Factor-based Portfolio Management with Corporate Bonds

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List of Abbreviations

A	Rating category A
AA	Rating category AA
AAA	Rating category AAA
ADF	Augmented Dickey-Fuller
APT	Arbitrage Pricing Theory
Avg.	Average
BAML	Bank of America Merrill Lynch
BBB	Rating category BBB
BM	Benchmark
bps	Basis points
CAPM	Capital Asset Pricing Model
CDS	Credit Default Swap
DUR	Duration
e.g.	for example
ESG	Environmental, social and corporate governance
et al.	and others
EW	Equal-weighted
HY	High yield

IG	Investment grade
MA	Moving average
MCW	Market-capitalization weighted
MF	Multi-factor
MPT	Modern Portfolio Theory
OAS	Option-adjusted Spread
PRI	Principles for Responsible Investment
RTG	Rating
SR	Sharpe ratio
SRI	Sustainable and Responsible Investing
S&P	Standard and Poor's
t-stat	t-statistic
UN	United Nations
USD	U.S. Dollar
U.S.	United States of America
VIX	Volatility index
Vol.	Volatility

1 Introduction

1.1 Introduction to Factor Investing

Over the past 50 years financial asset pricing theories have evolved from simple single-factor models to more complex multi-factor models. Initially, Sharpe's (1964) Capital Asset Pricing Model (CAPM) postulated that security markets can be described by a single factor (market beta). The basic premise of the model is that market participants require a risk premium for investing in high-beta assets that are typically considered more risky than low-beta assets. However, in the aftermath of the 2008 global financial crisis, two major trends emerged in the investment industry that laid the groundwork for the rise of factor-based investment strategies: 1) Investors started to evaluate and implement portfolio diversification in terms of underlying systematic risk factors given the failure of active management to provide adequate downside protection. 2) Investors demanded cost-effective, transparent and systematic alternative investment vehicles that could capture most or at least parts of active managers' excess return.

As a consequence, factor-based investing has grown in popularity and rapidly attracted academics, asset managers and institutional investors. Even

though factor-based investing gained widespread recognition and adoption after 2008, it has been around for several decades as a well-established approach for equity markets. The underlying idea is to capture equity risk factors, such as size, value, momentum, low beta and quality, and to harvest the corresponding risk premia. These risk factors are inconsistent with the CAPM developed by Sharpe (1964), which states that market beta is the only risk that should be compensated. In addition, Markowitz's (1952) Modern Portfolio Theory (MPT) suggests that investors hold a portfolio of stocks to diversify idiosyncratic risk. Therefore, the CAPM builds on the MPT and predicts that all investors hold the market portfolio in equilibrium. As a result, only systematic risk should be priced in equilibrium as idiosyncratic risk can be diversified away. It is important to note that prior to the CAPM, there was not a theoretically sound benchmark for returns.

However, for various reasons investors in reality may not hold perfectly diversified portfolios and since the introduction of the CAPM, academic research has put forward convincing evidence that additional systematic sources of return exist. Beginning in the 1980s, numerous studies started to uncover patterns in the cross-section of stock returns that contradicted the central prediction of the CAPM. For example, firms that have high earnings-to-price ratios (Basu 1977; 1983), low market capitalization (Banz, 1981), or high book-to-market equity (Rosenberg et al., 1985) were shown to be associated with high average returns, even after controlling for betas.

Nowdays, it has been widely documented that certain factors generate higher risk-adjusted returns than the broad market over a long-term investment

horizon and as suggested by the CAPM (see Ang, 2014 and Harvey et al., 2016).

Back in 1923 the first market-capitalization weighted index (cap-weighted index) was constructed by the Standard Securities Corporation[1] which included 233 equities. In such a weighting scheme, each company has a weight in proportion to the total market value of the outstanding shares. A few years later, benchmarks[2] were introduced to the financial industry and had a huge impact on active portfolio management since then.

There is a remarkable difference between equity index and bond index construction which is far more complex because of the characteristics of fixed-income securities. On one hand, most companies have only one class of equity outstanding but the same companies may have many bonds that will be adequate for an index. On the other hand, compared to a broad market equity index that contains either dividend or non-dividend paying stocks, a broad market fixed-income index comprises securities with numerous properties and cash flow structures. Some of the bond properties include maturity, coupon, coupon frequency, and ratings to name a few.

Broad bond benchmarks contain a large number of securities, and these securities are maturing. Besides, historical prices are often not reliable and some securities are very illiquid. As a result, broad bond indices are not completely investable. The first challenge for a factor based bond approach is therefore to be

[1] Today known as Standard & Poor's
[2] An index that can be used for performance measurement of actively managed funds

investable, which is a serious concern given the difficult access to data and the lack of liquidity. Cap-weighted equity indices tend to be heavily concentrated because of strong cross-sectional differences across market capitalization. This problem is known as the "bums problem" (Siegel, 2003) for bond indices because they will have a tendency to overweight bonds with large amounts of outstanding debt, which in turn leads to an overweight in riskier assets. In addition, risk exposures in cap-weighted indices are uncontrolled for. Siegel (2003) notes that the cap-weighted indexing scheme in equity markets enables an investor without specific knowledge into security analysis to hold a mean-variance efficient portfolio. When applied to fixed-income indices, cap-weighting creates difficulties. He further states that the duration of an index is not necessarily the ideal duration for fixed-income investors whose preferred durations and interest rate risk exposures depend on their individual return objectives and investment time horizons.

Therefore, a cap-weighted broad fixed-income index does not represent the optimal benchmark for all bond investors. The main shortcomings of existing bond indices, beside interest rate and credit risk, are therefore lack of investability, insufficient diversification and undesired risk exposures. Keeping that in mind, the key conditions for successful factor-based portfolio management with corporate bonds are therefore the ability to provide investable solutions, ability to provide better diversification and the ability to provide superior risk exposures. Index providers have responded in kind with a proliferation of subindices, customized indices, and new weighting schemes. Because an index may define the universe of securities in which an investment manager may invest, the choice of an index as a benchmark can directly affect portfolio risk exposures and relative performance

measurement. For these reasons, investors should thoroughly understand an index before selecting it as a benchmark. Once an index is chosen, a well-thought-out investment policy must be put in place to avoid risk exposures and performance divergence from the benchmark that are unanticipated.

This realization is leading to a new investment paradigm, with substantial welfare improvements expected for both institutional and individual investors. This new paradigm is called factor-based investing which subsumes the popular marketing names such as smart, strategic, scientific, exotic or alternative beta products as all of them at heart represent factor strategies no matter if they are considered as an anomaly, puzzle or risk premium.

However, when considering any active strategy, investors should have a clear understanding of the sources of expected returns, the stability and sustainability of those returns, the risk exposures and risk controls as well as the liquidity demands of the underlying investment strategy.

1.2 Defining Factors

Sharpe (1964) shows that Tobin's (1958) tangency portfolio corresponds to the market-capitalization portfolio and formalizes the relationship between the expected return of asset i and the expected return of the market-capitalization portfolio as:

$$\mathbf{E}[R_i] - R_f = \beta_i^{market}(\mathbf{E}[R_{market}] - R_f) \tag{1.1}$$

where R_i and R_{market} are the asset and market returns and R_f is the risk-free rate, respectively. The coefficient β_i^{market} represents the beta of asset i with respect to the market-capitalization portfolio and is calculated as:

$$\beta_i^{market} = \frac{cov(R_i, R_{market})}{\sigma^2(R_{market})} \tag{1.2}$$

Contrary to idiosyncratic risks, systematic risk cannot be diversified away, and therefore, investors should be compensated for taking this risk. The implication of this assumption is that the market risk premium, ϕ_{market} , should be positive (equation 1.3) while the expected return on idiosyncratic risk is equal to zero (equation 1.4). This idiosyncratic risk (also referred to as unsystematic or company specific risk) should not be rewarded because it can be diversified away.

$$\phi_{market} = \mathbf{E}[R_{market}] - R_f > 0 \tag{1.3}$$

$$\epsilon_i = (R_i - R_f) - \beta_i^{market}(\mathbf{E}[R_{market}] - R_f), where\ \mathbf{E}[\epsilon_i] = 0 \tag{1.4}$$

Finally, according to the CAPM, there is a single risk premium only. It is equal to the excess return of the market-capitalization portfolio with respect to the risk-free asset. This risk premium is a compensation for being exposed to the non-diversifiable risk. However, in practice investors consider several risk premia,

that is one risk premium for each asset class.[3]

Ross (1976) introduces an alternative model to the CAPM, namely the arbitrage pricing theory (APT). According to this model, the return on asset i is driven by a standard linear factor model:

$$R_i = \alpha_i + \sum_{j=1}^{n_\theta} \beta_i^j \theta_j + \epsilon_i \tag{1.5}$$

where α_i is the intercept, β_i^j is the sensitivity of asset i to factor j and θ_j is the value of factor j. ϵ_i is the idiosyncratic risk of asset i, implying that $\mathbf{E}[\epsilon_i] = 0$, $cov(\epsilon_i, \epsilon_k) = 0$ for $i \neq k$ and $cov(\epsilon_i, \theta_j) = 0$. Using arbitrage theory, we can show that the expected return of asset i is a linear function of the expected returns of the factors:

$$\mathbf{E}[R_i] - R_f = \sum_{j=1}^{n_\theta} \beta_i^j (\mathbf{E}[\theta_j] - R_f) \tag{1.6}$$

The underlying idea of APT is that systematic risks are not entirely captured by a single market risk figure. Unlike CAPM, which relies on the validity of the Markowitz model[4], APT does not assume a specific utility function. However, it assumes that it is possible to select from a large number of assets to build a portfolio that is sufficiently diversified with no specific risk in respect of individual assets.

The market risk premium in CAPM is deduced from an equilibrium argument, implying that the one-factor model is a consequence of the existence of

[3]For instance, asset classes could be classified in: equities, sovereign bonds, corporate bonds, commodities, foreign exchange etc.

[4]This implies that investors adopt a mean-variance analysis.

the risk premium:

$$R_i = \alpha_i + \beta_i^{market} R_{market} + \epsilon_i \tag{1.7}$$

where $\alpha_i = (1 - \beta_i^{market})R_f$ and $\epsilon_i = \epsilon_i - \beta_i^{market}(R_{market} - \mathbf{E}[R_{market}])$ is a white noise process. In APT, the risk model is determined ex-ante meaning that equation (1.6) is deduced from the model described in equation (1.5). However, this model does not provide information about the sign of the excess return $\phi(\theta_j) = \mathbf{E}[\theta_j] - R_f$. The excess return $\phi(\theta_j)$ is generally misinterpreted as a risk premium. Indeed, the issue is that the value taken by $\phi(\theta_j)$ is exogenous. Therefore, it can be positive, but it can also be negative, zero or even undefined.

Examples of the APT framework include the three-factor model (equation 1.8) of Fama and French (1992; 1993) as well as the four-factor model (equation 1.9) of Carhart (1997).

$$R_i = \alpha_i + \beta_i^{market}(R_{market} - R_f) + \beta_i^{SMB} R_{SMB} + \beta_i^{HML} R_{HML} + \epsilon_i \tag{1.8}$$

$$R_i = \alpha_i + \beta_i^{market}(R_{market} - R_f) + \beta_i^{SMB} R_{SMB} + \beta_i^{HML} R_{HML} + \beta_i^{WML} R_{WML} + \epsilon_i \tag{1.9}$$

where R_{SMB} is the return on small stocks minus the return on large stocks, R_{HML} is the return on stocks with high book-to-market values minus the return on stocks with low book-to-market values and R_{WML} is the return difference of winner and loser stocks over the past twelve months. The model of Carhart is an extension of the three-factor model of Fama and French (1993) and has become standard

in the asset pricing literature as well as the asset management industry since its publication.

1.3 Return Dynamics Between Equity and Debt

Rational asset pricing models suggest that risk premia in the equity market should be consistent with those of the corporate bond market, assuming that the two markets are integrated. The earliest formalized structural credit risk model developed by Merton (1974) provides important intuition why changes in equity and corporate bond returns of a given firm should be related as they represent contingent claims against the assets of the same company.

The only state variable in the model is the value of the firm, V_t, and one of the main assumptions is that the value of a company's assets follows a geometric Brownian motion W_t where μ and σ are the drift and volatility, respectively.

$$dV_t = \mu V_t dt + \sigma V_t dW_t \tag{1.10}$$

It is assumed that the company issues only a single zero-coupon bond with face value F payable at T where the payoff to the creditors D_T at date T is:

$$\begin{aligned} D_T = min\{V_T, F\} &= F + min\{V_T - F, 0\} \\ &= F - max\{F - V_T, 0\} \end{aligned} \tag{1.11}$$

The creditors payoff is thus the sum of a safe claim payoff and a short position in a put option written on the firm's assets where the put option represents the loss given default. Otherwise, equity holders receive:

$$E_t = max\{V_T - F, 0\} \tag{1.12}$$

To relate equity and debt in the Merton model, equity is valued as a call option on the value of assets. Applying the put-call parity yields the value of debt, D_t, and equity, E_t, as $E_t + D_t = V_t$ where:

$$E_t = Call_{BS}(V_t, F, \mu, T - t, \sigma) \tag{1.13}$$

$$D_t = P_t - Put_{BS}(V_t, F, \mu, T - t, \sigma) \tag{1.14}$$

P_t in equation (1.14) represents the nominal value of liabilities. According to the model the spread between risky credit debt and risk-free debt is the value of the put option.[5] Consequently, determinants of credit spreads are: company's business risk of the assets σ, time to maturity T and the face value F.

The theoretical link that equities and corporate bonds of a company are connected through their exposure to the underlying company value is an important insight from the formalized Merton model. Therefore, equity market factors are relevant for pricing corporate debt only if they capture changes in firm value (V_t) or changes in risk neutral probabilities (W_t). Fama and French (2015) motivate

[5] $Call_{BS}$(V_t, F, μ, T - t, σ) denotes the value of a call option and Put_{BS}(V_t, F, μ, T - t, σ) is the value of a put option according to Black and Scholes (1973).

their five-factor model for equities from the Miller and Modigliani (1961) valuation model:

$$P_{it} = \sum_{\tau=1}^{\infty} E[D_{it+\tau}]/(1+r_i)^{\tau} \tag{1.15}$$

The dividend discount model assumes that the market value of firm i's stock, P_{it}, is the present value of its expected dividends where D_{it} denotes dividends and r_i the internal rate of return (or firm's long-term average expected stock return). According to the clean surplus relation, dividends equal to the earnings minus the change in book equity: $D_{it+\tau} = Y_{it+\tau} - \Delta B_{it+\tau}$, where $\Delta B_{it+\tau} = B_{it+\tau} - B_{it+\tau-1}$. The dividend discount model can then be written as:

$$\frac{P_{it}}{B_{it}} = \frac{\sum_{\tau=1}^{\infty} E[Y_{it+\tau} - \Delta B_{it+\tau}]/(1+r_i)^{\tau}}{B_{it}} \tag{1.16}$$

In their paper, Fama and French (2015) claim that equation (1.16) makes three predictions: First, fixing everything except the current market value (P_{it}) and the expected stock return (r_i), a low P_{it} or a high book-to-market equity (B_{it}/P_{it}) implies a high expected return. Second, fixing everything except the expected profitability and the expected stock return, high expected profitability implies a high expected return. Finally, fixing everything except the expected growth in book equity and the expected return, high expected growth in book equity implies a low expected return. This is in the spirit of Fama and French (2015): *"Most asset pricing research focuses on short-horizon returns–we use a one-month horizon in our tests"*.

1.4 Literature Review

Ever since the development of MPT by Markowitz (1952) and the CAPM by Sharpe (1964), researchers doubt that one factor-models suffice to explain the complexities of global stock markets. The APT introduced by Ross (1976) provides a multi-factor approach in explaining asset returns and is based on the absence of arbitrage and the law of one price. Explaining the market based on factors capturing common characteristics and risks of a particular class of investment vehicles is a tempting proposition, as it is an intuitive approach to understand the dynamics of the underlying asset class, and if chosen properly, may ultimately be used to determine alternative risk premia.

In the past, empirical research on relevant pricing factors focused predominantly on equity markets. In the early 1990s Fama and French (1992; 1993) introduce a factor model based on firm-specific factors to explain cross-sectional stock returns. They demonstrate that size, value and beta factors can account for up to 95% of variability in U.S. stock market returns. This stunning result opened the door for many extensive studies on factor-based investing, leading to a multitude of new factors (sometimes referred to as "the factor zoo") and factor models in the equity space (see Cochrane, 2011 or Harvey et al., 2016). A substantial amount of these studies suggest that size, value, profitability and investment have explanatory power to describe the cross-section of future stock returns.[6] Moreover, Hou et al. (2015) present a "q-factor" model containing size, profitability and in-

[6] See Banz (1981) for size, Basu (1977) for value, Haugen and Baker (1996) or Novy-Marx (2013) for profitability and Titman et al. (2004) or Watanabe et al. (2013) for investment, to name a few.

vestment which is able to explain a significant amount of stock market anomalies. Finally, Fama and French (2015) enrich their traditional three-factor model by adding a measure of firm profitability and investment, showing that the new five-factor model performs better than their three-factor model.[7]

Despite the apparent success of factor-based investing, the abundance of academic research on factor-based investing in equity markets and the fact that global fixed-income markets are bigger than global equity markets (see Crawford et al., 2015, Israel et al., 2016 or Goldstein et al., 2017), similar research for fixed-income securities is less mature. Documented corporate bond factors in the literature include low volatility (Ilmanen et al., 2004 or Frazzini and Pedersen, 2014), momentum (Pospisil and Zhang, 2010 or Jostova et al., 2013), value (Correia et al., 2012) and size (Houweling and van Zundert, 2017). Moreover, Choi and Kim (2016) note that asset growth and investment anomalies exist in corporate bond markets and Chordia et al. (2017) state that size, profitability and past equity returns are strong predictors of corporate bond returns. Additionally, Crawford et al. (2015) examine the predictive power of over thirty accounting-based fundamental variables related to equity returns on corporate bond returns. Finally, Israel et al. (2016) find that carry, low volatility, momentum and value explain nearly 15% of the cross-sectional variation in U.S. corporate bond excess returns.

[7] By adding profitability and investment to their model, the value factor of the three-factor model becomes redundant for describing average returns in the U.S. stock market. Nevertheless, investors interested in portfolio tilts towards size, value, profitability and investment premia should consider all five factors recommended by Fama and French (2015).

1.5 Contribution to Literature

This dissertation extends the existing literature in several ways. First, the chapter "Common Equity Factors in Corporate Bond Markets" departs from previous research by employing the original equity factor definitions of size, value, momentum and low-beta for corporate cash bonds. Thus, portfolios are formed by sorting the cross-section of bonds into deciles based on corresponding company characteristics and then their time series performance is examined. If these factors are rational pricing factors (or mispricings caused by behavioral biases), their factor risk premia estimated in one market should be consistent with those estimated in the other. According to structural credit risk models both equity and corporate debt are driven by the fundamentals of the same underlying corporations implying that stock prices and credit spread changes must be related to ensure the absence of arbitrage. Consequently, risk premia in equity and corporate bond markets should be related. Additionally, with the increasing size of the Credit Default Swap (CDS) market, capital structure arbitrage grew in popularity and aims to profit from temporal mispricing between firm's equity and corporate bonds or CDS's (see Yu, 2006 or Duarte et al., 2007). Finally, while the relationship between firm's default risk and equity risk premia has been analyzed in numerous studies (see Vassalou and Yuhang, 2004 or more recently Chava and Purnanandam, 2010 and Friewald et al., 2014), there is little evidence that investigates if corporate bond returns exhibit anomalies similar to those in stock markets. However, this chapter analyzes if size, value, momentum and low-beta factors extend their success in equity markets to U.S. credit markets. While size, value and momentum are economically and statistically significant in the U.S. high yield space, only size and momentum

have explanatory power for the U.S. investment grade market. In addition, size, value, momentum and beta are combined in order to construct equal-weighted, investable, long-only, multi-factor portfolios and these portfolios outperform traditional fixed-income benchmarks on a risk-adjusted basis. The results highlight the importance of company level characteristics on the joint return dynamics of equities and corporate bonds.

Second, the chapter "ESG Factors in Corporate Bond Returns" contributes to the literature by proposing environmental, social, and governance (ESG) factors that are theoretically motivated and firmly grounded in equity markets. Moreover, the main contribution is to provide novel insights and misconceptions on ESG factors in credit markets. Since the development of sustainable and ethical investing, there has been a vigorous and ongoing debate on whether ESG factors in corporate bond markets enhance returns. Unfortunately, empirical evidence on ESG factors in corporate bond markets is mixed and inconclusive. Some evidence supports positive returns, other evidence suggests a negative relation, and a third strand of the literature finds that the relation is unstable. However, research on this topic is seemingly contradictory and here, I address this disconnect in empirical research as well as with factors in general. Finally, analyzing the relation between firm's ESG factors and the corresponding corporate bond excess return is promising for corporate bond investors for at least the following two reasons. On the one hand, the growing importance and awareness for ESG in financial markets can for certain no longer be denied by looking at current figures. On the other hand, a high ESG factor strategy is usually less risky and exhibits relatively high risk-adjusted returns especially in market downturns which makes it an important building block

of every investor's portfolio.

Third, the chapter "Exploiting Uncertainty with Market Timing in Corporate Bond Markets" contributes to the literature in several important points. For instance, the study provides novel results on cross-sectional profitability of technical analysis in corporate bond markets. Unlike existing literature that applies technical analysis to either market indices or individual securities, it is applied to corporate bond portfolios sorted by measures that reflect information uncertainty, namely option-adjusted spread (OAS) and equity volatility of the corresponding firm. The rationale behind the analysis is that many investors and fund managers use technical analysis to make trading decisions and that proponents of this investment approach use the most widespread indicator, moving averages, to time investments. Furthermore, empirical evidence is provided for behavioral finance theories suggesting that asset prices can display patterns of predictability that cannot be explained with risk-based expectation theories of price formation. However, previous literature on this topic does not include credit markets (see Daniel and Hirshleifer, 2015). Additionally, the results contribute to the debate whether well-known strategies from equity markets can be extended to corporate bond markets. While factors based on fundamental data deliver inconclusive results at best for corporate bonds implying market segmentation (see Choi and Kim, 2016 or Chordia et al., 2017), this chapter shows that technical analysis translates to the realm of credit markets. For portfolios with high uncertainty, as measured by the OAS, the abnormal returns generate economically and statistically significant returns relative to the CAPM, the Carhart 4-factor model and additionally the bond factor model from Asness et al. (2013). The results remain robust to

different moving average formation periods, transaction costs, long-short portfolio construction techniques and alternative definitions of information uncertainty. Therefore, these findings provide important insights for corporate bond investors, hedgers and arbitrageurs.

2 Common Equity Factors in Corporate Bond Markets[8]

2.1 Introduction

Factor models are the core of empirical asset pricing. Initially, Sharpe's (1964) CAPM demonstrates that equity markets can be characterized by a single factor (market beta). The basic premise of the model is that market participants require a risk premium for investing in high-beta assets that are typically considered more risky than low-beta assets.

In the wake of the CAPM, researchers have identified other factors that reliably explain the variability of asset returns such as value (Basu, 1977), size (Banz, 1981) and momentum (Jegadeesh and Titman, 1993). The development of these new factors lead to the seminal multi-factor models by Fama and French (1992; 1993) and Carhart (1997) that describe market dynamics more accurately and therefore have received ample attention in recent years by researchers and

[8] A version of this chapter was published in Bektić et al. (2017).

market practitioners alike.[9] In fact, over recent years asset managers have designed investment vehicles guided entirely by factors (e.g. value or momentum) rather than traditional metrics (e.g. sectors or regions).

In general, any variable that accurately and reliably captures a risk or return characteristic of an asset class can be considered a factor. For example, momentum has been thoroughly vetted across regions and asset classes, and has been shown to exhibit explanatory power for asset returns. While factors are employed in various settings and for many different reasons, a common trait of factor-based investing is, however, to exploit one or more factors to harvest associated risk premia and benefit from diversification effects, which may ultimately lead to superior risk-adjusted returns when compared to market-capitalization weighted (cap-weighted) benchmarks (see Ang, 2014).

For decades, investment portfolios were partitioned into one of two broad investment vehicles or a combination thereof: traditional index funds and actively managed funds. Traditional index funds are passive strategies designed to replicate indices based on conventional weighting schemes (market-capitalization) that allow investors to acquire the underlying indices in a simple, transparent and cost-effective manner. By contrast, actively managed funds aim to execute specific, often more complex investment strategies, that typically lure investors with the promise of superior returns when compared to their passive counterparts, despite higher expense ratios typically associated with active portfolio manage-

[9] Fama and French (2015) enrich their traditional three-factor model by adding operating profitability and investment, showing that the new five-factor model performs better than their original three-factor model.

ment.[10] However, increased complexity in securities and regulations as well as failure of active managers to deliver on their promises allowed for a new, factor-based investment approach to emerge (see Ang et al., 2009). Factor-based investing aims to combine the cost-effectiveness and transparency of passive strategies with the promise of superior risk-adjusted returns of actively managed strategies.[11] By using factors, rather than traditional metrics to guide asset allocation decisions, factor-based investing offers a new investment paradigm that has profoundly changed management of equity portfolios. Nowadays factor-based strategies in the equity space are not only firmly grounded in academic literature but they are also implemented by many asset managers globally (see BlackRock, 2015, p.21).

Despite its success in the equity space and the intuitive link between holders of equity and debt (both own claims against the same underlying assets of a firm, see Merton, 1974), factor-based investing in the fixed-income space is less mature. Here, it is investigated if four of the most thoroughly studied and most broadly accepted equity factors (size, value, momentum and beta)[12] do also offer a risk premium in U.S. credit markets. While size, value and momentum are economically and statistically significant in the U.S. high yield (HY) space, only size and momentum have explanatory power for the U.S. investment grade (IG) market.

[10] Actively managed funds typically charge a management and/or performance fee.

[11] Since risk premium, return driver, and characteristic are all terms referring to variables carrying explanatory power of market dynamics (risk, return, correlation), alternative beta, smart beta, advanced beta, scientific beta, exotic beta etc. can all be subsumed under the term factor-based investing.

[12] Harvey et al. (2016) provide an excellent summary on factor-based investing in the equity space and recount more than 300 papers on cross-sectional return patterns published in various journals.

In addition, the performance and diversification benefits of an equal-weighted, investable, long-only, multi-factor portfolio is analyzed and demonstrated that higher risk-adjusted returns can be achieved by combining all four factors.

The remainder of this chapter is organized as follows. Section 2.2 highlights the shortcomings of a typical fixed-income index that simultaneously serves as a motivation for why factor-based strategies could represent a promising alternative for investors. Section 2.3 defines and motivates the four factors at the heart of this analysis. The data and empirical methodology are detailed in Section 2.4. Finally, the findings are presented and summarized in Sections 2.5 and 2.6.

2.2 Traditional Indices in Fixed-Income Markets

As stated in the introduction, the first cap-weighted index was constructed by the Standard Securities Corporation in 1923 and included 233 equities. Each company in this index was weighted according to its market value of outstanding shares. This very first index served as a prototype for many indices used to benchmark the performance of actively managed portfolios just a few years later. This dynamic profoundly changed active portfolio management, as deviations from benchmark portfolios, for the first time, posed additional risks (tracking error)[13] to active asset managers, leading to portfolio allocations that were more in line with those of their corresponding benchmark portfolios.

However, investing in equities is considerably different from investing in

[13]Standard deviation of the active returns.

corporate bonds. While investors in equity securities can typically rely on a bijective mapping between firms and corresponding equities, the surjective mapping between firms and their outstanding bonds frequently complicates the selection process of credit portfolios. Moreover, credit securities of a given firm frequently differ in features, indentures, covenants and most importantly in maturity and position in the capital structure, further exacerbating the selection process of credit securities. Due to these substantial differences in credit and equity securities, it is not surprising that construction algorithms for equity and credit portfolios differ profoundly as well.

Not only are the underlying asset classes of equity and credit markets fundamentally different, implications of benchmarking actively managed portfolios against cap-weighted benchmarks for each asset class are as well. Firstly, while both equity and credit benchmarks contain a large number of securities, constituents of fixed-income indices are continuously changing due to the maturing nature of fixed-income securities, while constituents of equity indices are relatively stable. This leads to significantly higher turnover rates in fixed-income indices when compared to equity indices. Secondly, liquidity is much less of an issue for equity securities when compared to trading over-the-counter (OTC) corporate bonds. As a result, investing in a significant portion of credit securities of a typical credit index is infeasible due to lack of liquidity, while all constituents of equity indices are typically attainable. Lastly and most importantly, while cap-weighted equity benchmarks enable investors to hold mean variance efficient portfolios, cap-weighted indices in credit space push investors into the most prolific issuers of debt, which intuitively are associated with elevated levels of risk. This counterin-

tuitive dynamic of tracking cap-weighted indices in bond markets is known as the "bums problem" (Siegel, 2003) and leads to assigning the largest weight to those corporations (or countries) with the largest amounts of outstanding debt in the index.

The introduction of benchmark indices, the complexities of credit securities and the counter-intuitive herding into most prolific issuers of debt in the credit space are all reasons why it is difficult and suboptimal to track a cap-weighted bond index. Yet, theses dynamics in credit markets simultaneously and intuitively motivate why factor-based strategies may significantly and sustainably outperform their cap-weighted peers.

2.3 Factor Investing in Credit Markets

Factor-based investing, in a nutshell, is the systematic identification and exploitation of sustainable risk premia existing in a given market, that when combined properly can ultimately lead to superior risk-adjusted returns. As market capitalization rarely is an attractive factor (especially in credit markets), portfolios derived from factor-based investment strategies may and in credit markets should deviate from traditional benchmarks significantly. Factor-based investing is a tantalizing proposition, as it allows investors to customize the risks assumed and to harvest associated risk premia. At the heart of factor-based investing is, therefore, the identification of factors via a diligent vetting process. That is, each factor should be rooted in sound economic or behavioral rationale, exhibit significant premia that are expected to persist in the future, display the same characteristics

across regions and must be implementable through liquid investment vehicles (see Ang et al., 2009 or Amenc et al., 2012). The four factors at the heart of this study meet these requirements in the equity space (see Harvey et al., 2016 for a summary review of the literature). Due to structural models based on contingent claims, it stands to reason that size, value, momentum and beta factors could potentially offer risk premia in credit markets as well.

2.3.1 Size

Smaller companies are typically associated with lower liquidity, higher distress, and more downside risk than larger firms. Hence, smaller companies should outperform larger firms to compensate investors for taking on the additional risk (see Banz, 1981). The behavioral argument for a size premium is given by limited investor attention to smaller companies and subsequent mispricing (see Stambaugh et al., 2012). Here, size is defined as the market capitalization of the company's equity:

$$Size_t = SO_t \times PPS_t \tag{2.1}$$

where SO_t denotes the number of shares outstanding and PPS_t the price per share in month t. To study size in credit markets, a size factor portfolio is constructed containing the bonds of the smallest 20% of all eligible companies.

2.3.2 Value

Fama and French (1992) use the book-to-market ratio (BE/ME) as a measure of equity value. A high BE/ME is indicative of a cheap stock in relative terms while a low BE/ME signals the opposite. According to Zhang's (2005) "costly reversibility of investments" rationale, companies with high sensitivity to economic shocks are inherently riskier and hence should offer a risk premium. According to behavioral finance, investors overreact (underreact) to bad (good) news and extrapolate recent price movements into the future, which results in underpricing (overpricing). Here, the Fama and French (1992) definition of value is adopted:

$$Value_t = \frac{BE_{t-6}}{ME_t} \tag{2.2}$$

where BE_{t-6} and ME_t denote book equity and market equity in month $t-6$ and t, respectively. Analogous to the construction of the size factor portfolio, a value factor portfolio is constructed by combining the bonds of the 20% most undervalued firms in the eligible investment universe.

2.3.3 Momentum

Momentum attempts to forecast future asset returns by looking at the changes in asset-specific, return-relevant variables in the past (e.g. changes in asset prices or earnings per share). The most frequently studied momentum factor in equity space is equity price momentum. The simple rationale for this factor in equity markets is that winners will keep on winning while losers will keep on loosing. Jegadeesh and Titman (1993) show that this is indeed the case by demonstrating that steady

positive monthly stock returns predict future positive stock returns. Asness et al. (2013) demonstrate an omnipresence of momentum across asset classes and regions. A behavioral explanation behind the momentum anomaly is that stock prices initially underreact to information. Conversely, prices may overreact and continue to rise above their fundamental value implicating herding behavior. Momentum is defined as:

$$Momentum_t = \frac{EP_t}{EP_{t-12}} - \frac{EQMKT_t}{EQMKT_{t-12}} \tag{2.3}$$

where EP_t and EP_{t-12} denote equity price in month t and $t-12$, and $EQMKT_t$ and $EQMKT_{t-12}$ denote equity market in month t and $t-12$, respectively. To study momentum in credit markets a quintile portfolio is constructed based on the bonds of the firms with the highest equity momentum.

2.3.4 Beta

Contrary to efficient market theory, the low-beta anomaly postulates that investors are not adequately compensated for investing in high-beta stocks. In fact, Haugen and Heins (1972) and Black et al. (1972) find that a portfolio that is short riskier stocks against a long position in low-beta stocks generates sustainable positive risk-adjusted returns. Frazzini and Pedersen (2014) provide an overview of possible explanations for the existence of this low-beta anomaly. These explanations range from human behavior and incentive structures to specific investment constraints, and in theory are equally applicable to corporate bond markets as well. Beta is defined as:

$$Beta_t = \frac{cov(r_s, r_m)}{var(r_m)} \tag{2.4}$$

where r_m, r_s, $cov(r_s, r_m)$ and $var(r_m)$ denote the monthly stock returns of stock s, monthly market returns, covariance of monthly stock and market returns, and the variance of monthly market returns over a period of twelve months, respectively. The factor portfolio used to study beta in credit markets contains the bonds of the 20% of issuers with the lowest equity beta.

Due to structural models based on contingent claims, extending arguments for each of the above mentioned factors from equity to corporate bond markets is not only intuitive but also grounded in sound academic theory (see Merton, 1974), and hence studying these factors in the credit space is warranted.

2.4 Data and Methodology

2.4.1 Data

Similar to De Carvalho et al. (2014) and Israel et al. (2016), monthly data of the Bank of America Merrill Lynch (BAML) is used for this analysis. Prices are provided by BAML traders and are used as primary pricing source. The data set includes monthly data of all senior U.S. HY and U.S. IG corporate bond issues rated by at least one of the three major rating agencies (S&P, Moody's and Fitch) and issued U.S. Dollar (USD). The employed BAML indices only include bonds with a minimum amount outstanding of 250 million for IG and 100 million for HY

in local currency terms[14], a fixed coupon schedule, and a minimum remaining time to maturity of one year. Newly issued bonds must exhibit a time to maturity of at least 18 months.[15]

As in Elton et al. (2001) puttable bonds are excluded. Subordinated and contingent capital securities ("cocos") are eliminated as well as taxable and tax-exempt U.S. municipal, equity-linked, securitized, DRD-eligible[16] and legally defaulted securities as these have distinctly different payout characteristics compared to standard senior coupon bonds.

The data set in Table 2.1 covers the period from December 1996 to November 2016 for U.S. HY and IG bonds. Since some factors are based on financial statement ratios and equity market data obtained from FactSet Fundamentals, only publicly traded corporations are considered in this analysis.[17] Furthermore, a 6-month lag is used to ensure that financial statement information is completely priced in by bond market participants and to avoid a forward-looking bias in the analysis (see Bhojraj and Swaminathan, 2009).

[14] This is similar to equity market anomaly literature where too small stocks are typically removed to ensure that results are not driven by market microstructure or liquidity.

[15] Removing bonds that have less than one year to maturity is applied to all major corporate bond indices like Citi Fixed Income Indices, Barclays Capital Corporate Bond Index as well as BAML Corporate Master Index. The 18 month cutoff for newly issued bonds is a standard choice of BAML.

[16] A dividends received deduction (DRD) is a tax deduction received by a corporation on the dividends paid by companies in which it has an ownership stake.

[17] Typically between 85% and 90% of the companies considered for this study publish accounting data and between 50% and 55% are publicly traded firms.

Table 2.1: Summary of Universe Statistics

Average monthly number of total firms, public firms, private firms and bonds as well as the average duration, spread and rating for each year.

U.S. High Yield Universe

YEAR	Avg. # Firms	Avg. # Public Firms	Avg. # Private Firms	Avg. # Bonds	Avg. Modified Duration	Avg. Option Adjusted Spread	Avg. Rating
1997	333	155	178	329	4.18	287	13.68
1998	381	180	201	346	4.36	422	13.71
1999	465	230	235	421	4.39	607	13.79
2000	485	245	240	515	4.2	663	13.85
2001	501	265	236	622	3.87	1133	14.09
2002	511	297	215	783	3.92	1378	14.14
2003	615	362	253	981	4.12	800	14.14
2004	719	410	309	1036	4.28	411	14.04
2005	745	421	324	1025	4.16	360	14.00
2006	757	424	333	966	4.15	328	13.97
2007	709	405	304	799	4.25	331	13.76
2008	819	461	358	891	4.09	923	13.84
2009	782	478	304	982	3.68	1644	14.26
2010	876	529	346	1106	3.94	662	14.12
2011	1054	619	435	1279	4.18	605	13.95
2012	1124	678	446	1414	3.85	682	14.04
2013	1231	743	488	1573	3.89	559	14.24
2014	1314	802	512	1733	3.89	494	14.21
2015	1347	871	476	1979	3.95	760	14.19
2016	1292	875	417	2051	3.74	946	14.29

Rating description: AAA=1, AA+=2, AA=3, AA-=4, A+=5, A=6, A-=7, BBB+=8, BBB=9, BBB-=10, BB+=11, BB=12, BB-=13, B+=14, B=15, B-=16, CCC+=17, CCC=18, CCC-=19

Summary of Universe Statistics - Continued

U.S. Investment Grade Universe

YEAR	Avg. # Firms	Avg. # Public Firms	Avg. # Private Firms	Avg. # Bonds	Avg. Modified Duration	Avg. Option Adjusted Spread	Avg. Rating
1997	816	560	256	2488	5.62	62	6.71
1998	909	617	291	3010	5.65	101	6.87
1999	860	609	251	3004	5.61	139	6.90
2000	738	560	178	2595	5.29	181	6.91
2001	736	578	158	2785	5.19	201	7.11
2002	756	620	136	2939	5.21	208	7.25
2003	752	621	131	3019	5.38	151	7.38
2004	799	647	152	3186	5.48	100	7.44
2005	700	548	152	2399	5.68	91	7.22
2006	717	559	158	2484	5.70	101	7.21
2007	759	594	165	2267	6.06	124	7.40
2008	809	649	160	2751	5.64	332	7.46
2009	789	640	149	3036	5.41	435	7.58
2010	855	700	155	3396	5.69	192	7.60
2011	928	765	163	3894	5.86	194	7.67
2012	994	820	175	4388	5.94	219	7.78
2013	1117	922	195	5021	6.08	174	7.86
2014	1220	1000	220	5545	6.00	142	7.85
2015	1294	1055	239	6055	6.00	172	7.85
2016	1306	1053	253	6484	5.89	186	7.88

Rating description: AAA=1, AA+=2, AA=3, AA-=4, A+=5, A=6, A-=7, BBB+=8, BBB=9, BBB-=10, BB+=11, BB=12, BB-=13, B+=14, B=15, B-=16, CCC+=17, CCC=18, CCC-=19

2.4.2 Methodology

All issuers are partitioned into an IG and a HY bond universe according to their rating to accommodate the fact that bonds with varying credit risks exhibit different market behavior (see Merton, 1974) and transaction costs (see Chen et al., 2007). A separation that also prevails in practice as most investors are looking for either HY or IG bonds.

A common practice in the academic literature (see Benartzi et al., 1997 or Frazzini and Pedersen, 2014), is to investigate the existence of factor premia via quintile analysis. That is, issuers are ranked and grouped into five quintiles according to their factor scores. This approach is adopted here and each issuer is weighted equally to ensure that quintile portfolios are not dominated by large issuers of bonds. Accordingly, equal-weighted benchmarks are used to ensure comparability of factor and benchmark portfolios. Given the weighting scheme and monthly excess returns of each bond, the performance of each quintile for each factor portfolio and bond universe can be computed. Quintile portfolios and corresponding benchmarks are rebalanced on a monthly basis.

While long-short portfolios might lead to improved risk-adjusted returns, the focus is on long-only strategies as most of corporate bond investors are restricted to long-only portfolios and as shorting credit-securities is not as easy as it is with equity securities.

Moreover, trading OTC corporate bonds involves significantly higher trans-

action costs that vary in time, rating and transaction size (see Edwards et al., 2007) when compared to trading stocks. However, existing literature either ignores transaction costs completely, assumes fixed costs (see Gebhardt et al., 2005 or Jostova et al., 2013) or focuses on low turnover strategies in order to minimize transaction costs (see Amenc et al., 2012). Here, transaction costs are estimated as a function of issue rating, maturity and total turnover associated with each factor portfolio similar to Chen et al. (2007). Besides single-factor portfolios, also multi-factor portfolios are analyzed following Israel et al. (2016) and Houweling and van Zundert (2017).

2.5 Empirical Results

2.5.1 Comparing Factor Portfolio Returns in Credit Markets

To compare factor portfolios in credit markets, first risk-adjusted returns are computed for all factor portfolios. In addition, multi-factor portfolio returns are regressed on credit market excess returns and credit market excess returns with equity returns of Fama-French factors size, value and momentum to extract the alpha of multi-factor portfolios in corporate bond markets. Hence, risk is adjusted in three ways:

1) Sharpe ratio (SR) in Table 2.2 panel A: Measures returns for each factor portfolio relative to its total risk:

$$SR_i = \frac{r_i}{\sigma_i} \tag{2.5}$$

where r_i is the annual average excess return (based on monthly returns) of factor portfolio i divided by the annual average standard deviation σ_i of those returns.

2) Regression in Table 2.2 panel B: Corrects for systematic risk of multi-factor portfolio i by regressing its returns on the default premium:

$$R_{it} = \alpha_{it} + \beta_i DEF_t + \varepsilon_{it} \tag{2.6}$$

where R_{it} is the return of the multi-factor portfolio i and DEF_t is the default premium in month t. The intercept in this regression is the equivalent to the CAPM-alpha for the corporate bond market, where the default premium represents the market factor. As excess returns are used over duration-matched Treasuries we do not need to include the term factor.

3) Regression in Table 2.4 panel C: Corrects for systematic risk using the default premium, equity momentum and the Fama-French three factor model.[18] The following regression results are analyzed:

$$R_{it} = \alpha_{it} + \beta_{i1} MKT_t + \beta_{i2} SMB_t + \beta_{i3} HML_t + \beta_{i4} UMD_t + \beta_{i5} DEF_t + \varepsilon_{it} \tag{2.7}$$

where *MKT* (market), *SMB* (small minus big), *HML* (high minus low) and *UMD* (up minus down) are the equity market, equity size, equity value and the equity momentum premium, respectively.

[18] Data on MKT, SMB, HML and UMD is obtained from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

2.5.2 Single-Factor Performance

Panel A of Table 2.2 reports results for each of the individual factors across both segments. Average size returns are 6.01% per year in U.S. HY and 1.73% in U.S. IG credit markets. Value generates average returns of 6.54% (U.S. HY) and 1.51% (U.S. IG) compared to the market returns of 4.37% and 1.25% for the U.S. HY and IG markets, respectively. The annualized returns for the momentum factor are 6.40% (U.S. HY) and 2.22% (U.S. IG). Average beta returns are 4.49% (U.S. HY) and 1.22% (U.S. IG). Corresponding volatilities are reported in Table 2.2.

Panel B of Table 2.2 reports statistically significant excess returns for size and momentum premia in both U.S. credit segments. Value, however, is significant in the U.S. HY market only, whereas excess returns are not statistically significant for beta. The information ratios range from 0.04 (beta) to 0.50 (momentum) in the U.S. HY market and from -0.03 (beta) to 1.05 (momentum) in the U.S. IG market.

However, the single-factor tracking errors suggest that investing in factor portfolios can be risky in relative terms. Tracking errors range from 2.64% to 5.43% for U.S. HY and 0.93% to 1.49% for U.S. IG corporate bonds and thus are quite large compared to the market volatilities of 9.84% and 3.80%. Due to these higher tracking errors single-factor portfolios might not be conducive for investors looking for benchmark-oriented portfolio management. Instead, investors who consider factor investing with corporate bonds should strategically allocate to factors in order to harvest risk premia on a consistent basis (see Ang et al., 2009).

Table 2.2: Performance Summary of Single-Factor Portfolios

Results for market, size, value, momentum and beta for the U.S. HY as well as the U.S. IG corporate bond market. At the beginning of each calender month equal-weighted long-only portfolios are constructed from the 20% issuers with the highest factor exposure to equity size, equity value, equity momentum and equity beta. Statistical significance is denoted by *, ** and *** corresponding to the 90%, 95% and 99% confidence levels, respectively.

U.S. High Yield	Market	Size	Value	Momentum	Beta
Panel A: Top-Decile Risk/Return					
Mean	4.37%	6.01%	6.54%	6.40%	4.49%
Volatility	9.84%	13.38%	13.40%	7.89%	9.09%
Sharpe ratio	0.44	0.45	0.49	0.81	0.49
Panel B: Excess Return					
alpha		1.64%*	2.17%**	2.03%**	0.12%
t-stat		1.49	2.10	1.76	0.05
Tracking error		5.43%	4.92%	4.09%	2.64%
Information ratio		0.30	0.44	0.50	0.04

U.S. Investment Grade	Market	Size	Value	Momentum	Beta
Panel A: Top-Decile Risk/Return					
Mean	1.25%	1.73%	1.51%	2.22%	1.22%
Volatility	3.80%	4.41%	4.57%	3.24%	3.52%
Sharpe ratio	0.33	0.39	0.33	0.69	0.35
Panel B: Excess Return					
alpha		0.48%*	0.26%	0.97%***	-0.03%
t-stat		1.50	0.82	4.16	0.17
Tracking error		1.37%	1.49%	0.93%	0.94%
Information ratio		0.35	0.18	1.05	-0.03

Figures 2.1 and 2.2 show the single-factor portfolio performance versus their corresponding benchmarks.

Figure 2.1: Cumulative U.S. HY Single-Factor Portfolio Returns (Dec 1999 - Nov 2016)

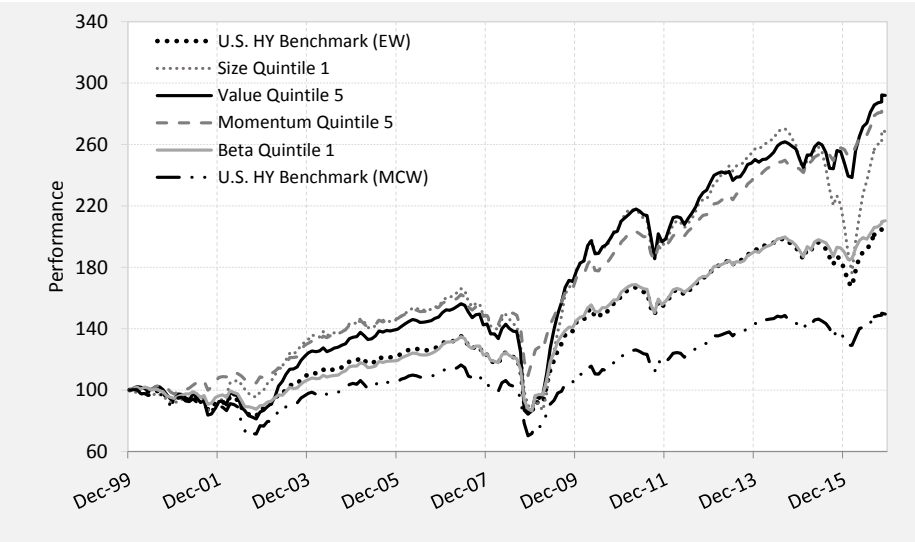
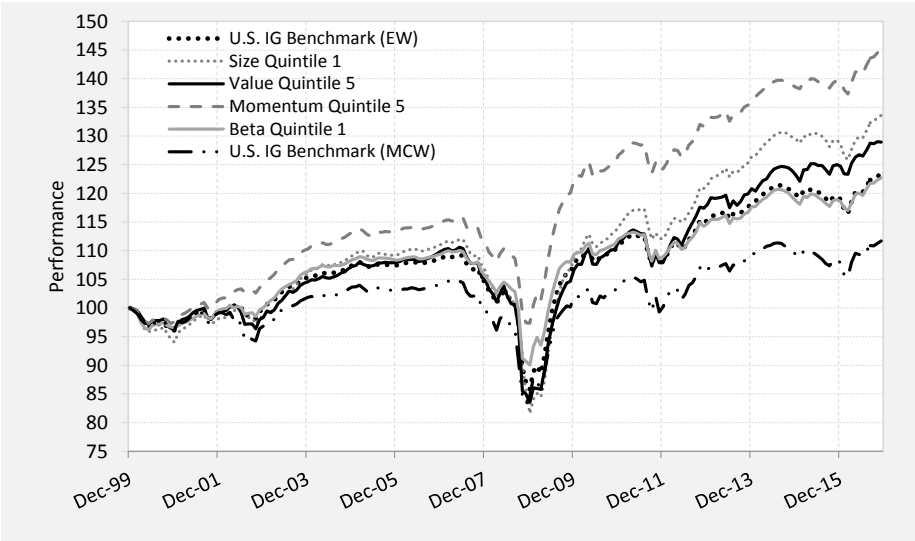


Figure 2.2: Cumulative U.S. IG Single-Factor Portfolio Returns (Dec 1999 - Nov 2016)



2.5.3 Multi-Factor Performance

Ever since the development of MPT in the 1950s (see Markowitz, 1952) the idea of diversification survived by proposing that a portfolio constructed of different assets (here factors) will, on average, generate higher risk-adjusted returns than any individual asset found within the portfolio (only true if the assets or factors in the portfolio are not perfectly correlated). Table 2.3 shows correlations of excess returns[19] of the four factors as well as the multi-factor portfolios for U.S. HY and IG credit markets. The lowest correlations are between the factors HY momentum and HY size (-0.54) as well as between IG beta and IG size (-0.47). Hence, a combination of these factors offers significant diversification benefits. In addition, all factors exhibit equal or higher Sharpe ratios compared to the market. Therefore, all four factors are combinded into a multi-factor portfolio.

In addition, equal-weighted long-only multi-factor portfolios are also constructed by combining size, value, momentum and beta, as described by:

$$r_t^{MultiFactor} = 0.25r_t^{Size} + 0.25r_t^{Value} + 0.25r_t^{Momentum} + 0.25r_t^{Beta} \tag{2.8}$$

where r_t denotes the return of each corresponding single-factor portfolio as well as the multi-factor portfolio in month t.

Table 2.4 reports the multi-factor portfolio statistics. The multi-factor portfolio delivered an annual average excess return of 5.95% in the U.S. HY market and 1.68% in the U.S. IG market. Interestingly, the alphas of the multi-factor

[19]Here excess return denotes return over benchmark.

Table 2.3: Correlation Summary of Factor Portfolio Outperformances

Return correlations between U.S. HY and IG single- and multi-factor portfolios (Size, Value, Momentum (MOM), Beta and multi-factor (MF)) over the period December 1999 to November 2016.

	IG Size	IG Value	IG MOM	IG Beta	IG MF	HY Size	HY Value	HY MOM	HY Beta	HY MF
IG Size	1.00									
IG Value	0.07	1.00								
IG MOM	-0.38	-0.33	1.00							
IG Beta	-0.47	0.20	0.45	1.00						
IG MF	0.32	0.70	0.16	0.48	1.00					
HY Size	0.41	0.13	-0.40	-0.37	0.02	1.00				
HY Value	0.04	0.59	-0.39	0.01	0.27	0.29	1.00			
HY MOM	-0.33	-0.31	0.58	0.34	-0.03	-0.54	-0.43	1.00		
HY Beta	-0.01	-0.06	0.18	0.27	0.15	-0.27	-0.13	0.33	1.00	
HY MF	0.15	0.31	-0.18	0.02	0.25	0.57	0.64	-0.01	0.27	1.00

portfolios remain significant in both markets after controlling for corresponding equity factor exposures, indicating that the combination of factors add value beyond the equity factors.

Table 2.4: Performance Summary of Multi-Factor Portfolios

Results of multi-factor portfolios compared to the market-capitalization weighted (MCW) and equal-weighted (EW) U.S. HY as well as the U.S. IG corporate bond market. The multi-factor portfolio consists of an equal-weighted combination of all four analyzed factors. Statistical significance is denoted by *, ** and *** corresponding to the 90%, 95% and 99% confidence levels, respectively.

U.S. High Yield	Market (MCW)	Market (EW)	Multi-Factor
Panel A: Top-Decile Risk/Return			
Mean	2.40%	4.37%	5.95%
Volatility	10.42%	9.84%	10.47%
Sharpe ratio	0.23	0.44	0.57
Panel B: Excess Return vs. Market (EW)			
alpha			1.58%***
t-stat			3.73
Tracking error			1.73%
Information ratio			0.91
Panel C: 5-Factor Alpha vs. Market (EW)			
alpha			1.32%***
t-stat			3.26
U.S. Investment Grade	Market (MCW)	Market (EW)	Multi-Factor
Panel A: Top-Decile Risk/Return			
Mean	0.66%	1.25%	1.68%
Volatility	4.17%	3.80%	3.82%
Sharpe ratio	0.16	0.33	0.44
Panel B: Excess Return vs. Market (EW)			
alpha			0.43%***
t-stat			3.34
Tracking error			0.52%
Information ratio			0.82
Panel C: 5-Factor Alpha vs. Market (EW)			
alpha			0.42%***
t-stat			3.32

Moreover, the equal-weighted combination of size, value, momentum and beta within the different markets and segments generates higher Sharpe ratios than the equal-weighted market index. These findings suggest that the combination of all four factors leads to diversification benefits.

Over the analyzed sample period the equal-weighted multi-factor portfolios demonstrate an annualized Sharpe ratio of 0.57% for U.S. HY and 0.44% for U.S. IG corporate bonds while Sharpe ratios of their corresponding markets are 0.44% and 0.33%, respectively. Figures 2.3 and 2.4 show the multi-factor portfolio performance versus the benchmark as well as the cumulative outperformance.

Figure 2.3: Cumulative U.S. HY Multi-Factor Portfolio Returns (Dec 1999 - Nov 2016)

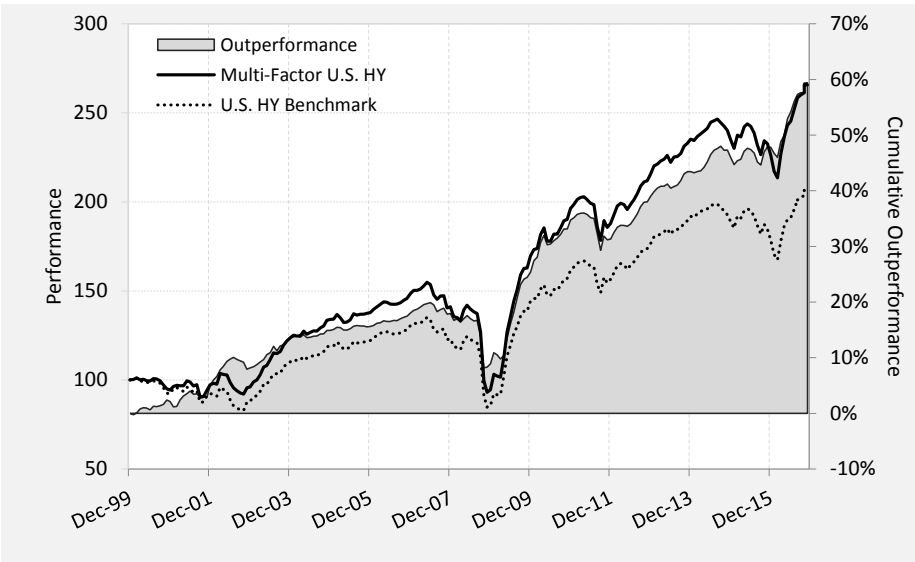
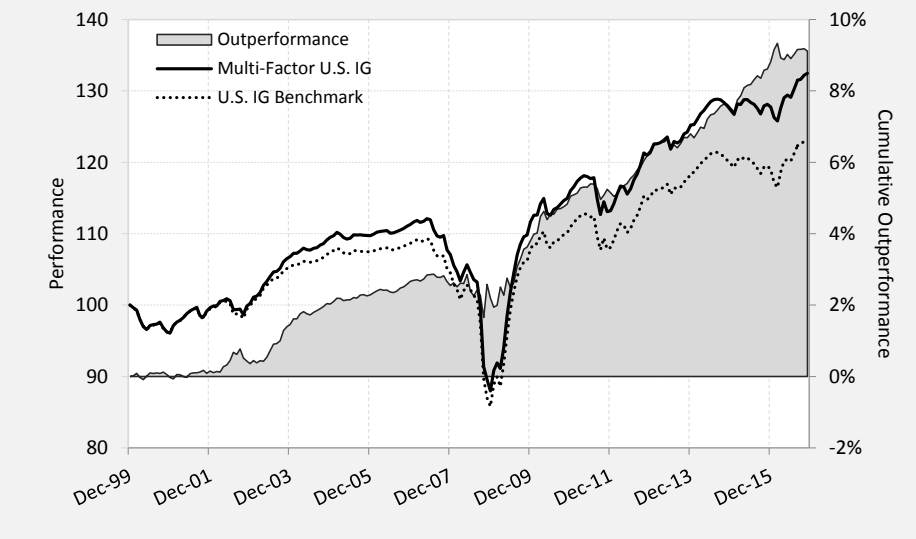


Figure 2.4: Cumulative U.S. IG Multi-Factor Portfolio Returns (Dec 1999 - Nov 2016)



2.5.4 Factor Performance after Transaction Costs

Corporate bonds are typically traded less frequently than stocks. Therefore, most academic research focuses on low turnover strategies in order to avoid high transaction costs. Here (see Table 2.5), transaction costs are estimated as a function of issue rating, maturity and total turnover associated with each factor portfolio according to Chen et al. (2007).

The results remain economically feasible after accounting for transaction costs. Thus, the factors studied here are not only properly motivated, theoretically sound but can also be implemented. As the employed definitions are based on existing academic literature, the selection is not based on ex post results, thereby freeing the results of data mining biases.

Table 2.5: Performance Summary of Factor Portfolios after Transaction Costs

Performance results of the market, size, value, momentum, beta and multi-factor portfolios for the U.S. HY as well as the U.S. IG corporate bond markets after transaction costs. Transaction costs are calculated according to Chen et al. (2007). Gross returns, transaction costs, net returns, volatilities and Sharpe ratios are annualized.

U.S. High Yield	Market	Size	Value	Momentum	Beta	Multi-Factor
Gross return	4.37%	6.01%	6.54%	6.40%	4.49%	5.95%
Transaction costs	0.31%	0.38%	0.48%	0.59%	0.42%	0.45%
Net return	4.06%	5.63%	6.06%	5.81%	4.07%	5.50%
Volatility	9.84%	13.38%	13.40%	7.89%	9.09%	10.47%
Net Sharpe ratio	0.41	0.42	0.45	0.74	0.45	0.53
U.S. Investment Grade	Market	Size	Value	Momentum	Beta	Multi-Factor
Gross return	1.25%	1.73%	1.51%	2.22%	1.22%	1.68%
Transaction costs	0.12%	0.14%	0.21%	0.31%	0.18%	0.21%
Net return	1.13%	1.59%	1.30%	1.91%	1.04%	1.47%
Volatility	3.80%	4.41%	4.57%	3.24%	3.52%	3.82%
Net Sharpe ratio	0.30	0.36	0.28	0.59	0.30	0.38

2.6 Conclusion

In this chapter, evidence is provided that the classical equity factors size, value, momentum and beta, factors well-known for their robust risk premia in the equity space, should be considered for corporate bond investing.

Investing in multi-factor portfolios substantially improves performance compared to investing in market indices. The main inference that the four analyzed factors generate positive risk-adjusted returns, especially when viewed in a multi-factor context, is unaffected by the impact of transaction costs. Moreover,

investing in a multi-factor portfolio reduces tracking error and drawdowns while preserving higher risk-adjusted returns when compared to market indices.

Finally, the results remain robust after accounting for Fama-French equity factors size, value and momentum. The results indicate that factor-based investing with corporate bonds does indeed offer value to corporate bond investors beyond equity factors. Interestingly, all factors but beta lead to economically and statistically significant results for the U.S. HY market. This observation is mostly due to the more equity-like features of HY bond markets compared to IG bond markets (see Hong et al., 2012). As the traditional factors have shown to hold significant explanatory power for equity market returns, it is not surprising that these equity factors perform better in more equity-like bond markets (see Bektić et al., 2016).

3 ESG Factors in Corporate Bond Returns[20]

3.1 Introduction

In this chapter, I examine the evidence on the validity and persistence of ESG factors in corporate bond returns and the debate about the usefulness (in terms of risk and return) of these factors for bond investors. Furthermore, I also assess the implications for academic research as well as the implementation into investors' portfolios.

Climate change and its risks as well as sustainable finance in general have become one of the mainstream research topics from both an academic as well as a practitioner perspective because financial data alone is no longer considered as sufficient to evaluate the success of a company. ESG factors, which relate to environmental, social and governance characteristics, include numerous aspects like the climate change and greenhouse gas emissions (environmental), working

[20] A version of this chapter was published in Zeitschrift für Umweltpolitik & Umweltrecht/Journal of Environmental Law and Policy (see Bektić, 2017).

conditions and local communities (social) as well as executive pay, bribery and corruption (governance).[21] Despite the historic nature and the general importance of the Paris climate accord as well as the fact that the United States resigned from the agreement, two factors remain crucial: global peer pressure and the actions of future governments. For instance, on the one hand, Apple issued a $1 billion green bond after President Trump's Paris climate exit and said that its businesses are still committed to the goals of the 194-nations accord. On the other hand, governments are also appreciating the use of green bonds as a way to meet a 2015 pledge by world leaders to limit global warming below 2 degrees Celsius.

The integration of ESG related factors in financial measures and investment decisions still undergoes exponential growth in financial markets. The global market for sustainable and responsible investing (SRI) - as the collective term for all kind of ESG related investment strategies - accounted for $22.89 trillion of assets being professionally managed in 2016, which equates to an increase of 25% since 2014. In Europe, SRI strategies increased by 12%, now accounting for 12.04 trillion of assets (53% of total Assets under Management in SRI managed strategies) and the United States account for 38% of SRI assets.[22] When looking at the Assets under Management in the European market, particular attention should be given to the surge in bonds (corporate, supranational, sovereign and local bonds) beginning with 40% in 2013 up to 64% in 2016. In particular, corporate bonds increased by over 142% to more than 50% in 2016 and the main reason for this was the rise of *green bonds* (up to $44 billion in August 2016).[23] Although green bonds

[21]See PRI (2017).
[22]See GSIA (2016), p. 7.
[23]See EUROSIF (2016), p. 56.

represent a small fraction of the overall bond market, demand for lower-carbon investments has grown significantly.

Despite the evolving demand for socially responsible fixed-income products, the abundance of academic research on ESG investing in equity markets and the fact that global fixed-income markets are larger than global equity markets (see Goldstein et al., 2017), similar research for corporate bonds is less mature. Unfortunately, existing empirical evidence on ESG factors in corporate bond markets is still mixed and inconclusive. Some evidence supports positive risk premia, other evidence suggests a negative relation, and a third strand of the literature finds that the relation is unstable.[24]

I argue that there are two reasons why we need further empirical and theoretical research on ESG factors in corporate bond markets. First, because it is premature to conclude that ESG factors are unusable (in terms of risk and return) for bond investors. Corporate bond returns can be very volatile (especially for lower-rated securities) and hence, standard errors around risk factors can be large, so it is not obvious if ESG factors should be totally written off. The international evidence is also inconclusive. Second, while the theoretical explanations offered for ESG factors are potentially valuable, if and how existing asset pricing models can be reconciled with known patterns in the returns on low- and high-ESG corporate bond issuers is not clear.

This chapter is organized as follows. I present an overview of the latest

[24]Hörter (2017) provides an excellent summary on ESG factors in the corporate bond space.

empirical evidence on ESG factors in U.S. and international corporate bond markets in Section 3.2. In section 3.3, I discuss a number of objections to the methods used in the empirical literature. In Section 3.4, I examine alternative perceptions of ESG factors in corporate bond markets. In section 3.5, I asses the current state of the empirical and theoretical literature and discuss implications and directions for further research. Section 3.6 is the conclusion.

3.2 Empirical evidence on ESG factors in corporate bonds

In this section, I survey empirical studies on ESG factors in U.S. corporate bond returns. Aditionally, I also present an overview of the international evidence on ESG factors in corporate bond markets. I am interested in examining the ESG factors in international corporate bond returns for several reasons. First, because understanding the effects in various countries is important for sustainable finance and investment decisions in those countries. Second, because the strength of ESG factors can depend on market characteristics such as the trading mechanism, the type of investors, regulation and market efficiency in general. Third, because eventual strong and robust results in different markets and in different time periods would make a strong argument against data mining concerns.

Although many studies try to determine an empirical coherence between ESG criteria and financial performance, no exclusive and explicit positive link could be found yet. Whereas the relation between the performances of stock port-

folios has broadly been investigated, research on fixed-income funds is rare (see Hoepner and Nilsson, 2017a). In a recently published study by Polbennikov et al. (2016), the authors question if the incorporation of ESG factors in the investment process improves financial performance of bond portfolios. The authors analyze 4366 U.S. corporate bonds and report the following results: (i) Introducing ESG factors into the investment process results in a small but steady performance benefit for corporate bond investors and no evidence of a negative impact was found. (ii) The performance advantage of portfolios with an ESG tilt was not caused by high-ESG bonds becoming more expensive than their low-ESG peers. Therefore, no evidence of excess demand for high-ESG bonds was found. (iii) Governance appears to be the strongest factor while environmental and social factors exhibited weaker results. Moreover, bonds with a high governance-score also suffered credit downgrades less often than those with a low governance-score. Aditionally, Henke (2016) provides evidence that U.S. and Eurozone SRI bond funds, that applied an ESG screening (meaning that asset managers hold a broad portfolio but exclude companies with the lowest ESG scores), outperformed by 0.5% during the period 2001 to 2014. Furthermore, the positive effect could directly be related to times of recession but not to non-crisis periods.

Similar findings are provided by Hoepner and Nilsson (2017b). These authors investigate the effect that ESG ratings have on companies issuing bonds. In their study, 5240 bonds from 425 U.S. companies were analyzed in the period from 2001 to 2014. Based on the ESG rating of the issuing firm, cap-weighted high and low ranked portfolios were constructed, both on an aggregated and individual level. Hoepner and Nilsson show that bonds issued by companies with neither

strengths, concerns nor controversies, outperform by more than one percent per year compared to bonds with strengths and concerns. These findings are especially supportive in times of market turbulence. In addition, these authors intensified their research by exploring the relation between SRI fixed-income funds and their management companies. Here, they analyze the performance of a global sample of 108 global SRI fixed-income funds from 2000 to 2013 and provide evidence that incorporation of ESG improves performance. Especially management companies not involved in ESG activities show lower performance in their managed funds. According to Hoepner and Nilsson, the essential reason for that is lack of commitment and expertise of those companies.

Leite and Cortez (2016) develop these empirical studies even further by expanding their research to the European market. In their study, 63 SRI fixed-income funds were compared with conventional funds in the main European markets (France, Germany and the UK) between 2002 and 2014. The results are based on a conditional multi-factor model with time-varying coefficients, and show that European SRI balanced funds exhibit no statistically significant differences in performance in relation to conventional funds. Furthermore, these results hold during the overall sample period as well as during recession and expansion periods, respectively. Finally, regarding SRI bond funds, empirical evidence is mixed. While French SRI bond funds match the performance of their conventional peers and German funds slightly outperform, UK funds significantly underperform compared to conventional funds. With regard to bond funds, the study of Leite and Cortez (2016) supports the effect that Henke (2016) already described: bond funds from the Euro-area are able to outperform conventional funds during market downturns,

concluding that SRI fixed-income funds provide additional protection to investors in times of recession. However, balanced funds in most cases do not exhibit significant differences between SRI funds and conventional funds (see Leite and Cortez, 2016).

In contrast to the studies mentioned above, Li and Zhang (2016) present different results on the relation between ethical investing, returns and volatility: by examining 1283 U.S. corporate bonds in the period from 2004 to 2015 and by applying sin screening (covering adult entertainment, alcohol, gambling, tobacco and weapons as well as fossil fuel screening), no significant impact could be observed on corporate bond returns.

3.3 Critique on the methods of empirical studies

In this section, I assess the criticisms of various studies' methods and their empirical evidence on corporate bond returns.

The process of incorporating ESG into fixed-income is different compared to equities, although both share commonalities. For instance, the most common strategies include 1) negative/exclusionary screening, 2) integration of ESG factors, 3) corporate engagement and shareholder action, 4) norms-based screening, 5) positive/best-in-class screening, 6) sustainability themed investing and 7) impact/community investing. Therefore, not only the implemented strategy and ESG factor definition preferences but also the specific implementation design like

investment universe as well as rebalancing frequency, transaction costs, weighting scheme and definition of portfolio configuration has a significant impact on performance and explains why two portfolios (or funds) based on the same ESG factors may perform differently.

Lo and MacKinlay (1990) study the extent to which the use of characteristic-sorted portfolios in the empirical asset pricing literature impacts standard statistical inference. Although sorting corporate bonds into portfolios (or analyzing funds) reduces the measurement error and enhances the validity of the tests, grouping securities by some characteristic that is socially responsible motivated can lead to incorrect rejections of the null hypothesis that the asset pricing model is true. As asset pricing tests focus on the degree of the alphas (excess returns), tests based on combinations of alphas for portfolios of securities can be more powerful. Yet, estimated alphas are equal to the sum of true alphas and corresponding measurement errors. If quantitative analysts choose the factor on which the corporate bonds are sorted only on an empirical analysis of a single data set, then it is impossible to know if the resulting cross-sectional relations between the alpha of a portfolio and the factor is due to a relation between the factor and the true alphas or a relation between the factor and measurement errors. Lo and MacKinlay (1990) provide evidence that the type I error of such statistical tests is up to 100% with a 5% significance level. This result does not necessarily imply that the ESG effect is spurious as there may be a relation between firm's ESG score and true alphas. Nevertheless, statistical tests should be aware of this shortcoming since this is a highly complex problem in general.

Finally, when analyzing alphas of ESG corporate bond portfolios (or funds) one should also take into account the possibility of omitted risk factors as well as considering investable portfolios. While a theoretical long-short portfolio usually leads to higher risk-adjusted returns, implementing long-short corporate bond portfolios is complex and nonpractical due to operational difficulties and high transaction costs associated with shorting corporate bonds, especially for lower-rated and illiquid securities. In addition, the majority of corporate bond investors is restricted to long-only portfolios (see Bektić and Regele, 2017 or Houweling and van Zundert, 2017).

Given the scale of interest in investable ESG fixed-income products, progress needs to be made especially in the quality and availability of ESG data of corporate bond issuers as well as further development of ESG investment strategies which are suitable for the manifold needs of fixed-income investors.

3.4 Explanations for ESG factors

The question why firms with high ESG scores should earn higher returns than traditional asset pricing models predict has become the subject of a heated debate. Some papers argue that the systematic risk of corporate bonds is driven by multiple risk factors, and that a firm's ESG score is a proxy for the exposure to state variables that describe time-variation in the investment opportunity set. Furthermore, they claim that ESG factors are subsumed by a quality factor.[25] Especially

[25] Recent studies from the equity space show that the well-known low beta or low volatility factor is subsumed by a quality factor.

in times of relatively high volatilities, "flight to quality" investment approaches become important for investors. The quality factor has a long track record as an investment approach (ever since Benjamin Graham) but it is less well accepted compared to size, value, and momentum and has no generally accepted definition. An issuer's quality can, for instance, be measured by operating profitability, low accruals, asset growth and corporate governance. While the first three measures are transparent and regularly available from financial statements, corporate governance is much more difficult to observe and hence to measure. Finally, according to empirical studies, larger companies usually exhibit a higher quality factor than smaller companies, and should therefore exhibit higher ESG scores. I conclude that this is due to the fact that larger companies, as they usually have a higher profitability, are able to afford an incorporation of ESG guidelines more easily than smaller companies with low profitability.[26]

Alternative interpretations are that asset pricing models relax the assumption that investors are fully rational or that the ESG effect is a statistical fluke[27], but solely form a risk and return perspective as the investment objective of sustainable and responsible investing has different economic and ethical implications for asset owners and asset managers.

[26] For instance, Stanwick and Stanwick (1998) show that company size, competitive environment as well as financial performance are important factors related to firm's sustainability activities. Additionally, Jones (1999) finds that characteristics like economic development, social culture and industry features have an impact on a firm's decision to engage in a socially responsible fashion.

[27] The empirical finding of a positive ESG effect in corporate bond returns could be a chance result driven by data mining, extreme and missing observations, that have nothing to do with risk or behavioral based theories.

Finally, in the spirit of Lo and MacKinlay (1990) and MacKinlay (1995), the majority of quantitative analysts uses the same data to uncover ESG effects and other asset pricing anomalies. As usually only the most successful and striking results are published, it is practically impossible to assess their statistical significance (depends on the number of attempts made to detect a certain effect). Therefore, out-of-sample tests and some more years of high-quality and -quantity data is needed to disagree with the data mining argument.

3.5 Implications for academic research and investors

In this section, I evaluate the current state of empirical and theoretical research on ESG factors in corporate bond markets. Many of the early empirical studies identify a significant and consistent ESG performance in U.S. corporate bond returns (see Attig et al., 2013 or Bauer and Hann, 2014), but more recent papers report that the effect may not be robust over time and in an international context (see Leite and Cortez, 2016, Polbennikov et al., 2016 or Li and Zhang, 2016). Strikingly, hardly any research addresses the question if structural or institutional changes could account for the magnitude of ESG factors in corporate bond returns. However, further robustness checks are required to make a truly compelling case for the existence of significant ESG factors in international corporate bond returns.

I identify three promising strands of theoretical literature. (i) Models of firm-level investment decisions generate an endogenous relation between firm's ESG score and corporate bond returns. This body of research is still in a relatively early stage and it is not sufficiently clear to what extent these models can explain

patterns uncovered by empirical research on ESG factors. (ii) Asset pricing models predict that corporate bond returns not only depend on transaction costs, but also on liquidity risk. The available evidence indicates that liquidity is an important factor in asset pricing. However, most studies do not explicitly examine whether ESG factors can be explained by liquidity factors. How ESG factors and liquidity interact is an important area for future research, similar to the above mentioned observation that quality factors may subsume ESG factors. (iii) ESG factors can be linked to the behavior of less rational investors, in the sense that either these investors may prefer assets with specific characteristics or that ESG proxies for the mispricing that their behavioral biases cause. I am not aware of any paper that formalizes these arguments.

Where does that leave practitioners? Regulators, investors and global society give increasing attention towards sustainability in the financial markets - as current figures of the SRI market show. Additionally, the global landscape for policy tools and initiatives confirms this statement: In 2016 the PRI mapped out almost 300 responsible investment-related public tools and initiatives in the largest 50 economies in the world, more than half of them were created between 2013 and 2016 (see PRI, 2016a). When looking at the drivers of ESG, a closer look at the UN Principles for Responsible Investment (PRI) is crucial. An international group of investors founded the initiative in 2006 in partnership with the UNEP Finance Initiative and the UN Global Compact. Today, PRI covers $59 trillion of assets - including 1400 signatories in more than 50 countries. The main aim of the investor initiative is to support its signatories in understanding the investment implications of ESG issues and helping them to integrate these issues into investment decisions.

Almost half of the analyzed countries were already developing regulations for pensions funds. In contrast to this mandatory regulation for pension funds, most stewardship codes and corporate disclosure guidelines work on a voluntary basis (see PRI, 2016a). One of the most prominent examples for integrating sustainability into an investment process is the Norwegian Government Pension Fund (the largest one worldwide). As the above overview shows, a wide range of policies and initiatives focusing on corporate disclosure regulations is already set in place on a national, European and international level. Nevertheless, the analysis also makes clear that mandatory government regulations regarding disclosure and reporting are rare, not to mention agreements to incorporate ESG or mandatory investments prohibitions in non-ESG or non-sustainable companies that could change the investment landscape even more towards a sustainable and long-term thinking industry.

Another strand is that some of the signatories to the PRI made an important step in enhancing the use of ESG factors for financial analysis by signing a statement on ESG in credit ratings. Six leading credits rating agencies, among them S&P and Moody's as well as more than 100 institutional investors, signed the initiative in order to incorporate ESG criteria in the assessment of creditworthiness of borrowers and to share this considerations transparently (see PRI, 2016b). However, the leading rating agencies such as S&P, Moody's and Fitch have different approaches towards the importance and integration of ESG in their credit rating processes. While S&P considers ESG as a substantial part of their credit analysis, it is not directly incorporated in their measurement system but taken

into account in the overall assessment of a company's management.

Nevertheless, governance is seen as the most likely dimension to impact credit ratings and is therefore directly examined in the rating process (see S&P, 2015). Moody's considers ESG as one of several factors that determines credit risk and therefore does not see a clear and direct impact of ESG risks. However, ESG considerations are captured in the agencies long-term credit risk analysis if the ESG factors are expected to have a large impact on credit default risk (see Moody's, 2015). Fitch states that poor governance practices are most likely to affect credit ratings, but notes that good governance, analyzed isolated, cannot influence a credit rating positively (see FitchRatings, 2010).

Bauer and Hann (2014) document that environmental concerns are associated with a higher cost of debt financing and lower credit ratings, and that proactive environmental practices are associated with a lower cost of debt. In addition, Henke (2016) notes that a separation of crisis and non-crisis periods further indicates that the outperformance is especially likely to occur during recessions or bear market periods. Furthermore, Leite and Cortez (2016) document that SRI funds in the fixed-income space provide additional protection to investors in market downturns. Hence, it seems to be important to consider ESG factors at least in the risk management process of corporate bond portfolios as high ESG scores are usually associated with high quality companies.

Finally, while asset owners allocate money to sustainable companies in order to make the world a better place (while also maintaining financial perfor-

mance), asset managers desire to be recognized as ESG conform to attract ESG mandates and assets, but also need to deliver appropriate returns in order to protect those assets.

3.6 Conclusion

In this analysis, I argue that the conclusions on ESG factors in corporate bond returns are still mixed and therefore premature. In short, we simply do not have enough high-quality data to conclude that ESG factors are significant drivers of abnormal returns in corporate bond markets. In fact, the enhancement is driven generally by the positive payoff in adverse market environments. Therefore, the value of downside protection provided by ESG factors is economically important.

The growing importance and awareness for ESG in financial markets can for certain no longer be denied by looking at current figures. The PRI and its initiative for ESG on credit ratings can be named as an important progress in establishing and integrating ESG in the daily decision process of investors and investment managers, although empirical research does not show a clear evidence for the relation between the integration of ESG factors and corporate bond performance. Nevertheless, many studies conducted in the U.S. and European markets were able to find a small but positive correlation between performance, volatility and corporate bond funds including ESG, especially in times of recession. In addition, the impact ESG has on credit ratings should also be taken into account. Isolating the E, S and G dimension, governance appears most likely to have an impact on performance and credit risk.

However, more sustainable performance does not automatically translate to more financial performance. If an engagement in sustainable investment products would help to enhance financial performance, there would be no sound reason for not implementing it. Therefore, the link between performance and ESG factors is crucial. However, I am convinced that much more investors would be attracted to ESG based investment products if their investments would at least not suffer from underperformance compared to classical investment approaches.

In general, relating ESG factors to fixed-income instruments is multidimensional and therefore differs to equity markets. As bond issuers can issue different types of bonds with different maturities, the relevance of ESG factors may also vary. In fact, the emphasis is focused on expectations about the issuers creditworthiness and hence its financial strength. However, ethical investing considers both financial and non-financial aspects. Therefore, it is important for both investors and investment managers to be aware of the potential pitfalls when constructing ethical and socially responsible fixed-income investment products.

Finally, Barclays' conclusion on a study about sustainable investing and corporate bond returns can definitely be agreed: *"As ESG considerations play out over a long horizon, and as they increasingly become a priority for company managers, they may help alleviate the pressure for short-termism and rather encourage a focus on long-term value creation to the mutual benefit of the firm, its investors and the world at large" (Desclée et al., 2016, p. 3).*

4 Exploiting Uncertainty with Market Timing in Corporate Bond Markets[28]

4.1 Introduction

The ultimate goal of many financial market participants is to earn money and for the majority of fund managers to outperform their respective benchmarks. Fundamental analysis, which is based primarily on accounting data, and technical analysis, which is based on historical performance or other past statistics, are often employed to reach these goals. Despite its widespread acceptance by practitioners, academics have been sceptical about the added value of technical analysis. For instance, Malkiel (1981) states that *"technical analysis is anathema to the academic world"* (p.139). The main reason for this point of view is that the theoretical basis for technical analysis is scarce. Since the majority of financial models assumes a random walk for prices, any profitability from technical trading is per se ruled out

[28] A version of this chapter was published in the Journal of Asset Management (see Bektić and Regele, 2017).

(see Fama, 1995). However, during the last couple of years evidence has grown steadily in the favour of technical analysis. For example, Brock et al. (1992) and Lo et al. (2000) or more recently Zhu and Zhou (2009), Moskowitz et al. (2012) and Han et al. (2013) document strong evidence of profitability from such kind of trading strategies. Furthermore, Covel (2005) and Schwager (2012) show how successful hedge funds rely solely on technical analysis without taking into account any fundamental indicators.

Manifold studies investigate the value of fundamental (Harvey et al., 2016 count more than 300 factors) and technical analysis (see Brock et al., 1992, Zhu and Zhou, 2009 or Han et al., 2013) for equity portfolios. While some recent papers on the value added of fundamental analysis for investing in corporate bonds exist (see Crawford et al., 2015, Bektić et al., 2016 or Chordia et al., 2017), similar studies about the impact of technical analysis on corporate bonds are surprisingly rare. Thus, despite the fact that the market for corporate bonds has increased monotonically over the last 30 years[29], we know fairly little about the profitability of technical analysis in this asset class. Therefore, a detailed examination of the usefulness of technical analysis in corporate bond markets is crucial to understanding the true return potential to investors' portfolios.[30]

This chapter attempts to close that gap and analyze the profitability of

[29]The U.S. bond market is considered as the largest security market in the world and according to Federal Reserve data, the total market value of U.S. corporate bonds had a growth rate of 8.5% per year from 1990 to 2014.

[30]Since government bond yields are on historically low levels, the demand for credit securities plays a much larger role than in the past. Usually, institutional investors such as pension funds, mutual funds and insurance companies invest in these securities.

technical analysis in corporate bond portfolios at the example of moving average strategies.[31] In fact, moving average strategies represent so-called trend-following strategies and their profitability depends heavily on whether there are pronounced trends in the cross section of the corporate bond market. To this end, the focus is on returns of moving average strategies in a universe of U.S. investment grade (IG) and high yield (HY) corporate bonds. Thus, the analysis tries to answer the following question: Can past information be used to predict future returns in corporate bond markets? If these market were efficient in the sense that current prices reflect all past information, the answer would be clearly no. Barberis and Thaler (2003) argue that the existence of profitable investment strategies builds on two main pillars: (i) (some) investors deviate from perfect rationality, for instance due to behavioral biases and (ii) limits to arbitrage prevent that this irrationality is fully exploited by other market participants (see Shleifer and Vishny, 1997).

Indeed, evidence is provided that past information does help to predict future returns under certain circumstances, that relate to both behavioral biases and limits to arbitrage. More precisely, the results indicate that moving average strategies can be profitable, especially if they are applied to portfolios with a high degree of informational uncertainty. The key idea, which was suggested for equity portfolios by Han et al. (2013), states that (i) behavioral biases – which could lead to mispricing – should be stronger for portfolios with high degrees of uncertainty and (ii) assets with a high degree of uncertainty typically face stronger limits to arbitrage. For stock markets, Zhang (2006) argues that price continuation is pre-

[31] For instance, Brock et al. (1992), Lo et al. (2000) and Han et al. (2013) use simple moving average schemes to forecast the equity market.

dominantly due to underreaction to public information by investors, and investors will underreact stronger in case of greater information uncertainty. Since returns of equity and bonds of the same entity should be related, according to structural credit risk models like Merton's (1974), this idea translates to returns of corporate bonds. Merton introduces in his seminal paper the notion that corporate debt and equity both represent claims on the firm value. In that framework, corporate debt reflects a risk-free bond in combination with a short put option on the firm's equity. Therefore, yield spreads on corporate debt should widen if equity volatility increases because the put option will become more valuable if equity volatility increases. Consequently, the correlation between equity volatility and yield spreads on corporate debt is expected to be positive and sorting bonds on either of these two variables should lead to similar results. In line with that thought, Campbell and Taksler (2003) find that both, equity volatility and credit risk have explanatory power for the movement of yield spreads of corporate bonds. Consequently, moving average strategies are applied to portfolios of corporate bonds sorted by equity volatility and option-adjusted spreads (OAS). Finally, the profitability of moving average strategies is analyzed for portfolios with high and low levels of informational uncertainty.

The results are surprisingly strong. For instance, the employed strategy generates a monthly alpha of 0.42% (t = 3.05) for IG corporate bonds and even 1.33% (t = 2.70) for HY corporate bonds against their respective benchmarks for portfolios with a high degree of uncertainty, contrasting 0.04% (t = 0.55) and 0.06% (t = 1.14) for portfolios with low degrees of uncertainty. These results are insensitive to measures of uncertainty used to construct the portfolio. In addition, the

results are robust to different time lags used to create the moving average strategy.

The cumulative returns, one would have obtained by following such a moving average strategy, are substantial for portfolios with a high degree of informational uncertainty. For example, the cumulative excess return (over duration-matched U.S.Treasuries) for the moving average strategy applied to a portfolio of IG corporate bonds in the highest quintile with respect to their OAS are about 111% over the time period from December 1996 to November 2016 assuming 30 bps round-trip transaction costs, while the benchmark delivered only 20% over the same period. For high yield corporate bonds, the effect is even stronger with more than 784% for the strategy over the time period from December 1996 to November 2016 assuming 50 bps round-trip transaction costs versus about 97% for the benchmark.

Technical analysis is based on the belief that prices of securities are influenced by sentiment-affected investment decisions of investors, such as herding behavior. Daniel et al. (1998; 2001) and Jiang et al. (2005) show that the impact of biased investment decisions, and therefore, the profitability of technical analysis, should be stronger for higher degrees of information uncertainty since psychological biases are more pronounced if information uncertainty is greater.

The findings presented in this chapter are consistent with the idea that the profitability of technical strategies is driven by irrational investors and therefore particularly pronounced if information uncertainty is strong and arbitrage is limited. Moreover, the results indicate that profitability is stronger for HY bonds

(which manifest more uncertainty) compared to IG bonds. Finally, most HY bonds exhibit equity-like behavior which links the results neatly to the findings of Han et al. (2013).[32]

Recent literature on technical analysis focuses exclusively on equity markets (see Brock et al., 1992, Lo et al., 2000, Han et al., 2013 or Neely et al., 2014) and government bonds (Goh et al., 2013 show that technical indicators predict the bond market much better than fundamental factors). In addition, various studies examine the profitability of futures and forward contracts on equity indexes, currencies, commodities as well as government bonds (see Moskowitz et al., 2012, Hurst et al., 2013, Baltas and Kosowski, 2013 or Baltas and Kosowski, 2017). However, none of these studies considers credit markets. Given the recent interest in studying technical indicators in the major asset classes, analysis of the profitability of technical indicators in corporate bond markets seems warranted.

The contribution of this chapter to the literature is manifold. First, it provides the first study on cross-sectional profitability of technical analysis in corporate bond markets. Unlike existing literature that applies technical analysis to either market indices or individual securities, here it is applied to corporate bond portfolios sorted by measures that reflect information uncertainty, namely OAS and equity volatility of the corresponding firm. The rationale behind the employed analysis is that many investors and fund managers use technical anal-

[32] See, for example, Hong et al. (2012) reporting that stocks lead HY bonds and to a lesser degree IG bonds as well or Bao and Hou (2014), who show that the comovement between equities and bonds is stronger for firms with higher credit risk for a variety of measures of this firm characteristic.

ysis to make trading decisions and that proponents of this investment approach use the most widespread indicator, moving averages, to time investments. Second, empirical evidence is provided for behavioral finance theories suggesting that asset prices can display patterns of predictability that cannot be explained with risk-based expectation theories of price formation.[33] However, previous literature on this topic does not include credit markets (see Daniel and Hirshleifer, 2015). Third, the results contribute to the debate whether well-known strategies from equity markets can be extended to corporate bond markets. While factors based on fundamental data deliver inconclusive results at best for corporate bonds implying market segmentation (see Chordia et al., 2017, Choi and Kim, 2016, and Bektić et al., 2016), evidence is provided that technical analysis almost fully translates to the realm of credit markets. Finally, these findings provide important insights for corporate bond investors, hedgers and arbitrageurs.

The remainder of the chapter is structured as follows: The next section describes the data and empirical methodology. Section 4.3 provides evidence for the profitability of the moving average timing strategy and Section 4.4 documents the robustness of the findings. Section 4.5 concludes.

[33]Chordia et al. (2017) state that sophisticated institutions, who in fact dominate corporate bond markets, price risk in the neoclassical sense.

4.2 Data and Methodology

4.2.1 Data

The analysis is based on an extensive Bank of America Merrill Lynch (BAML) data set of U.S. HY and IG corporate bonds between December 1996 and November 2016 on a monthly frequency, similar to chapter 1. The focus is on senior debt only as junior debt is usually an unsecured form of debt and has different payout characteristics compared to standard senior coupon bonds. In addition, there is a differentiation between IG and non-investment grade (or HY) corporate bonds rated by at least one of the following rating agencies: S&P, Moody's or Fitch. In the spirit of Merton (1974), bonds with varying credit risks exhibit different market behavior and according to Chen et al. (2007) they also manifest different transaction costs. This segmentation is also widespread in practice as index providers offer either HY or IG indexes. Summary statistics on the average duration, spread and rating characteristics of the analyzed data set over time are provided in Table 2.1.

Since the main uncertainty measure is based on OAS, all traded firms from the U.S. corporate HY & IG indexes are considered in this analysis. For the alternative measure, equity volatility, only publicly traded companies are considered. This provides a further robustness check to the results since the universe almost halves when taking into account listed firms only. The resulting sample includes 1,076,376 unique bond-month observations (236,280 for U.S HY and 840,096 for U.S. IG). Table 4.1 reports the basic characteristics of the quintile portfolios.

Table 4.1: Descriptive Statistics

Average duration (Avg. DUR), spread (Avg. OAS), rating (Avg. RTG) and annualized standard deviation (Avg. VOL) as well as the average past cumulative 12 month return (Avg. Past Cum. 12m Return) and average lag 1 month return (Avg. Lag 1m Return) of all quintiles and the corresponding market for U.S. High Yield as well as Investment Grade corporate bonds in the period from December 1996 until November 2016 sorted by option adjusted spread (OAS) and equity volatility (Eq. Vol.), respecitvely.

OAS

High Yield	Q1	Q2	Q3	Q4	Q5	Market
Avg. DUR	4.13	4.30	4.12	3.86	3.17	3.92
Avg. OAS	271.36	410.26	553.09	801.53	2391.47	885.54
Avg. RTG*	12.49	13.48	14.48	15.35	16.73	14.51
Avg. VOL	5.69%	7.27%	9.32%	12.46%	19.17%	10.25%
Avg. Past Cum. 12m Return	0.02%	2.36%	3.27%	4.41%	10.85%	3.72%
Avg. Lag 1m Return	0.01%	0.22%	0.30%	0.38%	0.72%	0.33%

Investment Grade	Q1	Q2	Q3	Q4	Q5	Market
Avg. DUR	3.84	5.41	6.18	6.52	6.29	5.65
Avg. OAS	71.33	121.35	160.47	206.68	336.06	179.18
Avg. RTG*	4.83	6.59	7.60	8.32	8.97	7.26
Avg. VOL	1.87%	2.89%	3.51%	4.18%	6.61%	3.68%
Avg. Past Cum. 12m Return	-0.53%	-0.12%	0.43%	1.10%	3.68%	0.88%
Avg. Lag 1m Return	-0.05%	-0.01%	0.04%	0.10%	0.32%	0.08%

Eq. Vol

High Yield	Q1	Q2	Q3	Q4	Q5	Market
Avg. DUR	4.17	4.13	4.09	4.03	3.85	4.05
Avg. OAS	543.03	588.80	602.51	644.69	1040.00	683.81
Avg. RTG*	13.51	13.59	13.69	13.99	15.17	13.99
Avg. VOL	6.67%	8.31%	8.60%	10.16%	15.12%	9.33%
Avg. Past Cum. 12m Return	3.83%	4.12%	4.04%	4.52%	5.96%	4.42%
Avg. Lag 1m Return	0.35%	0.37%	0.36%	0.40%	0.51%	0.40%

Investment Grade	Q1	Q2	Q3	Q4	Q5	Market
Avg. DUR	5.87	5.83	5.67	5.53	5.39	5.66
Avg. OAS	143.86	152.92	166.51	181.84	225.78	174.18
Avg. RTG*	6.90	7.11	7.35	7.60	7.99	7.39
Avg. VOL	2.90%	3.20%	3.42%	4.01%	4.75%	3.59%
Avg. Past Cum. 12m Return	0.77%	0.70%	0.94%	1.08%	1.32%	0.96%
Avg. Lag 1m Return	0.07%	0.07%	0.08%	0.10%	0.12%	0.09%

*Rating Description: AAA=1, AA+=2, AA=3, AA-=4, A+=5, A=6, A-=7, BBB+=8, BBB=9, BBB-=10, BB+=11, BB=12, BB-=13, B+=14, B=15, B-=16, CCC+=17, CCC=18, CCC-=19

The key variables are OAS and equity volatility, respectively. Equity volatility is the standard deviation of the firm's stock and OAS is the fixed spread (notation is in basis points) in addition to the Treasury curve where the corporate bond's discounted payments matches its traded market price (including possible option features). For instance, Lu et al. (2010) show that corporate bond yield spreads represent a compensation for information uncertainty and information asymmetry. Therefore, credit spreads are suitable measure of uncertainty entailed in corporate bonds. The option-adjusted spread accounts for possible optionality in credit securities. For example, a callable bond is generally more risky to investors than an otherwise identical straight bond, as it incorporates an additional risk of being called. The OAS accounts for this additional risk and therefore constitutes a natural measure of uncertainty for corporate bonds. BAML provides total returns as well as excess returns, which are equal to total returns minus the return of a duration-matched Treasury. Since the main purpose of investing in corporate bonds is to earn the default premium besides the term premium, only excess returns should be considered to evaluate unbiased corporate bond returns (see Israel et al., 2016, Bektić et al., 2016 and Houweling and van Zundert, 2017).

4.2.2 Methodology

As common in academic literature (see Frazzini and Pedersen, 2014 or Jacobs, 2016), the existence of market timing strategies is investigated in corporate bond markets according to uncertainty measures via quintile analysis. That is, issuers are ranked and grouped into five quintiles according to their OAS and equity

volatility score, respectively. To ensure that the resulting quintile portfolios are not dominated by single large issuers, each issuer is weighted equally rather than employing a market-capitalization weighting scheme (see Baker and Wurgler, 2012, Choi and Kim, 2016 or Bektić et al., 2016). Accordingly, equal-weighted benchmarks are used. The quintile portfolios are rebalanced on a monthly basis. Given the weighting scheme and monthly excess returns of each bond, the performance of each quintile for each OAS and equity volatility sorted factor portfolio and bond subsample can be computed.

The employed moving average timing strategy works as follows: At time t the moving average of excess returns of the respective portfolio is computed under consideration over the past K months starting at *t-2*:

$$MA_{t-1} = \frac{1}{K} \sum_{i=2}^{K+1} r_{t-i} \tag{4.1}$$

Then, MA_{t-1} is compared to the excess return of the portfolio r_{t-1} in *t-1*. If and only if

$$r_{t-1} > MA_{t-1} \tag{4.2}$$

one would invest in the portfolio at time t and otherwise, one would hold cash. Note that the one month time lag between the computation of the investment decision criterion and the actual investment prevents any forwarded looking bias

that might result from delayed data availability. Therefore, this lag ensures the practical implementability of the strategy. This strategy is applied to each of the quintile portfolios constructed from sorts on OAS and equity volatility for each rating bucket, i.e. HY and IG.

4.3 Empirical Analysis

We start by conducting an analysis of excess returns generated by a moving average timing strategy. In this baseline analysis, $K = 3$ in equation (1), i.e., one quarter is used for the computation of the moving average. This length is chosen because the recency bias indicates that the value of information decays over time (see Furham, 1986).

For each combination of rating bucket and measure of uncertainty, benchmark excess returns are constructed by computing the equal-weighted average of excess returns of each quintile. Therefore, four benchmarks are computed in total. To assess profitability excess returns are computed, alphas against the respective benchmark and Sharpe ratios for moving average strategies applied to each of the quintiles constructed from sorts on OAS and equity volatility. Table 4.2 displays the baseline results.

Panel A shows the findings for portfolios based on OAS of the underlying bonds. For IG bonds, excess returns increase monotonically from quintile one to quintile five. The excess return over maturity matched Treasuries amounts to 35

basis points (bps) per month for quintile five with a t-statistic of 2.22. Moreover, the alpha versus the benchmark is substantial with 29 bps per month and a t-statistic of 2.66. Sharpe ratios also increase monotonically across quintiles, which indicates that excess returns increase even on a risk-adjusted basis.

For HY bonds, the results are even stronger. Excess returns increase monotonically across quintiles from 11 bps per month (t-statistic 1.86) for quintile one to 104 bps per month (t-statistic 2.58) for quintile five. Notably, alphas versus the benchmark increase from insignificant 7 bps per month to significant 86 bps per month (t-statistic 3.31). These alphas and excess returns are surprisingly large. Likewise, the Sharpe ratio increases from 0.14 to 0.31.

Results in panel B show a similar picture for portfolios based on equity volatility of listed bond issuing companies. In general, the results are weaker compared to the results in panel A, in particular for IG bonds. Nevertheless, the moving average strategy generates an alpha of 12 bps per month (t-statistic 2.11) versus the benchmark in quintile five of IG bonds. Also, note that because equity volatility is only available for publicly traded companies, the amount of bonds per quintile is smaller compared to portfolios based on OAS sorts.

For HY bonds in panel B, excess returns and alphas are smaller than in panel A, but still quite sizeable. For instance, for quintile five, the monthly excess return amounts to 68 bps per month (t-statistic 2.45) which corresponds to a monthly alpha of 49 bps (t-statistic 2.53) versus the benchmark.

Table 4.2: Moving Average Strategies - Baseline Results

This table reports return characteristics for a moving average strategy based on portfolios of corporate bonds sorted on measures of uncertainty, separately for the rating buckets *Investment Grade* and *High Yield*. Corporate bonds are sorted into five equally sized portfolios based on their option adjusted spread in panel A and based on their issuer's equity volatility in panel B. The table shows the equally weighted average of excess returns over maturity matched treasuries, alphas as the intercept from a regression of the time series of excess returns on the excess returns of the benchmark together with the respective t-statistics. Benchmarks for each combination of rating bucket and measure of uncertainty are computed as equally weighted average of excess returns over each quintile. Further, the table reports the Sharpe ratios of the portfolios. We adjust t-statistics for serial correlation using Newey and West (1987) standard errors. * indicates significance at the 10% level, ** indicate significance at the 5% level and *** indicate significance at the 1% level.

Panel A: Portfolios Sorted by OAS						
	Investment Grade			High Yield		
	Excess Return	α	Sharpe Ratio	Excess Return	α	Sharpe Ratio
MA: Q1	0.01	0.00	0.02	0.11*	0.07	0.14
t-value	0.29	0.03		1.86	1.33	
MA: Q2	0.04	0.02	0.09	0.24**	0.17**	0.20
t-value	1.09	1.78		2.47	2.26	
MA: Q3	0.09*	0.07**	0.17	0.37***	0.28***	0.25
t-value	1.82	2.00		2.67	2.92	
MA: Q4	0.15**	0.12**	0.22	0.50**	0.37**	0.24
t-value	2.08	2.51		2.45	2.89	
MA: Q5	0.35**	0.29***	0.27	1.04***	0.86****	0.31
t-value	2.22	2.66		2.58	3.31	
BM	0.08		0.08	0.33		0.11
t-value	0.70			1.06		
Panel B: Portfolios Sorted by Equity Volatility						
	Investment Grade			High Yield		
	Excess Return	α	Sharpe Ratio	Excess Return	α	Sharpe Ratio
MA: Q1	0.09**	0.07**	0.20	0.31***	0.20**	0.24
t-value	2.10	2.34		2.75	2.75	
MA: Q2	0.10**	0.08**	0.20	0.36***	0.26***	0.28
t-value	2.05	2.36		3.14	3.14	
MA: Q3	0.12**	0.10***	0.22	0.40***	0.27***	0.27
t-value	2.14	2.62		2.79	2.83	
MA: Q4	0.12*	0.09**	0.20	0.43**	0.28**	0.24
t-value	1.86	2.18		2.52	2.37	
MA: Q5	0.16*	0.12**	0.20	0.68***	0.49**	0.37
t-value	1.85	2.11		2.45	2.53	
BM	0.09		0.09	0.40		0.15
t-value	0.78			1.58		

In sum, the results indicate that the profitability of the moving average strategy is particularly pronounced for quintile five, which represents a portfolio of bonds with the highest informational uncertainty. This finding is insensitive to the specific measure of uncertainty used to construct the portfolios. As higher uncertainty is usually associated with both, stronger psychological biases and stronger limits-to-arbitrage, both factors should contribute to the large abnormal returns documented in this chapter. This is in line Barberis and Thaler (2003) who claim that anomalies in capital market should arise only if both psychological biases and limits-to-arbitrage are present.

4.3.1 Market Timing

In order to shed some light on the sources of profitability of the moving average strategy applied to the portfolios with high informational uncertainty, its market timing ability is analyzed.

To this end, the analysis follows two approaches suggested by Treynor and Mazuy (1966) and Henriksson and Merton (1981), respectively. For the former, the following regressions for each combination of measure of uncertainty and rating bucket are calculated:

$$r_{t,\mathrm{MAQ5}} = \alpha + \beta_{\mathrm{BM}} r_{t,\mathrm{BM}} + \beta_{\mathrm{BM}^2} (r_{t,\mathrm{BM}})^2 + \epsilon \tag{4.3}$$

where $r_{t,\mathrm{MAQ5}}$ denotes the return of the moving average strategy applied to the fifth

quintile constructed on the measure of uncertainty and $r_{t,\mathrm{BM}}$ denotes the return of the respective benchmark. A positive and significant β_{BM^2} indicates market timing ability. Intuitively, if β_{BM^2} is significant and positive, the quadratic term in the regression positively affects the returns of the moving average strategy regardless of the sign of the benchmark return. For instance, if the benchmark delivers a negative return, the squared benchmark return will nonetheless be positive. Therefore, a positive and significant β_{BM^2} indicates market timing ability.

In addition, the analysis follows the approach from Henriksson and Merton (1981) and regresses (again for each combination of measure of uncertainty and rating bucket):

$$r_{t,\mathrm{MAQ5}} = \alpha + \beta_{\mathrm{BM}} r_{t,\mathrm{BM}} + \beta_{\mathrm{BM}>0}(r_{t,\mathrm{BM}} \cdot I_{r_{t,\mathrm{BM}}>0}) + \epsilon \tag{4.4}$$

where $I_{r_{t,\mathrm{BM}}>0}$ equals one if and only if $r_{t,\mathrm{BM}} > 0$ and zero otherwise. As before, $\beta_{\mathrm{BM}>0}$ signals market timing ability. Tables 4.3 and 4.4 below illustrate the findings.

As Tables 4.3 and 4.4 demonstrate, both analyses show that the moving average strategy indeed exhibits market timing ability. Any combination of rating bucket and measure of uncertainty yields positive and significant coefficients $\beta_{\mathrm{BM}>0}$ and β_{BM^2}. These findings agree with the results presented in Han et al. (2013).

Table 4.3: Treynor and Mazuy (1966) Market Timing Test

This analysis tests whether the quadratic regression of Treynor and Mazuy (1966) has a significantly positive coefficient β_{BM^2}, indicating successful market timing, for long-short moving average portfolio returns for U.S. HY as well as IG corporate bonds in the period from December 1996 until November 2016 for the uncertainty variables OAS and equity volatility. Alphas are excess returns in percent per month. Statistical significance is denoted by *, ** and *** corresponding to the 90%, 95% and 99% confidence levels, respectively.

HY	OAS	Eq. Vol.
Q5	0.66***	0.97***
t-stat	4.83	3.98
IG	OAS	Eq. Vol.
Q5	1.89***	3.35***
t-stat	6.43	6.39

Table 4.4: Henriksson and Merton (1981) Market Timing Test

This analysis tests whether the regression of Henriksson and Merton (1981) has a significantly positive coefficient $\beta_{BM>0}$, indicating successful market timing, for long-short moving average portfolio returns for U.S. HY as well as IG corporate bonds in the period from December 1996 until November 2016 for the uncertainty variables OAS and equity volatility. Alphas are excess returns in percent per month. Statistical significance is denoted by *, ** and *** corresponding to the 90%, 95% and 99% confidence levels, respectively.

HY	OAS	Eq. Vol.
Q5	0.66***	0.97***
t-stat	4.83	3.98
IG	OAS	Eq. Vol.
Q5	1.89***	3.35***
t-stat	6.43	6.39

4.3.2 Cumulative Excess Returns

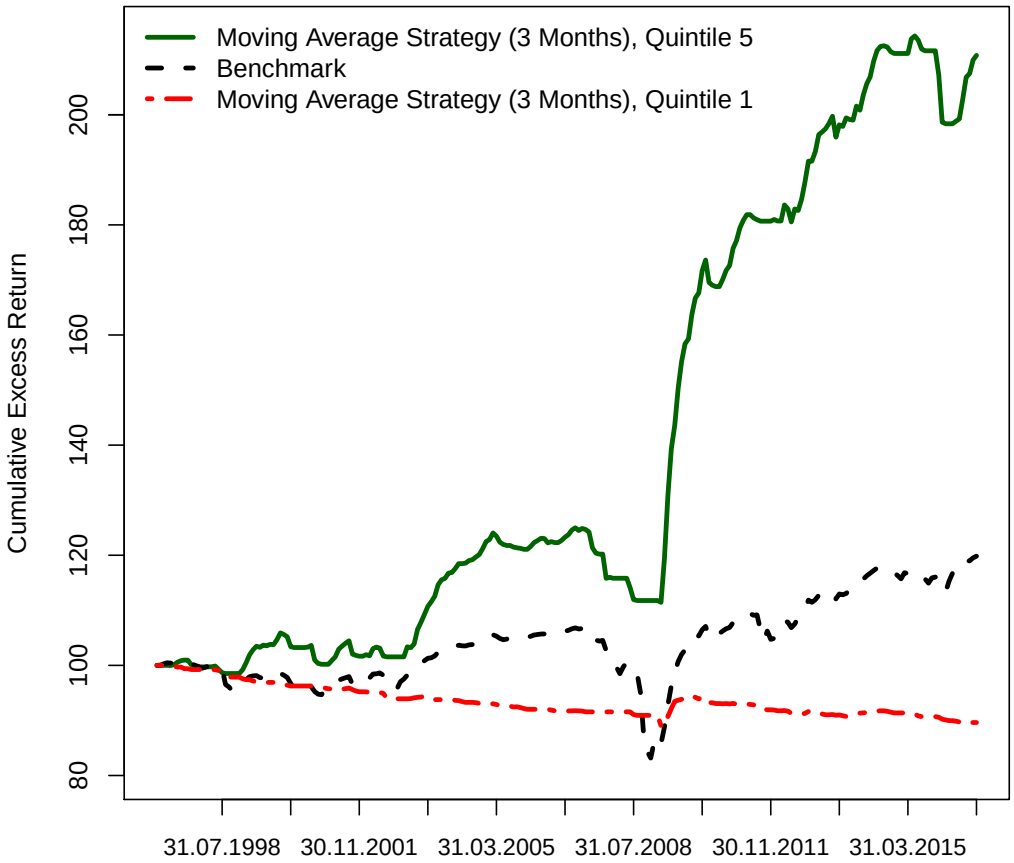
To assess the long-run performance of the moving average strategy presented in the previous sections, cumulative excess returns are calculated over the entire sample period. To this end, $K = 3$ as in the baseline analysis. Then, for each portfolio P under consideration

$$\text{Cumulative Excess Return(P)} = \prod_{t=1}^{T}(1 + \text{Excess Return(P)}_t) \tag{4.5}$$

The analysis summarizes the moving average strategy applied to quintile one and five as well as the benchmark. Figure 4.1 shows the resulting time series for the rating bucket IG and portfolios sorted by OAS. For the other rating bucket and measure of uncertainty combinations, results are very similar.

The graph shows that the moving average strategy for quintile five avoids some downside risk and therefore profits strongly in a cumulative perspective. Because of the limited downside, the higher volatility of quintile five compared to quintile one seems quite beneficial. In contrast, cumulative excess returns for the moving average strategy applied to quintile one appear rather weak. The lower volatility of this portfolio profits less and ends even weaker than the benchmark from a cumulative perspective. These findings are in line with Han et al. (2013) who also document similar results for equity portfolios.

Figure 4.1: Cumulative Excess Returns for Moving Average Strategies Applied to Portfolios Sorted on Option Adjusted Spreads



This figure shows cumulative excess returns of moving average strategies using a moving average of three months. For the portfolio construction, bonds are sorted into five equally sized portfolios based on their option adjusted spreads (OAS). Excess returns of the resulting portfolios over the maturity matched treasuries are computed as equally weighted averages of excess returns of all bonds contained in the respective portfolio. The moving average strategy is applied to the top and the bottom quintile portfolio constructed from this sort, denoted as quintile 5 and quintile 1, respectively. This figure also shows the cumulative excess returns of quintile 5, quintile 1 and the benchmark. All excess returns are normalized to 100 at the beginning of the sample period. The sample period ranges from December 1996 to November 2016.

4.4 Robustness Checks

4.4.1 Different Formation Periods

As a robustness check, the analysis is recalculated with different time periods over which the moving average strategy is computed. Specifically, the analyzed periods include $K = 6$ and $K = 9$, where moving averages are computed over half a year and three quarters. Thereby, it is ensured that the findings are robust with respect to the chosen time horizon used for the calculation of the moving averages. As before, excess returns are computed over duration-matched Treasuries, alpha against the respective benchmarks and Sharpe ratios.

As the focus is on the impact of information uncertainty on the profitability of moving average strategies, results are reported for quintile one and quintile five for a combination of rating buckets and measure of uncertainty in Table 4.5. The findings indicate that results are essentially unchanged for portfolios sorted by OAS. Thus, irrespective of the time horizon that is used for computing the moving average, the strategy performs better for quintile five compared to quintile one. Furthermore, the findings remain robust across rating buckets. For instance, the moving average strategy delivers an excess return of 27 bps per month (t-statistic 2.19) for IG bonds when twelve months are used for the computation of the moving average, compared to 34 bps (t-statistic 2.04) when only three months are used.

Looking at the second measure of uncertainty, namely equity volatility, results are weaker, however generally in line with the baseline findings. Similar to the other measure of uncertainty, results tend to be stronger for HY bonds

Table 4.5: Moving Average Strategies: Robustness Check

This table reports return characteristics for moving average strategies based on portfolios of corporate bonds sorted on measures of uncertainty, separately for the rating buckets *Investment Grade* and *High Yield* on a 6 and 9 month basis, respectively. Corporate bonds are sorted into five equally sized portfolios based on their option adjusted spread in panel A and based on their issuer's equity volatility in panel B. The table shows the equally weighted average of excess returns over maturity matched treasuries, alphas as the intercept from a regression of the time series of excess returns on the excess returns of the benchmark together with the respective t-statistics. Benchmarks for each combination of rating bucket and measure of uncertainty are computed as equally weighted average of excess returns over each quintile. Further, the table reports the Sharpe ratios of the portfolios. The t-statistics are adjusted for serial correlation using Newey and West (1987) standard errors. * indicates significance at the 10% level, ** indicate significance at the 5% level and *** indicate significance at the 1% level.

Panel A: 6 months						
	HY OAS			HY Eq. Vol		
	Excess Return	α	Sharpe Ratio	Excess Return	α	Sharpe Ratio
MA: Q1	0.06	0.02	0.07	0.29	0.1	0.18
t-stat	0.91	0.36		1.84	1.52	
MA: Q5	0.95**	0.77***	0.28	0.62**	0.43**	0.25
t-stat	2.19	2.71		2.25	2.23	
	IG OAS			IG Eq. Vol		
MA: Q1	0.01	0	0.03	0.09	0.06	0.16
t-stat	0.34	0.03		1.42	1.41	
MA: Q5	0.34**	0.28***	0.26	0.12	0.09	0.16
t-stat	2.04	2.59		1.46	1.43	
Panel B: 9 months						
	HY OAS			HY Eq. Vol		
	Excess Return	α	Sharpe Ratio	Excess Return	α	Sharpe Ratio
MA: Q1	0.01	-0.03	0.02	0.17	0	0.1
t-stat	0.21	0.64		1.12	0.03	
MA: Q5	0.76*	0.6*	0.24	0.53**	0.39*	0.25
t-stat	1.89	1.86		2.02	1.95	
	IG OAS			IG Eq. Vol		
MA: Q1	0	0	0.02	0.07	0.05	0.15
t-stat	0.33	0.08		1.46	1.3	
MA: Q5	0.24*	0.20**	0.22	0.12	0.09	0.16
t-stat	1.95	2.06		1.45	1.34	

compared to IG bonds when applying such kind of strategy. Since HY bonds are typically stronger correlated with equity[34], this is in line with Han et al. (2013).

As table 4.5 shows, the results are particularly strong for portfolios constructed by OAS but weak for public IG firms, which indicates that the results are stronger for non-public firms as compared to private firms. These findings are in line with the expectations, because of the lower transparency and visibility - and therefore higher uncertainty - of non-public firms. Additionally, uncertainty should be higher for HY than for IG firms, which is reflected by higher OAS and equity volatility (for public firms) as shown in Table 4.1. Therefore, it is naturally expected that the results are less strong for public IG firms, which is confirmed in Table 4.5.

These results corroborate the notion that information uncertainty enhances the profitability of technical analysis.

4.4.2 Risk-adjusted Excess Returns

To analyze the extent to which excess returns of the moving average strategy are attributable to known risk factors, regressions based on the Carhart (1997) model are calculated. If the moving average strategy would generate its excess returns by taking additional risk, the intercept of the regression would be expected to vanish. If, however, the intercept remains positive and significant, known risk factors would unlikely provide an explanation of the excess returns of the strategy. Table

[34]See Hong et al. (2012) or Bao and Hou (2014).

Table 4.6: Carhart (1997) 4-Factor Alpha

Alphas are estimated from the time-series regression using *MKT* as the equity market premium in addition to the Fama–French factors *SMB* (size) and *HML* (value) as well as the Carhart (1997) *UMD* (momentum) factor for U.S. HY as well as IG corporate bonds in the period from December 1996 until November 2016 for the uncertainty variables OAS and equity volatility. Alphas are intercepts of the regression in percent per month. Statistical significance is denoted by *, ** and *** corresponding to the 90%, 95% and 99% confidence levels, respectively.

HY	OAS	Eq. Vol.
MA: Q5	0.90***	0.58***
t-stat	4.36	3.69
IG	OAS	Eq. Vol.
MA: Q5	0.31***	0.13***
t-stat	3.98	2.63

4.6 summarizes the regression results for each combination of rating bucket and measure of uncertainty. Although the intercepts vary across rating buckets and measures of uncertainty, all are positive and significant. For instance, the monthly Carhart (1997) 4-factor alpha for IG bonds and OAS as measure of uncertainty amounts to 0.31% with a t-statistics of 3.98.

In sum, the findings suggest that the anomalous profits of the moving average strategy cannot be explained by the Carhart model. Additionally, the returns of the moving average strategy are regressed on the benchmark returns together with a bond momentum factor and bond value factors as suggested by Asness et al. (2013).[35] The results displayed in Table 4.7 document that the findings cannot be

[35]The data on bond value and bond momentum factors is obtained from AQR's website: https://www.aqr.com/library/data-sets/value-and-momentum-everywhere-factors-monthly.

Table 4.7: Asness et al. (2013) 3-Factor Alpha

Alphas are estimated from the time-series regression using the benchmark returns and in addition to the AQR fixed income factors *Value* and *Momentum* in the period from December 1996 until November 2016 for the uncertainty variables OAS and equity volatility. Alphas are regression intercepts in percent per month. Statistical significance is denoted by *, ** and *** corresponding to the 90%, 95% and 99% confidence levels, respectively.

HY	OAS	Eq. Vol.
MA: Q5	0.88***	0.51***
t-stat	4.62	3.65
IG	OAS	Eq. Vol.
MA: Q5	0.30***	0.13***
t-stat	4.69	2.89

explained even by these bond specific factors. In particular, the obtained alphas are significant for all specifications and hence, the results are robust.

4.4.3 Long-Short Portfolios and Impact of Expected Volatility

Since the main conjecture states that informational uncertainty enhances the profitability of moving average strategies, long-short portfolios are constructed to underline that assumption. These portfolios offset a long position in the moving average strategy applied to quintile five with a short position in the moving average strategy applied to quintile one. Then the mean return of the resulting long-short portfolio is computed and tested for significance. Again, this exercise is conducted for each rating bucket and each measure of uncertainty. Table 4.8 displays the findings. All long-short portfolios deliver positive and significant returns

Table 4.8: Long-Short Performance

This analysis tests whether the outperformance of long-short moving average portfolio returns for U.S. HY as well as IG corporate bonds in the period from December 1996 until November 2016 for the uncertainty variables OAS and equity volatility is larger than 0. Alphas are excess returns in percent per month. Statistical significance is denoted by *, ** and *** corresponding to the 90%, 95% and 99% confidence levels, respectively.

HY	OAS	Eq. Vol.
MA: Q5-Q1	0.92***	0.37***
t-stat	4.55	2.79
IG	OAS	Eq. Vol.
MA: Q5-Q1	0.35***	0.07**
t-stat	4.61	2.24

ranging from 0.07% per month (t-statistic 2.24) for IG bonds and equity volatility as measure of uncertainty to 0.92% per month (t-statistic 4.55) for HY bonds with OAS as measure of uncertainty.

In a next step, the analysis investigates how market volatility, as measured by the volatility index VIX, affects the excess returns of the employed strategy. The VIX is a measure of expected future volatility which is well-accepted by practitioners and in the academic literature (see Whaley, 2009). It is computed as a weighted average of implied variances of a wide set of options at different strike levels and captures the risk-neutral expected return variance over the next 30 days (see Exchange, 2009). Intuitively, a higher VIX is associated with a higher level of uncertainty. Because the augmented Dickey-Fuller test for unit roots with three legs indicates that the VIX is stationary in the analyzed sample ADF = -3.78 ,

Table 4.9: Long-Short Performance and the VIX Index

This table presents regression coefficients and t-statistics of long-short moving average portfolio returns for U.S. HY as well as IG corporate bonds regressed on the VIX index level in the period from December 1996 until November 2016 for the uncertainty variables OAS and equity volatility, respectively. Regression coefficients are in percent per month. Statistical significance is denoted by *, ** and *** corresponding to the 90%, 95% and 99% confidence levels, respectively.

HY	OAS	Eq. Vol.
MA: Q5-Q1	0.07***	0.03**
t-stat	2.69	1.97
IG	OAS	Eq. Vol.
MA: Q5-Q1	0.04***	0.01**
t-stat	4.04	2.34

p-value = 0.02, the performed regressions are based on the level of the VIX.

Intuitively, portfolios with high levels of informational uncertainty should be affected more strongly by increasing market volatility due to the additional informational risk they entail. Therefore, the performance of the moving average strategy applied to quintile five should outpace the performance of the moving average strategy applied to quintile one more strongly for higher levels of market volatility. Consequently, the profitability of the long-short portfolio introduced above is expected to increase as market volatility increases. Regression results shown in Table 4.9 support that claim. Irrespective of the rating bucket or measure of uncertainty, the results suggest that the performance of the long-short portfolio is positively related to market volatility.

4.4.4 Transaction Costs

As a final robustness test, the break-even transaction costs of the moving average strategies applied to quintile one and five for each combination of rating bucket and measure of uncertainty are determined. Following the literature (see Houweling and van Zundert, 2017), break-even transaction costs are defined as the amount of transaction costs that would lead to a CAPM alpha of zero. Table 4.10 shows the findings. The determined break-even transaction costs are quite large. For instance, the break-even transaction for the moving average strategy applied to quintile five of IG bonds sorted by equity volatility amounts to 55 bps, which substantially exceeds assumed levels of transaction costs in the literature (see Gebhardt et al., 2005 or Jostova et al., 2013). This finding highlights the relevance of the findings also from a practitioner's perspective.

Table 4.10: Break-Even Transaction Costs

Break-even transaction costs of a portfolio are defined as the costs that would lower its CAPM-alpha to 0 (see Houweling and van Zundert, 2017). The costs are calculated in basis points (bps) per transaction for U.S. HY as well as IG corporate bonds in the period from December 1996 until November 2016 for the uncertainty variables OAS and equity volatility, repectively.

HY	OAS	Eq. Vol.
MA: Q5	367	219
MA: Q1	21	87
IG	OAS	Eq. Vol.
MA: Q5	152	55
MA: Q1	1	26

4.5 Conclusion

The findings in this chapter document strong and robust anomalous excess returns for moving average timing strategies applied to corporate bond portfolios with high levels of informational uncertainty. Whenever the current return exceeds the moving average of past returns, the strategy invests in the portfolio and holds cash the rest of the time. Interestingly, excess returns increase with the degree of uncertainty of the underlying portfolio, irrespective of the measure of uncertainty employed.

Exposure to classical risk factors, such as Carhart's (1997) 4-factor model, is unable to explain the obtained excess returns. The variation in the return differential of moving average strategies applied to portfolios with different levels of informational uncertainty is positively related to the level of market volatility. Because high informational uncertainty tends to amplify both investor biases and limits-to-arbitrage, these two theories are likely to explain the results.

The results of this chapter complement the findings of (Han et al., 2013) who document similar results for equity markets. The fact the the results are stronger for HY bonds compared to IG bonds is also coherent with these authors. Further, the findings contribute to a growing strand of literature that analyzes the link between corporate bond markets and equity markets. Finally, evidence is provided that technical analysis can be profitable in corporate bond markets and that profitability is likely to increase with both, the uncertainty of the underlying portfolio and the general uncertainty in the market.

5 Conclusions

This dissertation shows that factor models are not only relevant for stocks, but for corporate bonds as well. However, the concept of factor investing is not new. As we have seen, the first investment factors were discovered over 50 years ago. What is new is that sophisticated quantitative models and an increased interest from market participants, who realized the shortcomings of traditional indices weighted by market capitalization, have turned academic theory into investable products. Furthermore, beside investment strategies, many investors adopted factors in their portfolio construction processes as well as in risk management. Finally, the recent shift towards factor-based investment strategies in general (sometimes referred to as smart beta), has led to a revived interest into risk factors.

In general, fixed-income indices can vary greatly in their risk and return profiles and are usually non-investable benchmarks. Hence, the demand for improved fixed-income indices will continue to grow especially in the context of diversification, liquidity and management costs. I hope the findings presented here will engage academic researchers to advance research on factor-based investing in the credit space and market practitioners to deploy factors in their daily asset management decisions. However, the main questions remain why certain factors

are associated with persistent excess returns while other underperform as well as how predictable are returns associated with these factors and how to harvest the corresponding performance systematically and effectively. In addition, the debate about optimal integration of factors into investable portfolios and tactical factor timing has not finished yet. Finally, empirical asset pricing has also to answer how many factors exist, which factors are priced, how stable are factors over time and to provide a sound economic or behavioral interpretation for the existence of a certain factor.

The empirical phenomena presented in this dissertation are a first step towards identifying factors in credit markets, yet a theoretical framework to underpin these results is still needed. Therefore, new implications about factor-based investing in credit markets, the finding of asset-pricing factors that are able to consistently price cross-asset returns as well as the investigation of additional significant and robust factors in global corporate bond markets should remain a fruitful area for future research.

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Erklärung zur Dissertation

Hiermit erkläre ich, dass ich gemäß § 9, Abs. 1 der Promotionsordnung der Technischen Universität Darmstadt vom 12. Januar 1990 (in der Fassung der VII. Änderung vom 28. September 2010) die vorliegende Dissertationsschrift selbstständig verfasst, keine anderen als die angegebenen Hilfsmittel verwendet und die Stellen, die anderen Werken im Wortlaut oder dem Sinne nach entnommen sind, mit Quellenangaben kenntlich gemacht habe.

Diese Arbeit hat in gleicher oder ähnlicher Form noch keiner Prüfungsbehörde vorgelegen.

Mörfelden-Walldorf, den 13. Februar 2018

Demir Bektić