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Impact of green bonds on traditional equity markets

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ABSTRACT

This study examines the broader U.S. green bond market, with focus on its association with the U.S traditional equity market from 2016–2021. For this purpose, we use the S&P Green Bond Index, the S&P U.S. Aggregate Bond Index, and the S&P 500 to build the connection between the markets based on both univariate generalized autoregressive conditional heteroskedasticity (GARCH) and multivariate vector autoregression (VAR) models. Our empirical results show that the patterns of returns and the volatility behavior of green bonds included significant changes over the years of study. The findings highlight the importance of the emergence and evolution of the promising green bonds market, thus providing useful policy implications for portfolio and risk management as well as asset pricing. This study contributes to a deeper understanding of the impact of green bonds on equity markets.

1. Introduction

Sustainable infrastructure is “critical to achieving global climate targets and Sustainable Development Goals, and to a strong and resilient global economy” (PPIAF/World Bank, 2024, p. 1). It is also a mean for providing economic, social, and environmental benefits in the long run. Among the many innovative green financial instruments, green bonds (GBs) have emerged as the most powerful securities for financing (completely or partially) projects and initiatives, providing clear benefits for the environment (Fatica and Panzica, 2021), corroborating the notion of sustainable infrastructure (Hammoudeh et al., 2020; Pham, 2021), and aligning with the environmental, social, and governance (ESG) criteria (Bouteska et al., 2024).

The first GBs were issued by supranational and subsovereign agencies such as the European Investment Bank (EIB) (Ferrer et al., 2021), the World Bank, the International Finance Corporation (IFC), national development banks, and local funding organizations (Kaminker, 2017). In 2007, the EIB issued the Climate Awareness Bond (CAB) for an amount of $630 million, with a 5-year maturity. Its returns were connected to the environmental index, which was created to account for the performance of European companies involved with sustainable models. The CAB was completely subscribed, after which a second tranche was issued in 2009 for

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approximately $252 million, through the brokerage of the private bank Dresdner Kleinwort (Mathews and Kidney, 2012). In 2008, the World Bank issued a 6-year GB in Swedish currency, in cooperation with Skandinaviska Enskilda Banken, for a total amount of $262 million. The investment grade instrument was oversubscribed, due to a 0.25 % higher interest rate than the Swedish bond rates and an influx of numerous institutional investors, especially pension funds (Mathews and Kidney, 2012).

In 2013, the GB market witnessed a real evolution, due to the market entrance of private actors with labeled and unlabeled green debt securities. In this case, the "labeled" GBs represented fixed-income instruments formally recognized by independent third parties, while the "unlabeled" GBs were issued by entities with the ability to influence the environment based on their business activities (e.g., the production of wind or solar energy). The latter type also involved climate-aligned bonds, as defined by the Climate Bonds Initiative (CBI), the only international, investor-focused, not-for-profit organization to mobilize $100 trillion in global capital for climate action (Kaminker, 2017). In the same year, the first corporate GBs were issued by Électricité de France, the Bank of America, and a Swedish real estate company. Meanwhile, municipalities and local governments entered the market by triplicating its dimensions.

The first asset-backed security (ABS) was issued by a U.S. public company financing investments that reduce greenhouse gas (GHG) emissions. This debt instrument was backed by hundreds of renewable energy systems installed in different properties (Kaminker, 2017). Given the central debate on the ESG criteria in the economic scenario, many companies from widely different sectors have decided to participate in the market, especially organizations involved in transport and waste. In 2014, Toyota was the first company in the automotive industry to use a green ABS (for an amount of $1.75 billion) to finance loan/lease contracts for more electric and hybrid cars, satisfying the criteria of fuel efficiency (Toyota Motor credit corporation, 2015). The same year saw the issuance of the first emerging market municipal GB to finance low-carbon projects and transports in South Africa. As the first technology company, Apple issued a $1.5 billion GB in 2016 to help reduce global warming and pollution through renewable energies. In South America, the Brazilian development bank BNDES issued a $1 billion GB in 2017 to finance green projects related to solar and wind energies. In 2018, the partnership between the IFC and the asset manager Amundi launched the world's largest GB fund, i.e., Amundi Planet Emerging Green One, with the main goal of increasing the issuance of debt securities by local financial institutions in emerging markets (Kaminker, 2017). For the issuers, the direct and indirect participation in GBs guaranteed impressive reputational growth, since they could improve their ESG performance and visibility to the markets, thus attracting more investors and resulting in improved corporate financial performance, including higher stock valuations (Baker et al., 2018; Tang and Zhang, 2020; Chai et al., 2022).

In recent years, a growing number of studies have analyzed and documented GB performance, evidencing their correlation with other financial markets and similar volatility behaviors (Reboredo, 2018). On the one hand, the issuance of GBs in the U.S. dollar (USD) and the euro (EUR) can help establish an intuitive connection between currency appreciation/depreciation and the value of GBs (Jiang et al., 2022). When a particular financial market oscillates, investors adjust the strategies associated with managing their portfolios and move the investments from one market to another, causing a "butterfly effect" of shifting accumulated risks to other markets (Gao et al., 2021; Dhifaoui et al., 2022). On the other hand, as an investment and hedging asset, GBs display a similarity of pricing factors with other financial assets (Reboredo and Ugolini, 2020; Reboredo et al., 2020), causing comovements. GBs also share common features (except "greenness") with fixed-income assets, such as treasury and corporate bonds, and appear to be a substitute for these assets (Reboredo, 2018). Positive abnormal returns that the companies produce based on their engagement in GBs (Krüger, 2015) can also lead to stock market reactions and enhanced corporate reputation and stakeholder trust (Flammer, 2021). For example, following the announcement of GB issuance, stock prices tend to increase, resulting in improved financial metrics, higher stock returns, and lower volatility (Baker et al., 2018; Tang and Zhang, 2020; Chai et al., 2022; Bouteska, et al., 2024b).

Against these backdrops, since a functional connectedness between GBs and financial assets can be postulated, an understanding of this nexus is crucial for assessing the prospective roles of GBs in hedging and managing portfolio risks (Reboredo, 2018). Meanwhile, since the nonfinancial motives of green investors tend to differ in response to diverse market situations over different time periods, it will be timely to hold further investigations of the price transmission between GBs and other financial markets (Jiang et al., 2022; Yadav et al., 2023). Moreover, given that GBs are a contemporary phenomenon that should proliferate around the world, the recent literature on GBs deserves some insightful enhancements (Gianfrate and Peri, 2019).

Therefore, the present study reviews the literature and related methodologies to examine the relationship between the GB and equity markets, since they represent some of the most important financial tools. In line with the empirical results of Pham (2016) and Reboredo (2018), the application of univariate GARCH models has evidenced the presence of a higher level of volatility clustering for the GB index, compared with the conventional bond and equity markets. Equivalent results have been obtained with the implementation of bivariate and multivariate GARCH models. As for the GB market, it has been positively affected by the conventional bond index and, to a lesser extent, by the stock market. Conversely, the conventional bond index has slightly benefited from the positive influence of the GB market, whereas it has suffered from the performance of the equity index. In sum, we can conclude that there have not been diversification benefits for investors in the conventional bond market and, to a lesser extent, for the risk management of equity investments. However, conventional bonds have provided greater diversification benefits for equity investors.

This study contributes to the extant literature in multiple ways. First, to the best of our knowledge, this is the first study to employ a combination of the daily closing prices of the S&P Green Bond Index, the S&P U.S. Aggregate Bond Index, and the S&P 500 from September 2016–December 2021. Second, we focus on the empirical studies conducted by Bollerslev (1986), Engle (2002), and Pham (2016), who analyzed the volatility behavior of the GB market in relation to the conventional bond and equity markets. Then, we compare our findings with those of Pham (2016) and Reboredo (2018) to establish a basis for understanding the behavior of GBs in relation to established financial theories. The observed volatility clustering both affirms certain aspects of such theories, such as the efficient market hypothesis (EMH) and the modern portfolio theory (MPT), while challenging others such as market segmentation and sustainable finance theories. Thus, this study adds value to the current GB literature by providing a deeper and more nuanced discussion of these points and exploring the discrepancies with previous studies. Third, we implement multivariate GARCH models and analyze the relationship among the markets and their volatility behavior (Bouteska et al., 2023a), after which we apply a VAR model to verify the presence of spillover effects among the indexes (Ha et al., 2024). Given the analysis of the financial markets and the empirical results obtained, we confirm that the GARCH models are effective tools for analyzing the volatility behavior of markets, with respect to the VAR model.

The remainder of this study is organized as follows. Section 2 reviews the literature on GBs and the financial markets, while Section 3 describes our data and methodologies for examining the volatility behavior and spillover effects between the conventional bond market and the GB market. Sections 4 and 5 present our volatility behavior analysis and discussion of the results, respectively. Finally, Section 6 concludes this study.

2. Literature review

Given the benefits provided by GBs, this section examines the main financial features of the market, especially its risk profile and return characteristics. It also analyzes the relationship between green debt securities and other financial markets, given the growing interdependence among the financial instruments. Prior to these aspects, we provide a brief introduction to the GB market and its recent international development, with focus on its evolution and the advantages provided to investors.

2.1. GBs: categories, theories, and volatility behaviors

2.1.1. Categories of GBs

"The lack of universally acceptable standards for defining "green" and for measuring the application of GBs and the potential for self-regulation of issuers are some challenges affecting the effectiveness of GBs today" (Lebelle et al., 2020, p. 4). Recent literature has discussed the benefits of GBs with respect to conventional debt instruments, providing useful insights into the relationship between the two markets (Reboredo, 2018; Tang and Zhang, 2020; Bouteska et al., 2024a). However, in terms of conceptualizing GBs, it is important to understand the ways that they are issued in the form of various debt instruments, which include 1) Corporate bonds: Bonds issued by corporate entities financing initiatives with a positive environmental impact; 2) Project bonds: Bonds backed by a specific project (or a set of projects) in which the investors assume the associated risk; 3) Asset-backed securities: Bonds collateralized by a pool of assets, which provide investors with the assurance to rely on both the issuers and the underlying assets in case of default); 4) Municipal bonds: Fixed-income securities issued by region, city, or municipal government; 5) Sovereign bonds: Bonds issued by a national government; and 6) Subsovereign, supranational, and agency bonds: Bonds issued by international financial institutions such as the EIB, the World Bank, etc. As for the latter, these bonds have similar characteristics to those of corporate bonds, municipal bonds, and sovereign bonds. In their empirical study, Partridge and Medda (2020) compared the yield curve of a set of U.S. green-labeled municipal bonds with those of similar regular municipal bonds issued by the same issuers. They found that the "greenium" (or green premium) affects both primary and secondary markets by promoting the issuance of municipal GBs, due to the benefits provided to both issuers and investors. In this case, the former may reduce the cost of capital, while the latter may realize higher profits by selling the GBs in the secondary market.

2.1.2. Theoretical foundation

This study of GBs and their impact on equity markets is based on several key theoretical frameworks. The most relevant theories are as follows.

EMH: The EMH posits that financial markets are "informationally efficient." In this regard, if the GB market is efficient, then the information regarding the environmental benefits and sustainability of green projects is quickly and accurately incorporated into the prices of GBs and related equity markets (Fama, 1970). However, recent studies have examined the efficiency of GB markets and found mixed results, suggesting that while some GB markets may be efficient, others are still developing (Bouteska et al., 2024).

MPT: Introduced by Markowitz (1952), the MPT suggests that investors can achieve optimal portfolios by diversifying their investments to balance risk and return. In this regard, GBs offer a new avenue for diversification, especially for socially responsible investors. Recent empirical evidence has supported the inclusion of GBs in diversified portfolios, indicating that they can enhance portfolio performance by reducing risk and increasing returns, especially in volatile markets (Baker et al., 2018; Flammer, 2021).

Stakeholder Theory: Stakeholder theory emphasizes that companies should create value for all stakeholders, not just shareholders. In this regard, issuing GBs can be seen as a strategy for companies to address the interests of various stakeholders, including customers, employees, and communities, by financing environmentally sustainable projects (Freeman, 1984). Recent literature has suggested that companies issuing GBs tend to experience improved stakeholder relations and enhanced corporate reputation, which can positively impact their stock prices (Tang and Zhang, 2020).

2.1.3. Volatility behaviors of GBs

Numerous studies have analyzed the performance of GB indexes, evidencing their correlation and similar volatility behaviors (Reboredo, 2018). First, as reported by the GBP-SBP Databases & Indices Working Group (2018), the Solactive Green Bond Index is a market value–weighted index that measures the total return of debt securities, denominated in USD. It involves bonds with a face value of at least $100 million and a time to maturity of at least six months. Bonds linked to inflation, convertible bonds, municipal bonds, ABS, or other forms of structured securities are excluded from this index (BNP Paribas, HSBC, 2018).

Second, the S&P Green Project Bond Index and the Green Bond Index include corporate, government, and multilateral bonds, which are in line with the green definition of the CBI and are adequately disclosed by the issuers as debt instrument financing projects with a positive environmental impact. In this case, the bonds must be rated by at least one ratings agency, even if specific credit ratings are not specified (BNP Paribas, HSBC, 2018).

Third, the Bank of America Merrill Lynch Green Bond Index includes green-labeled bonds issued by quasi-governments and corporations that have clearly expressed their commitment to use the proceeds to finance projects that are environmentally friendly. However, securitized and collaterized securities are not included in the index as well as the debt obligations of corporations involved in green industries. The bonds are also issued in different currencies and each one is characterized by a fixed minimum issue size. Moreover, the index includes securities with a fixed coupon schedule and with a minimum of 18 months to maturity from the time of issuance (BNP Paribas, HSBC, 2018).

Finally, the Barclays Morgan Stanley Capital International (MSCI) Green Bond Index includes government-related, corporate, securitized, and treasury bonds issued in different currencies, whose proceeds are involved in a minimum of one of the six MSCI-defined environmental categories: energy efficiency, pollution prevention and control, alternative energy, sustainable water, climate, and green buildings. Bonds whose proceeds are not adequately disclosed by the issuers may be excluded, while more than 10 % of the funds raised are used for projects beyond these categories (BNP Paribas, HSBC, 2018).

2.2. Geographical proliferation of GBs

2.2.1. GBs in the U.S. and European Financial Markets

In Europe, the government of Poland issued its first sovereign GB in 2016 to finance environmentally friendly projects related to renewable energy, sustainable agricultural operations, clean transportation, afforestation, and reclamation of heaps and national parks (Kaminker, 2017). In France, the most impressive rise of the GB market occurred from 2016–2017, with the participation of new nonfinancial corporations and the engagement of government-backed entities. In 2017, the country issued the second sovereign bond to finance projects and initiatives in line with the target set by the Paris Agreement (OECD, 2021). During those two years, green investments in buildings, water, and waste management significantly increased. Meanwhile, an important role in the European GB market was also played by Germany, registering the highest number of Certified Climate Bonds and launching Solactive, the first GB index.

In 2018, Germany ranked second in the European GB market after France, and fourth in the world. The majority of the funds raised was invested in renewable energies, as a result of the country's "energy revolution" or "Energiewende." Additionally, in response to the impressive goals set by the Paris Agreement, Germany decided to limit GHG emissions by substituting the use of nuclear energy with wind and solar energies (Clean Energy Wire). Since then, there has been an increasing percentage of proceeds allocated to low-carbon building, followed by water, waste management, and transport. In this case, the main issuers of short-term debt have been development banks, while the primary issuers of medium-term debt have been financial and nonfinancial corporations.

The third GB market of importance is represented by Italy, where the first green fixed-income instrument was issued in 2014 by the multiutility company Hera. The development of the market has since been supported by the issuances of various energy companies, such as Enna Energia, Innovatec, and Enel, which boosted investments in renewable energies. The following two years were characterized by a significant increase in the number of issuers, with the issuance of the first bond by the public company Ferroviedello Stato Italiane, and the introduction of a dedicated segment in the Italian Stock Exchange to sustainable and green finance. From the policy perspective, Hachenberg and Schiereck (2018) analyzed the impact of environmental regulations on the GB market and suggested that stringent regulations can enhance the positive effects of GB issuance on corporate performance. Moreover, companies in highly regulated markets tend to benefit more from issuing GBs, due to greater investor demand and lower perceived risk.

2.2.2. GBs in Asian Financial Markets

Among the Asian economies, China and India have been the two leading protagonists in the GB market. Specifically, the need to finance new sustainable initiatives corresponding to the Paris Agreement has favored the expansion of the GB market, with the first green debt instrument issued by the Agricultural Bank of China in 2015. In this regard, the majority of the proceeds have been used to finance low-carbon transportation, especially the construction of new metro lines or the extension of previous ones in new cities. The second most important sector has been renewable energies, followed by the construction of infrastructure projects to improve air and water quality.

Despite the vital role of the nation in the global context of green securities, the Chinese market has been suffering from fragmented regulation, represented by three different sets of guidelines issued by the Chinese Central Bank, the National Development & Reform Commission, and the Shanghai Stock Exchange. In collaboration with the Green Finance Committee and the China Society for Finance & Banking, some areas have been identified such as pollution control, clean energy and energy conservation, resource utilization, clean transportation, and adaptation (Dai et al., 2016; Wang et al., 2024). In recent years, the China Green Bond Index and the China Green Bond Select Index have been introduced to trace the performance of publicly issued debt instruments and financing projects with a positive environmental impact. The first one comprises bonds that satisfy one or more criteria defined by the Climate Bond Standards, the Green Bond Principles and Categories, and the Green Bond Issuance Guidelines, while the second refers to GBs meeting all of the standards.

In India, the first GB was issued by YES Bank in February 2015, after which a significant percentage of funds raised has been used to finance renewable energy projects. Meanwhile, investments in transports, waste, and water management have remained insufficient. The first set of guidelines issued by the Securities and Exchange Board of India suggested several categories for defining the "greenness" of investments. However, these guidelines did not boost the transparency of the market, given that the evaluation of projects/initiatives to be financed occurred on a case-to-case basis. More recently, India's Bombay Stock Exchange has assumed a key role in the green scenario, establishing the region's first International Exchange (India INX) (Agarwal and Singh, 2018).

Finally, since 2016, the Asian–Pacific region has dominated the issuance of GBs in emerging markets. In fact, among the Association of Southeast Asian Nations region, six of the 10 countries have issued GBs, i.e., Malaysia, Indonesia, the Philippines, Thailand, Singapore, and Vietnam. Among them, Indonesia, Singapore, and Malaysia have been the leading issuers of GBs. However, most of the region's green securities are issued by nonfinancial corporations, with the first green sukuk issued by a Malaysian company involved in renewable energy technologies and the first green sovereign sukuk issued by the Republic of Indonesia.

2.3. Relationship between the green bond and financial markets

The relationship between bonds and stocks is not only considered crucial for the risk diversification of investment portfolios (Li, 2003), but also for economists and monetary policy authorities. The empirical findings based on daily data of U.S., U.K., and German stock and bond returns evidence a time-varying correlation between the two asset classes. However, given the contemporary nature of GBs, the study of Pham (2016) is considered a pioneering work, who documented the relationship between the green and conventional bond markets by using the daily closing prices of the S&P Green Bond Indices (the S&P Green Bond Index and the S&P Green Project Bond Index) and the S&P U.S. Aggregate Bond Index from April 2010–April 2015, respectively. Based on the analysis of the volatility behavior of each market, the study revealed that the labeled GB market is influenced by a higher level of volatility clustering, compared to the conventional bond market, indicating that it is possible to distinguish quite long periods of both high and low volatility. Meanwhile, the higher correlation in the volatility behavior of both types of bonds reflects the growing interdependence between the two markets, evidencing the presence of spillover effects. More recently, Reboredo (2018) used the daily data of GB indexes from October 2014–August 2017 to investigate the dynamics of the Barclays MSCI Green Bond Index. The study found a high degree of correlation with the Corporate Index (the Barclays Global Aggregate) and the Total Return Index Value (the Bloomberg Barclays Global Treasury). This implies that the GB market is basically a substitute for the global graded fixed-rate corporate debt market and the global government bond market, as evidenced by their comovement both on average and in the tails of their joint distributions. However, the study also highlighted that the GB and equity markets have low symmetric tail dependence, suggesting that green debt securities can effectively reduce the risk involved with stock investments.

Moreover, the GB market appears to be significantly affected by price spillovers in the conventional bond market, but not by price fluctuations in the stock market. Febi et al. (2018) compared the yield spreads of the two markets by addressing the presence of a liquidity risk for GBs. Through a sample of green and conventional debt securities listed on the Luxembourg Stock Exchange and the London Stock Exchange, the researchers analyzed the effect of the excess GB demand on the yield spreads of the two bond markets, evidencing higher liquidity of green debt instruments, compared to the conventional ones from 2014–2016. More recently, based on an investigation of the nexus between the Chinese GB market and other conventional financial markets (e.g., stocks, bonds, forex, commodities, etc.), Gao et al. (2021) reported various spillovers between the GB market and other markets. Conversely, Flammer (2021) investigated the role of GBs in portfolio diversification and found that GBs can enhance portfolio performance, especially in volatile markets. The study found that GBs have lower correlation with traditional asset classes, making them valuable for risk management. Finally, the OECD (2021) suggested that, given a unique issuer, GBs and conventional bonds share the same financial characteristics, including the credit quality, the yield, and the price at which they are issued. This implies that investors are not willing to pay a premium for GBs at the time of issuance, making GBs subject to a type of "flat pricing."

2.4. Conceptual framework and hypotheses

Based on the aforementioned literature review on the nature, evolution, and proliferation of GBs, particularly the association between the GB market and the equity and broader conventional bond markets, we propose a conceptual model, postulating the links between GB issuance, corporate financial performance, and equity market reactions. Specifically, this model hypothesizes that GB issuance positively affects corporate financial performance and equity market reactions through several channels, i.e., reputational gains, risk reduction, and market differentiation (Table 1).

Finally, we address the main research objective of comparing the behavior of GBs with the two financial instruments, especially in terms of volatility and return characteristics. Thus, we present the following hypotheses:

H1. : The issuance of GBs is positively associated with that of a company's stock returns.

Table 1
Channels of the nexus between the GB and financial markets.

Channels	Description	Reference
Reputational gains:	GB issuance signals a company's commitment to sustainability, leading to enhanced reputation and potentially increased demand for its products and services.	Flammer (2021)
Risk reduction:	Financing through GBs can reduce a company's risk profile by aligning its operations with environmental regulations and reducing exposure to environmental liabilities.	Chai et al. (2022)
Market differentiation:	Companies that issue GBs may differentiate themselves in the market, attracting socially responsible investors and gaining a competitive advantage.	Hachenberg and Schiereck (2018)

Source: Literature review.

H2. : Companies that issue GBs experience lower volatility in their stock returns, compared to companies that do not issue such bonds.

H3. : The impact of GB issuance on stock returns and volatility is more pronounced in markets with higher levels of environmental awareness and regulation.

3. Data and methodology

3.1. Data and variables

This study focuses on the U.S. green and conventional bond markets as well as the stock market, given the important dimensions of these financial markets. In our main analysis, we select the S&P Green Bond Index Total Return (SPUSGRN Index) as representative of the GB market, based on the fact that it has been issued by the same index provider of the indexes chosen for the bond and equity markets, represented by the S&P U.S. Aggregate Bond Index (SPUSBMIT) and the S&P 500 (SPX), respectively.

The S&P Green Bond Index Total Return is a market value–weighted index launched in July 2014, due to the collaboration between the S&P Down Jones Indices and the Infrastructure Credit Alpha Group LLC. It includes bonds that follow the CBI criteria and are issued by corporate, government, and multilateral issuers in any currency (GBP-SBP Databases & Indices Working Group, 2018). The S&P U. S. Aggregate Bond Index, also launched in July 2014, represents publicly issued USD-denominated higher rated bonds. Given the information on the S&P U.S. Dow Jones Indices website, the index includes debt securities issued by U.S. treasuries, corporations, quasi-governments, taxable municipal, supranational, foreign agency, federal agency, and covered bonds. The S&P 500, launched in March 1957, is a market capitalization–weighted index that measures the performance of the 500 largest U.S. publicly traded companies, as described by the S&P U.S. Dow Jones Indices website. The rationale for including these variables is based on previous studies. For instance, Bachelet et al. (2019) highlighted the importance of including these indices when analyzing the performance of GBs, while Tang and Zhang (2020) emphasized the role of stock market indices in capturing investor sentiment and market dynamics related to GBs.

For each index, we obtain the daily closing prices from Bloomberg from September 30, 2016–December 31, 2021, covering a period of significant growth and development in the GB market. The inclusion criteria are as follows: 1) GB issuances from reputable sources such as the CBI; 2) Stock market indices from major stock exchanges; and 3) Bond indicators from reliable databases such as Bloomberg. Additionally, to ensure the robustness of the analysis, data points with significant missing values/anomalies are excluded.

Fig. 1 plots the dynamics of daily closing prices for the three indexes, indicating that the conventional and green bond markets are quite similar from 2018 onward, especially in terms of upturns and downturns. Conversely, the performance of the U.S. equity markets is different (and at times even divergent) from the bond markets.

At this point, we compute the daily returns by dividing the difference between the price of the second day and the price of the previous day by the price of the second day, according to the following formula:

$$R_t = P_t - P_{t-1}/P_{t-1} \tag{1}$$

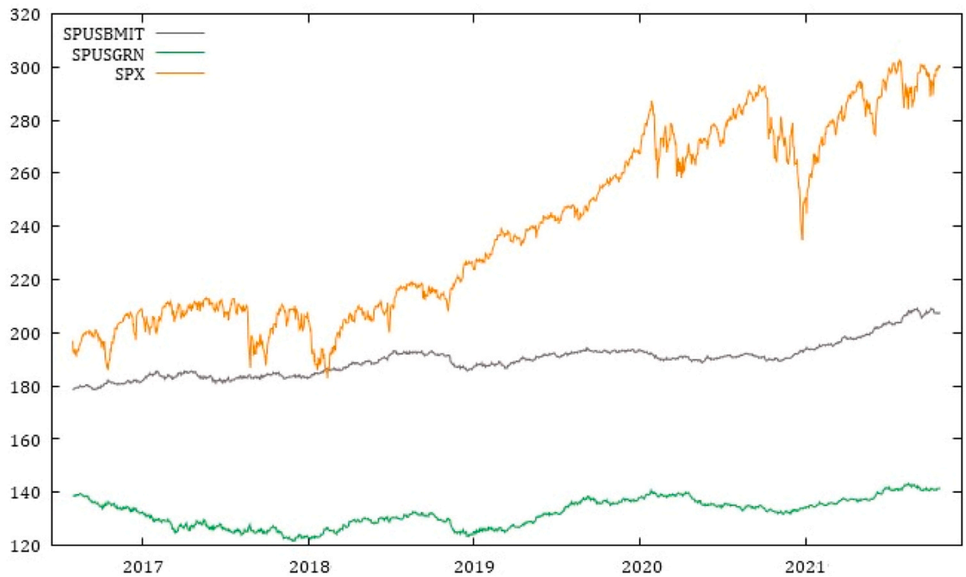


Fig. 1. Daily closing prices of the S&P U.S. Aggregate Bond Index (SPUSBMIT), the S&P Green Bond Index (SPUSGRN), and the S&P 500 (SPX) from 09/30/2016–12/31/2021.

Table 2 presents the descriptive statistics and correlation coefficients for the daily returns. The findings are as follows. First, the average returns are close to zero for all three series, with the highest average returns for the S&P 500 (SPX), while the mean values of all three indexes are larger than their standard deviations. Second, the GB market has higher volatility than the conventional bond market, but it is significantly lower than the equity market. Third, all three series evidence negative skewness, with the lowest value for the S&P Green Bond Index (SPURSGRN), indicating that the return distributions are weakly shifted to the left, especially for the equity market. Fourth, the high values of the Jarque–Bera tests rejects the null hypothesis of the data normally distributed for the time series of the three returns, which is confirmed by the values of kurtosis. Finally, there is a leptokurtic distribution of the stock index whose kurtosis is higher than 3.

As shown in Fig. 2a, the daily returns of the S&P Green Bond Index are characterized by higher volatility during the first two years. This evidence is confirmed by the squared (Fig. 2b) and absolute value of returns (Fig. 2c), which can be considered as a proxy of the realized volatility.

Similarly, the conventional bond market provides evidence of significant volatility until the first half of 2019. This is confirmed by Fig. 3, which displays the daily returns (Fig. 3a), the squared returns (Fig. 3b), and the absolute value of returns (Fig. 3c).

The volatility behavior of the S&P 500 has been quite different over the years, with periods of high and low stability. Fig. 4 presents the daily returns (Fig. 4a) of the equity market, displaying their low volatility from the second half of 2018–2020. This is confirmed by the squared returns (Fig. 4b) and the absolute value of returns (Fig. 4c).

3.2. Data reliability and validity

3.2.1. Cross-verification

In this study, data points are cross verified with secondary sources (when available). Specifically, key metrics from the S&P indices are compared with similar indices from other providers to check for consistency. As for cross-verification, it involves checking the data points from the primary source (the Bloomberg database) against other available secondary sources. The purpose is to ensure the data's accuracy by confirming that different sources report similar figures. For example, if Bloomberg reports a particular value for an index, then the same value should ideally be found in other financial databases/reports.

To ensure consistency, key metrics from the S&P indices are compared with those from similar indices provided by other organizations. This involves examining comparable indices from different providers (such as the MSCI, the Financial Times Stock Exchange, etc.) and determining if they exhibit similar trends and values. This step is important because it identifies any discrepancies that might suggest errors/anomalies in the data from any single source.

3.2.2. Statistical validation

In order to illustrate the preliminary statistical tests in this study, we present our dataset and conduct the Ljung–Box test for autocorrelation and the Jarque–Bera test for normality on the S&P Green Bond Index Total Return (SPUSGRN), the S&P U.S. Aggregate Bond Index (SPUSBMIT), and the S&P 500 (SPX). The results of both tests in relation to the three indexes are presented in Tables 3 and 4, respectively.

Specifically, the Ljung–Box test checks for the presence of autocorrelation in the time series. In this case, the null hypothesis is that the data are independently distributed (i.e., no autocorrelation). A high p-value (>0.05) indicates that we cannot reject the null hypothesis, suggesting no significant autocorrelation. For the SPUSGRN Index, the p-value is 0.49, while the p-value is 0.72 for the SPUSBMIT Index and 0.26 for the SPX Index, all indicating no significant autocorrelation.

As for the Jarque–Bera test, it determines whether the data distribution is normal. The null hypothesis is that the data follow a normal distribution. A high p-value (>0.05) indicates that we cannot reject the null hypothesis, suggesting that the data are normally distributed. For the SPUSGRN Index, the p-value is 0.46, while the p-value is 0.64 for the SPUSBMIT Index, both indicating a normal distribution. For the SPX Index, the p-value is 0.11, indicating that the data are approximately normally distributed, but less so than the

Table 2
Descriptive statistics.

	SPUSBMIT	SPUSGRN	SPX
Mean	0.00011174	0.0000208	0.0003632
Maximum	0.00665	0.01492	0.05234
Minimum	−0.00910	−0.01451	−0.04325
Variance	2.880E−06	9.194E−06	7.416E−05
Std.Dev.	0.00174	0.00311	0.00885
Skewness	−0.17569	−0.17412	−0.44337
Kurtosis	1.1428	1.9472	3.9550
JB	77.0881	211.036	885.9435
Correlation matrix			
SPUSBMIT	1		
SPUSGRN	0.4379	1	
SPX	−0.3480	−0.0967	1

Note: This table reports the descriptive statistics and correlations of the indexes. The sample period is 09/30/2016–12/31/2021. The variables include the S&P U.S. Aggregate Bond Index (SPUSBMIT), the S&P Green Bond Index Total Return (SPUSGRN Index), and the S&P 500 (SPX).

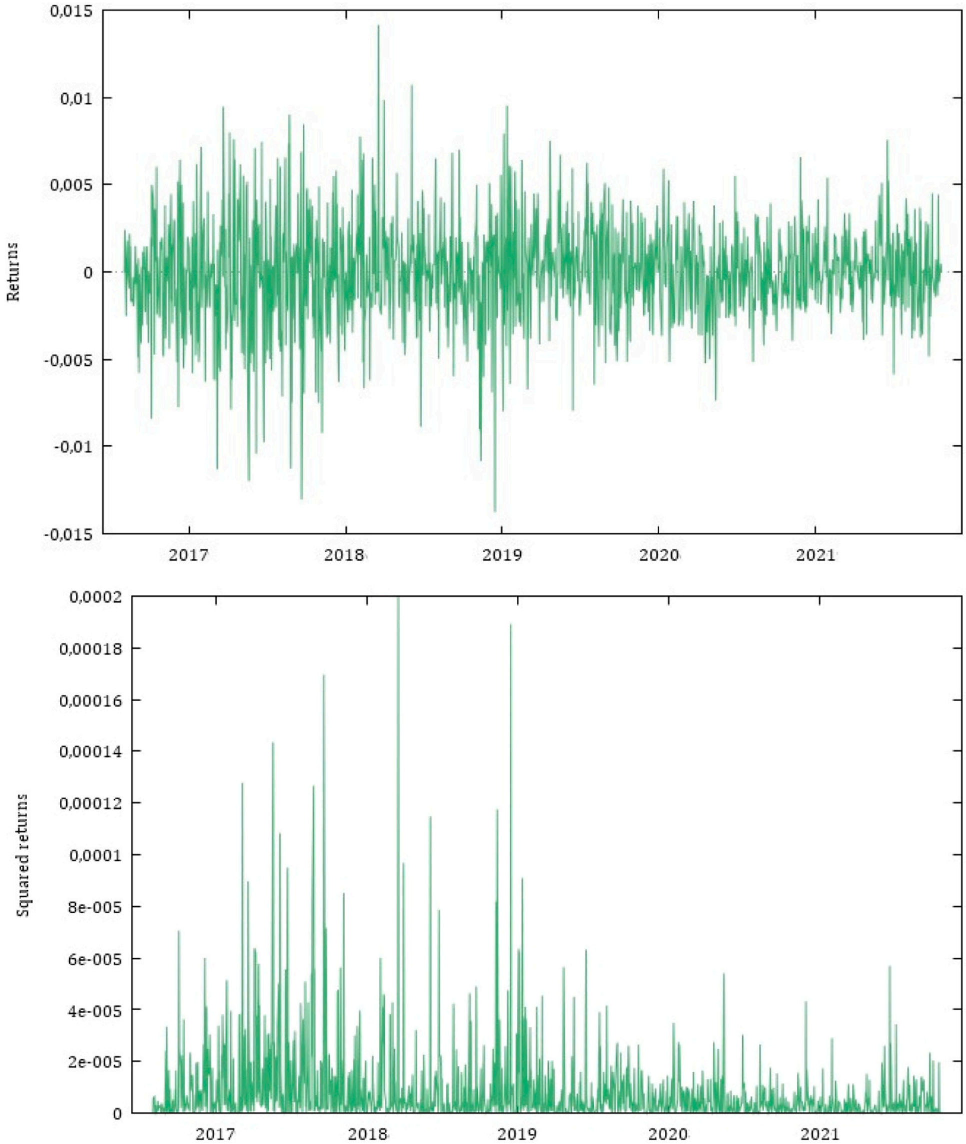


Fig. 2. a. S&P Green Bond Index daily returns, 09/30/2016–12/31/2021. **b.** S&P Green Bond Index daily returns (squared returns), 09/30/2016–12/31/2021. **c.** S&P Green Bond Index daily returns (absolute value), 09/30/2016–12/31/2021.

other indices.

3.2.3. Model robustness

Based on the results of the preliminary tests, the independence and normality assumptions required for further analysis appear to be satisfied for the synthetic data of the S&P Green Bond Index, the S&P U.S. Aggregate Bond Index, and the S&P 500. This allows for more robust statistical modeling and analyses in subsequent parts of this study. Based on this connection, the application of GARCH models will further validate the data by demonstrating expected volatility clustering patterns that are in line with financial market behavior. These models are robust tools for analyzing time-series data in finance, providing an additional layer of reliability to our findings.

3.3. Methodology

3.3.1. GARCH models

In their empirical studies, Pham (2016) and Broadstock and Cheng (2019) used the GARCH model to further investigate the trend of different financial instruments by considering the change in their conditional variances and covariances over time and by defining

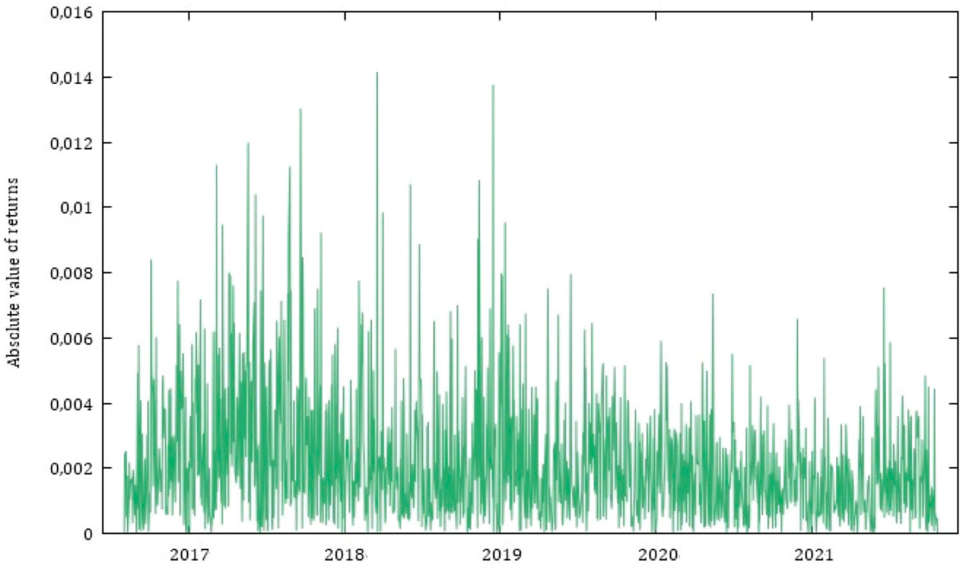


Fig. 2. (*continued*).

them as a function of previous errors (Bollerslev, 1986). The GARCH model is particularly well-suited for analyzing financial time-series data characterized by volatility clustering, which is a common feature in both the equity and bond markets, including GBs. The primary advantage of this model is its ability to capture the persistence and mean-reverting nature of financial market volatility (Engle, 1982; Bollerslev, 1986; Bouteska et al., 2023a).

The efficacy of GARCH models in analyzing the GB market has been demonstrated in recent studies. For instance, Reboredo and Ugolini (2020) used GARCH models to examine the volatility spillover effects between GBs and conventional bonds, and found significant spillover effects, implying the interconnectedness of these markets. Similarly, Bouteska et al. (2024a) applied GARCH models to examine the volatility dynamics of GBs, and discovered that GBs exhibit unique volatility patterns (compared to traditional bonds), justifying the use of such models for a nuanced analysis.

Under the GARCH (p, q) model, the behavior of a specific asset is described by

$$R_t = E_{t-1}[R_t] + e_t e_t | I_{t-1} \sim N\left(0, \sigma_t^2\right) \tag{2}$$

where $E_{t-1}[R_t]$ represents the conditional mean of the asset returns, e_t is the error term, and σ_t^2 is the conditional variance at time t, given the information set I_{t-1} (Pham, 2016; Broadstock and Cheng, 2019). The volatility is formulated as

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i e_{t-1}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \tag{3}$$

where $\alpha_0 > 0$, $\alpha_i \geq 0 \ \forall \ i \in [1,p]$, and $\beta_i \geq 0 \ \forall \ i \in [1,q]$.

The time-varying conditional variance (the hypothesis of heteroskedasticity) is expressed as a linear combination of q lagged values of σ_t^2 (representative of its past values) and p lags of e_t^2 (representative of market news). High and significant values of α_i and β_i indicate the presence of volatility clustering. Given the presence of heteroskedasticity and extreme outliers, the regression of the independent variable Y_t on the dependent variables $X_{1,t},\ldots,X_{p,t}$ is as follows:

$$Y_t = f\left(X_{1,t}, \ldots, X_{p,t}\right) + \sigma\left(X_{1,t}, \ldots, X_{p,t}\right) e_t \tag{4}$$

where f (usually a linear function) is the conditional expectation of Y_t, given $X_{1,t},\ldots,X_p$, and $\sigma\left(X_{1,t}, \ldots, X_{p,t}\right) e_t$ is the conditional standard deviation of Y_t, given $X_{1,t},\ldots,X_p$ (Ruppert, 2004).

$$Y_t = \beta_0 + \beta_1 X_{1,t} + \cdots + \beta_p X_{p,t} + \sqrt[2]{\sigma^2\left(X_{1,t}, \ldots, X_{p,t}\right)} e_t \tag{5}$$

Before applying the GARCH model, it is important to verify the independence of the time series by conducting the Ljung–Box test. Specifically, this test is verifies the absence of serial autocorrelation in the errors by providing further information about the fit quality of the time series. In fact, under the null hypothesis H_0, the errors are independent and identically distributed (i.e., "white noise") and the time series does not evidence a "lack of fit" (Burns, 2005). In this regard, Pham (2016) did not accept H_0, confirming the presence of volatility clustering and indicating that the present volatility is influenced by its past behavior.

In this study, the p and q lagged values are chosen by using the Bayesian Information Criterion (BIC), also known as the Schwartz

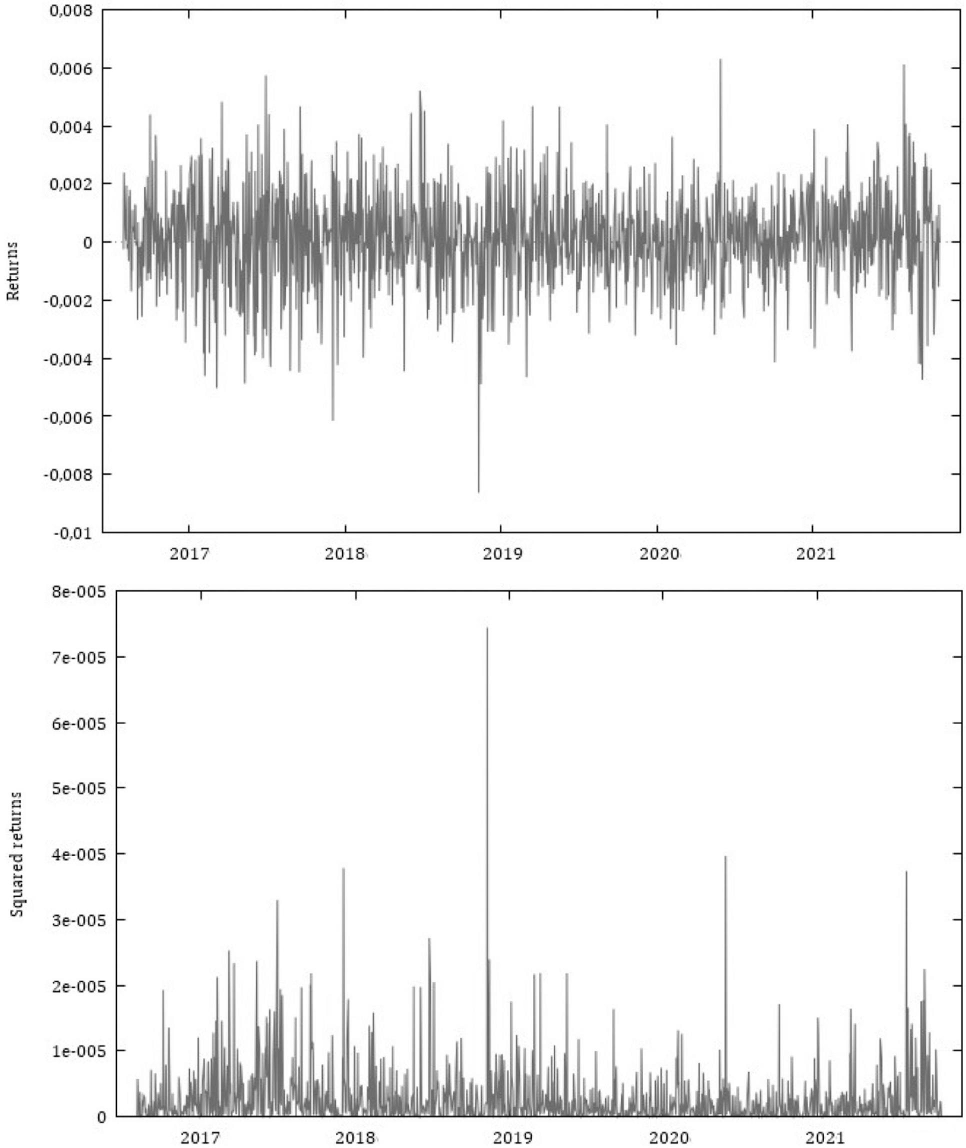


Fig. 3. a. S&P U.S. Aggregate Bond Index daily returns, 09/30/2016–12/31/2021. **b.** S&P U.S. Aggregate Bond Index daily returns (squared returns), 09/30/2016–12/31/2021. **c.** S&P U.S. Aggregate Bond Index daily returns (absolute value), 09/30/2016–12/31/2021.

Information Criterion. In addition to the univariate GARCH model used to compare the volatility behavior for the return time series for the GB and conventional bond markets, a multivariate GARCH model is implemented to analyze the presence of spillover effects between the two markets. The setting of this second model allows the evaluation of covariances between different asset classes, indicating that the returns of one financial instrument may be affected by the volatility of another security. This multivariate model is implemented with the use of the dynamic conditional correlation (DCC) model for the conditional standard deviations of each return time series and for the conditional correlations among them. Similarly, Pham (2016) estimated the volatility for each return time series with a univariate GARCH model and the conditional correlations between the standardized residuals with a bivariate GARCH model. In the present study, we combine the two estimates to compute the conditional covariance matrix.

3.3.2. VAR model

In the section, we consider the presence of spillover effects between the three financial time series, and use a VAR model to analyze the dynamic evolution of each market over time in relation to the other markets. The VAR model is advantageous for examining the dynamic relationship between multiple time-series variables, allowing for an analysis of interdependencies and causality (Ha et al., 2024). This model is particularly useful in the context of the GB and equity markets, since they enable researchers to capture the

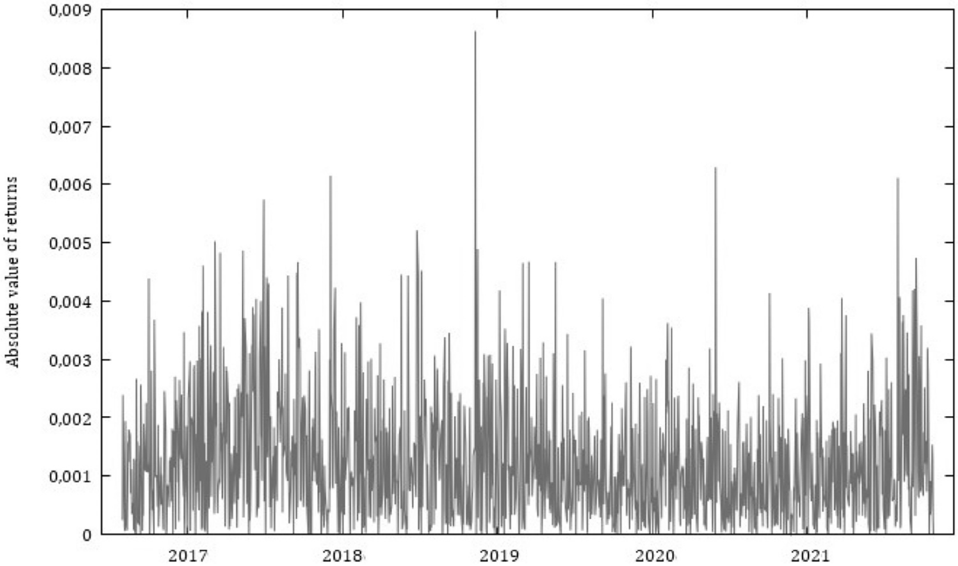


Fig. 3. (*continued*).

bidirectional influences between GB issuances and equity market performance.

The applicability of the VAR model to green finance has been substantiated in recent literature. For example, Pham (2021) utilized the VAR model to investigate the impact of GB issuance on stock market indices, revealing significant interactions between these variables. The study also highlighted that GBs can influence stock market performance through investor sentiment and risk perception. In related research, Li et al. (2022) employed the VAR model to assess the effect of GB announcements on stock prices, confirming that the model is effective for capturing the short- and long-term impacts of GB activities on the equity market.

First, a basic p-lag VAR (VAR (p)) model is defined by the following regression:

$$Y_t = v + A_1 y_{t-1} + \cdots + A_p X_{t-p} + u_t \tag{6}$$

where p is a positive integer, v is a fixed (n x 1) vector of intercepts, A_i are fixed (n x n) coefficient matrices, and u_t is an n-dimensional white noise or innovation process (Lütkepohl, 2005). Given the three different variables, each one representing a financial market, the three-dimensional VAR (1) model is defined as follows:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{pmatrix} = \begin{pmatrix} v_{1t} \\ v_{2t} \\ v_{3t} \end{pmatrix} + \begin{pmatrix} a_{11}a_{11}a_{11} \\ a_{21}a_{22}a_{23} \\ a_{31}a_{32}a_{33} \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \\ y_{3t-1} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \end{pmatrix} \tag{7}$$

In our empirical study, we conduct a three-dimensional VAR model with three lags, assuming that it takes several days for information propagation across the markets. Other models with more lagged values have been estimated, but no significant information has been provided.

4. Results

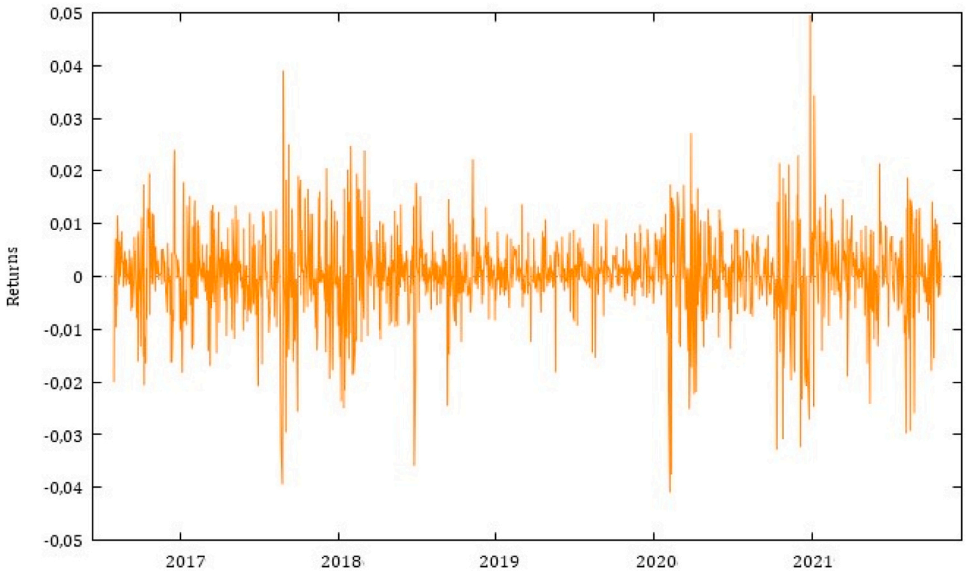
4.1. Relationship between the markets

4.1.1. Relationship between the GB and conventional bond markets

Fig. 5 compares the daily returns of the S&P Green Bond Index with the S&P U.S. Aggregate Bond Index, evidencing the common high volatility of the markets until the first half of 2019, especially for the green debt securities. The last two years are characterized by a more stable performance, with slightly higher volatility for the broader conventional bond market. Their positive correlation, whose value is equal to 0.4379 (Table 2), indicates that approximately 50 % of the time, the two series move in the same direction.

The association between the two bond markets is better displayed in Fig. 6, which presents their 1- and 2-month rolling correlations. Until the first half of 2018, the two correlations are lower than the correlation of the entire period. However, from 2019 onward, there is a significant change.

We also analyze the behavior of an investment in both asset classes from the first day of the sample period until the last day of the time window. By investing an initial principal amount of $1, we compute the daily compound interest by multiplying the principal (which includes the interest of the previous day) by one plus the current daily return. Fig. 7 shows the opposite behavior of the two markets during the first two years and their weak co-movement from 2018 onward. Overall, the performance of the green investment



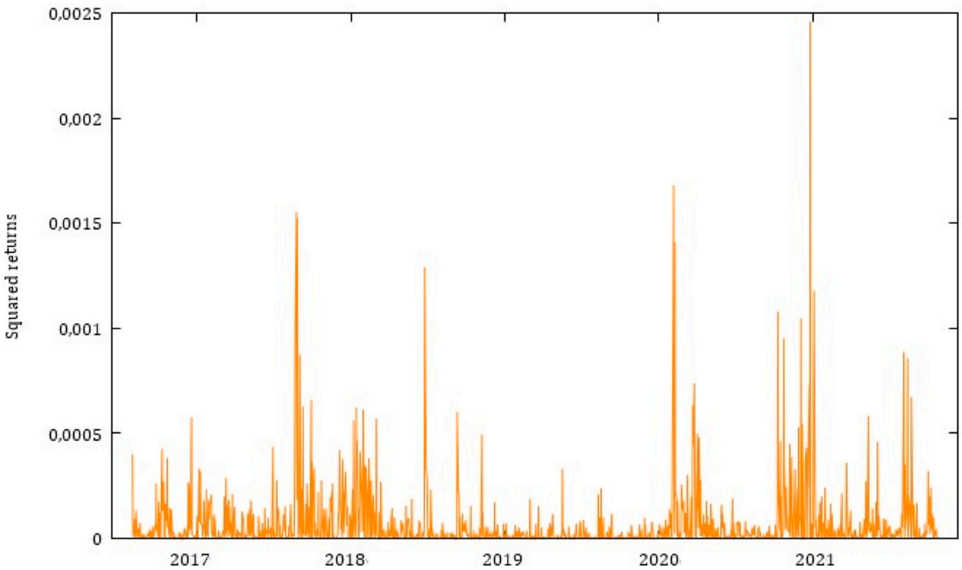


Fig. 4. a. S&P 500 daily returns, 09/30/2016–12/31/2021. **b.** S&P 500 daily returns (squared returns), 09/30/2016–12/31/2021. **c.** S&P 500 daily returns (absolute value), 09/30/2016–12/31/2021.

accentuates the downturns and upturns of the conventional one.

A comparison of the volatility behaviors is presented in Fig. 8, which displays the 30-, 60-, and 90-day volatilities. In this case, the higher the pace of the volatility, the less accentuated the downturns and upturns of the two markets, which exhibit quite different instability until the first half of 2019. However, from the second half of the year onward, the two indexes evidence quite similar behavior, with a reduction in the distance between the two lines.

4.1.2. Relationship between the GB and equity markets

Fig. 9 compares the daily returns of the S&P Green Bond Index with the S&P 500, evidencing the higher instability characterizing the performance of the GB market until the first half of 2019. If the second part of the time window shows stable behavior in the green index, then the last two years are dominated by significant volatility in the stock market. Thus, the hypothesis of the absence of comovements is confirmed by the correlation value, which is equal to −0.0967 (Table 2).

The relationship between the two markets is better represented in Fig. 10, which presents their 1- and 2-month rolling correlations. Until the first half of 2018, the rolling correlations are mainly lower than the correlation of the entire period, whereas the other part of the period is characterized by a reverse change.

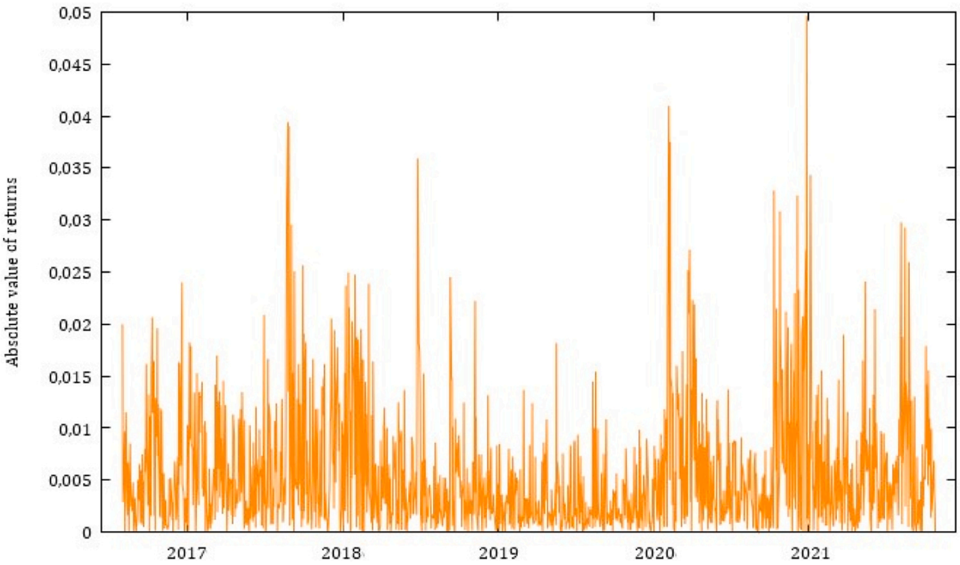


Fig. 4. (*continued*).

Table 3
Ljung–Box test results.

Index	Ljung–Box statistic	p-value
SPUSGRN	8.42	0.49
SPUSBMIT	6.21	0.72
SPX	12.34	0.26

Source: Authors' own estimations.

Table 4
Jarque–Bera test results.

Index	JB statistic	p-value
SPUSGRN	1.56	0.46
SPUSBMIT	0.89	0.64
SPX	4.45	0.11

Source: Authors' own estimations.

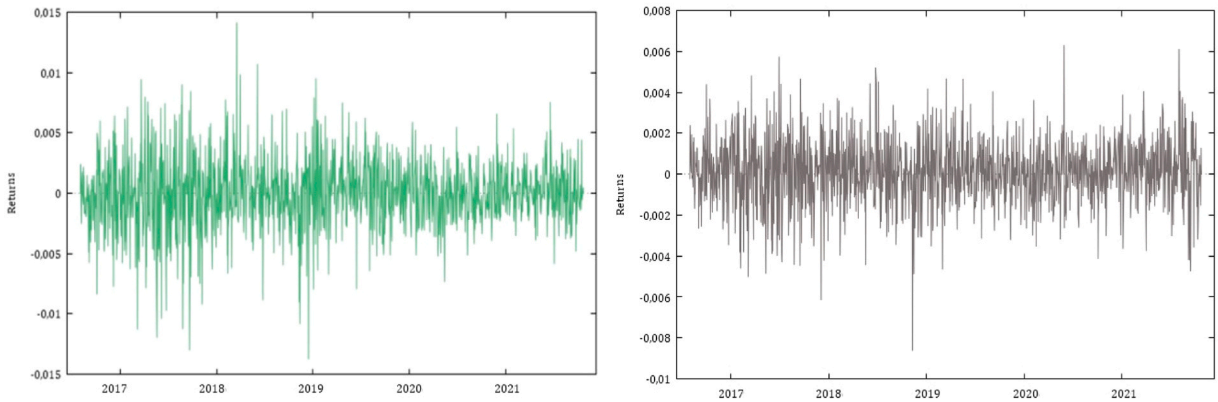


Fig. 5. Daily returns for the S&P Green Bond Index and the S&P U.S. Aggregate Bond Index, 09/30/2016–12/31/2021.

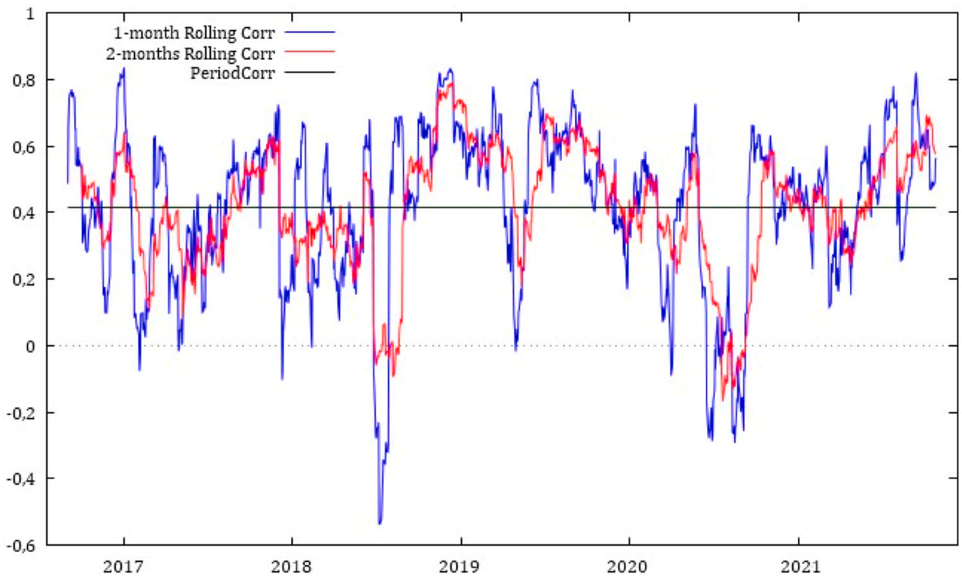


Fig. 6. Rolling correlations between the S&P Green Bond Index and the S&P U.S. Aggregate Bond Index, 09/30/2016–12/31/2021. Note: The line represents the conditional correlation between the two-time series during the entire sample period.

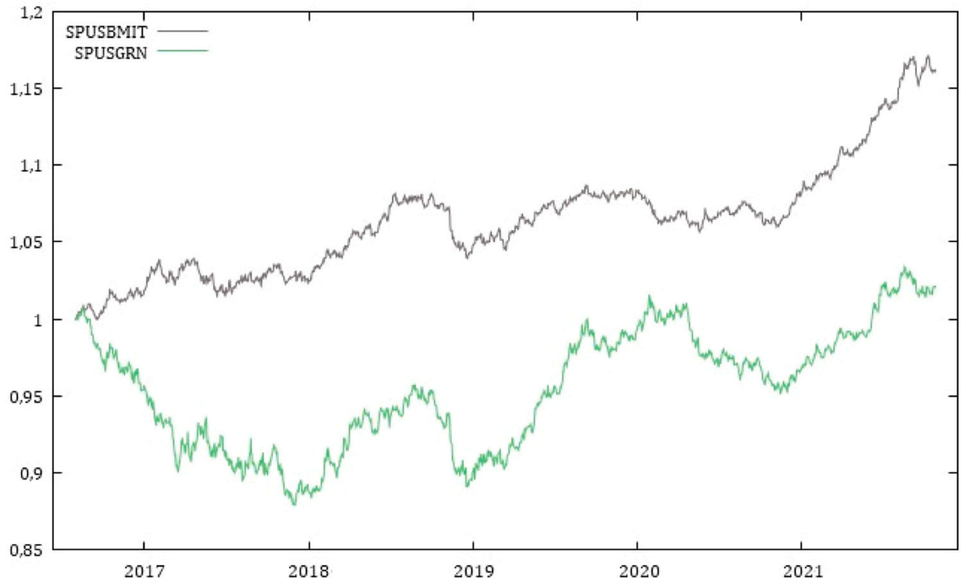


Fig. 7. Daily compound interest during the entire sample period, 09/30/2016–12/31/2021.

A better investigation about the behavior of the two asset classes is presented in Fig. 11, representing two investments in the markets. While the green debt securities are characterized by a stable behavior with bearable shocks, the stocks tend to suffer from more black swans and financial crises.

Finally, Fig. 12 compares the volatility behavior of the two asset classes, displaying their 30-, 60-, and 90-day volatilities, and confirming the significant differences during the initial and final part of the sample period.

4.1.3. Relationship between conventional bond and equity markets

Fig. 13 compares the daily returns of the S&P U.S. Aggregate Bond Index with the S&P 500, evidencing the different performances of the two markets. The different movements of the securities are confirmed by the period correlation, which is equal to −0.3480 (Table 2).

The relationship between the two markets is better represented in Fig. 14, which displays their 1- and 2-month rolling correlations. In the first half of the time window, the blue and red lines are mainly lower than the period correlation. Additionally, in 2019, the

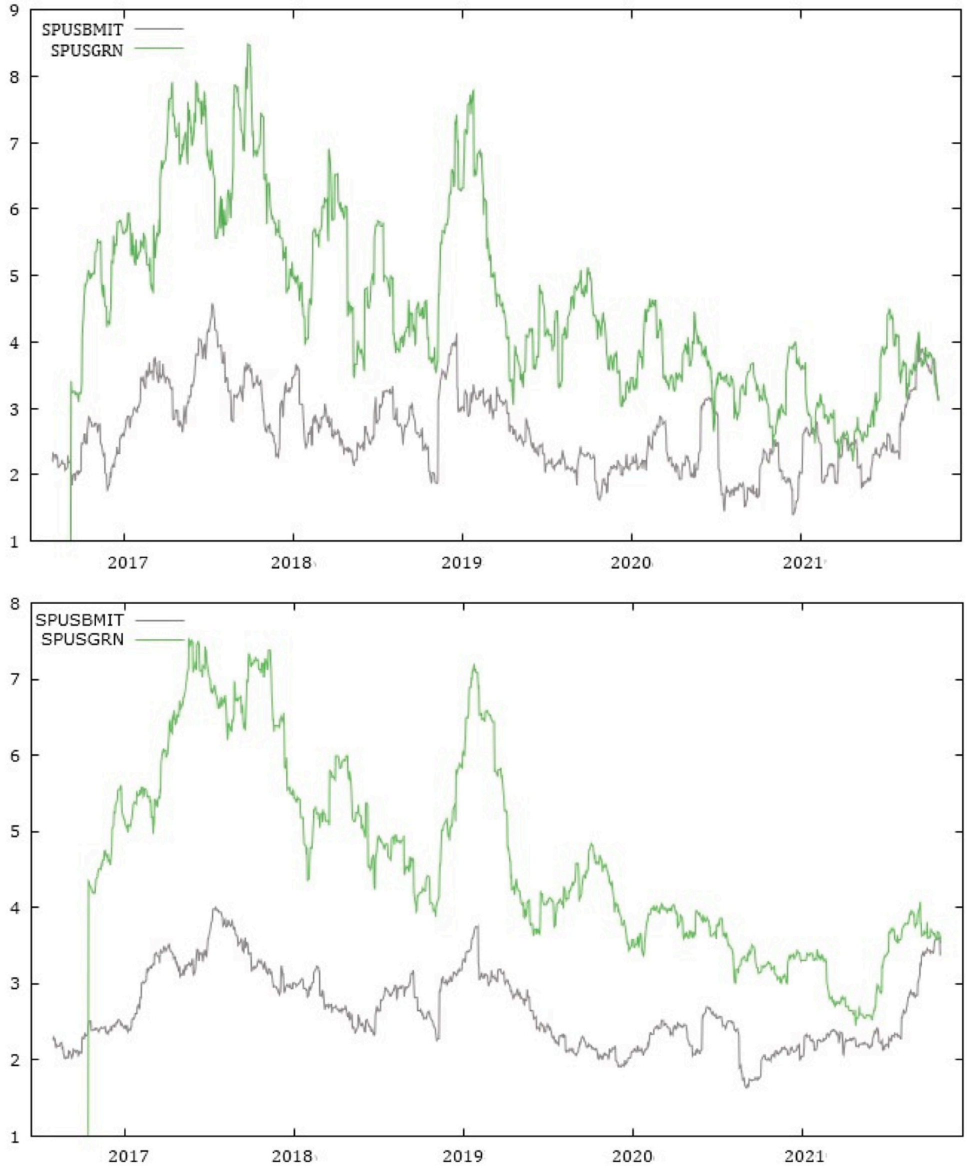


Fig. 8. **a.** 30-day volatilities, 09/30/2016–12/31/2021. **b.** 60-day volatilities, 09/30/2016–12/31/2021. **c.** 90-day volatilities, 09/30/2016–12/31/2021.

rolling correlations are mainly higher than the straight line, whereas during the last year, there is a reverse change.

The two markets are also compared in Fig. 15, which displays the behaviors of the investments in the two markets. While the conventional bond index is characterized by a stable behavior with bearable shocks, the equity market is affected by considerable variations, with accentuated downturns and upturns.

The volatility behaviors of the two indexes are analyzed in Fig. 16, which presents their 30-, 60-, and 90-day volatilities, and confirms the significant differences during the initial and final part of the sample period.

4.2. Univariate GARCH estimation and preliminary tests

In this study, the implementation of the GARCH models is preceded by the Ljung–Box test, which verifies the independence of the time series. Given the initial hypothesis H_0 regarding the absence of autocorrelation, the Ljung–Box test rejects it and provides evidence of serial correlations in the S&P Green Bond Index (squared returns), confirming the hypothesis of volatility clustering (Fig. 17). This finding is line with that reported by Pham (2016).

The test for the conventional bond market is displayed in Fig. 18, which confirms the absence of serial correlations.

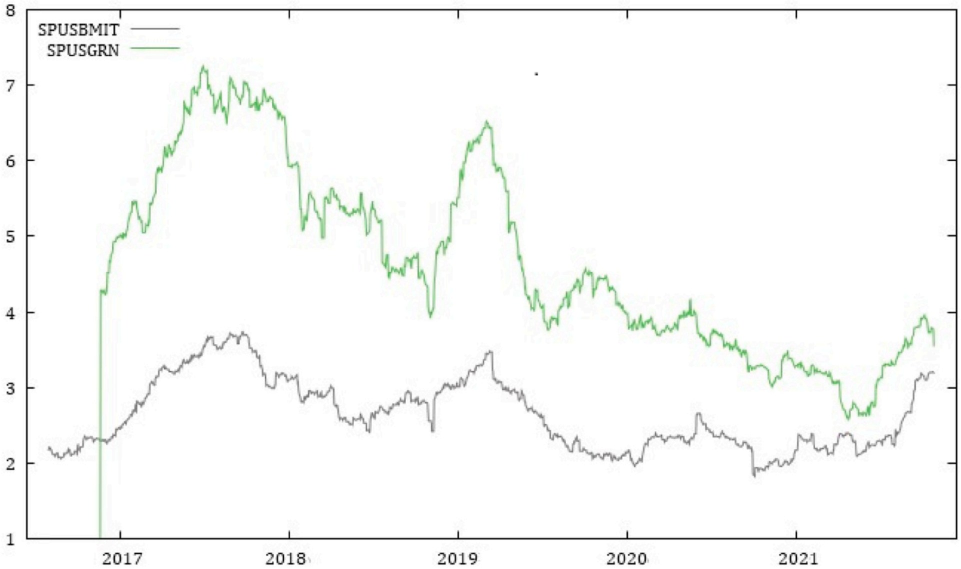


Fig. 8. (*continued*).

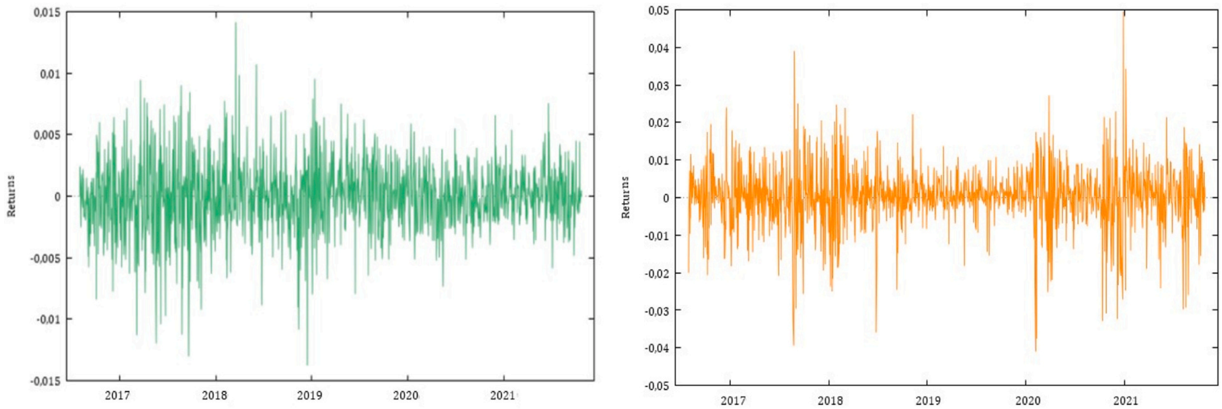


Fig. 9. Daily returns for the S&P Green Bond Index and the S&P 500, 09/30/2016–12/31/2021.

The hypothesis of serial correlation in the squared returns is also confirmed for the equity market, represented in Fig. 19.

The three index behaviors are also compared through the estimation of a univariate GARCH model. Given the GARCH (1,1) model in Table 5, the GB market is characterized by a higher level of volatility clustering with respect to the conventional debt securities, as confirmed by the higher value of α_1. Meanwhile, the slightly lower coefficient β_1 of the GB index affects the half-life of a shock, which is approximately 358 days. Conversely, a shock to the conventional bond market only takes about 109 days to decrease by half its impact. As for the stock market, it is characterized by a higher value of α_1 and a lower value of β_1 with respect to both debt securities. The final effect on the half-life of a shock is significantly lower than that for the bond index, with a value of roughly 13 days.

The presence of conditional heteroskedasticity is examined by conducting the ARCH test, which verifies and assesses the significance of autoregressive conditional heteroskedastic effects. As reported by Cermak (2017), the test is defined by the following regression:

$$e_t^2 = \gamma_0 + \sum_{i=1}^{n} \gamma_1 e_{t-1}^2 + v \tag{8}$$

With the null hypothesis H_0 regarding the absence of time-varying conditional variance in the residuals e_t, i.e., $\gamma_i = 0$, Table 6 demonstrates the estimated parameters of the test that rejected H_0.

4.3. Bivariate GARCH estimation

This section analyzes the volatility behavior of the two debt security indexes (in relation to the other markets) through the use of

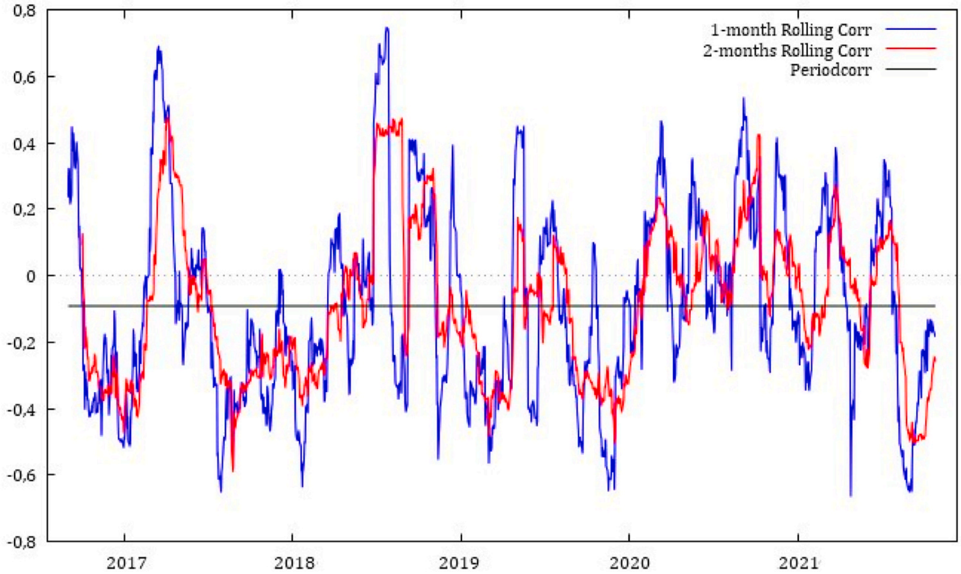


Fig. 10. Rolling correlations between the S&P Green Bond Index and the S&P 500, 09/30/2016–12/31/2021. Note: The line represents the conditional correlation between the two-time series during the entire sample period.

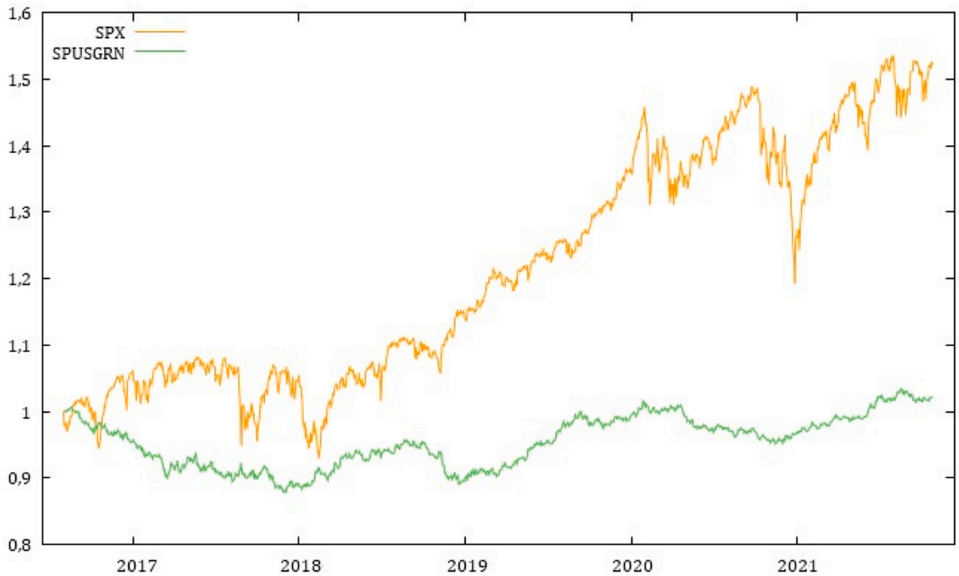


Fig. 11. Daily compound interest during the entire sample period, 09/30/2016–12/31/2021.

GARCH models with one and more explanatory variables. First, we implement a bivariate GARCH model to examine the movement of the GB market, compared to the conventional market and the equity index. The results, presented in Table 7, confirm the estimations of the univariate model. Specifically, both coefficients of the markets are significantly positive, especially for the conventional bond index, indicating that an increase in the GB market positively affects the conventional bond market in a higher measure. Table 8 presents the results of the ARCH LM tests, confirming the presence of heteroskedasticity.

The volatility behaviors of the conventional bond market in relation to the GB market and the equity index are estimated in Table 9, evidencing only slight differences with the coefficients of the univariate GARCH model (Table 5). Specifically, the coefficients of the markets display opposite signs, suggesting that only the two debt securities move in the same direction. Table 10 presents the results of the ARCH LM test, confirming the absence of homoskedasticity.

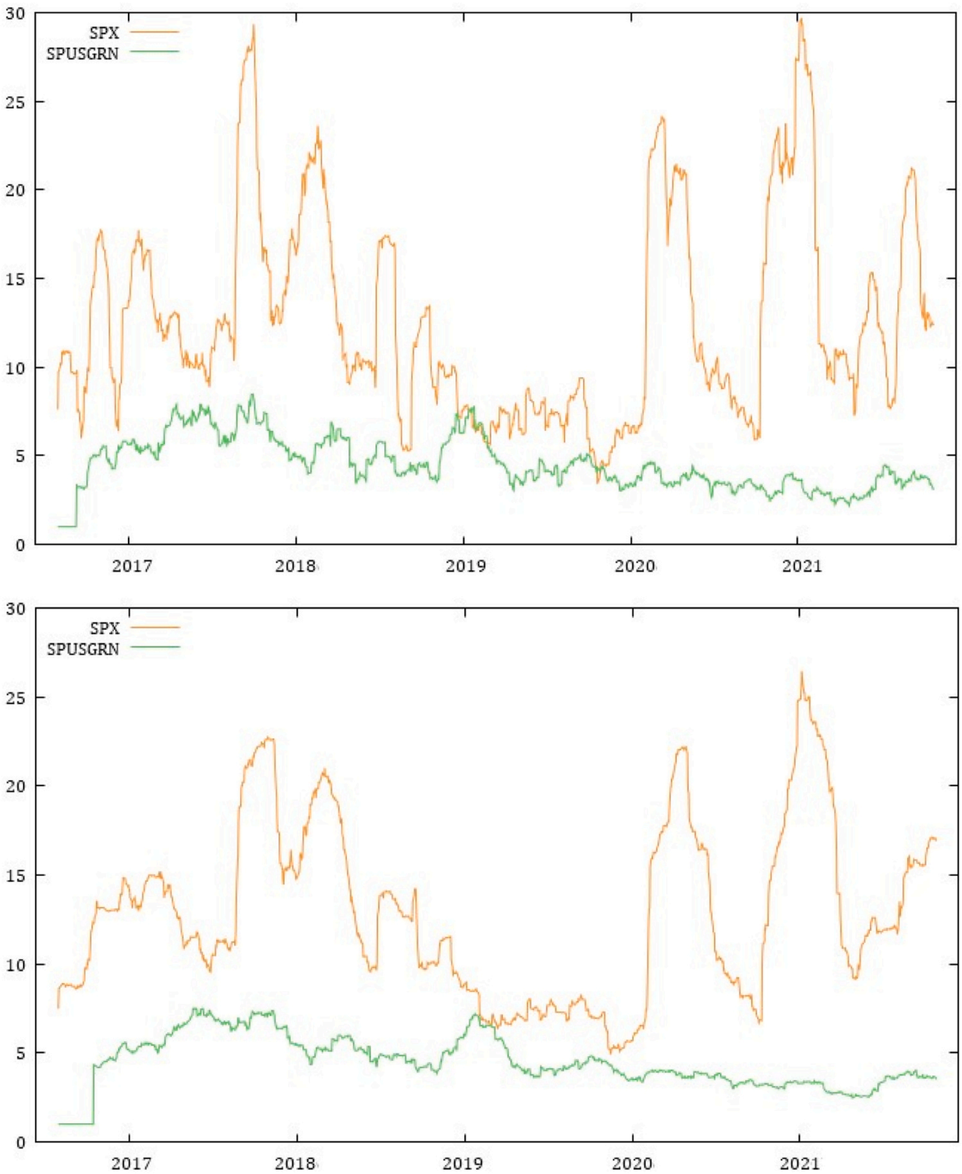


Fig. 12. a. 30-day volatilities, 09/30/2016–12/31/2021. **b.** 60-day volatilities, 09/30/2016–12/31/2021. **c.** 90-day volatilities, 09/30/2016–12/31/2021.

4.4. Multivariate GARCH models

In this section, we employ multivariate GARCH models to analyze the joint volatility behavior of each market in relation to the other market. Table 11 displays the estimations of the GARCH models with two explanatory variables. The first model analyzes the movement of the GB market in relation to the conventional market and the equity index, evidencing that the inclusion of both markets does not reveal additional or significantly different information with respect to the bivariate models, indicating slightly lower estimates (Table 7). The second model estimates the behavior of the conventional bond index with those of the GB and stock markets, evidencing no variations with respect to the values of the previous models. Thus, the ARCH LM test rejects the null hypothesis of homoskedasticity (Table 12).

Finally, the bivariate and multivariate settings of the GARCH models indicate that the debt securities are positively correlated, especially when comparing the GB index with the conventional bond market. Meanwhile, there are lower correlation results with the equity market, with a negative association with the conventional bond market.

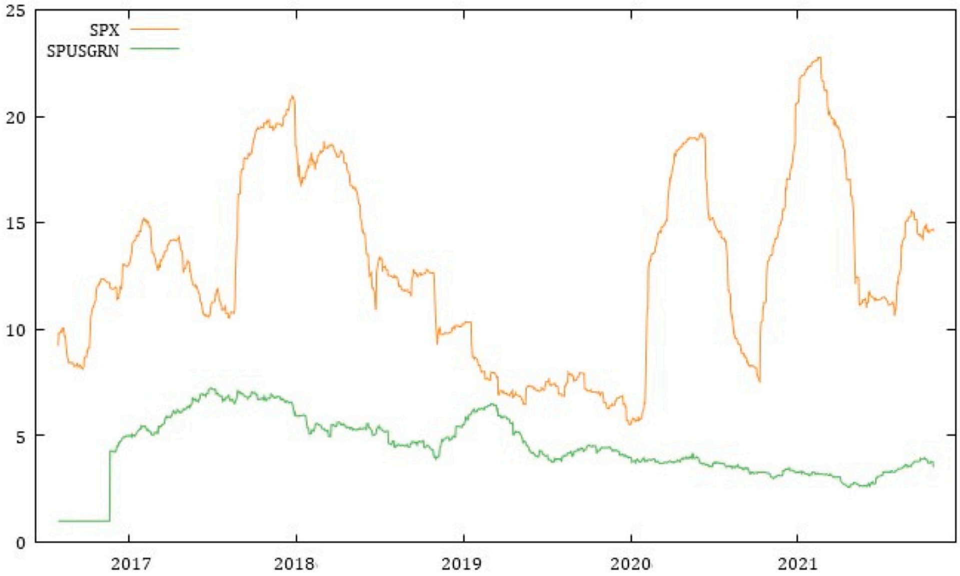


Fig. 12. (*continued*).

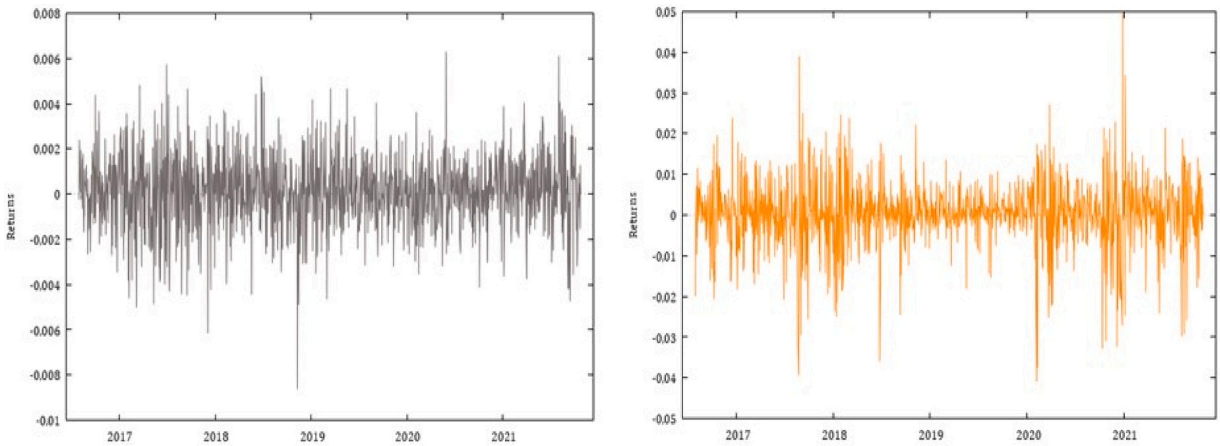


Fig. 13. Daily returns for the S&P U.S. Aggregate Bond Index and the S&P 500, 09/30/2016–12/31/2021.

4.5. Vector Autoregressive (VAR) estimation

In this section, we consider the presence of spillover effects between the three financial time series and use a VAR model to analyze the dynamic evolution of each market across the years and in relation to the other markets. In this case, a basic p-lag VAR (VAR (p)) model is defined by the following regression:

$$Y_t = v + A_1 y_{t-1} + \cdots + A_p X_{t-p} + u_t \tag{6}$$

where p is a positive integer, v is a fixed (n x 1) vector of intercepts, A_i are fixed (n x n) coefficient matrices, and u_t is an n-dimensional white noise or innovation process (Lütkepohl, 2005). Given the three different variables, with each one representing a financial market, the three-dimensional VAR (1) model is defined as follows:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{pmatrix} = \begin{pmatrix} v_{1t} \\ v_{2t} \\ v_{3t} \end{pmatrix} + \begin{pmatrix} a_{11}a_{11}a_{11} \\ a_{21}a_{22}a_{23} \\ a_{31}a_{32}a_{33} \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \\ y_{3t-1} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \end{pmatrix} \tag{7}$$

In this empirical study, we run a three-dimensional VAR model with three lags, assuming that it takes several days for the propagation of information across the markets. Other models with more lagged values are estimated, but no further information is

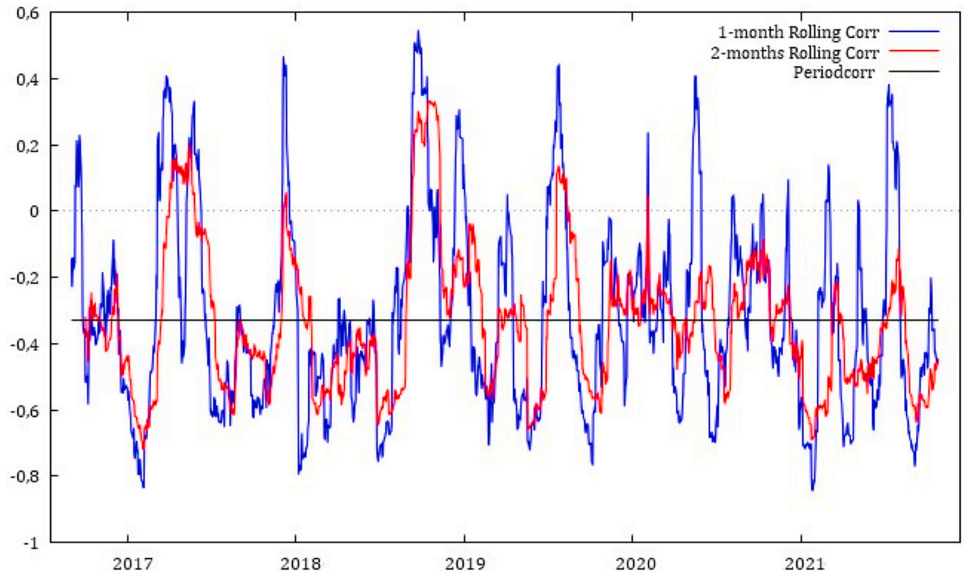


Fig. 14. Rolling correlations between the S&P U.S. Aggregate Bond Index and the S&P 500, 09/30/2016–12/31/2021. Note: The line represents the conditional correlation between the two-time series during the entire sample period.

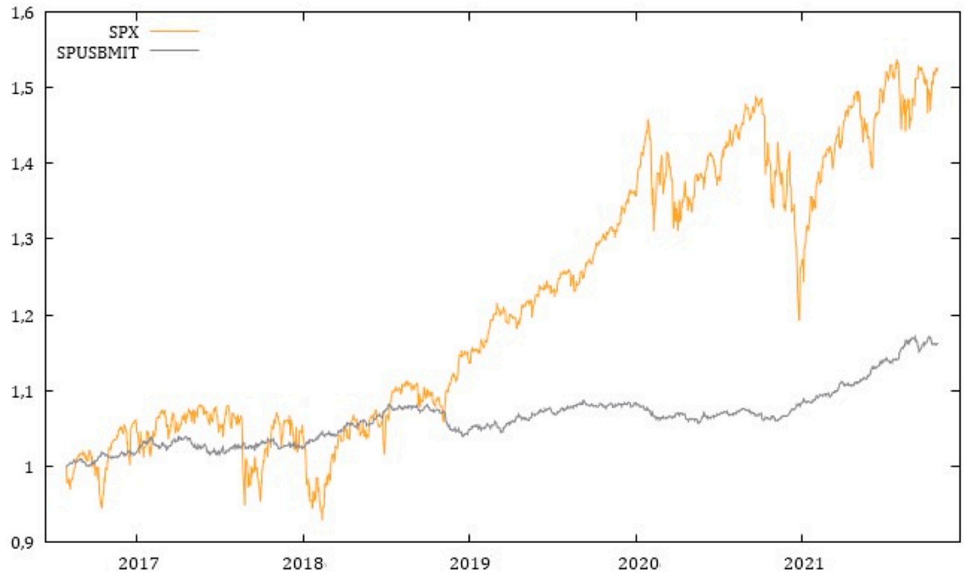


Fig. 15. Daily compound interest during the entire sample period, 09/30/2016–12/31/2021.

provided.

Table 13 presents the VAR estimates for the changes in the three markets. The first equation considers the GB market, evidencing that the information becomes significant from the second day onward. In this case, the GB index suffers from its previous performance, evidencing a significant negative coefficient of its third lag. Conversely, it is positively influenced by the returns of the conventional bond market in the previous two days. The significant positive second lagged value of the stock index suggests that the two markets are positively correlated, which is in contrast to the empirical results of Reboredo (2018). Hence, the information provided by the model is not completely meaningful, since it rejects the hypothesis of volatility clustering of the GB market previously confirmed by the Ljung–Box test. In addition, the model evidences a positive association between the GB and equity indexes.

The second equation refers to the conventional bond market, evidencing an ambiguous relationship with its previous performance and the GB index. The coefficient of the previous day is significantly negative, while its third lag is significantly positive. Conversely, the first lag of the GB market is significantly positive, whereas the third lag is significantly negative. Meanwhile, the coefficient for the stock index is not statistically significant. As for the first equation, the model does not provide meaningful information, since it rejects

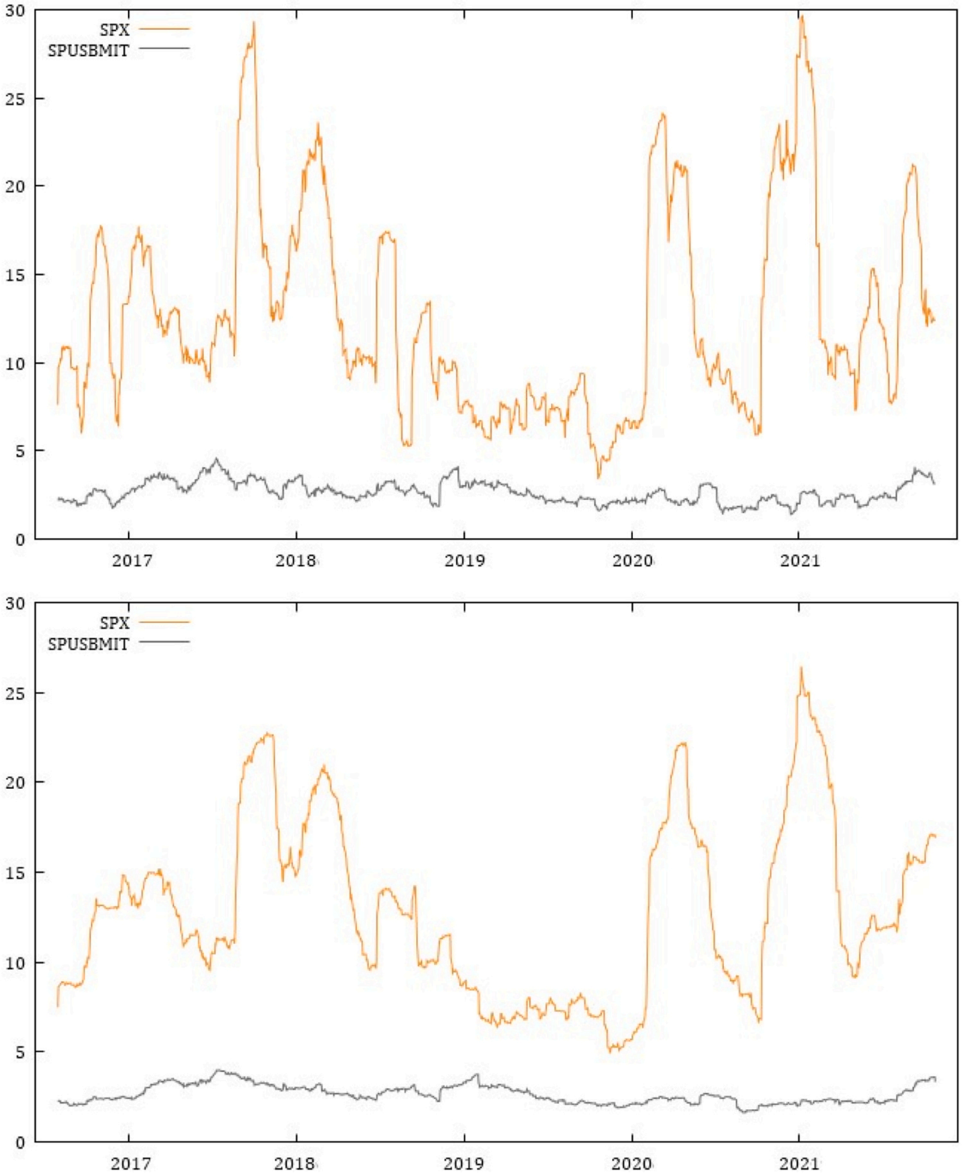


Fig. 16. a. 30-day volatilities, 09/30/2016–12/31/2021. **b.** 60-day volatilities, 09/30/2016–12/31/2021. **c.** 90-day volatilities, 09/30/2016–12/31/2021.

the hypothesis of volatility clustering for the conventional bond market and does not explicate its relationship with the other index.

The third equation refers to the equity market, again evidencing vague information. Although the second and third lagged values of the market are both statistically significant, they show opposite signs. Only the first lagged value of the GB index is significantly negative, which is in line with the empirical results of Reboredo (2018). Given the results of our VAR model, we do not have clear and meaningful information about the relationship among the markets. Thus, we conclude that the VAR (3) model is not a powerful tool for our empirical study, which is probably due to the relatively short time period and the considerable variations in market volatility.

5. Discussion

The findings of this study affirm the efficient markets hypothesis (EMH), the modern portfolio theory (MPT), and behavioral finance theories. The presence of volatility clustering in GBs (similar to the conventional bond and equity markets), aligns with the EMH, which posits that markets efficiently incorporate information into asset prices. In an efficient market, new information impacts volatility, leading to periods of high and low volatility clustering. The observed patterns in our study support this theory by

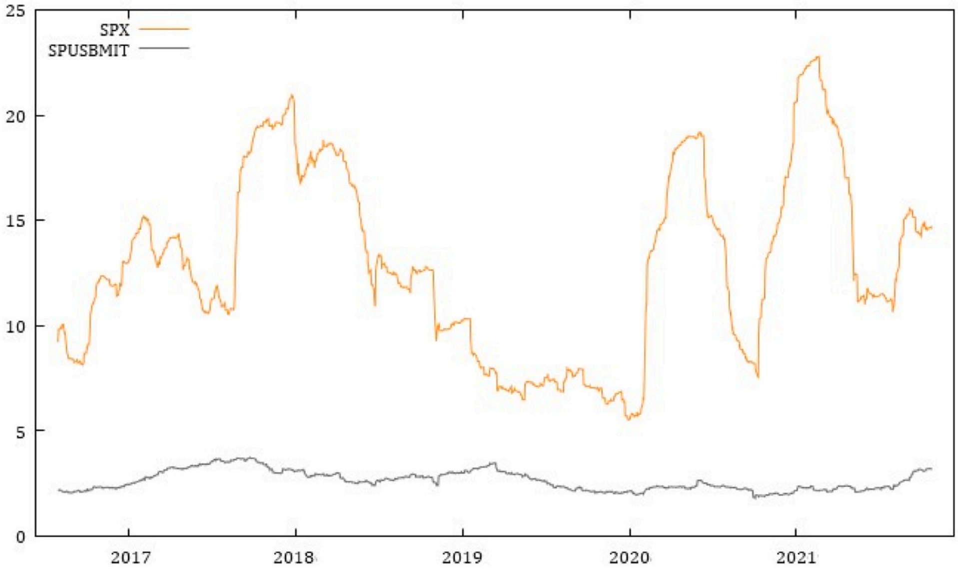


Fig. 16. (*continued*).

demonstrating that GB markets react to new information in a manner consistent with other established financial markets. As for the MPT, it suggests that investors aim to optimize their portfolios based on risk and return trade-offs. The volatility clustering observed in GBs indicates that these instruments carry specific risks that investors must consider when diversifying their portfolios. This aligns with the MPT's emphasis on understanding individual asset volatility to manage overall portfolio risk. Meanwhile, behavioral finance theories suggest that investor behavior, including herding and overreaction, contributes to volatility clustering. Similar patterns observed in GBs suggest that investors in GBs may exhibit similar behaviors to those in conventional markets, reinforcing behavioral finance principles.

Conversely, the findings pose challenges to existing financial theories such as market segmentation theory (MST) and sustainable finance theories (SFTs). Specifically, the MST posits that different market segments (e.g., GBs vs. conventional bonds) may behave differently, due to varying investor bases and objectives. The similar volatility patterns challenge this theory by suggesting that GBs, despite being a distinct market segment, exhibit volatility characteristics akin to conventional bonds, implying less segmentation than previously thought. Regarding the SFTs, they argue that GBs should exhibit different risk and return profiles, due to their specific focus on environmentally friendly projects and the associated regulatory and reputational risks. However, the findings of similar volatility clustering challenge this notion by indicating that GBs might not be as differentiated from conventional bonds in terms of market behavior as these theories suggest.

The results of this study regarding the correlation and risk diversification also contradict the findings of Reboredo (2018), who found a negative correlation between GBs and stock indices, indicating that GBs provide diversification benefits and act as a hedge against equity market movements. It should be noted that at the time of Reboredo's study, the GB market was relatively nascent. Hence, the negative correlation most likely reflects the initial phase in which GBs were primarily sought by niche investors who focused on sustainability, leading to different market dynamics than those of broader equity markets.

Finally, our study indicates a positive lagged relationship between GBs and stock indices, implying changing market dynamics or evolving investor perceptions of GBs. In this case, movements in stock indices can predict similar movements in GBs after a certain lag. This discrepancy warrants a discussion on potential shifts in the market, such as increased integration of GBs into mainstream portfolios, which might reduce their diversification benefits. In terms of market maturity and integration, the GB market is relatively new and evolving. The similar volatility patterns might indicate that as the market matures, GBs will be increasingly traded and similarly valued to conventional bonds. This trend could challenge the theories that position GBs as a distinct asset class and suggest that they should be integrated into the broader financial system.

6. Conclusion

Based on our analysis of the financial markets and the empirical results, this study indicates that GARCH models are effective tools for analyzing the volatility behaviors of markets, with respect to the VAR model. In line with the results of Pham (2016) and Reboredo (2018), the application of univariate GARCH models provides evidence of a higher level of volatility clustering for the GB market (compared to the conventional bond and equity markets), with equivalent results from the bivariate and multivariate GARCH models.

Overall, the GB market has been positively affected by the conventional bond index and, to a lesser extent, by the stock market. Conversely, the conventional bond index has slightly benefited from the positive influence of the GB market, whereas it has suffered from the performance of the equity index. Thus, we can conclude that there have been no diversification benefits for investors in the

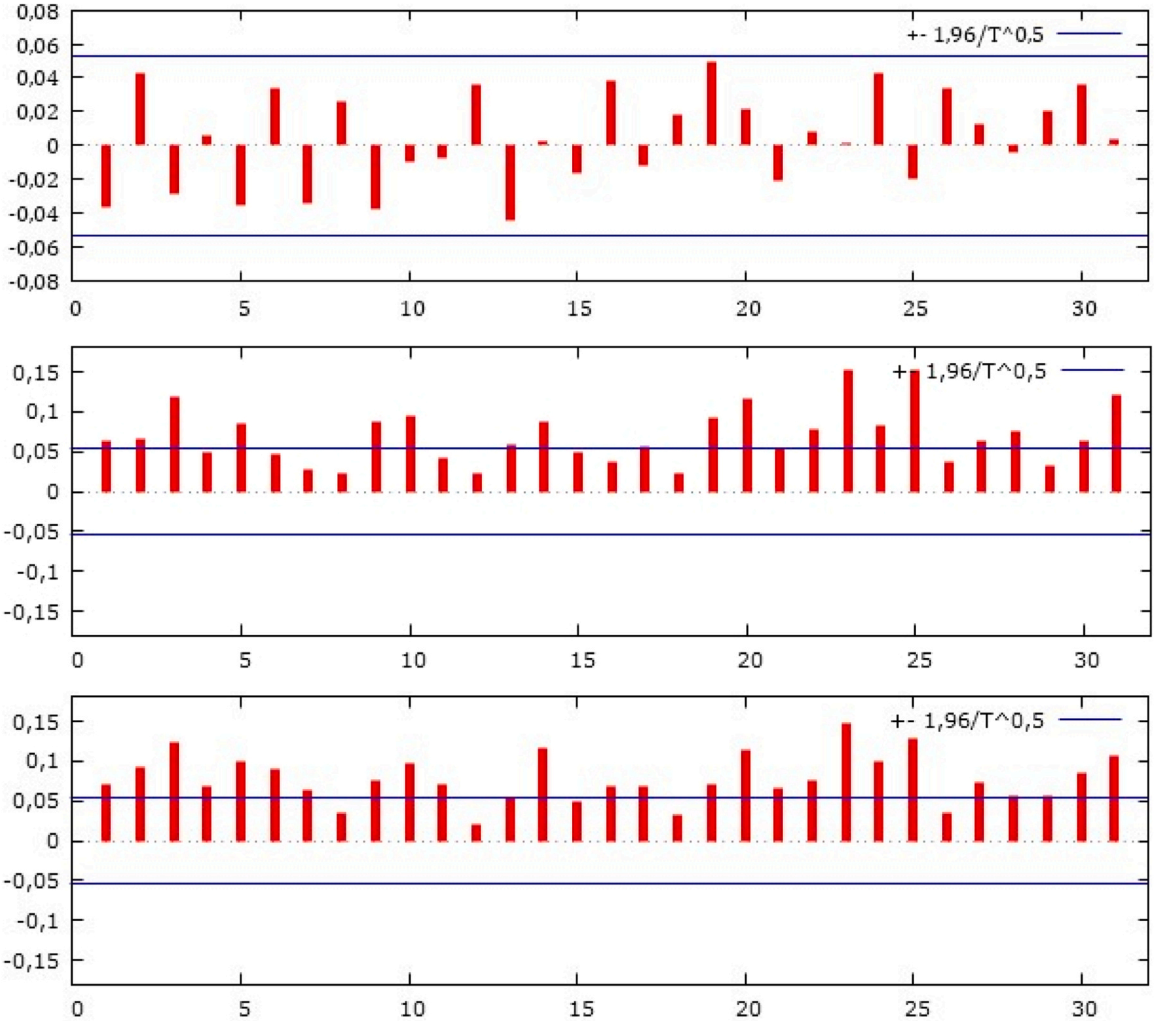


Fig. 17. a. Ljung–Box test for autocorrelation of the S&P Green Bond Index (returns), 09/30/2016–12/31/2021. **b.** Ljung–Box test for autocorrelation of the S&P Green Bond Index (squared returns), 09/30/2016–12/31/2021. **c.** Ljung–Box test for autocorrelation of the S&P Green Bond Index (absolute value), 09/30/2016–12/31/2021.

conventional bond market and, to a lesser extent, for the risk management of equity investments. Conversely, conventional bonds have provided greater diversification benefits for equity investors. This indicates that the implementation of the VAR model has not provided meaningful results for obtaining an overview of the volatility behavior of each market in relation to the others. This is probably due to the significant variations that have occurred in the markets over the years and the relative low data availability.

However, we acknowledge that the VAR model, despite its widespread use in capturing linear interdependencies among multiple time series, may not have yielded meaningful results in this study. This could be due to several reasons, including model assumptions and high volatility and outliers. Additionally, although the VAR model assumes linear relationships between the variables, financial markets (particularly those involving GBs) may exhibit nonlinear behaviors and structural changes that are not well-captured by a linear VAR framework. The presence of extreme outliers and high volatility in the GB market can also distort the results of a VAR model. These factors can introduce white noise and reduce the model's ability to accurately capture the underlying relationships. Meanwhile, the interactions between GBs and other financial instruments might be dynamic and change over time. In this case, VAR models, which assume constant parameters over the sample period, may not be flexible enough to capture these evolving dynamics.

By comparing our findings with those of Pham (2016) and Reboredo (2018), we establish a basis for understanding the behavior of GBs in relation to established financial theories. The observed volatility clustering both affirms certain aspects of financial theories (e.g., the EMH and the MPT), while challenging others (e.g., market segmentation and SFTs). In line with behavioral finance theories, we argue that GBs may primarily attract ESG-focused investors, but as the market grows, traditional investors may become involved. This shift can change the correlation dynamics, since these investors might react similarly to market-wide economic factors. Moreover, as institutional investors (who dominate both the bond and equity markets) incorporate GBs into their portfolios, as part of a broader risk management strategy (rather than purely for diversification), GBs are becoming more closely aligned with equity market movements.

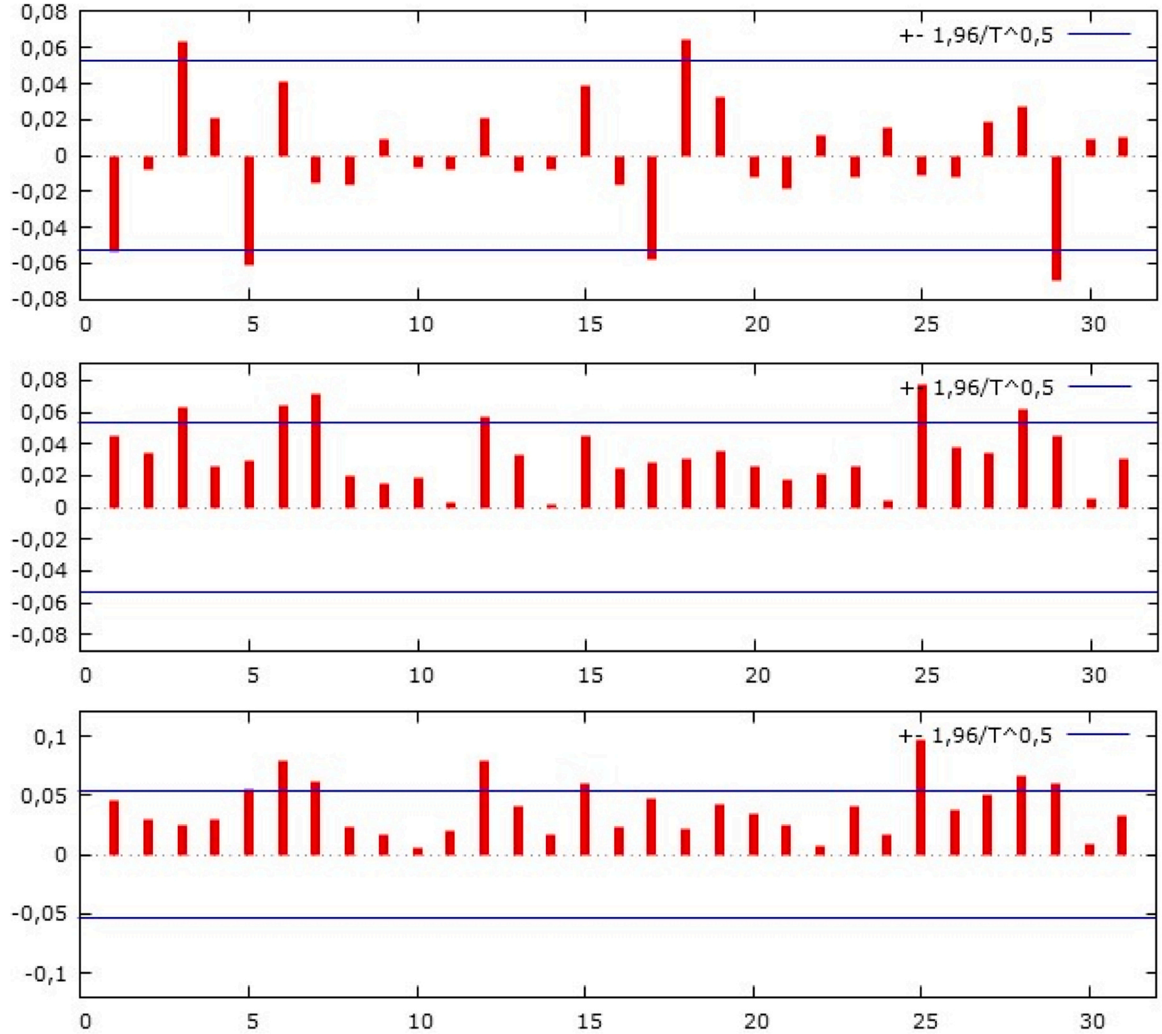


Fig. 18. a. Ljung–Box test for autocorrelation of the S&P U.S. Aggregate Bond Index (returns), 09/30/2016–12/31/2021. **b.** Ljung–Box test for autocorrelation of the S&P U.S. Aggregate Bond Index (squared returns), 09/30/2016–12/31/2021. **c.** Ljung–Box test for autocorrelation of the S&P U.S. Aggregate Bond Index (absolute value), 09/30/2016–12/31/2021.

As for the shift from a negative to a positive correlation between GBs and stock indices can be explained by the influence of the overall economic and financial environment. Specifically, during periods of economic expansion, both equities and GBs might show positive performance, due to increased investor confidence and risk-taking behavior. Meanwhile, policy and regulatory changes have important roles to play. For instance, since Reboredo's (2018) study, there have been significant policy initiatives and regulatory changes aimed at promoting sustainable finance. These changes may have led to greater alignment between GBs and broader financial markets, especially as they became more mainstream.

Furthermore, the increasing liquidity and market depth of GBs could explain the shift in correlation. In this regard, greater liquidity makes GBs more responsive to overall market conditions, mirroring equity market trends. Then, as GBs become more integrated into the financial system, their prices may increasingly reflect broader market sentiment, leading to the observed positive lagged relationship with stock indices. The positive lagged relationship found in this study suggests that the GB market has matured and is more closely integrated with the financial markets. This also implies that GBs are being traded by a broader base of investors, including those who actively participate in the equity market.

At this point, this study recommends some future research avenues. First, future studies could involve a longitudinal approach to determine how the volatility patterns in GBs evolve over time and whether they continue to mirror those of conventional bonds. Second, cross-market analyses could be conducted (alongside other sustainable financial instruments) to develop a broader understanding of how different segments of the sustainable finance market interact and behave. Third, the impact of regulatory changes on GB volatility could be examined to extract valuable insights into how policy developments influence market behavior and whether they lead to divergence from conventional market patterns. Fourth, in order to address the limitations of the VAR model and enhance the robustness of the analysis, the following methodological improvements could be considered: 1) Employing nonlinear models, such

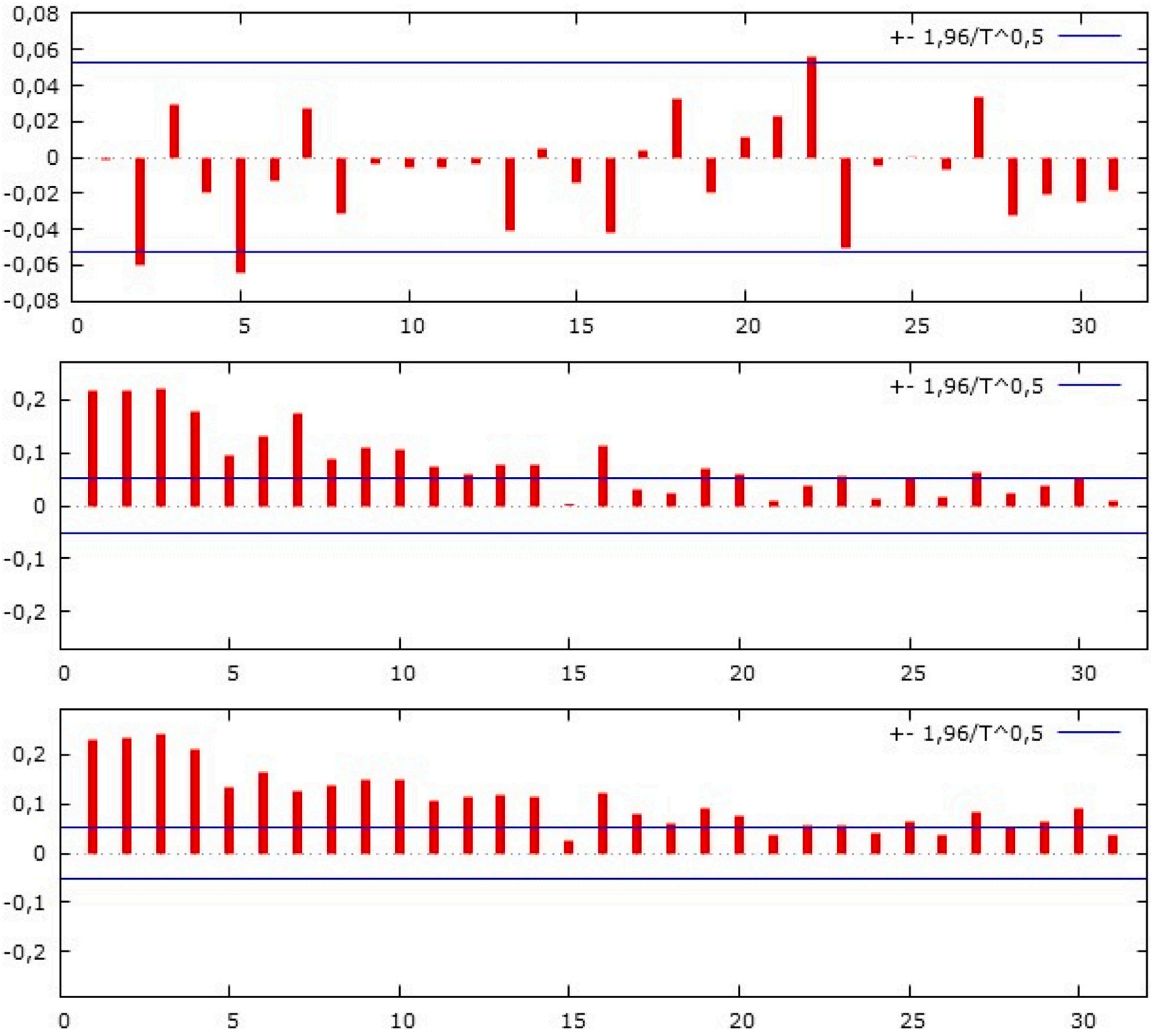


Fig. 19. a. Ljung–Box test for autocorrelation of the S&P 500 (returns), 09/30/2016–12/31/2021. **b.** Ljung–Box test for autocorrelation of the S&P 500 (squared returns), 09/30/2016–12/31/2021. **c.** Ljung–Box test for autocorrelation of the S&P 500 (absolute value), 09/30/2016–12/31/2021.

Table 5
Univariate GARCH model.

	SPUSGRN	SPUSBMIT	SPX
α_0	0.0000000173403	0.0000000201190	0.00000448870***
	(0.0000000173448)	(0.0000000129762)	(0.000000764072)
α_1	0.0228296***	0.0171878***	0.202751***
β_1	(0.00686318) 0.981740***	(0.00509801) 0.982448***	(0.02664534) 0.765574***
	(0.00772819)	(0.00799052)	(0.02739733)
Unconditional mean (μ)	0.00003	0.000127	0.000363
Persistence ($\alpha_1 + \beta_1$)	0.9983997	0.9935020	0.95475683
Unconditional variance ($\alpha_0/(\alpha_1 + \beta_1)$)	0.0000000173757	0.0000000202543	0.0000047524275
Half-life (days) (ln(0, 5)/ln ($\alpha_1 + \beta_1$)	358.002	109.131	13.077

Source: Authors' own estimations.
Notes: This table presents the coefficient estimates based on the GARCH (1,1) model for the S&P Green Bond Index Total Return (SPUSGRN Index), the S&P U.S. Aggregate Bond Index (SPUSBMIT), and the S&P 500 (SPX). Standard errors are in parentheses. ***, **, and * denote significance at the 1 %, 5 %, and 10 % levels, respectively. The sample period is 09/30/2016–12/31/2021.

as the threshold VAR (TVAR) or Markov-Switching VAR (MS-VAR), can help capture regime changes and nonlinear dynamics in financial time series; 2) Using high-frequency data can help better capture the short-term dynamics and volatility patterns in GB markets; 3) Extending the GARCH framework to a multivariate setting, such as the dynamic conditional correlation GARCH (DCC-

Table 6
ARCH Lagrange multiplier (LM) test.

SPUSGRN	SPUSBMIT	SPX
γ_0 0.00000844336***	0.00000277025***	0.0000551038***
(0.000000390675)	(0.000000127079)	(0.00000263723)
γ_1 0.087638***	0.0443332	0.274089***
(0.0314142)	(0.0283953)	−0.0432485

Source: Authors' own estimations.
Notes: This table presents the ARCH LM test for the S&P Green Bond Index Total Return (SPUSGRN), the S&P U. S. Aggregate Bond Index (SPUSBMIT), and the S&P 500 (SPX). Standard errors are in parentheses. ***, **, and * denote significance at the 1 %, 5 %, and 10 % levels, respectively. The sample period is 09/30/2016–12/31/2021.

Table 7
Bivariate GARCH model (SPUSGRN) SPUSGRN.

SPUSBMIT	0.156732***	
	(0.047728)	
SPX		0.0190150**
		(0.008761)
α_0	0.0000000178703	0.0000000175538
	(0.0000000177068)	(0.0000000169965)
α_0	0.0235542***	0.0232604***
	(0.00710531)	(0.00671455)
β_1	0.980983***	0.981317***
	(0.00795456)	(0.00741336)

Source: Authors' own estimations.
Notes: This table presents the coefficient estimates based on the bivariate GARCH model. The dependent variable is the S&P Green Bond Index (SPUSGRN), while the independent variables are the S&P U.S. Aggregate Bond Index (SPUSBMIT) and the S&P 500 (SPX). Standard errors are in parentheses. ***, **, and * denote significance at the 1 %, 5 %, and 10 % levels, respectively. The sample period is 09/30/2016–12/31/2021.

Table 8
ARCH LM Test (SPUSGRN) SPUSGRN.

SPUSBMIT	0.171754***	
	(0.0524683)	
SPX		−0.0691123***
		(0.00542577)
γ_0	0.00000824415***	0.00000244963***
	(0.000000391752)	(0.000000114189)
γ_1	0.106467***	0.0551761*
	(0.0343855)	(0.0303952)

Source: Authors' own estimations.
Notes: This table presents the results of the ARCH LM test. The dependent variable is the S&P Green Bond Market Index (SPUSGRN), while the independent variables are the S&P U.S. Aggregate Bond Index (SPUSBMIT) and the S&P 500 (SPX). Standard errors are in parentheses. ***, **, and * denote significance at the 1 %, 5 %, and 10 % levels, respectively. The sample period is 09/30/2016–12/31/2021.

GARCH) model, can provide insights into the time-varying correlations and volatility spillovers between GBs and other financial instruments; and 4) Using copula models to study the dependence structure between different financial instruments (without relying on the assumption of normality) can capture tail dependencies and provide a more nuanced understanding of the relationships during extreme market conditions.

Finally, by addressing the limitations of the VAR model and considering the appropriateness of different methodological approaches, the analysis of GB markets can be significantly strengthened. In this regard, incorporating nonlinear models, high-frequency data, and advanced econometric techniques, such as copulas and multivariate GARCH models, can provide a more comprehensive understanding of market dynamics and enhance the robustness of our conclusions.

Ethics approval and consent to participate

Not applicable

Table 9
Bivariate GARCH model (SPUSBMIT) SPUSBMIT.

SPUSGRN	0.483825***	
	(0.016364)	
SPX		−0.0660949***
		(0.005168)
α_0	0.0000000202506	0.0000000188263*
	(0.0000000131156)	(0.0000000111076)
α_0	0.0175694***	0.0186026***
	(0.00519648)	(0.00505544)
β_1	0.982015***	0.980717***
	(0.00816379)	(0.00742025)

Source: Authors' own estimations.
Notes: This table presents the coefficient estimates based on the bivariate GARCH model. The dependent variable is the S&P U.S. Aggregate Bond Index (SPUSBMIT), while the independent variables are the S&P Green Bond Index (SPUSGRN) and the S&P 500 (SPX). Standard errors are in parentheses. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively. The sample period is 09/30/2016–12/31/2021.

Table 10
ARCH LM Test (SPUSBMIT) SPUSBMIT.

SPUSGRN	0.459996***	
	(0.0163151)	
SPX		−0.0729433***
		(0.00542577)
γ_0	0.00000274928***	0.00000244963***
	(0.000000126008)	(0.000000114189)
γ_1	0.471552*	0.0551761*
	(0.0283411)	(0.0303952)

Source: Authors' own estimations.
Notes: This table presents the results of the ARCH LM test. The dependent variable is the S&P U.S. Aggregate Bond Index (SPUSBMIT), while the independent variables are the S&P Green Bond Index (SPUSGRN) and the S&P 500 (SPX). Standard errors are in parentheses. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively. The sample period is 09/30/2016–12/31/2021.

Table 11
Multivariate GARCH models (SPUSGRN, SPUSBMIT).

SPUSGRN		SPUSBMIT	
SPUSBMIT	0.218487***	SPUSGRN	0.0586536***
	(0.0505469)		(0.0155475)
SPX	0.0327252***	SPX	−0.0669533***
	(0.00920863)		(0.00513731)
α_0	0.0000000183148	α_0	0.0000000183012*
	(0.0000000171710)		(0.0000000108290)
α_1	0.024650***	α_1	0.0193841***
	(0.00693793)		(0.00515940)
β_1	0.980006***	β_1	0.980140***
	(0.00763522)		(0.00742418)

Source: Authors' own estimations.
Notes: This table presents the coefficient estimates based on the multivariate GARCH model. The dependent variables are the S&P Green Bond Index (SPUSGRN) and the S&P U.S. Aggregate Bond Index (SPUSBMIT). Standard errors are in parentheses. ***, **, and * denote significance at the 1 %, 5 %, and 10 % levels, respectively. The sample period is 09/30/2016–12/31/2021.

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Author statement

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Table 12
ARCH LM Test (SPUSGRN, SPUSBMIT).

	SPUSGRN	SPUSBMIT
SPUSGRN		0.0527381*** (0.0155244)
SPUSBMIT	0.219933*** 0.05630056	
SPX	0.0253744** 0.0105741	−0.0696917*** (0.00541116)
γ_0	0.00000817417*** (0.00000039210)	0.00000242637*** (0.000000112134)
γ_1	0.111501*** (0.0353890)	0.0572106* (0.0295884)

Source: Authors' own estimations.
Notes: This table presents the results of the ARCH LM test. The dependent variables are the S&P Green Bond Index (SPUSGRN) and the S&P U.S. Aggregate Bond Index (SPUSBMIT). Standard errors are in parentheses. ***, **, and * denote significance at the 1 %, 5 %, and 10 % levels, respectively. The sample period is 09/30/2016–12/31/2021.

Table 13
VAR estimates (p = 3) for the changes in the GB market (SPUSGRN), the conventional bond market (SPUSBMIT), and the equity market (SPX).

Independent Variable		Dependent Variable		
	Lag Order	$R_i^{SPUSGRN}$	$R_i^{SPUSBMIT}$	R_i^{SPX}
$R_i^{SPUSGRN}(-1)$	(1)	−0.0404722 [−1.5818] (0.028834)	0.247246*** [17.79] (0.014693)	−0.293622*** [−3.808] (0.081385)
$R_i^{SPUSGRN}(-2)$	(2)	0.019706 [0.6549] (0.317592)	−0.015984 [−1.0423] (0.016187)	0.067956 [0.8001] (0.089641)
$R_i^{SPUSGRN}(-3)$	(3)	−0.058232* [−1.9409] (0.316710)	−0.027993* [−1.8301] (0.016139)	0.084044 [0.9923] (0.088392)
$Adjusted R^2$		0.013264		
$F-statistics$		2.019463***		
$R_i^{SPUSBMIT}(-1)$	(1)	0.059056 [1.0456] (0.059611)	−0.066297** [−2.3029] (0.030377)	0.327945* [2.0570] (0.168216)
$R_i^{SPUSBMIT}(-2)$	(2)	0.156936*** [2.7758] (0.059663)	0.007055 [0.2449] (0.030403)	−0.396810** [−2.486] (0.168355)
$R_i^{SPUSBMIT}(-3)$	(3)	0.053576 [1.0385] (0.054446)	0.054658** [2.0792] (0.027745)	0.121893 [0.8371] (0.153678)
$Adjusted R^2$			0.194702	
$F-statistics$			35.94509***	
$R_i^{SPX}(-1)$	(1)	0.004063 [0.3999] (0.010726)	0.005906 [1.1409] (0.005566)	0.033355 [1.1630] (0.030275)
$R_i^{SPX}(-2)$	(2)	0.021622** [2.1351] (0.010690)	0.002795 [0.5415] (0.005478)	−0.089508*** [−3.1304] (0.030169)
$R_i^{SPX}(-3)$	(3)	−0.012065 [−1.1918] (0.010688)	−0.003147 [−0.6099] (0.005426)	0.049995* [1.7489] (0.030150)
$Adjusted R^2$				0.02347
$F-statistics$				3.60869***

Source: Authors' own estimations.
Notes: This table presents the coefficient estimates based on the VAR model. The proper lag order of this model is chosen by the goodness-of-fit BIC criteria. The t-statistics for the significance of the variables are in brackets, while the standard errors are in parentheses. ***, **, and * denote significance at the 1 %, 5 %, and 10 % levels, respectively. The sample period is 09/30/2016–12/31/2021.

CRediT authorship contribution statement

Faruk Bhuiyan: Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Methodology, Conceptualization. **Ahmed Bouteska:** Writing – original draft, Software, Resources, Methodology, Investigation, Data curation, Conceptualization. **Badir Miftah:** Writing – review & editing, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Taimur Sharif:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Investigation, Data curation, Conceptualization. **Mohammad Zoynul Abedin:** Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare no conflict of interest.

Data availability

Data will be made available on request.

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Consent for publication

All authors are very positive to publish this manuscript on this journal.

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