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Factor Investing in the Green Bond Market

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Abstract

This paper extends upon factor investing in the bond market by exploiting seven investment strategies in the green bond market. The considered factors are based on measures of Carry, Value, Momentum and Quality. It is found that the individual factor portfolios, except Value, neither substantially outperform the risk free rate nor exhibit abnormal returns. Moreover, there is evidence that long-only portfolios compare favourably with long-short portfolios in terms of Sharpe ratios. Finally, it is found that diversifying across the individual factor portfolios in a sophisticated way substantially improves Sharpe ratio.

Keywords— Factor Investing, Green Bonds, Sustainability

Contents

1 Introduction

Green bonds, also known as climate bonds, are a relatively new phenomenon in fixed-income markets. Bonds can be labelled as green when their proceeds are used to finance environmental or climate-friendly projects. A voluntary guideline to align rules on the greenness of bonds and promote issuer's disclosure and transparency are the Green Bond Principles (GBP), launched by the International Capital Market Association (ICMA) in 2014.

In this paper, I apply the idea of factor investing to the green bond market. To do so, I follow upon the existing literature on factor investing in the conventional bond market. More specifically, I construct factors based on characteristics of bond returns: the existence of a term premium (Carry), the relationship between credit spread and credit risk (Value), return persistence (Momentum) and high risk-adjusted returns of safe bonds (Quality). I rank the signals that are generated by these factors to construct portfolios. The remainder of the research is twofold. Firstly, I investigate the profitability of the individual factor portfolios. I do this by analyzing several statistics of the excess returns. Moreover, I elaborate on the abnormal returns by examining the significance of the CAPM alpha. Because shorting bonds is practically difficult, I consider the Sharpe ratios of long-only portfolios as well.

In the second part of the research, I exploit potential diversification benefits by combining the individual factor portfolios. Specifically, I allocate the weights that correspond to the maximal Sharpe ratio on the Markowitz mean-variance efficient frontier. I choose for this way of portfolio optimization, because Sharpe ratio is a straightforward and widely-used statistic to assess portfolio performance. By using an expanding window to estimate the conditional moments of the return distribution of the individual factor portfolios, this generates a dynamic allocation strategy. In the analysis, I evaluate the Sharpe ratio of the optimal portfolio against those of the individual portfolios. Moreover, I elaborate on the evolution of the weights over time. This provides valuable insight in the efficiency of the estimators of the sample moments. Finally, I compare the returns of the optimal portfolio against the naive diversified portfolio to examine the added value of using a sophisticated way of portfolio combination.

Therefore, the overarching direction of the research is captured in the following research questions:

- Does factor investing in the green bond market exhibit significant alpha?
- To what extent does combining factor portfolios enhance the overall performance of the investor's green bond portfolio?

Though green bonds accounted for less than 0.1% of the bond market in 2016, the market is growing rapidly with strong demand from investors. In 2007, the European Investment Bank (EIB) was the first to raise a €600M Climate Awareness bond, focused on renewable energy and energy efficiency. Since then, the outstanding amount of green bonds has grown exponentially: between 2012 and 2018, the market has grown from $2.6B to $167.3B, corresponding with an annual growth rate of more than 100%.

Despite the thriving development in the green bond market, only a few studies have been done to the financial performance of green bonds. I refer to a number of papers in recent literature. Zerbib (2017, 2019) uses a matching pairs method between green and conventional bonds from the same issuer and finds that the average green bond premium is significantly negative. Moreover, Karpf and Mandel (2017) obtain a similar outcome for the US municipal bond market, but also find that this negative premium can be largely explained by properties of the respective issuing entity and the bond. Flammer (2018) studies the impact of green bond issuance on long run stock performance of the issuing entity and obtains confirmatory results. Finally, Reboredo (2018) studies the co-movement between the green bond market and other financial markets on a global level and finds that the green bond market weakly co-moves with stock and energy commodity markets, but couples with corporate and treasury markets.

The rapid expansion of the green bond market in conjunction with current academic research on the existence of a green bond premium and the co-movement of the green bond market with other financial markets makes it relevant and interesting for both academics and practitioners to empirically investigate the success of investment strategies in the green bond market. To the best of my knowledge, there are currently no papers that address this. Moreover, the choice for studying investment strategies in the green bond market, apart from the conventional or brown bond market, can be substantiated in other ways. First of all, investors can add green bond portfolios to their existing bond portfolio for diversification reasons. In addition, comparing similar green bond and conventional bond portfolios provides academics valuable insight in the existence of a green bond premium on a portfolio level, as opposed to the individual bond level.

The main findings of the research are as follows. First of all, most individual portfolios do not outperform the risk free rate in the long run. Only the value portfolio is a clear exception. Portfolios of risky bonds should at least outperform the risk free rate in terms of returns, in other words carry a positive premium. The CAPM delivers a similar conclusion: only the value portfolio generates abnormal returns. As a separate green bond high-yield index is not available in the market, it is not yet possible to examine the existence of abnormal returns in the multi-factor model that adds the term and default factor to the CAPM. Next, it is found that long-only portfolios do not necessarily harm performance in terms of Sharpe ratio. Especially, the long-only low-volatility portfolio delivers an excessive high Sharpe ratio, compared to its long-short counterpart. Finally, combining the individual factor portfolios with a holding period of six months clearly improves the overall portfolio performance. While, the highest Sharpe ratio across the individual long-short portfolios equals only 1.08, the optimal Markowitz mean-variance portfolio generates a Sharpe ratio of 1.39.

The remainder of the paper is organized as follows. In Section 2, the existing literature on factor investing in the conventional bond market is reviewed. In Section 3, I elaborate on the applied criteria to construct the data set and discuss its statistics. Section 4 contains the methodology on the construction of the factors and allocation of the weights. In Section 5, I discuss the empirical results. The paper ends with Section 6 which summarizes the results in a brief conclusion.

2 Literature framework

In this section, I briefly review the existing literature on risk factors and factor investing that has been widely documented for equities, but recently has found its applications in other assets classes as well. First, I elaborate on the literature concerning risk factors in the bond market. Next, I discuss a number of papers that make use of these factors to develop investment strategies.

The literature on risk factors of financial securities originates in the CAPM, developed by Sharpe (1964), which has been extended to the five factor model of Fama and French (2015). As of today, a vast number of risk factors have been proposed in the literature, also referred to as the factor zoo. Feng et al. (2017) develop a factor model selection tool, which they apply to 99 equity risk factors. These studies have been extensively extrapolated to the bond (both corporate and governmental) market. Among the best known bond factors are carry, momentum, value and quality or low risk. Example studies include Koijen et al. (2018) for carry, Pospisil and Zhang (2010), Jostova et al. (2013) and Asness, Moskowitz, and Pedersen (2013) for momentum, L'Hoir and Boulhabel (2010) and Correia et al. (2012) for value and Frazzini and Pedersen (2014) and De Carvalho et al. (2014) for quality.

Following the literature on risk factors in the bond market, several studies have been done to the empirical success of factor portfolios that attempt to realize returns which cannot be explained by these risk factors. This has been investigated for both the corporate and governmental bond market. Beekhuizen et al. (2016) study carry investment strategies in the governmental bond market and find that curve carry exhibits returns that cannot be explained by other factors. Moreover, Israel et al. (2017) study carry, defensive, momentum and value in the US bond market and conclude that these factors explain a substantial portion of the cross-sectional variation in corporate bond returns. In addition, they find that their results are robust to portfolio construction choice and macroeconomic effects.

In line with that, Brooks et al. (2018) study the returns of these factor portfolios in the international governmental and corporate bond market. Their findings are similar to Israel et al. (2017). Another example is the study of Houweling and Van Zundert (2017), who examine the performance of size, low-risk, value and momentum portfolios using only bond characteristics, contrary to firm characteristics, accounting data or equity market information. They find that bond factor portfolios deliver economically meaningful and statistically significant risk-adjusted returns. Finally, Bai et al. (2019) investigate the cross-sectional determinants of corporate bond returns and find that downside risk is the strongest predictor of future bond returns.

3 Data

In order to construct a suitable database of green bonds, I extract data from the Bloomberg Fixed Income database. Initially, all active and matured corporate and governmental bonds whose use of proceeds comply with *"Green Bond/Loan"*, are selected. Bloomberg's Industry Classification System (BICS) qualifies bonds as either *"Goverment"* or *"Corporate"*, where the latter includes all bonds that are issued by private firms or institutions. This includes bonds issued by development banks, supranational entities, financial institutions and agencies. These bonds bear default and liquidity risk, though probably negligible, as opposed to governmental bonds. I choose not to analyse the governmental and corporate market separately, because the size of the current green bond market is too small to split it. Still, it would be better to analyse these separately. The resulting dataset consist of 2,167 bonds.

Consequently to the first sort, three technical restrictions are applied: the remaining bonds should carry an International Securities Identification Number (ISIN) and a known issueing currency and should be supplied with either an active or withdrawn rating from Moody's (*2,076 bonds*). Moreover, all bonds that possess Junior specifications are excluded. Junior bonds are bonds that carry lower priority for repayment than regular, senior bonds in case of default. Including Junior bonds would harm the cross sectional comparison of yields between bonds and make the portfolio prone to losses, following the risk from potential defaults. The remaining bonds qualify as "1st Lien", "Senior Unsecured", "Senior Secured" or "Senior Non-Preferred", "Senior Subordinated", "Secured" or "Unsecured" (*2,058 bonds*).

For convenience, I then exclude all bonds that do not pay certain fixed coupons (*1,645 bonds*) and bullet payment of principal at maturity (*1,377 bonds*). Including bonds with floating and/or uncertain coupons does not contribute to the purpose of the research, because these bonds do not carry a term premium, in which I am particularly interested. Moreover, it complicates the calculation of bonds returns, given the challenge in tracking the floating coupons with a time-varying benchmark, which is usually the Euribor. Finally, all bonds that are extremely illiquid or depict incredible trading data are erased (*993 bonds*).

For each of the remaining 993 bonds, I obtain a number of general statistics, among which the issuer name and ticker, the country where the issuer's headquarter is located, the currency of issuance, the issued amount in USD, the annual coupon rate, the issue date, the maturity date and the credit rating, as assigned by Moody's. Moreover, I obtain the returns of the Barclays Green Bond Aggregate Index, which I use as the market portfolio in the CAPM. A sample of the first and last 25 bonds in the data set is provided in Appendix A. To illustrate the growth of the market, the cumulative issued amount in USD for the green bonds in the dataset is shown in Figure 1. Clearly, the majority of all green bonds are issued in euros or dollars. As of today, most green bonds are issued in euros, giving rise to the idea that climate awareness is living mostly in the eurozone. Interesting to note is the break on 31 January 2017, when the French government issued a €19bn green bond, which is by far the largest ever.

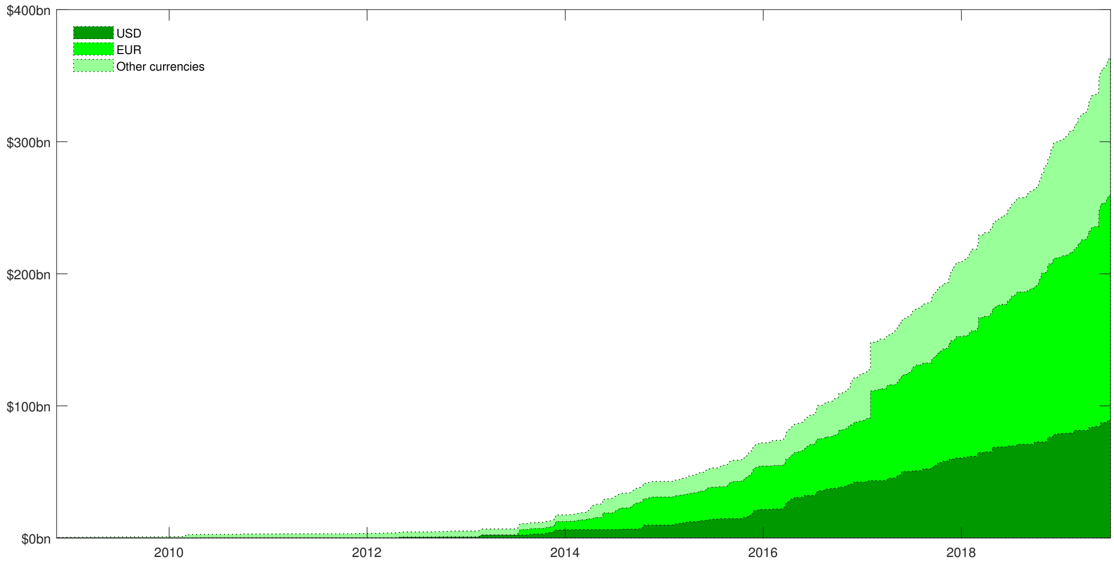


Figure 1: Cumulative issued amount of green bonds in the data set

In order to exploit interesting investment strategies in the green bond market, I extract trading data to develop these strategies and back test them. Though the first green bond was already issued in 2007, I collect weekly bond data from 3 January 2014 up to and including 9 August 2019. This choice can be argued by the illiquidy of the green bond market prior to 2014. In addition, it can be seen that in the early stage of the market, virtually all green bonds were issued by governments or supranational banks, like the European Investment Bank, the European Bank for Reconstruction and Development, the Asian Development Bank, the African Development Bank and the International Bank for Reconstruction and Development. Including this data will likely bias the outcome of the research.

For each bond in each week, I obtain the mid price in relation to its par value, where a price of 100 indicates that a bond trades on par. Moreover, Bloomberg provides the mid yield to maturity and credit spread for each bond in every week. The credit spread I use, is the G-spread or nominal spread, which is the difference between yield on Treasury bonds and yield on green bonds of the same maturity. This indicates that the credit spread on green bonds might not only reflect compensation for credit risk, but also carry a premium for the 'greenness' of the bonds. Table 1 depicts the summary statistics of the entire bond data set.

Table 1: Summary statistics of the entire data set, 3 January 2014 - 9 August 2019

	Mean	5%	25%	50%	75%	95%
Annualized excess return (%)	1.44	-52.20	-12.50	0.03	13.51	50.20
Yield to maturity (%)	3.39	0.05	1.01	2.86	5.41	9,53
Time to maturity (years)	5.84	0.93	2.80	4.27	7.54	12.94
Credit rating	3.90	1	1	3	6	10
Credit spread (bps)	127	-38	31	73	164	410

Note: The annualized excess return is the weekly bond return over the risk free rate, multiplied by 52. The yield to maturity is the annual return on the bond under the assumption that it is held until maturity. The time to maturity is the number of remaining years between today and the bond's expiration date. The credit rating is the Moody's credit rating, converted to a numerical scale: Aaa = 1, Aa1 = 2, ..., C = 21. The credit spread is the bond's G-spread (nominal spread) in basis points, which is the difference between the yield on Treasury bonds and green bonds of same maturity. Each statistic is first computed cross-sectionally and then averaged over time.

It can be observed that green bonds pay on average 3.39% yield. The means of the bond yields and returns are higher than the median. Moreover, the average remaining time to maturity is 5.84 years, which is also slightly higher than the median (4.27 years). Finally, it can be noted that the bonds are rated between "Aa2" and "Aa3" on average, indicating that it is relatively safe to invest in green bonds.

Table 2 displays the summary statistics for each bond credit rating. First of all, it can be observed that the bonds carry varying positive and negative average returns per rating. There is no clear pattern between the average returns and the credit rating. The same holds for the volatility. Though a clear positive relationship between volatility and credit rating would expected, it should be noted that the estimates might be slightly biased. This is due to the low number of observed bonds per rating, especially the Non-Investment Grade bonds. Moverover, the skewness is mostly positive, sometimes slightly negative and the kurtosis is on average around 3.00 and is clearly lower for low-rated bonds. The latter can possibly be attributed to the illiquidity of low rated bonds. In addition, all minimum and maximum returns are negative and positive respectively. Finally, the vast majority of green bonds carries an Investment Grade rating (96.4%). Actually, almost half of the bonds (44.8%) of the bonds is "Aaa" rated. Non-Investment Grade or high yield bonds are rarely issued, which is why I chose not to perform the analysis for these markets separately. For completeness, Appendix B contains the correlation matrix between the returns per rating.

Table 2: Summary statistics of the returns for each credit rating, 3 January 2014 - 9 August 2019

Grade	Rating	Return	Volatility	Skewness	Kurtosis	Min	Max	Obs
Investment Grade	Aaa	0.65%	4.46%	0.02	14.51	-9.88%	12.09%	173
	Aa1	1.09%	2.88%	0.20	4.03	-2.58%	2.56%	15
	Aa2	2.62%	4.49%	0.14	3.98	-5.15%	5.38%	33
	Aa3	0.01%	2.41%	0.00	4.79	-2.50%	1.80%	20
	A1	-0.61%	1.90%	0.10	5.65	-3.61%	1.91%	35
	A2	3.10%	2.81%	0.23	3.91	-2.20%	3.72%	17
	A3	0.42%	3.27%	0.29	5.23	-5.60%	3.58%	19
	Baa1	2.04%	3.76%	0.10	4.38	-4.65%	5.47%	27
	Baa2	1.92%	2.93%	-0.12	3.58	-2.81%	1.83%	22
	Baa3	-0.33%	3.73%	-0.07	4.82	-8.54%	4.11%	11
Non-Investment Grade	Ba1	–	–	–	–	–	–	0
	Ba2	0.16%	4.68%	0.06	2.34	-4.47%	2.18%	5
	Ba3	–	–	–	–	–	–	0
	B1	-0.56%	4.17%	0.06	2.34	-2.18%	4.33%	2
	B2	–	–	–	–	–	–	0
	B3	-1.96%	6.77%	0.19	4.88	-2.67%	10.07%	6
	Caa1	–	–	–	–	–	–	0
	Caa2	1.82%	4.61%	0.09	5.19	-5.36%	15.03%	1
	Caa3	–	–	–	–	–	–	0
	Ca	–	–	–	–	–	–	0
	C	–	–	–	–	–	–	0

Note: This table depicts the summary statistics of the excess returns on the green bonds for each available rating, assigned by Moody's. The return is the average annualized excess return, which is the return over the risk free rate. The volatility is the annualized standard deviation of the excess return. Skewness and kurtosis are the alternative unbiased estimates for the population skewness and kurtosis. Min and max correspond with the minimum and maximum excess return respectively. Obs is the number of bonds for each rating. Each statistic, except the minimum and maximum return and the number of observations, is first computed cross-sectionally and then averaged over time.

4 Methodology

The return of bond i in week t with remaining time to maturity τ can be expressed as:

$$r_{it} = \frac{P_{it}(\tau) + AI_{it} + C_i \cdot \mathbb{1}_{[t \in \{coupon\, dates\}]}}{P_{i,t-1}(\tau+1) + AI_{i,t-1}} - 1, \quad i = 1, \ldots, N_t \quad t = 1, \ldots, T \tag{1}$$

where $P_{it}(\tau)$ is the bond's clean price[1], AI_{it} is the accrued interest and C_i the coupon payment, if any, in week t. Moreover, I denote the excess return of the bond as $R_{it} = r_{it} - r_t^f$, where r_t^f indicates the borrowing rate, defined as the annualized one-month T-Bill rate, divided by 52.

For each strategy at each rebalancing date, I reallocate the portfolio by ranking the bonds, corresponding to their factor signal. In each week t the factor signal for bond i is defined as X_{it}. Extensive reference on the construction of the factors can be found in the subsections hereafter. Largely in line with Asness et al. (2013), asset weights are allocated by computing the cross-section rank of the signal for each bond over the cross-sectional average rank of the signals. I dinstict from their method in the sense that I perform the weight allocation procedure for the long and short positions separately, hence allowing contemporaneously unequal numbers of long and short positions. The choice for rank weighting, as opposed to weighting by the pure factor signals or the signs of the signals is argued by the risk of overweighting bonds that depict unlikely extreme returns (pure signals), as well as ignoring the exposure of each individual bond to certain factor (sign signals). To be able to describe the allocation of the asset weights, I introduce two subsets of X_{it},

$$\begin{aligned} X_{it}^{+} &= \{X_{it} | X_{it} > 0\} \\ X_{it}^{-} &= \{X_{it} | X_{it} < 0\} \end{aligned} \tag{2}$$

such that the asset weights are defined as,

$$\begin{aligned} w_{it}^{+} &= \quad c_t^{+} \cdot rank(X_{it}^{+}) \\ w_{it}^{-} &= -c_t^{-} \cdot rank(-X_{it}^{-}) \\ w_{it} &= \quad w_{it}^{-} + w_{it}^{+} \end{aligned} \tag{3}$$

[1] In fixed income markets, transactions are closed against the dirty price. Accrued interest harms the analysis of bond prices. Most financial databases, like Bloomberg, already correct for this anomaly by providing the clean price.

where c_t^+ and c_t^- are the scaling factors to ensure that the portfolio exposure remains stable over time. Specifically, these are constructed such that the long and short positions in the portfolio sum up to 1 and -1 respectively,

$$\begin{aligned} c_t^+ &= \left(\sum_{X_{it}>0} rank(X_{it}^+) \right)^{-1} \\ c_t^- &= \left(\sum_{X_{it}<0} rank(-X_{it}^-) \right)^{-1} \end{aligned} \tag{4}$$

Rebalancing the entire portfolio every week is practically impossible for bond investors in the light of transaction costs. Therefore, I construct more realistic portfolios that are held for longer periods than one week. In this paper, I implement holding periods of one month, three months and six months as well. Considering a holding period of K periods, I follow an overlapping portfolio approach where I run K portfolios simultaneously. At each time t, I remove the portfolio that was constructed at time $t-K$ and add a new portfolio. Therefore, the weight of each position in the factor portfolio at time t is equal to the sum over the K portfolios that were constructed from $t-K$ to t, divided by K,

$$w_{it}^K = \frac{1}{K} \sum_{k=0}^{K-1} w_{i,t-k}. \tag{5}$$

Given a particular strategy $s \in S$ where $S = \{\text{C1}, \text{C2}, \text{M1}, \text{M2}, \text{V1}, \text{Q1}, \text{Q2}\}$, the excess return of each factor portfolio in week t equals,

$$R_t^s = {w_{t-1}^s}' R_t. \tag{6}$$

In order to evaluate the performance of each factor portfolio, I examine several statistics. First of all, I analyze the central moments (mean, volatility, skewness and kurtosis) of the excess return distribution and the portfolio's Sharpe ratio. Moreover, I investigate downside risk of each factor portfolio by evaluating maximum drawdown. To do so, I relate to the drawdown definition of Hamelink and Hoesli (2004). I distinct from their method by considering the cumulative portfolio return instead of portfolio value to detect peaks and troughs. This can be argued by the fact that long-short portfolios are likely to be valued close to zero, implying an unlikely massive drawdown. To assess maximum drawdown, I first define the cumulative return of each factor portfolio,

$$V_t = \prod_{\tau=1}^{t} (1 + R_\tau^s), \tag{7}$$

and subsequently the maximum cumulative return until time t,

$$V_t^{\max} = \max_{j \le t} V_j. \tag{8}$$

Next, maximum drawdown is defined as the portfolio loss return when bought at the local maximum and sold at the next local minimum,

$$\text{MDD} = \max_{t \le T} \left\{ \frac{V_t^{\max} - V_t}{V_t^{\max}} \right\}. \tag{9}$$

Increasing the holding period of positions in a portfolio comes at the benefit of lower transaction costs. In order to assess this, I take portfolio turnover into account. The portfolio turnover ratio is the average fraction of the portfolio that has been bought or sold over the period of interest,

$$\text{TR} = \frac{1}{T} \sum_{t=1}^{T} \sum_{i=1}^{N_t} \left(|w_{i,t+1} - w_{i,t^+}| \right), \tag{10}$$

where w_{i,t^+} is the portfolio weight in bond i before rebalancing but at $t+1$ and $w_{i,t+1}$ is the portfolio weight after rebalancing, implying that the turnover ratio is equal to the sum of the absolute value of the rebalancing trades across the N_t available bonds and over the T trading dates, normalized by the number of trading dates.

Finally, I analyse the CAPM alphas in order to provide a concrete answer to the first research question. For each factor portfolio, I regress the excess returns on the Barclays Green Bond Aggregate Index, which is extracted from Bloomberg,

$$R_t^s = \alpha + \beta \cdot \text{INDEX}_t + \varepsilon_t, \tag{11}$$

where α is the abnormal return and β the sensitivity of the portfolio to the market index. Significant alpha provides evidence for the profitability of factor investing in the green bond market.

In the second part of the research, I exploit the merits from diversification by linearly combining the individual factor portfolios. The aggregate portfolio return is given by,

$$R_t^p = \sum_s q_t^s R_t^s, \tag{12}$$

where q_t^s is the weight, allocated to strategy s at time$t$. To allocate the optimal weights, I minimize the aggregate portfolio risk, given a certain required mean portfolio return and under the condition that the individual factor portfolio weights should add up to one,

$$\begin{aligned} \min_{q_t} \quad & \frac{1}{2} q_t' \Sigma_t q_t \\ \text{s.t.} \quad & q_t' \mu_t = \mu_p \\ & q_t' \mathbf{1}_S = 1 \\ & q_t^s \in [-1, 1], \quad \forall s \in S \end{aligned} \tag{13}$$

Here, Σ_t is the $S \times S$ conditional covariance matrix, μ_t is the $S \times 1$ conditional mean, $\mathbf{1}_S$ is the $S \times 1$ vector of ones and μ_p is the required mean return. Both moments are estimated by their sample counterparts using all available historical returns of the individual factor portfolios. The solutions to this problem construct the mean-variance efficient frontier, also known as the Markowitz Bullet. Because it can be shown that mean and variance of the portfolios on the efficient frontier have a parabolic relation, the Sharpe ratio as a function of the required mean return μ_p, is a concave function. At eacht time t, I choose q_t, such that the Sharpe ratio is maximized,

$$\max_{q_t} \frac{q_t' \mu_t}{\sqrt{q_t' \Sigma_t q_t}} = \max_{q_t} \frac{\mu_p}{\sqrt{q_t' \Sigma_t q_t}}. \tag{14}$$

In the following sections, I elaborate on the construction of the factors, which are based on measures of Carry, Momentum, Value and Quality. All factors are constructed using bond data, that includes the time series of returns, yields to maturity, credit spreads and remaining times to maturity, as well as the individual bond characteristics, especially credit rating.

4.1 Carry

The expected return of a security can be decomposed into carry and expected price appreciation. Carry measures the return on a security, if nothing happens, besides passage of time. In the context of bonds, carry can be seen as the return on the bond, resulting from price change as the bond approaches maturity. There are more than one ways to assess carry return of bonds. I follow the line of Koijen et al. (2018). Consider a corporation that issues a bond with par value $\bar{P}$, expires in T months, pays fixed coupons C and is priced at $P_t(\tau)$. The first definition of carry in the context of bonds is simply the current yield or the coupon return $C/P_t(\tau)$, hereby assuming that the bond price does not change over time. However, this definition of carry cannot be applied to zero-coupon bonds. Moreover, it is incorrect to assume that the bond price remains constant when time passes and the bond approaches maturity. This can simply be proven by considering the fundamental value of a bond, namely the present value of the future payoff of coupons and principal, concluding that time to maturity is an important variable in the pricing of bonds. Therefore, it is better to assume that the yield to maturity remains constant over time when addressing carry. Note that the price of the coupon bond satisfies,

$$P_t(\tau) = \sum_{j \in \{coupon\, dates > t\}} C(1 + y_t^\tau)^{-(\tau - j)} + \bar{P}(1 + y_t^\tau)^{-\tau}, \tag{15}$$

and under the assumption that the yield to maturity remains constant, the value of the bond at time $t+1$ including potential coupon payment can be described as,

$$P_{t+1}(\tau - 1) + C \cdot \mathbb{1}_{[t+1 \in \{coupon\, dates\}]} = \sum_{j \in \{coupon\, dates > t\}} C(1 + y_t^\tau)^{-(\tau - j)} + \bar{P}(1 + y_t^\tau)^{-(\tau-1)}. \tag{16}$$

The carry return in excess of the risk-free rate then becomes,

$$\frac{P_{t+1}(\tau - 1) + C \cdot \mathbb{1}_{[t+1 \in \{coupon\, dates\}]} - P_t(\tau)}{P_t(\tau)} - r_t^f = y_t^\tau - r_t^f, \tag{17}$$

which is the excess yield that the bond provides, given that the yield to maturity does not change over time, also known as the term spread. Following a carry investment strategy implies investing in bonds that exhibit high carry returns, corresponding with Equation 17. To ensure a fair comparison of carry between bonds, the effects of credit and liquidity risk premia should be cancelled out. Therefore, all possible pairs of bonds from the same issuer are paired. The carry spread at time t for two bonds issued by a particular issuer with maturity τ_1 and τ_2 is then defined as,

$$\mathrm{CR}_t = \frac{(y_t^{\tau_2} - r_t^f) - (y_t^{\tau_1} - r_t^f)}{\tau_2 - \tau_1} = \frac{y_t^{\tau_2} - y_t^{\tau_1}}{\tau_2 - \tau_1}, \tag{18}$$

where $\tau_2 > \tau_1$. When the yield spread is positive, this generates a buy signal for the bond with remaining time to maturity τ_2 and a sell signal for the bond with remaining time to maturity τ_1. To capture this information, the carry factor value for bond i that matures in τ months is defined as,

$$X_{it}^{C1} = \frac{\mathrm{CR}_{it}}{2}(\mathbb{1}_{\tau=\tau_2} - \mathbb{1}_{\tau=\tau_1}). \tag{19}$$

Moreover, I set the factor values to zero whenever bonds cannot be paired, implying that no more than one bond has been issued by a certain issuer. The corresponding bonds will therefore not be included in the portfolio.

The above definition treats carry as the contemporaneous yield spread between separate bonds from a certain issuer. In that sense, the factor emphasizes cross-sectional component of carry. On the other hand, carry can assessed in the time series as well. Recall that the return on a security can be decomposed into carry and expected price appreciation. Assuming the expected price appreciation to be zero, an increase in the yield to maturity of a certain bond implies an increase in carry return and hence generates a buy signal. Obviously, the reverse holds for a decrease in yield to maturity. To construct the factor signal, I compare the current yield to maturity of each bond against the 6-month moving average,

$$X_{it}^{C2} = y_{it}^{\tau} - \frac{1}{L}\sum_{l=1}^{L}, y_{i,t-l}^{\tau+l} \tag{20}$$

where L equals 26. Because default risk is captured in both today's yield to maturity and it's moving average, this element cancels out. Finally, I restrict the investment universe to the shortest maturity bonds for each issuer to avoid high correlations across bonds in this second carry portfolio. Therefore, the factor values for the longer maturities are set equal to zero.

4.2 Value

Value is the tendency of cheap securities to outperform securities that are expensive. The concept of value has been extensively investigated for the stock market. Fama and French (1993) included the HML factor in their three-factor model, which captures value versus growth in the cross-section of stocks. More recently, Chan and Lakonishok (2004) conclude that value investing in the stock market still exhibits superior returns. The effect of value in the bond market has been investigated to a lesser extent. Qian et al. (2009) find that value investing across several asset classes including bonds provides several diversification opportunities. Moreover, Correia et al. (2012) investigate the relation between credit spreads and default rates and find that the physical default probability is absorbed in the credit spread with substantial delay, hence creating opportunities for value investors: a cheap bond exhibits relatively high spread over its actual credit risk. Indeed, Norden and Weber (2004) and Norden (2017) illustrate that credit markets react to rating modification announcements inefficiently. Moreover, Chen, Lesmond, and Wei (2007) and Perraudin and Taylor (2003) find that liquidity premia explain a substantial portion of the spread of defaultable bonds. In order to find overvalued and undervalued bonds with respect to credit quality, I compare the credit spread of the bonds against their credit rating. Both the bond's credit quality and the time series of creidt spread are present in the dataset. Specifically, I perform a cross sectional regression of each bond's standardized (to correct for heteroscedasticity) credit spread on its Moody's credit rating and remaining time to maturity,

$$\frac{z_{it}}{\sigma^z_{it}} = \alpha_t + \sum_{r \in ratings} \beta_{rt} \mathbb{1}_{ir} + \gamma_t \tau_i + \varepsilon_{it}, \quad i = 1, \dots, N \tag{21}$$

where σ^z_{it} is the sample standard deviation of the returns from $t - L$ to t (L equals 26, corresponding to six months), $\mathbb{1}_{ir}$ is the indicator function that equals one when bond i contains rating r and τ_i is the remaining time to maturity of bond i. The latter is included in the model to isolate the credit component by correcting for potential term spread. The factor for bond i at time t is defined the difference between the actual credit spread and the fitted spread,

$$X^V_{it} = z_{it} - \hat{z}_{it}. \tag{22}$$

Large absolute differences between the actual and model-implied spread indicate potential overvaluation or undervaluation and therefore generate investment signals. Finally, X^V_{it} is set equal to zero, when the corresponding bond is not supplied with any rating and hence will not be assigned a weight unequal to zero.

4.3 Momentum

Momentum is the persistence of securities to exhibit high or low returns. The phenomenon has been extensively investigated in equity markets. Jegadeesh and Titman (1993) document that stocks that have outperformed in the past tend to exhibit high returns going forward. More recently, Jostova et al. (2013) and Pospisil and Zhang (2010) provide evidence for the existence of momentum in the bond market. This gives rise to the idea that momentum can be used as a predictor of future green bond returns. To construct momentum factors, I restrict the investment universe to the shortest maturity bonds for each issuer to avoid high correlations across bonds in the factor portfolio. Following Moskowitz et al. (2012), I define two distinct measures of momentum: time series momentum and cross sectional momentum. Time series momentum is defined as the average return over the past six months,

$$X_{it}^{M1} = \frac{1}{L}\sum_{l=1}^{L} r_{i,t-l-4}, \tag{23}$$

where L equals 26. Moreover, cross sectional momentum is defined as the average return over the past six months, subtracted by the average past six months return in the cross section,

$$X_{it}^{M2} = \frac{1}{L}\sum_{l=1}^{L} r_{i,t-l-4} - M\left\{\frac{1}{L}\sum_{l=1}^{L} r_{t-l-4}\right\}, \tag{24}$$

where $M\{\cdot\}$ is the cross-sectional median. For both measures, a burn-in period of one month (four weeks) is used to construct both factors, which is related to the 1-month reversal anomaly. Similarly to carry, the definitions address the factor in separate dimensions. The first definition treats positive (negative) momentum for each bond as a trigger to invest, while the second definition treats momentum as trigger to invest when it is higher than the median of the market. Therefore, factor portfolios that are constructed based on the second definition of momentum might long (short) in bonds that exhibit negative (positive) momentum.

4.4 Quality

Quality is the tendency of low risk bonds to deliver high risk-adjusted returns, contrary to risky, high yielding bonds. Measures for quality can be both market and fundamental based. In this research, I propose a two measures of market risk that make use of solely bond data. The first factor corresponds to the momentum effect in bond volatility: bonds that have portrayed low volatility in the past tend to continue this pattern in the future and vice versa. I restrict the investment universe to the shortest maturity bonds for each issuer to avoid high correlations across bonds in the factor portfolio. For each bond i, I define the low volatility factor as the excessive standard deviation over the past six months,

$$X_{it}^{Q1} = \sum_{i=1}^{N_t} \sqrt{\frac{1}{L-1}\sum_{l=1}^{L}\left(r_{i,t-l} - \sum_{l=1}^{L} r_{i,t-l}\right)^2} - \sqrt{\frac{1}{L-1}\sum_{l=1}^{L}\left(r_{i,t-l} - \sum_{l=1}^{L} r_{i,t-l}\right)^2}, \qquad (25)$$

where L equals 26. In words this can be described as a strategy that takes long (short) positions in bonds that exhibit below (above) average volatility. Though the first term is constant across the individual bonds, it is essential for determining the sign of the factor. Next to the low volatility factor, I construct another measure of quality that directly assesses the credit risk of a bond. The factor is constructed such that long (short) positions are taken in bonds with high (low) credit rating. As the bonds in the data set contain either no credit rating or a credit rating that is assumed to last for the entire lifetime of the bond, I scale the factor by the remaining time to maturity to favour bonds with lower duration. More specifically, the credit quality factor is defined as,

$$X_{it}^{Q2} = \frac{\sum_{r \in IG} \mathbb{1}_{ir} - \sum_{r \in NIG} \mathbb{1}_{ir}}{\tau_i}, \qquad (26)$$

where IG is the subset that contains all Investment Grade ratings, NIG is the subset that contains all Non-Investment Grade ratings, $\mathbb{1}_{ir}$ is the indicator function that equals one when bond i contains rating r and τ_i is the remaining time to maturity of bond i. Both factors address a separate definition of quality: the first factor directly assesses the market risk of a bond in terms of volatility, while the second factor considers a bond's credit quality as an indirect measure of market risk.

5 Results

This section contains the results of the factor investment strategies in the green bond market. First, I elaborate on the performance of the individual factor portfolios in terms of excess returns and CAPM alphas. Next, I discuss the strategies that combine the individual factor portfolios into one portfolio in order to exploit diversification benefits. Note, I refer to the individual factor portfolios by mentioning the first letter of the factor, followed by the number of the strategy. For example, the first carry strategy becomes C1, the second momentum strategy becomes M2 et cetera.

5.1 Factor portfolios

The weekly returns of the factor portfolios are evaluated for holding periods of one week, one month, three months and six months. Table 3 displays the summary results for these portfolios. For the weekly rebalanced portfolios in Panel A, it can be observed that the V1 portfolio exhibits the highest Sharpe ratio of 1.64, which can be attributed to both high returns and relatively low volatility. On the other hand, the quality portfolios exhibit negative Sharpe ratios. Looking into the downside risk, it is noted that the maximum drawdown in the highest for Q1, 14.67%, and low for C1 and V1, 1.67% and 1.94% respectively. The latter can be partly explained by the rationale behind the C1 strategy, which is hedging default risk, and the fact that the V1 portfolio is largely diversified, because it not constructed in a restricted investment universe. Finally, it is noted that the C2 and Q2 portfolios exhibit the highest and lowest turnover rate respectively. As the Q2 portfolio is primarily driven by the time-invariant credit rating, this low rate of 0.05 is expected.

Panel B depicts the results for the portfolios that are rebalanced monthly. A few observations are made. First of all, the Sharpe ratios of all portfolios decrease, except C2 and Q2. In fact, these increase to 0.08 and 0.06 respectively. In addition, it can be noted that the maximum drawdown of the Q1 portfolio decreases. However, it still exhibits the highest maximum drawdown. Together with M2 and Q2, Q1 belongs to the portfolios that have a more than 5% maximum drawdown. Finally, it is noted that the turnover rates of all portfolios logically decrease, though the effect is the weakest for the Q2 portfolio.

For the longer holding periods of one quarter and one half-year in Panel C and Panel

D, it is observed that the turnover rate keeps on decreasing, though the marginal benefits decrease as well. For example, the turnover rate of the C2 portfolio almost halved from 0.70 to 0.34, when the portfolio is rebalanced monthly instead of weekly. When the holding period increases to three months or six months, the turnover rate decreases only to 0.18 and 0.16 respectively. In terms of performance, it is seen that the Sharpe ratios of the momentum and value portfolios keep on decreasing with the rebalancing frequency. The Sharpe ratios of the M2 and quality portfolios are negative, when rebalanced bi-annually. On the other hand, the Sharpe ratio of C2 increases to 0.26 and 0.76 in Panel C and Panel D. Moreover, the Sharpe ratios of C1, Q1 and Q2 do not exhibit a clearly visible increasing or decreasing pattern. Finally, it is noted that decreasing the rebalancing frequency to three months or six months does not necessarily decrease maximum drawdown.

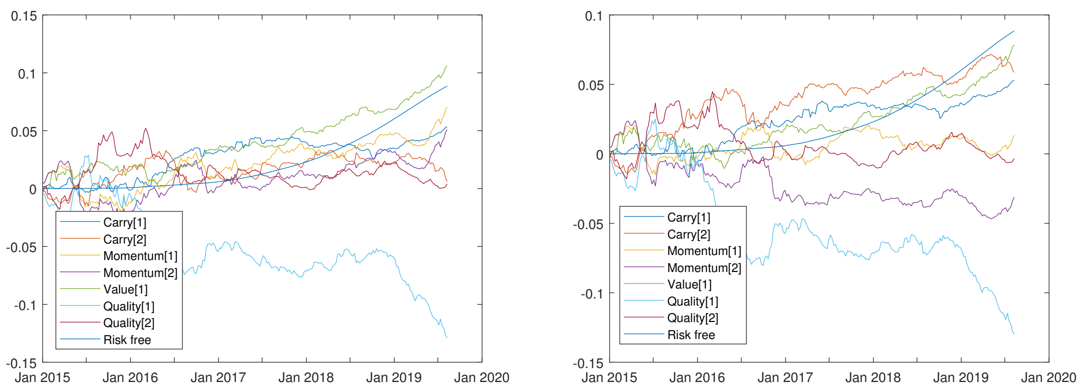
In general, the value portfolio outperforms all other portfolios, both in terms of Sharpe ratio and maximum drawdown. Moreover, its turnover is the third lowest across all possible holding periods. Secondly, it is observed that the momentum effect is present in green bonds, though the performance of the momentum portfolios substantially weakens when the holding period increases. Time series momentum (M1) clearly outperforms cross-sectional momentum (M2) in terms of Sharpe ratio and maximum drawdown. Thirdly, the cross-sectional carry strategy (C1) seems to be a safe portfolio for both short term and long term investors. Its Sharpe ratio is not very much affected by the rebalancing frequency. Moreover, it's volatility and maximum drawdown is the lowest across the portfolios in all panels, which can be likely attributed to the fact that default risk is hedged. Finally, the quality portfolios perform very bad with most Sharpe ratios being negative. Later on in this research, I illustrate how to construct a profitable low-volatility portfolio.

Table 3: Summary statistics for each factor portfolio, 2 January 2015 - 9 August 2019

Factor	Strategy	Return	Volatility	SR	Skewness	Kurtosis	Min	Max	MDD	TR
A: 1-week holding period										
Carry	1	1.43%	1.41%	1.01	-0.08	8.22	-0.94%	0.77%	1.67%	0.34
	2	-0.36%	1.97%	-0.18	0.22	7.02	-1.17%	1.12%	3.99%	0.70
Momentum	1	1.15%	1.95%	0.59	-0.41	5.58	-1.19%	0.94%	4.74%	0.58
	2	0.75%	2.23%	0.34	-0.68	7.35	-1.59%	1.19%	6.65%	0.46
Value	1	2.35%	1.43%	1.64	-0.04	7.29	-0.75%	1.04%	1.94%	0.25
Quality	1	-2.80%	2.87%	< 0	1.15	9.63	-1.41%	2.41%	14.67%	0.17
	2	-0.01%	1.90%	< 0	0.94	9.33	-1.03%	1.48%	5.08%	0.05
B: 1-month holding period										
Carry	1	1.16%	1.37%	0.85	-0.31	8.42	-0.96%	0.77%	1.94%	0.16
	2	0.16%	1.99%	0.08	-0.15	6.99	-1.22%	1.01%	3.55%	0.34
Momentum	1	1.53%	2.01%	0.76	-0.22	5.51	-1.22%	1.15%	3.88%	0.27
	2	1.12%	2.28%	0.49	-0.60	7.83	-1.63%	1.38%	5.33%	0.25
Value	1	2.30%	1.48%	1.56	-0.12	6.93	-0.79%	1.02%	1.96%	0.12
Quality	1	-2.73%	2.83%	< 0	0.93	8.13	-1.40%	2.19%	14.62%	0.10
	2	0.11%	1.91%	0.06	0.87	8.99	-1.03%	1.48%	5.16%	0.04
C: 3-months holding period										
Carry	1	1.03%	1.29%	0.80	-0.69	9.36	-0.99%	0.64%	1.67%	0.10
	2	0.48%	1.87%	0.26	-0.90	10.04	-1.63%	0.77%	3.75%	0.22
Momentum	1	0.85%	1.90%	0.44	-0.43	5.11	-1.16%	1.01%	3.44%	0.18
	2	0.21%	2.22%	0.09	-0.57	7.61	-1.59%	1.31%	4.67%	0.17
Value	1	1.82%	1.54%	1.18	-0.46	7.71	-1.00%	1.04%	2.67%	0.08
Quality	1	-2.75%	2.79%	< 0	0.76	6.84	1.33%	-1.93%	14.56%	0.08
	2	0.13%	1.94%	0.07	0.68	7.07	-1.03%	1.17%	5.08%	0.04
D: 6-months holding period										
Carry	1	1.14%	1.38%	0.83	-0.70	10.08	-1.04%	0.68%	1.81%	0.08
	2	1.29%	1.71%	0.76	-0.33	5.95	-1.07%	0.77%	2.82%	0.16
Momentum	1	0.30%	1.69%	0.18	-0.59	6.71	-1.19%	0.78%	3.50%	0.14
	2	-0.65%	2.01%	< 0	-0.74	9.10	-1.58%	1.01%	6.81%	0.14
Value	1	1.70%	1.57%	1.08	-0.59	8.23	-1.07%	1.04%	2.90%	0.06
Quality	1	-2.68%	2.74%	< 0	0.75	6.58	-1.19%	1.83%	14.36%	0.06
	2	-0.05%	1.99%	< 0	0.61	7.36	-1.04%	1.22%	5.35%	0.04

Note: This table depicts the excess return statistics for each of the individual factor portfolios. The return is the annualized average excess portfolio return. The volatility is the annualized standard deviation of the excess portfolio return. The Sharpe ratio is the annualized excess portfolio return per unit of volatility. As negative Sharpe ratios do not convey any useful information, these are not reported. Skewness and kurtosis are the alternative unbiased estimates for the population skewness and kurtosis of the excess returns of each factor portfolio. Min and max correspond with the minimum and maximum observed excess portfolio return respectively. The maximum drawdown (MDD) is the maximum observed loss return from a peak to a trough before a new peak is attained. The turnover rate (TR) is the sum of the absolute value of the rebalancing trades across the bonds and over the trading dates, normalized by the number of trading dates.

Next to the summary results, the factor portfolios are evaluated in terms of cumulative performance over time. Figure 2 depicts the cumulative log returns of the factor portfolios against the risk-free benchmark for holding periods of one month and six months. A number of observations are made from both sub-figures. First of all, it is seen that most portfolios outperform the benchmark until approximately the middle of the sample. In the long run though, most portfolios do no outperform the benchmark. For monthly rebalancing, only V1 generates cumulative returns above the cumulative risk free rate at the end of the sample. When the rebalancing frequency increases to six months, the V1 portfolio also drops below the benchmark and the C2 portfolio. In addition, it is noted that, when comparing both figures, especially the momentum portfolios suffer massively from decreasing rebalancing frequency. Furthermore, the Q1 portfolio performs bad in both cases, which is in line with the earlier described summary results. Finally, it seems that the cumulative log returns are more volatile in the beginning of the sample. This can possibly be attributed to the initialization of the portfolio weights that needs to be done when implementing a holding period that is longer than the data frequency of one week. These results provide soft evidence that factor portfolios are not substantially profitable. However, it should be noted that these figures only provide insight in the cumulative returns, ignoring other performance statistics, like CAPM alphas.



(a) 1-month holding period *(b)* 6-months holding period

Figure 2: Cumulative log return of the factor portfolios for different holding periods. In accordance with the portfolio weight construction, the cumulative log returns are evaluated against twice the cumulative log risk-free rate.

To give more insight in the construction of the factors, I analyze the number of positions over time. Figure 3 displays the sum of long and short positions for each factor portfolio. It is clearly observed that each portfolio grows in size over time. This is in line with the growth of the aggregate green bond market, as illustrated in Figure 1. Furthermore, the V1 and Q2 portfolio are largest in size, which can be attributed to the fact that these portfolios are not limited to the nearest contracts. The C1 portfolio is the smallest in size, which is partly explained by the minimum criterion of two tradable bonds per issuer. Appendix C provides the number of long and short positions over time for every factor portfolio. A number of observations are made. First of all, the number of long and positions are exactly equal in the C1 and M2 portfolio. This is in line with the underlying strategy of C1 that invests (long and short) in the pair of bonds for each issuer with the highest yield spread and the fact that M2 evaluates momentum in the cross-section. Secondly, the dynamics in the long and short positions are negatively related, except for the C1, M2 and Q2 portfolio. Specifically, the correlations between the change in the number of long and short positions are 1.00 for C1, -0.98 for C2, -0.97 for M1, 1.00 for M2, -0.89 for V1, -0.66 for Q1 and 0.11 for Q2. The negative correlations between the long and short weight changes can be argued by the fact that portfolio weights are constructed by evaluating factor the signal (yield in case of C2, return in case of M1, spread in case of V1, standard deviation in case of Q1) to a certain benchmark, normally the last six months average. This implies that a certain positive (negative) signal leads to an additional long (short) positions and likely to the loss of one short (long) position as well. Finally, it can be seen that both quality portfolios depict more long than short positions. Referring to the summary statistics in Table 2, this finding may be argued by the feature in the data set which contains substantial more green bonds with an Investment Grade rating than a Non-Investment Grade rating.

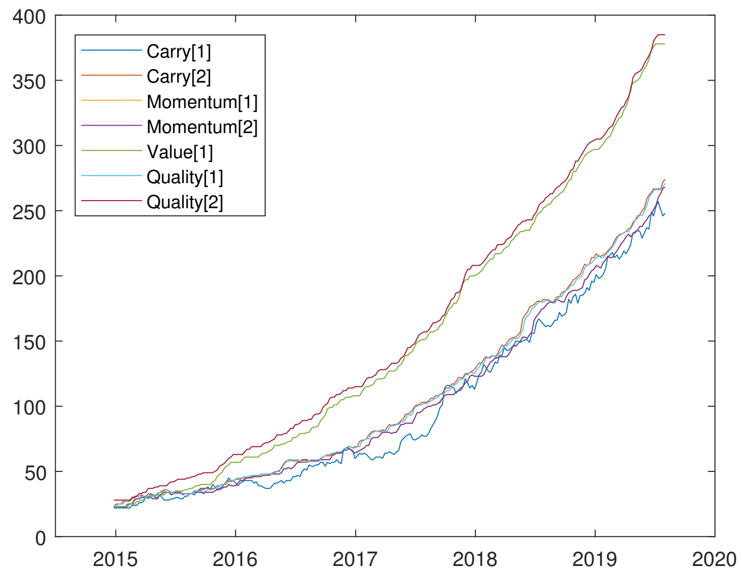


Figure 3: Number of positions of the factor portfolios for a one-month holding period

Finally, I analyze the CAPM alphas by regressing the excess portfolio returns on the market index, which is the hedged Barclays Green Bond Aggregate Index. The results are displayed in Table 4. Clearly, the performance of the portfolios in terms of alpha weakens when the rebalancing frequency decreases from one month to six months. Furthermore, V1 exhibits significant alphas. This holds for both holding periods, though the significance is less in case of bi-annual rebalancing. Moreover, V1 is the only portfolio, whose market beta is insignificant. Hence, this portfolio is interesting for investors, both in terms of abnormal returns and its independence from the market portfolio. In addition, most portfolios exhibit a significant positive market beta, which suggest that these can be (partly) replicated by simply investing in the market portfolio. The exceptions are C2 (insignificant beta for 1-month holding period), V1 (insignificant positive beta), Q1 (significant negative beta) and Q2 (negative beta). Finally, it should be noted that the adjusted R^2 is generally low and greatly varies across the portfolios. The former can possibly be reasoned by the fact that in essence, the index is a long-only portfolio, while the factor portfolios are long-short portfolios. The latter however, is hard to explain. It could be argued that there is low volatility in both the Q1 portfolio and the index, potentially explaining the high R^2. Moreover, there are indications that the index bears relatively low default risk, which can be derived from the R^2 of C1, which is higher than most portfolios that do not hedge default risk. It is difficult to substantiate these indications though.

Table 4: Performance statistics for each factor portfolio, 2 January 2015 - 9 August 2019

Variable	Carry		Momentum		Value	Quality	
	1	2	1	2	1	1	2
A: 1-month holding period							
α	0.58%	-0.07%	0.85%	0.43%	2.20%**	-0.51%	0.22%
	(0.58%)	(1.09%)	(0.90%)	(1.03%)	(0.69%)	(0.81%)	(0.90%)
β	0.21**	0.03	0.23**	0.23**	0.03	-0.84**	-0.02
	(0.03)	(0.06)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)
Adjusted R^2	0.17	0.01	0.09	0.07	0.02	0.63	0.03
B: 6-months holding period							
α	0.56%	-0.23%	-0.48%	-1.45%	1.54%*	-0.52%	0.27%
	(0.59%)	(0.92%)	(0.71%)	(0.88%)	(0.74%)	(0.77%)	(0.93%)
β	0.21**	0.22**	0.27**	0.27**	0.05	-0.81**	-0.10*
	(0.03)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
Adjusted R^2	0.16	0.08	0.18	0.13	0.01	0.64	0.02

Note: This table shows the performance statistics for each of the factor portfolios. Panel A reports the CAPM alphas with respect to the Barclays Green Bond Aggregate Index (hedged) for a holding period of 1 month. Panel A reports the CAPM alphas with respect to the Barclays Green Bond Aggregate Index (hedged) for a holding period of 6 months. Alphas are annualized. The standard errors of the coefficients are those of the standard multiple linear regression model, assuming no heteroscedasticity and serial correlation in the error terms. Statistical significance of alpha is determined by means of a two-sided t-test.

* indicates $p < 0.05$

** indicates $p < 0.01$

It can be concluded that the value portfolio clearly generates abnormal returns. Moreover, the abnormal returns of all portfolios decrease along with the rebalancing frequency. Finally, the portfolios correlate on average positively with the green bond market portfolio.

5.1.1 Long-only portfolios

As shorting in bond markets is unrealistic in practice, I analyse the potential loss in performance by considering long-only portfolios. To do so, I split the earlier described long-short portfolios in two and analyse the Sharpe ratios of the long positions. These are displayed in Table 5 for each holding period. I discuss each factor portfolio separately.

The long-only C1 portfolio depicts lower Sharpe ratios than the long-short portfolio. Moreover, its performance weakens, as the holding period increases. Removing the short positions, introduces default risk and makes the portfolio resemble a momentum in yield strategy. Also the C2 portfolio generates lower Sharpe ratios, compared to the long-short C2 portfolio. However, the pattern in Sharpe ratio for increasing holding period is similar. Hence, it seems that the profitability of the long-short C2 portfolio is generated by both long and short positions. For M1, the opposite holds: the long-only portfolio performs better than the long-short portfolio, suggesting that investors better opt for the long-only portfolio. The M2 portfolio produces variable results: for a holding period of 1 week and 1 month, the long-short portfolio outperforms the long-only portfolio, but for the other holding periods, the reverse holds. The long-only value portfolio depicts lower Sharpe ratios, but the pattern is similar, compared to the corresponding long-short portfolio. Hence, it can be said that profits are generated not only in overvaluation, but also in undervaluation. Finally, the most striking results are found in the quality portfolios. The Sharpe ratios of the long-only Q1 portfolio are all close to 3, which is a substantial improvement, compared to the long-short Q1 portfolio. These findings suggest that low-volatile bonds produce positive returns on average, but that these are offset by higher returns of high-volatile bonds. However, comparing the Sharpe ratios of the long-only Q1 portfolio with those of the long-short Q1 portfolio indicates that the risk-reward ratio is much higher for low-volatile bonds. Hence, this suggests that the low-volatility effect is present in the green bond market. In terms of Sharpe ratios, the Q2 portfolio performs weaker when high-yield bonds (which contain a low credit rating) are excluded. These findings for the quality portfolios give rise to the idea to invest in high-yield bonds, as long as they trade with low volatility.

Table 5: Performance of long-only factor portfolios, 2 January 2015 - 9 August 2019

Holding period	Carry		Momentum		Value	Quality	
	1	2	1	2	1	1	2
1 week	0.58	-0.25	0.54	0.32	0.62	2.82	-0.19
1 month	0.37	0.02	0.55	0.39	0.59	2.90	-0.23
3 months	0.29	0.20	0.35	0.18	0.48	2.96	-0.21
6 months	0.21	0.41	0.20	-0.07	0.47	3.01	-0.20

Note: This table displays the Sharpe ratios of long-only portfolios for each holding period.

In short, it is said that long-only portfolios do not clearly perform worse, compared to long-short portfolios. Moreover, shorting high-volatile substantially weakens performance, as can be read from the performance of the Q1 portfolio.

5.2 Combining portfolios

This section elaborates on the benefits from diversification by combining the individual factor portfolios into one portfolio. The remainder of the analysis is based on the portfolios that implement a holding period of six months. This holding period is realistic and prevents extreme turnover. Table 6 depicts the correlations between the individual portfolios. As the portfolio returns exhibit low cross-correlations, there is room for diversification. Also, it is noted that the momentum portfolios correlate very much with each other. This is in line with the construction of the momentum portfolios. Across the two momentum strategies, only the cutoff of the underlying factor differs. The worst momentum strategy (M2) is therefore excluded in the remainder of the analysis. In addition, the largest negative correlations are found between the momentum and C2 portfolios. This is explained by the negative relationship between bond prices and yields. When the price of bond rises substantially, this generates a momentum signal. However, this often goes alongside with a drop in yield, which generates the opposite signal in the C2 strategy.

Table 6: Correlations between factor portfolio returns for a 6-months holding period

		Carry		Momentum		Value	Quality	
		1	2	1	2	1	1	2
Carry	1	1.00	-0.03	0.15	0.14	-0.04	-0.33	-0.03
	2		1.00	-0.64	-0.65	-0.29	0.01	0.18
Momentum	1			1.00	0.94	0.13	-0.45	-0.29
	2				1.00	0.16	-0.37	-0.31
Value	1					1.00	-0.06	-0.13
Quality	1						1.00	0.34
	2							1.00

The weights of the optimal Markowitz mean-variance portfolio are allocated according to Equation 14 using sample estimates of the conditional mean and covariance matrix. Here, an expanding window is applied. The first mean-variance portfolio is constructed using one year historical data, corresponding to 52 weekly observations. Similar to Table 3, the summary statistics of the portfolio return are displayed in Table 7. The statistics are evaluated against the naive diversified portfolio.

The optimal portfolio performs better than the naive diversified portfolio, both in terms of annual return and Sharpe ratio. Moreover, its Sharpe ratio of 1.39 is higher than each individual factor portfolio (Table 3). Next, it is observed that the optimal portfolio compares favourably with the naive diversified portfolio, when examining other returns statistics, like skewness and kurtosis. The turnover rate of the optimal portfolio equals 0.11, which is higher than the naive diversified portfolio and the individual portfolios C1, V1, Q1 and Q2, but lower than C2, M1 and M2. This suggests that the naive diversified portfolio is worthy to consider for investors who want to keep transaction costs low. Finally, the maximum drawdown of the optimal portfolio equals only 0.92%. This is lower than the naive diversified portolio, as well as all individual factor portfolios.

Table 7: Summary statistics for each factor portfolio, 1 January 2016 - 9 August 2019

Allocation method	Return	Volatility	SR	Skewness	Kurtosis	Min	Max	MDD	TR
Markowitz	0.84%	0.61%	1.39	-0.85	6.74	-0.41%	0.25%	0.92%	0.11
Naive	0.19%	0.49%	0.38	-0.55	6.07	-0.25%	0.21%	1.38%	0.05

Note: This table depicts the summary statistics of the return distribution for the Markowitz and naive diversified portfolio. The latter is constructed by simply allocating 1/6 to each individual factor portfolio (except M2). The statistics in this table are computed similarly to those in Table 3.

Next, I compare the cumulative returns of the optimal portfolio against those of the naive portfolio. From the y-axis, it is read that the former clearly outperforms the latter in terms of cumulative return. In addition, both cumulative returns depict a trend upwards. This trend seems to be more stable and significant for the optimal portfolio.

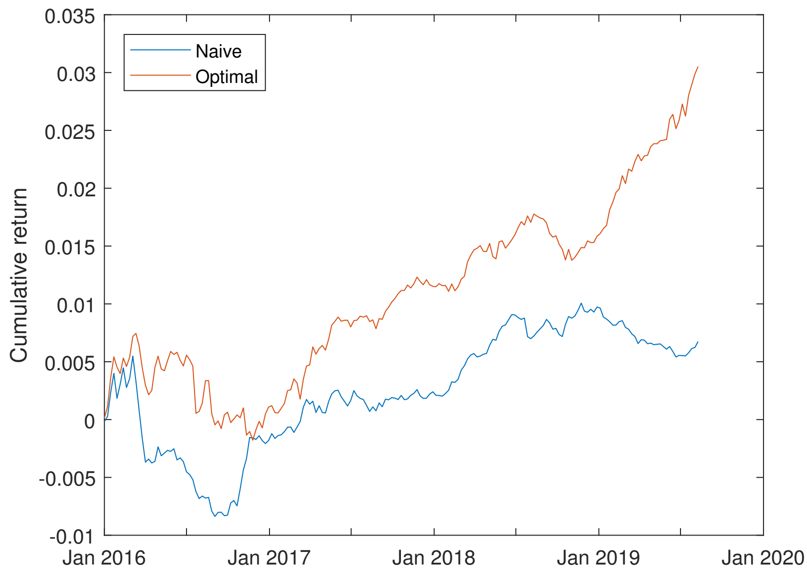


Figure 4: Cumulative log returns of the optimal and naive diversified portfolio

Finally, I analyse the weights in the optimal portfolio over time. Figure 5 depicts these. A number of observations are made. First of all, the weights fluctuate more in the beginning of the sample, contrary to the end of the sample. From July 2017 on, the weights seem to have converged to relatively stable values. Obviously, this pattern can be attributed to the effect of the expanding window in the sample estimates of the conditional mean and covariances. Moreover, the largest weights are allocated to the C2 and V1 (and M1) portfolios, as opposed to the quality portfolios. This is roughly in line with the conclusions drawn from Panel D in Table 3. Finally, it seems that an uptick (a downtick) in one or more portfolios is compensated by a downtick (an uptick) in other portfolio(s). For example, between July 2018 and January 2019 there is a clear break in the portfolio weights of C1, C2 and V1, which decrease substantially. However, this goes along with an increase in the weights of portfolios M1, Q1 and Q2.

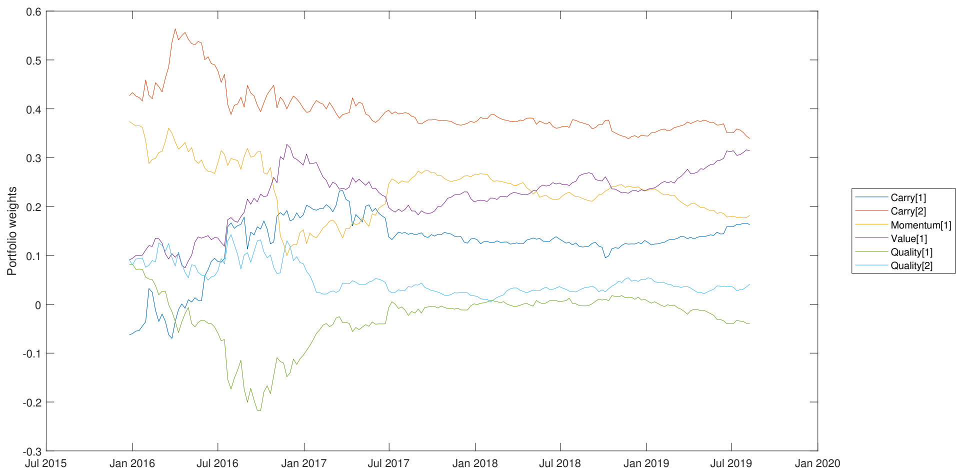


Figure 5: The weights that are allocated to the individual factor portfolios

To sum up, combining the individual factor portfolios realizes superior performance. The Sharpe ratio of the optimal portfolio is higher than each individual factor portfolio. Moreover, the portfolio outperforms the naive diversified portfolio in terms of Sharpe ratios and cumulative returns. This provides an affirmative answer to the second research question, namely that combining factor portfolios indeed enhances the overall performance of the investor's green bond portfolio.

6 Conclusion

This paper studies factor investing in the green bond market. The first part of the research studies the performance of seven factor portfolios. These portfolios are constructed using factors Carry, Value, Momentum and Quality. The returns are evaluated against the risk free rate and the market portfolio. It turns out that most individual portfolios do not clearly outperform the risk free rate or realize significant abnormal returns. An exception is the value portfolio, which outperforms the risk free rate in the long run and exhibits significant abnormal returns. Next to that, long-only portfolios are constructed and evaluated against the long-short portfolios. It becomes clear that omitting the possibility of shorting bonds does not necessarily harm portfolio performance. In fact, the performance of the low-volatility (Q1) portfolio substantially improves, indicating that longing low-volatile bonds provides high Sharpe ratios. Finally, decreasing the rebalancing frequency generally decreases portfolio performance. However, the reverse holds for the timing carry (C2) and low-volatility (Q1) portfolio.

The second part of the research elaborates on the benefits from diversification by combining the seven individual factor portfolios in the Markowitz mean-variance setting. It turns out that allocating the weights such that the Sharpe ratio on the efficient frontier is maximized, delivers higher Sharpe ratios. The resulting portfolio generates a Sharpe ratio of 1.39. Moreover, the above portfolio outperforms the naive diversified portfolio in terms of cumulative returns. Finally, it is noted that the weights converge to stable values.

To the best of my knowledge, there are currently no papers that study the profitability of factor investment strategies in the green bond market. Hence, there is enough room for future research. First of all, specific research could be done to the green bonds that contain a Non-Investment Grade rating, commonly referred to as high yield bonds. Moreover, it would be interesting to do extensive research to the similarities and differences in factor investing between the green bond market and the conventional bond market. Perhaps, the performance on the bonds, issued by polluting corporations could be introduced as an investment factor in the green bond market and vice versa. Finally, this study could also be empirically implemented for social bonds, which are bonds whose proceeds are used to fund projects with positive social outcomes.

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Appendix

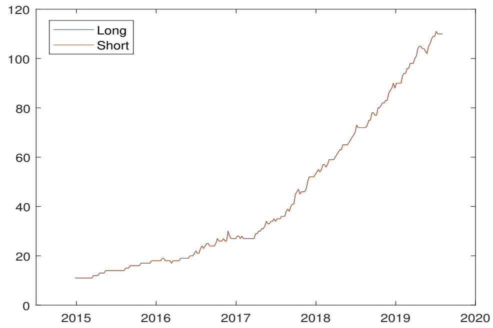
A Green bond overview

Ticker	Country	Currency	Amount	Coupon	Issue Date	Maturity Date	Rating
ABN AMRO BANK NV	NE	EUR	$929M	0,88%	18-4-2018	22-4-2025	A1
ABN AMRO BANK NV	NE	EUR	$563M	0,75%	9-6-2015	9-6-2020	A1
ABN AMRO BANK NV	NE	EUR	$557M	0,63%	31-5-2016	31-5-2022	A1
ABN AMRO BANK NV	NE	EUR	$848M	0,50%	15-4-2019	15-4-2026	A1
CREDIT AGRICOLE CIB	FR	BRL	$4M	72,00%	25-2-2013	24-8-2016	WR
CREDIT AGRICOLE CIB	FR	MXN	$5M	1,00%	17-6-2013	18-12-2017	WR
CREDIT AGRICOLE CIB	FR	JPY	$1M	9,60%	8-7-2013	9-7-2018	WR
CREDIT AGRICOLE CIB	FR	BRL	$2M	4,00%	8-7-2013	9-7-2020	NR
CREDIT AGRICOLE CIB	FR	JPY	$55M	1,36%	24-9-2013	24-9-2020	NR
CREDIT AGRICOLE CIB	FR	JPY	$136M	0,70%	30-10-2013	26-10-2017	WR
CREDIT AGRICOLE CIB	FR	MXN	$20M	8,44%	25-11-2013	26-11-2018	WR
CREDIT AGRICOLE CIB	FR	AUD	$54M	9,08%	18-12-2013	18-12-2018	WR
CREDIT AGRICOLE CIB	FR	USD	$52M	4,02%	18-12-2013	18-12-2018	WR
CREDIT AGRICOLE CIB	FR	JPY	$104M	0,66%	27-1-2014	25-1-2018	WR
CREDIT AGRICOLE CIB	FR	TRY	$17M	16,22%	30-1-2014	31-1-2017	WR
CREDIT AGRICOLE CIB	FR	TRY	$69M	19,20%	14-2-2014	14-2-2018	WR
CREDIT AGRICOLE CIB	FR	JPY	$124M	0,60%	5-3-2014	5-3-2018	WR
CREDIT AGRICOLE CIB	FR	JPY	$75M	0,60%	2-6-2014	4-6-2018	WR
CREDIT AGRICOLE CIB	FR	BRL	$8M	18,90%	25-6-2014	26-6-2017	WR
CREDIT AGRICOLE CIB	FR	AUD	$43M	6,74%	2-7-2014	20-6-2018	WR
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
TLFF I PTE LTD	SI	USD	$15M	35,50%	23-2-2018	23-2-2025	NR
TLFF I PTE LTD	SI	USD	$15M	8,00%	23-2-2018	23-2-2033	NR
TOYOTA FINANCE CORP	JN	JPY	$536M	0,16%	19-4-2019	19-4-2024	Aa3
TOYOTA MOTOR CREDIT CORP	US	EUR	$705M	0,00%	21-11-2017	21-7-2021	Aa3
TRANSPORT FOR LONDON	EN	GBP	$607M	2,13%	24-4-2015	24-4-2025	Aa3
TERNA SPA	IT	EUR	$1170M	1,00%	23-7-2018	23-7-2023	Baa2
TERNA SPA	IT	EUR	$564M	1,00%	10-4-2019	10-4-2026	Baa2
CITY OF TORONTO CANADA	CA	CAD	$231M	6,40%	1-8-2018	1-8-2048	Aa1
UNIONE DI BANCHE ITALIAN	IT	EUR	$564M	1,50%	10-4-2019	10-4-2024	Baa3
UNILEVER PLC	EN	GBP	$414M	2,00%	26-3-2014	19-12-2018	WR
CITY OF VANCOUVER	CA	CAD	$66M	6,20%	21-9-2018	21-9-2028	Aaa
VERBUND AG	AS	EUR	$627M	1,50%	20-11-2014	20-11-2024	Baa1
VODAFONE GROUP PLC	EN	EUR	$840M	0,90%	24-5-2019	24-11-2026	Baa2
HYPO VORARLBERG BANK AG	AS	EUR	$359M	0,63%	19-9-2017	19-9-2022	A3
WOOLWORTHS GROUP LTD	AU	AUD	$284M	5,70%	23-4-2019	23-4-2024	Baa2
WESTPAC BANKING CORP	AU	EUR	$590M	0,63%	22-11-2017	22-11-2024	Aa3
WESTPAC BANKING CORP	AU	AUD	$92M	5,70%	27-2-2018	27-2-2023	Aa3
WESTPAC BANKING CORP	AU	AUD	$367M	6,20%	3-6-2016	3-6-2021	Aa3
WESTPAC SEC NZ/LONDON	NZ	EUR	$568M	0,30%	25-6-2019	25-6-2024	A1
THREE GORGES FNCE II	CI	EUR	$725M	1,30%	21-6-2017	21-6-2024	A1

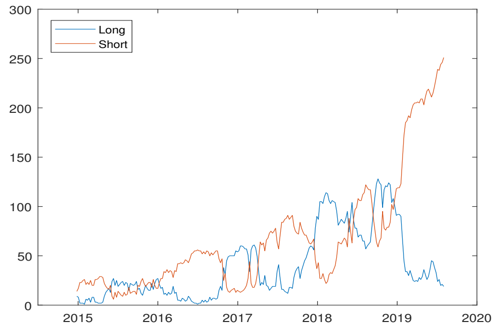
B Return correlations

	Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B1	B2	B3	Caa1	Caa2	Caa3	Ca	C
Aaa	1,00	0,88	0,77	0,80	0,77	0,80	0,76	0,74	0,76	0,58	–	-0,01	–	0,18	–	0,15	–	0,10	–	–	–
Aa1		1,00	0,81	0,72	0,71	0,84	0,61	0,67	0,66	0,52	–	-0,03	–	0,16	–	0,14	–	0,10	–	–	–
Aa2			1,00	0,67	0,74	0,73	0,59	0,69	0,65	0,40	–	0,04	–	0,08	–	0,17	–	0,05	–	–	–
Aa3				1,00	0,69	0,80	0,72	0,75	0,69	0,51	–	-0,18	–	0,16	–	0,12	–	0,09	–	–	–
A1					1,00	0,81	0,78	0,87	0,79	0,56	–	0,11	–	0,17	–	0,13	–	0,11	–	–	–
A2						1,00	0,67	0,78	0,72	0,43	–	0,12	–	0,13	–	0,14	–	0,19	–	–	–
A3							1,00	0,86	0,82	0,58	–	0,06	–	0,29	–	0,03	–	0,18	–	–	–
Baa1								1,00	0,89	0,61	–	0,10	–	0,27	–	0,20	–	0,09	–	–	–
Baa2									1,00	0,63	–	0,15	–	0,34	–	0,17	–	0,01	–	–	–
Baa3										1,00	–	0,34	–	0,40	–	0,06	–	-0,03	–	–	–
Ba1											–	–	–	–	–	–	–	–	–	–	–
Ba2												1,00	–	0,26	–	-0,03	–	0,03	–	–	–
Ba3													–	–	–	–	–	–	–	–	–
B1														1,00	–	0,05	–	0,05	–	–	–
B2															–	–	–	–	–	–	–
B3																1,00	–	-0,11	–	–	–
Caa1																	–	–	–	–	–
Caa2																		1,00	–	–	–
Caa3																			–	–	–
Ca																				–	–
C																					–

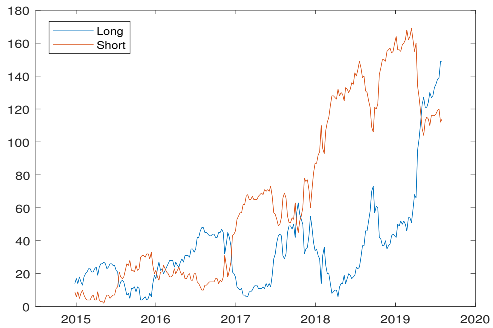
C Long and short positions



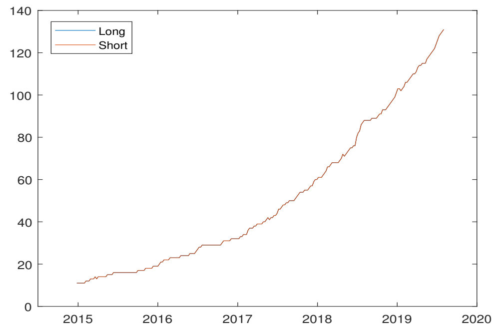
(a) Carry 1



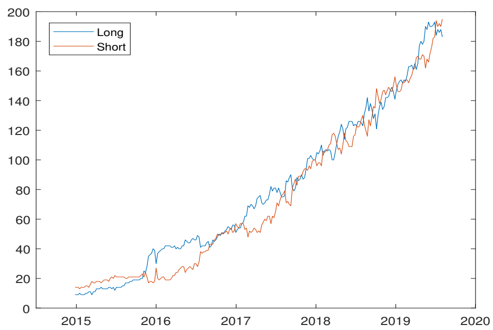
(b) Carry 2



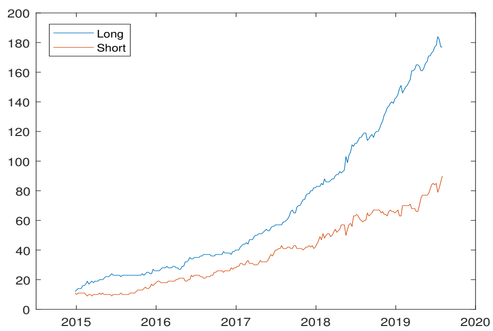
(c) Momentum 1



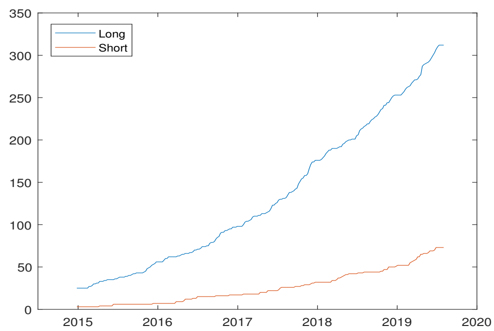
(d) Momentum 2



(e) Value 1



(f) Quality 1



(g) Quality 2

Figure 6: The number of long and short positions in each factor portfolio for a one-week holding period