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ESG Investing through ETFs – An effective way to circumvent volatility?

An econometric approach using the GARCH model.

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Abstract

This study highlights relatively new investment phenomena such as ETF investing and forthcoming trends in placement strategies to incorporate long-term visions and sustainable holdings. ETFs are popular for several reasons, but the investment vehicle also has some embodied volatility, in contrast to more traditional securities, making them less desirable for the risk-averse investor. This thesis's central purpose is to examine how to circumvent some of this embedded volatility through sustainable investment strategies in ETFs. The definition of sustainable and green investments is made based on MSCIs ESG-rating. The purpose of the problem question is to make rational investing in ETFs more applicable for the private investor. The study's result is consistent with the claim that green and sustainable investments are the future of finance. The quantitative analysis made through the DCC-GARCH model indicated a significant difference in daily volatility between green and non-green ETFs. The analysis is based on five years of daily return data compared between 80 ETFs listed in the US.

Keywords: ETFs, ESG, sustainability, volatility, conditional variance, GARCH.

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1 Introduction

1.1 Background

One can view the financial market as a reflection of the economy, influences of the present, our contemporary challenges, and opportunities. As in any other market, movements in the financial market often reflect the trends of today. One of today's most critical global issues has been particularly prominent in influencing our investments – the climate crisis. Countries, companies, and individuals are joining forces to combat the climate threats facing our planet, making the area of green finance perhaps more relevant than ever (Berrou, Dessertine, and Migliorelli, 2019).

Initially, green finance mainly focused on climate-related aspects of an asset. With time, the concept of green finance has come to include more perspectives on sustainability. Today, both social and governmental sustainability are hot topics among investors and forms an integral part of sustainable investments. With a broader definition of sustainability, there is also greater variation in what is considered a sustainable investment. Critics argue that it is easier to market as sustainable, even though one might only work actively within a small portion of the areas of sustainability. On the other hand, the broader definition has created opportunities where assets within specific industries that, by nature, are not climate-smart can work with several other aspects of sustainability. Today, a private investor can choose from a wide range of assets whose focus can vary from ethical sustainability to securing a low carbon footprint (Berrou, Dessertine, and Migliorelli, 2019).

With many categories of assets to choose from, the private investor can perceive it as overwhelming, deciding what to invest in. Therefore, investing in funds has become a popular alternative to investing in individual stocks to achieve diversified exposure to more than one market easily. As sustainability has become an increasingly important part of financial investments, green funds are today an essential part of an investor's portfolio. However, there is no universal agreement on how to measure the sustainability of fund investments. One of the most common measurements of a fund's sustainable impact is the Morgan Stanley Capital International (MSCI) ESG-rating system. The rating is based on the ESG label, which defines an investment's societal impact by reviewing three measures of sustainability; Environmental, Social, and Governance (Hale, 2017).

As in other parts of finance, trends within fund investment can also be seen. In recent years, passive investing has become increasingly popular, where exchange-traded funds (ETFs) have become a strong player in the area. ETFs offer the best attributes of two popular assets: They have the diversification benefits of ordinary funds while at the same time getting the ease of how stocks are traded as they are listed on an exchange. In addition, ETFs are usually designed to follow an underlying index, which is in line with the increased interest in passive investments (Madhavan, 2016). This implies a wide range of investment possibilities, which could be one explanation for the rapid growth in the ETF market, now at an estimated size of 5,3 trillion USD, according to Business Insider (2019).

Moreover, ETFs have quickly established themselves within green finance, and today there are countless ETFs to choose from that work with a sustainable portfolio. However, ETFs have proven to be highly volatile compared to mutual funds precisely because of their liquidity. For a professional investor, volatility can be somewhat sought after, making ETFs a common tool for investing in volatility (ETF Authority, 2020). Nonetheless, the question remains as to how these attributes affect the private investor.

1.2 Exchange Traded Funds

ETFs are often compared to other investment vehicles, such as individual stocks, traditional active mutual funds, and index funds. As a fact, ETFs share similarities and dissimilarities with all of them. ETFs have the same pooled structure as mutual funds, in the sense that buying a share of an ETF or a mutual fund implies exposure to multiple assets and usually hundreds of holdings. ETFs also share some outstanding features with index funds since they usually apply a passive investment strategy, tracking a benchmark index. This feature differs from traditional mutual funds mainly because traditional mutual funds are actively managed and thus often charge a hefty fee for their services. In contrast, ETFs and index funds only charge a fraction of that fee (Madhavan, 2016). Additionally, ETFs are distinguished from both index funds and traditional mutual funds through the possibility of intraday trading which makes for greater liquidity. The function of intraday trading in ETFs makes them similar to simple stocks, attracting investors who want the same flexibility as trading individual stocks when investing in pooled vehicles. Nonetheless, ETFs will again be more cost-efficient than buying each stock separately and combining them to a portfolio matching the ETF holdings (Madhavan 2016).

There is a unique mechanism in creating and redemption of ETF shares that substantially differ from mutual funds. Unlike a mutual fund, ETFs use an authorized participant (AP) to create and redeem shares, making for more tax-efficient, fair-priced, less costly, and seamless transactions (ETF authority, 2020). ETFs also possess highly appreciated attributes of transparency and tax efficiency compared to other resembling investment alternatives. Mutual funds by customs and laws only need to disclose their holdings quarterly and only list their current holdings with a 30-day lag. On the contrary, ETFs must by customs, report and disclose their holdings each day, and this information must be easily accessible to all investors. This transparency level is greatly valued by investors who want to ensure that their investment is placed under the united terms (ETF authority, 2020). Furthermore, ETF investors' tax efficiency lies within the structure of selling and buying shares. If an ETF investor wishes to sell some shares, the investor can instantly do so on an exchange. Since there is no sale of the underlying security, this easy exchange trade of shares creates tax efficiency. Nevertheless, traditional mutual funds need to sell some of their underlying assets whenever an investor wishes to redeem shares, leading to more considerable taxation burdens. (ETF Authority, 2020).

ETFs are, in fact, a great alternative to more traditional investment vehicles by enabling an efficient way to get exposure to a broader range of holding without facing high expense ratios. However, just as with any other type of vehicle, ETFs have many risks associated with them. One of the most significant risks is market risk; as ETFs usually track an index, there is no immediate remedy when the market goes down. The ETF investors will then be faced with the same blunt downturn as the overall market. Furthermore, it can be somewhat complicated for the ordinary investor to know which ETFs will perform and which will not. There is also more extensive risk exposure because ETFs are traded intraday, making for more volatile share prices during the day. The high volatility can result in an immense temptation to day trade when given the possibility to track the price movements in real-time. This temptation generally makes it harder for the risk-averse investor to hold their share for the wanted investment period. A traditional index fund or mutual fund can, in this case, be a better option (ETF Authority, 2020).

1.3 Problem statement

One of ETFs' essential qualities is their exceptional liquidity, enabling them to be easily bought and sold. However, due to their liquidity, ETFs can result in higher daily volatility than other investment vehicles, such as mutual funds. Nonetheless, higher volatility is often considered a higher risk for a private investor rather than a possibility of a higher return. With ETFs being highly volatile, this could lead to avoidance of investing in them. In previous studies, presented in the next chapter, the focus has been to examine why ETFs are more volatile and what effects this can have on its holdings. These studies are aimed primarily at professional investors, who in many cases use different investment strategies based on trading volatility. However, we have not found studies examining whether it is possible to get around the higher volatility through the type of ETF one chooses to invest in. Therefore, the gap in previous research lacks a perspective on ETF investment that is relevant to the private investor.

Based on the assumption that investors are risk-averse, there is a need to conduct in-depth research on the opportunities to reduce volatility exposure when investing in ETFs. Despite the many attractive attributes' ETFs offer for the private investor, the high volatility can cause one to avoid entering the ETF market. When investigating which ETFs tend to show lower volatility, we found an interesting pattern where ETFs with a high ESG-rating displayed lower standard deviation than ETFs with a low ESG-rating. This founding opened up the question of whether ETFs with a high sustainability-rating have attributes that make them less volatile. In connection with the fact that green investments are in high demand and in line with promoting sustainable development, we find it vital to examine how these ETFs differ and how we can increase the motives for investing in them.

In order to contribute to minimizing the gap in previous research, as well as opening up for further research on sustainable ETFs, this paper seeks to answer the following research question:

- Do sustainable ETFs yield lower daily volatility than non-sustainable ETFs?

An econometric study with applicable volatility models will be conducted on a large sample of ETFs to answer the research question.

1.4 Purpose

The purpose of this bachelor thesis is to investigate whether investing in ETFs with a high ESG-rating results in lower volatility exposure than investing in ETFs with a low ESG-rating.

Our research aims to contribute with a new perspective on ETF investing that can appeal to the private investor. As a private investor often does not have the time, knowledge, or interest in performing investment strategies such as volatility play, the possibility of escaping some of the high volatility could further increase the motive for investing in ETFs. By focusing on the volatility perspective of ETFs and incorporating a sustainability perspective, we want to convey an investment perspective that is in line with today's climate challenges. Additionally, we hope to drive future research towards conducting more studies on what characteristics drive ETFs' volatility and open up for further discussion on how one can successfully combine investments with a sustainable footprint.

1.5 Delimitations

In this essay, we exclusively examine passive ETFs. Our delimitation is based on the fact that ETFs are generally passive and that passive investments have increased in popularity, thus more relevant to study. Furthermore, we classify the ETFs' sustainability according to one ESG-rating: the MSCI ESG-rating. The delimitation is based upon MSCI being the leading provider of ESG-ratings and that the Bloomberg Terminal, from which we retrieve data, applies the same system. Furthermore, to avoid displaying data in different currencies, this thesis exclusively analyze ETFs traded on the US exchange. Additionally, the thesis excludes data from 2020 due to the COVID-19 outbreak. Without this delimitation, the results would be distorted due to extreme movements on the exchange not explained by the ETFs' characteristics but by the economic crisis and uncertainty that followed the pandemic.

1.6 Outline

This thesis's structure is conducted in the sense that all forthcoming chapters will be presented as such: Chapter two will present some previous research regarding the topics of this thesis. This will give the reader an introductory understanding of the question at issue and why there is a gap of knowledge to be filled. The third chapter will summarize the central hypothesis. Following, the fourth and fifth chapters will present the data and review all relevant theories and models that are used in order to conduct the intended analysis. The reader will, in these chapters, gain the necessary knowledge to understand the primary analysis. The sixth and seventh chapters will present the result and how these results were conducted using the models explained in the fourth and fifth chapters. Finally, chapter eight will review and discuss the empirical results and suggest future research on the topic.

2 Previous Research

Our study relates to several strands of literature and earlier research within the area of ETFs, volatility, and ESG-labeled assets. However, previous research focuses on either examining ETFs and volatility or ESG-labelled assets and volatility. To date, we have not found any research that combines these areas and examines whether an ESG-labelled ETF shows a different pattern of volatility than a non-ESG ETF. Furthermore, most studies are written to reach out to professional investment managers rather than private investors. To deepen current research on volatility and ETFs, we, therefore, chose to apply the ESG perspective in the area of volatility and ETFs. Our study also differs from the past by targeting the interests of private investors.

2.1 Previous studies on ETFs and volatility

Numerous studies have been conducted on the relationship between ETFs and volatility. Ben-David, Franzoni, and Moussawi (2017) focused on investigating arbitrage activity between ETFs and the underlying baskets. The study analyzed data on ETFs that were listed on the US exchange, whose baskets contained US stocks. By, among other methods, applying IV and OLS regressions, the authors could constitute that stocks with a higher ETF ownership displayed significantly higher volatility. This result supported their hypothesis: that the attributes of an ETF could be a catalyst for liquidity shocks and that these shocks do, in fact, increase the non-fundamental volatility of securities in the ETF's basket. Even more interesting, they discovered that the increase in volatility appeared to introduce undiversifiable risk in the stock prices with higher ETF ownership.

Further on ETFs and volatility, Bystedt and Lundkvist (2019) dedicated their bachelor thesis to investigate whether the conclusion made by Ben-David et al. (2017) would hold outside the US exchange. In the essay, they discover that the conclusion does not go beyond the US exchange and provides the reader with a new perspective through further research on what potential factors drive higher stock volatility. By applying similar research as Ben-David et al. (2017) on the western European market, their results showed a negative relationship between ETF ownership and stock volatility. Furthermore, they deepened the research by investigating the importance of company size and the effect of crises. Their research showed that the negative relationship between ETF ownership and stock volatility increased for big companies and periods out of a crisis.

Lastly, we have discovered several studies that apply GARCH and ARMA methodology to investigate spillover effects between ETFs and different markets. For example, Dedi and Yavas (2016) analysed daily data on country exchange-traded funds and discovered volatility and return spillovers in several equity markets such as Germany, UK, and Russia. Rompotis (2018) supports the findings made by Dedi et al. (2016) with a study focused on spillover effects between US ETFs and emerging stock markets. The author finds a high degree of comovement between the US ETF market and the underlying stock markets and significant return spillovers between ETFs and benchmarks. Further, the study concludes the same empirical findings for volatility spillovers.

2.2 Previous studies on ESG and volatility

When it comes to ESG-labeled assets, the range of previous studies is somewhat smaller. To our knowledge, there is not any study that examines ESG-labeled ETFs and how the ESG-attributes may affect volatility. However, we have found some studies that examine how ESG attributes can affect an asset's volatility. Jain, Sharma, and Srivastava (2019) conducted a study focused on whether sustainable investment alternatives offer better financial returns than the conventional indices from developed and emerging markets. Applying GARCH-type modeling, Vector Error Correction Model, and Johansen's cointegration test on 5-year daily closing prices of financial returns on a number of selected ESG indexes, they test the volatility spillover between the sustainable indices and the conventional indices. Jain et al. (2019) found no significant difference in the performance between traditional conventional indices and sustainable indices, making them suitable substitutes to another. In their conclusion, they suggest that investment managers should consider both the indices with the perspective of hedging and diversifying the risk.

In a study from this year, Guo, Jamet, Beatrix, Piquet, and Hauptmann (2020) conducted an interesting approach to ESG investing through investigating the predictive power of ESG related financial news on stock volatility. The authors developed a pipeline of ESG news extraction, news representations, and Bayesian inference of deep learning models. By experimental evaluation on different markets and real data, Guo et al. (2020) could conclude a superior predicting performance as well as the relation of high volatility prediction to stocks with potentially high risk and low return. Furthermore, they found that the proposed pipeline's prospect was a flexible predicting framework for various textual data and target variables.

3 Hypothesis

The hypothesis of the thesis is based on the thought that ETFs with a low ESG-rating might be a driver of higher volatility. With the increased interest in sustainable investments, as well as increasing requirements and regulations on sustainable business - the future for non-green investments may be at the end of its era. Hence, one could argue that investing in ETFs with a low ESG-rating could be associated with even higher volatility exposure. Therefore, the leading hypothesis is that investing in ETFs with a high ESG-rating imposes lower exposure to volatility than investing in ETFs with a low ESG-rating.

It follows that the hypothesis of the thesis is defined as:
Ho: Daily volatility of green ETFs = daily volatility of non-green ETFs
H1: Daily volatility of green ETFs ≠ daily volatility of non-green ETFs

4 Theory and models

4.1 Sustainability measure

4.1.1 ESG – Environmental, Social and Governance.

During recent decades, ESG has become the focal point for sustainable and responsible investing. The ESG label defines an investment's societal impact by reviewing three measures of sustainability; Environmental, Social, and Governance. Furthermore, ESG investing refers to the act of investing in companies and other securities consisting of issuers that actively incorporate these three measures in their core business models. Additionally, by implementing the ESG perspective in one's investing strategy, these aspects of different businesses can be used to achieve more significant positive environmental and societal impact (MSCI 2020).

Hence, the ESG framework can be viewed as an essential tool when performing company valuation. It sheds light on assets and attributes whose values are not traditionally captured by the financial statement (Hansson and Fraser 2013).

The environmental commitments captured by the ESG label primarily refers to energy efficiency as defined by Hansson and Fraser (2013). Furthermore, the environmental aspect of ESG captures the importance of pollution and waste, management of natural resources, and the effects and risks connected to climate change (MSCI, 2019). Environmental concerns and proper energy usage can act as drivers for companies to establish sustainable comparative advantages, leverage greater market shares, and create investment incentives (Hansson and Fraser, 2013).

The social responsibility companies carry can be viewed as how well a company acts towards its different stakeholders. Creating a social standing point within the operation can be a critical determinant of how different stakeholders perceive the company. Further, one core objective for a company's social standing is reciprocity to its stakeholders. Reciprocity refers to creating a mutual benefit from an exchange of interest instead of taking advantage of one of the parties. In turn, this can portray both good moral and common sense within the organization. Other essential parts of the social commitments made by a company are safety and employee engagement. Safety for employees and employee engagement calls for sustainable relationships within the workforce, leading to greater productivity (Hansson and Fraser, 2013).

Corporate governance is mainly concerned with the relationship between management and shareholder. Corporate governance commitments are to mitigate the distinct differences that appear in the level of information and control between management and shareholders. Part of the commitments treat the issue of management not acting in favor of the shareholders and the lack of control that shareholder has over this matter (Hansson and Fraser, 2013). Corporate governance also refers to business ethics, tax transparency, anti-competitive behavior, and corruption (MSCI, 2019).

4.1.2 MSCI ESG-rating

The Morgan Stanley Capital International (MSCI) ESG-rating system is created for both institutional and private investors to receive an overview of equity, funds, and overall portfolios standing points regarding their work within ESG commitments. The MSCI ESG-rating ranges from CCC to AAA, where the former represents the worst-performing issuer, and the latter represents the best. The MSCI ESG-rating in the context of ETFs indicates how well the included issuers manage different types of ESG risk. According to MSCI (2020), the interpretation of this is that different issuers handle risk arising from ESG events in a spectrum of efficiency. The ESG risk measurement can help investors identify the risk not captured by traditional financial analysis, which helps investors make better informed and rational investment decisions. ESG risks are, for instance, the impact of environmental climate changes, environmental management, the care and respect of working human capital (MSCI 2020). The above mentioned are all essential aspects that could impact the financial performance of a company. Hence, managing the risk of ESG factors is crucial when making a long-term investment decision.

The MSCI ESG-rating becomes relevant in terms of ETFs, as this label of social- and environmental responsibility can be recognized as a benchmark when dividing listed ETFs as green ETFs or non-green ETFs. The listed ETFs used in this thesis with the highest MSCI ESG (AAA-AA)-rating will be referred to as 'green.' ETFs with ratings between BB-CCC as 'non-green'. The argumentation for this distinction is based on the definition set by MSCI, where high rated issuers are defined as leaders in the sense that they are prominent actors in managing ESG risk and opportunities. Hence, these issuers have successfully incorporated a responsible and sustainable strategy in their business model and are therefore devoted to positively impacting all ESG aspects (MSCI 2019). Issuers with an MSCI ESG-rating below the BB level threshold will be referred to as non-green, and this definition is further based on the MSCI definition of BB-CCC as average and laggers. The average issuer (A-BB) is seen as the mediocrity of ESG commitments. These issuers take the ESG risk and opportunities into account but lack efficiency measures to obtain the leaders' standard. The lagging issuers are often highly exposed to ESG risk. Their business model and strategy are not yet equipped with the right tools to accurately manage these risks and are, therefore, not sufficiently contributing to sustainable and responsible business models (MSCI 2019).

The MSCI ESG-rating of listed ETFs used in this thesis's core analysis is based on assessing MSCI-ratings of issuers included in each fund. The ETF's overall rating depends heavily on how exposed the funds holding are to leaders, average and laggers, and how individual funds are weighted in these different categories. Therefore, it is important to stress that some of the ETFs classified as 'non-green' can *de facto* hold some highly rated issuers but for which is partially offset by other lower-ranked holdings (MSCI 2019).

4.2 Stationarity

4.2.1 Stochastic process

The concept of stationarity is essential when dealing with time series analysis and its various applications. As defined by Pattersson (2012), an observed time series is a sample path or realization of a sequence of random variables over an interval of time. To understand how such sample paths, arise as well as the implications of a stationary and non-stationary process, it is necessary to understand the concept of a stochastic process (Patterson, 2012).

Firstly, two separate definitions are required to define a stochastic process.
Probability space: A probability space is a triple (Ω, F, P), where
(i) Ω is a nonempty set, called the sample space.
(ii) F is a σ-algebra of subsets of Ω, i.e., a family of subsets closed with respect to countable union and complement with respect to Ω.
(iii) P is a probability measure defined for all members of F.

Random variable: A random variable can, in the most intuitive sense, be described as when a variable's values depend on the output of a random phenomenon. Mathematically, a random variable on (Ω,F,P) is a measurable function x: $\Omega \rightarrow \mathbb{R}$, such that the inverse image of any interval *(-∞,a]* belongs to *F*.

Secondly, with respect to the definitions above, a stochastic process can be defined as a family of random variables X_t, t_T defined on the probability space (Ω, F, P), where the set T is called the index set of the process (Brockwell, Davis, 1991).

4.2.2 Stationary processes

After defining what is meant by a stochastic process, the concept of stationarity can now be presented. Simply put, a time series process is said to be stationary when the statistical properties of a stochastic process do not change over time, i.e., specific properties of a stochastic process generating the data are unchanging. Econometric literature states several definitions of stationarity, referring to it as different ‘strengths’ or ‘levels’ of stationarity. Before moving on to the mathematical definition of stationarity, it is important to note that stationarity is a property of a stochastic process despite the ‘type’ of stationarity, not of any finite or infinite realization of it (Patterson, 2012).

The discrete stochastic process X_t, t_T is said to be weakly stationary if its ensemble distribution satisfies the following three conditions:

1. The mean of the distribution is independent of time: $E[X_t] = \mu$
2. The variance of the distribution is independent of time: $var(X_t) = var(X_{t-1}) = X_2$
3. The covariance between its values at any two time points, $cov(X_t, X_{t+k})$ depends only on the distance ‘k’ between those points, and not on time (Dougherty, 2016).

Additionally, for the definition of strong stationarity (also called strict stationarity), condition (1) and (2) are replaced by the condition that the whole potential distribution is independent of time, i.e., the distribution of a finite sub-sequence of random variables of the stochastic process remains the same as the finite set moves along the time index axis (Dougherty, 2016). The following volatility models (ARCH and GARCH) all have the necessary condition of a stationary data set.

4.3 Measures of volatility

4.3.1 Standard deviation

Standard deviation is considered a fundamental element when assessing the historical volatility of different securities types such as funds, equity, and commodities. Standard deviation is based on the difference in return compared to its expected return (mean) that individual securities experience through a period of time or in a sample of assets. In other words, the standard deviation is recognized as a measurement of how much the return of an asset (as determined through time series sample) or a sample of assets (asset class) on average deviates from the mean, i.e., expected return. The measurement of standard deviation can be used as a measure of volatility when creating an investment strategy. As volatility represents movement in asset prices, and thus its return - a higher standard deviation implies more volatile assets and a more risky investment. In this thesis, the standard deviation will be used as an essential tool to get an overview of the volatility of the different types of ETFs, classified as green ETFs and non-green ETFs:

$$\sigma_x = \sqrt{\frac{\sum(x_i - \mu)^2}{N}}$$

$\sigma_x =$ standard deviation of fund group x.

$x_i =$ day to day return net dividend.

$\mu =$ average daily return.

$N =$ number of funds included in the fund group.

4.3.2 The ARCH model

The Autoregressive Conditional Heteroscedasticity model, also called the ARCH model, was developed by Engle (1982) and has since become a frequently used volatility model in finance. This is partly because of the model's simplicity and ability to capture historical volatility patterns (volatility clustering). The ARCH model is based on assessing an autoregressive function (conditional mean equation) of the error term connected to the endogenous variable of one's research and then capturing the error term's behavior, which is allowed to be heteroscedastic (in contrast to CLRM). Heteroscedastic error terms can be explained as the opposite of homoscedastic error terms where the variance is assumed to be normally distributed $\mu_t \sim N(0, \sigma^2)$ and where the variance of the error term is constant over time: $var(\mu_t) = \sigma^2$. The assumption of constant error terms is not likely to hold when analyzing financial data, such as daily return; hence, the ARCH model is used instead. The ARCH model instead assumes the conditional variance of the error term to be consistent, $var(\mu_t | \mu_{t-1}, \mu_{t-2}, \dots \mu_{t-k}) = \sigma_t^2$. The ARCH model will capture the autocorrelation in the variance of the error term (the variance at time t is correlated with the variance at time t-1, and so on) by allowing the conditional variance of the error term to be affected by the squared error of the time period before (Brooks, 2016).

Conditional mean equation:

$$y_t = \delta + \phi y_{t-1} + \mu_t$$
$$\mu_t \sim N(0, \sigma^2)$$

y_t = endogenous variable.
$\delta =$ intercept
ϕ = coefficient of the lagged dependent variable.

An ARCH(q) model could be explained as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \mu_{t-i}^2$$
$$\mu_t | \psi_{t-1} \sim N(0, \sigma_t^2)$$

q = number of lagged squared residuals.

ψ_{t-1} = information set at time t-1.

ω = intercept.

α_i = coefficient of observation i.

μ_{t-i}^2 = squared residuals at time t – i.

The ARCH model and all of its extensions have a non-negativity constraint, which means that none of the estimated parameters can be negative such as $\omega > 0$, $\sum_{i=1}^{q} \alpha_i > 0$. Negative parameters could imply negative conditional variance, for which would be meaningless. Since all the explanatory variables in the ARCH model are squared errors for which they cannot be negative, all parameters must be positive to assure positive conditional variance (Brooks, 2016).

There is some explicit limitation to the ARCH model. The most central one is how the value of q is determined; How many lags of squared residuals must be incorporated in the model to get a valid estimation of the conditional variance? (There are some different approaches to this problem that are beyond the scope of this thesis). The ARCH model can become relatively large when incorporating all of the significant squared residuals, which makes it a non-parsimonious model with a lot of different parameters that need to be estimated. A large number of lags can also prevent the model from satisfying the non-negativity constraint (Brooks, 2016).

4.3.3 The GARCH model

The Generalized Autoregressive Conditional Heteroscedastic model or the GARCH model with other notation, is an extension of the ARCH model (Engle 1982) made independently by Bollerslev (1986) and Taylor (1986). The GARCH model extents the ARCH model in the sense the GARCH model allows the conditional variance to depend on its own past lags as well as past lagged squared residuals, which will solve the problematic limitations of the ARCH model. By adding the lagged conditional variance, the GARCH model captures the effect that lagged residuals had on the fitted value of the conditional variance from the period before, hence the issue of a high value of q diminishes and the model becomes parsimonious. The GARCH model will display how the conditional variance at time t is affected by the long-term average value of the fitted conditional variance (dependent on the intercept), the volatility of past error terms (depended on the lagged squared residuals) and the fitted value of conditional variance from the period before (dependent on lagged conditional variance) (Brooks, 2016).

An GARCH(p,q) model can be explained as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \mu_{t-1}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-j}^2$$

$$\mu_t | \psi_{t-1} \sim N(0, \sigma_t^2)$$

$q =$ number of lagged squared residuals.

$p =$ number of lagged fitted conditional variances.

$\psi_{t-1} =$ information set at time t-1.

$\omega =$ intercept, long-term average fitted conditional variance.

$\alpha_i =$ coefficient of lagged squared residuals.

$\mu_{t-i}^2 =$ squared residuals at time t-i.

$\beta_j =$ coefficient of lagged fitted conditional variance.

$\sigma_{t-j}^2 =$ fitted conditional variance at time t-j.

The non-negativity constraint must hold in the GARCH model just as in the ARCH model. The requirement is extended to constraining all the parameters in the model to be positive and their sum to be equal to or less than one: $\omega > 0$, $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j > 0$ and $\omega + \sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j \leq 1$.

Log-Likelihood Estimation

The most common method when estimating an ARCH or GARCH model is the maximum likelihood estimation (MLE). ARCH and GARCH models are non-linear, for which it is not appropriate to use the standard OLS technique when estimating model parameters. The MLE is instead used as this technique can be employed to non-linear models such as GARCH. The maximum likelihood method will estimate the most appropriate parameters from the given data by finding which values the parameters must take to maximize the likelihood function (LF). The LF is a multiplicative function of the data, which will make the maximization process rather difficult; hence, it is more common to take the logarithm of the likelihood function, which will make the function an additive function. The log-likelihood function (LLF) is based on the conditional mean equation and the conditional variance equation. The LLF used to estimate the parameters in a GARCH model can be explained as such (Brooks, 2016):

The conditional mean equation:

$$y_t = \delta + \phi y_{(t-1)} + \mu_t$$

The conditional variance equation (GARCH (1,1)):

$$\sigma_t^2 = \omega + \alpha \mu_{t-1} + \beta \sigma_{t-1}^2$$

Log-likelihood function for estimating GARCH models:

$$LLF = -\frac{T}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T} \ln(\sigma_t^2) - \frac{1}{2}\sum_{t=1}^{T} (y_t - \delta - \phi y_{t-1})^2 / \sigma_t^2$$

In the LLF displayed above, 2π is treated as a constant and the rest of the components are defined as in the conditional mean equation and the conditional variance equation already explained. The LLF is maximized by finding the optimal values of the parameters. In other word, under the maximum log-likelihood estimation, the estimated parameters will represent the value for which are most likely to have produced the observed data in the time series sample (Brooks, 2016).

4.3.4 Multivariate GARCH

The DCC- GARCH model developed by Engle (2002) and Engle and Sheppard (2001) is a type of multivariate GRACH model that incorporates the Dynamic Conditional Covariance (DCC) of more than one variable. The DCC-GARCH can be used to estimate conditional variances for more than one dependent variable and the covariance and the correlation between them, making this model extremely relevant when analyzing financial data, such as portfolio returns. The DCC-GARCH becomes superior to other univariate GARCH models when analyzing multiple variables because the former captures the relationship between the variables in the conditional covariance estimated in the model. The dynamic conditional covariance (DCC) differs from previous multivariate GARCH models such as the Constant Conditional Covariance (CCC), which was developed by Bollerslev (1999), in the sense that DCC allows the conditional correlation matrix R_t to be time-varying (in contrast to CCC which assumes the conditional correlation matrix to be time-invariant, $R_t = R$) (Engle and Sheppard, 2001). The allowance for the time-varying conditional correlation matrix makes the DCC-GARCH a more appropriate model to use when analyzing time series in financial data, thus assuming constant conditional correlation, but time-varying variances are not likely to hold (Silvernnoinen and Terasvirta, 2008).

The DCC-GARCH can be described as a nonlinear combination of multiple univariate GARCH models, which estimates GARCH parameters independently on each variable and then composes a conditional covariance matrix from the estimated parameters. In the DCC-GARCH, the conditional covariance matrix H_t can be explained by the conditional correlation matrix R_t and the conditional standard deviation matrix D_t. Here, both D_t and R_t are described as time-varying, and H_t will be positive definite (a symmetric matrix with all positive eigenvalues) if R_t is positive definite at every period t that is covered by the information set used in the analysis (Engle and Sheppard, 2001).

Martin and Vern et al (2008) describes the DCC-GARCH as:

$$H_t = D_t R_t D_t$$

Where the conditional standard deviation matrix D_t is conducted as a diagonal matrix such as:

$$D_t = \begin{bmatrix} \sigma_{1t} & 0 & \cdots & 0 \\ 0 & \sigma_{2t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{kt} \end{bmatrix}$$

$i = 1,2 \dots, k =$ Number of asset types.

The conditional standard deviation matrix is built on the univariate GARCH model preformed on each endogenous variable:

$$\sigma_{it}^2 = \omega_i + \sum_{q=1}^{Q_i} \alpha_{it}\mu_{i,t-q}^2 + \sum_{p=1}^{P_i} \beta_{it}\sigma_{i,t-p}^2$$

All definition remains the same as in the explanation of the univariate GARCH given above but with the extension that:

$Q_i =$ Number of lagged squared residuals of asset type i.

$P_i =$ Number of lagged fitted conditional variances of asset type i.

$\mu_{i,t-q}^2 =$ lagged squared residuals of asset type i at time period t-q.

$\sigma_{i,t-p}^2 =$ lagged fitted conditional variances of asset type i at time period t-p.

Further, the conditional correlation matrix R_t is explained as:

$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2}$$

$Diag(Q_t) =$ Diagonal vector with the elements of Q_t on the main diagonal.

Where Q_t is defined as an GARCH (1,1) with the specifications:

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

Where α and β are unknown non-negative scalar parameters and $\bar{Q}$ is defined as the covariance matrix of the standardized residuals.

The standardized residuals are defined as:

$$z_{it} = \frac{\mu_{it}}{\sigma_{it}}$$

Following the covariance matrix of z_{it} defined as:

$$\bar{Q} = \frac{1}{T}\sum_{t=1}^{T}\begin{bmatrix} z_{1t}^2 & z_{1t}, z_{2t} & \cdots & z_{1t}, z_{kt} \\ z_{2t}, z_{1t} & z_{2t}^2 & \cdots & z_{2t}, z_{kt} \\ \vdots & \vdots & \ddots & \vdots \\ z_{kt}, z_{1t} & z_{kt}, z_{2t} & \cdots & z_{kt}^2 \end{bmatrix}$$

Where T represent the number of time series observations and k the number of fund groups (portfolios). In this thesis we only discuss two groups of ETFs, denoted as 'green' and 'non-green' ETFs, thus we will cover the process of a *bivariate* DCC-GARCH.

Estimating the DCC-GARCH with MLE.

The DCC-GARCH model is estimated using the log-likelihood maximization process, just as in the univariate GARCH case. The primary MLE method is in the DCC-GARCH case extended to embody the complexity of estimating multiple model parameters simultaneously. However, the basic concept of the log-likelihood maximization remains the same, as the method aims to find the most appropriate value of the estimated parameter for which will be most likely to have produced the observed data set. The log-likelihood function for the multivariate GARCH model, as explained by Engle and Sheppard (2001), can take the shape of:

$$LLF = -\frac{1}{2}\sum_{t=1}^{T}(k * \ln(2\pi) + \ln(|H_t|) + \mu_t' H_t^{-1} \mu_t)$$

$$H_t = D_t R_t D_t$$

As LLF defined by Engle and Sheppard (2001) illustrated above, the LLF will incorporate the multivariate dimension in the DCC-GARCH model through the conditional covariance matrix H_t. The rest of the LLF is interpreted as in the univariate case.

5 Data

5.1 Panel Data

The data used to investigate the hypothesis of this thesis is collected from the official Bloomberg terminal. We have used the day to day total return net dividend from the time period of 31/10/2014 to 31/10/2019 for 80 different ETFs listed in the US. The raw data of each ETF's five years daily return is further divided into two portfolios composed of the two different fund classes. One portfolio includes ETFs with the classification 'green,' and the other portfolio includes ETFs with 'non-green' classification. The division between 'green' and 'non-green' is based on each ETFs MSCI ESG-rating, where we classify AAA-AA as green and BB-CCC as non-green. Each portfolio will represent the average daily return for that ETF category. The definition and distinction between the different fund types are discussed above. The processed data will now consist of approximately 1300 days (five years, excluding when the market is closed) for two different portfolios, structured by 40 ETFs each, taking the form of panel data appropriated for the intended analysis. A fraction example of the processed data is given in table 5.1.

Table 5.1 Average day to day total return (net dividend), Bloomberg (2020).

Dates	**Daily return 'Green'**	**Daily return 'Non-green'**
31-Oct-2014	0.9615561	0.8359175
03-Nov-2014	-0.5765610	-0.1123475
04-Nov-2014	-0.4786951	-0.7362275
05-Nov-2014	0.7829585	-0.1910775
06-Nov-2014	-0.5253439	-0.1103775
07-Nov-2014	0.1575659	0.4756100
10-Nov-2014	0.5828415	0.4315700
11-Nov-2014	0.4233463	0.3785900
12-Nov-2014	-1.0435756	0.2663450
13-Nov-2014	-0.0511415	-0.5473725

Where the average daily return is calculated such as:

$r_{it} = \frac{\sum_{i=1}^{N} r_{it}}{N}$, i = 1,2,3…N,

N = Number of ETFs included in the portfolio.

5.2 Test for stationarity

5.2.1 Augmented Dicky-Fuller (ADF) test.

The daily return data must be stationary in order to be used in the GARCH and DCC-GARCH model. This is a necessary condition for both models, and we used the Augmented Dicky-Fuller test (Dicky and Fuller, 1984) in STATA16 to conduct the assessment. The ADF test is a widely used method to test for stationarity in time series data, making the ADF test appropriate for financial data, such as daily return used in this thesis. The test is executed on the time series of daily return for each portfolio separately.

The ADF test determines whether the time series data set is stationarity or not by conducting a unit root test for the autoregressive process of the endogenous variable. The ADF test challenge the hypothesis that there is a unit root in the autoregressive process, which would imply that the process is non-stationary.

An AR (1) process can be describes as:

$$y_t = \gamma + \rho y_{t-1} + \varepsilon_t$$

Where γ is the intercept and ε_t is the shock (error term) at time t. $\rho \in [0,1]$ and if ρ = 1 then the AR(1) process of the endogenous variable has a unit root.

The simple AR (1) process is rearranged by deducting the lagged endogenous variable on both sides such as:

$$\Delta y_t = \beta + (\rho - 1)y_{t-1} + \varepsilon_t$$

The complete hypothesis test then looks like:

$$H_0: \rho = 1$$

$$H_1: \rho < 1$$

The results of the ADF performed on each group of time series data presented below:

Table 5.2 Green ETFs:

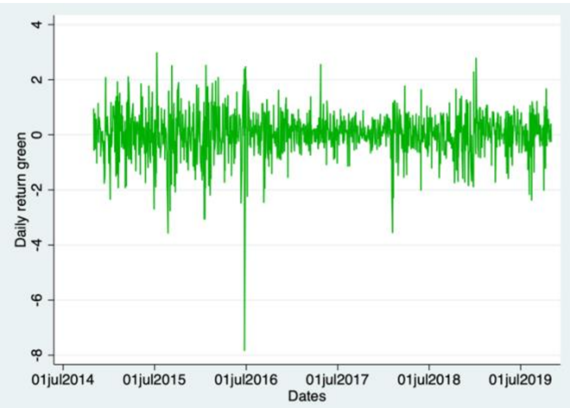
Dickey-Fuller test for unit root	Number of obs	1304	
Interpolated Dickey-Fuller ---------	Critical Values:		
Test statistic	1%	5%	10%
Z(t) = -34.077	-3.43	-2.86	-2.57
MacKinnon approximate p-value for Z(t) = 0.0000			

Table 5.3 Non-green ETFs:

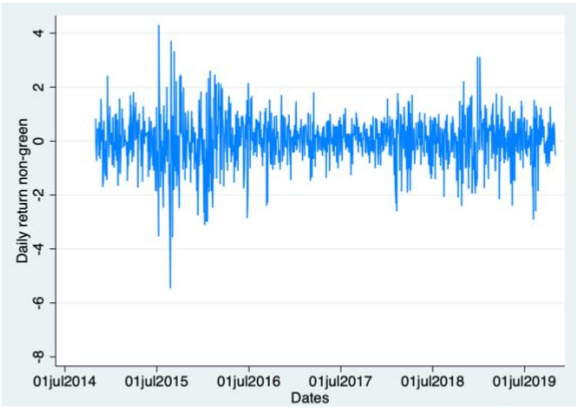
Dickey-Fuller test for unit root	Number of obs	1304	
Interpolated Dickey-Fuller ---------	Critical Values:		
Test statistic	1%	5%	10%
Z(t) = -31.977	-3.43	-2.86	-2.57
MacKinnon approximate p-value for Z(t) = 0.0000			

By analyzing table 5.2 and 5.3, we can conclude that the data in both the green and non-green portfolio are stationary. To analyze the result of the tests, we look at the test statistic Z(t) and compare this value to the critical values (note that the critical values used in the ADF test will differ from the critical values in the normal distribution) where we can easily conclude that the Z(t) value from each test is smaller than the critical values on all level of significance ($\alpha = 10\%, \alpha = 5\%, \alpha = 1\%$).We can also come to the same conclusions by analyzing the p-value of the z-statistics, which must be less α than to reject the null hypothesis. Both the p-value and the z-statistics indicate that ρ is significantly less than 1, hence; we reject the null hypothesis and define that our data is stationary.

Graph 5.1



Graph 5.2



The graphs display the daily return for the green (left) and the non-green (right) portfolio over the five-year period.

Graph 5.1 and 5.2 stress the same results as the ADF test, as the graphic presentation of the daily return over the five-year period indicates that each time series is stationary. We can realize stationarity by just analyzing the graphic presentation. We clearly see that the there is no upward or downward trend in the data set which suggest that the data is stationary.

6 Method

6.1 Test for volatility

6.1.1 Initial testing

The simplistic measure of standard deviation is used as a first stage analysis of the difference in volatility between the two portfolios. We received an overview of the level of volatility by calculating the standard deviation of the whole time series for each fund group and then comparing the results.

The standard deviation is calculated as such:

$$\sigma_i = \sqrt{\frac{\sum_{i=1}^{T}(x_i - \mu)^2}{T}}$$

The standard deviation of five-year period of each fund type:

Table 6.1

	Green	Non-green
Standard Deviation	0,8111	0,8924

As table 6.1 shows, there is a difference in standard deviation between the portfolio of green ETFs and the portfolio of non-green ETFs, which we saw as a valid indicator to further invest the question at issue with more sophisticated volatility models.

6.2 Applying GARCH-models

6.2.1 GARCH (1.1)

In this thesis, we will use the GARCH (1,1) as it is one of the most frequently used method to model volatility through conditional variance. We will use the GARCH (1,1) model to analyze volatility where the GARCH (1,1) model implies one lagged ARCH term and on lagged GARCH term, which reflects the previous shocks included in the model. To choose the optimal order of lags in each category, we tested different combinations of lags such as GARCH (1,1), GARCH (1,2), GARCH (2,1), and GARCH (2,2). We then concluded that the GARCH (1,1) model was the best fit for our data set by looking at the estimated parameters for each order of lags. We saw that the level of significance of the estimated parameters decreased as the number of lags increased.

6.2.2 DCC-GARCH

The DCC-GARCH model is a multivariate GARCH model that embodies multiple endogenous variables in the analysis. The DCC-GACRH is an appropriate model for our data set as it contains two different portfolios, which will be treated as two endogenous variables in the model. The DCC-GARCH model is superior to running two separate GARCH estimations; thus, the DCC-GARCH will incorporate the conditional covariance between the two portfolios; hence the DCC-GARCH captures more relevant information compared to the univariate GARCH in this case. This thesis will cover the process of a bivariate DCC-GARCH (1,1) model, as there are only two fund classes. The DCC-GARCH estimates the conditional variance of each ETF type through a univariate GARCH (1,1) estimation, and the conditional covariance is further conducted from a nonlinear combination of the conditional variances. The DCC-GARCH (1,1) is estimated in STATA16 by optimizing the log-likelihood function through the iteration technique, for which STATA systematically test some initial iteratives and the values of the parameters at these iterative, until an optimum has been found.

The GARCH (1,1) is defined as:

$$\sigma_{it}^2 = \omega_i + \alpha_i \mu_{i,t-1} + \beta_i \sigma_{i,t-i}^2$$

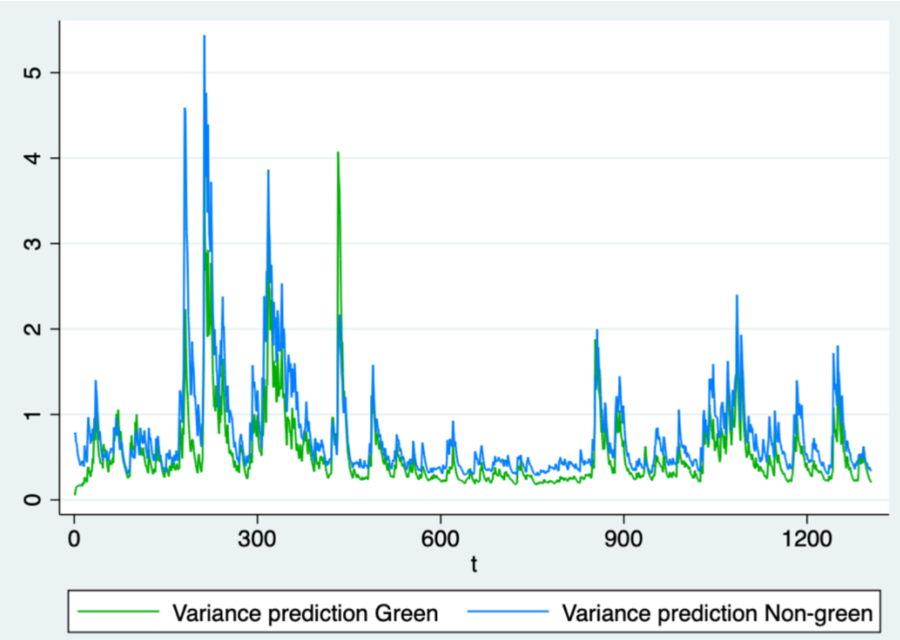
Table 6.2

DCC MGARCH model					
Sample: 1 - 1305				Number of obs	1,305
Distribution: Gaussian				Wald chi2(.)	.
Log likelihood = -2416.307				Prob > chi2	.
	Coefficient	Standrad error	z	P>z	[95% Conf. Interval]
Green					
_cons	0.0524841	0.0173352	3.03	0.002	.0185077 .0864604
ARCH_green					
arch					
L1.	0.1753934	0.0230584	7.61	0.000	.1301998 .220587

garch					
L1.	0.7440645	0.0304229	24.46	0.000	.6844368 .8036923
_cons	0.0528502	0.0101443	5.21	0.000	.0329677 .0727327
Non-green					
_cons	0.0595467	0.0194647	3.06	0.002	.0213966 .0976968
ARCH_nongreen					
arch					
L1.	0.12233	0.0167597	7.3	0.000	.0894816 .1551785
garch					
L1.	0.8156088	0.0243829	33.45	0.000	.7678191 .8633985
_cons	0.0428828	0.0093203	4.6	0.000	.0246154 .0611502
corr(green,nongreen)	0.7636858	0.02118757	34.91	0.000	.7208103 .8065614
/Adjustment					
lambda1	0.0519163	0.0120166	4.32	0.000	.0283642 .0754685
lambda2	0.8936554	0.0276739	32.29	0.000	.8394155 .9478952

As table 6.2 shows, all the estimated parameters are significant at the 95% confidence level. The result is established by analyzing the p-value of the z-statistics of each estimated parameter. We see that all coefficients associated with the green portfolio and the non-green portfolio have high significance levels because the p-value associated with the z-statistic is significantly less than all value of α. This means that past shocks and past movements can explain the volatility of today. The volatility in the DCC-GARCH model is explained by the conditional variance, and the estimate model tells us that the conditional variance can be partly explained by the past shocks (squared residuals) and the past conditional variance. Additionally, we see that the coefficient associated with the GARCH term is the largest one, implying that the volatility tends to 'remember' its past behavior. The coefficient of the ARCH term is also significant but far from as large as the GARCH coefficient, which means that the conditional variance will be affected by the most recent shock, but more so by the incorporated shocks in the long-term memory captured by the lagged conditional variance. We also see significance in the constants, reflecting that the conditional variance will be affected by the long-term trend, making the process mean reversing. We can conclude that it appears to be clusters of volatility in the data set of daily returns for both portfolios over the five years. We state that both the green portfolio and the non-green portfolio have ARCH and GARCH effects up to the order of 1. *We will not discuss the conditional covariance in this thesis; thus, it is not relevant for the question at issue.*

Graph 6.1



The graph displays the fitted conditional variance for the green (green colored) and the non-green (blue colored) portfolio over the five-year period. The graph is conducted from the parameters estimated in the DCC-GARCH (presented above).

Graph 6.1 illustrates that volatility clustering is appearing in the data set. The graph shows how the conditional variance for both portfolios tend to cluster, as shocks in daily return tend to get followed by shocks of the same magnitude i.e large movements generate subsequent large movements (of either sign), and small movements generate subsequent small movements (of either sign). The graph also indicates that the conditional variance of the non-green portfolio tends to be higher than the conditional variance of the green portfolio. We can see this by analyzing how each graph moves according to time, which shows that the green ETF portfolio has experienced smaller shocks over the five years compared to the portfolios of non-green ETFs. Nevertheless, both portfolios tend to move in the same direction and experiencing the same type of volatility clustering. The graphic illustrations are consistent with the result presented in the DCC-GARCH table, as the GARCH coefficients of the non-green portfolio is larger than the one for the green portfolio, meaning that past shocks and behavior will affect the non-green ETFs more, hence display higher levels of conditional variance.

6.3 Hypothesis testing

6.3.1 Wald Chi-squared test

The DCC-GARCH model presented in Table 6.2 shows that there are differences in conditional variance between the two types of ETFs analyzed in this thesis. The differences appear in the coefficients estimates in the DCC-GARCH model, which means that the conditional variance tends to be larger for the non-green ETFs. However, there is a need to perform a Wald Chi-square test to state whether the difference is significant or not. The Wald test will tell us if the difference in the estimated parameters is sufficiently important to the analysis. The Wald test conducts a test statistic, which is then compared to the Chi-squared distributions critical value for the appropriate level of significance. The test statistic of the Wald test is conducted as such:

$$W_t = (\hat{\theta}_n - \theta_0)' [var(\hat{\theta}_n)]^{-1} (\hat{\theta}_n - \theta_0)$$
$$W_t \sim \chi_n^2 \ (under\ H_0)$$

$\hat{\theta}_n =$ The maximum likelihood estimates of a n x1 vector of parameters (n = number of parameters).
$\theta_0 =$ The value of the vector parameters under the null hypothesis.
$Var(\hat{\theta}_n) =$ The variance matrix of the q number of maximum likelihood estimates.

The null hypothesis can be expressed such as:
H_0: (1) ARCH_green – ARCH_nongreen = 0 (i.e ARCH_green = ARCH_nongreen)
(2) GARCH_green – GARCH_nongreen = 0
(3) Green_cons – Nongreen_cons = 0

The Wald Chi-squared test conducted in STATA16 presented the following results:
Table 6.3

$Chi^2(3)$ (Test statistic)	9.14
Prob > $chi^2(3)$	0.0275

As table 6.3 show, the value of the Wald test t-statistic is significant at the 95 % confidence level. We see this by analyzing the p-value of the t-statistic at the significance level $\alpha = 5\%$. We can clearly state that the p-value of the t-statistic of the Wald test is less than the alpha as: $0.0275 < 0.05$. The result of the Wald Chi-square test indicates that there is a significant difference in the estimated ARCH and GARCH parameters for the two different types of ETFs analyzed in this thesis at a 5% significance level.

7 Results

This thesis aims to investigate how different characteristics of ETFs can affect their volatility, hence their riskiness. We choose to look at the ESG label as the only separating factor; thus, we believe that the future of finance will embody sustainable and responsible investment strategies and that the ESG factor will become more relevant to any valuation process. Our quantitative analysis is based on the comparison of two ETF portfolios, where we question whether there is a difference in volatility between green and non-green ETFs. Hereafter, the result and interpretations of the given results will be presented.

7.1 Conditional variance and ESG characteristics

The primary research was based on measuring risk through conditional variance, conducted through a DCC-GARCH model. The conditional variance will illustrate the appearance of volatility clustering and embrace heteroscedastic error terms; hence, conditional variance acts as a focal point for both volatility forecasting and analyzing historical volatility patterns. Furthermore, the conditional variance can give private and institutional investors insights into implied behavior in asset prices, which can be used to make more rational and well-informed investment decisions.

The research and analysis assessed on the daily return data indicated early on that the two ETF portfolios show different behaviors, in the sense that we could spot differences in the magnitude of movement by just analyzing the simple measure of standard deviation. Thereafter, we studied the graphic illustrations of the daily returns, which were clearly consistent with the findings in standard deviation. However, both the graphic illustrations and the measurement of standard deviations are relatively simplistic approaches to analyzing risk and could easily be affected by sample size and averages. Nevertheless, the DCC-GARCH incorporates more factors that could explain movements in portfolio returns because the model consolidates the unexpected shocks in past times and how this could affect an asset's conditional variance today. The assessment of the DCC-GARCH also generated results that were in line with the early findings of our research. The DCC-GARCH showed that the estimated coefficients associated with and GARCH parameters of the non-green portfolio were more extensive than the one of the green portfolio. However, the ARCH term of the non-green portfolio was smaller than the one for the green portfolio, which could indicate that the non-green portfolio is less affected by the squared residual of the most recent time.

Nonetheless, the sum of the ARCH and the GARCH parameters presented below show that both sums are close to one, which means that the shocks to the conditional variance are highly persistent in both portfolios. Additionally, the difference in estimated parameters conducted in the DCC-GARCH model is significant at a 5% significance level. This means that we can state that there is a striking difference in the magnitude of movement between the green and the non-green portfolio and that this difference has essential relevance when making investment decisions.

Table 7.1

Green	Coefficient
ARCH_green	
arch	
L1.	0.1753934
garch	
L1.	0.7440645
∑	0.9194579

Table 7.2

Non-green	Coefficient
ARCH_nongreen	
arch	
L1.	0.12233
garch	
L1.	0.8156088
∑	0,9379388

The more considerable sum of the estimated coefficient related to the non-green portfolio indicates that this portfolio tends to be more affected by past unexpected events. The sum of the ARCH and GARCH terms of this portfolio is closer to one as: 0,9379388 > 0.9194579. This could imply that the non-green portfolio has a more substantial ‘memory’ in terms of how today’s movements in daily returns remembers the movements yesterday’s shocks. Moreover, strong memory can lead to more prominent ‘clusters’ of volatility. This means that more of past unexpected events will be seen in today’s portfolio behavior, as large (small) negative (positive) movements will take longer to ride out (convert into more stable movements); thus, the portfolio will experience prolonged periods of high (low) volatility. With a larger tendency of volatility clustering comes more risk as greater uncertainty will be incorporated in the portfolio’s expected behavior.

The classification of the two ETF portfolios analyzed in this thesis is solely based on their MSCI ESG-rating. We classified the green portfolio as one only consisting of ETFs with the MSCI ESG-rating of AAA-AA because these ETFs are seen as the leaders of responsible and sustainable holdings. The blunt classification is noteworthy; thus, the ETF grouping is the only separating factor of our analysis, which could indicate that some of the differences in volatility can be explained by ESG characteristics. This strengthens our claim that investment vehicles that incorporate the importance of ESG in their placement strategies could be the less risky choice; hence a way to circumvent some of the volatility embedded in ETFs but still yield the perks of owning them.

8 Discussion and Conclusion

The results of our study support the research question: ETFs with a higher sustainability-rating yield significantly lower daily volatility than ETFs with a low sustainability-rating. Following chapter contains a discussion on how the results should be interpreted based on the delimitations made in the thesis, and what omitted explanatory variables may exist. The results are also weighed against previous research, where differences and similarities are discussed. We further discuss weaknesses in the results, recommended improvements and further research to be conducted.

8.1 Discussion: Results

The analysis results show that there are differences in conditional variance, hence the volatility of the green and the non-green portfolio conducted in this study. Consistent with the Ben-David, Franzoni, and Moussawi (2017) study, our results confirm that the volatility of ETFs is affected by past shocks. In contrast to their study, examining if the ETF's assets are affected by the ETF's volatility, we examine how the ETF's volatility can be affected by the assets' attributes. Furthermore, in Ben et al.s (2017) research, they also find an undiversifiable risk in stock prices with higher ETF ownership. Based on our studies, however, it appears possible to reduce the risk by investing in ETFs with high ESG-ratings. This result is exciting and opens up for further research questions in line with the Bystedts and Lundkvist (2019) study: whether it is possible to compensate for the higher volatility by investing in ETFs whose assets possess specific attributes.

Further, the analysis only has one separating factor, which is the ESG-rating for the two portfolios. This is noteworthy because even though our study does not examine other factors that may affect the volatility of the ETFs treated in the analysis, there are notable differences in the overall structure of the green ETFs and the non-green ETFs. The green ETF portfolio (see appendix) has a majority of ETFs with holdings within sectors such as utilities and energy, which are generally defensive. This means that holdings within these sectors tend to react less to market movements than the overall market. Defensive sectors usually have a beta less than one, which illustrates that these sectors are less reactive to negative and positive market turns (MSCI, 2014). The defensiveness of the ETF holdings in the green portfolio could explain why this portfolio shows lower conditional variance than the non-green portfolio.

Moreover, the non-green portfolio seems to include ETFs with holdings in more cyclical sectors such as materials (steel and other mining products), financials, and real estate, which usually display a beta value of more than one. The cyclical sectors tend to react more than the market, showing larger magnitude movements, both positive and negative, compared to the benchmark (Morningstar, 2011). This could be another explanation for higher conditional variance in the non-green portfolio found in our study. However, both the green and the non-green portfolio comprehends both cyclical and defensive sectors. In this study, there is no evidence that the overrepresentation of, for instance, utilities in the green portfolio cancel out the existence of the cyclical holdings in the same portfolio, such as financials.

Another interesting finding in each portfolio structure is that the green portfolio has some overrepresentation of ETFs with holdings in Europe. The non-green portfolio has, on the other hand a larger proportion of ETFs with holdings in China. MSCI (2019) noted that the revenue exposure to the Chinese market where mostly targeted at cyclical sectors, with a 15% revenue exposure to Information Technology and 9% exposure to materials, compared to Utilities that had a 0% revenue exposure in China, conducted in the same study (MSCI, 2019). The representation of cyclical sectors in China could make some of the ETFs with a majority of holdings in the overall Chinese market overexposed to these cyclical sectors, resulting in more volatile ETFs. Furthermore, the holding of the green ETFs tends to be localized in Europe, for which the extent of cyclical in contrast to the defensive markets and sectors are ambiguous. Mosselaar (2019) stated that some European markets, such as the German and Italian markets, demonstrate a relatively high-risk profiles, while the Switzerland market shows more defensive behavior. Therefore, the effect of the ETF holdings' geographic location in the green portfolio is not as straightforward as the holding in the non-green portfolio (Robeco, 2019). It is important to stress that it is not clear whether the geographic location affects the ETFs' volatility. However, it is also necessary to underline a notable difference in where ETFs with high ESG-ratings have most of their placements.

Additionally, ESG companies are viewed as well managed by investors in many aspects, in the sense that a high ESG-rating, as explained in the introductory part of this thesis, requires efficiency in management on both ESG risk and opportunities. The management itself can be viewed as a variable that should be taken into account when making company valuation and valuation of other securities such as ETFs. A high ESG-rating could indicate that more long-term trust is embedded in the ETF pricing, hence the daily return. One could argue that ESG investors believe that these ETFs will perform better in the long run than ETFs with lower ESG commitments, which could lead to less intraday trading. Further, this could be one explanation of why the green portfolio showed lower daily volatility (McKinsey, 2020).

The results imply that a risk-averse private investor is desirable to invest in assets with lower volatility, thus possessing a smaller DCC-GARCH parameter. Since the green portfolio has a lower DCC-GARCH parameter, and we have shown a significant difference between the green and non-green portfolios' parameters, it appears more appropriate for the private investor to trade green ETFs rather than non-green ETFs. Our result that a high ESG-rating seems to indicate lower volatility differs from previous studies that address ESG attributes' effect on asset volatility. Jain, Sharma, and Srivastava (2019), for example, could not find a significant difference between sustainable assets and assets without a high ESG-rating. In a later section of the discussion, we address the contradictory result: one should question whether the thesis result is precisely due to the ETFs having a high ESG-rating or if other factors may underlie the result.

Lastly, the difference between the two portfolios is significant at the 95% confidence level. The test's p-value is 0,0275, which can be interpreted as a 2.75% probability that the difference in the parameters is random. In other words, a 2,75% probability that the null hypothesis is rejected when it should not be. Further, a p-value of 2,75% implies that the difference is not significant at the 99% confidence level. As a rule, the smaller the p-value the better, i.e., a lower p-value than 2.75% would have given us even more statistically assured results than at the current 95% confidence level.

8.2 Discussion: Delimitations in the results

It is essential to highlight that, as, in other studies, delimitations are implemented in the thesis. By clear delimitations, we have been able to address the question at issue in its entirety. Additionally, formulating a clear scope of the thesis enables one to frame the study's purpose, thus answer the research question as concretely as possible. However, the delimitations also mean that the result, thereby the conclusion, only concerns a small area within the subject; therefore, the result should be applied with some caution. First and foremost, we have limited ourselves to one measure of sustainability: MSCI ESG-rating. Although MSCI is the leading distributor of sustainability-ratings, this also implies restrictions. As mentioned earlier in the thesis, sustainability is a broad concept without a universal definition. Therefore, sustainability can be interpreted in several different ways. Thus, our view of a sustainable ETF depends entirely on the areas and criteria that MSCI examines. It is also important to note that not all ETFs have received an ESG-rating yet. Thus, there is a risk that certain ETFs lacking a rating, that would otherwise be included in our sample, are not included in our selection of data. Hence, the result could have been different if these missing funds would have been incorporated and displayed a different return data pattern. On the other hand, one can ensure that based on our selection of ETFs, the result is statistically significant. The implication of this is, more concretely, that if one were to invest in the thesis 'green portfolio,' one would achieve lower volatility than with an investment in the non-green portfolio (with a statistical error margin of 2.75%).

Furthermore, the sample is limited to passive ETFs traded on the US exchange. The sample is thereby affected by trends on the US exchange, in addition to movements linked to the specific ETFs or industries in which they are part. As previously mentioned, Ben-Davids, Franzoni, and Moussawi's (2017) conclusions did not apply outside the US stock market as data from the Western European market gave the opposite result. Therefore, it is appropriate to assume that this risk exists in our conclusions as well, implying one should carry out further research in other exchanges to investigate this further. Additionally, the ETFs in the thesis sample is a wide selection with broad exposure to several industries and parts of the world. One can look at the wide selection from both a positive and negative point of view. On the one hand, the wide selection can generate a result that can be applied in a broader context. Since the varied assets generate exposure to the whole world and countless industries, our result could be less industrydependent and affected by geographical location. On the other hand, the wide range may imply that there are many other factors and characteristics of these ETFs that affect volatility, thus not linked to the ESG factor in particular.

Moreover, we decided to exclude the year 2020 in our selection of data points. As the stock market, and not least the world economy, has been strongly negatively affected by COVID-19, data from this year are not comparable with the previous ones. Major movements have taken place on the stock exchange due to the crisis, which are not directly related to the assets themselves but results from the pandemic. As we study the difference in volatility of ETFs with one separating factor, their ESG-rating, erroneous conclusions could be drawn about the impact of the sustainability-rating on volatility when in reality attributed to the economic effects of the pandemic. Nevertheless, studying how the two portfolios move during an economic crisis and whether they demonstrate the same difference in volatility could have yielded more reliable results. However, an analysis of further complexity is required, which extends beyond this thesis.

8.3 Improvements and Future Research

In order to achieve more reliable results and be able to determine precisely how the ESG-rating affects an ETF's volatility, further in-depth research is required. As ETFs are a relatively new instrument in the financial market, as well as green finance and ESG, there is a limited supply of long-term return data. To achieve smaller error terms and possibly achieve a higher level of significance, a more extensive selection of ESG-labeled ETFs is preferable. Additionally, although the ETFs included in the sample have common attributes, for instance, they are passive and traded on the US exchange - it is impossible to conclude that the difference in ESG-rating is the origin of the green portfolio's lower volatility. Therefore, further research on what other factors may be the reason for the difference in volatility is necessary. For instance, one could research how the volatility is correlated to different industries, indexes, or geographical market differences. To further strengthen the results, a comparison between the impact of different factors on the ETF's volatility should also be carried out. We do not currently know whether the ESG-rating has more or less influence than other factors, only that the green portfolio generated lower volatility than the non-green portfolio.

To further confirm whether the volatility of an ETF decreases as the ESG-rating increases, future research needs to be expanded to include the (B-AA)-ratings. This thesis has only looked at the ETFs with the highest rating and those with the lowest. Our results open up to examine the full range of ESG-ratings, where a grouping could instead be made according to each-rating - thus, be able to study whether volatility decreases as the ESG-rating increases. In-depth research on the characteristics within the ESG-rating that tend to affect volatility more or less, or for that matter not at all, can also provide further guidance for the private investor regarding which ESG-traits to seek in order to achieve lower volatility. Finally, similar to Bystedt and Lundkvist's (2019) study, this thesis's results should further be tested beyond the US exchange to achieve more reliable results, either disproving or strengthening our outcomes.

8.4 Conclusion

The outcome of the study, performed in this thesis, is consistent with our central hypothesis that investing in ESG-labeled ETFs can be a way to circumvent some of the volatility embedded in the nature of ETFs. This result is also coherent with sustainable investing trends that has been one of the most relevant topics for many institutional and corporate investors. The purpose of this thesis is to give a more easily accessible approach for private investors who want to enter the ETF market. Our result indicates that the portfolio conducted of green ETFs do show less volatile behavior. ESG investing could be viewed as a strategy for both private and professional investors to circumvent some risk entering the ETF market. Our technical analysis results are significant on the 5% significance level, which tells us that there is sufficient importance in our result. However, our study has several limitations, where we stress that we only examine one separating factor, the ESG-rating, which makes the results and the interpretations of the result rather ineffectual. There could be several explanations in the ETF holdings structure, such as sector representation, geographic location, and long-term trust. There is a risk that the outcome could take different shapes if the European ETF market were examined instead of the US ETF market. Nevertheless, our results' significance can guide the risk-averse investor on where to find possible less risky ETFs. Our result opens up to further research in the same field and a promising future for the ESG label's importance.

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10 Appendix

An assortment of Exchange traded funds, for which this thesis is based on. All ETFs are listed in the U.S. Exchange

Green ETF	Ticker	Non-green ETF	Ticker
Vanguard FTSE Europe ETF	VGK US Equity	iShares iBoxx High Yield Corporat bond	HYG US Equity
Utilities Select Sector SPDR F	XLU US Equity	SPDR Bloomberg Barclays High Yield	JNK US Equity
iShares U.S. Medical Devices E	IHI US Equity	SPDR S&P Biotech ETF	XBI US Equity
ProShares S&P 500 Dividend Aristocrats	NOBL US Equity	Alerian MLP ETF	AMLP US Equity
Vanguard Utilities ETF	VPU US Equity	Xtrackers Harvest CSI 300 China	ASHR US Equity
iShares Core MSCI Europe ETF	IEUR US Equity	iShares Mortgage Real Estate ETF	REM US Equity
iShares International Select D	IDV US Equity	KraneShares Bosera MSCI China	KBA US Equity
iShares Global 100 ETF	IOO US Equity	Invesco BulletShares 2022 High	BSJM US Equity
iShares MSCI United Kingdom ET	EWU US Equity	Renaissance IPO ETF	IPO US Equity
iShares MSCI USA ESG Select ET	SUSA US Equity	Global X MLP ETF	MLPA US Equity
SPDR EURO STOXX 50 ETF	FEZ US Equity	Global X MLP & Energy Infrastructure	MLPX US Equity
iShares MSCI Switzerland ETF	EWL US Equity	ETFMG Prime Junior Silver Mine	SILJ US Equity
iShares Europe ETF	IEV US Equity	iShares Residential and Multis	REZ US Equity
Fidelity MSCI Utilities Index	FUTY US Equity	iShares J.P. Morgan EM High Yield bond	EMHY US Equity
iShares MSCI Europe Financials	EUFN US Equity	iShares MSCI Turkey ETF	TUR US Equity
WisdomTree International Hedge	IHDG US Equity	Invesco Dynamic Biotechnology	PBE US Equity
iShares US Utilities ETF	IDU US Equity	VanEck Vectors Mortgage REIT	MORT US Equity
iShares MSCI Spain ETF	EWP US Equity	Invesco KBW Premium Yield Equity	KBWY US Equity
Xtrackers MSCI Europe Hedged Equity	DBEU US Equity	iShares MSCI Brazil Small-Cap	EWZS US Equity
iShares MSCI Sweden ETF	EWD US Equity	iShares MSCI Qatar ETF	QAT US Equity
First Trust Global Wind Energy	FAN US Equity	VanEck Vectors Steel ETF	SLX US Equity
iShares MSCI Netherlands ETF	EWN US Equity	VanEck Vectors Brazil Small-Cap	BRF US Equity
First Trust STOXX European Sel	FDD US Equity	First Trust NASDAQ Global Auto	CARZ US Equity
Invesco S&P 500 Equal Weight Utilities	RYU US Equity	First Trust China AlphaDEX Fund	FCA US Equity
iShares MSCI New Zealand ETF	ENZL US Equity	Invesco Dynamic Media ETF	PBS US Equity
SPDR Portfolio Europe ETF	SPEU US Equity	VanEck Vectors ChinaAMC SME-China	CNXT US Equity
iShares MSCI Denmark ETF	EDEN US Equity	IQ US Real Estate Small Cap ETF	ROOF US Equity
iShares Global Utilities ETF	JXI US Equity	VanEck Vectors China Growth	GLCN US Equity
First Trust NASDAQ Clean Edge	GRID US Equity	Invesco S&P SmallCap Consumer	PSCC US Equity
Invesco International BuyBack	IPKW US Equity	Invesco S&P SmallCap Energy ETF	PSCE US Equity
iShares MSCI United Kingdom Small cap	EWUS US Equity	Xtrackers MSCI All China Equity	CN US Equity
iShares MSCI Austria ETF	EWO US Equity	Invesco S&P SmallCap Financial	PSCF US Equity
Global X MSCI Norway ETF	NORW US Equity	ALPS REIT Dividend Dogs ETF	RDOG US Equity
Global X Dax Germany ETF	DAX US Equity	Invesco DWA Energy Momentum ETF	PXI US Equity

iShares MSCI Finland ETF	EFNL US Equity	Invesco Dynamic Energy Exploration	PXE US Equity
Global X FTSE Nordic Region ETF	GXF US Equity	Global X MSCI China Communications	CHIC US Equity
iShares MSCI Norway ETF	ENOR US Equity	KraneShares CICC China Leaders	KFYP US Equity
First Trust United Kingdom Alpha	FKU US Equity	Global X MSCI China Industrial	CHII US Equity
Global X MSCI Portugal ETF	PGAL US Equity	Global X MSCI China Materials	CHIM US Equity
ProShares Ultra Utilities	UPW US Equity	Global X MSCI China Energy ETF	CHIE US Equity