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Traditional and Alternative Factors in Investment Grade Corporate Bond Investing

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Abstract

The concept of factor investing and the debate around passive and active management has emerged since the end of the 2000s and has completely changed the landscape of equity investing. Today, institutional investors structure their strategic equity allocations essentially around risk factors. Size, value, low beta, momentum and quality are among the most popular factors in use. The factor-investing approach has recently been extended to multi-asset portfolio management and it is known as the Alternative Risk Premia (ARP) model. This model recognizes that the construction of large diversified portfolios cannot be reduced to an allocation policy between asset classes alone, between stocks, bonds and other investments. Indeed, diversification is multifaceted and must also take into account alternative risk factors.

More recently, research efforts are being made in the field of fixed income, in particular in the corporate bond space. The industry is still digesting the knowledge on the risk factors that are prevalent for this asset class, which go beyond the generally accepted notion that corporate bond prices are sensitive to credit spreads. The relevance of new risk factors that are being found is still being debated. It is not clear as it stands whether the factors may be viewed as a reformulation of traditional bond risk, or whether they represent genuine risk sources. The tests that have been carried out to date mainly based on decile analysis do not allow us to make this assessment.

In this paper we analyze and amend specifications for new alternative factors in the corporate investment grade bond market when deemed necessary and we integrate them with traditional factors in a multi-factor framework. We apply this multi-factor framework to both the cross-section and time-series angle so as to have a comprehensive view of how our alternative factors complement our traditional factors.

In addition to being the starting point of massive quantitative easing pro- grams, we find that 2009 marks the start of a new environment in the corporate investment grade bond market. We identify that new alternative factors are necessary to augment traditional factors' explanatory power. While the traditional duration-times-spread factor remains a mainstay, value with our specifications is the factor which improves the most in terms of significance for active managers who need to pick the most significant factors.

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We test our statistical findings in a real fund management setting. In the case of corporate investment grade bonds, alternative factors can be detected on an aggregate portfolio level, less so for individual bonds. Once traditional risk factors are neutralized in an invested portfolio with respect to the market averages, a tilt towards a particular factor can diverge the performance away from the average market trend and actually produce significant superior returns. This approach can be used in an enhanced index environment.

That said, the management of corporate bond portfolios is de facto complex and multifaceted: in order to be effectively in control of all risks that play, both traditional and alternative bond factors must be proactively managed in a concerted way. The complexity of this task is not commented on very much in the portfolio management literature. In this paper, we discuss a bond-factor investment strategy that does this; it takes into account the habitual risks that play on the corporate bond markets and focuses on factor-related performance opportunity within that. We consider our bond-factor investment strategy to be the first of its kind.

Keywords: Factor investing, corporate bond, credit risk premium, duration, spread, liquidity, size, value, momentum

JEL classification: G11, G12.

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Key findings

- We define a traditional bond risk factor model with duration times spread, duration and liquidity.
- We define new alternative factors for value, momentum and we test low risk and size.
- Our specification for momentum which considers adjustment by duration does not display a reversal feature.
- We observe a change in the market conditions in the euro corporate investment grade bond space in our analysis period which runs from 2003 to 2018. We have a first period between 2003 and 2008 and a second between 2009 and 2018.
- In the first period from 2003 to 2008, the market is better explained with the set of traditional factors than with CAPM alone.
- In this first period, the addition of new alternative factors increases explana- tory power but comes with increased collinearity. We retain value, momentum and size as new alternative factors.
- In the second period from 2009 to 2018, traditional factors in a multi-factor framework need to be augmented by alternative factors to keep the multi-factor framework relevant against CAPM alone.
- Corporate investment grade bonds require additional research for statistically significant factor investing. DTS remains the outstanding bond factor. How- ever investors can function in a more active management environment with lower factor intensity.
- Our definition of value and momentum are relevant in a factor picking frame- work.
- If we have to select three factor time-series to explain the euro investment grade bond market, we choose DTS, value and momentum in this order.
- Both value and momentum alternative factors display desirable properties for investors in a DTS-matched portfolio construction and in a rule-based active management framework.
- In our innovative multi-factor rule-based active management portfolio con- struction, value and momentum display complementary pay-offs.
- We replicate our analysis of EUR-denominated corporate investment grade on a USD-denominated universe. We identify that in the USD universe, value was already a significant factor for active managers in the 2003-2008 period and remains significant in the 2009-2018 period. Factors in the USD universe carry higher collinearity between themselves than in the EUR universe. We confirm that our implementations in a DTS matched enhanced index and in a rule-based active management are relevant in the USD-denominated universe.

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1 Introduction

Perceptions of equity and bond risk have not evolved in the same way in the investment profession. Equity risk is basically defined with respect to the Capital Asset Pricing Model (CAPM) (Sharpe, 1964), which breaks-down price variance into a systematic market component plus asset-specific residual components. Since the 1990s, it has become popular to add other systematic risk factors (Fama and French, 1992). In this framework the systematic risk of a stock is measured by means of betas, that is the market or CAPM beta plus alternative betas (for size, value, etc.). This way of measuring risk is widely adopted by portfolio managers and investors, and has become the backbone of equity investment theory. In particular, it structures the distinction that is habitually made between active and passive management.

For bonds the CAPM is not a standard reference. A '*bond beta*' is not an established concept among practitioners, and the framework of risk factor models *à la* Fama-French has only recently been adopted. Houweling and van Zundert's (2014) publication marks a turning point, as it offers "*empirical evidence that size, low-risk, value, and momentum factor portfolios generate economically meaningful and statistically significant alphas in the corporate bond market*". This research result has opened the door to seriously considering the factor-investing approach for corporate bond investments. Other studies followed suit, confirming that the new risk factors indeed explain part of the cross-section over bond returns (Bektic *et al.*, 2016 and Israel *et al.*, 2018).

The findings are not fully conclusive though; they differ from one region to another (Bektic *et al.*, 2016) and from one portfolio to another (Bektic *et al.*, 2017). Martellini and Milhau (2015) question whether factor investing will become a truly new investment paradigm and include corporate bonds in their study. The stakes are high. If factor investing eventually fails for corporate bonds, the Alternative Risk Premia Model will stay put with it. The idea this model espouses, namely to manage large multi-asset mandates in a neat interconnected factor framework, will stay in limbo given that all-but-one of the asset classes can be managed in a singular setup while one stays put in a traditional framework. There seems to be a standoff going on between the '*old school*' of bond management and a newly emerging school. We try to see whether there is a way to reconcile the two worlds and make the best of both.

Settling the debate on what factors drive corporate bond prices is not trivial because, for one thing of the conditions in which bonds are managed. Bond databases are less comprehensive than equity databases and more difficult to constitute, as most bonds are traded on over-the-counter (OTC) markets. The use of both market and fundamental data is less common in the bond sector. This is because buy-and-hold strategies largely dominate rebalancing and trading strategies in terms of management style. Moreover, liquidity is a major problem when it comes to implementing a bond strategy. For that matter, one must be careful to distinguish between the empirical back-tests, when explaining the cross-section of corporate bond returns, and the actual implementation, whilst designing an actual bond investment strategy.

The paper is organized as follows. In section 2, we review the bond literature, covering both traditional and alternative factors. We specify a first bond risk-factor model which we restrict to traditional factors so as to have a reference point for understanding and analyzing alternative factors.

We use this model to grasp the attractiveness (before 2008) and limitations of this traditional factor approach (after 2008). In section 3 we test the new alternative factors that we have identified in our literature review. When deemed necessary we amend their specification. Once we have assembled traditional and alternative factors, we make sense of the factor puzzle in a multi-factor framework. We use both cross-section and time-series analyses. Later, in section 4 we provide implementation examples for new alternative factors both in a tilted enhanced index framework and in a rule-based active management environment. We then conclude and provide mathematical results and USD-denominated corporate investment grade bond results.

2 Literature review and traditional risk factor model

2.1 Literature Review: traditional and alternative factors

Unlike for equities, there is no obvious consensus among investors on how to evaluate bond risk. To understand why this is so, it is worthwhile taking a step back and looking at how the notion of investment risk has evolved over time. Since Markowitz' (1952) Modern Portfolio Theory investment risk is generally defined by asset price variance. In an efficient market, trade prices convey all information that is relevant for an investor and thus price return variance effectively reflects risk, according to the theory. The Capital Asset Pricing Model of Sharpe (1964) introduces a breakdown of the variance into a systematic market component and a residual asset-specific component. Even though it is not clearly stated in the literature, the assets the model refers to are, above all, equity shares. This is particularly evident in earlier studies (Black *et al.*, 1972; Fama and MacBeth, 1976) that focus on NYSE stocks.

Bond risk modelling starts to receive serious attention in financial literature much later. Nelson and Siegel (1987) and Litterman and Scheinkman (1991) are seminal works on modelling sovereign bond risk:

> "*Market participants have long recognised the importance of identifying the common factors that affect the returns on U.S. government bonds and related securities. To explain the variation in these returns, it is critical to distinguish the systematic risks that have a general impact on the returns of most securities from the specific risks that influence securities individually and hence a negligible effect on a diversified portfolio*" (Litterman and Scheinkman, 1991, page 54).

Both articles contend that most of the variation in sovereign bond returns is explained by three factors called the level, the steepness and the curvature[1]. These factors have since become the standard reference among bond practitioners for defining sovereign bond risk.

In the same period Fama and French (1992, 1993) introduce the concept of style factors for equities, proposing a three-factor model that consists of a market factor, a size style factor and

[1] Diebold and Li (2006) make evident that the two models specify essentially the same three factors, the former by means of an analytical model and the latter via a statistical approach. The factors are also called shift or translation, rotation, and twist or butterfly.

a value style factor. It seems to be forgotten that, whilst the 1992-paper is exclusively dedicated to stocks, the 1993-paper deals with both stocks and bonds. Interestingly, two bond factors are put forward in this paper called TERM and DEF, standing for term structure and default risk respectively. The first factor is specified by the difference in long-term and short-term government bond returns, i.e. the one-month treasury bill rate, and is thus close to the steepness factor. The second factor is specified by the spread of corporate bonds with respect to sovereign bonds, thereby capturing default or credit risk.

It is worth noting that the two bond factors of Fama and French (1993) originated from the macro-financial model of Chen *et al.* (1986), which includes an expected and an unexpected inflation factor, plus a factor for industrial output growth as well. Fama and French explain both stock and bond returns using a five-factor model consisting of the three equity and the two bond factors. They conclude that "*except for low-grade corporates, the bond market factors capture the common variation in bond returns*". The diverging approaches between the latter two may explain why bond risk premia are being analyzed so differently depending on whether they concern sovereigns or corporate bonds. As to sovereigns the literature has focused on the risk factors underlying the yield curve and on the information embedded in forward rates (Fama and Bliss, 1987; Cochrane and Piazzesi, 2005).

As to research on corporate bonds, progress has been sluggish and has produced relatively little compared to the extensive literature on stocks. Exceptions are the works of Houweling *et al.* (2005) and of Gebhardt *et al.* (2005a, 2005b), who build bond risk models using the DEF and TERM factors. In fact, during the 2000s research on corporate bonds has mainly focused on the problems of market liquidity. That said, the string of literature this has produced remains scattered as well and is lacking consensus. Longstaff *et al.* (2005) find that "*the majority of the corporate spread is due to the default risk*", while to them the non-default component is related to bond market liquidity. Their conclusion contrasts with a previous result obtained by Huang and Huang (2012) –a paper published in 2012, but written in 2003– who found that the liquidity component explains more than half of the corporate bond spread. Other academic studies followed (Chen *et al.*, 2007; Bao *et al.*, 2011; de Jong and Driessen, 2012), confirming that liquidity is a supplementary systematic risk factor for explaining corporate bond returns over the cross-section.

Rather than studying price impact, Konstantinovsky *et al.* (2016) take a practical approach to the question of market liquidity, and develop a system that captures the costs involved in trading corporate bonds. They build so-called liquidity cost scores that are based on bid-ask spread quotes. Bonds for which such quotes are not available or not reliable, are scored in a different manner making use of the characteristics of the bond indentures. The older a debt obligation, the higher the cost score typically, or on the same token, the longer the time-to-maturity or the smaller the debt issue, the higher the score. Inspired by this work Ben Slimane and de Jong (2017) develop a scoring model that fully relies on bond characteristics.

The research of Houweling and van Zundert (2014) marks a veritable turning point in the realm of bond risk modelling, for it forces one to think about the Fama-French-Carhart philosophy for corporate bonds. In the article the authors explore the performance of bond portfolios ranked by four style factors, namely by size, low risk, value and momentum. They compare long-only portfolios with respect to the market index, and look at long-short factor portfolios as well. They also combine the four style factors into a long-only multi-factor portfolio, and conclude that "*single-factor and multi-factor corporate bond portfolios generate economically meaningful and statistically significant alphas*".

This ground-breaking study has been followed by other research papers that test similar factors. Bektic *et al.* (2016) explore four risk factors that were put forward quite recently by Fama and French (2015), namely size, value, profitability and investment. Unlike Houweling and van Zundert (2014), their risk factors are equity-oriented, in the sense that factor portfolios are built by sorting bonds on pure equity-related scores. For instance, their size score corresponds to the equity market capitalization and not to the issuer's outstanding debt. They motivate this choice by referring to the structural credit model of Merton (1974), which links the credit risk of a firm to its capital structure. In this model the price of a bond is directly related to the price of the corresponding equity share.

Bektic *et al.* (2016) provide empirical evidence that an equally-weighted multi-factor portfolio outperforms its corresponding corporate bond benchmark, although they note that "*while all factors exhibit economically and statistically significant excess returns in the U.S. high yield market, we find mixed evidence for U.S. and European investment grade markets*". The evidence appears to be stronger for the size, value, momentum and low beta factors (Bektic *et al.*, 2017). The authors find the risk factors to have more explanatory power for the US high yield market than for the US investment grade market. An explanation for this could be the more equity-like features of high-yield bonds.

Israel *et al.* (2018) write a paper in the same field, testing new factors on bonds by which both equity and bond data are being used. They define a carry factor on bond data, namely on option-adjusted spreads (OAS). Their value risk factor is a mix of two scores[2], more precisely, they are the residuals of a cross-sectional regression of the OAS onto two sets of exogenous variables. Their momentum risk factor mixes the six-month trailing bond return momentum and the six-month trailing equity return momentum. And they develop a defensive[3] risk factor by combining three scores: leverage, duration and profitability. When testing these factors onto US corporate bonds, they found that value, momentum and the defensive factor exhibit a significant positive risk premium, yet not the carry factor.

Table 1 summarizes the new alternative risk factors that have been put forward in the four researches and indicates the databases on which they have been tested. In all we note that data broadly cover US corporate bonds, and that the focus is on four main risk factors: low risk, momentum, size and value.

In the four articles presenting the new bond factors, it is not questioned whether the factors represent new risk sources that are complementary to traditional bond risks, or whether they are

[2]For the first regression, the exogenous variables are the duration, rating and the volatility of excess bond returns over the interest-rate return. For the second regression, the exogenous variable is the implied default probability calculated by means of a structural credit model.

[3]Ng and Phelps (2015) point out that the defensive factor and to a certain extent the carry factor may be considered as two versions of the low-risk factor.

Table 1: Overview of the new bond factors in the literature and their specifications

Study	HZ	BWWSS	IPR	BNWW
Period	1994-2013	1996-2016 (US) 2000-2016 (EU)	1997-2015	1999-2016
Universe	Bloomberg Barclays US IG & HY	BAML US IG & HY, EU IG	BAML US IG & HY	BAML US IG & HY
Investment		1Y variation in total assets		
Low risk	Short maturity + High rating		Leverage $\times$ Duration $\times$ Profitability	1Y equity beta
Momentum	6M bond return		6M bond return + 6M stock return	1Y stock return
Profitability		Earnings-to-book		
Size	Market value of issuer	Market capitalization		Market capitalization
Value	Comparing OAS to Maturity $\times$ Rating $\times$ 3M OAS variation	Price-to-book	Comparing OAS to Duration $\times$ Rating $\times$ Bond return volatility + Implied default probability	Price-to-book

HZ = Houweling and van Zundert (2014)
BWWSS = Bektic, Wenzler, Wegener, Schiereck and Spielmann (2016)
IPR = Israel, Palhares and Richardson (2018)
BNWW = Bektic, Neugebauer, Wegener and Wenzler (2017)

Source: this information is retrieved from the discussed articles.

redundant. This omission leaves people bewildered, and enflames the debate that we see ongoing between traditional bond managers – the old school – and self-declared 'modern' or 'smart' fund managers – the new school. To answer this question, we will proceed to the specification of a traditional risk factor model which will be our reference point for understanding the new alternative factors.

2.2 Specifications of a traditional factor model

The value of a corporate bond is being established at the confluence of three market environments: the macroeconomic environment, the business environment and the bond trading conditions. As to the first, interest rates move depending on the state of the economy. If interest rates rise, yields on outstanding bonds decline relative to new bond issues that will consequently be paying higher coupons. This is referred to as duration risk. Second, corporate bonds are part of the business environment. The capacity of the issuing firm to be successful and to be able to honor its debt obligations is another determinant of prices. This is referred to as credit risk. Third, the functioning of the bond market itself plays a role. For corporate bonds in particular, difficulty trading has a considerable impact on the value of a bond. This is liquidity risk.

We combine the three sources of risk into one regression model[4]:

$$R_i(t) = a(t) - \mathrm{MD}_i(t) \cdot R^I(t) - \mathrm{DTS}_i(t) \cdot R^S(t) + \mathrm{LTP}_i(t) \cdot R^L(t) + u_i(t) \tag{1}$$

where $R_i(t)$ is the total return of Bond i at time t, $a(t)$ is a constant, $\mathrm{MD}_i(t)$ is the modified duration, $\mathrm{DTS}_i(t)$ is the duration-times-spread, $\mathrm{LTP}_i(t)$ is the liquidity-time-price and $u_i(t)$ is the residual. $R^I(t)$, $R^S(t)$ and $R^L(t)$ are the return components due to interest rate movements, credit spread variation and liquidity dynamics. They do not depend on the characteristics of the bond, but they vary over time. Then, it follows that $\mathrm{MD}_i(t)$, $\mathrm{DTS}_i(t)$ and $\mathrm{LTP}_i(t)$ are the sensitivity of Bond i with respect to the three risk factors $R^I(t)$, $R^S(t)$ and $R^L(t)$.

Let us analyze the rationale of each term in Equation (1). The impact of an interest rate movement on the bond return is equal to minus the duration times the interest rate variation in the first-order approximation. By regressing bond returns over the cross-section of modified durations, we can then estimate the implied return component $R^I(t)$ priced by the corporate bond market as a whole. The time series of $R^I(t)$ gives information on the duration risk factor.

We proceed likewise for the credit factor. The return due to an option-adjusted spread (OAS) is equal to minus the duration times the spread variation. By multiplying and respectively dividing the two terms by the spread level, the credit component becomes minus the DTS times the relative variation of the spread (Ben Dor *et al.*, 2007). This parametrization is justified by the observation that relative variations of credit spread adapt better to the Gaussian distribution than absolute variations of credit spread (Roncalli, 2013). Therefore, the DTS specification is better suited in a linear regression model.

[4] This linear model is developed in Appendix A in Page 58.

The third factor is related to the liquidity risk. However, as shown in Appendix A, liquidity risk is multi-faceted, implying that it is difficult to estimate. Here, we proxy bid-ask spreads by the liquidity score built by Ben Slimane and de Jong (2017). This measure is based on the characteristics of the bond indentures. The older a debt obligation, the wider the spread typically, or by the same token, the longer the time-to-maturity, the wider the spread. A total of seventeen characteristics have been identified and assembled by Ben Slimane and de Jong (2017), who found that these liquidity scores are highly correlated to bid-ask spreads. Therefore, we use the liquidity score times the bond price, denoted LTP, as a proxy of the illiquidity cost. Contrary to bid-ask spreads, this measure has the advantage of being calculated at each date. We can then estimate the implied liquidity return priced by the corporate bond market.

Compared to the standard practice, this is a parsimonious model with only three risk factors. We could specify interest rate movements by a set of two or three factors capturing translation, rotation and twist risks. In case where several currency zones are involved and thus several interest rate curves, the number of factors multiplies accordingly. By specifying a single factor as we do, we limit the eligibility of our model to a single currency zone, and we reduce yield movements to vertical shifts. This is admittedly very schematic. Practitioners usually specify credit risk by multiple factors, one per economic sector or one per credit rating. The single factor we define is set to give a global account of how the risk of credit events – rating migration, default and correlation shocks – is priced over time. In our model this factor is represented by a normalized credit spread curve that can shift up or down. The liquidity factor is set to capture the divergence in price behavior between relatively liquid and illiquid bonds. This factor is less frequently integrated into bond risk models in practice, probably because of the difficulties in acquiring the data for doing so. In all, the model is a parsimonious way of specifying conventional bond risks, which leaves the maximum space for introducing alternative risk factors.

2.3 Traditional model estimation

Following Fama and MacBeth (1973), the model is estimated by cross-sectional regression since the factor loadings are specified. This is the standard approach to estimate the risk premium of risk factors. This method is particularly suited for bond data, since it circumvents the condition of stationarity that is required for considering time-series regression. This condition does not hold for bonds in principle because the risk profile fades in time. The model is estimated on a set of bonds that are denominated in one and the same currency. We have opted for the euro in this article, and report in the appendix that the tests run on dollar-denominated bonds lead to very similar estimation results.

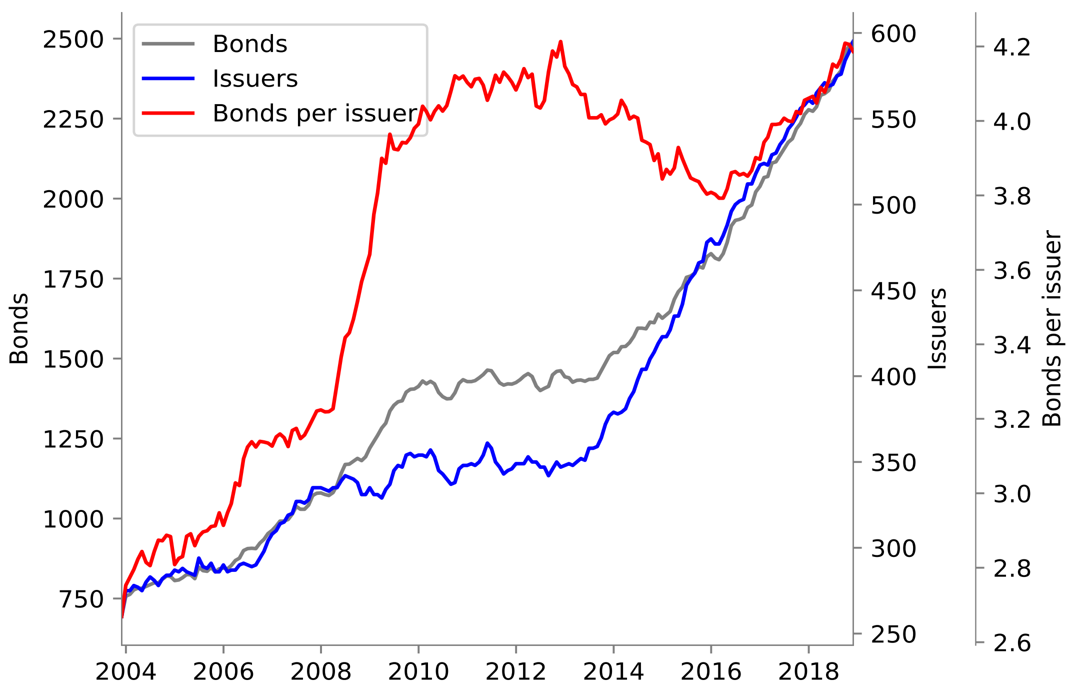
The database we use is constituted by selecting all bonds denominated in euros from the Intercontinental Exchange Bank of America Merrill Lynch (ICE BofAML) Large Cap (Investment Grade) Corporate Bond Index on a monthly basis from November 2003 through to November 2018. We use the individual bond returns, modified durations, credit spreads, yields-to-maturity and the sector classification as provided by the data vendor[5], and we calculate liquidity scores using the methodol-

[5]Source ICE Data Indices, LLC ("ICE DATA"), is used with permission. ICE DATA, its affiliates and their

ogy developed by Ben Slimane and de Jong (2017). These scores are built on the data underlying the Bloomberg Barclays Multiverse Bond Index in combination with bid-ask spread quotes retrieved from Bloomberg.

We make use of the returns in excess of the government-bond returns of similar duration, thus only reflecting the credit component of the corporate bonds, not the interest-rate component. We do this to be in line with the studies that we review which are carried out on the excess returns as well. And more importantly we want to concentrate on the credit component in the investment strategy that we build. As we explain in section 4, we will hedge out the interest-rate, or duration component by means of a derivatives overlay. Further references to *excess return* or *credit excess return* in this study will be referring to this credit component of return, not to be confused with the also widespread notion of excess return over a benchmark return.

Figure 1: Constituents of the euro corporate bond index



Source ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

To give an idea of the universe's size, the database contains 6 008 distinct bonds issued by a total

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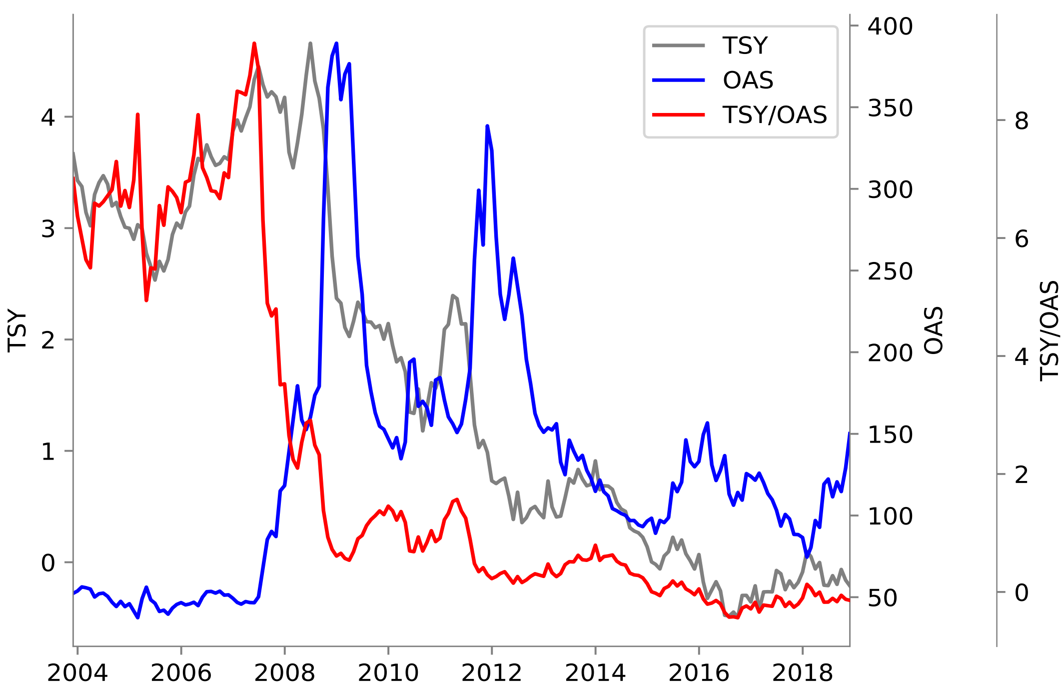
of 1 096 issuers. In Figure 1, the number of bonds and their issuers in the (euro) index are displayed over time. It shows that the composition has expanded by a factor three over the last fifteen years. The same figure shows the ratio of bonds per issuer. Note that this ratio has increased gradually over time and has stabilized after 2010, as can be seen, hinting at a maturing of the bond market since that date. At the same time, we have also constituted a database of bonds denominated in US dollars, selecting from the same global market index, and we have repeated all the same analysis on that data. In the Appendix C on Page 64, the main test results that we present are provided for USD-denominated corporate bonds.

2.4 Lessons from our traditional risk factor model

The risk factor returns $R^I(t)$, $R^S(t)$, $R^L(t)$ have been extracted from the known factor loadings and the credit excess returns from the ICE BofAML Large Cap Investment Grade Corporate Bond Index components, namely with Equation(1).

Figure 2: Evolution of EUR treasury yields and credit spreads



Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

We are interested to illustrate the explanatory power of this traditional model. We split the analysis period into two periods: 2003 to 2008 and 2009 to 2018. Figure 2 shows the evolution of treasury yields and credit spreads. Interest rates on government bonds have been at all-time lows following the 2008 financial crisis leading the OAS component to have a more important place in terms of explaining a corporate bond yield. The ratio treasury yield to OAS points out this magnitude.

As we are motivated by a description of the market environment for factor investing, we use a similar methodology as developed by Bennani *et al.* (2018b) on the analysis of ESG as an exogenous factor within a global equity universe. We start by analyzing the traditional risk factor model against a simple bond market risk premium which we assimilate to CAPM. The risk factor returns $R^I(t)$, $R^S(t)$, $R^L(t)$ have been re-injected in the traditional regression model.

The regression models are:

$$\text{CAPM: } R_i(t) = \alpha_i^C + \beta_i^{MKT} R^{MKT}(t) + \varepsilon_i^C(t) \quad (2)$$

$$\text{TRAD: } R_i(t) = \alpha_i^T - \beta_i^{MD} R^I(t) - \beta_i^{DTS} R^S(t) + \beta_i^{LTP} R^L(t) + \varepsilon_i^T(t) \quad (3)$$

where $R_i(t)$ is the excess return of Bond i at time t, α_i^C and α_i^T are constants, $R^{MKT}(t)$ is the market excess return and $\varepsilon_i^C(t)$ and $\varepsilon_i^T(t)$ are the residuals.

Table 2: Comparison of CAPM and the traditional factors

2003-2008	*Average* R^2(%)	VIF	$Hit - ratio$ (%) MKT	DTS	Duration	Liquidity
CAPM	48.51		81.8			
TRAD	56.74	3.93		64.8	19.81	44.83
2009-2018	*Average* R^2(%)	VIF	$Hit - ratio$ (%) MKT	DTS	Duration	Liquidity
CAPM	59.35		94.11			
TRAD	52.58	3.61		72.58	21.84	24.62

Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

The R^2, the variance inflation factor (VIF), which measures the multi-collinearity of the exogenous variables (O'Brien, 2007) and the hit-ratio, which quantifies the percentage of statistical significance at 95% confidence level of a given independent variable, are calculated as we first want to understand if the traditional factor setting makes sense. Through both periods – as displayed in Table 2 – we confirm that with hit-ratios over 50%, DTS is an outstanding risk factor and the VIF level indicates a low collinearity between factors of the traditional model. Most importantly, we observe that during the first period between 2003 and 2008, the R^2 of the traditional factor model is superior to the simpler CAPM. However after 2008, the traditional factor model carries less explanatory power than the simpler CAPM. This surprising result points our attention towards what we should expect from the addition of alternative factors: we want to augment the factor approach's explanatory power while controlling for redundancies.

3 Alternative corporate bond factors and multi-factor framework

3.1 Alternative corporate bond factors

Inspired by the recent articles on bond factor investing, we focus on four alternative risk factors in this study: low risk, momentum, size and value. Compared to the list of style factors that prevail in the equity space, we are missing out on the quality factor. We are aware that it is not straightforward to define such factor for corporate bonds. Quality is associated with a high profitability and low leverage, and, since quality firms are low-debt companies a priori, they mechanically represent a small portion of outstanding corporate debt. In itself it can make sense to tilt a bond portfolio towards a quality pattern, as evidenced by de Jong and Wu (2014) as well as de Jong and Stagnol (2016). However, the construction of an investible quality portfolio is not trivial and preliminary test results seem unconvincing (Belmiloud, 2016).

In this section we start with the same test setup as in the four previously mentioned studies, thus running percentile tests factor by factor. At the end of each month, bonds are ranked according to style scores, equally-weighted percentile portfolios are built, and the performance over the next month is calculated. The systematic monthly rebalancing and the equal-weighting regime that we replicate would be difficult to put in practice, we reckon, however the objective here is merely to investigate if the factors seem promising from a theoretical standpoint. This is what the decile tests[6] do, each decile portfolio containing about 100 bonds since 2006. The performance difference between the highest and lowest decile gives an indication of a theoretical alpha potential. Note that this setup is standalone, in that no connection can be made to asset pricing theory. We believe that it is necessary to go one step further and distinguish between systematic and residual risk, analyze the redundancy or complementarity between factors.

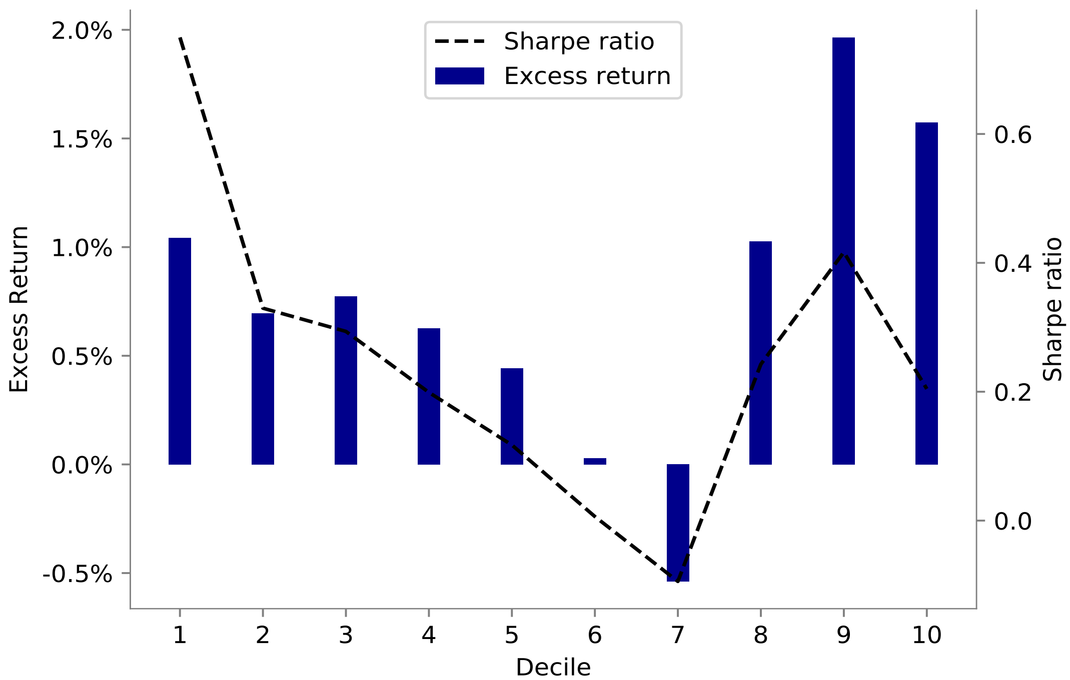
3.1.1 Low risk

In order to define a low-risk factor we follow Ilmanen (2011) and Houweling and van Zundert (2014), who both mix bond duration and credit rating data. The shorter the duration and the higher the rating, the lower the risk of the bond. When sorting bonds based on these criteria we obtain deciles that are ranked in terms of return and inversely in terms of risk-adjusted returns (Sharpe ratios), as can be seen in Figure 3. Low-risk bonds systematically perform less than high-risk bonds. However, when looking at the Sharpe ratios, we conclude that low-risk bonds offer the best risk-return trade-off. This result corroborates with the low-beta anomaly described by Frazzini and Pedersen (2014), who contend that low-risk assets have a better Sharpe ratio than high-risk assets. From our point of view, the time-varying exposures of the long short low-risk factor displayed in Figure 4 are an eminent illustration of a short DTS risk. The time varying exposure of Low risk on DTS is persistently negative. We inevitably end up comparing near-cash with long-duration low-graded bonds which

[6] With the exception of Israel *et al.* (2018) who run quintile tests

results in the low-risk factor being a "bad-times" factor as we highlight in Figure 5. We ignore this bond convexity issue in a linear factor framework, therefore we discard this factor.

Figure 3: Low risk - Excess returns and Sharpe ratio



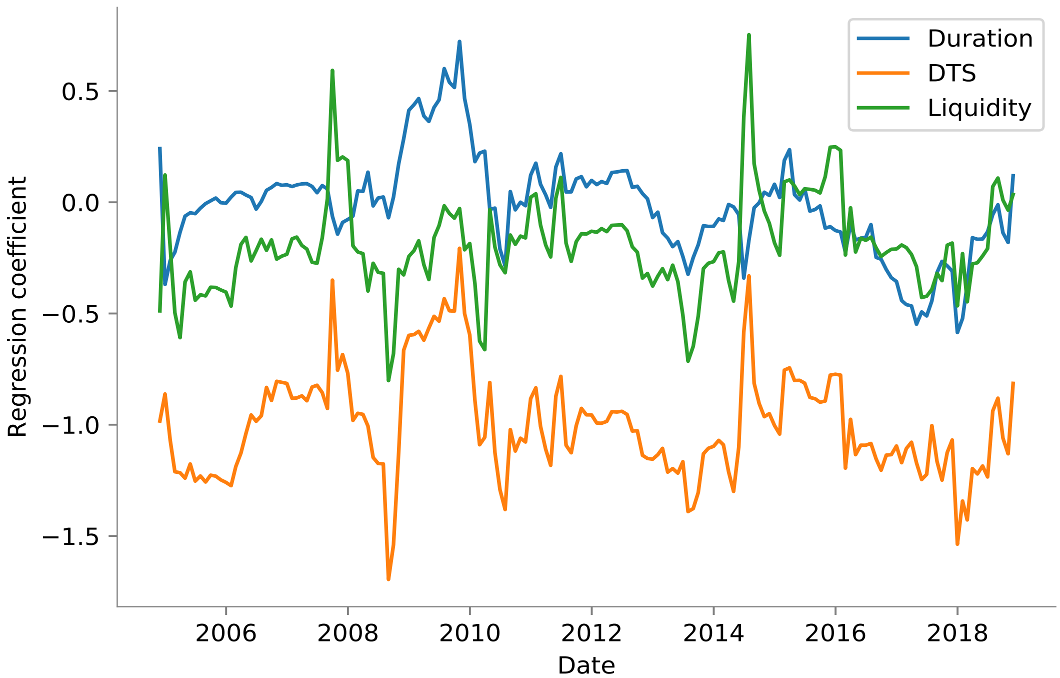
Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

3.1.2 Momentum

Turning to momentum next, whereas the existence of a cross-section momentum effect is extensively documented for equities (Jegadeesh and Titman, 1993; Carhart, 1997), few studies have been carried out on bonds, and the sporadic results that are reported in the literature are generally negative. Gebhard *et al.* (2005b) conclude that "*investment grade corporate bonds do not exhibit momentum at the three-to-twelve-month horizons; rather there is evidence of reversals*". Pospisil and Zhang (2010) confirm this, as do Jostova *et al.* (2013), who find that momentum profits only play up in high-yield bonds. For investment-grade bonds Pospisil and Zhang (2010) exhibit more of a reversal pattern.

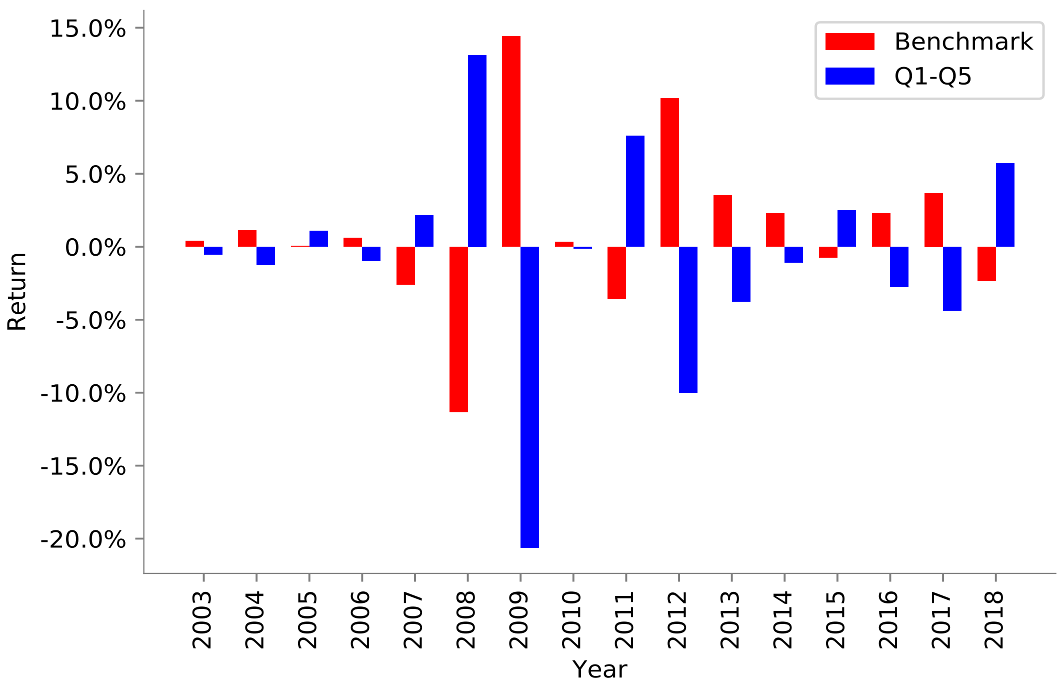
Using momentum scores based on six-month trailing bond returns, we obtain test results that are given in Figure 6. To be precise, the returns are measured over the seventh to first month prior to the observation date leaving a one month lag for a short-lived reversal effect if there is one. We notice that the portfolio of the recent winners (D1) indeed outperforms the market. Yet, interestingly, the portfolio of the recent losers (D10) does well also. In other words, we observe a convexity in the performance with respect to the momentum ranking. We also note that the two extreme deciles

Figure 4: Low risk - Time varying exposure



Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

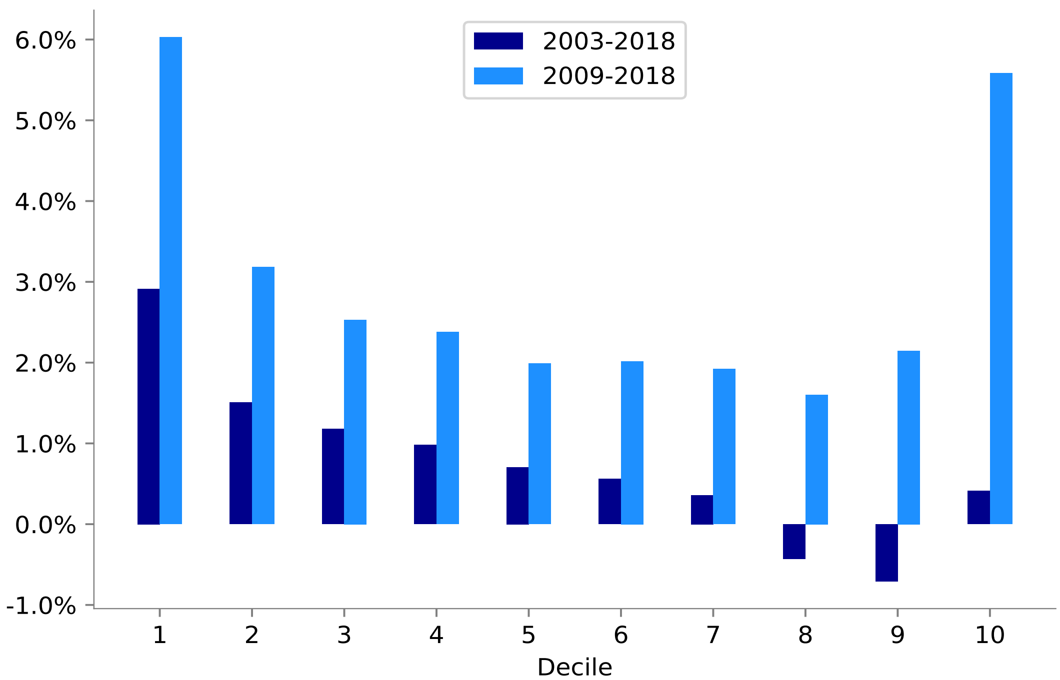
Figure 5: L/S Low risk - calendar returns



Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

(D1 and D10) embed more traditional credit risk as measured by the Duration-Times-Spread (DTS) measure (Ben Dor *et al.*, 2007), more duration risk and more liquidity risk (see Table 3). The habitat probability, defined as the probability of remaining in the same decile the next month, exhibits also a convexity with respect to the momentum ranking, peaking when a bond belongs to D1 and D10.

Figure 6: Momentum excess returns



Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

These results call into question if corporate bonds exhibit strictly a momentum effect, or a combination of momentum and reversal. If we look more closely at the deciles, most of the time corporate bonds seem to exhibit a momentum pattern, but on few occasions they face a strong reversal. Focusing on the D10 decile we notice that its return distribution is highly risky and skewed, as the good performance of this decile seems to stem from some particular dates of trend reversal.

In addition, when bonds are ranked by their past credit excess returns, the longest-duration and lowest-rated bonds which typically have significant fluctuations in returns, will mechanically end up in the top and in the bottom decile. These bonds have large price swings when comparing over the cross-section. The price swings are not necessarily large with respect to their own past. It is not clear whether the top and bottom deciles constructed in this way are populated by bonds with genuinely high and low momentum, however we can consider that they are populated by the riskiest bonds according to the specifications of our traditional risk factor model.

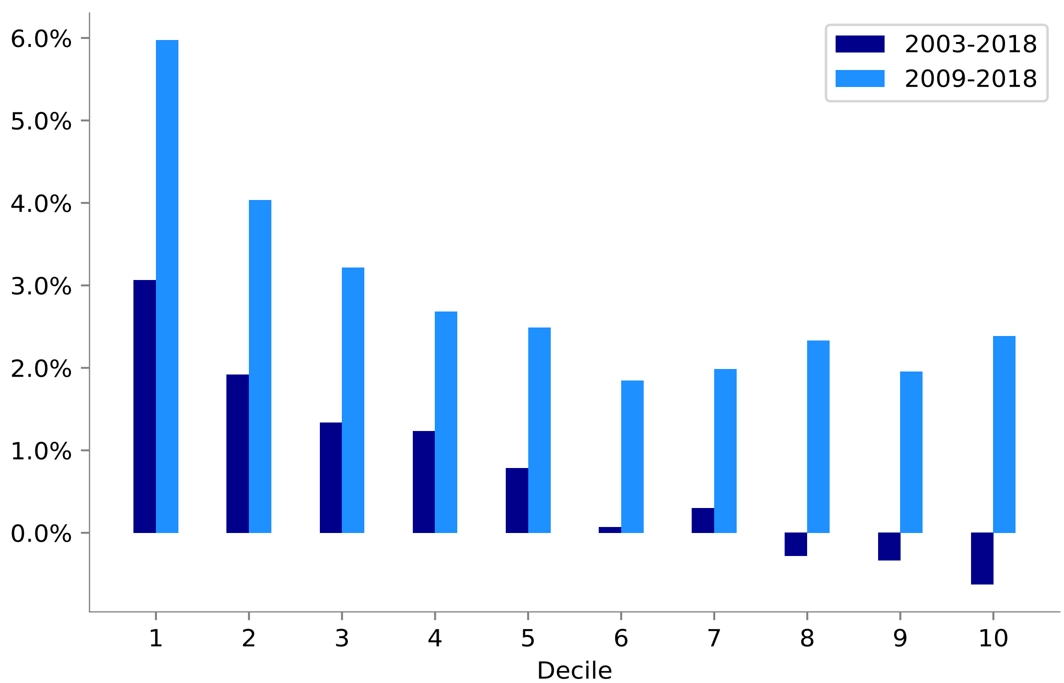
[7]DTS, duration and liquidity are respectively the weighted average DTS, duration and liquidity of bonds belonging to the decile. cf. appendix A

Table 3: Momentum metrics - 2003-2018

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Return(%)	2.91	1.50	1.18	0.98	0.71	0.56	0.36	-0.43	-0.71	0.41
Volatility(%)	5.84	3.03	2.36	2.26	2.22	2.50	2.94	4.26	6.54	**13.89**
Skew	0.54	-0.38	-0.35	-0.89	-1.23	-1.76	-1.67	-1.67	-0.63	**0.26**
Sharpe	0.50	0.50	0.50	0.43	0.32	0.22	0.12	-0.10	-0.11	0.03
DTS [7]	912	624	527	482	473	483	512	580	702	**1082**
Duration	4.99	4.71	4.5	4.36	4.33	4.32	4.33	4.42	4.60	5.40
Liquidity	3.74	3.35	3.19	3.09	3.05	3.01	2.98	2.99	3.05	3.59
Habitat(%)	**62.6**	39.4	31.0	27.8	26.5	26.3	28.2	32.0	39.7	**65.2**

Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

Figure 7: Amended momentum excess returns



Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

In order to rectify the flaw we highlight, we define a momentum per issuer and we rescale the returns by dividing them by the spread duration[8].

$$\text{Amended momentum} = \frac{\text{Compounded average weighted excess returns} - 1}{\text{Average weighted spread duration}} \tag{4}$$

The amendment seems effective, as can be seen in Figure 7, in that the decile returns are now all aligned from high momentum D1 down to low momentum D10. This demonstrates a genuine momentum effect: recent winners outperform recent losers. We do not exclude the fact that stale prices are at stake which are due to a deteriorated market liquidity situation in the context of the ECB's quantitative easing program. The momentum effect may in part also stem from herding behavior among bond managers who tend to get in and out of investment positions following their momentum.

With our definition of momentum, we find that the liquidity cost (see Table 4) and duration are slightly increasing with the deciles. DTS and habitat exhibit the same convexity with regard to the ranking. The last decile (D10) remains risky with regards to the traditional risk factor model.

Table 4: Amended momentum metrics - 2003-2018

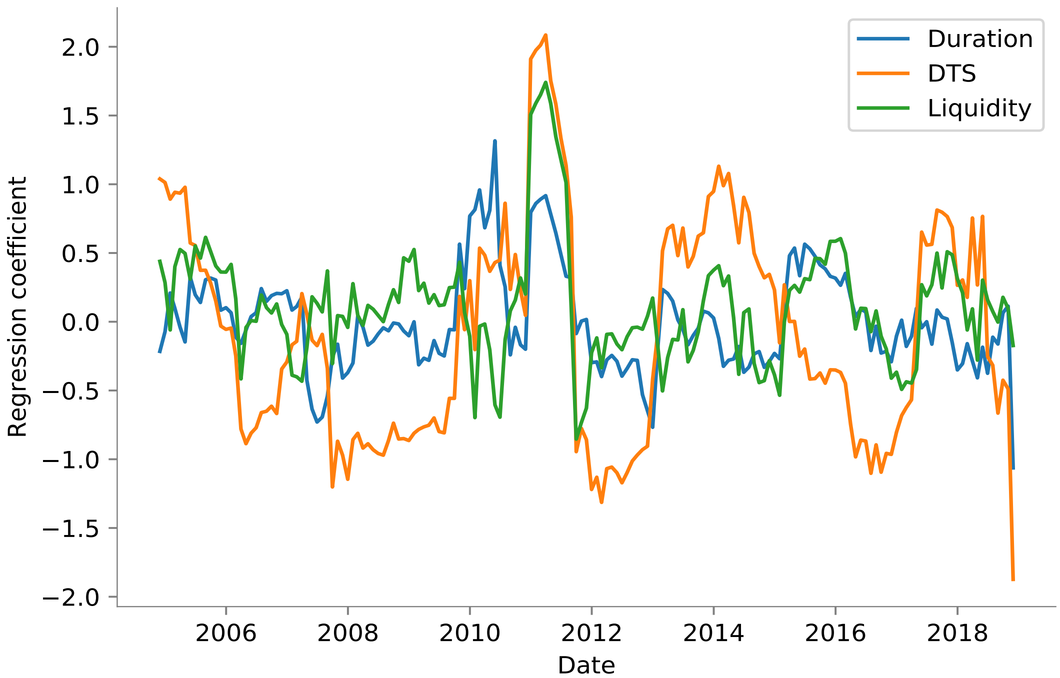
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Return(%)	3.06	1.92	1.34	1.23	0.79	0.07	0.30	-0.28	-0.34	-0.63
Volatility(%)	5.20	3.47	3.16	2.50	2.68	3.37	3.37	4.91	5.38	8.96
Skew	0.88	0.68	0.09	0.32	-1.04	-3.13	-0.26	-2.05	-0.69	-0.75
Sharpe	0.59	0.55	0.42	0.49	0.29	0.02	0.09	-0.06	-0.06	-0.07
DTS	750	652	614	580	593	600	621	638	697	896
Duration	4.13	4.37	4.48	4.64	4.75	4.9	5.04	5.07	5.13	5.04
Liquidity	3.01	3.04	3.13	3.19	3.25	3.27	3.31	3.28	3.26	3.24
Habitat(%)	54.6	34.5	28.1	24.8	23.2	23.2	23.8	26.5	34.4	56.8

Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

We illustrate in Figure 8 that the interrelations between our momentum and our traditional factors are not static. We run 12-month rolling regression between the quintile long short momentum and the premia from the traditional factors as expressed previously. The regression coefficient with DTS in particular has shown swings into the negative territory. This illustrates the diversification potential of the amended momentum which is attractive for hard-times in the credit market. We retain the amended specifications for defining bond momentum in the multi-factor strategy we present later.

[8]This definition fixes the flaw in both EUR and USD universes. Scaling the bond returns instead of the issuer weighted average return by the spread duration does not produce the desired effect in the USD universe

Figure 8: Amended momentum - Time varying exposure



Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

3.1.3 Size

In order to test a size effect, we follow Houweling and van Zundert (2014), who measure the size of a bond by the total debt value of the issuing firm. The data are thus aggregated from issue to issuer level before building the deciles. Again, we obtain mixed test results. After 2008, we observe a decreasing relationship for the D2 down to D10 deciles, meaning that small issuers tend to outperform big issuers (Figure 9), however the effect is not significant over the entire period. We also notice that the first decile which contains the smallest issuers, is an outlier. It produces low returns. In fact, we find a mid-cap effect rather than a small-cap effect. In-line with Houweling and van Zundert (2014) who found the alpha of the long short size factor to be rather weak.

3.1.4 Value

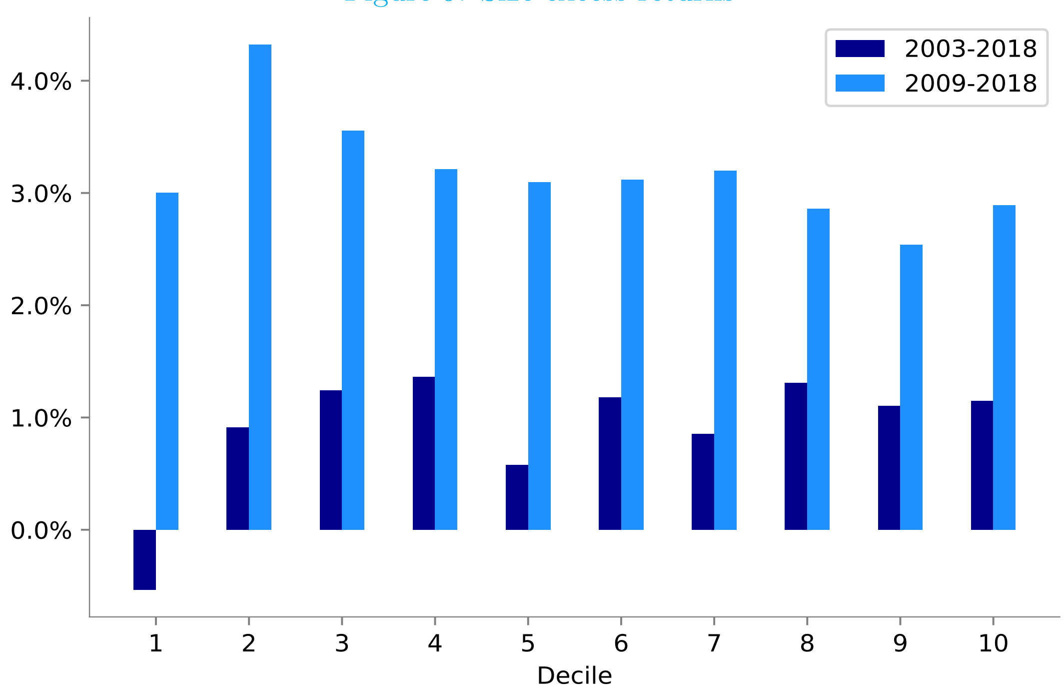
Different approaches have been taken to define cheapness in the credit market. The underlying idea of a value factor is to detect whether bonds are over or undervalued with respect to the market average, and to see if the level of valuation influences the return behavior. Most of them are trying to model spreads or changes in spreads. Attempts have been made to import results from the equity space by restricting the bond universe to issuers with listed equity and saying bonds of these issuers are cheap if the equity is cheap. Another example is Correia *et al.* (2012) who model the default probability of an issuer explicitly, but add that "*credit spreads are a function of more than just*

Table 5: Size metrics - 2003-2018

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Return(%)	-0.53	0.91	1.24	1.36	0.58	1.18	0.85	1.31	1.10	1.15
Volatility(%)	5.06	4.38	4.15	3.70	3.18	3.42	2.94	3.16	2.92	3.94
Skew	-2.42	-0.68	0.01	0.70	-2.00	-0.69	-0.74	-0.61	-0.97	-0.59
Sharpe	-0.11	0.21	0.30	0.37	0.18	0.34	0.29	0.41	0.38	0.29
DTS	846	741	700	664	616	592	588	590	551	624
Duration	4.59	4.52	4.51	4.64	4.71	4.72	4.83	4.61	4.63	4.62
Liquidity	3.57	3.59	3.64	3.57	3.57	3.49	3.43	3.28	3.05	2.82
Habitat(%)	95.0	93.8	93.8	94.1	94.8	95.4	96.2	97.3	98.6	99.8

Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

Figure 9: Size excess returns



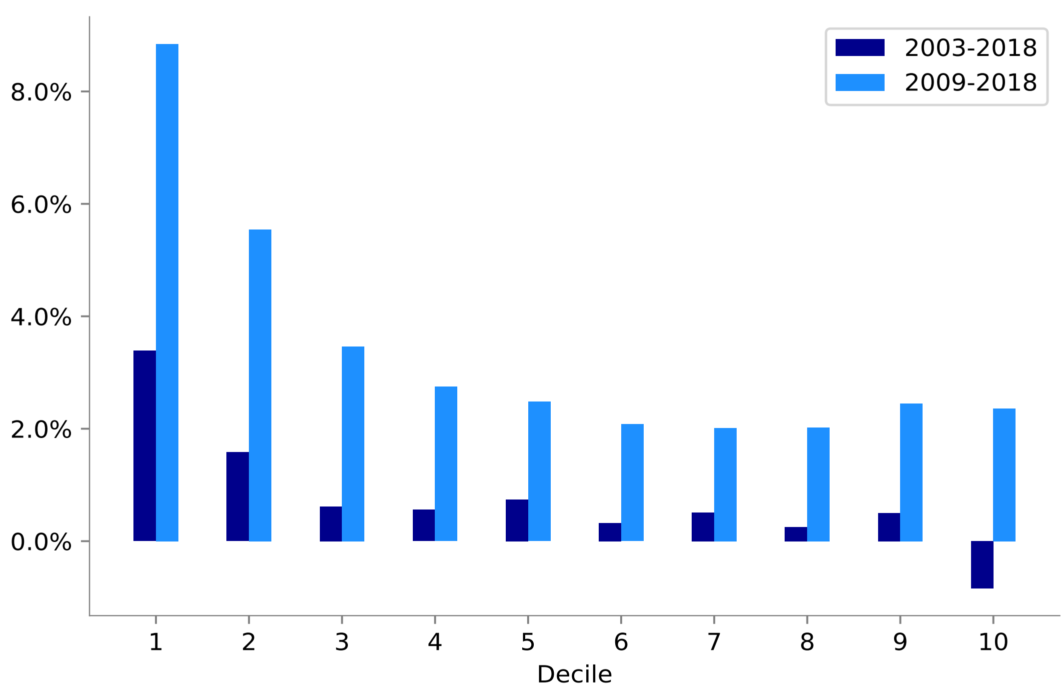
Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

physical default probabilities". Default probability models rely heavily on balance sheet data, which is published infrequently.

L'Hoir and Boulhabel (2010) have built a cross-sectional valuation model for spreads. They combine credit ratings, the economic sector classification and subordination levels in combination with more equity-specific measures. More recently in the factor investing literature, Israel *et al.* (2018) have found the default probability alone not to be the best proxy for value. They use a combination of rating, duration and the volatility level of bond excess returns. Houweling and van Zundert (2014) choose maturity, rating, and the 3-month change in spread for their cross-sectional regression. We test this valuation approach by performing linear regressions of the credit spreads onto these three explanatory variables. Value scores are defined by comparing the fitted credit spreads, which are interpreted as the fair values, with the observed market credit spreads. Specified in this way we obtain a clear ranking of the value deciles, as can be seen in Figure 10. Our tests confirm that indeed cheap bonds outperform expensive bonds generally, especially since 2009.

Table 6 shows that the first decile (D1) embeds a huge DTS risk and high volatility compared to the other deciles. No duration bias is observed among the deciles. This indicates that in average, D1 contains bonds with the highest spreads.

Figure 10: Value excess returns



Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

The Houweling and van Zundert (2014) value factor which we have analyzed avoids the drawbacks of using equity-specific or balance sheet data. However, they do not account for important systematic

Table 6: Value metrics - 2003-2018

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Return(%)	3.39	1.58	0.62	0.56	0.74	0.32	0.51	0.25	0.50	-0.84
Volatility(%)	10.08	6.09	4.08	3.17	2.65	2.63	2.49	2.85	2.95	4.98
Skew	1.37	-0.04	-0.97	-0.92	-0.47	-1.08	-1.43	-1.95	-1.63	-1.83
Sharpe	0.34	0.26	0.15	0.18	0.28	0.12	0.20	0.09	0.17	-0.17
DTS	1419	827	625	534	498	498	498	517	540	604
Duration	4.80	4.50	4.40	4.34	4.41	4.58	4.73	4.94	5.12	5.17
Liquidity	3.48	2.94	2.76	2.77	2.90	3.11	3.29	3.47	3.65	3.78
Habitat(%)	67.2	43.2	34.4	31.5	30.4	31.4	35.0	40.8	51.8	79.1

Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

features of corporate bonds (failing to account for the subordination level for example). This bears the risk that such a factor is selecting securities with a higher, but systematic spread and thus only increasing credit risk as opposed to exploiting idiosyncratic cheapness patterns.

We choose to focus on a value factor that explains the cross-section of spreads taken in logarithm, allowing as such for a larger variety of modelling of spread curves. We do not restrict the universe to issuers with listed equity and use only publicly-available bond-specific data. Our value factor stands out from the ones presented in the literature in that we try to capture as many systematic effects in the market as we can, accounting for the complexity of the securities in the credit markets. It does mean that the value factor needs to be tuned regularly over time in lockstep with the new developments in the credit universe. If new bonds are issued with specific covenants or features for example, these need to be taken into account as determinants of cross-sectional spread.

For our value factor we currently regress the option-adjusted spreads in logarithms on the time-to-maturities, the face values (both in logarithms as well), on Boolean variables for being callable and for being hybrid, as well as on dummy variables for sectors, credit ratings and regions, whereby certain sectors are subdivided into different subordination categories. Taking logarithms of the explained and explanatory variables appears to be innovative with respect to the existing literature. The advantage is that it allows for nonlinear spread curves which are actually often observed in practice. The regression allows us to calculate the implied spread which the bond should theoretically attain if only the features outlined above were determinant. Thus, we define the cheapness of the bonds as the residuals of this regression, or the difference between observed and implied spread. If we interpret the implied spread as the intrinsic value, this difference is the appreciation potential of the bond and therefore a suitable indicator for a value strategy.

The decile test results of our value definition are displayed in Table 7. It can be seen that the potential alpha it embeds is substantial. However, by doing the analysis this way, by construction, we will introduce bonds with high absolute spread levels into the portfolio. The question remains whether the investor is compensated in excess of this credit risk.

From Table 7, we understand that we have not altered the "smile" structure of the deciles' exposures to DTS risk. The probability of a bond remaining in this decile is 79.5%.

The time-varying exposures of the long short value factor displayed in Figure 12 reflect that our amended value displays positive exposure to DTS, however we identify that this relation can have high amplitude. As we did previously for our amended momentum specification, we retain these amended value specifications in the following multi-factor framework.

Table 7: Amended value metrics - 2003-2018

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Return(%)	3.72	1.56	1.15	0.81	0.66	0.49	0.31	0.08	-0.07	-0.23
Volatility(%)	7.73	4.48	3.38	2.83	2.42	2.52	2.25	2.36	2.59	4.46
Skew	0.36	-1.06	-1.1	-1.69	-1.48	-2.0	-1.29	-1.69	-1.57	-1.60
Sharpe	0.48	0.35	0.34	0.29	0.27	0.20	0.14	0.03	-0.03	-0.05
DTS	1342	851	667	563	510	501	491	497	503	700
Duration	4.78	4.85	4.67	4.55	4.52	4.65	4.73	4.80	4.76	4.71
Liquidity	3.27	3.09	2.97	2.94	2.98	3.10	3.22	3.35	3.39	3.48
Habitat(%)	79.5	54.8	44.0	39.7	38.2	39.5	42.9	48.9	59.8	82.8

Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

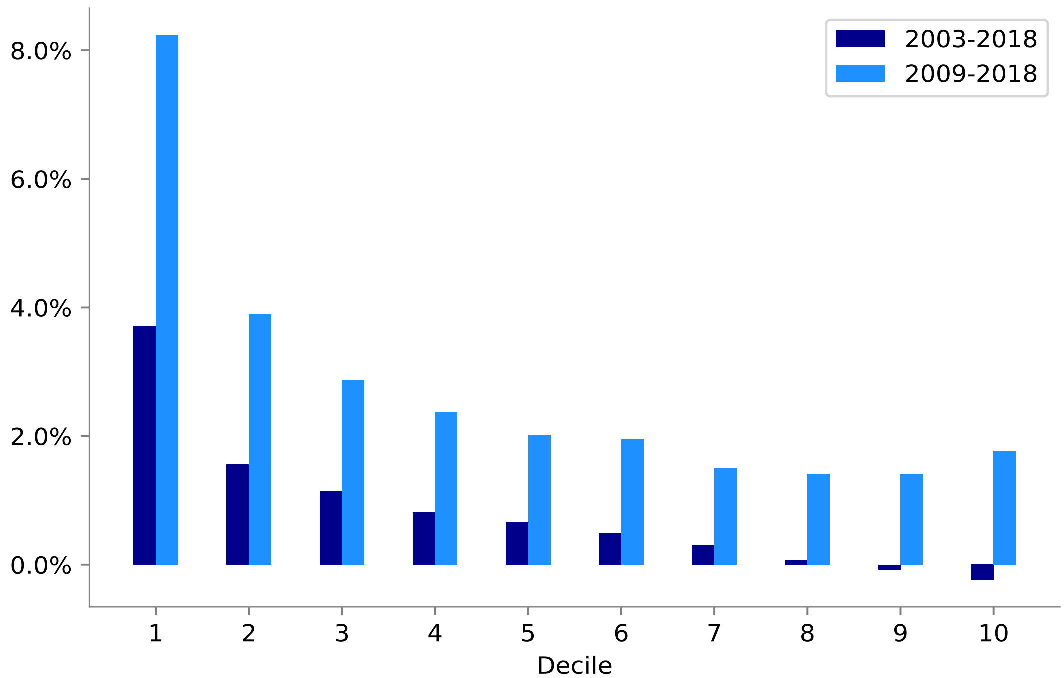
3.2 Navigating in a multi-factor framework

We have specified a traditional bond factor model in section 2. In this section, our aim is to level the field regarding traditional and alternative factors in the sense that we will analyze their explanatory power. We will keep the split of the analysis period in two periods: 2003 to 2008 and 2009 to 2018.

3.2.1 Traditional and alternative: how to make sense of the puzzle

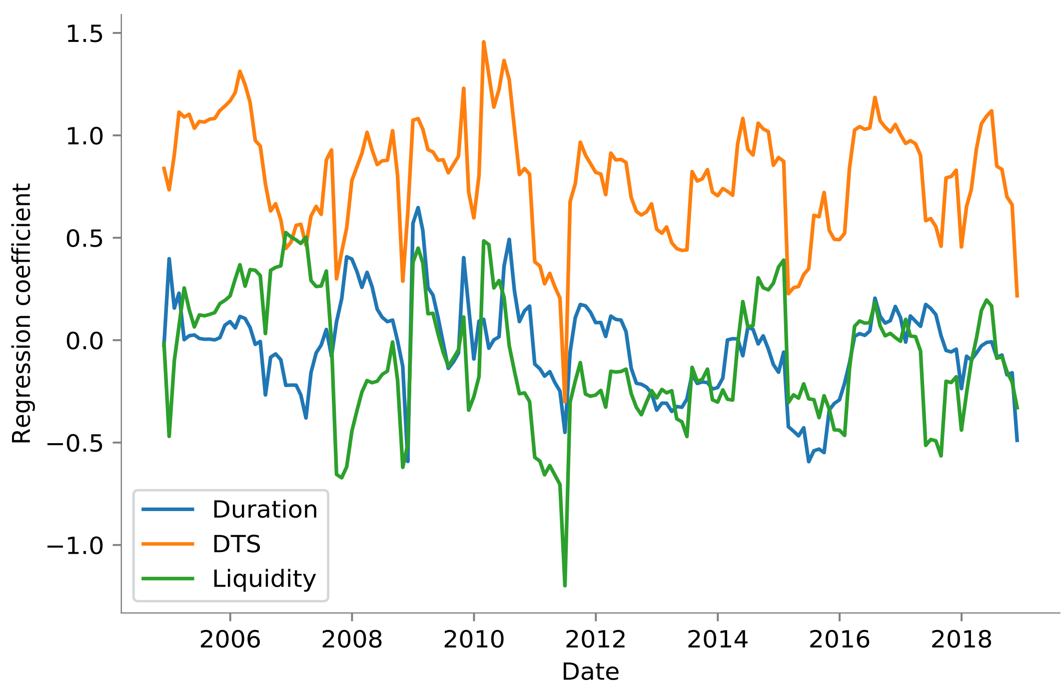
As we are motivated by a description of the market environment for factors investing, we continue our analysis with a similar methodology to the one developed by Bennani *et al.* (2018b) on the analysis of ESG as an exogenous factor within a global equity universe. In section 2, we calculated the R^2, VIF and T-statistics using the market as the only exogenous variable (CAPM model), and we compared it with cross-section multi-factor regressions considering the traditional factors (TRAD model). In this section we add the three alternative factors to obtain a six-factor model and we also

Figure 11: Amended value excess returns



Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

Figure 12: Amended value - Time varying exposure



Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

consider a five-factor model excluding the Size factor. We add the following regression models :

$$\begin{aligned}
\text{Five Factor:} R_i(t) &= \alpha_i^F - \beta_i^{MD} \cdot R^I(t) - \beta_i^{DTS} \cdot R^S(t) + \beta_i^{LTP} \cdot R^L(t) \\
&\quad + \beta_i^{HML} \cdot F^{HML}(t) + \beta_i^{WML} \cdot F^{WML}(t) + \varepsilon_i^F(t) \qquad (5)
\end{aligned}$$

$$\begin{aligned}
\text{Six Factor:} R_i(t) &= \alpha_i^{SX} - \beta_i^{MD} \cdot R^I(t) - \beta_i^{DTS} \cdot R^S(t) + \beta_i^{LTP} \cdot R^L(t) \\
&\quad + \beta_i^{SMB} \cdot F^{SMB}(t) + \beta_i^{HML} \cdot F^{HML}(t) \\
&\quad + \beta_i^{WML} \cdot F^{WML}(t) + \varepsilon_i^{SX}(t) \qquad (6)
\end{aligned}$$

where $R_i(t)$ is the excess return of Bond i at time t, α_i^F and α_i^{SX} are constants, $\varepsilon_i^F(t)$ and $\varepsilon_i^{SX}(t)$ are the residuals, $F^{SMB}(t)$, $F^{HML}(t)$ and $F^{WML}(t)$ are the time-series of the long short factor returns for the size, value and momentum factors, respectively.

We observed in section 2 that during the first period 2003-2008, the R^2 of the traditional factor model is higher than the simple CAPM. However, after 2008, the traditional factor model carries less explanatory power than the simple CAPM. As such, we want to understand if the addition our alternative factors improves the factor approach's explanatory power.

Table 8: Comparison of CAPM, traditional factors and traditional factors augmented by alternative factors

2003-2008	*Average* R^2	VIF	*Hit − ratio* (%) MKT	DTS	Duration	Liquidity	*Hit − ratio* (%) Momentum	Value	Size
CAPM	48.51		81.8						
TRAD	56.74	3.93		64.8	19.81	44.83			
Six-Factor	73.09	15.05		43.62	7.14	45.07	46.11	38.49	37.93
Five-Factor	68.57	11.45		38.65	12.59	42.66	46.03	35.20	
2009-2018	*Average* R^2	VIF	*Hit − ratio* (%) MKT	DTS	Duration	Liquidity	*Hit − ratio* (%) Momentum	Value	Size
CAPM	59.35		94.11						
TRAD	52.58	3.61		72.58	21.84	24.62			
Six-Factor	64.44	10.8		44.03	24.31	23.46	27.66	21.08	24.81
Five-Factor	61.52	8.43		43.09	24.71	28.79	28.06	26.67	

Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

Table 8 shows that for the 2003-2008 period, the VIF which measures the multi-collinearity of the exogenous variables (O'Brien, 2007) is high for the six-factor model which consists of the three traditional and three alternative factors. There is collinearity between these variables for the 2003-2008 period. We note that the same VIF is improved for the 2009-2018 period, meaning that the collinearity between the traditional factors and the alternative factors has decreased.

With the addition of alternative factors, the six-factor model improves the explanatory power over the traditional factors for the 2009-2018 period with a R^2 of 64.4% and brings it over the explanatory power of CAPM.

We pay special attention to the five-factor model which uses amended specifications for momentum and value in the alternative factor bucket. We observe that the five-factor model has less collinearity than the six-factor model as measured by the VIF for both periods being considered.

With regards to statistical significance, DTS is strong within the traditional factor model for the entire 2003-2018 period but overall the significances of the factors are not outstanding. We conclude that statistical significance for factor investing in corporate bond requires additional research efforts. We therefore turn our attention to active management driven by factors within a lower factor intensity framework.

3.2.2 Picking within traditional and alternative factors

In order to identify the most pertinent explanatory variables of the benchmark excess return among the members of our six-factor model, we perform the LASSO[9] analysis method[10]. The LASSO, introduced by Tibshirani (1996) is a shrinkage and selection method for linear regression. It minimizes the residual sum of squares with a penalty on the sum of the absolute values of the coefficients.

$\widehat{\beta^{lasso}}(\tau)$, the LASSO estimate, is then defined by:

$$
\begin{aligned}
\widehat{\beta^{lasso}}(\tau) = \underset{\beta}{\operatorname{argmin}} \sum_{t=1}^{N} \Big(\frac{R_t - \bar{R}}{\sigma_R} - \sum_{j=1}^{6} \beta_j \frac{F_{t,j} - \bar{F}_j}{\sigma_{F_j}} \Big)^2 \\
\text{subject to} \sum_{j=1}^{6} |\beta_j| \leq \tau
\end{aligned}
\tag{7}
$$

where $\bar{R}$ and σ_R are respectively the average and standard deviation of the benchmark excess returns, $\bar{F}_j$ and σ_{F_j} are respectively the average and standard deviation of the factor returns.

If no penalty is set on coefficients, we end up with the ordinary least squares coefficients ($\widehat{\beta^{lasso}}(\infty) = \widehat{\beta^{OLS}}$).

If we constrain the coefficients, we induce sparsity in the estimate and cause some β_j to be exactly zero. The smaller the value of τ, the fewer the number of nonzero coefficients. Thus, this sparsity leads us to rank factors by their order of showing up(i.e.$|\beta_j| > 0$), when we vary $\tau^{\star}$[11] in the [0, 1] range.

[9] **L**east **A**bsolute **S**hrinkage and **S**election **O**perator

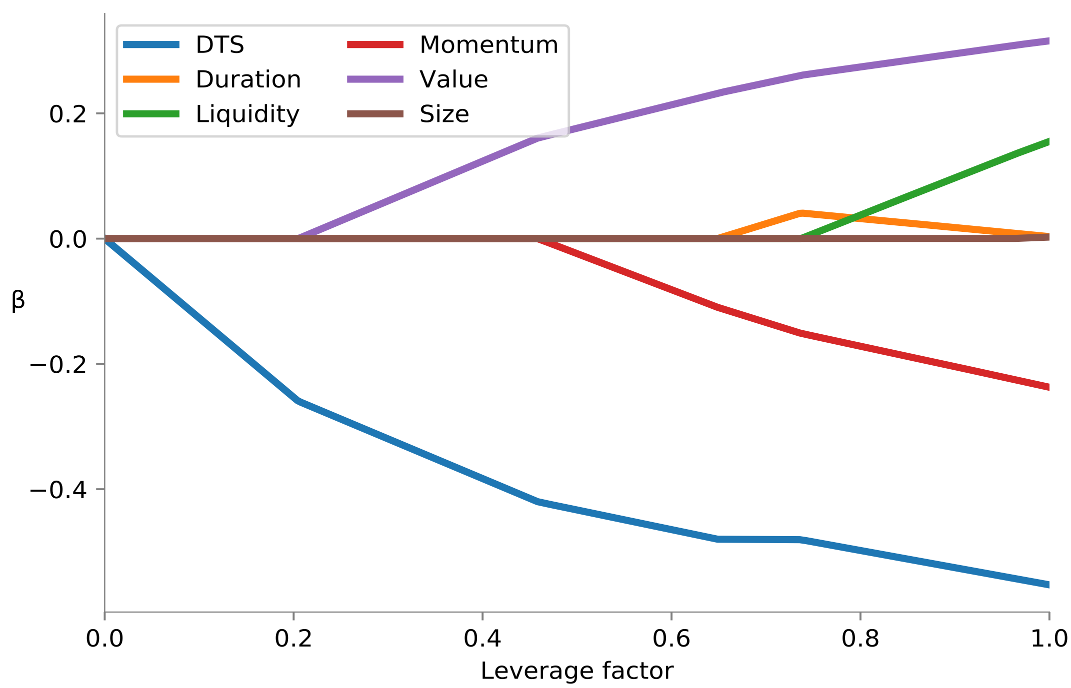
[10] In appendix B, we report the results of the LASSO analysis applied either to the time-series of excess returns of each bond of the benchmark or to the cross-section.

[11] We define the leverage factor: $\tau^{\star} = \dfrac{\tau}{\sum_{j=1}^{6} \left|\widehat{\beta_j^{OLS}}\right|}$

As mentioned earlier, the risk premiums of the credit, duration and liquidity factors are estimated using (1). As far as the alternative risk factors are concerned, we consider their long short quintile returns

Figure 13 shows that for the entire 2003-2018 period the most relevant explanatory variable is the duration-time-spread component. This gives some background to the industry practice to refer to the DTS as the credit beta. The value factor is the runner-up. Momentum is third. Duration, liquidity and size factor come last in this order. The size factor seems to have no effect and the effect attributed to duration is marginal and fades away with the incorporation of the liquidity factor. Interestingly, the regression coefficients related to the first three factors do not decrease in absolute values with the successive onboarding of value and momentum. Figure 14, which focuses on the 2009-2018 period, does not point either to any overlap between the three first factors and shows the same order of relevance with the last three factors having marginal effects.

Figure 13: LASSO regression analysis for 2003-2018



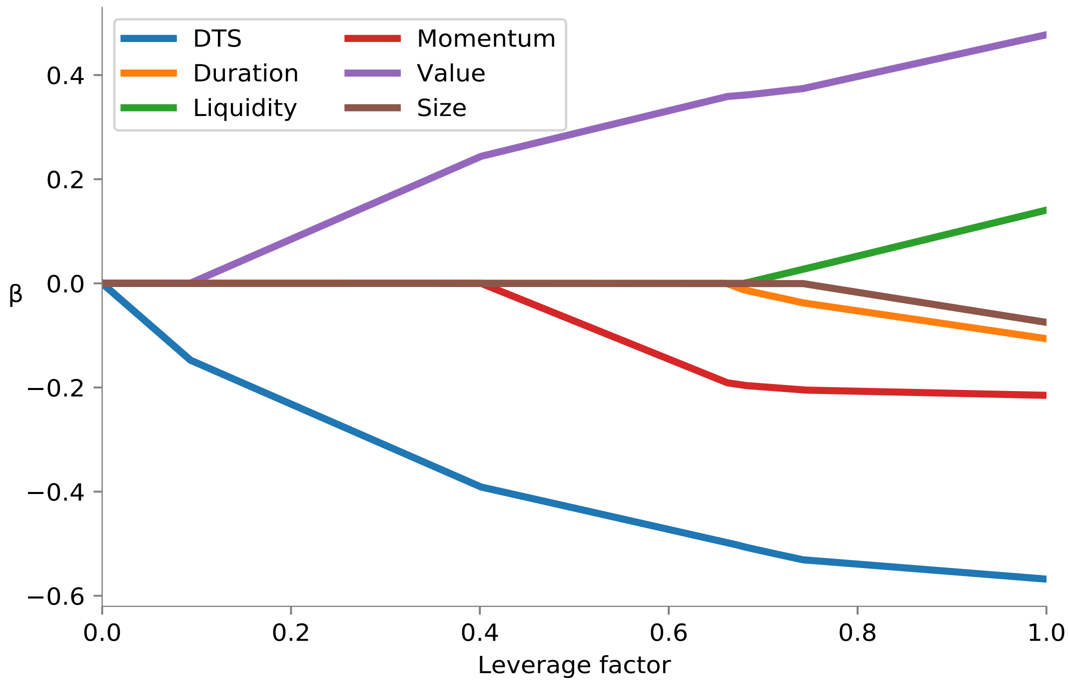
Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

The negative sign of DTS's beta is attributed to the minus sign in equation (1). Unsurprisingly, the betas related to value and liquidity are positive. However, the momentum's beta is negative for the entire 2003-2018 period and also for 2003-2008 and 2009-2018 periods. The sign of this sensitivity stems from the difference in credit betas, estimated by DTS, in favour of the short leg of the momentum factor. For reference, the average DTS in momentum's Q1 is 697 versus 791 in Q5.

Table 9 shows that the OLS regressions explain over 80% of the excess return variance in all.

The VIF of the entire period regression is 3.33 indicating a medium dependence between the six risk factors.

Figure 14: LASSO regression analysis for 2009-2018



Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

The LASSO analysis for factor picking solves the puzzle of selecting relevant factors in a low factor-intensity framework. We understand as reported in Table 9 that DTS remains an essential component of corporate bond factor management. Within the factors which have been described, value is the factor which improves the most in terms of factor picking ranking between 2003-2008 and 2009-2018. For the full 2003-2018 period, value and momentum's long short factor returns' time-series are significant in the ordinary least squares regression. Moreover, for the 2009-2018 period, if we have to select one factor to explain the euro corporate investment grade bond market, we would select DTS. If we want to select two factors, we would select DTS and our value factor. And if we want to select three factors, we would add our momentum factor.

Table 9: LASSO factor picking rank

	$R^2(\%)$	VIF	DTS	Duration	Liquidity	Momentum	Value	Size
2003-2008	91.93	6.19	1	3	4	2	5	6
2009-2018	87.14	3.83	1	4	5	3	2	6
2003-2018	81.48	3.33	1	4	5	3	2	6

Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

Table 10: Results of the time-series regression

2003-2018	Beta	Factor Picking Rank	T-statistic	P-value
DTS	-0.55	1	-9.20	***
Duration	0.00	4	0.06	
Liquidity	0.16	5	3.08	***
Momentum	-0.24	3	-6.51	***
Value	0.32	2	5.73	***
Size	0.00	6	0.06	
$R^2 = 81.48\%$ — $VIF = 3.33$				

Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

4 Implementing our alternative factors

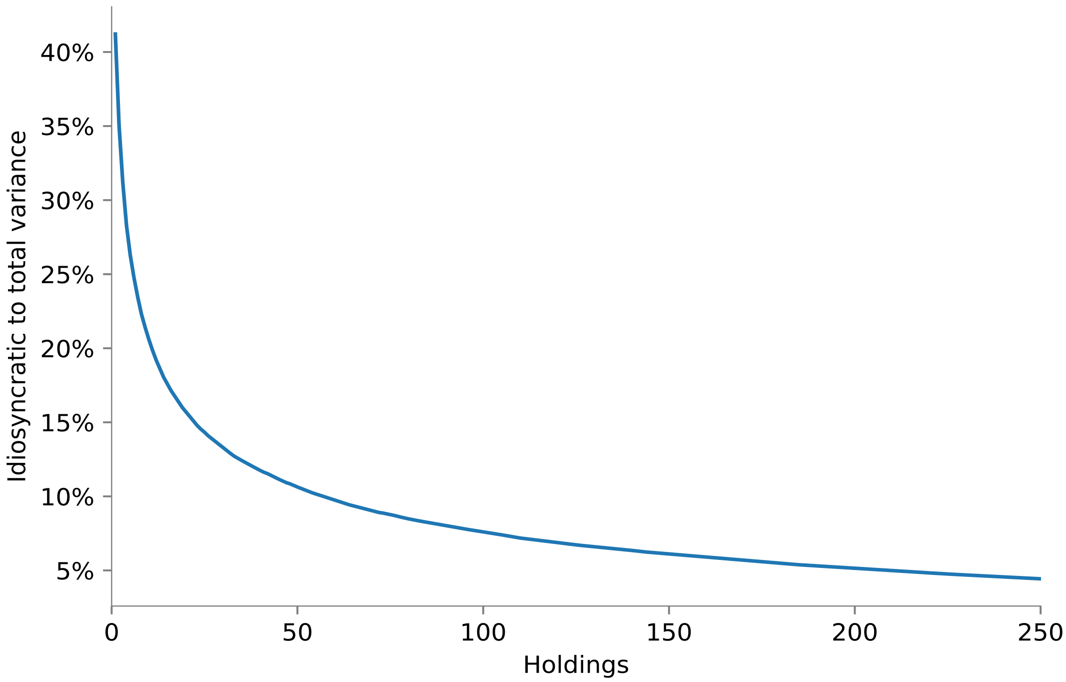
4.1 Using our alternative factors in an enhanced low risk approach

In this subsection, we elaborate the construction of an enhanced low-risk approach to confirm that the relevant alternative factors that we have identified can add value. Factor tilt is a way to make factor effects apparent. We neutralize the identified systematic component in the returns.

In order to demonstrate the speed of diversification as a function of the number of bonds in a portfolio, we carry out the following test. We randomly draw a limited set of bonds (N) from the market universe and compare their aggregate equally-weighted return with that of the market index. We measure how much of the return variance is explained by the common market factor simply by taking the ratio of the idiosyncratic return to the total return variance. For a given N we repeat this simulation experiment 3 000 times per month over the eighteen-year test period, so a total of 648 000 times. The sample averages are reported for N varying between 5 and 225, in Figure 15.

It can be seen that the idiosyncratic variance shrinks rapidly compared to the total variance when the number of portfolio holdings increases. A random portfolio containing 50 bonds contains less than 10% of idiosyncratic risk for EUR-denominated bonds, meaning that it is for the most part driven by common systematic price movements. The phenomenon amplifies importantly if we replace the naïve equal-weighting scheme by one where we deliberately neutralize the credit risk exposure of the portfolio. If we aim to match the DTS of the portfolio with that of the market index sector by sector, as few as five portfolio holdings leave 10% of idiosyncratic risk on average. The test results are comparable for dollar-denominated bonds.

Figure 15: Idiosyncratic-to-total variance of equally-weighted random portfolios



Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

As far as our investment strategy is concerned, the interest is to neutralize the traditional factors' component in the returns so as to concentrate on the part that is left over.

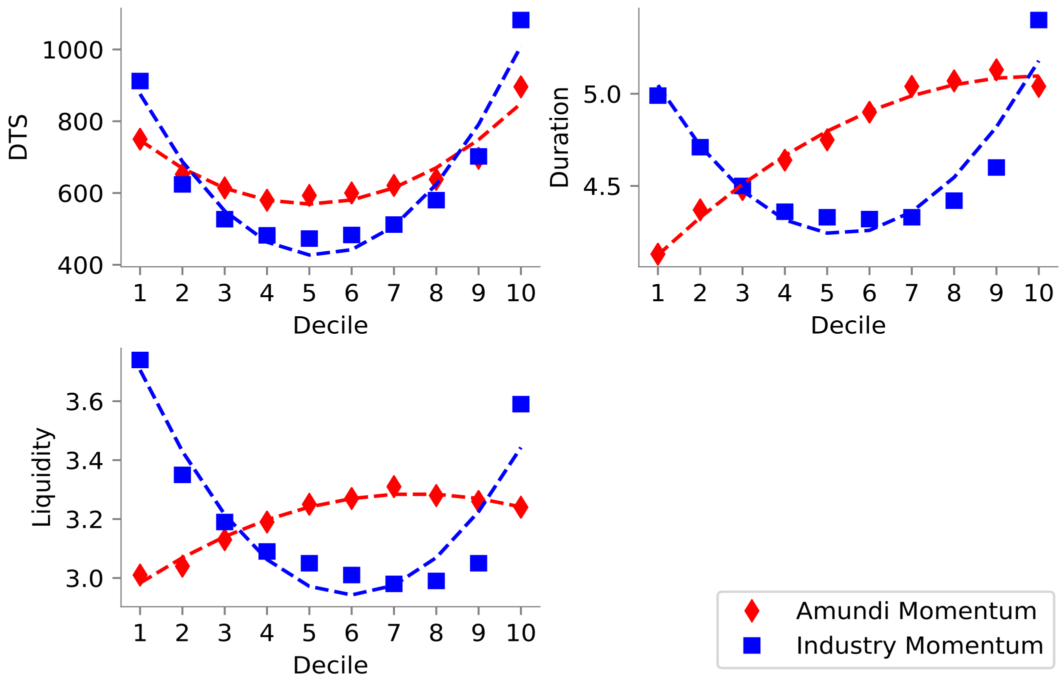
This implementation analysis is particularly welcome as we have identified in Figures 16 and 17 that the "smile" of momentum and value's DTS exposure implies that attractive deciles have high DTS. Although we have identified that the time-series of value and momentum does not reduce the beta of DTS when they appear in the Lasso regressions, we test the implementation of DTS-matched tilted portfolios.

4.1.1 Enhanced index design

To learn more following our single factor decile tests and multi-factor analysis, we adopt a method which Grinold and Kahn (1999) discuss in their book using what-they-call factor-tilted portfolios. We adapt the method they describe for equities to make it work for bonds. Hence, in an effort to isolate the particular bond pricing effects that may be attributable to size, value and momentum, we build size-, value- and momentum-tilted portfolios and run regression analysis tests on their return series.

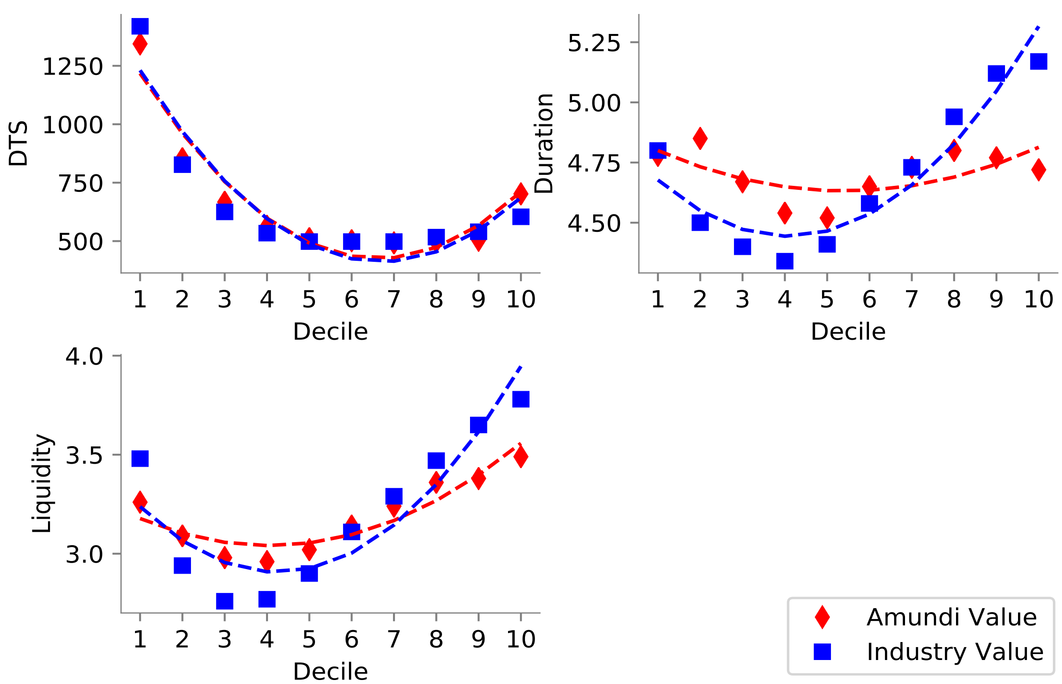
We build the tilted portfolios such that they are overweight towards the respective factors, while remaining neutral with respect to basic characteristics. Concretely, we make sure that the portfolios

Figure 16: Before and after Momentum exposures on traditional factors



Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

Figure 17: Before and after value exposures on traditional factors



Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

are stratified over the economic sectors in the market, meaning that they are sector-neutral, and that they possess the same DTS exposure per sector. It has been demonstrated, by Dynkin *et al.* (2007) in Chapter 5 of their book as well as by De Jong *et al.* (2014), that portfolios that are stratified in this way, have virtually the same return behavior as that of the market index. They effectively replicate the market as a whole.

We make note that building stratified bond portfolios is actually a complex combinatorial optimization problem. It requires a powerful search algorithm which is able to find (close to) optimal solutions. Building a style tilt into the portfolios adds to the complexity. And the problem becomes even more complex if implementation constraints are considered for the purpose of making the test portfolios more realistic to investing. In our tests, we have introduced three implementation constraints: (i) a cardinality constraint, limiting the number of portfolio holdings, (ii) a turnover constraint plus (iii) a liquidity constraint, making use of our liquidity scores.

The portfolio construction method we have built in-house relies on the technique of stratified sampling. It goes beyond the scope of this paper to describe the method exactly, but basically an initial portfolio is built at the start and then improved step by step by means of a local-search algorithm. At each iteration, a combination of bonds is selected that possess certain qualities. We build a portfolio per month in this way over the eighteen-year test period. In order to keep the turnover down we introduce a bonus-penalty system into the bond selection process, giving a bonus to those already held the previous month and applying a penalty for those that aren't. The search process is made manageable thanks to the stratification setup, i.e. dividing the market universe into subsamples that represent relatively independent sources of risk. In our procedures we rely on a division into seven sectors. Eventually we seek to represent the credit risk exposure of each sector.

The initial starting portfolios are created by applying a double screening that filters out (i) the least liquid bonds according to our liquidity cost scores, and (ii) the bonds that are lowest-ranked according to the style criterion. In particular, to build the size portfolio we discard the biggest bond issuers, to build the value portfolio we discard the expensive bonds, and to build the momentum portfolio we discard the recent losers. The tilt is thus introduced by discarding the lowest-ranked deciles. We build tilted portfolios with and without the implementation constraints. The interest of doing so is to test to what extent the outperformance that is made apparent in the tests, the alpha, is affected by the implementation constraints. This question of feasibility is much more important in the bond space than in the equity space, as trading in these instruments is cumbersome.

Naturally, the implementation constraints will reduce the alpha potential of the style factors. We make note that the full-sample portfolios contain approximately 2000 bonds on average, whereas the stratified portfolios contain around 130 bonds, which are picked so as to control the turnover. However, we are not in the position to verify more realistic implementation constraints in our backtests. On an ongoing basis for portfolios that we manage at Amundi we run through the buy-and-sell list we intend to carry out with our in-house traders who are able to assess their feasibility with respect to the actual market situation.

Since the tilted portfolios are built such that they possess stable features over time and therefore a stable price behavior, the conditions are met for carrying out time-series regressions. We regress the three portfolio returns, denoted T, over the market return (M) one by one by doing simple OLS regressions:

$$T(t) = \hat{\alpha} + \hat{\beta} M(t) + \hat{\epsilon}(t) \tag{8}$$

The regression results are presented in the next subsection. In these tests we have taken our factor specifications as described previously.

4.1.2 Results

The parameter estimates for the full-sample tilted portfolios are displayed in Table 11, as are the active portfolio return series, meaning $T_t - M_t$, for the three style factors. The estimated betas fall very close to one, indicating that the portfolios were indeed effectively neutralized and that the outperformances (alphas) are thus not driven by other tilts or unintended biases. The three alphas are positive for the period and are all statistically significant after 2008, which is an encouraging result. As such, we find that on an aggregate portfolio level, systematic pricing effects related to size, value and momentum exist and can in fact be captured. And we observe that taking on the risks related to these effects has been rewarded overall over the observation period.

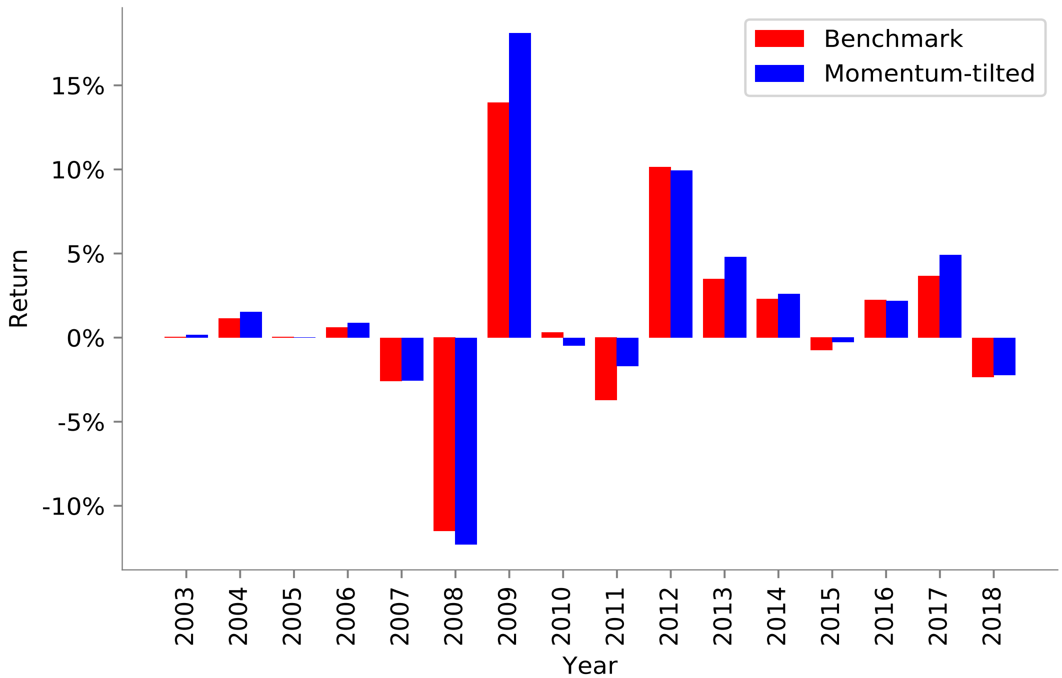
Table 11: Parameter estimates

2003-2008	Retained deciles	Alpha	Beta	T-stat	P-Value
Momentum	[D1,D2]	-0.02	1.00	-0.44	
Value	[D1,D8]	0.54	1.00	2.04	**
Size	[D2,D8]	-0.27	1.00	-0.77	
2009-2018	**Retained deciles**	**Alpha**	**Beta**	**T-stat**	**P-Value**
Momentum	[D1,D2]	0.78	0.98	2.70	***
Value	[D1,D8]	0.27	1.00	4.18	***
Size	[D2,D8]	0.18	1.00	2.91	***
2003-2018	**Retained deciles**	**Alpha**	**Beta**	**T-stat**	**P-Value**
Momentum	[D1,D2]	0.52	0.98	1.96	**
Value	[D1,D8]	0.39	1.00	5.21	***
Size	[D2,D8]	-0.00	1.00	0.27	

Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

It is interesting in itself that the size effect holds out after controlling for the traditional bond factors. As debt size is an important determinant for liquidity risk, one would expect the effect to cease after the liquidity screen. To us it means that the bid-ask-spread proxies that are used in the liquidity scores, capture one aspect of liquidity only, namely the level of trading costs, but not all aspects. The possibility to trade is another aspect and this is inherently related to debt size, i.e. to the amount of debt securities outstanding. In that respect the size factor may well be regarded as an auxiliary liquidity risk factor for corporate bonds. In addition, as our factor picking analysis in section 3 filtered value and momentum within the first three factors for the period 2009-2018, we will focus on these two factors.

Figure 18: Calendar excess performance of the Momentum tilted portfolio



Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

As to the momentum factor, its premium remains convincingly positive after neutralizing for traditional bond risk exposures, except for the 2003-2008 period (Figure 18). This provides evidence that momentum captures an authentic risk factor that is largely complementary to systematic bond risks. We make note that this result is actually achieved by holding the very recent winners. Holding recent winners in a momentum portfolio would generate far too much turnover for the strategy to be cost effective.

Interestingly the value premium also remains very positive after market-neutralization (Figure 19). It shows that taking on these cross-sectional credit risks as identified by our factor definition, pays off.

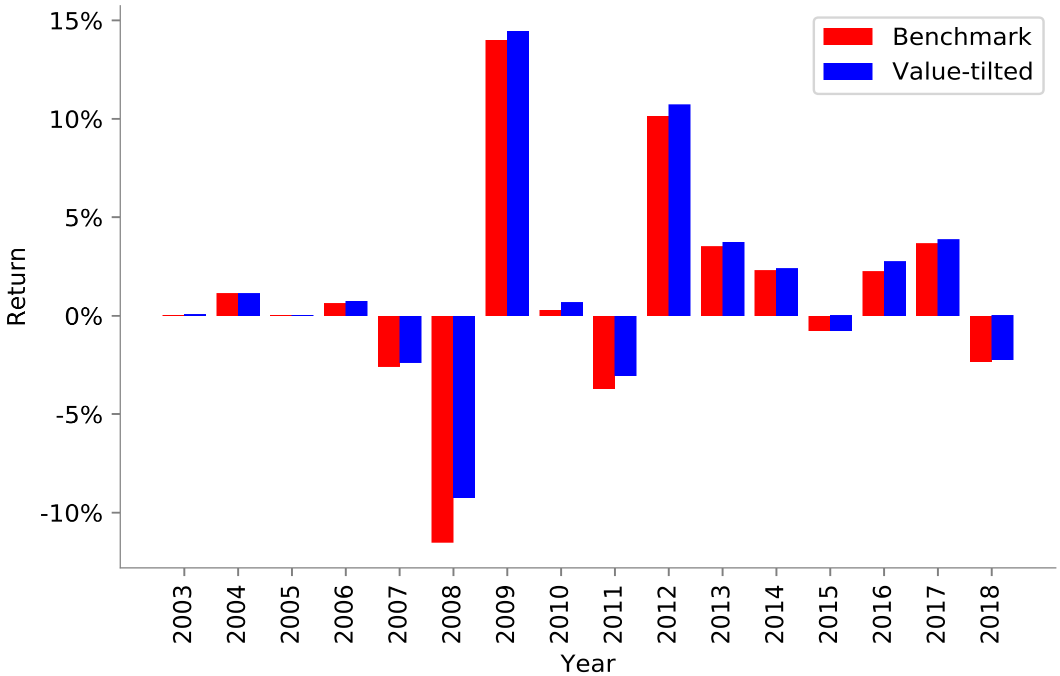
4.2 Combining our alternative factors in a rule-based active management approach

4.2.1 Rule-based active management design

In this subsection we describe the investment strategy that we have built based on the insights we gained. In a nutshell, we learned four things:

i) Systematic bond risks related to duration, credit risk and liquidity, are too dominant to ignore.

Figure 19: Calendar excess performance of the value tilted portfolio



Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

In a bond-factor investment strategy they must be proactively dealt with and are thus part of the design.

ii) We detect a significant value effect in corporate bonds that is compensated. A value strategy, when applied to corporate bonds, zooms in on cheapness opportunities. If not accounted for, this will automatically lead to an investment in higher than average spread securities and thus a high credit beta. However, one is compensated in excess of credit risk after adjusting for this systematic exposure.

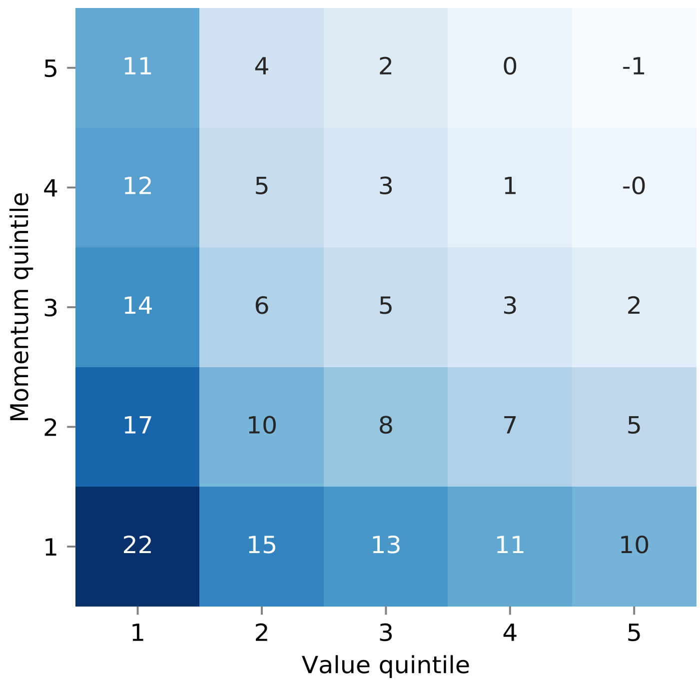
iii) We detect a significant momentum effect in corporate bond returns that is compensated. Since this strategy invests in bonds that have performed well, it will mechanically induce an exposure to lower-than-average spreads thus a lower credit beta, unless this bias is proactively corrected.

iv) And we find evidence of a size effect.

The investment strategy we build essentially plays on the value and momentum factors. It leads to a rule-based actively-managed portfolio that is fully invested in corporate bonds, which benefits from the performance opportunity that we detect thanks to our in-house valuation model and our momentum screening facility. As such, we make two types of factor portfolios on an ongoing basis, that we manage side by side in two separate pockets. We find that a portfolio-blending approach is superior to blending the value and the momentum scores first and then constructing the portfolio. Similar analysis has been performed by Patel (2018) for equities.

In a separate test, we split the investment universes into quintiles along both factors, then calculate an equal-weighted portfolio of all the pairwise combinations and plot the average monthly excess return in basis points. We can see the result in Figure 20.

Figure 20: Average monthly excess return of the value and momentum mix

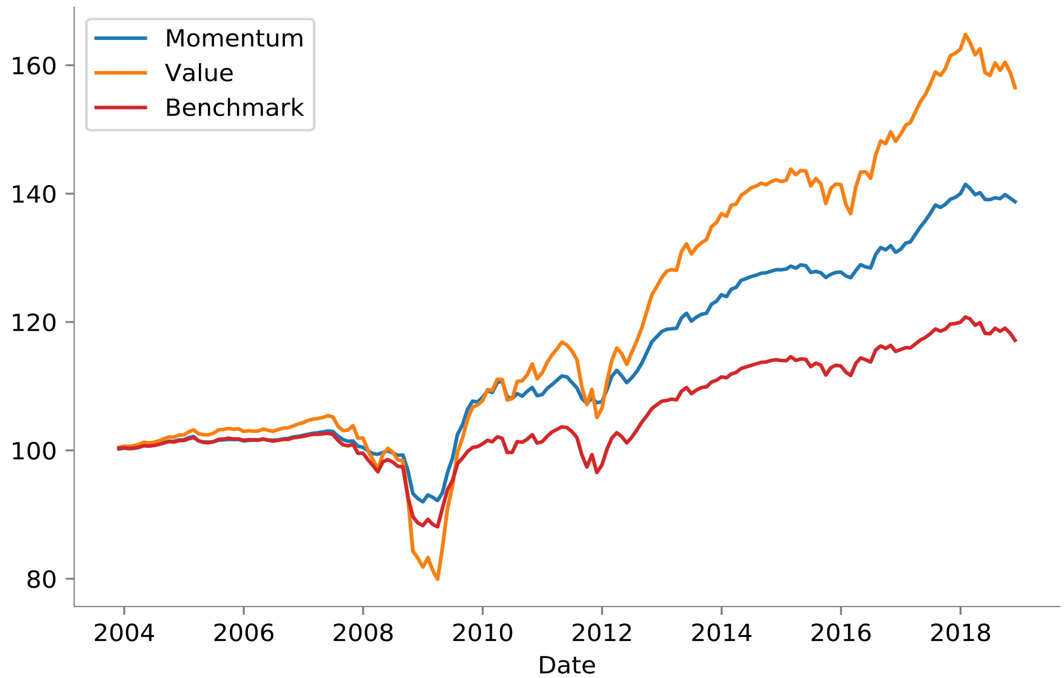


Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

If we are mixing factor portfolios, the performance of each sub-portfolio will correspond to the quintiles in the column/row of the first quintile of the respective factor – the highest performance numbers will form an L-shape. If we mix the factor scores first and then build a portfolio, we will choose bonds outside of this L-shape – for example a bond that is in the second quintile in both factors will be in the second quintile of the signal blended portfolio. However, we see that these bonds both underperform bonds from quintiles (1,3) and (3,1), respectively. This is why we resort to portfolio blending the factors. The recipe is as follows: Take high scoring bonds in each factor that do not score too bad in the other factor. This makes intuitive sense : We concentrate on undervalued bonds that do not show a strong negative momentum and on bonds with strong momentum that are not too expensive yet.

A second observation is that the payoff of concentrated long-only factor portfolios shows potential for a fruitful combination. For the purpose of this analysis, we choose a pragmatic portfolio construction approach: For both factors we choose an equal weighting that takes the highest scoring bond per issuer and then selects the top 90 issuers (that is currently about 20% of the Euro IG universe and corresponds roughly to the first two deciles of every factor in terms of issuers). We discard the 10 top picks when building the value portfolio in order to avoid some value-trap type idiosyncratic stories, especially in the outlier region of the value scores. These most underpriced securities are the highest potential for extreme value traps. We consider this portfolio one of the most concentrated value portfolios we can get while still diversifying issuers (by equally weighting them with a max weight of 1.1%). We see the resulting excess returns in Figure 21 and associated metrics in Table 12.

Figure 21: Excess performance of the rule-based active management value and momentum portfolios



Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

Table 12: Metrics of the rule-based active management value and momentum portfolios - Annualized excess returns and volatilities

	Benchmark	Momentum	Value
Excess return (%)	1.10	2.21	3.14
Volatility (%)	3.27	2.83	5.83
Sharpe	0.34	0.78	0.54
Skew	-0.73	0.14	-0.54

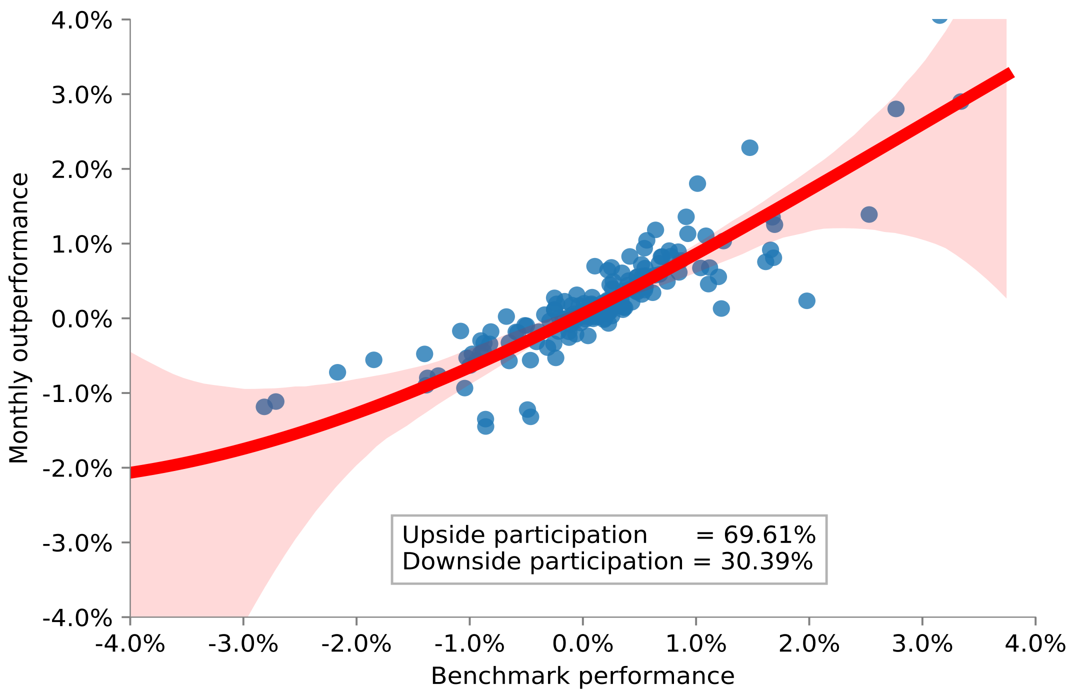
Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

The back-test of this investment strategy is encouraging. However, we stress that these portfolios do not necessarily have a credit beta close to 1 – something we need to take into account before judging the quality of our multifactor strategy prematurely.

For the value factor, we expect such a strategy to have a beta higher than 1 because selecting bonds with high spreads will systematically have a higher DTS than the market-weighted universe. Indeed, this is what we observe in the payoff chart, given in Figure 22. Here, the outperformance of this strategy is plotted against the index excess performance where one point corresponds to one month of data. For illustration of the payoff, a local regression line is added.

Figure 22: Value rule-based active management implementation

95% confidence interval is used for the regression estimates



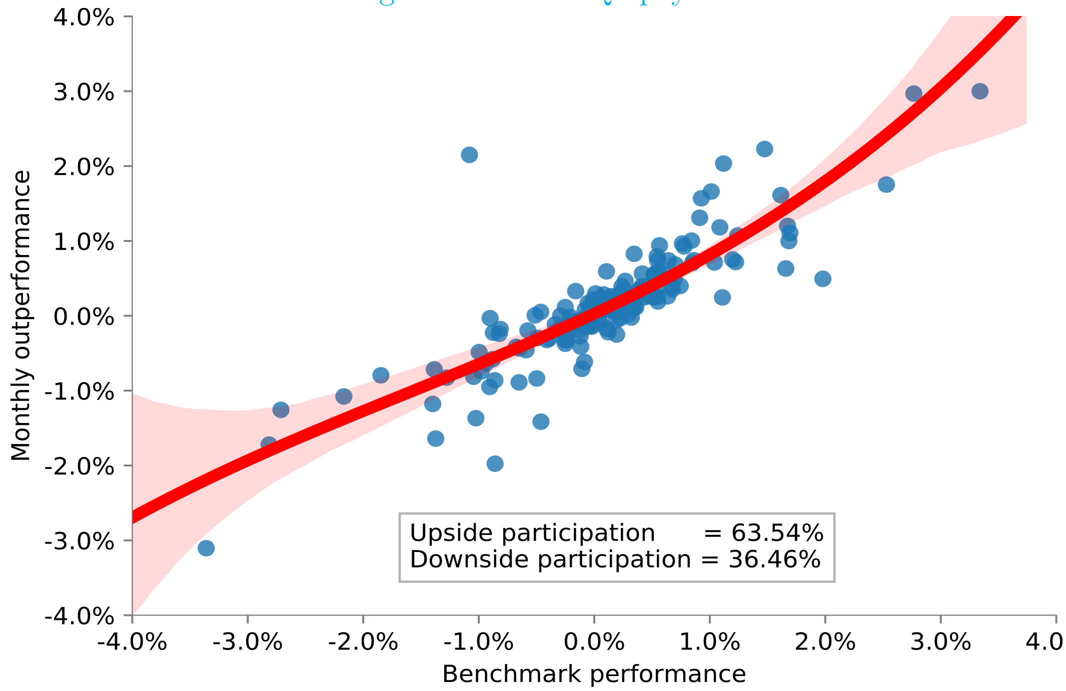
Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

We consider that rule-based active management value could maintain a payoff structure close to the theoretical quintile-based payoff structure (Figure 23). Being conservative, we expect that we will not be able to capture all theoretical upsides in strong positive market movements.

A simple regression analysis analogous to subsection 4.1.1 finds a beta of 1.45 with a regression alpha of 14bps per month which corresponds to an annualized 1.71%. For the momentum factor, we expect the strategy to select bonds with a good historical performance in relative terms and thus a tendency to select lower spreads and lower beta. The payoff diagram of our momentum strategy, given in Figure 24, confirms this.

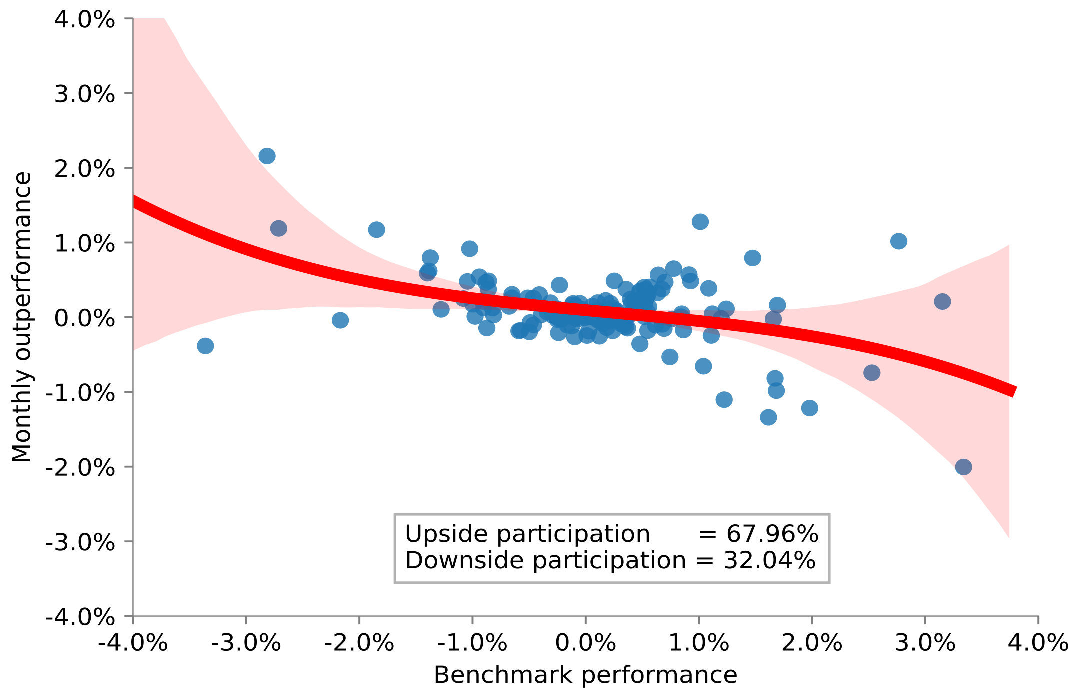
We consider that the rule-based active management momentum has a payoff structure which differs from its theoretical quintile-based payoff structure (Figure 25). We will not expect to outperform

Figure 23: Value Q1 payoff



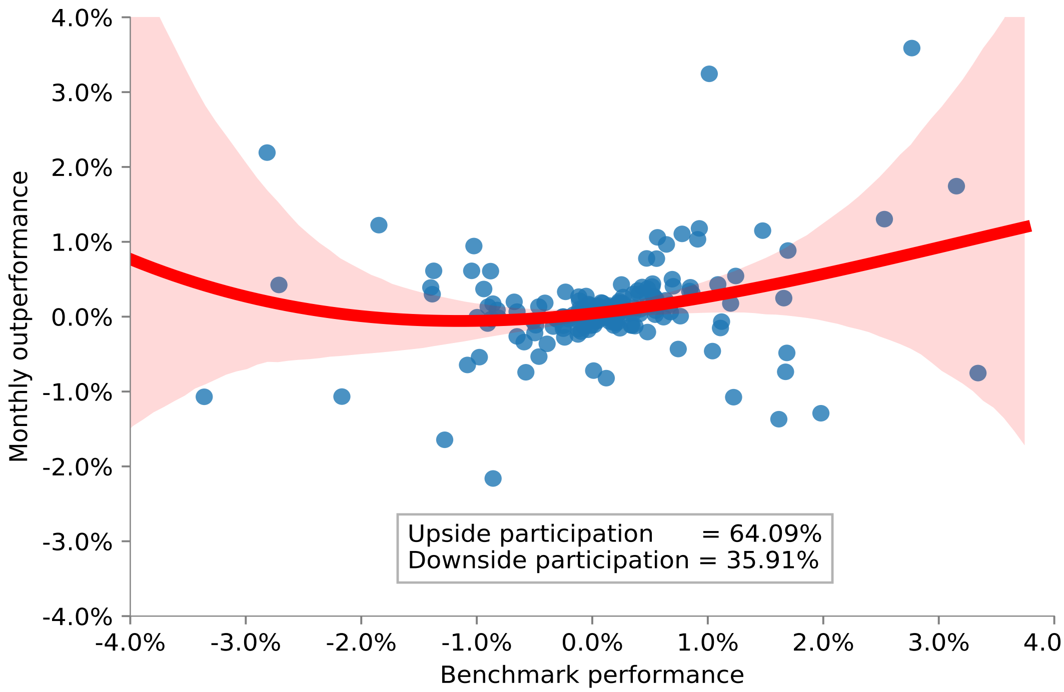
Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

Figure 24: Momentum rule-based active management implementation



Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

Figure 25: Momentum Q1 payoff



Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

in strong positive market movements however we observe that the strategy has a very interesting contrarian feature in market downsides.

A regression as carried out in subsection 4.1.1 shows that the strategy has a market beta of 0.76 and an alpha of 12bps per month, or 1.44% per year.

As to the size or liquidity factors, it is not an easy task to fully control the price effects inherent to liquidity risk. What we do is monitor the liquidity status of the invested portfolio on an ongoing basis using our (timely) liquidity scores. We actually consider size to be a second source of liquidity risk. The fact that small bond issues have distinctly different return patterns from big issues is inherently linked to liquidity in our view and is treated as such in our investment strategy. Size can be regarded as a source of return as well. The Amundi trading desk has a favorable position in negotiating deals on the European bond markets. We have the capacity to benefit from that and reap a liquidity premium. However, this is highly dependent on the opportunities at hand and the market environment. So instead of employing a strategy on the size factor systematically, this should be left under the responsibility and at the discretion of the portfolio manager.

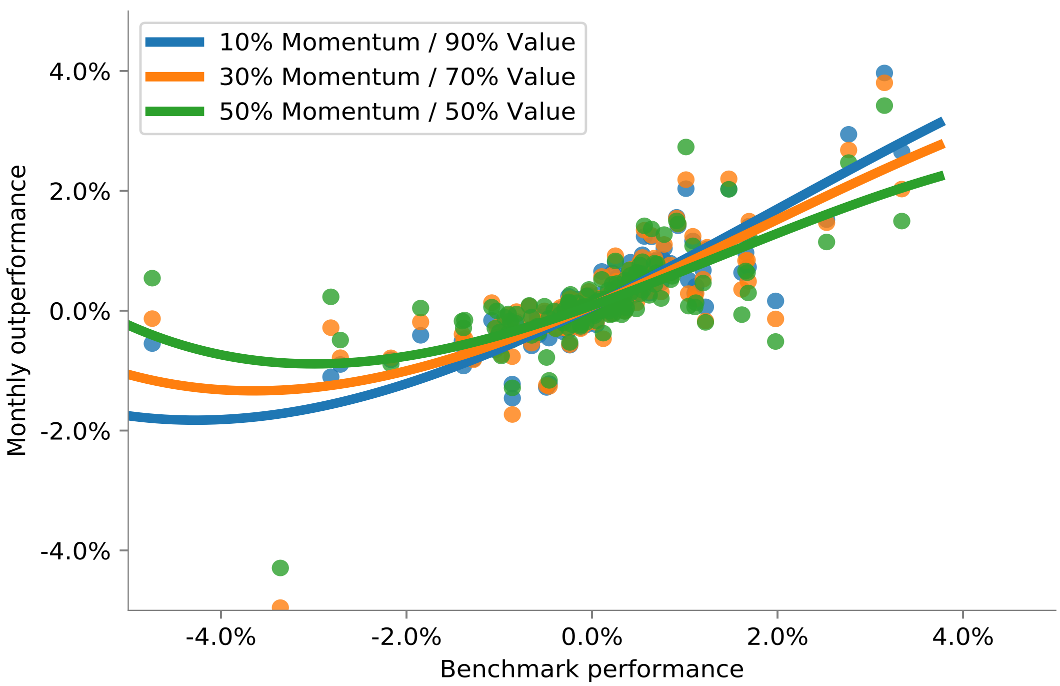
Over the invested portfolio we install an overlay of derivative instruments that hedges out duration risk. We deliberately cancel out the exposure to interest-rate movements by this overlay because we don't want interest rates to dominate the active positions we are taking.

4.2.2 Combining payoffs

The benefits of combining the value and momentum strategies can best be assessed by looking at their respective payoffs. The synergies of employing these strategies is relatively obvious. We have one that shows a higher beta than the reference universe and one that shows a lower beta. To combine the portfolios here, we take a best-in-class approach. For a 70%/30% mix we do not scale the portfolios accordingly here, but take the highest scoring bonds in each factor portfolio.

For different combinations of both factor portfolios we get the payoff pattern depicted in Figure 26. Here, each point corresponds to a 90/10,70/30 or 50/50 mix of value/momentum, respectively.

Figure 26: Payoff of the value and momentum mix

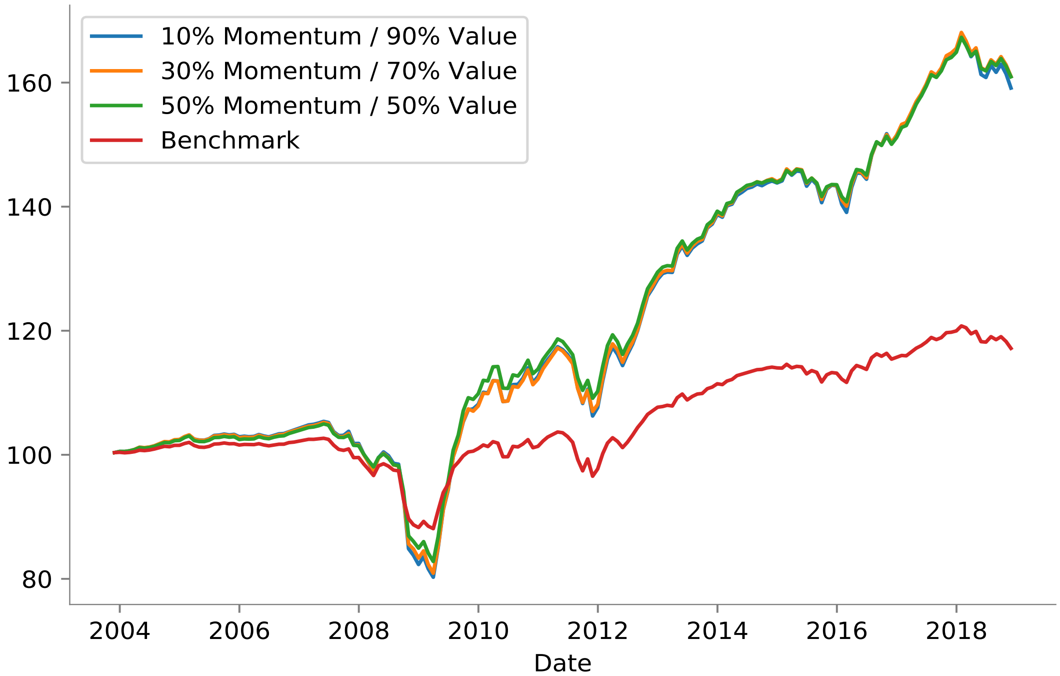


Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

4.2.3 Results

On average, the relative performance looks closer to market neutral, with some positive beta when the market is outperforming. However, this is just the average case and of course the specific scenarios can deviate significantly from that. Nonetheless, the factor diversification effect helps to model the portfolio to be more diversified across different market phases. The corresponding excess performance of this long-only strategy looks as depicted in Figure 27. The betas of these combined portfolios are still exceeding 1 – with a diminishing magnitude as we increase the momentum portion of the portfolio. Monthly returns over benchmark range from 19bps to 21bps in all these multi-factor portfolios. Figure 28 shows the calendar excess performance of the 50/50 portfolio.

Figure 27: Excess performance of combinations of the value and momentum mix



Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

The findings of this section are twofold: First, there is an indication that blending portfolios is superior to blending the factor scores. This holds especially true for more active portfolios and will be less important with smaller tracking errors. Second, when combining the factors, analysis and skilful combination of the payoff is paramount. In the long-only corporate bond world, there is diversification potential of the two strategies with respect to the control of the strategies' beta.

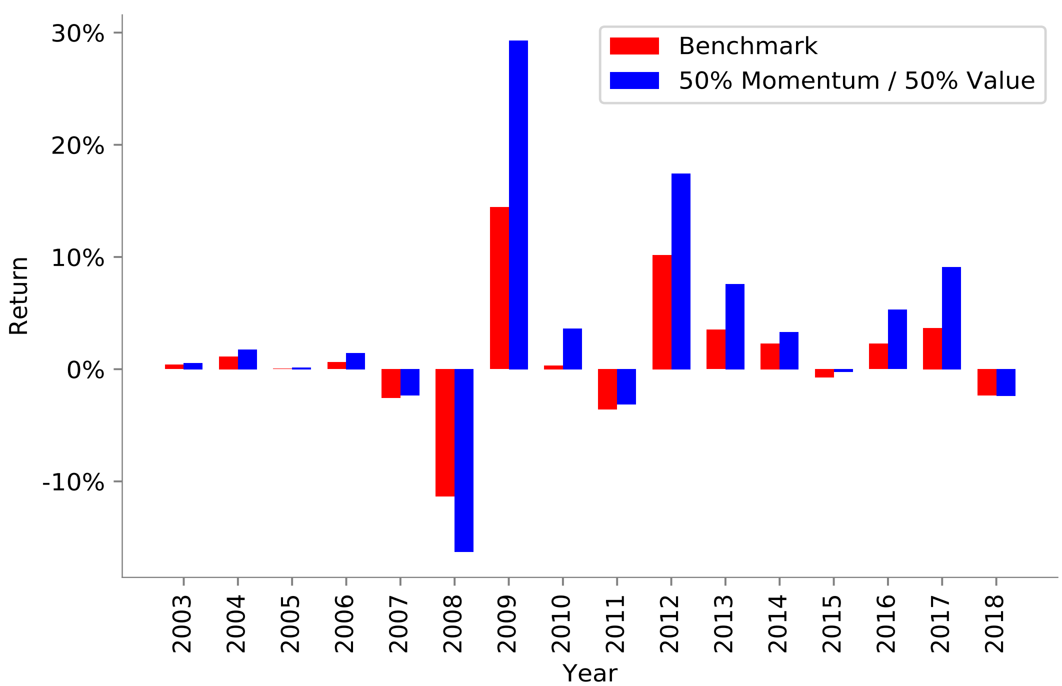
In practice we find that these effects of the long-only factor portfolios hold up with different portfolio construction methods. However, the concrete implementation is highly dependent on the constraints and risk appetite of the respective investor.

Table 13: Metrics of combinations of the value and momentum mix - Annualized excess returns and volatilities

	Benchmark	10% Momentum 90% Value	30% Momentum 70% Value	50% Momentum 50% Value
Excess return (%)	1.10	3.25	3.31	3.29
Volatility (%)	3.27	5.76	5.46	5.08
Sharpe	0.34	0.56	0.61	0.65
Skew	-0.73	-0.48	-0.33	-0.19
Upside (%)		67.40	65.75	66.30
Downside (%)		32.60	34.25	33.70

Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

Figure 28: Calendar excess performance of the 50/50 portfolio



Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

5 Conclusion

We have aimed to level the discussion around corporate bonds by identifying what factor is consistent in a multi-factor framework. To that end we have defined a traditional multi-factor model with duration-times-spread, duration and liquidity. It has appeared that moving from a simple CAPM approach to our first traditional multi-factor risk model is relevant before 2008. Indeed, in our analysis period of 2003-2008, we obtain a better explanation of the cross-section of returns in our universe. Surprisingly, in the following period of 2009-2018 the traditional multi-factor risk model carries less explanatory power than the simple CAPM.

We then move to the analysis of new alternative factors which we have identified in our literature review. We do not retain the low risk factor which is mainly a short duration-time-spread exposure and is in its essence a "bad-times-only" risk reward. We introduce specifications for the momentum factor which seems to clean up the reversal feature, which is witnessed in the factor specifications from the literature review. We retain a debt value-based size specification. As for the value factor, we introduce as much credit security descriptions as we can to "box" comparability. We monitor time-varying exposures of these new alternative factors against the factors in the traditional risk model. We confirm that momentum and value cannot be explained by static exposures to DTS, duration or liquidity.

Following our analysis of the traditional multi-factor risk model vs. CAPM, we identify that the addition of the three new alternative factors previously retained improve the explanation of the cross-section of returns in our universe. Specifically, for the second period of 2009-2018, the traditional model was inferior to the simple CAPM, while traditional augmented by alternative end-up with a higher R^2 than the simple CAPM. However, we recognize that although the addition of momentum and value are interesting for the R^2, the collinearity between factors have increased - while remaining acceptable - but the factors themselves carry less statistical significance in a traditional and alternative multi-factor model.

Leaving aside the asset level cross-sectional analysis, we switch to an analysis of factor time-series. We determine with a Lasso penalized regression that if we seek three factors to explain the euro corporate investment grade market in the 2009-2018 period, we select duration-times-spread then value, then momentum (both with our specifications). Moreover, between the first period of 2003-2008 and the second period, value is the factor which increases the most in priority. This is a very powerful result: We confirm the predominance of DTS, but we provide a quantified proof of the emergence of value in the bond factor mix. This result is specifically significant for active managers who operate in the low factor-intensity space where picking the right factors is critical.

We have conducted statistical analysis which show increase in collinearity with the addition of momentum and value to the three traditional duration-time-spread, duration and liquidity factors. DTS comes out as the most statistically significant factor. We also confirm that capturing momentum and value time-series does not decrease the beta of duration-time-spread in the penalized Lasso time-series regressions. These analyses indicate that momentum and value carry information beyond duration-time-spread. We manage to confirm through DTS-matched tilted portfolio constructions that this is indeed the case.

We also propose implementating value and momentum together in a rule-based active management setting and we confirm that both engines together can add value to a corporate bond investor. Interestingly our payoffs' complementarity is stronger with our rule-based active management implementation than we could have expected from a theoretical exposure.

Through our research we have identified areas where we can expect to have higher capture of the corporate bonds' pricing and liquidity dynamics. We will continue research in these directions. Namely, we have extensively used monthly based data but we have also built weekly and daily data sets. We have also tested several forms of value and momentum and there are directions in which we believe that there is potential to enhance our factor specifications. We have not touched much on quality in this analysis, but we have identified interpretations of quality for an investment grade credit investor which we will test. Beyond bond specific characteristics, we have also explored analysis inspired by Bektic *et al.* (2016) driven by equity-based style criteria. We will evaluate the alignment of this potential risk source with traditional and alternative risk factors. In addition, we believe that ESG has impacted the asset pricing in the equity market (Bennani *et al.* 2018a). If that is valid, why would there be barriers for the pricing of ESG considerations in the corporate bond market ?

References

[1] Acharya, V.V., and Pedersen, L.H. (2005), Asset Pricing with Liquidity Risk, *Journal of Financial Economics*, 77(2), pp. 375-410.

[2] Ang, A. (2014), *Asset Management – A Systematic Approach to Factor Investing*, Oxford University Press.

[3] Bao, J., Pan, J., and Wang, J. (2011), The Illiquidity of Corporate Bonds, *Journal of Finance*, 66(3), pp. 911-946.

[4] Bektic, D., Wenzler, J-S., Wegener, M., Schiereck, D., and Spielmann, T. (2016), Extending Fama-French Factors to Corporate Bond Markets, *SSRN*, www.ssrn.com/abstract=2715727.

[5] Bektic, D., Neugebauer, U., Wegener, M. and Wenzler, J.S. (2017), Common Equity Factors in Corporate Bond Markets, in Jurczenko, E. (Ed.), *Factor Investing and Alternative Risk Premia*, ISTE Press-Elsevier.

[6] Ben Dor, A., Dynkin, L., Hyman, J., Houweling, P., van Leeuwen, E., and Penninga, O. (2007), Duration Times Spread, Journal of Portfolio Management, 33(2), pp. 77-100.

[7] Bennani, L., Le Guenedal, T., Lepetit, F., Ly, L., Mortier, V., Roncalli, T., Sekine, T. (2018a), How ESG Investing Has Impacted the Asset Pricing in the Equity Market ? *SSRN*, www.ssrn.com/abstract=3316862.

[8] Bennani, L., Le Guenedal, T., Lepetit, F., Ly, L., Mortier, V., Sekine, T. (2018b), The Alpha and Beta of ESG Investing, *Amundi Working Paper*, 76, http://research-center.amundi.com.

[9] Ben Slimane, M., and de Jong, M. (2017), Bond Liquidity Scores, *Journal of Fixed Income*, 27(1), pp. 77-82.

[10] Belmiloud, Y. (2016), Smart Beta Bond Investing and the Quality Factor, *Amundi Internal Report*.

[11] Black, F., Jensen, M.C. and Scholes, M.S. (1972), The Capital Asset Pricing Model: Some Empirical Tests, in Jensen, M.C. (Ed.), *Studies in the Theory of Capital Markets*, Praeger Publishers Inc., pp. 79-121.

[12] Carhart, M.M. (1997), On Persistence in Mutual Fund Performance, *Journal of Finance*, 52(1), pp. 57-82.

[13] Chen, L., Lesmond, D.A., and Wei, J. (2007), Corporate Yield Spreads and Bond Liquidity, *Journal of Finance*, 62(1), pp. 119-149.

[14] Chen, N.F., Roll, R., and Ross, S.A. (1986), Economic Forces and the Stock Market, *Journal of Business*, 59(3), pp. 383-403.

[15] Cochrane, J.H., and Piazzesi, M. (2005), Bond Risk Premia, *American Economic Review*, 95(1), pp. 138-160.

[16] Correia, M., Richardson, S. and Tuna, A. (2012), Value Investing in Credit Markets, *Review of Accounting Studies*, 17(3), pp. 572-609.

[17] de Jong, F., and Driessen, J. (2012), Liquidity Risk Premia in Corporate Bond Markets, *Quarterly Journal of Finance*, 2(2), pp. 1-34.

[18] de Jong, M., and Stagnol, L. (2016), A Fundamental Bond Index Including Solvency Criteria, *Journal of Asset Management*, 17(4), pp. 280-294.

[19] de Jong, M., and Wu, H. (2014), Fundamental Indexation for Bond Markets, *Journal of Risk Finance*, 15(3), pp. 264–274.

[20] Diebold, F. and Li, C. (2006), Forecasting the Term Structure of Government Bond Yields, *Journal of Econometrics*, 130, pp. 337-364.

[21] Dynkin, L., Gould, A., Hyman, J., and Phelps, B. (2007), *Quantitative Management of Bond Portfolios*, Princeton University Press.

[22] Fama, E.F., and Bliss, R.R. (1987), The Information in Long-maturity Forward Rates, *American Economic Review*, 77(4), pp. 680-692.

[23] Fama, E.F., and French, K.R. (1992), The Cross-Section of Expected Stock Returns, *Journal of Finance*, 47(2), pp. 427-465.

[24] Fama, E.F., and French, K.R. (1993), Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics*, 33(1), pp. 3-56.

[25] Fama, E.F., and French, K.R. (2015), A Five-Factor Asset Pricing Model, *Journal of Finance*, 116, 1-22.

[26] Fama, E.F., and MacBeth, J.D. (1973), Risk, Return, and Equilibrium: Empirical Tests, *Journal of Political Economy*, 81(3), pp. 607-636.

[27] Frazzini, A., and Pedersen, L.H. (2014), Betting Against Beta, *Journal of Financial Economics*, 111(1), pp. 1-25.

[28] Gebhardt, W.R., Hvidkjaer, S., and Swaminathan, B. (2005a), The Cross-section of Expected Corporate Bond Returns: Betas or Characteristics?, *Journal of Financial Economics*, 75(1), pp. 85-114.

[29] Gebhardt, W.R., Hvidkjaer, S., and Swaminathan, B. (2005b), Stock and Bond Market Interaction: Does Momentum Spill Over?, *Journal of Financial Economics*, 75(3), pp. 651-690.

[30] Gouzilh, L., de Jong, M., Lebaupain, T., and Wu, H. (2014), The Art of Tracking Corporate Bond Portfolios, Amundi Working Paper, 42, http://research-center.amundi.com.

[31] Grinold, R., and Kahn, R. (1999), *Active Portfolio Management*. McGraw-Hill.

[32] Houweling, P., Mentink, A. and Vorst, T. (2005), Comparing Possible Proxies of Corporate Bond Liquidity, *Journal of Banking & Finance*, 29(6), pp. 1331-1358.

[33] Houweling, P., and Van Zundert, J. (2014), Factor Investing in the Corporate Bond Market, *Robeco Quantitative Strategies Working Paper*.

[34] Huang, J.Z., and Huang, M. (2012), How Much of the Corporate-treasury Yield Spread is Due to Credit Risk?, *Review of Asset Pricing Studies*, 2(2), pp. 153-202.

[35] Ilmanen, A. (2011). *Expected Returns: An Investor's Guide to Harvesting Market Rewards*, John Wiley & Sons.

[36] Israel, R., Palhares, D., and Richardson, S.A. (2018), Common Factors in Corporate Bond and Bond Fund Returns, *Journal of Investment Management*, 16(2), pp. 17-46.

[37] Jegadeesh, N., and Titman, S. (1993), Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance*, 48(1), pp. 65-91.

[38] Jostova, G., Nikolova, S., Philipov, A., and Stahel, C.W. (2013), Momentum in Corporate Bond Returns, *Review of Financial Studies*, 26(7), pp. 1649-1693.

[39] Konstantinovsky, V.N., Ng, K.Y., and Phelps, B. (2016), Measuring Bond-Level Liquidity, *Journal of Portfolio Management*, 42(2), pp. 116-128.

[40] L'Hoir, M. and Bouhabel, M. (2010), A Bond-Picking Model for Corporate Bond Allocation, *Journal of Portfolio Management*, 36(3), pp. 131-139.

[41] Litterman, R.B., and Scheinkman, J. (1991), Common Factors Affecting Bond Returns, *Journal of Fixed Income*, 1(1), pp. 54-61.

[42] Longstaff, F.A., Mithal, S., and Neis, E. (2005), Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market, *Journal of Finance*, 60(5), pp. 2213-2253.

[43] Markowitz, H. (1952), Portfolio Selection, *Journal of Finance*, 7(1), pp. 77-91.

[44] Martellini, L., and Milhau, V. (2015), Factor Investing: A Welfare-Improving New Investment Paradigm or Yet Another Marketing Fad?, *Edhec-Risk Working Paper*.

[45] Merton, R.C. (1974), On the Pricing of Corporate Debt: The Risk Structure of Interest Rates, *Journal of Finance*, 29(2), pp. 449-470.

[46] Nelson, C. and Siegel, A. (1987), Parsimonious Modelling of Yield Curves, *Journal of Business*, 60(4), pp. 473-489.

[47] Ng, K.Y., and Phelps, B. (2015), The Hunt for a Low-risk Anomaly in the USD Corporate Bond Market, *Journal of Portfolio Management*, 42(1), pp. 63-84.

[48] O'Brien, R.M. (2007), A Caution Regarding Rules of Thumb for Variance Inflation Factors, *Quality & Quantity*, 41(5), pp. 673-690.

[49] Patel, K. (2018), In Practice: Comparing Portfolio Blending and Signal Blending When Constructing Multifactor Portfolios, *Financial Analysts Journal*, 74(3), pp. 70-85.

[50] Pospisil, L., and Zhang, J. (2010), Momentum and Reversal Effects in Corporate Bond Prices and Credit Cycles, *Journal of Fixed Income*, 20(2), pp. 101-115.

[51] Roncalli, T. (2013), *Introduction to Risk Parity and Budgeting*, Chapman & Hall/CRC Financial Mathematics Series.

[52] Sharpe, W.F. (1964), Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk, *Journal of Finance*, 19(3), pp. 425-442.

[53] Tibshirani, R. (1996), Regression Shrinkage and Selection via the Lasso, *Journal of the Royal Statistical Society B*, 58(1), pp. 267-288.

A Mathematical results

A.1 Conventional bond risk model

We note $B_i(t, D_i)$ the zero-coupon bond price with maturity (or duration) D_i. If we assume that the recovery rate is zero, we have:

$$B_i(t, D_i) = e^{-(R(t)+S_i(t))\cdot D_i}$$

The bond return $R_i(t)$ is then the sum of the risk-free interest rate $R(t)$ and the credit spread $S_i(t)$. Following Acharya and Pedersen (2005), the liquidity can be introduced in the model by considering net returns in place of gross returns. It follows that:

$$B_i(t, D_i) = e^{-((R(t)+S_i(t))\cdot D_i - L_i(t))}$$

where $L_i(t)$ is the illiquidity cost of Bond i. We deduce that:

$$\begin{aligned} \mathrm{d}\ln B_i(t, D_i) &= -D_i \cdot \mathrm{d}R(t) - D_i \cdot \mathrm{d}S_i(t) + \mathrm{d}L_i(t) \\ &= -D_i \cdot \mathrm{d}R(t) - \mathrm{DTS}_i(t) \cdot \frac{\mathrm{d}S_i(t)}{S_i(t)} + \mathrm{d}L_i(t) \end{aligned}$$

where $\mathrm{DTS}_i(t) = D_i \cdot S_{i,t}$ is the duration-time-spread factor (Ben Dor *et al.*, 2007). Acharya and Pedersen (2005) show that liquidity is multi-faceted and impacts the net return in several ways. In particular, we can decompose the illiquidity premium $\mathrm{d}L_{i,t}$ into an illiquidity level component and three illiquidity covariance risks. The illiquidity level component depends on the (beta-adjusted) difference between the expected liquidity cost of Bond i and the expected liquidity cost of the bond market. Let $L_{M,t}$ be the illiquidity cost of the bond market. The illiquidity covariance risks consists in three liquidity betas:

- $\beta(L_i, L_M)$
  An asset that becomes illiquid when the market becomes illiquid should have a higher risk premium.
- $\beta(R_i, L_M)$
  An asset that perform well in times of market illiquidity should have a lower risk premium.
- $\beta(L_i, R_M)$
  Investors accept a lower risk premium on assets that are liquid in a bear market.

Since this decomposition is relevant from a theoretical point of view, Acharya and Pedersen (2005) find that the 4 liquidity premia are highly correlated. Therefore, we propose to measure the liquidity return as follows:

$$\mathrm{d}L_{i,t} = \alpha_i(t) + \beta(L_i(t), L_M(t)) \cdot \mathrm{d}L_M(t)$$

where α_i is the liquidity return that is not explained by the liquidity commonality. Therefore, we obtain:

$$R_i(t) = \alpha_i(t) - D_i \cdot \mathrm{d}R(t) - \mathrm{DTS}_i(t) \cdot \frac{\mathrm{d}S_i(t)}{S_i(t)} + \beta(L_i(t), L_M(t)) \cdot \mathrm{d}L_M(t)$$

More generally, $\alpha_i(t)$ represents the return component that is not explained by the three factors. By decomposing $\alpha_i(t)$ into a common factor $a(t)$ and an idiosyncratic risk factor $u_i(t)$, we finally deduce that:

$$R_i(t) = a(t) - D_i \cdot \mathrm{d}R(t) - \mathrm{DTS}_i(t) \cdot \frac{\mathrm{d}S_i(t)}{S_i(t)} + \beta(L_i(t), L_M(t)) \cdot \mathrm{d}L_M(t) + u_i(t)$$

A.2 Calculating portfolio's Duration, DTS and Liquidity-time-Price

Let $R(t)$ be the return of a portfolio holding N bonds. We have:

$$R_p(t) = \sum_{i=1}^{N} \omega_i(t) R_i(t)$$

where $\omega_i(t)$ and $R_i(t)$ are the weight and the return of bond i at time t.

Using equation (1) for each bond, we derive:

$$\begin{aligned} R_p(t) = a(t) &- \sum_{i=1}^{N} \omega_i(t) \mathrm{MD}_i(t) \cdot R^I(t) - \sum_{i=1}^{N} \omega_i(t) \mathrm{DTS}_i(t) \cdot R^S(t) \\ &+ \sum_{i=1}^{N} \omega_i(t) \mathrm{LTP}_i(t) \cdot R^L(t) + \sum_{i=1}^{N} \omega_i(t) u_i(t) \end{aligned}$$

It follows that the duration, DTS and Liquidity-time-Price of the portfolio at time t are:

$$\begin{aligned} MD_p(t) &= \sum_{i=1}^{N} \omega_i(t) \mathrm{MD}_i(t) \\ DTS_p(t) &= \sum_{i=1}^{N} \omega_i(t) \mathrm{DTS}_i(t) \\ LTP_p(t) &= \sum_{i=1}^{N} \omega_i(t) \mathrm{LTP}_i(t) \end{aligned}$$

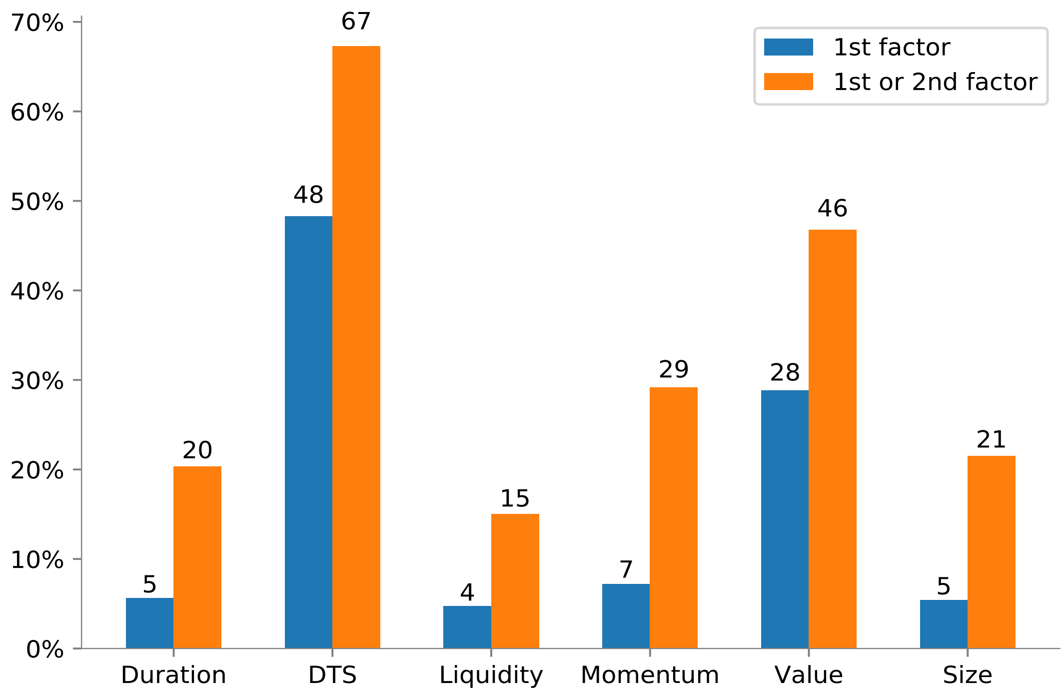
B Additional results for EUR-denominated bonds

B.1 Time-series LASSO

We generalize the LASSO analysis to every bond in the ICE BoA Merrill Lynch Euro Large Cap Corporate Bond index by applying equation (7) to the time-series of its excess returns. We confirm the intuition that the most significant factors are, on average, duration-times-spread and value.

Figures 29 and 30 illustrate the probability for each factor to be picked as the first or in the first two factors in a LASSO penalised regression, Duration-times-spread and value stand out with a probability to be first or second factor, of around 66% and 48% respectively when we consider the 2003-2018 or the 2009-2018 periods.

Figure 29: Period 2003-2018 - Probability to be picked first or in the first two factors

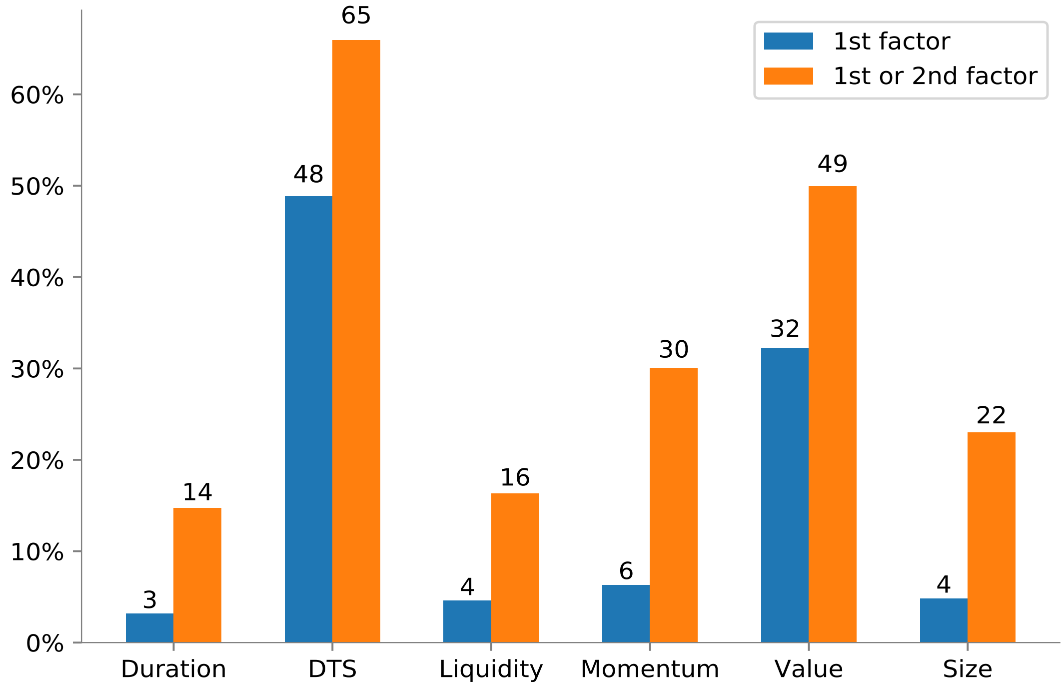


Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

B.2 Cross-section LASSO

In this subsection, we conduct the LASSO analysis on the cross-section. For this purpose, we apply equation (7) for each bond that belongs to the ICE BoA Merrill Lynch Euro Large Cap Corporate Bond index at a given date. The traditional factors are the duration, the DTS and the liquidity-times-price of the considered bond. Regarding the alternative factors, we consider the 12 month rolling sensitivity of the bond's excess returns to the long/short factors' excess returns.

Figure 30: Period 2009-2018 - Probability to be picked first or in the first two factors

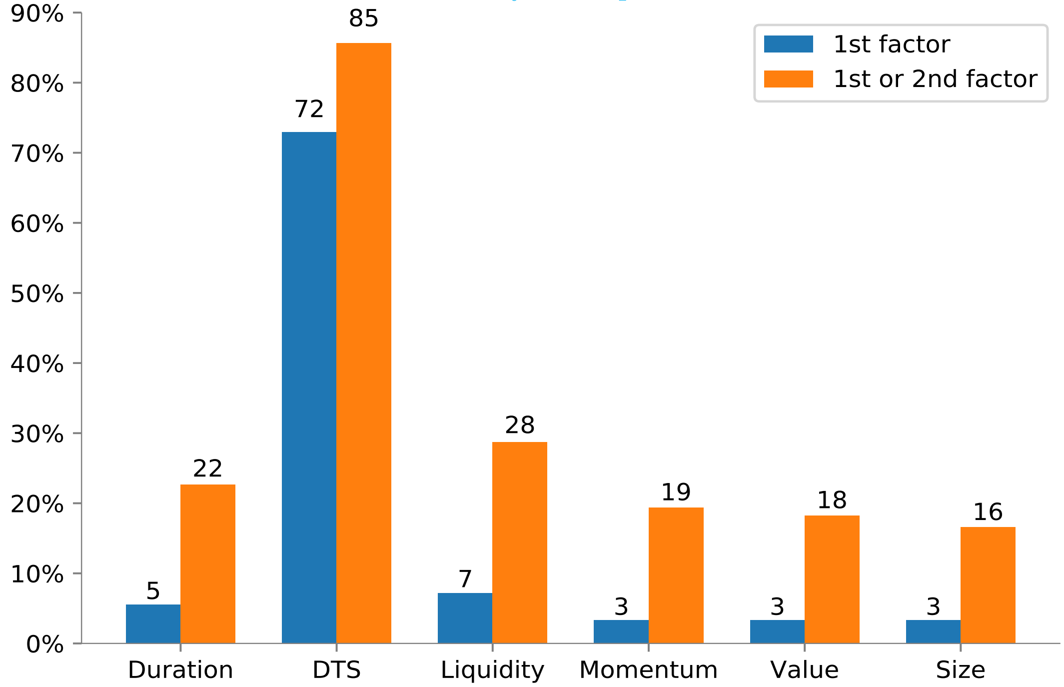


Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

The results for 2003-2018 and 2009-2018 periods, shown in figures 31 and 32, point up the duration-times-spread as the main factor with a probability above 80% to be picked in the first two factors. Duration and Liquidity are relatively ahead of the alternative factors.

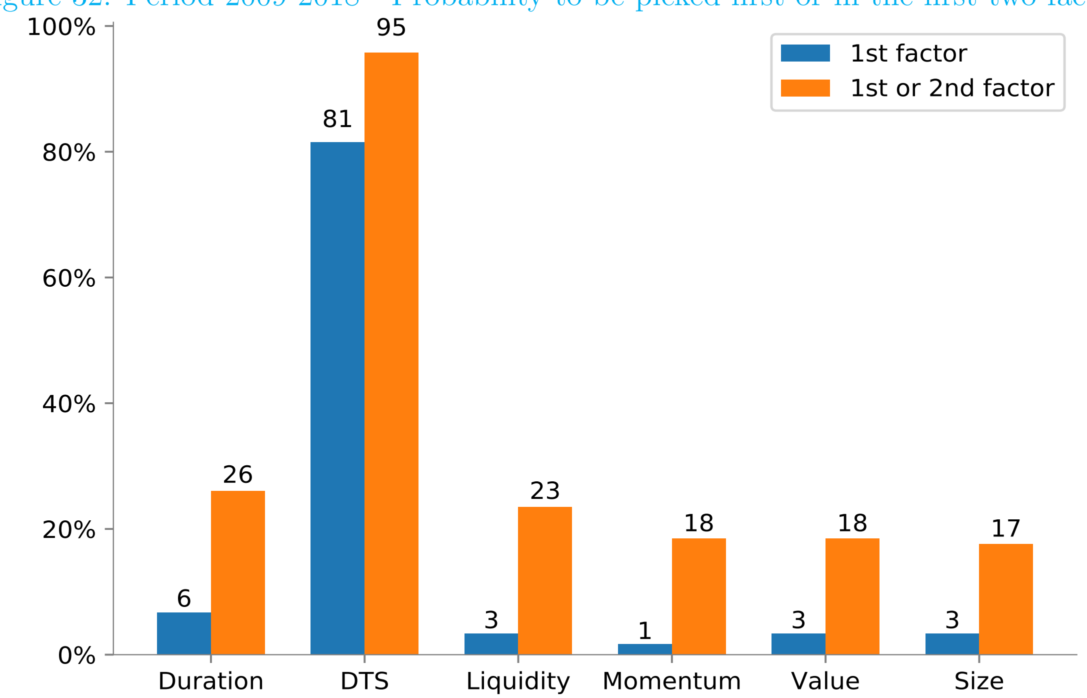
B.3 Tables

Figure 31: Period 2003-2018 - Probability to be picked first or in the first two factors



Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

Figure 32: Period 2009-2018 - Probability to be picked first or in the first two factors



Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

Table 14: Comparison of CAPM, traditional factors and traditional factors augmented by alternative factors - 90% significance

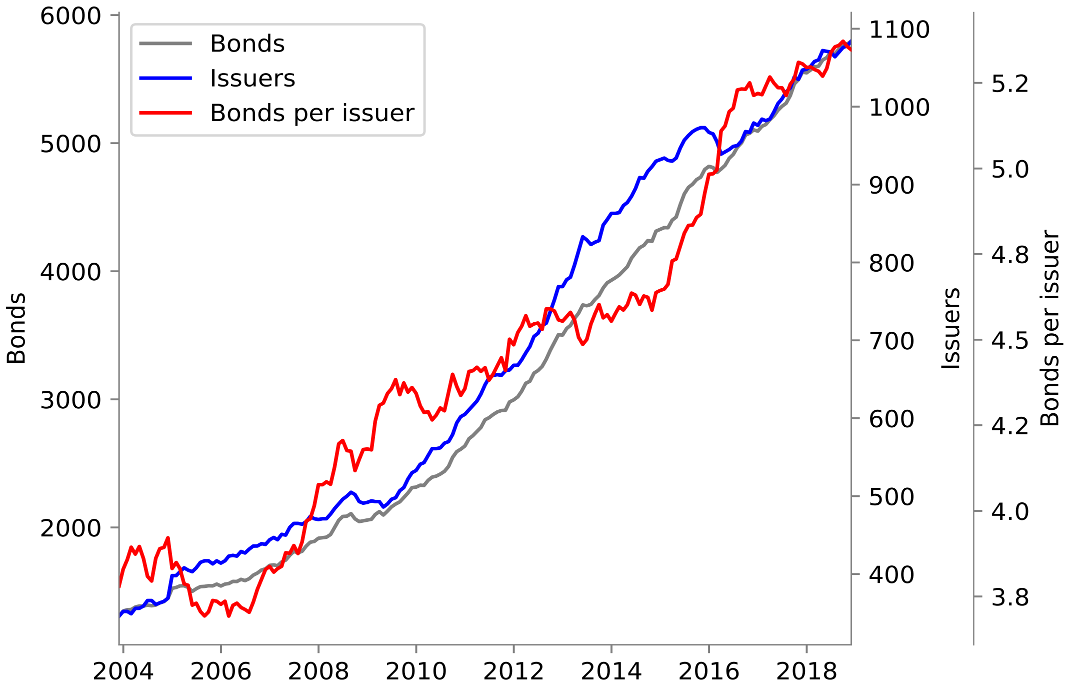
2003-2008	*Average* $R^2(\%)$	VIF	*Hit − ratio* (%) MKT	DTS	Duration	Liquidity	*Hit − ratio* (%) Momentum	Value	Size
CAPM	48.51		86.21						
TRAD	56.74	3.93		71.13	26.7	51.56			
6-Factor	73.09	15.05		50.92	13.15	51.24	52.77	45.23	45.47
5-Factor	68.57	11.45		47.47	20.69	49.72	52.61	43.30	
2009-2018	*Average* $R^2(\%)$	VIF	*Hit − ratio* (%) MKT	DTS	Duration	Liquidity	*Hit − ratio* (%) Momentum	Value	Size
CAPM	59.35		95.36						
TRAD	52.58	3.61		77.81	28.57	32.41			
6-Factor	64.44	10.80		52.46	31.66	30.37	34.28	27.75	31.43
5-Factor	61.52	8.43		51.43	32.32	36.16	34.13	32.63	

Source: ICE BoA Merrill Lynch Euro Large Cap Corporate Bond Index. Authors' calculations

C Results for USD-denominated bonds

C.1 Figures

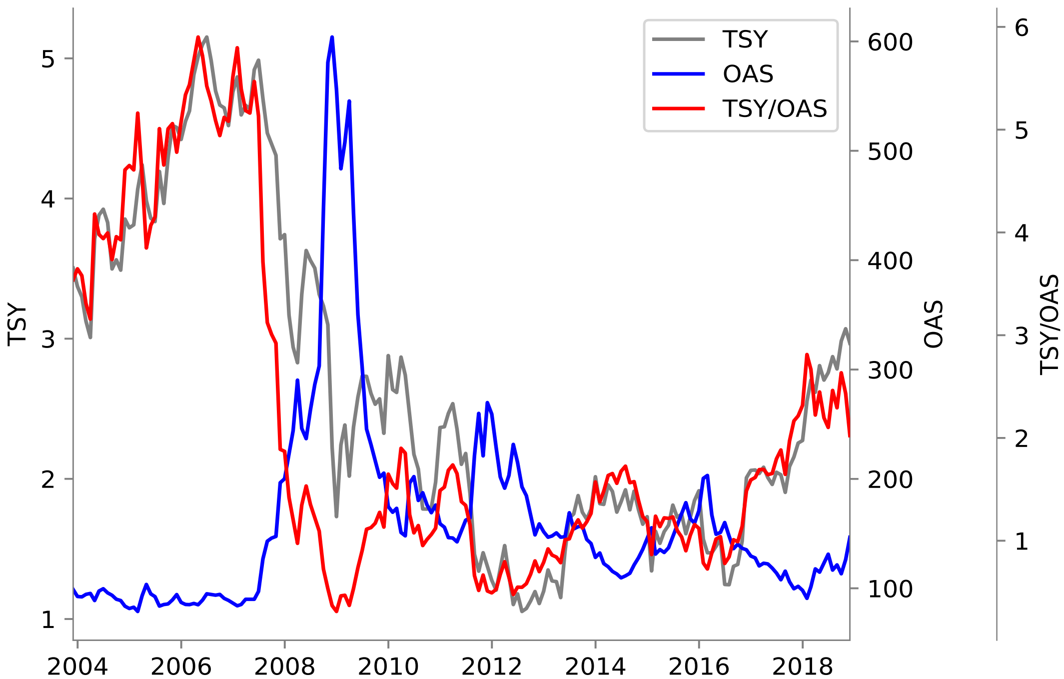
Figure 33: Constituents of the USD corporate bond index



Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

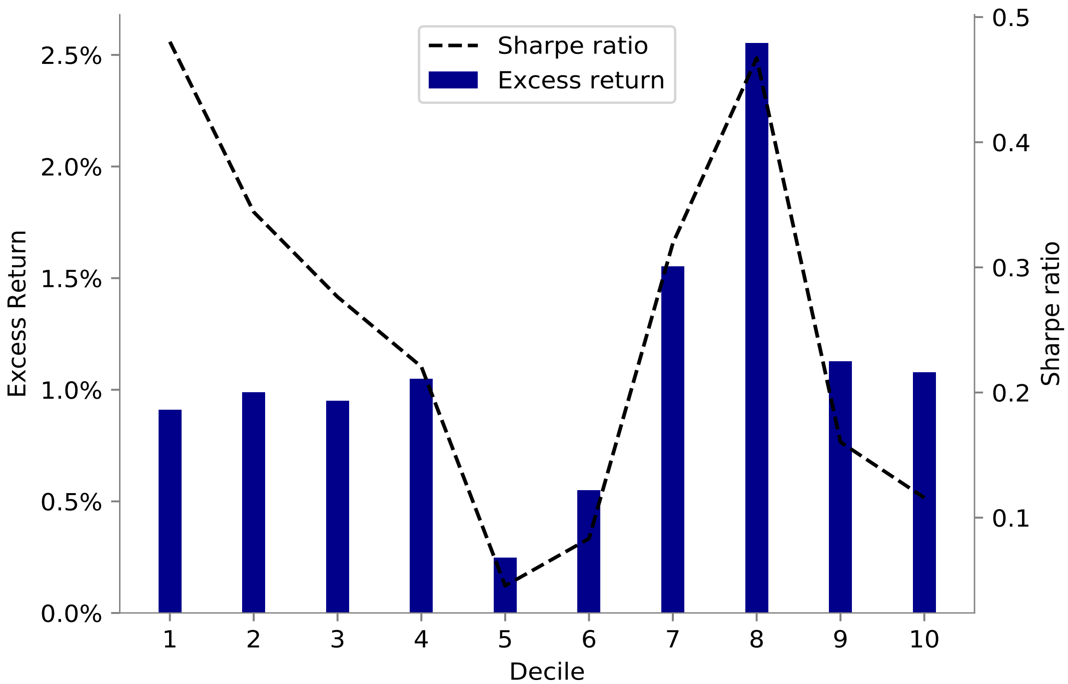
C.2 Tables

Figure 34: Evolution of USD treasury yields and credit spreads



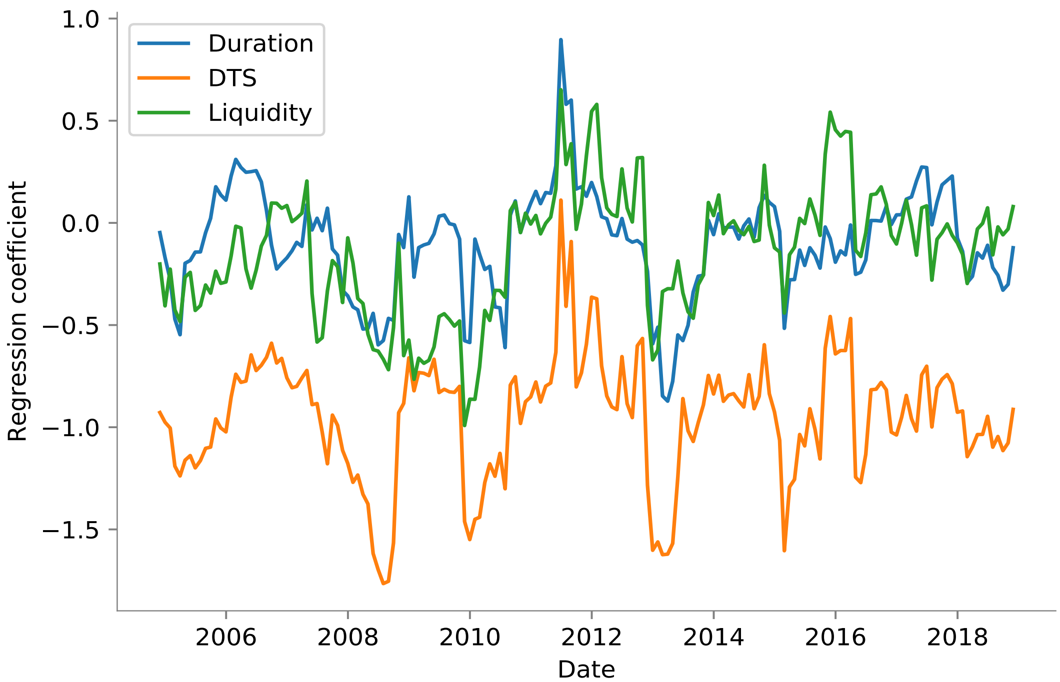
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 35: Low risk - Excess returns and Sharpe ratio



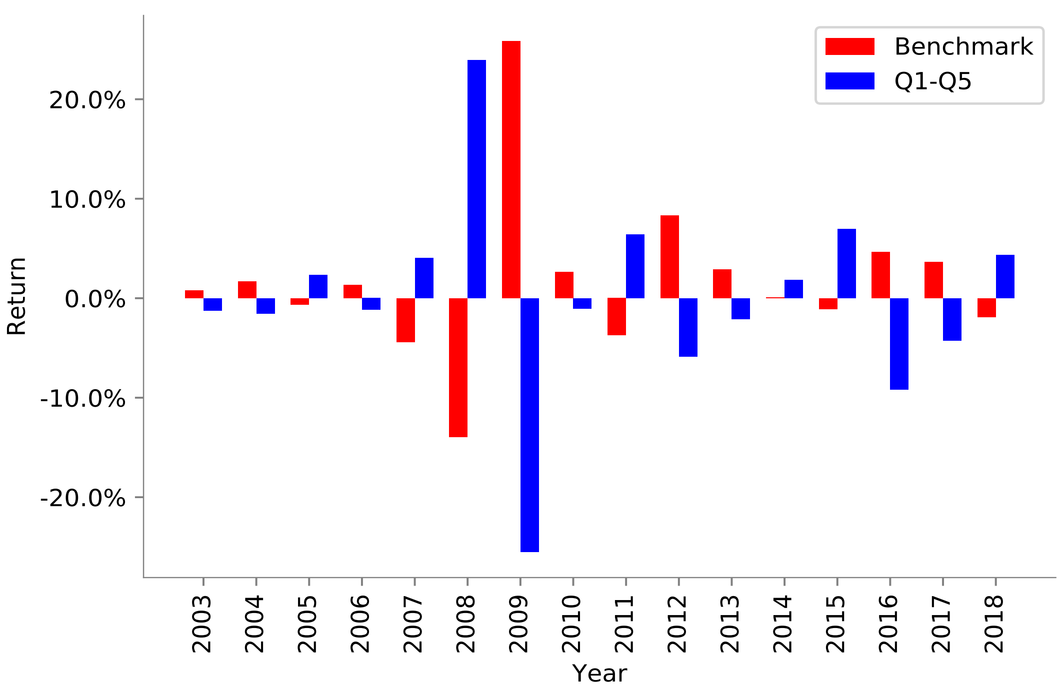
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 36: Low risk - Time varying exposure



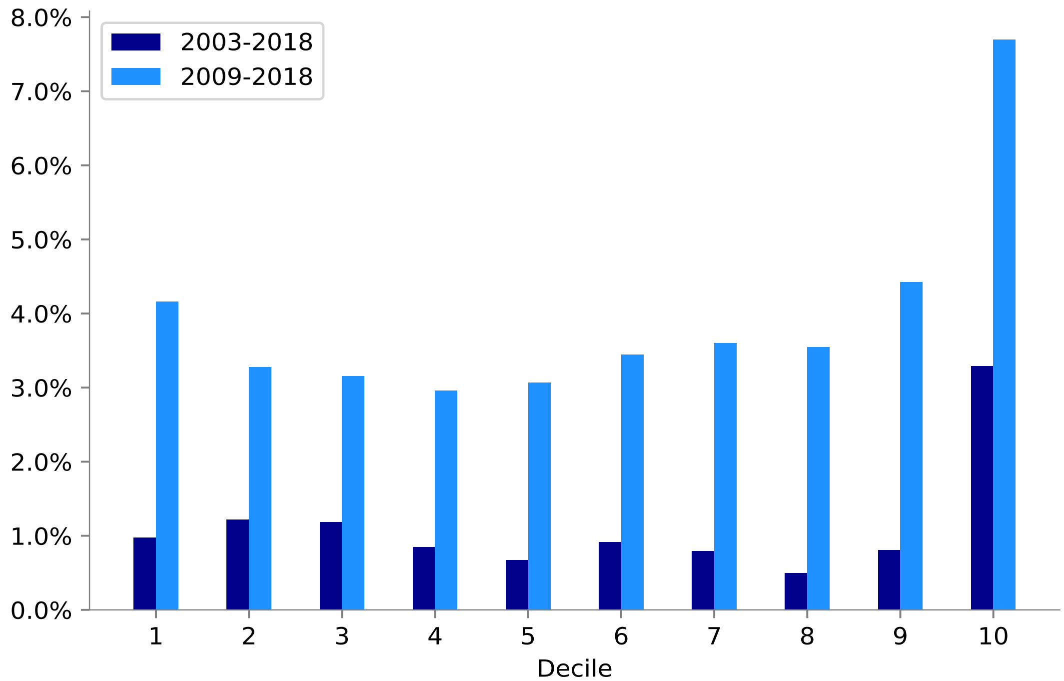
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 37: L/S Low risk - calendar returns



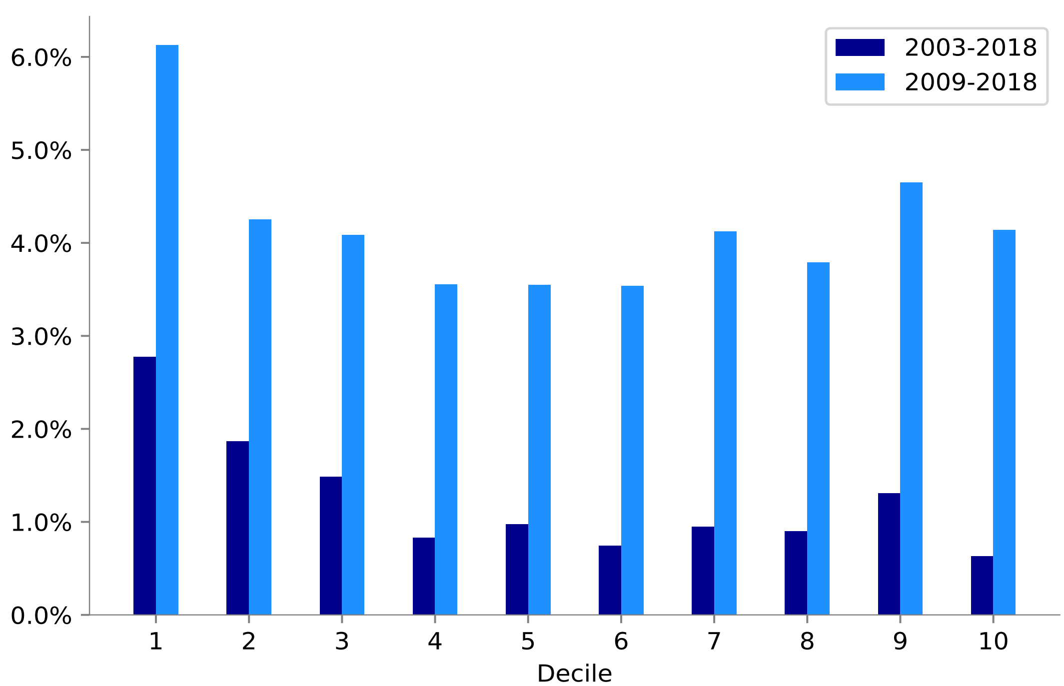
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 38: Momentum excess returns



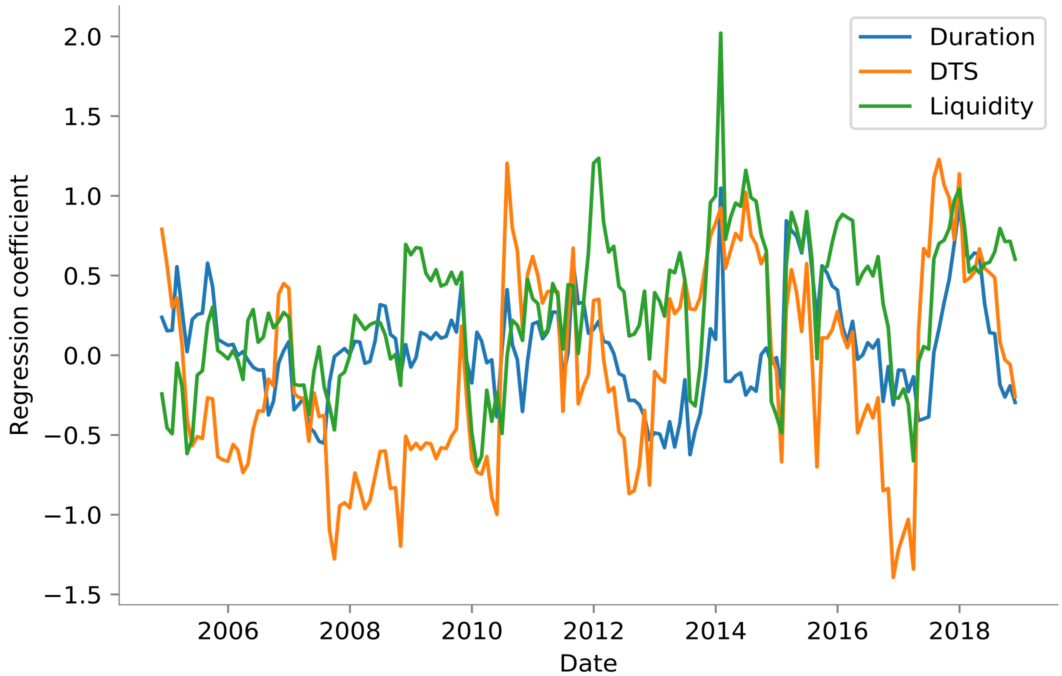
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 39: Amended momentum excess returns



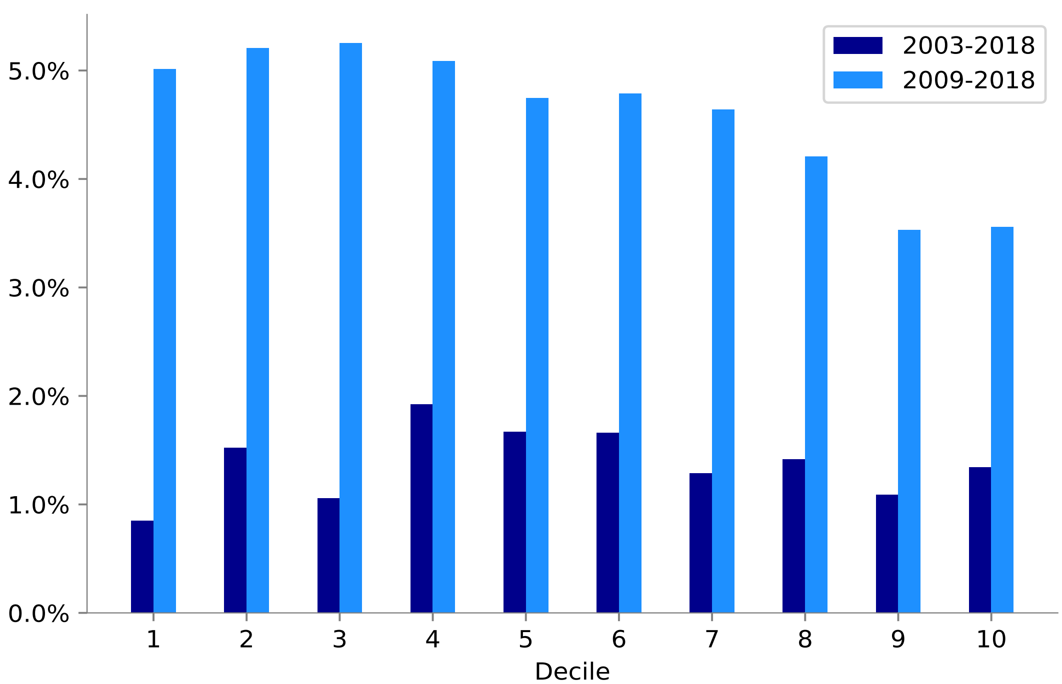
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 40: Amended momentum - Time varying exposure



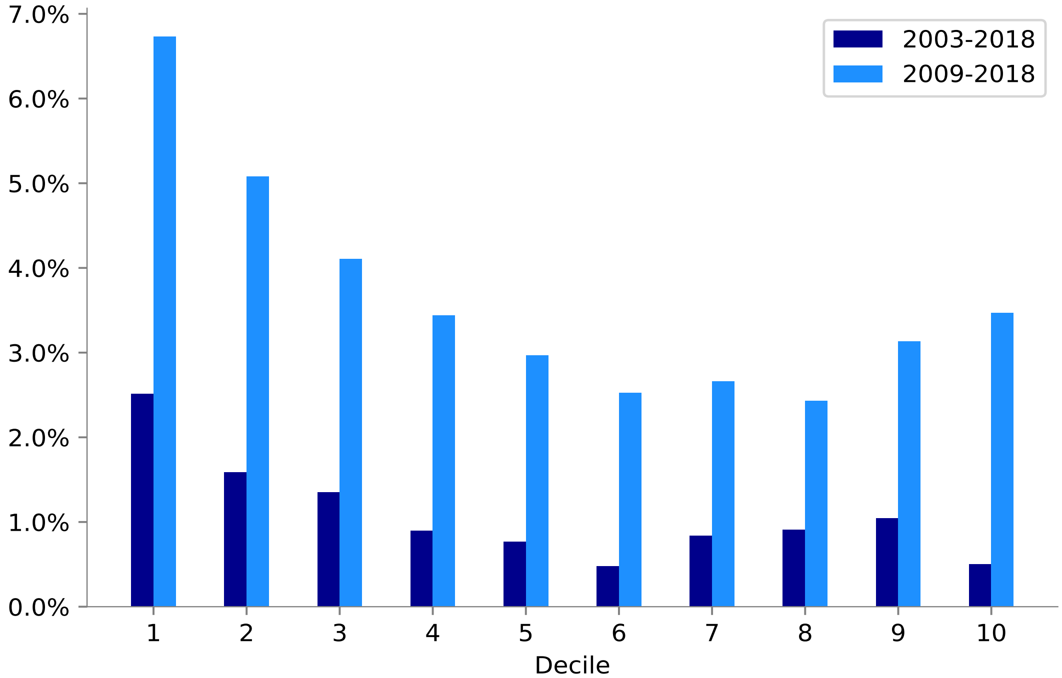
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 41: Size excess returns



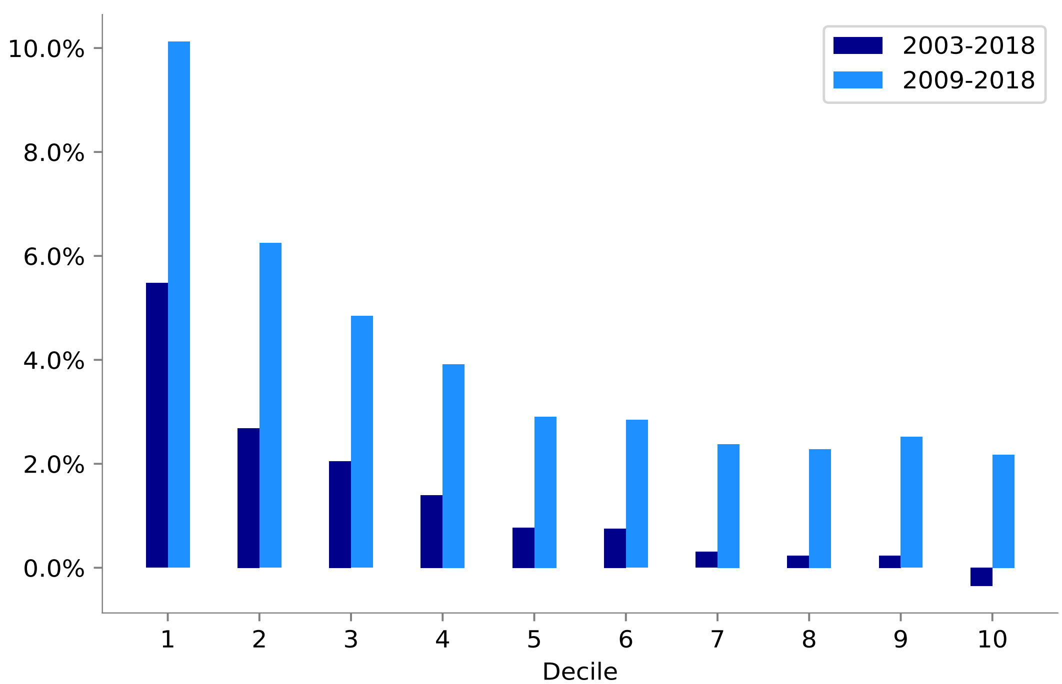
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 42: Value excess returns



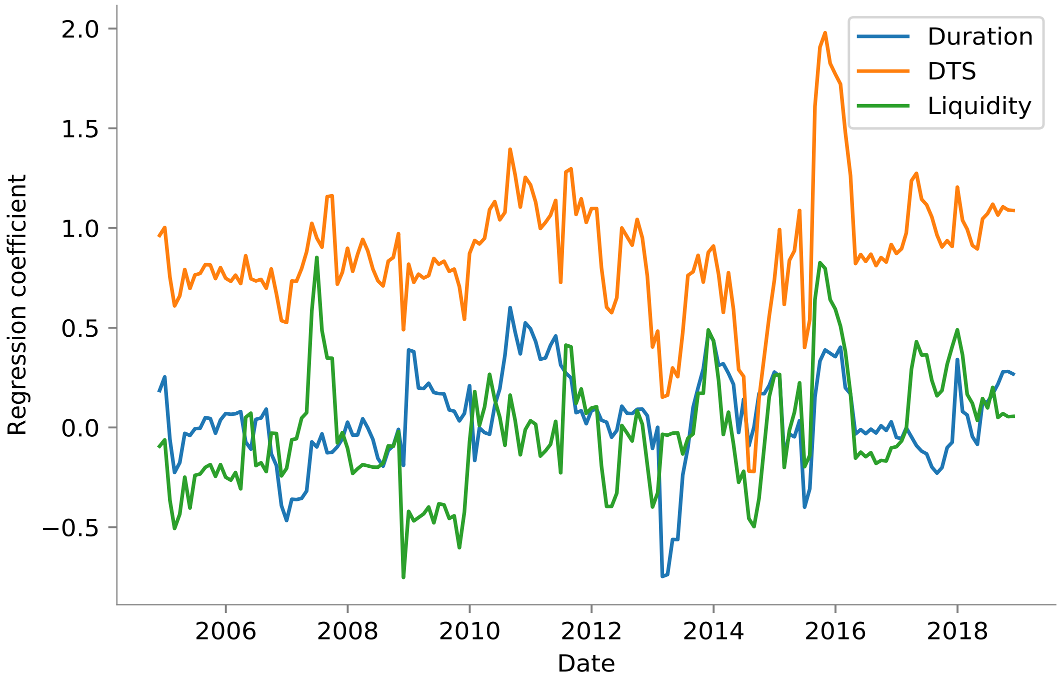
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 43: Amended value excess returns



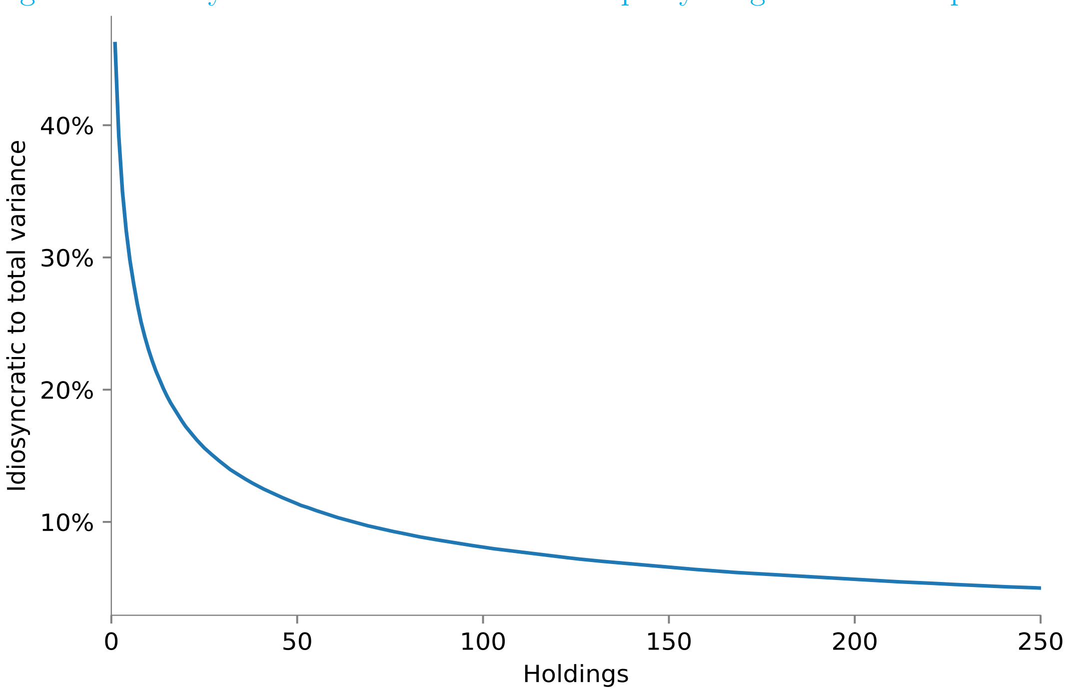
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 44: Amended value - Time varying exposure



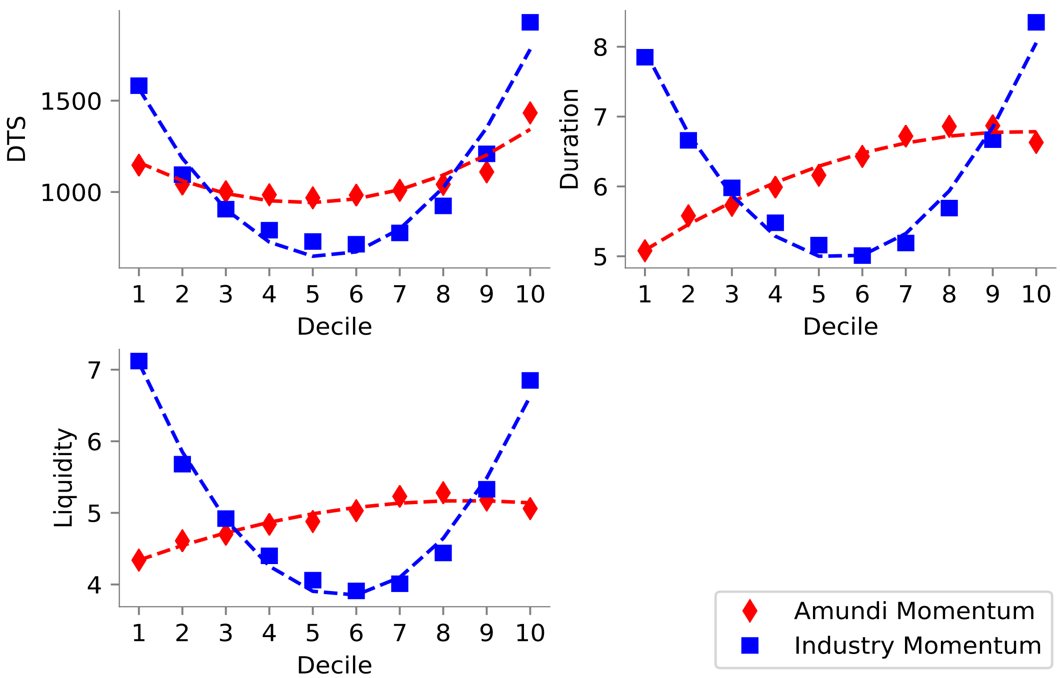
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 45: Idiosyncratic-to-total variance of equally-weighted random portfolios



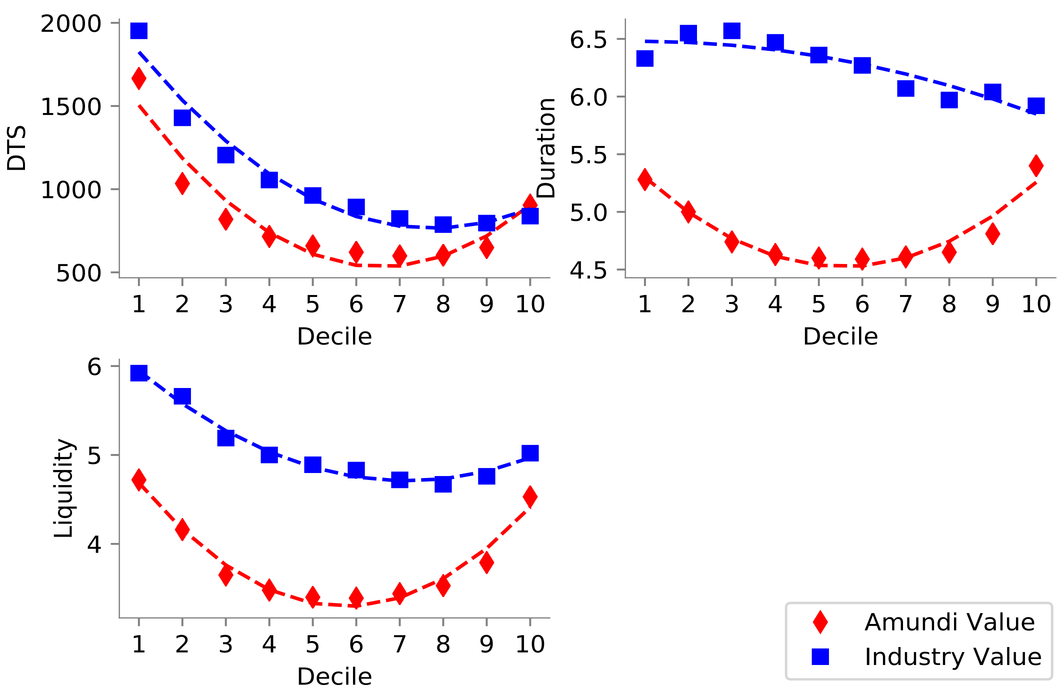
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 46: Before and after momentum exposures on traditional factors



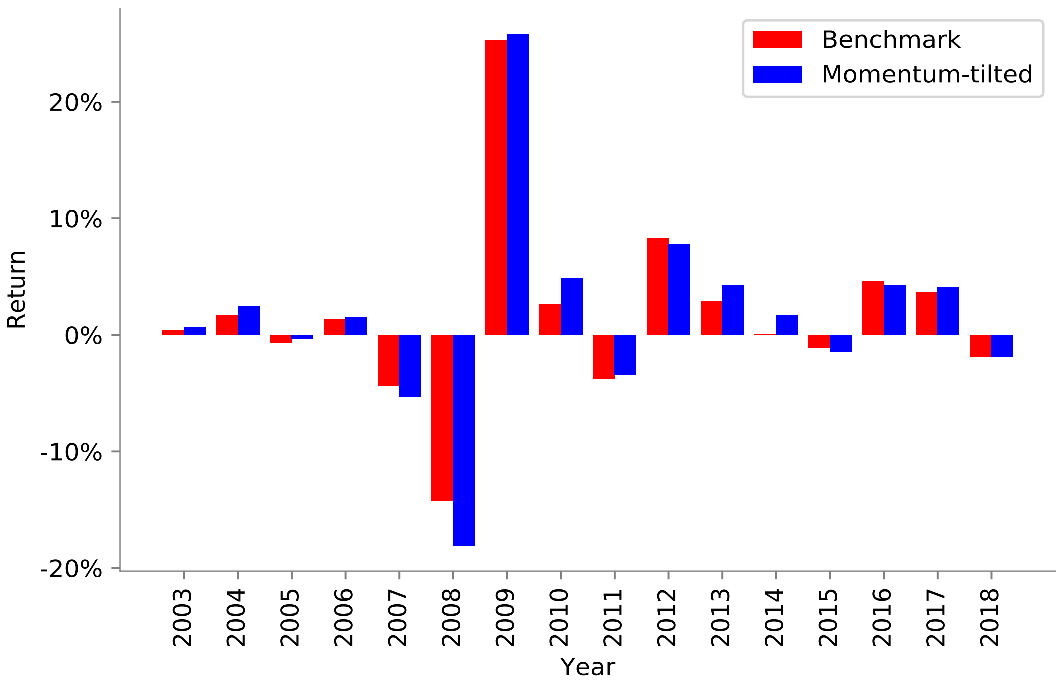
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 47: Before and after value exposures on traditional factors



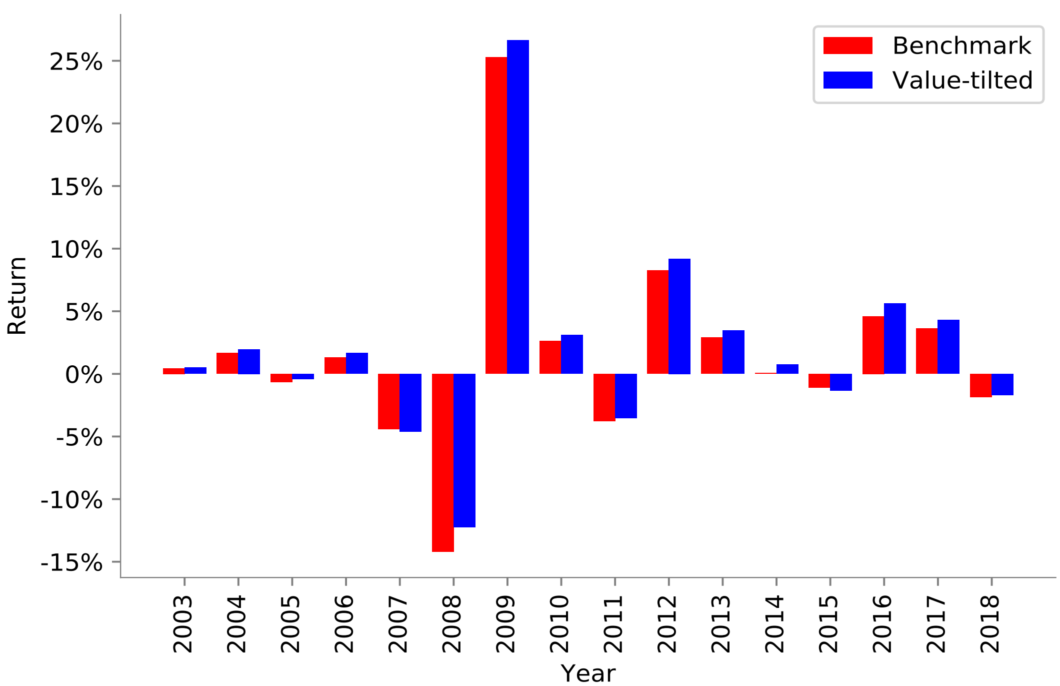
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 48: Calendar excess performance of the momentum tilted portfolio



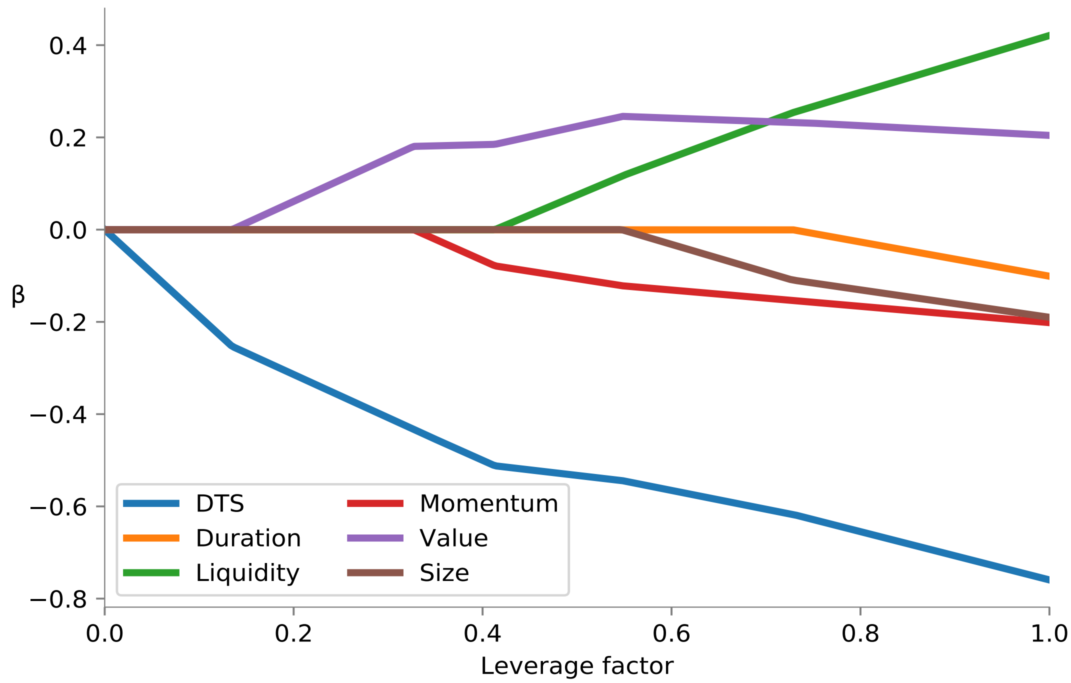
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 49: Calendar excess performance of the value tilted portfolio



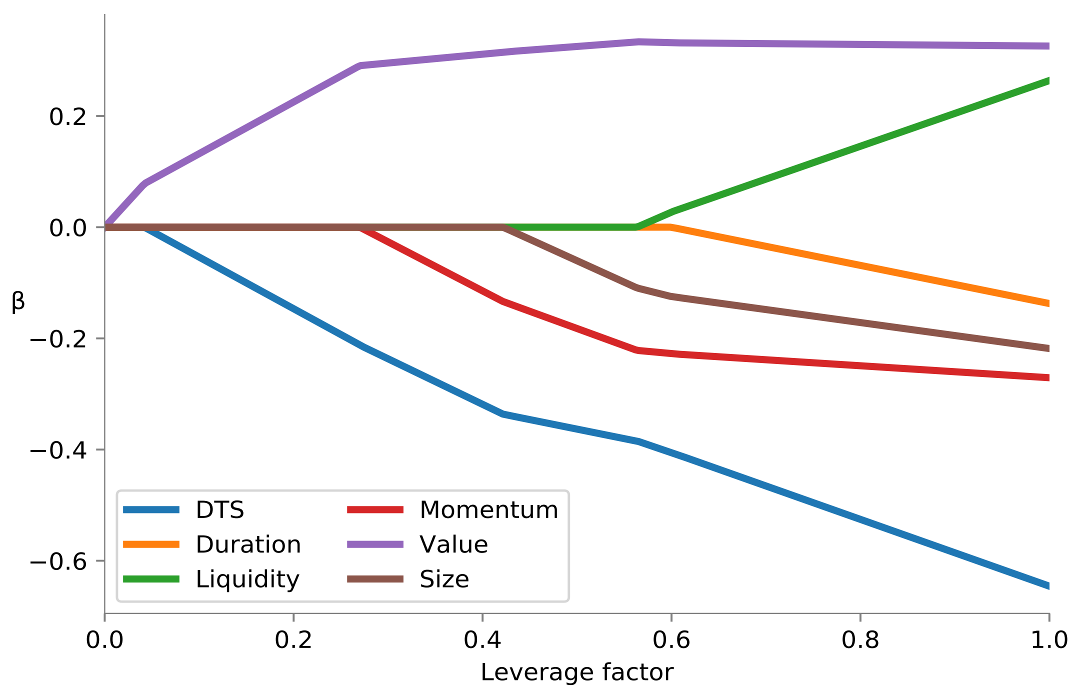
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 50: LASSO regression analysis for 2003-2018



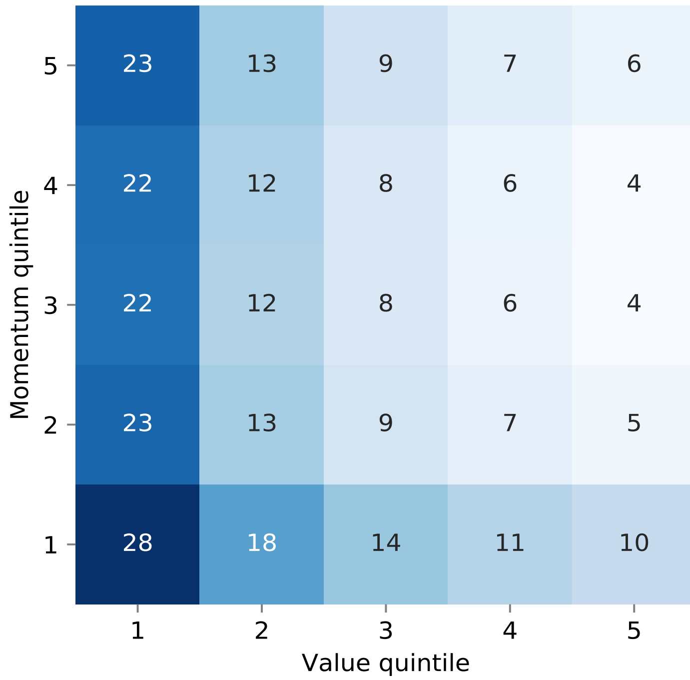
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 51: LASSO regression analysis for 2009-2018



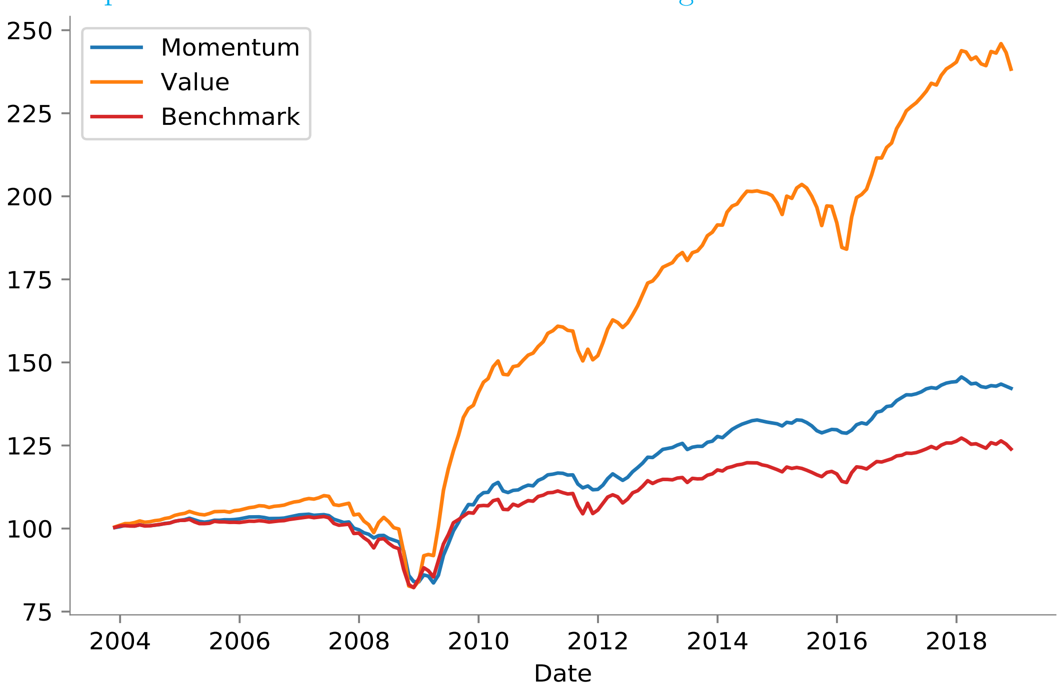
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 52: Value and momentum mix



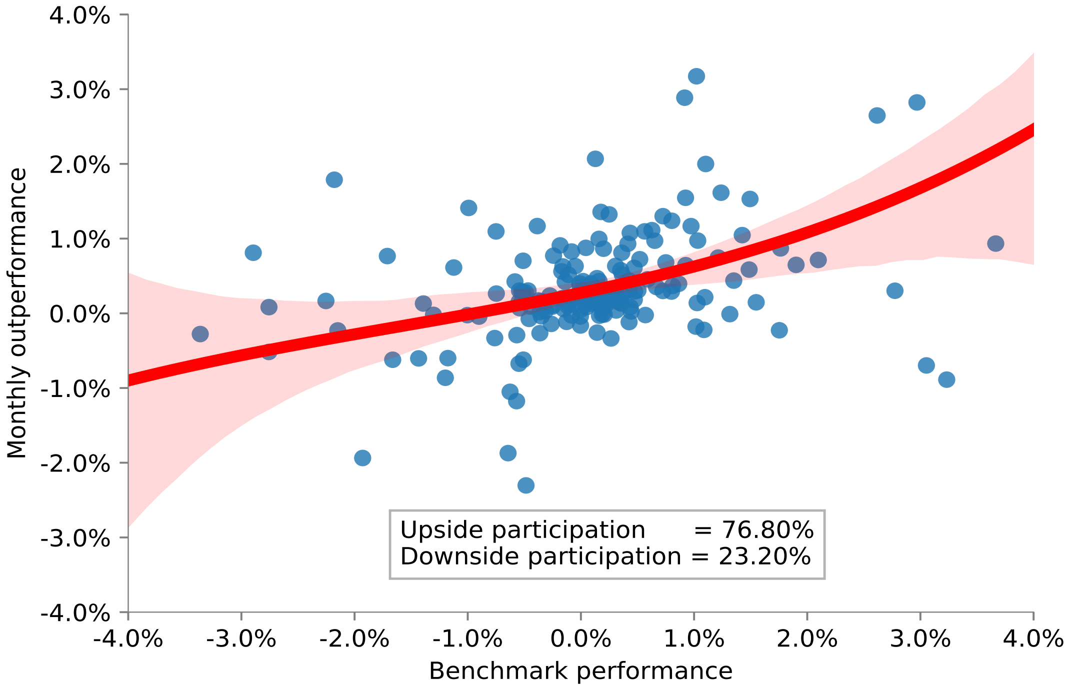
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 53: Excess performance of the rule-based active management value and momentum portfolios



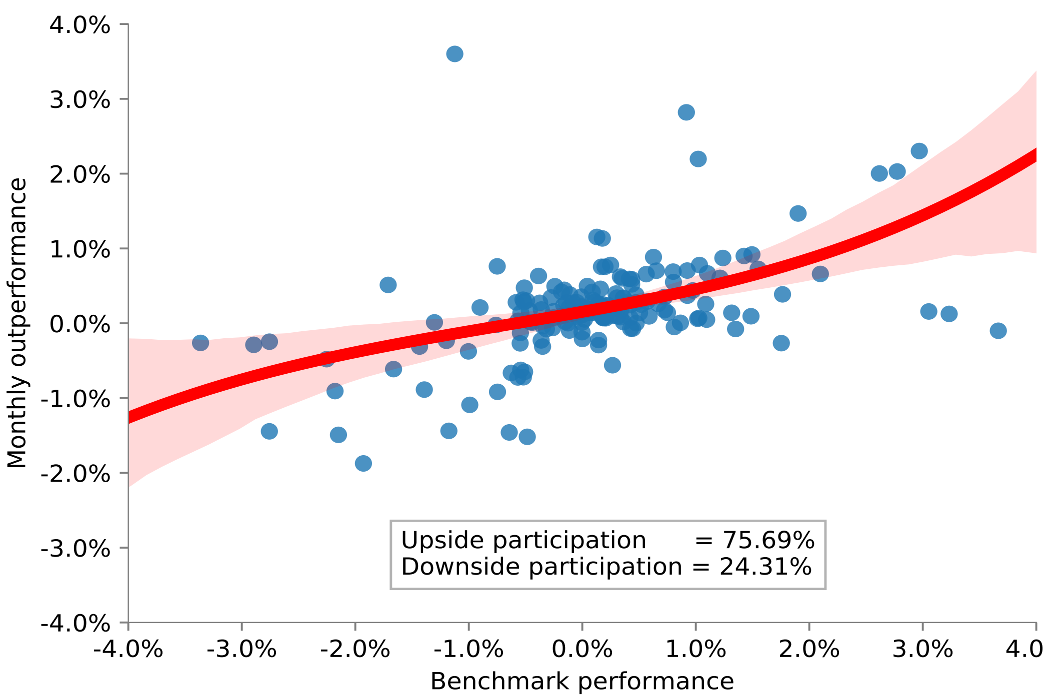
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 54: Value rule-based active management implementation



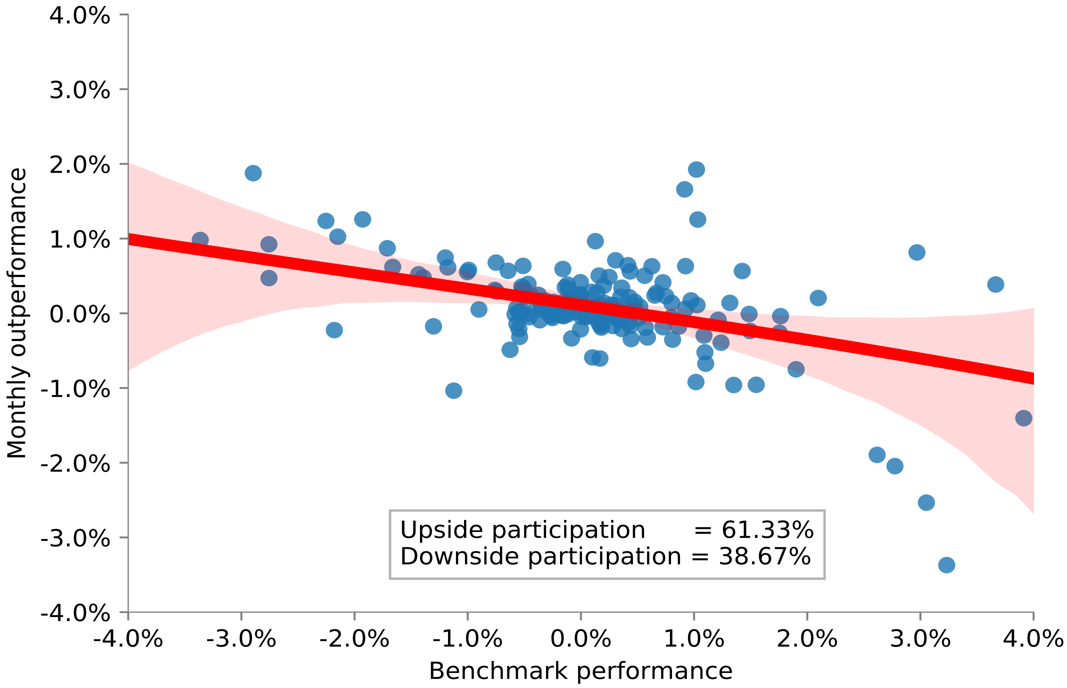
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 55: Value Q1 payoff



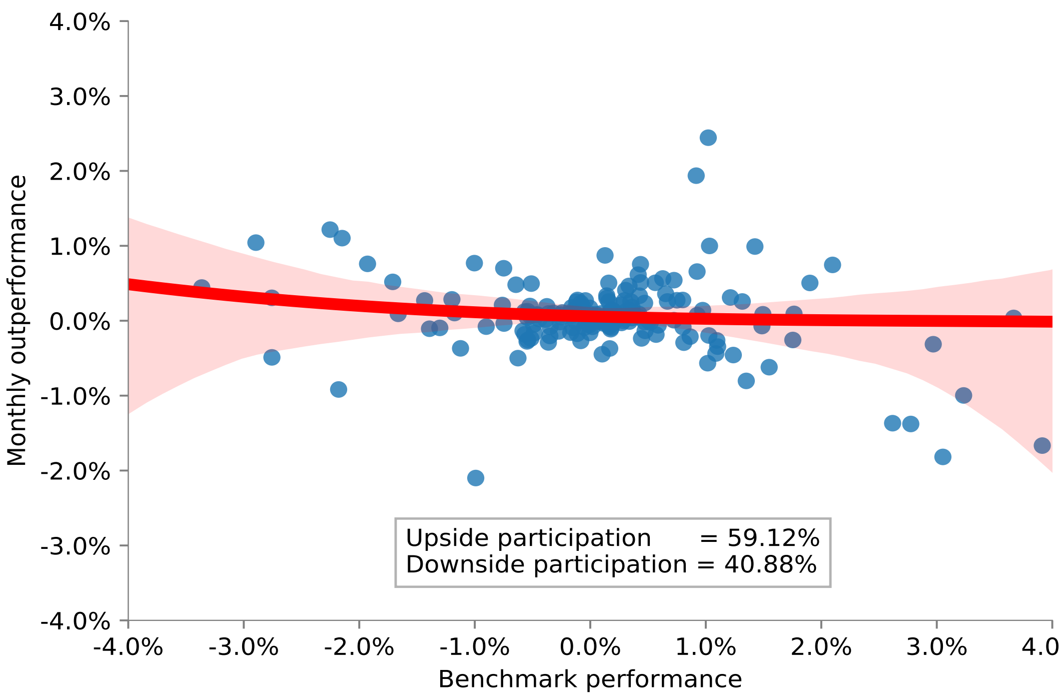
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 56: Momentum rule-based active management implementation



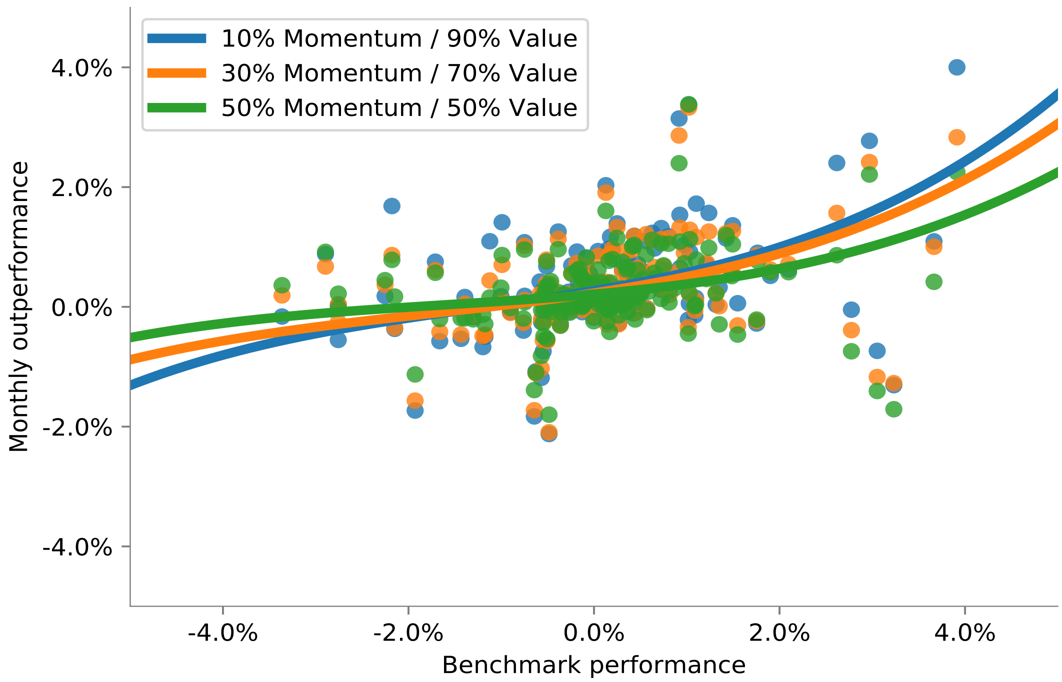
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 57: Momentum Q1 payoff



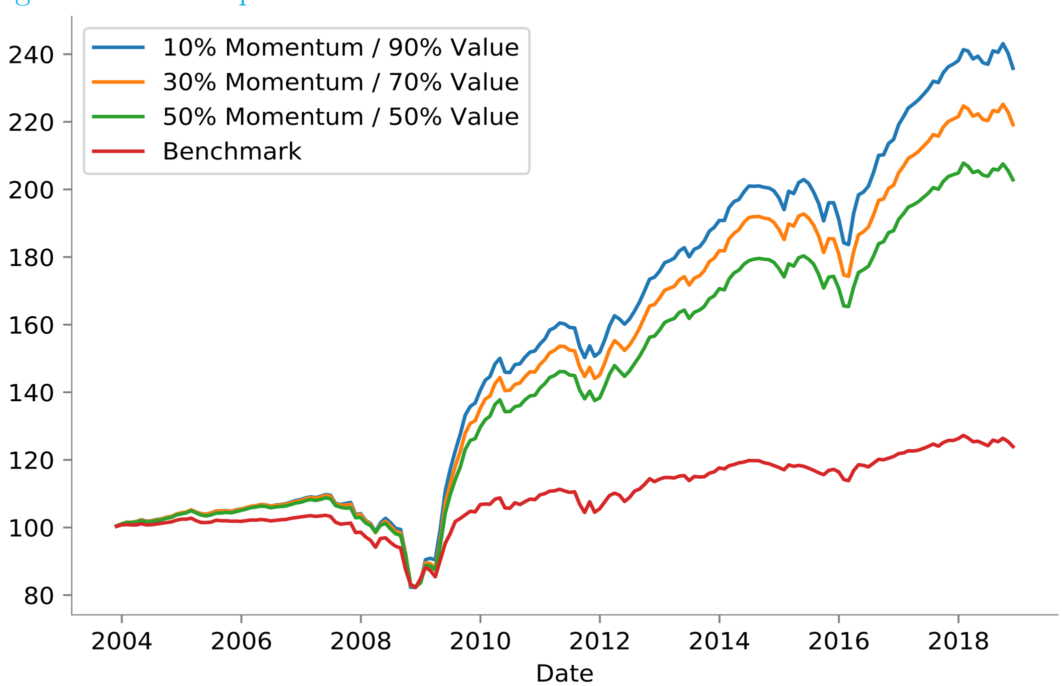
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 58: Payoff of the value and momentum mix



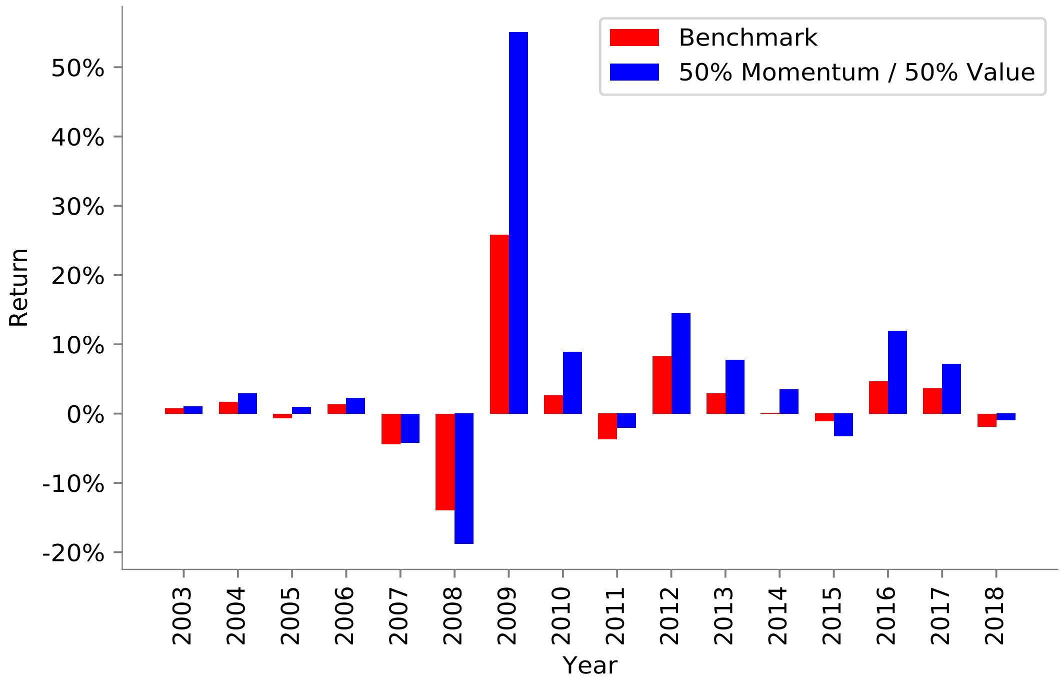
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 59: Excess performance of combinations of the value and momentum mix



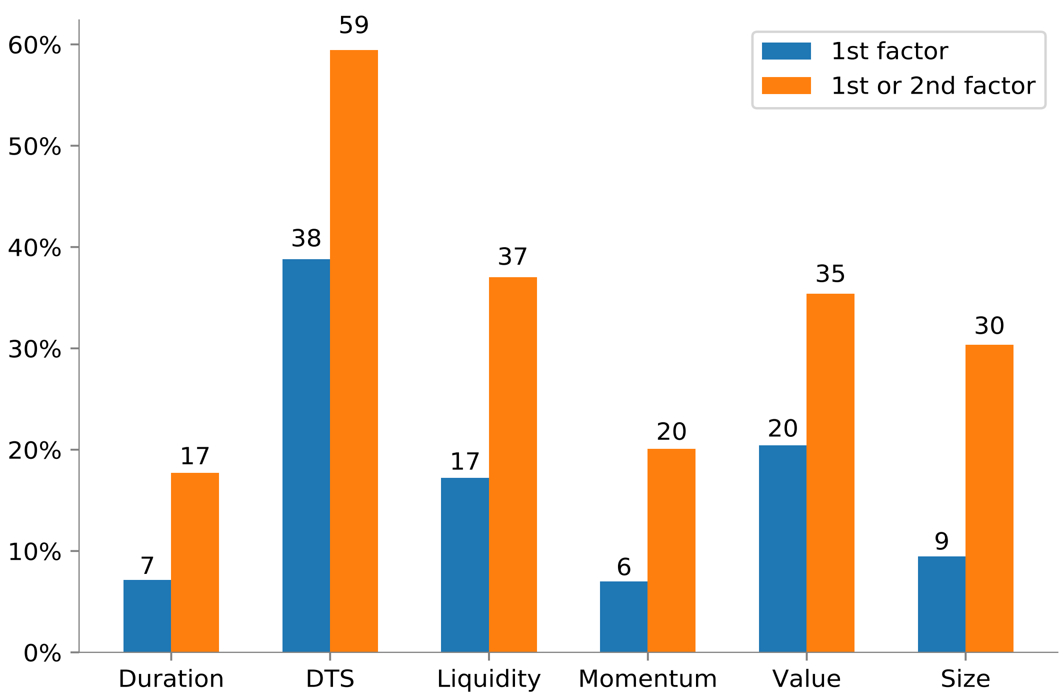
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 60: Calendar excess performance of the 50/50 portfolio



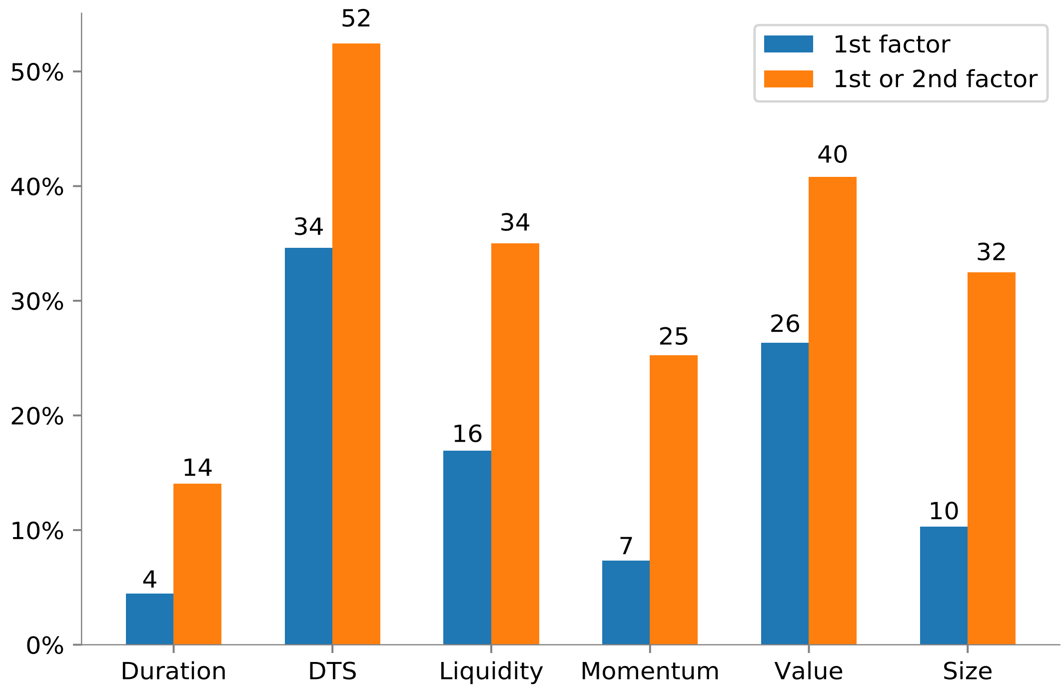
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 61: Period 2003-2018 - LASSO time-series analysis



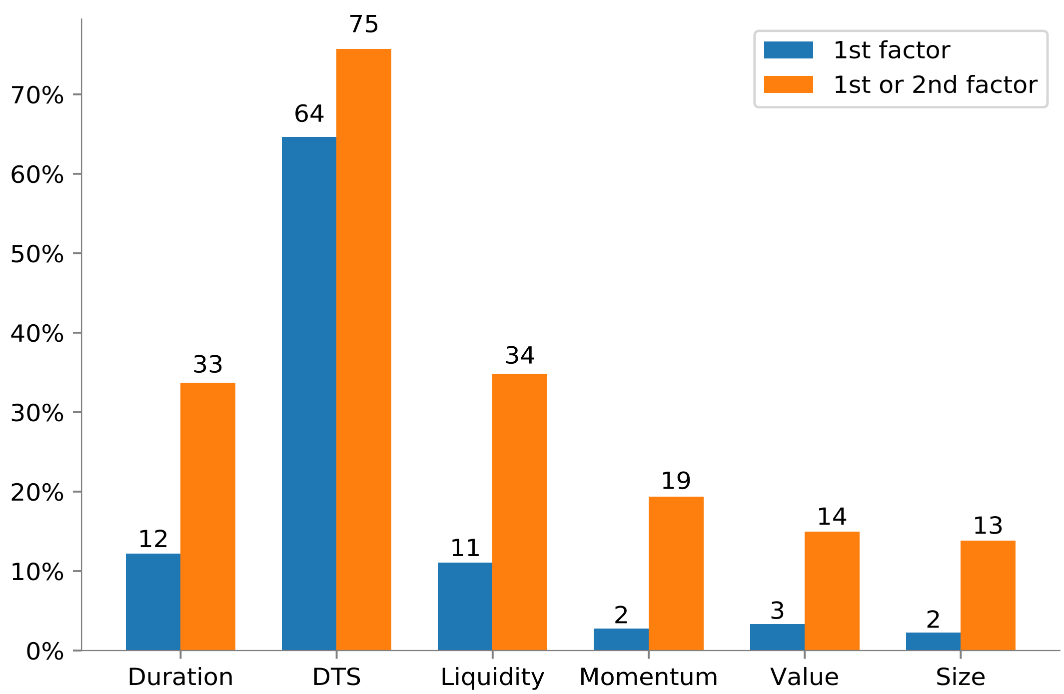
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 62: Period 2009-2018 - LASSO time-series analysis



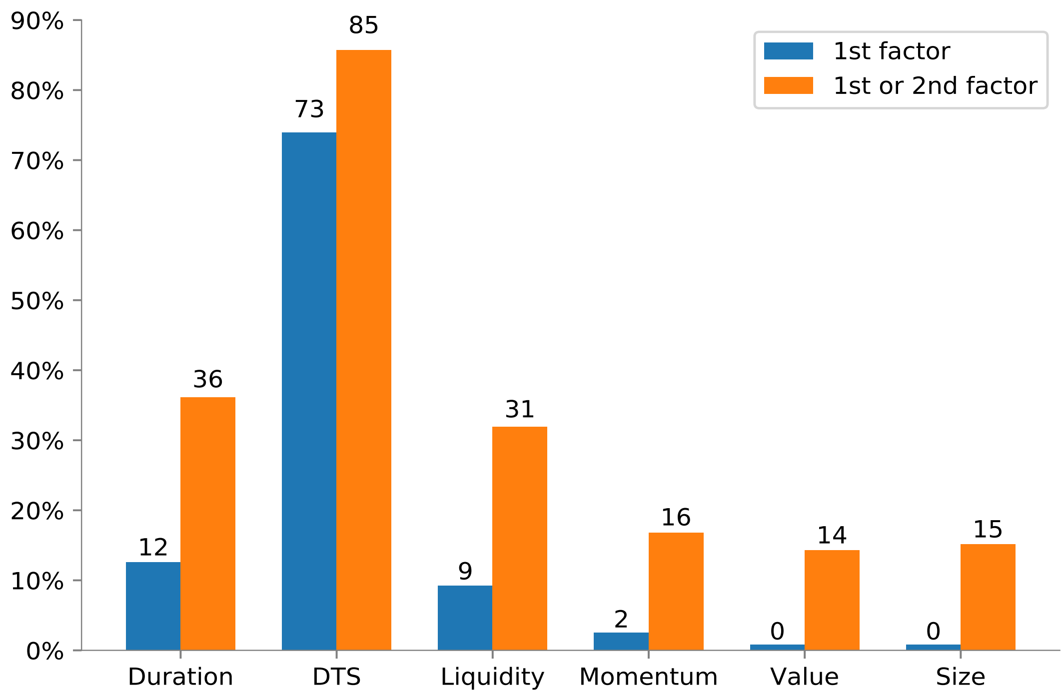
Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 63: Period 2003-2018 - LASSO cross-section analysis



Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Figure 64: Period 2009-2018 - LASSO cross-section analysis



Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Table 15: Momentum metrics - 2003-2018

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Return(%)	0.98	1.22	1.18	0.85	0.67	0.92	0.80	0.50	0.81	3.29
Volatility(%)	5.87	4.20	3.63	3.73	4.07	4.12	5.03	5.57	6.94	11.92
Skew	-0.62	-0.39	-0.56	-2.24	-2.73	-1.52	-1.86	-1.01	0.31	1.26
Sharpe	0.17	0.29	0.33	0.23	0.16	0.22	0.16	0.09	0.12	0.28
DTS	1582	1095	906	791	729	714	776	924	1209	1929
Duration	7.85	6.66	5.98	5.48	5.16	5.01	5.19	5.69	6.67	8.35
Liquidity	7.12	5.68	4.92	4.4	4.06	3.91	4.01	4.44	5.33	6.85
Habitat(%)	59.6	33.8	26.8	23.4	22.2	22.0	23.5	26.5	33.7	60.8

Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Table 16: Amended momentum metrics - 2003-2018

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Return(%)	2.77	1.87	1.48	0.83	0.97	0.74	0.95	0.90	1.31	0.63
Volatility(%)	5.63	4.48	4.37	4.62	4.40	4.85	5.34	4.93	6.51	9.35
Skew	0.65	-0.72	-0.98	-1.9	-1.69	-1.72	0.03	0.12	1.04	-0.92
Sharpe	0.49	0.42	0.34	0.18	0.22	0.15	0.18	0.18	0.20	0.07
DTS	1147	1043	1002	985	968	983	1009	1042	1110	1433
Duration	5.08	5.58	5.73	5.99	6.16	6.43	6.72	6.86	6.87	6.63
Liquidity	4.34	4.61	4.7	4.84	4.88	5.03	5.23	5.28	5.18	5.06
Habitat(%)	57.4	36.9	30.1	25.6	25.4	24.3	25.0	27.2	34.4	57.6

Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Table 17: Size metrics - 2003-2018

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Return(%)	0.85	1.52	1.06	1.92	1.67	1.66	1.29	1.42	1.09	1.34
Volatility(%)	6.16	5.33	5.07	4.80	5.16	5.09	4.70	4.70	4.98	4.68
Skew	-2.85	-0.07	-1.97	-0.16	-1.02	-1.25	-1.01	-0.9	-0.61	-0.02
Sharpe	0.14	0.29	0.21	0.40	0.32	0.33	0.27	0.30	0.22	0.29
DTS	1238	1218	1189	1133	1107	1062	1073	1103	1071	1005
Duration	5.35	5.72	5.74	5.77	5.87	6.09	6.23	6.46	6.65	6.43
Liquidity	5.53	5.92	5.64	5.55	5.55	5.71	5.56	5.47	5.33	4.63
Habitat(%)	96.0	95.1	94.9	95.5	95.9	96.5	97.1	98.1	98.9	99.9

Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Table 18: Value metrics - 2003-2018

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Return(%)	2.51	1.59	1.35	0.90	0.77	0.48	0.84	0.91	1.05	0.50
Volatility(%)	8.66	6.20	5.42	4.97	4.77	4.48	4.46	4.20	4.38	5.22
Skew	1.19	-0.06	-0.01	-0.68	-0.84	-1.39	-1.19	-1.13	-1.23	-1.54
Sharpe	0.29	0.26	0.25	0.18	0.16	0.11	0.19	0.22	0.24	0.10
DTS	1952	1429	1205	1055	962	893	824	787	796	838
Duration	6.33	6.55	6.57	6.47	6.36	6.27	6.07	5.97	6.04	5.92
Liquidity	5.92	5.66	5.19	5.0	4.89	4.83	4.72	4.67	4.76	5.02
Habitat(%)	73.2	47.8	39.7	36.0	34.8	36.0	40.1	45.5	55.6	79.4

Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Table 19: Amended value metrics - 2003-2018

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Return(%)	5.48	2.69	2.05	1.40	0.77	0.76	0.31	0.23	0.23	-0.35
Volatility(%)	9.60	5.53	4.89	4.34	3.76	3.69	3.59	3.68	3.74	4.60
Skew	-0.03	-0.25	-0.95	-0.95	-1.81	-1.72	-2.0	-2.25	-1.08	-0.86
Sharpe	0.57	0.49	0.42	0.32	0.21	0.20	0.09	0.06	0.06	-0.08
DTS	1665	1034	818	715	658	621	599	603	648	903
Duration	5.28	5.0	4.75	4.63	4.6	4.59	4.62	4.65	4.81	5.4
Liquidity	4.7	4.07	3.59	3.42	3.36	3.35	3.39	3.47	3.72	4.43
Habitat(%)	76.7	49.7	39.0	34.7	33.1	34.0	36.8	43.5	56.4	83.0

Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Table 20: Comparison of CAPM, traditional factors and traditional factors augmented by alternative factors

2003-2008	*Average* R^2(%)	VIF	*Hit − ratio* (%) MKT	DTS	Duration	Liquidity	*Hit − ratio* (%) Momentum	Value	Size
CAPM	45.17		71.37						
TRAD	55.34	2.56		64.6	37.72	49.36			
6-Factor	70.43	26.37		45.05	14.34	53.57	23.47	36.87	30.0
5-Factor	65.52	23.02		41.08	25.6	51.35	20.49	24.33	
2009-2018	*Average* R^2(%)	VIF	*Hit − ratio* (%) MKT	DTS	Duration	Liquidity	*Hit − ratio* (%) Momentum	Value	Size
CAPM	47.26		89.34						
TRAD	42.78	4.43		49.49	13.51	19.74			
6-Factor	56.83	13.10		32.17	16.18	25.66	21.53	36.99	24.49
5-Factor	50.96	11.66		28.13	14.78	20.00	17.90	21.38	

Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Table 21: LASSO factor picking rank

	R^2	VIF	DTS	Duration	Liquidity	Momentum	Value	Size
2003-2008	82.39	10.76	1	6	3	5	2	4
2009-2018	78.63	5.75	2	6	5	3	1	4
2003-2018	72.19	3.47	1	6	4	3	2	5

Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Table 22: Results of the time-series regression

2003-2018	Beta	Factor Picking Rank	T-statistic	P-value
DTS	-0.76	1	-9.80	***
Duration	-0.10	6	-1.73	*
Liquidity	0.42	4	6.34	***
Momentum	-0.20	3	-3.43	***
Value	0.20	2	2.46	**
Size	-0.19	5	-3.09	***
$R^2 = 72.19\%$ — $VIF = 3.47$				

Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Table 23: Parameter estimates

2003-2008	Retained deciles	Alpha	Beta	T-stat	P-Value
Momentum	[D1,D2]	-0.76	0.96	-1.02	
Value	[D1,D8]	0.56	1.01	1.74	*
Size	[D2,D9]	-0.70	0.98	-0.92	
2009-2018	Retained deciles	Alpha	Beta	T-stat	P-Value
Momentum	[D1,D2]	0.62	0.97	2.33	**
Value	[D1,D8]	0.53	0.99	4.03	***
Size	[D2,D9]	0.38	1.00	3.05	***
2003-2018	Retained deciles	Alpha	Beta	T-stat	P-Value
Momentum	[D1,D2]	0.07	0.97	0.46	
Value	[D1,D8]	0.57	1.00	4.29	***
Size	[D2,D9]	0.08	0.99	0.35	

Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Table 24: Metrics of the rule-based active management value and momentum portfolios - Annualized excess returns and volatilities

	Benchmark	Momentum	Value
Excess return (%)	1.53	2.43	6.04
Volatility (%)	4.73	4.26	7.38
Sharpe	0.32	0.57	0.82
Skew	-0.16	-0.36	0.34

Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Table 25: Metrics of combinations of the value and momentum mix - Annualized excess returns and volatilities

	Benchmark	10% Momentum 90% Value	30% Momentum 70% Value	50% Momentum 50% Value
Excess return (%)	1.53	5.97	5.45	4.90
Volatility (%)	4.73	7.33	6.95	6.36
Sharpe	0.32	0.81	0.78	0.77
Skew	-0.16	0.43	0.55	0.40
Upside (%)		77.90	78.45	75.69
Downside (%)		22.10	21.55	24.31

Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Table 26: Comparison of CAPM, traditional factors and traditional factors augmented by alternative factors - 90% significance

2003-2008	*Average* R^2(%)	VIF	$Hit-ratio$ (%) MKT	DTS	Duration	Liquidity	$Hit-ratio$ (%) Momentum	Value	Size
CAPM	45.17		74.63						
TRAD	55.34	2.56		68.67	43.92	54.66			
Six-Factor	70.43	26.37		50.92	21.11	57.79	30.29	44.34	37.67
Five-Factor	65.52	23.02		47.33	34.17	55.8	27.69	31.8	
2009-2018	*Average* R^2(%)	VIF	$Hit-ratio$ (%) MKT	DTS	Duration	Liquidity	$Hit-ratio$ (%) Momentum	Value	Size
CAPM	47.26		92.11						
TRAD	42.78	4.43		59.25	20.12	26.94			
Six-Factor	56.83	13.10		40.47	23.88	33.23	28.61	45.32	31.02
Five-Factor	50.96	11.66		36.41	21.74	27.5	25.18	27.89	

Source: ICE BoA Merrill Lynch USD Large Cap Corporate Bond Index. Authors' calculations

Cross asset

INVESTMENT STRATEGY

February 2019 | Working paper

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