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The Systematic Risk of Green Bonds

whether adding green bonds to a portfolio increases risk-adjusted returns

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Abstract

This paper evaluates the profitability of adding green bonds to a portfolio consisting of stocks and conventional bonds. To determine the profitability, ten portfolios with varying weights on green bonds, conventional bonds and stocks, are constructed. The risk-adjusted returns on the portfolios are implemented in time series regressions of several asset pricing models, including the Capital Asset Pricing Model and an extended Fama-French framework. The intercept of the models, Jensen's alpha, is used to measure the risk-adjusted performance of the portfolios. Also, the results are checked for robustness by applying various performance measures to the data. For the time period employed in this study, 12.05.2016-31.12.2018, the results suggest that adding green bonds to a portfolio can increase the risk-adjusted returns. The best performing portfolio is a portfolio with 60% stocks and equal weights on green bonds and conventional bonds. This result is consistent throughout all the models and performance measures included in the paper, when the bond returns are proxied by the yields of the bonds. Implementing this proxy is in line with the assumption that private investors hold the bonds to maturity. However, if the assumption is dropped and the price changes are used as the proxy, the results differ. In this case, investing in a pure stock portfolio produces the highest risk-adjusted returns.

Keywords: Risk-Adjusted Returns, Systematic Risk, Green Bonds, Asset Pricing Models, Fama-French Factors, Portfolio Performance Evaluation

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Contents

List of Figures

List of Tables

1 Introduction

One of the most severe challenges of our time is climate change. As the young Swedish climate activist Greta Thunberg said at the World Economic Forum 2019, "our house is on fire" (Workman 2019 n.p.). Action needs to be taken in order to combat climate change and reduce the impact it has on our planet. In the last decade, this insight has reshaped the world of investment. Our study focuses on the profitability of the inclusion of one financial asset in portfolios that has gotten significantly more attention during the last years: green bonds. While in 2007, there was not a single green bond issued in the world, the green bond market amounted to 167.3 billions of US dollars in 2018 (CBI 2018). Still, the total value of the green bond market represents only one per cent of the entire global bond market (Lindberg 2018). However, the green bond market has been growing exponentially since the Green Bond Principles (GBP) were established in 2014 and the Paris Agreement was signed in 2015 (Lewis and Birt 2018). The market is expected to continue on this path of growth to encompass a volume of investments of 23 trillion dollars in 2030 (IFC 2018). The World Bank issued it's first green bond in 2008 and the concept of green bonds was developed together with Skandinaviska Enskilda Banken (SEB) (The World Bank Group 2018). Through green bonds environmentally friendly projects such as green buildings, solar panels and wind parks can be supported financially. However, strict regulations on requirements for bonds to deserve the label "green bond" have not been agreed upon yet. It is still unclear whether a green bond needs to be connected to a sustainable pro-environmental project in a direct manner or if it is enough for the bond to support other funds that in turn partly finance projects with an environmental focus. Are social projects sufficient for obtaining the label? These questions still remain and the resulting lack of transparency deters investors from giving the new investment product a chance. During the last years, the regulation and transparency of green bonds have increased. The most commonly known guidelines in defining the green bond label are the Green Bond Principles (GBP) and the Environmental, Social and Governance criteria (ESG).

Asset pricing is ultimately about covariance risk. Despite this the majority of previous research on green bonds has compared the yield spreads of conventional bonds to those of green bonds, ignoring potential differences in covariance risk and hence diversification benefits from green bonds. In this paper, we therefore aim to assess whether adding green bonds to a portfolio of stocks and conventional bonds increases the risk-adjusted returns of the portfolio and whether the increase in risk-adjusted returns depends on the weights assigned to the different assets. In addition, we evaluate which risk factors influence the risk-adjusted returns of the portfolios. For this purpose, we create ten portfolios with varying weights put on stocks, conventional bonds and green bonds and run time series regressions using several asset pricing models. Specifically, the study is conducted with the traditional Capital Asset Pricing Model (CAPM) as well as an extended Fama-French framework. By this it takes into account different equity and bond factors that are capturing the major part of the underlying fundamentals in the bond market (Fama and French 1993). We employ the Sharpe-Lintner CAPM, the Fama-French Three-Factor Model, the Carhart Four-Factor Model, the Fama-French Five-Factor Model and a Six-Factor Model to assess whether adding green bonds to the portfolios increases the portfolios' risk-adjusted returns and to determine which risk factors have an impact on the portfolios' risk-adjusted returns. Moreover, we use various performance measures as well as two different proxies for the returns of green bonds, the yield and the price changes of the bonds, in order to test the robustness of our results. The results of our study are of interest and highly relevant to investors who are considering to include green bonds in their investments.

Green bonds attract investors not only because, as previous research has shown, green bonds perform just as well as conventional bonds (Hamilton et al. 1993), but because green bonds increase transparency and generate additional value due to their socially responsible characteristic. In order to assess whether green bonds themselves really perform just as well as conventional bonds or stocks and to see how the varying risk factors influence the returns of the individual asset classes, we create fictive portfolios that consist of only one type of asset: green bonds, conventional bonds or stocks. We are aware of the fact that no rational investor would ever invest in these portfolios. They are solely added for comparability. The sample of green bonds used in this study can be found under the "@green" Bloomberg-tag that follows the Green Bond Principles.

In this paper, we come to the conclusion that adding green bonds to the portfolios of stocks and conventional bonds does enhance the risk-adjusted returns and thus the performance of the portfolios, when the yields are implemented as the proxy for the bond returns. The best performing portfolio, according to our results, is a portfolio with 60% stocks, 20% green bonds and 20% conventional bonds. In addition, our results show that the pure green bond portfolio and the pure conventional bond portfolio depend to the greatest extent on the two bond factors established by Fama and French (1993), while the pure stock portfolio depends on the systematic risk factor and the Fama-French value premium factor the most. However, our results are not robust to the implementation of different proxies for the returns on bonds. When the price changes are implemented as the proxy for the bond return, the results suggest that the pure stock portfolio performs the best.

The structure of the rest of the paper is as follows: Section 2 presents previous literature related to the topic at hand, while also mentioning the distinguishing aspects of this paper. Section 3 displays the mathematical representations and explanations of the implemented models and the performance evaluation measures. Section 4 describes the data collection process and the construction of the portfolios. Section 5 explains the econometric tests performed and displays the results of the tests. In Section 6, we present and analyze our results from running the regressions in line with the different asset pricing models. Section 7 explains and elaborates on the different robustness checks employed in this study. Finally, in Section 8, we state our general results, the limitations of our study and recommendations for future research.

2 Previous Research

In this Section, we will present previous research on socially responsible investment performance, the performance of green bonds and the asset pricing models that we implement in this study.

2.1 Socially Responsible Investment Performance

In recent years, the interest in socially responsible investments (SRI) has grown and hence researchers have increasingly focused on answering the question if social responsibility affects returns. However, the results have been ambiguous. Some studies found a positive relationship between SRI and returns (e.g., Consolandi et al. 2009; Gil-Bazo et al. 2010; Fernandez-Izquierdo and Matallin-Saez 2008), while others found a neutral relationship (e.g., Blanchett 2010; Cortez et al. 2009; Collison et al. 2008) and still others presented a negative relationship (Jones et al. 2008; Renneboog et al. 2008; Adler and Kritzman 2008).

Hamilton et al. (1993) found no statistically significant difference between the financial performance of socially responsible mutual funds and conventional mutual funds. Schröder (2004) supported these findings, stating that an investor who focuses on the investment in SRI instead of conventional assets does not have to fear a decrease in risk-adjusted returns. Kempf and Osthoff (2007) conducted an analysis of the profitability of using screening techniques in the construction of portfolios with socially responsible assets. They found that the implementation of the social responsibility screens generate high abnormal returns of up to 8.7% per year. Diltz (1995) concluded that there is a significant link between the usage of environmental and military screens and high abnormal returns, while Guerard (1997) found no significant difference in performance of socially screened and unscreened portfolios. According to Konar and Cohen (2001), there was a positive link between a firm's environmental performance and the market value of the firm. Thus, the more environmentally friendly the firm was, the higher was its market value. This would make SRI more favorable. The literature review of Friede et al. (2015) summarized the results of previously conducted research on the relationship between ESG criteria and financial performance. They stressed that while results are ambiguous, roughly 90% of the studies came to the conclusion that there was a non-negative relationship between ESG criteria and financial performance. These diverging results are obviously unsatisfactory, especially for those working in the asset management industry. We believe further research needs to be conducted in this field, in order to obtain a clearer picture of the relationship between SRI and returns.

2.2 The Performance of Green Bonds

In our study, we will focus on one asset class within the range of SRI: green bonds. We asses their influence on risk-adjusted returns and expect to find a non-negative effect of green bonds on portfolio returns, since Wagner Ley's (2017) results indicated that while green bonds carry an additional social value, they fare financially just as well as conventional bonds. Thus, investors should increase their share of investment into green bonds, since there is no reduction in return but a social reward. Flammer (2018) showed the effectiveness of green bonds. She demonstrated that green bonds not only yield positive announcement returns, as well as improvements in long-term value and operating performance but also generate an increase in green innovations.

However, previous research on the asset class fixed income has mostly focused on the comparison of the performance of individual green bonds and conventional bonds. Hachenberg and Schiereck (2018) matched daily i-spreads of conventional bonds and similar green bonds and assessed the differences in the prices of the assets. They claimed that green bonds with rating classes from A to BBB trade at a lower price than their conventional counterparts. Furthermore, they suggested that these differences in the prices could compensate investors for the additional costs that are related to green bonds (second-/third- party opinion, certification of transaction). They asserted that the variables that are significant in the explanation of the pricing differentials are the type of issuer (government or financial issuer) and the existence of an ESG issuer rating. Matching green bonds to conventional bonds, Zerbib (2019) estimated and evaluated the green bond premium. The green bond premium was defined as the difference in the yield of green bonds and their conventional matches after controlling for liquidity. He found evidence for a significantly negative average green bond premium.

Various studies have addressed the factors that explain price levels of green bonds and thus the performance of individual green bonds. However, to our knowledge, a study on the performance of portfolios with green bonds has not been conducted yet.

2.3 Asset Pricing Models

In this Subsection, we will introduce the models used in our analysis and portray recent findings in research connected to these models. All models implemented in our study are based on the modern portfolio theory established by Markowitz (1952).

We use the traditional CAPM (Sharpe 1964; Lintner 1965), the Fama-French Three-Factor Model (Fama and French 1992), Carhart's Four-Factor Model (Carhart 1997), the Fama-French Five-Factor Model (Fama and French 1993) and a Six Factor Model which adds the momentum factor (Carhart 1997) to the Five-Factor Fama-French Model. Graham and Harvey (2001) showed in their survey that roughly 75% of American chief executive officers employed the CAPM in the estimation of the cost of equity. This is astonishing since more sophisticated models have been developed throughout the 50 years between the invention of the CAPM and the conduction of the survey. According to the study of Bartholdy and Peare (2005), it was generally the case that, while the single-factor CAPM was preferred in the estimation of an individual stock's expected return, academics promoted the Fama-French Three-Factor Model for the evaluation of portfolio returns.

Traditionally, asset pricing models have been used to determine the appropriate rate of return on the asset, given its underlying risk. Thus, they have been used in gaining insight on the relationship between risk-adjusted returns and the systematic risk. Erdinç (2017) and Wagner Ley (2017) agreed that the Fama-French Five-Factor Model could explain the common variation in asset returns better than the traditional Sharpe-Lintner CAPM and the Fama-French Three-Factor Model. Generally, it could be argued that comparing the Fama-French Five-Factor Model to the CAPM model, the Fama-French Five-Factor Model takes additional statistically significant risk factors into account and thus its explanatory power should be greater than the CAPM's or the Fama-French Three-Factor Model's. Nonetheless, there was also evidence against this hypothesis. Lam (2005) showed that, during varying time periods and across different portfolios, the Fama-French Models did not always outperform the CAPM in the explanation of cross-sectional variation in returns.

In the determination of the factors, we follow the work of Griffin (2002) and use factors that are computed for the US market instead of including global factors into our regressions. Griffin (2002) used factors computed for the US market and found that the country-specific version of the Fama-French Three-Factor Model had more explanatory power than the global version of the model in the estimation of the time series regressions for portfolios.

Over the years, some researchers questioned a few of the findings of Fama and French (1992; 1993) and consequently argued for other risk factors that seem to be of importance. Chen et al. (2011) suggested that a three-factor model consisting of the market factor, an investment factor and a return-on-equity factor performed well and decreased the magnitude of abnormal returns. Frankel and Lee (1998) found that the ratio of a firm's fundamental valuation to its price did a good job in explaining long-term cross-sectional returns. Brennan and Peare (1998) showed evidence for the significance of a momentum factor and the effect of trading volumes on risk-adjusted returns. However, the most widely known models are the Fama-French Models. These models have been tested in various settings, across countries and asset classes (e.g., Evbayiro-Osagie, Osamwonyi, et al. 2017; Malin and Veeraraghavan 2004; Bhatti and Mirza 2014). While most of the aforementioned studies focused on the stock market variation, Johansson and Lundgren (2012) showed that the CAPM as well as the Fama-French Three-Factor Model produced significant results for the estimation of the cross-sectional variation in returns of conventional bonds. Following these findings, in our study we focus on the implementation of the Fama-French Models in time series regressions to assess whether adding green bonds to our portfolios increases the risk-adjusted returns of our portfolios. Thereby, we conduct an analysis implementing the first step of the Fama-Macbeth (1973) regression procedure.

3 Theoretical Framework

This Section portrays the mathematical representations and explanations of the implemented models and the performance evaluation measures that we use as robustness tests.

3.1 Portfolio Selection and Mean-Variance

The foundation of modern portfolio management was laid by Markowitz (1952) in his article "Portfolio Selection", where he emphasized the importance of portfolio diversification and stressed that an investor's objective should be to minimize the variance given expected returns and maximize expected returns given the variance. This is known as the Mean-Variance (MV) theory (Markowitz 1959).

3.2 The Capital Asset Pricing Model

Based on the MV theory of portfolio choice by Markowitz (1959), the single factor CAPM was developed by Sharpe (1964) and Lintner (1965). Fama and French (2004) mark the CAPM as "the birth of asset pricing theory" (p25). They assert that the CAPM describes the relation between risk and expected returns of a security or a portfolio. In addition, the abnormal return, Jensen's alpha, can be estimated by running a time series regression of the CAPM (Jensen 1968). According to Fama and French (2004) the CAPM can be defined as follows:

$$r_{it} - r_{ft} = \alpha_i + \beta_{1,i} RPM_t + u_{it} \tag{1}$$

r_{it}: return for portfolio i at time t.
r_{ft}: risk free rate at time t.
α_i: intercept (Jensen's alpha) for portfolio i.
$\beta_{1,i}$: coefficient of RPM for portfolio i.
RPM_t: excess market return at time t.
u_{it}: error term for portfolio i at time t.

3.3 The Fama-French Three-Factor Model

In 1992, Fama and French developed what is now commonly known as the Fama-French Three-Factor Model (FF3FM) to explain cross-sectional variation in expected returns on equity (Fama and French 1992). In addition to the market risk factor of the Sharpe-Lintner CAPM, they include the variables for the size premium, SMB, and the value premium, HML, in their estimations. How the SMB factor and the HML factor are computed can be read in Subsection 4.5. Fama and French (1992) conclude that these two variables in combination with the systematic risk factor explain most of the variation in the cross-section of expected returns on NYSE, Amex and NASDAQ stocks. All the variables that are not described have the same interpretation as in the prior model. Fama and French (1992) define their FF3FM as:

$$r_{it} - r_{ft} = \alpha_i + \beta_{1,i} RPM_t + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + u_{it} \tag{2}$$

r_{it}: return for portfolio i at time t.
r_{ft}: risk free rate at time t.
$\beta_{2,i}$: coefficient of SMB for portfolio i.
$\beta_{3,i}$: coefficient of HML for portfolio i.
SMB_t: size premium at time t.
HML_t: value premium at time t.
u_{it}: error term for portfolio i at time t.

3.4 The Carhart Four-Factor Model

Carhart (1997) extended the framework of the FF3FM by adding an additional factor, the momentum factor, MOM. The computation of the MOM factor is explained in detail in Subsection 4.6. As stated earlier, all the variables that have no description in this model are to be interpreted the same way as in the Subsection above. The Carhart Four-Factor Model (C4FM) is formulated as follows:

$$r_{it} - r_{ft} = \alpha_i + \beta_{1,i} RPM_t + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \beta_{4,i} MOM_t + u_{it} \tag{3}$$

r_{it}: return for portfolio i at time t.
r_{ft}: risk free rate at time t.
$\beta_{4,i}$: coefficient of MOM for portfolio i.
MOM_t: momentum effect at time t.
u_{it}: error term for portfolio i at time t.

3.5 The Fama-French Five-Factor Model

In 1993, Fama and French expanded their previous model to a five-factor model (FF5FM). They no longer only focused on equity as their sole asset class but added bonds to their analysis. Two new term-structure variables, that were likely to be important in the analysis of bond returns, were implemented into the model. The two term-structure variables were $TERM$ and DEF. $TERM$ is a proxy for the risk in bond returns that arises due to changes in the interest rates. The second new variable, DEF, proxies for the probability of default of the respective company or institution. How $TERM$ and DEF are computed can be read in Subsections 4.7.1 and 4.7.2. Once again, the variables that are not described in the Equation below are to be interpreted as stated in the Subsection above. The FF5FM is defined as follows:

$$r_{it} - r_{ft} = \alpha_i + \beta_{1,i} RPM_t + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \beta_{4,i} TERM_t + \beta_{5,i} DEF_t + u_{it} \tag{4}$$

r_{it}: return for portfolio i at time t.
r_{ft}: risk free rate at time t.
$\beta_{4,i}$: coefficient of $TERM$ for portfolio i.
$\beta_{5,i}$: coefficient of DEF for portfolio i.
$TERM_t$: term premium at time t
DEF_t: default premium at time t.
u_{it}: error term for portfolio i at time t.

3.6 The Six-Factor Model

The six-factor model (6FM) employed in our study adds one more factor to the FF5FM, the MOM factor that was first introduced by Carhart (1997). All the explanatory variables have been described in the previous models. The 6FM is defined as follows:

$$r_{it} - r_{ft} = \alpha_i + \beta_{1,i} RPM_t + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \beta_{4,i} TERM_t + \beta_{5,i} DEF_t + \beta_{6,i} MOM_t + u_{it} \quad (5)$$

r_{it}: return for portfolio i at time t.
r_{ft}: risk free rate at time t.
$\beta_{6,i}$: coefficient of MOM for portfolio i.
u_{it}: error term for portfolio i at time t.

3.7 Sharpe Ratio

The Sharpe ratio received its name from its developer William F. Sharpe (1966). It is widely used in asset management since it measures an asset's return relative to its risk. In particular, as seen in Equation 6, the nominator is the average excess return and the denominator shows the volatility of the asset, represented by the standard deviation of the excess returns. In general, a high Sharpe ratio is linked to greater risk-adjusted returns of an investment, and thus it is a measure of the investment's profitability.

$$SR_i = \frac{r_i - r_f}{\sigma_i} \quad (6)$$

$r_i - r_f$: average excess return for portfolio i over time.
σ_i: standard deviation of the excess returns for portfolio i.

3.8 Sortino Ratio

The Sortino ratio, seen in Equation 7, is a version of the Sharpe ratio that only takes the downside risk of the asset or portfolio into account, which is reasonable since it is the downside risk that is of most interest to the investor (Morningstar 2019a). Upside volatility yields higher returns and thus investors would actually prefer a portfolio with more upside deviation. The denominator differs from that of the Sharpe ratio in the way that only the standard deviation of returns that are below the average returns is included, instead of the total standard deviation. For the Sortino ratio, the higher the value, the better the performance of the portfolio.

$$Sortino_i = \frac{r_i - r_f}{\sigma_{d,i}} \tag{7}$$

$r_i - r_f$: average excess return for portfolio i over time.
$\sigma_{d,i}$: standard deviation of the downside excess returns for portfolio i.

3.9 Treynor Ratio

The Treynor ratio measures excess return per unit of systematic risk (Morningstar 2019b), see Equation 8. A good performance is given by a high ratio. β_i represents portfolio i's beta, which is used to measure the systematic risk. Generally, if β_i is less than one, portfolio i is less volatile than the market, while for a β_i greater than one, the volatility of portfolio i is higher than the market's. When β_i is equal to one, portfolio i and the market are equally volatile.

$$TR_i = \frac{r_i - r_f}{\beta_i} \tag{8}$$

$r_i - r_f$: average excess return for portfolio i over time.
β_i: beta of portfolio i.

3.10 Information Ratio

The information ratio measures a portfolio's performance by dividing the difference between the returns of a portfolio and the returns of a benchmark by the tracking error (TE), as seen in Equation 9. The tracking error shows whether the portfolio can consistently follow the trend of the benchmark, thus the market. As for the other performance measures, a higher value is linked to a better portfolio performance.

$$IR_i = \frac{\alpha_i}{TE_i} \tag{9}$$

α_i: difference between returns for portfolio i and the returns for a benchmark.
TE_i: standard deviation of the difference between portfolio $i's$ and benchmark returns.

3.11 Modigliani-Modigliani Measure

The Modigliani-Modigliani measure, also known as the "M^2-measure", is used to evaluate the risk-adjusted returns of portfolios. It was derived from the Sharpe ratio, but has the distinctive advantage of being in percentages, as opposed to a dimensionless utility level in the Sharpe ratio, which makes it a lot easier for investors to interpret it (Modigliani and Modigliani 1997). The M^2-measure relates the risk-adjusted return of the portfolio to the return of a benchmark, usually the market. The higher the M^2-measure, the better is the performance of the portfolio. The M^2-measure is given by Equation 10.

$$M_i^2 = (\frac{\sigma_m}{\sigma_i})(r_i - r_f) + r_f \tag{10}$$

σ_m: standard deviation of the market.
σ_i: standard deviation of portfolio i.
$r_i - r_f$: average excess return for portfolio i over time.
r_f: risk free rate.

3.12 Expected Utility Theory and Atkinson Index

The above mentioned risk-adjusted performance measures do not account for investors' different degrees of risk aversion[1]. The Atkinson index and the Morningstar rating, which is a special case of the Atkinson index, are both motivated by expected utility theory, where investors rank different portfolios with the help of a utility function (Fischer and Lundtofte 2018). The Atkinson index measures the financial risk of an asset or a portfolio, where different values for ρ are used in order to represent the investors' diverging degrees of risk aversion (Fischer and Lundtofte 2018). A high value for ρ corresponds to a high degree of risk aversion. Instead of ρ, the Morningstar rating uses γ[2] to represent the investors' degree of risk aversion (Morningstar 2016b). The Morningstar rating is the Atkinson index with Constant Relative Risk Aversion (CRRA) utility and a coefficient of relative risk aversion of three, $\rho = 3$, hence $\gamma = 2$ (Fischer and Lundtofte 2018). According to Fischer and Lundtofte (2018), the utility function under CRRA, which they assert to be more realistic than a quadratic utility function or a CARA (Constant Absolute Risk Aversion) utility function, is given by Equation 11.

$$u(w) = \frac{w^{1-\rho} - 1}{1 - \rho} \tag{11}$$

w: wealth.
ρ: degree of risk aversion, where $\gamma = \rho - 1$.

1. Risk averse investors dislike risk and prefer safe bet portfolios over the fair gamble, whereas risk-seeking investors like risk and choose the gamble over the safe bet. Risk-neutral investors are indifferent between the two (Bodie, Kane, and Marcus 2014).

2. When the investor is risk averse, γ is larger than -1, whereas when an investor is risk-loving, γ is less than -1 and for risk-neutral investors, γ is equal to -1 (Morningstar 2016b).

Originally, the Atkinson index was an inequality index (Atkinson 1970). However, as shown by Fischer and Lundtofte (2018), it can be used as a measure of financial risk. They define the Atkinson index in general as follows:

$$A = 1 - \frac{x^{CE}}{E[x]} \tag{12}$$

x^{CE}: certainty equivalent rate of return.
$E[x]$: mean of returns.

Fischer and Lundtofte (2018) state that the Atkinson index can only take values between zero and one, with zero corresponding to no financial risk. Furthermore, according to Fischer and Lundtofte (2018), in Equation 12 we can see that for a given expected return, the Atkinson index is decreasing in the risk-adjusted return (x^{CE}). Hence, higher values indicate higher financial risk of the investment. In order to compute the Atkinson index, the returns have to be transformed into gross returns. Fischer and Lundtofte (2018), show that the Atkinson index under CRRA is then given by:

$$A(\rho) = \begin{cases} 1 - \frac{1}{E[x]}(E[x^{1-\rho}])^{\frac{1}{1-\rho}} & \rho > 0, \rho \neq 1, \\ 1 - \frac{1}{E[x]}e^{E[lnx]} & \rho = 1. \end{cases} \tag{13}$$

In addition, the certainty equivalent (CE) rate of return can be used as a performance measure for portfolios according to Fischer and Lundtofte (2018). Rearranging Equation 12, gives the following:

$$x^{CE} = E[x](1 - A) \tag{14}$$

$E[x]$: mean of returns.
A: Atkinson index.

As opposed to the standard performance measures displayed in the earlier Sections, which only take the first two statistical moments, mean and variance, into account, the Atkinson index, and thus the CE, allow for higher statistical moments to be included in the analysis of risk-adjusted performance.

3.13 Summary of the Performance Measures

In this Subsection, we will give a summary of the different performance measures, their advantages and disadvantages and explain why we use a vast number of the measures to test for the robustness of our results.

The Sharpe ratio measures the ratio of risk-adjusted returns of a portfolio per unit of risk quantified by the standard deviation, where a higher Sharpe ratio indicates a higher profitability of the investment. The Sharpe ratio is the performance measure that investors use the most in the assessment of the performance of individual assets and portfolios. Investors generally favor this performance measure due to its simplicity. However, the Sharpe ratio has two major drawbacks, both related to the use of standard deviation as a risk measure. First, the standard deviation assumes that the excess returns are normally distributed, which is not always true (Morningstar 2016b). Second, the standard deviation equally measures the risk below and above the mean, and thus it does not account for the fact that investors usually dislike downside risk more than upside risk (Morningstar 2016b). The Sharpe ratio considers only the second statistical moment (variance), and it thus does not account for higher moments that are implied by higher risk aversion (Fischer and Lundtofte 2018).

The Sortino ratio is very similar to the Sharpe ratio. The distinct advantage of the Sortino ratio is that it accounts for the fact that investors generally particularly dislike downside risk by only taking the downside risk of the asset into account, instead of the total risk used in the Sharpe ratio (Morningstar 2019a). Hence, when the distribution of the returns is symmetric, the results from the Sharpe ratio and the Sortino ratio should not differ. The results will only diverge if the distribution is skewed.

As the Sharpe ratio and the Sortino ratio, the Treynor ratio relates risk-adjusted returns to a measure of risk. Instead of the total risk of the asset, measured by the standard deviation, the Treynor ratio uses beta, which represents the systematic risk that cannot be diversified away (Morningstar 2019b). A disadvantage in using the Treynor ratio to evaluate the portfolios' performance, is that it only accounts for the systematic risk and thus does not take the idiosyncratic risk, as in the risk related to a specific asset or portfolio, into account. The Treynor ratio will yield similar results to those of the Sharpe ratio whenever there is a close link between the level of idiosyncratic risk of the asset in question and the systematic risk. However, if the two risks are disparate, this might cause an over- or underestimation of the individual asset's profitability. If the idiosyncratic risk, for example, is a lot lower than the systematic risk, then the Treynor ratio would underestimate the performance of the asset.

The information ratio is a risk-adjusted performance measure that evaluates the performance of an investment relative to a benchmark (Morningstar 2016a). For a given deviation from the benchmark, represented by the TE, the higher the difference between the return of the investment and the return of the benchmark, the higher the information ratio, where a higher information ratio is better than a lower (Informa Investment 2016). Whenever the value of the information ratio is less than zero, it shows that the investor failed to outperform a passive benchmark (Informa Investment 2016). The information ratio does not only measure whether the investor is able to outperform the market but also how consistent the outperformance is. The more consistent, the longer is the time period in which the investor manages to beat the market. However, it is also a disadvantage that the information ratio is so closely linked to the benchmark. There is a possibility for an investor to obtain a high information ratio but still acquire significant losses when the benchmark is performing poorly (Informa Investment 2016).

The M^2-measure is derived from the Sharpe ratio but exhibits the distinct advantage of being in percentages, while the Sharpe ratio is given in a dimensionless utility level (Modigliani and Modigliani 1997). This facilitates the interpretation for investors. The M^2-measure also relates the risk-adjusted returns of an investment to a benchmark, which is usually the market. One more advantage of the

M^2-measure is that it also yields sensible results for negative returns, whereas e.g. the Sharpe ratio becomes very hard to interpret (Modigliani and Modigliani 1997).

The Atkinson index implemented in this study has the advantage of taking into account varying degrees of risk aversion (Fischer and Lundtofte 2018). Furthermore, the Atkinson index considers higher moments, such as skewness and kurtosis, in the assessment of the risk-adjusted performance. In that manner, it is a more general performance measure than the other performance measures that are based on strict mean-variance theory. In addition, the Atkinson index also performs well when returns are non-normally distributed and a special case of the Atkinson index is the Morningstar rating (Fischer and Lundtofte 2018).

In the asset pricing models that are implemented in this study, Jensen's alpha (Jensen 1968) is used as a performance measure, based on risk-adjusted returns. It relates the risk-adjusted performance of an asset or a portfolio to a benchmark index, which is usually an index that proxies for systematic risk. We extend the usual CAPM setting, in which Jensen's alpha is calculated, to models that encompass a greater number of significant risk factors than only the systematic risk. Hence, we relate the risk-adjusted performance of the ten constructed portfolios not only to a benchmark index, but also to proxies for other underlying risks.

It should be kept in mind that all the above mentioned performance measures only show the past performance of an investment. A past performance cannot ensure a similar future performance (Fidelity 2018). In addition, none of the commonly used risk-adjusted performance measures account for varying degrees of risk aversion. Only the Atkinson index, together with the CE, allows for diverging degrees of risk aversion. An investor should always take many different performance measures into account to be able to conduct a more accurate analysis of the investment's risk-adjusted performance, just like in the health care sector, where a vast number of tests are run to ensure a valid diagnosis of a patient. This is the main argument for why an investor should use many different performance measures, and it is also the reason for us to apply an extensive number of them in our paper. In addition, all the performance measures have their own advantages and disadvantages. So, in order to assess whether our results are robust to the characteristics of the different measures, we compare the rankings that the measures generate.

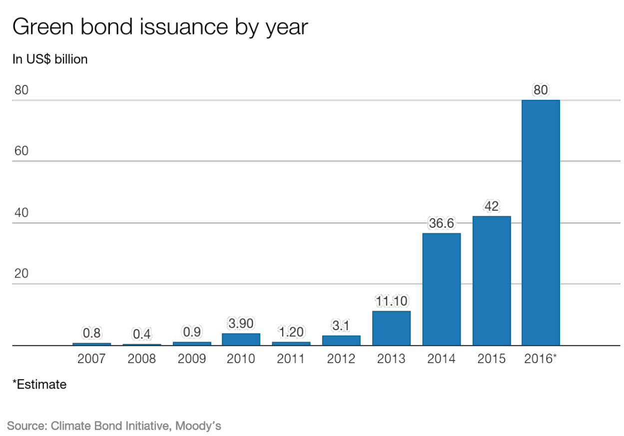
4 Methodology

This Section describes the collection of the data on green bonds, conventional bonds, stocks, the Fama-French factors and the implemented indexes in detail and illustrates the methodology used in our analysis. In addition, it is clarified how we construct the two bond factors, $TERM$ and DEF.

4.1 Bond Data

We use a bond's yield as the proxy for the return of a bond, following the literature (e.g., Bessis 2015; Gebhart et al. 2005). The yield is the appropriate proxy for the returns of the bonds when we assume that the investor holds the bonds to maturity. This assumption will later be dropped in some parts of the analysis. Then, the bond price changes, that we compute from the yields[3], are used as the proxy for the bond return. The daily yields[4] on green bonds and conventional bonds used in this analysis are obtained from the Bloomberg Terminal. To find the green bonds in Bloomberg, we apply the tag "@green". The Bloomberg-tag "@green" selects bonds that have a use of proceeds that is in line with the Green Bond Principles. The description of the green bond tag on Bloomberg is the following: "Labelled green bonds are fixed income instruments for which the proceeds will be applied towards projects or activities that promote climate change mitigation or adaptation or other environmental sustainability purposes" (Bloomberg New Energy Finance, 2016). To avoid potential bias, we search for bonds that are both active and matured, resulting in 2038 green bonds. In order to decrease the initial sample and obtain green bonds that are similar to the conventional bonds in a lot of characteristics, various restrictions are imposed on the green bonds as well as the conventional bonds. As a first step, only bonds that are issued in the period from 01.01.2014 to 31.12.2018 are added to the sample, reducing the initial sample of green bonds to 1689. This specific time frame is chosen since the green bond market first started growing in 2014, and thus, there is a limited amount of data available on green bonds before this period, see Figure 1.

Figure 1: Growth on the Green Bond Market - Climate Bond Initiative



3. See Subsection 4.3.

4. The Bloomberg code used is YL017, which is the yield of a fixed income security that solves for the mid price when valuing the security to maturity.

As a next step, the sample is further reduced to exclusively contain bonds with a fixed coupon rate. This gives us a sample of 1259 green bonds. Thereafter, exclusively bonds with a S&P rating in a range from AAA-CCC are chosen, resulting in 405 green bonds. This is done to avoid green bonds which have no rating, since bonds without a rating are exposed to liquidity risk and default risk to a greater extent. Also, those bonds for which the daily yield isn't available on Bloomberg are dropped from our sample. Including the selection criterion of rating also helps reducing our sample of conventional bonds. Furthermore, only bonds with an amount issued greater than or equal to 150 million dollars are included in the sample to diminish our portfolios' exposure to liquidity risks, resulting in 323 green bonds. Additionally, the sample is restrained to solely encompass securities issued on the US market and in US Dollars, giving us 135 green bonds, to avoid a potential currency bias. Further, we eliminate duplicates, as in only keeping one bond per issuer name, leaving us with 76 green bonds. Lastly, we make sure that we have a sample of bonds corresponding to issuers from different industries and with a varying time to maturity. However, to have consistent data on all green bonds included in the analysis, the sample period has to be restricted even further. The final sample period is then set to 12.05.2016-31.12.2018, resulting in a sample of 35 green bonds. The conventional bonds are restricted in the same way as the green bonds. After the implementation of the aforementioned restrictions, we have 1566 conventional bonds. See Table 1 for a summary of the restrictions imposed on the bonds in the construction of the sample.

Table 1: Restrictions Imposed on the Sample of Bonds

The applied restrictions together with a number, indicating the order in which the restrictions are imposed on the sample of green bonds and conventional bonds. The green instrument indicator, @green, is not used as a selected criteria for the conventional bonds.

1.	Security Status: Bonds all (active and matured)
2.	Green Instrument Indicator: @green
3.	Issue Date: 12.05.2016 to 31.12.2018
4.	Coupon Type: Fixed
5.	S&P Rating: AAA - CCC
6.	Amount Issued: $\geq$ 150MM
7.	Currency: US Dollars
8.	Issuer Name: One bond per issuer name
9.	Across Industries with Varying Maturities

4.2 Stock Data

Daily closing prices[5] for all the firms in the S&P 500 Index are collected for the time period 12.05.2016-31.12.2018, using the Bloomberg Terminal. Out of the 500 firms in the sample, 30 are randomly selected to represent our dataset of stocks. The daily returns on the stocks that are implemented in this study are computed from the daily closing prices of the stock. We take the natural logarithm of the ratio of two consecutive daily prices, see Equation 15, to calculate the daily returns.

$$r_t = ln\left(\frac{p_t}{p_{t-1}}\right) \tag{15}$$

5. The Bloomberg code used is PX_LAST.

In the end, this leaves us with 19.920 daily observations for the stocks. The construction of the portfolios is explained in Section 4.4.

4.3 Computation of the Bond Price Changes

In order to see whether the results of our study differ when we use the bond price changes, instead of the yields, as a proxy for the bond returns, we compute the price changes from the yields according to Equations 16 and 17, where Equation 16 is an approximation of the bond price that is in line with the calculation of the yield on the Bloomberg Terminal. Intuitively, the variation in the bond price changes should be greater than the variation in the yield.

$$p_t = \left(\frac{1}{(1 + yield_t)^{TTM}} \right) \tag{16}$$

$$r_t = ln \left(\frac{p_t}{p_{t-1}} \right) \tag{17}$$

Since the average time to maturity (TTM) of our bond sample is five years, we use $TTM = 5$.

4.4 Construction of Portfolios

In order to create our portfolios, we randomly select 30 green bonds, 30 conventional bonds and 30 stocks, with a total of 59.760 daily observations, from our dataset for our final sample[6]. Following the work of Statman (1987), we create portfolios of green bonds, conventional bonds and stocks with a total number of assets equal to 30. According to Statman (1987) investors will at least need 30 assets to achieve sufficient diversification. Whereas other authors, e.g. Evans and Archer (1968) state that a total number of ten stocks would be satisfactory and they question the benefit of increasing portfolio sizes beyond ten or more assets. According to their study, adding more assets to the portfolio would solely impede keeping track of the all the asset's financial performance by the investor, while bringing next to no benefits.

The bond yields from the Bloomberg Terminal are obtained in percentages and are divided by 100 to match the format of the downloaded daily closing prices of the stocks. Ten portfolios are created. As a benchmark portfolio we create a portfolio with 60% stocks and 40% conventional bonds, Z_1. This relates to the traditional portfolio allocation that has widely been used by investors over the last decades. However, according to Kazanchy (2012), this traditional portfolio is not truly risk-balanced.

In addition, we imply that the fictive investor in our model follows the naive $1/N$ investment rule (Tu and Zhou 2011) and decides to invest equally within the asset classes. So, for example, if 60% of stocks (this equals 18 stocks in our setting) are to be included in the portfolio, then the investor will invest equally across those 18 stocks and put 1/18 of weight onto each individual stock. The 18 stocks then correspond to 60% of the total amount of assets included in a portfolio. This leads us

6. For a list of the final sample of assets implemented in this study, send an e-mail to: janina.viebrock.7358@student.lu.se or hanna.brannstrom.788@student.lu.se

to the two following questions. Can risk-adjusted returns be increased by adding green bonds to the portfolios in a naive diversification setting? Also, do returns depend on the weights assigned to the two asset classes: equities and fixed income? In addition, we will assess which risk factors influence the returns of the different portfolios the most. The expected returns of the portfolios are computed according to Equation 18.

$$E(r_i) = w_1 * E(r_s) + w_2 * E(r_{gb}) + w_3 * E(r_{cb}) \tag{18}$$

where $E(r_i)$ is the expected return of portfolio i, $E(r_s)$ is the expected return on the stocks included in the portfolio, $E(r_{gb})$ is the expected return on the green bonds in the portfolio and $E(r_{cb})$ represents the expected return on the conventional bonds included. The weights assigned to each component are represented by w_i. The first portfolio, Z_1, is our benchmark portfolio. It consists of 60% stocks and 40% conventional bonds. The second portfolio, Z_2, still contains 60% stocks, but we include green bonds in the portfolio. It consists of 60% stocks, 20% green bonds and 20% conventional bonds. In the third portfolio, Z_3, we substitute the conventional bonds with green bonds. Thus, it consists of 60% stocks and 40% green bonds. In the fourth portfolio, Z_4, we reduce the share of green bonds to 30%, increase the percentage of conventional bonds to 10% and keep the share of stocks at 60%. The fifth portfolio, Z_5, is the first portfolio with less than 60% stocks. It consists of 40% stocks, 30% green bonds and 30% conventional bonds. The next three portfolios, all encompass only one type of asset each. We are aware of the fact that no rational investor would even consider investing in these portfolios. However, running the asset pricing models, we think it will be of great interest to see which risk factors can explain the excess return generated by the individual type of assets the best. Hence, the sixth portfolio, Z_6, solely consists of green bonds. To compare the factor loadings of green bonds and conventional bonds in a direct manner, we set up the seventh portfolio, Z_7, which only consists of conventional bonds. In order to see whether our study is in line with previous research on the stock market, we construct the eighth portfolio, Z_8, with 100% stocks. To assess whether a diversified portfolio with a very low share of stocks might be more profitable, we construct the ninth portfolio, Z_9, which encompasses only 20% stocks, 40% green bonds and 40% conventional bonds. The tenth portfolio, Z_{10}, is comprised of an equal share of green bonds and conventional bonds. A summary of the different portfolios can be seen in Table 2.

Table 2: The Different Portfolios

The ten constructed portfolios with their assigned weights in the two asset classes: equities and fixed income.

Portfolio	Stocks	Green Bonds	Conventional Bonds
Z_1	60%	.	40%
Z_2	60%	20%	20%
Z_3	60%	40%	.
Z_4	60%	30%	10%
Z_5	40%	30%	30%
Z_6	.	100%	.
Z_7	.	.	100%
Z_8	100%	.	.
Z_9	20%	40%	40%
Z_{10}	.	50%	50%

4.5 Fama-French Factors

The Fama-French factors are downloaded from the CRSP database. For the size and book-to-market factors, Fama and French (1993) employ the mimicking portfolio approach. They construct six portfolios (Small Value, Small Neutral, Small Growth, Big Value, Big Neutral, Big Growth) by grouping their stocks according to their size and their book-to-market equity, respectively. SMB (Small Minus Big), the size premium, is the average return on the three small portfolios minus the average return on the three big portfolios, Equation 19.

$$SMB = \frac{SV + SN + SG}{3} - \frac{BV + BN + BG}{3} \tag{19}$$

SV: Small Value.
SN: Small Neutral.
SG: Small Growth.
BV: Big Value.
BN: Big Neutral.
BG: Big Growth.

HML (High Minus Low), the value premium, is the average return on the two value portfolios minus the average return on the two growth portfolios, Equation 20. The notations are the same as in the Equation above.

$$HML = \frac{SV + BV}{2} - \frac{SG + BG}{2} \tag{20}$$

4.6 Momentum Factor

The momentum factor, MOM, was first implemented into an asset pricing model by Mark Carhart (1997). The monthly momentum in an asset can be described as the asset price's tendency to rise up further when it is increasing and to continue declining when it is going down. The MOM factor is calculated as the difference between the equally weighted average return of the highest performing firms (winners) and the equally weighted average return of the lowest performing firms (losers), lagged one month (Carhart 1997), seen in Equation 21. When an asset has momentum, its previous twelve-month average of returns is positive (Carhart 1997).

$$MOM = \frac{S/W + B/W}{2} - \frac{S/L + B/L}{2} \tag{21}$$

S/W: Small Stock/Winners.
B/W: Big Stock/Winners.
S/L: Small Stock/Losers.
B/L: Big Stock/Losers.

4.7 Bond Factors

The bond factors are constructed with daily data. We implement the two term-structure factors, $TERM$ and DEF, established by Fama and French (1993). They find that these two bond factors, a term premium and a default premium, can explain most of the common variation in the returns on the bonds employed in their study.

4.7.1 TERM

Fama and French (1993) state that one commonly acknowledged risk factor in bond returns is the unexpected occurrence of changes in interest rates. Their factor, $TERM$, is a proxy for this risk factor. In the literature (Fama and French 1993), the $TERM$ factor is defined as the difference between the long-term government bond return and the one-month Treasury Bill rate, where the Treasury Bill rate stands for the return that can be obtained when there is no change in the interest rates, see Equation 22. This study implements the ten-year constant maturity rate from the database FRED of the Federal Reserve Bank of St. Louis as a proxy for the long-term government bond return, following the work of Wagner Ley (2017). The Treasury Bill rate is downloaded together with the other Fama-French factors, including the momentum factor, from the CRSP database. All data is obtained in a daily frequency.

$$TERM = \textit{Long Term Government Bond Return - One Month Treasury Bill Rate} \tag{22}$$

4.7.2 DEF

Fama and French's second bond factor, DEF, proxies the likelihood of default for corporate bonds. It is defined as the difference between the return on a market portfolio of long-term corporate bonds and the long-term government bond return (Fama and French 1993), see Equation 23. In our study, we proxy the return on a market portfolio of long-term corporate bonds with the ICE BofAML US Corp 10-15yr Total Return Index Value downloaded in a daily frequency from the FRED database of the Federal Reserve Bank of St. Louis.

$$DEF = \textit{Return On Long Term Corporate Bonds - Long Term Government Bond Return} \tag{23}$$

4.7.3 LIQ

Previous research on the influence of liquidity risk on green bond yields has produced ambiguous results. Various studies have shown that liquidity risk is an important factor in the analysis of risk-adjusted returns on bonds (e.g., Bao et al. 2011; Connolly et al. 2007). However, Febi et al. (2018) applied two different liquidity measures, the LOT measure and the bid-ask spread, to analyze whether liquidity risk affects green bond yields and they concluded that while the factor seemed to be important in explaining returns when the market for green bonds started growing, the factor has recently lost its explanatory power. Hence, Febi et al. (2018) asserted that ”nowadays, liquidity risk is negligible for green bonds” (p.19). Moreover, we could have implemented the Pastor-Stambaugh liquidity factor, which measures the liquidity on the stock market (Pástor and Stambaugh 2003). However, the factor is only available in a monthly frequency on the CRSP database. Due to our time constraint, we cannot compute the liquidity market risk factor in a daily frequency ourselves and hence, we leave this factor to future research. It would definitely be interesting to see how the results differ after implementing a liquidity risk factor.

5 Econometric Testing

This Section explains the econometric tests we perform before running the regressions and presents the results from the tests. The diagnostics tests are implemented to evaluate the validity of the variables and to see if the data fulfills the assumptions needed to perform a time series analysis [7].

5.1 Stationarity

For time series data, stationarity is a necessary property. Using non-stationary data can cause spurious regression results. When the variables in a regression are non-stationary, the coefficient estimates, R-squared values and t-statistics will not be valid (Brooks 2019). Weak stationarity requires that a variable's mean, variance and autocorrelation are constant. To test for stationarity, the augmented Dickey-Fuller (ADF) test, that detects whether a variable follows a unit-root process, can be used (Brooks 2019). The null hypothesis of the ADF test is the presence of a unit root, and thus non-stationarity, and the alternative is that the variable was generated by a stationary process. For the variables that are non-stationary, the first difference is taken in line with Brooks (2019). To confirm that the first difference is enough and no further differences have to be taken, the ADF test is used again on the new first-difference variables, verifying stationarity for all our variables. The results of the first ADF test can be found in Table 18 in the Appendix. To affirm the results from the ADF test, the time series for the different variables are plotted, see Figure 2-4 in the Appendix.

5.2 Heteroskedasticity and Autocorrelation

The variance of the error terms should always be constant, as stated in Equation 24, which is known as homoskedasticity (Brooks 2019). Heteroskedasticity is a problem and arises when the variance of the error terms is not constant. This would lead to the variance of the error terms exploding over time and hence it would cause misleading statistical inference of the standard errors (Brooks 2019).

$$var(u_t) = \sigma^2 < \infty \tag{24}$$

To tell whether the error terms are heteroskedastic or not, the Breusch-Pagan LM test can be applied (Baum and Christopher 2006). The null hypothesis states constant variance, thus homoskedasticity. Results from the tests can be found in Table 22 in the Appendix. The results differ depending on the asset pricing model that is employed in the analysis. When using the CAPM, portfolio Z_6,Z_7 and Z_{10} are homoskedastic, while all other portfolios exhibit heteroskedasticity. Under the FF3FM, all portfolios, except for portfolio Z_7, display heteroskedasticity. When running the C4FM, the majority of the portfolios are homoskedastic whereas for the FF5FM and our 6FM, only portfolio Z_6 and portfolio Z_7 are homoskedastic. Further, the assumption in Equation 25 states that the errors should be uncorrelated with each other, if they are not, the problem of autocorrelation arises (Brooks 2019).

$$cov = (u_i, u_j) = 0 \tag{25}$$

7. Applying the same econometric tests on the portfolios when the bond return is proxied by the price changes shows that while the portfolio returns proxied by the price changes are stationary, the other tests produce the same results as the ones mentioned in this Section.

To test for autocorrelation in the models' residuals, the Breusch-Godfrey LM test can be used, where the null hypothesis of the test is in line with no serial correlation of the error terms (Brooks 2019). The results can be found in Table 23 in the Appendix. The results are independent of the employed asset pricing model and suggest that portfolio Z_6, Z_8 and Z_{10} contain error terms that are serially correlated. Hence, in order to correct for the heteroskedasticity and autocorrelation in the error terms of our regressions, we apply HAC (Heteroskedasticity and Autocorrelation Consistent) standard errors, sometimes also referred to as Newey-West robust standard errors (Brooks 2019).

5.3 Normality

The assumption in Equation 26 states that the error term should be normally distributed with zero mean and constant variance (Brooks 2019).

$$u_t \sim N(0, \sigma^2) \tag{26}$$

The error terms in the different models were tested for non-normality. It was found that the errors are normally distributed, see Table 21 in the Appendix. A perfectly normally distributed data process has a kurtosis of three and a skewness of zero. However, according to Kim (2013), non-normality in a sample that is greater than 300 is only confirmed if the absolute values for the skewness and the kurtosis are greater than two and seven, respectively. Thus, we assume that the residuals are normally distributed. However, we find that the returns of the ten constructed portfolios in our study do not follow a normal distribution. See Table 3 in Section 6 for the descriptive statistics of the portfolio returns.

5.4 Multicollinearity

The explanatory variables in a model should not be correlated with each other, when they are highly correlated the problem of multicollinearity arises. Multicollinearity causes misleading results due to wider confidence intervals, high standard errors and unreliable probability values (Brooks 2019). Increasing the sample size or dropping one of the highly correlated variables can correct for multicollinearity. To investigate whether multicollinearity is present, one can look at the coefficients of the explanatory variables in a correlation matrix (Brooks 2019) or calculate the variance inflation factor (VIF) for each explanatory variable (Verbeek 2008). The VIF of a variable, shown in Equation 27, displays how much of the variance in the i:th explanatory variable is explained by the other explanatory variables in the regression model.

$$VIF_i = \frac{1}{1 - R_i^2} \tag{27}$$

where R_i^2 is ESS/RSS for the i:th explanatory variable. The higher the VIF value, the greater the multicollinearity, where R_i^2=0 equals the lowest VIF value of one (Verbeek 2008). In addition to the VIF, we also construct a correlation matrix for the explanatory variables, which, like the results from the VIF, showed that multicollinearity is not a problem. For the correlation matrix and the VIF values, see Table 19 and 20 in the Appendix.

6 Results and Analysis

In the following Section, we present and analyze the descriptive statistics of the portfolio returns when two different proxies for the returns on bonds are used: the yield and the bond price changes, see Table 3 and Table 4, respectively. In the consecutive Subsections, we report and interpret our results from running the regressions in the different asset pricing models. We use the yield in all the models. The only model that is run twice, once with each proxy implemented, is the 6FM. This is done to assess whether the results are robust to changing the proxy for the bond returns. All regressions are conducted using robust standard errors after the confirmation of heteroskedasticity and autocorrelation, presented in Table 22 and Table 23 in the Appendix. The intercept (α) is multiplied by 250 in all the asset pricing models, corresponding to the number of trading days in a year, to assess the annual excess returns of the portfolios instead of the daily excess returns.

6.1 Descriptive Statistics

Table 3: Descriptive Statistics For The Portfolio Returns with Yields

The descriptive statistics for the annual returns of the ten constructed portfolios, when the yield is used as a proxy for bond returns. Portfolio 1 (Z_1) is the benchmark portfolio consisting of 60% stocks and 40% conventional bonds. Portfolio 2 (Z_2) consists of 60% stocks, 20% green bonds and and 20% conventional bonds. Portfolio 3 (Z_3) consists of 60% stocks and 40% conventional bonds. Portfolio 4 (Z_4) consists of 60% stocks, 30% green bonds and 10% conventional bonds. Portfolio 5 (Z_5) consists of 40% stocks, 30% green bonds and and 30% conventional bonds. Portfolio 6 (Z_6) consists of 100% green bonds. Portfolio 7 (Z_7) consists of 100% conventional bonds. Portfolio 8 (Z_8) consists of 100% stocks. Portfolio 9 (Z_9) consists of 20% stocks, 40% green bonds and and 40% conventional bonds. Portfolio 10 (Z_{10}) consists of 50% green bonds and 50% conventional bonds.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variable	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7	Z_8	Z_9	Z_{10}
Mean	9.413	18.759	7.591	15.203	17.165	0.007	0.004	0.032	16.961	0.013
Std. Dev	2.401	2.921	2.277	2.977	3.100	0.060	0.062	2.017	3.299	0.133
Variance	5.766	8.533	5.184	8.865	9.607	0.004	0.062	4.070	10.885	0.018
Skewness	0.160	0.293	-0.193	0.067	0.149	0.488	0.987	-0.747	0.298	1.201
Kurtosis	6.022	4.344	6.301	4.297	4.263	15.243	4.900	8.072	3.727	10.757

As we can observe in Table 3, when we use the yield as a proxy for the bond returns, portfolio Z_2 has the highest mean in returns, whereas the stock portfolio, Z_8, and the bond portfolios, Z_6, Z_7 and Z_{10}, have a mean that is very close to zero. The annualized standard deviation, and in turn the annualized variance, of the portfolio returns are especially low for the bond portfolios, Z_6, Z_7 and Z_{10}. Hence, this analysis of the descriptive statistics shows that there was very little variation in the returns on bonds, proxied by the yields, during our assessed time period from 12.05.2016-31.12.2018.

The results for the skewness are close to zero for all portfolios but portfolio Z_{10}, which indicates that the return data is approximately symmetric around the mean. The skewness would have to be larger than two for a data sample of our size to be considered non-normal. The kurtosis varies between the different portfolios. The annual returns of the pure green bond portfolio, Z_6 and the pure bond portfolio, Z_{10}, show very high results for the kurtosis, which demonstrates that these portfolios are subject to sudden extreme deviations from the mean. So, while these portfolios have a very low standard deviation over time, there are a few extreme data points, which can be seen in Figure 5 in the Appendix. Also, the stock portfolio, Z_8 and portfolios Z_1 and Z_3, display a high kurtosis compared to a kurtosis of three for the normal distribution. Hence, we can conclude that the portfolio returns do not follow a normal distribution. This result is in line with the work of Fischer and Lundtofte (2018).

Table 4: Descriptive Statistics For The Portfolio Returns with Price Changes

The descriptive statistics for the annual returns of the ten constructed portfolios, when the price changes are used as a proxy for the bond returns. Portfolio 1 (Z_1) is the benchmark portfolio consisting of 60% stocks and 40% conventional bonds. Portfolio 2 (Z_2) consists of 60% stocks, 20% green bonds and and 20% conventional bonds. Portfolio 3 (Z_3) consists of 60% stocks and 40% conventional bonds. Portfolio 4 (Z_4) consists of 60% stocks, 30% green bonds and 10% conventional bonds. Portfolio 5 (Z_5) consists of 40% stocks, 30% green bonds and and 30% conventional bonds. Portfolio 6 (Z_6) consists of 100% green bonds. Portfolio 7 (Z_7) consists of 100% conventional bonds. Portfolio 8 (Z_8) consists of 100% stocks. Portfolio 9 (Z_9) consists of 20% stocks, 40% green bonds and and 40% conventional bonds. Portfolio 10 (Z_{10}) consists of 50% green bonds and 50% conventional bonds.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variable	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7	Z_8	Z_9	Z_{10}
Mean	-0.005	-0.009	0.000	-0.018	-0.033	-0.033	-0.032	0.022	-0.042	-0.059
Std. Dev	2.892	2.850	2.819	2.803	3.503	0.295	0.294	2.018	2.316	0.608
Variance	8.364	8.124	7.944	7.859	12.274	0.087	0.086	4.072	5.363	0.370
Skewness	-0.675	-0.682	-0.647	-0.635	-0.552	0.205	-0.489	-0.750	-0.634	0.235
Kurtosis	6.316	6.192	6.498	6.059	5.642	23.704	4.565	8.066	5.086	22.561

Table 4 shows the statistical moments of the portfolio returns when the bond returns are proxied by the bond price changes. Intuitively, the returns proxied by the bond price changes should show more variation than the returns of bonds that are proxied by the yield. Comparing the results in Table 4 to those in Table 3, the standard deviation increases for the returns of the bond portfolios. However, when we employ the price changes, these portfolios still exhibit the lowest variation in returns compared to all the other portfolios. In addition, the means of the returns are very close to zero for all portfolios. They are significantly lower than in the previous setting, where the returns on bonds were proxied by the yield. Further, the portfolio with the highest mean in returns is no longer portfolio Z_2, but the pure stock portfolio, Z_8. This is also the only portfolio that exhibits an average annual return above zero.

However, the kurtosis of all the portfolios is different from three. As mentioned earlier, according to Kim (2013) the data can only be considered to be non-normally distributed if the value for the kurtosis is bigger than seven. This indicates that some of the portfolios' returns are non-normally distributed. Especially the results for the kurtosis of portfolio Z_6 and portfolio Z_{10} display very large values. This is in line with the previous results of the descriptive statistics for portfolio returns when they are proxied by the yield, see Table 3.

6.2 Capital Asset Pricing Model Results

Table 5: Capital Asset Pricing Model: Regression Output

The natural logarithm of the annual excess returns on our ten constructed portfolios are regressed on the excess returns on the market (RPM), using time series regressions. To obtain the annual excess returns, the daily excess returns used in this analysis are multiplied by 250. Portfolio 1 (Z_1) is the benchmark portfolio consisting of 60% stocks and 40% conventional bonds. Portfolio 2 (Z_2) consists of 60% stocks, 20% green bonds and and 20% conventional bonds. Portfolio 3 (Z_3) consists of 60% stocks and 40% conventional bonds. Portfolio 4 (Z_4) consists of 60% stocks, 30% green bonds and 10% conventional bonds. Portfolio 5 (Z_5) consists of 40% stocks, 30% green bonds and and 30% conventional bonds. Portfolio 6 (Z_6) consists of 100% green bonds. Portfolio 7 (Z_7) consists of 100% conventional bonds. Portfolio 8 (Z_8) consists of 100% stocks. Portfolio 9 (Z_9) consists of 20% stocks, 40% green bonds and and 40% conventional bonds. Portfolio 10 (Z_{10}) consists of 50% green bonds and 50% conventional bonds. Alpha (α), is Jensen's alpha, and is the constant in the regressions. Robust standard errors are reported in parentheses. The last two rows show the number of observations (N) and the R-squared (R^2). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variable	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7	Z_8	Z_9	Z_{10}
RPM	0.826***	0.811***	0.845***	0.812***	0.863***	0.006***	-0.000	0.916***	0.801***	0.011***
	(0.04)	(0.06)	(0.04)	(0.06)	(0.06)	(0.00)	(0.00)	(0.02)	(0.07)	(0.00)
α	9.323***	18.670***	7.499***	15.114***	17.071***	1.594**	0.004	-0.067**	16.873***	0.012**
	(0.07)	(0.09)	(0.06)	(0.10)	(0.10)	(0.01)	(0.00)	(0.03)	(0.11)	(0.01)
N	664	664	664	664	664	518	518	664	664	518
R^2	0.486	0.317	0.565	0.305	0.319	0.042	0.000	0.845	0.242	0.023

Table 5 summarizes the coefficients for the ten portfolios regressed using CAPM. The intercept of the model is Jensen's performance index (α). All the alphas are statistically significant, except for the pure conventional bond portfolio, Z_7. The alpha is the additional annual excess return that cannot be explained by the risk the investors face when they invest in a given portfolio. Thus, the higher the annual excess return, the more profitable the investment, while a negative alpha, as in the results for portfolio Z_8, shows that a portfolio is unprofitable. As we can observe, the portfolio that generates the highest statistically significant additional annual excess return ($\alpha = 18.670$) and thus outperforms the other portfolios is portfolio Z_2. This portfolio is made up of 60% stocks, 20% green bonds and 20% conventional bonds. It is especially interesting to compare the performance of portfolio Z_2 to our benchmark portfolio, Z_1, which is comprised of 60% stocks and 40% conventional bonds, representing the traditional structure of a portfolio. This comparison is a first indicator for the fact that the inclusion of green bonds in a portfolio can enhance the portfolio's performance. Portfolio Z_5 performs the second best and has a share of 40% stocks, 30% green bonds and 30% conventional bonds. It is closely followed by portfolio Z_9, which is made up of 20% stocks, 40% green bonds and 40% conventional bonds. Out of the six portfolios that generate annual excess returns that are significant to the 1%-level, five contain varying amounts of green bonds. The only portfolio that produces highly significant annual excess returns without incorporating any green bonds is the benchmark portfolio. This shows that, while traditionally comprised portfolios can still achieve an excess return, in a CAPM setting, during the time period from 12.05.2016-31.12.2018, portfolios with green bonds included generally fare financially better than portfolios without green bonds.

The number of observations is restricted for portfolios Z_6, Z_7 and Z_{10} because the returns of these portfolios were non-stationary and hence the first difference had to be taken to ensure stationarity. It should be kept in mind that it is highly unlikely that any rational investor would choose to invest in the pure bond portfolios, Z_6, Z_7 and Z_{10}. These portfolios are solely employed in our study for comparison. Moreover, an investor should not focus only on the fixed income market. As we can see in Table 5, portfolio Z_{10}, which is composed of 50% green bonds and 50% conventional bonds, does not exhibit high annual excess returns. The same goes for the three portfolios, Z_6, Z_7, and Z_8, that are comprised of only one type of asset: green bonds, conventional bonds or stocks. In addition, it should also be noticed that the alphas of those portfolios are only significant to the 5%-level and the alpha of portfolio Z_7 is not significant at all. Hence, while our results indicate that investing in green bonds generally is profitable, the investor should not forget the profitability of diversification.

The R-squared is low for some of the CAPM regressions. This result is in line with previous research and was the reason for Fama and French to include additional factors to the regressions (Fama and French 1992). Especially, the single-factor CAPM has almost no explanatory power for the bond portfolios, Z_6, Z_7 and Z_{10}. This supports the hypothesis that there are other unobserved factors that could play an important role in the explanation of risk-adjusted portfolio returns. First, we extend the CAPM framework to increase its explanatory power following the work of Fama and French (1992).

6.3 Fama-French Three-Factor Model Results

Table 6: Fama-French Three-Factor Model: Regression Output

The natural logarithm of the annual excess returns of our ten constructed portfolios are regressed on the excess returns on the market (RPM), small-minus-big (SMB) and high-minus-low (HML), using time series regressions. To obtain the annual excess returns, the daily excess returns used in this analysis are multiplied by 250. Portfolio 1 (Z_1) is the benchmark portfolio consisting of 60% stocks and 40% conventional bonds. Portfolio 2 (Z_2) consists of 60% stocks, 20% green bonds and and 20% conventional bonds. Portfolio 3 (Z_3) consists of 60% stocks and 40% conventional bonds. Portfolio 4 (Z_4) consists of 60% stocks, 30% green bonds and and 10% conventional bonds. Portfolio 5 (Z_5) consists of 40% stocks, 30% green bonds and and 30% conventional bonds. Portfolio 6 (Z_6) consists of 100% green bonds. Portfolio 7 (Z_7) consists of 100% conventional bonds. Portfolio 8 (Z_8) consists of 100% stocks. Portfolio 9 (Z_9) consists of 20% stocks, 40% green bonds and and 40% conventional bonds. Portfolio 10 (Z_{10}) consists of 50% green bonds and 50% conventional bonds. Alpha (α), is Jensen's alpha, and is the constant in the regressions. Robust standard errors are reported in parentheses. The last two rows show the number of observations (N) and the R-squared (R^2). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variable	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7	Z_8	Z_9	Z_{10}
RPM	0.853***	0.836***	0.871***	0.839***	0.897***	0.007***	0.000	0.945***	0.820***	0.012***
	(0.04)	(0.06)	(0.04)	(0.06)	(0.06)	(0.00)	(0.00)	(0.02)	(0.07)	(0.00)
SMB	-0.038	-0.049	-0.035	-0.074	0.003	0.003	0.003	-0.008	-0.008	0.007
	(0.06)	(0.08)	(0.05)	(0.08)	(0.08)	(0.00)	(0.00)	(0.02)	(0.10)	(0.00)
HML	0.256***	0.229***	0.262***	0.222***	0.390***	0.012***	0.010***	0.319***	0.202**	0.026***
	(0.06)	(0.08)	(0.05)	(0.08)	(0.09)	(0.00)	(0.00)	(0.02)	(0.10)	(0.00)
α	9.328***	18.675***	7.505***	15.119***	17.080***	0.007***	0.004	-0.060**	16.878***	0.012**
	(0.07)	(0.09)	(0.06)	(0.10)	(0.10)	(0.00)	(0.00)	(0.03)	(0.11)	(0.01)
N	664	664	664	664	664	518	518	664	664	518
R^2	0.507	0.328	0.589	0.316	0.347	0.116	0.047	0.889	0.249	0.093

Comparing the CAPM and the FF3FM regression results, summarized in Table 6, the alphas only changed marginally. Thus, the ranking in terms of the annual profitability of the portfolios does not change. However, the R-squared is higher for all the portfolio regressions. The most profound increase in the R-squared can be observed for the three pure bond portfolios, Z_6, Z_7 and Z_{10}. This yields evidence for the fact that the returns of green bonds and conventional bonds in our sample do not depend on the excess return on the market, RPM, since the coefficients for the market factor are close to zero and by including other factors the returns could be explained to a greater extent. The by far highest R-squared is obtained from the regression of the 100% stock portfolio, Z_8. This is in line with the work of Fama and French (1993), who state that the factors SMB and HML mainly explain variation on the stock market. One more noticeable feature of the results is the insignificance of the SMB factor for all portfolios. This insignificance of the factor might arise due to the fact that we have only included stocks from the S&P 500 Index, which encompasses the 500 largest U.S. publicly traded firms. Furthermore, the HML factor is significant to the 1%-level for all portfolios, except for portfolio Z_9. To further increase the explanatory power of the models, we include the momentum factor, MOM, first introduced by Carhart (1997), in the next model.

6.4 Carhart Four-Factor Model Results

Table 7: Carhart Four-Factor Model: Regression Output

The natural logarithm of the annual excess returns on our ten constructed portfolios are regressed on the excess returns on the market (RPM), small-minus-big (SMB), high-minus-low (HML) and the momentum factor (MOM), using time series regressions. To obtain the annual excess returns, the daily excess returns used in this analysis are multiplied by 250. Portfolio 1 (Z_1) is the benchmark portfolio consisting of 60% stocks and 40% conventional bonds. Portfolio 2 (Z_2) consists of 60% stocks, 20% green bonds and and 20% conventional bonds. Portfolio 3 (Z_3) consists of 60% stocks and 40% conventional bonds. Portfolio 4 (Z_4) consists of 60% stocks, 30% green bonds and and 10% conventional bonds. Portfolio 5 (Z_5) consists of 40% stocks, 30% green bonds and and 30% conventional bonds. Portfolio 6 (Z_6) consists of 100% green bonds. Portfolio 7 (Z_7) consists of 100% conventional bonds. Portfolio 8 (Z_8) consists of 100% stocks. Portfolio 9 (Z_9) consists of 20% stocks, 40% green bonds and and 40% conventional bonds. Portfolio 10 (Z_{10}) consists of 50% green bonds and 50% conventional bonds. Alpha (α), is Jensen's alpha, and is the constant in the regressions. Robust standard errors are reported in parentheses. The last two rows show the number of observations (N) and the R-squared (R^2). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variable	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7	Z_8	Z_9	Z_{10}
RPM	0.879***	0.862***	0.896***	0.862***	0.928***	0.007***	-0.001	0.964***	0.856***	0.011***
	(0.04)	(0.06)	(0.03)	(0.06)	(0.06)	(0.00)	(0.00)	(0.01)	(0.06)	(0.00)
SMB	-0.075	-0.085	-0.070	-0.106	-0.041	0.003	0.004	-0.036*	-0.060	0.008
	(0.05)	(0.08)	(0.05)	(0.08)	(0.08)	(0.00)	(0.00)	(0.02)	(0.09)	(0.00)
HML	0.150***	0.124	0.161***	0.128	0.262***	0.014***	0.012***	0.242***	0.054	0.029***
	(0.06)	(0.08)	(0.05)	(0.08)	(0.09)	(0.00)	(0.00)	(0.02)	(0.10)	(0.00)
MOM	-0.256***	-0.253***	-0.243***	-0.226***	-0.308***	0.004**	0.006***	-0.186***	-0.356***	0.008*
	(0.04)	(0.06)	(0.04)	(0.07)	(0.06)	(0.00)	(0.00)	(0.02)	(0.08)	(0.00)
α	9.334***	18.681***	7.510***	15.124***	17.087***	0.007***	0.004	-0.056**	16.886***	0.012**
	(0.06)	(0.09)	(0.06)	(0.10)	(0.10)	(0.00)	(0.00)	(0.02)	(0.11)	(0.01)
N	664	664	664	664	664	518	518	664	664	518
R^2	0.530	0.344	0.612	0.328	0.367	0.123	0.063	0.906	0.272	0.101

Looking at Table 7, the alphas, and thus the annual excess returns, again only change marginally when we implement the C4FM. Thus, the profitability ranking of the portfolios does not differ from the one established in the CAPM- and FF3FM regressions. The R-squared has increased compared to the previous two models and the MOM factor is statistically significant for all regressions. Thus, we can see that the MOM factor has explanatory power for the risk-adjusted returns of portfolios, independent of how the portfolios are constructed. In addition, the pure bond portfolios are affected positively by the MOM factor. The HML factor, on the other hand, loses some of its explanatory power and is now only significant in seven out of the ten portfolio regressions. The coefficient of RPM is statistically significant on a 1% significance level for all the portfolios, except for the pure conventional bond portfolio, Z_7. This is in line with the results from the two previous models. Similar to the FF3FM, the SMB is not significant for any of the models. Next, we include two bond factors into the regressions. These bond factors were first introduced by Fama and French (1993) in their five-factor model.

6.5 Fama-French Five-Factor Model Results

Table 8: Fama-French Five-Factor Model: Regression Output

The natural logarithm of the annual excess returns on our ten constructed portfolios are regressed on the the excess returns on the market (*RPM*), small-minus-big (*SMB*), high-minus-low (*HML*), the proxy for unexpected changes in the interest rate (*TERM*) and the proxy for the likelihood of default for corporate bonds (*DEF*), using time series regressions. To obtain the annual excess returns, the daily excess returns used in this analysis are multiplied by 250. Portfolio 1 (Z_1) is the benchmark portfolio consisting of 60% stocks and 40% conventional bonds. Portfolio 2 (Z_2) consists of 60% stocks, 20% green bonds and and 20% conventional bonds. Portfolio 3 (Z_3) consists of 60% stocks and 40% conventional bonds. Portfolio 4 (Z_4) consists of 60% stocks, 30% green bonds and and 10% conventional bonds. Portfolio 5 (Z_5) consists of 40% stocks, 30% green bonds and and 30% conventional bonds. Portfolio 6 (Z_6) consists of 100% green bonds. Portfolio 7 (Z_7) consists of 100% conventional bonds. Portfolio 8 (Z_8) consists of 100% stocks. Portfolio 9 (Z_9) consists of 20% stocks, 40% green bonds and and 40% conventional bonds. Portfolio 10 (Z_{10}) consists of 50% green bonds and 50% conventional bonds. Alpha (α), is Jensen's alpha, and is the constant in the regressions. Robust standard errors are reported in parentheses. The last two rows show the number of observations (N) and the R-squared (R^2). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variable	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7	Z_8	Z_9	Z_{10}
RPM	0.907***	0.897***	0.924***	0.889***	0.951***	0.001	-0.006***	0.981***	0.861***	-0.003*
	(0.04)	(0.07)	(0.05)	(0.08)	(0.07)	(0.00)	(0.00)	(0.02)	(0.08)	(0.00)
SMB	-0.020	-0.024	-0.018	-0.048	0.017	-0.001	-0.001	-0.015	0.019	-0.002
	(0.06)	(0.09)	(0.06)	(0.09)	(0.09)	(0.00)	(0.00)	(0.03)	(0.11)	(0.00)
HML	0.266***	0.200**	0.259***	0.156*	0.349***	-0.001	-0.003*	0.341***	0.070	-0.005
	(0.07)	(0.09)	(0.06)	(0.10)	(0.10)	(0.00)	(0.00)	(0.03)	(0.11)	(0.00)
TERM	-0.018**	-0.008	-0.018*	-0.001	-0.004	0.150***	0.160***	-0.021***	0.017	0.018***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
DEF	0.063***	0.102***	0.050***	0.105***	0.105***	0.057***	0.090***	-0.003	0.140***	0.005***
	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.04)	(0.00)
α	9.307***	18.646***	7.491***	15.096***	17.046***	0.005***	0.002	-0.055*	16.800***	0.008*
	(0.07)	(0.11)	(0.06)	(0.11)	(0.11)	(0.00)	(0.00)	(0.03)	(0.13)	(0.00)
N	518	518	518	518	518	518	518	518	518	518
R^2	0.496	0.323	0.576	0.308	0.335	0.523	0.458	0.883	0.253	0.566

Jensen's alpha is again in line with the previous models, and hence, the annual profitability ranking has not changed. The number of observations is restricted to 518 for all portfolio regressions because the two bond factors were non-stationary and thus, we had to take the first difference of the two factors to ensure stationarity.

It is of special interest to implement the FF5FM to our data sample, since the FF5FM extends the FF3FM by adding two bond factors, $TERM$ and DEF. Looking at the results from the FF5FM, the most profound increase in the R-squared, compared to the previous models, can be observed for the three pure bond portfolios, Z_6, Z_7 and Z_{10}. Adding the two bond factors, $TERM$ and DEF, results in the insignificance of the RPM factor for the pure green bond portfolio, Z_6. Hence the RPM factor does not have any significant influence on the risk-adjusted returns for green bonds. In the previous models the influence of the RPM factor on the risk-adjusted returns of portfolio Z_6 was low but significant. For the pure bond portfolio, Z_{10}, the RPM is only significance on a 10%-level. Including the bond factors leads to an increased R-squared of 0.523 for portfolio Z_6, compared to the previous R-squared of 0.123. A similar effect can be seen in the case of the conventional bond portfolio, Z_7, and the third bond portfolio, Z_{10}. This result highlights the importance of the bond factors in the estimation of risk-adjusted bond returns and thus supports the work of (Fama and French 1993). For the pure stock portfolio, Z_8, the R-squared actually decreases compared to the C4FM, and the

DEF factor is statistically insignificant. However, in all other portfolio regressions, the DEF factor is significant to the 1%-level. It should also be acknowledged that, given the estimates, the DEF factor has the biggest impact on the risk-adjusted returns of those portfolios, Z_4, Z_5, and Z_9, that are the most diversified.

The results for the $TERM$ factor are ambiguous. In four portfolio regressions, Z_6, Z_7, Z_8 and Z_{10}, the factor is significant to the 1%-level. The first three are the portfolios that are comprised of only one type of asset, while the last portfolio, Z_{10}, contains an equal amount of green and conventional bonds. The only other two portfolios, that the $TERM$ factor has a very low but significant negative impact on, are the benchmark portfolio, Z_1 and portfolio Z_3. For the other portfolios the factor is insignificant. In essence, the $TERM$ factor is only relevant for those portfolios that are less diversified. There is a negative significant relationship between the $TERM$ factor and the risk-adjusted returns for two of the portfolios with 60% stocks, Z_1 and Z_3 and the pure stock portfolio, Z_8.

As in the previous models, the SMB factor stays insignificant across all portfolios. The HML factor yields ambiguous results. It is significant for the three portfolios with 60% stocks as well as for the pure stock portfolio. This would lead us to interpret it to be of sole importance for stock returns. However, it is also highly significant for portfolio Z_5, which consists of 40% stocks and an equal amount in green and conventional bonds. Why this is the case should be further investigated by future researchers. The RPM factor is of high importance for eight out of the ten portfolios. Only the returns of the green bond portfolio, Z_6, have a completely insignificant relationship to the market. It should also be noted, that the returns of the pure conventional bond portfolio, Z_7, and the equal amount in green and conventional bonds portfolio, Z_{10}, have a slight negative relationship to the RPM factor. This implies that there is a slight negative relationship between conventional bonds and the market.

Since some explanatory power is lost when we drop the MOM factor from the model, we will next perform the analysis with a 6FM, that contains the five Fama-French factors and Carhart's momentum factor.

6.6 Six-Factor Model Results

In this Subsection, we will employ the 6FM with two different proxies for the return on a bond: the yield of the bonds and the price changes of the bonds. The bond price changes are computed in line with the equations stated in Subsection 4.3. The results can be found in Table 9 and Table 10, respectively. We run these two models to assess whether dropping the assumption that investors hold the bonds to maturity, which is consistent with using the yield of a bond as the proxy, significantly changes the results.

Table 9: Six-Factor Model with Yields: Regression Output

The natural logarithm of the annual excess returns on our ten constructed portfolios are regressed on the the excess returns on the market (RPM), small-minus-big (SMB), high-minus-low (HML), the proxy for unexpected changes in the interest rate ($TERM$), the proxy for the likelihood of default for corporate bonds (DEF) and the momentum factor (MOM), using time series regressions. To obtain the annual excess returns, the daily excess returns used in this analysis are multiplied by 250. Portfolio 1 (Z_1) is the benchmark portfolio consisting of 60% stocks and 40% conventional bonds. Portfolio 2 (Z_2) consists of 60% stocks, 20% green bonds and and 20% conventional bonds. Portfolio 3 (Z_3) consists of 60% stocks and 40% conventional bonds. Portfolio 4 (Z_4) consists of 60% stocks, 30% green bonds and and 10% conventional bonds. Portfolio 5 (Z_5) consists of 40% stocks, 30% green bonds and and 30% conventional bonds. Portfolio 6 (Z_6) consists of 100% green bonds. Portfolio 7 (Z_7) consists of 100% conventional bonds. Portfolio 8 (Z_8) consists of 100% stocks. Portfolio 9 (Z_9) consists of 20% stocks, 40% green bonds and and 40% conventional bonds. Portfolio 10 (Z_{10}) consists of 50% green bonds and 50% conventional bonds. Alpha (α), is Jensen's alpha, and is the constant in the regressions. Robust standard errors are reported in parentheses. The last two rows show the number of observations (N) and the R-squared (R^2). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variable	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7	Z_8	Z_9	Z_{10}
RPM	0.935***	0.924***	0.950***	0.912***	0.984***	0.012	-0.204***	1.002***	0.902***	-0.004*
	(0.05)	(0.07)	(0.05)	(0.08)	(0.08)	(0.03)	(0.04)	(0.02)	(0.07)	(0.00)
SMB	-0.050	-0.053	-0.046	-0.073	-0.019	-0.016	-0.014	-0.039*	-0.027	-0.001
	(0.06)	(0.09)	(0.05)	(0.09)	(0.09)	(0.05)	(0.05)	(0.02)	(0.10)	(0.00)
HML	0.176***	0.114	0.175***	0.083	0.245**	-0.007	-0.058	0.271***	-0.065	-0.004
	(0.07)	(0.08)	(0.06)	(0.09)	(0.10)	(0.05)	(0.00)	(0.03)	(0.11)	(0.00)
$TERM$	-0.014	-0.005	-0.015*	0.002	-0.001	0.149***	0.157***	-0.019***	0.022	0.012***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.00)
DEF	0.068***	0.106***	0.054***	0.108***	0.110***	0.056***	0.088***	0.001	0.146***	0.004***
	(0.02)	(0.07)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.04)	(0.00)
MOM	-0.229***	-0.220***	-0.214***	-0.186**	-0.268***	0.002	0.108**	-0.179***	-0.345***	0.004
	(0.05)	(0.07)	(0.05)	(0.08)	(0.08)	(0.00)	(0.04)	(0.02)	(0.09)	(0.00)
α	9.311***	18.651***	7.496***	15.100***	17.052***	0.005***	0.002	-0.051*	16.807***	0.008*
	(0.07)	(0.10)	(0.06)	(0.11)	(0.11)	(0.00)	(0.00)	(0.03)	(0.12)	(0.00)
N	518	518	518	518	518	518	518	518	518	518
R^2	0.514	0.334	0.594	0.316	0.350	0.525	0.464	0.900	0.275	0.567

The alphas and the subsequent annual profitability ranking of the portfolios once more approximately correspond to the ones in the previous models. The R-squared is a little higher compared to the FF5FM but lower than the R-squared of the C4FM for all portfolios. Nevertheless, the DEF factor, the RPM factor, the MOM factor and alpha are statistically significant for most of the regressions. Again, the $TERM$ factor shows 1%-level significance for all pure bond portfolios, Z_6, Z_7 and Z_{10}, and the pure stock portfolio, Z_8.

Similar to the FF5FM, the excess return of the market, RPM, does not have any influence on the excess returns of the pure green bonds portfolio, Z_6. Furthermore, neither the SMB factor nor the HML factor have an impact on the risk-adjusted returns for green bonds. Not surprisingly, the highest and the only significant effect on the risk-adjusted returns of green bonds is clearly linked to the two bond factors, $TERM$ and DEF. In the case of conventional bonds, the excess return on the market, RPM, as well as both the $TERM$ and DEF factor, are significant to the 1%-level, while the MOM factor is significant to the 5%-level. Also quite interesting is the fact that the conventional bond portfolio, Z_7 moves in the opposite direction of the market, since the coefficient of the RPM factor is negative and significant. Hence, when the annual excess return on the market rises, this leads to a significant decrease in the annual excess return on the conventional bond portfolio Z_7.

Table 10: Six-Factor Model with Price Changes: Regression Output

The natural logarithm of the annual excess returns, on our ten constructed portfolios are regressed on the the excess returns on the market (*RPM*), small-minus-big (*SMB*), high-minus-low (*HML*), the proxy for unexpected changes in the interest rate (*TERM*), the proxy for the likelihood of default for corporate bonds (*DEF*) and the momentum factor (*MOM*), using time series regressions. To obtain the annual excess returns, the daily excess returns used in this analysis are multiplied by 250. Portfolio 1 (Z_1) is the benchmark portfolio consisting of 60% stocks and 40% conventional bonds. Portfolio 2 (Z_2) consists of 60% stocks, 20% green bonds and and 20% conventional bonds. Portfolio 3 (Z_3) consists of 60% stocks and 40% conventional bonds. Portfolio 4 (Z_4) consists of 60% stocks, 30% green bonds and and 10% conventional bonds. Portfolio 5 (Z_5) consists of 40% stocks, 30% green bonds and and 30% conventional bonds. Portfolio 6 (Z_6) consists of 100% green bonds. Portfolio 7 (Z_7) consists of 100% conventional bonds. Portfolio 8 (Z_8) consists of 100% stocks. Portfolio 9 (Z_9) consists of 20% stocks, 40% green bonds and and 40% conventional bonds. Portfolio 10 (Z_{10}) consists of 50% green bonds and 50% conventional bonds. Alpha (α), is Jensen's alpha, and is the constant in the regressions. Robust standard errors are reported in parentheses. The last two rows show the number of observations (N) and the R-squared (R^2). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Variable	(1) Z_1	(2) Z_2	(3) Z_3	(4) Z_4	(5) Z_5	(6) Z_6	(7) Z_7	(8) Z_8	(9) Z_9	(10) Z_{10}
RPM	1.399***	1.384***	1.360***	1.361***	1.634***	-0.002	0.032***	1.002***	1.018***	0.024***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.00)	(0.01)	(0.02)	(0.04)	(0.01)
SMB	-0.011	-0.003	-0.005	0.006	0.045	0.003	0.003	-0.039*	0.035	0.006
	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)	(0.01)	(0.01)	(0.02)	(0.05)	(0.01)
HML	0.299***	0.299***	0.292***	0.298***	0.454***	0.000	0.010	0.271***	0.105*	0.014
	(0.06)	(0.06)	(0.06)	(0.06)	(0.08)	(0.01)	(0.01)	(0.03)	(0.06)	(0.02)
TERM	-0.068***	-0.097***	-0.062***	-0.103***	-0.099***	-0.023***	-0.025***	-0.019***	-0.072***	-0.049***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
DEF	0.001	-0.010	0.013	-0.004	0.003	-0.009***	-0.014***	0.001	0.012	-0.020***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.00)	(0.00)	(0.01)	(0.02)	(0.01)
MOM	-0.398***	-0.382***	-0.390***	-0.394***	-0.524***	-0.009*	-0.017**	-0.179***	-0.394***	-0.024*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)	(0.01)	(0.01)	(0.02)	(0.05)	(0.01)
α	-0.109*	-0.114*	-0.108*	-0.116**	-0.160**	-0.033***	-0.019**	-0.051*	-0.131**	-0.048***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.08)	(0.01)	(0.01)	(0.03)	(0.06)	(0.02)
N	518	518	518	518	518	518	518	518	518	518
R^2	0.791	0.781	0.788	0.777	0.730	0.512	0.479	0.900	0.639	0.504

As can be observed in Table 10, the results of the 6FM are not robust to the type of bond return proxy used in the analysis. In all the previous models, our constructed portfolios were able to generate significant positive annual excess returns, whereas in this specification it looks as if none of the portfolios can generate positive annual excess returns. The alphas of all our regressions in the 6FM case are negative when we employ the bond price changes as the proxy for the return on the bonds. Furthermore, the pure bond portfolios now perform the best, while portfolio Z_5, consisting of 40% stocks, 30% conventional bonds and 30% green bonds, performs the worst.

The RPM factor is significant for all portfolios except for the green bond portfolio, Z_6. This is in line with the previous results. However, the results differ greatly for the two bond factors, $TERM$ and DEF. The $TERM$ factor shows a high significance for all portfolios, whereas the DEF factor is only significant for the pure bond portfolios. These results are completely contradictory to our previous results, see Table 9. As in the previous models, the SMB factor is insignificant across all regressions. The HML factor is insignificant for the bond portfolios, Z_6, Z_7 and Z_{10}, and for portfolio Z_9 the HML factor is only significant to the 5%-level. The MOM factor gains a little explanatory power compared to the previous models and is now significant for all portfolios. The lowest significance of the MOM factor can be seen in the regressions for portfolios Z_6 and Z_{10}.

6.7 Summary of Results

A summary of the resulting profitability ranking, given Jensen's alpha, of our constructed portfolios for the time period from 12.05.2016 to 31.12.2018, can be found in Table 11. The values within the brackets indicate the ranking of the portfolios according to our estimated models. For example, [1] indicates the best performance, whereas [10] is assigned to the portfolio that performs the worst. As we can see in Table 11, the ranking of the portfolios is mostly robust across the different asset pricing models when we use the yield as the proxy for the return on bonds. The only difference can be seen in the ranking of portfolios Z_6 and Z_{10}. In the FF3FM and the C4FM, the pure green bond portfolio, Z_6, has rank eight, whereas it is ranked as number seven in the other three models. Portfolio Z_6 thus switches rankings with the pure bond portfolio Z_{10}, which is assigned rank seven in the FF3FM and the C4FM, and rank eight in all the other models. The best performing portfolio, regardless of the employed asset pricing model, is portfolio Z_2, followed by portfolio Z_5. Worst performing is the pure stocks portfolio, Z_8, which actually yields negative annual excess returns and is thus unprofitable for investors, followed by the pure conventional bonds portfolio, Z_7. In the case when we employ bond price changes as the proxy for the returns on bonds, the pure bond portfolios perform the best and portfolio Z_5 performs the worst.

Table 11: Summary of Results

Jensen's alpha for the ten portfolios given the regression results from applying the different asset pricing models. The values within the brackets show the ranking of the portfolios, where [1] is assigned to the best performing portfolio. The higher the Jensen's alpha, the better the ranking.

Portfolio	CAPM	FF3FM	C4FM	FF5FM	6FM	6FMPriceChanges
Z_1	9.323 [5]	9.328 [5]	9.334 [5]	9.307 [5]	9.311 [5]	-0.109 [6]
Z_2	18.670 [1]	18.675 [1]	18.681 [1]	18.646 [1]	18.651 [1]	-0.114 [7]
Z_3	7.499 [6]	7.505 [6]	7.510 [6]	7.491 [6]	7.496 [6]	-0.108 [5]
Z_4	15.114 [4]	15.119 [4]	15.124 [4]	15.096 [4]	15.100 [4]	-0.116 [8]
Z_5	17.071 [2]	17.080 [2]	17.087 [2]	17.046 [2]	17.052 [2]	-0.160 [10]
Z_6	1.594 [7]	0.007 [8]	0.007 [8]	0.005 [7]	0.005 [7]	-0.033 [2]
Z_7	0.004 [9]	0.004 [9]	0.004 [9]	0.002 [9]	0.002 [9]	-0.019 [1]
Z_8	-0.067 [10]	-0.060 [10]	-0.056 [10]	-0.055 [10]	-0.051 [10]	-0.051 [4]
Z_9	16.873 [3]	16.878 [3]	16.886 [3]	16.800 [3]	16.807 [3]	-0.131 [9]
Z_{10}	0.012 [8]	0.012 [7]	0.012 [7]	0.008 [8]	0.008 [8]	-0.048 [3]

7 Robustness Tests

To evaluate the different portfolios in terms of investment performance, as in highest risk-adjusted returns, and to compare those evaluations with our previously shown results for Jensen's alpha in Table 11, different performance measures are applied. In all these performance measures the proxy for the return on bonds is the yield, except for the Atkinson index and the CE, which are computed twice.

7.1 Sharpe Ratio, Sortino Ratio and Treynor Ratio

The results for the first three performance measures, the Sharpe ratio (SR), the Sortino ratio and the Treynor ratio (TR), can be seen in Table 12. Just like the Sharpe ratio, the higher the Sortino- and the Treynor ratio are, the better is the performance of the portfolio. The values within the brackets represent the ranking of the portfolios given the specific performance measure. For example, [1] indicates the best performance, whereas [10] is assigned to the portfolio that performs the worst. In accordance with the results from the asset pricing models, looking at the Sharpe ratio, portfolio Z_2 performs the best followed by portfolio Z_5. Four portfolios, Z_2, Z_5, Z_9 and Z_4, outperform the benchmark portfolio, Z_1. Worst performing, in line with the results from the different asset pricing models, are the pure stock portfolio Z_8 followed by the pure conventional bond portfolio, Z_7.

The Sortino ratio gives identical results, and thus the same ranking of the portfolios, as the Sharpe ratio. Beta is not a performance measure itself. It corresponds to the coefficient values for the RPM factor in the CAPM model, seen in Table 5. Given that the values are the same, it can thus be assumed to be robust for interpretation. The beta for Z_1, the benchmark portfolio, is smaller than one, implying that the systematic risk is lower than the total risk of the market. All the portfolios have a beta less than one, implying that their systematic risks are all below the overall risk on the market. Intuitively, beta is closest to one for Z_8, the pure stock portfolio, indicating a strong correlation to the market. Comparing the beta of the pure stock portfolio to the betas of the other portfolios, which include different percentages of bonds, we can say that adding bonds to the portfolios will decrease the betas. Thus, having a diversified portfolio will decrease the volatility and hence the risk an investor is facing. Interesting is that the beta for Z_7, the pure conventional bonds portfolio, is less than zero, indicating an inverse relation to the market. For portfolio Z_{10}, with only green and conventional bonds and Z_6, the pure green bonds portfolio, the beta remains positive, but low. It is important to point out that Z_6, pure green bonds, Z_7, pure conventional bonds and Z_{10}, equal weights in green and conventional bonds, are rather fictive portfolios and are solely included as portfolios throughout our paper for comparison.

Looking at the Treynor ratio and comparing the performance of the different portfolios, Z_2, with an equal amount of green as well as conventional bonds and a high percentage of stocks, performs the best with the highest ratio. This is in line with all the previous results. For all the performance measures in Table 12, apart from the Treynor ratio, the second best performing portfolio in terms of risk-adjusted returns, is portfolio Z_5, just like in the regression results in Table 11. Identical to the regression results, the two pure bond portfolios Z_6 and Z_7, together with the pure stock portfolio, are the three worst performing portfolios. This indicates that these portfolios are the ones with the lowest risk-adjusted returns. It should be noted that the negative Treynor ratio value for portfolio Z_7 is in line with the result of our estimated CAPM, where the correlation between the annual excess return on portfolio Z_7 and the market is also negative. The results from the first three robustness checks show that through diversification of the portfolio an investor can obtain higher risk-adjusted returns. For an investor having a well diversified portfolio is essential, meaning that, in reality, the pure bond portfolios are highly unlikely to be invested in. Next, we compare the asset pricing models' results and aforementioned three ratios to additional performance measures to see if they yield a similar ranking of the portfolios.

Table 12: Sharpe ratio, Sortino ratio and Treynor ratio

The higher the Sharpe ratio, Sortino ratio, and Treynor ratio, the better performing is the portfolio. The values within the brackets show the ranking of the portfolios, where [1] is assigned to the best performing portfolio and [10] to the worst performing.

Portfolio	SR	Sortino	β	TR
Z_1	3.92291 [5]	6.38587 [5]	0.82648	0.04551 [5]
Z_2	6.43097 [1]	11.83792 [1]	0.81126	0.09244 [1]
Z_3	3.33531 [6]	4.85976 [6]	0.84468	0.03590 [6]
Z_4	5.11327 [4]	8.69587 [4]	0.81181	0.07486 [4]
Z_5	5.54505 [2]	9.73642 [2]	0.86336	0.07948 [3]
Z_6	0.11820 [7]	0.23625 [7]	0.19305	0.00444 [8]
Z_7	0.05773 [9]	0.10240 [9]	-0.01448	-0.03010 [10]
Z_8	0.01077 [10]	0.01311 [10]	0.91625	0.00009 [9]
Z_9	5.14761 [3]	9.61172 [3]	0.80126	0.08462 [2]
Z_{10}	0.09429 [8]	0.17845 [8]	0.01054	0.00475 [7]

7.2 Information Ratio and M^2-Measure

Table 13 depicts the results from the computed information ratio (IR) and the M^2-measure. Identical to the results shown in Table 12, four portfolios, Z_2, Z_5, Z_9 and Z_4, outperform the benchmark portfolio, Z_1. Similar to the results for the Sharpe- , the Sortino- and the Treynor ratio, Z_2, with equal weights in green respective conventional bonds and a high percentage in stocks, performs the best in the information ratio and the M^2-measure. The second best performing portfolio is once more portfolio Z_5, that has a lower percentage in stocks and a higher equal percentage in green bonds and conventional bonds. In line with the Sharpe- and the Sortino ratio, the worst performing is portfolio Z_8, the pure stock portfolio, differing from the results of the Treynor ratio, where portfolio Z_7 performs the worst. Overall, higher risk-adjusted returns can be obtained from adding not just green bonds but also conventional bonds to the portfolio, which again conforms with the hypothesis that diversification is profitable.

Table 13: Information Ratio and M^2-measure

The higher the information ratio and M^2-measure, the better performing is the portfolio. The values within the brackets show the ranking of the portfolios, where [1] is assigned to the best performing portfolio and [10] to the worst performing.

Portfolio	IR	M^2
Z_1	5.41895 [5]	0.03178 [5]
Z_2	7.73590 [1]	0.05207 [1]
Z_3	4.99460 [6]	0.02703 [6]
Z_4	6.09410 [3]	0.04141 [4]
Z_5	6.67449 [2]	0.04490 [2]
Z_6	0.09731 [7]	0.00099 [7]
Z_7	0.05150 [9]	0.00051 [9]
Z_8	-0.08430 [10]	0.00013 [10]
Z_9	5.87731 [4]	0.04169 [3]
Z_{10}	0.07758 [8]	0.00080 [8]

So far, the different computed performance measures, that we employ to test the robustness of the asset pricing models, present consistent results. The portfolio with the highest risk-adjusted returns is portfolio Z_2 which contains 60% stocks and equal weights in green- and conventional bonds.

7.3 Atkinson Index and Certainty Equivalent

In this Subsection, we will report and evaluate the results from applying the Atkinson index and the CE to our data sample. In doing this, we use two different proxies for the return of a bond: the yield and the price change of a bond. Using the yield of a bond as the proxy implicitly supports the assumption that an investor holds the bonds to maturity. This assumption can be dropped when we use the price changes of the bonds as the proxy for their returns.

In Table 14, we present the results[8] from applying the Atkinson index to our sample when we use the yield as a proxy for the bond returns. In line with Fischer and Lundtofte (2018), the parameter representing the relative risk aversion, γ[9], is varied between one and ten. The ranking of the different portfolios is included in brackets. The [1] indicates the lowest financial risk, whereas [10] is assigned to the portfolio with the highest financial risk. By looking at the different values for gamma, we can see that the ranking of the portfolios is independent of the relative risk aversion. However, the values for the Atkinson index increase along with the increased values of gamma. The more risk averse an investor is, the stronger the investor dislikes financial risk and the higher is the financial risk calculated by the Atkinson index.

8. For full results of the Atkinson index with the yield as the proxy for bond returns, see Table 24 in the Appendix.
9. Fischer and Lundtofte (2018) use ρ as the parameter for relative risk aversion, it is equal to using γ since $\gamma = \rho - 1$.

Table 14: Atkinson Index with Yields

The lower the Atkinson index, the lower the financial risk of the portfolio. The degree of risk aversion is varied by varying gamma, here $\gamma = 1$, $\gamma = 5$ and $\gamma = 10$. The values within the brackets show the ranking of the portfolios, where [1] is assigned to the portfolio with the lowest financial risk and [10] to the portfolio with the highest.

Portfolio	$\gamma = 1$	$\gamma = 5$	$\gamma = 10$
Z_1	0.000012 [5]	0.000060 [5]	0.000119 [5]
Z_2	0.000018 [7]	0.000091 [7]	0.000182 [7]
Z_3	0.000011 [4]	0.000053 [4]	0.000107 [4]
Z_4	0.000019 [8]	0.000094 [8]	0.000187 [8]
Z_5	0.000021 [9]	0.000102 [9]	0.000204 [9]
Z_6	0.000004 [2]	0.000018 [2]	0.000037 [2]
Z_7	0.000003 [1]	0.000015 [1]	0.000030 [1]
Z_8	0.000008 [3]	0.000041 [3]	0.000082 [3]
Z_9	0.000023 [10]	0.000116 [10]	0.000231 [10]
Z_{10}	0.000017 [6]	0.000086 [6]	0.000171 [6]

In addition, the CE rate of return can be applied as a performance measure (Fischer and Lundtofte 2018). The ranking[10] of the portfolios is in agreement with the CE, when we use the yield of a bond as the proxy for the returns on bonds, can be seen in Table 15. It is independent of the values assigned to gamma. The resulting ranking of the portfolios is mostly in line with the ranking of the portfolios according to our estimated asset pricing models and the previous robustness checks. So, even if higher statistical moments are considered, portfolio Z_2 performs the best, while the pure stock portfolio, Z_8, is the worst performing one. It is striking that portfolio Z_{10}, which consists of 50% green bonds and 50% conventional bonds, is the second best performing portfolio according to the CE. This portfolio was on rank eight in the asset pricing models and the more common performance measures.

Table 15: Certainty Equivalent with Yields

The higher the Certainty Equivalent, the better the performance of the portfolio. The degree of risk aversion is varied by varying gamma, here $\gamma = 1$, $\gamma = 5$ and $\gamma = 10$. The values within the brackets show the ranking of the portfolios, where [1] is assigned to the best performing portfolio and [10] to the worst performing.

Portfolio	$\gamma = 1$	$\gamma = 5$	$\gamma = 10$
Z_1	1.03836 [6]	1.03831 [6]	1.03825 [6]
Z_2	1.07793 [1]	1.07785 [1]	1.07776 [1]
Z_3	1.03082 [9]	1.03078 [9]	1.03072 [9]
Z_4	1.06271 [5]	1.06263 [5]	1.06253 [5]
Z_5	1.07109 [3]	1.07100 [3]	1.07089 [3]
Z_6	1.03605 [8]	1.03604 [8]	1.03606 [8]
Z_7	1.03762 [7]	1.03761 [7]	1.03759 [7]
Z_8	1.00011 [10]	1.00008 [10]	1.00004 [10]
Z_9	1.07022 [4]	1.07012 [4]	1.07000 [4]
Z_{10}	1.07332 [2]	1.07325 [2]	1.07316 [2]

10. Full results for the CE with the yield as the proxy for bond returns can be found in Table 25 in the Appendix.

Next, we will assess whether using the price changes of a bond as a proxy for the returns will generate results that differ from our previously estimated results. When using the price changes of the bonds, we can drop the assumption that an investor holds the bond to maturity.

Even though the standard deviations of the pure bond portfolios increase when we implement the bond price changes as the proxy for bond returns[11], the results[12], found in Table 16, show that the financial risk is lowest for the pure conventional bond portfolio, Z_7, followed by the pure green bond portfolio, Z_6. The results for these two portfolios are the only ones similar to the previous Atkinson index results. In addition, the portfolio with the highest financial risk is now portfolio Z_5, whereas it was portfolio Z_9 previously. The ranking of the portfolios remains independent of the values assigned to gamma.

Table 16: Atkinson Index with Prices

The lower the Atkinson index, the lower the financial risk of the portfolio. The degree of risk aversion is varied by varying gamma, here $\gamma = 1$, $\gamma = 5$ and $\gamma = 10$. The values within the brackets show the ranking of the portfolios, where [1] is assigned to the portfolio with the lowest financial risk and [10] to the portfolio with the highest.

Portfolio	$\gamma = 1$	$\gamma = 5$	$\gamma = 10$
Z_1	0.000016643 [9]	0.000083625 [9]	0.000168347 [9]
Z_2	0.000016166 [8]	0.000081226 [8]	0.000163511 [8]
Z_3	0.000015813 [7]	0.000079429 [7]	0.000159832 [7]
Z_4	0.000015644 [6]	0.000078571 [6]	0.000158078 [6]
Z_5	0.000024422 [10]	0.000122695 [10]	0.000246972 [10]
Z_6	0.000000174 [2]	0.000000871 [2]	0.000001741 [2]
Z_7	0.000000173 [1]	0.000000864 [1]	0.000001728 [1]
Z_8	0.000008113 [4]	0.000040722 [4]	0.000081863 [4]
Z_9	0.000010681 [5]	0.000053608 [5]	0.000107737 [5]
Z_{10}	0.000000740 [3]	0.000003698 [3]	0.000007394 [3]

The results[13] from applying the CE on the portfolio returns that are proxied by the price changes of the bonds can be seen in Table 17. In general, we can conclude that the ranking of the portfolios according to the CE is not robust to the type of proxy used in the analysis. In fact, the two estimations give vastly contradicting results. While the CE with the yield as the proxy ranks the pure stock portfolio, Z_8, on the last rank, the CE with the price changes as the proxy ranks it on the first place. The pure bond portfolios, Z_6 and Z_7, are ranked eighth and seventh, respectively, in both CE estimations when gamma is one. Yet, in the second estimation of the CE, the rankings of the pure bond portfolios improves with an increase in gamma. So, when the investor becomes more risk averse, the pure bond portfolios receive a better ranking. This is in line with the very low variation of the bond portfolios reported in Table 4. The most profound change in the ranking is linked to the earlier mentioned pure bond portfolios as well as portfolio Z_5. While the fifth portfolio has a rank of six when gamma is equal to one, its ranking gradually declines and when gamma is equal to ten Z_5 is ranked last.

11. See Descriptive Statistics in Table 4.
12. For full results for the Atkinson index with the price changes as a proxy for bond returns, see Table 26 in the Appendix.
13. For full results for the CE with price changes as the proxy for bond returns, see Table 27 in the Appendix.

The only portfolios that remain independent of the values assigned to gamma are the less diversified portfolios with a large share in stocks, Z_1, Z_3 and Z_8. Also, portfolio Z_4 is placed on rank five in both estimations. The other portfolios change their ranks, some with quite drastic alterations in the rankings.

Table 17: Certainty Equivalent with Prices

The higher the Certainty Equivalent, the better the performance of the portfolio. The degree of risk aversion is varied by varying gamma, here $\gamma = 1$, $\gamma = 5$ and $\gamma = 10$. The values within the brackets show the ranking of the portfolios, where [1] is assigned to the best performing portfolio and [10] to the worst performing.

Portfolio	$\gamma = 1$	$\gamma = 5$	$\gamma = 10$
Z_1	1.000028 [3]	0.999961 [3]	0.999876 [3]
Z_2	1.000013 [4]	0.999948 [4]	0.999865 [6]
Z_3	1.000051 [2]	0.999987 [2]	0.999907 [2]
Z_4	0.999976 [5]	0.999913 [5]	0.999834 [7]
Z_5	0.999941 [6]	0.999843 [8]	0.999719 [10]
Z_6	0.999867 [8]	0.999867 [7]	0.999866 [5]
Z_7	0.999874 [7]	0.999873 [6]	0.999872 [4]
Z_8	1.000111 [1]	1.000079 [1]	1.000038 [1]
Z_9	0.999865 [9]	0.999822 [9]	0.999768 [8]
Z_{10}	0.999767 [10]	0.999764 [10]	0.999761 [9]

There are only a few aspects that the two estimations of the Atkinson indexes for both proxies agree on. One is the low financial risk of the pure bond portfolios, Z_6 and Z_7. Another one is that both Atkinson measures assign high financial risk to portfolio Z_5. The ranking in line with the CE differs substantially and thus it is dependent on the proxy used for the bond returns. While the ranking changes with gamma in the case when bond returns are proxied by the change in the bond prices, the ranking is independent of the investor's risk aversion when the yield is employed as the proxy. Overall, we can conclude that the assumption of whether an investor will hold a bond to maturity or not results in different rankings of the portfolios according to the Atkinson index and the CE.

8 Conclusion

In this Section, the general results of the paper, its limitations and suggestions for future research are presented.

8.1 General Results

In this study, we arrive at contradicting results for the profitability of including green bonds in a portfolio. The results greatly depend on the proxy used for the bond return, either the yield or the price changes of the bonds. While in previous research the yield is most commonly used as a proxy for bond returns, it is dependent on the assumption that the investor holds the bond to maturity.

When we use the yield as the proxy, we come to the conclusion that, for the time period between 12.05.2016-31.12.2018, adding green bonds to a portfolio can increase its risk-adjusted returns compared to the benchmark portfolio, which is set up in the traditional way with only stocks and conventional bonds. The portfolio that performs the best is portfolio Z_2, which consists of 60% stocks, 20% green bonds and 20% conventional bonds. However, investors should not forget the profitability of diversification. They would probably also benefit from investing in not just green bonds, conventional bonds and stocks but also other asset classes, such as commodities or real estate. When the yield is used as the proxy, the enhanced risk-adjusted returns that can be generated by adding green bonds to the portfolio are robust to changes in the asset pricing models and the performance measures. What is also worth mentioning in the asset pricing models, is the immense impact that the $TERM$ factor and the DEF factor have on the portfolios with a large share of bonds. This result is in line with the work of Fama and French (1993), who state that these two bond factors can explain the vast majority of the variation in bond returns. In addition, the SMB factor is insignificant through all of our models with the yield as a proxy. We assume that this is the case because we only include firms that are listed on the S&P 500 Index in our empirical models. Another interesting result is that, in the asset pricing models, the conventional bonds move in the opposite direction of the market, and can thus be used to hedge against the systematic risk. As a result, for the asset pricing models that implement the yield as the proxy for the bond returns, we can thus safely agree with Hamilton and Statman (1993) and say that it is possible to do well by doing good.

However, the results are not robust to the type of proxy used for the bond returns. The inclusion of green bonds in a portfolio does not lead to increased risk-adjusted returns, when we implement the price change of a bond as the proxy. Hence, it is only possible to generate positive risk-adjusted returns if we assume that the investor holds the portfolio to the maturity of the bonds. In addition, the ranking of the different portfolios differs from our previous results. According to the 6FM with price changes as the proxy, the pure bond portfolios, Z_6, Z_7 and Z_{10}, perform the best, while the former best performing portfolio, Z_2, takes rank seven. These results stay robust when applying the Atkinson index. However, the results change when applying the CE, showing that the pure stock portfolio, Z_8, is the best performing.

Taking into account that the previous literature favors the yield as a proxy for the returns on bonds, we prioritize our findings in the models where the yield was implemented and come to the conclusion that green bonds, in fact, are able to increase the risk-adjusted returns of the constructed portfolios.

8.2 Limitations

We have applied a various number of robustness tests and the results of our study, when yields are implemented as the proxy for bond returns, are robust to changes in the models and the performance measures. However, the results only confirm the profitability of adding green bonds to a portfolio of stocks and conventional bonds during the time period of 12.05.2016-31.12.2018. Hence, the study is definitely limited by the time period assessed. We strongly recommend future researchers to conduct this study again when more data is available on green bonds. In addition, we used the yields and the price changes as proxies for the returns of the two fixed income securities, green and conventional bonds. However, the exact accuracy of the proxies is open for discussion. The two proxies suggest contradictory results and their accuracy and validity should thus be investigated further. Moreover, we were not able to compute a liquidity risk factor for the market due to the limited time we had for conducting the thesis.

8.3 Future Research

A first suggestion for future researchers is computing a market liquidity risk factor and adding it to the models applied in our study. Also, the Pastor-Stambaugh liquidity factor, available on the CRSP database, could be used if monthly data on the risk-adjusted returns is applied. However, then the time period would have to be expanded. A longer time period would generally enhance the study's validity. In addition, more asset classes than equities and fixed income could be added to the portfolios. This could address whether a higher degree of diversification would alter the effect of green bond returns on the risk-adjusted returns of the portfolios. Another interesting modification would be to include stocks of firms with more diverse company sizes. Then, it could be assessed whether the sole implementation of large firms, that are listed on the S&P 500 Index, is responsible for the insignificance of the SMB factor. It could also be interesting for future researchers to include a portfolio with optimal weights computed with the Solver in Excel. Finally, due to our ambiguous results concerning the influence of the type of proxy used, the validity and accuracy of the implemented proxies for bond returns should be examined more closely.

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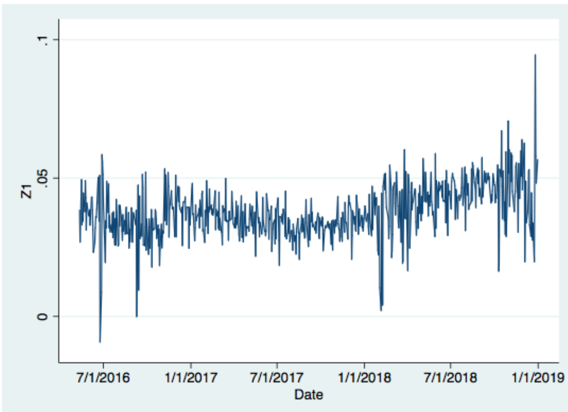
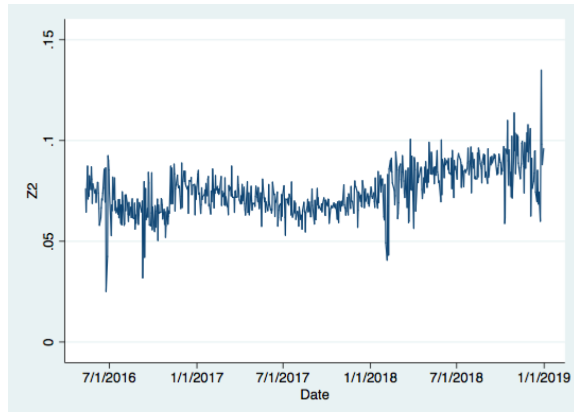
10 Appendix

Figure 2: Time Series Plot of Portfolio 1-6

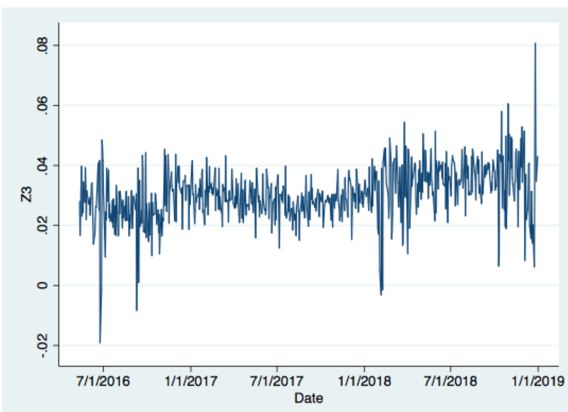
(a) Portfolio 1



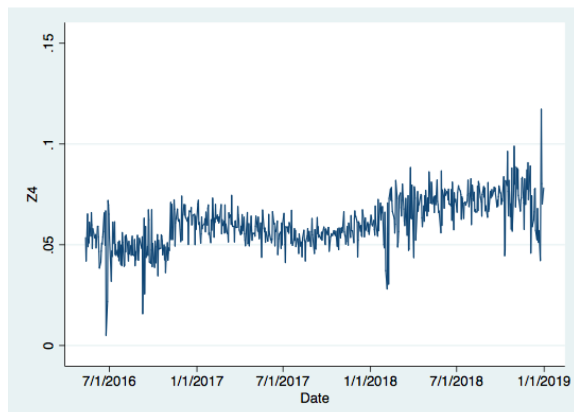
(b) Portfolio 2



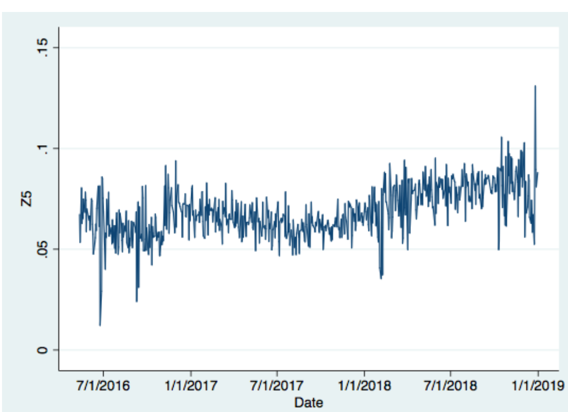
(c) Portfolio 3



(d) Portfolio 4



(e) Portfolio 5

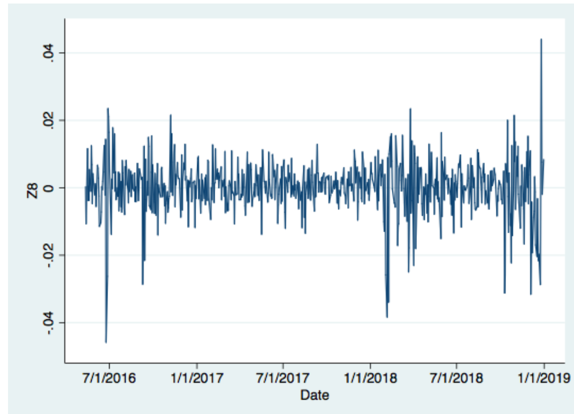


(f) Portfolio 6

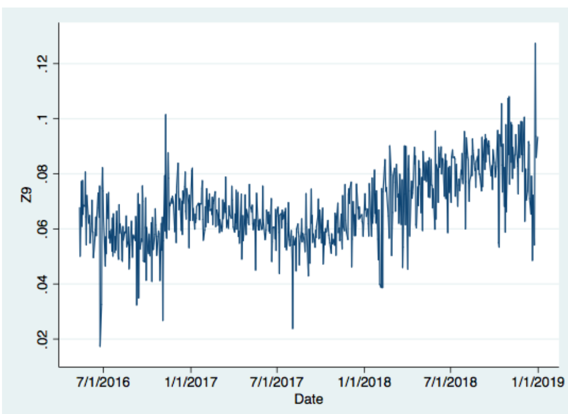
Figure 3: Time Series Plot of Portfolio 7-10

(a) Portfolio 7

(b) Portfolio 8



(c) Portfolio 9



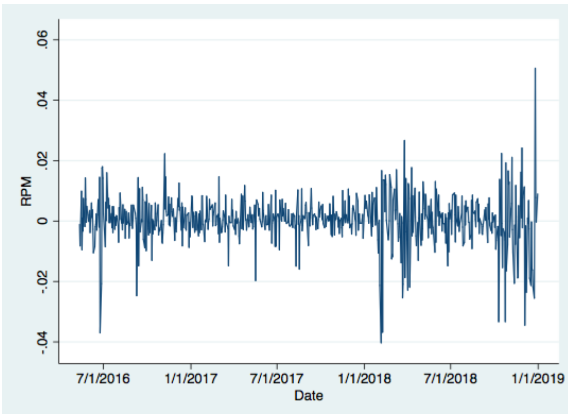
(d) Portfolio 10

Table 18: Augmented Dickey-Fuller Test for Unit Root

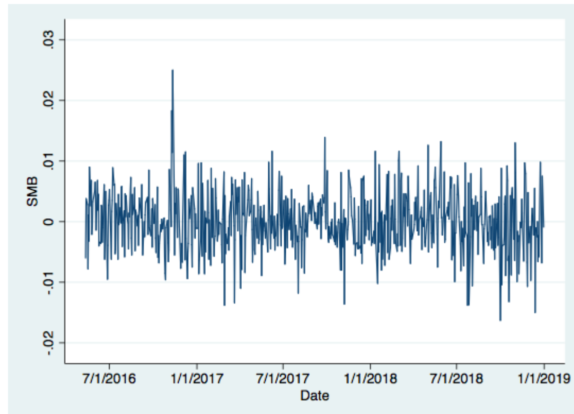
Variable		Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value	Fail to Reject H_0
Z_1	Z(t)	-17.203	-3.430	-2.860	-2.570	No
Z_2	Z(t)	-12.991	-3.430	-2.860	-2.570	No
Z_3	Z(t)	-18.593	-3.430	-2.860	-2.570	No
Z_4	Z(t)	-12.519	-3.430	-2.860	-2.570	No
Z_5	Z(t)	-14.478	-3.430	-2.860	-2.570	No
Z_6	Z(t)	-0.258	-3.430	-2.860	-2.570	Yes
Z_7	Z(t)	0.037	-3.430	-2.860	-2.570	Yes
Z_8	Z(t)	-22.704	-3.430	-2.860	-2.570	No
Z_9	Z(t)	-13.250	-3.430	-2.860	-2.570	No
Z_{10}	Z(t)	0.238	-3.430	-2.860	-2.570	Yes
RPM	Z(t)	-24.465	-3.430	-2.860	-2.570	No
SMB	Z(t)	-21.648	-3.430	-2.860	-2.570	No
HML	Z(t)	-22.464	-3.430	-2.860	-2.570	No
TERM	Z(t)	-1.495	-3.430	-2.860	-2.570	Yes
DEF	Z(t)	-1.316	-3.430	-2.860	-2.570	Yes
MOM	Z(t)	-25.677	-3.430	-2.860	-2.570	No

Figure 4: Time Series Plot of the Factors

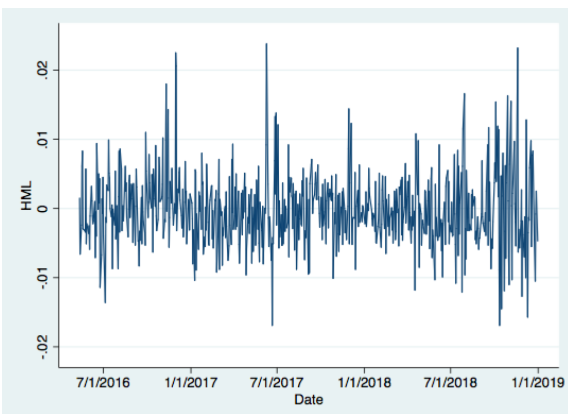
(a) RPM



(b) SMB



(c) HML



(d) TERM

(e) DEF

(f) MOM

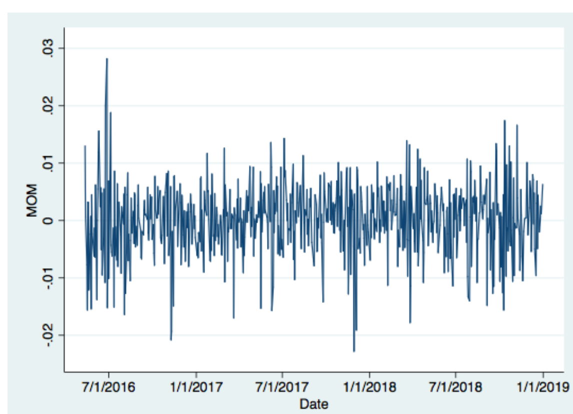


Table 19: Correlation Matrix of the Explanatory Variables

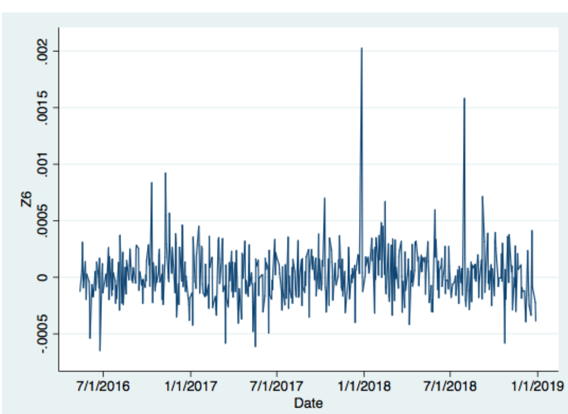
Variable	RPM	SMB	HML	$TERM$	DEF	MOM
RPM	1.0000					
SMB	0.2196	1.0000				
HML	-0.1351	-0.0511	1.0000			
$TERM$	0.2803	0.1513	0.3617	1.0000		
DEF	-0.2599	-0.0761	-0.1970	-0.4797	1.0000	
MOM	0.1877	-0.0520	-0.3319	-0.0323	0.0407	1.0000

Table 20: VIF Values of the Explanatory Variables

Model	Variable	VIF
CAPM	RPM	1.00
FF3FM	RPM	1.05
	SMB	1.03
	HML	1.02
C4FM	RPM	1.07
	SMB	1.05
	HML	1.17
	MOM	1.19
FF5FM	RPM	1.23
	SMB	1.07
	HML	1.25
	$TERM$	1.56
	DEF	1.34
6FM	RPM	1.26
	SMB	1.08
	HML	1.38
	$TERM$	1.57
	DEF	1.34
	MOM	1.17

Figure 5: Returns Over Time For Portfolio 6 and 10

(a) Portfolio 6's returns



(b) Portfolio 10's returns

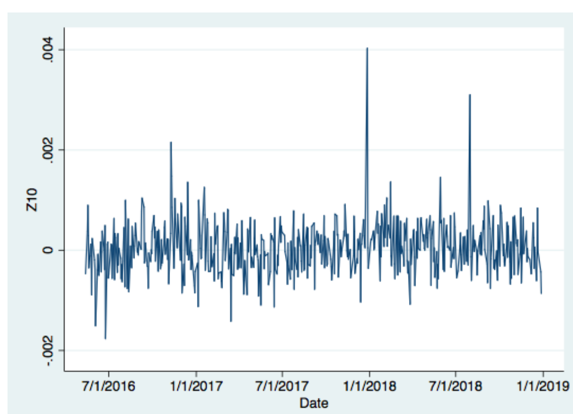


Table 21: Test for Normality in Residuals

Model	Portfolio	Kurtosis	Skewness	Normally Distributed
CAPM	Z_1	3.096826	0.6086153	Yes
	Z_2	2.498516	0.4999177	Yes
	Z_3	3.228896	0.3470619	Yes
	Z_4	2.441843	0.2617596	Yes
	Z_5	2.599686	0.3888018	Yes
	Z_6	2.249329	0.7983772	Yes
	Z_7	2.644501	0.9767845	Yes
	Z_8	4.349621	0.198529	Yes
	Z_9	2.928723	0.4867184	Yes
	Z_{10}	2.444364	0.8931229	Yes
FF3FM	Z_1	2.840356	0.534789	Yes
	Z_2	2.359288	0.4675161	Yes
	Z_3	2.863063	0.2355735	Yes
	Z_4	2.288058	0.2313091	Yes
	Z_5	2.314254	0.3565575	Yes
	Z_6	2.227684	0.7810784	Yes
	Z_7	2.608789	0.9568011	Yes
	Z_8	3.763551	-0.153074	Yes
	Z_9	2.847277	0.4461914	Yes
	Z_{10}	2.415009	0.8740033	Yes
C4FM	Z_1	2.816156	0.5750194	Yes
	Z_2	2.337235	0.4832924	Yes
	Z_3	2.85721	0.2316792	Yes
	Z_4	2.25065	0.2297727	Yes
	Z_5	2.300536	0.3867518	Yes
	Z_6	2.232962	0.7804992	Yes
	Z_7	2.609041	0.9564449	Yes
	Z_8	3.886687	-0.1018432	Yes
	Z_9	2.71028	0.4533849	Yes
	Z_{10}	2.416948	0.873212	Yes
FF5FM	Z_1	2.815506	0.4960643	Yes
	Z_2	2.349822	0.4180875	Yes
	Z_3	2.878686	0.1993515	Yes
	Z_4	2.356848	0.1836854	Yes
	Z_5	2.302651	0.292107	Yes
	Z_6	2.301238	0.7382011	Yes
	Z_7	2.612513	0.9053142	Yes
	Z_8	3.887454	-0.1409707	Yes
	Z_9	2.893837	0.3550696	Yes
	Z_{10}	2.465621	0.8291372	Yes
6FM	Z_1	2.77794	0.5537345	Yes
	Z_2	2.323273	0.4399398	Yes
	Z_3	2.789598	0.2191593	Yes
	Z_4	2.288877	0.1882343	Yes
	Z_5	2.273402	0.3297277	Yes
	Z_6	2.314365	0.7378819	Yes
	Z_7	2.610433	0.9037557	Yes
	Z_8	3.945277	-0.0461965	Yes
	Z_9	2.716187	0.3862545	Yes
	Z_{10}	2.46936	0.8272155	Yes

Table 22: Breusch-Pagan LM Test for Heteroskedasticity

Model	Portfolio	Chi2(1)	Prob > chi2	Fail to Reject H_0
CAPM	Z_1	22.23	0.0000	No
	Z_2	13.75	0.0002	No
	Z_3	40.79	0.0000	No
	Z_4	17.10	0.0000	No
	Z_5	21.96	0.0000	No
	Z_6	1.24	0.2649	Yes
	Z_7	0.74	0.3883	Yes
	Z_8	16.14	0.0001	No
	Z_9	12.97	0.0003	No
	Z_{10}	0.19	0.6654	Yes
FF3FM	Z_1	4.73	0.0296	No
	Z_2	4.44	0.0352	No
	Z_3	13.71	0.0002	No
	Z_4	7.47	0.0063	No
	Z_5	5.31	0.0213	No
	Z_6	7.23	0.0072	No
	Z_7	0.61	0.4342	Yes
	Z_8	4.78	0.0288	No
	Z_9	4.74	0.0294	No
	Z_{10}	4.66	0.0308	No
C4FM	Z_1	3.81	0.0510	Yes
	Z_2	3.07	0.0796	Yes
	Z_3	6.02	0.0141	No
	Z_4	3.59	0.0580	Yes
	Z_5	3.77	0.0523	Yes
	Z_6	5.02	0.0251	No
	Z_7	0.11	0.7360	Yes
	Z_8	1.30	0.2538	Yes
	Z_9	2.70	0.1003	Yes
	Z_{10}	3.85	0.0498	No
FF5FM	Z_1	12.03	0.0005	No
	Z_2	9.09	0.0026	No
	Z_3	19.81	0.0000	No
	Z_4	10.93	0.0009	No
	Z_5	9.54	0.0020	No
	Z_6	77.77	0.0000	No
	Z_7	3.03	0.0818	Yes
	Z_8	1.86	0.1732	Yes
	Z_9	8.91	0.0028	No
	Z_{10}	77.16	0.0000	No
6FM	Z_1	10.04	0.0015	No
	Z_2	7.25	0.0071	No
	Z_3	11.63	0.0006	No
	Z_4	7.34	0.0068	No
	Z_5	7.79	0.0052	No
	Z_6	69.41	0.0000	No
	Z_7	1.49	0.2222	Yes
	Z_8	0.03	0.8725	Yes
	Z_9	6.83	0.0090	No
	Z_{10}	70.10	0.0000	No

Table 23: Breusch-Godfrey LM Test for Autocorrelation

Model	Portfolio	Chi2	Prob > chi2	Fail to Reject H_0
CAPM	Z_1	200.133	0.0000	No
	Z_2	335.014	0.0000	No
	Z_3	132.385	0.0000	No
	Z_4	346.023	0.0000	No
	Z_5	248.168	0.0000	No
	Z_6	2.502	0.1137	Yes
	Z_7	9.159	0.0025	No
	Z_8	0.195	0.6589	Yes
	Z_9	249.491	0.0000	No
	Z_{10}	3.101	0.0782	Yes
FF3FM	Z_1	233.708	0.0000	No
	Z_2	363.161	0.0000	No
	Z_3	166.967	0.0000	No
	Z_4	374.141	0.0000	No
	Z_5	293.320	0.0000	No
	Z_6	1.529	0.2163	Yes
	Z_7	7.988	0.0047	No
	Z_8	0.112	0.7383	Yes
	Z_9	263.137	0.0000	No
	Z_{10}	2.133	0.1442	Yes
C4FM	Z_1	257.337	0.0000	No
	Z_2	381.481	0.0000	No
	Z_3	193.037	0.0000	No
	Z_4	392.449	0.0000	No
	Z_5	316.097	0.0000	No
	Z_6	1.404	0.2360	Yes
	Z_7	7.910	0.0049	No
	Z_8	0.013	0.9109	Yes
	Z_9	281.737	0.0000	No
	Z_{10}	1.882	0.1701	Yes
FF5FM	Z_1	137.104	0.0000	No
	Z_2	232.560	0.0000	No
	Z_3	92.479	0.0000	No
	Z_4	241.808	0.0000	No
	Z_5	185.649	0.0000	No
	Z_6	1.066	0.3018	Yes
	Z_7	5.315	0.0211	No
	Z_8	1.325	0.2497	Yes
	Z_9	169.144	0.0000	No
	Z_{10}	0.394	0.5302	Yes
6FM	Z_1	151.114	0.0000	No
	Z_2	243.717	0.0000	No
	Z_3	106.685	0.0000	No
	Z_4	251.769	0.0000	No
	Z_5	199.977	0.0000	No
	Z_6	1.191	0.2752	Yes
	Z_7	5.160	0.0231	No
	Z_8	1.869	0.1716	Yes
	Z_9	182.997	0.0000	No
	Z_{10}	0.524	0.4692	Yes

Table 24: Atkinson Index with Yields

Portfolio	$\gamma = 1$	$\gamma = 2$	$\gamma = 3$	$\gamma = 4$	$\gamma = 5$	$\gamma = 6$	$\gamma = 7$	$\gamma = 8$	$\gamma = 9$	$\gamma = 10$
Z_1	0.000012 [5]	0.000024 [5]	0.000036 [5]	0.000048 [5]	0.000060 [5]	0.000072 [5]	0.000083 [5]	0.000095 [5]	0.000107 [5]	0.000119 [5]
Z_2	0.000018 [7]	0.000037 [7]	0.000055 [7]	0.000073 [7]	0.000091 [7]	0.000110 [7]	0.000128 [7]	0.000146 [7]	0.000164 [7]	0.000182 [7]
Z_3	0.000011 [4]	0.000021 [4]	0.000032 [4]	0.000043 [4]	0.000053 [4]	0.000064 [4]	0.000075 [4]	0.000085 [4]	0.000096 [4]	0.000107 [4]
Z_4	0.000019 [8]	0.000038 [8]	0.000056 [8]	0.000075 [8]	0.000094 [8]	0.000112 [8]	0.000131 [8]	0.000150 [8]	0.000169 [8]	0.000187 [8]
Z_5	0.000021 [9]	0.000041 [9]	0.000061 [9]	0.000082 [9]	0.000102 [9]	0.000123 [9]	0.000143 [9]	0.000164 [9]	0.000184 [9]	0.000204 [9]
Z_6	0.000004 [2]	0.000007 [2]	0.000011 [2]	0.000015 [2]	0.000018 [2]	0.000022 [2]	0.000026 [2]	0.000029 [2]	0.000033 [2]	0.000037 [2]
Z_7	0.000003 [1]	0.000006 [1]	0.000009 [1]	0.000012 [1]	0.000015 [1]	0.000018 [1]	0.000021 [1]	0.000024 [1]	0.000027 [1]	0.000030 [1]
Z_8	0.000008 [3]	0.000016 [3]	0.000024 [3]	0.000032 [3]	0.000041 [3]	0.000049 [3]	0.000057 [3]	0.000065 [3]	0.000073 [3]	0.000082 [3]
Z_9	0.000023 [10]	0.000046 [10]	0.000070 [10]	0.000093 [10]	0.000116 [10]	0.000139 [10]	0.000162 [10]	0.000185 [10]	0.000208 [10]	0.000231 [10]
Z_{10}	0.000017 [6]	0.000035 [6]	0.000052 [6]	0.000069 [6]	0.000086 [6]	0.000103 [6]	0.000120 [6]	0.000137 [6]	0.000154 [6]	0.000171 [6]

Table 25: Certainty Equivalent with Yields

Portfolio	$\gamma=1$	$\gamma=2$	$\gamma=3$	$\gamma=4$	$\gamma=5$	$\gamma=6$	$\gamma=7$	$\gamma=8$	$\gamma=9$	$\gamma=10$
Z_1	1.03836 [6]	1.03835 [6]	1.03834[6]	1.03833 [6]	1.03831 [6]	1.03830 [6]	1.03829 [6]	1.03828 [6]	1.03826 [6]	1.03825 [6]
Z_2	1.07793 [1]	1.07791 [1]	1.07789 [1]	1.07787 [1]	1.07785 [1]	1.07783 [1]	1.07781 [1]	1.07779 [1]	1.07778 [1]	1.07776 [1]
Z_3	1.03082 [9]	1.03081 [9]	1.03080 [9]	1.03079 [9]	1.03078 [9]	1.03076 [9]	1.03075 [9]	1.03074 [9]	1.03073 [9]	1.03072 [9]
Z_4	1.06271 [5]	1.06269 [5]	1.06267 [5]	1.06265 [5]	1.06263 [5]	1.06261 [5]	1.06259 [5]	1.06257 [5]	1.06255 [5]	1.06253 [5]
Z_5	1.07109 [3]	1.07107 [3]	1.07105 [3]	1.07102 [3]	1.07100 [3]	1.07098 [3]	1.07096 [3]	1.07094 [3]	1.07091 [3]	1.07089 [3]
Z_6	1.03605 [8]	1.03605 [8]	1.03604 [8]	1.03604 [8]	1.03604 [8]	1.03603 [8]	1.03603 [8]	1.03602 [8]	1.03602 [8]	1.03606 [8]
Z_7	1.03762 [7]	1.03762 [7]	1.03761 [7]	1.03761 [7]	1.03761 [7]	1.03760 [7]	1.03760 [7]	1.03760 [7]	1.03760 [7]	1.03759 [7]
Z_8	1.00011 [10]	1.00010 [10]	1.00010 [10]	1.00009 [10]	1.00008 [10]	1.00007 [10]	1.00006 [10]	1.00005 [10]	1.00005 [10]	1.00004 [10]
Z_9	1.07022 [4]	1.07020 [4]	1.07017 [4]	1.07015 [4]	1.07012 [4]	1.07010 [4]	1.07008 [4]	1.07005 [4]	1.07003 [4]	1.07000 [4]
Z_{10}	1.07332 [2]	1.07331 [2]	1.07329 [2]	1.07327 [2]	1.07325 [2]	1.07323 [2]	1.07321 [2]	1.07320 [2]	1.07318 [2]	1.07316 [2]

Table 26: Atkinson Index with Prices

Portfolio	$\gamma = 1$	$\gamma = 2$	$\gamma = 3$	$\gamma = 4$	$\gamma = 5$	$\gamma = 6$	$\gamma = 7$	$\gamma = 8$	$\gamma = 9$	$\gamma = 10$
Z_1	0.000016643 [9]	0.000033325 [9]	0.000050049 [9]	0.000066816 [9]	0.000083625 [9]	0.000100478 [9]	0.000117375 [9]	0.000134319 [9]	0.000151309 [9]	0.000168347 [9]
Z_2	0.000016166 [8]	0.000032370 [8]	0.000048615 [8]	0.000064900 [8]	0.000081226 [8]	0.000097595 [8]	0.000114007 [8]	0.000130464 [8]	0.000146964 [8]	0.000163511 [8]
Z_3	0.000015813 [7]	0.000031661 [7]	0.000047546 [7]	0.000063468 [7]	0.000079429 [7]	0.000095428 [7]	0.000111467 [7]	0.000127547 [7]	0.000143668 [7]	0.000159832 [7]
Z_4	0.000015644 [6]	0.000031322 [6]	0.000047035 [6]	0.000062785 [6]	0.000078571 [6]	0.000094395 [6]	0.000110256 [6]	0.000126157 [6]	0.000142098 [6]	0.000158078 [6]
Z_5	0.000024422 [10]	0.000048901 [10]	0.000073438 [10]	0.000098036 [10]	0.000122695 [10]	0.000147418 [10]	0.000172205 [10]	0.000197059 [10]	0.000221980 [10]	0.000246972 [10]
Z_6	0.000000174 [2]	0.000000348 [2]	0.000000522 [2]	0.000000697 [2]	0.000000871 [2]	0.000001045 [2]	0.000001219 [2]	0.000001393 [2]	0.000001567 [2]	0.000001741 [2]
Z_7	0.000000173 [1]	0.000000345 [1]	0.000000518 [1]	0.000000691 [1]	0.000000864 [1]	0.000001037 [1]	0.000001209 [1]	0.000001382 [1]	0.000001555 [1]	0.000001728 [1]
Z_8	0.000008113 [4]	0.000016241 [4]	0.000024385 [4]	0.000032545 [4]	0.000040722 [4]	0.000048915 [4]	0.000057126 [4]	0.000065354 [4]	0.000073599 [4]	0.000081863 [4]
Z_9	0.000010681 [5]	0.000021383 [5]	0.000032104 [5]	0.000042846 [5]	0.000053608 [5]	0.000064391 [5]	0.000075196 [5]	0.000086021 [5]	0.000096868 [5]	0.000107737 [5]
Z_{10}	0.000000740 [3]	0.000001480 [3]	0.000002219 [3]	0.000002959 [3]	0.000003698 [3]	0.000004438 [3]	0.000005177 [3]	0.000005916 [3]	0.000006655 [3]	0.000007394 [3]

Table 27: Certainty Equivalent with Prices

Portfolio	$\gamma = 1$	$\gamma = 2$	$\gamma = 3$	$\gamma = 4$	$\gamma = 5$	$\gamma = 6$	$\gamma = 7$	$\gamma = 8$	$\gamma = 9$	$\gamma = 10$
Z_1	1.000028 [3]	1.000011 [3]	0.999995 [3]	0.999978 [3]	0.999961 [3]	0.999944 [3]	0.999927 [3]	0.999910 [3]	0.999893 [3]	0.999876 [3]
Z_2	1.000013 [4]	0.999997 [4]	0.999980 [4]	0.999964 [4]	0.999948 [4]	0.999931 [4]	0.999915 [4]	0.999898 [4]	0.999882 [4]	0.999865 [6]
Z_3	1.000051 [2]	1.000035 [2]	1.000019 [2]	1.000003 [2]	0.999987 [2]	0.999971 [2]	0.999955 [2]	0.999939 [2]	0.999923 [2]	0.999907 [2]
Z_4	0.999976 [5]	0.999961 [5]	0.999945 [5]	0.999929 [5]	0.999913 [5]	0.999897 [5]	0.999882 [5]	0.999866 [7]	0.999850 [7]	0.999834 [7]
Z_5	0.999941 [6]	0.999917 [6]	0.999892 [6]	0.999868 [7]	0.999843 [8]	0.999818 [8]	0.999794 [9]	0.999769 [9]	0.999744 [10]	0.999719 [10]
Z_6	0.999867 [8]	0.999867 [8]	0.999867 [8]	0.999867 [8]	0.999867 [7]	0.999867 [7]	0.999866 [7]	0.999866 [6]	0.999866 [6]	0.999866 [5]
Z_7	0.999874 [7]	0.999874 [7]	0.999874 [7]	0.999873 [6]	0.999873 [6]	0.999873 [6]	0.999873 [6]	0.999873 [5]	0.999873 [5]	0.999872 [4]
Z_8	1.000111 [1]	1.000103 [1]	1.000095 [1]	1.000087 [1]	1.000079 [1]	1.000070 [1]	1.000062 [1]	1.000054 [1]	1.000046 [1]	1.000038 [1]
Z_9	0.999865 [9]	0.999854 [9]	0.999843 [9]	0.999833 [9]	0.999822 [9]	0.999811 [9]	0.999800 [8]	0.999789 [8]	0.999779 [8]	0.999768 [8]
Z_{10}	0.999767 [10]	0.999767 [10]	0.999766 [10]	0.999765 [10]	0.999764 [10]	0.999764 [10]	0.999763 [10]	0.999762 [10]	0.999761 [9]	0.999761 [9]