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Factor Investing Strategies Applied to Corporate Bond ETF Constituents

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Abstract:

This paper applies the technique of factor investing to the US corporate bond market. The research utilizes data from December 2014 until July 2019, obtained from investment grade and high yield ETFs constituents, and we study the effects of five different factors: size, low risk, value, momentum and liquidity. CAPM and 5 Factor Fama-French, adjusted to fixed income markets, are employed in order to calculate alphas for long-short and long-only single factor and multi-factor portfolios. For investment grade bonds, size alpha measures between 0.64% and 0.80%, value alpha amounts to 0.71%, momentum alpha ranges between 7.60% and 19.62%. For high yield bonds, size alpha assumes values around 11%, value alpha between 11.93% and 18,22%, momentum alpha between 4.80% and 18.22% and liquidity alpha around 2.50%. We do not detect any statistically significant alpha for low risk. Low correlation is observed among all of the factors, which translates into multi-factor portfolios that achieve better risk-adjusted returns. Finally, the study discovers that even though long-short factor portfolios lead to higher excess returns, long-only factor portfolios bring more consistent outperformance against the benchmark.

Keywords: Asset management; Factor Investing; Factor premiums; Corporate Bonds; Size; Value; Low risk; Momentum; Liquidity.

JEL Classification: C23, G11, G12, G14

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1. Introduction

The analysis proposed by this paper broadens existing studies in two main fields: (1) the research for effectiveness of factor investing applied to the corporate bond markets and (2) the analysis of the competitive advantages of long-only and long-short investment strategies.

Assets earn risk premiums because they are exposed to underlying risk factors. A factor can be thought of an any characteristic common to a set of investment instruments that is important in explaining their risk and return (Bender et al 2013a). Blitz and Vidojevic (2019) define factors as systematic drivers of stock returns. Factors should be able to explain why certain stocks co-move and why some stocks earn higher or lower expected returns than others. Certain factors have historically earned a significant long-term risk premium. Factor investing permits to harvest these risk premia, while being exposed to these risk factors. Some of the most academically documented factors are value, size, low volatility, quality and momentum.

The concept of factor has existed for decades. Originally, it dates back to the beginning of the 1960s, when the Capital Asset Pricing Model was first theorized. The model states that a security's expected return is a function of its market beta – measure of the systematic risk. It was the first theory to demonstrate that the risk of an asset was not independent from other classes of assets and from the market. "Market" was identified as the first investment factor.

During more recent years, numerous theories giving evidence to new factors blossomed. The ones best covered by literature are size and value, proposed under the Fama-French 3 factor model in 1993. They found that, over the long-term, stocks of small-capitalized companies earn a premium over stocks of large-capitalized companies, as well as stocks of undervalued companies, related to their fundamentals (Price/Earning and Book/Market ratio) outperform stocks of overvalued companies, over the long run. Factors are cyclical and they earn risk premiums over the long run. Another fundamental factor is momentum, which is the strategy to invest in stocks that had recent positive performances, discovered by Jegadeesh and Titman in 1993. More contributions came next, bringing to the attention of researchers and investors factors like quality, low volatility and investment.

An abundance of literature has tried to give clarity by proposing explanation for the existence of factors, because they appear to be clashing against the efficient market theory. The intrinsic meaning of investing in a factor is to get exposure to different underlying risks. Usually, the higher the risk, the higher the expected return. The schools of explanation are divided in risk explanations and behavioural explanations: the former stream aims at embedding rational investor theories, while the latter stream aims at including irrationalities and inefficient investors' biases.

We aim at broadening the literature about fixed income factor investing by investigating the effects of size, low risk, value, momentum and liquidity factors in the US corporate bond market. Liquidity investing has been previously proved to not carry significant premiums for the investor (Blitz, van Brakel, Vidojevic, 2018); we are going to challenge those findings. We employ CAPM and 5 Factor Fama-French, adjusted to fixed income markets, to calculate alphas for long-short and long-only single factor and multi-factor portfolios. Additionally, we employ outperformance measures such as Sharpe Ratio, Information Ratio and Sortino Ratio to assess whether a long-short or a long-only investment strategy is more advisable for an investor.

The hypothesis we want to test are the following:

Hypothesis 1: single factor portfolios built with long-short investing strategies are able to obtain positive significant returns.

Hypothesis 2: the liquidity factor leads to a significant positive risk premium over the investment grade and high yield US corporate debt securities.

Hypothesis 3: single factor portfolios built with long-short investing strategies perform better than long-only, against the relative benchmark, but have higher risk. We consider as benchmark the market performance of investment grade and high yield bonds.

Hypothesis 4: multi-factor portfolio leads to better risk-adjusted returns because it can leverage onto the benefit of factor diversification.

The findings reveal that single factor portfolios built with a long-short investing strategy are able to harvest significant positive alphas. Investing in illiquid bonds brings positive returns, but only in the high yield market. Long-only portfolios have slightly lower returns but are characterized by more solid and consistent performances. Ultimately, it is discovered that, especially in the investment grade market, multi-factor portfolios exploit the benefits of diversification by achieving better risk-adjusted returns.

The following of the paper is organized as follows: Section 2 explores the findings of related literature about factor-based investing, beginning from the equity market until the more recent, and scarce, fixed income market. Section 3 describes the data used to conduct the study. Section 4 explains the methodologies adopted throughout the research. Section 5 reports the key results of the paper. Section 6 brings the concluding remarks and the recommendations for potential further research.

2. Literature Review

The first theory of factor risk was proposed by the works of Treynor (1961), Sharpe (1964), Lintner (1965) and Mossin (1966). These famous papers formulated the Capital Asset Pricing Model (CAPM). The model states that there is only one factor that moves all the asset returns: this factor is the sensitivity to systematic non-diversifiable risk (beta). Basically, the CAPM is a model for pricing an individual security or portfolio. It relates the expected return to the systematic risk as it shows how the market is going to price individual securities in relation to their risk class. The three main assumptions of the CAPM are pointed out by Berk and DeMarzo (2014). In the first place, all investors have the homogeneous expectation regarding asset returns, their standard deviation and correlations. Secondly, investors are price takers, i.e. they cannot influence prices and are also allowed to borrow and lend money at the risk-free interest rate, independently from the amount borrowed or lent. Finally, investors act rationally and risk-aversely. In other words, they prefer lower returns with known risks rather than higher returns with unknown risks (Berk and DeMarzo, 2014).

The risk of an individual asset is measured in terms of the factor exposure of that asset. If a factor holds a positive risk premium, then the higher the exposure to that factor, the higher the expected return of that asset. The risk premium on an individual asset is a function of that asset's beta. Beta measures how that asset comoves with the market. The higher the comovements, the higher the asset's beta.

The CAPM Equation is as follows:

$$E(r_i) - r_f = \frac{cov(r_i, r_m)}{var(r_m)} \left(E(r_m) - r_f\right) = \beta_i\left(E(r_m) - r_f\right),$$

where $E(r_i) - r_f$ is the risk premium of the asset over the risk-free rate, $\beta_i = \frac{cov(r_i, r_m)}{var(r_m)}$ is the asset's specific beta and $\left(E(r_m) - r_f\right)$ is the market premium over the risk-free rate. The beta is a measure of how an individual asset co-moves with the market portfolio. To higher co-movement coincides a higher beta. High betas mean low diversification benefits from investing in that particular instrument (Ang 2014).

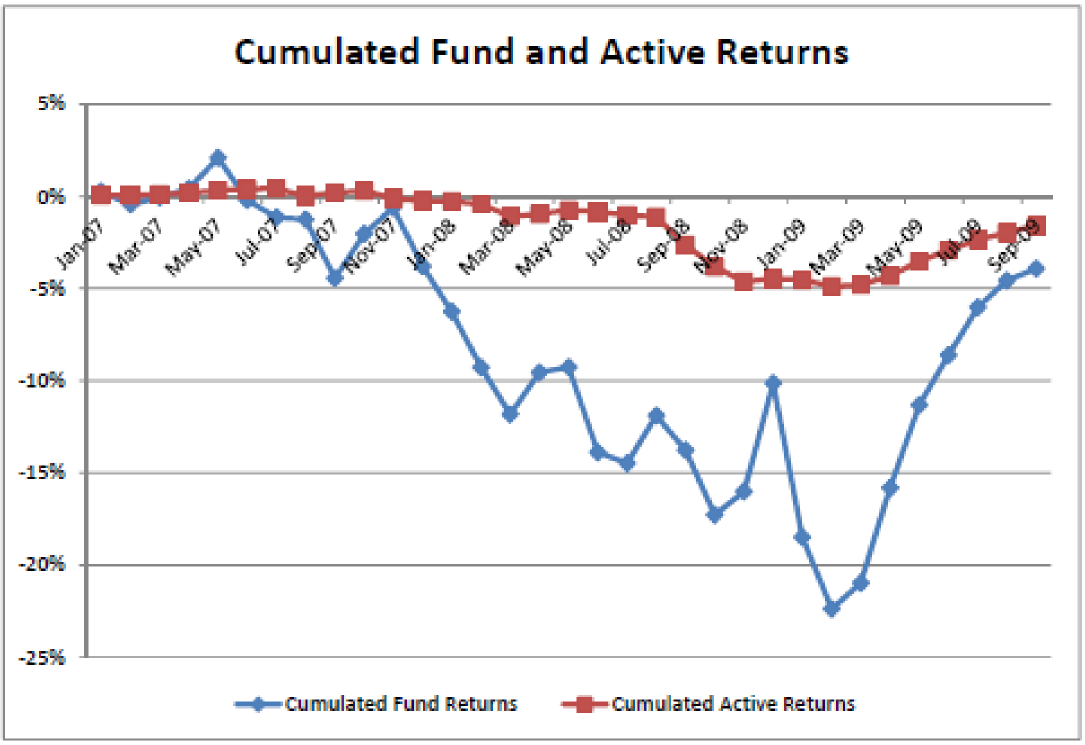
The CAPM was revolutionary since it was the first theory to demonstrate that the risk of an asset was not independent from other classes of assets and from the market. But the CAPM also has limitations. In fact, the principle that asset risk premia depend only on the asset's beta and that there is only one factor that is involved has been proved to be imprecise in many empirical studies (Ang 2014). Among the first who were doubtful towards the CAPM are Black, Jensen and Scholes (1972). Moreover, in the CAPM, negative asset returns coincide with negative returns of the market portfolio – this is very restrictive though, as there are many more factors than just the market itself. Despite CAPM's appealing simplicity, its empirical limitations are eager to invalidate its use in many applications (Fama, French 2004).

The first multifactor model – the arbitrage pricing theory (APT) – was introduced by Ross (1976). While the CAPM captures the notion of bad times exclusively by moments of low returns in the market portfolio, APT implies that the expected return of an asset can be modelled as a function of different macroeconomic factors (Bender et al 2013a). In Ross's model, arbitrageurs push the expected return of assets toward a value which is coherent with an equilibrium trade-off between risk and return. The factors in the APT model are systematic ones, as they cannot be diversified away, and investors must be rewarded for bearing the relative risks.

The concept of factor investing quickly gained popularity in the professional investors' environment (Robeco research paper 2017). The real breakthrough for factor investing came after a research conducted by Ang et al (2009) which focused and reported the performances of the Norwegian Government Pension Fund. The fund was formed in 1990 with the purpose to invest national revenues derived from oil and gas reserves in the North Sea. The amount managed by the fund at the end of 2012 amounted at $650 billion. As of today, the fund's market value stands at around $1,08 trillion (Norges Bank Investment Management) – around 250% of Norway current GDP.

Figure 1 plots the cumulated fund returns and the cumulated active returns. The fund's cumulated returns were roughly stable up until the second half of 2007 but began to plummet as the subprime mortgage crisis erupted in the financial markets. As shown in Figure 1, they registered -17% in October 2008. Thanks to the initial regulatory and bail-out policies by the U.S. government, the Norwegian fund was able to obtain positive returns up until January 2009, after which followed the lowest cumulated return of -22% (Ang 2014). But this was not the biggest concern for Norwegians: instead, the general public was upset by the poor active management returns of the fund. Active returns are calculated by subtracting the benchmark returns from the fund's returns.

Figure 1. *Cumulated Fund and Active Returns by Norwegian Government Pension Fund. January 2007 – September 2009.*



Source: Ang 2014 – Chapter 14: Factor Investing, Figure 14.1, page 443

Ang et al (2009) study revealed that most of the fund's active returns could be explained by non-intentional exposure to systematic factors, coming to the conclusion that the best way to collect these premia in the long run was to adopt a factor investing approach, but in a more deliberate way, especially for dynamic factors. Dynamic factors require a constant rebalancing of long-short positions, to adjust portfolio weights, i.e. value-growth or momentum strategies. Static factors, on the contrary, are factors whose risk premia are extracted by simply entering a long-only position, i.e. equities and bonds. As said, the exposure to such factors may be more appropriate for a long-term investor, since most factors earn risk premia over the long run. Ang et al (2009) therefore suggested that the factor exposure should be treated as key component of the portfolio and benchmark construction.

There are two types of factors that drive risk premia. There are fundamental-based factors, which include economic growth, inflation, volatility and liquidity. The second type is investment-style factors such as the value-growth strategy and momentum investing. The two types of factors are connected, and fundamental-based factors are often embedded in the performance of investment factors.

In order to be valid, a factor should entail determinate characteristics. A factor should be persistent through time, pervasive across markets, robust to alternative specifications, investable and sensible (Felix 2019). For a factor to be persistent, it should be consistent through time and not be limited to a specific time period; to be pervasive, a factor must hold true across various countries, regions and/or sectors; robust to alternative specifications means that the factor should not be affected if the features that defined it are slightly changed; the investable characteristic is fundamental: it means that if a factor cannot be cost-effectively captured in a portfolio, then it is not helpful for investors at all; lastly, sensibility is linked to the persistence of a factor. It means that if there is not a sensible explanation for a factor, then it may not be expected to persist.

A study contributed by Litterman and Scheinkman (1991) investigates factor investing in the US government bonds market, as well as related securities. In the paper, the two authors use an empirical approach in order to explain the variation in returns among US Treasury securities and determine what common factors had historically caused the price movements. The results show that there are three main factors that influence the variation in bonds returns; the three factors though, are characteristics of the zero-yield curve, scaled by one standard deviation: level, steepness and curvature. These factors are able to explain most of the returns of the Treasury securities.

Table 1. *Selected explanation for observed factor premiums*

	Risk Explanation – Premiums are coherent with rational expectations	Behavioural explanation – Premiums are result of suboptimal investor behaviour
Market	Economic uncertainty about long-term risks	Loss aversion and concern over short-term volatility
Size	Cyclical risk of smaller firms being more exposed to negative market returns and default risk	Asymmetrical loss function: Small-cap stocks are more volatile, and they can potentially offer higher returns
Low risk	Leverage, institutional and regulatory limitations	Asymmetrical loss function: Preference towards high-volatility stocks with small probability of large pay-outs
Value	Cyclical risk of positive correlation between market and security's returns	Recency bias leads investors into getting rid of distressed firms and overpaying for recent growth
Momentum	Beta and cost of capital of past winners increases as well as their cash flow risk/risk exposure	Underreaction to new information incorporated in asset prices
Liquidity	Risk largely driven by microcaps securities	Perception that less liquid stocks are riskier than more liquid securities

Source: Pappas and Dickson 2015, Vanguard

The existence of the factor premiums is explained by two different, non-exclusive, tracks: Pappas and Dickson (2015) name them Risk Explanations and Behavioural Explanations. The former expression consists in considering the reasons why a rational investor would want to apply factor-based strategy to its portfolio construction. The latter, instead, looks at the decision-making process of an investor from a behavioural standpoint; it considers that investors are, most of the times, not fully rational and are nudged by biases towards solutions that are not coherent with the efficient market theory. Table 1 proposes both of these explanations for market, size, low risk, value, momentum and liquidity factors.

The risk explanations are mainly driven by the rational expectations of an investor, who is able to appropriately measure returns, any kind of risk, adapt the strategy to his/her investment horizon and take into account a possible cyclicality of a factor. Pappas and Dickson (2015) did not discover any risk explanation for the momentum factor. On the other hand, a study conducted by Moskowitz (2010) contributes by gathering literature in support to a risk-based explanation: an example is Johnson (2002), who shows that expected future performances are a function of a company's growth rate. So, whenever a company has a big positive shock to returns, it communicates to investors that the long-term cash flows have improved. Thus, the long-term growth prospects of the company have improved and with this, also its profitability.

The behavioural explanations are mainly driven by the idea that investors act influenced by biases. Voorhees (2006) states that mistakes in future expectations are attributable to the phenomenon of consistent underestimation bias due to asymmetrical loss or loss aversion. Other reasons are that new information is not efficiently absorbed by the market participants, but also recency bias – phenomenon of an investor most easily remembering events that happened recently, compared to remembering events that happened further in the past.

Our study focuses on U.S. Corporate bonds during recent years (2014-2019), since literature about fixed income factor investing is still quite limited, if compared to the more mainstream and broad equity factor investing literature. The five factors that are taken into consideration for the sake of our study are size, value, momentum, low-risk and liquidity. As definition of liquidity factor, we intend that by getting exposed to more illiquid securities, we may be enabled to obtain better risk-adjusted returns. In the beginning, single-factor portfolios and relative performance are measured. Following, a multi-factor portfolio is constructed and the relative performance analysed. The reason for this, is that investing in generic single-factor portfolios leads to subpar investment results. Thus, a portfolio in which multiple-factor exposure can be obtained is going to bring higher risk-adjusted returns, coherent with a diversification principle (Blitz and Vidojevic 2019). This process is repeated for long-short and long-only portfolio, similarly.

2.1 Size

The size effect was first discovered by Banz (1981) and refers to the fact that small stocks tended to outperform large stocks, on average. As outperformance we intend higher risk-adjusted returns. Banz adopted an augmented version of the CAPM which allows the expected return of an asset to be function of general market risk Beta and an additional new size factor – the market value of the asset minus the average market value, divided by the average market value. If no relationship is found between the size factor and the expected return, the Banz model reduces to the original CAPM. The researcher concluded that, despite the absence of a theoretical foundation, such effect exists and is predominant on the smallest firms in the sample.

The Fama-French (1993) model explains asset returns with three factors. The equation that describes it is displayed below:

$$E(r_i) = r_f + \beta_{i,MKT}E\left(r_m - r_f\right) + \beta_{i,SMB}E(SMB) + \beta_{i,HML}E(HML).$$

The model is inspired by the CAPM, from which the authors employ the market factor, and introduces two additional factors to capture size effect and value-growth effect. The size effect is meant to capture the outperformance of small firms relative to large firms; such effect is captured by the differential returns of small stocks minus big stocks (SMB), where small and big refer to the market capitalization of the stocks. The third factor is defined as the difference between the returns of a high book-to-market stock and a low book-to-market stock (HML).

2.2 Low risk

Literature in support of low risk investing strategies is highlighted by a plethora of studies. It came with a degree of surprise, that well-constructed low-risk portfolio could contradict the fact that risker assets deliver, on average, higher returns as compensation for bearing such risk. Starting with Haugen and Heins (1972) and in more recent years with Baker and Haugen (2012), a number of articles supplied global evidence supporting the low-risk anomaly – low risk assets steadily providing greater risk-adjusted returns than high risk assets. Such findings are robust to numerous markets and different time periods selection. Multiple kinds of explanations have been proposed, most of which are behavioural based (Grassi et al 2012). For example, Barberis and Huang (2008) debate that investors tend to not fully comprehend the risks of assets that offer high payoffs. Highly risky assets will therefore have their prices bid up, which plummets their returns. With regards to less demanded, low-risky and cheaper assets, the process goes the other way around. Rational-based explanations to this anomaly involve shorting constraints and leverage constraints. We intend leverage as the ratio of the asset value of a portfolio in relation to the cash needed to purchase it. Leverage is achieved, for example, by getting exposure to derivative contracts. The primary purpose of leverage is to amplify possible returns. At the same time, though, leverage will also multiply the potential loss of the investment, in adverse scenarios. Leverage constraints are adopted, or imposed, especially to contain this downside risk.

If we looked at institutional investors, we would find that they are constrained in the amount of leverage they can take, and this would explain the low yields on the high-risk assets (Frazzini and Pedersen 2014).

Also, a paper by Boguth and Simutin (2018) concludes by showing that the tightness of leverage constraints has major implications for asset prices. Hsu and Li (2013) illustrate the benefit of incorporating low-risk equity strategies in an asset allocation exercise: their inclusion can significantly enhance the portfolio's overall risk/return profile, expressed by Sharpe ratios and Information ratios.

2.3 Value

Fama, French (1996) discovered that value stocks outperform growth stocks vast majority of main markets between 1975-1995. In a nutshell, a value strategy consists of buying stocks that have a low price compared to their fundamental value – book-to-market, for example – and selling stocks that are overpriced compared to their fundamental value. Beforehand, Basu (1977) questioned the validity of the efficient market hypothesis, according to which all security prices should reflect available information in a quick and unbiased process of embedding. Basu's objective was to determine whether the belief that low P/E ratio securities tend to outperform high P/E ratio securities. Basu concludes saying that the efficient market hypothesis is not able to completely describe the diverse risk-adjusted returns of low and high P/E ratios.

L'Hoir and Boulhabel (2010) were among the first to theoretically incorporate factor strategies to the credit market, especially to corporate bond portfolio construction. Their strategy of "signal combination" of three different signals – valuation, equity return and earnings momentum – delivers positive and consistent risk-adjusted returns. Additionally, the performance correlation of the three signals is low and the effect of diversification is remarkable. Hence, it is feasible to combine them efficiently in order to obtain greater portfolio performance.

The ultimate lowest point in the value of a firm is bankruptcy. An interesting research conducted by Correa et al (2012) offers insight on the physical default probability, it being the primary determinant of corporate credit spreads. Focusing on the U.S. credit market, they are able to link corporate default models to actual credit spreads. To their opinion, the changes in credit spread are a great predictor to changes in a firm's probability of default; therefore, its value.

Another contribution by Fama and French (1996) presents that value stocks tend to have higher returns than growth stocks, in almost every market around the world (12 out of 13 major markets) between 1975 and 1995. The results are robust to different definition of value proxy, be it book-to-market, price/earnings, cash flow/price and dividend/price. An important result from this study is that it was established that the value premium was real, and not just an anomaly which is present in the U.S. market (Fama and French, 1996).

2.4 Momentum

Another strongly important contribution was brought up by Jegadeesh and Titman (1993), that with their study were able to prove that strategies based around buying securities that have had high performances in the past, while selling securities that have performed poorly in the past, generate significant positive returns over short/mid-term holding periods. These returns are not dependent on exposures to systematic risk or frictions in the market; the roots are to be sought in the behavioural finance as investors' biases, instead. The strategy that was examined in most detail consist in selecting stocks based on their past 6-month return, with a holding period of 6 months. This anomalous strategy has been defined as momentum factor, or momentum investing. It is revealed that returns deriving from this kind of strategy are only persistent, on average, during the first 12 months after the formation date. Longer holding periods will face a dissipation of about 50% of the returns deriving from the momentum effect.

Pospisil and Zhang (2010) and Jostova et al (2013) documented the existence of momentum profits in the corporate bond market. Considering different holding periods and discriminating between investment grade and high-yield bonds, it is found that the momentum strategy returns derive primarily from the long side – buying winners, rather than selling losers. This is quite different from the case of equity momentum, according to which the momentum profitability comes from the short side of the transaction. Jostova et al (2013) find that momentum strategy is only profitable in high-yield bonds, while it is not existent among investment grade bonds.

2.5 Liquidity

Liquidity is defined as the facility and quickness of executing a transaction without being exposed to excessive costs or not settling for a price much lower than the fair market price.

A paper by Houweling et al (2005) compares possible proxies of corporate bond liquidity; the authors consider nine different proxies (issued amount, listed, euro, on-the-run, age, missing prices, yield volatility, number of contributors and yield dispersion) to measure corporate bond liquidity. From their results, particularly from Table 1, we can learn that the age proxy is the one that carries better significant results than the others. Sarig and Warga (1989) observed that as a bond gets older, a higher share of its issued amount is hold in investors' buy-and-hold positions. Hence, the older a bond becomes, the less trading takes place and the less liquid it gets. Moreover, once a bond is "classified" as illiquid, it remains illiquid until it reaches maturity. McGinty (2001) and Schultz (2001) also reported that new issues trade more actively than old issues. For these reasons we are going to be using bond age, as well as issued amount, as proxy for the liquidity factor.

Another important contribution belongs to De Jong and Driessen (2007). The paper explores the role of liquidity risk and the liquidity premium in corporate bonds. It is found that the liquidity premium is a priced factor for the returns on corporate bonds. In terms of expected returns, the liquidity premium estimated to US long-maturity investment grade bonds is around 0.6% per annum. For high yield US corporate bonds with exposures to the liquidity factor, the liquidity premium is worth about 1.5% per annum.

Lastly, a salient research conducted by Blitz et al (2018) explains that broad evidence can be found in support of four factor premiums in stock markets: low risk, value, momentum and quality. Liquidity is another factor that is considered to be important in order to better explain certain stocks' returns. The authors investigate whether a liquidity premium truly exists; they are able to conclude that, even though liquidity is of utmost importance in portfolio construction and rebalancing, there is currently no evidence in support of a strategy aimed at implementing specifically illiquid stocks, as they are not earning significant liquidity premiums.

2.6 Exchange Traded Funds

For the purpose of our study, we will extract our data from Exchange-Traded Funds (ETF) constituents. An ETF is a portfolio of securities. It can contain many types of investments, including stocks, commodities and bonds. Because there are multiple assets within an ETF, they are a simple and popular choice for diversification seekers. Therefore, similarly to mutual funds, ETFs carry the benefits of pooled investing: these benefits include diversification, economies of scale and low-costs, professional management and regulation. They differ from mutual funds on the basis that ETFs can be traded throughout the day on an exchange (hence the nomenclature) at a market-determined price. Mutual funds' shares, instead, are sold and bought at the end of each trading day at the fund's net asset value. Moreover, ETFs aim to track a benchmark and are commonly considered an efficient indexing tool.

The first ETF in the U.S. was introduced in 1993. During those years, ETFs were mainly employed by institutional investors wanting to execute sophisticated trading strategies. It was only after the market became more mature, that individual investors and financial advisors embraced ETFs. Surprisingly, the first Bond ETF was introduced only 10 years after, in 2003. Nowadays, Bond ETFs are tremendously popular products that seek to track various bonds. Investor's demand fed the ETF growth in popularity. At the end of 2010, assets under management in U.S. ETFs reached the grand total of $1.0 trillion. The market of this mean of investment continued to widen and this process helped scoring every year new records for number of new ETFs issued, trading volume and assets under management (Vanguard 2015). By the end of September 2017, assets under management had reached $4.4t worldwide (Kealy et al 2017). Today this asset class is worth $2.5t in assets under management in the sole United States, accounting for about 35% of the volume in U.S. markets (Ben-David et al 2018). Despite the steep rise and increasing importance, there lacks a limpid understanding of why composite securities like ETFs have become so popular, or the ways they can influence trading and pricing (Cong and Xu 2016).

In the past few years, an abundance of papers studying the fast-growing ETF world had blossomed. Ben-David et al (2018) attribute a large part of the success of ETFs to the fact that these means of investment offer a unique vehicle of diversification at low cost and high liquidity. Effects of ETFs on the efficiency of the underlying basket of assets have been studied, and the evidence is mixed: on the one hand, authors have found that ETFs permit information to be absorbed with more efficiency into asset prices. On the other hand, evidence shows that asset prices have embedded more noise (Ben-David et al 2016). Additionally, since ETFs rely on arbitrage to match their prices with prices of the underlying bucket of assets, trading activity at the ETF level translates to trading of the underlying securities, with a chance to increase their volatility. Leippold et al (2015) reveal correlations of underlying assets' return in the presence of ETFs. Glosten et al (2015) also document that ETF trading increases co-movement and return correlation, but ultimately conclude that ETFs can increase informational efficiency for smaller stocks. Madhavan and Sobczyk (2014) find evidence indicating that ETFs are more liquid than the underlying basket of assets, while Bradley and Litan (2011) and Hamm (2014) express concerns towards the possibility that ETFs and passive mutual funds may drain the liquidity of already struggling securities. Chang and Xu (2016) propose a model illustrating that financial innovations such as ETFs and other composite securities trading products encourage factor investing, while transparency is the major characteristic distinguishing ETFs from the same composite securities.

In the research paper "Reshaping around the investor – Global ETF Research" issued by EY in 2017, it is stated that Fixed Income ETFs will remain the industry's major area of focus over upcoming years and will drive the ETF growth in the medium term. As today, Fixed Income ETFs remain small relative to the massive fixed income and credit markets. Despite this, the survey from EY reveals strong growth potentials, especially in the U.S. Their estimates show global fixed income ETF assets to reach $1.6t by 2020, compared with $0.6t at the end of 2016.

2.7 Multi-Factor Portfolios

The idea of multi-factor investing is not necessarily something innovative. On average markets do a good job pricing risk, but not all risks are necessarily rewarded equally. According to the original ideas of indexing, dated back to the 1960s and 1970s, there was this one risk, the market risk, following the CAPM theory. What was learnt after many more years of data and enhanced technology, is that there are many factors that describe risk and returns of markets; not just the market risk. The single factor model – traditional indexing via market capitalization – which treats all risks equally, is not efficiently and correctly applicable to reality. A multi-factor approach to investing assumes that different risks, reward investors differently. Additionally, there must be one or more strategies that combine these risks to such a degree, where investors might have some ability to earn returns better than the traditional CAPM market model, while still embracing the principles of indexing: reasonable fees, large amount of diversification, buy and hold, low turnover.

Single factor portfolios, on average and over long periods of time, realize better risk-adjusted returns than the market's; but there are cases in which this is not true. It is very possible unreal to witness factor portfolios underperform a market index. By diversifying across multiple factors, it is possible to reduce the risks that, for example, low capitalization companies would not outperform large capitalization companies; or more, the case when past winners do not outperform past losers.

Related to the portfolio construction, be it single or multi-factor, there has been researching about what is the best way to implement an investment strategy. Blitz et al (2018) empirically compare long-short and long-only approaches and find that, even though the former is theoretically superior, the latter approach seems to be the most ideal alternative in most scenarios. In their conclusions, the authors consider benchmark restrictions, implementation costs and factor decay. These last two features have the power to offset the benefits from a long-short approach; main reasons of this is that long-short strategies require double the turnover and therefore higher costs, as well as a stronger dependence on the magnitude of factor premiums.

Factor index-based investing can be intended as active decisions implemented through passive replication (Bender et al 2013b). Traditionally, institutional investors built their asset allocation around two main sources of return: Beta and Alpha. The first is the return that the investor earns from a wide exposure to the market, achievable by investing in a portfolio that passively tracks the market. The latter coincides with the additional return that active management can provide – it is the excess return over the market capitalization weighted index. As mentioned by in the research by Bender et al (2013b), multi-factor investing offers an innovative solution to obtain exposure to systematic factors that previously could only be harvested via active management.

A research about factor-based investing conducted by Pappas and Dickson (2015) analyses the effectiveness of factor-based investing and how that depends on the way that the factor strategies are implemented. The study shows a comparison between long-short and long-only implementations, from 2000 until 2014. The main point of the argument is that factor investing has demonstrated its potential to improve diversification in a portfolio, so the target for an investor should be to reduce correlation between each factor portfolio and the market. For the Momentum, Size and Value factors, the findings report that over the period, long-short strategy revealed significantly lower levels of correlation, as opposed to the long-only strategy, which had levels of correlation close to 1 across all three factors. Under these circumstances, the preferable strategy is the long-short, as t is able to remove a considerable amount of the market-factor exposure through offsetting short positions. So, the potential diversification advantages greatly depend on the factor is implemented in the portfolio.

This paper provides contribution to the existing body of literature examining factor-based investing, with the main objective to broaden the research about fixed-income securities. This paper replicates part of the methodology adopted by Houweling and van Zundert (2017) and applies it to US corporate bond ETFs constituents, with the main objective to bring better understanding to the current question whether risk factors are pervasive of the market or they are mainly cyclical. For this purpose, only very recent years are studied. Using more recent data allows for the chance to gain information about the market in its most advanced and matured moments. First, to the knowledge of the author, this is the first study that applies factor investing strategies to fixed income-based ETFs constituents. This is particularly important given the fact that ETFs are a relatively new, extremely popular, investment vehicle.

3. Data

Houweling and Van Zundert (2017) had access to and utilized Bloomberg Barclays data about U.S. Corporate Investment Grade and High Yield Indexes, such as market value, time to maturity, credit spread and bond return. Unfortunately, Erasmus University of Rotterdam does not have access to the Barclays datasets and Bloomberg does not provide constituents of the Barclays U.S. Corporate Investment Grade Index and the U.S. Corporate High Yield Index. Therefore, we decided to focus our study towards Exchange-Traded Funds (ETFs) tracking the same underlying classes of assets as the two Indexes studies by Houweling and Van Zundert, in order to assess whether their discoveries are coherent to more recent years.

We decided to select the iShares iBoxx $ Investment Grade Corporate Bond ETF and the iShares iBoxx $ High Yield Corporate Bond ETF. The iShares iBoxx $ Investment Grade Corporate ETF aims at tracking the investment performances of an index composed of US dollar-denominated, investment grade bonds, and takes as benchmark the Markit iBoxx USD Liquid Investment Index. The Fund invests in a representative group of fixed income instruments included in the index that collectively has an investment profile similar to the index. The iShares iBoxx $ High Yield Corporate ETF aims at tracking the investment performances of an index composed of US dollar-denominated, high yield corporate bonds, and takes as benchmark the Markit iBoxx USD High Yield Investment Index. The Fund invests in a representative group of fixed income instruments included in the index that collectively has an investment profile similar to the index.

These two ETFs were chosen as they are the most widely used ETFs, based on 20 Day Average Volume (Bloomberg), have exposure to a broad range of U.S. corporate bonds and, due to their nature, are only rebalanced and modified at the end of the month. Figure 2 and 3 show, respectively, excess monthly returns of the two ETFs. The excess returns are calculated by initially computing the monthly return of the two ETFs; secondly, the risk-free rate is subtracted. The ETF return data is provided by Thomson Reuters Datastream, while the risk-free rate is provided by the Kenneth French data library.

We downloaded end-of-the-month constituents' ISIN codes from Bloomberg for both the ETFs and for U.S. Treasuries, from December 2014 until July 2019, for a grand total of 56 months. The reason of this time span selection is that, before 2015, the ETFs were growing but the number of constituents in each of them was too small for the scope of our research. It was a trade-off between longer time series with less observations per month, or shorter time series with numerous observations per month. We opted for the second.

Followingly, we made use of the bonds' ISIN codes just collected in order to obtain useful variables like Company Name, Amount Issued, Amount Outstanding, Issue Date, Redemption Date, Market Value, Composite Mid Price, Issue Price, Rating, Yield, Spread from Benchmark Curve for month t and t-3, Total Return Index for month t, t-1 and t-6, Modified Duration from Thomson Reuters Datastream.

Datastream calculates the Total Return (TR) Index as a cumulative theoretical growth in value of a bond holding over a specified period. The formula used is the following:

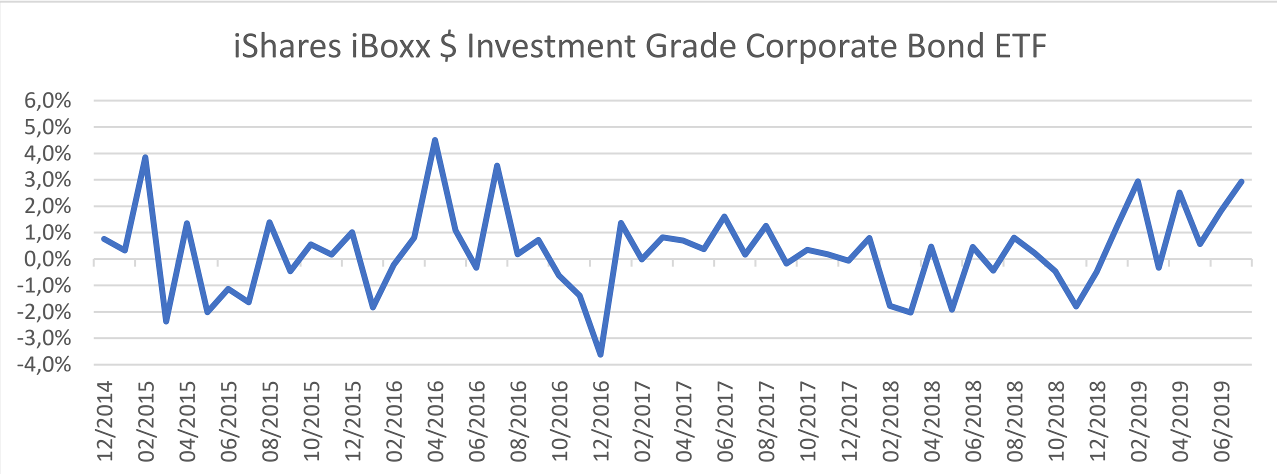
$$TR_t = TR_{t-1} * \frac{P_t}{P_{t-1}}$$

So, the monthly return of a specific bond can be calculated simply by having the ratio of TR at time t and TR at time t-1, minus one:

$$Monthly\ Return_t = ({}^{TR_t}/_{TR_{t-1}}) - 1$$

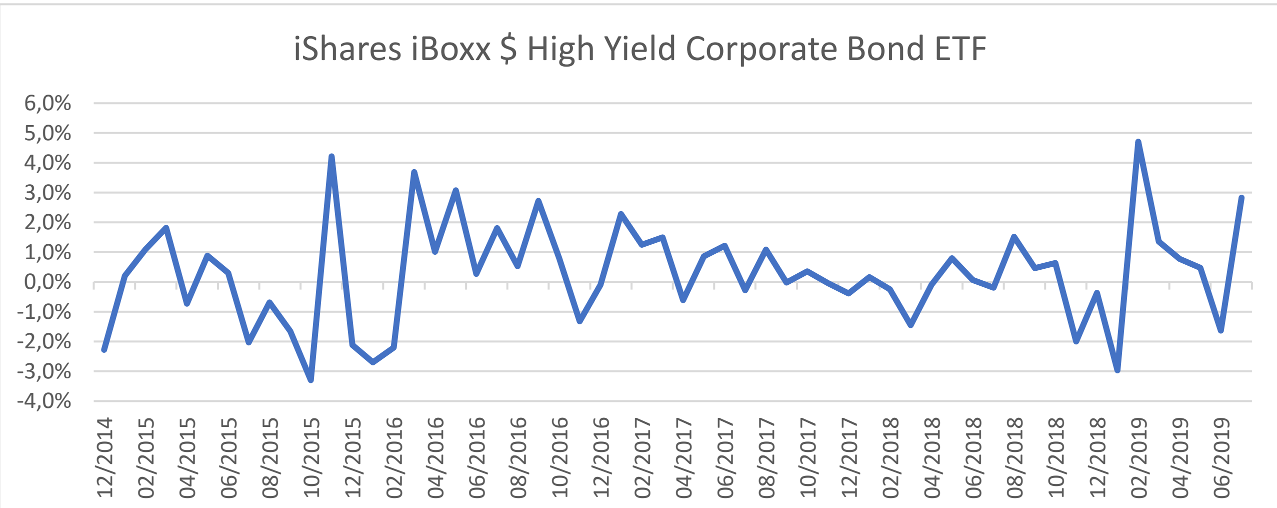
Spread from Benchmark Curve is measured as the option-adjusted yield of the bond in excess of the yield of the duration-matched risk-free government bond of the same currency, in basis points.

Figure 2. *Monthly excess return of Investment grade ETF, December 2014 – July 2019*



Source: Thomson Reuters Datastream. Excess returns are calculated by subtracting the risk-free rate from the ETFs monthly returns.

Figure 3. *Monthly excess return of Investment grade ETF, December 2014 – July 2019*



Source: Thomson Reuters Datastream. Excess returns are calculated by subtracting the risk-free rate from the ETFs monthly returns.

The two ETFs follow a quite similar trend. More data about the ETFs can be found in the Appendix section. As one would expect, the Investment Grade ETF appears to show a lower dispersion around the 0% return line, if compared to the High Yield ETF.

Table 2 shows summary statistics for the two separate datasets we collected. These are the constituents of the iShares iBoxx $ Investment Grade Corporate Bond ETF and the iShares iBoxx $ High Yield Corporate Bond ETF. The annualized excess return is the monthly return of the debt security minus the return of Treasuries with same duration, multiplied by square root of 12. Time to maturity indicates the number of years until the bond reaches its maturity. Credit rating represents the credit rating by S&P and Fitch after the credit scores were converted from letters (AAA, AA+, AA, etc.) to numbers (1, 2, 3, etc.) where the lower numbers coincide with better credit ratings. Credit spread is the option adjusted yield of the debt security in excess of the duration-matched government bond. Market value of company indicates the sum of the market values of all bonds of a certain company which are present in the ETFs. The number of observations is the average amount of bonds per month in the ETFs. For every variable, the mean and five significative percentiles are reported (5%, 25%, 50%, 75% and 95%). Each statistic is first calculated cross- sectionally each month and only then averaged over time.

Table 2. *Summary descriptive statistics of all constituents of the two US corporate bond investment grade and high yield ETFs, December 2014 – July 2019*

Table 2. Summary Statistics of Dataset, December 2014 - July 2019

	Investment Grade						High Yield					
	Mean	5%	25%	50%	75%	95%	Mean	5%	25%	50%	75%	95%
Annualized excess return (%)	1,65%	-32,70%	-10,15%	1,34%	14,11%	54,72%	4,43%	-41,51%	-8,89%	3,29%	17,51%	83,42%
Time to maturity (years)	11,96	3,20	4,72	7,67	19,73	28,84	5,49	1,80	3,90	5,54	7,09	9,12
Credit rating	6,92	3,52	6,85	7,39	9,80	10,46	13,16	10,12	12,48	13,77	15,31	17,91
Credit spread (bps)	134,20	50,30	85,00	121,30	168,00	257,90	449,68	161,40	195,20	335,70	469,25	960,20
Market value of company ($ billions)	4,04	0,73	1,11	2,35	4,98	12,85	1,93	0,38	0,77	1,25	2,23	5,50
Average bond-month observations	1547						907					

Source: own calculations with data from Bloomberg and Thomson Reuters Datastream

The data collecting phase through Thomson Reuters Datastream was very inefficient and time consuming because of limitations of the platform itself. Only a rather small amount of inputs could be provided – in our case, the inputs were the bonds' ISIN codes. Therefore, the process had to be repeated numerous times and for each time there was a waiting time before the output from the data collection was available. The silver lining about Datastream is that it covers a vast number of instruments and variables, a clear explanation about each variable is provided as well as how the values were computed. We would like to express our concerns about the size of our sample. The observation for each month, for both investment grade and high yield, are more than satisfactory for the sake of our study; although, the size of the times series could not be very wide. If that would turn out to be so, some of our results may lack of significance and no real conclusions can be drawn.

The final dataset is a relatively information-dense one. In total, our dataset contained over 160,000 bond-month observations, of which about 100,000 are for investment grade and about 60,000 for high yield. The main layers of data cleaning process were due to missing data: observation with missing returns, rating, maturity information, credit spreads, duration and market value were eliminated from the final sample whenever needed for each respective factor. Table 3 and Table 4 explain in detail how much data was discarded from either the investment grade or high yield datasets, giving a breakdown for each one of the "invoices". On average 1570 investment grade and 913 high yield bond-month observations.

Table 3. *Investment grade data cleaning information*

	Number of observations
Initial Sample	99375
Missing duration	1219
Missing rating	428
Missing redemption date	224
Missing excess returns	3386
Missing spread over benchmark T	1740
Missing spread over benchmark T-3	4375
Final Sample	88003
Missing momentum returns	1556
Final Sample for Momentum factor	86447

Table 4. *High yield data cleaning information*

	Number of observations
Initial Sample	60482
Missing duration	667
Missing rating	711
Missing redemption date	753
Missing excess returns	2663
Missing spread over benchmark T	2
Missing spread over benchmark T-3	4509
Final Sample	51177
Missing momentum returns	2872
Final Sample for Momentum factor	48305

Source: own calculations with data from Bloomberg and Thomson Reuters Datastream

Since we measure the performance of factor portfolios using annualized bonds' excess returns over duration-matched U.S. Treasuries, as benchmark for the single-factor and multi-factor portfolios we use the market value-weighted average excess return of all ETFs constituents, through which we can calculate outperformances, alphas of the factor portfolios and statistical significance of results.

We imported and incorporated all the dataset into Excel, specifically in one file for Investment Grade ETF constituents, and one for the High Yield ETF constituents. We disposed of the data to make it acceptable for Stata, the statistics software provided by Erasmus University. This is where we completed the data cleaning process, calculated the excess returns over duration-matched Treasuries, operated the identification of the five factors proxies as well as the creation of the long and short portfolios. Ultimately, we gathered the monthly excess returns for each portfolio and exported them onto Excel once again.

Here we calculated the measures of outperformance and applied the regression models: CAPM and the fixed income-adapted Fama-French 5 factor model. The market factor in the CAPM model has not been the equity factor but the bond market factor – calculated as the full-sampled investment grade and high yield monthly excess return, against duration matched treasuries. It is more intuitive to expect a bigger relation between our dataset of bonds and the U.S. corporate markets, than the equity market instead. We downloaded risk-free rate and US factor returns from the Kenneth-French Data Library.

The next step was to analyse both long-short and long-only portfolios and measure returns, as well as ratios that describe the success of portfolio management: Sharpe Ratio, Tracking Error, Information Ratio and Sortino Ratio. Each of these ratios is fundamental for the investor, as they are able to communicate how well the portfolio is performing with respect to the risk-free rate, the benchmark and what is the level of the dispersion of the returns.

Lastly, we operate a correlation analysis between the investment factors we calculated, and the factors by Houweling & van Zundert (2017), over the same period. They keep a dataset available on Robeco Insights, with the updated factor returns for size, low risk, value, momentum and the equally weighted multi-factor portfolio.

4. Methodology

We are going to study the effect of factor investing in five different factors: size, momentum, value, low risk and liquidity. For each factor in each month, we build equally weighted top and bottom portfolios, respectively containing the 10% corporate bonds with the highest and the lowest exposure to that specific factor. We formed our long-short strategy by including in the long portfolio the first decile by exposition to the factor while adopting a short position in the lowest decile portfolio.

Defining the factors:

4.1 Size

In order to define the *size* factor in the corporate bond market, we employ the total sum of the market value of each company that has at least one bond included in the ETFs. As market value it was used a company's total amount of public debt outstanding, calculated as the sum of the all bonds from that same company found inside the ETF. Followingly, all the bonds present in each month sample were ranked by the factor size. Since smaller companies tend to issue smaller bonds (Sarig and Warga 1989), we believe this is a valid proxy to isolate the size factor. To construct the size decile portfolios, we ranked all debt securities by their issuer's size for every month, with the top portfolio containing the bonds of the 10% smallest companies and the bottom portfolio, understandably, containing the bonds of the 10% biggest companies.

4.2 Low risk

In order to develop a proxy for low risk bonds we combined two different variables. In the first place, all bonds observations were ranked, from high to low, by their credit rating. Next, we took the top 20% and the bottom 20% and ranked the remaining bonds by their option-adjusted duration, from low to high. Since duration is a measure that approximates the price sensitivity of a bond to changes in interest rates; it basically measures the interest rate risk of a debt security. After this second ranking, we selected the top 50% of the bonds of the top 20% portfolio, as well as the bottom 50% of the bottom 20% portfolio. The bonds that are left in our new top portfolio, are bonds with high credit rating and low duration (hence bonds with lower credit and interest rate risks), while in our newly created bottom portfolio can be found bonds with worse credit rating and higher duration (these bonds have higher credit and interest rate risks). A long position in the lower risk bonds is taken, while a short position is taken on the higher risk bonds.

4.3 Value

The value factor was defined through a value-score. We followed the methodology adopted by Houweling and van Zundert (2017). The score was constructed through a cross-sectional regression of credit spread on credit rating, time to maturity and the three-month credit spread change. These are all bond characteristics that define in a certain way the fundamental value of the bond itself, so a linear combination of them would provide a proxy for the value factor:

$$S_i = \alpha + \sum_{t=1}^{22} \beta_t I_{it} + \gamma M_i + \delta \Delta S_i + \varepsilon_i \,,$$

where S_i is the credit spread of bond i, I_{ir} is the rating of the bond converted into numbers, M_i is the maturity and finally ΔS_i is the three-month change in the credit spread of the bond. The next step, coherently with the research by Correia et al. (2012), we measured the percentage difference between the market credit spread and the credit spread obtained by the regression, for each month-bond observation. The principle is to identify which bonds are fairly valued by the market and which bonds are not. If the difference between the market credit spread and the regression credit spread is zero, then it can be inferred that the market is fairly valuing the bond, considering all available information. Ultimately, we ranked all corporate debt securities on this difference, from high to low and, once more, constructed the top value portfolio with the highest 10% of bonds and the bottom portfolio with the lowest 10% of bonds.

4.5 Momentum

Coming up with a momentum proxy is intuitive and immediate. We begin to define the momentum factor by calculating the past 5 months excess return over duration matched treasuries, from T-1 back to T-6. Then, for each month, we ranked the bonds by the past 5-month excess return. We finally selected the top 10% bonds with the bonds with highest past excess returns in order to compose our long portfolio, while the short portfolio was composed by the lowest 10% past excess returns bonds.

4.6 Liquidity

To obtain a proxy that would isolate the liquidity factor we combined two different variables. The first exclusion involved the ranking with regards to the issued amount per single bond. We believe that the size of a bond issue is directly proportional to its liquidity. the top 20% and the bottom 20% bonds ranked on issued amount were selected, for every month. The second distinction is based on the age of a bond. We mentioned the research by Houweling et al (2005), where they identify bond age as the proxy for liquidity that leads towards the most significant results. In order to calculate the bond age, we first introduce the "current date", which simply is the date when each observation was taken (e.g. if an observation if measured on April 2015, the current date for each one of them is 30th April 2015). Next, bond age is given by the difference between current date and issue date. The smaller this difference, the younger a bond is. Finally, the remaining bond-month observation were ranked by the age measure, from youngest to oldest. For our most liquid portfolio, we select the top 50% of the 20% highest issued amount bonds. For our least liquid portfolio, we select the bottom 50% of the 20% lowest issued amount bonds. We enter a long position on our least liquid portfolio, while simultaneously entering a short position on our most liquid portfolio.

4.7 Regressions

Now that the proxies for each factor are defined, we invest by taking a long position in the portfolio with most exposure to the factor, whilst investing in a short position in the portfolio with least exposure to the factor. We annualize the monthly returns as we assume an investment horizon of 12 months. This period is realistic and can prevent extreme turnover. Momentum investing strategies, in particular, need a constant and methodical portfolio rebalancing, in order to include new winner and loser securities caused by market movements.

The CAPM model we applied to our regressions is the following:

$$E(R) = \alpha + \beta(CorporateMarket) + \varepsilon,$$

Where $CorporateMarket$ stands for the investment grade market excess return for the investment grade dataset, while it stands for the high yield market excess return for the high yield dataset.

The 5 single-factor portfolios are then analysed in order to capture what is the excess return against the market, represented by alpha. We employ two different models. The first one is the classic CAPM. We regress the portfolio returns against the respective corporate market return – investment grade corporate market excess monthly return (IGCM) and high yield corporate market excess monthly return (HYCM). Given the well-known limitations of the CAPM, we also calculate alphas through the application of a, fixed income adjusted, 5 factor Fama-French model:

$$E(R) = \alpha + \beta(RMRF) + \gamma(SML) + \delta(HML) + \theta(MOM) + \vartheta(CorporateMarket) + \varepsilon,$$

Where α is the excess return of the investment strategy, RMRF is the total equity return over the risk-free rate, SML and HML are the size and value factors of the 3 factor Fama-French model, MOM is the momentum factor and the *CorporateMarket* factor is IGCM for the investment grade us corporate bonds, and is HYCM for the high yield us corporate bonds; ε is the standard error. All of the alphas and outperformances that are discussed in the tables during the results section are annualized. Our method for the calculation of annualized returns is different from the one used in Houweling & van Zundert (2017), as that publication simply multiplies the return by a factor of 12. We calculate annualized alphas and annualized volatility as:

$$Annualized\ alpha = (1 + Monthly\ alpha)^{12} - 1,$$

$$Annualized\ volatility = Monthly\ volatility * \sqrt{12}.$$

Moving forward, we want to combine all the factor strategies into a multi-factor portfolio. We expect it to show better risk-adjusted returns that derive from diversification among the factors. Shorting corporate bonds can be difficult and costly – it is most commonly done by short selling ETFs that track the bond market or with derivative instruments, like put options on bonds and bond futures. This said, for the sake of complete information, we are constructing the multi-factor portfolios by entering both long-short and long-only strategies.

4.8 Outperformance Statistics

Outperformance statistics are Sharpe ratio, Tracking Error, Information Ratio and Sortino Ratio.

Sharpe Ratio was developed by W. Sharpe and is used to compare returns to the investment's risk. It was the first performance metric to isolate excess return per unit of total risk taken (Kidd 2011). The ratio is calculated as the average return earned in excess of the risk-free rate divided by the return's volatility. It is the most popular measure of risk-adjusted performance attribution (Rollinger and Hoffman 2013). The formula reads:

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p}$$

The Sharpe Ratio has some limitations though: it cannot tell the investor when a high standard deviation is due to large upside or downside deviations. It works best when the distribution of the excess returns is a symmetrical distribution.

The tracking error is the standard deviation of the difference between a portfolio's return and the benchmark it is trying to outperform. In our case the benchmarks are represented by the two ETFs. Conceptually, tracking error gives an understanding of the divergence between the performances of a portfolio and its benchmark. Interpretation: a small tracking error means that the portfolio is closely following the benchmark – this is best desirable in passive investing strategies. An example of passive investing strategy is the one pursued by an institutional investor like a pension fund: the liabilities of a pension fund embed many risks, such as interest rate risk. Through passive investing the pension fund invests in a hedging portfolio. The effectiveness of the hedging portfolio is measured, among other indicators, by the tracking error. The lower the tracking error (values around 1%-3%), the most effective the hedging solution is. If we consider active management investing, on the other hand, the scope of the strategy is to beat the benchmark and to deviate (positively) from it. In this case, it would be natural to witness higher levels of tracking error (around 5%-9%).

$$Tracking\ Error = Standard\ Deviation\ (R_p - R_b)$$

The information ratio is also a measurement of portfolio returns, but in excess to the benchmark returns. Often, the information ratio is used as an indicator of a portfolio manager's skill to generate excess returns relative to the benchmark; but it also incorporates the tracking error in the computing formula. Conceptually, the information ratio tells an investor how much excess return is generated from the amount of excess risk taken, under the form of tracking error, against the relative benchmark. This shows how consistent the performance is. The ratio assumes higher values whenever there is a better level of consistency of the outperformance (Kidd 2011). Low levels of tracking error contribute to higher values of Information Ratio.

$$Information\ Ratio = \frac{R_p - R_b}{Tracking\ Error}$$

We argue that both Sharpe Ratio and Information Ratio are useful measures of portfolio outperformance. Since the Information Ratio is based on a larger amount of data, it should be more accurate and desirable.

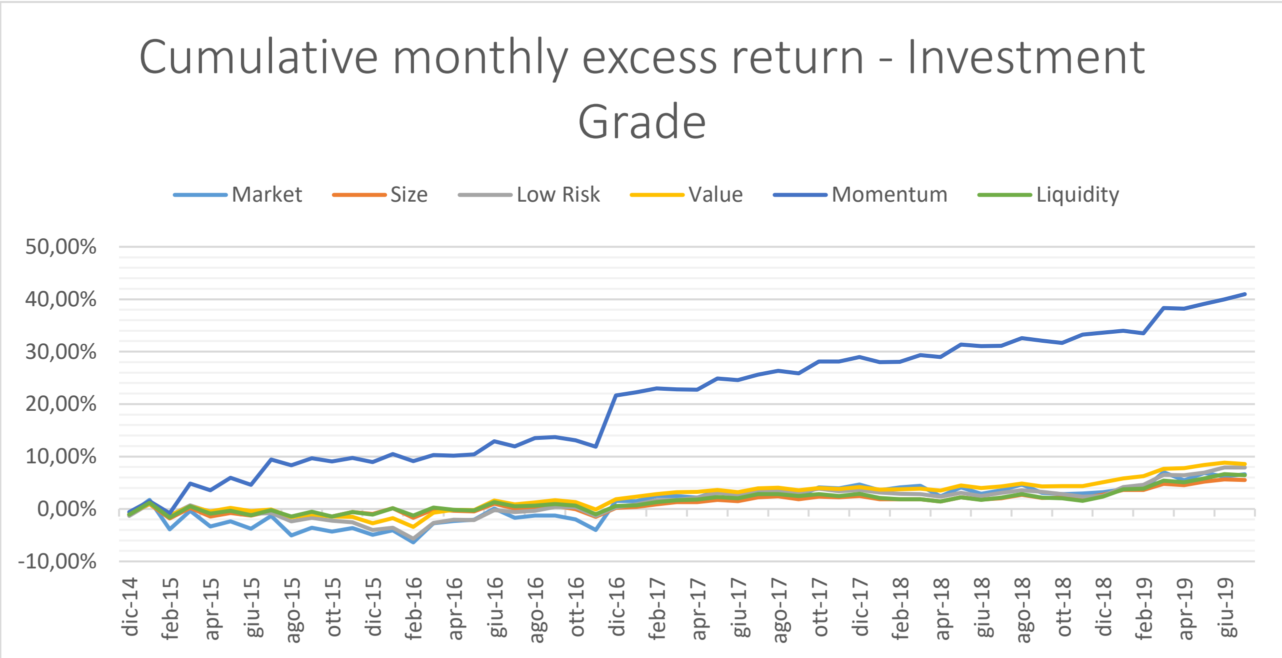
A further step can be taken by introducing the Sortino Ratio. It takes as starting point the Sharpe ratio, but differs from it because the Sortino Ratio only considers the standard deviation of the downside risk, rather than the entire distribution of portfolio returns. Because of this, the Sortino ratio is capable of giving a better indication of a portfolio's risk, if we accept the idea that positive-side volatility is a benefit.

$$Sortino\ Ratio = \frac{R_p - R_f}{\sigma_d},$$

where σ_d stands for the standard deviation of only the returns below the mean of the distribution and at the same time ignores the volatility of the returns above it. We ultimately decided to include the Sortino Ratio because evidence (Chaudhry and Johnson 2008) shows that it is superior at performance measurement than Sharpe Ratio, as it exhibits more power and less bias when the distribution of excess returns is skewed. As it can be assessed from Table 5, the distribution of excess returns of investment grade US corporate bonds are relatively symmetric – skeweness values are close to zero; some have a principle of fat tails but that is not a concern for our research. We can tell from looking at Table 6, the tails of the distributions have even fatter tails and they also show some very high values of skeweness – those distributions are not symmetrical. Kurtosis assumes extremely high values. In those cases, the Sortino Ratio is going to be a better indication of risk-adjusted outperformance compared to the Sharpe Ratio.

Figure 4 proposes the time series of the cumulative monthly excess return for investment grade bonds. We observe a general upward-going trend where all of the factors, excluding momentum, achieve quite similar results. All of the factors have been outperforming the market from December 2014, until December 2016. After that period, Size, Low Risk and Liquidity have roughly been performing just as well as the market, while Value has been able to achieve slightly higher results. Momentum, on the other hand, revealed itself to be the most profitable investment strategy from a return point of view (we would like to remind the reader that our study does not include transaction costs and turnover. Results are likely to be different if these characteristics were to be included, because a momentum strategy needs constant rebalancing of the investment portfolio, in order to be effective)

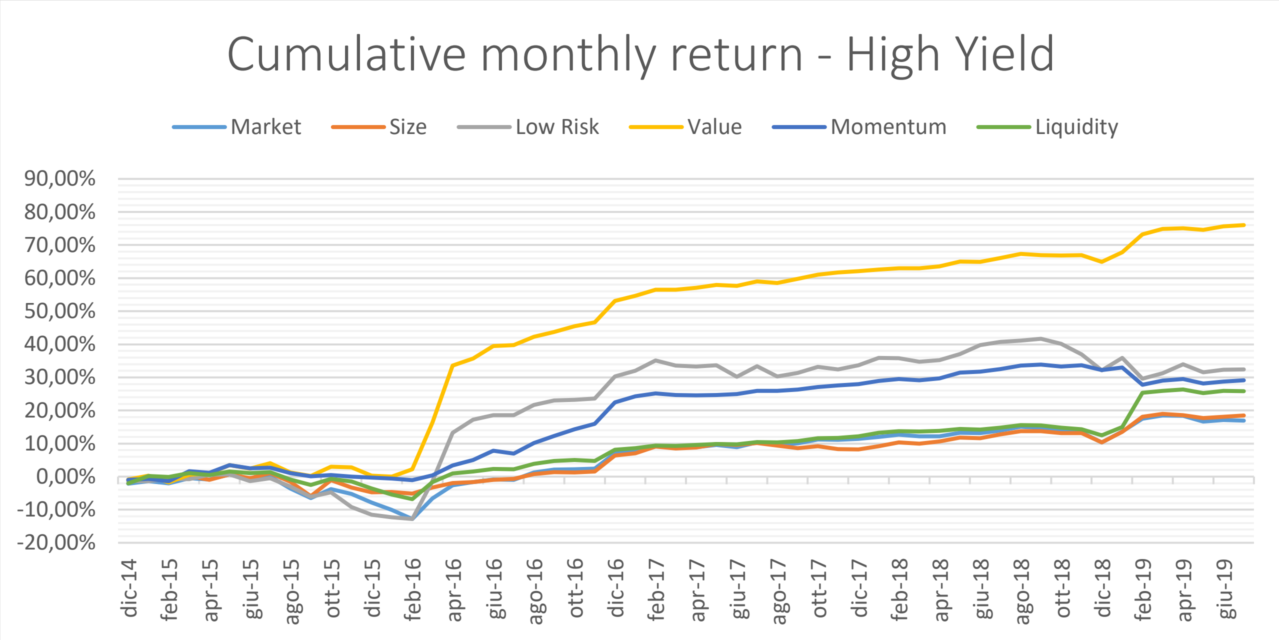
Figure 4. *Cumulative monthly excess return for each Investment Grade factor, December 2014 – July 2019*



Source: own calculations using data from Bloomberg and Thomson Reuters Datastream

Figure 5 proposes the time series of the cumulative monthly excess return for high yield bonds. This time, we observe a common trend from December 2014 until February 2016, during which all of the factors, excluding low risk, were able to outperform the market – from a cumulatively point of view, of course. After that date, size and liquidity factors followed the market closely. Momentum, low risk and value distinguished themselves as they were able to outperform the market by a great amount. During more recent months, momentum strategy obtained negative returns and was overtaken by the liquidity-driven factor portfolio.

Figure 5. *Cumulative monthly excess return for each High Yield factor, December 2014 – July 2019*



Source: own calculations using data from Bloomberg and Thomson Reuters Datastream

Table 5 and Table 6 show some of the most valuable descriptive statistics relative to the Investment Grade and High Yield excess return distribution, for each factor. Returns are calculated monthly (not annualized). Skewness and Kurtosis values tell how a distribution "looks like" as they measure the asymmetry of the distribution and how fat the tails are.

Table 5. *Descriptive statistics for Long-Only Investment Grade US corporate bonds excess returns over duration matched treasuries*

	Market	Size	Low Risk	Value	Momentum	Liquidity
Mean	0,12%	0,10%	0,14%	0,15%	0,73%	0,11%
Volatility	1,87%	0,92%	1,05%	0,92%	1,98%	0,98%
Max	5,57%	2,03%	3,02%	2,70%	9,77%	2,27%
Min	-5,60%	-2,77%	-2,24%	-2,25%	-2,31%	-2,84%
Skewness	-0,02	-0,42	0,17	0,13	2,24	-0,21
Kurtosis	1,68	1,07	0,57	0,93	7,51	0,59

Source: own calculations using data from Bloomberg and Thomson Reuters Datastream

Table 6. *Descriptive statistics for Long-Only High Yield US corporate bonds excess returns over duration matched treasuries*

	Market	Size	Low Risk	Value	Momentum	Liquidity
Mean	0,30%	0,33%	0,58%	1,36%	0,52%	0,46%
Volatility	1,88%	1,67%	3,38%	3,26%	1,60%	1,89%
Max	6,26%	4,81%	14,65%	17,24%	6,52%	10,34%
Min	-3,58%	-4,37%	-6,25%	-2,83%	-5,23%	-2,28%
Skewness	0,60	0,36	1,70	3,29	0,29	2,85
Kurtosis	1,46	1,94	6,10	13,52	5,04	13,39

Source: own calculations using data from Bloomberg and Thomson Reuters Datastream

From Table 5, we can already see that Size and Liquidity, on average do not outperform the relative benchmark (market). All of the investment grade factors have lower volatility than the benchmark. Size and Momentum are the most asymmetric and the last one is a fat-tailed distribution, revealed by the 7.51 kurtosis.

From Table 6, we can see that all of the factors outperform their reference benchmark (market) and have similar volatility levels – exception made for low risk and value. Skewness is stronger in high yield than in investment grade, as well as kurtosis. The most asymmetric distributions are low risk, value and liquidity, while the fatter tails belong to value and liquidity, with values as high as 13.52 and 13.39.

5. Results

We present in the following section the results found by our analysis for the long-short single-factor portfolios, distinguishing from investment grade and high yield US corporate bonds. Then, we show our results for the long-only strategy for each of the five explored factors and for the multi-factor portfolio. In both cases, alphas are calculated with CAPM and with a fixed income adapted 5 Factor Fama-French model.

5.1 Long-Short Portfolios

Table 7 shows performance statistics of the size, low risk, value, momentum and liquidity factors for both US investment grade and high yield corporate bond ETFs: iShares iBoxx $ Investment Grade Corporate Bond ETF and the iShares iBoxx $ High Yield Corporate Bond ETF. We built the factor portfolios taking, on a monthly basis, equally weighted long positions in the top 10% (short positions in the bottom 10%) of the bonds exposed to each factor. To isolate the size factor, we took the debt instruments with the smallest (largest) market value of debt in the ETF; to isolate the low risk factor, the highest rated, short duration (lowest rated, longer duration) bonds; for the value factor, the debt securities with highest (lowest) percentage difference between the observed market credit spread and the theoretical spread obtained through a regression that included rating, maturity and three-month spread change; for the momentum factor, the bonds with the bigger (smaller) past five-month excess return; for the liquidity factor, the debt instruments with small-sized (big-sized) issued bonds and with old (young) age. Panel A shows the CAPM excess return alpha and CAPM beta relative to the investment grade and high yield corporate bond market (IGBM and HYBM). Panel B shows a Fama-French augmented model (RMRF, SMB, HML, MOM, IGBM/HYBM). Alphas are annualized. All the returns are measured against duration matched US Treasuries. Statistical significance is determined by a one-tailed Student t-test with 55 degrees of freedom, with assumption of heteroskedasticity. *significance at the 10% level. ***significance at the 1% level. We use a one-tailed test because the null hypothesis H_0 we are interested in testing is whether the factors' alpha is greater than zero.

Table 7. *Regression statistics for CAPM, 5 factor Fama-French models and correlations of long-short portfolios. December 2014 – July 2019. All alphas are annualized*

Table 7. Regression Statistics and Correlations of Long-Short Factor Portfolios, December 2014 - July 2019

	Investment Grade					High Yield				
	Size	Low Risk	Value	Momentum	Liquidity	Size	Low Risk	Value	Momentum	Liquidity
Panel A. CAPM statistics										
Alpha	0,64%*	1,05%	0,70%	19,12%***	0,45%	11,02%***	1,78%	14,98%***	16,77%***	2,65%
t-Value	1,46	1,17	1,28	4,08	1,08	2,67	0,37	3,50	3,23	0,83
Beta	-0,01	0,07	0,00	-0,53	0,05	-0,92	0,65	0,27	-3,49	-0,17
R^2	0,03	0,05	0,04	0,12	0,12	0,34	0,15	0,04	0,42	0,03
Panel B. 5 Factor Fama-French statistics										
Alpha	0,80%**	0,45%	0,71%*	19,62%***	0,41%	10,38%***	3,30%	18,22%***	14,49%***	2,45%
t-Value	1,72	0,63	1,45	3,97	0,95	2,37	0,68	4,32	2,64	0,74
R^2	0,06	0,48	0,33	0,17	0,18	0,35	0,27	0,21	0,45	0,10
Panel C. CAPM alpha correlations										
Size		-50%	-63%	26%	40%		-46%	-18%	91%	15%
Low risk			57%	-39%	25%			50%	-49%	-67%
Value				-41%	-34%				-18%	-18%
Momentum					2%					12%
Liquidity										

Source: own calculations, replication of Table 2 of Houweling and van Zundert (2017)

By looking at Panel A, where alphas are calculated with CAPM, the only significant values for investment grade bonds are given by Size and Momentum strategies (0.64% significant at the 10% level and 19.12% significant at the 1% level, respectively). Next, we observe high yield CAPM alphas for the size factor, which measures 11.02%, the value factor, which measures 14.98% and momentum factor, which measures 16.77%, all statistically significant at the 1% level.

Calculating alphas via the 5 Factor Fama-French model brings a higher level of significance, for investment grade factors. Now, size alpha is equal to 0.80%, significant at the 5% level, value alpha is equal to 0.71% and significant at the 10% level and finally momentum alpha measures 19.52% with a 1% statistical significance. High yield size alpha measures 10.38%, value alpha measures 18.22% and momentum alpha equals to 14.49%, all significant at the 1% level. We witness a lack of significance for both low risk and liquidity factors, irrespective of the utilized model.

Panel C, as mentioned, shows CAPM alpha correlations. Most of the correlations tend to be around the 30-50% interval. The highest number is between high yield size and momentum (91%) while the lowest is represented by high yield low risk and liquidity (-67%). The rather small values observed, often also negative, suggest potential benefits from diversifications, which can be captured by a multi-factor portfolio combination. Momentum and value factors being negatively correlated with each other is coherent with the findings of Asness, Moskowitz & Pedersen (2013).

Next, long-short portfolio construction strategy was adopted. Table 8 reports performance statistics of the corporate bond market. It includes the market (return and volatility of the US corporate bond investment grade and high yield ETFs), single-factor portfolios constructed by long-short exposition to the factors of size, low risk, value, momentum, liquidity and a multi-factor portfolio constructed by taking an equally weighted position in all five of the single-factor portfolios, as well as the respective Sharpe Ratio. Panel A reports the return statistics and Panel B the outperformance statistics. These include Tracking Error, Information Ratio, Sortino Ratio and t-value of the outperformance. Significant levels imply that the outperformance is different from zero. Panel C reports the CAPM alpha and the 5 Factor Fama-French alpha. Statistical significance is determined by a one-tailed Student t-test with 55 degrees of freedom, with assumption of heteroskedasticity. We use a one-tailed test because the null hypothesis H_0 we are interested in testing is whether the Outperformance measure, the CAPM alpha and 5-factor Fama-French alpha are greater than zero. *significance at the 10% level. **significance at the 5% level. ***significance at the 1% level.

In panel A of Table 8, as already observed in Table 7, many of the investment grade factors – size, low risk, value, liquidity – perform worse than the reference market, but the momentum portfolio and multi-factor portfolio compound by all five factors are able to perform better than the market portfolio (Sharpe Ratio of 0.47 and 0.49). The fact that the Sharpe Ratio of the Multi-Factor portfolio is higher than every Sharpe Ratio of the single factor is proof of the benefits of diversification. The factors that bring the highest risk-adjusted returns, for high yield, are size, value and the Multi-Factor (0.18, 0.47 and 0.33 respectively). Factor portfolios built with high yield bonds are responsible not only for higher mean returns, but also for better risk-adjusted returns in the terms of Sharpe Ratio, with exception made for low risk and liquidity.

The poor results achieved by most of the investment grade factor portfolios is reflected onto the outperformance statistics of Panel B: the only significant result for investment grade is given by momentum. Tracking errors are moderately high, which tells us that the returns of the portfolios tend to slightly deviate from their benchmark. The poor results also translate in small (or negative) Information Ratios. Sortino Ratio is mostly affected by the downside deviation, which is the volatility of the observations smaller than the mean, the ones responsible for the poor performances. The way the Sortino Ratio is computed allows it to obtain values close to the Sharpe Ratio or even higher if the volatility of the downside is quite modest.

Table 8. *Performance statistics of long-short factor portfolios and the equally weighted multi-factor portfolio, December 2014 – July 2019. Mean returns, volatility and Alphas are annualized.*

Table 8. Performance Statistics of Long-Short Factor Portfolios, December 2014 - July 2019														
	Investment Grade							High Yield						
	Market	Size	Low risk	Value	Momentum	Liquidity	Multi-Factor	Market	Size	Low risk	Value	Momentum	Liquidity	Multi-Factor
A. Return Statistics														
Mean	1,42%	0,63%	1,15%	0,70%	18,24%	0,52%	4,05%	3,69%	7,41%	4,20%	16,11%	9,75%	2,02%	7,80%
Volatility	6,47%	0,94%	1,97%	1,17%	9,85%	0,94%	1,81%	6,51%	10,24%	10,99%	8,67%	26,19%	6,78%	5,80%
Sharpe Ratio	0,02	-0,08	0,04	-0,05	0,47	-0,03	0,49	0,12	0,18	0,08	0,47	0,09	0,05	0,33
B. Outperformance Statistics														
Outperformance		-0,79%	-0,27%	-0,72%	16,82%***	-0,90%	2,63%		3,72%	0,51%	12,42%**	6,06%*	-1,68%	4,10%
Tracking Error		6,58%	6,32%	6,59%	13,54%	6,20%	7,23%		15,00%	10,41%	9,71%	31,27%	10,15%	11,35%
Information Ratio		-0,12	-0,04	-0,11	1,23	-0,14	0,36		0,24	0,05	1,24	0,19	-0,16	0,35
Sortino Ratio		-0,15	0,07	-0,07	0,68	-0,24	0,85		0,27	0,11	1,46	0,07	0,11	0,44
t-value		0,26	0,08	0,24	2,84	0,30	0,82		0,63	0,08	2,27	1,38	0,38	1,20
C. Alpha Statistics														
CAPM		0,64%*	1,05%	0,70%	19,12%***	0,45%	4,17%***		11,02%***	1,78%	14,98%***	16,77%***	2,65%	10,24%***
t-value		1.46	1,17	1,28	4,08	1,08	5,07		2,67	0,37	3,50	3,23	0,83	4,97
5 Factor Fama-French		0,80%**	0,45%	0,71%*	19,62%***	0,41%	4,16%***		10,38%***	3,30%	18,22%***	14,49%***	2,45%	10,61%***
t-value		1.72	0,63	1,45	3,97	0,95	4,67		2,37	0,68	4,32	2,64	0,74	4,95

Source: own calculations, replication of Table 3 of Houweling and van Zundert (2017)

On the contrary, if the downside risk is significantly high, the Sortino Ratio assumes values very close to the ones of the Sharpe Ratio. We can observe Sortino Ratios higher than Sharpe Ratio for value, momentum and multi-factor portfolios, in the investment grade universe. The reason hides in the downside risk: the observations that drag the mean returns towards lower values are not very volatile; the downside risk is ideal and holding these portfolios does not carry a great risk of harsh negative returns.

High yield outperformance results are positive and significant for value and momentum strategies. This time, tracking errors are rather elevate; this translates into small Information Ratios. Value and Multi-Factor achieve the highest levels of Sortino Ratio. Sortino Ratio is more accurate than Sharpe Ratio in this instance because of the accentuated skewness of the distribution due to the asymmetry of the excess returns around the mean (see Tables 5 and 6). CAPM and 5 Factor Fama-French regression statistics of long-short portfolios are already discussed in Table 7, where no statistical significance was found neither for low risk nor liquidity results.

5.2 Long-Only Portfolios

Table 9 shows the same results of Table 8 but applied to long-only factor portfolios. The first difference we notice is that returns of long-only portfolios are much higher; this translates into higher levels of volatilities for long-only portfolios. An exception is made for both momentum and investment grade multi-factor portfolios. The outperformance statistics are not very significant across all the long-only factor portfolios; we are interested in the very low tracking errors (almost half of long-short tracking error), which ultimately positively affects the Information Ratio. This means that with a long-only portfolio, our performance would be more consistent over time at exceeding the benchmark. Sortino Ratio of investment grade factors improves substantially as opposed to the investment grade Multi-Factor's, which slightly declines. Same pattern is discovered in the high yield Sortino Ratio measures, only expection made for the value factor, which declines by a small amount.

Table 9. *Performance statistics of long-only factor portfolios and the equally weighted multi-factor portfolio, December 2014 – July 2019. Mean returns, volatility and Alphas are annualized*

Table 9. Performance Statistics of Long-Only Factor Portfolios, December 2014 - July 2019

	Investment Grade							High Yield						
	Market	Size	Low risk	Value	Momentum	Liquidity	Multi-Factor	Market	Size	Low risk	Value	Momentum	Liquidity	Multi-Factor
A. Return Statistics														
Mean	1,42%	1,19%	1,70%	1,86%	9,14%	1,39%	3,02%	3,69%	4,02%	7,16%	17,57%	6,42%	5,68%	8,08%
Volatility	6,47%	3,17%	3,65%	3,19%	6,86%	3,38%	3,73%	6,51%	5,78%	11,71%	11,28%	5,54%	6,54%	6,57%
Sharpe Ratio	0,02	0,03	0,06	0,09	0,33	0,04	0,16	0,12	0,15	0,15	0,39	0,28	0,21	0,30
B. Outperformance Statistics														
Outperformance		-0,23%	0,28%	0,44%	7,72%**	-0,03%	1,59%		0,33%	3,47%	13,87%***	2,73%	1,99%	4,38%
Tracking Error		3,76%	3,87%	3,84%	3,64%	3,76%	3,13%		3,52%	8,65%	7,32%	6,10%	3,69%	2,70%
Information Ratio		-0,06	0,07	0,11	2,09	-0,01	0,50		0,09	0,39	1,83	0,43	0,52	1,57
Sortino Ratio		0,04	0,10	0,13	1,00	0,06	0,27		0,24	0,28	1,21	0,42	0,47	0,63
t-value		0,07	0,08	0,13	1,69	0,01	0,45		0,08	0,53	2,10	0,66	0,45	0,97
C. Alpha Statistics														
CAPM		0,55%	1,02%	1,22%**	7,77%***	0,72%	2,22%***		1,24%	2,47%	11,93%***	4,80%**	2,50%*	4,53%***
t-value		0,94	1,13	1,88	4,46	1,01	4,13		0,84	0,61	3,46	2,06	1,47	3,53
5 Factor Fama-French		0,73%	0,75%	1,40%**	7,60%***	0,89%	2,24%***		0,77%	3,91%	14,71%***	5,15%**	2,58%*	5,32%***
t-value		1,26	0,88	2,17	4,08	1,26	3,96		0,50	0,97	4,32	2,22	1,46	4,23

Source: own calculations, replication of Table 3 of Houweling and van Zundert (2017)

For what concerns the CAPM and 5 Factor Fama-French models, we experience smaller alphas, but with more statistically significant results overall: investment grade value factor gains significance, momentum and multi-factor maintain the significance but the magnitude halves for both; high yield size factor loses its significance, value factor loses between 3 to 4 percentage points, momentum alphas are quartered but still remain significant, multi-factor alphas are halved but still remain significant. But the most important results are achieved by the liquidity high yield long-only factor portfolio: we observe, for the CAPM and 5 Factor Fama-French models respectively, alphas of 2.50% and 2.58% statistically significant at the 10% level.

5.3 Factors Correlation

Houweling & van Zundert (2017) study the effect of factor investing in the U.S. corporate fixed income market, including the size, low risk, value, momentum as well as multi-factor. They use monthly constituent data of the Barclays US Corporate Investment Grade Index and the Barclays US Corporate High Yield Index. Houweling updates a quickly accessible database on Robeco Insights. The database is comprehensive of up-do-date, long-only, monthly excess returns for each of the aforementioned factors. We would like to test whether our long-only monthly excess factor returns are coherent with the ones calculated by Houweling and van Zundert, and for this, we will measure the correlation among all of the factors. Table 10 and 11 propose the correlation between the two sets of factor returns, discriminating for investment grade and high yield markets, over the same period.

Table 10. *Correlation between Houweling & van Zundert factors and our factors. Long-only portfolios constructed with Investment Grade factors, December 2014 – July 2019*

		Houweling & van Zundert factors				
		Size	Low Risk	Value	Momentum	Multi Factor
Our factors	Size	-21,9%	18,5%	-8,3%	-8,5%	-10,3%
	Low Risk	3,4%	43,1%	26,8%	22,2%	23,2%
	Value	-12,5%	28,5%	12,4%	4,3%	6,1%
	Momentum	-19,7%	3,4%	-6,7%	-3,2%	-7,6%
	Multi Factor	-15,0%	21,4%	4,2%	3,0%	1,2%

Source: our data was collected via Thomson Reuters Datastream , Houweling & van Zundert factors returns are available at https://www.robeco.com/en/insights/2018/12/data-sets-factor-investing-in-corporate-bonds.html

With regards to Table 10, the highest correlation (43.1%) is ascribable to the two Low Risk factors, while the lowest (1.2%) is due to the two Multi-Factor portfolios. The remainder of the correlations levels is relatively low, and sometimes also negative.

On the other hand, Table 11 offers very high levels of correlation between the two sets of factors. The highest correlation (74.7%) is attributable to the two Multi-Factor portfolios – pattern opposite to the one described by Table 10. The lowest observation is the correlation between Houweling & van Zundert Low Risk and our Momentum factor (33.3%).

Table 11. *Correlation between Houweling & van Zundert factors and our factors. Long-only portfolios constructed with High Yield factors, December 2014 – July 2019*

		Houweling & van Zundert factors				
		Size	Low Risk	Value	Momentum	Multi Factor
Our factors	Size	40,3%	55,2%	46,8%	51,1%	49,3%
	Low Risk	67,4%	69,4%	74,6%	67,0%	73,8%
	Value	64,1%	64,6%	69,3%	53,4%	66,7%
	Momentum	50,4%	33,3%	43,5%	37,6%	45,0%
	Multi Factor	70,3%	71,0%	75,3%	65,7%	74,7%

Source: our data was collected via Thomson Reuters Datastream , Houweling & van Zundert factors returns are available at [*https://www.robeco.com/en/insights/2018/12/data-sets-factor-investing-in-corporate-bonds.html*](https://www.robeco.com/en/insights/2018/12/data-sets-factor-investing-in-corporate-bonds.html)

We do not believe that the way we defined our factors has influenced the correlation metrics. On the contrary, if the way we defined our factors has influenced in some way the correlation metrics, we would witness the same pattern in both Table 10 and 11. Since there are clearly two different patterns between the two Tables, this could be due to raw data differences, particularly in the investment grade universe and how the iShares iBoxx US Investment Grade Corporate Bond ETF and the Bloomberg Barclays US Corporate Bond Index are constructed, or what kind of bonds are included. Alternatively, if we have an overlook at the rating quality and composition by sector of the iShares ETFs and Barclays Indexes, we do not notice significant differences (See Appendix for information about rating quality and composition by sector). Therefore, we cannot draw a conclusion regarding to why we observe such differences between Table 10 and 11.

6. Concluding Remarks

This paper studies factor investing in the US corporate investment grade and high yield bond markets, with focus on the constituents of two different ETFs: the iShares iBoxx $ Investment Grade Corporate Bond ETF and the iShares iBoxx $ High Yield Corporate Bond ETF. In particular, we study the following five factors: size, low risk, value, momentum and liquidity. The factors are defined and calculated each month and equally weighted portfolios are built taking a long position in the top 10% and a short position in the bottom 10% bonds exposed to each factor. For investment grade long-short portfolios, we find statistically significant CAPM alphas and 5 Factor Fama-French, fixed income adjusted, of 19.12% and 19.62%, respectively, for momentum strategy. For high yield long-short portfolios, we find significant CAPM alphas of 11.02& for size, 14.98% for value and 16.77% for momentum. We find 5 Factor Fama-French, fixed income adjusted, significant alphas of 10.38% for size, 18.22% for value and 14.49% for momentum.

With regards to long-only portfolios, instead, we find significant CAPM alphas for investment grade US corporate credit of 1.22% for value and 7.77% momentum. 5 Factor Fama-French, fixed income adjusted, alphas equal to 1.40% for value and 7.60% for momentum. CAPM alphas for high yield US corporate credit equal to 11.93% for value, 4.80% for momentum and 2.50% for the liquidity factor. 5 Factor Fama-French, fixed income adjusted, alphas equal to 14.71% for value, 5.15% for momentum and 2.58% for liquidity. All of the Multi-Factor portfolios, either long-short or long-only, bring statistically significant results, positive outperformances and better risk-adjusted returns, thanks to diversification benefits. All alphas are annualized. The paper does not measure any significant result related to the low risk factor.

Furthermore, we found that long-short factor portfolios are responsible for higher excess returns against duration matched treasuries and higher CAPM and 5 Factor Fama-French alphas. This comes with very high volatility and tracking error. Long-only single factor portfolios are able to achieve positive outperformance ratios; thus, they have the potential to consistently bring better risk-adjusted returns to the investor.

Liquidity factors results are significant at the 10% level, only when investing in a high yield long-only portfolio. Our results for the liquidity factor are in contrast with the paper by Blitz et al (2018), where evidence is found against the usefulness of trying to harvest a liquidity premium in an investment opportunity. Additionally, we are comparing our liquidity premiums resulting from the factor portfolios with the ones obtained by De Jong and Driessen (2007), that find a total estimated liquidity risk premium around 0.6% per annum, for long-maturity investment grade bonds. For high yield long-maturity bonds, the liquidity risk premium measures about 1.5% per annum. Results are similar in both the US and European markets. Our results for the long-only liquidity factor portfolios are of the same magnitude.

The correlation between Houweling & van Zundert (2017) factors and the factors that emerged from our research, over the same period, shows two different patterns: first, the correlation of investment grade bonds reveals overall small, sometimes negative numbers; second, the correlation of high yield bonds displays consistent high numbers.

The main limitation of this study is the number of periods considered. We collected data for 56 months, which may be a reason for the statistically non-significant results of some of the factors. Finally, we could not give an explanation for the differences in the correlation statistics obtained between the two sets (investment grade and high yield) of Houweling & van Zundert (2017) factors and the factors constructed by us. Future research may also be able to examine different factor proxies, especially for low risk and liquidity, as well as a larger time series – this would lead to more robust results.

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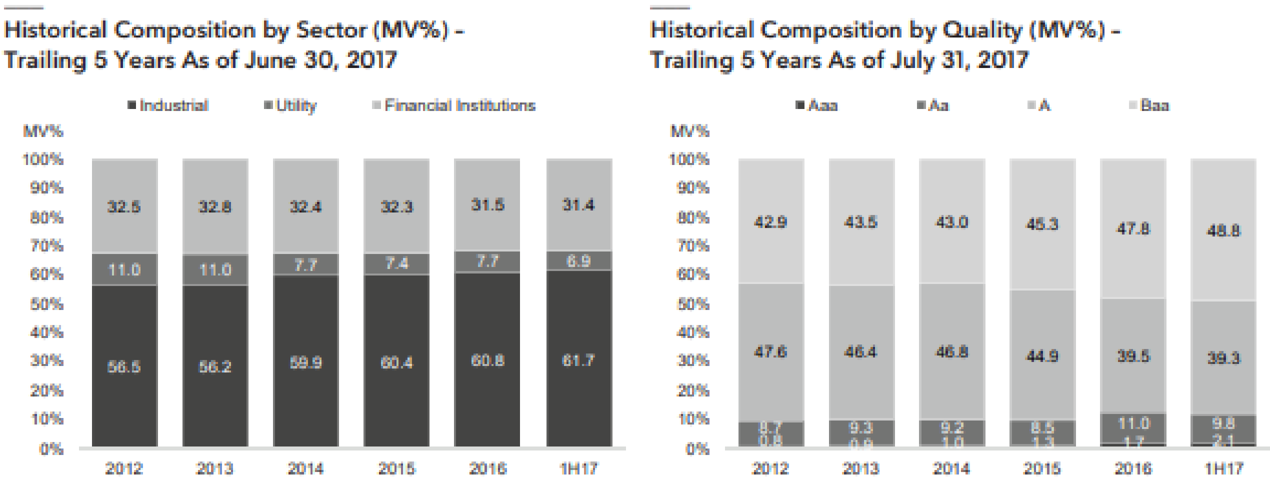
Appendix

Index Facts – Investment Grade Index | Data as of 2017

Figure 6. *Bloomberg Barclays US Corporate Investment Grade Index, Historical Composition by Sector and Quality. 2017*



Source: https://data.bloomberglp.com/indices/sites/2/2016/08/2017-08-08-Factsheet-US-Corporate.pdf

Bloomberg Barclays Index – US Corporate Index, page 1

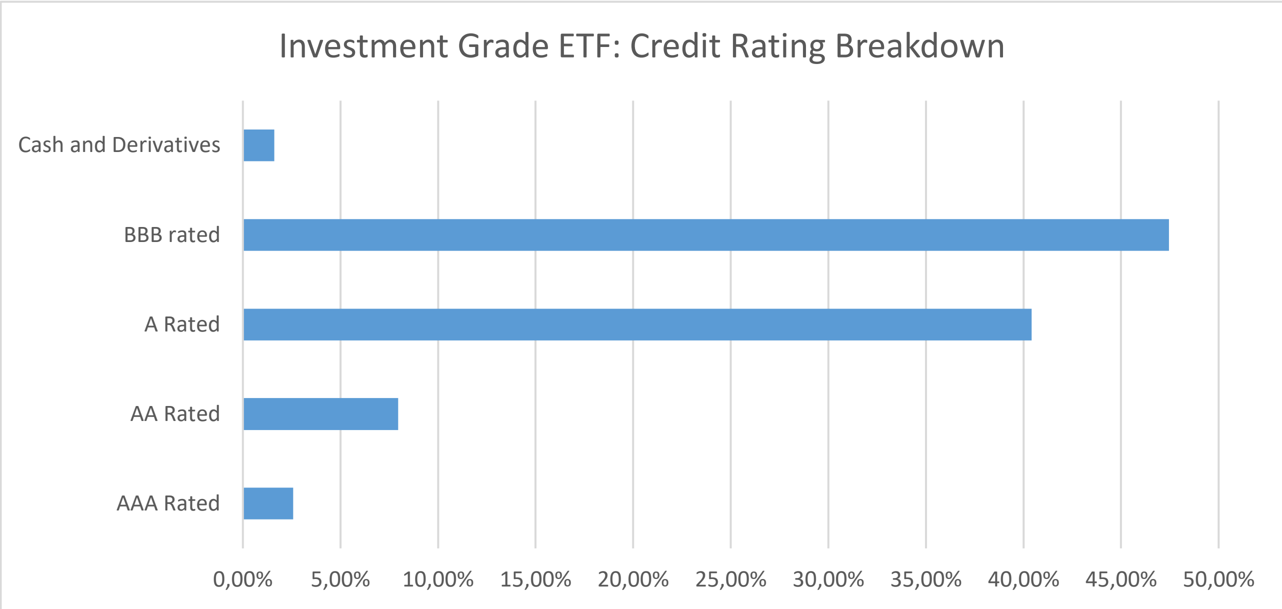
Fund Facts – Investment Grade ETF | Data as of March 2020

Table 12. *iShares iBoxx $ Investment Grade Corporate Bond ETF description. March 2020*

Asset Class	Fixed Income
Exchange	NYSE Arca
Benchmark Index	Markit iBoxx Liquid Investment Grade Index
Net Assets	32.292.527.190,00
Shares Outstanding	249.900.000,00
Daily Volume	30.024.740,00
Effective Duration	9,21
Option Adjusted Spread	183

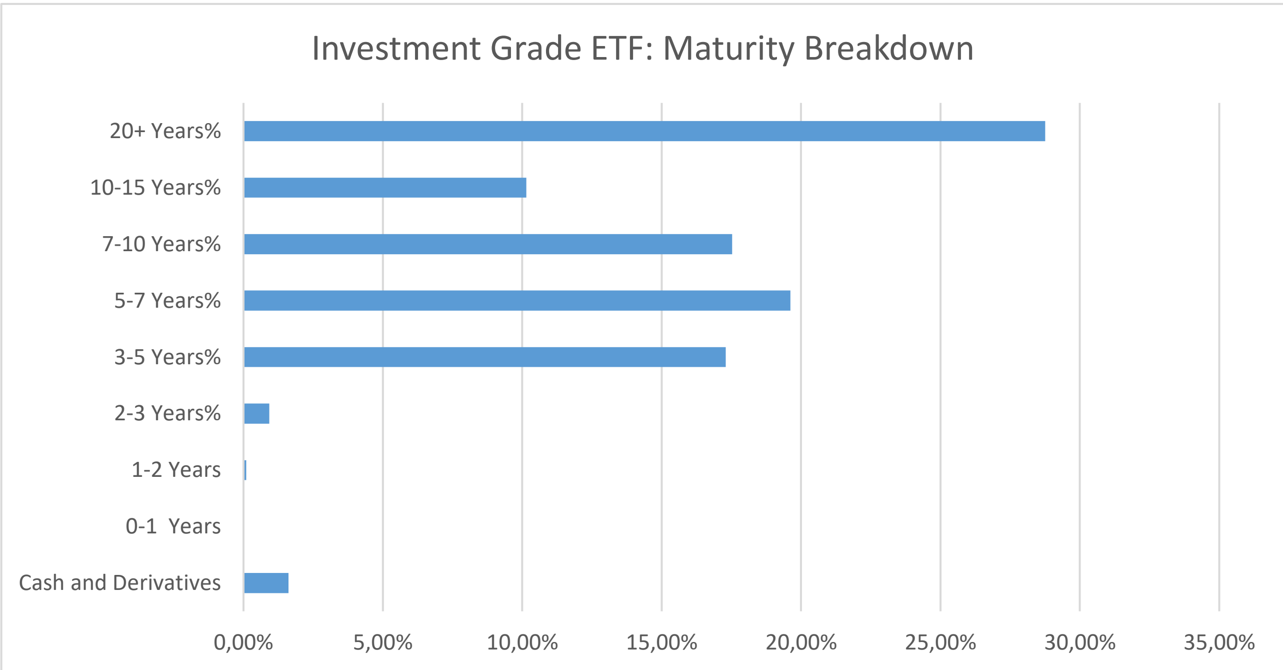
Source: iShares by BlackRock

Figure 7. *iShares iBoxx $ Investment Grade Corporate Bond ETF Credit Rating Breakdown. March 2020*



Source: iShares by BlackRock

Figure 8. *iShares iBoxx $ Investment Grade Corporate Bond ETF Maturity Breakdown. March 2020*



Source: iShares by BlackRock

Table 13. *iShares iBoxx $ Investment Grade Corporate Bond ETF Sector Type Breakdown. March 2020*

Sector Type	% of Market Value
Banking	25,64%
Consumer Non-Cyclical	19,24%
Communications	11,83%
Technology	10,59%
Energy	8,64%
Consumer Cyclical	7,19%
Capital Goods	3,85%
Insurance	3,53%
Basic Industry	2,03%
Electric	1,80%
Cash and/or Derivatives	1,61%
Transportation	1,43%
Reits	0,85%
Finance Companies	0,66%
Brokerage/Asset Managers/Exchanges	0,55%
Natural Gas	0,33%
Owned No Guarantee	0,19%
Utility Other	0,06%

Source: iShares by BlackRock

Table 14. *iShares iBoxx $ Investment Grade Corporate Bond ETF top 10% issuers by weight. March 2020*

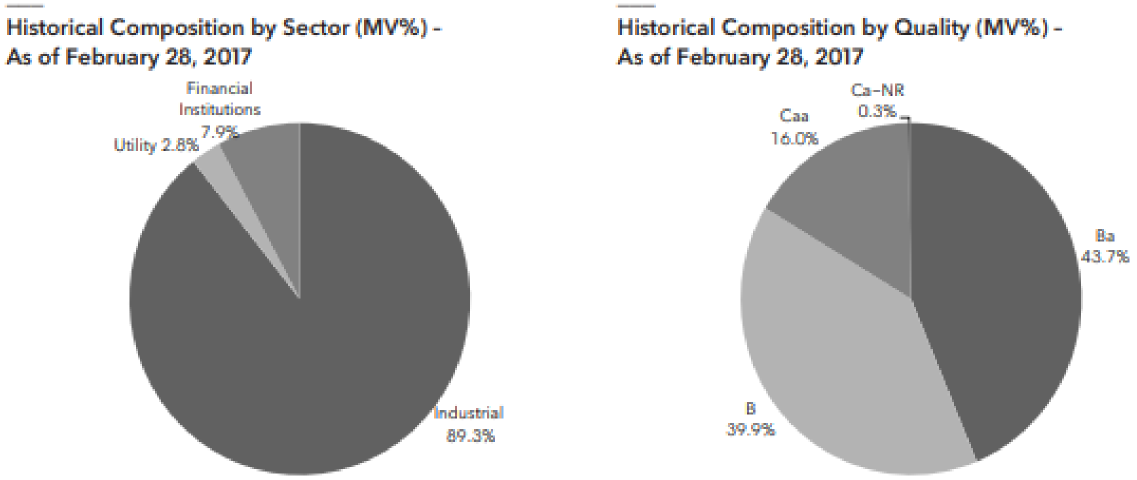
Top 10 Issuers	Weight (%)
JPMORGAN CHASE & CO	2,96%
BANK OF AMERICA CORP	2,90%
AT&T INC	2,50%
COMCAST CORPORATION	2,33%
WELLS FARGO & COMPANY	2,16%
CITIGROUP INC	2,13%
VERIZON COMMUNICATIONS INC	2,07%
GOLDMAN SACHS GROUP INC/THE	2,02%
MICROSOFT CORPORATION	1,94%
APPLE INC	1,94%

Source: iShares by BlackRock

Index Facts – High Yield Index | Data as of 2017

Figure 8. *Bloomberg Barclays US Corporate High Yield Index, Historical Composition by Sector and Quality*

Source: https://data.bloomberglp.com/indices/sites/2/2017/04/2017-03-31-Factsheet-US-High-Yield-Very-Liquid-



Index.pdf Bloomberg Barclays Index – US High Yield Index, page 1

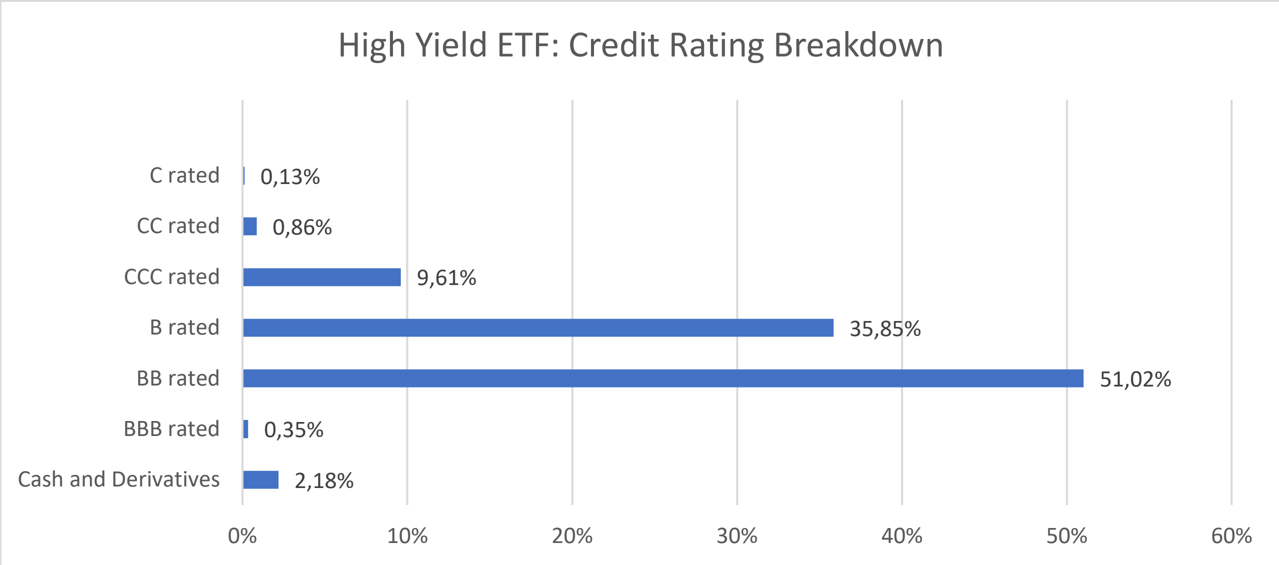
Fund Facts – High Yield ETF | Data as of March 2020

Table 15. *iShares iBoxx $ High Yield Corporate Bond ETF description. March 2020*

Asset Class	Fixed Income
Exchange	NYSE Arca
Benchmark Index	Markit iBoxx Liquid High Yield Index
Net Assets	14.947.983.413,00
Shares Outstanding	181.400.000,00
Daily Volume	575.979,76
Effective Duration	4,01
Option Adjusted Spread	565

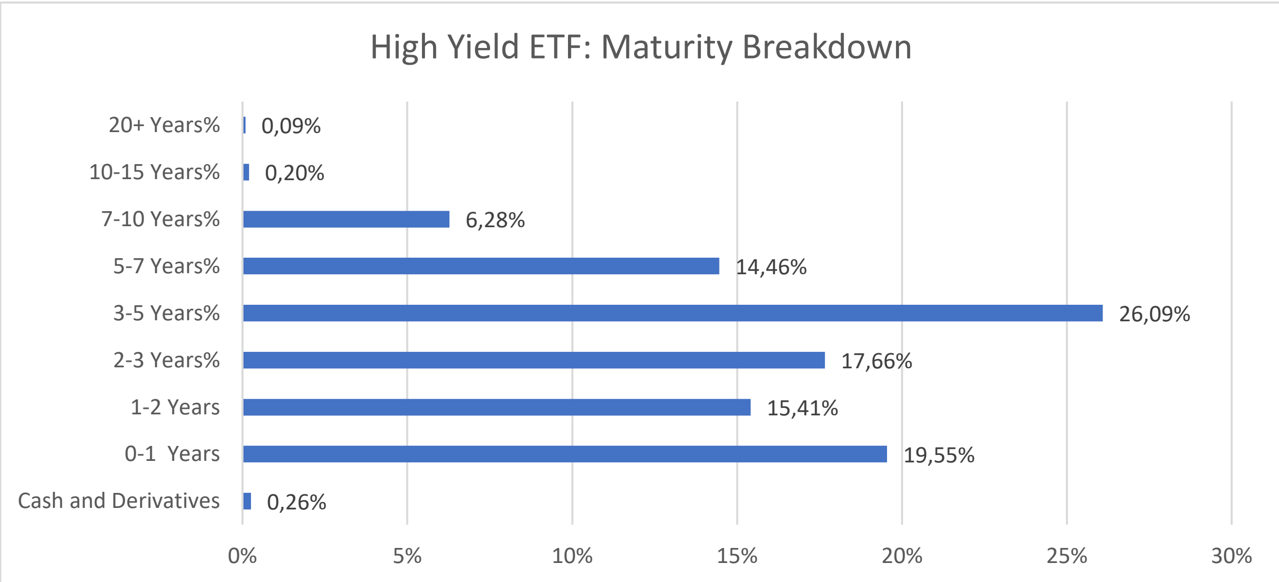
Source: iShares by BlackRock

Figure 9. *iShares iBoxx $ High Yield Corporate Bond ETF Credit Rating Breakdown. March 2020*



Source: iShares by BlackRock

Figure 10. *iShares iBoxx $ High Yield Corporate Bond ETF Maturity Breakdown. March 2020*



Source: iShares by BlackRock

Table 16. *iShares iBoxx $ High Yield Corporate Bond ETF Sector Type Breakdown. March 2020*

Sector Type	% of Market Value
Communications	24,78
Consumer Non-Cyclical	16,90
Consumer Cyclical	14,94
Capital Goods	8,84
Energy	8,79
Technology	6,86
Basic Industry	3,14
Electric	2,84
Finance Companies	2,45
Insurance	2,43
Cash and/or Derivatives	2,18
Reits	1,44
Financial Other	1,17
Banking	1,16
Transportation	0,85
Industrial Other	0,64
Owned No Guarantee	0,49
Brokerage/Asset Managers/Exchanges	0,10

Source: iShares by BlackRock

Table 17. *iShares iBoxx $ Investment Grade Corporate Bond ETF top 10% issuers by weight. March 2020*

Top 10 Issuers	Weight (%)
CCO HOLDINGS LLC	2,78%
CSC HOLDINGS LLC	1,87%
CENTENE CORPORATION	1,85%
BAUSCH HEALTH COMPANIES INC	1,81%
HCA INC	1,78%
SPRINT CORP	1,75%
TENET HEALTHCARE CORPORATION	1,73%
CHS/COMMUNITY HEALTH SYSTEMS INC	1,47%
T-MOBILE USA INC	1,40%
TEVA PHARMACEUTICAL FINANCE NETHERLANDS III BV	1,35%

Source: iShares by BlackRock