INSTITUTO
UNIVERSITÁRIO
DE LISBOA

Department of Political Economy

The Role of Pension Funds in Promoting Green Finance:

Green Bond Investments and their Influence on CO2 Emissions

Patricia Pascoal Quiterres

Master in Monetary and Financial Economics

Supervisor:
Ph.D. Sofia Sousa Vale, Associate Professor, Vice-Rector for Financial Affairs
Iscte - Instituto Universitário de Lisboa

September, 2024

CIÊNCIAS SOCIAIS
E HUMANAS

Department of Political Economy

The Role of Pension Funds in Promoting Green Finance:

Green Bond Investments and their Influence on CO2 Emissions

Patricia Pascoal Quiterres

Master in Monetary and Financial Economics

Supervisor:
Ph.D. Sofia Sousa Vale, Associate Professor, Vice-Rector for Financial Affairs
Iscte - Instituto Universitário de Lisboa

September, 2024

Acknowledgments

I want to express my heartfelt thanks to my parents, whose encouragement has carried me through every step of this journey. To my brother, thank you for always standing by my side, offering a much-needed laugh when I needed it most.

I am incredibly grateful to my aunt and uncle, Amélia and António, for their constant support and wise guidance throughout my academic journey. To my godmother, your kindness and faith in me have been an inspiration and I’m truly thankful for your unwavering support.

I would also like to extend my sincere thanks to Ph.D. Sofia Sousa Vale for her constant availability, guidance, and support. Without her valuable insights and mentorship, this dissertation would not have been possible.

To my friends and colleagues, thank you for being by my side through every challenge. Your companionship has made this journey more meaningful.

Resumo

Este estudo analisa os investimentos de fundos de pensão em *green bonds* da zona Euro, em particular, a sua relação com as emissões de dióxido de carbono. A pesquisa utilizou um modelo VAR para analisar as interações entre seis variáveis: emissões de CO2 (CO2E), rácio de investimento em *green bonds* (GBIR), índice de produção industrial (IPI), preços de energia (EP), consumo de energia (EC) e a *benchmark yield* a 10 anos (10YBY). Os resultados da análise mostram que as emissões de CO2 aumentaram inesperadamente, possivelmente devido às atividades intensivas em carbono, financiadas pelas *green bonds*, durante as fases iniciais dos projetos. Contudo, apesar das emissões de CO2 serem inicialmente impulsionadas por choques próprios, o investimento em *green bonds* passa a explicar uma parte substancial da variância das emissões CO2. O estudo sublinha assim a importância de compreender a dinâmica temporal dos investimentos verdes, mostrando que os investimentos em *green bonds* podem não resultar em reduções imediatas de CO2, sendo crucial reconhecer o impacto diferido destes investimentos. Embora exista um aumento temporário de emissões, o crescimento constante no GBIR reflete o progresso do financiamento sustentável, reforçando a necessidade de se continuar a investir em *green bonds*, focando-se nos benefícios ambientais a longo prazo.

Palavras-Chave: Fundos de Pensão; Green Bonds; Emissões de CO2; Zona Euro; Modelo VAR

Códigos JEL: G23 C32 O44

Abstract

This study analyses pension fund investments in green bonds within the Eurozone, particularly their relationship with carbon dioxide emissions. The research employed a VAR model to examine the interactions between six variables: CO2 emissions (CO2E), green bond investment ratio (GBIR), industrial production index (IPI), energy prices (EP), energy consumption (EC), and the 10-year benchmark yield (10YBY). The results of the analysis show that CO2 emissions unexpectedly increased, possibly due to the carbon-intensive activities financed by green bonds during the early stages of the projects. However, despite CO2 emissions initially being driven by their own shocks, green bond investments increasingly account for a substantial part of the variance in CO2 emissions over time. The study thus highlights the importance of understanding the temporal dynamics of green investments, demonstrating that green bond investments may not result in immediate CO2 reductions, and it is crucial to recognise the delayed impact of these investments. Although there is a temporary increase in emissions, the steady growth in GBIR reflects the progress of sustainable finance, reinforcing the need to continue investing in green bonds, with a focus on long-term environmental benefits.

Keywords: Pension Funds; Green Bonds; CO2 Emissions; Eurozone; VAR Model

JEL Codes: G23 C32 O44

Contents

List of Figures

List of Tables

List of Equations

Acronyms Glossary

ACF – Autocorrelation Function

ADF – Augmented Dickey-Fuller

AIC – Akaike Information Criterion

ARCH - Autoregressive Conditional Heteroskedasticity

AUM - Assets Under Management

BIC – Bayesian Information Criterion

CBS - Climate Bonds Standard

CO2 - Carbon Dioxide Emissions

COP21 - 21st Conference of the Parties

CREA – Centre for Research on Energy and Clean Air

DSPF – Debt Securities held by Pension Funds

EA – Euro Area

ECB – European Central Bank

EC - Energy Consumption

ENTSOG – European Network of Transmission System Operators for Gas

ENTSOE – European Network of Transmission System Operators for Electricity

EP - Energy Prices

EU - European Union

FEVD - Forecast Error Variance Decomposition

FPE – Final Prediction Error

GBP - Green Bond Principles

GBIR - Green Bond Investment Ratio

GDSPF – Green Debt Securities held by Pension Funds

GPFG - Government Pension Fund Global

GWh - Gigawatt-hours

HQIC – Hannan-Quinn Information Criterion

ICMA - International Capital Market Association

IFC - International Finance Corporation

IPI - Industrial Production Index

IPCC - Intergovernmental Panel on Climate Change

JB - Jarque-Bera

KPSS – Kwiatkowski-Phillips-Schmidt-Shin

LM – Lagrange Multiplier

OIRFs – Orthogonal Impulse Response Function

OLS – Ordinary Least Squares

OECD - Organisation for Economic Co-operation and Development

PACF – Partial Autocorrelation Function

PP – Phillips-Perron

USD - United States Dollar

UN SDGs - United Nations Sustainable Development Goals

UNFCCC - United Nations Framework Convention on Climate Change

10YBY - 10-year Bench-mark Yield

VAR - Vector Autoregression

Introduction

As scientific evidence increasingly highlights the warming of the planet and the exacerbation of extreme weather events, public awareness and concern have reached unprecedented levels. Climate change has become a central issue in global discourse among governments, environmental organizations, and individuals, prompting various international efforts to achieve carbon neutrality. Key initiatives include the 2015 Paris Agreement, the United Nations Sustainable Development Goals (UN SDGs), and, more recently, the European Union's Green Deal.

Achieving these ambitious goals requires substantial financial commitments, with institutional investors playing a crucial role in financing green initiatives. Pension funds, in particular, have significant potential to drive green finance initiatives, especially through their investments in green bonds. These bonds are attractive due to their liquidity and ability to support environmentally sustainable projects, with previous studies, such as Al Mamnun (2020), showing that the issuance of green bonds directly correlates with a reduction in CO_2 emissions.

Indeed, existing literature on green finance primarily focuses on green bond issuance, pricing, and the green bond premium, although there are limited studies examining the measurable positive environmental outcomes of green bond investments (Boermans, 2023). Specifically, there is a lack of investigation into the direct relationship between green bond investments by pension funds and CO_2 emissions.

This analysis seeks to fill that gap by examining how investments in green bonds by pension funds may influence CO_2 emissions. Its goal is to provide answers to the following questions: What is the extent of pension fund investments in green bonds? How do pension funds contribute to promoting green finance, specifically CO_2 reduction, through their investments in green bonds?

By shifting the focus from traditional green bond analyses to the direct impact of pension funds on carbon footprint reduction, this study aims to build upon existing literature and provide new insights into the potential of pension funds to drive meaningful environmental change.

This study's methodology will follow a Vector Autoregression (VAR) analysis to explore the interplay between pension funds' investments in green bonds and a range of financial and environmental variables, particularly, CO2 emissions in Europe. As such, the data collected covers the Euro Area 20 (fixed composition) as of 1 January 2023.

Given that EA pension funds favour green bonds (Boermans, 2023), this study includes data on green debt securities (GDSPF) and debt securities held by pension funds (DSPF) from the European Central Bank (ECB), spanning from December 2020 to December 2023 on a monthly basis, in millions of euros. EU CO2 emissions (CO2E) data was sourced from the Centre for Research on Energy and Clean Air (CREA).

To provide control for factors affecting carbon emissions, the industrial production index (IPI) from the ECB was included. Additionally, energy prices (EP) and electricity consumption (EC) data from Eurostat were incorporated, as these factors are recognised in green finance literature for their impact on carbon emissions. The EA 10 Years Government Benchmark Bond Yield (10YBY), sourced from ECB, was also included as a control variable.

Finally, the study includes the Green Bond Investment Ratio (GBIR), that serves as a metric indicating the share of pension fund investments in green bonds within their bond portfolio. This ratio provides insight into the extent to which pension funds prioritise green bond investments.

In this context, this thesis contributes to the literature by providing new insights into the relationship between pension fund investments in green bonds and carbon emissions, offering empirical evidence from the Euro Area and applying econometric techniques, such as a VAR model.

The thesis main results point to several key conclusions. Firstly, pension funds have evidently increased their investments in green bonds, with the Green Bond Investment Ratio rising, reflecting a growing commitment to integrating green bonds into investment portfolios. However, the study shows that there was an unexpected rise in CO2 emissions, likely due to the carbon-intensive activities involved in the early stages of green projects. Despite this short-term increase in emissions, the consistent growth of influence of GBIR on CO2 emissions indicates that as green bond-funded projects mature, their long-term environmental benefits should become more evident.

To frame this research, chapter one establishes a robust framework for this study by providing a comprehensive overview of the current discourse on climate change. Building on this framework, chapter two presents a detailed literature review, exploring the rise of green bonds as a financial instrument, detailing their growth, and their appeal to pension funds.

Subsequently, chapter three outlines the data and methodology employed to investigate the relationship between pension funds' investments in green bonds and CO2 emissions in the Euro Area (EA), with a focus on the VAR model and related tests. Following this, chapter four presents the empirical findings of the research, including the analysis of sample data and results from the VAR model, along with impulse response and variance decomposition analyses.

Finally, the conclusion will analyse the primary findings and draw insights from the study, offering policy recommendations informed by the research outcomes and highlighting potential directions for future research.

1. Framework

As scientific evidence continues to indicate the warming of the planet and the exacerbation of extreme weather events, public awareness and concern have reached unprecedented levels, making climate change a focal point in global discourse amongst governments, environmental organizations, and individuals worldwide.

In 2021, Glocalities, an international research agency based in Amsterdam, in cooperation with Global Citizen, an action platform dedicated to eradicating poverty, released an in-depth study on how people feel about climate change. The findings, drawn from 247,722 interviews spanning a six-year period across 20 countries, indicate that 78% of respondents experienced a growing sense of apprehension about the adverse impact of human activities on the environment (Glocalities, 2021).

The study highlighted a particularly pronounced surge in environmental worries among young adults aged 18 to 24, with 59% of global youth now viewing climate change as a very serious issue. Notably, the research underscores a willingness among people to act and exert pressure on leaders to address these pressing environmental concerns.

As the world recognizes the imperative to transition towards a more sustainable and environmentally friendly model, global efforts promoting green practices have gained significant traction. Consequently, numerous initiatives and policies have been implemented to encourage and support sustainable development on a global scale, with some of the most pivotal ones including the 2015 Paris Agreement, the United Nation's Sustainable Development Goals (UN SDGs) and, more recently, the European Union's Green Deal.

The 2015 Paris Agreement, a landmark international accord under the UN Framework Convention on Climate Change (UNFCCC), was adopted by 196 countries at the UN Climate Change Conference (COP21), with the primary objective of restraining the increase in the global average temperature below 2ºC and to limit temperature increase to 1.5ºC, whilst making finance flows consistent with pathway towards low greenhouse gas emissions [2: Art. 2.1c].

In efforts to reach these goals, nations pledged to achieve the global peaking of greenhouse gas emissions by the year 2025, and, additionally, committed to a substantial reduction in carbon emissions, with a specific target of attaining a 43% reduction by the year 2030 (The Paris Agreement, 2015).

Aligned with the principles of the Paris Agreement, the year 2015 witnessed the unanimous approval by all UN member states of the 2030 Agenda for Sustainable Development – an action plan encompassing 17 SDGs which address key objectives related to climate action, urging nations to combat climate change and mitigate its impacts, paving the way for a zero-emission future (United Nations, 2015). Moreover, the European Union's Green Deal, approved in 2020 by the European Commission, represents a comprehensive set of policy initiatives aimed at promoting green finance and investments with the overarching goal of positioning the European Union as the first climate-neutral continent by 2050 (European Commission, 2019).

However, to achieve carbon neutrality, a substantial financial commitment is essential. According to the European Commission (2024), a staggering EUR 185 trillion is required, while the International Monetary Fund predicts climate mitigation investment will soar to USD 2 trillion by 2030 (World Economic Forum, 2023).

Recognizing the urgent need to bridge the "Green Financing Gap", UN Secretary General, António Guterres (2023), has called on stakeholders to boost financing efforts. However, despite encouraging engagement from private investors in the climate capital market (European Commission, 2024), a sobering report by the German environmental NGO "Urgewald" (2023) highlights the significant presence of banks, insurance companies, and pension funds among the largest investors in fossil fuel companies in Europe.

According to the report, Europe alone holds the second largest number of fossil fuel investors globally, with investments exceeding EUR 336 billion in shares and bonds, leading Guterres (2023) to emphasise the critical role of financial institutions in addressing the climate crisis, calling for immediate action to reallocate investments away from fossil fuels and towards renewable energy sources.

Sustainable investments offer a dual benefit: they not only serve the greater good by supporting environmental initiatives but also play a crucial role in safeguarding long-term financial returns. As the risks associated with climate change continue to grow, impacting both the global economy and businesses, integrating sustainable considerations into investment strategies becomes imperative for ensuring stability (Egli et al., 2022).

In addition, the increased interest in green finance has led to the development of various financial instruments, particularly, green bonds (Ma et al., 2023), reflecting a commitment within the financial sector to foster sustainability while simultaneously addressing the urgent challenges posed by climate change.

Interestingly, it was pension funds that emerged as the driving force behind these titles. Prompted by the 2007 Intergovernmental Panel for Climate Change (IPCC) report, which linked human actions to global warming, a group of Swedish pension funds took the lead in seeking sustainable solutions. In collaboration with their bank (Skandinaviska Enskilda Banken AB) and CICERO, the Centre for International Climate and Environmental Research, they approached the World Bank with the goal of creating "a liquid, tradeable, fixed income product that would support climate-friendly solutions" (World Bank, 2018).

That is the central component of a green bond – the allocation of proceeds to environmentally beneficial projects. Various guidelines governing green bonds outline specific categories of projects deemed environmentally sustainable, including renewable energy, pollution prevention and control, sustainable land use, biodiversity conservation, clean transportation, and climate adaptation (Sartzetakis, 2020).

Considering that pension funds are major players in financial markets due to the size of their assets; by aligning their investments with climate-oriented commitments through green bonds, they're contributing to the broader goal of achieving sustainable development and mitigating the impact of climate change. Still, despite the growing importance of green finance and the recognition that institutional investors can play a vital role in its advancement, it remains a notable gap in our understanding of how pension funds specifically contribute to it.

Existing literature on green finance mainly focuses on green bonds issuance, pricing, or green bond premium, however, there are limited studies examining the measurable positive environmental outcomes by green bond investments, particularly by pension funds. This study aims to build upon existing literature by shifting the focus from traditional green bond analyses to the direct impact of pension funds' investments in these titles on carbon reduction.

As a result, this study aims to assess how pension funds contribute to promoting green finance, particularly through their investments in green bonds, by first measuring what is the extent of pension funds' investments in green bonds? And then, what is the efficacy of green bonds in promoting positive environmental outcomes, particularly in reducing CO2 emissions?

2. Literature Review

The emerging field of finance and environmental sustainability, commonly referred to as "Green Finance", represents a paradigm shift in financial thinking, emphasising the incorporation of environmental considerations into financial decision-making processes.

According to Bhatnagar and Sharma (2022) the term "Green Finance" can be traced back to the concept of "Green Economy", first discussed in the 1980s by Pearce, Markandya, and Barbier in their work "The Blueprint of Green Economy". The concept was driven by the environmental and climatic challenges experienced by Western countries, as a result of rapid industrialization, making them reevaluate their economic models and transition towards a more sustainable and environmentally conscious approach (Pearce et al., 1989).

More recently, as societies face increasing environmental challenges, such as climate change and pollution, Wang and Zhi (2016) argued that "Green Finance" represents an innovative financial paradigm geared towards environmental protection, by using financial products to control pollution emissions and mitigate environmental risks. This perspective aligns with the growing recognition of the importance of incorporating environmental considerations into financial decision-making.

However, it’s important to acknowledge that financial mechanisms alone are insufficient to address complex environmental challenges and that broader systemic changes are needed. Zhang et al. (2019) conducted an analysis of the literature surrounding "Green Finance" and found policy to be one of the primary concerns amongst researchers, recognising the pivotal role of regulatory frameworks in fostering environmentally responsible investments.

This viewpoint resonates with the understanding that policy interventions are often necessary to create incentives for sustainable practices, outlining a crucial disparity between Green Finance and conventional financial practices: the former is fundamentally driven by policy imperatives.

Despite its growing prominence, a clear and universally accepted definition for "Green Finance" remains elusive, being often intertwined with other related concepts such as "Sustainable Finance", "Carbon Finance", or "Climate Finance".

Zhang et al. (2019) drew attention to the blurred distinction between "Green Finance" and "Climate Finance", highlighting that, the first pertains to financing investments aimed at delivering environmental benefits, as defined by the International Finance Corporation (IFC) (2017), while "Climate Finance" refers to financing actions that support climate change mitigation and adaptation, as proposed by the UNFCCC (1992).

On the other hand, Bhatnagar and Sharma (2022) defend that "Green Finance" is broadly defined and includes the term "Climate Finance" thereby advocating for their interchangeable application. Building upon that, the authors define Green Finance as "Financing renewable and green energy projects with the objective of reducing carbon emissions and developing climate resilient and environmentally sustainable infrastructure" (p.1), emphasising the tangible environmental impact of investments, particularly in the areas of energy and infrastructure.

Aligned with that, Long et al. (2022) developed a study with the purpose of summarising the literature around climate finance, finding that green financing has its focus on the financial markets, including green bonds, financing sustainable business models and sustainability transition. Their perspective not only highlights the broader scope of green finance but underscores the role of financial mechanisms in driving environmentally conscious initiatives.

In essence, "Green Finance" is an innovative approach that combines finance with environmentally friendly practices across different economic sectors, complemented with regulation and implementation of policies. It encompasses a spectrum of financial activities, ranging from specific project financing for renewable energy and climate-resilient infrastructures, to a broader focus on financial markets.

Ultimately, the discourse surrounding "Green Finance" reflects a dynamic and multifaceted landscape, with scholars and institutions offering diverse perspectives on its definition and scope. Despite the lack of a universally accepted definition, the consensus among researchers highlights the imperative role of policy frameworks, financial markets, and collaborative efforts across sectors in driving investments towards sustainable development priorities.

Unfortunately, the transition to a green economy requires significant investment, and despite the numerous collaborative accords and policies implemented, the challenge of securing funding for a low-carbon and climate-resilient economy persists. According to a report from the OECD, the committed USD 100 billion for green investments in the Paris Agreement is projected to fall short of what is needed (OECD, 2017) prompting the call for increased flows of private capital on a much larger scale.

In this context, institutional investors, entrusted with managing substantial assets, assume a pivotal role in financing green initiatives. An analysis conducted by Sangiorgi and Schopohl (2021) reveals that 48 European institutional investors collectively hold EUR 13.68 trillion in assets under management (AUM) and have an accumulated fixed income of EUR 4.30 trillion. As such, there is no doubt that with such substantial AUM, European institutional investors could allocate a considerable portion of their funds towards green investments.

Among institutional investors, pension funds emerge as significant contributors to long-term financing for clean energy projects, as highlighted by Polzin and Sanders (2020), potentially mobilising investments exceeding USD 77 billion annually for clean energy initiatives. These institutions offer distinct advantages compared to traditional banks, primarily due to their possession of long-term resources, being well-suited to finance projects in the green sector (Taghizadeh-Hesary & Yoshino, 2020).

Nonetheless, despite efforts to promote sustainability, a considerable portion of pension funds continue to prioritise investments in fossil fuels. Rempel and Gupta (2020) highlight this trend, indicating that pension funds within the OECD hold a substantial sum, ranging from EUR 238 to 828 billion, in assets associated with fossil fuels, while Gunningham (2020) suggests an even higher estimate, from EUR 800 to 940 billion.

Notably, the Norwegian Government Pension Fund Global (GPFG) stands out as Europe's largest fossil fuel investor, with substantial holdings totalling over EUR 37.25 billion. Similarly, the Dutch Algemeen Burgerlijk Pensioenfonds (ABP) and the Swedish public pension fund are significant players, collectively investing billions in fossil fuel assets (Urgewald, 2023).

While pension funds have historically shown a strong inclination towards investing in fossil fuels, it is imperative to recognise that there are alternatives that offer greater sustainability. Interestingly, Boermans and Galema's (2019) study on Dutch pension funds indicates that actively divesting from fossil fuels does not carry negative risk-adjusted performance implications.

However, despite divesting from fossil fuels, pension funds are inefficient in decarbonizing their portfolios and fall short of meeting the climate targets outlined in the Paris Agreement (Rempel and Gupta, 2020). These findings imply that although divestment may not harm financial performance, it alone is insufficient to drive meaningful change towards sustainability within pension fund investments.

Therefore, reallocating more funds towards sustainable investment opportunities appears a feasible approach for pension funds to pursue without compromising their primary mandate – to safeguard and grow the wealth of their beneficiaries. Fiduciary duty serves as the cornerstone of trust and accountability in pension fund management ensuring the financial security of retirees and the integrity of funds over the long term, encompassing not only investment decisions but also governance and administration.

Soneryd (2024) reveals a striking disparity between lucrative returns and financial stability on one hand, and apprehension regarding the environmental and social repercussions of investment decisions on the other, concluding that, overall, savers prioritise both their carbon footprint and financial security. As such, by aligning their investments with environmentally conscious initiatives, pension funds stand to benefit financially, capitalizing on the increasing demand for clean energy and eco-friendly solutions.

As a result of their fiduciary duty, pension funds exhibit a preference for lower-risk investments that offer a stable and inflation- adjusted income stream. Pension funds operate under regulatory frameworks that require them to manage their assets in a way that matches their long-term liabilities. Due to their ongoing payment obligations, they must prioritise investments in liquid assets to ensure they can meet their financial commitments (Hafner et al., 2020).

Although they have multiple avenues to explore green investments, including equity (indices, mutual funds, and ETFs) and private equity (real estate funds and infrastructure funds), the allure of fixed-income securities, particularly green bonds, has understandably grown, making these bonds an additional channel through which funds can be directed towards environmentally sustainable projects (Croce et al., 2011).

Green bonds typically offer a level of liquidity comparable to traditional bonds, making them an attractive option for institutional investors with long-term liabilities (Hafner et al., 2020). By investing in green bonds, these institutions can diversify their portfolios, manage risk, and contribute to environmental sustainability – all while meeting their regulatory requirements for asset-liability management.

Since their first creation, green bonds have experienced rapid growth in investments, particularly in Europe. According to a 2023 report by the Climate Bonds Initiative, the volume of green bonds reached USD 2.6 trillion, with Europe dominating the market with a 37% share, followed by USD at 23%, and CNY contributing 8%. In addition, the euro remains the currency of choice for 47% of cumulative green bond volumes, reflecting a high number of dedicated investors in the region (Climate Bonds Initiative, 2023).

Boermans (2023) also supported this trend, stating that despite green bonds constituting only 1.5% of the total bond market, they have a larger presence (3.7%) in the euro area bond portfolios, also indicating a heightened allocation towards environmentally conscious investments in Europe. Furthermore, the author concluded that green bond preferred habitat investors are exclusively European mutual funds and pension funds. This investment institutions display a strong preference to hold green bonds and are relatively price insensitive which can be explained by their relative long investment horizons and commitment to combat climate change.

Despite de growing acceptance of green bonds, lingering concerns persist among investors and issuers regarding their implementation. Shi et al. (2023) highlight a significant concern surrounding green bonds: the issue of greenwashing. The practice occurs when companies falsely portray their policies as environmentally friendly, casting doubt on the true impact of green bonds in channelling funds towards genuinely sustainable initiatives.

Even though green bonds offer pension funds an opportunity to align their investment strategies with sustainability objectives, challenges such as greenwashing must be addressed to ensure that their investments genuinely contribute to environmental objectives.

In order to mitigate the risk of greenwashing and enhance transparency in the green bond market, in 2014 the International Capital Market Association (ICMA) introduced the Green Bond Principles (GBP) providing clear guidelines on the use and disclosure of proceeds from green bonds (ICMA, 2014). Additionally, certification under the Climate Bonds Standard (CBS) verifies the alignment of green bond projects with the goals of the Paris Agreement investments (Jankovic et al., 2022), therefore, by adhering to these standards, issuers can provide investors with assurance regarding the environmental integrity of their green bond investments.

The green bonds market has attracted widespread attention from investors, policymakers, and researchers due to its potential to direct financial resources towards projects that play a pivotal role in fostering a more sustainable and low-carbon future. In response to this interest, a study conducted by Al Mamun et al. (2022) aimed to explore the influence of green finance on decarbonization.

The authors gathered data on green finance, specifically on green bond issuance, across a sample of 46 countries and found a substantial and negative correlation between green finance and CO_2 emissions, a trend observed in both short and long-term scenarios. Moreover, the study underlined the significant role played by green bonds in advancing the broader decarbonization agenda, highlighting the tangible contributions of these financial instruments to the overarching goal of reducing carbon emissions.

The study provides valuable insights into the potential of green finance, particularly green bonds, to drive positive environmental outcomes and contribute to global efforts to address climate change. It serves as a compelling argument for stakeholders, including pension funds, to prioritise and support initiatives that promote sustainable finance practices and accelerate the transition to a greener economy.

Overall, the literature underscores the transformative potential of Green Finance in addressing environmental challenges and advancing the transition towards a low-carbon economy. Despite debates regarding its definition and scope, there's a consensus among researchers on the imperative role of policy frameworks, financial markets, and collaborative efforts across sectors in driving investments towards sustainable development priorities.

Undoubtedly, key global initiatives such as the 2015 Paris Agreement and the European Union's Green Deal serve as crucial frameworks guiding efforts towards environmental sustainability and climate resilience, however, substantial financial commitments are required to achieve carbon neutrality.

Pension funds hold significant potential to drive investments towards green initiatives, and while some pension funds continue to prioritize investments in fossil fuels, there's evidence suggesting that divesting from fossil fuels doesn't necessarily harm financial performance, opening the door for reallocating funds towards sustainable opportunities.

Green bonds emerge as a promising financial instrument, attracting pension funds due to their liquidity and potential to support environmentally sustainable projects, even though challenges such as greenwashing persist, underscoring the importance of stringent standards and certifications to ensure the integrity of green bond investments.

To conclude, it is evident that pension funds, by directing financial resources towards environmentally friendly investments and adhering to rigorous standards, can play a crucial role in driving meaningful change while safeguarding long-term financial returns. Through strategic investments in green bonds, specifically tailored to fund eco-friendly projects, these funds can actively contribute to a carbon-neutral economy while aligning with international climate agreements such as the Paris Agreement.

3. Data and Methodology

Drawing upon existing literature highlighting the role of pension funds in promoting sustainable practices through green bond investments, this chapter seeks to explore the connection between Pension Funds' investments in green bonds and CO2 emissions. The chapter is structured into two sections: the first section outlines the data used, while the second section delves into the methodology employed.

3.1. Data Description

Through empirical analysis, this study aims to shed light on ongoing sustainability efforts within the Euro Area (EA) pension funds by conducting a comprehensive examination of crucial environmental and economic indicators. The data collected covers the Euro Area 20 (fixed composition) as of 1 January 2023.

Given that EA pension funds are the preferred investors in green bonds (Boermans, 2023), this study will include the outstanding amounts of green debt securities (GDSPF) and the debt securities held by pension funds (DSPF) sourced from the European Central Bank (ECB). These datasets serve as experimental indicators, spanning from December 2020 to February 2024 on a monthly basis, denoted in millions of euros.

To provide context and control for factors influencing carbon emissions, the industrial production index (IPI) was integrated, also sourced from the ECB. This index includes the overall industrial sector, encompassing manufacturing, mining, and utilities, excluding data related to construction activities. The industrial production index, offers insights into changes in production output across Euro Area industries, acting as proxy for economic activity and industrial growth, particularly considering the unavailability of monthly GDP data.

Moreover, energy prices (EP) and electricity consumption (EC) data were incorporated, aligning with the existing literature on green finance that recognises their potential impact on carbon emissions, and consequently, their significance in evaluating the effectiveness of green bonds in fostering positive environmental outcomes. Both datasets were sourced from Eurostat. Energy Prices are presented as an index, while electricity consumption is measured in gigawatt-hours (GWh).

Filimonova et al. (2022) highlights the direct link between electricity consumption and CO_2 emissions, driven by fossil fuel use, whilst stressing the association with economic growth, since higher economic development requires higher electricity consumption. Additionally, Alestra et al. (2022) underscore the efficacy of energy price signals in mitigating carbon emissions, suggesting that these signals hold significant promise in mitigating the impacts of climate change by discouraging the utilisation of carbon-intensive energy sources.

In line with Hammoudeh et al. (2020) the EA 10 Years Government Benchmark Bond – Yield (10YBY) was also incorporated as a control variable. This yield is a critical benchmark for long-term interest rates, reflecting government borrowing costs and influencing pension funds, by a stable measure of long-term economic conditions and investor confidence, the 10YBY clarifies the impact of borrowing costs on green bond investments. The data was sourced from the ECB and is expressed in percent per annum.

Lastly, following Al Mamun et al. (2022) and Hammoudeh et al. (2020) EU CO_2 emissions (CO2E) data are used, sourced from the Centre for Research on Energy and Clean Air (CREA). This set of data uses estimates from fossil fuel consumption from Eurostat and applies the Intergovernmental Panel on Climate Change (IPCC) default emissions factors. The CREA CO_2 Tracker provides estimates of CO_2 emissions, measured in metric tons per day, however, to ensure consistency with the remaining datasets, the daily values were aggregated and summed to generate monthly data, facilitating comparison and analysis over time.

In addition, it includes data from European Network of Transmission System Operators for Gas (ENTSOG) for natural gas, and from European Network of Transmission System Operators for Electricity (ENTSOE) for electricity generation, allowing for a comprehensive assessment of total carbon dioxide emissions within the European Union, offering invaluable insights into the region's environmental footprint and its progress toward emission reduction targets.

Furthermore, it’s possible to calculate the Green Bond Investment Ratio (GBIR), which serves as a metric indicating the share of pension fund investments specifically allocated to green bonds within their bond portfolio. By employing this calculation, we gain insight into trends and patterns in pension funds' investment behaviour, specifically the degree to which pension funds investors prioritise investments through green bonds.

The ratio was calculated as follows:

$$\frac{GDSPF}{DSPF} \quad (1)$$

The GBIR reveals a clear and consistent growth trend from December 2020 (4.21%) to December 2023, peaking at 9.42%. Even though there are fluctuations, overall, the data suggests a positive trajectory towards more significant investments in green bonds by euro area pension funds, reflecting a growing emphasis on environmentally sustainable investments within the pension fund sector.

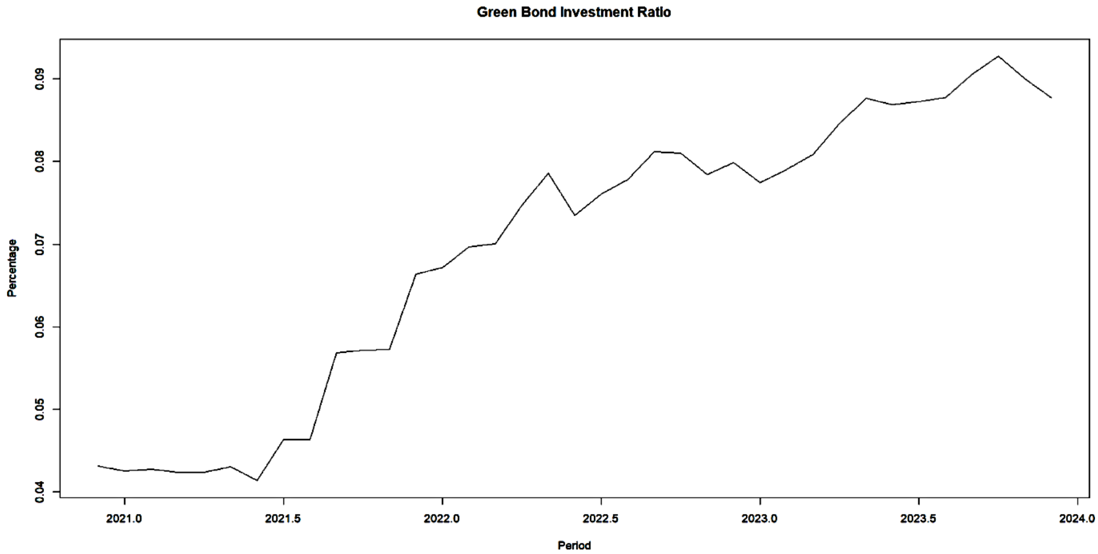

Figure 1 - Green Bond Investment Ratio Evolution. Source: Own Elaboration

Incorporating both the Green Bond Investment Ratio (GBIR) into the research allows for a comprehensive and nuanced understanding of the role of green bond investments in the Euro Area pension funds, helping to illuminate the direct and relative contributions of these investments towards environmental sustainability and economic growth.

The GBIR highlights investment behaviours in the prioritisation of green investments, allowing to identify whether increases in green investments are due to overall portfolio growth or a strategic shift towards greener assets.

3.2. Research Methodology

Despite the number of research in green finance, limited focus has been given to green bond investors (Boermans, 2023). Specifically, there's a lack of investigation into the direct relationship between green bond investors, particularly pension funds, and CO2 emissions. This analysis seeks to fill that gap by examining how investments in green bonds by pension funds may influence CO2 emissions.

Most literature surrounding green finance, and green bonds specifically, relies on cross-sectional panel data analysis. Namely, Boermans (2023) and Al Mamun et al. (2022) both employed this method to explore various aspects of green bond characteristics, such as investors preferences and issuance’s impact on CO2 emissions.

However, alternative methodologies have been employed. Specifically, Hammoudeh et al. (2020) employed a distinct methodology, using a Vector Autoregression (VAR) analysis to explore the interplay between green bonds and a range of financial and environmental variables. Given constraints in data availability regarding pension funds' investments in green bonds across various countries, this methodology will follow Hammoudeh et al.'s (2020) approach.

Building upon prior research indicating that Green Bond issuance correlates with a direct reduction in CO2 emissions (Al Mamun, 2020), it is reasonable to anticipate that investments in green bonds will yield similar outcomes. Therefore, this research hypothesis centres on exploring whether investments by Pension Funds in Green Bonds exhibit a noticeable effect on mitigating CO2 emissions in Europe. As such, the endogenous variables in the model are the CO2E, IPI, EP, EC, GBIR and 10YBY.

Through a thorough examination of this relationship, the aim is to provide meaningful contributions to the ongoing dialogue surrounding sustainable investment strategies and their implications for the environment.

3.2.1. VAR Model

The Vector Autoregressive (VAR) model serves as an effective tool in time series analysis, offering a robust framework to grasp the intricate dynamics among multiple variables over time, capturing not only a variable's own past observations but also its relationship with the past observations of other variables within the system.

In essence, a VAR model elucidates the evolution of a set of k endogenous variables, denoted as Yt = (y1t, …, yk, …, yKt) for k = 1, …, K. These variables are intricately linked through a linear relationship with their historical states and dependencies on lagged values (up to lag p) of all K variables, supplemented by an error term ν.

The model is parameterized employing the Ordinary Least Squares (OLS), a method that minimizes the discrepancies between observed values of Yt and those predicted by the VAR framework. This optimization process determines the optimal values of φ1, . . ., φp, γ1, …, γp, encapsulating the observed dynamics within the data.

In addition, to ensure the model's robustness and applicability, is crucial to preform diagnostic assessments. These encompass selecting an appropriate lag order (p), scrutinizing residuals for autocorrelation absence, validating normality assumptions, and evaluating homoscedasticity.

In order to select the optimal lag order for the model, researchers often rely on criteria such as the Akaike Information Criterion (AIC), the Hannan-Quinn Information Criterion (HQIC), the Schwarz Information Criterion (also known as the Bayesian Information Criterion, BIC), and the Final Prediction Error (FPE). These metrics strike a balance between model fit and complexity, aiding in identifying the lag order that minimizes forecasting errors while avoiding overfitting.

Diagnostic tests play a pivotal role in validating the model's assumptions and refining its utility. Among these, the Jarque-Bera test confirms error normality, the Breusch-Godfrey test evaluates residual autocorrelation, and the ARCH test assesses the model’s homoscedasticity. Adhering to these tests ensures the reliability of the VAR model in informing policy decisions and forecasting future trends.

3.2.2. Granger Causality

Granger causality, introduced by Clive Granger in 1969, is a crucial statistical hypothesis test for determining whether one time series can predict another. Given that VAR models are designed to capture the interdependencies among multiple variables over time, assessing Granger causality becomes paramount in understanding the directional influences among these variables.

The idea behind the Granger causality test is to assess whether past values of a potential causal variable contain information that helps forecast a dependent variable beyond what is already provided by past values of the dependent variable itself and any other variables in the model.

The null hypothesis (H_0) of the Granger causality test is that the lagged values of the potential causal variable do not provide significant predictive power for the dependent variable(s) beyond what is already captured by the lagged values of the dependent variable(s) themselves and any other variables in the model. In other words, $\beta 1=\beta 2=...=\beta k=0$, suggesting that the potential causal variable does not Granger cause the dependent variable.

The alternative hypothesis (H_1) is that the lagged values of the potential causal variable do provide significant predictive power for the dependent variable(s) beyond what is captured by the lagged values of the dependent variable(s) and other variables in the model. This means at least one β coefficient is not equal to zero, indicating that the potential causal variable Granger causes the dependent variable.

The test uses the Wald F-statistics to determine if the lagged values of the potential causal variable significantly improve the model's predictive power. If the p-value is below the convectional significance level, we reject the null hypothesis, indicating Granger Causality.

Identifying causality within a VAR model not only enhances its ability to accurately depict the temporal sequencing of shocks and their impacts on the involved variables but also facilitates the development of more precise and insightful impulse response functions.

3.2.3. Impulse Response Functions

Impulse response functions (IRFs) are a powerful tool in econometrics for understanding the dynamic effects of shocks on a system of variables over time, depicting the responses of endogenous variables to a one-time shock in one of the exogenous variables, while holding all other variables constant. In this research, the IRFs are orthogonalized—known as Orthogonal Impulse Response Functions (OIRFs)—where the shocks are uncorrelated or orthogonal, meaning that each shock can be interpreted as an isolated event, independent of the others.

IRFs offer several insights into the dynamics of the system showing the magnitude and timing of the responses of endogenous variables to the initial shock which helps to understand the short-term and long-term effects of shocks on the economy. Besides, IRFs reveal whether the responses of endogenous variables are positive or negative, providing insights into the direction of causality among variables. In addition, IRFs illustrate how shocks propagate through the system, showing whether the effects of a shock dissipate quickly or persist over time and by examining the pattern of responses across variables, IRFs can help identify dynamic relationships and feedback mechanisms within the system.

3.2.4. Variance Decomposition

To understand the relative importance of different shocks in explaining the variation in endogenous variables over time, Variance Decomposition is employed by calculating the percentage of the forecast error variance of each endogenous variable that can be attributed to shocks in each of the variables in the system.

A specific application of variance decomposition focuses on the decomposition of forecast error variance. Forecast Error Variance Decomposition (FEVD), quantifies the extent to which forecast errors in endogenous variables can be attributed to shocks originating from each variable in the system, facilitating the identification of dynamic relationships and feedback mechanisms within VAR models, by understanding how shocks influence each other over time.

Overall, variance decomposition, particularly through techniques like FEVD, enhances the analytical capabilities of VAR models by providing a nuanced understanding of the sources of variability and forecast uncertainty.

4. Empirical Results

4.1. Sample Analysis

The sample consists of 37 monthly observations spanning from December 2020 to December 2023, containing 6 series, presented in their natural logarithms, except for the GBIR and the 10YBY. For each series, descriptive statistics including the average, median, standard deviation, minimum, maximum, skewness, and kurtosis were computed to characterise the data. The results of the analyses are presented in Table 1.

Table 1 – *Descriptive Statistics of the Variables. Source: Own Elaboration.*

Variable	Mean	Median	Stand. Dev	Min	Max	Skewness	Kurtosis
CO2E	8.3852	8.3791	0.0429	8.3115	8.4769	0.2056	-0.7944
IPI	2.0231	2.0241	0.0299	1.9375	2.0715	-1.1094	1.4957
EP	2.2471	2.2833	0.1363	1.9921	2.4490	-0.5149	-1.0377
EC	5.2040	5.2028	0.0599	4.9196	5.2843	-2.8123	11.2692
GBIR	0.0694	0.0761	0.0174	0.0413	0.0927	-0.4803	-1.3186
10YBY	1.7836	2.0583	1.3943	-0.0915	3.7239	-0.0915	-1.7955

The overall sample exhibits several notable characteristics in its distribution. Firstly, the variables show relatively smaller dispersions in comparison to their means, as indicated by the standard deviation, suggesting a degree of consistency in the data. However, it's important to highlight that EP and 10YBY stand out with the highest relative dispersion, indicating greater variability in those aspects.

Furthermore, all variables display left-skewed distributions, except for CO2E, which demonstrate a slightly right-skewed distribution, suggesting a higher concentration of lower values across most variables, with fewer occurrences of higher values.

Regarding kurtosis, EC stands out with exceptionally high kurtosis, indicating a pronounced concentration of values around the mean and the presence of extremely low values, as opposed to the negative kurtosis in the remaining variables that suggest distributions with fewer extreme values. Thus, EC's high kurtosis indicates a more leptokurtic distribution, with a peakier shape and heavier tails compared to a normal distribution.

The correlation among the series was examined to detect signs of multicollinearity issues in the estimated models. The Pearson linear correlation coefficient was employed, the results of which are presented in Table 2.

Table 2 – *Matrix of Correlations. Source: Own Elaboration*

Variable	CO2E	IPI	EP	EC	GBIR	10BYBY
CO2E	1.0000					
p-value	Na					
IPI	0.1145	1.0000				
p-value	0.4996	Na				
EP	-0.1567	0.2153	1.0000			
p-value	0.3541	0.2007	Na			
EC	0.3976	0.0398	-0.1854	1.0000		
p-value	0.0148	0.8149	0.2719	Na		
GBIR	-0.4090	0.1200	0.8340	-0.4435	1.0000	
p-value	0.0120	0.4790	0.0000	0.0060	Na	
10YBY	-0.5362	0.1349	0.7430	-0.4537	0.9285	1.000
p-value	0.0006	0.4259	0.0000	0.0048	0.0000	Na

Overall, the variables exhibit a mix of significant and non-significant correlations amongst themselves. The correlation coefficients fall between -1 and 1, which is typical, however, most p-values are greater than the conventional statistical threshold of 5%, indicating that many of the observed correlations are not statistically significant.

Nonetheless, the correlation between energy prices (EP) and both green bonds investment by pension funds (GBIR) and the 10-year benchmark yield (10YBY) is relatively high (0.8340 and 0.7430, respectively) and statistically significant (p-value < 0.05). This suggests that the relationships between these variables are unlikely to be due to random chance.

Additionally, the correlation between GBIR and 10YBY is very high, with a correlation coefficient of 0.9285 and a p-value lower than 5%, indicating a potentially meaningful relationship between these two variables.

4.2. Stationarity Analysis

In this study, stationarity was assessed by examining the graphical representations of each series, as well as their respective autocorrelation and partial autocorrelation functions (ACF and PACF). Additionally, the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests were employed.

From the graphical analysis, clear trends were observed in all series. In particular, the GBIR, EP and 10YBY (figures A1, A2, A3, respectively) series exhibited increasing trends, while the CO2E and EC series (figures A4 and A5, respectively) showed a decreasing trend, indicating non-stationarity. On the other hand, the IPI (figure A6) series displayed values closer to the mean, suggesting potential stationarity. Upon analysing the ACFs and PACFs of each variable (figures A7 – A12), an exponential decline was noted in the series, indicating non-stationarity for all except the IPI series which hinted at stationarity.

Further examination using the ADF, PP and KPSS tests, it was confirmed that the GBIR, CO2E, EP and 10YBY variables were non-stationary at their initial level, achieving stationary after computing the first differences. The EC variable required second differencing for stationarity. Notably, the variable IPI was already stationary without the need for differencing. Table 3 presents the results of the stationarity tests conducted.

Table 3 – *Unit Root Tests. Source: Own Elaboration.*

Test		ADF		PP		KPSS	Conclusion
		Intercept	Intercept + Trend	Intercept	Intercept + Trend	Short	
t-statistic	**CO2E**	**-2.47**	**-2.37**	**-2.55**	**-2.49**	**0.06**	Non-Stationary
	p-value	0.06 *	0.12	0.00***	0.00***	0.10*	
	Δ CO2E	**-3.61**	**-3.58**	**-5.57**	**-5.60**	**0.06**	Stationary
	p-value	0.00***	0.00***	0.90	0.72	0.10*	
	IPI	**-5.29**	**-5.20**	**-7.00**	**-6.85**	**0.12**	Stationary
	p-value	0.00***	0.00***	0.51	0.80	0.10*	
	EP	**-1.81**	**-0.71**	**-1.98**	**-0.60**	**0.64**	Non-Stationary
	p-value	0.00***	0.01***	0.00***	0.00***	0.02**	
	Δ EP	**-2.39**	**-3.07**	**-3.51**	**-4.08**	**0.10**	Stationary
	p-value	0.01***	0.00***	0.00***	0.00***	0.05**	
	EC	**-0.43**	**-0.52**	**-0.95**	**-0.19**	**0.13**	Non-Stationary
	p-value	0.60	0.41	0.00***	0.00***	0.02**	
	Δ EC	**-1.18**	**-1.26**	**-3.26**	**-3.41**	**0.12**	Non-Stationary
	p-value	0.02**	0.01***	0.35	0.27	0.10*	
	Δ^2 EC	**-3.19**	**-3.40**	**-8.96**	**-9.53**	**0.12**	Stationary
	p-value	0.00***	0.00***	0.01***	0.01***	0.10*	
	GBIR	**-1.27**	**-0.97**	**-1.11**	**-1.32**	**0.19**	Non-Stationary
	p-value	0.33	0.46	0.00***	0.00***	0.01***	
	Δ GBIR	**-3.96**	**-4.09**	**-6.53**	**-6.62**	**0.10**	Stationary
	p-value	0.00***	0.00***	0.42	0.43	0.10*	
	10YBY	**-1.25**	**-1.09**	**-1.11**	**-0.89**	**0.13**	Non-Stationary
	p-value	0.24	0.33	0.00***	0.00***	0.01***	
	Δ 10YBY	**-4.19**	**-4.17**	**-3.97**	**-4.00**	**0.17**	Stationary
	p-value	0.00***	0.00***	0.25	0.32	0.1*	

*Significance Codes: '***'0.01 '**'0.05 '*'0.1'*

4.3. Lags Selection

Selecting the optimal number of lags is essential for effective VAR modelling, as the number of lags significantly influences both the forecasting accuracy and the stability of the model. Given that the lag length determines how many previous time periods are included in the model to predict the current value, an incorrect number of lags can either lead to underfitting or overfitting, both of which compromise the model's performance.

The most common method for determining the optimal number of lags in a VAR model involves the use of information criteria, namely the Akaike Information Criterion (AIC), the Hannan-Quinn Information Criterion (HQIC), the Schwarz Information Criterion (also known as the Bayesian Information Criterion, BIC), and the Final Prediction Error (FPE). These criteria balance model fit with model complexity, penalising the addition of more parameters to avoid overfitting. Table 4 represents the optimal number of lags selection criteria for this model.

Table 4 – *Lag Selection Criteria. Source: Own Elaboration*

Lags	AIC	HQ	SC	FPE
1	-42.38	-41.81	-40.34	0.00
2	-42.04	-40.98	-38.24	0.00
3	-47.30	-45.76	-41.74	0.00
4	-Inf*	-Inf*	-Inf*	NaN
5	-Inf	-Inf	-Inf	0.00*

**Indicates lag order selected by the criterion*

The analysis reveals a consistent trend across multiple criteria, indicating the optimal lag for the VAR model. While AIC, HQ, and SC converge on the 4th lag as optimal, FPE suggests considering the 5th lag. However, it's crucial to note the sharp decline in values (to -Inf or zero) for all criteria beyond the 5th lag. This pattern suggests that incorporating more than 5 lags leads to overfitting, where the model captures noise instead of the underlying signal.

Therefore, based on this analysis, the 4th lag will be used to ensure a balanced model that maximizes forecasting accuracy while maintaining stability.

4.4. Diagnostic Tests

For VAR models to be considered adequate and reliable, the residuals must have three properties: follow a normal distribution, be uncorrelated over time, and exhibit constant variance. To ensure that these criteria are being met, it's necessary to perform diagnostic tests on the residuals.

4.4.1. Normality of the Residuals

To validate that the residuals in each equation conform to a normal distribution, the Jarque-Bera (JB) test, introduced by Jarque and Bera (1987), is employed. This test aims to evaluate whether the residuals exhibit a distribution similar to the normal curve. In addition, the skewness test, which assesses the asymmetry of the distribution, as well as the kurtosis test, which measures the tail heaviness of the distribution, were applied as both tests can indicate deviations from a normal distribution.

The null hypothesis (H_0) of these tests imply that the data adheres to a normal distribution. Should the associated p-value fall below the significances levels the null hypothesis is rejected, indicating compelling evidence that the data does not conform to a normal distribution. The results are presented in Table 5.

Table 5 – *Normality Tests. Source: Own Elaboration*

Test	Chi-squared	df	p-value
JB	7.35	12	0.83
Skewness	1.73	6	0.94
Kurtosis	5.62	6	0.47

The results show that the p-values associated with all three tests are not significant, as all are above the typical significance levels, consequently, the null hypothesis for each test is not rejected, meaning that the residuals follow a multivariate normal distribution, and their skewness and kurtosis are consistent with that distribution.

In summary, these tests provide no strong evidence to suggest that the residuals of the VAR model deviate significantly from a multivariate normal distribution, therefore, the assumptions of normality, skewness, and kurtosis are reasonably met by the residuals of the VAR model.2

4.4.2. Residual Autocorrelation

To assess the autocorrelation of the residuals, the LM test proposed by Breusch-Godfrey was performed. The Breusch-Godfrey LM test is a statistical test used to detect the presence of autocorrelation in the residuals of a regression model, particularly useful for evaluating multivariate models, such as a VAR model.

The null hypothesis (H_0) of the Breusch-Godfrey LM test states that there is no autocorrelation in the residuals up to the specified lag. The alternative hypothesis (H_1) posits that there is autocorrelation in the residuals. The results are presented in Table 6.

Table 6 – *Autocorrelation Test. Source: Own Elaboration*

Test	Chi-squared	df	p-value
Breusch-Godfrey LM	186	180	0.36

The results show that the p-value is not significant at the 5% significance level consequently, we fail to reject the null hypothesis for the test, meaning that there is sufficient evidence to conclude that there is no autocorrelation in the residuals of the model up to the 4^{th} lag.

This lack of autocorrelation supports the adequacy and reliability of the VAR model, indicating that the model's residuals are uncorrelated over time.

4.4.3. Heteroskedasticity Test

To assess whether the assumption of constant error variance in the VAR model holds true, an analysis of heteroskedasticity, using the ARCH (Autoregressive Conditional Heteroskedasticity) test was conducted.

This test aims to investigate whether it exists a systematic pattern of conditional heteroskedasticity within the residuals of the VAR model, by examining whether the squared residuals exhibit serial correlation over time.

In the ARCH test, the null hypothesis (H_0) is that there is no conditional heteroskedasticity in the residuals, meaning that the variance of the residuals is constant over time. The alternative hypothesis (H_1) tests for conditional heteroskedasticity in the residuals, indicating that the variance of the residuals is not constant and exhibits some systematic pattern or dependence on past values. The results of the test are presented in Table 7.

Table 7 – *Heteroskedasticity Test. Source: Own Elaboration.*

Test	Chi-squared	df	p-value
ARCH test	546	2205	1

The test shows a p-value of 1, suggesting that there is no evidence of autocorrelation in the squared residuals, which is indicative of no ARCH effects. This implies that the variance of the residuals in the VAR model does not exhibit a systematic pattern of dependence on past values, therefore, the assumption of homoskedasticity (constant variance) in the residuals is met.

This finding enhances the reliability of the VAR model, indicating that the assumption of constant error variance holds true, thereby contributing to the robustness of the model's forecasts.

4.5. Causality Test

Causality tests aim to determine the direction and strength of the relationship between two or more variables, in order to investigate the causal relationships among variables.

The commonly causality tests used in VAR analysis is the Granger causality test, which assesses whether one variable in a VAR model can help predict another variable beyond its own lagged values and the lagged values of the other variable(s) in the model, essentially, evaluating whether one variable "Granger-causes" another variable.

In the context of this research, for the Granger Causality test, the null hypothesis (H_0) tests whether changes in the Green Bond Investment Ratio (GBIR) Granger-cause changes in CO2E, IPI, EP and 10YBY. The results are presented in Table 8.

Table 8 – *Causality Test. Source: Own Elaboration.*

Model	F-Test	Residual df	p-value
CO2E	5.78	25	0.00***
IPI	1.23	25	0.33
EP	0.87	25	0.52
EC	1.96	24	0.13
10YBY	3.95	25	0.01***

*Significance. Codes: '***' 0.01 '**' 0.05 '*' 0.1'*

The analysis reveals varied degrees of causality between GBIR, and the dependent variables examined. Specifically, the relationship between GBIR and CO2E shows a statistically significant result with a strong F-statistic and a p-value indicating significance at the 1% level. This suggests that past values of GBIR Granger-cause changes in CO2E.

Regarding 10YBY, the analysis reveals a significant relationship with GBIR, evidenced by a p-value significant at the 1% level, implying that lagged values of GBIR Granger-cause changes in 10YBY at this significance level.

Conversely, the tests for IPI, EP and EC do not demonstrate a significant relationship with GBIR, indicating that lagged values of GBIR do not Granger-cause changes in IPI or EP.

4.6. VAR Analysis

Vector Autoregression models offer a robust framework for delving into the complex interactions among the six endogenous variables in their differenced from: CO2E, GBIR, IPI, EP, EC and 10YBY, aiming to show the nuanced connections between fluctuations in green bond investments by pension funds and CO2 emissions.

Tables A1 to A6 shows the results of the estimated values in the VAR model, with a lag order of 4 (p=4) and including a constant term. Overall, the statistical analysis reveals varying degrees of explanatory power and model fit, with some equations demonstrating significant relationships concerning certain lagged variables, while others exhibit weak or insignificant effects.

The analysis unveils a negative and significant lag (l3) for industrial production index (IPI) concerning CO2 emissions, indicating a potential adverse effect of industrial activities on environmental sustainability suggesting that a one-unit increase in industrial production leads to a corresponding increase in CO2 emissions in the subsequent period, underscoring the short-term contribution of industrial activity to higher CO2 emissions.

However, it's noteworthy that equations related to the green bond investment ratio, 10-year bond yield, industrial production and electricity consumption do not exhibit statistical significance, suggesting minimal impact of their past values.

The equation for EP reveals a significant negative impact observed at the 10% level at EC. l1, suggesting that changes in electricity consumption have an immediate positive effect on energy prices. The substantial positive coefficient for GBIR.l3 implies that investments on green bonds (captured by GBIR) have a more delayed but significant effect on energy prices.

Moving forward, the analysis will delve deeper into the implications of these findings through Impulse Response Function (IRF) and Forecast Error Variance Decomposition (FEVD) analyses. These additional analyses will provide further insights into the short-term and long-term effects of shocks to green bond investments and CO2 emissions, enriching our understanding of the complex dynamics at play in the intersection of finance and environmental sustainability.

4.6.1. Impulse Response Function Analysis

The Impulse Response Function (IRF) is an analytical tool used in VAR models, to examine how one variable in a system responds to a shock in another variable over time. When a variable in a VAR model is perturbed by a positive shock of one unit at a specific time period, the IRF illustrates how other variables in the system react to this shock over several subsequent periods.

In this research, the IRFs are orthogonalized—known as Orthogonal Impulse Response Functions (OIRFs)—where the shocks are uncorrelated or orthogonal, meaning that each shock can be interpreted as an isolated event, independent of the others.

Since the aim of this research is to analyse the impact of green bond investments by pension funds on CO_2 emissions, the IRF was computed to illustrate how a shock to the variable "GBIR" affects the remaining variables over time. The results are presented in Figure 2 below, along with the coefficients provided in Table A2.

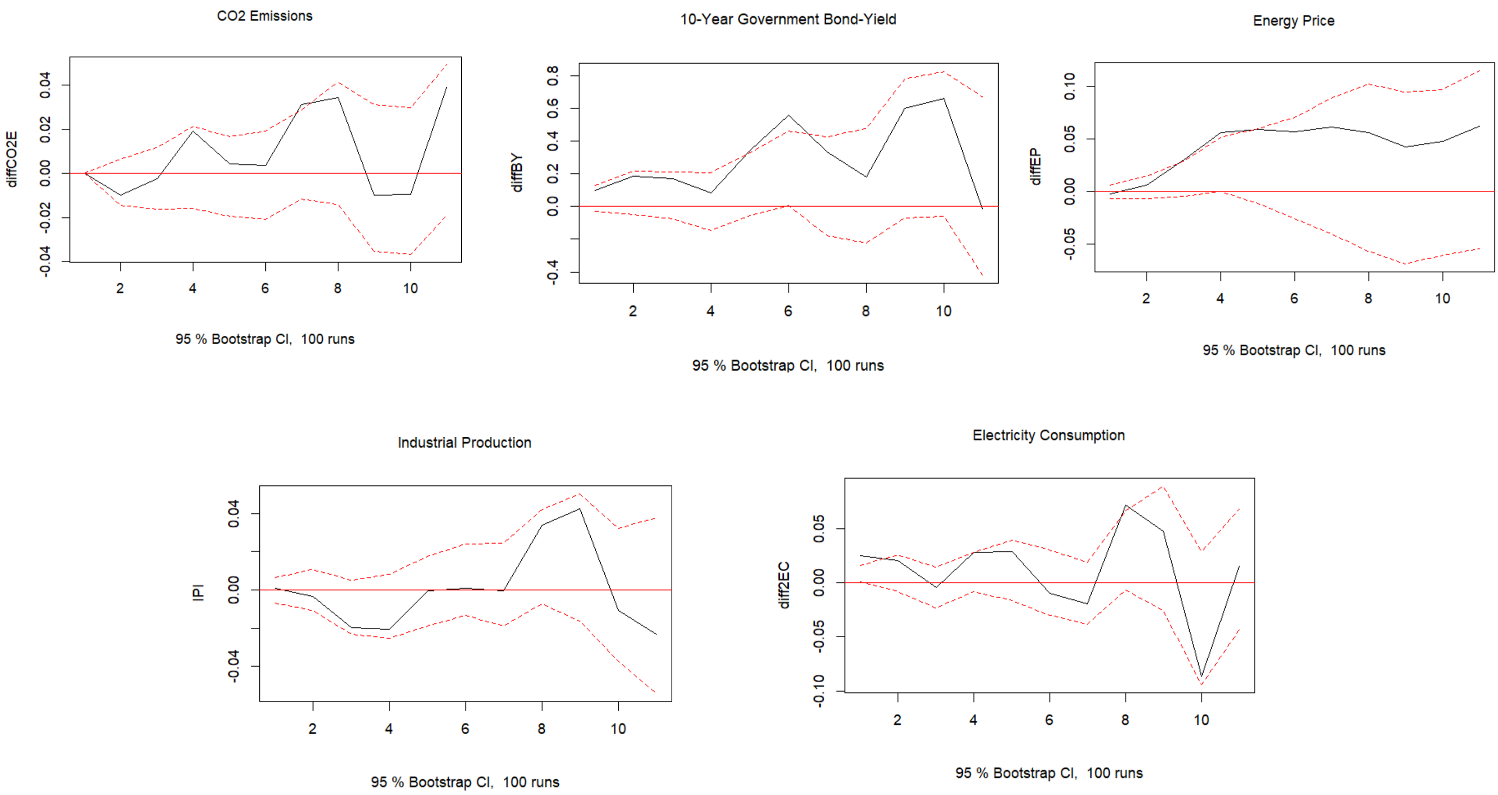

Figure 2 - Orthogonal IRF of the Variables. Source: Own Elaboration

The impulse response analysis reveals intriguing dynamics between green bond investments by pension funds (GBIR) and the remaining variables, particularly CO2 emissions.

Initially, the coefficients suggest that a shock in green bond investments may not have a significant immediate impact on CO2 emissions, as indicated by the coefficients close to zero (the coefficients for periods 1 through 3 range from -0.0098 to -0.025, indicating a slight reduction in emissions, but not statistically significant as evidenced by the confidence intervals). However, in the short term (periods 4 to 7) the impact on CO2 emissions becomes more positive, suggesting an increase in emissions.

From period 8 onwards, the positive impact on CO2 emissions continues, peaking at period 11, indicating a more substantial increase in emissions. The negative coefficients in periods 9 and 10 suggest some fluctuations in the impact, but the overall trend indicates a positive influence of green bond investments on CO2 emissions.

The response of the remaining variables exhibits similar patterns. The 10YBY responds positively and increasingly over time, peaking around the 6^{th} and 10^{th} periods suggesting higher yields demanded by investors as investments in green bonds increase. After peaking, the 10YBY gradually declines, suggesting a stabilization or reduction in the premium required by investors.

Regarding EP, the response is slightly negative initially, turning positive from the 2^{nd} period onwards, indicating a positive response to green bond investments. In addition, the response from EC to shocks from GBIR fluctuates, peaking around the 8^{th} period, turning negative until period 10, and then increasing thereafter.

The coefficients for IPI start positive but become negative in period 2 and 3, with a positive spike around the 8^{th} and 9^{th} periods, suggesting that green bond investments positively impact industrial production during this time. However, after reaching this peak, a subsequent decrease indicates that the impact may not be sustained over time.

The impulse response analysis indicates that green bond investments by pension funds initially have a negligible or mixed effect on CO2 emissions, with some fluctuations in the short term. However, over time, the investments appear to have a positive influence on CO2 emissions, contrary to the expectation that green investments would reduce emissions.

4.6.2. Variance Decomposition Analysis

Variance decomposition analysis, employed through techniques like Forecast Error Variance Decomposition (FEVD), serves as a powerful tool in understanding the intricate dynamics within VAR models.

In the context of VAR models, FEVD is used to analyse the proportion of the forecast error variance of each variable that is attributable to shocks from each variable in the system, helping to understand the dynamic interactions and the relative importance of different shocks over time.

In order to analyse the impact of green bond investments by pension funds on CO2 emissions, it was identified the proportion of the forecast error variance of CO2E attributed to GBIR in different time periods, which allowed for an understanding of how changes in GBIR influence the forecasts of CO2E and, by extension, CO2 emissions.

Therefore, by interpreting the FEVD, it is possible to identify the periods in which GBIR has a more significant impact on CO2 emissions. The results are presented in figure 3 and coefficients for each variable are presented in Table A3.

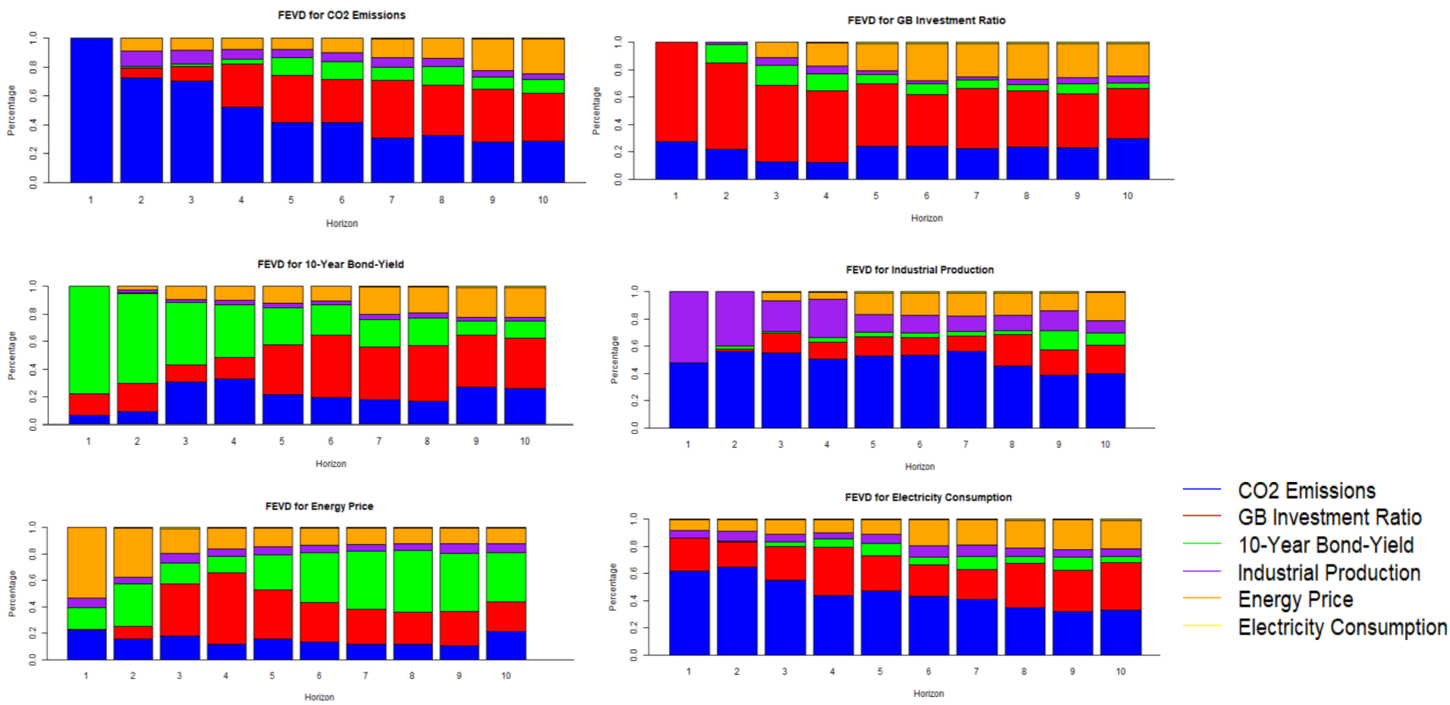

Figure 3 - FEVD of the variables. Source: Own Elaboration

Initially, Green Bond Investments (GBIR) are fully explained by their own variability over time, and while their influence on its own forecast error decreases, it remains relatively high throughout (36.76% in period 10). Contributions from CO2 Emissions increases, explaining about 29.47% of the forecast error variance after 10 periods, while EP explains 23.75% at period 10, indicating an influence of both variables on GBIR.

Turning to CO2E, there's a similar initial patter where nearly all the forecast error variance (72.23%) is due to its own shocks. However, by the tenth period, this self-explanatory power diminishes to 28.33%, with significant contributions from GBIR (33.65%) indicating that shocks in green bond investments explain a notable portion of the variance in CO2 emissions. On the other hand, fluctuations in energy prices also have a moderate effect on CO2E explaining about 23.91% in period 10 while contributions from 10YBY, IPI and EC have minimum effect.

Regarding the IPI, it exhibits a notable pattern where its forecast error variance is initially driven largely by itself (52.07%) and CO2E (47.72%). Although its own explanatory power decrease, CO2E remains significant across all periods (decreasing slightly, to 40% at period 10) suggesting that CO2 emissions affect industrial production to a moderate extent. The influence of GBIR and EP increases moderately by period 10 (20.51% and 20.31%, respectively) indicating that green bond investments and energy prices have a growing impact on industrial production over time.

For EP, the initial forecast error variance is largely explained by itself (53%) but this influence decreases significantly over time (to just 12.15% at period 10). By the tenth period, the variance explained by CO2E (21.26%), GBIR (22.31%) and 10YBY (37.47%) also contributes significantly, suggesting that investments in green bonds and the 10-year bond yields are critical drivers of energy prices over time, possibly due to their influence on investment decision in energy sectors. Similarly, changes in CO2 emissions strongly affect energy prices, likely through energy production costs.

Initially, EC is largely explained by CO2E (61.67%) and although this influence decreases overtime, it remains marginally high (at 32.89% in period 10), suggesting that CO2 emissions have a lasting impact on electricity consumption. On the other hand, GBIR and EP also have some influence in EC explaining about 35.03% and 20.87% respectively at period 10 implying that green bond investments and energy prices also play significant roles in driving economic activity.

Finally, looking at 10YBY in the first period the majority (77.74%) of the forecast error variance is attributed to itself, however this influence decreases to 12.23% in period 10. By that time, CO_2 emissions and EP explain respectively, 25.99% and 21.44% of the 10YBY forecast variance, indicating a strong initial impact of environmental factors on the variable. Still, but the largest contribution comes from Green Bond Investments, which contribute 36.17% to the forecast error variance of 10YBY in period 10.

To conclude, the FEVD shows significant interconnectedness among the variables. The green bond investments by pension funds emerge as a significant driver for most variables, influencing CO_2 emissions, energy prices and industrial production over time.

4.7. Robustness Assessment

Given the complexity and sensitivity of VAR models to different specifications, it is crucial to test the stability of the findings under various conditions. This assessment involved re-estimating the VAR model using various adjustments, such as experimenting with different variable orderings, and testing alternative model versions, including the removal of electricity consumption or energy prices, which could be influenced by industrial production and electricity consumption.

Despite these modifications, the re-estimated models consistently produced nearly identical impulse response functions, demonstrating that the results were robust to changes in variable sequencing and model specifications, reinforcing the stability of the findings.

The robustness checks greatly strengthened the credibility of the VAR model, offering a reliable basis for the conclusions drawn from the impulse response functions. By thoroughly examining these variations, it’s shown that the conclusions are not reliant on any particular model configuration, thus further validating the insights gained from the impulse response functions.

Conclusion

This study examined pension fund investments in green bonds, focusing on their contributions to green finance and their impact on CO_2 emissions.

One key aspect of the study was assessing the extent of these investments through the Green Bond Investment Ratio (GBIR), which demonstrated a consistent upward trend, increasing from 4.21% in December 2020 to 9.42% by December 2023, despite fluctuations. This growth represents a commitment by pension funds to integrate green bonds into their portfolios and support environmentally sustainable investments.

To understand how green bond investments contribute to reducing CO_2 emissions, the study analysed the interactions among six endogenous variables: CO_2 emissions (CO2E), Green Bond Investment Ratio (GBIR), Industrial Production Index (IPI), Energy Prices (EP), Energy Consumption (EC), and 10-Year Bond Yields (10YBY), using a VAR model.

The IRF analysis showed that a sudden increase in green bond investments initially has little immediate impact on CO_2 emissions. This outcome is expected, as green bond-funded projects typically require time for development and implementation before their environmental benefits, such as CO_2 reduction, can materialise. Investments in green bonds are often directed toward long-term infrastructure and sustainability projects, such as renewable energy facilities, energy efficiency upgrades, or sustainable transport, which take time to become fully operational, and, as a result, the immediate impact on CO_2 emissions is not evident right away.

In the early stages of the analysis, the coefficients suggested a modest reduction in CO_2 emissions, although this change was not statistically significant. However, in the short term the trend reversed, revealing an unexpected increase in emissions. This result contradicts prior expectations, including findings from Al Mamun et al. (2022), which indicated that green bond issuance is negatively correlated with CO_2 emissions.

This counterintuitive result may be explained by the nature of green bond projects, which often require intensive construction, manufacturing, or initial energy use during their early stages, which are carbon-intensive activities, making these upfront emissions outweigh the long-term environmental benefits.

However, while initial CO_2 emissions are primarily driven by their own shocks, green bond investments increasingly explain a substantial portion of the variance in CO_2 emissions over time. So, it’s expected that as these projects mature and become operational, the long-term environmental benefits of green bonds start to manifest.

In summary, the findings of this study emphasise the importance of understanding the temporal dynamics of green investments. They underscore that green bond investments may not yield immediate reductions in CO_2 emissions, highlighting the importance of understanding the delayed impact of these investments. Investors, policymakers, and stakeholders need to recognize that while green bonds are designed to promote environmental sustainability, their benefits often take time to manifest.

Moreover, the study revealed a short-term increase in CO_2 emissions associated with green bond-funded projects. This increase can be attributed to the carbon-intensive activities involved in the early stages of project development, such as construction and manufacturing. To address this, it is crucial for policymakers and project developers to implement strategies that mitigate these upfront emissions. This could involve adopting carbon management practices or utilizing cleaner technologies during the construction phase to offset the initial carbon footprint.

Despite the short-term rise in emissions, the consistent growth in the Green Bond Investment Ratio (GBIR) reflects a strong commitment by pension funds towards environmentally sustainable investments. This trend reinforces the idea that green finance is gaining traction and supports the need for continued investment in green bonds. Investors and financial institutions should align their strategies with this understanding, focusing on the long-term environmental benefits rather than expecting immediate results.

While the research offers valuable insights into the impact of green bond investments on CO_2 emissions, it is crucial to acknowledge the study's limitations and recognise that certain constraints may affect the scope and applicability of the results. This study is subject to some limitations, primarily related to data constraints, model specification, and external validity.

Firstly, the study faces data limitations concerning sample size and time frame. Given that green bond investments are a relatively recent development, the analysis relies on just 37 monthly observations, which may affect the broader applicability of the results. Additionally, the short time frame (December 2020 to December 2023) may not fully capture long-term trends of green bond investments. This period is also significantly affected by the COVID-19 pandemic, which may have influenced market dynamics and investment behaviours in ways that could've affected the results.

Secondly, the study's findings are specific to the Euro Area and may not be directly applicable to different economic environments or regions without further adjustments. Thirdly, although the VAR model employed in this study effectively captures dynamic interactions, it may not adequately address non-linear effects or complex interactions that other methodologies, such as structural or non-linear time series models, might capture more effectively.

Lastly, it is important to note that the confidence intervals provided for the impulse response functions of the variables don't reveal statistically significant results, thereby leaving open the possibility of a null effect. Therefore, although the study offers valuable perspectives on the interactions between green bond investments and various economic and environmental indicators, these findings should be interpreted with caution.

To address these limitations, future research could start by exploring alternative data sources, by examining the long-term effects of green bond investments on environmental and economic variables over a longer period of time. In addition, expanding the analysis to include cross-country comparisons would help determine whether the findings are consistent across different economic contexts or are specific to particular regions.

Employing more advanced methodologies for data validation could also be beneficial. Examining non-linear relationships and potential structural breaks in the data could offer deeper insights into the dynamics of green finance and its economic and environmental impacts. While this study recognizes the complexity of these relationships and explores them within the constraints of the VAR model, future research could benefit from applying more sophisticated modelling techniques to gain deeper insights.

References

Al Mamun, M., Boubaker, S., & Nguyen, D. K. (2022). Green finance and decarbonization: Evidence from around the world. *Finance Research Letters*, 46.

Bhatnagar, S., & Sharma, D. (2022). Evolution of green finance and its enablers: A bibliometric analysis. *Renewable and Sustainable Energy Reviews* (Vol. 162).

Boermans, M. A., & Galema, R. (2019). Are pension funds actively decarbonizing their portfolios? *Ecological Economics, 161*, 50–60.

Boermans, M. (2023). Preferred habitat investors in the green bond market. *Journal of Cleaner Production*, 421.

Climate Bonds Initiative. (2023). State of the Market Q3 2023.

Croce, D., Kaminker, C., Stewart, F., Croce, R. Della, Kaminker, C., & Stewart, F. (2011). The Role of Pension Funds in Financing Green Growth Initiatives. OECD Publishing, Paris.

Egli, F., Schärer, D., & Steffen, B. (2022). Determinants of fossil fuel divestment in European pension funds. *Ecological Economics, 191*.

European Commission. (2019). The European Green Deal.

European Commission. (2024). Bridging the climate financing gap: seizing the opportunity.

Glocalities. (2021). Environmental trends 2021.

Gunningham, N. (2020). A quiet revolution: Central banks, financial regulators, and climate finance. *Sustainability (Switzerland), 12*(22), 1–22.

Hafner, S., Jones, A., Anger-Kraavi, A., & Pohl, J. (2020). Closing the green finance gap – A systems perspective. *Environmental Innovation and Societal Transitions*, *34*, 26–60.

IFC. (2017). Green Finance: A Bottom-Up Approach to Track Existing Flows. International Finance Corporation, Washington, D.C.

International Capital Market Association (ICMA). (2021). Green Bond Principles.

Jankovic, I., Vasic, V., & Kovacevic, V. (2022). Does transparency matter? Evidence from panel analysis of the EU government green bonds. *Energy Economics*, 114.

Long, S., Lucey, B., Kumar, S., Zhang, D., Zhang, Z. (2022). Climate finance: What we know and what we should know? *Journal of Climate Finance*, 1, 100005.

Ma, M., Zhu, X., Liu, M., & Huang, X. (2023). Combining the role of green finance and environmental sustainability on green economic growth: Evidence from G-20 economies. *Renewable Energy, 207*, 128–136.

OECD. (2017). Mobilising bond markets for a low-carbon transition. Paris, France: OECD Publishing.

Pearce, D., Markandya, A., & Barbier, E. (1989). Blueprint 1: For a Green Economy (1st ed.). Routledge.

Polzin, F., & Sanders, M. (2020). How to finance the transition to low-carbon energy in Europe? *Energy Policy*, *147*.

Rempel, A., & Gupta, J. (2020). Conflicting commitments? Examining pension funds, fossil fuel assets and climate policy in the organisation for economic co-operation and development (OECD).

Sangiorgi, I., & Schopohl, L. (2021). Why do institutional investors buy green bonds: Evidence from a survey of European asset managers. *International Review of Financial Analysis*, *75*.

Sartzetakis, E. S. (2020). Green bonds as an instrument to finance low carbon transition. *Economic Change and Restructuring*.

Shi, X., Ma, J., Jiang, A., Wei, S., & Yue, L. (2023). Green bonds: Green investments or greenwashing? *International Review of Financial Analysis*, *90*.

Soneryd, L. (2024). Futures for the uncommitted? Translating net-zero to pension savers. *Futures*, *156*.

Taghizadeh-Hesary, F., & Yoshino, N. (2020). Sustainable solutions for green financing and investment in renewable energy projects. *Energies*, *13*(4).

United Nations Framework Convention on Climate Change (UNFCCC). (1992).

United Nations Framework Convention on Climate Change (UNFCCC). (2015). Paris Agreement.

United Nations. (2015). Transforming our world: The 2030 Agenda for SustainableDevelopment.

United Nations. (2023). Secretary-General's Opening Remarks at Press Conference onClimate.

Urgewald. (2023). NGOs release data on fossil fuels holdings of 6,500 institutionalinvestors.

Wang, Y., & Zhi, Q. (2016). The Role of Green Finance in Environmental Protection:Two Aspects of Market Mechanism and Policies. *Energy Procedia*, *104*,311–316.

World Bank. (2018). From Evolution to Revolution: 10 Years of Green Bonds.

World Economic Forum. (2023). The training gap in green finance could hold back climate progress – here's how we fix it.

Zhang, D., Zhang, Z., & Managi, S. (2019). A bibliometric analysis on green finance: Current status, development, and future directions. *Finance Research Letters*, *29*, 425–430.

Appendix

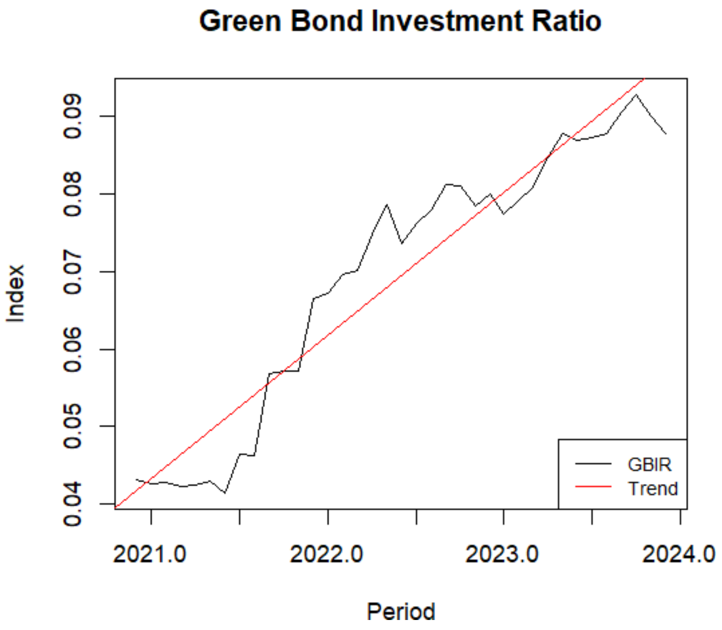

Figure A1 - Green Bond Investment Ratio Trend. Source: Own Elaboration

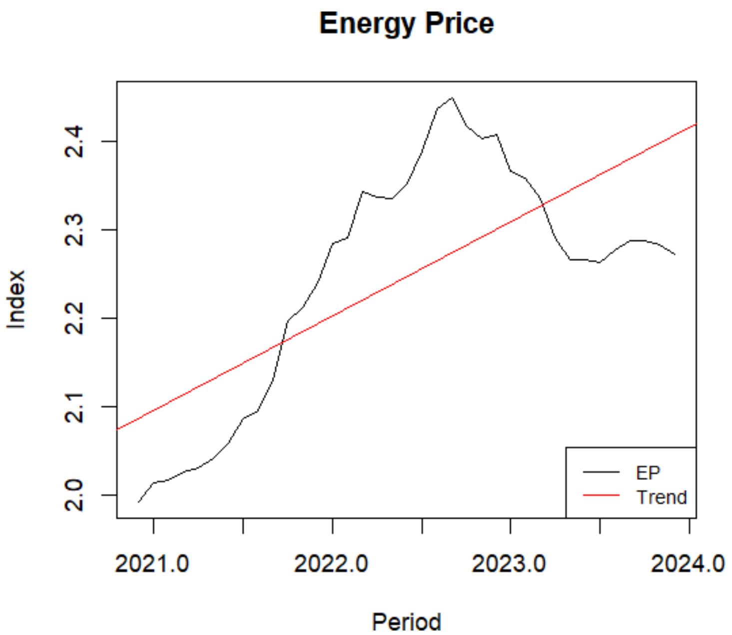

Figure A2 - Energy Price Trend. Source: Own Elaboration

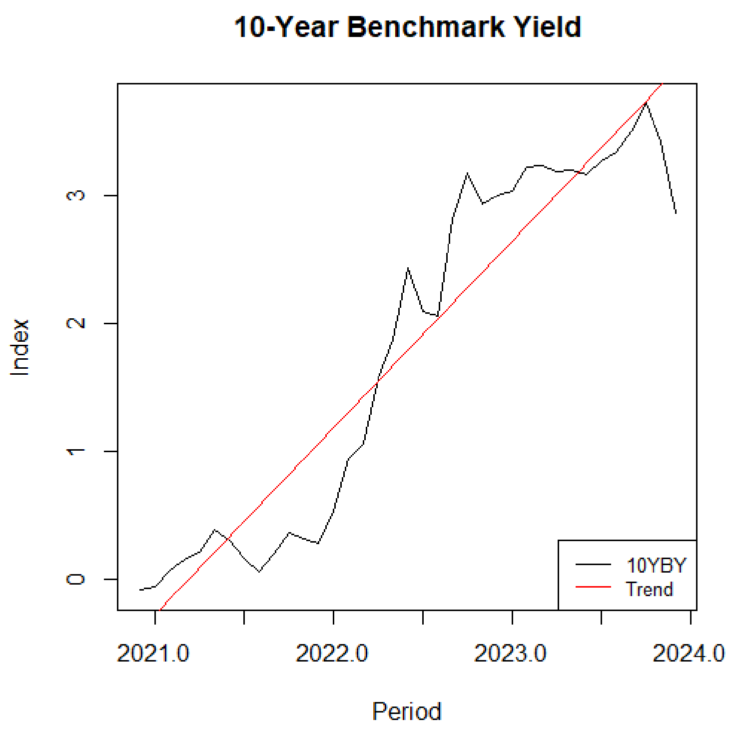

Figure A3 - 10-Year Benchmark Yield Trend. Source: Own Elaboration

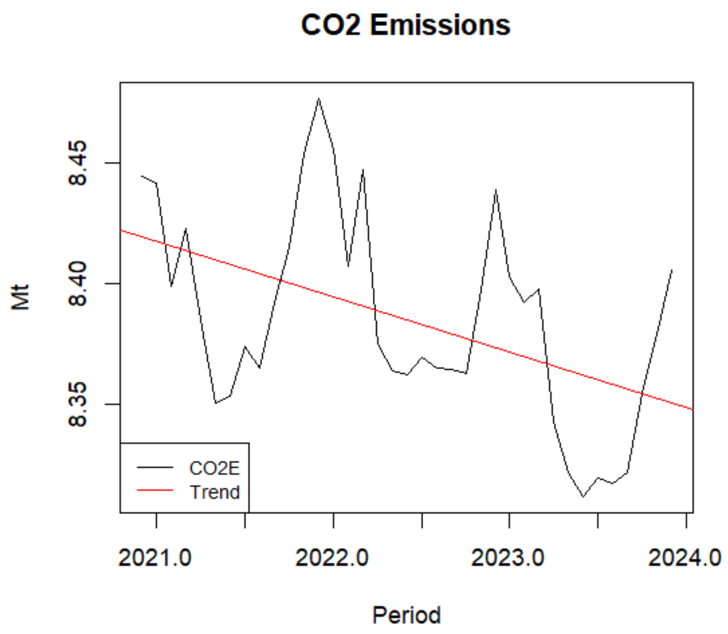

Figure A4 - CO2 Emissions Trend. Source: Own Elaboration

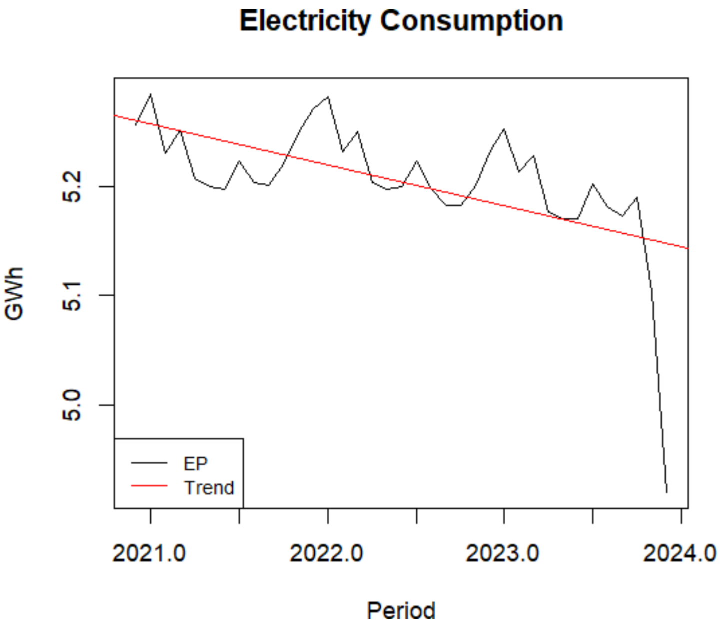

Figure A5 - Electricity Consumption Trend. Source: Own Elaboration

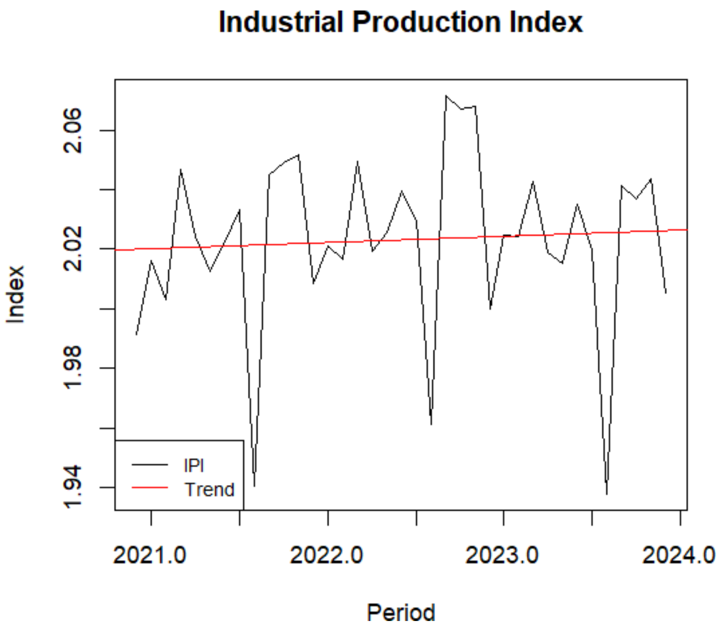

Figure A6 - Industrial Production Index Trend. Source: Own Elaboration

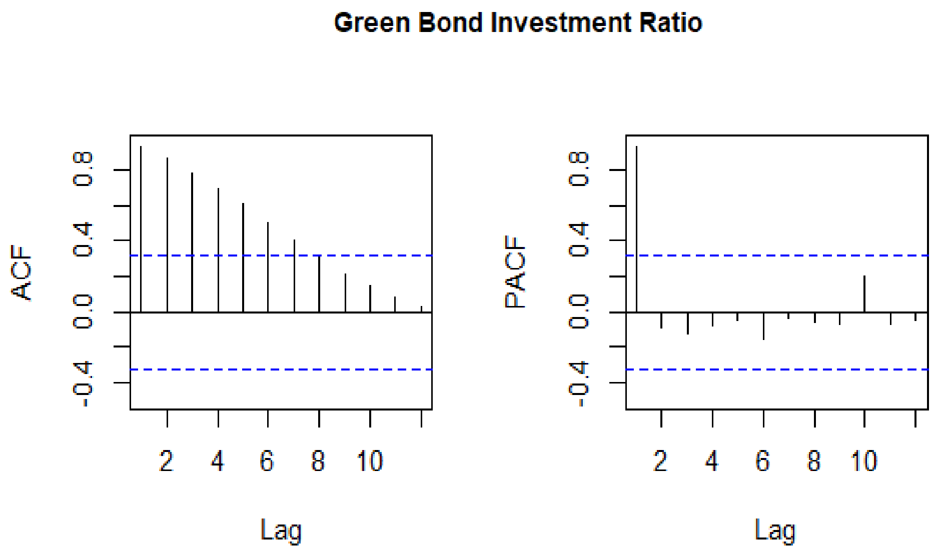

Figure A7 - Green Bond Investment Ratio ACF and PACF. Source: Own Elaboration

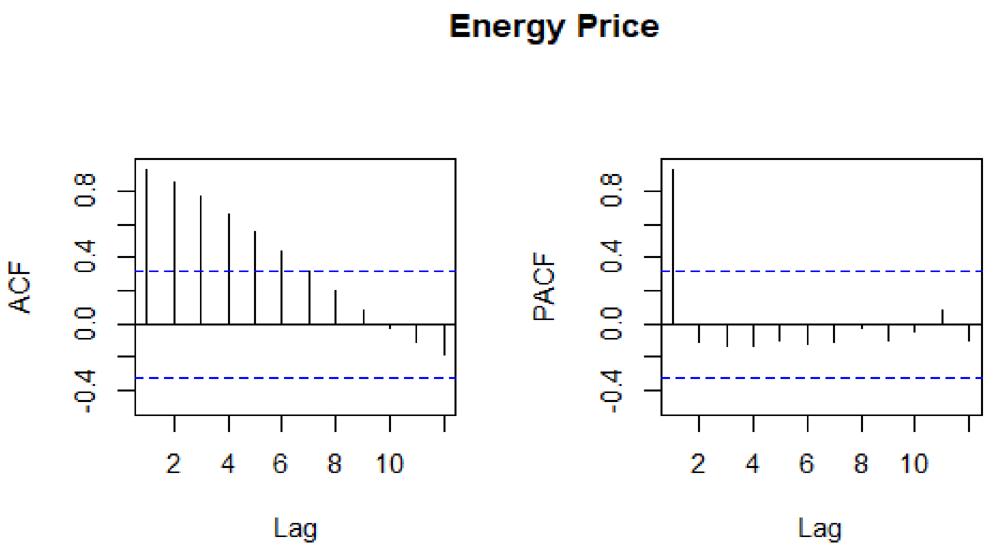

Figure A8 - Energy Price ACF and PACF. Source: Own Elaboration

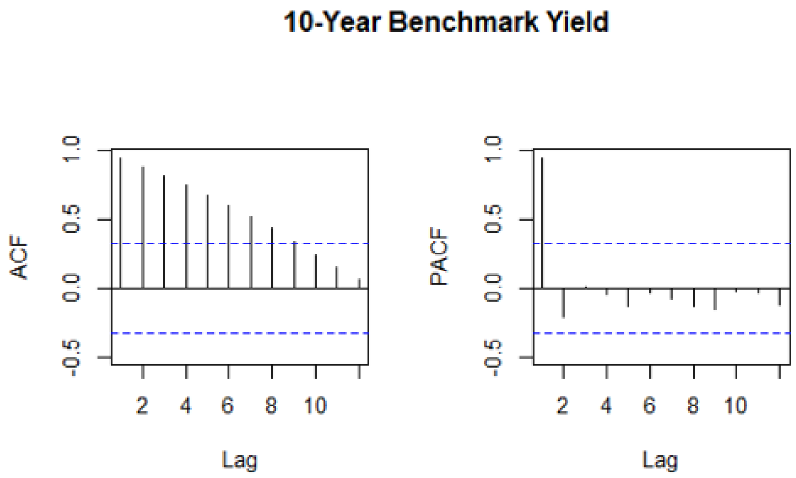

Figure A9 - 10-Year Benchmark Yield ACF and PACF. Source: Own Elaboration

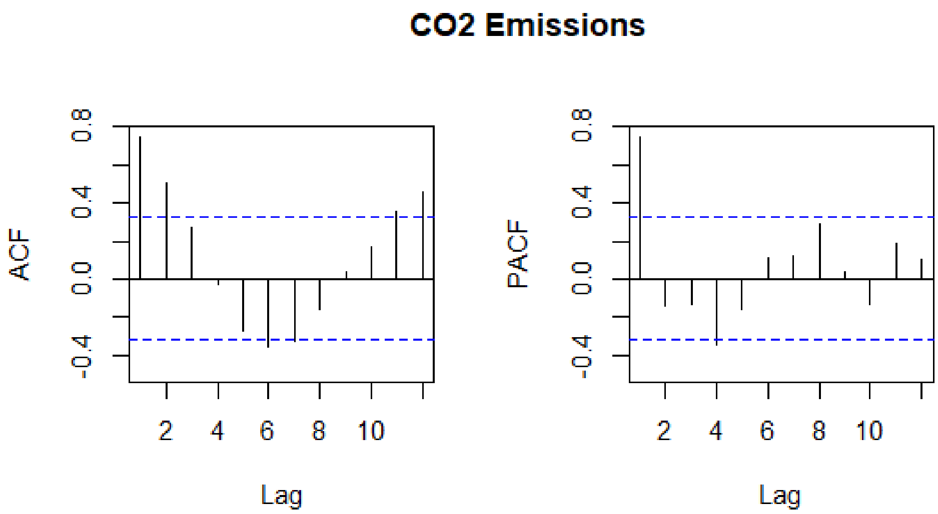

Figure A10 - CO2 Emissions ACF and PACF. Source: Own Elaboration

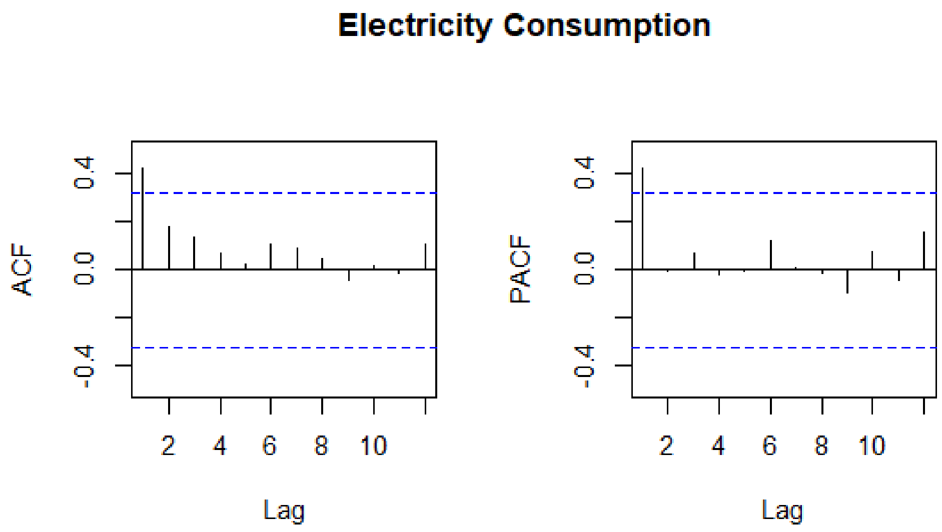

Figure A11 – Electricity Consumption ACF and PACF. Source: Own Elaboration

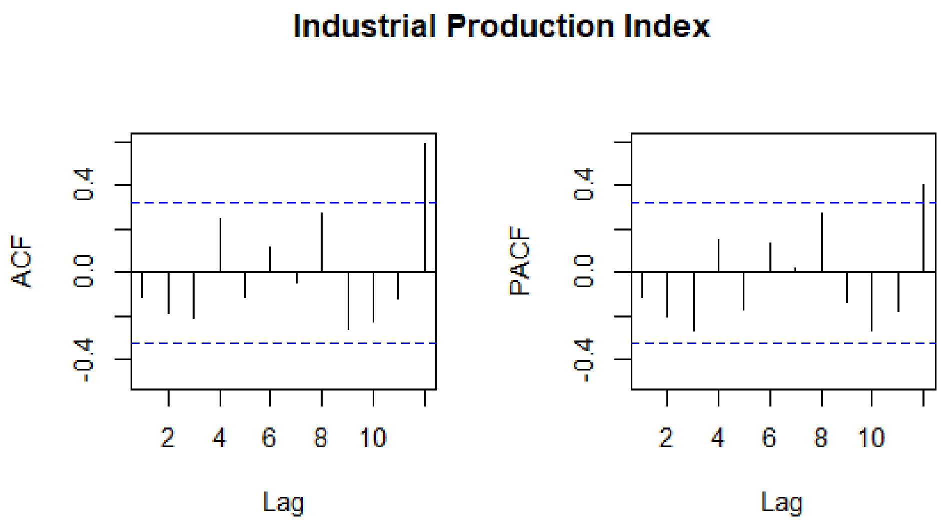

Figure A12 - Industrial Production Index ACF and PACF. Source: Own Elaboration

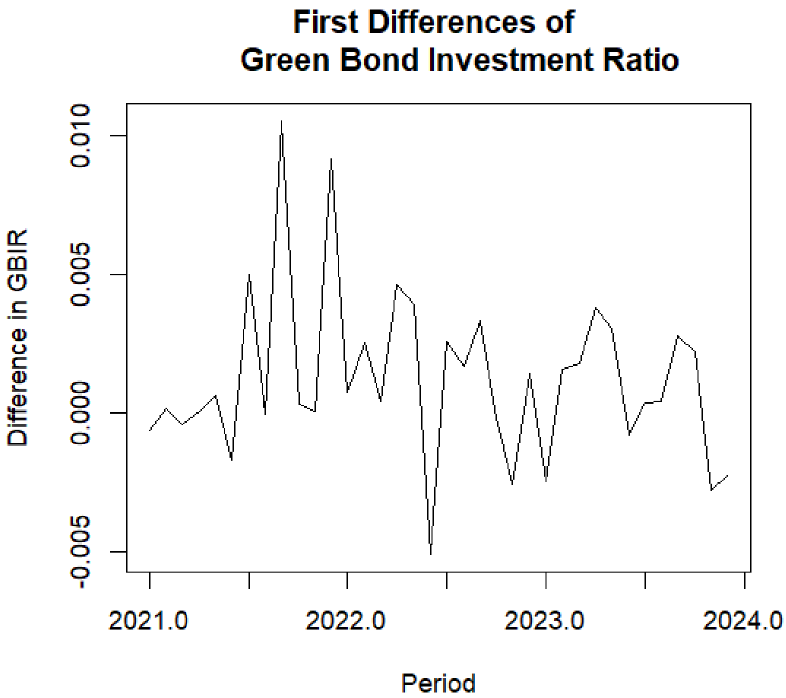

Figure A13 - First Differences of Green Bond Investment Ratio. Source: Own Elaboration

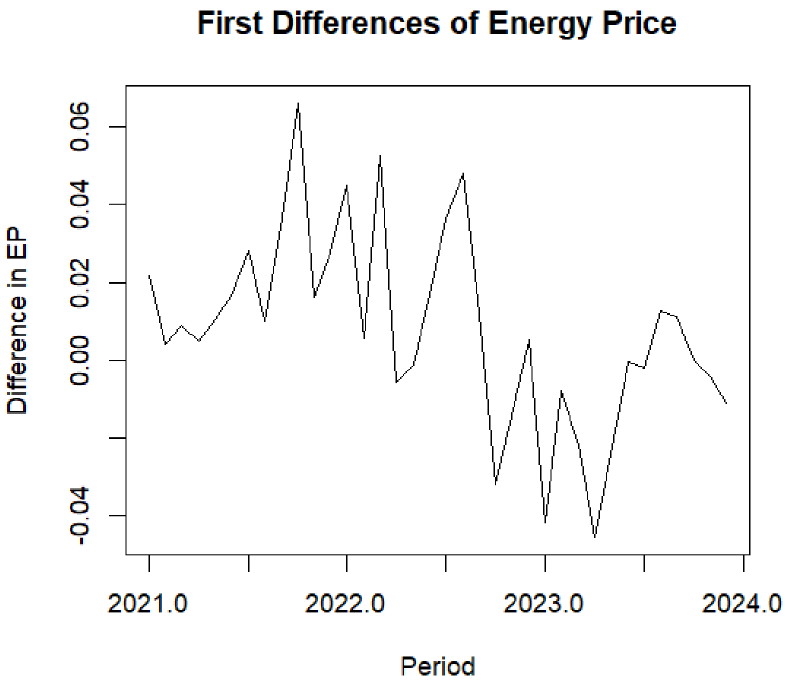

Figure A14 - First Differences of Energy Price. Source: Own Elaboration

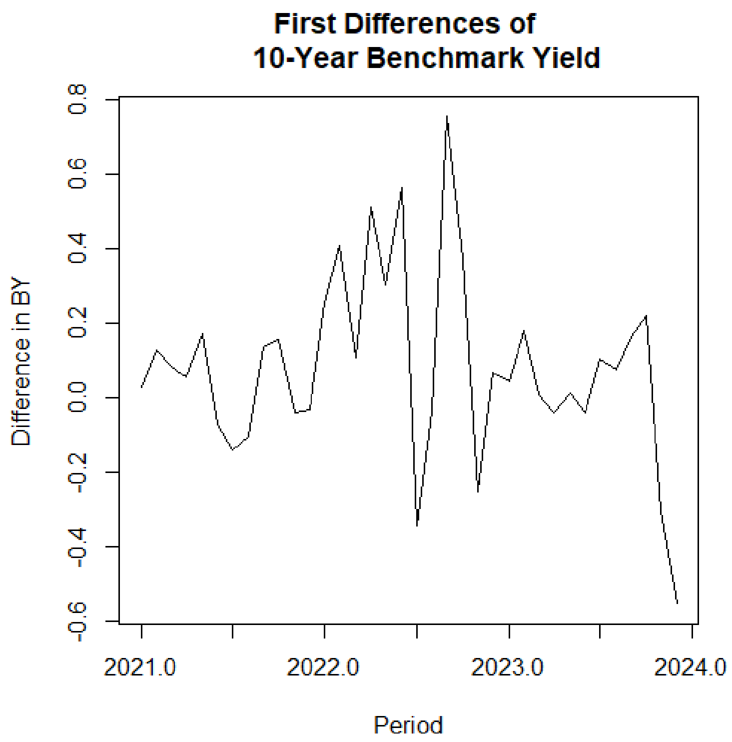

Figure A15 - First Differences of 10-Year Benchmark Yield. Source: Own Elaboration

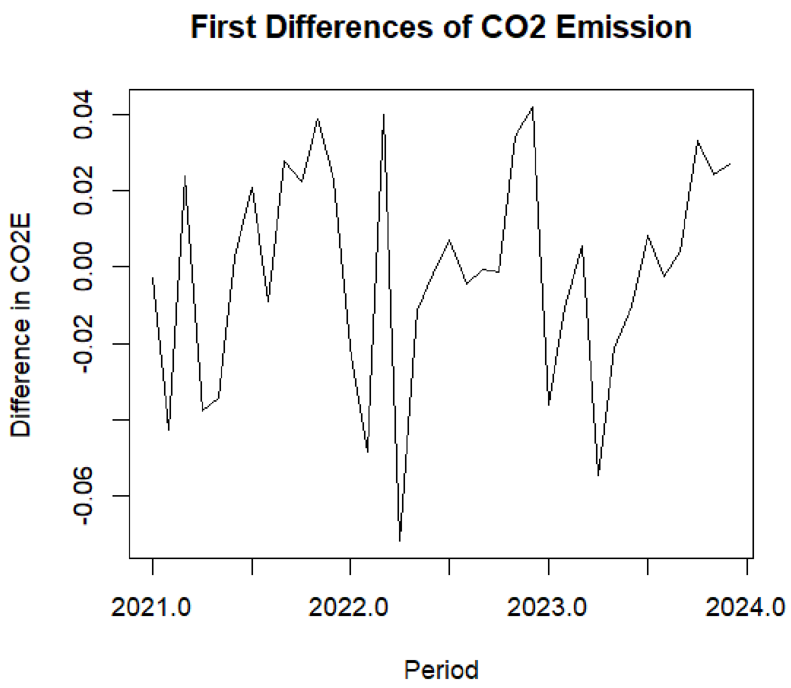

Figure A16 - First Differences of CO2 Emissions. Source: Own Elaboration

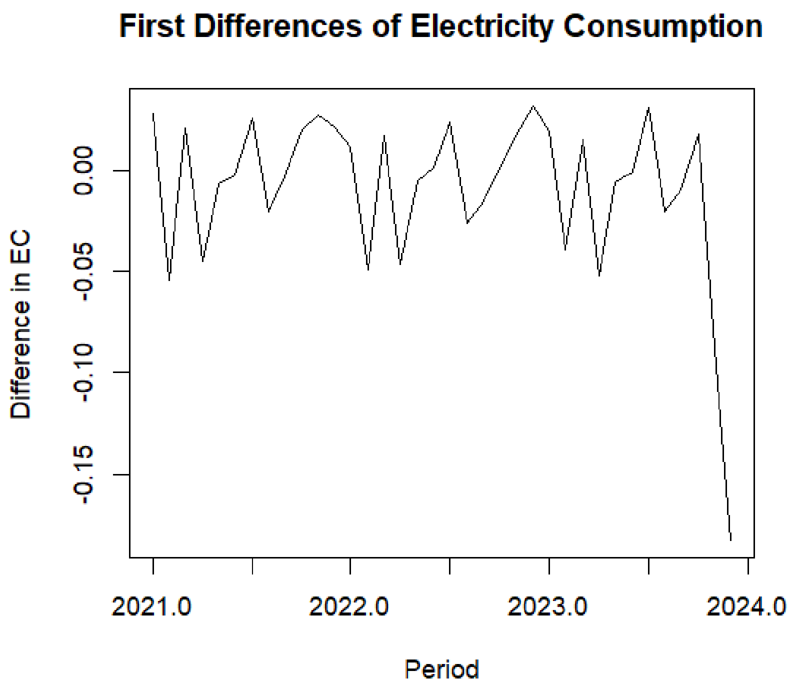

Figure A17 - First Differences of Electricity Consumption. Source: Own Elaboration

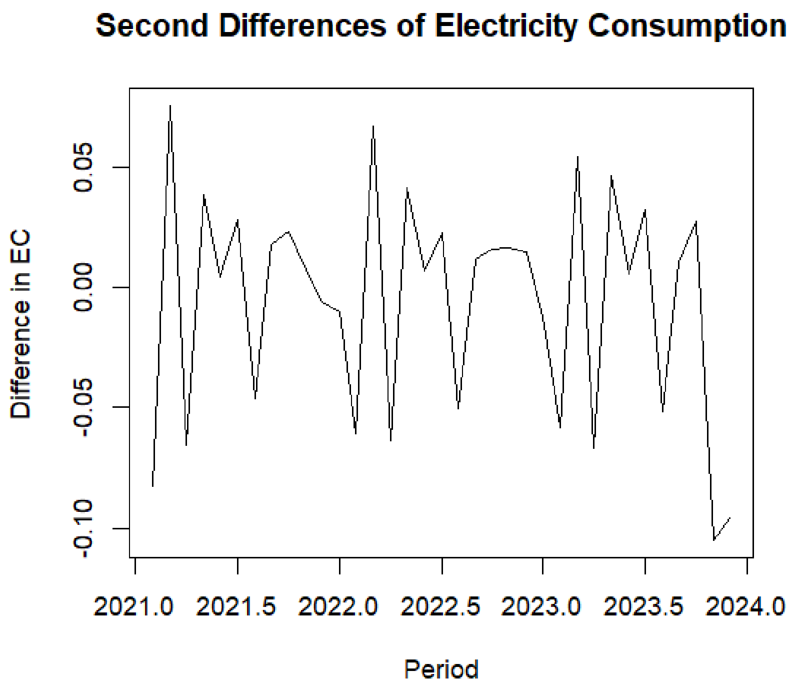

Figure A18 - Second Differences of Electricity Consumption. Source: Own Elaboration

Table A1 – VAR Estimation Results. Source: Own Elaboration

```
VAR Estimation Results:

=========================
Endogenous variables: diffCO2E, diffGBIR, diffBY, IPI, diffEP, diff2EC
Deterministic variables: const
Sample size: 31
Log Likelihood: 638.478
Roots of the characteristic polynomial:
1.293 1.293 0.9981 0.9981 0.9464 0.9464 0.9435 0.9435 0.935 0.935 0.93
47 0.9172 0.9172 0.909 0.8799 0.8799 0.8662 0.8662 0.8573 0.8573 0.814
6 0.8146 0.6888 0.5685
Call:
VAR(y = dataseries, p = 4, type = "const")


Estimation results for equation diffCO2E:
=========================================
diffCO2E = diffCO2E.l1 + diffGBIR.l1 + diffBY.l1 + IPI.l1 + diffEP.l1
+ diff2EC.l1 + diffCO2E.l2 + diffGBIR.l2 + diffBY.l2 + IPI.l2 + diffEP
.l2 + diff2EC.l2 + diffCO2E.l3 + diffGBIR.l3 + diffBY.l3 + IPI.l3 + di
ffEP.l3 + diff2EC.l3 + diffCO2E.l4 + diffGBIR.l4 + diffBY.l4 + IPI.l4
+ diffEP.l4 + diff2EC.l4 + const

            Estimate  Std. Error t value Pr(>|t|)
diffCO2E.l1 -0.301886 0.689310   -0.438  0.6767
diffGBIR.l1 -2.126989 3.690344   -0.576  0.5853
diffBY.l1   -0.043238 0.049558   -0.872  0.4165
IPI.l1      0.415012  0.589079   0.705   0.5075
diffEP.l1   -0.702927 0.602557   -1.167  0.2876
diff2EC.l1  0.004143  0.407064   0.010   0.9922
diffCO2E.l2 -0.460232 0.695214   -0.662  0.5326
diffGBIR.l2 -0.222872 4.024609   -0.055  0.9576
diffBY.l2   -0.044280 0.062325   -0.710  0.5041
IPI.l2      -0.427891 0.607598   -0.704  0.5077
diffEP.l2   0.064218  0.645391   0.100   0.9240
diff2EC.l2  0.737173  0.797305   0.925   0.3909
diffCO2E.l3 0.240329  0.569529   0.422   0.6877
diffGBIR.l3 3.754929  3.990649   0.941   0.3831
diffBY.l3   0.023824  0.047652   0.500   0.6349
IPI.l3      -1.063861 0.500381   -2.126  0.0776   .
diffEP.l3   0.035295  0.679204   0.052   0.9602
diff2EC.l3  1.096224  0.694715   1.578   0.1657
diffCO2E.l4 -0.312785 0.671777   -0.466  0.6579
diffGBIR.l4 2.077913  5.006107   0.415   0.6925
diffBY.l4   0.015044  0.048719   0.309   0.7679
IPI.l4      -0.421590 0.549610   -0.767  0.4721
diffEP.l4   0.613610  0.658817   0.931   0.3876
diff2EC.l4  0.805824  0.709258   1.136   0.2992
const       3.032180  2.930054   1.035   0.3406
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 0.03127 on 6 degrees of freedom
Multiple R-Squared: 0.7554,    Adjusted R-squared: -0.2228
F-statistic: 0.7722 on 24 and 6 DF,  p-value: 0.7029
```

```
Estimation results for equation diffGBIR:
==========================================
diffGBIR = diffCO2E.l1 + diffGBIR.l1 + diffBY.l1 + IPI.l1 + diffEP.l1
+ diff2EC.l1 + diffCO2E.l2 + diffGBIR.l2 + diffBY.l2 + IPI.l2 + diffEP
.l2 + diff2EC.l2 + diffCO2E.l3 + diffGBIR.l3 + diffBY.l3 + IPI.l3 + di
ffEP.l3 + diff2EC.l3 + diffCO2E.l4 + diffGBIR.l4 + diffBY.l4 + IPI.l4
+ diffEP.l4 + diff2EC.l4 + const

            Estimate   Std. Error t value Pr(>|t|)
diffCO2E.l1 -4.444e-02 9.002e-02  -0.494  0.639
diffGBIR.l1 -3.593e-01 4.819e-01  -0.746  0.484
diffBY.l1   -6.949e-03 6.472e-03  -1.074  0.324
IPI.l1      -4.268e-02 7.693e-02  -0.555  0.599
diffEP.l1   2.734e-02  7.869e-02  0.347   0.740
diff2EC.l1  2.875e-02  5.316e-02  0.541   0.608
diffCO2E.l2 6.398e-02  9.079e-02  0.705   0.507
diffGBIR.l2 -1.446e-01 5.256e-01  -0.275  0.792
diffBY.l2   -3.005e-03 8.139e-03  -0.369  0.725
IPI.l2      2.720e-02  7.935e-02  0.343   0.743
diffEP.l2   3.495e-02  8.429e-02  0.415   0.693
diff2EC.l2  -8.799e-02 1.041e-01  -0.845  0.430
diffCO2E.l3 -3.215e-02 7.438e-02  -0.432  0.681
diffGBIR.l3 4.096e-01  5.212e-01  0.786   0.462
diffBY.l3   2.204e-03  6.223e-03  0.354   0.735
IPI.l3      4.772e-02  6.535e-02  0.730   0.493
diffEP.l3   5.234e-02  8.870e-02  0.590   0.577
diff2EC.l3  -4.920e-02 9.073e-02  -0.542  0.607
diffCO2E.l4 -2.959e-02 8.773e-02  -0.337  0.747
diffGBIR.l4 -3.973e-01 6.538e-01  -0.608  0.566
diffBY.l4   -5.984e-03 6.363e-03  -0.941  0.383
IPI.l4      3.578e-05  7.178e-02  0.000   1.000
diffEP.l4   -2.716e-02 8.604e-02  -0.316  0.763
diff2EC.l4  4.057e-02  9.263e-02  0.438   0.677
const       -6.230e-02 3.827e-01  -0.163  0.876


Residual standard error: 0.004084 on 6 degrees of freedom
Multiple R-Squared: 0.6873,    Adjusted R-squared: -0.5633
F-statistic: 0.5496 on 24 and 6 DF,  p-value: 0.8624
```

```
Estimation results for equation diffBY:
=======================================
diffBY = diffCO2E.l1 + diffGBIR.l1 + diffBY.l1 + IPI.l1 + diffEP.l1 +
diff2EC.l1 + diffCO2E.l2 + diffGBIR.l2 + diffBY.l2 + IPI.l2 + diffEP.l
2 + diff2EC.l2 + diffCO2E.l3 + diffGBIR.l3 + diffBY.l3 + IPI.l3 + diff
EP.l3 + diff2EC.l3 + diffCO2E.l4 + diffGBIR.l4 + diffBY.l4 + IPI.l4 +
diffEP.l4 + diff2EC.l4 + const

            Estimate Std. Error t value Pr(>|t|)
diffCO2E.l1 1.6301   5.4953     0.297   0.777
diffGBIR.l1 31.2064  29.4200    1.061   0.330
diffBY.l1   0.4341   0.3951     1.099   0.314
IPI.l1      4.2082   4.6962     0.896   0.405
diffEP.l1   0.6450   4.8037     0.134   0.898
diff2EC.l1  -2.5690  3.2452     -0.792  0.459
diffCO2E.l2 -5.3459  5.5423     -0.965  0.372
diffGBIR.l2 19.6872  32.0848    0.614   0.562
diffBY.l2   -0.1311  0.4969     -0.264  0.801
IPI.l2      0.9219   4.8439     0.190   0.855
diffEP.l2   7.0356   5.1451     1.367   0.221
diff2EC.l2  -1.6241  6.3562     -0.256  0.807
diffCO2E.l3 4.1810   4.5404     0.921   0.393
diffGBIR.l3 -29.7641 31.8140    -0.936  0.386
diffBY.l3   0.3486   0.3799     0.918   0.394
IPI.l3      6.8841   3.9891     1.726   0.135
diffEP.l3   -4.2480  5.4147     -0.785  0.463
diff2EC.l3  -1.8282  5.5384     -0.330  0.753
diffCO2E.l4 -6.2054  5.3555     -1.159  0.291
diffGBIR.l4 42.9557  39.9094    1.076   0.323
diffBY.l4   -0.3483  0.3884     -0.897  0.404
IPI.l4      1.5519   4.3816     0.354   0.735
diffEP.l4   -1.9357  5.2522     -0.369  0.725
diff2EC.l4  3.3229   5.6543     0.588   0.578
const       -27.5432 23.3588    -1.179  0.283


Residual standard error: 0.2493 on 6 degrees of freedom
Multiple R-Squared: 0.8324,   Adjusted R-squared: 0.1621
F-statistic: 1.242 on 24 and 6 DF,  p-value: 0.4242
```

```
Estimation results for equation IPI:
====================================
IPI = diffCO2E.l1 + diffGBIR.l1 + diffBY.l1 + IPI.l1 + diffEP.l1 + dif
f2EC.l1 + diffCO2E.l2 + diffGBIR.l2 + diffBY.l2 + IPI.l2 + diffEP.l2 +
diff2EC.l2 + diffCO2E.l3 + diffGBIR.l3 + diffBY.l3 + IPI.l3 + diffEP.l
3 + diff2EC.l3 + diffCO2E.l4 + diffGBIR.l4 + diffBY.l4 + IPI.l4 + diff
EP.l4 + diff2EC.l4 + const

             Estimate  Std. Error t value Pr(>|t|)
diffCO2E.l1 -0.354972 0.592372   -0.599  0.571
diffGBIR.l1 -0.369966 3.171369   -0.117  0.911
diffBY.l1    0.018471 0.042589    0.434  0.680
IPI.l1       0.329402 0.506237    0.651  0.539
diffEP.l1   -0.147081 0.517819   -0.284  0.786
diff2EC.l1  -0.201371 0.349818   -0.576  0.586
diffCO2E.l2 -0.062003 0.597445   -0.104  0.921
diffGBIR.l2  0.014449 3.458626    0.004  0.997
diffBY.l2   -0.043017 0.053560   -0.803  0.453
IPI.l2       0.270463 0.522151    0.518  0.623
diffEP.l2   -0.163020 0.554629   -0.294  0.779
diff2EC.l2  -0.665551 0.685179   -0.971  0.369
diffCO2E.l3  0.418630 0.489436    0.855  0.425
diffGBIR.l3  1.649679 3.429442    0.481  0.648
diffBY.l3    0.020501 0.040951    0.501  0.634
IPI.l3      -0.272506 0.430012   -0.634  0.550
diffEP.l3    0.162059 0.583687    0.278  0.791
diff2EC.l3   0.004988 0.597016    0.008  0.994
diffCO2E.l4 -0.514233 0.577305   -0.891  0.407
diffGBIR.l4  1.296211 4.302095    0.301  0.773
diffBY.l4    0.027928 0.041868    0.667  0.530
IPI.l4      -0.479201 0.472318   -1.015  0.349
diffEP.l4    0.120137 0.566167    0.212  0.839
diff2EC.l4   1.121374 0.609514    1.840  0.115
const        2.325521 2.517998    0.924  0.391


Residual standard error: 0.02688 on 6 degrees of freedom
Multiple R-Squared: 0.8553,   Adjusted R-squared: 0.2766
F-statistic: 1.478 on 24 and 6 DF,  p-value: 0.3303
```

```
Estimation results for equation diffEP:
=======================================
diffEP = diffCO2E.l1 + diffGBIR.l1 + diffBY.l1 + IPI.l1 + diffEP.l1 +
diff2EC.l1 + diffCO2E.l2 + diffGBIR.l2 + diffBY.l2 + IPI.l2 + diffEP.l
2 + diff2EC.l2 + diffCO2E.l3 + diffGBIR.l3 + diffBY.l3 + IPI.l3 + diff
EP.l3 + diff2EC.l3 + diffCO2E.l4 + diffGBIR.l4 + diffBY.l4 + IPI.l4 +
diffEP.l4 + diff2EC.l4 + const

            Estimate  Std. Error t value Pr(>|t|)
diffCO2E.l1 -0.744357 0.466969   -1.594  0.1620
diffGBIR.l1 0.144612  2.500001   0.058   0.9558
diffBY.l1   -0.058710 0.033573   -1.749  0.1309
IPI.l1      -0.416438 0.399068   -1.044  0.3369
diffEP.l1   0.095403  0.408198   0.234   0.8230
diff2EC.l1  0.557824  0.275763   2.023   0.0895    .
diffCO2E.l2 -0.011366 0.470968   -0.024  0.9815
diffGBIR.l2 0.176566  2.726446   0.065   0.9505
diffBY.l2   0.007915  0.042222   0.187   0.8575
IPI.l2      -0.651034 0.411613   -1.582  0.1648
diffEP.l2   -0.230426 0.437216   -0.527  0.6171
diff2EC.l2  0.838388  0.540129   1.552   0.1716
diffCO2E.l3 -0.031631 0.385824   -0.082  0.9373
diffGBIR.l3 5.704493  2.703441   2.110   0.0794    .
diffBY.l3   0.019945  0.032282   0.618   0.5594
IPI.l3      -0.556058 0.338980   -1.640  0.1520
diffEP.l3   0.563957  0.460122   1.226   0.2662
diff2EC.l3  0.728942  0.470630   1.549   0.1724
diffCO2E.l4 0.447658  0.455091   0.984   0.3633
diffGBIR.l4 1.070280  3.391356   0.316   0.7630
diffBY.l4   0.026107  0.033005   0.791   0.4590
IPI.l4      -0.252468 0.372330   -0.678  0.5230
diffEP.l4   0.195373  0.446311   0.438   0.6769
diff2EC.l4  0.186596  0.480482   0.388   0.7112
const       3.790490  1.984947   1.910   0.1048
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 0.02119 on 6 degrees of freedom
Multiple R-Squared: 0.8753,   Adjusted R-squared: 0.3767
F-statistic: 1.755 on 24 and 6 DF,  p-value: 0.2497
```

```
Estimation results for equation diff2EC:
========================================
diff2EC = diffCO2E.l1 + diffGBIR.l1 + diffBY.l1 + IPI.l1 + diffEP.l1 +
diff2EC.l1 + diffCO2E.l2 + diffGBIR.l2 + diffBY.l2 + IPI.l2 + diffEP.l
2 + diff2EC.l2 + diffCO2E.l3 + diffGBIR.l3 + diffBY.l3 + IPI.l3 + diff
EP.l3 + diff2EC.l3 + diffCO2E.l4 + diffGBIR.l4 + diffBY.l4 + IPI.l4 +
diffEP.l4 + diff2EC.l4 + const

            Estimate  Std. Error t value Pr(>|t|)
diffCO2E.l1 -0.701617 1.113276   -0.630  0.552
diffGBIR.l1 2.416441  5.960122   0.405   0.699
diffBY.l1   -0.009788 0.080039   -0.122  0.907
IPI.l1      0.940988  0.951397   0.989   0.361
diffEP.l1   0.175531  0.973164   0.180   0.863
diff2EC.l1  -0.492038 0.657431   -0.748  0.482
diffCO2E.l2 -0.207046 1.122811   -0.184  0.860
diffGBIR.l2 1.173350  6.499979   0.181   0.863
diffBY.l2   -0.063613 0.100658   -0.632  0.551
IPI.l2      1.190238  0.981306   1.213   0.271
diffEP.l2   -0.014566 1.042344   -0.014  0.989
diff2EC.l2  -1.049468 1.287694   -0.815  0.446
diffCO2E.l3 -0.451682 0.919823   -0.491  0.641
diffGBIR.l3 8.176496  6.445132   1.269   0.252
diffBY.l3   0.054757  0.076962   0.711   0.503
IPI.l3      0.522126  0.808144   0.646   0.542
diffEP.l3   0.194515  1.096954   0.177   0.865
diff2EC.l3  0.558296  1.122005   0.498   0.636
diffCO2E.l4 -1.612609 1.084959   -1.486  0.188
diffGBIR.l4 -2.993975 8.085155   -0.370  0.724
diffBY.l4   -0.100846 0.078684   -1.282  0.247
IPI.l4      0.387654  0.887652   0.437   0.678
diffEP.l4   -0.034511 1.064028   -0.032  0.975
diff2EC.l4  1.816904  1.145492   1.586   0.164
const       -6.171830 4.732208   -1.304  0.240


Residual standard error: 0.05051 on 6 degrees of freedom
Multiple R-Squared: 0.7384,    Adjusted R-squared: -0.3078
F-statistic: 0.7058 on 24 and 6 DF,  p-value: 0.7509



Covariance matrix of residuals:
         diffCO2E   diffGBIR   diffBY     IPI        diffEP     dif
f2EC
diffCO2E 9.781e-04  -6.668e-05 -2.015e-03 5.806e-04  3.122e-04  1.240
e-03
diffGBIR -6.668e-05 1.668e-05  4.802e-04  -3.710e-05 -2.867e-05 2.381
e-06
diffBY   -2.015e-03 4.802e-04  6.216e-02  -1.351e-03 -2.725e-03 -1.071
e-05
IPI      5.806e-04  -3.710e-05 -1.351e-03 7.223e-04  8.314e-05  9.839
e-04
diffEP   3.122e-04  -2.867e-05 -2.725e-03 8.314e-05  4.489e-04  5.611
e-05
diff2EC  1.240e-03  2.381e-06  -1.071e-05 9.839e-04  5.611e-05  2.551
e-03

Correlation matrix of residuals:
diffCO2E diffGBIR          diffBY     IPI     diffEP   diff2EC
diffCO2E   1.0000 -0.52202 -0.2584803 0.6908  0.47117  0.7852551
diffGBIR  -0.5220  1.00000 0.4715465  -0.3380 -0.33128 0.0115406
diffBY    -0.2585  0.47155 1.0000000  -0.2016 -0.51585 -0.0008504
IPI        0.6908 -0.33802 -0.2015983 1.0000  0.14601  0.7247846
diffEP     0.4712 -0.33128 -0.5158458 0.1460  1.00000  0.0524293
diff2EC    0.7853  0.01154 -0.0008504 0.7248  0.05243  1.0000000
```

Table A2 – Impulse Response Coefficients. Source: Own Elaboration

Impulse response coefficients

$diffGBIR

	diffCO2E	diffBY	IPI	diffEP	diff2EC
[1,]	0.000000000	0.09839644	0.0007119705	-0.002119374	0.024958265
[2,]	-0.009775475	0.18733067	-0.0032390108	0.006031215	0.020430699
[3,]	-0.002454922	0.17039813	-0.0194869379	0.030138239	-0.004283103
[4,]	0.019282071	0.08235656	-0.0206645578	0.056521079	0.028329644
[5,]	0.004186145	0.34360287	-0.0004451177	0.059063026	0.028963060
[6,]	0.003483954	0.55983640	0.0010446722	0.057102593	-0.009410838
[7,]	0.031099472	0.33514211	-0.0004165978	0.061923965	-0.019285934
[8,]	0.034545700	0.18144619	0.0338911594	0.056460186	0.072015360
[9,]	-0.009738038	0.59785515	0.0423176722	0.042745479	0.047736122
[10,]	-0.009422080	0.65911742	-0.0105378781	0.048000031	-0.086376284
[11,]	0.038930166	-0.01612825	-0.0231890667	0.062387162	0.015304113

Lower Band, CI= 0.95

$diffGBIR

	diffCO2E	diffBY	IPI	diffEP	diff2EC
[1,]	0.000000000	-0.036222890	-0.007184845	-0.006397604	0.0009671674
[2,]	-0.012694118	-0.043702892	-0.010465277	-0.008843739	-0.0098495456
[3,]	-0.014933927	-0.066734927	-0.018384557	-0.006267281	-0.0222403069
[4,]	-0.009697872	-0.115394810	-0.020670020	-0.003941095	-0.0038457810
[5,]	-0.020971538	-0.009998168	-0.015655063	-0.015940334	-0.0091714956
[6,]	-0.022360118	0.054443288	-0.013382945	-0.030744411	-0.0285289370
[7,]	-0.008817848	-0.107876059	-0.014675279	-0.046584146	-0.0298114795
[8,]	-0.011379036	-0.228474882	-0.013108563	-0.053422115	-0.0030455632
[9,]	-0.039575524	-0.082766602	-0.016399293	-0.061635568	-0.0255965918
[10,]	-0.028917014	-0.141464328	-0.040238864	-0.072706097	-0.0937106140
[11,]	-0.019183969	-0.464355723	-0.037779598	-0.076518492	-0.0409676475

Upper Band, CI= 0.95

$diffGBIR

	diffCO2E	diffBY	IPI	diffEP	diff2EC
[1,]	0.000000000	0.1149868	0.006369976	0.00499328	0.01693338
[2,]	0.004244384	0.1919092	0.008771660	0.01140723	0.02111416
[3,]	0.008521665	0.2147040	0.003448159	0.02456507	0.01548787
[4,]	0.019826222	0.2011084	0.006150810	0.04007384	0.02351134
[5,]	0.016815976	0.3276990	0.019083915	0.05061236	0.02936798
[6,]	0.016387943	0.4394054	0.018945974	0.06742303	0.01968192
[7,]	0.035451524	0.4027137	0.018456509	0.08035515	0.01560353
[8,]	0.043994559	0.3893064	0.030323554	0.09190445	0.07030451
[9,]	0.036513106	0.5015469	0.040167208	0.09242396	0.04886161
[10,]	0.026172218	0.6137395	0.022778621	0.10341302	0.00890066
[11,]	0.049190741	0.4764993	0.019784029	0.11091567	0.04489056

Table A3 – FEVD Coefficients. Source: Own Elaboration

```
$ $diffCO2E
       diffCO2E   diffGBIR    diffBY        IPI      diffEP       diff2EC
[1,]   1.0000000 0.000000000.00000000 0.00000000  0.00000000 0.0000e+00
[2,]   0.7223416 0.070458460.01143527 0.10727912  0.08848526 2.4130e-07
[3,]   0.7043352 0.097655680.01532882 0.09567379  0.08582130 1.1851e-03
[4,]   0.5192399 0.299509540.03415968 0.07059762  0.07544017 1.0530e-03
[5,]   0.4148766 0.324771110.12617421 0.05729021  0.07605025 8.3759e-04
[6,]   0.4123874 0.301468040.12549475 0.05649871  0.10336533 7.8578e-04
[7,]   0.3088923 0.398375700.09175187 0.06583986  0.13162092 3.5193e-03
[8,]   0.3239606 0.349308540.12916538 0.05928293  0.13521769 3.0643e-03
[9,]   0.2790460 0.364601870.08425053 0.04453390  0.22082340 6.7443e-03
[10,]  0.2833152 0.336527930.09348305 0.04119141  0.23914562 6.3367e-03

$diffGBIR
       diffCO2E  diffGBIR   diffBY       IPI        diffEP    diff2EC
 [1,] 0.2725040 0.7274960 0.00000000 0.00000000 0.000000e+000.0000000
 [2,] 0.2164178 0.6314659 0.13264970 0.01872508 2.251663e-050.0007189
 [3,] 0.1308017 0.5538483 0.14426115 0.05656720 1.114439e-010.0030777
 [4,] 0.1241926 0.5207712 0.12498977 0.05291709 1.727196e-010.0044097
 [5,] 0.2421054 0.4536683 0.06691011 0.02995149 1.969896e-010.0103752
 [6,] 0.2396159 0.3767275 0.07734941 0.02335344 2.721375e-010.0108163
 [7,] 0.2260166 0.4353526 0.06430303 0.02255395 2.406312e-010.0111426
 [8,] 0.2365339 0.4099045 0.04609190 0.03561386 2.605644e-010.0112915
 [9,] 0.2321931 0.3901917 0.07629638 0.04154020 2.486757e-010.0111029
[10,] 0.2947055 0.3675985 0.03759055 0.05138670 2.374580e-010.0112607

$diffBY
        diffCO2E diffGBIR    diffBY       IPI     diffEP      diff2EC
[1,]   0.066812060.1557528  0.7774351 0.00000000 0.00000000 0.000000000
[2,]   0.091976720.2059539  0.6495582 0.02639383 0.02464444 0.001472943
[3,]   0.306926170.1259482  0.4463503 0.02269835 0.09704014 0.001036844
[4,]   0.330642500.1491232  0.3836590 0.03675490 0.09889584 0.000924511
[5,]   0.218006350.3600994  0.2638799 0.03262162 0.12374815 0.001644503
[6,]   0.195604620.4487530  0.2218652 0.02816107 0.10303779 0.002578298
[7,]   0.179259030.3839194  0.1948466 0.03740569 0.19952933 0.005039895
[8,]   0.168963540.4058895  0.1963449 0.03567978 0.18818418 0.004938052
[9,]   0.268334960.3754450  0.1006027 0.03315019 0.21232429 0.010142848
[10,]  0.259900340.3616951  0.1223090 0.03199006 0.21442012 0.009685369
```

```
$IPI
      diffCO2E   diffGBIR    diffBY      IPI      diffEP      diff2EC

[1,]  0.4772043  0.000701765 0.001443094 0.5206509 0.0000000000.000000
[2,]  0.5613141  0.016012046 0.024843622 0.3967806 0.0002816260.000767
[3,]  0.5484972  0.147169437 0.013281096 0.2246942 0.0599454110.006412
[4,]  0.5049598  0.122220969 0.035645350 0.2821540 0.0497162330.005303
[5,]  0.5301715  0.135623781 0.034394084 0.1299137 0.1611382970.008758
[6,]  0.5340377  0.130654814 0.033833394 0.1249863 0.1677588740.008728
[7,]  0.5622229  0.111937541 0.035511724 0.1110741 0.1697510780.009502
[8,]  0.4561620  0.226779490 0.028452420 0.1162913 0.1631508070.009164
[9,]  0.3857672  0.188230109 0.140858751 0.1441029 0.1311708270.009870
[10,] 0.4007415  0.205111906 0.088032102 0.0943818 0.2030628970.008669


$diffEP

      diffCO2E     diffGBIR diffBY    IPI          diffEP     diff2EC

[1,]  0.2220021  0.01000682 0.1617188 0.07087860 0.5353938 0.000000000
[2,]  0.1581727  0.09385633 0.3220083 0.04736145 0.3707514 0.007849841
[3,]  0.1761202  0.39681756 0.1557001 0.07178880 0.1875248 0.012048539
[4,]  0.1164132  0.53886266 0.1267750 0.05566915 0.1543176 0.007962355
[5,]  0.1589351  0.37010878 0.2633327 0.06198375 0.1401357 0.005503952
[6,]  0.1313080  0.29809246 0.3801879 0.05404329 0.1315055 0.004862894
[7,]  0.1153694  0.26637583 0.4384517 0.04794633 0.1274514 0.004405403
[8,]  0.1141484  0.24618721 0.4637456 0.05180063 0.1200603 0.004057852
[9,]  0.1070920  0.25775045 0.4364344 0.07526936 0.1195111 0.003942615
[10,] 0.2126205  0.22311569 0.3746756 0.06426179 0.1215254 0.003801081



$diff2EC

      diffCO2E  diffGBIR     diffBY         IPI      diffEP     diff2EC

[1,]  0.6166256  0.2441629 6.506343e-05 0.05521206 0.07646217 0.0074721
[2,]  0.6470337  0.1818679 6.582521e-03 0.07666961 0.08115326 0.0066929
[3,]  0.5517233  0.2432393 3.733991e-02 0.05288123 0.10781498 0.0070013
[4,]  0.4357028  0.3545279 6.418470e-02 0.04563962 0.09379514 0.0061498
[5,]  0.4728575  0.2556513 9.235087e-02 0.06411723 0.10711970 0.0079033
[6,]  0.4315989  0.2285037 5.624024e-02 0.08639941 0.18931509 0.0079426
[7,]  0.4086534  0.2216777 9.418457e-02 0.08430072 0.18295411 0.0082294
[8,]  0.3499172  0.3219901 5.487601e-02 0.05727226 0.20642636 0.0095180
[9,]  0.3184399  0.3067592 9.179506e-02 0.05625153 0.21809957 0.0086548
[10,] 0.3288563  0.3503007 4.632543e-02 0.05482118 0.20866191 0.0110344
```