Extending Fama–French Factors to Corporate Bond Markets

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ABSTRACT

The explanatory power of size, value, profitability and investment has been extensively studied for equity markets. Yet, the relevance of these factors in global credit markets is less explored although equities and bonds should be related according to structural credit risk models. We investigate the impact of the four Fama–French factors in the U.S. and European credit space. While all factors exhibit economically and statistically significant excess returns in the U.S. high yield market, we find mixed evidence for U.S. and European investment grade markets. Nevertheless, we show that investable multi-factor portfolios outperform the corresponding corporate bond benchmarks on a risk-adjusted basis. Finally, our results highlight the impact of company level characteristics on the joint return dynamics of equities and corporate bonds.

JEL classification: G11, G12, G14.

Keywords: corporate bonds, risk premia, factors, size, value, profitability, investment

1. Introduction

Do equity market factors explain corporate bond return dynamics? This empirical relationship is of substantial importance to investors (interested in return and diversification characteristics), economists (want to know the mechanisms that connect these markets) and not least policymakers (concerned about the stability of the financial system). As long as some investors have access to both equity and corporate bond markets, the absence of arbitrage opportunities imposes cross-market restrictions on the stochastic discount factor (SDF)[1]. While the relevant empirical studies can be traced back to the seminal work by Fama and French (1993), there is limited direct evidence in the literature concerning the pricing of risk across stock and bond markets. On the theoretical side, besides the contingent-claim approach to corporate bond pricing (see Merton, 1974), we still lack helpful guidance about which risk factors are necessary to achieve consistent risk pricing in stock and credit markets. We aim to fill this gap by examining whether the four risk factors in the Fama and French (2015) framework - size (SMB), value (HML), profitability (RMW) and investment (CMA) - are priced in the corporate bond market.

Analyzing the link between equity and corporate bond factors is a tempting proposition for at least the following three reasons. First, over the years evidence has mounted that alternative risk premia beyond the traditional asset class risk premia (e.g., equity and term premium) do indeed exist. Harvey et al. (2016) provide an excellent summary on factors in the equity space and recount more than 300 papers on cross-sectional return patterns published in various journals. According to structural credit risk models both equity and corporate debt are driven by the fundamentals of the same underlying corporation implying that stock prices and credit spread changes must be related to ensure the absence of arbi-

[1] The stochastic discount factor is sometimes referred to as the pricing kernel and reflects the fact that the price of an asset can be computed by discounting the future cash flow by a stochastic factor.

trage. Consequently, risk premia in equity and corporate bond markets should be related.[2] Second, 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). Third, 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.

To alleviate this shortcoming and to provide a more comprehensive insight into return dynamics between equity and debt, we explore the proposition that size, value, profitability and investment, as originally defined by Fama and French (2015) for equity markets, do indeed extend their explanatory power to U.S. high yield (HY) as well as U.S. and European investment grade (IG) credit markets.

We contribute to the literature in several ways. First, we depart from previous research by employing the original Fama and French (2015) equity factor definitions of size, value, profitability and investment for corporate cash bonds. Thus, we form portfolios by sorting the cross-section of bonds into deciles based on corresponding company characteristics and then we examine their time series performance. 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 theory. We formalize this intuition by combining the Merton (1974) model with the Miller and Modigliani (1961) valuation model, which serves as a motivation of Fama and French's five-

[2] Kapadija and Pu (2012) argue that there is cross-sectional variation in the correlation of equity and credit markets and that short-horizon pricing discrepancies across equities and corporate bonds are common and predominantly anomalous due to limited arbitrage activity. However, these authors also suggest that Merton's (1974) model is appropriate for longer time scales.

factor model for equities. Second, in addition to U.S. IG and HY corporate bonds, we extend our findings to a market not previously studied (European IG credits) shedding some light on the debate whether country-specific or global versions of Fama–French factors better explain international asset returns (see Griffin, 2002 for equity markets) and if corporate bond risk premia can be harvested internationally. Given the recent interest in studying equity factors in the U.S. corporate bond market, analysis of if and how such factors carry their explanatory power into other corporate bond markets seems warranted. Third, we contribute to the growing literature on capital structure arbitrage where mispricings between equity and debt are of crucial concern. Our results point up the importance of company level characteristics on the joint return dynamics of equities and corporate bonds. 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.

Our paper relates to the recent literature that examines factors in credit markets and closest to our paper are Houweling and van Zundert (2017) and Israel et al. (2016). Our paper differs in two ways. The key difference between these papers and ours is that both examine discretionary bond-specific factor definitions, whereas we focus on well-documented equity factor definitions as well as the link between equities and corporate bonds. Our article is also related to Choi and Kim (2016) and Chordia et al. (2016). Since properties of alternative risk premia in credit markets have mostly been studied in isolation, these authors focus solely on the cross-section of separate anomalies and do not study the benefits of investable multi-factor portfolios. Furthermore, all four related papers only consider U.S. corporate bond markets in their analysis while we also take into account the European IG market. Unfortunately, empirical evidence on factors in credit markets is 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. For instance, while Collin-Dufresne et al.

(2001) do not find strong explanatory power of the equity factors and uncover evidence of a missing factor, Avramov et al. (2007) document that common factors play a much large role for investment grade bonds while firm level characteristics are much stronger determinants for high yield credit spreads.

In addition to individual factor portfolios, we investigate the performance of investable equal-weighted multi-factor portfolios by combining size, value, profitability and investment. While we concede that a long-short portfolio might lead to superior risk-adjusted returns in theory, we consider long-short credit portfolios somewhat impractical due to operational difficulties and high transaction costs associated with shorting corporate bonds (especially for lower-rated or illiquid securities). Moreover, the majority of corporate bond investors is restricted to long-only portfolios. However, performance and diversification benefits can be achieved by combining all four factors which improves investor's overall portfolio return. Interestingly, the Sharpe ratios of multi-factor portfolios are up to 30% higher compared to those of the market. These results remain robust even after accounting for transaction costs.

Finally, our results suggest that corporate bond returns cannot be fully subsumed by traditional equity risk factors as corporate bond factor risk premia are not the same across the two markets. These findings indicate that the four Fama and French equity risk factors are priced differently in credit markets, a puzzle for modern asset-pricing theory that implies market segmentation (see Choi and Kim, 2016) and needs further investigation. As we conduct an out-of-sample study only (we use established equity factor definitions), it is ensured that our results do not suffer from in-sample bias.

Related Literature 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. A stunning result that opened the door for a lot of extensive studies on factor-based investing, leading to a multitude of new factors (sometimes referred to as "the factor zoo")[3] and factor models in the equity space.[4] 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.[5] Moreover, Hou et al. (2015) present a "q-factor" model containing size, profitability and investment 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.[6]

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, Goldstein et al., 2015 or Israel et al., 2016), similar research for fixed-income securities is less mature. However, 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. (2016) state that size, profitability and past equity returns

[3]See Cochrane (2011).

[4]See Harvey et al. (2016).

[5]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.

[6]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).

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.

The remainder of this paper is structured as follows: In section 2 we describe the models, in section 3 the data and empirical methodology, and in section 4 we introduce the four factors. In sections 5 and 6 we document the empirical results and the robustness of these findings. Section 7 is the discussion followed by our conclusion in section 8.

2. Return dynamics between equity and debt

Relating equity and corporate bond returns is not trivial but represents a natural starting point. 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 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 and one of the main assumptions is that the value of a company's assets follows a geometric Brownian motion W under the risk neutral martingale measure Q where μ and σ are the drift and volatility, respectively.

(1) $$dV_t = V_t \mu dt + V_t \sigma dW_t^Q$$

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 at date T is:

$$D(V_T, T) = min(V_T, F) = F - (F - V_T)^+ \tag{2}$$

To relate equity and debt in the Merton model, equity is valued as a call option on the value of assets and applying the accounting identity or put-call parity equates the value of debt D and equity E:

$$E(V_t, t) = Call_{BS}(V_t, F, \mu, T - t, \sigma) \tag{3}$$

$$D(V_t, t) = P(t, T) - Put_{BS}(V_t, F, \mu, T - t, \sigma) \tag{4}$$

The model makes it clear that the spread between risky credit debt and risk-free debt is the value of the put option.[7] Consequently, possible determinants of credit spreads and hence the key factors that influence credit spreads are: Company's business risk of the assets σ, Maturity of the debt T and the leverage 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

[7] $Call_{BS}$(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).

debt only if they capture changes in firm value or changes in risk neutral probabilities. Fama and French (2015) motivate their five-factor model for equities from the Miller and Modigliani (1961) valuation model:

$$P_{it} = \sum_{\tau=1}^{\infty} E[D_{it+\tau}]/(1+r_i)^{\tau} \tag{5}$$

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:

$$\frac{P_{it}}{B_{it}} = \frac{\sum_{\tau=1}^{\infty} E[Y_{it+\tau} - \Delta B_{it+\tau}]/(1+r_i)^{\tau}}{B_{it}} \tag{6}$$

In their paper, Fama and French (2015) claim that equation (6) 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"*.

3. Data and methodology

3.1. Data

Similar to Israel et al. (2016), we use monthly data of the Bank of America Merrill Lynch (BAML) 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, U.S. IG and European IG corporate bond issues rated by at least one of the three major rating agencies (S&P, Moody's and Fitch), issued in Euro (EUR) or 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[8], 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.[9]

European HY bonds are not included in this analysis due to insufficient size of the European HY market until 2013. As in Elton et al. (2001) puttable bonds are excluded. We further eliminate subordinated and contingent capital securities ("cocos") as well as taxable and tax-exempt U.S. municipal, equity-linked, securitized, DRD-eligible[10] and legally defaulted securities as these have distinctly different payout characteristics compared to standard senior coupon bonds.

The data set covers the period from December 1996 to December 2016 for U.S. HY and IG bonds and the period from December 2000 to December 2016 for European

[8] 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.

[9] 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.

[10] 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.

IG bonds.[11] Since the adoption of the Euro in 1999, BAML gradually introduced Euro denominated bonds into their indices. EUR denominated IG indices reached critical mass of at least 100 unique publicly traded issuers to be included in this study in December of 2000. Since all four factors are based on financial statement ratios and equity market data obtained from FactSet Fundamentals, only publicly traded corporations are considered in this analysis.[12] Furthermore, we use a 6-month lag to ensure that financial statement information is completely priced in by bond market participants and to avoid a forward-looking bias in our analysis (see Bhojraj and Swaminathan, 2009).

In total, our sample contains 1,272,900 unique bond-month observations: 248,820 in U.S. HY and 849,684 (174,396) in U.S. IG (European IG). Table 1 reports the descriptive statistics of the time-series averages. The average number of observations per month is 1,036 in U.S. HY markets and 3,540 (855) in U.S. IG (European IG) markets.

Table 1 provides further summary statistics of our data set including the most important bond characteristics such as duration, spread and rating.

[Please insert Table 1 here]

The total return of corporate bonds is predominantly driven by two components: interest rates (term premium) and credit spreads (default premium). Only the latter component is relevant in the context of factor-based investing in credit markets, as interest rate changes are usually independent of credit spreads and the main purpose of investing in credit securities is to additionally earn the default premium. Therefore, to evaluate unbiased factor returns

[11] Trade Reporting and Compliance Engine (TRACE) transaction data is available for U.S. bonds only and starts not before July 2002.

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

of credit portfolios one must consider excess returns of corporate bonds versus duration-matched sovereign bond returns. These returns, which are provided by BAML as well, are net of interest rate effects and thus reflect the credit premium component of corporate bonds only. Futhermore, BAML accounts for all defaults in its monthly excess returns, thereby freeing the data set of survivorship bias.

3.2. Empirical methodology

The factors at the heart of this study require equity data, therefore only publicly traded issuers are included in this analysis. The resulting number of issuers in the universe are further subdivided into three subsamples according to their ratings and issuance currencies (USD HY, USD IG and EUR IG) to accommodate the fact that bonds with varying credit risks and currencies 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 denominated in a particular currency. Moreover, leading index providers as well as regulation authorities consequently split these two market segments.[13] Therefore, our U.S. HY & IG subsamples consist of all USD denominated HY & IG bonds included in the data set. Similarly, the European IG universe contains all EUR denominated IG bonds.

As suggested by Jegadeesh and Titman (1993) for equities and by Jostova et al. (2013) for corporate bonds, we investigate the existence of factor premia for each of the three bond subsamples via decile analysis. That is, issuers are ranked and grouped into ten deciles according to their size, value, profitability and investment scores. The weighting scheme for each bond in each decile is based on the total number of issuers in the particular

[13]Chen et al. (2014) provide empirical evidence that credit ratings segment the corporate bond market in IG and HY securities.

bond subsample. Similar to Baker and Wurgler (2012) and Choi and Kim (2016) we ensure that decile portfolios are not dominated by single large issuers and weigh each issuer equally rather than employing a market-capitalization weighting scheme. Accordingly, we use equal-weighted benchmarks for each market and segment we study.

Let N be the number of unique issuers in the universe and let $M(n)$ be the total number of bonds corresponding to issuer n. Then the weight for each issuer is given by $1/N$ and the weight for each bond m of issuer n by $1/N \times 1/M(n) = \omega_{nm}$. The total weight is then given by $\sum_{n=1}^{N} \sum_{m=1}^{M(n)} \omega_{nm} = 1$ which is distributed equally among all deciles to ensure that each decile accounts for 10% of the total weight. The decile portfolios are rebalanced on a monthly basis (see Israel et al., 2016). Given the weighting scheme and monthly excess returns of each bond, the performance of each decile for each factor portfolio and bond subsample can be computed.

4. Defining corporate bond factors

In general, a factor can be any characteristic that explains a security's return and/or risk component. However, to be deemed relevant a factor should a) exhibit significant explanatory power for cross-sectional returns and must be supported by a sound economic rationale, b) have exhibited significant premia that are expected to persist in the future, where the mentioned rationale can be motivated by an economic or behavioral explanation, c) have return history available in non-U.S. countries and regions including drawdowns, and d) be implementable in liquid instruments (see Ang et al., 2009 and Amenc et al., 2012).

In the context of equity markets, size, value, profitability and investment conform with these requirements. In the tradition of Merton (1974), changes in equity and corporate bond prices should be related as they represent claims against the assets of the same company according to equations (3) and (4). For instance, if the equity price increases to incorporate positive news, the probability of default decreases and this should affect the bond price positively, and vice versa. The correlation in this relationship suggests, that any factor which has predictive power for equity returns is in principle an eligible candidate to forecast corporate bond returns as well due to the no-arbitrage principle. However, the question if equity factors indeed extend into the corporate bond space still remains open.

We employ the original equity factor definitions rather than using proprietary bond factor definitions. However, we assume that using bond-only information for factor definitions in credit markets could probably lead to different results.

Size

From an economic point of view, smaller companies are typically associated with lower liquidity, higher distress, and more downside risk than larger firms. Therefore, smaller companies should outperform larger firms to compensate investors for taking on the additional risk (see Banz, 1981). The behavioral bias argument for a size risk premium is given by limited investor attention to smaller companies.[14]

As empirical evidence for size premia in credit markets is relatively sparse and its definition less consensual than for the other three factors analyzed in this paper[15], we follow Banz (1981) and Fama and French (1993; 2015) and define size in the corporate bond space

[14] See, for exapmle, Carlson et al. (2006) for rational explanations and Stambaugh et al. (2012) for behavioral explanations of cross-sectional equity returns.

[15] Houweling and van Zundert (2017) use the index weight of each company from the Barclays U.S. Corporate IG index and the Barclays U.S. Corporate HY index suggesting that the size of a company's public debt in a given index represents the size factor in credit markets.

as the market capitalization of the company's equity:

$$Size_t = SO_t \times PPS_t \tag{7}$$

where SO_t denotes the number of shares outstanding and PPS_t the price per share in month t. The same arguments for a size premium in the equity space apply to the realm of credit markets, as investor should demand higher returns for the additional risks inherent to smaller issuers. As firm size decreases, equity volatility increases and so does the probability of default (see Merton, 1974). From a bondholder's perspective these firms are likely to be more risky and should therefore offer higher risk premia.

To harvest the size premium in credit markets, we construct the decile portfolio containing the bonds of the smallest 10% of the companies as measured by equity market capitalization and rebalance it on a monthly basis.

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 suggests the opposite. According to Zhang (2005), a rationale for the value premium is based on costly reversibility of investments. Hence, companies with high sensitivity to economic shocks in bad times should offer higher returns. A behavioral based explanation suggests that investors overreact to bad news and extrapolate recent price movements into the future, which results in underpricing.

We use the Fama and French (1993; 2015) definition of value and adjust it according to Asness and Frazzini (2013), using the last available share price:[16]

$$Value_t = \frac{BE_{t-6}}{ME_t} \tag{8}$$

where BE_{t-6} and ME_t denote book equity and market equity in month $t-6$ and t, respectively. Fama and French (1995) and Chen and Zhang (1998) show that firms with a high book-to-market equity ratio are more likely to exhibit persistently low earnings, more earnings uncertainty, high financial leverage, and are more likely to cut their dividend, which in turn leads to an increased volatility. High equity volatility implies a higher probability of default in the Merton (1974) model and hence value should have the same directional impact on equity and bond prices.

We construct the decile portfolio containing the bonds of the most valuable 10% of the issuers as measured by book-to-market value and rebalance it on a monthly basis.

Profitability

Fama and French (2015) use the dividend discount model to show that firms with high earnings relative to book equity have higher expected returns. The behavioral explanation suggests that investors do not differentiate between high and low profitability in growth firms and therefore bonds of companies with high profitability have higher returns. Chordia et al. (2016) note that highly profitable companies generate healthy cashflows and thus have a smaller probability of default.

We measure operating profitability, OP, using accounting data available at end of month t-6 and define it as earnings before taxes, EBT (revenues minus cost of goods sold,

[16] See Correia et al. (2012), Houweling and van Zundert (2017), or Israel et al. (2016) for other definitions of value in credit markets.

minus selling, general, and administrative expenses, minus interest expenses) divided by book equity, BE (see Fama and French, 2015).

$$OP_t = \frac{EBT_{t-6}}{BE_{t-6}} \tag{9}$$

We construct the decile portfolio containing the bonds of the most profitable 10% of the firms as measured by operating profitability and rebalance it on a monthly basis.

Investment

Fama and French (2015) motivate the existence of an investment premium in equity markets using the dividend discount model and define the investment factor as the change in total assets, TA, from the fiscal year ending in t-18 to the fiscal year ending in t-6, divided by total assets in t-18. A risk-based explanation of the investment factor is linked to the fact that corporations with low levels of investment tend to have higher costs of capital, and therefore only engage in projects that are most likely to lead to future earnings and ultimately to higher returns for equity investors. The behavioral explanation is based on the premise that investors misprice low investment companies due to expectation errors. According to Kahneman and Tversky's (1979) prospect theory, investors prefer and overprice firms that engage in excessive investment strategies due to their lottery-like payoffs which could explain the low average returns of such lotteries. Conversely, they tend to underprice companies that pick their investments wisely.

Based on the definition of Fama and French (2015), we define the investment factor,

Inv, for credit markets in month t as:

$$Inv_t = \frac{TA_{t-6} - TA_{t-18}}{TA_{t-18}} \tag{10}$$

We construct the decile portfolio every month which contains the bonds of the 10% of the companies with the lowest investment and rebalance it on a monthly basis.

4.1. Comparing Corporate Bond Factor Portfolio Returns

To compare factor portfolios, we compute risk-adjusted returns for all portfolios. Furthermore, we regress factor portfolio returns on corporate bond market excess returns (DEF) representing the credit default premium, and equity returns of Fama–French factors market (MKT), size (SMB), value (HML), profitability (RMW) and investment (CMA)[17] as well as the bond factor $TERM$ representing the term premium that can be harvested by investing in interest rate securities like Treasury bonds. For the U.S. HY and IG credit markets, the Term factor is constructed as the total return of the BAML US Treasuries 1-10 year index minus the 1-month T-bill rate which is also available on Kenneth French's website. For the European IG corporate bond market this factor is constructed as the total return of the BAML German Federal Government 1-10 year index minus the 1-month Euro Interbank Offered Rate (EURIBOR) as the T-bill equivalent for European money markets. For each currency (EUR and USD) and rating segment (HY and IG), we calculate corporate bond market excess returns by computing the equal-weighted average of excess returns of each decile to ensure comparability. Accordingly, we compute three benchmarks and therefore three DEF factors.

[17]The data on MKT, SMB, HML, RMW, and CMA is obtained from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

We adjust for risk in three ways to extract the added value (intercept or alpha) of each factor portfolio in credit markets, as is commonly done in literature (see Fama and French, 1993, Gebhardt et al., 2005, Bhojraj and Swaminathan, 2009, Bessembinder et al., 2009 or Jostova et al., 2013):

First, we use the Sharpe ratio (SR) to measure returns for each factor portfolio i relative to its total risk:

$$SR_i = \frac{r_i}{\sigma_i} \tag{11}$$

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 these returns.

Second, we correct for systematic risk of factor portfolio i by regressing its returns on the Default premium:

$$R_{it} = \alpha_{it} + \beta_i DEF_t + \varepsilon_{it} \tag{12}$$

where R_{it} is the return of 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 with the default premium being the market factor.

Third, we correct for systematic risk using the Fama–French five factor model, the default premium and the term premium. We run the following regression:

$$R_{it} = \alpha_{it} + \beta_{i1}MKT_t + \beta_{i2}SMB_t + \beta_{i3}HML_t + \beta_{i4}RMW_t + \beta_{i5}CMA_t + \\ \beta_{i6}DEF_t + \beta_{i7}TERM_t + \varepsilon_{it} \tag{13}$$

where *MKT* (market), *SMB* (small minus big), *HML* (high minus low), *RMW* (robust minus weak) and *CMA* (conservative minus aggressive) are the equity market, equity size, equity value, equity profitability and equity investment premium, respectively. The idea behind this approach is to analyze the impact of and dynamics between traditional equity factors and corresponding factors in corporate bond markets.

5. Empirical results

In Table 2 we report annualized mean returns, standard deviations (volatilities), Sharpe ratios, excess returns, tracking errors, maximum drawdowns and information ratios for size, value, profitability and investment factor-portfolios for all three corporate bond subsamples as well as the corresponding market characteristics. Regression intercepts (or alphas) and their t-statistics of the regression analysis as described above for each factor are also provided in Table 2 for each market segment.

[Please insert Table 2 here]

5.1. Single-factor performance

Panel A of Table 2 reports results for each of the individual factors across markets and segments. Average top-decile size returns are 6.94% per year in U.S. HY, 1.41% in U.S. IG, and 1.27% in European IG credit markets. Value generates average returns of 5.99% (U.S.

HY), 1.37% (U.S. IG), and 1.01% (European IG) compared to 4.28% (U.S. HY), 0.97% (U.S. IG), and 0.99% (European IG) of the market. The annualized returns for the profitability factor are 5.86% (U.S. HY), 0.78% (U.S. IG), and 0.77% (European IG). Average investment returns are 7.21% (U.S. HY), 1.19% (U.S. IG), and 1.68% (European IG). Corresponding volatilites (annualized standard deviations) and maximum drawdowns differ across factors. For instance, size and value exhibit the highest volatilities across markets and rating segments. Maximum drawdowns are also largest in size and value for U.S. HY and EUR IG corporate bonds while size and investment have the largest drawdowns in U.S. IG markets. Sharpe ratios are up to 30% higher compared to market. For instance, in U.S. HY markets the Sharpe ratio ranges from 0.46 (value) to 0.62 (profitability) compared to 0.45 of the market. In U.S. IG markets the Sharpe ratio ranges from 0.24 (profitability) to 0.33 (size) and in European IG markets from 0.27 (value) to 0.68 (investment). For completeness, bottom-decile factor portfolio returns are also included in Table 2 and are described in more detail in the robustness section in the context of long-short portfolios.

Panel B reports the excess returns over benchmark returns. In the U.S. HY segment, all factors exhibit statistically significant premia in both U.S. credit segments. However, for U.S. IG markets only size is significant at the 10% level. For European IG credit markets only the investment factor generates economically and statistically significant returns. Interestingly, profitability is negatively priced in both IG credit markets and this is in line with the findings of Chordia et al. (2016) and Campbell et al. (2016).[18]

Panel C reports the excess returns versus DEF (CAPM alpha) and Panel D reports the excess return statistics after controlling for Fama–French equity factors MKT, SMB, HML, RMW and CMA as well as the bond market factors TERM and DEF. Here, for

[18] In contrast, Choi and Kim (2016) report that profitability has no explanatory power for the U.S. IG credit market.

U.S. HY markets, profitability and investment are still significant factors while for U.S. IG markets none factor exhibits statistical significance. In European IG markets investment generates economically and statistically significant returns also after controlling for DEF as well as the 7-factor model. In addition, it is not surprising that DEF carries the majority of the explanatory power for long-only factor portfolios due to the common market exposure incorporated in long-only portfolios.

However, single-factor tracking errors suggest that investing in factor portfolios can be risky in relative terms.[19]

Tracking errors range from 3.45% (profitability) to 7% (size) for U.S. HY, 0.88% (profitability) to 2.01% (value) for the U.S. IG, and 0.94% (profitability) to 1.87% (value) for European IG top-decile corporate bond factor portfolios and thus are quite large compared to the market volatilities of 9.47%, 3.59%, and 2.36%, respectively. The information ratios range from 0.28 (value) to 0.52 (investment) in the U.S. HY market, from -0.21 (profitability) to 0.29 (size) in the U.S. IG market, and from -0.23 (profitability) to 0.58 (investment) in the European IG market. The Sharpe ratios in combination with the relatively high active risk imply that factor portfolios may underperform the benchmark on shorter investment horizons (see Houweling and van Zundert, 2017). Hence, single-factor portfolios are rather unattractive for portfolio managers as well as 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). Figures 1, 2, and 3 show the top decile single-factor portfolio perfor-

[19] Information ratio (IR_i) is defined as the active return of a portfolio i divided by tracking error, where active return is the difference between the return of the portfolio (R_i) and the return of a selected benchmark index (R_b), and tracking error is the standard deviation of the active return ($\sigma_i^{R_i - R_b}$).

$$IR_i = \frac{R_i - R_b}{\sigma_i^{R_i - R_b}} \tag{14}$$

mance versus the benchmark.

[Please insert Figure 1, 2, and 3 here]

5.2. Multi-factor performance

It is well documented that a portfolio constructed of different assets (here factors) will, on average, generate higher risk-adjusted returns than any individual security within the investment universe (only true if the assets or factors in the portfolio are not perfectly correlated). Table 3 shows the outperformance correlations between our four analyzed factors size, value, OP and Inv for U.S. HY as well as U.S. and European IG credit markets and the original Fama–French equity factors MKT, SMB, HML, RMW, CMA as well as the bond factors TERM and DEF. For U.S. HY markets, the corporate bond factor correlations range from -0.15 (OP and DEF) to 0.56 (Size and Inv). For U.S. IG markets, the corporate bond factor correlations range from -0.44 (OP and DEF) to 0.58 (Size and DEF). Finally, for European IG markets, the corporate bond factor correlations range from -0.67 (OP and DEF) to 0.51 (Value and DEF). Low and negative correlations between equity and bond factors suggest that the single factors capture different aspects across asset classes.[20] However, these low and negative correlations suggest that a combination of two or more factors offers significant diversification benefits.

[Please insert Table 3 here]

[20]Interestingly, CMA and HML exhibit a relatively high positive correlation of 0.63 for the period from Dec 1996 to Dec 2016 and this is probably the reason why Fama–French argue that the HML factor of the three-factor model becomes redundant for describing average returns in the U.S. stock market when incorporating CMA and RMW, respectievly.

Therefore, we also construct equal-weighted long-only multi-factor portfolios by combining size, value, profitability and investment, as described by:

$$r_t^{MultiFactor} = 0.25r_t^{Size} + 0.25r_t^{Value} + 0.25r_t^{OP} + 0.25r_t^{Inv} \tag{15}$$

where r_t denotes the return of each corresponding sinlge-factor portfolio as well as the multi-factor portfolio in month t. These equal-weighted portfolios are another way to examine the efficacy of the four analyzed factors across markets and segments. Table 4 reports the multi-factor portfolio statistics. The multi-factor portfolios deliver annual average excess returns of 2.33% in the U.S. HY market (t-stat 3.12), 0.23% in the U.S. IG market (t-stat 1.63), and 0.21% in the European IG market (t-stat 1.39). Moreover, the equal-weighted combination of size, value, profitability and investment within the different markets and segments generates higher Sharpe ratios than the equal-weighted market index. Sharpe ratios are still up to 30% higher compared to market. One possible explanation is that multi-factor portfolios are more diversified because more securities in the cross section have nonzero weights and the weights are less extreme than in single-factor portfolios. However, when controlling for Fama–French equity factors MKT, SMB, HML, RMW and CMA as well as the bond market factors TERM and DEF, the alphas of multi-factor portfolios are still economically and statistically significant for U.S. HY markets while U.S. and European IG markets cannot withstand the test.

[Please insert Table 4 here]

These findings suggest that the combination of all four factors leads to diversification benefits. The equal-weighted multi-factor portfolios demonstrate an annualized Sharpe ratio of 0.59%

for U.S. HY, 0.31% for U.S. IG, and 0.45% for European IG corporate bonds while Sharpe ratios of their corresponding markets are 0.45%, 0.23%, and 0.42%, respectively. Maximum drawdowns are comparable to those of the market and thus similar to the results of Lettau et al. (2014), we find that downside risk is not able to explain corporate bond returns. Figures 4, 5, and 6 show the multi-factor portfolio performance versus the benchmark as well as the cumulative outperformance.

[Please insert Figure 4, 5, and 6 here]

6. Robustness checks

In this section we check the robustness of our results. On the one hand, we consider transaction costs and on the other hand, we look at long-short factor portfolios which is common in the academic literature. In addition, we analyze correlations between long-short corporate bond factor returns and the original Fama and French equity factor returns as well as bond factors TERM and DEF.

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. Edwards et al. (2007) find that bid/ask spreads for U.S. corporates vary significantly through time and depend on the bond's quality and transaction size. However, the majority of the existing literature either ignores costs completely or assumes transaction costs to be a fixed amount of 13bp (Gebhardt et al., 2005) or 12bp (Jostova et al., 2013). According to Amenc et al. (2012) it is possible to achieve lower turnover by setting a rebalancing treshold where a portfolio is not rebalanced until two-way turnover reaches 70% in a quarter. The main idea is to avoid rebalancing when new weights deviate from the current weights by a relatively small amount. By applying this rule, portfolio turnover and corresponding trading costs can be reduced. Novy-Marx and Velikov (2016) confirm that most factor-based strategies continue to generate statistically significant alphas despite low turnover. Nevertheless, we estimate transaction costs as a function of issue rating, maturity and total turnover associated with each factor portfolio similar to Chen et al. (2007).

[Please insert Table 5 here]

We document that our results remain unchanged after accounting for transaction costs. Thus, the factors studied here are not only properly motivated, theoretically sound but can also be implemented. However, the specific implementation design[21] has an impact on performance and explains why two portfolios based on the same factor may perform differently.

As our definitions are based on existing academic literature, our selection is not based on ex post results and we refrain from optimizing portfolio constituents weights, we argue that the results of our analyzed four factors are largely free of data mining.[22]

Panels A, B and C of Table 6 report results for each of the individual long-short decile factor portfolios as well as the multi-factor portfolios across markets and segments. In particular, the multi-factor portfolios still exhibit higher Sharpe ratios than the market. Sharpe ratios are 0.51 (U.S. HY), 0.34 (U.S. IG) and 0.56 (European IG). However, the results of our long-short single-factor portfolios suggest that not all of the analyzed four factors

[21] Investment universe, rebalancing frequency, weighting scheme and definition of portfolio configuration (e.g., decile, quintile etc.)

[22] In this study, we do not control for rating, duration or spread. However, additional tests show that our results remain unchanged if we control for duration. Furthermore, our results remain robust if we use market-capitalization-weighted rather than equal-weighted portfolios. In addition, our results are unchanged during subperiods or if financials are excluded, indicating robust findings.

represent usable investment solutions. Panel C reports the excess returns of the long-short portfolios versus DEF (CAPM alpha) and Panel D reports the excess return statistics of long-short portfolios after controlling for Fama–French equity factors MKT, SMB, HML, RMW and CMA as well as the bond market factors TERM and DEF. For U.S. HY markets, profitability and investment again exhibit economically and statistically significant returns while for U.S. IG markets none factor exhibits statistical significance. In European IG markets investment again generates economically and statistically significant returns also after controlling for DEF as well as the 7-factor model. As expected, DEF carries much less of the explanatory power compared to long-only factor portfolios as common market exposure is lower in multi-factor portfolios.

[Please insert Table 6 here]

Table 7 shows the correlations between long-short decile factor portfolios and corresponding Fama and French (1993; 2015) equity factors as well as bond factors TERM and DEF. For U.S. HY markets, the corporate bond factor correlations range from -0.54 (OP and DEF) to 0.43 (Size and Inv). For U.S. IG markets, the corporate bond factor correlations range from -0.53 (Size and OP) to 0.48 (Value and DEF). Finally, for European IG markets, the corporate bond factor correlations range from -0.58 (Value and Inv) to 0.60 (Value and DEF).

[Please insert Table 7 here]

We find that investing in certain single-factor portfolios as well as in multi-factor portfolios can substantially improve performance compared to investing in the market index. Our main inferences, especially when viewed in a long-only as well as a multi-factor context, is unaffected even after accounting for transaction costs or long-short portfolio construction techniques. These robustness checks imply that factor-based investing in credit markets does indeed offer additional benefit to corporate bond investors.

7. Discussion and interpretation of the results

Frazier and Liu (2016) show that risk aversion is still a fundamental concept in theory as well as in practice and state that, all else equal, investors require additional reward for bearing additional risk. The relationship between equities and corporate bonds in general is explained by Merton (1974) who claims that a corporate bond, in essence, consists of a default-free bond and a short put on the issuer's equity. As such each corporate bond is described by a risk free component (for example government bond) and an equity component (equity put). For higher rated IG bonds, the probability of default (PD) is small and hence the value of the put is small compared to the risk free component of the credit security, leading to a more risk-free-bond like behavior of IG bonds. In contrast, the elevated PD of issuers of HY debt, increases the value of the put and hence leads to a more equity-like behavior of HY debt. In other words, just like equity investors, HY bond investors bet on the future prosperity of the issuer by writing at the money puts. If the issuer's stock price increases, so does the value of the put and hence the value of the bond and vice versa.

In the following paragraphs we discuss our findings for each factor and compare these to extant literature. First, our results agree with Choi and Kim (2016) who show that cross-sectional return premia in U.S. corporate bonds are not equal to those in equity markets implying market segmentation. Second, our profitability findings in the U.S. IG corporate bond market are in agreement with Chordia et al. (2016), Franke et al. (2016) and Campbell et al. (2016), who note that this factor is negatively priced within this market segment due to the fact that bonds of more profitable firms tend to underperform while higher performance of low profitability firms compensates for default risk. Moreover, we extend this finding to European IG credit markets. In contrast to the cited papers above, we find that profitability is a statistically significant factor but positively priced for the U.S. HY corporate bond market which we attribute to the more equity-like features of HY debt. However, our results suggest that there is no equity value risk premium for corporate bonds. Furthermore, we provide empirical evidence that the equity size factor is not statistically significant for IG credit markets. One possible explanation for this finding is given by Shumway and Warther (1999), who show that the small-cap anomaly in the equity space is a data phenomenon only.

Finally, while Chordia et al. (2016) and Franke et al. (2016) report that investment is not statistically significant for U.S. IG corporate bonds, we find that indeed investment is significant for U.S. HY and European IG credit markets. One possible explanation for the significance of investment in Europe is a structural break in the market structure after the bailout announcement by the European Central Bank (ECB) and the subsequent quantitative easing of monetary policy followed by the so-called trash rally where risky assets outperformed the market. This effect might have been enhanced by the debt crisis in Greece as well as in Portugal, Ireland, Italy and Spain (also known as the PIIGS-crisis), as due to this crisis an additional country spread significantly impacted the performance of corporate bonds. Finally, we conjecture that the heterogeneity of the European IG corporate bond market additionally leads to an imbalance especially in terms of broker coverage, taxation and liquidity.

However, we cannot entirely disentangle whether our results can be considered an anomaly in the corporate bond market or whether it is just bond prices adjusting for equity prices due to the correlation of the two markets. The lead-lag relationship between stock returns and corporate bond returns (especially HY bonds) has been debated in the literature, yet findings are still inconclusive. Subrahmanyam and Titman (1999) find that stock markets usually incorporate new information faster due to its greater liquidity and larger clientele, despite the fact that on average bond market investors are more sophisticated than those in the stock market. However, Hotchkiss and Ronen (2002) find no evidence that stocks lead HY bonds. In contrast, Downing et al. (2009) find that the bond market is less informationally efficient than the stock market and show that stocks do not lead high quality non-convertible bonds (rated AAA-A) but do indeed lead non-convertible bonds rated BBB or lower. Moreover, Hong et al. (2012) report that stocks lead HY bonds and to a lesser degree IG bonds as well. In addition, Bao and Hou (2014) find that the comovement between bonds and equities is stronger for firms with higher credit risk. Finally, Li et al. (2016) state that heterogeneous agents are constantly revising their investment portfolios by taking into account the time-varying stock-bond return comovements and market conditions. This collective investment behavior impacts the stock-bond interlinkage and has an effect on capital allocations of these agents. Especially when the market volatility is high during periods of extreme market uncertainty, flight-to-quality is empirically observable.

In general, these conflicting results might imply suboptimal factor definitions because well-defined and robust factors should exhibit explanatory power regardless of market segment and region. According to Hodrick and Vassalou (2002) the dynamics of fixed-income assets in globalized markets should be affected mainly by international rather than domestic factors. Interestingly, the results are stronger for HY markets. We conjecture that this observation is due to the more equity-like features of HY bond markets compared to IG bond markets. As the Fama–French 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, though further research is needed to support this hypothesis.

8. Conclusion

In this analysis, we investigate if the Fama–French equity factors size, value, profitability and investment, factors well known for their robust risk premia in the equity space, can be extended to corporate bond markets. Although bonds and stocks are driven by the same firm fundamentals and therefore should react to the same factors, our empirical results show that these factors do not fully translate into fixed-income markets as suggested by structural equity-bond relations like Merton's (1974). On the one hand, a possible explanation could be market segmentation as bonds occupy a different position in a firm's capital structure (see Choi and Kim, 2016). On the other hand, market segmentation could also be caused by institutional investors who in fact dominate the corporate bond market and perceive risk differently compared to individual investors (see Chordia et al., 2016). Therefore, corporate bond markets seem to have its own unique features.

Nevertheless, after controlling for corresponding equity factor exposures, some factors do add value to corporate bond investors. In particular, our results suggest that the examined factors exhibit stronger returns in HY corporate bond markets (especially profitability and investment) probably due to the equity-like features of HY bonds, which is in line with theory. In contrast, no factor is significant for U.S. IG securities while the investment factor generates economically and statistically significant returns in the European IG market. Interestingly, profitability is negatively priced in both IG markets. While the original Fama and French (1993) factors size and value do not seem to add significant value to corporate bond investors, the two newly proposed Fama and French (2015) factors profitability and investment do offer return potential to investor portfolios. Finally, our results show that an investable equal-weighted long-only multi-factor portfolio reduces tracking error and drawdown, while higher risk-adjusted returns are preserved.

These empirical phenomena 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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Table 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	151	182	324	4.18	285	13.65
1998	381	173	208	337	4.38	405	13.65
1999	465	220	245	406	4.37	579	13.73
2000	485	239	246	503	4.2	660	13.81
2001	501	259	242	611	3.89	1110	14.06
2002	511	293	218	779	3.92	1369	14.12
2003	615	361	255	980	4.13	802	14.14
2004	719	410	309	1036	4.28	411	14.04
2005	745	420	325	1021	4.16	360	14.00
2006	757	424	334	965	4.15	329	13.97
2007	709	404	305	798	4.25	330	13.76
2008	819	460	359	890	4.09	921	13.84
2009	782	477	305	981	3.68	1639	14.26
2010	876	529	346	1106	3.94	662	14.12
2011	1054	619	435	1278	4.18	605	13.95
2012	1124	677	447	1412	3.84	682	14.04
2013	1231	742	489	1570	3.89	559	14.24
2014	1314	799	514	1722	3.89	494	14.21
2015	1347	869	478	1963	3.95	761	14.19
2016	1292	876	415	2053	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

Table 1 - 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	563	253	2516	5.61	62	6.72
1998	909	619	290	3026	5.65	101	6.86
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	1057	249	6501	5.89	186	7.87

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

Table 1 - Continued

European Investment Grade Universe

YEAR	Avg. # Firms	Avg. # Public Firms	Avg. # Private Firms	Avg. # Bonds	Avg. Modified Duration	Avg. Option Adjusted Spread	Avg. Rating
2000	221	142	79	289	4.73	104	5.73
2001	266	173	93	402	4.39	113	6.01
2002	320	225	96	551	4.09	128	6.33
2003	319	230	90	591	3.95	90	6.41
2004	340	245	95	624	4.01	56	6.59
2005	325	233	92	569	4.3	46	6.48
2006	324	237	87	602	4.46	51	6.4
2007	350	263	87	567	4.84	64	6.46
2008	388	293	95	725	4.17	199	6.4
2009	383	292	91	918	3.81	288	6.47
2010	385	293	92	1034	3.98	154	6.63
2011	386	292	94	1069	3.96	174	6.82
2012	387	295	92	1125	3.88	181	7.19
2013	395	300	95	1187	4.32	121	7.35
2014	436	322	113	1270	4.72	102	7.41
2015	486	362	124	1415	5.17	109	7.44
2016	545	411	134	1595	5.18	121	7.54

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

Table 2: Performance summary of factor portfolios

Results for market, size, value, profitability and investment factor portfolios for the U.S. HY as well as the U.S. and European IG corporate bond markets. At the beginning of each calender month equal-weighted portfolios are constructed from the 10% issuers with the highest (top) and lowest (bottom) factor exposure to size, value, profitability and investment. Panel A summarizes risk and return statistics. Panel B shows the excess return statistics. Panel C displays the CAPM-alpha and -beta. In Panel D alphas are estimated from the time-series regression using *DEF* as the credit default premium, *MKT* (minus the risk-free rate *RF*) as the equity market premium in addition to the Fama–French factors *SMB* (size) and *HML* (value), *RMW* (profitability), *CMA* (investment) and *TERM* in the 7-factor model. Means, volatilities, Sharpe ratios, excess returns, tracking errors, maximum drawdowns, information ratios and alphas are annualized. We test whether the outperformance of a factor compared to the market is larger than 0 (Panel B, t-test), and whether the alphas of a factor portfolio are larger than 0 (t-test in Panel C, and D). Statistical significance is denoted by *, ** and *** corresponding to the 90%, 95% and 99% confidence levels, respectively.

U.S. HY	**Market**	**Size**		**Value**		**OP**		**Inv**	
Panel A: Risk/Return		Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom
Mean	4.28%	6.94%	6.77%	5.99%	5.49%	5.86%	2.10%	7.21%	3.00%
Volatility	9.47%	13.88%	9.95%	13.00%	9.49%	9.53%	13.23%	11.77%	12.43%
Maximum Drawdown	-38.21%	-47.78%	-33.03%	-41.15%	-35.93%	-40.65%	-49.99%	-39.50%	-47.01%
Sharpe ratio	0.45	0.50	0.68	0.46	0.58	0.62	0.16	0.61	0.24
Panel B: Excess Return									
alpha		2.66%**	2.5%**	1.71%*	1.21%	1.59%**	-2.17%*	2.93%***	-1.27%
t-stat		1.95	2.01	1.49	1.22	1.97	1.39	2.41	0.82
Tracking Error		7.00%	5.35%	6.20%	4.27%	3.45%	5.38%	5.60%	4.81%
Information Ratio		0.38	0.47	0.28	0.28	0.46	-0.40	0.52	-0.26
Panel C: CAPM alpha									
alpha		1.63%	2.9%**	1.00%	1.61%*	1.79%**	-3.12%***	2.55%**	-1.96%**
beta		1.30	0.89	1.23	0.90	0.94	1.32	1.10	1.23
t-stat		1.14	2.45	0.76	1.72	2.34	3.10	2.05	2.04
Adjusted R^2		0.79	0.72	0.80	0.81	0.87	0.89	0.78	0.88
Panel D: 7-Factor alpha									
alpha		1.09%		-0.19%		2.66%***		2.99%**	
t-stat		0.70%		0.13		3.14		2.06	
MKT-RF		0.00		0.06		0.00		-0.02	
SMB		0.05		0.05		0.03		0.04	
HML		-0.01		-0.08		-0.05		-0.01	
RMW		0.18		0.09		0.05		0.05	
CMA		0.05		0.06		0.07		0.09	
TERM		0.24		0.60		-0.14		0.02	
DEF		1.28		1.19		0.86		1.03	

Table 2 - Continued

U.S. IG	**Market**	**Size**		**Value**		**OP**		**Inv**	
Panel A: Risk/Return		Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom
Mean	0.97%	1.41%	0.59%	1.37%	0.76%	0.78%	1.17%	1.19%	0.95%
Volatility	3.59%	4.22%	2.93%	4.59%	3.11%	3.30%	4.38%	4.15%	4.19%
Maximum Drawdown	-21.47%	-27.23%	-14.85%	-23.31%	-17.96%	-18.08%	-27.12%	-24.37%	-24.75%
Sharpe ratio	0.27	0.33	0.20	0.30	0.24	0.24	0.27	0.29	0.23
Panel B: Excess Return									
alpha		0.45%*	-0.37%	0.41%	-0.20%	-0.19%	0.20%	0.22%	-0.01%
t-stat		1.33	1.18	1.00	1.02	1.01	0.72	0.98	0.06
Tracking Error		1.57%	1.48%	2.01%	0.95%	0.88%	1.43%	1.10%	0.91%
Information Ratio		0.29	-0.25	0.20	-0.21	-0.21	0.14	0.20	-0.01
Panel C: CAPM alpha									
alpha		0.37%	-0.13%	0.28%	-0.05%	-0.09%	0.06%	0.11%	-0.14%
beta		1.10	0.75	1.16	0.84	0.89	1.17	1.12	1.15
t-stat		1.08	0.5	0.65	0.31	0.49	0.20	0.50	0.88
Adjusted R^2		0.87	0.84	0.82	0.94	0.94	0.91	0.94	0.97
Panel D: 7-Factor alpha									
alpha		0.55%		-0.33%		-0.07%		0.16%	
t-stat		1.49		0.72		0.37		0.64	
MKT-RF		-0.01		0.03		0.00		0.00	
SMB		0.00		0.00		0.01		0.01	
HML		0.03		-0.02		0.00		0.00	
RMW		-0.02		0.01		0.01		0.00	
CMA		-0.02		0.04		-0.03		0.00	
TERM		-0.01		0.13		0.01		-0.01	
DEF		1.10		1.16		0.89		1.12	

Table 2 - Continued

European IG	**Market**	**Size**		**Value**		**OP**		**Inv**	
Panel A: Risk/Return		Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom
Mean	0.99%	1.27%	0.53%	1.01%	0.86%	0.77%	0.95%	1.68%	0.47%
Volatility	2.36%	3.47%	2.34%	3.68%	2.04%	1.87%	3.12%	2.48%	3.10%
Maximum Drawdown	-11.91%	-17.98%	-10.24%	-17.54%	-10.59%	-9.04%	-15.10%	-10.36%	-16.25%
Sharpe ratio	0.42	0.37	0.23	0.27	0.42	0.41	0.30	0.68	0.15
Panel B: Excess Return									
alpha		0.29%	-0.46%**	0.02%	-0.13%	-0.22%	-0.04%	0.69%***	-0.52%**
t-stat		0.70	1.65	0.14	0.54	0.96	0.05	2.31	1.63
Tracking Error		1.80%	1.10%	1.87%	0.98%	0.94%	1.47%	1.19%	1.21%
Information Ratio		0.16	-0.42	0.01	-0.13	-0.23	-0.03	0.58	-0.43
Panel C: CAPM alpha									
alpha		0.02%	-0.33%	-0.34%	0.08%	0.04%	-0.20%	0.76%***	-0.72%***
beta		1.29	0.88	1.4	0.79	0.73	1.18	0.92	1.23
t-stat		0.05	1.24	0.82	0.38	0.25	0.55	2.57	2.37
Adjusted R^2		0.77	0.79	0.81	0.83	0.86	0.79	0.78	0.88
Panel D: 7-Factor alpha									
alpha		-0.20%		-0.52%		-0.14%		0.80%**	
t-stat		0.44		1.15		0.72		2.47	
MKT-RF		0.00		0.02		0.01		0.00	
SMB		0.02		0.01		0.00		-0.02	
HML		0.03		0.00		0.00		0.01	
RMW		0.02		0.02		0.01		-0.01	
CMA		-0.02		-0.03		0.01		0.02	
TERM		-0.01		0.03		0.03		0.00	
DEF		1.28		1.36		0.72		0.95	

Table 3: Correlation summary of factor portfolios

Return correlations between the Fama–French factors MKT, SMB, HML, RMW, CMA and the bond market factors TERM and DEF as well as the outperformance of the analyzed bond factors size, value, profitability and investment for the U.S. HY and IG universe over the period December 1996 to December 2016 (December 2000 to December 2016 for European IG bonds).

U.S. HY	Size	Value	OP	Inv	Mkt-RF	SMB	HML	RMW	CMA	TERM	DEF
Size	1.00										
Value	0.23	1.00									
OP	0.06	-0.08	1.00								
Inv	0.56	-0.12	0.17	1.00							
Mkt-RF	0.17	0.28	-0.15	-0.01	1.00						
SMB	0.07	0.13	0.00	0.07	0.22	1.00					
HML	0.15	-0.06	0.01	0.12	-0.14	-0.11	1.00				
RMW	0.07	-0.11	0.10	0.04	-0.49	-0.50	0.46	1.00			
CMA	0.04	-0.10	0.10	0.12	-0.34	0.01	0.63	0.31	1.00		
TERM	-0.14	0.03	-0.03	-0.08	-0.30	-0.19	-0.04	0.24	0.02	1.00	
DEF	0.41	0.35	-0.15	0.14	0.61	0.28	0.03	-0.35	-0.14	-0.52	1.00

U.S. IG	Size	Value	OP	Inv	Mkt-RF	SMB	HML	RMW	CMA	TERM	DEF
Size	1.00										
Value	-0.08	1.00									
OP	-0.30	-0.05	1.00								
Inv	0.42	-0.06	-0.34	1.00							
Mkt-RF	0.37	-0.06	-0.22	0.17	1.00						
SMB	0.21	-0.05	-0.01	0.14	0.22	1.00					
HML	0.15	-0.23	-0.09	0.03	-0.14	-0.11	1.00				
RMW	-0.24	-0.03	0.12	-0.10	-0.49	-0.50	0.46	1.00			
CMA	-0.05	-0.13	-0.13	-0.03	-0.34	0.01	0.63	0.31	1.00		
TERM	-0.31	0.02	0.22	-0.20	-0.30	-0.19	-0.04	0.24	0.02	1.00	
DEF	0.58	-0.07	-0.44	0.40	0.50	0.24	0.02	-0.26	-0.11	-0.42	1.00

EUR IG	Size	Value	OP	Inv	Mkt-RF	SMB	HML	RMW	CMA	TERM	DEF
Size	1.00										
Value	0.19	1.00									
OP	-0.26	-0.40	1.00								
Inv	-0.04	-0.42	-0.03	1.00							
Mkt-RF	0.23	0.36	-0.36	-0.13	1.00						
SMB	0.20	0.14	-0.13	-0.14	0.32	1.00					
HML	0.18	0.01	0.05	0.12	0.06	0.22	1.00				
RMW	-0.04	-0.15	0.24	0.08	-0.59	-0.30	0.16	1.00			
CMA	0.02	-0.14	0.18	0.18	-0.14	0.11	0.58	0.20	1.00		
TERM	-0.15	-0.17	0.30	0.06	-0.42	-0.16	-0.03	0.24	0.07	1.00	
DEF	0.38	0.51	-0.67	-0.15	0.61	0.20	0.05	-0.32	-0.11	-0.36	1.00

Table 4: Performance summary of long-only multi-factor portfolios

Results for the U.S. HY as well as the U.S. and European IG benchmarks (BM) as well as long-only multi-factor corporate bond portfolios (MF). At the beginning of each calender month equal-weighted portfolios are constructed from the 10% issuers with the highest factor exposure to size, value, profitability and investment. Panel A summarizes risk and return statistics. Panel B shows the excess return statistics. Panel C displays the CAPM-alpha and -beta. In Panel D alphas are estimated from the time-series regression using *DEF* as the credit default premium, *MKT* (minus the risk-free rate *RF*) as the equity market premium in addition to the Fama–French factors *SMB* (size) and *HML* (value), *RMW* (profitability), *CMA* (investment) and *TERM* in the 7-factor model. Means, volatilities, Sharpe ratios, excess returns, tracking errors, maximum drawdowns, information ratios and alphas are annualized. We test whether the outperformance of a factor compared to the market is larger than 0 (Panel B, t-test), and whether the alphas of a factor portfolio are larger than 0 (t-test in Panel C, and D). Statistical significance is denoted by *, ** and *** corresponding to the 90%, 95% and 99% confidence levels, respectively.

	U.S. HY BM	**U.S. HY MF**	**U.S. IG BM**	**U.S. IG MF**	**Eur. IG BM**	**Eur. IG MF**
Panel A: Risk/Return		Long Only		Long Only		Long Only
Mean	4.28%	6.61%	0.97%	1.20%	0.99%	1.19%
Volatility	9.47%	11.27%	4.22%	3.88%	2.36%	2.64%
Maximum Drawdown	-38.21%	-41.76%	-21.47%	-23.18%	-11.91%	-13.22%
Sharpe ratio	0.45	0.59	0.23	0.31	0.42	0.45
Panel B: Excess Return						
alpha		2.33%***		0.23%*		0.21%*
t-stat		3.12		1.63		1.39
Tracking Error		3.46%		0.66%		0.61%
Information Ratio		0.67		0.35		0.34
Panel C: CAPM alpha						
alpha		1.74%**		0.17%		0.12%
beta		1.14		1.07		1.09
t-stat		2.43		0.14		0.85
Adjusted R^2		0.92		0.98		0.95
Panel D: 7-Factor alpha						
alpha		1.65%**		0.08%		-0.01%
t-stat		1.96		0.52		0.09
MKT-RF		0.01		0.00		0.01
SMB		0.04		0.00		0.00
HML		-0.04		0.00		0.01
RMW		0.09		0.00		0.01
CMA		0.07		0.00		0.00
TERM		0.18		0.03		0.01
DEF		1.09		1.07		1.08

Table 5: Performance summary of factor portfolios after transaction costs

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

U.S. High Yield	Market	Size	Value	OP	Inv	Multi-Factor
Gross return	4.28%	6.94%	5.99%	5.86%	7.21%	6.61%
Transaction costs	0.35%	0.41%	0.52%	0.44%	0.47%	0.46%
Net return	3.93%	6.53%	5.47%	5.42%	6.74%	6.15%
Volatility	9.47%	13.88%	13.00%	9.53%	11.77%	11.27%
Net Sharpe ratio	0.41	0.47	0.42	0.57	0.57	0.55

U.S. Investment Grade	Market	Size	Value	OP	Inv	Multi-Factor
Gross return	0.97%	1.41%	1.37%	0.78%	1.19%	1.20%
Transaction costs	0.14%	0.15%	0.21%	0.17%	0.19%	0.18%
Net return	0.83%	1.26%	1.16%	0.61%	1.00%	1.02%
Volatility	4.22%	4.22%	4.59%	3.30%	4.15%	3.88%
Net Sharpe ratio	0.20	0.30	0.25	0.18	0.24	0.26

European Investment Grade	Market	Size	Value	OP	Inv	Multi-Factor
Gross return	0.99%	1.27%	1.01%	0.77%	1.68%	1.19%
Transaction costs	0.16%	0.18%	0.23%	0.19%	0.21%	0.20%
Net return	0.83%	1.09%	0.78%	0.58%	1.47%	0.99%
Volatility	2.36%	3.47%	3.68%	1.87%	2.48%	2.64%
Net Sharpe ratio	0.35	0.31	0.21	0.31	0.59	0.37

Table 6: Performance summary of long-short (top minus bottom) decile factor portfolios

U.S. HY	Market	Size	Value	OP	Inv	Multi-Factor
Panel A: Risk/Return		L/S	L/S	L/S	L/S	L/S
Mean	4.28%	0.06%	0.55%	3.02%	3.61%	2.10%
Volatility	9.47%	10.69%	8.53%	6.62%	8.48%	4.14%
Maximum Drawdown	-38.21%	-39.96%	-23.36%	-27.11%	-35.49%	-11.73%
Sharpe ratio	0.45	0.01	0.06	0.46	0.43	0.51
Panel B: CAPM alpha						
alpha		-1.26%	-0.61%	4.92%***	4.51%**	1.89%**
beta		0.41	0.33	-0.38	-0.14	0.06
t-stat		0.56	0.34	3.91	2.39	2.04
Adjusted R^2		0.13	0.13	0.28	0.02	0.01
Panel C: 7-Factor alpha						
alpha		-2.75%	-2.65%	4.49%***	4.32%**	0.85%
t-stat		1.15	1.38	3.39	2.13	0.88
MKT-RF		-0.02	0.03	-0.01	-0.03	-0.01
SMB		0.02	0.02	0.11	0.08	0.06
HML		-0.01	-0.04	-0.04	0.06	-0.01
RMW		0.19	0.06	0.20	0.05	0.13
CMA		0.14	0.00	-0.06	0.09	0.04
TERM		0.10	0.72	-0.29	-0.28	0.06
DEF		0.51	0.40	-0.35	-0.15	0.10

U.S. IG	Market	Size	Value	OP	Inv	Multi-Factor
Panel A: Risk/Return		L/S	L/S	L/S	L/S	L/S
Mean	0.97%	0.82%	0.64%	-0.45%	0.22%	0.33%
Volatility	4.22%	2.81%	2.38%	2.04%	1.36%	0.96%
Maximum Drawdown	-21.47%	-17.47%	-8.82%	-17.93%	-4.78%	-4.20%
Sharpe ratio	0.23	0.29	0.27	-0.22	0.16	0.34
Panel B: CAPM alpha						
alpha		0.50%	0.33%	-0.15%	0.26%	0.24%
beta		0.35	0.32	-0.27	-0.03	0.09
t-stat		0.89	0.72	0.36	0.84	1.17
Adjusted R^2		0.20	0.23	0.23	0.00	0.11
Panel C: 7-Factor alpha						
alpha		0.80%	-0.26%	-0.49%	0.40%	0.11%
t-stat		1.32	0.52	1.16	1.20	0.51
MKT-RF		-0.03	0.04	0.00	-0.01	0.00
SMB		0.00	-0.01	0.02	0.01	0.01
HML		0.05	-0.01	0.00	0.02	0.01
RMW		-0.04	-0.01	0.02	-0.01	-0.01
CMA		-0.03	0.05	-0.03	-0.02	-0.01
TERM		-0.01	0.12	0.13	-0.02	0.06
DEF		0.37	0.29	-0.25	-0.03	0.10

Table 6 - Continued

EUR IG	Market	Size	Value	OP	Inv	Multi-Factor
Panel A: Risk/Return		L/S	L/S	L/S	L/S	L/S
Mean	0.99%	0.74%	0.17%	-0.22%	1.16%	0.48%
Volatility	2.36%	2.49%	2.42%	1.98%	2.11%	0.85%
Maximum Drawdown	-11.91%	-11.46%	-8.61%	-11.81%	-4.70%	-3.18%
Sharpe ratio	0.42	0.30	0.07	-0.11	0.55	0.56
Panel B: CAPM alpha						
alpha		0.36%	-0.42%	0.24%	1.49%***	0.41%**
beta		0.41	0.61	-0.44	-0.31	0.07
t-stat		0.61	0.85	0.56	2.97	1.99
Adjusted R^2		0.15	0.36	0.27	0.11	0.03
Panel C: 7-Factor alpha						
alpha		0.10%	-0.43%	-0.06%	1.50%***	0.27%
t-stat		0.16	0.80	0.13	2.73	1.23
MKT-RF		-0.01	0.01	0.01	-0.02	0.00
SMB		0.04	0.02	0.01	-0.03	0.01
HML		0.05	0.00	0.03	0.02	0.02
RMW		0.03	0.01	0.01	-0.02	0.01
CMA		-0.02	-0.03	-0.03	0.04	-0.01
TERM		-0.05	-0.01	0.06	0.01	0.00
DEF		0.40	0.55	-0.47	-0.23	0.06

Table 7: Correlation summary of long-short decile factor portfolios

Return correlations between the Fama–French factors MKT, SMB, HML, RMW, CMA and the bond market factors TERM and DEF as well as the long-short decile size, value, profitability and investment portfolios for the U.S. HY and IG universe over the period December 1996 to December 2016 (December 2000 to December 2016 for European IG bonds).

U.S. HY	Size	Value	OP	Inv	Mkt-RF	SMB	HML	RMW	CMA	TERM	DEF
L/S Size	1.00										
L/S Value	0.05	1.00									
L/S OP	-0.23	-0.22	1.00								
L/S Inv	0.43	-0.40	0.01	1.00							
Mkt-RF	0.13	0.25	-0.40	-0.18	1.00						
SMB	0.05	0.10	-0.10	0.02	0.22	1.00					
HML	0.16	-0.02	0.01	0.16	-0.14	-0.11	1.00				
RMW	0.06	-0.09	0.34	0.14	-0.49	-0.50	0.46	1.00			
CMA	0.10	-0.09	0.07	0.20	-0.34	0.01	0.63	0.31	1.00		
TERM	-0.17	0.00	0.20	0.01	-0.30	-0.19	-0.04	0.24	0.02	1.00	
DEF	0.38	0.36	-0.54	-0.17	0.61	0.28	0.03	-0.35	-0.14	-0.52	1.00

U.S. IG	Size	Value	OP	Inv	Mkt-RF	SMB	HML	RMW	CMA	TERM	DEF
L/S Size	1.00										
L/S Value	0.24	1.00									
L/S OP	-0.53	-0.21	1.00								
L/S Inv	0.30	-0.19	-0.20	1.00							
Mkt-RF	0.14	0.38	-0.22	-0.11	1.00						
SMB	0.14	0.11	-0.05	0.09	0.22	1.00					
HML	0.12	0.00	-0.07	0.06	-0.14	-0.11	1.00				
RMW	-0.13	-0.19	0.13	-0.01	-0.49	-0.50	0.46	1.00			
CMA	0.01	-0.02	-0.05	0.04	-0.34	0.01	0.63	0.31	1.00		
TERM	-0.20	-0.10	0.36	-0.01	-0.30	-0.19	-0.04	0.24	0.02	1.00	
DEF	0.45	0.48	-0.48	-0.08	0.50	0.24	0.02	-0.26	-0.11	-0.42	1.00

EUR IG	Size	Value	OP	Inv	Mkt-RF	SMB	HML	RMW	CMA	TERM	DEF
L/S Size	1.00										
L/S Value	0.31	1.00									
L/S OP	-0.16	-0.36	1.00								
L/S Inv	-0.10	-0.58	-0.10	1.00							
Mkt-RF	0.22	0.41	-0.28	-0.28	1.00						
SMB	0.23	0.19	-0.04	-0.15	0.32	1.00					
HML	0.22	-0.01	0.10	0.12	0.06	0.22	1.00				
RMW	-0.05	-0.22	0.20	0.15	-0.59	-0.30	0.16	1.00			
CMA	0.05	-0.15	0.07	0.20	-0.14	0.11	0.58	0.20	1.00		
TERM	-0.18	-0.25	0.24	0.16	-0.42	-0.16	-0.03	0.24	0.07	1.00	
DEF	0.39	0.60	-0.53	-0.34	0.61	0.20	0.05	-0.32	-0.11	-0.36	1.00

Figure 1: Cumulative U.S. HY Single-Factor Long-Only Portfolio Returns (Dec 1996 - Dec 2016)

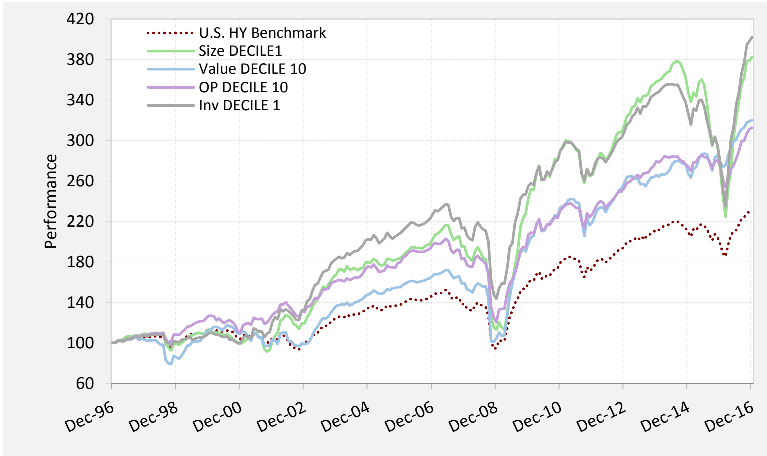

Figure 2: Cumulative U.S. IG Single-Factor Long-Only Portfolio Returns (Dec 1996 - Dec 2016)

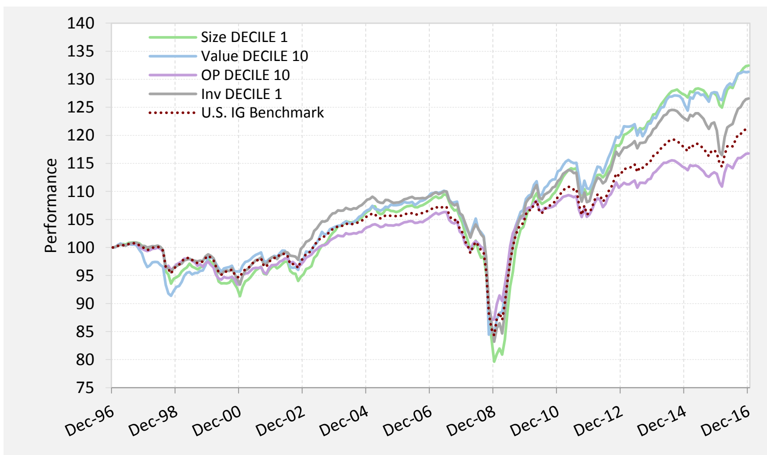

Figure 3: Cumulative European IG Single-Factor Long-Only Portfolio Returns (Dec 2000 - Dec 2016)

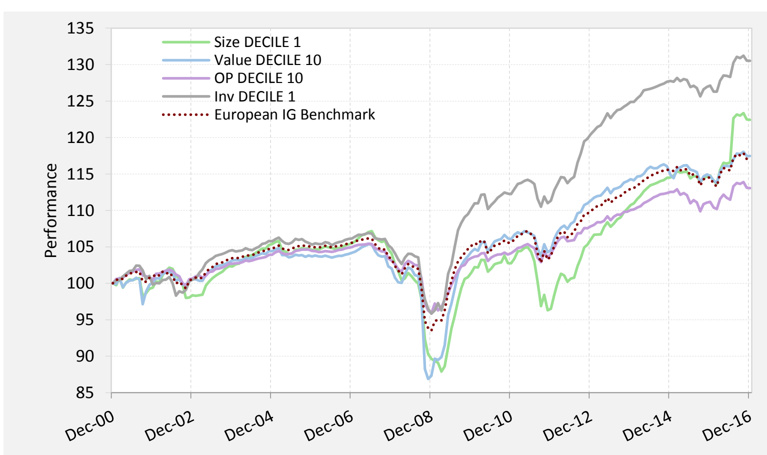

Figure 4: Cumulative U.S. HY Multi-Factor Long-Only Portfolio Returns (Dec 1996 - Dec 2016)

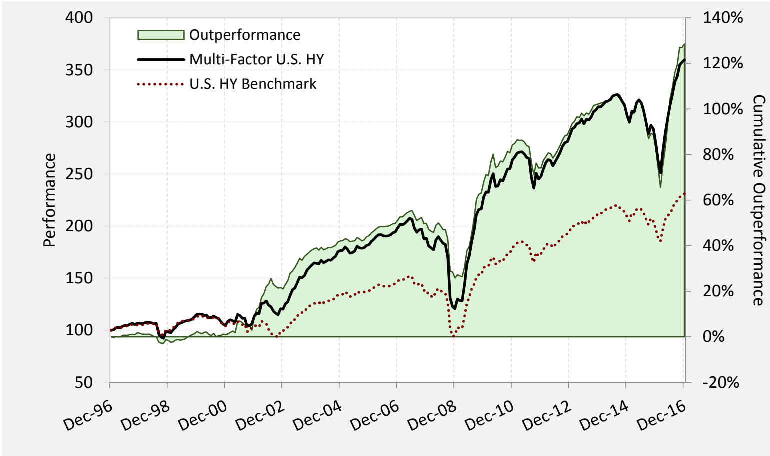

Figure 5: Cumulative U.S. IG Multi-Factor Long-Only Portfolio Returns (Dec 1996 - Dec 2016)

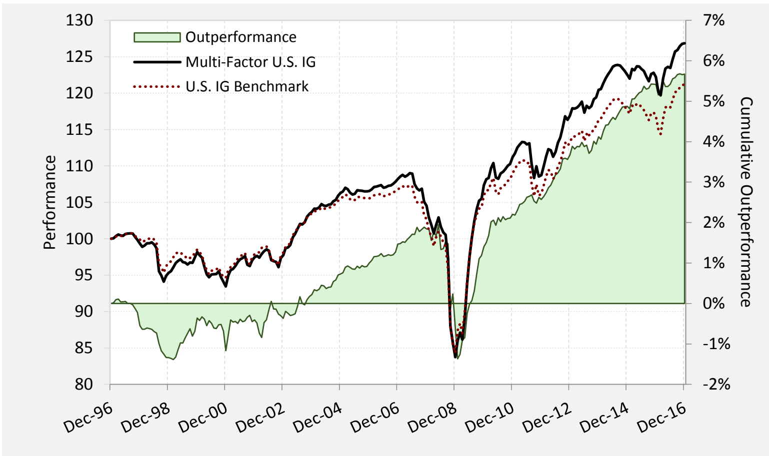

Figure 6: Cumulative European IG Multi-Factor Long-Only Portfolio Returns (Dec 2000 - Dec 2016)