff (2010), we adopt the notion that financial contagion refers to a significant increase in cross-market linkages following a shock in one market. It is widely recognized that returns become more strongly correlated when markets undergo large negative movements compared to normal market conditions (Campbell et al., 2002). The phenomenon of financial contagion carries significant implications for portfolio and risk management, as asset correlation plays a vital role in diversifying risk within a portfolio (Campbell et al., 2002; Liu et al., 2021). Thus, an upsurge in asset correlations following a crisis event can impede the ability of market participants to effectively diversify risk. As noted by Nguyen et al. (2021), the correlation between green bonds and other asset markets emerged and peaked after the GFC. Therefore, we expect to observe similar upswings in the correlations between green bonds and other asset markets around the periods of the COVID-19 pandemic, Ukraine-Russia war, and the 2022 bear market.

3 Theoretical Framework

Based on the findings from prior research regarding the connectedness between green bonds and other financial assets, we observe that the green bond market has considerable diversification and hedging benefits on the commodity, and stock market (Reboredo, 2018; Reboredo and Ugolini, 2020; Naeem et al., 2021b; Nguyen et al., 2021; Han and Li, 2022; Arif et al., 2022; Yadav et al., 2023). Additionally, more recent studies demonstrate that the green bond potentially serves as safe haven for the commodity and stock market (Arif et al., 2022; Martiradonna et al., 2023). Consequently, we propose our first two hypotheses:

H1: *"The green bond serves as a hedge and/or safe haven for the commodity market."*

$$\rho_{xy} = \begin{cases} \rho_{xy} \leq 0, & \text{(Hedge)} \\ \rho_{xy} \leq 0 \mid \text{Crisis} & \text{(Safe haven)} \end{cases}$$

where x denotes the green bond and y the commodity market. ρ_{xy} denotes the correlation between the green bond and the commodity market.

H2: *"The green bond serves as a hedge and/or safe haven for the stock market."*

$$\rho_{xy} = \begin{cases} \rho_{xy} \leq 0, & \text{(Hedge)} \\ \rho_{xy} \leq 0 \mid \text{Crisis} & \text{(Safe haven)} \end{cases}$$

where x denotes the green bond and y the stock market. ρ_{xy} denotes the correlation between the green bond and the stock market.

Furthermore, the green bond market has been identified as a hedge and safe haven for the carbon market, as indicated by studies conducted by Jin et al. (2020) and Yadav et al. (2023). Given that high volatility in the carbon market increases carbon market risk, it becomes crucial for environmental policymakers, energy-intensive firms, portfolio managers, and carbon investors to comprehend the extent to which this risk can be mitigated through the use of green bonds (Jin et al., 2020). Therefore, we propose our third hypothesis to delve deeper into this aspect.

H3: *"The green bond serves as a hedge and/or safe haven for the carbon market."*

$$\rho_{xy} = \begin{cases} \rho_{xy} \leq 0, & \text{(Hedge)} \\ \rho_{xy} \leq 0 \mid \text{Crisis} & \text{(Safe haven)} \end{cases}$$

where x denotes the green bond and y represents the carbon market. ρ_{xy} denotes the correlation between the green bond and the carbon market. It is worth noting that the first three hypotheses propose that the green bond may serve as a hedge and/or safe haven for the carbon market. Therefore, it is plausible for the green bond to fulfill both roles when the correlation is less than or equal to zero during both non-crisis and crisis periods.

Moreover, empirical evidence suggests that the green bond market offers significant diversification benefits for the low-carbon stock market (Reboredo et al., 2022). Building upon this observation, we propose our fourth hypothesis:

H4: *"The green bond serves as a diversifier for the low-carbon stock market."*

$$0 < \rho_{xy} < 1 \quad \text{(Diversifier)}$$

where x denotes the green bond and y represents the low-carbon stock market. ρ_{xy} denotes the correlation between the green bond and the low-carbon stock market.

While the relationship between oil prices and macroeconomic aggregates or financial markets has garnered considerable attention in recent years, there remains a notable gap in understanding the interaction between oil prices and the dynamics of green bonds (Lee et al., 2021). This represents valuable information for investors and holds significance for the promotion of environmentally friendly investments. In addition, research conducted by Naeem et al. (2021b) underscores the strong diversification benefits of green bonds in relation to fluctuations in the crude oil and natural gas market. Thus, based on these findings, we formulate the following hypothesis:

H5: *"The green bond serves as a diversifier for the oil and gas market."*

$$0 < \rho_{xy} < 1 \quad \text{(Diversifier)}$$

where x denotes the green bond and y represents the oil and gas market. ρ_{xy} denotes the correlation between the green bond and the oil and gas market.

Importantly, the return connectedness between green bonds and other financial instruments is influenced by various macroeconomic factors, including heightened volatility, geopolitical risk, oil prices, and interest rates (Broadstock and Cheng, 2019; Saeed et al., 2021; Lee et al., 2021). This observation is further supported by the findings of Martiradonna et al. (2023), who emphasize the impact of stock market conditions on the role of green bonds within a portfolio. Based on these insights, we propose our sixth hypothesis as follows:

H6: *"Changes in macroeconomic circumstances affect the return connectedness between the green bond and other financial markets."*

To test this hypothesis, our study will analyze whether the return connectedness between the green bond and other financial markets varies across different regimes, specifically during non-crisis and crisis periods. This approach enables us to investigate the presence of financial contagion during the crisis regime. Additionally, we will follow the recommendation of (Naeem et al., 2021a) to explore whether specific macroeconomic variables drive the return connectedness of green bonds with other assets, particularly in the context of the COVID-19 pandemic.

Considering the widespread integration of global markets, we investigate our research question and hypotheses using an 8-variable system (Jin et al., 2020). This system incorporates the impact of geopolitical risk (GPR), which encompasses fluctuations such as political upheavals, terror attacks, and geopolitical tensions. GPR is considered a significant influencing factor on business cycles and exhibits a strong correlation with financial market performance (Lee et al., 2021). Consequently, GPR is often cited as a determinant of portfolio allocation. However, previous empirical studies have largely overlooked the influence of geopolitical risks on financial markets within the broader context of global uncertainty (Lee et al., 2021). Moreover, it is crucial to concurrently examine the dynamics of oil price shocks, geopolitical risks, and the green bond market to shed light on their transmission mechanisms (Lee et al., 2021). Similarly, our analysis includes the VIX index, which captures stock market volatility and serves as an investor fear gauge. Empirical evidence has consistently demonstrated a strong negative relationship between the VIX and stock market returns on a global scale (Sarwar, 2012). In addition, empirical evidence has demonstrated that the VIX is a reliable predictor of future stock market volatility and returns, particularly during the COVID-19 pandemic (Wang et al., 2020). As a result, the inclusion of both the GPR index and the VIX index holds substantial value in our analysis, particularly within our TVTP MS-VAR analysis where these indices will be utilized to predict the probabilities of regime switches, allowing us to gain deeper insights into the market dynamics.

4 Empirical Strategy

4.1 Data Collection and Description

In our analysis, we use daily price data on 8 market indices over the period, February 5, 2016, to March 10, 2023. We use the Solactive Green Bond Index to represent the green bond market. To proxy for the global stock market, we use the Refinitiv Global Price Return Index, which covers over 10,000 stocks over 51 markets. Additionally, we use the Refinitiv Core Commodity CRB index as representative indicator of the global commodity market; the STOXX Global 1800 Low-Carbon Index to capture the performance of ESG oriented firms globally; The IHS Markit Global Carbon Index that tracks the most liquid segment of the tradable carbon credit futures markets globally; and the Refinitiv Global Oil and Gas Price Return Index to capture global oil and gas prices. The daily price data on these indices is obtained from Refinitiv. Moreover, we use the CBEO Volatility Index (VIX) as a measure of market uncertainty and the Caldara and Iacoviello (2022) Geopolitical Risk Index (GPR) as a measure of adverse geopolitical events and risks. These Indices are obtained from Yahoo Finance and the website of the authors Caldara and Iacoviello (2022), respectively. For the analysis, we calculate the daily log returns for each of the aforementioned indices. As the data on the STOXX Global 1800 Low-Carbon Index only goes back to February 5, 2016, this is the longest possible sample for our analysis.

4.2 Preliminary Data Analyis

From Table 1, it is evident that the null hypothesis of normality is rejected for all indices based on the JB statistics. This indicates that our data on the closing prices of the indices in levels does not follow a normal distribution. Furthermore, it is observed that the null hypothesis of non-stationarity cannot be rejected based on both the DF and PP statistics for all indices, except for GPR and VIX. Additionally, the null hypothesis of no trend stationarity is rejected for each variable in the analysis based on the KPSS statistic. These results strongly suggest that all indices exhibit non-stationarity and, therefore, possess a unit root. While the GPR and VIX indices pass the ADF and PP tests for stationarity, it is important to note that they display a deterministic trend, which is inconsistent with stationary behavior. The presence of a deterministic trend in each of the variables can also be observed when visually inspecting the time series graphs in Figure 1. While it may be less apparent in Figure 1f, the remaining graphs clearly demonstrate that the series' trend persists even after the shock caused by the COVID-19 pandemic in early 2020.

Table 1: Descriptive Statistics of Prices in Levels

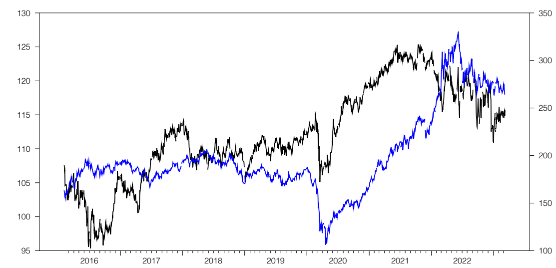
	Green Bond	Commodity	Oil & Gas	Global Stock	Low Carbon	Carbon Price	GPR	VIX
Sum	193115	343202	360330	378530	347453	536620	197264	32801
Mean	112.15	199.30	209.25	219.82	201.77	311.63	114.56	19.05
SD	6.95	43.07	47.81	39.08	40.21	213.39	55.54	8.18
Min	95	106	89	143	129	71	9	9
Max	125	330	353	303	287	796	540	83
Skewness	-.0952	1.042	.315	.431	.428	.705	2.359	2.349
Kurtosis	2.371	3.632	3.341	2.277	2.132	2.202	13.765	13.444
N	1,722	1,722	1,722	1,722	1,722	1,722	1,722	1,722
JB	31***	340.6***	36.87***	90.78***	106.5***	188.4***	9912***	9412***
ADF	-1.821	-0.761	-1.016	-1.728	-1.541	0.030	-19.688***	-5.220***
PP	-5.314	-1.701	-4.100	-4.454	-3.603	0.162	-769.802***	-43.455***
KPSS	.876***	3.250***	2.470***	.882***	0.928***	2.490***	.867***	.441***
Correlation Matrix								
Green Bond	1.0000							
Commodity	0.4423***	1.0000						
Oil & Gas	0.1134***	0.8139***	1.0000					
Global Stock	0.9373***	0.5297***	0.1658***	1.0000				
Low Carbon	0.9408***	0.5464***	0.1718***	0.9958***	1.0000			
Carbon Price	0.8058***	0.7606***	0.4244***	0.8502***	0.8841***	1.0000		
GPR	0.0831***	0.4440***	0.3487***	0.1456***	0.1507***	0.2702***	1.0000	
VIX	0.2774***	0.0504*	-0.2229***	0.1757***	0.2316***	0.3770***	0.0459	1.0000

Note: This table reports statistics for the green bond and financial market indices indicated in each column. JB denotes the Jarque and Bera (1980) statistic for normality; ADF, PP and KPSS are the empirical statistics for the Augmented Dickey and Fuller (1979) and Phillips and Perron (1988) unit root tests and the Kwiatkowski et al. (1992) stationarity test, respectively; *, **, and *** indicate the rejection of the null hypothesis at the 10%, 5%, and 1% level, respectively.

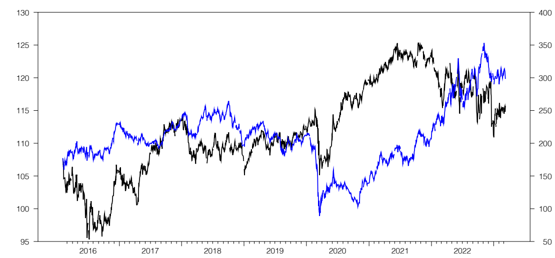
When examining the graphs in Figure 1, it is intriguing to observe the evident co-movement between the green bond index and the other indices. Particularly, the global stock index and the low carbon index exhibit strikingly similar trajectories. In line with Sarwar (2012), the upward spikes in the VIX index correspond to negative movements in the green bond and other indices.

Figure 1: Time Series Graphs for Closing Prices in Levels

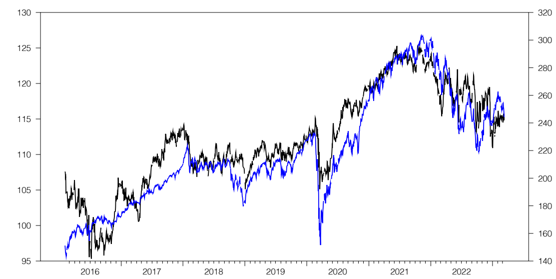
Note: This figure displays the time series graphs for the closing prices of the indices in levels. Each graph features the Green Bond Index, represented by the black line, with its corresponding values displayed on the left-hand side of the y-axis. The blue line represents the index specified below the graph, and its values are presented on the right-hand side of the y-axis.



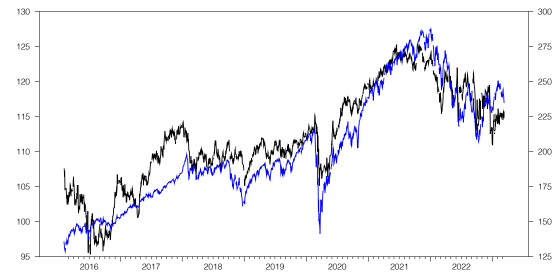
(a) Commodity



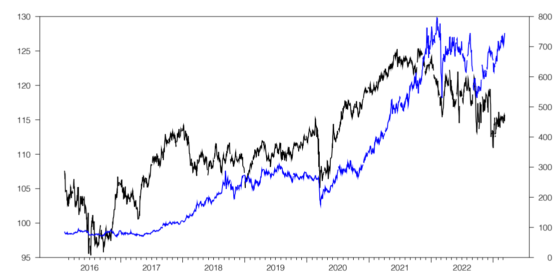
(b) Oil & Gas



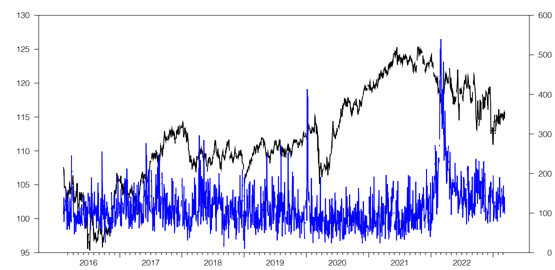
(c) Global Stock



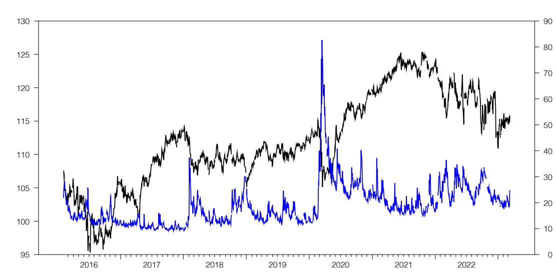
(d) Low Carbon



(e) Carbon Price



(f) GPR



(g) VIX

Furthermore, we can discern that the upward spike in the GPR index at the start of 2020 precedes the downward spike in the other indices, suggesting that the GPR index may possess some predictive power regarding the trajectory of the other indices (Lee et al., 2021). From Table 2, we observe that transforming the data from prices in levels to log returns has affected the statistical properties of the series. Firstly, the first observation was excluded when calculating the returns, resulting in a sample period spanning from February 6, 2016, to March 10, 2023. Secondly, the high levels of kurtosis observed across all series leads us to reject the null hypothesis of normality, as indicated by the JB statistics for each index.

Table 2: Descriptive Statistics of Log Returns

	Green Bond	Commodity	Oil & Gas	Global Stock	Low Carbon	Carbon Price	GPR	VIX
Sum	0.049	0.472	0.471	0.393	0.483	2.108	187.423	0.322
Mean	0.000	0.000	0.000	0.000	0.000	0.001	0.109	0.000
SD	0.005	0.011	0.018	0.010	0.010	0.022	0.526	0.081
Min	-0.051	-0.111	-0.219	-0.098	-0.104	-0.156	-2.996	-0.300
Max	0.023	0.059	0.136	0.079	0.085	0.104	2.551	0.768
Skewness	-0.913	-1.030	-1.296	-1.288	-1.149	-0.528	0.412	1.439
Kurtosis	12.163	12.875	22.489	20.285	20.345	7.769	5.230	11.222
N	1721	1721	1721	1721	1721	1721	1721	1721
JB	6259***	7297***	28000***	22000***	22000***	1711***	405.4***	5441***
ADF	-45.481***	-40.402***	-40.228***	-40.610***	-42.094***	-42.463***	-55.767***	-45.187***
PP	-1836.745***	-1678.990***	-1818.459***	-1786.419***	-1832.669***	-1744.727***	-1979.113***	-1717.982***
KPSS	0.062	0.101	0.065	0.036	0.033	0.061	0.141	0.015
Correlation Matrix								
Green Bond	1.000							
Commodity	0.161***	1.000						
Oil & Gas	0.453***	0.612***	1.000					
Global Stock	0.326***	0.421***	0.685***	1.000				
Low Carbon	0.361***	0.398***	0.664***	0.987***	1.000			
Carbon Price	0.129***	0.212***	0.262***	0.278***	0.282***	1.000		
GPR	-0.016	0.029	0.046	0.017	0.014	-0.004	1.000	
VIX	-0.265***	-0.275***	-0.471***	-0.653***	-0.658***	-0.122***	-0.055*	1.000

Note: This table reports statistics for the green bond and financial market indices indicated in each column. JB denotes the Jarque and Bera (1980) statistic for normality; ADF, PP and KPSS are the empirical statistics for the Augmented Dickey and Fuller (1979) and Phillips and Perron (1988) unit root tests and the Kwiatkowski et al. (1992) stationarity test, respectively; *, **, and *** indicate the rejection of the null hypothesis at the 10%, 5%, and 1% level, respectively.

Furthermore, we find evidence to reject the null hypothesis of non-stationarity based on both the ADF and PP statistics. Additionally, the acceptance of the null hypothesis of trend stationarity based on the KPSS statistics provides further support for the trend stationarity of the series. These findings collectively indicate that all the indices included in our analysis exhibit stationarity.

Another notable aspect lies in the nature and disparity of the correlations observed among the variables in Table 1 and Table 2. According to Table 1, we observe that the closing prices of the indices exhibit significant correlations with each other at the 1% level, except for the commodity and VIX pair, as well as the GPR and VIX pair. The former is significant at the 10% level, while the latter shows no significant correlation. Furthermore, it is worth noting that all the correlations presented in Table 1 exhibit positive values, with the exception of the correlation between the VIX and the oil & gas index. The negative correlation between these two variables can be attributed to the impact of the COVID-19 pandemic, during which volatility reached its peak and simultaneously led to a significant decline in oil prices (Naeem et al., 2021b). However, upon examining the correlations in Table 2, we notice that the all the pairwise correlations including the VIX index have a negative sign. This aligns with our expectations since an increase in the VIX corresponds to heightened market volatility, which is often associated with downturns in financial markets (Sarwar, 2012). Furthermore, our analysis reveals a significant correlation between the GPR and VIX indices at the 10% level. However, we observe that the remaining pairwise correlations involving the GPR are found to be statistically insignificant. This suggests that there may be no meaningful association between the GPR and the other indices. Notably, it is important to highlight that all pairwise correlations involving the green bond, with the exception of the GPR and VIX, demonstrate a positive sign.

Table 3: Granger Causality Matrix

	Predictor Variables (x)							
Response Variables (y)	Green Bond	Commodity	Oil & Gas	Global Stock	Low Carbon	Carbon Price	GPR	VIX
Green Bond	1.000	0.108	0.007***	0.000***	0.000***	0.073	0.038**	0.224
Commodity	0.165	1.000	0.001***	0.000***	0.000***	0.000***	0.322	0.000***
Oil & Gas	0.011**	0.002***	1.000	0.000***	0.000***	0.000***	0.003***	0.000***
Global Stock	0.005***	0.000***	0.005	1.000	0.000***	0.000***	0.258	0.000***
Low Carbon	0.007***	0.000***	0.006	0.000***	1.000	0.000***	0.337	0.000***
Carbon Price	0.726	0.056*	0.109	0.145	0.135	1.000	0.141	0.046**
GPR	0.026**	0.016**	0.034**	0.012**	0.014**	0.029**	1.000	0.878
VIX	0.000***	0.000***	0.000***	0.000***	0.000***	0.005***	0.487	1.000

Note: This table presents the p values obtained from the Granger (1969) causality tests conducted for each pair of time series variables. The rejection of the Null hypothesis, which assumes that the predictor variable (x) does not Granger-cause the response variable (y), signifies that the past values of (x) exert a statistically significant impact on the current value of (y). The significance levels *, **, and *** correspond to the rejection of the null hypothesis at the 10%, 5%, and 1% levels, respectively.

We further analyze the relationship between the variables by performing Granger-causality tests on each pair. The results, presented in a matrix format in Table 3, provide valuable insights. Of particular interest is the examination of causality involving the green bond index. We observe that the past values of the oil & gas, global stock, low-carbon, and GPR indices all have a highly significant impact on the current value of the green bond index. This Granger-causality is bi-directional, as the past values of the green bond index also exert a statistically significant impact on the aforementioned variables. Furthermore, there is evidence of Granger-causality from the green bond index to the VIX, indicating an influence in one direction, but not vice versa. Regarding the GPR, it is evident that its past values have a significant impact on the current values of both the green bond and oil & gas indices. This observation aligns with previous research findings (Naeem et al., 2021b; Broadstock and Cheng, 2019; Lee et al., 2021). Surprisingly, our analysis does not provide evidence of Granger-causality running from the carbon price index to the green bond index, or vice versa. This finding contrasts sharply with the results reported by Jin et al. (2020). However, in line with Hammoudeh et al. (2020), we do observe significant Granger-causality running from the carbon price index to the green bond index.

Table 4: Johansen Cointegration Test Results

	Trace Statistic	5% Critical Value
Green Bond	2303.93*	143.6691
Commodity	1917.33*	111.7797
Oil & Gas	1555.01*	83.9383
Global Stock	1212.84*	60.0627
Low Carbon	894.48*	40.1749
Carbon Price	601.29*	24.2761
GPR	362.08*	12.3212
VIX	156.67*	4.1296

Note: This table presents the results of the Johansen (1991) cointegration tests, including the trace statistics and corresponding critical values. The significance level * denotes the rejection of the null hypothesis at the 5% level, indicating the presence of at least one cointegrating relationship among the variables.

To investigate the existence of long-term relationships among the variables, Johansen cointegration tests were conducted for each variable. The outcomes of these tests are presented in Table 4. Based on the trace statistics and the critical values at the 5% level for each of the variables, we can reject the null hypothesis that no cointegrating relationships exist among the variables. This indicates the presence of stable long-run relationships within the system. Additionally, individual cointegration tests were performed for each pair of variables, revealing cointegration between every pair. For the sake of brevity, these specific results are reported in the Appendix.

To comprehensively analyze the dynamic relationships among the variables in our system, it is necessary to estimate a VAR model. However, the selection of the appropriate lag length plays a crucial role in specifying our VAR model (Hacker and Hatemi-J, 2008). While economic theory recognizes the dynamic nature of economic processes, it generally lacks specific guidance on determining the length of these dynamic processes. As a result, the determination of the optimal lag length in a VAR model often relies on empirical analysis rather than theoretical foundations (Hacker and Hatemi-J, 2008). In Table 5, multiple information criteria are presented to assist in determining the suitable lag length for our VAR model. Considering that our system already comprises 8 variables and additional lags would introduce computational complexity, the maximum lag was set to 5. Notably, both the FPE and AIC criteria suggest an optimal lag order of 5. However, we select a lag order of 1 based on the HQIC and SBIC criteria. This choice is motivated by the fact that the SBIC is a preferred criterion for selecting lag length in many scenarios, particularly for financial data characterized by intermittent periods of high volatility (Hacker & Hatemi, 2008).

Table 5: Lag-Order Selection Statistics

Lag	LL	LR	d.f.	p	FPE	AIC	HQIC	SBIC
0	36700.5				3.7e-29	-65.4775	-65.4775	-65.4775
1	36967.1	533.21	64	0.000	2.9e-29	-65.7136	-65.6385*	-65.5105*
2	37076.2	218.12	64	0.000	2.8e-29	-65.7662	-65.6158	-65.3598
3	37146.2	140.06	64	0.000	2.7e-29	-65.7732	-65.5476	-65.1636
4	37220.4	148.36	64	0.000	2.7e-29	-65.7851	-65.4843	-64.9723
5	37294.8	148.76*	64	0.000	2.7e-29*	-65.7972*	-65.4212	-64.7813

Note: This table reports the Akaike (1969) final prediction error (FPE), Akaike (1974) information criterion (AIC), Hannan and Quinn (1979) information criterion (HQIC), and the Schwarz (1978) Bayesian information criterion (SBIC), lag-order selection statistics for the series of vector autoregressions of order 1 through a maximum lag of 5. The optimal lag order selected by a criterion is indicated by *.

4.3 The Econometric Methodology

Sims (1980) endorsement of Vector Autoregressive (VAR) models marked a turning point in economic analysis, leading to their widespread popularity as an effective tool for analyzing multiple time series (Lütkepohl, 2009). The growing popularity of VAR models since the 1980s can be attributed to the increased availability of longer and more frequent data. This shift in data availability highlighted the necessity for models that capture the dynamic structure of variables (Lütkepohl, 2009). In this regard, VAR models emerged as valuable tools, offering both effectiveness and ease of use due to their linear nature. In addition to this advantage, VAR models possess the flexibility to treat all observed variables as endogenous from the outset (Lütkepohl, 2009). Consequently, instead of relying solely on theory, VAR models allow for the application of statistical procedures to impose restrictions on the models. Moreover, VAR models are valuable as they enable the examination of both long-term relationships and short-term dynamic adjustments among the variables (Hacker and Hatemi-J, 2008). In this way, multivariate dependence and the network links across markets are accurately characterized (Reboredo and Ugolini, 2020).

Leveraging the flexibility and user-friendly nature of the VAR model, we examine the dynamic relationships among our time series variables by employing ordinary least squares (OLS) estimation. Consistent with existing literature examining the impact of crises, we initially estimate connectedness using a full sample, thereby capturing the complete picture of connectedness throughout the entire period under investigation (Naeem et al., 2021a). Following Lütkepohl (2005), our VAR model takes the following form:

$$
\begin{aligned}
y_{1,t} &= c_1 + A_{1,1}y_{1,t-1} + A_{1,2}y_{2,t-1} + \ldots + A_{1,k}y_{k,t-1} + e_{1,t} \\
y_{2,t} &= c_2 + A_{2,1}y_{1,t-1} + A_{2,2}y_{2,t-1} + \ldots + A_{2,k}y_{k,t-1} + e_{2,t} \\
&\vdots \\
y_{k,t} &= c_k + A_{k,1}y_{1,t-1} + A_{k,2}y_{2,t-1} + \ldots + A_{k,k}y_{k,t-1} + e_{k,t}
\end{aligned}
\tag{1}
$$

where $y_{i,t}$ represents the i-th dependent variable at time t, c_i denotes the constant term specific to each variable, $A_{i,j}$ represents the coefficient of the j-th variable lagged by one period for the i-th dependent variable, and $e_{i,t}$ represents the error term associated with each variable at time Our VAR model captures the dynamic relationships between the 8 dependent variables, where the lagged values of all variables are considered as predictors for each dependent variable. The coefficients $A_{i,j}$ quantify the impact of the lagged variables on the contemporaneous values of the dependent variables. The error terms $e_{i,t}$ represent the unexplained variation in each dependent variable at time t.

First, we test the model for serial correlation by computing the Durbin and Watson (1971) test statistic for each equation as follows:

$$d = \frac{\sum_{i=1}^{T-1} \left(\hat{\epsilon}_{i+1} - \hat{\epsilon}_i\right)^2}{\sum_{i=1}^{T} \hat{\epsilon}_i^2} \tag{2}$$

where d is the Durbin-Watson test statistic, T is the number of observations in the VAR model, $\hat{\epsilon}_i$ represents the estimated residuals or errors at time i.

Next, we examine the stability of our VAR model by forming the companion matrix A, which takes the following form:

$$A = \begin{bmatrix} A_1 & A_2 & \dots & A_{p-1} & A_p \\ I_0 & \mathbf{0} & \dots & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{I} & \mathbf{0} \end{bmatrix} \tag{3}$$

where I denotes the identity matrix, and $\mathbf{0}$ represents a matrix of zeros. We then obtain the eigenvalues of matrix A and determine the stability of our VAR model by examining the modulus of the complex eigenvalues. We adopt the stability criterion outlined by Lütkepohl (2005), which states that a VAR model is considered stable if the absolute value of each eigenvalue of the matrix A is strictly less than 1.

Given that Granger-causality alone may not provide a comprehensive understanding of the interactions among variables within a system, it is of interest to examine the response of one variable to a shock in another variable within a multidimensional system involving other variables. Therefore, it is valuable to investigate the impulse response relationship between two variables within a higher-dimensional system. In order to explore the relationships among the variables in our VAR model more deeply, we estimate the impulse response functions (IRFs) as outlined in Lütkepohl (2005)).

$$IRF_{i,j}(h) = \sum_{k=0}^{h-1} A_{i,j}(k) \cdot e_j(h-k) \tag{4}$$

where $IRF_{i,j}(h)$ represents the impulse response function between variables i and j at horizon h. $A_{i,j}(k)$ denotes the coefficient of the lagged value of variable j on variable i at lag k, and $e_j(h-k)$ represents the forecast error of variable j at horizon $h-k$. The impulse response function is computed as the sum of the products of the coefficients and forecast errors over the lagged periods.

Despite the widespread use of VAR models in this field of research, the current academic literature still lacks robust models that accurately capture the relationships between the green bond and other variables, particularly in extreme cases (Saeed et al., 2021). To bridge this gap and provide a more in depth analyses on the dynamic relationship between our time series variables in both non-crisis and crisis periods, we use a two-state Markov-switching VAR model. Utilizing this particular model enables the endogenous selection of crisis periods, incorporates the absence of significant news events during the crisis period, and takes into account the heteroskedasticity of financial assets within the framework of regime-switching (Flavin and Sheenan, 2015). Although the non-crisis and crisis regimes will be determined endogenously, we need to assign labels to these regimes based on the variances of the variables. The regime with higher variances in all variables will be identified as the crisis regime, as higher variance indicates higher standard deviation and thus greater volatility. This labeling criterion allows us to differentiate between periods of relative stability (non-crisis regime) and periods characterized by higher levels of volatility (crisis regime) in our analysis. Ultimately, this procedure enables us to analyze the non-linear dynamics among our time series variables and evaluate the correlations specific to each regime. By doing so, we align with previous empirical findings that demonstrate the time-varying, non-linear, and asymmetric nature of the relationships between green bonds and other assets (Han and Li, 2022; Lee et al., 2021; Jin et al., 2020). Our model takes the following form:

$$
\begin{aligned}
y_{i,t} = \alpha(s_t) + \sum_{k=1}^{K} \beta_k s_t y_{i,t-k} + \epsilon_{i,t}^{st} \\
s_t \in \{1, 2\} \\
s_t \sim \text{i.i.d.} N(0, \sigma_s^2)
\end{aligned}
\tag{5}
$$

in which $y_{i,t}$ is an n-dimensional time series vector of dependent variables, α is a matrix of state-dependent intercepts, $\beta_1 \dots \beta_k$ are matrices of the state-dependent autoregressive coefficients, ε_t is a state-dependent noise vector, and s_t is an unobserved random variable that causes the system to change from one regime to another. As proposed by Filardo (1994), we use the time-varying transition probability (TVTP) specification of the MS-VAR model. This method provides us with more flexibility by allowing the transition probabilities to vary over time and be modelled as functions of the information variables (Flavin and Sheenan, 2015). Additionally, it enables us to test if the conditional variables have explanatory power over the regime switches. According to Filardo (1998), the information variable must be uncorrelated with the contemporaneous regime. Therefore, it is common to select lagged, predetermined variables on which the regime path is conditioned. Consequently, the regime paths evolve according to a first order Markov-chain and are directly affected by the information variable z_{t-1}:

$$\begin{aligned} p[s_t = 1 \mid s_{t-1} = 1] &= p_{11}(z_{t-1}) \\ p[s_t = 2 \mid s_{t-1} = 2] &= p_{22}(z_{t-1}) \\ p[s_t = 2 \mid s_{t-1} = 1] &= p_{21}(z_{t-1}) \\ p[s_t = 1 \mid s_{t-1} = 1] &= p_{12}(z_{t-1}) \end{aligned} \tag{6}$$

in which z_{t-1} represents our information variable, which is the lagged daily log return on either the VIX or GPR, depending on the model specification. We posit that both the VIX and GPR possess explanatory power concerning regime switches, given that the sample period encompasses crisis periods characterized by increased volatility in stock markets and heightened geopolitical risk globally, as a result of events such as the COVID-19 pandemic and Ukraine-Russia war. However, since the contemporaneous VIX and GPR cannot be regarded as completely uncorrelated with the system's state, we address this issue by employing the first lag of the variables. In other words, we set $l = 1$ in Eq. (7). According to Filardo (1998), this approach is reasonable for many problems as long as z_{t-1} is considered to be predetermined with respect to s_t.

Based on the work of Flavin and Sheenan (2015), we model the transition probabilities as a logistical functional form:

$$\begin{aligned} p_{11}(z_{t-l}) &= \frac{\exp(\theta_0 + \sum_{l=1}^{L} \theta_l z_{t-l})}{1 + \exp(\theta_0 + \sum_{l=1}^{L} \theta_l z_{t-l})} \\ p_{22}(z_{t-l}) &= \frac{\exp(\gamma_0 + \sum_{l=1}^{L} \gamma_l z_{t-l})}{1 + \exp(\gamma_0 + \sum_{l=1}^{L} \gamma_l z_{t-l})} \end{aligned} \tag{7}$$

We use the simplex algorithm as preliminary estimation method to refine our initial parameter values before switching to the Broyden-Fletcher-Goldfarh-Shanno (BFGS) algorithm for the optimization of our parameter values. To enhance computational efficiency, we have partitioned the system into two models, each comprising one information variable and four dependent variables. The first model encompasses the green bond, commodity, oil % gas, and global stock indices. The second model consists of the green bond, low-carbon stock, carbon price, and GPR or VIX indices, depending on which information variable is used. We intentionally include the green bond index in both models to investigate regime-dependent correlations between this index and other financial indices. Consequently, we conduct separate analyses for each model, employing the VIX and GPR as information variables. This approach yields a total of four distinct model specifications.

5 Results and Interpretation

5.1 VAR Analysis

5.1.1 Model Estimates

The estimation results of our VAR model are presented in Table 6. In Table 6a, we can observe that all the equations included in the model are statistically significant. This significance implies that the included equations enhance the overall explanatory power of the model and provide valuable insights into the dynamics and interdependencies among the variables.

Table 6: VAR Model Estimation Results

(a) R^2 and Significance of Equations

Equation	R^2	χ^2	p value
Green Bond	0.031	55.273	0.000
Commodity	0.010	16.692	0.034
Oil & Gas	0.010	17.994	0.021
Global Stock	0.015	26.482	0.001
Low Carbon	0.018	31.851	0.000
Carbon Price	0.010	17.041	0.030
GPR	0.087	164.589	0.000
VIX	0.015	26.551	0.001

(b) Results for Green Bond Equation

Variable	Coefficient
Green Bond (1)	-0.069**
Commodity (1)	-0.043***
Oil & Gas (1)	0.020
Global Stock (1)	0.654***
Low Carbon (1)	-0.600***
Carbon Price (1)	0.009
GPR (1)	-0.000
VIX (1)	0.004***

Note: (a) presents the explained variance (R^2) and significance of the equations in our VAR Model. (b) specifically focuses on the coefficients for the green bond index equation. The notation (1) signifies the variable at lag 1. For the sake of brevity, the constant term, standard errors, t-statistics, and p-values have been omitted. However, these details can be found in the complete VAR model output in Appendix A The significance of the coefficients is denoted by *, **, and ***, representing the 10%, 5%, and 1% significance levels, respectively.

Nevertheless, the R^2 of each of equations is relatively low, with GPR having the highest R^2 of 0.087, which means that the variation in the GPR index explained by the independent variables included in the equation is approximately 8.7%. This actually indicates that all the other lagged variables perform exceptionally well in explaining the variation in the contemporaneous value of the GPR index.

As stated in Table 6b, The lagged commodity index is statistically significant at the 1% level. This suggests that an increase in the value of the lagged commodity index leads to a decrease in the contemporaneous value of the green bond index, assuming other variables remain unchanged. The lagged values of the oil & gas, carbon price, and GPR indices do not have statistically significant coefficients. This implies that these variables may not have a significant impact on the contemporaneous value of the green bond index. The lagged values of the global stock, low-carbon, and VIX indices have coefficients with positive, negative, and positive signs, respectively, all of which are statistically significant at the 1% level. This indicates that the lagged values of these variables have a significant influence on the contemporaneous value of the green bond index. An increase in the value of the lagged global stock index leads to an increase in the contemporaneous value of the green bond index, while an increase in the lagged low-carbon index results in a similar decrease, in terms of magnitude, in the contemporaneous value of the green bond index. Similarly, an increase in the lagged VIX corresponds to an increase in the contemporaneous value of the green bond index, although much smaller in magnitude. It is worth noting the significant findings from Table 3, which indicate that both the global stock index and the low-carbon index exhibit Granger-causality with respect to the green bond index. These results provide additional evidence for the relationship between these variables.

5.1.2 Model Checking

Table 7a shows the Durbin-Watson statistic for each variable in the model. The Durbin-Watson statistic ranges from 0 to 4, where a value around 2 suggests no significant autocorrelation. In this case, all variables in the VAR model have Durbin-Watson statistics close to 2, indicating that there is no substantial autocorrelation in the residuals. This suggests that the model adequately captures the serial correlation patterns in the data.

Based on the results presented in Table 7b, we observe the presence of several eigenvalues with non-zero moduli. These significant eigenvalues indicate the existence of important dynamic relationships among the variables in the VAR model. However, it is crucial to assess the stability condition of the VAR model by examining whether the modulus of each eigenvalue is strictly less than one (Lütkepohl, 2005). Fortunately, our model meets this criterion as all eigenvalues have moduli that are strictly less than one. This implies that all

Table 7: Statistical Tests for VAR Model

(a) Durbin-Watson Test Results

Variable	d
Green Bond	2.02
Commodity	2.00
Oil & Gas	2.02
Global Stock	2.07
Low Carbon	2.07
Carbon Price	2.01
GPR	2.01
VIX	2.06

(b) Eigenvalue Test Results

Eigenvalue	Modulus
-0.297	0.297
-0.263	0.263
0.146	0.146
-0.063 + 0.082i	0.103
-0.063 - 0.082i	0.103
-0.067	0.067
0.017 + 0.042i	0.045
0.017 - 0.042i	0.045

Note: This table reports the results of two statistical tests that assess the adequacy of our VAR model (Lütkepohl, 2009) (a) reports the Durbin and Watson (1971) statistics to detect the presence of autocorrelation in the residuals. (b) reports the eigenvalues and moduli, which are used to evaluate the stability of our VAR model.

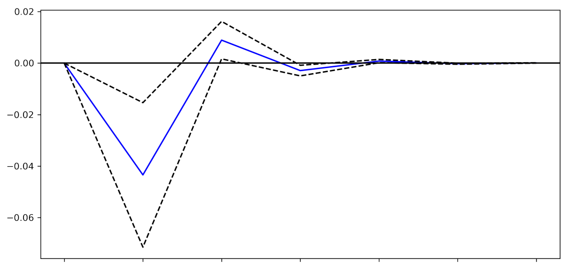
eigenvalues lie inside the unit circle, indicating the VAR model satisfies the stability condition. Meeting the stability condition is important as it ensures that the dynamic relationships among the variables remain well-behaved over time and that the model's predictions are reliable. The stability of our VAR model also indicates that there is no clear indication of a structural break in the data. Nevertheless, it is still feasible to estimate a regime switching model to capture the non-linear dynamics of the system and test for regime switches endogenously.

5.1.3 Impulse Response Functions

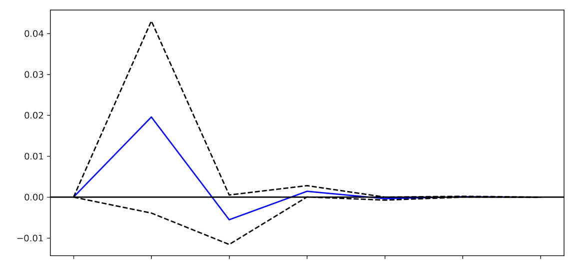
Figure 2 depicts the non-orthogonalized impulse response functions (IRFs) for the green bond index as response variable. The non-orthogonalized IRFs provide insights into the short-term dynamic response of the green bond index to a shock in one of the other indices, without imposing any restrictions on the contemporaneous correlations among the variables (Lütkepohl, 2005). More specifically, the IRFs show the instantaneous effects of one-standard deviation shocks to the green bond index. This allows for a comprehensive analysis of the short-term responses of variables, taking into account the potential feedback effects and contemporaneous interactions (Lütkepohl, 2005).

Figure 2: Impulse Response Functions

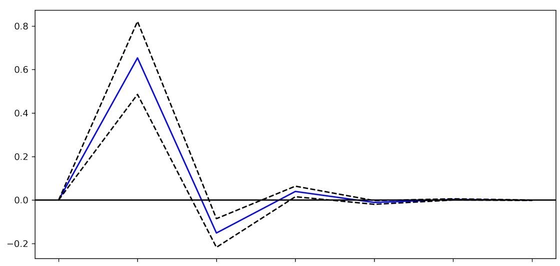
Note: This figure presents the non-orthogonalized IRFs for the green bond index as the response variable over a 6-step period. Each graph represents a different impulse variable specified below. The blue line depicts the trajectory of the response variable, while the dotted lines represent the confidence bounds at the 5% significance level. The complete set of IRFs can be found in Appendix B



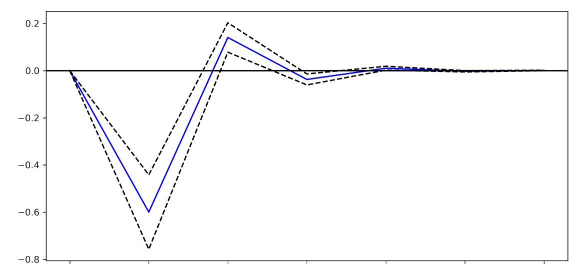
(a) Commodity



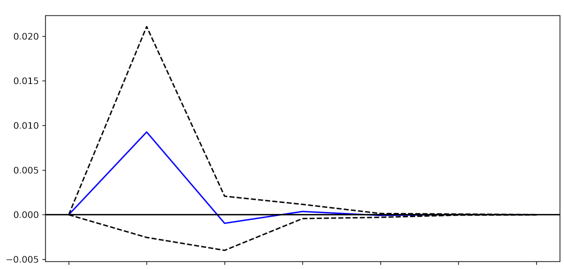
(b) Oil & Gas



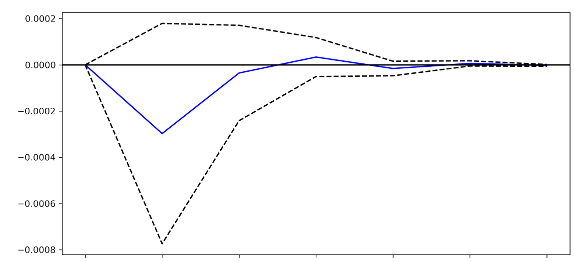
(c) Global Stock



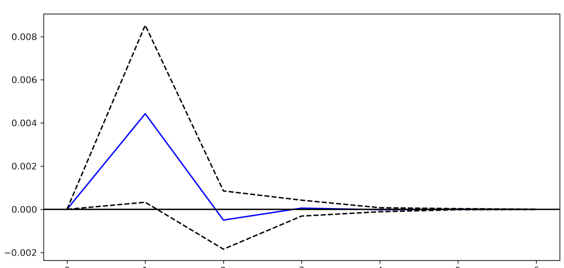
(d) Low Carbon



(e) Carbon Price



(f) GPR



(g) VIX

When examining the IRFs, it is crucial to consider the confidence bounds as they provide insights into the significance and interpretability of the IRFs. In Figure 2b, Figure 2e, and Figure 2f, we observe that the lower confidence bounds are well below zero. This implies that we cannot reject the null hypothesis that the green bond index's response to shocks from the oil & gas, carbon price, and GPR indices is not statistically significant. However, in Figure 2a, we can see that a one standard deviation increase in the commodity index leads to a 0.04 standard deviation decrease in the green bond index in the first period. By the second period, the effect of the shock becomes statistically insignificant, and around the fourth period, the shock dissipates as the green bond index returns to its long-term equilibrium. In contrast, we find that a one standard deviation increase in the global stock index results in a 0.6 standard deviation increase in the green bond index in the first period. Similar to the commodity index, the effect of the shock becomes insignificant in the second period. Interestingly, the response of the green bond index to a one standard deviation shock in the low-carbon index exhibits the opposite pattern compared to the global stock index. Lastly, a one standard deviation increase in the VIX index leads to a 0.003 standard deviation increase in the green bond index in the first period. However, shortly after, the shock becomes statistically insignificant, and its effect dissipates over time.

5.1.4 Summary of Results and Findings

Based on the results of our VAR model and the corresponding IRFs, we can draw several important conclusions. Firstly, our VAR model appears to be properly specified as the equations in the model are all significant, the model adequately captures the serial correlation patterns in the data, and the stability condition is met.

Secondly, we find a statistically significant negative relationship between the lagged commodity index and the contemporaneous green bond index. This indicates a persistent inverse relationship between these variables over time. Moreover, the statistically significant short-term response of the green bond index to an impulse in the commodity index suggests that the short-term relationship between the two variables aligns with the long-term pattern. Consistent with our first hypothesis, this finding offers preliminary evidence supporting the hypothesis that the green bond serves as a hedge with respect to the commodity market.

Thirdly, both the global stock index and the low-carbon index exhibit statistically significant relationships with the green bond index, with similar magnitudes in both the long and short term. However, there is a notable difference in the nature of these relationships. The green bond index exhibits a positive relationship with the global stock index, while conversely, the low-carbon index demonstrates a negative relationship. Both findings are contrary to our expectations, as we would anticipate observing a negative relationship between the green bond and the global stock index, as well as a positive relationship between the green bond and the low-carbon index. However, previous research has shown that the relationships between green bonds and other assets are characterized by non-linearity. Therefore, our linear VAR model may not fully capture the dynamics of the system accurately (Han and Li, 2022; Lee et al., 2021; Jin et al., 2020).

Furthermore, it is intriguing to note the presence of a positive relationship between the green bond and the VIX index based on the coefficients and the IRFs. This finding is somewhat unexpected, as one would typically anticipate an inverse relationship, where an increase in the VIX index corresponds to a decrease in most other financial indices Sarwar (2012). A plausible explanation for this observation is the surge in oil and gas prices resulting from the ongoing Ukraine-Russia war. As higher oil prices decrease the demand for oil and, consequently, increase the demand for responsible investments, it is possible that this drives the positive relationship observed between the VIX and the green bond index (Broadstock and Cheng, 2019). Deng et al. (2022) also provide evidence supporting this notion. However, given the opposite trend observed in oil prices during the COVID-19 pandemic, drawing conclusions at this stage is challenging.

In conclusion, the obtained results underscore the necessity for additional investigation and exploration of the underlying dynamics between the variables, employing time-varying non-linear modeling techniques.

5.2 TVTP MS-VAR Analysis

5.2.1 Regimes

To investigate the non-linear dynamics within our system of time series variables, we employ a TVTP MS-VAR model. Unfortunately, during the estimation of the model, the econometric software encountered convergence issues due to the high number of parameters and the resulting computational complexity of our 8-variable TVTP MS-VAR with a lag of 1. Consequently, we had to divide the model into two separate specifications, each containing 4 variables. Since our focus was on the utilization of the VIX and GPR as information variables, we ended up with a total of 4 different model specifications. Table 8 and Table 9 display the TVTP MS-VAR model estimates for these four model specifications using the VIX and GPR as information variables, respectively.

To initiate our TVTP MS-VAR analysis, it is crucial to distinguish between the non-crisis and crisis regimes and assign appropriate labels to each. We can accomplish this by closely examining the variances of the market indices incorporated in the model. Specifically, we observe that the variances in the crisis regime, denoted as regime 1 in our model, consistently exceed those in the non-crisis regime, with exception of the GPR. The overall increase in the variances of the indices makes intuitive sense, as crises are typically characterized by increased volatility in the stock market (Naeem et al., 2021a; Mbah and Wasum, 2022; Maheu and McCurdy, 2000; Campbell et al., 2002; Longstaff, 2010; Flavin and Sheenan, 2015). The volatility of each of these indices can be measured by its standard deviation, which is calculated as the square root of the variance.

Table 8: Transition Probabilities, Expected Returns, and Variances

Model 1 (VIX)					Model 2 (VIX)				
Panel A: Transition probabilities					Panel A: Transition probabilities				
p_{11}	1.902***				p_{11}	2.060***			
p_{12}	-3.196***				p_{12}	-1.837			
p_{21}	-3.091***				p_{21}	-2.845***			
p_{22}	6.851**				p_{22}	3.623			
Panel B: Expected returns and standard deviations					Panel B: Expected returns and standard deviations				
	Non-crisis regime		Crisis regime			Non-crisis regime		Crisis regime	
	α	σ	α	σ		α	σ	α	σ
Green Bond	0.00018	0.00001	-0.00041	0.00007	Green Bond	0.00021	0.00001	-0.00037	0.00006
	(1.945**)	(33.798***)	(-1.139)	(-28.718***)		(1.861*)	(20.284***)	(-1.103)	(14.769***)
Commodity	0.00064	0.00006	-0.00087	0.00034	Low Carbon	0.00083	0.00003	-0.00106	0.00027
	(3.663***)	(39.063***)	(-1.245)	(-50.680***)		(4.825***)	(16.314***)	(-1.497)	(14.405***)
Oil & Gas	0.00060	0.00014	-0.00078	0.00091	Carbon Price	0.00213	0.00031	-0.00066	0.00088
	(2.897***)	(71.491***)	(-0.933)	(-73.978***)		(4.903***)	(25.218***)	(-0.465)	(14.535***)
Global Stock	0.00742	0.00003	-0.00142	0.00028	GPR	0.14965	0.28832	0.11349	0.17561
	(5.890***)	(43.722***)	(-2.404**)	(38.441***)		(11.308***)	(34.249***)	(5.437***)	(12.889***)

Note: Panel A reports the coefficients on the transition probabilities from Eq. (7). Panel B reports the regime-specific constant terms and variances from Eq. (5). T-statistics are reported in parenthesis. *, **, and *** indicate the rejection of the null hypothesis at the 10%, 5%, and 1% level, respectively.

Table 8 reveals a decrease in the variance of the GPR index during the transition from the non-crisis to the crisis regime. One plausible explanation for this discrepancy is that the GPR index reaches its peak earlier than the other indices, as indicated by Figure 1. Notably, the GPR index attains its peak at the beginning of 2022 during the COVID-19 pandemic, whereas the remaining indices reach their lows in February or March. Consequently, the periods of highest variance for the GPR index may not align with those of the other indices. This finding further strengthens the notion that the GPR index can be used as an early determinant of stock market returns and therefore plays a significant role in portfolio allocation decisions (Lee et al., 2021).

5.2.2 Expected Returns and Transition Probabilities

As we delve deeper into our analysis, we shift our focus to the expected returns on the indices. The observed disparities between the non-crisis and crisis regimes align with our expectations. In the non-crisis regime, we find positive expected returns for each of the indices, whereas in the crisis regime, the expected returns turn negative. However, we observe an interesting exception when examining the expected returns on the VIX index. In the non-crisis regime, the expected return on the VIX index is negative, but in the crisis regime, the expected return is positive. This finding aligns with our intuition, as the VIX index tends to increase during times of crisis and decrease during periods of relative stability. This inverse relationship between the VIX index and stock market returns is well-documented (Sarwar, 2012). Another noteworthy observation from Table 8 and Table 9 is that the expected returns in the non-crisis regimes are mostly highly significant, while in the crisis regime, very few expected returns exhibit significance. This discrepancy can be attributed to the notion that during the non-crisis regime, the market demonstrates more stable and predictable behavior, enabling the intercepts to effectively capture the expected returns. However, in the crisis regime, the market dynamics undergo significant changes, characterized by heightened uncertainty and volatility, which diminishes the informativeness and significance of the intercepts in explaining the expected returns.

Another important aspect to consider are the coefficients of the transition probabilities presented in Panel A of Table 8 and Table 9. Focusing on the VIX index as information variable, we find that the coefficients associated with the VIX index are highly significant, except for the coefficient of p_{22}, which demonstrates moderate significance. This indicates that the lagged return on the VIX index contains valuable information for predicting regime switches during the observed sample period. The signs of the coefficients on the information variables reveal that an increase in the lagged VIX index is associated with an increase in the probabilities of remaining in either the crisis or non-crisis regime, as indicated by p_{11} and p_{22}, respectively. Conversely, an increase in the lagged VIX index is associated with a decrease in the probabilities of switching from regime 1 to 2, or vice versa, as indicated by p_{12} and p_{21}, respectively. Regarding the GPR index, only the coefficients of p_{11} and p_{21} are found to be significant, suggesting that for Model 1, the lagged return on the GPR index provides valuable information for predicting the regime switch from regime 2 to 1.

Table 9: Transition Probabilities, Expected Returns, and Variances

Model 1 (GPR)					Model 2 (GPR)				
Panel A: Transition probabilities					Panel A: Transition probabilities				
p_{11}	1.900***				p_{11}	1.060***			
p_{12}	-0.349				p_{12}	-0.408			
p_{21}	-3.010***				p_{21}	-2.413***			
p_{22}	0.051				p_{22}	-0.364			
Panel B: Expected returns and standard deviations					Panel B: Expected returns and standard deviations				
	Non-crisis regime		Crisis regime			Non-crisis regime		Crisis regime	
	α	σ	α	σ		α	σ	α	σ
Green Bond	0.00018	0.00001	-0.00039	0.00007	Green Bond	0.00020	0.00001	-0.00060	0.00008
	(1.752*)	(22.363***)	(-1.123)	(12.627***)		(1.711*)	(20.459***)	(-1.331)	(12.361***)
Commodity	0.00066	0.00000	-0.00090	0.00033	Low Carbon	0.00080	0.00003	-0.00162	0.00034
	(2.995***)	(20.119***)	(-0.954)	(13.976***)		(4.622***)	(16.985***)	(-1.752*)	(13.225***)
Oil & Gas	0.00060	0.00014	-0.00079	0.00090	Carbon Price	0.00213	0.00033	-0.77504	0.00102
	(1.840*)	(20.189***)	(-0.585)	(12.345***)		(4.903***)	(23.146***)	(-0.465)	(13.438***)
Global Stock	0.00075	0.00003	-0.00142	0.00028	VIX	-0.00547	0.00359	0.11349	0.01597
	(4.484***)	(17.014***)	(-2.044**)	(11.806***)		(-3.098***)	(18.278***)	(5.437***)	(13.183***)

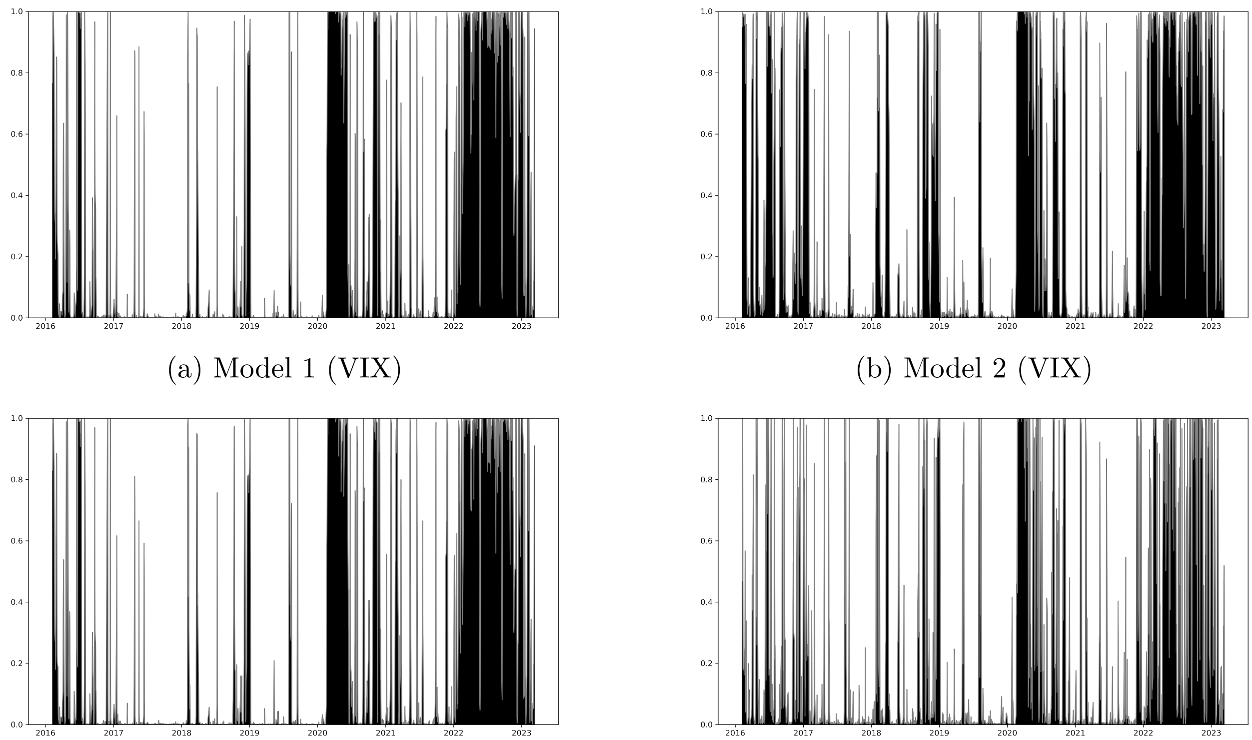
Note: Panel A reports the coefficients on the transition probabilities from Eq. (7). Panel B reports the regime-specific constant terms and variances from Eq. (5). T-statistics are reported in parenthesis. *, **, and *** indicate the rejection of the null hypothesis at the 10%, 5%, and 1% level, respectively.

When examining the estimates for Model 2 and its transition probabilities, we observe that the coefficients for the GPR index as an information variable are remarkably similar to those of Model 1. However, it appears that the lagged return on the VIX index does not provide as much valuable information for predicting regime switches in Model 2, as the coefficients of p_{12} and p_{22} are not significant. Nevertheless, the lagged VIX index still offers some valuable insights into regime switches, as the coefficients for p_{11} and p_{21} remain significant.

5.2.3 Regime Probabilities

Figure 3 displays the smoothed probabilities that indicate the occurrence of a crisis regime in the system. While Figure 3a to Figure 3d display slight variations, they all exhibit similar starting and ending points for the crisis period linked to the COVID-19 pandemic. Similarly, different model specifications show comparable starting points for the crisis period associated with Ukraine-Russia war and the 2022 bear market.

Figure 3: Smoothed Probabilities of Crisis



(a) Model 1 (VIX)

(b) Model 2 (VIX)

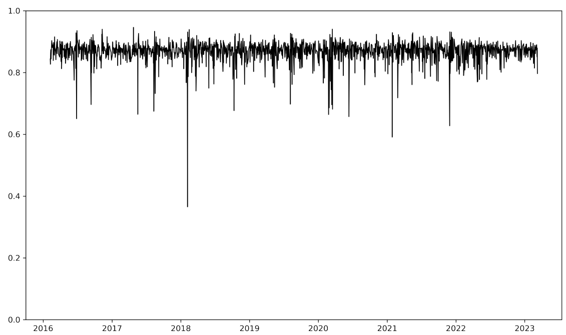
(c) Model 1 (GPR)

(d) Model 2 (GPR)

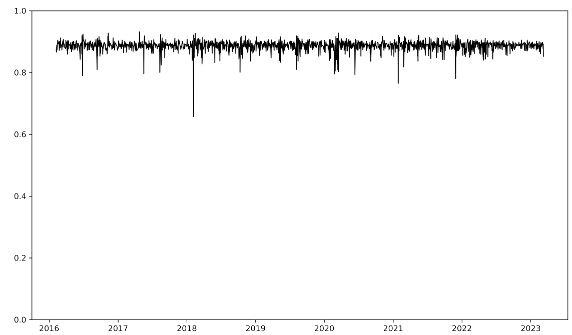
The black color in the graphs represents the consistency and intensity of the system being in a crisis regime, allowing us to distinguish between the crisis period associated with the COVID-19 pandemic and the crisis period associated with the Ukraine-Russia war and the 2022 bear market. While the latter is more prolonged, the former shows a higher intensity and consistency of the smoothed probabilities being equal to 1. The consistency in the smoothed probabilities provided by each model specification underscore the robustness of our results. Additionally, we observe that the disparity in probabilities primarily stems from the variations in model specifications as we include different endogenous variables in the system. This suggests that both the VIX and GPR index exert similar influences on the regime paths in the model.

Figure 4 presents the probabilities of remaining in a non-crisis regime, specifically denoted as $p_{22}(z_{t-l})$ in Eq. (7), derived from the estimation of each specified model. Upon visual examination of the graphs, it becomes apparent that they lack the similarity observed in the graphs of Figure 3.

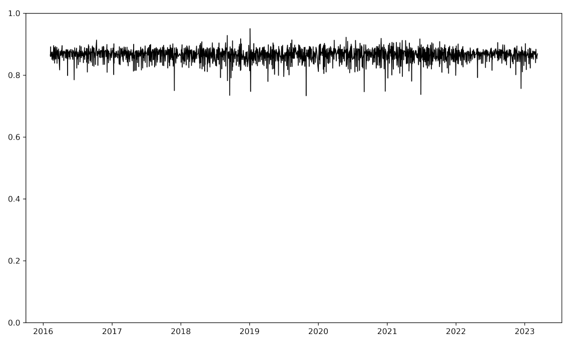
Figure 4: Probabilities of Remaining in Non-Crisis Regime



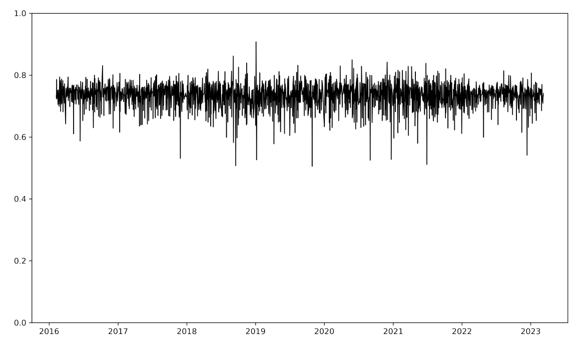
(a) Model 1 (VIX)



(b) Model 2 (VIX)



(c) Model 1 (GPR)



(d) Model 2 (GPR)

One notable observation is that in graphs Figure 4a to Figure 4c, the probability of staying in regime 2 remains relatively constant at around 0.9, with occasional negative spikes occurring at similar positions but varying magnitudes. However, in Figure 4d, the probability of remaining in regime 2 consistently appears significantly lower, centered around an approximate value of 0.75. It is noteworthy that the lowest probabilities are observed at the start of 2018 in the models where the lagged VIX index serves as the information variable. This is likely due to the spike in the VIX index and the subsequent decline in other financial indices during that period. However, as depicted in Figure 1, this movement was relatively mild compared to the impact caused by the COVID-19 pandemic. Table 8 reveals that only the lagged VIX coefficient in Model 1 is moderately significant and provides meaningful information regarding the probability of remaining in regime 2. Upon closer examination of Figure 4a, we observe that these probabilities make the most intuitive sense and align with the smoothed probabilities depicted in Figure 3. At the beginning of 2022, we observe a cluster of lower probabilities associated with staying in the non-crisis regime. The positioning of this cluster resembles the peak in smoothed probabilities during the crisis period related to the COVID-19 pandemic. Additionally, we observe a negative spike at the onset of the crisis period associated with the Ukraine-Russia war and the 2022 bear market.

5.2.4 Regime-Specific Correlations

Finally, let us focus on the core matter at hand: what valuable insights can be obtained from the regime-specific correlations among the variables in the system concerning the co-movement between the green bond index and other financial indices? Upon visually examining the regime-specific correlations generated by each model specification in Table 10, we observe that the results obtained from Model 1 remain robust even when varying the included information variable within the model specification. Similarly, Model 2 also maintains its overall consistency, although the results in the final column differ based on whether the information variable used is the GPR or VIX index. Regarding the outcomes for Model 2, it is noteworthy that the GPR index exhibits insignificant pairwise correlations with the other variables, except for the green bond index. However, this correlation is relatively small, measuring only 0.082, and is statistically significant solely in the non-crisis regime.

Furthermore, it is noteworthy that in Model 1, the correlations between the green bond index and the other indices consistently exhibit positive values, which intensify during the crisis regime. These findings are consistent with prior research conducted by Han and Li (2022), Naeem et al. (2021b), and Nguyen et al. (2021), who have observed that the correlations between green bonds and other asset classes tend to be stronger during periods of extreme market movements compared to normal market conditions (Han and Li, 2022). Moreover, the escalation of pairwise correlations between the indices during the crisis regime suggests the presence of financial contagion among these assets (Longstaff, 2010; Flavin and Sheenan, 2015). While statistical tests to assess the significance of the increase in cross-market linkage are beyond the scope of this research, we find suggestive evidence supporting the notion that returns become more strongly correlated during high volatility and negative returns in the markets Campbell et al. (2002). It is important to mention that the correlations between the green bond index and other indices in the crisis regime remain well below 1, indicating that the green bond index continues to serve as a diversifying asset in both non-crisis and crisis periods, particularly concerning the commodity, oil & gas, and global stock indices. In Model 2, aside from the correlations with the GPR index, all other pairwise correlations are statistically significant. Similar to Model 1, these correlations exhibit an increase across all assets during the transition to the crisis regime.

Table 10: Regime-Specific Correlations

(a) Model 1 (VIX)

	Green Bond	Commodity	Oil & Gas	Global Stock
Green Bond	1	0.171***	0.469***	0.354***
Commodity	0.129***	1	0.620***	0.415***
Oil & Gas	0.452***	0.597***	1	0.711***
Global Stock	0.263***	0.436***	0.634***	1

(b) Model 2 (VIX)

	Green Bond	Low Carbon	Carbon Price	GPR
Green Bond	1	0.366***	0.138***	-0.050
Low Carbon	0.350***	1	0.341***	0.023
Carbon Price	1.176***	0.167***	1	0.029
GPR	0.082***	0.003	0.032	1

(c) Model 1 (GPR)

	Green Bond	Commodity	Oil & Gas	Global Stock
Green Bond	1	0.172***	0.467***	0.354***
Commodity	0.127***	1	0.620***	0.415***
Oil & Gas	0.455***	0.597***	1	0.711***
Global Stock	0.263***	0.436***	0.632***	1

(d) Model 2 (GPR)

	Green Bond	Low Carbon	Carbon Price	VIX
Green Bond	1	0.391***	0.161***	-0.295***
Low Carbon	0.301***	1	0.371***	-0.652***
Carbon Price	0.091***	0.151***	1	-0.158***
VIX	-0.219***	-0.733***	-0.074***	1

Note: This table presents the regime-specific asset correlations derived from our TVTP MS-VAR models. The lower triangles of the table display the correlations for the non-crisis period, while the upper triangles show the correlations for the crisis period. These correlations are computed using the covariances and standard deviations obtained from the TVTP MS-VAR model estimations, as detailed in Appendix C

Once again, the green bond index demonstrates its role as a diversifier for the low-carbon and carbon price indices in both non-crisis and crisis periods. As expected, the pairwise correlations with the VIX index consistently display negative and significant values. This finding aligns with intuition, as the VIX index reflects the level of volatility in stock markets. Consequently, when volatility rises, the returns on the green bond index and other financial indices tend to decrease (Sarwar, 2012).

5.2.5 Regime-Specific Coefficients

Similar to the estimates obtained from our linear VAR model, the coefficients generated by our TVTP MS-VAR models capture the relationship between the lagged values of the variables and the contemporaneous value of the green bond index. To facilitate comparison and assess the robustness of the results, we have presented the estimates for Model 1 in Table 11 and for Model 2 in Table 12, incorporating both the VIX and GPR index as information variables. This allows us to examine the consistency of the findings across different information variables utilized in the analysis.

Table 11: Model 1 Estimates for Green Bond Equation

	Model 1 (VIX)		Model 1 (GPR)	
	Non-crisis regime ϕ	Crisis regime ϕ	Non-crisis regime ϕ	Crisis regime ϕ
Green Bond (1)	-0.167	-0.056	-0.168	-0.057
	(-7.793***)	(-1.473)	(-6.825***)	(-1.434)
Commodity (1)	-0.019	0.023	-0.021	-0.052
	(-1.591)	(1.061)	(-1.433)	(-0.423)
Oil & Gas (1)	0.017	-0.042	0.018	-0.042
	(2.224**)	(-3.902***)	(1.761*)	(-2.397**)
Global Stock (1)	0.055	0.065	0.058	0.064
	(3.664***)	(3.111**)	(3.290***)	(2.428**)

Note: This table presents the regime-specific coefficients for the Green Bond equation in our TVTP MS-VAR model estimations. The results correspond to Model 1 specification, where either the VIX or GPR is used as the information variable. T-statistics are reported in parentheses. The significance levels *, **, and *** denote the rejection of the null hypothesis at the 10%, 5%, and 1% level, respectively.

Upon analyzing the results in Table 11, several noteworthy observations can be made. Firstly, the same coefficients exhibit statistical significance in both model specifications, and their signs remain consistent across the specifications. It is evident that the lagged value of the green bond index shows a negative relationship with its contemporaneous value in the non-crisis regime. This implies that during periods of relative stability in the stock market, the return on the green bond index tends to decrease. This trend can be attributed to the decreasing risk associated with green investments globally, leading investors to demand lower returns (Kanamura, 2020). Additionally, we observe that the coefficient on the lagged oil & gas index switches from positive to negative as the regime shifts from non-crisis to crisis. This finding suggests that during periods of relative stability, an increase in the lagged return on the oil & gas index corresponds to an increase in the contemporaneous value of the green bond index, indicating a positive relationship between these variables. However, in times of crisis, this positive relationship turns inverse. This finding supports the notion that when the price of oil rises, the price of green bonds declines Broadstock and Cheng (2019). It also provides preliminary evidence for the safe haven properties of green bonds concerning the oil and gas market. Furthermore, we find a positive relationship between the global stock index and the green bond index in both the non-crisis and crisis regimes. These findings remain robust across changes in the model specifications.

Table 12: Model 2 Estimates for Green Bond Equation

	Model 2 (VIX)		Model 2 (GPR)	
	Non-crisis regime ϕ	Crisis regime ϕ	Non-crisis regime ϕ	Crisis regime ϕ
Green Bond (1)	-0.106	-0.122	-0.118	-0.114
	(-4.664***)	(-3.412***)	(-4.792***)	(-2.006**)
Low Carbon (1)	0.043	-0.065	0.026	0.004
	(3.193***)	(-0.840)	(1.128)	(0.034)
Carbon Price (1)	0.000	-0.002	0.000	-0.003
	(-0.045)	(-0.194)	(0.068)	(-0.181)
GPR / VIX (1)	0.000	0.000	-0.003	0.001
	(-0.102)	(-0.650)	(-1.414)	(0.219)

Note: This table presents the regime-specific coefficients for the Green Bond equation in our TVTP MS-VAR model estimations. The results correspond to Model 2 specification, where either the VIX or GPR is used as the information variable. T-statistics are reported in parentheses. The significance levels *, **, and *** denote the rejection of the null hypothesis at the 10%, 5%, and 1% level, respectively.

Moving on to Table 12, the empirical evidence presented is less pronounced. In this model specification, a notable difference is the heightened significance of the lagged value of the green bond index, extending to the crisis regime. Moreover, we observe a highly significant positive relationship between the lagged return on the low-carbon index and the contemporaneous value of the green bond index. However, it should be noted that this result does not appear to be robust to changes in the information variable employed.

5.2.6 Summary of Results and Findings

Overall, our findings suggest that the green bond index does not serve as a hedge or safe haven for any of the other financial assets included in the analysis. Therefore we do not find evidence in support of our first three hypotheses. However, we do find that the green bond index offers significant diversification benefits in relation to the other assets, including the low-carbon stock index and the oil & gas index, thus supporting our fourth and fifth hypothesis. Additionally, our sixth hypothesis receives strong empirical support as all four TVTP MS-VAR model specifications demonstrate an increase in pairwise correlations between the green bond index and the other indices. This implies that the observed diversification benefits from holding the green bond index diminish for investors during crisis periods. This is in line with the notion of financial contagion in stock markets and supports the findings by Han and Li (2022), Naeem et al. (2021b), and Nguyen et al. (2021). As a result, it may be strategically advisable for investors to reconsider holding the green bond index during such periods, challenging the conventional perception of it as a safe haven asset that investors could rely on during times of crisis. Contrary to our initial expectations, the regime-specific coefficients obtained from our TVTP MS-VAR model provide evidence suggesting that the green bond index exhibits safe haven properties in relation to the oil & gas index. Additionally, our finding of the oil & gas index Granger-causing the green bond index further reinforces the evidence supporting an inverse causal relationship between the two.

One possible explanation for the contradictory findings in our study compared to prior research may lie in the differences in sample periods. Previous studies often focused on relatively bullish market periods characterized by lower volatility, higher returns, and lower correlations (Reboredo, 2018; Broadstock and Cheng, 2019; Reboredo and Ugolini, 2020; Hammoudeh et al., 2020; Saeed et al., 2021; Lee et al., 2021; Naeem et al., 2021b). By simply observing Figure 1, the substantial disparity in volatility before the onset of the COVID-19 pandemic becomes apparent. However our findings still diverge from those of Martiradonna et al. (2023), who utilized the same green bond index and included the COVID-19 period in their study. This discrepancy could be attributed to variations in methodologies employed and the inclusion of the Ukraine-Russia war and the 2022 bear market in our sample, which introduced a prolonged period of high volatility and declining stock prices.

In conclusion, the findings presented in our TVTP MS-VAR analysis exhibit a reasonable level of robustness across various model specifications and information variables. Furthermore, the results presented in Table 8, Table 9, and Table 10 are consistent with previous studies that employed similar methodologies and examined similar sample periods in terms of stock market volatility, such as the research conducted by Flavin and Sheenan (2015). This consistency enhances the credibility and validity of our findings.

6 Discussion and Conclusion

We analyse the co-movement between the green bond index and other financial indices over a sample period ranging from February 5, 2016, to March 10, 2023. The findings from our linear VAR analysis reveal significant inverse relationships between the green bond index and the commodity index, as well as the low-carbon index, in both the short and long term. Conversely, we observe a significant positive relationship between the green bond index and the global stock index. These results are supported by Granger-causality tests, indicating the influence of the low-carbon and global stock markets on the green bond market

To further explore the nonlinear dynamics among the financial indices, we employ a TVTP MS-VAR model. This approach allows us to assess the pairwise relationships between the variables in both non-crisis and crisis regimes characterized by low and high volatility states. Our analysis reveals a notable shift in the relationship during the crisis regime, where the positive relationship between the green bond index and the oil & gas transforms into an inverse relationship. This suggests that the green bond index may serve as a safe haven for the oil & gas index and sheds light on the interaction between oil prices and the dynamics of green bonds (Lee et al., 2021) Additionally, we find that the lagged VIX index outperforms the lagged GPR index in predicting regime switches, particularly in Model 1, indicating its effectiveness in anticipating transitions between different volatility states. Moreover, it is evident that the linear and non-linear approaches yield significantly different results. This confirms the time-varying, non-linear, and assymetric nature of the relationship between green bonds and other assets (Han and Li, 2022; Lee et al., 2021; Jin et al., 2020).

Contrary to our expectations, the regime-specific correlations produced by our TVTP MS-VAR models suggest that the green bond index does not serve as a hedge or safe haven for any of the other financial indices included in the analysis. However, we do find that the green bond index offers significant diversification benefits in relation to the other assets, including the low-carbon stock market, thus supporting our fourth hypothesis. Additionally, our fifth hypothesis receives strong empirical support as all four TVTP MS-VAR model specifications demonstrate an increase in pairwise correlations between the green bond index and the other indices. This implies that the observed diversification benefits from holding the green bond index diminish for investors during crisis periods. Consequently, it may be strategically advisable for investors not to hold the green bond index during these times, contrasting the conventional notion of it as a safe haven asset that investors turn to in times of crisis.

Our study underscores the significance of considering sample periods and methodologies when interpreting research findings. While differences in sample periods may account for some of the discrepancies with previous studies that focused on relatively bullish market periods, our results also diverge from those of Martiradonna et al. (2023), who employed the same green bond index and analyzed the period encompassing the COVID-19 pandemic. Nonetheless, the disparity in outcomes could be attributed to the inclusion of the period covering the Ukraine-Russia war and the 2022 bear market, characterized by heightened volatility and a sustained decline in stock market returns.

We emphasize the robustness of our results, supported by statistical tests on the VAR model and the consistency observed across various aspects of the TVTP MS-VAR models. However, further research is warranted to estimate the entire model instead of partitioning it, enabling a more comprehensive understanding of the dynamic relationships between the variables. Additionally, examining the impulse response functions for both non-crisis and crisis periods would yield valuable insights into the behavior of the variables under diverse market conditions. Such investigations would contribute to refining our understanding of the intricate dynamics surrounding green bonds and their role within investment portfolios.

The overall findings of this study hold significant implications for investors in the green bond, commodity, oil & gas, global stock, low-carbon, and carbon markets. Contrary to the claim that the green bond serves as a hedge or safe haven for any of these markets, our results demonstrate that it does not exhibit such properties. However, it is important to note that the green bond market still offers notable diversification benefits, albeit to a lesser extent during crisis periods compared to non-crisis times. This finding holds particular relevance for investors in the low-carbon market, as it allows them to diversify their portfolio while aligning with their environmental stance. Additionally, our findings regarding the diversification benefits of green bonds in the carbon market are particularly relevant to various stakeholders, including environmental policymakers, energy-intensive firms, portfolio managers, and carbon investors. These findings offer them an effective instrument to mitigate the increasing carbon risk. Furthermore, the evident diversification benefits of green bonds are likely to attract more conventional investors in the future. This trend will spur sustainable investments and facilitate the transition to a low-carbon economy. Hence, policymakers should recognize and leverage this information to further stimulate the demand for environmentally-friendly investments.

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A Linear VAR Model

Method	OLS								
Results for equation Green Bond					**Results for equation Commodity**				
	coefficient	std. error	t-stat	prob		coefficient	std. error	t-stat	prob
const	0.000	0.000	0.557	0.578	const	0.000	0.000	1.127	0.260
L1.Green Bond	-0.069	0.028	-2.463	0.014	L1.Green Bond	0.041	0.060	0.677	0.498
L1.Commodity	-0.043	0.014	-3.033	0.002	L1.Commodity	0.003	0.031	0.096	0.923
L1.Oil & Gas	0.020	0.012	1.634	0.102	L1.Oil & Gas	0.027	0.026	1.048	0.294
L1.Global Stock	0.654	0.086	7.638	0.000	L1.Global Stock	0.598	0.184	3.251	0.001
L1.Low Carbon	-0.600	0.080	-7.449	0.000	L1.Low Carbon	-0.476	0.173	-2.753	0.006
L1.Carbon Price	0.009	0.006	1.538	0.124	L1.Carbon Price	-0.036	0.013	-2.747	0.006
L1.GPR	0.000	0.000	-1.223	0.222	L1.GPR	0.000	0.001	-0.241	0.809
L1.VIX	0.004	0.002	2.116	0.034	L1.VIX	0.019	0.004	4.279	0.000
Results for equation Oil & Gas					**Results for equation Global Stock**				
	coefficient	std. error	t-stat	prob		coefficient	std. error	t-stat	prob
const	0.001	0.000	1.188	0.235	const	0.000	0.000	1.288	0.198
L1.Green Bond	0.024	0.096	0.254	0.799	L1.Green Bond	0.258	0.051	5.063	0.000
L1.Commodity	0.008	0.049	0.171	0.864	L1.Commodity	0.042	0.026	1.621	0.105
L1.Oil & Gas	0.053	0.041	1.296	0.195	L1.Oil & Gas	-0.091	0.022	-4.205	0.000
L1.Global Stock	1.701	0.292	5.835	0.000	L1.Global Stock	1.293	0.155	8.333	0.000
L1.Low Carbon	-1.545	0.274	-5.634	0.000	L1.Low Carbon	-1.059	0.146	-7.258	0.000
L1.Carbon Price	-0.036	0.021	-1.775	0.076	L1.Carbon Price	0.004	0.011	0.333	0.739
L1.GPR	-0.002	0.001	-1.925	0.054	L1.GPR	-0.001	0.000	-1.407	0.159
L1.VIX	0.031	0.007	4.377	0.000	L1.VIX	0.024	0.004	6.400	0.000

Method	**OLS**								
Results for equation Low Carbon					**Results for equation Carbon Price**				
	coefficient	std. error	t-stat	prob		coefficient	std. error	t-stat	prob
const	0.000	0.000	1.430	0.153	const	0.001	0.001	2.585	0.010
L1.Green Bond	0.236	0.053	4.442	0.000	L1.Green Bond	0.084	0.119	0.705	0.481
L1.Commodity	0.033	0.027	1.210	0.226	L1.Commodity	-0.037	0.060	-0.615	0.539
L1.Oil & Gas	-0.090	0.023	-3.991	0.000	L1.Oil & Gas	-0.033	0.051	-0.648	0.517
L1.Global Stock	1.548	0.162	9.560	0.000	L1.Global Stock	0.566	0.361	1.567	0.117
L1.Low Carbon	-1.300	0.152	-8.534	0.000	L1.Low Carbon	-0.372	0.340	-1.094	0.274
L1.Carbon Price	0.005	0.011	0.468	0.640	L1.Carbon Price	-0.025	0.025	-0.999	0.318
L1.GPR	-0.001	0.000	-1.102	0.270	L1.GPR	-0.002	0.001	-1.642	0.101
L1.VIX	0.025	0.004	6.317	0.000	L1.VIX	0.023	0.009	2.595	0.009
Results for equation GPR					**Results for equation VIX**				
	coefficient	std. error	t-stat	prob		coefficient	std. error	t-stat	prob
const	0.140	0.012	11.242	0.000	const	0.116	0.017	6.912	0.000
L1.Green Bond	-1.468	2.685	-0.547	0.584	L1.Green Bond	0.388	0.361	1.074	0.283
L1.Commodity	1.988	1.369	1.452	0.146	L1.Commodity	0.264	0.185	1.430	0.153
L1.Oil & Gas	0.240	1.145	0.210	0.834	L1.Oil & Gas	0.146	0.154	0.945	0.345
L1.Global Stock	-3.925	8.181	-0.480	0.631	L1.Global Stock	2.079	1.103	1.884	0.060
L1.Low Carbon	3.418	7.692	0.444	0.657	L1.Low Carbon	-1.610	1.037	-1.554	0.120
L1.Carbon Price	0.105	0.576	0.182	0.856	L1.Carbon Price	0.002	0.078	0.032	0.974
L1.GPR	-0.288	0.023	-12.400	0.000	L1.GPR	-0.013	0.003	-4.048	0.000
L1.VIX	-0.017	0.200	-0.083	0.934	L1.VIX	0.760	0.027	28.242	0.000

B Impulse Response Functions

Figure 5: Impulse Response Functions

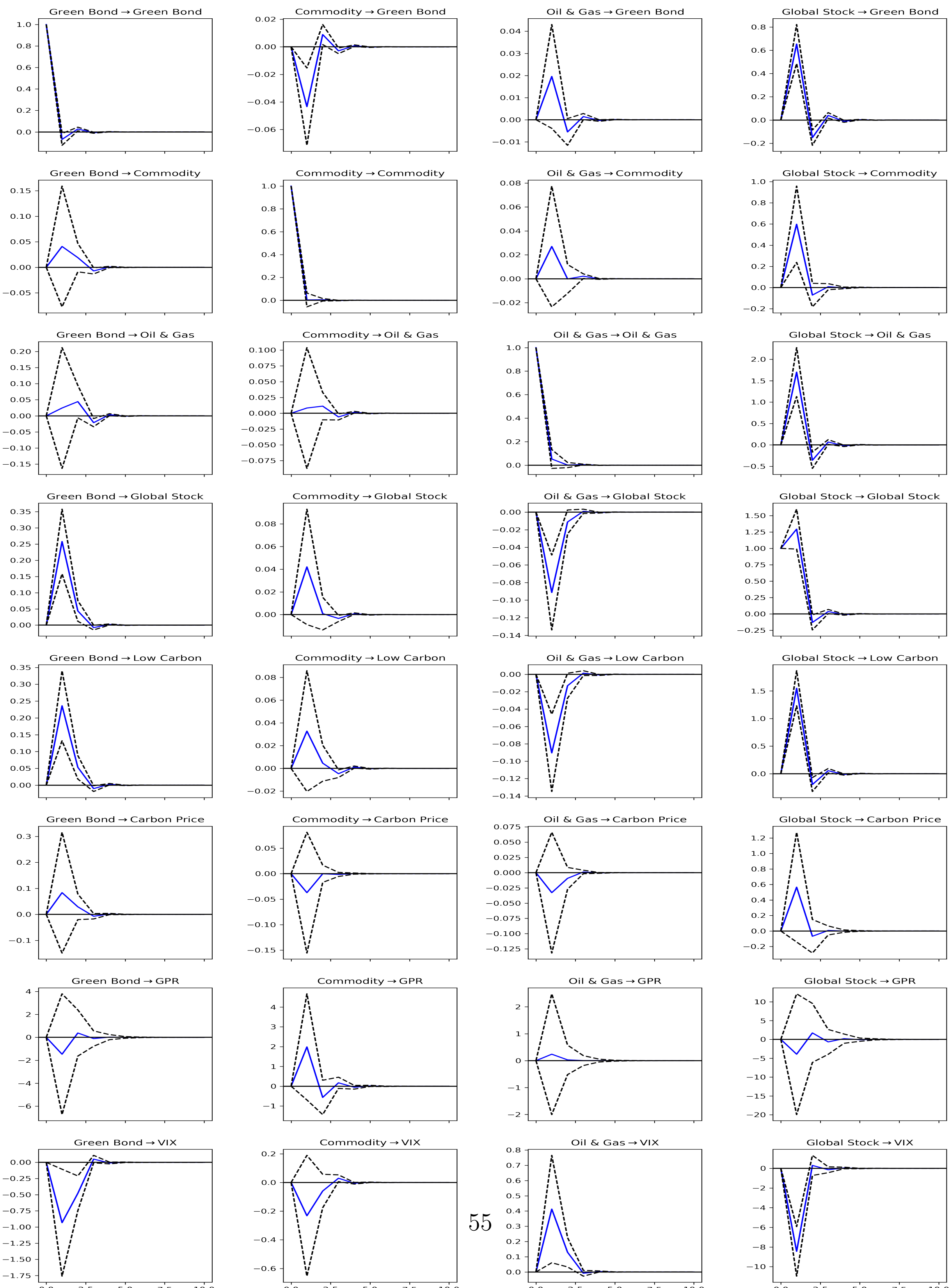
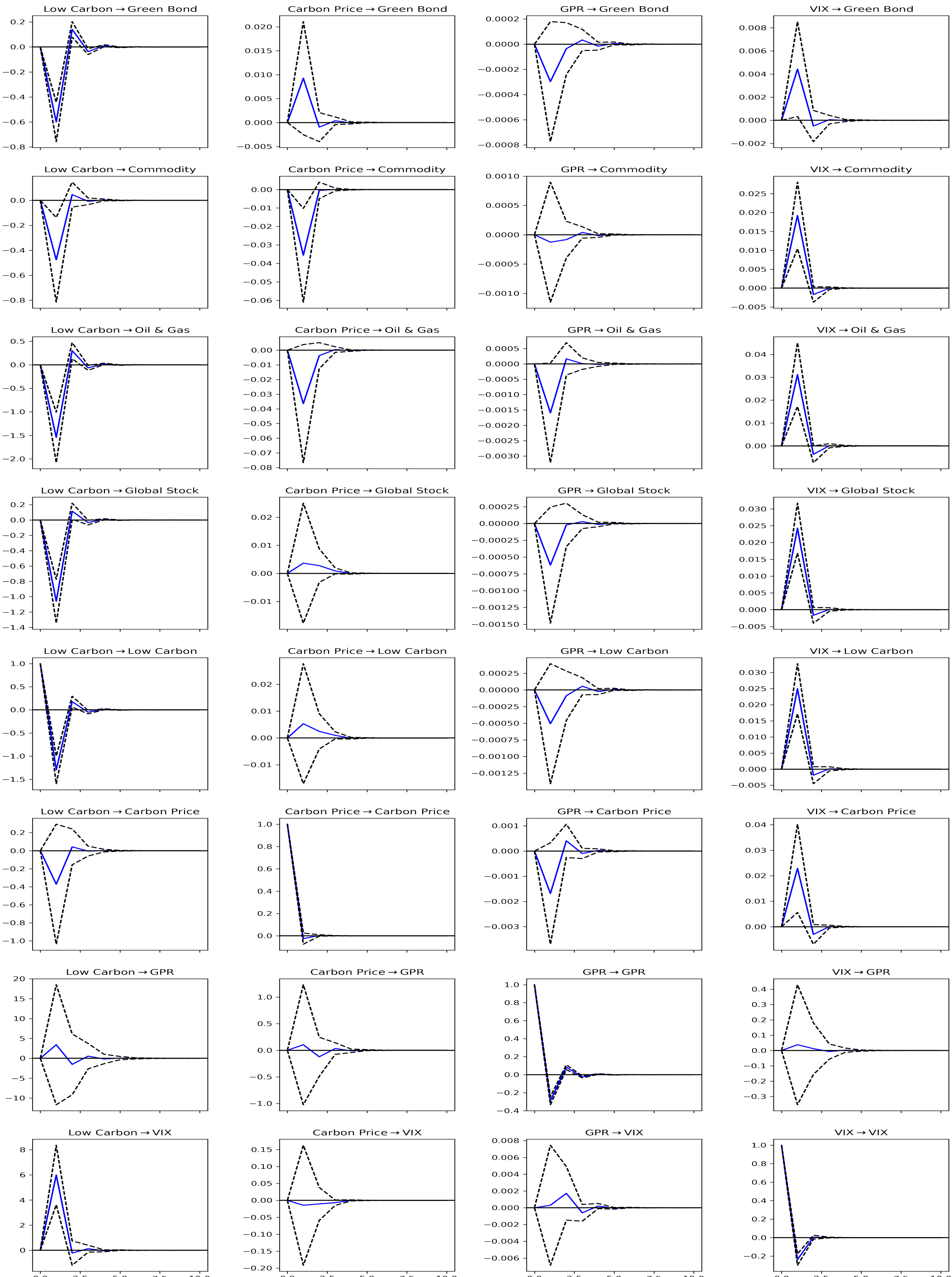


Figure 6: Impulse Response Functions (Continued)



C TVTP MS-VAR Models

TVTP MS-VAR model 1 (VIX)					TVTP MS-VAR model 2 (VIX)				
Variable	Coeff	Std. Error	T-Stat	Signif	Variable	Coeff	Std Error	T-Stat	Signif
V1(1)	1.902	0.139	13.650	0.000	V1(1)	2.060	0.216	9.557	0.000
V1(2)	-3.196	1.199	-2.666	0.008	V1(2)	-1.837	1.769	-1.039	0.299
V2(1)	-3.091	0.150	-20.597	0.000	V2(1)	-2.845	0.166	-17.102	0.000
V2(2)	6.851	2.193	3.124	0.018	V2(2)	3.623	2.601	1.393	0.164
MU(1)(1)	0.000	0.000	-1.139	0.255	MU(1)(1)	0.000	0.000	-1.103	0.270
MU(1)(2)	-0.001	0.001	-1.244	0.213	MU(1)(2)	-0.001	0.001	-1.497	0.134
MU(1)(3)	-0.001	0.001	-0.933	0.351	MU(1)(3)	-0.001	0.001	-0.465	0.642
MU(1)(4)	-0.001	0.001	-2.404	0.016	MU(1)(4)	0.113	0.021	5.438	0.000
MU(2)(1)	0.000	0.000	1.945	0.052	MU(2)(1)	0.000	0.000	1.861	0.063
MU(2)(2)	0.001	0.000	3.663	0.000	MU(2)(2)	0.001	0.000	4.825	0.000
MU(2)(3)	0.001	0.000	2.897	0.004	MU(2)(3)	0.002	0.000	4.904	0.000
MU(2)(4)	0.007	0.000	5.890	0.000	MU(2)(4)	0.150	0.013	11.308	0.000
PHIV(1, 1)(1 , 1)	-0.056	0.038	-1.474	0.141	PHIV(1, 1)(1 , 1)	-0.122	0.036	-3.412	0.001
PHIV(1, 1)(2,1)	-0.056	0.089	-0.629	0.529	PHIV(1, 1)(2,1)	-0.065	0.077	-0.840	0.401
PHIV(1, 1)(3,1)	0.062	0.123	0.505	0.613	PHIV(1, 1)(3,1)	0.202	0.178	1.133	0.257
PHIV(1, 1)(4,1)	0.031	0.067	0.461	0.645	PHIV(1, 1)(4,1)	-0.516	2.756	-0.187	0.852
PHIV(1, 1)(1 ,2)	0.023	0.022	1.061	0.289	PHIV(1, 1)(1 ,2)	0.026	0.020	1.264	0.206
PHIV(1 ,1)(2,2)	0.010	0.025	0.408	0.683	PHIV(1 ,1)(2,2)	-0.049	0.050	-0.979	0.328
PHIV(1 ,1)(3,2)	0.094	0.037	2.525	0.012	PHIV(1 ,1)(3,2)	-0.035	0.085	-0.413	0.680
PHIV(1 ,1)(4,2)	0.069	0.030	2.338	0.019	PHIV(1 ,1)(4,2)	-1.847	1.355	-1.363	0.173
PHIV(1, 1)(1 ,3)	-0.042	0.011	-3.902	0.000	PHIV(1, 1)(1 ,3)	-0.002	0.012	-0.194	0.846

TVTP MS-VAR model 1 (VIX)					TVTP MS-VAR model 2 (VIX)				
Variable	Coeff	Std. Error	T-Stat	Signif	Variable	Coeff	Std Error	T-Stat	Signif
PHIV(1 ,1)(2,3)	0.031	0.017	1.874	0.061	PHIV(1 ,1)(2,3)	0.006	0.023	0.259	0.796
PHIV(1 ,1)(3,3)	0.055	0.025	2.191	0.028	PHIV(1 ,1)(3,3)	-0.012	0.044	-0.262	0.793
PHIV(1 ,1)(4,3)	-0.057	0.016	-3.448	0.001	PHIV(1 ,1)(4,3)	-0.699	0.768	-0.911	0.362
PHIV(1, 1)(1,4)	0.065	0.021	3.111	0.019	PHIV(1, 1)(1,4)	0.000	0.001	-0.650	0.516
PHIV(1 ,1)(2,4)	-0.042	0.032	-1.322	0.186	PHIV(1 ,1)(2,4)	-0.001	0.001	-0.402	0.688
PHIV(1, 1)(3,4)	-0.206	0.046	-4.462	0.000	PHIV(1, 1)(3,4)	0.001	0.003	0.456	0.648
PHIV(1 ,1)(4,4)	0.010	0.027	0.385	0.700	PHIV(1 ,1)(4,4)	-0.267	0.048	-5.619	0.000
PHIV(2 ,1)(1,1)	-0.167	0.021	-7.793	0.000	PHIV(2 ,1)(1,1)	-0.106	0.023	-4.664	0.000
PHIV(2 ,1)(2,1)	-0.181	0.043	-4.212	0.000	PHIV(2 ,1)(2,1)	0.010	0.038	0.269	0.788
PHIV(2 ,1)(3,1)	-0.046	0.052	-0.883	0.377	PHIV(2 ,1)(3,1)	-0.059	0.117	-0.501	0.616
PHIV(2 ,1)(4,1)	0.035	0.033	1.051	0.293	PHIV(2 ,1)(4,1)	-2.530	3.319	-0.762	0.446
PHIV(2 ,1)(1,2)	-0.019	0.012	-1.591	0.112	PHIV(2 ,1)(1,2)	0.043	0.014	3.193	0.001
PHIV(2 ,1)(2,2)	-0.026	0.019	-1.377	0.169	PHIV(2 ,1)(2,2)	0.082	0.024	3.479	0.001
PHIV(2 ,1)(3,2)	-0.029	0.023	-1.249	0.212	PHIV(2 ,1)(3,2)	0.112	0.076	1.472	0.141
PHIV(2 ,1)(4,2)	-0.059	0.014	-2.491	0.013	PHIV(2 ,1)(4,2)	3.893	2.309	1.686	0.092
PHIV(2 ,1)(1,3)	0.017	0.008	2.224	0.026	PHIV(2 ,1)(1,3)	0.000	0.006	-0.045	0.964
PHIV(2 ,1)(2,3)	0.053	0.013	3.961	0.000	PHIV(2 ,1)(2,3)	-0.008	0.009	-0.988	0.323
PHIV(2 ,1)(3,3)	0.075	0.015	4.946	0.000	PHIV(2 ,1)(3,3)	-0.052	0.025	-2.079	0.038
PHIV(2 ,1)(4,3)	0.001	0.010	0.062	0.951	PHIV(2 ,1)(4,3)	-0.449	0.650	-0.691	0.489
PHIV(2 ,1)(1,4)	0.055	0.015	3.664	0.000	PHIV(2 ,1)(1,4)	0.000	0.000	-0.102	0.919
PHIV(2 ,1)(2,4)	0.043	0.027	1.624	0.104	PHIV(2 ,1)(2,4)	0.000	0.000	0.895	0.371
PHIV(2 ,1)(3,4)	-0.019	0.031	-0.620	0.535	PHIV(2 ,1)(3,4)	0.000	0.001	-0.323	0.747
PHIV(2 ,1)(4,4)	0.112	0.019	5.933	0.000	PHIV(2 ,1)(4,4)	-0.294	0.021	-13.707	0.000

TVTP MS-VAR model 1 (VIX)					TVTP MS-VAR model 2 (VIX)				
Variable	Coeff	Std. Error	T-Stat	Signif	Variable	Coeff	Std Error	T-Stat	Signif
SIGMAV(1)(I ,1)	0.000	0.000	28.718	0.000	SIGMAV(1)(I ,1)	0.000	0.000	14.769	0.000
SIGMAV(1)(2 ,1)	0.000	0.000	5.619	0.000	SIGMAV(1)(2 ,1)	0.000	0.000	7.818	0.000
SIGMAV(1)(2 ,2)	0.000	0.000	50.680	0.000	SIGMAV(1)(2 ,2)	0.000	0.000	14.405	0.000
SIGMAV(1)(3 ,1)	0.000	0.000	21.587	0.000	SIGMAV(1)(3 ,1)	0.000	0.000	3.457	0.001
SIGMAV(1)(3 ,2)	0.000	0.000	55.465	0.000	SIGMAV(1)(3 ,2)	0.000	0.000	7.595	0.000
SIGMAV(1)(3 ,3)	0.001	0.000	73.978	0.000	SIGMAV(1)(3 ,3)	0.001	0.000	14.535	0.000
SIGMAV(1)(4 ,1)	0.000	0.000	12.327	0.000	SIGMAV(1)(4 ,1)	0.000	0.000	-1.131	0.258
SIGMAV(1)(4 ,2)	0.000	0.000	19.826	0.000	SIGMAV(1)(4 ,2)	0.000	0.000	0.595	0.552
SIGMAV(1)(4,3)	0.000	0.000	53.291	0.000	SIGMAV(1)(4,3)	0.000	0.001	0.629	0.529
SIGMAV(1)(4 ,4)	0.000	0.000	38.441	0.000	SIGMAV(1)(4 ,4)	0.176	0.014	12.889	0.000
SIGMAV(2)(1 ,1)	0.000	0.000	33.798	0.000	SIGMAV(2)(1 ,1)	0.000	0.000	20.284	0.000
SIGMAV(2)(2 ,1)	0.000	0.000	6.956	0.000	SIGMAV(2)(2 ,1)	0.000	0.000	9.646	0.000
SIGMAV(2)(2 ,2)	0.000	0.000	39.063	0.000	SIGMAV(2)(2 ,2)	0.000	0.000	16.314	0.000
SIGMAV(2)(3 ,1)	0.000	0.000	35.475	0.000	SIGMAV(2)(3 ,1)	0.000	0.000	3.570	0.000
SIGMAV(2)(3 ,2)	0.000	0.000	49.931	0.000	SIGMAV(2)(3 ,2)	0.000	0.000	5.497	0.000
SIGMAV(2)(3 ,3)	0.000	0.000	71.491	0.000	SIGMAV(2)(3 ,3)	0.000	0.000	25.218	0.000
SIGMAV(2)(4 ,1)	0.000	0.000	16.147	0.000	SIGMAV(2)(4 ,1)	0.000	0.000	2.685	0.007
SIGMAV(2)(4 ,2)	0.000	0.000	27.047	0.000	SIGMAV(2)(4 ,2)	0.000	0.000	0.084	0.933
SIGMAV(2)(4 ,3)	0.000	0.000	57.400	0.000	SIGMAV(2)(4 ,3)	0.000	0.000	1.440	0.150
SIGMAV(2)(4 ,4)	0.000	0.000	43.722	0.000	SIGMAV(2)(4 ,4)	0.288	0.008	34.249	0.000

TVTP MS-VAR model 1 (GPR)					TVTP MS-VAR model 2 (GPR)				
Variable	Coeff	Std Error	T-Stat	Signif	Variable	Coeff	Std Error	T-Stat	Signif
V1(1)	1.900	0.177	10.737	0.000	V1(1)	1.060	0.219	4.841	0.000
V1(2)	-0.349	0.417	-0.836	0.403	V1(2)	-0.408	0.362	-1.127	0.260
V2(1)	-3.010	0.163	-18.516	0.000	V2(1)	-2.413	0.139	-17.323	0.000
V2(2)	0.051	0.397	0.128	0.899	V2(2)	-0.364	0.258	-1.414	0.157
MU(1)(1)	0.000	0.000	-1.123	0.261	MU(1)(1)	-0.001	0.000	-1.331	0.183
MU(1)(2)	-0.001	0.001	-0.954	0.340	MU(1)(2)	-0.002	0.001	-1.752	0.080
MU(1)(3)	-0.001	0.001	-0.585	0.559	MU(1)(3)	-0.001	0.002	-0.775	0.438
MU(1)(4)	-0.001	0.001	-2.044	0.041	MU(1)(4)	0.018	0.007	2.723	0.006
MU(2)(1)	0.000	0.000	1.752	0.080	MU(2)(1)	0.000	0.000	1.711	0.087
MU(2)(2)	0.001	0.000	2.995	0.003	MU(2)(2)	0.001	0.000	4.622	0.000
MU(2)(3)	0.001	0.000	1.840	0.066	MU(2)(3)	0.002	0.001	3.976	0.000
MU(2)(4)	0.001	0.000	4.484	0.000	MU(2)(4)	-0.005	0.002	-3.098	0.002
PHIV(1, 1)(1 , 1)	-0.057	0.040	-1.434	0.151	PHIV(1, 1)(1 , 1)	-0.114	0.057	-2.006	0.045
PHIV(1, 1)(2,1)	-0.052	0.122	-0.423	0.672	PHIV(1, 1)(2,1)	0.004	0.120	0.034	0.973
PHIV(1, 1)(3,1)	0.092	0.170	0.542	0.588	PHIV(1, 1)(3,1)	0.211	0.247	0.855	0.393
PHIV(1, 1)(4,1)	0.044	0.082	0.538	0.590	PHIV(1, 1)(4,1)	0.062	0.846	0.074	0.941
PHIV(1, 1)(1 ,2)	0.024	0.022	1.110	0.267	PHIV(1, 1)(1 ,2)	0.024	0.034	0.708	0.479
PHIV(1 ,1)(2,2)	0.010	0.047	0.211	0.833	PHIV(1 ,1)(2,2)	-0.186	0.070	-2.645	0.008
PHIV(1 ,1)(3,2)	0.097	0.083	1.170	0.242	PHIV(1 ,1)(3,2)	-0.091	0.134	-0.680	0.496
PHIV(1 ,1)(4,2)	0.070	0.047	1.498	0.134	PHIV(1 ,1)(4,2)	0.592	0.506	1.171	0.241
PHIV(1, 1)(1 ,3)	-0.042	0.018	-2.397	0.017	PHIV(1, 1)(1 ,3)	-0.003	0.017	-0.181	0.856
PHIV(1 ,1)(2,3)	0.030	0.034	0.866	0.387	PHIV(1 ,1)(2,3)	0.030	0.033	0.896	0.370
PHIV(1 ,1)(3,3)	0.046	0.068	0.682	0.495	PHIV(1 ,1)(3,3)	0.008	0.070	0.113	0.910

TVTP MS-VAR model 1 (GPR)					TVTP MS-VAR model 2 (GPR)				
Variable	Coeff	Std Error	T-Stat	Signif	Variable	Coeff	Std Error	T-Stat	Signif
PHIV(1 ,1)(4,3)	-0.062	0.040	-1.556	0.120	PHIV(1 ,1)(4,3)	0.099	0.240	0.411	0.681
PHIV(1, 1)(1,4)	0.064	0.026	2.428	0.015	PHIV(1, 1)(1,4)	0.001	0.005	0.219	0.826
PHIV(1 ,1)(2,4)	-0.040	0.059	-0.676	0.499	PHIV(1 ,1)(2,4)	-0.015	0.010	-1.538	0.124
PHIV(1, 1)(3,4)	-0.210	0.101	-2.090	0.037	PHIV(1, 1)(3,4)	-0.011	0.019	-0.566	0.571
PHIV(1 ,1)(4,4)	0.009	0.061	0.155	0.877	PHIV(1 ,1)(4,4)	-0.091	0.071	-1.281	0.200
PHIV(2 ,1)(1,1)	-0.168	0.025	-6.825	0.000	PHIV(2 ,1)(1,1)	-0.118	0.025	-4.792	0.000
PHIV(2 ,1)(2,1)	-0.189	0.047	-3.983	0.000	PHIV(2 ,1)(2,1)	-0.081	0.037	-2.201	0.028
PHIV(2 ,1)(3,1)	-0.086	0.075	-1.155	0.248	PHIV(2 ,1)(3,1)	-0.001	0.116	-0.012	0.991
PHIV(2 ,1)(4,1)	0.015	0.039	0.393	0.694	PHIV(2 ,1)(4,1)	0.133	0.368	0.361	0.718
PHIV(2 ,1)(1,2)	-0.021	0.015	-1.433	0.152	PHIV(2 ,1)(1,2)	0.026	0.023	1.128	0.259
PHIV(2 ,1)(2,2)	-0.027	0.031	-0.861	0.389	PHIV(2 ,1)(2,2)	0.045	0.036	1.252	0.210
PHIV(2 ,1)(3,2)	-0.039	0.049	-0.803	0.422	PHIV(2 ,1)(3,2)	-0.019	0.078	-0.242	0.809
PHIV(2 ,1)(4,2)	-0.040	0.022	-1.777	0.076	PHIV(2 ,1)(4,2)	1.097	0.350	3.139	0.002
PHIV(2 ,1)(1,3)	0.018	0.010	1.761	0.078	PHIV(2 ,1)(1,3)	0.000	0.006	0.068	0.946
PHIV(2 ,1)(2,3)	0.057	0.020	2.910	0.004	PHIV(2 ,1)(2,3)	-0.012	0.008	-1.480	0.139
PHIV(2 ,1)(3,3)	0.092	0.037	2.498	0.012	PHIV(2 ,1)(3,3)	-0.050	0.029	-1.700	0.089
PHIV(2 ,1)(4,3)	0.010	0.015	0.707	0.480	PHIV(2 ,1)(4,3)	0.051	0.078	0.649	0.516
PHIV(2 ,1)(1,4)	0.058	0.017	3.290	0.001	PHIV(2 ,1)(1,4)	-0.003	0.002	-1.414	0.157
PHIV(2 ,1)(2,4)	0.040	0.042	0.942	0.346	PHIV(2 ,1)(2,4)	-0.014	0.003	-4.454	0.000
PHIV(2 ,1)(3,4)	-0.003	0.068	-0.040	0.968	PHIV(2 ,1)(3,4)	-0.013	0.008	-1.555	0.120
PHIV(2 ,1)(4,4)	0.118	0.029	4.055	0.000	PHIV(2 ,1)(4,4)	0.041	0.032	1.269	0.205
SIGMAV(1)(I ,1)	0.000	0.000	12.627	0.000	SIGMAV(1)(I ,1)	0.000	0.000	12.361	0.000
SIGMAV(1)(2 ,1)	0.000	0.000	3.900	0.000	SIGMAV(1)(2 ,1)	0.000	0.000	7.460	0.000

TVTP MS-VAR model 1 (GPR)					TVTP MS-VAR model 2 (GPR)				
Variable	Coeff	Std Error	T-Stat	Signif	Variable	Coeff	Std Error	T-Stat	Signif
SIGMAV(1)(2 ,2)	0.000	0.000	13.976	0.000	SIGMAV(1)(2 ,2)	0.000	0.000	13.225	0.000
SIGMAV(1)(3 ,1)	0.000	0.000	7.988	0.000	SIGMAV(1)(3 ,1)	0.000	0.000	3.886	0.000
SIGMAV(1)(3 ,2)	0.000	0.000	10.641	0.000	SIGMAV(1)(3 ,2)	0.000	0.000	9.948	0.000
SIGMAV(1)(3 ,3)	0.001	0.000	12.345	0.000	SIGMAV(1)(3 ,3)	0.001	0.000	13.438	0.000
SIGMAV(1)(4 ,1)	0.000	0.000	6.443	0.000	SIGMAV(1)(4 ,1)	0.000	0.000	-6.053	0.000
SIGMAV(1)(4 ,2)	0.000	0.000	8.174	0.000	SIGMAV(1)(4 ,2)	-0.002	0.000	-11.088	0.000
SIGMAV(1)(4,3)	0.000	0.000	10.003	0.000	SIGMAV(1)(4,3)	-0.001	0.000	-4.579	0.000
SIGMAV(1)(4 ,4)	0.000	0.000	11.806	0.000	SIGMAV(1)(4 ,4)	0.016	0.012	13.183	0.000
SIGMAV(2)(1 ,1)	0.000	0.000	22.363	0.000	SIGMAV(2)(1 ,1)	0.000	0.000	20.459	0.000
SIGMAV(2)(2 ,1)	0.000	0.000	4.222	0.000	SIGMAV(2)(2 ,1)	0.000	0.000	9.127	0.000
SIGMAV(2)(2 ,2)	0.000	0.000	20.119	0.000	SIGMAV(2)(2 ,2)	0.000	0.000	16.985	0.000
SIGMAV(2)(3 ,1)	0.000	0.000	13.275	0.000	SIGMAV(2)(3 ,1)	0.000	0.000	2.844	0.004
SIGMAV(2)(3 ,2)	0.000	0.000	14.528	0.000	SIGMAV(2)(3 ,2)	0.000	0.000	5.323	0.000
SIGMAV(2)(3 ,3)	0.000	0.000	20.189	0.000	SIGMAV(2)(3 ,3)	0.000	0.000	23.146	0.000
SIGMAV(2)(4 ,1)	0.000	0.000	8.150	0.000	SIGMAV(2)(4 ,1)	0.000	0.000	-6.931	0.000
SIGMAV(2)(4 ,2)	0.000	0.000	11.553	0.000	SIGMAV(2)(4 ,2)	0.000	0.000	-15.475	0.000
SIGMAV(2)(4 ,3)	0.000	0.000	14.248	0.000	SIGMAV(2)(4 ,3)	0.000	0.000	-2.924	0.003
SIGMAV(2)(4 ,4)	0.000	0.000	17.014	0.000	SIGMAV(2)(4 ,4)	0.004	0.002	18.278	0.000