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SUSTAINABLE INVESTMENTS: ASSESSMENT OF RISKS

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Abstract. Sustainable investments become a more and more relevant topic in all fields of economics. It is essential to measure both the benefits of sustainable products and risks. This article examines the risks associated with sustainable investments, mainly focusing on green bonds. It highlights financial institutions' increasing interest in sustainable asset management, including central banks. The study addresses the complexity of integrating climate risk into existing risk management frameworks and the lack of tools for estimating and managing these effects. This research aims to measure the volatility of different fixed-income financial instruments, trying to identify which GARCH model is the best. Our research utilizes Bloomberg data from eight sustainable corporate fixed-income indices. The study's sample comprises sustainable investment indices within the fixed-income market, selected based on data availability and the representativeness of the asset class. The dataset includes daily closing prices and daily returns of these indices, covering a unified sample period from July 25, 2019, to September 28, 2022. The models used for the research are ARCH, GARCH, TGARCH, EGARCH, and PARCH. The results show that sustainable investments are not risk-free, emphasizing the need for comprehensive risk assessment and management. From the applied models, the results show that the PARCH model is the best for fixed-income indices volatility modeling.

Keywords: ARCH, GARCH, green bonds, sustainable bonds, sustainable investments, risk, volatility.

JEL Classification: D53, E44, G1, Q01.

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1. Introduction

The Paris Agreement and the 2030 Agenda for Sustainable Development have significantly influenced global sustainability initiatives, with institutions aiming to support these goals, such as limiting global temperature rise to below 2 °C (Eliza, 2024). Research suggests that ESG integration enhances risk management and stabilizes financial performance, with companies prioritizing ESG factors often achieving improved long-term returns and investor confidence (Eliza, 2024). However, ESG data quality, measurement, and comparability challenge investment decision-making (Yunus & Nanda, 2024). The absence of standardized ESG reporting frameworks and regulatory inconsistencies further exacerbates these issues, necessitating collaborative efforts for better data quality and regulatory coherence (Yunus & Nanda, 2024).

Institutional investors play a crucial role in mitigating environmental risks (O'Sullivan, 2024). Improving ESG data quality and fostering interdisciplinary collaboration between finance, sustainability, and regulatory policy is essential to navigating sustainable finance's complexities (Yunus & Nanda, 2024). Habib et al. (2024) highlighted sustainable investment practices for efficient capital management, while financial regulators are increasingly addressing climate risks within risk management systems.

This paper aims to measure sustainable investment risks across various fixed-income markets, adding value to both scientific literature and practical fields. As sustainable financial products grow in demand, it becomes crucial to assess risk more comprehensively, beyond focusing solely on the positive social impacts. Existing research on sustainable investments often focuses on comparisons with non-sustainable options. However, Wang et al. (2024a) found that sustainable finance remains underexplored, with gaps in understanding economic globalization's role in sustainability.

Several studies have shown that sustainable funds are less risky but do not necessarily provide higher returns (Yue et al., 2020; Hamilton et al., 1993; Bauer et al., 2005). Contrarily, Chang and Witte (2010) observed that sustainable funds sometimes yield lower returns with inconsistent risk parameters. Ibikunle and Steffen (2017) found that sustainable funds had the worst risk-adjusted performance. Meanwhile, Martinez Meyers et al. (2024) highlighted stronger ESG performance in European sustainable funds compared to those in North America.

This paper contributes by analyzing different sustainable fixed-income indices, helping investors and practitioners make informed strategic decisions. Understanding the risk factors in sustainable investments will enable better risk management and contribute to sustainable economic growth. Key challenges involve varying definitions of climate risk and the evolving nature of ESG data disclosures, but improvements are expected as the field advances.

This paper starts with a literature review of the most relevant studies. Section 3 covers data and methodology aspects. The results and discussion are presented in Section 4. Conclusions are presented at the end of the paper.

2. Literature review

This section will focus on the main findings in the scientific literature on sustainable investments and risk management issues.

Different groups of authors analyze sustainable investments from different points of view. Beisenbina et al. (2022) conducted significant research by analyzing 1091 studies related to sustainable investments and using bibliometric analysis with two different approaches. They found interesting points in how the research evaluated traditional investments to sustainable ones. The most exciting point and adding value for practitioners is that the authors identified how the strategies for managing sustainable investment portfolios have changed over time. Some authors focused even on the connection between financial literacy and sustainable investment decision processes (Aristei et al., 2024).

Various ways exist to analyze the sustainability idea and its connections with financial markets. For example, Karagiannopoulou et al. (2022) analyzed the impact of the Dow Jones Sustainability Index on carbon emissions and found different effects in different time frames. de Castro Sobrosa Neto et al. (2020) focused on sustainability issues and found a neutral relationship between the company's financial performance, sustainable development, and equity prices. Vu et al. (2025) analyzed ESG-focused stocks in different developed markets, and their findings indicated that there was a weak correlation between ESG ratings and expected returns, with some indication that high-ESG-rated stocks modestly underperformed compared to lower-rated ones during certain periods. The other research by Landi et al.

(2024) focused on the analysis of the impact of ESG risk metrics on the performance of ETFs with a specific concentration on the COVID-19 pandemic period. The referenced research findings demonstrated a positive correlation between higher ESG standards and financial performance, as reflected in the Sharpe ratio, with a notable shift towards bonds in response to rising ESG risks.

Understanding climate risk in the broad risk management framework differs significantly among researchers. For example, some authors analyze climate risk as a non-financial risk (Wee et al., 2021), while there are more views that climate risk is under the financial risks umbrella (Network for Greening the Financial System [NGFS], 2020; Rudebusch, 2021; NGFS, 2021; Breitenstein et al., 2019). Other groups of authors focus more on the climate risk management process (Climate Financial Risk Forum, 2020; World Bank, 2015b; Oldani & Timotić, 2020; Travis & Bates, 2014; Hubert et al., 2021; Monetary Authority of Singapore, 2020; Drill et al., 2016; Bol & van Niekerk, 2024; Witnes Karlson et al., 2024; Scolobig et al., 2024; Palutikof et al., 2024).

The taxonomy of climate risk analysis needs scientific discussion. The Network for Greening the Financial System (NGFS) (2020) defines "environmental risks" to include both environment-related and climate-related risks, with climate risk as a subset. Environmental risks cover air and water pollution, freshwater scarcity, land contamination, biodiversity loss, and deforestation. Climate risks involve climate change impacts like extreme weather events and asset devaluation in carbon-intensive sectors. Varying global understanding of these risks underscores the need for further research and discussion. Scientific discussion can be even more interesting because we still do not have a precise classification of different types of risk, and different authors on the impact of climate change refer to different risks (Katara, 2021; Locatelli et al., 2018; Management Solutions, 2020; Colas et al., 2019; Ozkan et al., 2021; Simpson et al., 2021; Saliya & Wickrama, 2021; World Bank, 2015a).

Climate risk issues can be analyzed among different levels in central banking: monetary policy level and prudential level (micro-prudential and macro-prudential levels) (Directorate General of the Treasury, 2015; Taskforce on Climate Related Financial Disclosures, 2018; Financial Stability Board, 2020; Dikau & Volz, 2021; Chenet et al., 2021; Feridun & Güngör, 2020a, 2020b; Gelzinis, 2021). Climate risk management issues in central banking are very important in the field of foreign reserves management as well (Fender et al., 2019; Baker et al., 2018; Torinelli & de Almeida da Silva Júnior, 2021; International Capital Market Association, 2018; Carè et al., 2024; Ramlall, 2023).

Climate risk significantly impacts the banking sector's financial and operational risks, including credit, market, and liquidity risks. Ge et al. (2024) assessed bank risk exposure by evaluating climate transition risks. Wu et al. (2024) analyzed climate risk and the systemic risk of banks and identified that higher bank systemic risk because of higher climate risk is caused by worsened credit quality rather than the depreciation of bank's investments. Feridun and Güngör (2020b) note that wildfires can raise credit risk by causing defaults due to production loss. Oustry et al. (2021) add that credit risk increases when collateral depreciates due to new energy-efficiency standards.

Because the topic is very relevant and, at the same time, very new, lots of financial institutions try to share best practices in the field of climate risk management in the banking sector (ACPR Banque De France, 2020; Asian Development Bank, 2021, 2015a; Agence Francais de Development et al., 2015; African Development Bank, 2009; Asian Development Bank, 2015b; Anwar et al., 2020; European Comission, 2019; DBS Bank, 2019; Francia, 2020; Deloitte LLP, 2020; Battiston et al., 2020; Mazars Groups, 2020; ING Group, 2020; Royal Bank of Canada, 2020).

Table 1 organizes the main findings and key references to provide a clear and concise summary of the literature review.

Table 1. Main ideas of the literature review

Main Idea	Details	References
Sustainable Investments and Portfolio Strategies	Evolution of strategies for managing sustainable investment portfolios.	Beisenbina et al. (2022)
Financial Literacy and Sustainable Investment Decisions	The connection between financial literacy and sustainable investment decisions.	Aristei et al. (2024)
Impact of Dow Jones Sustainability Index on Carbon Emissions	Effects vary across time frames.	Karagiannopoulou et al. (2022)
Relationship Between Sustainability and Financial Performance	Neutral relationship between financial performance, sustainable development, and equity prices.	de Castro Sobrosa Neto et al. (2020)
ESG Ratings and Expected Returns	There is a weak correlation between ESG ratings and returns; high-ESG-rated stocks may modestly underperform.	Vu et al. (2025)
Impact of ESG Risk Metrics on ETFs	Positive correlation between ESG standards and performance (e.g., Sharpe ratio); shift to bonds during rising ESG risks.	Landi et al. (2024)
Climate Risk: Non-Financial vs. Financial Risk	Debate on whether climate risk is financial or non-financial risk.	Wee et al. (2021), NGFS (2020, 2021), Rudebusch (2021), Breitenstein et al. (2019)
Climate Risk Management Process	Climate risk management principles include conceptualization, preparation, and implementation.	Watkiss et al. (2020)
Taxonomy of Climate Risks	Climate risks categorized as environmental risks, including physical risks (e.g., natural disasters) and transition risks (e.g., policy changes).	NGFS (2020), Rudebusch (2021)
Climate Risk Hedging in Investments	Hedging strategies for long-term passive investors to address climate risk.	Andersson et al. (2016)
Climate Risk and Banking Sector Risks	Climate risks affect credit, market, and liquidity risks.	Ge et al. (2024), Wu et al. (2024), Feridun and Güngör (2020b), Oustry et al. (2021)
Best Practices in Climate Risk Management (Banking Sector)	Shared practices by financial institutions in managing climate risk in the banking sector.	ACPR Banque De France (2020), Asian Development Bank (2021), ING Group (2020), Royal Bank of Canada (2020), Deloitte LLP (2020), Mazars Groups (2020)

The central hypothesis of this research is that sustainable investment instruments are risky assets, and investment bodies must consider this very seriously in any investment decision. There is still a lack of scientific research about sustainable bonds, so our article analyzes sustainable fixed-income indices to add value to this gap in the scientific literature.

3. Data and methodology

In this research, we focus on sustainable financial instruments and use the case of fixed-income securities indices. A sustainable fixed-income index typically refers to a bond index that includes companies or countries meeting specific sustainability criteria, reflecting their environmental, social, and governance (ESG) practices. The idea behind these indices is to provide investors with a benchmark that aligns with their sustainability values while also aiming to offer competitive returns.

Firstly, we would like to discuss the main features of different sustainable bonds. Based on the standard classification in financial markets in the sustainable fixed-income securities category, we can find three types of bonds: green, social, and sustainability (Table 2).

Table 2. The main characteristics of green, social, and sustainability bonds (source: done by authors)

Aspect	Green Bonds	Social Bonds	Sustainability Bonds
Purpose	Finance environmental projects (e.g., renewable energy, pollution prevention).	Finance social projects (e.g., affordable housing, education, healthcare).	Finance a mix of green and social projects (e.g., healthcare, education).
Use of Proceeds	Exclusively for environmental projects.	Exclusively for social projects.	For both environmental and social projects.
Target Investors	Investors are interested in environmental impact.	Investors are interested in social impact.	Investors with broader ESG interests.
Reporting and Transparency	Detailed environmental impact reporting.	Detailed social impact reporting.	Comprehensive reporting on environmental and social impacts.
Market and Development	Established market, Green Bond Principles.	Growing market, Social Bond Principles.	Evolving market, Sustainability Bond Guidelines.
Examples of Projects	Solar and wind farms, energy-efficient buildings, sustainable forestry, clean transportation.	Affordable housing, educational facilities, healthcare services, employment generation.	Combination projects like renewable energy in underprivileged communities, sustainable healthcare facilities.

After identifying three types of bonds, we analyzed financial market trends and issuance data across countries. Our analysis focuses on the main trends in the sustainable bond market. Figure 1 shows that in 2022, most countries issued green bonds, with Portugal, UAE, Indonesia, Singapore, Norway, and Denmark issuing only green bonds. The Philippines, Chile, Thailand, and Mexico actively issued sustainability bonds, while other countries were inactive in this market. Social bonds were most popular in France, South Korea, and Hungary.

The global sustainable bond market value based on 2022 (Figure 2) indicates that China issues the most sustainable bonds. The United States and Germany follow in second place. Other countries in the list have much less issued amount.

Our research focused on corporate green bond indices because, based on data (Figure 3), corporates are the biggest issuers in the green bond market. The 2022 year data shows that they took 35 percent of all green bond markets.

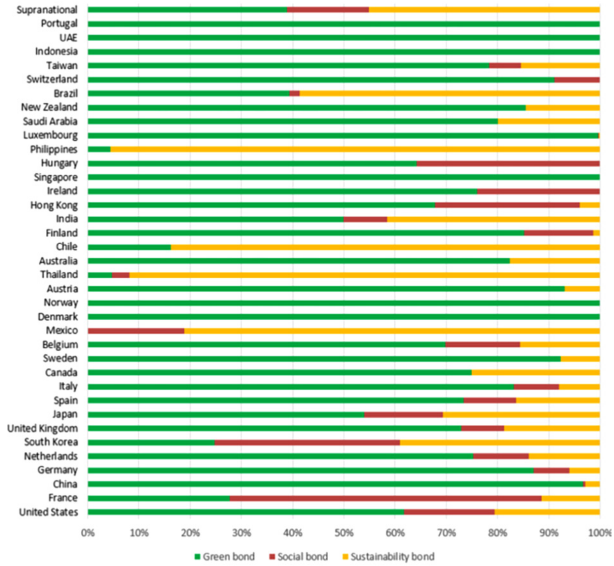


Figure 1. Global sustainable bond market value 2022, by category and country (source: data from Statista, 2024)

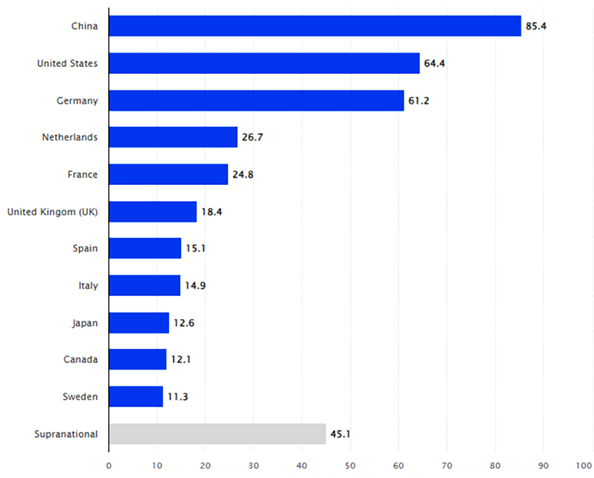


Figure 2. Global sustainable bond market value 2022, by category and country (source: data from Statista, (2024)

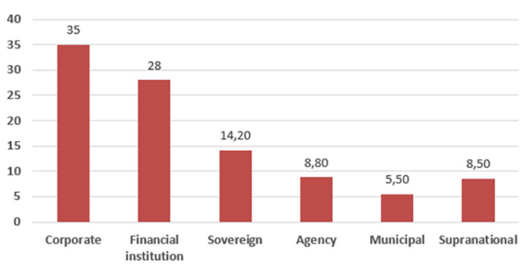


Figure 3. Distribution of green bonds issued worldwide in 2022 by issuer type, % (source: data from Statista, 2024)

Figure 4 shows the data on green bonds by region. Despite China and the United States having significant parts as countries in the sustainable bond market, Europe is the leader of green bonds. From 2017, Europe's role in the green bond market increased significantly. 2022 shows a slight decrease in green bond market emissions after solid growth in 2021.

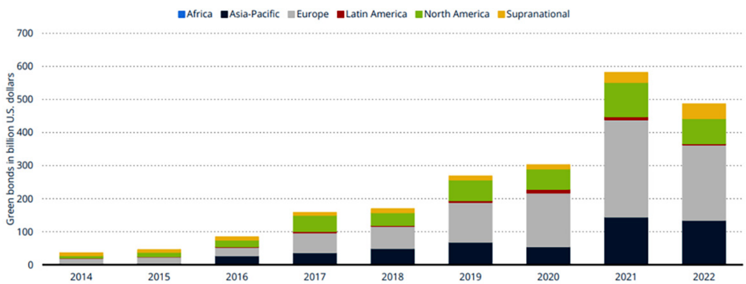


Figure 4. Value of green bonds issued worldwide from 2014 to 2022, by region (in billion U.S. dollars) (source: data from Statista, 2024)

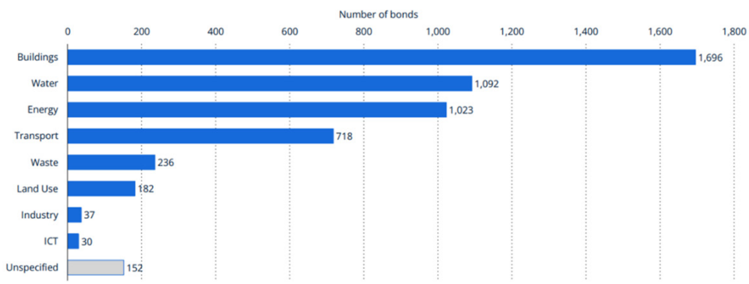


Figure 5. Number of green bonds issued worldwide in 2022 by sector (source: Data from Statista, 2024)

Based on the sector (Figure 5), the most significant amount of green bonds is issued in the building sector. Financial institutions and other investors should keep in mind sectorial diversification while investing in green bonds as well.

3.1. Data description

We focus on green bonds for the fixed-income market because these types of bonds take the biggest part of the sustainable bond market. Our research uses Bloomberg data of 8 sustainable corporate fixed-income indices. The sample for the study included sustainable investment indices of the fixed-income market. The sample was selected based on data availability and the asset class's representativeness. The data included daily closing prices of the sustainable investment indices as well as the daily returns of these indices. The common sample of all data starts from 2019-07-25 until 2022-09-28. The exact list with details about indices can be found in Table 3.

Table 3. Variables description

Short name	Name of sustainable financial instrument	Short description
BL1	Bloomberg MSCI EUR Corporate Liquid FRN 0-7 Year SRI Sustainable Index	It is an investment-grade corporate bond index with a fixed rate. This index features issuers rated BBB or higher by MSCI ESG and excludes those engaged in certain controversial activities, like controversial military weapons. It also omits issuers from emerging markets and caps individual issuer exposure at 5% of the index's total market value, redistributing any excess proportionally. Established in June 2019, it retrospectively includes data from April 2013.
Bl2	Bloomberg MSCI EUR Corporate Liquid SRI Sustainable Index	This index selectively includes issuers rated BBB or above by MSCI ESG Ratings. It excludes those engaged in activities conflicting with specific value-based criteria, like controversial military weapons, or those with a "red" score in MSCI ESG Controversies. It also omits issuers from emerging markets. Launched in May 2019, the index includes historical data dating back to April 2013.
BL3	Bloomberg MSCI Euro Corporate 0-3 Sustainable SRI Index	It is unhedged EUR.
BL4	Bloomberg MSCI Euro Corporate High Yield Sustainable BB+ SRI Bond Index	It is a fixed-rate, high-yield corporate bond benchmark, mirrors the Bloomberg Barclays Euro Corporate High Yield Index's guidelines. From June 2019, it incorporates issuers with MSCI ESG Ratings of BBB or above and excludes those engaged in specific restricted business activities or with a "Red" MSCI ESG Controversy Score. The index also mandates a minimum outstanding amount of EUR 300 million for bonds. Launched in October 2019, it retroactively includes April 1, 2013 data.
BL5	Bloomberg MSCI US Corporate Sustainable SRI	It is a benchmark for investment-grade, US dollar-denominated bonds. It excludes issuers with significant revenue from activities like adult entertainment, alcohol, gambling, tobacco, controversial military weapons, civilian firearms, nuclear power, and GMOs. The index includes only issuers with a minimum ESG rating of BBB. Following the Bloomberg Barclays US Corporate Index's broader criteria, it was launched in December 2019, with historical data from January 2008.
BL6	Bloomberg MSCI USD Corporate Liquid SRI Sustainable Index	It is a fixed-rate, investment-grade corporate bond benchmark adhering to the Bloomberg US Aggregate Corporate Index rules, with added sector and ESG criteria for security selection. It includes issuers rated BBB or higher by MSCI ESG and excludes those involved in certain restricted activities, like controversial military weapons, or with a "red" MSCI ESG Controversy Score. Issuers from emerging markets are also excluded. Launched in June 2019, it retrospectively includes data from January 2014.
EUR1	Euro Corporate Sustainability + SRI Index	It aligns with the Bloomberg Barclays Euro Aggregate Corporate Index's regulations, adding sector-specific and ESG criteria for choosing securities. This index incorporates issuers rated BBB or higher by MSCI ESG, filters out those engaged in certain restricted business practices, including controversial military weapons, and excludes issuers with a "red" MSCI ESG Controversies Score. Initiated in October 2016, it includes historical data going back to January 2007.
ICE1	ICE Euro Corporate Green, Social & Sustainable Bond Index	The index covers the European bond market's green, social, and sustainable bonds.

3.2. Methodology and methods

Eviews software was used to practically realize ARCH and GARCH methods, measure volatility, and identify other statistical parameters.

This research aimed to investigate the risk of sustainable investment indices of different fixed-income securities using ARCH and GARCH models.

ARCH models were used to model the heteroscedasticity in the daily returns of the indices. GARCH models were used to model the persistence of volatility in the returns of the indices. For the GARCH models, we tried various variations as EGARCH, TARCH, and PARCH models. We start our research with indices overview, descriptive statistics, and correlation matrix, then focus on ARCH/GARCH models.

The ARCH and GARCH models were estimated using the maximum likelihood estimation method. The model performance was evaluated using goodness-of-fit tests such as Akaike Information Criterion (AIC), Log likelihood, Schwarz Criterion, Hannan-Quinn Criterion. The study also made use of diagnostic tests such as residual diagnostics and autocorrelation tests to check for the adequacy of the models.

Sudha (2015) made a study on risk-return and volatility of S&P ESG India Index and analyzed conditional volatility using GARCH models. The results showed that volatility clusters existed in sustainable investments and that the sustainable index was less volatile than other broad equity indices. Sadorsky (2014) focused on Dow Jones sustainability index and compared it with gold and oil using multivariate GARCH models and concluded that DCC-GARCH model was better than other models for hedge ratios and optimal portfolio construction. Folqué et al. (2021) researched ESG risks in a sustainable portfolio management framework, analyzing different investment strategies. Authors of the latter research have used parametric analysis of variance method. Their results showed that investment funds with a negative screening strategy had worse ESG risk scores and carbon risk.

We add value to the scientific literature by analyzing different GARCH-type models in the sustainable bond market. Our study provided insights into the level of risk involved in investing in sustainable indices across different regions and types of sustainable bonds and helped investors make informed investment decisions.

Our paper uses ARCH and GARCH models to identify volatility differences among different sustainable fixed-income instruments. First, we start our research using the ARCH model (autoregressive conditional heteroscedasticity model). Second, we apply different GARCH models. And third, we compare results from ARCH and GARCH models. Our research process is explained in Figure 6.

Modeling financial data returns, we express returns as a series of log returns.

The Autoregressive Conditional Heteroskedasticity (ARCH) model is a statistical model used for modeling financial time series data, especially for capturing the phenomenon of volatility clustering, a common trait in financial markets where periods of high volatility are followed by high volatility and low volatility by low volatility. The ARCH model was introduced by Robert F. Engle in 1982. The ARCH model's basic form is ARCH(q). Conditional Variance Equation (ARCH component) can be defined as follows (Eq. (1)):

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 \epsilon_{t-2}^2 + \ldots + \alpha_q \epsilon_{t-q}^2. \tag{1}$$

The mean calculation is as follows (Eq. (2)):

$$y_t = \mu + \epsilon_t. \tag{2}$$

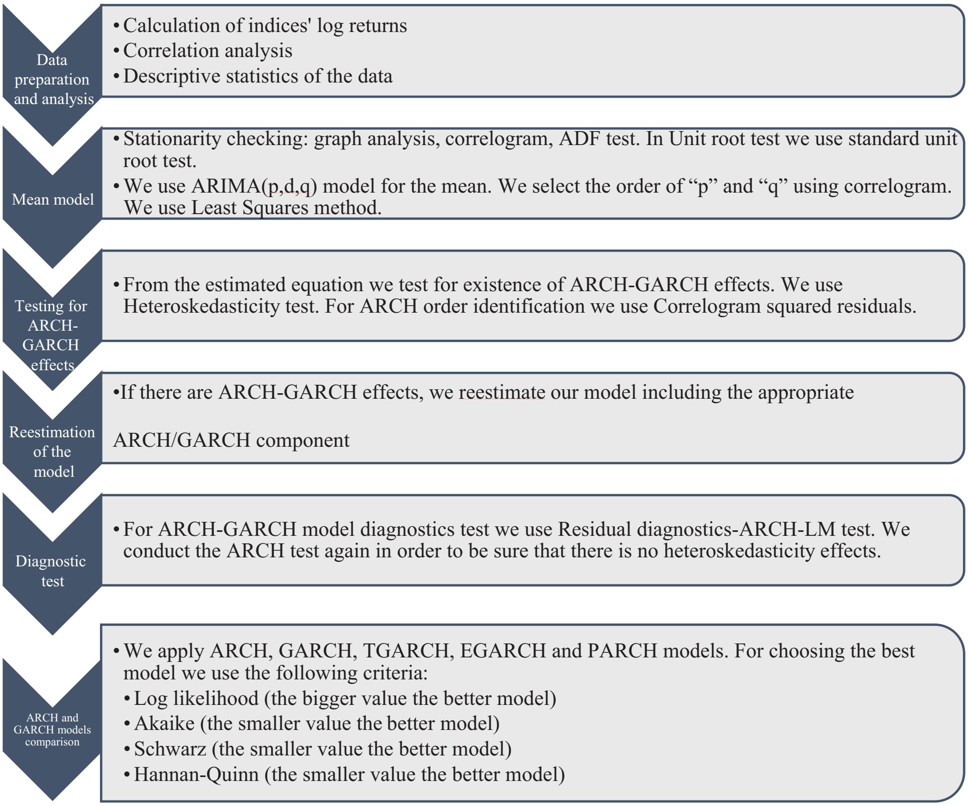


Figure 6. The research process

In the ARCH model, the conditional variance is modeled as a function of the past squared residuals. This captures the tendency for periods of high volatility to cluster together. The model parameters are typically estimated using maximum likelihood estimation.

The ARCH model has been notably extended by the Generalized ARCH (GARCH) model, created by Tim Bollerslev in 1986. The GARCH model includes lagged conditional variances in the variance equation, enhancing the flexibility and accuracy of volatility dynamics representation. This extension, building on the initial ARCH model by Robert F. Engle, addresses its limitations and is more effective in modeling financial time series data, particularly for capturing long-term volatility dependencies. The conditional variance in GARCH can be explained as follows (Eq. (3)):

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_1 \epsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2. \tag{3}$$

In our research, we use other models as well. All the models and the main features we tried to describe in Table 3.

The Threshold Autoregressive Conditional Heteroskedasticity (TARCH) model, also known as the GJR-GARCH model (after Glosten, Jagannathan, and Runkle), is a variation of the GARCH model. It accounts for different volatility responses to positive and negative shocks, commonly used to model the "leverage effect" where negative shocks increase volatility more than positive ones. The conditional variance of this model can be calculated as follows (Eq. (4)):

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_1 \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{q} \gamma_i I_{t-i} \epsilon_{t-i}^2. \tag{4}$$

The Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model, developed by Daniel B. Nelson in 1991, addresses the limitations of the GARCH model, especially asymmetry and leverage effects in financial data. The EGARCH model uses the logarithm of conditional variance, allowing for asymmetric shock effects without non-negativity constraints on parameters. The primary formula for the EGARCH model is as follows (Eq. (5)):

$$\log\left(\sigma_t^2\right) = \alpha_0 + \sum_{i=1}^{p} \beta_j + \log(\sigma_{t-i}^2) + \sum_{j=1}^{q} \left[\alpha_j \frac{\left|\epsilon_t - j\right|}{\sigma_t - j} + \gamma_j \frac{\epsilon_t - j}{\sigma_t - j} \right]. \tag{5}$$

The Power ARCH (PARCH) model is another extension of the ARCH family of models, designed to model financial time series data. The PARCH model is similar to the GARCH model but introduces a power term to the conditional variance equation, allowing for more flexibility in modeling volatility dynamics. This model's conditional variance formula can be expressed as follows (Eq. (6)):

$$\sigma_t^\delta = \alpha_0 + \sum_{i=1}^{q} \alpha_i \left|\epsilon_{t-1}\right|^\delta + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^\delta. \tag{6}$$

The PARCH model's introduction of the power term provides additional flexibility over the GARCH model, especially in capturing the asymmetry and leptokurtosis (fat tails) often observed in financial time series data. This feature makes it particularly useful for modeling and forecasting volatility in financial econometrics.

Table 4. TARCH, EGARCH, and PARCH models' main features

Feature/Model	TARCH (Threshold ARCH)	EGARCH (Exponential GARCH)	PARCH (Power ARCH)
Primary Characteristic	Models the different impact of positive and negative shocks on volatility.	Models the asymmetric effects of shocks and adjusts for leverage effects.	Introduces a power term to model the variance, allowing for flexible modeling of the volatility process.
Volatility Equation	Involves a term that changes depending on whether past shocks are positive or negative.	The logarithm of the variance is modeled, allowing for negative and positive shocks to have different impacts.	Uses a power transformation of the lagged errors and conditional variance in the variance equation.
Asymmetry in Shocks	Specifically designed to capture asymmetry in volatility due to positive and negative shocks.	Captures asymmetry and the leverage effect, where negative shocks might have a larger impact than positive ones.	Can capture asymmetries if the power parameter (δ) is different from 2.

End of Table 4

Feature/Model	TARCH (Threshold ARCH)	EGARCH (Exponential GARCH)	PARCH (Power ARCH)
Persistence of Shocks	Can model the persistence of shocks in volatility.	Models the persistence of shocks and their impact over time in an exponential format.	Like TARCH, it can model the persistence but with the added flexibility due to the power parameter.
Complexity	More complex than standard GARCH but simpler than EGARCH and PARCH.	Generally more complex due to the logarithmic specification.	More complex due to the additional power parameter.
Parameter Estimation	Standard maximum likelihood estimation (MLE).	MLE, with careful attention to the non-linear nature of the model.	MLE, with potential challenges due to the power term.
Typical Applications	Financial markets where the impact of shocks varies depending on their direction.	Financial time series with pronounced leverage effects and asymmetries.	Financial time series where a flexible modeling of variance is required.

Table 4 presents the main features of three different GARCH models: TARCH, EGARCH, and PARCH.

4. Results and discussion

The main goal of this research is to identify the volatility of different sustainable fixed-income indices and to find the best GARCH model for volatility estimation. For the analysis we use daily data of different bond indices (Table 2). Our analysis has limitations because some indices are new and do not have a long history. But despite this disadvantage, we analyze more indices because we aim to compare volatility issues in different sustainable financial products.

First, we plot our results to see if any volatility clusters in the data are serious (Figure 7). From the plotted results, we can see that every index has volatility clusters. Some indices are more volatile than others, but two volatility clusters in the analyzed period are apparent. The first volatility cluster is related to the COVID-19 pandemic, and the second cluster is connected with changes in monetary policy. The fixed-income market is susceptible to changes in the level of base interest rates. When central banks start increasing interest rates, then yields of fixed-income securities start growing, and the prices decrease. Usually, in financial markets, volatility is based on investors' expectations, so prices react earlier than the actual actions start. Investors' expectations regarding monetary policy changes during the analyzed period differed in comparing regions. Investors' expectations regarding the United States monetary policy started to change much earlier than the euro area. These differences in expectations are visible in the indices of the US market and positions in US dollars because changes in monetary policy are also related to changes in the foreign exchange rate.

Despite the idea that all sustainable fixed-income indices are very similar, we can still see some differences in their returns. For that purpose, we try to calculate the correlation in order to identify possible diversification effects, including sustainable fixed-income investments.

From the correlation matrix (Table 5), we can see that some peers of indices are strongly correlated, while others have very weak or even negative correlation.

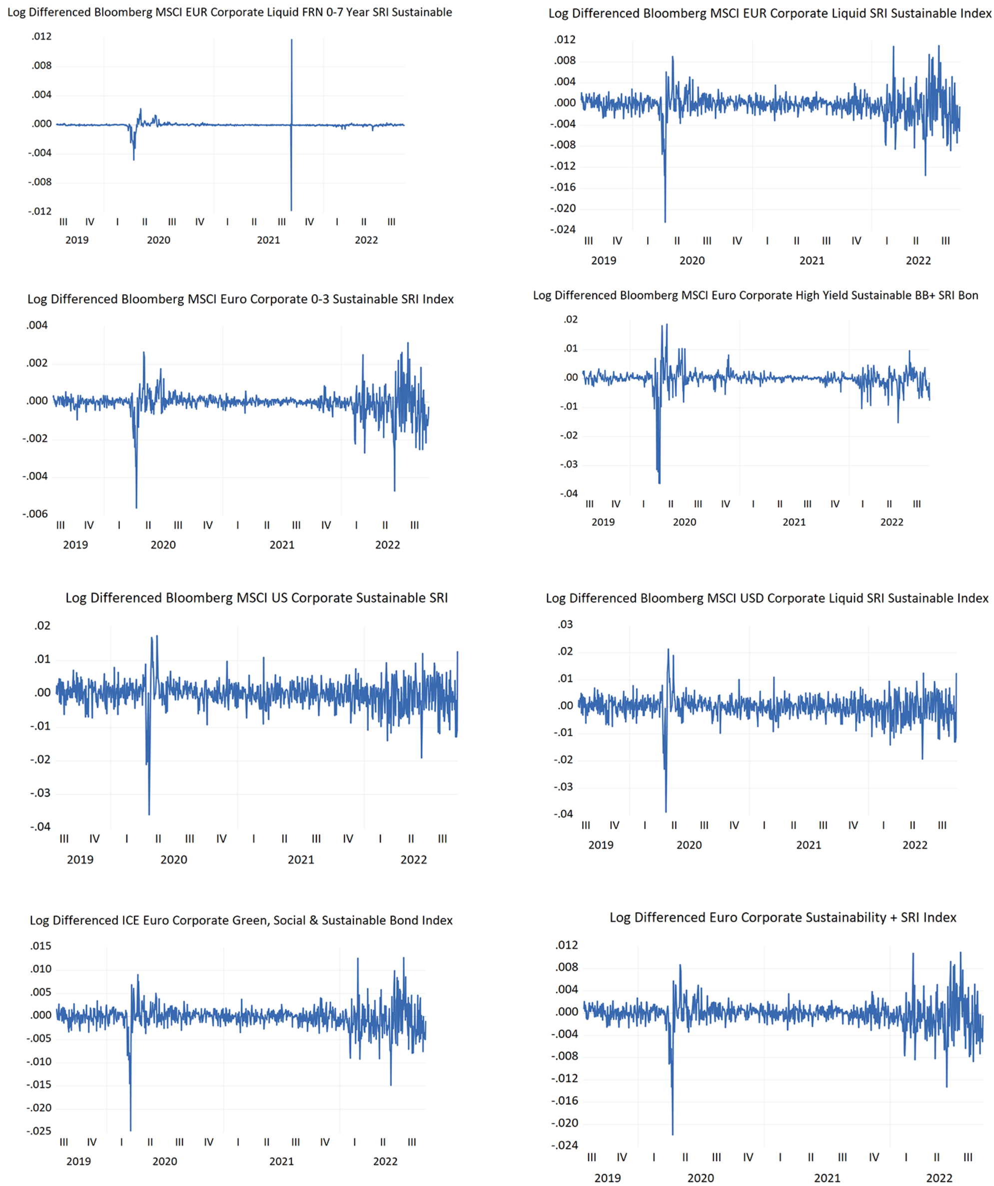


Figure 7. Volatility of sustainable fixed income indices

The lower the correlation, the more the pair of indices is suitable for diversification and risk management. Some fixed-income sustainable indices are strongly correlated and are not suitable as a pair for volatility risk management. Investors must pay attention to correlation issues by making strategic decisions. The best fixed-income sustainable index suitable for diversification in all cases is the ICE1 Euro Corporate Green, Social & Sustainable Bond Index. This index has negative correlations with most of the other indices. The index covers the European bond market and includes green, social, and sustainable bonds.

Table 5. Correlation matrix

	BL1	BL2	BL3	BL4	BL5	BL6	EUR1	ICE1
BL1	1.00	0.26	0.28	0.37	0.07	0.07	–0.01	–0.05
BL2	0.26	1.00	0.94	0.63	0.08	0.08	–0.08	–0.18
BL3	0.28	0.94	1.00	0.65	0.11	0.12	–0.12	–0.21
BL4	0.37	0.63	0.65	1.00	0.04	0.05	–0.07	–0.18
BL5	0.07	0.08	0.11	0.04	1.00	0.99	–0.09	–0.09
BL6	0.07	0.08	0.12	0.05	0.99	1.00	–0.08	–0.09
EUR1	–0.01	–0.08	–0.12	–0.07	–0.09	–0.08	1.00	0.95
ICE1	–0.05	–0.18	–0.21	–0.18	–0.09	–0.09	0.95	1.00

The next step in our research is to check the main descriptive statistics parameters (Table 6).

Table 6. Descriptive statistics

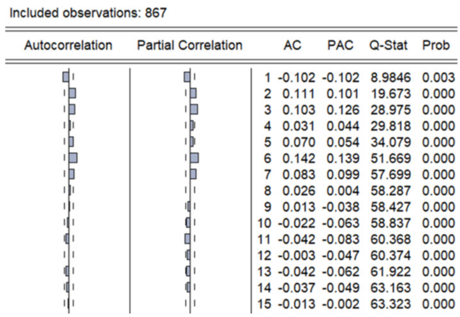
	BL1	BL2	BL3	BL4	BL5	BL6	EUR1	ICE1
Mean	0.00	0.01	0.00	0.01	0.00	0.00	0.01	0.01
Median	0.00	0.00	0.00	–0.01	–0.03	–0.02	–0.01	–0.01
Maximum	1.17	2.24	0.56	3.62	3.60	3.88	2.18	2.47
Minimum	–1.17	–1.36	–0.31	–1.88	–1.74	–2.57	–1.09	–1.28
Std.Dev.	0.07	0.25	0.05	0.37	0.41	0.47	0.20	0.25
Skewness	1.07	0.75	1.98	3.67	1.41	0.77	1.47	1.38
Kurtosis	164.10	14.76	24.96	40.66	12.82	13.08	19.92	18.01
Jarque-Bera	937741.61	5079.96	26630.37	50852.50	4291.98	3696.69	15783.69	9516.65.
Sum	0.12	8.70	3.00	8.12	–1.00	–0.79	8.99	10.47
Observations	867	867	1284	829	987	853	1284	980

Table 6 shows that the most significant volatility is identified for (BL6) index, which is the Bloomberg MSCI USD Corporate Liquid SRI Sustainable index, which is an investment grade index that should be more stable. The volatility of the mentioned index is even higher than the volatility for (BL4) Bloomberg MSCI Euro Corporate High Yield Sustainable BB+ SRI Bond Index. As we understand and see as based on credit risk assessment high yield bonds volatility usually is much higher. However, the mentioned conditions can be true when no other significant factors influence the bond yields, and everything is mostly based on credit risk measurement. This time, the main explanation is not in credit risk level but in monetary policy decisions between regions. Investors' expectations about changes in monetary policy have changed much earlier than expectations for the European region.

Based on our research design, the next step is estimating the ARCH model. We use the Augmented Dickey-Fuller (ADF) test to check for stationarity, a statistical test for unit roots in a time series. It enhances the original Dickey-Fuller test and is commonly used in econometrics to test the null hypothesis that a time series is non-stationary with a unit root. A unit root indicates a stochastic trend, meaning the series is non-stationary, with changing statistical properties like mean and variance over time, making modeling and forecasting difficult. The presence of a unit root means shocks have a permanent effect on the series.

After the unit root test, we identify that the returns of the Bloomberg MSCI EUR Corporate Liquid FRN 0-7 Year SRI Sustainable Index are stationary and that we can reject the null hypothesis that returns have a unit root.

We try different AR and MA combinations for mean model identification and find the best results with AR(3) and MA(3). The results are presented in Figure 8.



Included observations: 867

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.102	-0.102	8.9846	0.003
		2	0.111	0.101	19.673	0.000
		3	0.103	0.126	28.975	0.000
		4	0.031	0.044	29.818	0.000
		5	0.070	0.054	34.079	0.000
		6	0.142	0.139	51.669	0.000
		7	0.083	0.099	57.699	0.000
		8	0.026	0.004	58.287	0.000
		9	0.013	-0.038	58.427	0.000
		10	-0.022	-0.063	58.837	0.000
		11	-0.042	-0.083	60.368	0.000
		12	-0.003	-0.047	60.374	0.000
		13	-0.042	-0.062	61.922	0.000
		14	-0.037	-0.049	63.163	0.000
		15	-0.013	-0.002	63.323	0.000

Figure 8. Mean model identification

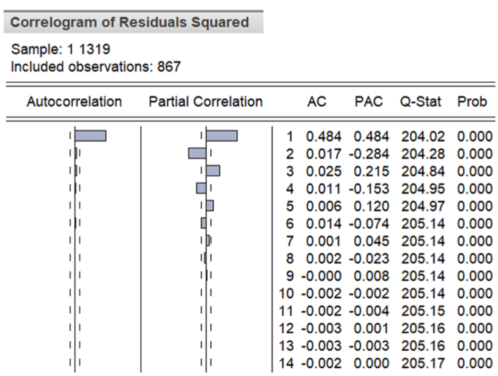
We conduct the Heteroskedasticity test and select the ARCH option.

H0 – there are no existing ARCH effects up to the specified lag

H1 – there are ARCH effects up to the specified lag.

If $p < 0.05$, we reject the null hypothesis and confirm the existence of ARCH effects.

Based on the results of calculations, we confirm ARCH effects in the data. For ARCH order identification, we use a correlogram of residuals squared (Figure 9).



Correlogram of Residuals Squared

Sample: 1 1319
Included observations: 867

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.484	0.484	204.02	0.000
		2	0.017	-0.284	204.28	0.000
		3	0.025	0.215	204.84	0.000
		4	0.011	-0.153	204.95	0.000
		5	0.006	0.120	204.97	0.000
		6	0.014	-0.074	205.14	0.000
		7	0.001	0.045	205.14	0.000
		8	0.002	-0.023	205.14	0.000
		9	-0.000	0.008	205.14	0.000
		10	-0.002	-0.002	205.14	0.000
		11	-0.002	-0.004	205.15	0.000
		12	-0.003	0.001	205.16	0.000
		13	-0.003	-0.003	205.16	0.000
		14	-0.002	0.000	205.17	0.000

Figure 9. ARCH order identification

We choose the ARCH lag one. If we increase the number of lags, we get negative lag results. After choosing the lag, we make ARCH(1) model estimation.

Our model for the mean equation includes a constant "c" and AR(3) and MA(3) components. We included 1 ARCH effect. The variance formula is as follows:

$$\sigma_t^2 = 0.0023 + 0.1702\varepsilon_{t-1}^2. \quad (7)$$

The variance because of only 1 ARCH lag adds up to 0,17. So, the persistence of the volatility is low in this case because the persistence of volatility is higher when it is closer to 1. Based on the calculation, the return of the index can be determined using the formula

$$bl1return_t = -0.0053 + 0.7176bl1return_{t-1} - 0.6077\grave{o}_{t-1} + \epsilon_t. \tag{8}$$

We conducted the ARCH test again to ensure that there were no ARCH effects. The results showed that residuals had no heteroskedasticity.

In the next step, we start using GARCH models. We start with the GARCH (1,1) model.

Our results indicate that volatility shocks persist, as presented by the sum of the ARCH and GARCH parameters, for a considerable period (Eq. (9)). This means that the effect of today's shock remains the forecasts of variance for many periods in the future.

$$\sigma_t^2 = 0.0013 + 0.5411\varepsilon_{t-1}^2 + 0.3344\sigma_{t-1}^2; \tag{9}$$

$$bl1return_t = -0.0040 + 0.2472bl1return_{t-1} + 0.2331\epsilon_{t-1} + \epsilon_t. \tag{10}$$

We do GARCH model diagnostics for residuals using the ARCH heteroskedasticity test to ensure no heteroskedasticity in our model.

Table 7. The comparison of ARCH(1) and GARCH(1,1) parameters

	Index	ARCH(1) MODEL VOLATILITY PARAMETERS		GARCH(1,1) MODEL VOLATILITY PARAMETERS		
Region/credit rating		C	RESID(–1)^2	C	RESID(–1)^2	GARCH(–1)
Europe, investment grade	BL1	0.003496	0.171429	0.003458	0.150000	0.600000
Europe, investment grade	BL2	0.036250	0.164971	0.010294	0.118050	0.568050
Europe	BL3	0.001884	0.171429	0.000321	0.148457	0.598457
Europe, high-yield	BL4	0.068312	0.151060	0.036809	0.099093	0.549093
US, investment grade	BL5	0.107123	0.168283	0.044184	0.085114	0.535114
US, investment grade	BL6	0.146144	0.170751	0.070227	0.075002	0.525002
Europe	ICE1	0.034869	0.166132	0.008669	0.118939	0.568939
Europe, investment grade	EUR1	0.021731	0.165957	0.006281	0.129374	0.579374

The results (Table 7) show that in a sustainable corporate bond market, volatility persistence is lower in Europe's high-yield corporate bonds. The other conclusion is that volatility persistence is lower in the US markets because they are more liquid.

We have tried the same GARCH models with all eight sustainable fixed-income indices and got the same results: the PARCH model is the best for volatility estimation. PARCH model is the best for a given financial time series (Table 8). It implies that the series has complex volatility patterns that are best captured by a model that allows for non-linear effects of shocks and potentially captures the asymmetric impacts of these shocks more accurately than simpler models. We did the same analysis with all other fixed-income sustainability indices and got the same results. The PARCH model was used by other authors as well. Guirguis (2024) analyzed the cryptocurrency market and identified that from EGARCH, TGARCH, and PARCH, the latter was the most suitable. Despite the market for analysis being different compared to our results but the idea remains the same. Meher's et al. (2024) research of different GARCH models also supports our results as they identified the PARCH model as the best for Austria and USA stock markets volatility modeling.

Table 8. The criteria of best model choice comparing different GARCH models

Criteria	ARCH (1)	GARCH (1,1)	EGARCH (1)	TARCH (1)	PARCH (1)	Best model
Log-likelihood (the bigger value, the better the model)	1306.795	1387.253	1394.321	1390.103	1407.836	PARCH
Akaike (the smaller value, the better model)	–3.013415	–3.197344	–3.203675	–3.196543	–3.237496	PARCH
Schwarz (the smaller value, the better model)	–2.985859	–3.164278	–3.165468	–3.163536	–3.20449	PARCH
Hannan-Quinn (the smaller value, the better model)	–3.002868	–3.184688	–3.189238	–3.183911	–3.224864	PARCH

Other authors got different results compared to us. Wang et al. (2021) made a volatility analysis based on GARCH-type models using data from the Chinese stock market. Their results were different compared to our research as they identified different best model for different indices of China stock market. ARMA (4,4)-GARCH (1,1) model under Student's t-distribution was the best for forecasting the Shanghai Composite Index return series, and for Shenzhen Component Index, ARMA(1,1)-TGARCH(1,1) showed the best results. The other authors also more focused on stock markets and got different results: Aman et al. (2024) used GARCH, TGARCH, EGARCH, IGARCH, PARCH, APARCH models for Hungary stock market and identified APARCH(1,1) as the best model.

The use of PARCH suggests the presence of volatility clustering in the data. This means periods of high volatility tend to be followed by high volatility, and periods of low volatility tend to be followed by low volatility.

The non-linearity implies that the effect of large and small shocks on volatility is different and more complex than what simpler models can capture. In our research, the model puts relatively more weight on more minor shocks than larger ones.

The most essential aspects for investors in investments should not be only return but also investment risk is essential. Volatility can be considered a measure of risk and helps explain how volatile investments can be.

For future research, we would like to apply different GARCH models to a sustainable stock market and compare the results with fixed-income market financial instruments.

5. Conclusions

This research highlights the inherent volatility of sustainable fixed-income indices, with two distinct volatility clusters identified: one linked to the COVID-19 pandemic and another to shifts in global monetary policy. These findings underscore the significant influence of external macroeconomic events on sustainable investments. Despite their ESG focus, these investments are susceptible to the same economic shocks affecting traditional financial products. Notably, the Bloomberg MSCI US Corporate Sustainable SRI Index (BL5) exhibited the highest volatility, surpassing even high-yield bond indices like the Bloomberg MSCI Euro Corporate High Yield Sustainable BB+ SRI Bond Index (BL4), suggesting that monetary policy, rather than credit risk, plays a significant role in volatility across regions.

The study emphasizes the profound impact of central bank policies on sustainable fixed-income markets. U.S. markets showed earlier responses to interest rate changes compared to European markets, indicating that investor expectations vary by region. This regional divergence creates opportunities for investors to manage cross-border portfolios by adjusting to varying volatility patterns.

The correlation matrix analysis reveals diversification opportunities within sustainable fixed-income indices. While some indices are highly correlated, others exhibit weak or negative correlations, offering investors the potential to manage risk. For example, the ICE1 Euro Corporate Green, Social & Sustainable Bond Index demonstrates negative correlations with several other indices, making it an attractive option for portfolio diversification.

Various GARCH models were tested for volatility estimation, with the PARCH model outperforming others. The PARCH model's ability to capture asymmetric and non-linear effects of market shocks suggests that sustainable fixed-income markets have complex volatility patterns that require sophisticated modeling techniques. This insight highlights the importance of using advanced models to forecast and manage volatility in sustainable investments accurately.

Volatility clustering has critical implications for risk management. Investors must manage risk carefully during periods of heightened volatility, as shocks from macroeconomic events or policy changes can have long-lasting effects.

The study also stresses that investors should consider volatility as a key measure of investment risk alongside returns. Sustainable investments, often marketed as more stable, can experience significant volatility. By incorporating advanced volatility models into their analyses, investors can better understand potential risks and make more informed decisions.

The findings suggest practical steps for portfolio managers, such as identifying suitable indices for diversification and using advanced models like PARCH for precise forecasting. Regional differences in market responses to monetary policy further highlight the need for tailored investment strategies across U.S. and European markets.

Our research has some limitations. The analysis is hindered by the limited availability of historical data for many sustainable investment indices, which are relatively new and lack long-term records. This issue, coupled with a primary focus on fixed-income securities and a regional bias towards Europe and the United States, leaves emerging markets and other asset classes underexplored. Challenges in standardizing and comparing ESG data further complicate the assessment of sustainability-related risks. While the study effectively employs ARCH/GARCH models to measure volatility, these models may not fully capture non-linear and extreme market dynamics, and other risk dimensions, such as credit, liquidity, and operational risks, are insufficiently addressed. The research emphasizes macroeconomic factors like monetary policy and the COVID-19 pandemic as drivers of volatility but does not thoroughly examine other potential influences, such as geopolitical risks and technological disruptions. Moreover, behavioral aspects of investor sentiment and forward-looking risk scenarios, such as climate stress testing, are absent from the analysis. Finally, limited attention to the evolving regulatory and policy landscape reduces the scope for understanding the broader implications of sustainable investment strategies. These limitations suggest a need for broader datasets, expanded focus, and more sophisticated methodologies to enhance the research's comprehensiveness and applicability.

Lastly, the study calls for further research to compare volatility patterns between fixed-income and equity markets, particularly in applying GARCH models to the sustainable stock market. Additionally, exploring the role of ESG factors in driving volatility could deepen understanding of how sustainability impacts financial performance in both returns and risk management.

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Author contributions

Conceptualization AKO, DŠ, DV; methodology DŠ, DV; formal analysis AKO, DV; investigation AKO, DŠ, DV; data curation AKO; writing – original draft preparation AKO, DV; writing – review and editing DV, DŠ; visualization AKO; supervision DŠ and DV. All authors have read and agreed to the published version of the manuscript.

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