A Comparative Analysis of the Performance of Euro-Denominated Green and Conventional Bonds

Authors:
Lois Anum (930318T706)
Liina-Johanna Leeve (930720T302)

Supervisor: Frederik Lundtofte

Abstract

The green bond market has seen exponential growth since its boom in 2013 but literature on this topic is considered woefully inadequate. This research paper therefore seeks to compare the performance of European green bonds against its conventional counterparts. Analysis was conducted on two data samples spanning from the year 2013 to 2019 using the matching principle and an extended Fama-French model. In comparison to other green bond studies, we uniquely use the Merton model to calculate the default factor for the Fama-French regressions.

The main results illustrate that conventional bonds outperform green bonds and shows that the Merton model fits the Fama-French model better than the DEF factor used in the original paper (Fama & French, 1993). This thesis therefore serves as a contribution to literature on the performance of bonds as an asset class and explains relevant models that can be used in analysing this performance.

Keywords: Green Bonds, Conventional Bonds, Sustainable Investments, Corporate Bonds, Fama-Macbeth Regression, Fama-French Model, Matching Principle, Merton Model

Acknowledgements

We would like to thank our supervisor Associate Professor Frederik Lundtofte of Department of Economics at Lund University for his helpful insights and supervisory contributions to this thesis.

Abbreviations

BG	Breusch-Godfrey
CAPM	Capital Asset Pricing Model
CBI	Climate Bond Initiative
CSR	Corporate Social Responsibility
DD	Distance to Default
DW	Durbin-Watson
ETF	Exchange Traded Funds
EUR	Euro currency
FMCG	Fast Moving Consumer Goods
GBP	Green Bond Principles
HML	High Minus Low
ICMA	International Capital Markets Association
PD	Probability of Default
SMB	Small Minus Big
SRI	Socially Responsible Investment
USD	United States Dollar
YTM	Yield to Maturity

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1. Introduction

"*The greatest threat to our planet is the belief that someone else will save it*" -Robert Swan, OBE

Increased awareness of the alarming and pervasive effects of global warming has influenced worldwide country and company strategy formulation. This has led to a noticeable spike in Corporate Social Responsibility (CSR) related projects and furthermore fuelled an increase in issuance of corporate green bonds. Green bonds are defined as debt instruments where the use of proceeds is restricted to the financing of green projects (ICMA, 2018).

The first green bond was issued in 2007 but the green bond market itself was almost non-existent before 2013, when there was a green bond boom that has continued till date (Morgan Stanley Research, 2017). The market, which is still small compared to other financial products, is widely regarded as unregulated and prone to greenwashing, prompting the formation of organizations and regulatory initiatives such as the Green Bond Principles and the Climate Bonds Initiative (NEPC Impact Investing Committee, 2016). Additionally, empirical research on the financial performance of green bonds relative to other financial products such as equities, is woefully inadequate.

The objective of this paper is therefore to help fill the literature gap with regards to the performance of green bonds against conventional bonds. The research question we aim to answer here is:

How are green bonds performing in comparison with conventional "brown bonds"?

To find an answer to this question, we first ascertain empirical evidence of a yield difference (a "greenium" or green bond premium) between green bonds and conventional bonds denominated in euro, to ensure consistency that could have otherwise been adversely affected by exchange rate fluctuations. We examine bonds issued between January 1, 2013 and April 1, 2019 using two approaches. First, we use a matching method to analyse the yield difference. We matched 70 pairs of conventional bonds to a green bond sample within the time period aforementioned and used these pairs in our analysis. The second methodology used is the extended six-factor Fama-French approach, where a comparative analysis is conducted on the performance of green against conventional bonds. Here, the data sample consists of a total of 132 bonds issued between January 1, 2013 and December 31, 2015. The Fama-French factors used are market risk premium, size and value premium, Carhart's momentum factor, term structure risk factor and default factor. Additionally, the Merton model is used to calculate the probability of default (PD) to be used as a proxy for the default factor. This model enhances the accuracy of PD estimation.

The main justification of this study is to provide insights into the market of euro currency green bonds and to serve as a brief overview for potential entrants into the market, as well as provide a foundation for further academic research into green bonds in this particular geographic area. Furthermore, this thesis is unique in the sense that, to our knowledge, it is the first empirical evidence on the performance of green bonds against conventional bonds which implements the Merton model to estimate PD to use as a factor in the Fama-French framework.

It is worthy to note that, this research uses pre-tax bond yields from Bloomberg and Datastream to simplify our study and to prevent any wrong inferences associated with after-tax pricing of bonds based on geographic factors and various tax laws in the different countries involved. This is because imposing taxes on bond transactions has been pinpointed as an important factor capable of causing illiquidity and dissuading primary issuance of corporate bonds (GEMC, 2002). Furthermore, in 2015, the growth of the corporate bond market in the EUR slowed down due to several factors including introduction of banking asset taxes and an unresolved issue of withholding tax on foreign investors (European Commission, 2017).

Issuers of green bonds tend to be highly rated, with only a small fraction rated below investment grade (Ehler & Packer, 2017). Furthermore, investment grade bonds are less risky and are for this reason known to have lower yield. Consequently, we could infer that our data sample of green bonds may have a lower yield and this serves as a bias and limitation for this study. We also encountered limitations of scope because the green bond market came into being about 12 years ago and the number of green bonds issued are not many, especially when compared with conventional peers; this limited the size of our data sample and caused us to conduct our research on a relatively unbalanced sample. This limitation was also echoed in Wagner (2017), Drage and Sundt (2018) and Zerbib (2019). Additionally we discovered that a large number of green bond issuers are private companies, making it difficult to attain any pertinent information that could have been used to further refine our research.

Furthermore, from our results and from the results of Johansson et al. (2012) and Wagner (2017), the Fama-French factors do not always show a statistical significance even after correction with the Newey-West estimator. The default factor most especially, seems not to be a very appropriate fit for this model. We therefore have cause to believe that the Merton model is a better predictor of default for the Fama-French model than the default factor.

The rest of this paper is organized as follows**.** Chapter Two provides background information on green bonds and the development of the green bond market in the euro area. Chapter Three reviews specific previous literature on the research question. Chapter Four and Five consist of a thorough description of the dataset used, sources of this data, methodology description and a discussion of the results obtained from both methodologies. Chapter Six concludes the entire study and provides potential recommendations to enhance further relevant research.

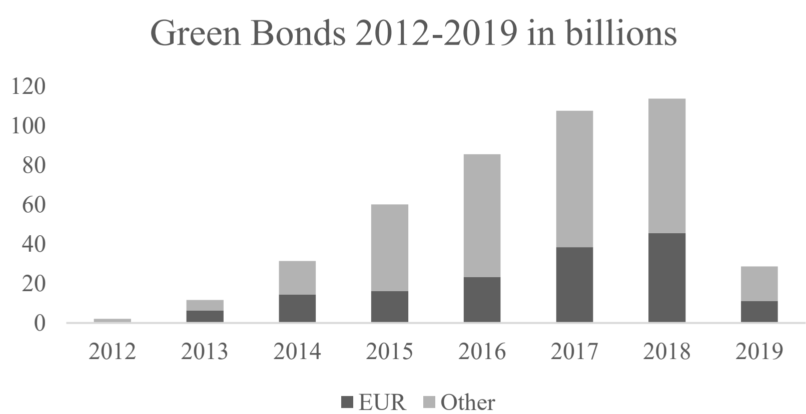
2. Background

Raising awareness of climate change and evident global warming has caused a shift to more sustainable lifestyles, work projects, general day-to-day activities around the world and the number of companies who desire to be perceived as sustainable, has rapidly increased. In response to the Paris Agreement on climate change in 2015, financial markets have evolved to meet the demand of responsible investments and a lot of attention has been generated around Socially Responsible Investments (SRIs). Consequently, green bonds, also referred to as climate bonds, have become one of the most common financial tools used by firms to both engage in the fight against climate change and reap the benefits of being ”green”. Green bonds are described as “financial instruments that are used to raise funds dedicated to climate-mitigation, adaptation, and other environment-friendly projects” (World Bank, 2015). The first green bond was issued by the European Investment Bank in 2007; after which the World Bank also issued one in 2008 (EY, 2016). Corporate green bonds entered the market in 2013, and by 2014, they formed a third of the total green bond market (NEPC Impact Investing Committee, 2016). Due to the rapid increase in the market, the purpose of this study is to examine the performance of corporate green bonds in comparison to otherwise similar corporate conventional bonds.

2.1 Evolution of the Green Bond Market

The green bond market comprises of all the bonds labelled green and as mentioned before, the first bond categorized as green was issued in 2007. At the time, the market was small, and did not grow substantially during the financial crisis of 2007-2008, but in 2013 the market boomed rapidly, with 11bn new green bonds issued[1]. Since then, the issuance of green bonds has doubled every year and at the moment there are 321 active issues denominated in EUR, amounting to 164bn EUR[1].

There are currently 135 issuers of green bonds in euro currency. The issuers vary from non-financial institutions to sovereign issuers, and bonds issued in France and Belgium comprise a half of the market (CBI, 2018). Graph 1 shows the evolution of corporate green bonds since 2012 until the end of the sample period of this study, 04/2019. It can be seen that the market has grown rapidly, and the euro area has gained more share on the total in recent years. The total amount issued in 2013 was 11bn USD and as of today, there are 1439 active issues, amounting to 400bn USD. This trend is likely to continue in future years, given the growing popularity of sustainable finance. Thus, considering the large size of the EUR market, this study is focused on euro currency green bonds.



Graph 1- Green Bond Evolution

1 Verified from the Bloomberg database on 20.4.2019.

New market issues are known to commonly feature oversubscription (Harrison, 2018). Investors' interests in responsible investments have been increasing since the Paris agreement and Rio Climate Summit (Chatterjee, et al., 2016) and it is evident that there is a high demand for green bonds; in fact as at the end of Q2 2017 green bonds were 2,3 and 2,8 times oversubscribed in the EUR and USD market, respectively (Harrison, 2018). It is also worth noting that this high demand might lead to lower liquidity risk in the green bonds. Although the market has emerged rapidly, analysts project that this is not only a phase that will pass but a sustainable market with steady growth potential (Morgan Stanley Research, 2017; Christopher, 2017; Allen, 2018). Schäfer et al. (2017) also observe that the liquidity risk impact on yield spread has become negligible which may mean the market is maturing.

2.2 Definitions and Standards

As stated early on, there are varying explanations aimed at spelling out what a green bond is and Karpf and Mandel (2017) argue that the green label is still poorly understood. Consequently, the predominant universally agreed fact has to do with the use of proceeds from issued green bonds, which instructs that these proceeds must be dedicated solely to funding environmentally sustainable projects of which the most common reported use of proceeds are energy, buildings and water (CBI, 2018).

There are however a number of organizations that have sought to develop standards to govern the issuance of green bonds. One such notable set of standards is the Green Bond Principles (GBP) established by a combined effort between the International Capital Markets Association (ICMA) and 13 investment banks[2] (Kidney, 2014). The GBP focuses on discussing rules regarding issuance of green bonds, financial reporting standards concerning green bonds and disclosure requirements (ICMA, 2018). Furthermore, in addition to using these principles, the GBP encourages seeking an external review for green bond project selection and evaluation.

[2] Namely JP Morgan Chase SEB, Goldman Sachs, Credit Agricole Corporate and Investment Bank, Daiwa, BNP Paribas, Bank of America Merrill Lynch, HSBC, Rabobank, Mizuho Securities, Morgan Stanley, Deutsche Bank and Citi.

Another noteworthy example of green bond rules is the Climate Bond Standards configured by the Climate Bond Initiative (CBI), which is an international investor-focused non-profit organization. While the GBP uses four criteria principles to classify a bond as green; use of proceeds, project evaluation and selection, management of proceeds and reporting, the CBI uses the Climate Bonds Taxonomy which constitutes grouping bonds according to energy, buildings, transport, water, waste/pollution control, land use, industry and Information & Communication Technologies (CBI, 2018). This grouping is very stringent in the sense that only bonds with 95% of proceeds dedicated to environmentally sustainable projects in congruence with the Climate Bonds Taxonomy, are included in the CBI green bond database, which currently lists 23,5bn USD worth of green bonds as aligned with CBI definitions. Nonetheless, the GBP and the Climate Bond Standards are undeniably intertwined (CBI, 2018).

3. Literature Review

This section provides a brief introduction to bond yields and discusses previous research on the performance of SRI and green bonds. There are several studies on the effect of social responsibility on stock returns and the financial performance of companies that are addressing environmental issues. Due to green bonds being a relatively new financial asset class, and having an ongoing development of its definition, studies on the subject of green bonds are not as extensive as similar studies focusing on equities. Even though majority of studies find that green bonds earn lower yields, the results are still contradicting, and it remains unclear what the conclusive effect of being green is. This section is constructed as follows: section 3.1 introduces the theory behind corporate bond yields, section 3.2 discusses previous research on green finance and SRIs and finally section 3.3 reviews previous literature on the yield difference, or so-called “greenium” of green bonds.

3.1 Yield of Corporate Bonds

There are several factors that have an effect on the yield of corporate bonds in the market. Yields are determined by the market, and therefore incorporate information on the interest rates, inflation rate, yield curve and economic growth. In addition to overall market conditions, the yield is affected by price factors such as maturity, liquidity, coupon, yield of comparable issues, demand and supply and the credit quality of the issuer (Choudhry, 2004).

3.1.1 Liquidity and Credit Risk

Liquidity is defined as the ease of an investor to trade a particular asset. A liquid asset is always more attractive for the investor than an asset that is difficult to trade, therefore a bond having a high liquidity risk needs to provide a higher yield as a compensation for the investor of bearing this risk (Choudhry, 2004). Schäfer et al. (2017) found that green bonds were on average more liquid than conventional bonds between 2014-2016, meaning that green bonds were less risky and earning a lower yield than conventional bonds. However, the study finds that the impact of liquidity risk is becoming more insignificant over time. This observation suggests that green bonds issued during the beginning of the green bond boom (2012-2015) would have a lower yield than conventional bonds, but that this effect would vanish over time leading to more recent green bond issues having a yield similar to that of conventional bonds.

Credit risk is the most essential risk for a bond and equity investor (Byström, 2006). Unlike government bonds, corporate bonds incorporate default risk, defined as the risk of the issuer to fail to fulfil its obligations to the bondholder (Choudhry, 2004). Credit risk, as well as interest rate risk and price volatility, increase with the age of the bond and only the issuers with high credit rating can issue debt with a relatively longer maturity. Consequently, CSR effect on firm credit risk has recently attracted researchers' interests. CSR activities are associated with lower risk as firms making CSR efforts enjoy better credit ratings (Jiraporn, et al., 2014). Also, default risk is lower for the firms implementing CSR strategies (Sun & Cui, 2014) and therefore may help these firms reduce credit risk in a turbulent market environment.

3.1.2 Demand and Supply

Supply and demand play an important role in determining yield and are interrelated with the effect of liquidity. High demand of a specific type of bond tends to result in higher liquidity of new issues of the same bond type leading to lower liquidity risk which generates lower yield. On the other hand, due to green bonds being a relatively new asset class, some investors might be cautious when investing and might require a higher yield to compensate any possible risk.

In the aftermath of the financial crisis a decade ago, the risk appetite of investors had diminished remarkably and investing in environmental projects was seen as risky due to its new form at the time. However, this shifted in 2013 with rapidly increasing demand for green bonds; the green bonds issued doubled from the previous year and the market exhibited oversubscription. For example Bank of America issued its first green bond, which was the biggest in size at that time, and despite a low interest rate, the bond was still oversubscribed. At the same time, other borrowers saw the opportunity and rushed to the market, resulting in rapid growth of the market (Heimer, 2018). In 2017, the green bond index outperformed the global bond index and the issue amount was also record high. Allen (2018) postulates that since the market for green bonds has grown rapidly, this can lead to a premium in prices resulting in lower yields for such debt. Also, the growing amount of reports and increasing awareness of sustainable finance, as well as green bonds, has evidently led to the expansion of the customer base for green bonds globally. This is assumed to result in lower yields in green bonds in comparison to conventional bonds.

3.2 Previous Literature on Socially Responsible Investments

Since studies on SRIs and equities are far more extensive than those on green bonds, we start by reviewing existing literature on the impact of environmental and social strategies on equity performance. Firms engaging in CSR often gain economic benefits (Sun & Cui, 2014). Several studies have examined the impact of CSR efforts on the company's financial performance and the results are divided. According to Oh et al. (2017), implementing CSR strategies is perceived as an expensive liability by the firms and to improve performance with CSR strategies, firms need to address not only CSR issues but actual strategic issues. Several studies find that CSR strategies have a positive effect on firm performance (Wu & Shen, 2013; Jiraporn, et al., 2014; Sun & Cui, 2014; Oh, et al., 2017). In contrast, Lloyd (2017) could not prove the direct impact of CSR on financial performance as well as Xiao et al. (2013), who showed that there is neither a financial cost nor benefit in SRIs, and Ziegler et al. (2007) found a negative relationship between social performance and stock return. The result may confirm the theory of sin stocks introduced by Hong and Kacperzyk (2009) who examine the performance of "sin" stocks (companies in the alcohol, tobacco and gaming business). They find that these ethically bad stocks outperform the otherwise comparable stocks by 21 bps per month and despite the fact that the relationship between performance of the firm and CSR remains unclear, Renneboog et al. (2008) also find that investors are willing to accept a lower return on investments in ethically and/or socially responsible firms to fulfil their personal values.

There are also studies on the relationship between environmental efforts and stock performance that might be even more applicable to our study of green bonds. Ziegler et al. (2007) found that environmental performance of the industry has a positive impact on stock returns. Ibikunle and Steffen (2017) find that green European mutual funds underperform in comparison to conventional mutual funds over the sample period of 1991-2014, with slight improvement in performance over time. These authors use the matching procedure and Carhart's (1997) multi-factor framework extension to CAPM and Fama-French four-factor model. Similarly, Gil-Bazo et al. (2010) find that a fund consisting of SRI stocks outperforms the non-SRI fund by using matching method. We adopt a similar method to that of Ibikunle and Steffen as well as Gil-Bazo, applying both matching procedure and Fama-French extended model, which will be presented in section 4 and 5, respectively.

3.3 Previous Research on Green Bonds

Previous studies on the yield difference between green bonds and conventional bonds find mostly negative green bond premiums and it seems that factors such as currency, country of issue and credit rating, have an effect on the sign of the yield premium. Negative green bond premium is consistent with the study of sin stocks (Hong & Kacperczyk, 2009) discussed in the previous section, where sin stocks outperform comparable issues. Ehler and Packer (2017) state that when a large number of investors are willing to pay a premium, allowing for lower credit spread, it will be reflected in the pricing of the green bonds, and they find 18 bps lower yield in green bonds. Zerbib (2019) studied the performance of green bonds in relation to the performance of conventional bonds, finding a negative green bond premium and that the premiums are more present for financial issuers and low-rated bonds. According to Preclaw and Bakshi (2015), investors are paying a premium for the green bonds in the secondary market and there is a 20 bps yield difference between green bonds and comparable issues. Bos et al. (2018) find that the yield difference is even wider; the research conducted over 2014-2017 found 100 bps higher yield for conventional US government bonds compared to similar green issues. Similar to Zerbib (2019), Wurgler et al. (2018) also find several basis points lower yield in US municipal green bonds, concluding that green bonds are priced at a premium.

Bos et al. (2018) also study bonds issued in European countries, finding opposite results from their study on US municipal bonds, where conventional bonds outperform green bonds. According to Bos et al. (2018) the yield for green bonds is higher than for conventional bonds issued in Europe, or the yield difference is very close to zero. Also Karpf and Mandel (2017) find that US municipal green bonds are penalized by the market with lower price and higher yield than what would be expected regarding the low credit risk profile of the issuing entities. Schäfer et al. (2017) observe that the liquidity risk impact on yield spread has become negligible which may mean the market is maturing. Also, the introduction of green Exchange Traded Funds (ETFs) could be an indication of a maturing market (Wurgler, et al., 2018). VanEck (2017) finds 90 bps higher yield for green bonds and argues that "greenium" exists only in markets where the demand is high, such as Europe, but any additional issuance satisfying this demand may remove any yield differential.

Previous literature uses various methods to analyse the yield spread. Regression analysis with Fama-French factors is adopted by Wagner (2017) and simple CAPM by Wurgler et al. (2018). Regression with common risk factors is run by Preclaw and Bakshi (2015) and Schäfer, et al. (2017) and Svensson method by (Karpf & Mandel, 2018). Matching method is the most common approach for green bond premium (VanEck, 2017; Bos, et al., 2018; Bachelet & Manfredonia, 2019; Zerbib, 2019). We therefore apply matching procedure for a sample consisting of all green bonds issued in EUR during 2013-2019. To further confirm our findings, we also run Fama-French regressions. Fama-French model is usually used to explain equity markets, but it has been proven by Fama-French (1993) and Johansson and Lundgren (2012) that Fama-French factors are sufficient to explain corporate bond returns.

According to our knowledge to this day, there has been relatively few studies that solely focus on the performance of euro-denominated corporate green bonds. Also, existing literature on the impact of social and environmental efforts on equities far outweighs the research on performance of bonds and other forms of debt. One of the aims of this paper is hence to potentially contribute to filling the literature gap on these topics by adopting similar methods with the studies on equities. The next sections will discuss the research data and methodology in detail.

4. Methodology and Data: Matching Method

4.1 Matching Method

The matching method, also called the model-free or direct approach, is applied by setting out the similarity of a treated group to a control group (Stuart, 2010). This method involves grouping according to specified characteristics. Matching methods are known to be advantageous because they are a more straightforward approach than the other methods but overall they are best used in conjunction with regression analysis, as seen in our study. There are varying forms of the matching method. These include nearest neighbour matching, weighting and assessing common support using a propensity score. For the purpose of this thesis, we employed the use of nearest neighbour matching with replacement, in cases where the treated group had more constituents than the control group and matching without replacement when the control group had more constituent bonds than the treated group. The treated group in our case is composed of green bonds and the control group is composed of conventional "brown" bonds.

To investigate various differences between green bonds and conventional bonds, we used a matching method similar to Zerbib (2019). We thereby established a well-matched database of green and conventional bonds denominated in euro in order to evaluate the yield differential between the two bond groups. For this purpose, we analysed the entire sample of 327 euro-denominated corporate green bonds complying with the Green Bond Principles indexed in Bloomberg on April 1, 2019. To reduce maturity bias, we decided to match each green bond with a synthetic conventional bond, and to create the aforementioned synthetic conventional bond we first searched for two conventional bonds with the closest maturity (i.e. not more than two years) to the green bond's maturity. This was done in order to estimate the yield as accurately as possible for equivalent synthetic conventional bond. We furthermore restricted the issue date to, at most, six years earlier or later than the green bond's issue date. We put in the restrictions on the maturity and the issue date to aid in the control of liquidity bias when calculating green bond premium. We also extracted data with relation to issued amount, amount outstanding, currency, maturity, coupon, Moody's credit rating and median yield-to-maturity for each bond from both Bloomberg and Datastream. The matching criteria is specified in table 1 below.

Table 1- Matching Criteria

Characteristic	Matching Criteria
Issuer	Exact match
Issue Date	6 years
Maturity Date	2 years
Payment Seniority	Exact match
Moody's Rating[3]	Exact match

After finding the pairs, we linearly interpolated the bond yield for the synthetic bond by the yields of the two conventional bonds, as shown in equation 1. The synthetic bond's maturity date was assumed to be the same with the green bond, to obtain a synthetic bond which shows the most similar properties to the green bond in each pair.

$$y = y_0 + \frac{x - x_0}{x_1 - x_0}\,(y_1 - y_0) \tag{1}$$

where y_0= YTM of prior year, y_1 = YTM of the next period, x_0= years to maturity of prior year, x_1= years to maturity of the next period, x stands for years to maturity of the missing data and y stands for the YTM of the interpolated bond.

With this method, we isolated the effect of the other factors, and were able to compare only the yields of green bond with its synthetic counterpart. The results are presented in section 4.4.

[3] Moody's Rating was extracted from Bloomberg (01.04.2019) and there were 3 matched pairs with no rating.

4.2 Paired *t*-test for Significance

The significance of the results was tested by paired *t*-test. Paired *t*-test is used to compare the mean of two separate samples, when the observations in one sample can be paired or matched to another observation in the other sample (Altman, 1991). The paired differences are then treated as one sample. In statistical literature, there is evident confusion on the use of two sample *t*-test and paired *t*-test (Xu, et al., 2017). The difference between paired *t*-test and two sample *t*-test is that the two sample *t*-test is used when there are two independent samples, meaning that the selection of the sample is independent from the selection of the second sample. In contrast, if the observations are paired with another specific observation in the other sample, the paired *t*-test should be used. Hence, the paired *t*-test is used in our research.

The paired *t*-test is conducted by first calculating the difference of each pair and then estimating the mean of this difference. The t-statistic is then calculated as:

$$t = \frac{\bar{d}}{\sqrt{s^2/n}} \tag{2}$$

where $\bar{d}$ is the mean yield difference between the observations in the two samples, s^2 is the sample variance of the yield differences and n is the sample size, hence the number of pairs. The null hypothesis of the test states that there is no yield difference, and is defined as:

$$\begin{aligned} H_0&: Y^{GB} = Y^{CB} \\ H_1&: Y^{GB} \neq Y^{CB} \end{aligned} \tag{3}$$

where Y^{GB} is the average yield of green bonds and Y^{CB} the average yield in synthetic conventional bonds.

4.3 Data

4.3.1 Dataset Description: Matching Principle

For the matching method, we initially retrieved a total of 5000 corporate bonds issued from the year 2013 to the year 2019 precisely at a data extraction date of 1st April, 2019. The rationale for choosing this time period was to capture the performance at the time that the green bond market rapidly picked up (in 2013) till this year (2019) in order to be able to include the most recently issued green and conventional bonds in our analysis. We exported euro-denominated green and conventional bond data from Bloomberg.

The dataset initially consisted of 327 green bonds issued by 45 companies from 15 countries, extracted from Bloomberg's fixed income database using the "Use of Proceeds" label. Specifically, we selected only bonds with a "Green Bond/Loan" label. This led to the successful elimination of all green bonds not apparently or aptly categorized by the issuer or those with insufficient classification information. The remaining bonds were deemed conventional bonds and non-investment-grade bonds were excluded to further ensure compliance with the Green Bond Principles (GBP).

Overall, our bond dataset had a mean maturity of 7,1 and 7,3 years respectively for green and synthetic bonds confirming that the data is well-matched and suitable for this thesis. Furthermore, the average yield-to-maturity (YTM) of the conventional bonds, for the period under study, amounts to 0,343 whilst green bonds have an average yield-to-maturity of 0,341. Also, the conventional bonds in our sample exhibit a standard deviation of 0,529 while the green bonds have a standard deviation of 0,531. It is worthy to note that our study assumes all coupon payments are reinvested at the computed YTM. The descriptive statistics of this dataset are illustrated in table 9 in the appendix of the paper.

4.4 Results: Matching Method

The results were obtained by computing the yield difference between treated (green) and control (conventional) groups with the following equation:

$$Yield\ difference = Y^{GB} - Y^{CB} \quad (4)$$

After matching, the sample consisted of 70 green bonds matched with 70 synthetic bonds, and any green bond having fewer than two corresponding conventional bonds, was eliminated. The matching was done by following the criteria described in section 4.1 (table 1).

The results are presented in table 2. The paired *t*-test was conducted for the whole sample and separately for the two subsamples, first subsample consisting of bonds issued in 2013-2015 and second issued in 2016-2019. We reject the null hypothesis of mean difference being equal to zero at 1% significance level in all three tests.

Table 2- Results from matching procedure

Yield difference sample (whole sample)		Yield difference sample (2013-2015)		Yield difference sample (2016-2019)	
Mean	0,0072***	Mean	-0,0433***	Mean	0,0247***
Standard Error	0,0201	Standard Error	0,0287	Standard Error	0,0249
Median	0,0010	Median	-0,0303	Median	0,0282
Mode	N/A	Mode	N/A	Mode	N/A
Standard Deviation	0,1684	Standard Deviation	0,1217	Standard Deviation	0,1795
Sample Variance	0,0284	Sample Variance	0,0148	Sample Variance	0,0322
Kurtosis	0,6790	Kurtosis	2,0470	Kurtosis	0,5842
Skewness	0,0866	Skewness	0,5312	Skewness	-0,1154
Range	0,9088	Range	0,5413	Range	0,9088
Minimum	-0,4384	Minimum	-0,2646	Minimum	-0,4384
Maximum	0,4705	Maximum	0,2767	Maximum	0,4705
Sum	0,5039	Sum	-0,7787	Sum	1,2827
Count	70	Count	18	Count	52

Significance marked with: * p<0,1 ** p<0,05 *** p<0,01

The results indicate that on average green bonds have 72 bps higher yield than conventional otherwise comparable bonds. The result is significant at 1% level and consistent with the result obtained by Karpf and Mandel (2018) and Bos et al. (2018), where the authors found a positive yield difference for green bonds. This results is also consistent with the study by VanEck (2017), in which a positive yield difference was found, and the authors argue that any greenium existing could only exist in markets that exhibit high demand, such as Europe.

In order to observe the yield difference during the green bond boom (2013-2015) and the more recent issues, the results were divided into two sub samples. Both samples have yield difference that is significant at 1% level. We also note that for the bonds issued between 2013 and 2015, the yield difference is negative. This subsample is comparable and consistent with the results from Fama-French method described below in section 5, since it contains the bonds issued during 2013-2015.

We also examine the yield difference by dividing the results into three other subsamples: year of issue, country of issue and credit rating. Table 3 presents the results divided by the year of issue. It seems that the green bond premium is present in the bonds issued in 2013, 2016 and 2018. The sign of the premium changes to opposite almost every other year, which could indicate imbalance in the supply and demand of green bonds. It is also observed, that even though the signs change, the yield differences become closer to zero for the bonds issued more recently (2016-2019). All yield differences are significant, except 2013 and 2019, which suffer from small sample size.

Table 3- Yield difference by year of issue

Year	Average Yield Difference
2013	0,1353
2014	-0,0820***
2015	-0,0581***
2016	0,0394***
2017	-0,0255***
2018	0,0883***
2019	-0,0077

Significance marked with: * p<0,1 ** p<0,05 *** p<0,01

Next, the results were divided by country. The results in table 4 indicate that the yield premium is positive in some countries and negative in other countries. Result for some countries, such as Belgium, Finland, Norway and Portugal, suffer from small sample size, and are hence insignificant.

Bos et al. (2018) found that green bonds issued in Finland have positive yield difference whereas those issued in Sweden and France have a yield difference that is close to zero. Furthermore, they also observe that the yield spread of bonds issued in Norway, is negative. It is interesting to note that for those countries, our results are similar to those of Bos et al. (2018). In contrast, our results are completely opposite for bonds issued in Germany, Spain and Italy, where Bos et al. found positive yield difference in Germany and Italy, and negative yield difference in green bonds issued in Spain. This contradiction in results might be due to the difference between the data sample used in Bos et al. (2018) and our sample. Bos et al. (2018) analysed all bond types issued in the countries aforementioned but denominated in the issuer's currency. However, we analysed only euro-denominated corporate issues.

Table 4 - Yield difference by country

Country	Average Yield Difference
Australia	0,2649**
Belgium	0,1228
Denmark	0,1148*
Finland	0,0643
France	-0,0091***
Germany	-0,0072***
Italy	-0,0141**
Japan	0,1602***
Luxembourg	-0,1203***
Netherlands	0,0261***
Norway	-0,0585
Portugal	-0,155
Spain	0,1294***
Sweden	0,0025**
UK	-0,3189***

Significance marked with: * p<0,1 ** p<0,05 *** p<0,01

We also compare the yield spread across issuer's credit rating, presented in table 5. It is observed that the green bond premium is close to zero for ratings Aaa, Aa2, A2, Baa1 and Baa2, and highly negative for A3 and Baa3 rated bonds. Some of the results are in line with the study of Zerbib (2019), who found that for Aaa rating the yield difference is negative, and for A2 and Baa2, the difference is positive, but in comparison, we did not find negative premium for Aa2, A2 and Baa2 rated bonds. Similar to Bos et al. (2018), there seems to be no evident relationship between credit rating and yield differential. We also note that, the sign of average yield differential for ratings Aaa, Aa1, A2, A3 and Baa2 in our green bond data sample is same with Bos et al. (2018).

Table 5- Yield Difference by Credit Rating

Rating	Average Yield Difference
Aaa	-0,0248***
Aa1	-0,1003**
Aa2	0,0025**
Aa3	0,1033***
A1	0,0555***
A2	0,0354
A3	-0,3504
Baa1	0,0263***
Baa2	0,0015
Baa3	-0,2212**
N/A	-0,0212**

Significance marked with: * p<0,1 ** p<0,05 *** p<0,01

4.4.1 Robustness Test – Stricter Matching Criteria

To verify the results obtained from the matching procedure, a robustness check with stricter matching criteria, is applied. In this robustness check, the matching was done by narrowing the criteria of the issue date to one year or less (previously 6 years) and eliminating the pairs that did not meet the new criteria. The original sample consisted of 70 matched pairs, and after eliminating all pairs with an issue date difference of more than 1 year, the new sample consisted of 44 pairs. All other criteria (issuer, credit rating, seniority, maturity) was held the same as described before in table 1.

The YTM was interpolated using the synthetic bond from one or two conventional bonds similarly as in the original matching (equation 1) and the yield difference was calculated between the green bond and synthetic bond as in equation 4. The results are opposite from the original matching, where a less strict matching criteria was used. With stricter matching, the yield difference between green and conventional bonds is -196 bps, indicating that the yield on green bonds is lower. This result is in line with the results we obtain from Fama-French method (section 5).

Table 6- Matching results from robustness test

Robustness check sample (whole sample)		Robustness check sample (2013-2015)		Robustness check sample (2016-2019)	
Mean	-0,0196***	Mean	-0,0380***	Mean	-0,0149***
Standard Error	0,0278	Standard Error	0,0526	Standard Error	0,0325
Median	-0,0003	Median	-0,0134	Median	0,0029
Mode	N/A	Mode	N/A	Mode	N/A
Standard Deviation	0,1842	Standard Deviation	0,1579	Standard Deviation	0,1921
Sample Variance	0,0339	Sample Variance	0,0249	Sample Variance	0,0369
Kurtosis	2,6650	Kurtosis	1,6079	Kurtosis	3,0109
Skewness	-1,0310	Skewness	0,4450	Skewness	-1,2402
Range	1,0006	Range	0,5497	Range	1,0006
Minimum	-0,6547	Minimum	-0,2730	Minimum	-0,6547
Maximum	0,3459	Maximum	0,2767	Maximum	0,3459
Sum	-0,8617	Sum	-0,3417	Sum	-0,5201
Count	44	Count	9	Count	35

Significance marked with: * p<0,1 ** p<0,05 *** p<0,01

With stricter matching criteria, the results might be more accurate, and the results are consistent with the majority of previous literature that find a lower yield for green bonds (Preclaw & Bakshi, 2015; Ehler & Packer, 2017; Wurgler, et al., 2018; Zerbib, 2019). Also Bos et al. (2018) find lower yield for US government issues.

The paired *t*-test is also conducted for our robustness check sample with 44 matched pairs and stricter matching criteria. In all three samples, we can see that the mean difference in yield between green and conventional bond is significant at 1% level.

Even though the results from original matching and the robustness check are inconsistent with each other, we conclude that the results obtained from robustness check with stricter matching may be more accurate, since the pairs of bonds are matched with stricter criteria to isolate any maturity bias or other characteristics that might affect the yield. We also believe our results from robustness sample are more accurate since they are consistent with the majority of previous literature, and with our own results obtained from Fama-French approach, that will be discussed in the next section.

5. Methodology and Data: Fama-French Method

For our thesis, we employ the use of the extended Fama-French (1993) approach which is an application of the Fama-Macbeth regression procedure. This is a procedure that aims to study the joint roles of specified factors in a cross-section of average returns (Fama & French, 1993). Grinblatt et al. (1995) and Carhart (1997) then constructed a momentum factor to further extend the model and increase its accuracy. The relevance of the Fama-French model in bond pricing was further proven by Johansson and Lundgren (2012). This proved that the extended model would be the best approach to use in our study.

5.1 Dataset Description: Fama-French Method

For the Fama-French method, we retrieved a total of 5000 corporate bonds issued from 2013 to 2015 at a data extraction date of May 7, 2019. The rationale for choosing this time period was to focus our Fama-French analysis strictly on the period of the beginning of the green bond boom, as confirmed in graph 1, to eliminate any probable errors associated with missing variables. To be precise, by focusing on this time period, we were able to obtain all pertinent metrics on the bonds in our dataset needed to successfully run the Fama-French regressions. The bond data was downloaded from both Bloomberg and Thomson Reuters Datastream.

The Fama-French model dataset initially consisted of 46 active green bonds issued by 36 companies from 21 countries, extracted from Bloomberg's fixed income database using the "Use of Proceeds" label. Similar to the matching principle, we selected only bonds for which the label stated "Green Bond/Loan". Additionally, we selected a sample of 86 active conventional bonds from our initial data sample of 5000 bonds, using the same conventional bond selection rationale stated in section 4.3.1. The final sample therefore consisted of a total of 132 bonds.

In the original Fama and French (1993) paper, the authors divided their dataset into seven portfolios consisting of two government bond portfolios with maturities of between 1-5 years and 6-10 years and five corporate bond portfolios with credit rating Aaa, Aa, Baa and Low grade. In our adaptation of this model, considering our sample size and observation period, we decided to divide our dataset into industry portfolios as done in Johansson et al. (2012), Piva (2017) and Flammer (2018), and obtained 14 equally-weighted industry portfolios to this effect. The number of bonds in each industry portfolio is shown in table 10 in the appendix.

5.1.1 Fama-French Regression

In the first step of the procedure we conducted separate time-series regressions of average excess monthly returns of every industry portfolio against six factors, to estimate factor loadings to be used in the second step of the procedure. The overall regression equation for the first step of our Fama-French model is hence given as:

$$\begin{aligned}\overline{r_{it}} - \overline{r_{ft}} = \alpha_{i,t} + \beta_{i,r_M-r_f}\left[r_{Mt} - r_{ft}\right] + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,MOM}MOM_t \\ + \beta_{i,TERM}TERM_t + \beta_{i,PD}PD_t + \epsilon_{i,t}\end{aligned} \tag{5}$$

For the second step, cross-sectional regressions are performed by regressing average excess returns of bonds against the coefficients (λ) of the factor loadings obtained from the time-series regression in the first step. Also, a GREEN dummy $GREEN_i$ is added as an additional x-variable, taking the value of 1 for green bonds and 0 for conventional bonds. λ_{GREEN} measures the effect of a bond being green. In this step, the regressions are performed using a bi-annual rolling window. The second step of the model is shown in the equation below:

$$\begin{aligned}\overline{r_i} - \overline{r_f} = \lambda_0 + \lambda_{r_M-r_f}\beta_{i,r_M-r_f} + \lambda_{SMB}\beta_{i,SMB} + \lambda_{HML}\beta_{i,HML} + \lambda_{MOM}\beta_{i,MOM} \\ + \lambda_{TERM}\beta_{i,TERM} + \lambda_{PD}\beta_{i,PD} + \lambda_{GREEN}GREEN_i + \epsilon_i\end{aligned} \tag{6}$$

The variables used in the regressions above, are explained in the following sections.

5.1.2 Dependent Variables

The dependent variable in the first and the second step is monthly excess return on each bond portfolio, for the observation period 2013-2015. The data is calculated by subtracting a European risk-free rate[4] (French, 2019) from average yield of the bond in each industry portfolio, extracted from Thomson Reuters Datastream.

5.1.3 Independent Variables

5.1.3.1 Fama-French Factors

In this research, we used the three factors identified by (Fama & French, 1993) as the common risk factors in both stock and bond returns. These are described in the below section.

Market Premium

Market premium was calculated as the difference between monthly market return data extracted from Bloomberg and the Europe risk-free rate[4]. This is given as $r_M - r_f$ in the regression equation and measured by the $\beta_{i,r_M - r_f}$ coefficient.

Size Premium

The size premium[4] (SMB) is based on the assumption that, on average, small firms earn higher returns than their larger counterparts to compensate for illiquidity risk. Consequently, the difference in returns between a large corporate portfolio and a small corporate portfolio is considered a valid factor to account for size risk. The same intuition can be further applied to value premium explained below (Petkova, 2011). The size premium, is the difference of the weighted average return of three small size portfolios (namely Small/Growth, Small/Neutral and Small/Value) and three big size portfolios (namely Big/Growth, Big /Neutral and Big /Value). In our regression, size premium is measured by the $\beta_{i,SMB}$ coefficient.

[4] Extracted from the Kenneth R. French website on 12.04.2019.

According to French (2019) the formula is given as:

$$SMB = \frac{1}{3}[Small\,Value + Small\,Neutral + Small\,Growth] - \frac{1}{3}[Big\,Value + Big\,Neutral + Big\,Growth] \tag{7}$$

Value Premium

The value premium[4] (HML) is the equal-weight of average return of two value portfolios minus the average return of two growth portfolios. In our regression, the $\beta_{i,HML}$ coefficient accounts for value premium.

According to French (2019) the formula is given as:

$$HML = \frac{1}{2}[Small\,Value + Big\,Value] - \frac{1}{2}[Small\,Growth + Big\,Growth] \tag{8}$$

5.1.3.2 Momentum Factor

The momentum factor[4] (MOM) is defined as the return difference between a portfolio of 12-months winner and 12-month loser stocks at time *t* (Wagner, 2017). In our Fama-French model, the $\beta_{i,MOM}$ coefficient measures the effect of momentum strategy on the return.

5.1.3.3 Bond Factors

Term Factor

The term factor ($TERM$) is defined as the difference between monthly long term government bond return and the one-month Treasury bill rate (Fama & French, 1993). This is calculated using the monthly Germany 10-year bund yield[5] as a proxy for the long-term government bond return and Europe risk-free rate[4]. The $\beta_{i,TERM}$ coefficient in our regression equation, measures the impact of term structure on bond return.

[5] Extracted from Bloomberg Germany 10-Year Bund Auction Average Yield Index on 07.05.2019.

Default Factor

This is the probability of default (PD), of all bond issuers in our sample. In this paper, we calculate the probability of default using the Merton model, discussed in the next section. The $\beta_{i,PD}$ coefficient measures the effect of default probability on bond return.

5.1.4 Merton Model

Probability of default is a component of the pricing of a bond. The higher the PD of the issuer, the higher the return investors require to compensate for risks they are bearing by holding the bond. Therefore, the return on corporate bonds is higher than risk-free returns (Hull, et al., 2012). Also, Altman (1989) found that all corporate bonds have higher returns than Treasury bonds. Hence, due to its explanatory power on bond returns, we include the PD as an independent variable in the Fama-French regression. We calculate real-world PDs, meaning that PD is calculated from actual historical data, for all issuers of the bonds in our sample. It is important to note that the green bond market has not existed for long, hence there is a small number of default events (Wurgler, et al., 2018).

To calculate PD, the Merton model is the most broadly used within finance and it outperforms the other models assessing PD (Afik, et al., 2016). In 1974, Merton presented a model that can be used to value stocks and corporate bonds using company's assets. The model is a structural model, meaning that it derives from the company's debt and equity structure, hence the model requires estimations of three variables: asset value, asset volatility and expected returns. The model was derived by Merton (1974) from the Black-Scholes option pricing formula (Black & Scholes, 1973) with an observation that value of equity and debt are like European type options.

The model has become a dominant model to predict credit risk, but its implementation in practice is complex. The distance to default (DD) is the number of standard deviations to default in a normal distribution and it is represented by the formula:

$$DD = \frac{lnA_0 + \left(\mu_A - \frac{\sigma_A^2}{2}\right) \times T - lnK}{\sigma_A \times \sqrt{T}} \tag{9}$$

where A_0 is today's market value of assets, μ_A is expected (adjusted) asset log-return, σ_A^2 is volatility of asset log-turn, K is face value of debt and T is time horizon. DD is calculated by first estimating a non-linear system of two equations to obtain market value of assets A and asset volatility σ_A that are unobservable, and can be estimated by solving the following equation system:

$$E = A \times N(d_1) - K \times e^{-r \times T} \times N(d_2) \tag{10}$$

$$\sigma_E = \frac{A}{E} \times N(d_1) \times \sigma_A \tag{11}$$

where r is the risk-free rate, σ_E is the yearly standard deviation of equity and d_1 and d_2 are represented as:

$$d_1 = \frac{\ln\left(\frac{A}{K}\right) + (r + \frac{\sigma_A^2}{2}) \times T}{\sigma_A \times T} \tag{12}$$

$$d_2 = d_1 - \sigma_A \times \sqrt{T} \tag{13}$$

Additionally, the equation for σ_E can be simplified into $\sigma_E = 2\sigma_A \Leftrightarrow \sigma_A = \frac{1}{2}\,\sigma_E$ by assuming $N(d_1) = 1$ and $\frac{A}{E} = 2$. The result $\frac{1}{2}\,\sigma_E$ is then substituted in the equation for E.

Finally, PD is equal to:

$$PD = N(-DD) \tag{14}$$

The time-varying default factor is calculated for each issuer of the bonds in our sample. According to Reisz and Perlich (2004), accounting-based measures outperform the market-based structural models in the short-term, and the authors recommend using a mix of structural model and accounting-based model. Therefore, we estimated PD using structural model, Merton model, but incorporated accounting measures for the assets, volatility and stock price for each company, extracted from Datastream. The PD was then calculated for each firm with these real world variables. The sample consisted of both private and public companies, and since the information for private companies is unobservable, we calculated PD for only public companies and categorized the firms into same industry portfolios described above (section 5.1). We calculated industry averages of PD, which were then applied to unobservable private firms as well. Finally, the PD factor was added as an explanatory variable in the Fama-French regression.

5.2 Statistical Tests Conducted

In our application of the Fama-French model, we used OLS regressions for both the time-series and cross-sectional regressions. Therefore, considering our data sample and observation period, we decided to test for heteroscedasticity and autocorrelation using the Breusch-Godfrey (BG) Test and White's Test described below. We also further corrected these using the Newey-West estimator and all the results are presented in the appendix.

5.1.5 Breusch-Godfrey (BG) Test

The Breusch-Godfrey test is a general test of autocorrelation that is used to determine autocorrelation up to an optimal number of lags. We therefore presumed that this would be a more suitable test for autocorrelation of the error terms in our time-series regressions than the Durbin-Watson (DW) statistic that tests for autocorrelation in the first lag only. After performing the Breusch-Godfrey statistical test for autocorrelation as described in (Brooks, 2014), we found that our Fama-French regressions showed signs of autocorrelation specifically in the Real Estate, Utilities, Energy and FMCG industries.

5.1.6 White's Test

White's test of heteroscedasticity is used to test if the error term of a regression is valid, based on an estimation of an additional regression of the squared residuals on the regressors, their squared values and their cross-products (Brooks, 2014). We therefore used this test to check for heteroscedasticity in both time-series and cross-sectional regressions in our data sample as described in Brooks (2014) and discovered that the Manufacturing, Construction and Energy industries exhibited heteroscedasticity.

5.1.7 Newey-West Estimator

The Newey-West estimator developed by Newey and West (1987) is a common method of correcting autocorrelation and heteroscedasticity in a data sample. As we had evidence of both autocorrelation and heteroscedasticity in some portfolios of our data sample for both the main and robustness tests, we decided to correct these using the Newey-West estimator as described in Brooks (2014). The results are described in the sections below.

5.2 Results: Fama-French with PD

Our results at the end of the Fama-French regressions showed that, in the first step, Real Estate was the only industry that exhibited autocorrelation, specifically in the second, third and fifth lags. After correction of the Real Estate time-series regression, all factor coefficients became more significant with the most significant factors being PD which was significant at the 10% level and RM-RF which was significant at the 5% level.

Additionally, in the first step, heteroscedasticity was exhibited by the Manufacturing and Construction industries. After correction of these regressions with the Newey-West estimator, the PD coefficient for Manufacturing became significant at the 10% level and for Construction the TERM factor coefficient is significant at the 5% level.

In the second step of our Fama-French model, we found heteroscedasticity in the 1st, 3rd, 4th and 5th rolling window sub-periods. After correction with the Newey-West estimator, for the 1st sub-period, all factors became significant at the 5% level except the momentum factor which is significant at the 10% level while the TERM and SMB factors remain insignificant. For the 3rd sub-period, after correction, the SMB factor was the only one that became less significant, whereas all other factors became slightly more significant. For the 4th sub-period, the momentum factor is significant at the 10% level and all other factors became slightly more significant except the SMB factor which becomes less significant. For the 5th sub-period, the HML factor, is significant at the 10% level and all other factors become slightly more significant. All results are illustrated in the appendix.

Table 7 below illustrates that, the GREEN dummy is significant at the 1% level for the 1^{st}, 3^{rd} and 6th sub-periods and significant at the 10% level for the 5^{th} sub-period. Furthermore, it has a negative coefficient of -0,063 on average, insinuating that conventional bonds perform better than green bonds over the sample period as confirmed in the robustness test of the matching method.

Table 7 - Green dummy coefficient (PD)

Period	λGREEN
1/2016 - 6/2016	-0,1956***
	(0,0526)
7/2016 - 12/2016	0,0061
	(0,0083)
1/2017 - 6/2017	0,0217***
	(0,0044)
7/2017 - 12/2017	-0,0064
	(0,0062)
1/2018 - 6/2018	-0,0665*
	(0,0382)
7/2018 - 12/2018	-0,0932***
	(0,0270)
1/2019 - 4/2019	-0,1189
	(0,1310)
Average Coefficient	-0,063

Significance marked with: * p<0,1 ** p<0,05 *** p<0,01

5.3 Robustness Test – Fama-French with DEF Factor

The default factor DEF is defined as the difference between the return on a market portfolio of long-term corporate bonds and long-term government bond return (Fama & French, 1993). For the robustness test of our Fama-French model, we chose to use the DEF factor instead of the credit rating of each bond because the DEF factor seeks to capture the time-varying default risk of bonds, whereas with credit ratings, there is the risk that recent information may not be aptly reflected in a bond's credit rating, making it a relatively inaccurate proxy for a bond's default risk (Byström, 2006). Our robustness test therefore involved the use of a DEF factor, as instructed in Fama and French (1993), in place of the PD used in Section 5.2 above. This is calculated using the Bloomberg European Corporate Investment Grade Index as a proxy for the long-term government bond return and the monthly Germany 10-year bund yield[6]. The $\beta_{i,DEF}$ coefficient measures the effect of default probability on bond return.

The two-step regression equations used for this robustness test are shown below:

$$r_{it} - r_{ft} = \alpha_{i,t} + \beta_{i,r_M - r_f}\left[r_{Mt} - r_{ft}\right] + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,MOM}MOM_t + \beta_{i,TERM}TERM_t + \beta_{i,DEF}DEF_t + \epsilon_{i,t} \tag{15}$$

$$\overline{r_i} - \overline{r_f} = \lambda_0 + \lambda_{r_M - r_f}\beta_{i,r_M - r_f} + \lambda_{SMB}\beta_{i,SMB} + \lambda_{HML}\beta_{i,HML} + \lambda_{MOM}\beta_{i,MOM} + \lambda_{TERM}\beta_{i,TERM} + \lambda_{DEF}\beta_{i,DEF} + \lambda_{GREEN}GREEN_i + \epsilon_i \tag{16}$$

Once again, after performing statistical tests for heteroscedasticity and autocorrelation, our result illustrates that the Fama-French regressions showed signs of autocorrelation and heteroscedasticity. Similarly as in the main test, we therefore corrected for both autocorrelation and heteroscedasticity by using the Newey-West (1987) estimator.

In the first step, Utilities, Energy and FMCG industries exhibited autocorrelation. After correction of the Utilities time-series regression, all factor coefficients become slightly more significant and the SMB factor becomes significant at the 10% level whereas the HML factor becomes significant at the 5% level. After correction of the Energy time-regression, the HML factor is significant at the 5% level.

Furthermore, in the first step, heteroscedasticity was exhibited by the Manufacturing and Energy industries. After correction of these regressions with the Newey-West estimator, all factors for Manufacturing became slightly more significant except for the HML factor which becomes less significant but is still significant at the 5% significance level, the SMB factor is also significant at the 10% level. For Energy, the HML factor becomes significant at the 5% level whilst the other factors remain insignificant.

[6] Extracted from Bloomberg Germany 10-Year Bund Auction Average Yield Index on 07.05.2019.

Same as in the result of the main test above, in the second step of our Fama-French model using the DEF factor this time, we found heteroscedasticity in the 1st, 3rd, 4th and 5th rolling window sub-periods. After correction with the Newey-West estimator, for the 1st sub-period, the SMB and TERM factors are significant at the 10% level, and the DEF factor is significant at the 5% level. For the 3rd sub-period only the RM-RF factor is significant at the 5% level. For the 4th sub-period, only the DEF factor becomes significant at the 10% level. For the 5th sub-period, all factors remain insignificant. All results are illustrated in the appendix.

Our results at the end of the Fama-French robustness check with DEF factor, illustrated in table 8 below, show that the GREEN dummy is significant at the 1% level for the 3rd and 6th period and significant at the 5% level for the 1st period. Furthermore, as confirmed in the results achieved with the use of PD as the default factor, the GREEN dummy still has a negative coefficient of -0,068, verifying that conventional bonds perform better than green bonds over the sample period.

Table 8- Green dummy coefficient (DEF)

Period	λGREEN
1/2016 - 6/2016	-0,2339**
	(0,0912)
7/2016 - 12/2016	0,0047
	(0,0077)
1/2017 - 6/2017	0,0219***
	(0,00423)
7/2017 - 12/2017	0,0041
	(0,0058)
1/2018 - 6/2018	-0,0641
	(0,0407)
7/2018 - 12/2018	-0,0930***
	(0,0271)
1/2019 - 4/2019	-0,1155
	(0,1240)
Average coefficient	-0,068

Significance marked with: * p<0,1 ** p<0,05 *** p<0,01

5.3.1 Comparison between PD and DEF Results

Our results illustrate that with the use of PD as a default factor, the results are more significant than in the robustness test when we use the DEF factor. We can hereby presume that the Merton model is a more accurate predictor of default probability than the Fama-French DEF factor.

Other trends in our data analysis also show that the manufacturing industry exhibits heteroscedasticity in both our main test and robustness tests. Additionally, the energy industry exhibits both autocorrelation and heteroscedasticity when the DEF factor is used. Also, for both the main test and the robustness check, the GREEN dummy was significant at the 5% level for the 1st, 3rd and 6th periods.

It is important to note that the matching sample consisted of bonds issued between 2013 and 2019, whereas the Fama-French sample consisted of bonds issued 2016-2019, which makes the results not directly comparable. Also, the main result from the Fama-French model is contradictory to the main results of the matching method but is however in agreement with the robustness test of the matching method. We therefore have cause to believe that, the result of the robustness matching test, which was conducted with stricter matching criteria, is a true reflection of our Fama-French result, which shows that conventional bonds outperform green bonds.

It is interesting to note that, our result is in line with that of Zerbib (2019) mentioned in literature review section 3 above, who found that conventional bonds outperform green bonds over an observation period of 2013-2017. In the same way that he did, we also find a negative premium. However, the differences between his study and ours are that he used only the matching method while we used both the matching and the Fama-French method, also he used the whole green bond universe whereas we used only euro-denominated green bonds and his yield differential is about 18 bps whereas ours is 72 bps. Nonetheless, it is interesting to see that even though our data samples are different, we have the same result.

Overall however, our Fama-French result exhibited low significance across the factors except for during the time period when there was the green bond boom in 2013, as observed in Wagner (2017), who also used the extended Fama-French model in his analysis. He does not attribute the low significance to any occurrence, but we presume that this low significance could be as a result of an unbalanced data sample and as mentioned early on, this was one of the limitations of our study. It was however difficult to draw a comparison between our Fama-French results and previous similar literature as there are not a great number of extensive studies on the use of the Fama-French model to analyse corporate bond returns. Furthermore, the results are not consistent across studies and mostly contradictory to each other, as previously stated in the literature review. This goes to further confirm our earlier statement about the results of studies on the performance of green against conventional bonds being inconclusive.

6. Conclusion

The aim of this paper was to examine green bond performance in comparison to conventional bonds denominated in euros. The study sought to find out whether investors are paying for a green bond premium in the market and how this differs between countries of issue and maturity. The data was collected according to Bloomberg Green Bond label, where the Use of Proceeds was denominated as environmental projects.

The matching procedure was used in order to isolate the effect of other factors, such as credit rating, maturity, seniority and issuer and then calculate the difference in yield between the treated and control group. The sample size consisted of 70 green bonds issued in 2013-2019 and were matched with 124 conventional bonds with the same characteristics. The sample period was chosen due to the boom of green bonds that started in 2013, when the amount of green bonds grew at an exponential pace during these years. According to the results, the green bonds on average have higher yield in comparison to conventional bonds, but the yield spread became tighter and turned to positive in the subsample of 2016-2019. This finding suggests that the green bonds issued during the boom, pay higher yield than the green bonds issued in 2016-2019.

For further testing, following Fama-Macbeth procedure we run time-series regression with five Fama-French factors extended with Carhart's momentum factor and time-varying, issuer specific PD, which was obtained with Merton model. The bonds were divided to 14 portfolios by the industry of the issuer and the coefficients from the time-series regressions were added into cross-sectional regressions. These cross-sectional regressions were run for each 6-month time period and the final results indicate that green bonds have lower yield on average than conventional bonds. The result is consistent with other literature on the topic, as well as the robustness test where the same procedure was adopted by substituting the PD factor by the default factor suggested by Fama-French.

Our results conclude that the effect of being green leads to less risky debt and lower yields for investors. Furthermore, the high demand suggests that the market is maturing and that the green bond market will develop further rather than being just a fading trend. The studies on this topic are still not quite extensive, calling for further future research on the topic. It will be interesting to see how the market of green bonds matures in the coming decades, and if it is just a boom or truly a mature market. According to our results obtained with matching procedure for the main sample, the green bonds issued earlier, in 2013-2015, have a lower yield than conventional bond yields, but as we saw, the yield spread between them gets tighter and even positive in bonds issued more recently, in 2016-2019.

It will be interesting to see the direction in which yield spread across bond markets develops in the upcoming years. Our recommendations for future study include research on the correlation between companies issuing green bonds and the evolution of their stock price. Another recommendation for further study could be to examine how the fear of an impending economic recession would affect green bond investments and whether there would be any flight to quality. Finally, a third topic for future research could be to examine the PD of ethical firms issuing green bonds and firms perceived as “too green to fail”.

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Appendix

TABLE 9

Descriptive Statistics for Matching Sample

This table shows the descriptive statistics for the data sample used in matching method. The table presents original sample, as well as the data obtained after elimination. The matching procedure and estimations were computed in MS Excel.

DATA SAMPLE FOR MATCHING

ORIGINAL SAMPLE

Green Bonds		Conventional Bonds	
No. Of Green Bonds	75	No. of Conventional Bonds	150
Average Yield	0,361	Average Yield	0,325

AFTER MATCHING

Green Bonds		Conventional Bonds		Synthetic Bonds	
No. of Green Bonds	70	No. of Conventional Bonds	124	No. of Conventional Bonds	70
Average Yield	0,342	Average Yield	0,283	Average Yield	0,335
Average Years to Maturity	7,101	Average Years to Maturity	5,882	Average Years to Maturity	7,369

Payment Seniority	No. of Bonds	Payment Seniority	No. of Bonds	Payment Seniority	No. of Bonds
Secured	5	Secured	7	Secured	5
Sr Non Preferred	5	Sr Non Preferred	7	Sr Non Preferred	5
Sr Preferred	12	Sr Preferred	23	Sr Preferred	12
Sr Unsecured	48	Sr Unsecured	87	Sr Unsecured	48

Credit rating	No. of Bonds	Credit rating	No. of Bonds	Credit rating	No. of Bonds
Aaa	17	Aaa	30	Aaa	17
Aa1	2	Aa1	4	Aa1	2
Aa2	3	Aa2	6	Aa2	3
Aa3	9	Aa3	18	Aa3	9
A1	12	A1	20	A1	12
A2	5	A2	8	A2	5
A3	1	A3	2	A3	1
Baa1	9	Baa1	15	Baa1	9
Baa2	5	Baa2	8	Baa2	5
Baa3	2	Baa3	4	Baa3	2
N/A	5	N/A	9	N/A	5

<u>TABLE 10</u>

Number of bonds in each industry portfolio

This table shows the number of bonds in each industry portfolio. The bonds were categorized in these industries in order to run the first-step of Fama-Macbeth procedure.

Industry	Number of Bonds
Energy	19
Utilities	8
Financial Services	47
FMCG	3
Retail	18
Waste	1
Chemicals	1
Construction	7
Manufacturing	8
Mining	2
Pharmaceuticals	4
Real Estate	1
Telecom	6
Transportation	7
Total	132

TABLE 11

Coefficients from time-series regressions for each industry

This table shows the coefficients obtained from 11 time-series regressions for each industry. It was conducted as the first-step of the Fama-Macbeth procedure. The test was conducted for regression with PD factor. The test was run in EViews.

Industry	α	βRM_RF	βMOM	βSMB	βHML	βTERM	βPD	R-squared
Manufacturing	0,9551***	0,0018	0,0026	0,0076	-0,0039	-0,1054	-0,9583*	0,2944
	(0,0246)	(0,0040)	(0,0080)	(0,0094)	(0,0081)	(0,0647)	(0,5374)	
Financial Services	0,9172***	-0,0035	-0,0010	-0,0005	-0,0103	-0,0836	2,2874*	0,1650
	(0,0316)	(0,0042)	(0,0113)	(0,0074)	(0,0067)	(0,0824)	(1,3334)	
Retail	0,9188***	0,0034	0,0039	0,0086	0,0060	-0,0082	-0,3497	0,1219
	(0,0209)	(0,0035)	(0,0106)	(0,0063)	(0,0056)	(0,0699)	(5,7778)	
Utilities	0,8804***	0,0039	0,0015	0,0028	-0,0014	0,0183	5905,187*	0,1814
	(0,0294)	(0,0044)	(0,0130)	(0,0080)	(0,0073)	(0,0883)	(2936,4720)	
Energy	0,9172***	0,0041	-0,0048	0,0047	0,0020	-0,0394	168257,30	0,1239
	(0,0179)	(0,0031)	(0,0086)	(0,0054)	(0,0050)	(0,0605)	(262060,90)	
FMCG	0,9073***	0,0079	0,0067	0,0068	0,0042	0,0156	0,7538	0,1079
	(0,0287)	(0,0052)	(0,0130)	(0,0095)	(0,0078)	(0,0970)	(0,7260)	
Telecom	1,6022***	-0,0632	0,0283	-0,0800	-0,0845	0,2773	-2,8886	0,1263
	(0,4770)	(0,0458)	(0,1152)	(0,0764)	(0,0677)	(0,8572)	(2,8049)	
Transportation	0,8231***	-0,0083	0,0716	0,0440	-0,0183	-0,5575	12,1428	0,1406
	(0,1517)	(0,0217)	(0,0591)	(0,0404)	(0,0346)	(0,4475)	(10,3093)	
Construction	1,0678***	-0,0098	-0,0218	0,0024	0,0023	-0,3628**	-0,3991	0,3116
	(0,0435)	(0,0114)	(0,0086)	(0,0135)	(0,0132)	(0,0826)	(0,4206)	
Pharmaceuticals	0,8984***	0,0062	0,0067	0,0040	-0,0036	-0,0833	0,1815	0,1492
	(0,0549)	(0,0046)	(0,0129)	(0,0084)	(0,0078)	(0,0941)	(0,2161)	
Real Estate	0,8869***	0,0055**	0,0075	0,0088	-0,0060	0,0507	13,9909*	0,3846
	(0,0253)	(0,0020)	(0,0054)	(0,0099)	(0,0057)	(0,0823)	(7,2280)	
Average	0,9795	-0,0047	0,0092	0,0008	-0,0103	-0,0799	15835,2043	0,1915

Standard errors in parentheses, Significance marked with: * p<0,1 ** p<0,05 *** p<0

<u>TABLE 12</u>

Coefficients from time-series regressions for each industry (robustness check)

This table shows the coefficients obtained from 14 time-series regressions for each industry. It was conducted as the first-step of the Fama-Macbeth procedure. The test was conducted for robustness check regression with DEF factor. The test was run in EViews.

Industry	α	βRM_RF	βMOM	βSMB	βHML	βTERM	βDEF	R-squared
Manufacturing	0,9017***	-0,0007	-0,0020	0,0170*	0,0191**	0,0178	0,0098	0,2867
	(0,0226)	(0,0036)	(0,0089)	(0,0092)	(0,0091)	(0,0686)	(0,0081)	
Financial Services	0,9237***	-0,0051	-0,0063	0,0088	0,0078	0,0328	0,0099	0,1041
	(0,0225)	(0,0044)	(0,0064)	(0,0107)	(0,0077)	(0,0848)	(0,0125)	
Retail	0,8873***	0,0007	0,0059	0,0148	0,0153*	0,0921	-0,0004	0,2383
	(0,0201)	(0,0039)	(0,0057)	(0,0096)	(0,0069)	(0,0759)	(0,0112)	
Utilities	0,8822***	-0,0018	0,0045	0,0191*	0,0130*	0,0828	0,0059	0,1430
	(0,0328)	(0,0023)	(0,0103)	(0,0096)	(0,0065)	(0,0924)	(0,0139)	
Energy	0,8863***	0,0002	0,0029	0,0069	0,0126**	0,0669	0,0041	0,1547
	(0,0246)	(0,0032)	(0,0082)	(0,0090)	(0,0053)	(0,0720)	(0,0076)	
Waste Management	0,8973***	-0,0012	-0,0082	0,0268*	0,0315***	0,0316	0,0146	0,3930
	0,0281	0,0054	0,0080	0,0134	0,0096	0,1059	0,0156	
FMCG	0,9755***	0,0115*	-0,0113	-0,0163	-0,0134	-0,1379	-0,0167	0,0996
	(0,0510)	(0,0057)	(0,0150)	(0,0236)	(0,0140)	(0,1744)	(0,0175)	
Telecom	1,0388***	-0,0640	-0,0777	0,0740	-0,0263	0,6215	0,1053	0,1218
	(0,2125)	(0,0412)	(0,0607)	(0,1014)	(0,0725)	(0,8019)	(0,1179)	
Mining	1,2152***	-0,0063	0,0287	-0,1123*	-0,0465	-0,8109	0,0098	0,2582
	(0,1324)	(0,0257)	(0,0378)	(0,0632)	(0,0452)	(0,4996)	(0,0734)	
Transportation	0,9819***	-0,0065	-0,0098	0,0437	0,0117	-0,6144	-0,0602	0,1246
	(0,1071)	(0,0208)	(0,0306)	(0,0511)	(0,0366)	(0,4043)	(0,0594)	
Construction	1,0013***	-0,0153**	-0,0022	-0,0015	0,0158	-0,1575	0,0326	0,2674
	(0,0367)	(0,0071)	(0,0105)	(0,0175)	(0,0125)	(0,1384)	(0,0203)	
Pharmaceuticals	0,9040***	0,0026	0,0016	0,0160	0,0129	0,0353	0,0055	0,1311
	(0,0263)	(0,0051)	(0,0075)	(0,0126)	(0,0090)	(0,0993)	(0,0146)	
Real Estate	0,8930***	0,0005	-0,0018	0,0173*	0,0207***	0,0576	0,0159	0,3496
	(0,0191)	(0,0037)	(0,0055)	(0,0091)	(0,0065)	(0,0720)	(0,0106)	
Chemicals	0,9302***	-0,0005	-0,0043	0,0197	0,0129	-0,0501	0,0019	0,1372
	(0,0302)	(0,0059)	(0,0086)	(0,0144)	(0,0103)	(0,1140)	(0,0168)	
Average	0,9513	-0,0061	-0,0057	0,0096	0,0062	-0,0523	0,0099	0,2007

Standard errors in parentheses, Significance marked with: * p<0,1 ** p<0,05 *** p<0

<u>TABLE 13</u>

Autocorrelation Tests for time-series regressions with PD

This table shows the results from Breusch-Godfrey test for autocorrelation. The test was conducted for time-series regression, the first-step of the Fama-Macbeth procedure, for each industry. We found autocorrelation in one time-series regression for real estate. The test was conducted for regression with PD factor. The test was run in EViews.

Portfolio	Lag1		Lag2		Lag3		Lag4		Lag5		Autocorrelation
Stat	F-stat	Chi	F-stat	Chi	F-stat	Chi	F-stat	Chi	F-stat	Chi	YES/NO
Manufacturing	0,35	0,29	0,65	0,56	0,49	0,37	0,65	0,51	0,77	0,63	NO
Financial Services	0,39	0,33	0,27	0,19	0,38	0,27	0,53	0,38	0,67	0,51	NO
Retail	0,40	0,34	0,70	0,62	0,85	0,79	0,88	0,81	0,83	0,72	NO
Utilities	0,57	0,52	0,30	0,22	0,27	0,17	0,40	0,26	0,42	0,27	NO
Energy	0,20	0,15	0,37	0,28	0,18	0,11	0,30	0,18	0,42	0,27	NO
FMCG	0,75	0,72	0,61	0,52	0,12	0,07	0,17	0,09	0,28	0,16	NO
Telecom	0,83	0,81	0,76	0,69	0,91	0,86	0,94	0,89	0,97	0,94	NO
Transportation	0,79	0,76	0,93	0,91	0,86	0,80	0,64	0,50	0,51	0,35	NO
Construction	0,89	0,87	0,82	0,77	0,50	0,37	0,59	0,45	0,74	0,59	NO
Pharmaceuticals	0,21	0,15	0,43	0,33	0,53	0,41	0,70	0,57	0,82	0,70	NO
Real Estate	0,22	0,16	0,02	0,01	0,06	0,03	0,10	0,05	0,09	0,05	YES

TABLE 14

Heteroscedasticity Tests for time-series regressions with PD

This table shows the results from White test for heteroscedasticity. The test was conducted for time-series regression, the first-step of the Fama-Macbeth procedure, for each industry. We found heteroscedasticity in two time-series regressions, manufacturing and construction. The test was conducted for the regression with PD factor. The test was run in EViews.

	WHITE		
Portfolio	F-stat	Chi	Heteroscedasticity YES/NO
Manufacturing	0,01	0,02	YES
Financial Services	0,91	0,88	NO
Retail	0,51	0,47	NO
Utilities	0,85	0,81	NO
Energy	0,13	0,13	NO
FMCG	0,33	0,30	NO
Telecom	0,97	0,95	NO
Transportation	0,95	0,93	NO
Construction	0,01	0,01	YES
Pharmaceuticals	0,58	0,53	NO
Real Estate	0,94	0,92	NO

TABLE 15

Heteroscedasticity Tests for cross-sectional regressions with PD

This table shows the results from White test for heteroscedasticity. The test was conducted for cross-sectional regression, the second-step of the Fama-Macbeth procedure, for each period. We found heteroscedasticity in four cross-sectional regressions, 1/2016 - 6/2016, 1/2017 – 6/2017, 7/2017 – 12/2017 and 1/2018 – 6/2018. The test was conducted for the regression with PD factor. The test was run in EViews.

	WHITE		
Period	F-stat	Chi	Heteroscedasticity YES/NO
1/2016 - 6/2016	0,00	0,00	YES
7/2016 - 12/2016	0,24	0,23	NO
1/2017 - 6/2017	0,00	0,00	YES
7/2017 - 12/2017	0,00	0,00	YES
1/2018 - 6/2018	0,00	0,00	YES
7/2018 - 12/2018	0,90	0,89	NO
1/2019 - 4/2019	0,94	0,93	NO

TABLE 16

Final result with PD

This table shows the results from the second-step of the Fama-Macbeth procedure. The cross-sectional regressions were run for each time period. The test was conducted with PD factor. The regressions were run in EViews.

Period	λ0	λRM_RF	λMOM	λSMB	λHML	λTERM	λPD	λGREEN	R-squared
1/2016 - 6/2016	1,1140***	-7,4883***	7,2424**	1,5287	-9,8253***	0,0870	-0,0000***	-0,1956***	0,458
	(0,0499)	(2,8059)	(3,6372)	(1,7116)	(3,6632)	(0,1015)	(0,0000)	(0,0526)	
7/2016 - 12/2016	0,9584***	-1,2615	-0,7129*	2,7178**	-1,4071	-0,0112	0,0000	0,0061	0,140
	(0,0149)	(0,9927)	(0,4015)	(1,3102)	(1,3933)	(0,0221)	(0,0000)	(0,0083)	
1/2017 - 6/2017	0,9252***	0,8595	-0,3623	-0,9289	0,0992	0,1278	0,0000	0,0217***	0,149
	(0,0093)	(1,2102)	(0,9906)	(1,1848)	(1,0425)	(0,1278)	(0,0000)	(0,0044)	
7/2017 - 12/2017	0,8796***	0,0795	-2,3481*	-3,2556	3,6968	0,3568	0,0000	-0,0064	0,132
	(0,0114)	(0,8966)	(1,3024)	(3,3858)	(2,2327)	(0,3266)	(0,0000)	(0,0064)	
1/2018 - 6/2018	0,9930***	-2,7622	-0,6938	1,6653	-6,3563*	0,1841	0,0000	-0,0665*	0,111
	(0,0570)	(3,1023)	(1,6882)	(2,5426)	(3,3452)	(0,1436)	(0,0000)	(0,0382)	
7/2018 - 12/2018	0,9706***	-6,2776*	-2,8614**	-1,6849	4,2314	-0,0456	0,0000	-0,0932***	0,172
	(0,0485)	(3,2343)	(1,3080)	(4,2686)	(4,5395)	(0,0719)	(0,0000)	(0,0270)	
1/2019 - 4/2019	1,0532***	-1,8640	-4,9474	-5,0583	-0,0053	-0,1544	0,0000	-0,1189	0,019
	(0,2359)	(15,7246)	(6,3590)	(20,7532)	(22,0703)	(0,3495)	(0,0000)	(0,1310)	

Standard errors in parentheses, Significance marked with * p<0,1 ** p<0,05 *** p<0

TABLE 17

Autocorrelation Tests for time-series regressions with DEF (robustness check)

This table shows the results from Breusch-Godfrey test for autocorrelation. The test was conducted for time-series regression, the first-step of the Fama-Macbeth procedure, for each industry. We found autocorrelation in three time-series regressions, utilities, energy and FMCG. The test was conducted for the robustness check with DEF factor. The test was run in EViews.

Breusch-Godfrey p-value

Portfolio	Lag1		Lag2		Lag3		Lag4		Lag5		Autocorrelation YES/NO
Stat	F-stat	Chi	F-stat	Chi	F-stat	Chi	F-stat	Chi	F-stat	Chi	NO
Manufacturing	0.73	0.70	0.93	0.91	0.94	0.91	0.87	0.80	0.59	0.44	NO
Financial Services	0.81	0.80	0.89	0.86	0.89	0.85	0.96	0.93	0.83	0.72	NO
Retail	0.31	0.25	0.30	0.22	0.30	0.20	0.45	0.32	0.30	0.18	NO
Utilities	0.13	0.09	0.11	0.07	0.07	0.04	0.12	0.07	0.11	0.06	YES
Energy	0.06	0.04	0.07	0.04	0.02	0.01	0.06	0.03	0.08	0.04	YES
FMCG	0.08	0.06	0.23	0.16	0.01	0.01	0.01	0.00	0.02	0.01	YES
Telecom	0.56	0.50	0.62	0.54	0.81	0.74	0.85	0.77	0.93	0.87	NO
Transportation	0.92	0.91	0.92	0.90	0.82	0.76	0.82	0.73	0.91	0.84	NO
Construction	0.61	0.56	0.66	0.59	0.63	0.52	0.33	0.22	0.26	0.15	NO
Pharmaceuticals	0.28	0.22	0.56	0.48	0.62	0.52	0.64	0.51	0.77	0.65	NO
Real Estate	0.30	0.24	0.21	0.15	0.37	0.27	0.44	0.31	0.24	0.14	NO

TABLE 18

Heteroscedasticity Tests for time-series regressions with DEF (robustness check)

This table shows the results from White test for heteroscedasticity. The test was conducted for time-series regression, the first-step of the Fama-Macbeth procedure, for each industry. We found heteroscedasticity in two time-series regressions, manufacturing and energy. The test was conducted for the robustness check with DEF factor. The test was run in EViews.

WHITE

Portfolio	F-stat	Chi	Heteroscedasticity YES/NO
Manufacturing	0,00	0,00	YES
Financial Services	0,90	0,87	NO
Retail	0,41	0,38	NO
Utilities	0,38	0,35	NO
Energy	0,01	0,01	YES
FMCG	0,92	0,90	NO
Telecom	0,94	0,92	NO
Transportation	0,94	0,92	NO
Construction	0,11	0,12	NO
Pharmaceuticals	0,85	0,82	NO
Real Estate	0,59	0,54	NO

TABLE 19

Heteroscedasticity Tests for cross-sectional regressions with DEF (robustness check)

This table shows the results from White test for heteroscedasticity. The test was conducted for cross-sectional regression, the second-step of the Fama-Macbeth procedure, for each period. We found heteroscedasticity in four cross-sectional regressions, 1/2016 - 6/2016, 1/2017 – 6/2017, 7/2017 – 12/2017 and 1/2018 – 6/2018. The test was conducted for the robustness check with DEF factor. The test was run in EViews.

WHITE

Period	F-stat	Chi	Heteroscedasticity YES/NO
1/2016 - 6/2016	0,0	0,0	YES
7/2016 - 12/2016	0,3	0,3	NO
1/2017 - 6/2017	0,0	0,0	YES
7/2017 - 12/2017	0,0	0,0	YES
1/2018 - 6/2018	0,0	0,0	YES
7/2018 - 12/2018	0,8	0,7	NO
1/2019 - 4/2019	1,0	1,0	NO

<u>TABLE 20</u>

Final result with DEF (robustness check)

This table shows the results from the second-step of the Fama-Macbeth procedure. The cross-sectional regressions were run for each time period. The test was conducted with DEF factor. The regressions were run in EViews.

Period	λ0	λRM_RF	λMOM	λSMB	λHML	λTERM	λDEF	λGREEN	R-squared
1/2016 - 6/2016	0,9615***	17,9703	0,9600	11,0454*	-10,4185	-0,8703*	11,6587**	-0,2339**	0,260774
	(0,0268)	(10,8792)	(3,4304)	(5,8779)	(6,7038)	(0,4470)	(5,7266)	(0,0912)	
7/2016 - 12/2016	0,9616***	0,1400	0,1478	1,5841*	-0,6393	-0,0875	0,9656	0,0047	0,171153
	(0,0073)	(1,6173)	(0,8671)	(0,9332)	(0,8400)	(0,0650)	(0,8654)	(0,0077)	
1/2017 - 6/2017	0,9254***	2,7868**	0,2585	0,1205	-0,9059	0,0451	1,1432	0,0219***	0,152941
	(0,0060)	(1,3607)	(0,4570)	(0,6614)	(0,7172)	(0,0832)	(0,8038)	(0,00423)	
7/2017 - 12/2017	0,8956***	5,7218	0,8740	0,2222	-0,8608	0,0598	3,8644*	0,0041	0,13474
	(0,0059)	(3,6760)	(0,6059)	(1,6680)	(0,9560)	(0,1757)	(2,3250)	(0,0058)	
1/2018 - 6/2018	0,9924***	-6,4839	-1,8258	-0,4158	-4,4807	0,3204	-2,0174	-0,0641	0,111089
	(0,0438)	(5,5274)	(4,2817)	(6,3190)	(7,9629)	(0,3157)	(4,6236)	(0,0407)	
7/2018 - 12/2018	0,9322***	-4,6297	-3,2452	1,6922	0,6812	-0,0075	-0,3214	-0,0930***	0,219352
	(0,0256)	(5,6781)	(3,0441)	(3,2765)	(2,9492)	(0,2282)	(3,0389)	(0,0271)	
1/2019 - 4/2019	1,0012***	-5,491935	-8,5943	2,3119	-6,3775	0,1291	-3,6886	-0,1155	0,035311
	(0,1169)	(25,9369)	(13,9054)	(14,9667)	(13,4719)	(1,0423)	(13,8782)	(0,1240)	

Standard errors in parentheses, Significance marked with: * p<0,1 ** p<0,05 *** p<0