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"European Green Bond Markets Versus European Stock Markets: A Volatility Analysis"

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Abstract

In this thesis the volatility behavior of the European green bond market is compared with the volatility behavior of the European stock market between 2014-2022. This thesis uses a sign and bias test to test for asymmetric volatility behavior in both markets. After establishing asymmetric volatilities in both markets the volatilities of the markets are modelled with a GJR-GARCH model. To investigate the volatility dynamics between the two markets an asymmetric DCC-GARCH model is modeled. The European green bond market exhibits significant asymmetric volatility spillovers. The European green bond market has significantly lower volatilities, however the volatility of the European green bond market has increased relative to the European stock market. There are significant long-run spillover effects from the European stock market on the European green bond market.

1 Introduction

In the past years, the momentum for climate awareness has reached an all-time high. Initiatives such as the European Green Deal motivate individuals, governmental bodies, and businesses to transform their operations into future-proof activities. Businesses are stimulated by regulations and societal sentiment to shift away from high-carbon investments and disclose their sustainability practices. To move along with this growing sentiment toward sustainable investing, financial institutions increasingly search for possibilities to finance sustainable, low-carbon projects. One way to finance these investments is through the issuance of green bonds. Green bonds are fixed-income investments designed to raise money for climate and environmentally friendly projects (NN Investment Partners, 2021). In the past decade, green bond issuances have grown exponentially. NN Investment Partners expects European green bond issuance to jump 25% to EUR 500 billion in 2022, (NN Investment Partners, 2021).

With the increasing volume of the green bond market, the wide range of financial institutions issuing and investing in these bonds, and the environmental and economic benefits of these bonds, it is crucial to understand the dynamics of the green bond market. Specifically for investors planning to invest in the European green bond market, it is important to know the risk behavior of these assets to evaluate its diversification benefits for example. Parallel with the fast growth of these bonds, a range of literature has been published on the characteristics of green bonds. A large part of the existing literature focuses on the return characteristics of green bonds, investigating the "Greenium", which is a premium, issuers receive for issuing green bonds instead of conventional bonds. However, the risk of green bonds is a relatively underdeveloped area of literature. Other than the paper published by Pham (2016) and Park et al. (2010), there is a minimal amount of literature on this topic and to my understanding, there is no literature extending the findings to the European green bond market. In this paper I will investigate the following research question:

"To what extent has the volatility of the European green bond market behaved differently compared to the European stock market between 2014-2022?"

I will answer this research question by comparing the selected European green bond index with the European stock index. The following sub-questions will be answered to form a conclusion on my research question: How do green bond volatilities react to returns? How much does a shock in the stock market affect the volatility in the green bond market? How has the relative volatility of the European green bond and the European stock market developed over time? The following sections are structured as follows: In Section 2 I explore the existing literature on green bond markets and volatility analyses, followed by a hypothesis development based on this literature. In Section 3 I outline and explain the various regressions used to test my hypotheses. In Section 4 I discuss the data used in my regressions and the descriptive statistics of both indices. In Section 5 I present the results of my regressions, followed by a discussion and conclusion in Sections 6 and 7.

2 Literature Review & Hypothesis Development

2.1 Previous Literature

Risk and volatility have been a widely developed field of economic literature in the past decades. By studying risk dynamics one can avoid these risks by changing their behavior. However, not all risks are avoided because sometimes the benefits of taking those risks may outweigh the costs (Engle, 2004). The association between risk and variance in a portfolio was first analyzed by Markowitz (1952) and Tobin (1958). By avoiding risks and studying the variance of this risk, portfolio and banking behavior can be optimized. Initially, the variance was estimated using historical volatility. The historical volatility implied calculating the variance of an asset's return over a historical period and using this as the volatility forecast for periods in the future. There were however many remaining questions around which historical time period to use for estimating the volatility and the fact that logical arguments could be made regarding the inconsistency to assume constant volatility throughout a time period (Brooks, 2019). To fill this gap Engle (2004) introduced the autoregressive conditional heteroskedasticity (ARCH) model, which assumes that the variance of an asset's return is not constant over time, thus heteroskedastic, and autocorrelated with prior values of itself and other assets. Noting this stylized fact of time series, the volatility analysis conducted in this paper is done based on the ARCH framework. More specifically, after testing for heteroskedasticity among the volatility of the returns, the generalized ARCH model (GARCH) is applied. The GARCH model generalizes the ARCH model to an autoregressive moving average model for which the weights on past squared residuals decline geometrically (Engle, 2004).

The methodology and research question in this thesis is inspired by the study titled *"Is it risky to go green? A volatility analysis of the green bond market"* (Pham, 2016). In this paper, the volatility of the global green bond market is investigated by comparing the daily closing prices of the S&P Green Bond Index and S&P U.S. Aggregate Bond Index from 2010-2015. Pham uses a univariate GARCH (1,1) model to suggest that there is significant volatility clustering in the green bond market. Moreover, using a multivariate GARCH (1,1), Pham (2016) concludes that shocks in the conventional bond market spillover to the green bond market. Pham (2016) also shows evidence that there is an upward trend in the conditional correlation of returns between the green and conventional bond markets between 2010-2015.

Park et al. (2020), also study the volatility dynamics of the green bond market by comparing it with the equity market. In contrast to Pham (2016), Park et al. (2020), conclude that green bond markets exhibit the asymmetric volatility phenomenon. Accounting for the asymmetric volatility phenomenon Park et al. (2020) proceed using an asymmetric multivariate GARCH model. Furthermore, their findings suggest that there are volatility spillover effects between the green bond and equity market however they seem irresponsive to negative shocks in the opposite market (Park et al., 2020).

Gao et al. (2021), analyze the risk spillover and network connectedness of the Chinese green bond market and other Chinees financial markets between 2015-2020. Their research is one of the papers extending the scope of Pham's (2016) research to a more recent timeframe. Based on DCC-GJRGARCH, a multivariate asymmetric model, Gao et al. (2021) find a significant two-way volatility spillover between the green bond and traditional bond market, and a one-way spillover from the stock and commodities market to the green bond market. The findings by Gao et al. (2021) also indicate that volatility spillovers between the Chinees green bond market and other financial markets are time-variant and do not exhibit periodicity or seasonality. Instead, volatility spillovers in the Chinese market are mainly driven by unexcepted incidents and market conditions (Gao et al., 2021).

Various studies investigate the relative volatility of aggregate bonds and stock markets over time. Reilly et al. (2000) research the US treasury bond and stock market volatility during a 50-year period (1950-1999). Reilly et al. (2000) measure the volatility of the bond and stock market, using the historical volatility technique, examining the standard deviation of monthly returns over a period of 12 months. By first analyzing both 12-month bond and stock market volatilities separately, Reilly et al. (2000) conclude that stock market volatility is on average three times higher than bond market volatility during the 50-year period. Next, Reilly et al. (2000) analyze the moving standard deviation between bonds and stocks over time by plotting the ratio of the standard deviations for the stock and bond markets. This analysis concludes that the ratio between the bond and stock market volatilities is very cyclical with wide ranges, but also identifies a significant positive trend throughout the period. The positive trend in the ratio implies that the volatility of the two markets converges during the 50-year period (Reilly et al., 2000).

Young and Johnson (2004) extend the methodologies of Reilly et al. (2000) to the Swiss governmental bond and the Swiss stock market. Contrary to Reilly et al. (2000), Young and Johnson (2004) find an insignificant positive standard deviation ratio slope. Young and Johnson's (2004) findings do find that the bond market standard deviation in Switzerland is less than one third of the stock market's standard deviation, agreeing with Reilly et al. (2000). Both papers by Reilly et al. (2000) and Young and Johnson (2004) do not use GARCH models to conduct their analysis. They instead use the historical variance technique, thereby indicating a limitation of their conclusions.

2.2 Risks and the Green Bond Market

Since the creation of the green bond in 2007, the market has grown rapidly in its volume, investors, and issuers. However, the lack of standardization has been one of the key barriers to greater expansion in the past decades. Multiple unique risks such as greenwashing, lack of transparency, and limited benchmarks are identified in the green bond market making it difficult to price and trade green bonds (Deschryver & De Mariz, 2020). In a study performed by Mazzacurati (2021), only a fifth of firms that issue green bonds worldwide, in 2021, disclose data on their GHG emissions, showing the low disclosure quality in the green bond market. However, with social and economic pressure on many companies to "go green", the risk of greenwashing has increased (Cicchiello et al., 2022). Nevertheless, the potential of a large and fundamental green bond market in tackling challenges related to climate change is realized by financial institutions. The European green bond standard proposed in January 2020, introduces requirements for green bonds to apply for these standards, including, taxonomy-alignment, transparency, external review, and supervision by EU authorities (European Commission, 2020).

A significant question for green bond investors, partially due to the lack of standardization, is the liquidity of the green bond market. The green bond market has experienced large oversubscription in the primary market, which may be driven by the additional investor base of green investors compared to the regular bond market (Weber & Saravade, 2019). Even though high demand makes it easier for the green bond holder to liquidate their positions, the secondary market for green bonds is relatively low, indicating that investors often hold green bonds until maturity (Mazzacurati, 2021). When comparing corporate green bonds with corporate conventional bonds of the same green bond issuers, Mazzacurati's (2021), findings suggest that green bond liquidity is tighter, although the difference is small and remained about constant during COVID-19.

Another significant risk for green bond investors is credit risk. Studying green bond behavior during COVID-19, Cicchiello et al. (2022), find that compared to conventional bonds, green bonds had a higher risk exposure and were less resilient to distress. Green bonds did however profit more from any upside during the COVID-19 pandemic compared to conventional bonds of the same issuers. Furthermore, the environmental and climate risks green bonds additionally assess may lower the risk of green bonds (Weber & Saravade, 2019). During COVID-19, triggered by the positive news of a vaccine, investors were relieved their focus shifted to the broader impact of the pandemic. This may have led to investors finding a value-enhancing strategy by commitment toward environmentally friendly attitudes, leading to lower credit spreads (Cicchiello et al., 2022).

2.3 Hypothesis Development

Black (1976) and Chrisite (1982), first studied the asymmetric volatility phenomenon. The asymmetric volatility phenomenon in stock markets implies that negative price shocks lead to higher volatility compared to positive price shocks. The existence of asymmetric volatilities is further studied in the context of the conditional (time-dependent) variance of stocks and bonds. Cappiello et al. (2006) find that bond returns show little asymmetry in the conditional variance, whereas for stock returns there is a strong asymmetry in its conditional variance. Pham (2016) confirms Cappiello et al.'s (2006), findings for the green bond market between 2010-2015. Nevertheless, Park et al.'s (2020), more recent study concludes that both green bonds and equity markets exhibit asymmetric volatilities, however, the green bond market has the unique characteristic that its volatility is also sensitive to positive shocks. Park et al. (2020), give the positive market response to eco-friendly financial instruments as a possible reason for this positive shock sensitivity. From these findings I develop the following hypothesis:

Hypothesis I: The European green bond market exhibits significant asymmetric volatility between 2014-2022

Due to the different structures of stocks compared to bonds, they exhibit significantly different returns and risks. Stock prices are fully dependent on the growth and profitability of the company invested in, thereby profiting, and losing usually in hand with fluctuations in the price. Alternatively, the fixed income structure of bonds, guarantee payouts to the lenders by the borrowers. At the maturity date of bond investments, the lender will receive the principal along with the interest rate payments. Due to this fixed payment, the price of bonds tends to fluctuate less than stock prices, implying lower expected returns and a less volatile market.

The analyses done by Reilly et al. (2000) and Young & Johnson (2004) supports the economic theory, showing that the standard deviation of stocks in the sample is on average around three times higher compared to the standard deviation of bonds. Although Pham (2016)'s findings show that the green bond market has a higher conditional standard deviation compared to the aggregate bond market, when comparing the global green bond market with the global equity market, Park et al. (2020), found that the global green bond has a lower conditional standard deviation than the equity market between 2010-2020. With this information I form the third hypothesis:

Hypothesis II: European green bond market returns exhibit significantly lower volatility than European stock market returns between 2014-2022

The European green bond market has experienced an exponential increase in constituents and value since its inception. It is expected that increasing the diversification of the market lowers the unsystematic risk of the market over time. Nevertheless, the increase in corporate issuers compared to the governmental issuer-dominated market at the beginning, increases the credit risk of the green bond market. Also, with the increase in corporate issuers, the risk of greenwashing has increased (Cicchiello et al., 2022). Other arguments can be made for lower volatilities in the European green bond market, namely, the increase of standardization and the shift of investors towards environmentally friendly behavior. However, I expect the lower expected volatilities arising from the European green bond standards and the attitude toward environmentally friendly behavior to be interrupted by the COVID-19 pandemic based on the findings of Cicchiello et al. (2022), forming the last hypothesis:

Hypothesis III: The ratio between the volatility of the European green bond and the European stock market has experienced a significant increase between 2014-2022

The volatility analysis conducted by Park et al. (2020), concludes that there are significant volatility spillover effects between the green bond and equity markets. However, these volatility spillover effects are limited to positive shocks in the other market. Negative shocks in the green bond market have no significant volatility spillover effects on the equity market and vice versa (Park et al., 2020). Besides Park et al. (2020), various literature has used GARCH models to analyze volatility spillovers between the aggregate bond and equity market. Chulia and Torro (2008), find that volatility spillovers between the stock and bonds markets occur in both directions. Furthermore, Dean et al. (2010) also find volatility spillover effects between the Australian bond and stock markets. More specifically volatilities in the Australian bond market spillover to the Australian equity market but vice versa is not true. From these findings, I expect the second hypothesis:

Hypothesis IV: There are significant volatility spillover effects from the European stock market onto the European green bond market between 2014-2022

3 Methodology

3.1 Univariate Model

To answer my hypotheses, I initially model the volatility of the green bond market. In my paper, I define volatility as the standard deviation of an asset's return, which is the square root of the variance. Inspired by the methodologies used in Pham (2016), Park et al. (2020) and, Reilly et al. (2000), I model the volatility green bond market using a GARCH model. The GARCH model is a widely used technique in economic literature to model the volatility of a time series. The GARCH model models the conditional variance of a time series using an autoregressive structure thereby allowing volatility shocks to persist over time and heteroskedastic behavior. To compare the volatility of the green bond market to the stock market I also model the volatility of the stock market for the same period. First, I model the assets return equation used in the GARCH model with the equation below:

$$Rt = E_{t-1}[R_t] + \varepsilon_t, \qquad \varepsilon_t | I_{t-1} \sim iid(0, \sigma_t^2) \tag{1}$$

In this equation $E_{t-1}[R_t]$ represents the conditional (time-dependent) mean of the assets return at time t for the given information set I_{t-1} with error term ε_t and conditional (time-dependent) variance σ_t^2. The conditional mean and variance are both specified using the following equations:

$$E_{t-1}[R_t] - \mu = \sum_{h=1}^{r} \phi_h (R_{t-h} - \mu) + \sum_{h=1}^{s} \psi_k \epsilon_{t-k} \tag{2}$$

$$\sigma_t^2 = a_0 + \sum_{i=1}^{p} a_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} b_j \sigma_{t-j}^2 \tag{3}$$

$\mu = E[R_t]$, from Equation (2), denotes the unconditional mean of the assets returns and σ_t^2 from Equation (3), denotes the conditional variance. The parameters a_i $(i = 1, \dots p)$ and b_i $(i = 1, \dots q)$ determine the extent of volatility clustering in the returns of the assets, where a high and significant value indicates high volatility clustering. The number of lags, p, q, r, s, needed to accurately model the time series is determined using the Akaike and Bayesian information criteria. When the lag lengths are determined a GARCH model of the form GARCH (p, q), will be used to model the conditional variance, σ_t^2.

3.1.2 Test for Asymmetric Volatility

To test for asymmetric volatility behavior in the green bond and stock market, both time series are tested for sign bias. The sign and size bias test was proposed by Engle and Ng (1993) to test for the leverage effect, where an asset's volatility tends to be negatively correlated with an asset's return. The sign and size bias test regress the squared residual term of the mean return model, Equation (1), $\hat{\varepsilon}_t^2$, on the dummy variable, $\hat{g}_{t-1}$, representing the sign of the residual term to analyze the change in volatility due to negative or positive return shocks (Brooks, 2019). The regression equation for the sign and size bias tests is shown in Equation (4):

$$\hat{\varepsilon}_t^2 = \delta_0 + \delta_1 \hat{g}_{t-1} + u_t \tag{4}$$

With the dummy variable $\hat{g}_{t-1}$, the sign and size bias tests can be conducted. Assuming $I(\cdot)$ is the indicator function and by indicating with it, we can define the following tests:

- Sign bias test if $\hat{g}_{t-1} = I(\hat{\varepsilon}_{t-1} < 0)$
- Negative size bias test if $\hat{g}_{t-1} = \hat{\varepsilon}_{t-1} I(\hat{\varepsilon}_{t-1} < 0)$ *(5)*
- Positive size bias test if $\hat{g}_{t-1} = \hat{\varepsilon}_{t-1} I(\hat{\varepsilon}_{t-1} > 0)$

To estimate the three regressions, a joint regression can be run to test all three effects:

$$\hat{\varepsilon}_t^2 = \delta_0 + \delta_1 I(\hat{\varepsilon}_{t-1} < 0) + \delta_2 \hat{\varepsilon}_{t-1} I(\hat{\varepsilon}_{t-1} < 0) + \delta_3 \hat{\varepsilon}_{t-1} I(\hat{\varepsilon}_{t-1} > 0) + u_{i,t} \qquad (6)$$

The coefficients of the bias tests (δ) determine the extent of the positive or negative shock effect. By comparing the absolute values of the coefficients, a conclusion can be made regarding the (a)symmetry of the time series' volatility.

3.1.3 GJR-GARCH Model

Once asymmetric volatility behavior in a time series has been established it is important to use an alternative GARCH model that captures this behavior. The GJR-GARCH model captures the leverage effect using the equation below:

$$\sigma_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + a_2 \sigma_{t-1}^2 + gI(\varepsilon_{t-1} < 0)\varepsilon_{t-1}^2 \qquad (7)$$

The conditional variance is denoted by σ_t^2 and the lagged squared residuals are denoted by ε_{t-1}^2. The indicator function $I(\varepsilon_{t-1} < 0)$ takes on a value of 1 if the lagged residual is negative, and zero if the lagged residual is positive. Comparing the GARCH model to the GJR-GARCH model, they both have the same mean equation. The difference between the GARCH and GJR-GARCH models is the addition of the indicator function: $gI(\varepsilon_{i,t-1} < 0)\varepsilon_{i,t-1}^2$ in the conditional variance equation to account for the asymmetric behavior. In the indicator function, g is the coefficient used to evaluate the leverage effect. If g is positive, negative shocks will impact the conditional volatility more than positive shocks, and vice versa if g is negative. In the case that coefficient g is equal to zero, there is no asymmetric behavior, and the GJR-GARCH model can be rewritten as a GARCH model.

3.2 Bivariate Model

3.2.1. DCC-GARCH Model

After modeling the volatility of the green bond and stock market separately, I investigate the interaction between the two markets. In the bivariate model, I assume that the volatility of an asset's returns does not only depend on previous values in the time series but also on the volatility of the other assets. Engel (2002) published the dynamic conditional correlation GARCH (DCC-GARCH) model, which models nonlinear combinations of univariate GARCH models. In the DCC-GARCH model, the volatility of each asset is specified separately, and thereafter the dependence between the two assets is specified. Compared to other multivariate models, the DCC-GARCH model has significant benefits versus other approaches to model the conditional variance-covariance matrix, including its flexibility allowing for the estimation of large matrices (Broadstock & Cheng, 2019).

The DCC-GARCH model is a generalization of the CCC-GARCH model, allowing for dynamic correlations between the time series over time. Consequently, the DCC-GARCH model allows accounting for conditional time-varying volatility and covariance between the returns of the green bond and stock market (Brooks, 2019).

In the following equations, the DCC-GARCH model will be explained, and the EUGRB and SPPX indices are represented by $i = 1, 2$ respectively. Firstly, in line with Engels' (2002) methodology, the variance-covariance matrix is decomposed as:

$$\Sigma_t = D_t R_t D_t \tag{8}$$

Where the diagonal matrix of the conditional standard deviations D_t, is derived from the univariate GARCH models represented by:

$$D_t = diag\left[\sqrt{\sigma_{i,t}^2}\right] \tag{9}$$

Additionally, $\sigma_{i,t}^2$ is defined as follows for $i = 1, 2$:

$$\sigma_{i,t}^2 = c_i + a_i \epsilon_{i,t-1}^2 + b_i h_{i,t-1} \tag{10}$$

And the dynamic conditional correlation matrix R_t is time-dependent, which is defined by the following equation:

$$R_t = diag\left(q_{11,t}^{-\frac{1}{2}}, q_{22,t}^{-\frac{1}{2}}\right) Q_t diag\left(q_{11,t}^{-\frac{1}{2}}, q_{22,t}^{-\frac{1}{2}}\right) \tag{11}$$

The estimators in matrix Q_t follow the univariate GARCH model, and for the GARCH(1,1) process it can be written as:

$$Q_t = (1 - \alpha - \beta)\bar{R} + \alpha z_{t-1} z'_{t-1} + \beta Q_{t-1} \tag{12}$$

Where z_{t-1} and $\bar{R}$ are defined as:

$$z_{t-1} = \begin{bmatrix} \epsilon_{1,t-1}/\sigma_{1,t-1} \\ \epsilon_{2,t-1}/\sigma_{2,t-1} \end{bmatrix} \tag{13}$$

$$\bar{R} = E[z_{t-1} z_{t-1}{}'] \tag{14}$$

In Equation (12), α and β are the time-invariant parameters, and $\bar{R}$ is the matrix of the unconditional correlation matrix of z. α and β take on the same values for both time series, hence they are scalars. To ensure that the process is stationary, the sum of α and β should be smaller than 1. Specifically, the parameters α and β reflect the short-term and long-term magnitude of volatility spillovers from one index to the other index, respectively.

It should also be noted that the, the parameter estimates of the DCC-GARCH model are estimated using a log-likelihood function. The first step of this function identified the univariate mean and variance equations, with θ_1 being the first set of univariate GARCH parameters, as:

$$LogL1(\theta_1) = -\frac{1}{2}\sum_{t=1}^{T}[log\{diag(D_t)\} + D_t^{-1}\varepsilon_t^2 \tag{15}$$

In the second step the dynamic correlation parameters are estimated with the following log-likelihood equation:

$$LogL1(\theta_1|\theta_2) = -\frac{1}{2}\sum_{t=1}^{T}\{log|R_t| + (D_{\varepsilon_t}^{-1})'R_t^{-1}(D_t^{-1}\varepsilon_t)\} \tag{16}$$

3.2.2. Asymmetric DCC-GARCH Model

To account for asymmetric volatility behavior in the univariate and bivariate model, the DCC-GARCH has to be extended to the asymmetric DCC-GARCH proposed by Capiello, Engle, and Sheppard (2006). The asymmetric DCC-GARCH conditional variance process is defined with the equations below:

$$\Sigma_t = D_t R_t D_t \tag{17}$$

Similar to the symmetric DCC-GARCH, D_t is defined as:

$$D_t = diag\left[\sqrt{\sigma_{i,t}^2}\right] \tag{18}$$

However, $\sigma_{i,t}^2$ is defined with an additional parameter reflecting the asymmetry, $\eta_{i,t}$:

$$\sigma_{i,t}^2 = c_i + a_i\epsilon_{i,t-1}^2 + b_i h_{i,t-1} + g_i\eta_{i,t-1}^2 \tag{19}$$

Where the asymmetry can be written as:

$$\eta_{i,t-1}^2 = max\,(0, -\epsilon_{i,t-1}) \tag{20}$$

Again, similar to the symmetric DCC-GARCH, the dynamic conditional correlation matrix, R_t is defined as:

$$R_t = diag\left(q_{11,t}^{-\frac{1}{2}}, q_{22,t}^{-\frac{1}{2}}\right) Q_t diag\left(q_{11,t}^{-\frac{1}{2}}, q_{22,t}^{-\frac{1}{2}}\right) \tag{21}$$

Where the estimators in matrix Q_t, with additional parameters reflecting the leverage effect, γ:

$$Q_t = (1 - \alpha^2 - \beta^2)\bar{R} - \gamma^2\bar{N} + \alpha^2 z_{t-1}z'_{t-1} + \gamma^2\eta_{t-1}\eta_{t-1}'\beta^2 Q_{t-1} \tag{22}$$

Where z_{t-1}, $\bar{R}$, η_t, and $\bar{N}$ are defined as:

$$z_{t-1} = \begin{bmatrix}\epsilon_{1,t-1}/\sigma_{1,t-1}\\ \epsilon_{2,t-1}/\sigma_{2,t-1}\end{bmatrix} \tag{23}$$

$$\bar{R} = E[z_{t-1}z_{t-1}'] \tag{24}$$

$$\eta_t = \begin{bmatrix}\eta_{1,t}\\ \eta_{2,t}\end{bmatrix} \tag{25}$$

$$\bar{N} = E[\eta_t\eta_t'] \tag{26}$$

The definitions of α and β and $\bar{R}$ are the same as in the previously discussed symmetric DCC-GARCH model. Additionally, γ is the third time-invariant parameter, reflecting the extent of asymmetry in the volatility spillover effect from one index onto the other index. $\bar{N}$ is the matrix of the unconditional correlation matrix of η. Similar to the symmetric DCC-GARCH model, the parameters are also estimated using the log-likelihood functions.

4 Data

4.1 Data Collection

To test the hypotheses from Section 2.3 I will use time-series data of the European green bond market and the European stock market performance. I collected the daily closing prices of the Bloomberg Barclays MSCI European Green Bond Index (EUGRB), as a proxy for the European green bond market and the Dow Jones STOXX 600 Index (SXXP), for the European stock market. The closing prices for EUGRB are retrieved through the Bloomberg terminal and the SXXP indices are retrieved from the Refinitiv Eikon (Datastream) database. The daily closing prices are collected for both indices during the period 14/10/2014 to 01/06/2022, resulting in 1,984 observations for both indices. The daily returns of the indices are calculated as follows:

$$R_t = ln\left(\frac{p_t}{p_{t-1}}\right)$$

where p denotes the closing price of the index at time *t* and R_t, denotes the return.

Both indices are one of the largest players and representatives in their field. The SXXP index represents a fixed number of 600 constituents representing large, mid, and small capitalization firms from 17 countries within the European region[1] (STOXX, 2022). The constituents of the SXXP index are updated every quarter to maintain representativeness. Similar studies on volatility spillovers have used the SXXP index to represent the European stock index (Arouri et al., 2012) (Mensi et al., 2021). When conducting my analysis of the SXXP it is important to consider that the index includes firms that are within the European region, but not in the European Union (ex. United Kingdom). When considering other European stock indices, I concluded that all large representative indices include firms beyond the European Union. Moreover, since the SXXP index is not a value-weighted index it is important to consider that there may be large-cap bias in my results, where large-cap firms are overrepresented in the index thereby not including many small-cap firms.

[1] Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland and the United Kingdom

The EUGRB index was introduced in 2014 when Bloomberg and MSCI ESG Research LLC introduced a new range of Green Bond Indices. The introduction of these indices was a response to the initial set of Green Bond Principles published by a consortium of banks in 2014. The criteria used to evaluate the eligibility of “Green” Bonds reflect the key elements of the Green Bond Principles. The market value of the EUGRB index has grown from 14,230 EUR (14/10/2014) to 482,024.90 EUR (01/06/2022) representing a growth of 3287,39% in the past eight years. Furthermore, there were 14 constituents at the start of the index, compared to 537 at the end of my dataset. The large increase in the index resembles the rapid growth of the global green bond market in the past decade. The introduction of new green bond standards throughout my time-period may be a reason for attrition bias, implying that the standard of green bonds in the index have increased. Nevertheless, the increase in green bond standards is a variable I accounted for when forming my hypotheses. The range of European green bond indices is very limited since most green bond indices focus on the global market. Nevertheless, financial institutions such as NN investment partners use the EUGRB Index as a benchmark and tracking tool for their research (NN Investment Partners, n.d.). Similar to the SXXP, the EUGRB includes constituents that are located in the European region but are not part of the European Union. The EU Green Bond standards only have a direct impact on firms within the European Union, therefore the inclusion of firms located in countries beyond the scope of the European Union must be realized as a potential weakness in my results.

I estimate the models outlined in Section 3 using the statistical software STATA. Since STATA does not include the asymmetric DCC-GARCH model in its software, I estimate this model separately using an alternative programming language, R, in the development environment, R Studio. Therefore, the results in Section 5 are all obtained from the regression output of STATA, except for the third column in Table 5, which is obtained from R Studio output.

4.2 Descriptive Statistics

Table 1 presents the descriptive statistics of the daily returns of the EUGRB and SXXP indices. Table 1 shows that the mean and standard deviation of the daily returns are negative for the EUGRB index and that they are lower compared to the SXXP index. Table 1 also shows that the daily returns of both indices have asymmetric structures with negative skewness. Furthermore, both indices’ daily returns show high kurtosis exhibiting leptokurtic distributions with fat tails. Leptokurtic behavior may imply that the daily returns do not follow a normal distribution, therefore this is important to consider when modeling the volatility.

Table 1. Descriptive Statistics

	EUGRB	SXXP
Mean	-0.0001	0.0002
Min	-0.01980	-0.1219
Max	0.0174	0.0807
Std. dev.	0.0025	0.0110
Skewness	-0.6708	-1.1358
Kurtosis	9.3268	15.9820
Correlation	-0.0829	
Obs.	1,984	1,984

Note: Table 1 summarizes the descriptive statistics for the daily returns of the Bloomberg Barclays MSCI European Green Bond Index (EUGRB) and the STOXX EU 600 Index (SXXP) within the timeframe: 14/10/2014-01/01/2022.

4.3 Preliminary Test

The daily returns and the squared returns, for the EUGRB index the SXXP are displayed in Figures 1 and 2. The squared return graphs for both indices indicate potential volatility clustering, where periods of high volatility are followed by high volatility and vice versa (Brooks, 2019). Furthermore, from these figures, we can see that both indices exhibit similar moments high squared returns, at the start of 2020 during the start of the COVID-19 crisis. Looking at the left panel of Figure 1, it seems that the EUGRB index exhibits mean-reverting behavior, suggesting stationarity. Moreover, an augmented Dicky-Fuller test (Table 2), is performed to test the null hypothesis that a unit root is present in the time series. The significant test statistic in Table 2 implies that the null hypothesis can be rejected, thus confirming stationarity in the GB index sample. Similarly, the STOXX EU 600 index daily returns, in the right panel of Figure 1, appears to exhibit mean-reverting return. According to the augmented Dickey-Fuller test, the STOXX EU 600 index daily returns in my sample reject the null hypothesis that a unit root is present, therefore being stationary.

Figure 1.

EU Green Bond and STOXX EU 600 indices daily returns (Source: Bloomberg and Datastream). Sampling period: Daily 14/10/2014-01/06/2022.

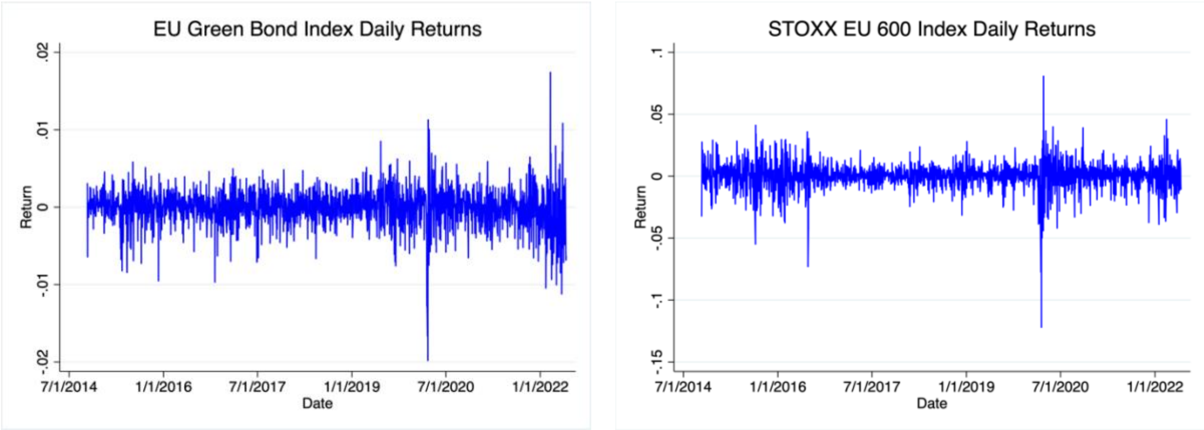


Figure 2.

EU Green Bond and STOXX EU 600 indices daily squared returns (Source: Bloomberg and Datastream). Sampling period: Daily 14/10/2014-01/06/2022.

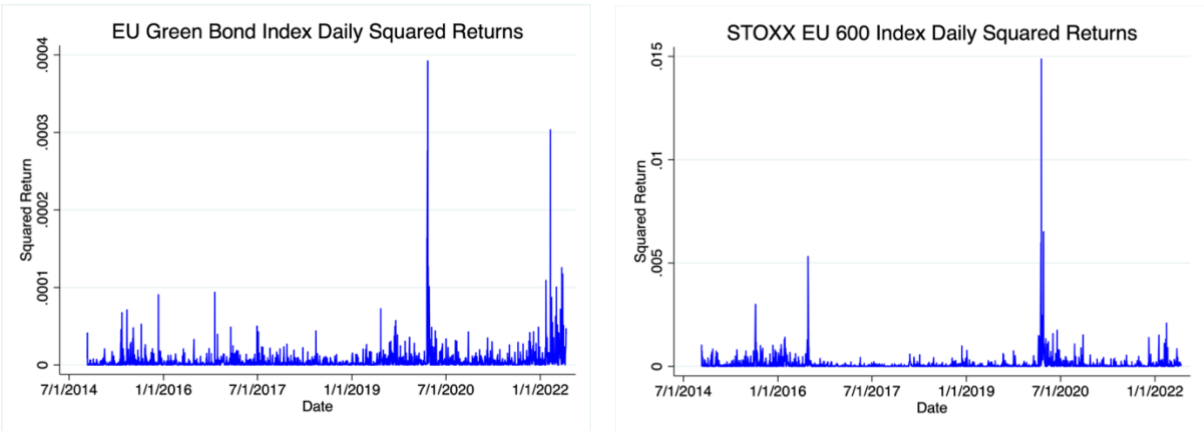


Table 2. Unit Root Test

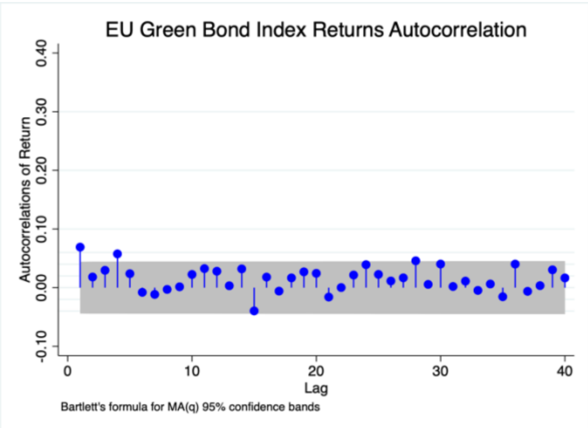
	ADF test statistic
Returns on EUGRB	-41.472***
Returns on SXXP	-44.678***

*Notes: Table 2 shows the test statistics of the Augmented Dickey-Fuller test on the daily returns of the Bloomberg Barclays MSCI European Green Bond Index (EUGRB) and the STOXX EU 600 Index (SXXP) within the timeframe: 14/10/2014-01/01/2022. The stars beside the test statistics are based on the p-value of the two-sided t-tests. * equals p-value < 0.10, ** p-value < 0.05 and *** p-value < 0.01.*

Figures 3 and 4 show the Ljung-Box tests to test for autocorrelation in the daily returns and squared returns of the EUGRB and SXXP indices. Figure 3 shows that the lags of the returns for both indices do not or barely exceed the critical value bands and that there is no clear pattern in the lags. Hence, I conclude that there is no autoregressive behavior in the mean equation for both indices. Figure 4 shows that the Ljung-Box Q-statistic is higher than the critical value for most of the lags EUGRB's and SXXP's squared returns autocorrelation. Therefore, Figure 4 demonstrates that there is autocorrelation in the squared returns, thus in the volatilities of EUGRB and SXXP. The periods of volatility clustering in Figure 2 and the Ljung-Box test indicate that the volatilities of EUGRB and SXXP have (G)ARCH effects, therefore, a GARCH model will be the most suitable to analyze the volatilities of the two indices.

Figure 3

Autocorrelation of Returns (Source: Bloomberg and Datastream). Sampling period: Daily 14/10/2014-01/06/2022.



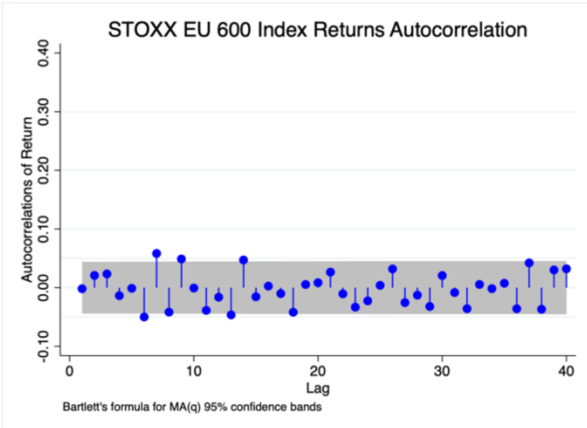
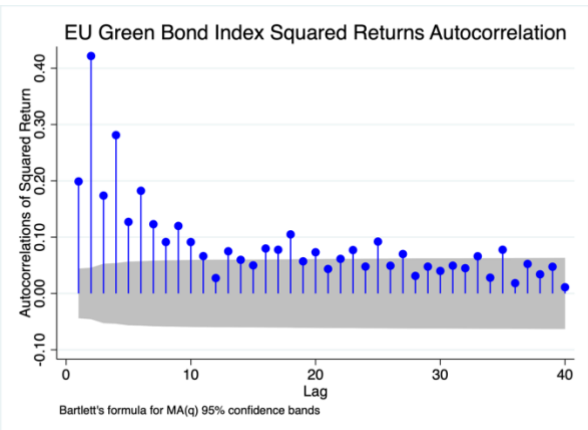
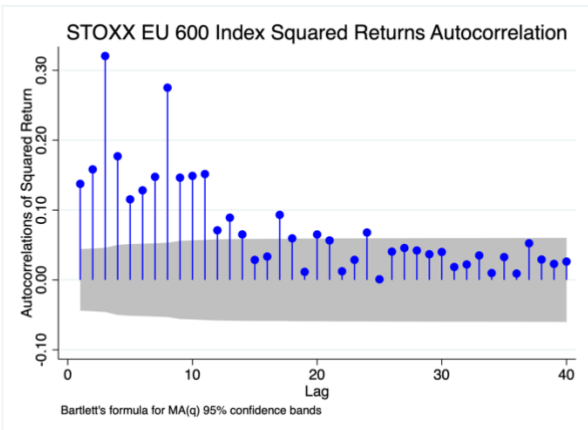


Figure 4

Autocorrelation of Squared Returns (Source: Bloomberg and Datastream). Sampling period: Daily 14/10/2014-01/06/2022.





5 Results

In this section, I present the results of my analysis of the volatilities of the EUGRB and SXXP indices to test the hypotheses outlined in Section 2.3 In Section 5.1 I analyze the effect of shocks in the returns of the EUGRB and SXXP on their volatilities to test for (a)symmetric behavior. Thereafter in Section 5.2, I model the volatilities of both indices using a GJR-GARCH model. Lastly, to research the relative behavior of both indices' volatilities and test the presence of volatility spillovers between the indices I present the results of the DCC-GARCH model in Section 5.3.

5.1 Asymmetric Volatility

To test for asymmetric volatilities, Engle and Ng (1993), proposed the sign and size bias tests. Table 3 shows the results of the sign and size bias tests on the volatilities of the EUGRB and SXXP indices. Following Engle and Ng's methodology, the values in Table 3 are the t-statistics for the sign, negative sign, and positive sign bias tests and the f-statistic for the joint bias test.

The positive and significant sign bias test value for both EUGRB and SXXP indicate that the volatilities of the indices exhibit sign bias. These findings are in line with the stylized fact that financial instruments usually respond more sensitive to bad news compared to good news. The negative size bias test coefficient is significant for the EUGRB, however, the positive size bias test coefficient is not significant, implying that its volatility is not sensitive to positive shocks. The insignificant positive size bias test coefficient contradicts the findings of Park et al. (2020), who find that the volatility of the global green bond market is sensitive toward positive shocks. Both size bias test coefficients are significant for the SXXP meaning that its volatilities are sensitive to positive and negative shocks.

Table 3. Sign and Size Bias Test

	EUGRB	**SXXP**
Sign bias test	2.71***	2.94***
Negative size bias test	-7.55***	-4.52***
Positive size bias test	0.58	-2.79***
Joint bias test	19.20***	9.59***

*Notes: Table 3 shows the t-values of the sign and size bias tests and the f-value of the joint bias test. EUGRB = European Green Bond Index and SXXP = STOXX EU 600 Index. The stars beside the test statistics are based on the p-value of the two-sided t-tests. * equals p-value < 0.10, ** p-value < 0.05 and *** p-value < 0.01.*

5.2 Univariate GJR-GARCH Results

Once asymmetric volatility behavior has been determined, it is important to use a GARCH model which can accommodate this behavior. To accompany the asymmetric volatility behavior, I chose the GJR-GARCH (1,1) model to analyze the volatilities of both indices.

Table 4 shows the regression results of the GJR-GARCH (1,1) model. The coefficient, g_1, represents the leverage parameter. Since the g_1 parameter is positive and significant for the SXXP index at the 99% confidence interval, and positive and significant for the EUGRB index at the 90% confidence interval, I can interpret this as evidence that bad news has a higher impact on the volatility compared to good news. To check the goodness of fit of my models I compared the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Log-likelihood ratio test (LL) of the symmetrical GARCH (1,1) model with the asymmetrical GJR-GARCH (1,1) model for both indices. All three goodness of fit tests confirmed that the GJR-GARCH (1,1) model fits the volatilities of the EUGRB and SXXP the best. Furthermore, to account for the high kurtosis and the fat tails discussed in Section 4.2, I used a t-distribution on the errors instead of the normal distribution to regress the volatilities. The t-distribution is an example of a leptokurtic distribution that accounts for fatter tails than the normal distribution. Regarding the distribution used in the regression, I used the same goodness of fit tests comparing the AIC, BIC, and LL of the normal distribution, t-distribution, and generalized standard error (GED) distribution, of which the t-distribution gave the highest magnitude.

Table 4. Asymmetric Univariate Volatility Model Results – GJR-GARCH (1,1)

	EU Green Bond Index	**STOXX EU 600 Index**
$\boldsymbol{\mu}$	0.0001	.0004604***
	(.0000431)	(.0001572)
$\boldsymbol{a_0}$	0.0000	3.23e-06***
	(0.0000)	(3.84e-07)
$\boldsymbol{a_1}$	0.0501***	0.0071014***
	(0.01510)	(.0225385)
$\boldsymbol{b_1}$	0.9101***	.8384487***
	(0.0158)	(.0131787)
$\boldsymbol{g_1}$	0.0351*	.2538103***
	(0.0210)	(.0230834)
LL	9386.890	6632.210
AIC	-18761.790	-13252.420
BIC	-18728.230	-13218.860
Obs.	1,984	1,984

*Notes: Table 4 shows the parameter estimates of the GJR-GARCH (1,1) model. Since there is stationarity in the mean equation, E(R)=μ. EUGRB = European Green Bond Index and SXXP = STOXX EU 600 Index. The stars beside the test statistics are based on the p-value of the two-sided t-tests. * equals p-value < 0.10, ** p-value < 0.05 and *** p-value < 0.01.*

Through the GJR-GARCH (1,1) regression, the conditional standard deviation for the EUGRB and SXXP are estimated. Figure 5 plots the conditional standard deviations of both indices by date. From Figure 5 it can be concluded that the conditional standard deviations of the EUGRB index are significantly lower throughout the sample compared to the conditional standard deviations of the SXXP index. Additionally, the mean of SXXP's conditional standard deviations is 329.35% higher than the mean of EUGRB's conditional standard deviations.

Figure 5

Conditional standard deviations of EUGRB and SXXP (Source: Bloomberg and Datastream). Sampling period: Daily 14/10/2014-01/06/2022.

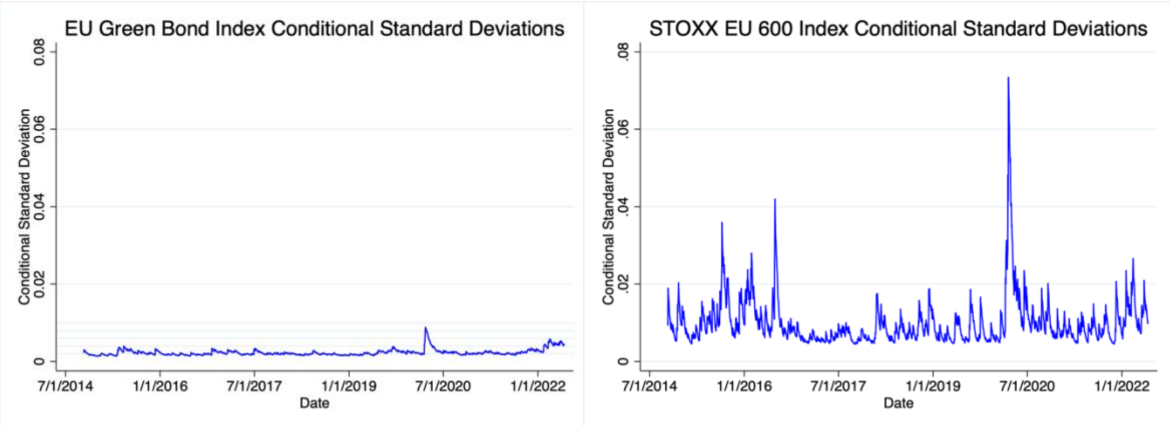
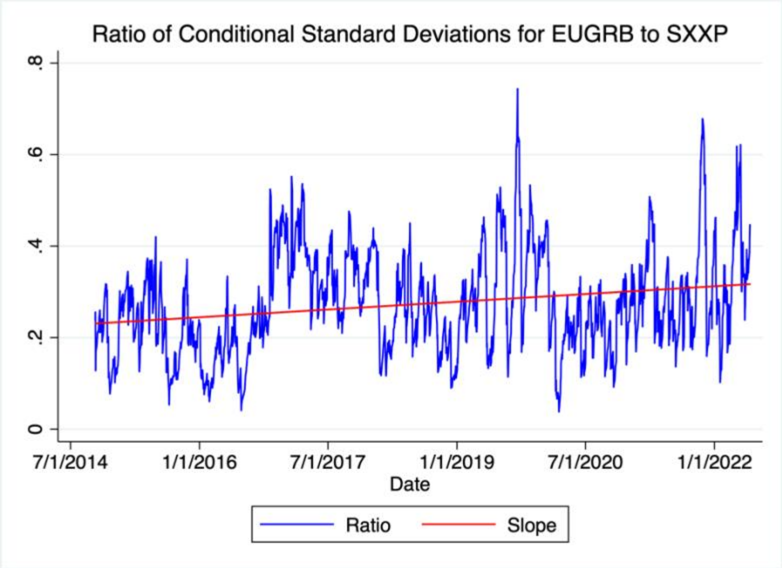


Figure 6 shows the movement of the ratio between the conditional standard deviations of EUGRB and SXXP throughout the time frame. A second red line has been added to the graph to show the average slope of the ratio throughout the timeframe. Looking at Figure 6, a few observations can be made. Firstly, the conditional standard deviation of EUGRB is never larger than the SXXP's conditional standard, at any point in the time frame, since the ratio never exceeds 1. Secondly, comparing Figures 5 and 6, it is striking that during moments of high conditional standard deviation in the SXXP index, such as 03/2022 at the start of COVID-19, the ratio drops significantly. Lastly, the value of the slope is 0.0000309, which may indicate that the ratio has increased throughout the timeframe, in other words, the conditional standard deviation of EUGRB has increased relative to the conditional standard deviation of SXXP.

Figure 6

The Ratio of EUGRB to SXXP conditional standard deviations over time (Source: *Bloomberg and Datastream). Sampling period: Daily 14/10/2014-01/06/2022*



5.3 Bivariate DCC-GARCH Results

To test for volatility spillovers from the SXXP index to the GRBD index I use a dynamic conditional correlation multivariate-GARCH (1,1) model (DCC-GARCH). The second column of Table 5 presents the regression results of the symmetric DCC-GARCH model. Since the results in Section 5.1 and Section 5.2, indicated that there is asymmetric volatility in both indices, I have also regressed the asymmetric DCC-GARCH model. The regression results for the asymmetric DCC-GARCH model are shown in the third column of Table 5. Comparing the log-likelihoods, AIC's, and BIC's of the two models, the asymmetric DCC-GARCH has the highest goodness of fit. Moreover, the asymmetric volatility behavior is also again confirmed by the significant, g_1, parameters of EUGRB and SXXP.

The α parameter represents the short-run volatility spillover effect, also known as the sensitivity, from the SXXP index to the EUGRB index. The estimate of α in the asymmetric DCC-GARCH is insignificant, meaning that there is no significant volatility spillover effect from SXXP to EUGRB in the short run. Nevertheless, the β parameter is significant at a 99% confidence interval for the asymmetric DCC-GARCH model, implying that there is a highly significant volatility spillover effect from SXXP to EUGRB in the long run, also known as high persistence. Lastly, the g_1, coefficient is not significantly different from zero, meaning that the volatility spillover effect is not asymmetric between the two markets.

Table 5. Bivariate Volatility Model Results – DCC M-GARCH (1,1)

	Symmetric DCC-GARCH	**Asymmetric DCC-GARCH**
Parameter estimates for SXXP Index:		
μ_{SXXP}	0.0008	0.0002
	(0.0249)	(0.0002)
a_{0SXXP}	0.0000***	0.0000***
	(0.0000)	(0.0000)
a_{1SXXP}	0.1605***	0.0068
	(0.0197)	(0.0108)
b_{1SXXP}	0.8154***	0.8382***
	(0.0197)	(0.0162)
g_{1SXXP}		0.2551***
		(0.0433)
Parameter estimates for EUGRB Index:		
μ_{EUGB}	0.0100**	-0.0000
	(0.0048)	(0.0000)
a_{0EUGB}	0.0000***	0.0000
	(0.0000)	(0.0000)
a_{1EUGB}	0.0592***	0.0339**
	(0.0097)	(0.0137)
b_{1EUGB}	0.9172***	0.9170***
	(0.0155)	(0.0158)
g_{1EUGB}		0.0451**
		(0.0185)
Estimates for conditional correlation parameters:		
α	0.0203*	0.0190
	(0.0110)	(0.0154)
β	0.8304***	0.8384***
	(0.1005)	(0.1205)
γ		0.0132
		(0.0268)
LL	15833.960	15895.570
AIC	-15.957	-16.010
BIC	-31569.210	-31692.439

Notes: EUGRB = European Green Bond Index and SXXP = STOXX EU 600 Index. Column 2 is regression output from STATA and column two is output from R Studio. The AIC in both columns is output from R Studio. The stars beside the *test statistics are based on the p-value of the two-sided t-tests. * equals p-value < 0.10, ** p-value < 0.05 and *** p-value < 0.01.*

6 Conclusion

To answer my research question: *"To what extent has the volatility of the European green bond market behaved differently compared to the European stock market between 2014-2022?"*, I summarize my findings from Section 5 along the four hypotheses I developed in Section 2.3.

Table 3 shows that sign bias and negative size bias tests are positive and highly significant for the EUGRB, meaning that the index responds asymmetrically to shocks in the return. Additionally, in the GJR-GARCH model, the leverage parameter, g_1, is positive and significant for the EUGRB index, which implies that the volatility of the EUGRB index is negatively correlated with its return. However, it should be noted that the leverage parameter is only at a 90% confidence interval. Even though further research should be done to test the significance of my findings, by extending the time frame, these results lead to the acceptance of the first hypothesis: the European green bond market exhibits asymmetric volatility between 2014-2022.

The conditional standard deviations throughout time in Figure 5 and the average standard deviation from my descriptive statistics in Table 1, shows that the EUGRB index exhibits significantly lower volatility that the SXXP index between 2014-2022. Eventhough both indices are used as a proxy for the European green bond market and the European stock market, these findings confirm economic theory on the risk-related differences between stocks and bonds. Thereby my second hypothesis can be accepted, that the European green bond market exhibits significantly lower volatility than the European stock market between 2014-2022.

I tested my third hypothesis by looking at the slope of the ratio between the volatilities of the EUGRB index and the SXXP index. My results indicated that the slope of the ratio has a small but positive and significant value implying that there has been a small increase in the ratio between 2014-2022, justifying my third hypothesis. However, for this conclusion should be viewed critically as the slope is an average measure of the relative volatility between the European green bond market and the European stock market, thus, possible shocks in this ratio are not clearly represented.

Lastly, by extending the univariate model to a multivariate scope, I find that the asymmetric DCC-GARCH model shows significant volatility spillover effects from the SXXP index to the EUGRB index. More specifically, the parameter β is significantly positive, showing that there are long-run volatility spillovers. Parameters, α and γ are insignificant showing that there are no significant short run volatility spillovers from the SXXP index to the EUGRB index, and that the asymmetric spillover effects are not significantly different than zero. Even so, I can accept my fourth hypothesis as there are significant long-run volatility spillovers from the European stock index to the European green bond index between 2014-2022.

Even though my results confirm most of my hypotheses, the conclusions above have significant limitations which must be considered in further research. In my methodology I used the GJR-GARCH and the asymmetric DCC-GARCH to model the univariate and multivariate models, however volatility modeling has been a widely research topic leading to the existence of other models such as the EGARCH, for asymmetric univariate volatility models and the BEKK-model, for multivariate volatility modelling. It would therefore be interesting to research whether the same conclusions would hold when using these models. Regarding spillover effects, I only investigated the one-way volatility spillover from the European stock market to the European green bond market, nevertheless for future research it would be interesting to investigate the vice versa spillover. Furthermore, it would also be interesting to investigate the determinants of volatility spillovers, including macro-economic determinants such as interest rates. Reilly et al. (2000) also look at the comparison of peaks in volatility between the bond and stock markets. In this thesis I only made a conclusion regarding comparison of the average volatilities of the European green bond and European stock market, however looking at peaks in volatilities, investors and policymakers can investigate the European green bond market behavior more accurately in highly volatile periods, such as during COVID-19 or the Russo-Ukrainian war.

Yet, the conclusions made in my thesis contribute to the existing economic research on European green bonds which has grown significantly also between the start of my thesis process to the end. The investigation of the volatility behavior of the European green bond market compared to the European stock market allows investors and policymakers to better understand the risk-return behavior of this still new type of bond.

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