The Cross-Section of Corporate Bond Returns

Guido Baltussen, Frederik Muskens, Patrick Verwijmeren*

January 2024

Abstract

We comprehensively examine the cross-section of U.S. corporate bond returns. By addressing challenges related to sample selection bias, the infrequent trading of corporate bonds, and duration-matching, we aim to establish a parsimonious factor model that most robustly prices the cross-section of U.S. corporate bonds. We find that four factors provide robust, sizable, and unique credit return premia in portfolio sorts. These factors are the market factor, a bond maturity factor, a valuation factor, and an equity momentum factor. We confirm that these factors are important across a wide set of testing choices.

JEL classification: G11, G12

EFM codes: 310, 340

Keywords: asset pricing, corporate bonds, factor premia, return anomalies, market, spread, value, low risk, momentum, accruals.

*Baltussen (baltussen@ese.eur.nl) is with Erasmus School of Economics and Northern trust Asset Management – Quantitative Strategies, Muskens (f.muskens@robeco.nl) is with Erasmus School of Economics and Robeco Quant Fixed Income, and Verwijmeren (verwijmeren@ese.eur.nl) is with Erasmus School of Economics and University of Melbourne. We would like to thank Amit Goyal, Patrick Houweling, Amar Soebhag, Laurens Swinkels, Pim Van Vliet and seminar participants at Robeco for valuable contributions and discussions. Robeco Institutional Asset Management, the firm that employs one of the authors, offers various multi-factor investment products. The construction of these products may, at times, draw on insights related to this research. The views expressed in this paper are not necessarily shared by Robeco Institutional Asset Management.

In this paper, we study the cross-section of corporate bond returns. Corporate bonds are an important asset class for investors and a vital source of financing for corporations. At the end of 2022, the U.S. corporate bond market comprised over $10 trillion in outstanding value (Securities Industry and Financial Markets Association, 2023). However, despite the economic size and investor importance of corporate bonds, the number of academic studies on the drivers of cross-sectional differences in corporate bond returns is relatively limited.

Seminal work by Fama and French (1993) prices the cross-section of bonds with a default and a term factor. More recently, Bai, Bali and Wen (2019; henceforth BBW) proposed (and retracted) a factor model comprising of the corporate bond market factor, a downside risk factor, a credit risk factor, a liquidity risk factor and a short-term reversal factor. Dickerson, Mueller and Robotti (2023) refute the BBW results and show that the BBW model does not outperform a single market-factor based model. In our study, we examine a wide set of drivers of expected corporate bond returns, based on studies proposing individual characteristics that predict corporate bond return in the cross-section (e.g., Gebhardt, Hvidkjaer and Swaminathan, 2005; Bhojraj and Swaminathan, 2009; Correia, Richardson and Tuna, 2012; Jostova et al., 2013; Chordia, et al., 2017; Choi and Kim, 2018, Bali, Subrahmanyam and Wen, 2019), with the goal of establishing a parsimonious factor model that most robustly prices the cross-section of U.S. corporate bonds.

When studying corporate bond returns, three challenges are particularly important. First, corporate bonds trade infrequently and over-the-counter (OTC). The use of sparse transaction prices introduces noise due to bid-ask effects. Consequently, reliable factor inference requires the use of a reliable data source with accurate prices and characteristics. The common data source used by corporate bond studies is the Trade Reporting and Compliance Engine (TRACE) platform, a dataset comprised of actual transaction prices of institutional investors with reporting requirements. By contrast, industry practice is to utilize data from index providers that serves as the official pricing source of corporate bond indices against which trillions of U.S. dollars are managed. We postulate several concerns with the TRACE dataset that potentially biases factor inference. This includes a relatively limited coverage after appropriate data quality filters, cross-sectional differences in synchronicity in prices, bid-ask bounces in transaction prices, and a lower quality of return data.[1]

Second, most corporate bonds are issued with a finite time-to-maturity, often between five and ten years. As the U.S. corporate bond market has grown tremendously since the 1990s and bonds cease to exist at maturity, new issues represent a major portion of the market (e.g., at the start of June 2022, 19% of the total amount outstanding was issued in the past twelve months). Consequently, factor definitions that require historical corporate bond prices cannot price bonds for a significant portion of their lifespan. This implicit sample selection is especially problematic since recent issues generally are the most important and liquid bonds of the corporate bond market.

Third, corporate bonds returns can be decomposed in two key components, namely duration and credit spread returns, which is a decomposition that is standardly applied in the industry. The duration component reflects compensation for bearing interest rate risk, whereas the credit return component reflects compensation for bearing credit risk. Most academic studies focus on corporate bond returns over the risk-free short-term rate, which resembles the

[1] Contemporaneous work by Dickerson, Robotti and Rossetti (2023), Andreani, Palhares and Richardson (2023), and Dick-Nielsen et al. (2023) also raise concerns with TRACE data and employ data from index providers instead.

approach commonly applied in equity factor studies.[2] However, in the cross-section, corporate bonds vary widely in their durations, which makes the duration component a major source of cross-sectional return differences that is relatively uncorrelated to credit return movements. In our sample, on average 72% (16%) of bond return variation is due to the duration component for U.S. investment grade (high yield) corporate bonds. To understand the pricing of credit risk in corporate bond returns, it is important to take duration into account, especially for investment grade bonds.

In this study, we propose an approach for examining asset pricing factors in corporate bonds that addresses these data-related concerns. First, our approach utilizes pricing data from the constituents of the major corporate bond indices. To this end, we utilize data from Bloomberg (former Lehman Brothers) U.S. investment grade and high yield corporate bond indices, the most widely used benchmarks in the industry. This dataset offers one of the deepest histories available to date, starting with reliable and comprehensive coverage as of 1994 (in comparison, the earliest TRACE data starts in July 2002), which allows us to study the period 1994 to 2022. Second, our approach addresses the implicit sample selection bias by focusing on all constituents in the indices and on those factors that can be estimated at issuance. Third, we focus on excess returns over duration-matched treasuries to effectively isolate the credit return component.

Our results using this approach show a parsimonious factor model that prices the cross-section of U.S. corporate bonds based on four factors. These factors are the market factor, a

---

[2] In addition, several studies include a term structure factor in spanning regressions. However, this approach implicitly assumes a constant linear term structure, which contrasts with the commonly observed concave term structures in government bonds and its important dynamics over time.

bond maturity factor, a valuation factor, and an equity momentum factor. We find that these factors offer robust and sizable return premia in portfolio sorts. Moreover, these factors are not spanned by others and when combined offer the best model fit in terms of traditional Gibbons-Ross-Shanken-test statistics and the squared Sharpe ratio measure proposed by Barillas and Shanken (2017) and Fama and French (2018). The set of factors excel in describing the cross-sectional variation in a wide set of corporate bond portfolios sorted on either bond characteristics or issuer characteristics, while outperforming alternative models like the one-factor model of Dickerson, Mueller and Robotti (2023), or common equity factor models. In additional tests, we confirm that these factors are important across a wide set of testing choices, including a split between investment grade bonds and high yield bonds.

We realize that an advantage of TRACE data for academic researchers is its accessibility. We establish that our four-factor model can be confirmed using standard TRACE data and processed TRACE data as provided by the WRDS platform. However, our exercise points out specific weaknesses of relying solely on TRACE data. Most notably, some factors emerge in the TRACE-WRDS dataset but disappear after certain data filters or when using Bloomberg data. One factor that researchers should be particularly skeptical of is the short-term reversal factor, driven by microstructure noise in TRACE transaction prices.

Our paper links to other contemporaneous papers examining common factor pricing in corporate bonds. Dickerson, Mueller and Robotti (2023) show that a one-factor model outperforms the BBW model but leaves substantial pricing errors. Dickerson, Robotti and Rossetti (2023) show that bond momentum and reversal factors cannot outperform the single bond market factor model. Key differences between these studies and our study are that we consider a wider set of drivers of corporate bond returns and examine economically logical factor models across the opportunity set of factor models. Kelly, Palhares and Pruitt (2023) propose a conditional factor model for the cross-section of corporate bonds based on Instrumental Principal Component Analysis (IPCA). They explicitly focus on predicting future risks of corporate bond returns and uncover several key factors that also show up in our work. Compared to their approach, which relies on machine learning techniques, our work focuses on traditional asset pricing models that can be more easily constructed, modeled, and applied.

Our work also relates to recent studies examining the importance of methodological choices for bond factors (Dick-Nielsen et al., 2023) and equity factors (Soebhag, Verwijmeren, and Van Vliet, 2023; Walter, Weber and Weiss, 2023). Dick-Nielsen et al. (2023) document replication failures for many corporate bond anomalies and find several anomalies that are robust across methodological choices. Compared to our study, their focus is on robustly testing anomalies without searching for the best asset pricing model. We propose a common approach across methodological choices to construct corporate bond factors. This approach considers double-sorted portfolios on characteristics and credit rating (as rating is a key driver of corporate bond spreads), value-weighting bonds per issuers (to prevent the test portfolio to become concentrated with single issuers), and value-weighting portfolios (as there are many bonds that are hard to invest in).

Overall, our results have strong implications for both corporate bond investors and corporations that attract capital through corporate bond issuance. Investors can use the factor model to price bonds, assess bond fund performances, and build portfolios, whereas corporations can use the factor model to assess their cost of debt capital.

I. Measuring the Cross-Section of Corporate Bond Returns

A. Data challenges of corporate bonds

Studying corporate bond returns requires a comprehensive high-quality dataset that covers the broad corporate bond market and its prices. In contrast to stocks, where high-quality cross-sectional equity samples are available in CRSP, the construction of a reliable high quality and bias-free dataset on the cross-section of corporate bonds is more challenging. When studying the cross-section of corporate bond returns, three challenges are particularly important.

[INSERT FIGURE I]

First, corporate bonds trade infrequently and OTC as there is no centralized exchange for corporate bonds. Sparse transaction prices introduce microstructure noise in prices due to bid-ask effects, as well as cross-sectional differences in synchronicity in prices. Microstructure noise in prices can create artificial return predictability for predictors that are based on prices or that correlate with bid-ask bounces (see also Dickinson, Robotti and Rossetti, 2023). Similarly, non-synchronicity can create spurious return predictability. Second, most corporate bonds are issued with a finite time-to-maturity, often between five and ten years. As such, in contrast to stock market, in which initial public offerings (IPOs) represent a small fraction of the market, new issues represent a major portion of the corporate bond market. Figure I shows the percentage of the total debt amount outstanding that is in bonds that were issued less than 1-month (grey line), 1-year (black line) or 3-years (dotted black line) ago. On average, 20.9% (54.7%) of the amount outstanding in corporate bonds is in bonds with that were issued less than 1-year (3-year) ago. Consequently, factor definitions that require at least one year of historical corporate bond prices cannot price bonds for a significant portion of their lifespan. This implicit sample selection is especially problematic since recent issues are generally the most traded and liquid bonds of the corporate bond market. We will return to these first two challenges when selecting our dataset in Section I.B.

[INSERT FIGURE II]

A third challenge is that corporate bonds returns can be decomposed in two key components, namely duration and credit spread returns, a decomposition that is standardly applied in the industry. The duration component reflects compensation for bearing interest rate risk, whereas the credit return component reflects compensation for bearing credit risk. In the cross-section, corporate bonds vary widely in their durations, which makes the duration component a major source of cross-sectional return differences that is relatively uncorrelated to credit return movements. To demonstrate this phenomenon, we sort corporate bonds from the Bloomberg U.S. Investment Grade and High Yield index constituents between January 1994 and June 2022 in 30 rating-maturity buckets, by assigning bonds to one of the six rating buckets (AAA-AA, A, BBB, BB, B, CCC-C) and five maturity buckets (1-3 years, 3-5 years, 5-7 years, 7-10 years, >10 years). In Figure II, we show the average variance contribution of the Treasury return for these 30 portfolios. For investment grade corporate bonds, the return variation is for at least 70% driven by Treasury returns, with even higher percentages for longer-dated bonds. For lower credit ratings, the percentage of the variance explained by Treasury returns declines monotonically but remains substantial for especially longer maturities. The lower the credit risk, the more the corporate bond excess return are driven by changes in the government bond yield curve. On average, 72% (16%) of bond return variation is due to the duration component for U.S. investment grade (high yield) corporate bonds included in our sample. Consequently, if we would study corporate bond returns without correcting for duration risk, we would mostly study Treasury returns, especially within the investment grade universe.

To deal with duration risk of corporate bonds, several academic studies focus on corporate bond returns over the short-term risk-free rate (see e.g., BBW, Chung, Wang and Wu, 2019; Bai, Bali and Wen, 2021), which resembles the approach commonly applied in equity factor studies. But, as shown above, the lower the credit risk, the more the corporate bond excess return will be driven by changes in the government bond yield curve. Another approach applied in several studies is to include a government bond term structure factor in spanning regressions (see, e.g., BBW). However, this approach implicitly assumes a constant linear term structure, which contrasts with the commonly observed concave term structures in government bonds, while also ignoring important dynamics in curvature over time.

In this study, we focus on corporate bond returns over duration-matched treasuries to effectively isolate the credit return component. The total return on corporate bonds can be decomposed as follows:

$$R_{i,t} = r_{i,t} + R_{i,t}^{DMT}, \tag{1}$$

where $R_{i,t}$ is the total return (upper case) of bond i in month t, $r_{i,t}$ is the credit return (lower case) and $R_{i,t}^{DMT}$ is the total return of the duration-matched Treasury. Total returns are computed based on the clean bond prices of bond i at time t, its accrued interest over month t, and its coupon over month t. More specifically, total returns can be computed as follows:

$$R_{i,t} = \frac{P_{i,t} + AI_{i,t} + C_{i,t}}{P_{i,t-1} + AI_{i,t-1}} - 1, \tag{2}$$

where $P_{i,t}$ is the last observed price within month t. $AI_{i,t}$ is the accrued interest, and $C_{i,t}$ is the paid coupon during month t. Monthly *total returns* are measured in USD over the full month.[3] We compute credit returns by subtracting the return of the duration-matched Treasury (obtained from Bloomberg) from the total return:

$$r_{i,t} = R_{i,t} - R_{i,t}^{DMT}. \tag{3}$$

Bessembinder, Kahle, Maxwell, and Xu (2009) describe how to compute the maturity-matched Treasury returns for an individual bond. The credit return measures the compensation for holding risky corporate bonds, and effectively hedges the return due to changes in the Treasury yield curve. Thus, we focus on the part of the return that is unique to corporate bonds.

B. Dataset Selection

The infrequent trading of corporate bonds and the potential sample selection bias highlight the importance of the choice of a particular dataset on corporate bond prices. Several corporate bond price datasets are available. To date, researchers commonly resort to FINRA's Trade Reporting and Compliance Engine (TRACE) as their main data source. FINRA members (e.g., brokers, dealers) are obliged to report all transactions in TRACE eligible securities. The TRACE dataset contains these historical corporate bond transactions, including time of execution, traded prices, and traded volumes from July 2002 onwards. Although nowadays easily accessible by researchers, the TRACE dataset faces problems when attempting to address the challenges mentioned above. Most importantly, TRACE is based on sparse

[3] Cash accrued throughout the month (due to e.g., coupon payments) does not earn a reinvestment return. In case of an intra-month default, the return is based on the last quoted price and thus reflects the market's anticipated recovery rate.

transaction prices. These prices include bid-ask spreads (i.e., buys typically transact at the ask and sells typically transact at the bid) and, due to the illiquid nature of corporate bonds, prices are only irregularly observed. Monthly returns are then based on daily volume-weighted average prices that are observed close to month-end. However, many bonds do not trade during the last business day of the month, let alone at the same point during the day. Indeed, we find that 53.5% of bonds were not traded more than one day from month-end based on the TRACE dataset, when examining data between July 2002 and June 2022. On average, 67.7% of all corporate bonds in the cross-section did not trade during the last day of a month for two consecutive months. Non-synchronicity in prices is often tried to address by focusing on prices not older than 1 or 5 days from month-end. However, this practice introduces two biases; (i) a backward-looking bias in which the bonds that are less traded (or appear less traded due to coverage of the dataset) are excluded from the investment universe, and (ii) a forward-looking bias in which the bonds that do not have a price at the end of the next period are removed. The latter introduces an ex-post bias on the researcher's analyses, which, given the fraction of bonds impacted by non-synchronicity, can be substantial. Consequently, the resulting monthly prices contain outliers, returns experience significant serial correlation, and cover only a fraction of the corporate bond market. Contemporaneous work also raises some of these concerns with TRACE data (Andreani, Palhares and Richardson, 2023; Dickinson, Robotti and Rossetti, 2023, Dick-Nielsen et al., 2023).

An alternative dataset relies on pricing data from the constituents of the major corporate bond indices like Bloomberg (BB; former Lehman Brothers and Barclays) or Intercontinental Exchange - Bank of America (ICE-BAML). Although costly to obtain for academics, index-data is the common source of industry research. Prices (and other items) from these data are standardly used in the industry to value mutual fund net asset values (NAVs) and benchmark exchange traded funds (ETFs) and mutual funds. In addition, index data offers one of the deepest histories available to-date, with BB starting the earliest with reliable and sufficient coverage as of 1994 (in comparison, the earliest TRACE data starts in July 2002). The main difference between ICE-BAML and BB data is coverage: ICE-BAML data contains all constituents of the ICE Bank of America investment-grade (C0A0) and high-yield (H0A0) corporate bond indices with data starting in January 1997 with slightly more lenient index inclusion criteria, while BB data contains all constituents of the Bloomberg U.S. Aggregate Corporate Investment Grade (IG) index and the Bloomberg U.S. Corporate High Yield (HY) indices with deeper time-series history. In general, more assets follow the BB indices. Consequently, our sample is based on BB data and spans the period January 1994 until June 2022.[4]

Prices in the Bloomberg dataset are quote-based and reflect a combination of transaction data, broker and dealer quotes. As we will show shortly, this substantially increases data coverage and cross-sectional comparability, and leads to higher quality returns. Since prices, returns and derived analytics represent end-of-month prices at the close of trading, no assumptions about the timing of the last trade during the month need to be made. This introduces homogeneity into the bond returns since all prices are sampled at the same time each month. As these quotes are extensively used in the industry to price mutual funds, mandates,

[4] Other corporate bond datasets are Datastream, which offers bond data based on dealer quotes, and the National Association of Insurance Commissioners database (NAIC), which contains transaction information by insurance companies. Lehman Brothers historically offered the Warga data with coverage between January 1973 and the start of our sample with monthly prices and returns based on actual quotes and matrix prices. Most of the early years contain primarily matrix prices with limited bonds available in the cross-section.

ETF values, and other related products, substantial effort is undertaken by industry participants to ensure prices are of the best quality.

The BB dataset includes characteristics, prices, total and credit returns, as well as several analytics such as market values, the credit spread and the spread-duration. Our sample consists of constituents of two widely used indices by investment managers and asset owners, the Bloomberg U.S. Aggregate Corporate (IG) index and the Bloomberg U.S. High Yield (HY) index. These indices cover a broad cross-section of publicly issued USD-denominated corporate bonds. Index membership is (among other things) based on a bond's amount outstanding and thereby removes smaller, less liquid bonds. Constituents have at least one year remaining to their maturity date, are not covered bonds, and are issued by industrials, utilities, or financials. From all bonds in the index, we subsequently exclude bonds based on ex-ante criteria at the start of the month if their price was below \$5 (excluding accrued interest) or if they were in default. Whenever a bond defaults, the final bond price is based on the last (quoted) prices, and thus is a reflection of the market appraisal of the recovery rate. Hence, in contrast to the TRACE dataset, whenever a bond defaults, no additional assumptions need to be made about prices or recovery rates, nor do we introduce a forward looking (or even delisting) bias by a priori excluding bonds with missing future prices. We also exclude bonds that are not rated, or if their credit spread, spread-duration, time-to-maturity or market value were missing.[5] Whenever an issuer has multiple bonds outstanding, we continue to include all bonds of that issuer in our sample. In the main analyses, we form market value-weighted bond portfolios, market value weighted cross-sectional regressions. Our results can thus also be

[5] Note that bonds included in our sample differ in optionable features such as callability, which are embedded in market prices and reflected in option adjusted spreads in BB.

viewed as being similar to first market value weighting bonds per issuer and then performing issuer level analyses.

Our final dataset contains 1,981,088 bond-month observations and covers an average of 3.4 trillion USD debt outstanding per month. Our filters remove 9,396 (0.47%) bond-month observations. At the end of our sample, we cover 7.9 trillion USD in corporate debt, thereby covering 78% of the 10.1 trillion USD corporate bond debt outstanding.

[INSERT TABLE I]

Table I compares the BB sample to the TRACE sample. It shows the average number of bonds and total amount outstanding in the cross-sections between August 2002 and June 2022 (the period that is covered with returns by both samples) (Panel A), and the average autocorrelation in total bond returns (Panel B). We separately show TRACE statistics that are based on the last day of the month (LDM), the last trade day within a five days window before the end-of-month (L5M), and the last trade day considering any day during the month (EOM). Besides the shorter sample period, TRACE LDM returns that are based on prices over the last business day of the month cover, on average, fewer bonds in the cross-section than BB; 2,990 in TRACE versus 6,311 in BB, or a drop of 53%.[6] In terms of market values, the drop in coverage is also sizable, with the BB sample covering on average 4,324bln USD bond market value versus 2,673bln USD for TRACE LDM, a difference of 38%. To limit the drop in coverage, many corporate bond studies often employ TRACE L5M returns, which are returns based on prices observed during up to five business days from month-end. This reduces the

[6] Most of the bonds included in the TRACE dataset but not in BB are smaller, convertible, have non-standard coupon structures, or have a maturity below one year.

drop in coverage to 5,554 bonds, or 12%, but comes at the cost of a loss in synchronicity. Overall, BB covers more market value, a difference that becomes especially pronounced when requiring TRACE last traded prices to be closer to month-end. Further, 1,218 (or 19%) of the bonds in BB have missing returns in TRACE, and hence would be excluded from TRACE samples. Note that these are bonds roughly of similar size as other bonds included in the BB sample.[7]

Panel B considers the average return autocorrelation of the BB and TRACE returns. TRACE returns exhibit significant negative monthly autocorrelation, which is, at least partly, driven by bid-ask bounces and market microstructure noise. The TRACE LDM returns exhibit -4.2% autocorrelation. Longer price windows around month-end further increase the negative autocorrelation, -7.7% for TRACE L5M returns. The rightmost column in Panel B shows that the bonds in TRACE and not in BB (i.e., those that are not part of the two major bond indices; typically these are smaller, more illiquid bonds) exhibit more negative autocorrelations, with negative autocorrelations between -11.3% or -21.8%. In contrast, the Bloomberg returns do not exhibit negative autocorrelation (+0.9%), signaling a lower return quality in TRACE. BB returns are consistently based on bid prices, and therefore do not suffer from bid-ask bounces, nor does microstructure noise directly influence composite prices that are based on quotes and traded prices.

[INSERT FIGURE III]

[7] By contrast, more bonds (on average 3,797) are only present in TRACE, but these bonds tend to be substantially smaller with a total average amount outstanding below that of the 1,218 missing BB bonds.

Next, we compare individual prices in BB and TRACE. Several studies raise concerns about the errors in, and the quality of, price data in TRACE (e.g., Dick-Nielsen, 2014; Dick-Nielsen et al., 2023; Andreani, Palhares and Richardson, 2023).[8] Figure III plots all prices for matched bonds in TRACE versus BB. We separately show TRACE statistics that are based on the last day of the month (LDM), the last five days window excluding the last day of the month (L5M), and based on any day prior to the last five days (EOM). TRACE and Bloomberg prices are generally highly correlated, most strongly when TRACE prices are observed at the last day of the month. However, the correlation – and thus return quality – drops for older prices. Further, all TRACE prices, irrespective of the lookback window exhibit more extreme outliers. One might argue that TRACE returns are based on actual trades and are therefore more informative. However, we like to stress that BB prices are the best estimate of index providers of the price of a bond based on a matrix of observed trades, order sizes, trades on other bonds of the same issuer (or related entities), and other inputs.

Overall, we believe BB to have a better quality of return data than TRACE, while covering more bonds cross-sectionally over a longer sample period.

II. Corporate Bond Variables

Our objective is to uncover the best-performing unconditional factor model for the cross-section of U.S. corporate bond returns. To this end, we focus on a wide set of sorting

[8] For example, there are several transactions marked as errors in TRACE and these errors are straightforward to delete using standard filters in Dick-Nielsen (2009) and Dick-Nielsen (2014). Nevertheless, after this initial filtering, many errors remain, and the literature deals with these errors in different ways. Dick-Nielsen et al. (2023) propose a manual approach to correct these errors.

characteristics that have been studied in previous corporate bond literature as published in the main finance journals or are part of the common equity factor literature. Appendix A provides an overview of the characteristics that we consider, including their definitions and most relevant references. Descriptive statistics appear in Table II.

[INSERT TABLE II]

A. Bond sorting characteristics

Credit rating and time-to-maturity are two term structure variables that likely play a role in (corporate) bond returns (Fama and French, 1993). *Rating* reflects a bond's creditworthiness and is a standard metric used in academia, by regulators (e.g. NAIC) and in the financial industry. Rating agencies like Standard & Poor (S&P), Moody's and Fitch assess credit risk and publish ratings ranging from AAA (i.e., the least credit risk) to C (i.e., highest credit risk). We use the middle of the Moody's, S&P and Fitch ratings when all three are available, or the worst rating otherwise. *Maturity* measures a bond's remaining time-to-maturity in years and is provided by Bloomberg. The longer a bond's time-to-maturity, the more exposed it is to changes in risk premia.[9] For fixed-to-floating rate perpetual bonds, the maturity is the time-to-conversion date. An alternative measure of a bond's sensitivity to changes in risk premia is duration-times-spread (DTS). *DTS* measures a bond's sensitivity to relative spread changes and is the product of a bond's spread duration and credit spread (Ben Dor, et al., 2007). Empirically, credit spreads tend to move in relative terms (e.g., spreads increase by 5%) rather than absolute terms (e.g., spreads widen by 5 basis points). As a result, DTS provides a more stable volatility

[9] Alternatively, one could use duration (spread-duration) to more directly measure a bond's price sensitivity to changes in the interest rate (credit spread). We use time-to-maturity because it can directly be observed.

estimate than spread-duration, which makes it a widely used concept among corporate bond investors and in the academic literature (see, e.g., Kelly, Palhares and Pruitt, 2020).

In contrast to stocks, price appreciations of corporate bonds are capped. When expectations about future earnings increase, expected future cashflows to equity holders increase and stock prices appreciate. Higher expected earnings do not increase future cashflows to bond holders. At most, bond holders receive coupon and principal payments. Yet, their downside risk is unlimited. Bond investors might lose their investment in case the issuer fails to meet its obligations and the bond defaults. Therefore, corporate bond returns are characterized by negative skewness (see, e.g., Bai, Bali and Wen, 2016). *5% VaR* is defined as the 5% value-at-risk, that is, a bond's second worst monthly total return over the past 36-month window and is estimated once 24 past monthly returns are available (BBW).

Carry is the expected credit return if prices stay the same and is measured by the credit spread (Koijen et al., 2018).[10] OAS is the option-adjusted credit spread, that is, the constant discount rate difference between the yield of the corporate bond and the US Treasury yield curve; it measures the ex-ante premium that investors demand for holding risky corporate bonds.[11]

In frictionless efficient markets, carry functions as an unbiased measure of expected return. In the presence of limits to arbitrage, however, asset prices can stay in disequilibria for

---

[10] Corporate bond expected returns can be approximated with $E[r] \approx \frac{S}{12} - D \times E[\Delta S]$. Similar to Koijen et al. (2018), we use a simple definition of carry that captures the spread pickup (the first term) and omits expected price changes due to bonds "rolling down" the credit curve (the second term).

[11] Due to imperfect coverage of OASD prior to 2001, we use the option-adjusted-duration (OAD) from 1994 to 2001.

prolonged periods of time. That is, limits to arbitrage prevent asset prices to directly reflect all relevant information. If the assumption of frictionless markets is violated, it is unlikely that all prices stay the same and carry becomes a biased measure of expected return. *Credit Relative Value (CRV)* measures the mispricing and assumes that asset prices (and thus corporate bond spreads) require time to reach their equilibria. We follow Correia, Richardson and Tuna (2012) and Houweling and van Zundert (2017) and measure corporate bond mispricing as the log difference between the observed spread and the expected spread. Correia, Richardson and Tuna (2012) use four issuer default probability forecasts and show that the difference between the observed and expected (i.e., default probability implied) spread is predictive of future spread changes and credit returns. Houweling and Van Zundert (2017) estimate the expected spread with a regression, and similarly show that the difference between the observed and expected (i.e., fitted) spread is predictive of future credit returns. Correia, Richardson and Tuna (2012) test CRV in a relatively homogeneous sample of corporate bonds of non-financials with durations close to 5 year. We test CRV in a more heterogeneous sample of bonds of financials and non-financials, with different durations. Therefore, we combine the approaches of Correia, Richardson and Tuna (2012) and Houweling and Van Zundert (2017) and incorporate the firm level default probability and term structure variables distance-to-default, credit rating and time-to-maturity. Specifically, we split our cross-section in financials and non-financials, and then within each rating category we estimate the expected spread by cross-sectionally regressing observed spreads on the long-term, short-term and medium term factors of Nelson and Siegel (1987) and the default probability measured by distance-to-default (Merton, 1974):

$$OAS_{i,t} = \gamma_t^0 + \gamma_t^1 \left[\frac{1-\exp\left(-\frac{m_{i,t}}{\tau}\right)}{\frac{m_{i,t}}{\tau}}\right] + \gamma_t^2 \left[\frac{1-\exp\left(-\frac{m_{i,t}}{\tau}\right)}{\frac{m_{i,t}}{\tau}} - \exp\left(-\frac{m_{i,t}}{\tau}\right)\right] + \gamma_t^3 DtD_{j,t} + \varepsilon_{i,t}, \tag{4}$$

where $OAS_{i,t}$ is the option-adjusted-spread, and $m_{i,t}$ is the time-to-maturity for bond i at time t. $DtD_{j,t}$ is the distance-to-default for issuer j of bond i at time t, and measures the distance between firm value and the face value of debt. Following Diebold and Li (2006), we set τ such that the medium-term factor peaks at 2.5 years. We follow Correia, Richardson and Tuna (2012) and define distance-to-default as:

$$DtD_{j,t} = \frac{log\left(\frac{V_{A_{j,t}}}{X_{j,t+k}}\right)}{\sigma_{A_{j,t+k}}\sqrt{k}}, \tag{5}$$

where $X_{j,t+k}$ is the sum of the book value of short-term debt and half of the book value of long-term debt of firm j at time t, as a proxy for the face value of debt one year from time t. $V_{A_{j,t}}$ is the market value of equity plus the book value of debt of firm j at time t, and $\sigma_{A_{j,t+k}}$ is the unlevered standard deviation of monthly equity returns estimated over the past 12 months for firm j at time t. We predict the probability of default over the next year, hence $k = 12$. Using the regressions in eq. (4 we estimate the fitted spread $\widehat{OAS_{i,t}}$ and obtain the credit relative value $CRV_{i,t} = \log\left(\frac{OAS_{i,t}}{\widehat{OAS_{i,t}}}\right)$.[12]

In the presence of market frictions, prices slowly react to news. In such markets, price momentum continues and past winners outperform past losers. This phenomenon is extensively studied in the literature (see, e.g., Jegadeesh and Titman, 1993; Carhart, 1997; and Asness, Moskowitz and Pedersen, 2013). Several studies investigate momentum in corporate bonds. Jostova et al. (2013) find a positive momentum effect in high yield corporate bond returns from month $t - 7$ to $t - 2$, but no momentum in investment grade corporate bonds. Chordia et al.

[12] We use Huber's robust regressions to lower the impact of outliers.

(2017) find signs of momentum in high yield corporate bonds as well. We define *credit momentum* as r_{7-1M}, that is, the credit return of bond i from month $t-7$ to $t-2$. We skip the return in month $t-1$ and study short-term reversal separately.

We define *short-term reversal* as the negative (for ease of interpretation) of the past one month total return; $-R_{1M}$. Illiquidity limits arbitrage, that is, buying (selling) can temporarily increase (decrease) asset prices. When price pressure dissipates, short term returns revert.[13] Gebhardt, Hvidkjaer and Swaminathan (2005) find that in investment grade, past six-month returns reverse in the subsequent seven months, especially in the first month after portfolio formation. These results are consistent with the findings of Chordia et al. (2017), who similarly find that past six month returns revert in investment grade, and additionally find that past one month returns strongly revert in both investment grade and high yield samples.

If markets overreact to recent news and investors become excessively optimistic (pessimistic) about good (bad) news, assets can temporarily get overvalued (undervalued). If asset prices overshoot, their reversal should be predictable from past return data (De Bondt and Thaler, 1985). De Bondt and Thaler (1985) show evidence of a long-term reversal in the equity market. Asness, Moskowitz and Pedersen (2013) also find a long-term reversal effect in commodity, currency and government bond markets. Bali, Subrahmanyam and Wen (2021) show that long-term reversals are also present in the corporate bond market and are especially

[13] Since we use quote-based bid prices, our returns are not contaminated with a bid-ask bounce. Returns based on traded prices suffer from a bid-ask bounce, that is, a return that is calculated from two prices, the first recorded from dealer-seller transaction and the second recorded from a dealer-buyer transaction, which contains the bid-ask spread. Dickerson, Robotti and Mueller (2023) and Dickerson, Robotti and Rosetti (2023) show that this short-term reversal is the result of microstructure noise in corporate bond transaction prices.

driven by long-term underperformers. We follow De Bondt and Thaler (1985) and Bali, Subrahmanyam and Wen (2021) and define *long-term reversal* as the negative of the corporate bond total return between month $t - 48$ to $t - 13$; $-R_{48-12M}$.

To maintain higher coverage, in our main analysis we do not include liquidity characteristics that require daily transaction prices. Note that we choose to not include non-traded factor exposures, such as the macro uncertainty factor introduced by Bali, Subrahmanyam, and Wen (2021), the aggregate volatility risk factor of Chung, Wang, and Wu (2019), or the aggregate liquidity risk factor of Lin, Wang, and Wu (2011). Estimating exposures to these non-traded factors require timeseries regressions, typically using 36 to 60 monthly past return observations, and bias our results by removing new issues and trimming our universe substantially, as explained in Section I.

B. Issuer characteristics

Stocks and bonds are both claims on the same firm assets (Merton, 1974). As such, if the corporate bond and equity market are integrated, then factors that price stocks should also matter for bonds, and vice versa. The Fama and French (2015) five factor model includes profitability (RMW) and investments (CMA), next to the market, size (SMB) and value (HML) factors. Equity size (*ME*) is the monthly stock price times total shares outstanding. We also include the bond size (*MB*) characteristic of Houweling and van Zundert (2017), which is defined as the sum of the market values of all corporate bonds of an issuer outstanding. Book-to-market equity (*BE/ME*) is book common equity for the fiscal year ending in calendar year t - 1, divided by market equity at the end of December of year t - 1, and we use it from end of June of year t to May of year t + 1. Investments (*INV*) is the change in total assets from the fiscal year ending in year t - 2 to the fiscal year ending in t - 1, divided by t - 2 total assets, available from the end of June in year t.[14] Operating profitability (*OP*) is revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses in fiscal year t - 1, divided by book common equity at the end of the fiscal year in t - 1.

If asset prices underreact to news, observed price reactions can proxy firm fundamentals. Gebhardt et al. (2005), Chordia et al. (2017) and Choi and Kim (2018) find that equity returns spill over to credits (see also Haesen, Houweling and van Zundert, 2017). *Equity momentum* measures the excess equity return of issuer j of bond i from $t-6$ to $t-1$; R_{6M}^{equity}.

Further, we include *working capital accruals* (WCA), defined as the change in operating working capital per split-adjusted share from the fiscal yearend t-2 to t-1 divided by book equity per share in t-1. Sloan (1996) shows that stocks with high accruals underperform those with low accruals, and that this underperformance is concentrated around future earnings announcements. Bhojraj and Swaminathan (2009) provide empirical evidence of an accrual anomaly in corporate bonds. Corporate bonds of firms with low accruals (i.e., high quality cash earnings) outperform those of firms with high accruals (i.e., low quality accrual earnings). In contrast, Chordia et al. (2017) do not find evidence of an accrual anomaly.

[14] Choi and Kim (2018) find evidence that corporate bonds of firms with low asset growth or investments-to-assets significantly outperform those of firms with high asset growth, both measures are closely related to the investments definition of Fama and French (2015).

III. Constructing Corporate Bond Factors

A. Characteristic-sorted portfolios

From a theoretical perspective, common sources of risk should be priced. However, market frictions can limit arbitrage and behavioral biases can lead to disequilibria for prolonged periods of time, resulting in higher expected returns that are not necessarily a compensation for risk. In this section we take a first look at what type of corporate bonds have higher risks and/or higher expected returns.

We start by sorting bonds on the 16 characteristics described in Section II. Every month we sort the cross-section of corporate bonds from low to high and assign bonds to market value weighted quintile portfolios. Each quintile contains the same number of bonds (issuers) when we sort on bond (issuer) characteristics. In our testing approach we choose to value-weight all bonds, hence issuer characteristics are effectively mapped to the value-weighted issuer returns across its issues.

[INSERT TABLE III]

Table III shows the average credit return and the credit return volatility (in round brackets) of the five quintile portfolios. For the long-short portfolio that goes long Q5 (high characteristics) and short Q1 (low characteristics) we separately test whether the credit return and the intercept and slope in the CAPM regression are significantly different from zero. We observe that bonds with worse *credit ratings*, higher *values-at-risk*, *DTS*, *carry*, *value* or *equity book-to-market*, and bonds of small firms are riskier. The credit return volatility monotonically increases with *credit rating*, *DTS*, *value-at-risk*, *carry*, *value* and *equity book-to-market*. Volatility decreases monotonically with *issuer bond market value* and *equity market value*. Bonds with longer *time-to-maturity* and worse *equity momentum* are more volatile, but this effect is not strictly monotonic. *Bond momentum* and *short-term reversal*, *long-term reversal*, *investments* and *working capital accruals* show a U-shaped volatility pattern, where the Q1 (low) and Q5 (high) portfolios show the highest credit return volatility.

Of the characteristics that predict credit return volatility, only the high minus low *value* portfolio has significantly positive expected credit returns. These higher expected returns are not a compensation for credit market risk, since also the CAPM alpha is significant at the 5% level.

The high minus low *long-term reversal* and *equity momentum* (*investments* and *working capital accruals)* have significantly positive (negative) expected credit returns. These significant expected returns are unlikely a compensation for risk, since none of these characteristics predict volatility. It is thus not a surprise that these expected returns remain significant after we control for their credit market exposure in the CAPM regressions.

After we control for market exposures, we also find signs of a short maturity effect, and short-term momentum. The high minus low *maturity* and *short-term reversal* portfolio CAPM alphas are significantly different from zero. Bonds with long maturities earn abnormally lower credit returns than bonds with short maturities. This low-risk effect has previously been documented, see e.g., Houweling and Muskens (2023). Our finding that bonds with high short-term reversal characteristics (i.e., low past month total returns) earn significantly lower credit returns than bonds with low short-term reversal characteristics (i.e., high past month total returns) is in stark contrast to Bai et al. (2019). Our analyses thus far are based on quoted prices. Bai et al. (2019) employ traded prices. Potentially, the bid-ask bounce in traded prices introduce a strong short-term reversal effect.

C. Factor-mimicking portfolios

Our aim is to distinguish the main factors that price the cross section of corporate bonds. Thus far we have seen that several characteristics can proxy bond volatility, but that only credit relative value (CRV) significantly distinguishes bonds with high and low expected credit returns. Moreover, we also found that corporate bonds exhibit long-term reversals, and that bonds with high equity momentum, conservative investments, or short maturities earn significantly higher (risk-adjusted) credit returns. In this section we will introduce factor mimicking portfolios, in spirit of Fama and French (1993).

We construct factor mimicking portfolios using 2 × 3 dependent double sorts. Our first sorting characteristic is *credit rating*. It is a natural first sort, since credit risk is arguably the most prominent and widely recognized source of risk in corporate bonds. Namely, it is used in academia (see e.g., Bai et al. (2019)), by regulators (e.g., NAIC and Solvency II), and in the investment industry. Each month we split the cross-section in BBB- or higher-rated *investment grade (IG)* and BB+ or lower-rated *high yield (HY)* corporate bonds. We use these fixed categories to keep the risk profile of the credit rating segments stable through time.[15] Within investment grade and high yield, we further sort bonds on the 8 (7) remaining bond (issuer) characteristics, and create market value weighted terciles, each containing the same number of bonds (issuers). We then construct the following bond and issuer factor mimicking portfolios:

Bond factors

[15] Rating up- and downgrades are cyclical, when credit increases (decreases) more bonds are downgraded (upgraded), which would lead to time variation in the credit risk profile of equally populated rating portfolios.

- **Credit Market Premium (MKT^{credit}):** the market value weighted average credit return of all corporate bonds in our sample.
- **Credit Rating Premium (CR):** the average credit return of the *HY* minus *IG* portfolios within each maturity segment.
- **Maturity Premium (MAT):** the average credit return of the *long maturity* minus *short maturity* portfolio within IG and HY.
- **DTS Beta Premium ($BETA$)**: the average credit return of the *high duration-time-spread* minus *low duration-times-spread* portfolio within in IG and HY.
- **Downside Risk Premium ($DOWN$)**: the average credit return of the *high value-at-risk* minus *low value-at-risk* portfolio within IG and HY.
- **Carry Premium ($CARRY$):** the average credit return of the *high option-adjusted spread* minus *low option-adjusted spread* portfolio within IG and HY.
- **Credit Value Premium (VAL^{credit}):** the average credit return of the *high credit relative value* minus *low credit relative value* portfolio within IG and HY.
- **Credit Momentum Premium (MOM^{credit}):** the average credit return of the *bond winners* minus *bond losers* portfolio within IG and HY.
- **Short-term Reversal Premium (STR):** the average credit return of the *high short-term bond reversal* minus *low short-term bond reversal* portfolio within IG and HY.
- **Long-term Reversal Premium (LTR):** the average credit return of the *high long-term bond reversal* minus *low long-term bond reversal* portfolio within IG and HY.

Issuer factors

- **Credit Size Premium ($SIZE^{credit}$)**: the average credit return of the *small bond market value issuers* minus *large bond market value issuers* portfolio within IG and HY.

- **Equity Size Premium ($SIZE^{equity}$):** the average credit return of the *small equity market value issuers* minus *large equity market value issuers* portfolio within IG and HY.
- **Equity Value Premium (VAL^{equity}):** the average credit return of the *high book-to-market equity* minus *low book-to-market equity* portfolio within IG and HY.
- **Operating Profitability Premium ($PROF$):** the average credit return of the *high operating profitability (robust)* minus *low operating profitability (weak)* portfolio within IG and HY.
- **Investment Premium (INV):** the average credit return of the *low investments (conservative)* minus *high investments (aggressive)* portfolio within IG and HY.
- **Equity Momentum Premium (MOM^{equity}):** the average credit return of the *equity winners* minus *equity losers* portfolio within IG and HY.
- **Accruals Premium (ACC):** the average credit return of the *low working capital accruals* minus *high working capital accruals* portfolio within IG and HY.

[INSERT TABLE IV]

In Table IV, we show the average credit returns of the factors and their loadings on a constant and the MKT^{credit} factor. Our first notable observation is that the average credit risk premium, MKT^{credit}, is indistinguishable from zero. The bond risk factors CR, MAT, $BETA$, $DOWN$, and $CARRY$ are indistinguishable from zero and do not seem to be priced either. Interestingly, controlling for exposures to the market factor reveals a significantly negative premium on MAT. Controlling for their exposures to the common market factor does not change our conclusion on CR, $BETA$, $DOWN$, and $CARRY$. Thus, investors do not require a premium for exposures to MKT^{credit}, CR, $BETA$, $DOWN$, and $CARRY$, and are even paying a premium for exposures to MAT. That is, long maturity bonds are in high demand, which lowers their expected returns. This maturity effect has previously been documented (see e.g., Frazzini and Pederson, 2014).

The VAL^{credit} factor premium is 0.25% and significant at the 10% level. VAL^{credit} is significantly exposed to market risk. Isolating the VAL^{credit} that is not explained by MKT^{credit}, lowers the VAL^{credit} premium to 0.16%, but it increases its statistical significance to the 5% level. These results show that investors demand a premium for credit value exposures or inefficiencies in the credit market that lead to abnormally high (low) returns in cheap (expensive) bonds.

MOM^{credit} s indistinguishable from zero and is not priced. STR, on the other hand, shows a significantly negative premium, meaning that bonds with low (high) past month total returns have high expected credit returns in the next month. This finding is in stark contrast to the findings of Bai et al. (2019), who find the opposite effect using traded prices. LTR is significantly positive. Bonds with low (high) total returns in the three-year period from month $t-48$ to $t-13$ have high (low) expected credit returns in the coming month.

Issuer factors $SIZE^{credit}$, $SIZE^{equity}$ and $VAL^{equity}$are not positively priced. When we control for exposure to the market factor, we even find that $SIZE^{equity}$is negatively priced. These results are not consistent with the findings of Fama and French (1993, 2015) in the equity market, who find that small (large) and high (low) book-to-market ratio firms have high expected stock returns. We do not find a significant premium in bonds of small firms or firms with high book-to-market ratios. Instead, we find that bonds of firms that are large in the equity market have higher expected credit returns.[16]

MOM^{equity} is the (economically and statistically) most significant factor of all the factors we test. We confirm earlier findings (see e,g., Jostova et al., 2013) and find that bonds of firms with high past stock returns have high expected credit returns. The lack of momentum in bond returns, but the strong spillover from the stock market to the corporate bond market indicates that these two markets are not integrated and that stocks lead bonds. For a more extensive analysis of market integration, see Chordia et al. (2017).

The issuer factors $PROF, INV$ and ACC are significantly positive at (at least) the 10% level. Controlling for exposures to the common MKT^{credit} factor increases their statistical significance. Bonds of firms with robust (weak) profitability, conservative (aggressive) investments or low (high) accruals have high (low) expected credit returns. These findings are consistent with the results of Fama and French (2015) and Sloan (1996) in the equity market and Choi and Kim (2018) and Bhojraj and Swaminathan (2009) in the corporate bond market.

We have found that exposures to MAT, VAL^{credit}, STR, LTR, $SIZE^{equity}$, $PROF$, INV, MOM^{equity}, and ACC are priced. Next, we will investigate whether these factors are distinct phenomena, and what their role in an asset pricing model is.

IV. Pricing the Cross-Section of Corporate Bond Credit Returns

We employ the so called "right-hand-side" (RHS) approach to investigate the unique pricing power of candidate factors. Barillas and Shanken (2016) demonstrate that one can

[16] Our conclusions on $SIZE^{equity}$ and VAL^{equity} do not change when we use the 2×3 sorts on equity size and book-to-market, similar to how Fama and French (1993, 2015) construct SMB and HML.

determine how much a factor contributes to an asset pricing model without test assets to. In this section, we run bivariate spanning regressions to explore which factors can provide unique pricing power, after which we compile several nested and non-nested competing asset pricing models and use the maximum squared Sharpe ratio approach of Fama and French (2018).

A. Spanning alphas

In our bivariate spanning regressions, we regress each candidate factor on MKT^{credit} and one other candidate factor. Table V shows the spanning alphas, where each cell shows the intercept and t-statistic of a candidate factor (in rows) regressed on MKT^{credit} one other candidate factor (in columns). We limit the set of results to the RHS factors that are not spanned by other factors, namely MAT, VAL^{credit}, MOM^{equity} and ACC.

[INSERT TABLE V]

We observe that only four factors show spanning alphas that are significant at (at least) the 10% level in all cases, namely MAT, VAL^{credit}, MOM^{equity} and ACC. The significant alphas for MAT show that the low expected returns of long maturity bonds is not explained by their exposures to any of the other candidate factors. While the bond risk factors are correlated, the robust positive premium of VAL^{credit} is driven by sources that are not correlated with MKT^{credit}, CR, MAT, $BETA$, $DOWN$ and $CARRY$. This is by construction what sets VAL^{credit} apart from these related risks, that is, it estimates the ex-ante premium that is uncorrelated with the credit term structure (i.e., rating, distance-to-default, and maturity). MOM^{credit} and MOM^{equity} showed to capture a common momentum factor, but the spanning alphas clearly show that MOM^{equity} dominates MOM^{credit}. In previous sections we found significant premia for $PROF, INV$ and ACC, consistent with the findings of Chordia et al. (2017), Choi and Kim

(2018) and Bhojraj and Swaminathan (2009), but also showed that these factors are correlated. Spanning alphas show that only ACC captures a distinct phenomenon.

Of the other factors that seemed to be priced in the previous sections, we find that their premia are explained by exposures to other priced factors as well. First, we see that the negative STR factor (i.e., positive short term momentum factor) is explained by exposures to MOM^{equity} and ACC. Second, LTR loses its significance after we control for MAT. Part of the LTR factor seems to be driven by a selection bias in short-term bonds. LTR is only available for bonds older than 4 years, which have a relatively short time-to-maturity by the time the characteristic becomes available. Houweling and Muskens (2023) show that such a selection bias leads to problematic factor inferences. Third, the $SIZE^{equity}$ factor is explained by exposures to MOM^{equity}. We thus confirm that the equity size factor captures the past equity return factor. We conclude that the unique risk that $SIZE^{equity}$ captures is not priced. Fourth, $PROF$ loses its significance in many spanning regressions and is thus not robust. Controlling for exposures to INV, MOM^{equity}, or ACC is especially relevant as these factors showed high pairwise correlations. Doing so explains the $PROF$ premium that we have observed previously. Fifth, the high expected credit return of INV are explained by exposures to MOM^{equity}. We thus conclude that STR, LTR, $SIZE^{equity}$, $PROF$ and INV are no distinct phenomena, but indirectly capture other priced factors.

We make several other noteworthy observations. First, CR is priced, after we control for MKT^{credit} and $PROF$, INV or MOM^{equity}. Second, the spanning alphas of $BETA$, $DOWN$ and $CARRY$ are significantly negative after we control for VAL^{credit}. This confirms that VAL^{credit} dominates these three alternative bond risk factors. Third, controlling $CARRY$ for $BETA$ exposures ($BETA$ for $CARRY$ exposures) leads to a significantly positive (negative) premium. These results indicate that their difference is priced.[17] Fourth, controlling bond risk factors for their MOM^{equity} exposures leads to significance in all of them. High risk is rewarded only after we control for momentum. VAL^{credit}, however, remains the dominant factor, with a t-statistic of 8.49 after we control for MKT^{credit} and MOM^{equity}. $VAL^{credit}$and MOM^{equity} thus seem highly complementary in pricing corporate bonds. Fifth, we also find that controlling MOM^{credit} for its VAL^{credit} exposure leads to a significant alpha. Note however that MOM^{equity} still dominates MOM^{credit}, as can be observed form the negative spanning alpha when we regress MOM^{credit} on MKT^{credit} and MOM^{equity}. Sixth, $SIZE^{credit}$ had no standalone alpha, but after controlling for $SIZE^{equity}$, the alpha turns positive, significantly. Small credit size, controlled for equity size might capture low leverage, and also point in the direction of high distance-to-default. Seventh, the VAL^{equity} significantly positive after we control for $SIZE^{equity}$.

In short, we conclude that MAT, VAL^{credit}, MOM^{equity} and ACC are the most prominent factors. STR, LTR, $SIZE^{equity}$, $PROF$ and INV are no distinct phenomena, but indirectly capture other priced factors.

B. Max $\boldsymbol{Sh^2(f)}$

Next, we expand beyond bivariate spanning regressions and evaluate which combination of factors best prices the cross-section of corporate bond returns. Competing asset pricing models can be judged on their maximum squared Sharpe ratio (Barillas and Shanken, 2016). Judging asset pricing models on their maximum squared Sharpe ratio follows from

[17] The difference between duration-times-spread ($D \times S$) and spread (S) can proxy maturity, since spread-duration (D) is highly correlated with maturity.

Gibbons et al. (1989). They show that the maximum squared Sharpe ratio of non-factor alphas, $Sh^2(a)$, is the difference between the maximum squared Sharpe ratio of the test assets and model factors combined $Sh^2(\Pi, f)$, and the maximum squared Sharpe ratio of the model factors $Sh^2(f)$.

$$Sh^2(a) = Sh^2(\Pi, f) - Sh^2(f)$$

The asset pricing model with the highest $Sh^2(f)$ thus has the lowest $Sh^2(a)$ and best prices the cross-section of asset returns. As Fama and French (2018) point out, $Sh^2(f)$ is likely biased upward. $Sh^2(f)$ is obtained by finding the optimal factor weights that maximize the squared Sharpe ratio. The maximum squared Sharpe ratio is found using:

$$Sh^2(f) = \frac{\widehat{w}f}{\widehat{w}'\Sigma\widehat{\mathrm{w}}} = f'\Sigma^{-1}f$$

The optimal factor weights through which one obtains the maximum squared Sharpe ratio, $\widehat{w}$, are prone to overfitting to noise in in-sample observations. Sampling error in the factor returns lead to overestimations of expected returns and underestimations of expected volatility, and thus an upward bias in $Sh^2(f)$. Fama and French (2018) develop a bootstrap in which the optimal factor weights are obtained in-sample, but the competing models are ranked on their out-of-sample squared Sharpe ratio.

We follow Fama and French (2018) and split the monthly time-series into adjacent pairs: months (1, 2), (3, 4) … (T-1, T). Then, for 100,000 simulations, we draw (with replacement) $T/2$ pairs and assign one of the two months in the pair as the in-sample month, and the other as the out-of-sample month. If a pair is drawn multiple times in the same simulation run (due to the replacement), the assignment of the in- and out-of-sample months is consistently applied within that simulation run.

Using the $T/2$ number of in-sample months, we find the optimal weights that maximize the squared Sharpe ratio in-sample and measure the out-of-sample (as well as the full-sample) squared Sharpe ratio. For our set of competing asset pricing models, Table VI shows the average and median in-sample, full-sample and out-of-sample squared Sharpe ratios over the 100,000 simulation runs, as well as the actual maximum squared Sharpe ratio.

[INSERT TABLE VI]

We are interested in finding distinct pricing factors. In other words, should corporate bond credit returns be decomposed into the several systematic premia? We start with our main benchmark model, the single factor credit market model (MKT^{credit}). We expand the single factor model by including MAT, VAL^{credit}, MOM^{equity} or ACC. We then continue with competing three, four and five factor models. Previous spanning alphas already showed the complementary pricing power of VAL^{credit} and MOM^{equity}. We therefore combine VAL^{credit} and MOM^{equity} with MKT^{credit} and MAT in the four-factor model. The five-factor model adds ACC.

All competing factor models increase the OOS Sh^2 of the single factor model. To test the null hypothesis that $Sh^2(f_j) \leq Sh^2(f_{h_0})$, we report the fraction of bootstrap samples in which a competing model with factors f_j does not outperform a benchmark model with factors f_{h_0}. The two factor models that include MAT, MOM^{equity} or ACC, and all three, four and five factor models significantly increase the squared Sharpe ratio of the single factor model. The competing three factor models further show that MOM^{equity} has the highest OOS Sh^2, and that only the three-factor model including MOM^{equity} significantly outperforms the two-factor model with MAT. This however does not directly lead us to conclude that VAL^{credit} is redundant. Previous spanning alphas showed that value and momentum are highly complementary. Indeed, we see a strong increase in the OOS Sh^2 of the four-factor model compared to all competing three factor models. The last column in Table VI shows that all competing three factor models significantly underperform the four-factor model. In other words, dropping either VAL^{credit} or MOM^{equity} from the four-factor model leads to a large drop in the OOS Sh^2. Expanding the four-factor model to a five-factor model that adds ACC does no longer lead to an improvement in the OOS Sh^2. We thus conclude that the cross-section of corporate bond credit returns is best explained by a four factor model that combines MKT^{credit}, MAT, VAL^{credit} and MOM^{equity}.

V. Pricing the Cross-Section of Corporate Bond Credit Returns

Our analysis thus far has focused on a parsimonious factor model that spans the efficient frontier. However, factors (or assets) with positive spanning alphas might differ from factors that drive return variations across other assets. In this section we take an alternative approach and examine which factors explain the cross-sectional variation in corporate bond credit returns and minimize pricing errors on a wide cross-section of left-hand-side (LHS) test assets.

A. Bond-level cross-sectional regressions

We start our LHS analysis by cross-sectionally regressing corporate bond credit returns on a set of factor exposures, characteristics and controls. We include the exposures to the MKT^{credit} factor, the exposures to, and the characteristics of, the three additional factors MAT, VAL^{credit} and MOM^{equity}. Specifically, we estimate the following regression:

$$r_{i,t} = \gamma_t^0 + \gamma_t^1 \beta_{i,t}^f + \gamma_t^2 z_{i,t}^x + \gamma_t^3 z_{i,t}^c + \varepsilon_{i,t}, \tag{6}$$

where $\beta_{i,t}^f$ is a set of the factor exposures to factors f, $z_{i,t}^x$ is a set of standardized factor characteristic and $z_{i,t}^c$ is a set of the standardized control characteristics for bond i at time t. In each cross-sectional regression individual bond observations are square root market value weighted such that the market value weighted average residual equals zero. Standardized factor and control characteristics are obtained by cross-sectionally winsorizing the data at the 1st and 99th percentile and subsequently demeaning and dividing by the cross-sectional standard deviation. Factor exposures are obtained by regressing the time-series of past 36 month (minimum 24) returns of 54 rating, maturity, value and equity momentum sorted portfolios. These portfolios are formed by independently sorting bonds and forming terciles using maturity, credit relative value and equity momentum in investment grade and high yield separately (i.e. the same characteristics that are used to form the factor mimicking portfolios MAT, VAL^{credit} and MOM^{equity}). Bonds within each test asset are market value weighted to mitigate the bias due to noise in corporate bond prices (Asparouhova, Bessembinder, and Kalcheva, 2013). At month t, we assign the estimated factor exposure $\beta_{t,k}^{f}$ to all bonds that belong to portfolio k at month t. We use these portfolio factor exposures for three reasons. First, bonds have constantly changing sensitivities to risk factors, which makes it difficult to benchmark them against a static return metric (Bessembinder et al., 2009). Bond characteristics change over time, due to, for example, a decline in time-to-maturity (and a lower exposure to e.g. MAT). When characteristics change, bonds migrates from one portfolio (i.e. test asset) to another. As a result, the composition of the portfolios change through time, but their characteristics and expected factor exposures stay relatively constant. Second, characteristics sorted portfolios contain less idiosyncratic noise. Individual bonds might trade infrequently, and their returns are influenced by idiosyncratic shocks. These noisy bond returns might spuriously correlate with certain factors. Averaging the individual bond returns reduces this noise, but keeps the systematic factor returns intact. Third, portfolios allow us to cover the full cross-section of corporate bonds. Factor exposures of individual bonds can only be estimated once bonds have been persistently quoted or traded in the secondary market. This would remove a significant portion of the cross-section and introduce a bias in estimated factor premia. By using characteristics sorted portfolios we can obtain a bond's expected factor exposures throughout its lifespan, thereby covering the full cross-section.

[INSERT TABLE VII]

Table VII reports the time-series average coefficients of γ^0, γ^1, γ^2 and γ^3 with Newey and West (1984) adjusted *t*-statistics in brackets for different model specifications. The first column (1) shows that the exposure to the corporate bond market factor alone is not priced. This finding is in line with the findings of Dickerson et al. (2023). We observe however that the exposure to the bond market factor is priced after we control the standardized *log maturity*, *credit relative value* and *equity momentum* characteristics in specification (2). Consistent with the results in Section IV, we find that short maturity bonds, bonds with high credit relative value scores and high equity momentum scores earn higher expected returns after we control for market risk exposures. Interestingly, in specification (3) we do not find that exposures to MAT or VAL^{credit} are priced. In specification (4) we show that average characteristics premium is robust to controlling for factor exposures, that is, coefficients and *t*-statistics in (4) are close to those in (2). In contrast, the price of beta risk in (3) remain insignificant (i.e. $\gamma^{\beta^{VAL^{credit}}}$), lose significance (i.e. $\gamma^{\beta^{MOM^{equity}}}$) or even switch sign (i.e. $\gamma^{\beta^{MAT}}$). In specification (5) we further show that the *maturity*, *credit relative value*, and *equity momentum* premia are robust to the inclusion of standardized control characteristics log amount outstanding and DTS, and a high yield dummy. We conclude that characteristics *maturity*, *credit relative value* and *equity momentum* are priced.

B. Test asset cross-sectional regressions

The bond level cross-sectional regressions in the previous section showed robust evidence of a short *maturity*, *credit value* and *equity momentum* premium in corporate bonds. The cross-sectional regressions however do not control for the potential error-in-variable (EIV) problem, nor do they account for potential misspecification errors (Kan, Robotti, and Shanken, 2013). Similar to Dickerson, Robotti and Mueller (2023), we use test assets and use the approach of Kan, Robotti and Shanken (2013) to correct for EIV and misspecification.[18] Note that in contrast to the bond level cross-sectional regressions, here we do not use time-varying exposures and characteristics, but expected (i.e., full sample factor average) factor exposures and characteristic z-scores instead. We therefore suppress the subscript t in the notation of Table VIII. Since our model nests the bond CAPM model, we do not explicitly need to test for the difference in R^2 between these specifications and the bond CAPM model. As noted by Kan, Robotti and Shanken (2013), in case of nested models, the misspecification robust *t*-statistics are sufficient to reject the null hypothesis that two model R^2s are equal. We also limit the results to two models, the bond CAPM model, and our model that additionally includes maturity, credit relative value and equity momentum characteristics.[19]

[INSERT TABLE VIII]

[18] We adept to code provide by Cesare Robotti and use the Appendix of Kan, Robotti and Shanken (2013) to also include (mean) characteristics in the cross-sectional regressions.

[19] In the previous section we failed to robustly reject the null hypothesis that factor exposures to MAT, VAL^{credit} and MOM^{equity} are priced. OLS and GLS regressions including the price of MAT, VAL^{credit} and MOM^{equity} beta risk and covariance risk are reported in the online appendix.

In Table VIII, we report the zero beta, the market beta rate and the price of standardized characteristics, γ^0, γ^1, and γ^2, respectively. OLS (left) and GLS (right) regression results are reported. t-stat$_c$ indicate the error-in-variable (EIV) robust *t*-statistics under correctly specified models. t-stat$_m$ is the misspecification robust *t*-statistics of Kan, Robotti, and Shanken (2013). We report the *t*-statistics under correctly specified models and the misspecification robust *t*-statistics to show the impact of the assumption of a correctly specified model on our results. In panel A, we use the same K test asset portfolios as were used in the previous section. Panel B reports the results for 5 rating, 5 maturity, 10 OAS and 10 sector portfolios in spirit of Dickerson, Robotti and Mueller (2023). Consistent with Dickerson, Robotti and Mueller (2023) and the previous section, Table VIII shows that in the bond CAPM the price of market beta risk ($\beta^{MKT^{credit}}$) is insignificant, both in the OLS and GLS regressions in panel A and panel B. The price of the *log-maturity* characteristic is robustly negative, both the *t*-statistic that assumes a correctly specified model and the misspecification robust *t*-statistic exceed conventional significance levels. Also, *CRV* is robustly priced, with *t*-statistics exceeding significance levels. *Equity momentum* shows the largest premium and highest *t*-statistics in the OLS regression in Panel A. The OLS regressions are most informative if one is interested in the expected return of specific test assets. In the GLS regression assets with low (high) covariances receive more (less) weight. The R^2 in the GLS regression is more directly related to the spanning of the efficient frontier. Interestingly, in panel A, the GLS regression estimates of the price of equity momentum and corresponding *t*-statistics are substantially lower. Thus, equity momentum seems especially relevant for corporate bonds with high covariances. It is not surprising that prices of risky bonds more closely follow price discovery in the equity market. Risky bonds with high covariances naturally trade at low prices, therefore have higher expected returns, that are expected to be earned through both price appreciations and the yield pickup. Since there is room for such bond prices to appreciate, they are expected to more closely follow stock prices. In contrast, safer bonds with low covariances trade at higher prices, and therefore have lower expected returns that are mostly earned through the yield. Positive shocks can lead to positive stock price reactions, but likely lead to no, or muted bond price reactions when bond prices are already high. The cross-sectional regressions use estimates of expected characteristics that are based on full sample averages. The explanatory power of the expected equity momentum characteristic is low in Panel B. The average equity momentum characteristic of the test assets in Panel B are low, while in Panel A, they are by construction more stable and more dispersed across test assets. We thus conclude that while *maturity* and *credit relative value* explain the cross-section of expected corporate bond credit returns, *equity momentum* is particularly important for specific assets, namely those with high covariances and recent shocks in their stock prices.

VI. Conclusion

We comprehensively examine the cross-section of U.S. corporate bond returns. With a value exceeding $10 trillion, corporate bonds are important for both investors and corporations. In our study, we examine a wide set of drivers of expected corporate bond returns, based on studies proposing individual characteristics that predict corporate bond return in the cross-section, with the goal of establish a parsimonious factor model that most robustly prices the cross-section of U.S. corporate bonds. We identify and address challenges related to sample selection bias, the infrequent trading of corporate bonds, and duration-matching. Our analysis indicates that four factors provide robust, sizable, and unique credit return premia in portfolio sorts. These factors are the market factor, a bond maturity factor, a valuation factor, and an equity momentum factor. We confirm that these factors are important across a wide set of testing choices. Investors can use the resultant factor model to price bonds, assess bond fund performances, and build portfolios, whereas corporations can use the factor model to assess their cost of debt capital.

References

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets, 5*(1), 31-56. doi:https://doi.org/10.1016/S1386-4181(01)00024-6

Ang, A., Chen, J., & Xing, Y. (2006). Downside Risk. *The Review of Financial Studies, 19*(4), 1191-1239. doi:https://doi.org/10.1093/rfs/hhj035

Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and Momentum Everywhere. *The Journal of Finance, 68*(3), 929-985. Retrieved from http://www.jstor.org/stable/42002613

Asparouhova, E., Bessembinder, H., & Kalcheva, I. (2013). Noisy Prices and Inference Regarding Returns. *The Journal of Finance, 68*(2), 665-714. doi:https://doi.org/10.1111/jofi.12010

Bai, J., Bali, T. G., & Wen, Q. (2016). Do the distributional characteristics of corporate bonds predict their future returns? *Unpublished working paper, Georgetown University.*

Bai, J., Bali, T. G., & Wen, Q. (2019). Common risk factors in the cross-section of corporate bond returns. *Journal of Financial Economics, 131*(3), 619-642. doi:https://doi.org/10.1016/j.jfineco.2018.08.002

Bai, J., Bali, T. G., & Wen, Q. (2020). Is There a Risk-Return Tradeoff in the Corporate Bond Market? Time-Series and Cross-Sectional Evidence. *Journal of Financial Economics,, Forthcoming*.

Bali, T. G., Subrahmanyam, A., & Wen, Q. (2021). Long-term reversals in the corporate bond market. *Journal of Financial Economics, 139*(2), 656-677. doi:https://doi.org/10.1016/j.jfineco.2020.08.007

Baltussen, G., Post, G. T., & Van Vliet, P. (2012). Downside risk aversion, fixed-income exposure, and the value premium puzzle. *Journal of Banking & Finance, 36*(12), 3382-3398. doi:https://doi.org/10.1016/j.jbankfin.2012.07.020

Bao, J., Pan, J., & Wang, J. (2011). The Illiquidity of Corporate Bonds. *The Journal of Finance, 66*(3), 911-946. doi:https://doi-org.eur.idm.oclc.org/10.1111/j.1540-6261.2011.01655.x

Barillas, F., & Shanken, J. (2017). Which Alpha? *The Review of Financial Studies, 30*(4), 1316-1338. doi:https://doi.org/10.1093/rfs/hhw101

Ben Dor, A., Dynkin, L., Hyman, J., Houweling, P., van Leeuwen, E., & Penninga, O. (2007). DTS (Duration Times Spread). *The Journal of Portfolio Management, 33*(2), 77-100.

Bessembinder, H., Kahle, K. M., Maxwell, W. F., & Xu, D. (2009). Measuring Abnormal Bond Performance. *The Review of Financial Studies, 22*(10), 4219-4258. Retrieved from http://www.jstor.org/stable/40468357

Bessembinder, H., Maxwell, W., & Venkataraman, K. (2006). Market transparency, liquidity externalities, and institutional trading costs in corporate bonds. *Journal of Financial Economics, 82*(2), 251-288. doi:https://doi.org/10.1016/j.jfineco.2005.10.002

Bhojraj, S., & Swaminathan, B. (2009). How does the corporate bond market value capital investments and accruals? *Review of Accounting Studies, 14*(1), 31-62. doi:https://doi.org/10.1007/s11142-007-9056-x

Black, F. (1972). Capital market equilibrium with restricted borrowing. *Journal of Business, 45*(3), 444-455.

Blitz, D., & van Vliet, P. (2007). The Volatility Effect. *The Journal of Portfolio Management, 34*(1), 102-113.

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance, 52*(1), 57-82. doi:https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Choi, J. (2013). What Drives the Value Premium?: The Role of Asset Risk and Leverage. *The Review of Financial Studies, 26*(11), 2845-2875. doi:https://doi.org/10.1093/rfs/hht040

Choi, J., & Kim, Y. (2018). Anomalies and market (dis)integration. *Journal of Monetary Economics, 100*, 16-34. doi:https://doi.org/10.1016/j.jmoneco.2018.06.003

Choi, J., & Richardson, M. (2016). The volatility of a firm's assets and the leverage effect. *Journal of Financial Economics, 121*(2), 254-277. doi:https://doi.org/10.1016/j.jfineco.2016.05.009.

Chordia, T., Goyal, A., Nozawa, Y., Subrahmanyam, A., & Tong, Q. (2017). Are Capital Market Anomalies Common to Equity and Corporate Bond Markets? An Empirical Investigation. *Journal of Financial and Quantitative Analysis, 52*(4), 1301-1342. doi:10.1017/S0022109017000515

Chung, K. H., Wang, J., & Wu, C. (2019). Volatility and the cross-section of corporate bond returns. *Journal of Financial Economics, 133*(2), 397-417. doi:https://doi.org/10.1016/j.jfineco.2019.02.002

Correia, M., Richardson, S., & Tuna, İ. (2012). Value investing in credit markets. *Review of Accounting Studies, 17*(3), 572-609. doi:https://doi.org/10.1007/s11142-012-9191-x

De Bondt, W. F., & Thaler, R. (1985). Does the Stock Market Overreact? *The Journal of Finance, 40*(3), 793-805. Retrieved from http://www.jstor.org/stable/2327804

Diebold, F. X., & Li, C. (2006). Forecasting the term structure of government bond yields. *Journal of Econometrics, 130*(2), 337-364. doi:https://doi.org/10.1016/j.jeconom.2005.03.005.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*(1), 3-56. doi:https://doi.org/10.1016/0304-405X(93)90023-5.

Fama, E. F., & French, K. R. (2008). Dissecting Anomalies. *The Journal of Finance, 63*(4), 1653-1678. Retrieved from http://www.jstor.org/stable/25094486

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics, 116*(1), 1-22. doi:https://doi.org/10.1016/j.jfineco.2014.10.010

Fama, E. F., & French, K. R. (2018). Choosing factors. *Journal of Financial Economics, 128*(2), 234-252. doi:https://doi.org/10.1016/j.jfineco.2018.02.012

Fama, E. F., & MacBeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy, 81*(3), 607-636. doi:https://doi-org.eur.idm.oclc.org/10.1086/260061

Feng, G., Giglio, S., & Xiu, D. (2020). Taming the Factor Zoo: A Test of New Factors. *The Journal of Finance, 75*(3), 1327-1370. doi:https://doi-org.eur.idm.oclc.org/10.1111/jofi.12883

Frazzini, A., & Pedersen, L. (2014). Betting Against Beta. *Journal of Financial Economics, 111*(1), 1-25.

Gebhardt, W. R., Hvidkjaer, S., & Swaminathan, B. (2005). Stock and bond market interaction: Does momentum spill over? *Journal of Financial Economics, 75*(3), 651-690. doi:https://doi.org/10.1016/j.jfineco.2004.03.005

Gibbons, M. R., Ross, S. A., & Shanken, J. (1989). A Test of the Efficiency of a Given Portfolio. *Econometrica, 57*(5), 1121-1152. Retrieved from http://www.jstor.org/stable/1913625

Haesen, D., Houweling, P., & Zundert, J. v. (2017). Momentum spillover from stocks to corporate bonds. *Journal of Banking & Finance, 79*, 28-41. doi:https://doi.org/10.1016/j.jbankfin.2017.03.003

Harvey, C. R., & Liu, Y. (2021). Lucky factors. *Journal of Financial Economics, 141*(2), 413-435. doi:https://doi.org/10.1016/j.jfineco.2021.04.014

Harvey, C., & Siddique, A. (2000). Conditional Skewness in Asset Pricing Tests. *The Journal of Finance, 55*(3), 1263-1295. doi:https://doi.org/10.1111/0022-1082.00247

Hou, K., & Moskowitz, T. J. (2005). Market Frictions, Price Delay, and the Cross-Section of Expected Returns. *The Review of Financial Studies, 18*(3), 981-1020. doi:10.1093/rfs/hhi023

Houweling, P., & van Zundert, J. (2017). Factor Investing in the Corporate Bond Market. *Financial Analyst Journal, 73*(2), 100-115.

Ilmanen, A., Byrne, R., Gunasekera, H., & Mnikin, R. (2004). Which Risks Have Been Best Rewarded? *The Journal of Portfolio Management, 30*(2).

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance, 48*(1), 65–91. doi:https://doi.org/10.2307/2328882

Jostova, G., Nikolova, S., Philipov, A., & Stahel, C. W. (2013). Momentum in Corporate Bond Returns. *The Review of Financial Studies, 26*(7), 1649-1693. doi:https://doi.org/10.1093/rfs/hht022

Kelly, B. T., Palhares, D., & Pruitt, S. (2020). Modeling Corporate Bond Returns. *The Journal of Finance, forthcoming*.

Koijen, R. S., Moskowitz, T. J., Pedersen, L. H., & Vrugt, E. B. (2018). Carry. *Journal of Financial Economics, 127*(2), 197-225. doi:https://doi.org/10.1016/j.jfineco.2017.11.002

Kraus, A., & Litzenberger, R. (1976). Skewness preference and the valuation of risk assets. *Journal of Finance, 31*(4), 1085-1100.

Lin, H., Wang, J., & Wu, C. (2011). Liquidity risk and expected corporate bond returns. *Journal of Financial Economics, 99*, 628-650.

Merton, R. C. (1974). On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. *The Journal of Finance, 29*(2), 449-470. doi:https://doi.org/10.2307/2978814

Nelson, C. R., & Siegel, A. F. (1987). Parsimonious Modeling of Yield Curves. *The Journal of Business, 60*(4), 473–489. doi:http://www.jstor.org/stable/2352957

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics, 108*(1), 1-28. doi:https://doi.org/10.1016/j.jfineco.2013.01.003

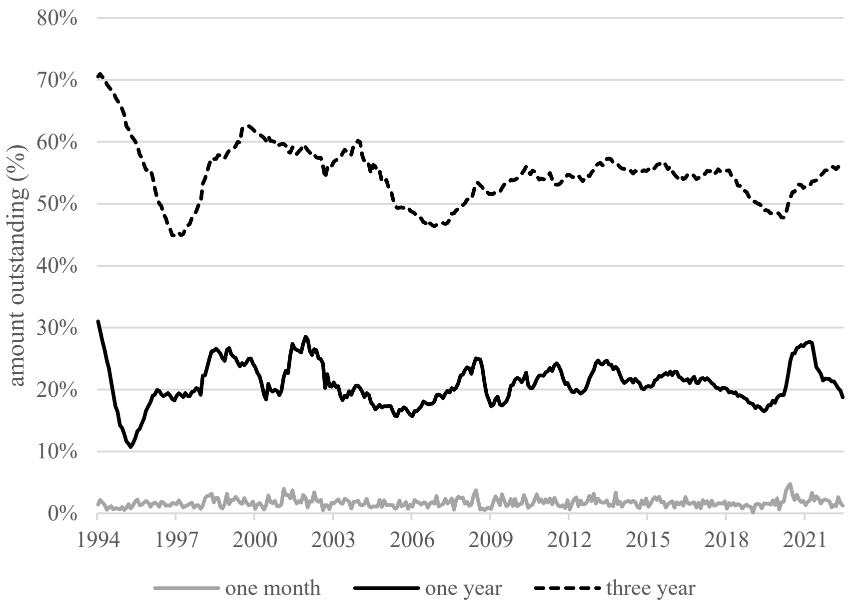
Pástor, Ľ., & Stambaugh, R. F. (2003). Liquidity Risk and Expected Stock Returns. *Journal of Political Economy, 111*(3), 642-685. doi:https://doi.org/10.1086/374184

Roll, R. (1984). A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market. *The Journal of Finance, 39*(4), 1127-1139. doi:https://doi.org/10.1111/j.1540-6261.1984.tb03897.x

Schneider, P., Wagner, C., & Zechner, J. (2020). Low-Risk Anomalies? *The Journal of Finance, 75*(5), 2673-2718. doi:https://doi.org/10.1111/jofi.12910

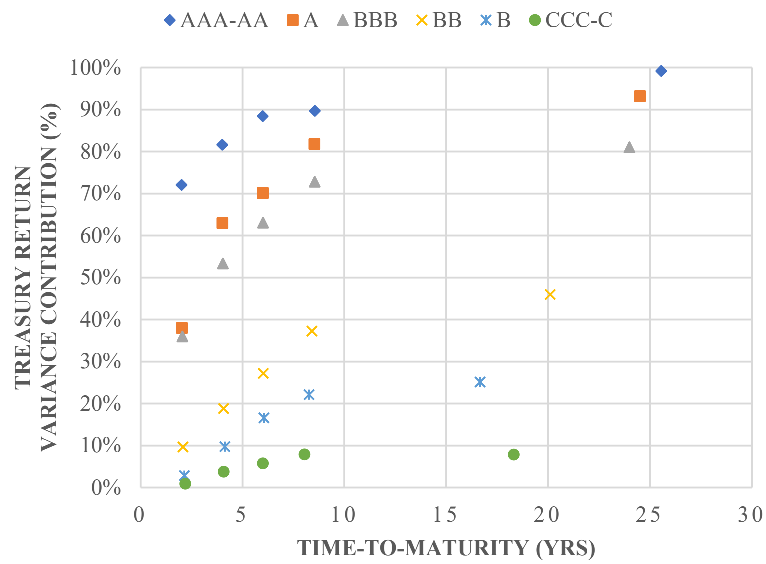
Sloan, R. G. (1996). Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings? *The Accounting Review, 71*(3), 289-315. Retrieved from http://www.jstor.org/stable/248290

Figure I: past new issues, percentage of amount outstanding



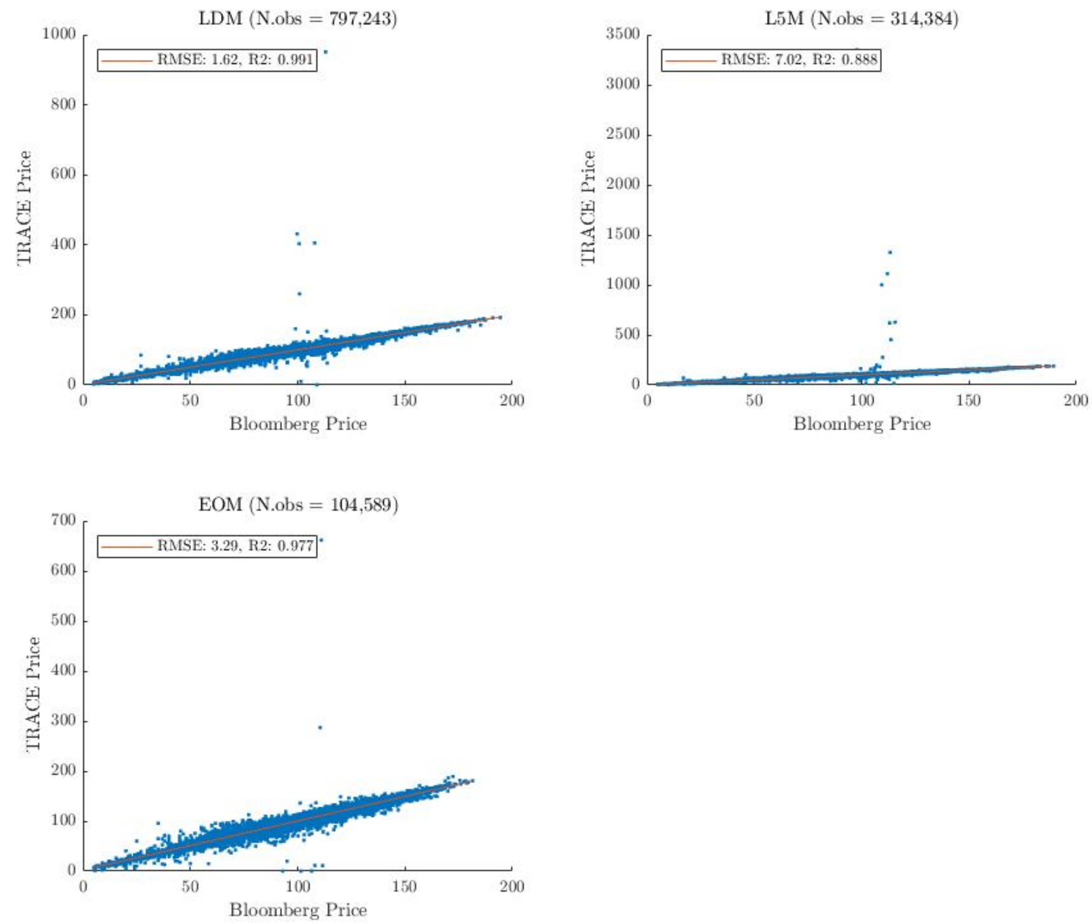
Note: from January 1994 to June 2022, at the start of each month we assign measure the amount of corporate bond debt outstanding of bonds that were issued in the past month (grey), past twelve months (black) or past three years (dotted black) as a percentage of total corporate bond debt outstanding in our sample.

Figure II: rating-maturity bucket Treasury return variance contribution



Note: from January 1994 to June 2022, at the start of each month we assign bonds to six rating categories (AAA-AA, AA, A, BBB, BB, B, CCC-C) and five maturity buckets (1-3 year, 3-5 year, 5-7 year, 7-10 year, >10 year). We measure the percentage of the return variance that is attributable to the return of the duration-matched Treasuries.

Figure III: Bloomberg vs TRACE prices



Note: scatters plot the panel of corporate bond Bloomberg prices (x-axis) and TRACE prices (y-axis). LDM covers the panel of corporate bonds for which TRACE price is based on prices during the last day of the month. L5M covers the panel of corporate bonds not part of LDM, for which TRACE prices are observed during the last five days of the month. EOM covers the panel of corporate bonds not part of LDM or L5M, for which TRACE prices are observed during any day of the month. Red lines indicate linear regression lines, with corresponding root mean squared error (RMSE) and R^2. Period August 2002 to June 2022.

Table I: Sample and return comparison between Bloomberg and TRACE

	Bloomberg	TRACE	only Bloomberg	only TRACE
A. Cross-sectional statistics: August 2002 – June 2022				
Bonds				
+ TRACE	5,089	8,890	0	3,801
+ TRACE EOM	5,027	7,535	0	2,508
+ TRACE L5M	4,335	5,554	0	1,219
+ TRACE LDM	2,583	2,990	0	407
+ Bloomberg	6,302	5,089	1,213	0
Amount outstanding (bln USD)				
+ TRACE	3,539	4,115	0	576
+ TRACE EOM	3,521	4,057	0	536
+ TRACE L5M	3,278	3,694	0	416
+ TRACE LDM	2,412	2,673	0	260
+ Bloomberg	4,321	3,539	782	0
B. Total return autocorrelation: August 2002 – June 2022				
TRACE EOM		-10.8%		-21.7%
TRACE L5M		-7.7%		-19.9%
TRACE LDM		-4.2%		-11.4%
Bloomberg	1.0%	1.1%	0.3%	

Note: The Bloomberg sample consists of index constituents of the Bloomberg US Aggregate Corporate index and the Bloomberg US High Yield index, excluding non-rated or defaulted bonds, bonds with a clean price below 5 USD, or if their credit spread, spread-duration, time-to-maturity or market value were missing. The TRACE sample consists of all observations in the WRDS Bond Database. The intersection consists of all observations that can be matched between TRACE and Bloomberg. The only Bloomberg (TRACE) samples contain observations in the Bloomberg (TRACE) sample that cannot be matched. Panel A shows the time-series average of the number of bonds and total amount outstanding in billion USD in each cross-section. Panel B shows the average total return autocorrelation, estimated by first obtaining the total return autocorrelation for each bond with at least 12 monthly total return pairs individually and second averaging over bonds. TRACE LDM, L5M and EOM returns are based on the daily volume weighted average prices observed on the last business day of the month (LDM), the last available day during the last five business days of the month (L5M), or the last available day on any business day during the month (EOM).

Table II: Descriptive statistics

	coverage	mean	percentile 5	25	50	75	95
A. Bond returns and characteristics							
Total return	100%	0.50%	-2.64%	-0.38%	0.47%	1.40%	3.72%
Credit return	100%	0.12%	-2.76%	-0.57%	0.11%	0.84%	3.07%
Market value	100%	560	188	277	402	649	1,493
Amount out.	100%	535	193	265	385	623	1,401
B. Bond sorting characteristics							
Rating	100%	9.2	3.8	6.3	8.6	11.4	16.6
Maturity	100%	10.2	1.7	4.1	6.9	11.4	28.3
DTS	100%	1,349	121	431	964	1,846	3,814
5% VaR	63%	3.77%	0.81%	1.72%	2.84%	4.55%	10.06%
OAS	100%	270	58	103	158	295	790
CRV	84%	-0.02	-0.53	-0.20	-0.02	0.17	0.57
r_{7-1M}	88%	1.09%	-6.42%	-1.04%	0.79%	2.85%	9.13%
$-R_{1M}$	98%	-0.53%	-3.72%	-1.42%	-0.48%	0.36%	2.57%
$-R_{48-12M}$	36%	-27.72%	-47.57%	-31.79%	-25.87%	-20.99%	-11.96%
C. Issuer sorting characteristics							
MB	100%	10,192	272	1,324	4,395	11,598	48,499
ME	89%	43,930	807	5,444	16,776	46,126	179,613
BE/ME	85%	0.63	0.12	0.31	0.50	0.74	1.34
OP	86%	0.74	0.08	0.23	0.34	0.54	1.54
INV	89%	0.30	-0.12	0.00	0.06	0.15	0.64
R_{6M}^{equity}	89%	2.3%	-35.5%	-7.8%	4.1%	15.1%	33.7%
WCA	86%	0.04	-0.12	-0.01	0.03	0.08	0.27

Note: This table shows the time-series average of cross-sectional coverage, mean and percentiles from January 1994 to June 2022. Characteristics are observed at the start of the month, returns over the month are observed at the end of the month. Coverage is the fraction of bonds in the cross-section with non-missing observations. Total returns are in USD, credit returns are total returns minus the total returns of key-rate duration matched Treasuries. Market value and amount outstanding are in million USD. Rating is the numerical rating, with AAA = 1, AA^{+} = 2, …, C = 21. Maturity is the time-to-maturity in years. OAS is the option adjusted spread in basis points. OASD is the option adjusted spread-duration. DTS is duration-times-spread. 5% VaR is the second worst total return over the past 36 months, with a minimum of 24 months. CRV is the credit relative value. r_{7-1M} is the past 6 minus 1 month bond credit return. $-R_{1M}$ is the negative of the past total return. $-R_{48-12M}$ is the negative of the past 48 minus 12 total return. MB is the sum of all corporate bond market values per issuer in our sample in million USD. ME is the equity market cap in million USD. BE/ME is book to market. OP is the operating profitability. INV is investments as measured by the change in total assets. R_{6M}^{equity} is the past six-month equity return. WCA is the working capital accruals.

Table III: Characteristics sorted value weighted quintile portfolios

	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5-Q1	CAPM bond Q5-Q1	
	Credit return						α	$\beta^{Mkt^{credit}}$
A. Bond characteristics								
Rating	0.04%	0.08%	0.07%	0.17%	0.21%	0.18%	0.07%	1.20***
	(1.06%)	(1.36%)	(1.55%)	(2.09%)	(3.09%)	[1.09]	[0.91]	[8.56]
Maturity	0.11%*	0.11%	0.10%	0.06%	0.07%	-0.04%	-0.12%***	0.94***
	(0.83%)	(1.25%)	(1.87%)	(1.80%)	(2.29%)	[-0.49]	[-2.94]	[10.61]
DTS	0.04%	0.05%	0.08%	0.11%	0.26%	0.22%	0.05%	2.00***
	(0.53%)	(1.01%)	(1.48%)	(2.15%)	(3.78%)	[0.97]	[0.60]	[10.79]
5% VaR	0.08%**	0.09%	0.10%	0.10%	0.24%	0.16%	0.02%	1.62***
	(0.57%)	(0.97%)	(1.42%)	(1.99%)	(3.21%)	[0.85]	[0.29]	[12.34]
OAS	0.00%	0.04%	0.07%	0.15%	0.32%	0.33%	0.17%*	1.76***
	(0.71%)	(1.14%)	(1.55%)	(2.13%)	(3.62%)	[1.52]	[1.95]	[10.53]
CRV	-0.06%	0.03%	0.09%	0.15%	0.23%	0.29%**	0.20%***	0.93***
	(1.02%)	(1.23%)	(1.39%)	(1.64%)	(2.57%)	[2.34]	[2.67]	[7.61]
r_{7-1M}	0.12%	0.12%	0.10%	0.08%	0.13%	0.00%	0.07%	-0.69***
	(3.06%)	(1.57%)	(1.20%)	(1.26%)	(1.91%)	[0.03]	[0.53]	[-3.10]
$-R_{1M}$	0.19%	0.11%	0.09%	0.05%	0.04%	-0.15%*	-0.17%**	0.29***
	(2.13%)	(1.31%)	(1.17%)	(1.40%)	(2.61%)	[-1.97]	[-2.27]	[2.60]
$-R_{48-12M}$	0.09%	0.06%	0.11%	0.14%*	0.27%*	0.18%**	0.19%**	-0.07
	(2.06%)	(1.39%)	(1.16%)	(1.23%)	(2.03%)	[2.03]	[2.01]	[-0.26]
B. Issuer characteristics								
MB	0.27%	0.14%	0.13%	0.12%	0.08%	-0.20%	-0.15%	-0.57***
	(2.70%)	(2.25%)	(2.13%)	(1.82%)	(1.48%)	[-1.45]	[-1.56]	[-5.45]
ME	0.00%	0.20%	0.12%	0.09%	0.07%	0.07%	0.19%	-1.30***
	(3.62%)	(2.32%)	(2.01%)	(1.75%)	(1.24%)	[0.35]	[1.58]	[-13.14]
BE/ME	0.06%	0.09%	0.09%	0.05%	0.13%	0.07%	0.04%	0.32***
	(1.33%)	(1.33%)	(1.49%)	(1.69%)	(1.86%)	[1.23]	[0.93]	[3.14]
OP	0.09%	0.07%	0.09%	0.08%	0.08%	-0.01%	0.02%	-0.31***
	(2.08%)	(1.47%)	(1.37%)	(1.42%)	(1.53%)	[-0.20]	[0.36]	[-4.18]
INV	0.18%	0.12%	0.08%	0.08%	0.01%	-0.17%***	-0.18%***	0.08**
	(1.73%)	(1.51%)	(1.39%)	(1.40%)	(1.87%)	[-4.74]	[-4.79]	[1.99]
R_{6M}^{equity}	-0.17%	0.06%	0.10%	0.16%**	0.30%***	0.47%***	0.54%***	-0.79***
	(2.71%)	(1.50%)	(1.33%)	(1.25%)	(1.38%)	[4.60]	[7.04]	[-10.29]
WCA	0.17%	0.12%	0.07%	0.06%	0.03%	-0.14%***	-0.14%***	-0.02
	(1.86%)	(1.57%)	(1.37%)	(1.36%)	(1.83%)	[-3.76]	[-3.52]	[-0.27]

Note: This table shows the mean month credit returns, Newey-West (1984) *t*-statistics in square brackets and monthly credit return volatilities in round brackets of market value weighted quintile portfolios (Q1 to Q5), long-short portfolios (Q5-Q1) and the CAPM bond regression coefficients of the long-short portfolios (CAPM bond Q5-Q1). Portfolios are formed by sorting bonds (panel A) and issuers (panel B) on the in Table II described sorting characteristics and splitting the cross-section in five quintiles containing the same number of bonds or issuers, respectively. Rating is the numerical rating, with AAA = 1, AA^{+} = 2, …, C = 21. Maturity is the time-to-maturity in years. OAS is the option adjusted spread in basis points. OASD is the option adjusted spread-duration. DTS is duration-times-spread. 5% VaR is the second worst total return over the past 36 months, with a minimum of 24 months. CRV is the credit relative value. r_{7-1M} is the past 6 minus 1 month bond credit return. $-R_{1M}$ is the negative of the past total return. $-R_{48-12M}$ is the negative of the past 48 minus 12 total return. MB is the sum of all corporate bond market values per issuer in our sample in million USD. ME is the equity market cap in million USD. BE/ME is book to market. OP is the operating profitability. INV is investments as measured by the change in total assets. R_{6M}^{equity} is the past six month equity return. WCA is the working capital accruals. The CAPM bond regression regresses the time-series of credit returns on a constant and the market value weighted average credit return of all bonds in our sample (Mkt^{credit}).

Table IV: Factor mimicking portfolios

			CAPM bond		
		credit return	**alpha**	**beta**	**Adj. R2**
	MKT^{credit}	0.09%			
		[0.88]			
Bond factors	CR	0.15%	0.08%	0.80***	0.496
		[1.34]	[1.28]	[6.87]	
	MAT	-0.06%	-0.12%***	0.69***	0.752
		[-0.88]	[-3.67]	[9.66]	
	$BETA$	0.10%	-0.04%	1.61***	0.806
		[0.51]	[-0.53]	[10.17]	
	$DOWN$	0.11%	-0.01%	1.30***	0.772
		[0.68]	[-0.11]	[12.03]	
	$CARRY$	0.17%	0.05%	1.35***	0.707
		[0.93]	[0.57]	[9.50]	
	VAL^{credit}	0.26%**	0.18%**	0.94***	0.649
		[2.09]	[2.20]	[7.79]	
	MOM^{credit}	0.06%	0.12%	-0.69***	0.298
		[0.47]	[1.22]	[-3.95]	
	STR	-0.16%**	-0.18%***	0.24**	0.090
		[-2.51]	[-2.81]	[2.50]	
	LTR	0.21%**	0.20%**	0.12	0.014
		[2.46]	[2.42]	[0.55]	
Issuer factors	$SIZE^{credit}$	0.05%	0.06%	-0.10	0.020
		[0.87]	[0.97]	[-1.01]	
	$SIZE^{equity}$	-0.15%	-0.20%**	0.58***	0.322
		[-1.34]	[-2.45]	[4.20]	
	VAL^{equity}	0.06%	0.03%	0.31***	0.242
		[0.92]	[0.62]	[3.58]	
	$PROF$	0.09%*	0.10%**	-0.19**	0.146
		[1.66]	[2.17]	[-2.53]	
	INV	0.16%***	0.16%***	-0.06	0.015
		[3.27]	[3.19]	[-1.15]	
	MOM^{equity}	0.44%***	0.50%***	-0.67***	0.479
		[4.45]	[6.84]	[-8.62]	
	ACC	0.15%***	0.15%***	0.05	0.008
		[3.39]	[3.30]	[0.96]	

Note: This table shows the monthly credit returns (left) and bond CAPM regression results for the factor mimicking portfolios. MKT^{credit} is the market value weighted average credit return of all bonds in the sample. CR is the average credit return of the HY minus IG portfolio within maturity terciles. Other factors are the average credit returns of the IG and HY long-short characteristics terciles. MAT is high minus low maturity, $BETA$ is high minus low DTS, $DOWN$ is high minus low 5% VaR, $CARRY$ is high minus low OAS, VAL^{credit} is high minus low credit relative value. MOM^{credit} is high minus low the past 6 minus 1 month bond credit return. STR is high minus low the negative of the past month bond total return, LTR is high minus low the negative of the past 48 minus 12 month bond total return. $SIZE^{credit}$ is small minus big issuer bond market value, $SIZE^{equity}$ is small minus big equity market cap, VAL^{equity} is high minus low book-to-market ratio, $PROF$ is high minus low operating profitability, INV is low minus high investments, MOM^{equity} is high minus low past 6 month equity return, ACC is low minus high working capital accruals. Newey-West (1984) t-statistics in square brackets.

Table V: Bivariate spanning alphas

LHS \ RHS	CR	MAT	$BETA$	$DOWN$	$CARRY$	VAL^{credit}	MOM^{credit}	STR	LTR	$SIZE^{credit}$	$SIZE^{equity}$	VAL^{equity}	$PROF$	INV	MOM^{equity}	ACC
CR		0.11%*	0.10%*	0.08%	0.06%	0.01%	0.10%*	0.09%	0.04%	0.08%	0.10%*	0.09%	0.12%**	0.11%	0.28%***	0.13%**
		[1.70]	[1.83]	[1.45]	[1.23]	[0.14]	[1.77]	[1.63]	[0.63]	[1.30]	[1.73]	[1.55]	[2.16]	[1.46]	[5.48]	[2.23]
MAT	-0.12%***		-0.12%***	-0.12%***	-0.12%***	-0.12%***	-0.12%***	-0.13%***	-0.10%***	-0.11%***	-0.13%***	-0.12%***	-0.09%**	-0.08%**	-0.15%***	-0.07%**
	[-4.00]		[-3.48]	[-3.65]	[-3.68]	[-3.95]	[-3.83]	[-4.03]	[-2.86]	[-3.54]	[-3.47]	[-3.61]	[-2.46]	[-2.39]	[-3.34]	[-2.18]
$BETA$	-0.08%	-0.02%		-0.04%	-0.08%***	-0.20%***	0.01%	-0.03%	-0.11%	-0.04%	0.00%	-0.04%	0.03%	0.03%	0.35%***	-0.03%
	[-1.06]	[-0.25]		[-0.87]	[-3.55]	[-6.35]	[0.17]	[-0.45]	[-1.50]	[-0.51]	[0.03]	[-0.55]	[0.44]	[0.44]	[3.72]	[-0.42]
$DOWN$	-0.03%	-0.02%	0.03%		-0.04%	-0.11%***	0.04%	0.00%	-0.08%	0.00%	0.04%	-0.01%	0.02%	-0.02%	0.29%***	-0.06%
	[-0.58]	[-0.32]	[0.85]		[-1.31]	[-2.83]	[0.57]	[-0.05]	[-1.54]	[-0.04]	[0.71]	[-0.20]	[0.45]	[-0.25]	[3.19]	[-1.10]
$CARRY$	0.02%	0.01%	0.09%***	0.06%		-0.14%***	0.11%	0.07%	-0.01%	0.04%	0.12%	0.04%	0.13%**	0.12%*	0.52%***	0.05%
	[0.20]	[0.16]	[3.61]	[1.32]		[-3.84]	[1.34]	[0.94]	[-0.09]	[0.54]	[1.49]	[0.56]	[2.06]	[1.67]	[5.65]	[0.77]
VAL^{credit}	0.15%*	0.18%**	0.21%***	0.18%***	0.15%***		0.22%***	0.21%***	0.16%**	0.18%**	0.21%**	0.18%**	0.27%***	0.29%***	0.53%***	0.23%***
	[1.84]	[2.03]	[5.74]	[3.14]	[3.47]		[3.07]	[2.85]	[1.98]	[2.36]	[2.52]	[2.40]	[4.55]	[4.24]	[8.06]	[3.18]
MOM^{credit}	0.14%	0.16%	0.09%	0.11%	0.15%*	0.26%***		0.10%	0.19%**	0.11%	0.11%	0.11%	0.08%	0.01%	-0.37%***	0.11%
	[1.54]	[1.63]	[0.88]	[1.17]	[1.66]	[2.92]		[1.17]	[2.14]	[1.16]	[1.06]	[1.22]	[0.89]	[0.12]	[-3.41]	[1.21]
STR	-0.18%***	-0.22%***	-0.17%***	-0.18%***	-0.18%***	-0.21%***	-0.17%**		-0.16%**	-0.15%***	-0.21%***	-0.16%***	-0.17%**	-0.17%**	-0.04%	-0.10%
	[-2.81]	[-3.41]	[-2.71]	[-2.80]	[-2.92]	[-3.56]	[-2.56]		[-2.59]	[-2.70]	[-3.04]	[-2.82]	[-2.52]	[-2.28]	[-0.57]	[-1.58]
LTR	0.18%**	0.13%	0.21%***	0.20%***	0.18%**	0.17%**	0.23%***	0.18%**		0.22%**	0.16%*	0.20%**	0.13%*	0.12%	0.23%**	0.08%
	[2.35]	[1.36]	[2.74]	[2.64]	[2.29]	[2.10]	[2.68]	[2.36]		[2.58]	[1.87]	[2.32]	[1.70]	[1.29]	[2.29]	[1.09]
$SIZE^{credit}$	0.07%	0.04%	0.06%	0.06%	0.06%	0.07%	0.05%	0.01%	0.10%*		0.19%***	0.04%	0.09%	0.04%	0.08%	0.03%
	[0.97]	[0.63]	[0.92]	[0.95]	[0.95]	[1.11]	[0.80]	[0.17]	[1.79]		[4.10]	[0.76]	[1.59]	[0.70]	[1.01]	[0.56]
$SIZE^{equity}$	-0.21%***	-0.25%***	-0.19%**	-0.20%**	-0.22%***	-0.25%***	-0.20%**	-0.24%***	-0.17%**	-0.27%***		-0.24%***	-0.13%*	-0.21%***	0.01%	-0.25%***
	[-2.67]	[-2.84]	[-2.34]	[-2.58]	[-2.83]	[-2.89]	[-2.27]	[-2.61]	[-2.30]	[-4.62]		[-3.46]	[-1.97]	[-2.62]	[0.14]	[-3.02]
VAL^{equity}	0.05%	0.02%	0.03%	0.03%	0.03%	0.04%	0.03%	0.00%	0.03%	0.00%	0.12%**		0.04%	-0.03%	0.02%	-0.03%
	[0.89]	[0.41]	[0.64]	[0.64]	[0.54]	[0.60]	[0.51]	[0.01]	[0.72]	[0.09]	[2.50]		[1.01]	[-0.61]	[0.34]	[-0.66]
$PROF$	0.11%**	0.06%	0.09%**	0.10%**	0.11%***	0.17%***	0.09%**	0.09%**	0.07%*	0.11%**	0.06%	0.10%**		0.01%	-0.05%	0.03%
	[2.42]	[1.37]	[2.38]	[2.31]	[2.90]	[3.82]	[2.11]	[2.13]	[1.66]	[2.38]	[1.28]	[2.26]		[0.34]	[-1.55]	[0.93]
INV	0.17%***	0.13%**	0.15%***	0.16%***	0.17%***	0.21%***	0.15%***	0.16%***	0.14%***	0.16%***	0.16%***	0.15%***	0.10%***		0.02%	0.08%*
	[3.06]	[2.57]	[3.48]	[3.21]	[3.37]	[3.79]	[3.32]	[3.33]	[2.75]	[3.44]	[2.93]	[3.99]	[2.75]		[0.62]	[1.91]
MOM^{equity}	0.52%***	0.52%***	0.47%***	0.49%***	0.53%***	0.62%***	0.45%***	0.46%***	0.50%***	0.50%***	0.44%***	0.50%***	0.42%***	0.39%***		0.45%***
	[7.71]	[7.72]	[7.10]	[7.18]	[8.43]	[9.39]	[7.03]	[7.20]	[6.73]	[7.14]	[5.77]	[7.20]	[7.67]	[5.84]		[6.65]
ACC	0.16%***	0.11%***	0.15%***	0.15%***	0.15%***	0.18%***	0.15%***	0.12%***	0.11%***	0.15%***	0.17%***	0.14%***	0.10%***	0.07%**	0.09%**	
	[3.41]	[2.62]	[3.44]	[3.30]	[3.17]	[3.36]	[3.51]	[3.29]	[2.74]	[3.45]	[3.41]	[3.93]	[3.09]	[2.51]	[2.09]	

Note: This table shows the alphas (intercepts) of left-hand-side (LHS) factors (rows) regressed on a constant, MKT^{credit} and a right-hand-side (RHS) factor (columns). See Table IV for factor definitions. Newey-West (1984) t-statistics in square brackets.

Table VI: RHS approach $Sh^2(f)$

	Actual	Full-sample Avg.	Full-sample Med.	In-sample Avg.	In-sample Med.	OOS Avg.	OOS Med.	Out-of-sample ≤ 0% (1)	Out-of-sample ≤ 0% (2)	Out-of-sample ≤ 0% (3)
Single factor model										
MKT^{credit} **(1)**	0.003	0.007	0.004	0.014	0.006	0.001	0.001	100.0%	95.8%	100.0%
Two factor models										
$MKT^{credit} + MAT$ **(2)**	0.039	0.050	0.045	0.072	0.059	0.039	0.032	4.2%	100.0%	100.0%
$MKT^{credit} + VAL^{credit}$	0.030	0.039	0.035	0.054	0.044	0.029	0.024	10.9%	60.9%	100.0%
$MKT^{credit} + MOM^{equity}$	0.213	0.224	0.221	0.247	0.238	0.213	0.201	0.0%	0.8%	99.9%
$MKT^{credit} + ACC$	0.051	0.059	0.056	0.074	0.067	0.049	0.044	1.9%	35.3%	100.0%
Three factor models										
$MKT^{credit} + MAT + VAL^{credit}$	0.066	0.081	0.077	0.110	0.100	0.058	0.052	2.5%	21.3%	100.0%
$MKT^{credit} + MAT + MOM^{equity}$	0.271	0.296	0.290	0.348	0.331	0.261	0.242	0.0%	0.0%	99.6%
$MKT^{credit} + MAT + ACC$	0.067	0.082	0.077	0.112	0.101	0.062	0.054	2.5%	11.9%	100.0%
$MKT^{credit} + VAL^{credit} + MOM^{equity}$	0.686	0.717	0.707	0.781	0.752	0.700	0.654	0.0%	0.0%	74.1%
$MKT^{credit} + VAL^{credit} + ACC$	0.099	0.114	0.111	0.142	0.133	0.094	0.086	0.6%	12.1%	100.0%
$MKT^{credit} + MOM^{equity} + ACC$	0.231	0.247	0.244	0.278	0.270	0.222	0.209	0.0%	0.5%	99.9%
Four factor models										
$MKT^{credit} + MAT + VAL^{credit} + MOM^{equity}$ **(3)**	0.781	0.831	0.816	0.929	0.895	0.766	0.710	0.0%	0.0%	100.0%
$MKT^{credit} + MAT + MOM^{equity} + ACC$	0.274	0.304	0.298	0.367	0.349	0.251	0.232	0.0%	0.1%	99.7%
$MKT^{credit} + MAT + VAL^{credit} + ACC$	0.111	0.131	0.127	0.171	0.162	0.096	0.088	0.8%	7.0%	100.0%
$MKT^{credit} + VAL^{credit} + MOM^{equity} + ACC$	0.735	0.770	0.761	0.843	0.817	0.705	0.669	0.0%	0.0%	66.6%
Five factor model										
$MKT^{credit} + MAT + VAL^{credit} + MOM^{equity} + ACC$	0.796	0.851	0.837	0.962	0.927	0.738	0.692	0.0%	0.0%	57.4%

Note: This table reports actual and Fama and French (2018) bootstrapped maximum squared Sharpe ratios for different factor models. Full sample, in-sample and out-of-sample (OOS) average (Avg.) and median (Med.) of 100.000 sampled squared Sharpe ratios are shown. The probability that a model (row) delivers a higher out-of-sample squared Sharpe ratio than the bond CAPM (1), the $MKT^{credit} + MAT$ model (2) or the $MKT^{credit} + MAT + VAL^{credit} + MOM^{equity}$ (3) are shown in columns. See Table IV for factor definitions.

Table VII: bond level cross-sectional regressions

		(1)	(2)	(3)	(4)	(5)
	γ^0	0.03%	-0.04%	0.01%	-0.05%	0.08%
		[0.78]	[-0.82]	[0.26]	[-0.71]	[0.65]
Factor exposures (γ^1)	$\gamma^{\beta_t^{MKT^{credit}}}$	0.06%	0.14%*	0.08%	0.15%**	0.02%
		[0.59]	[1.71]	[0.82]	[2.32]	[0.56]
	$\gamma^{\beta_t^{MAT}}$			0.09%	0.11%*	-0.03%
				[1.14]	[1.81]	[-0.80]
	$\gamma^{\beta_t^{VAL^{credit}}}$			0.13%	0.13%	0.02%
				[1.11]	[1.63]	[0.49]
	$\gamma^{\beta_t^{MOM^{equity}}}$			0.36%***	0.06%	0.12%**
				[3.51]	[0.89]	[2.59]
Characteristics (γ^2)	$\gamma^{z_t^{Log(Maturity)}}$		-0.06%**		-0.06%**	-0.08%***
			[-2.52]		[-2.57]	[-3.15]
	$\gamma^{z_t^{CRV}}$		0.13%***		0.12%***	0.10%***
			[3.93]		[3.81]	[4.99]
	$\gamma^{z_t^{ER_{6M}^{equity}}}$		0.26%***		0.22%***	0.22%***
			[6.19]		[4.69]	[4.87]
Controls (γ^3)	$\gamma^{z_t^{Log(AO)}}$					0.01%
						[1.15]
	$\gamma^{z_t^{DTS}}$					0.16%
						[1.45]
	$\gamma^{Dummy^{HY}}$					0.07%
						[1.08]
	Adj. R^2	0.128	0.187	0.171	0.203	0.267
	N. obs.	5037	5037	5037	5037	5037

Note: we report the time-series average coefficients of cross-sectional regressions, where we regress the cross-section of individual corporate bond credit returns on a set of factor exposures, model characteristics z-scores, control characteristic zscores and a high yield dummy. In each cross-sectional regression individual bond observations are square root market value weighted such that the market value weighted average residual equals zero. Factor exposures are obtained by regressing the time-series of past 36 month (minimum 24) returns of 54 rating, maturity, value and equity momentum sorted portfolios. These portfolios are formed by independently sorting bonds and forming terciles using maturity, credit relative value and equity momentum in investment grade and high yield separately. At month t, we assign the estimated factor exposure $\beta_{t,k}^{f}$ to all bonds that belong to portfolio k at month t. In specifications (1) and (2) the market factor exposure $\beta^{MKT^{credit}}$ is estimated using the single factor model time-series regression. In specifications (3), (4), and (5), the factor exposures, $\beta^{MKT^{credit}}$, β^{MAT}, $\beta^{VAL^{credit}}$, and $\beta^{MOM^{equity}}$ are estimated using the four factor model time-series regression. Newey-West t-statistics with 5 lags are reported in brackets. Period January 1996 to June 2022.

Table VIII: test asset cross-sectional regressions

	OLS		GLS	
A. 2x3x3x3 IG/HY maturity, value and equity momentum sorted portfolios				
γ^0	0.07%	-0.08%	-0.04%	-0.18%
t-stat$_c$	[1.45]	[-1.22]	[-4.27]	[-6.94]
t-stat$_m$	[1.34]	[-1.16]	[-2.94]	[-3.92]
$\gamma^{\beta^{MKT^{credit}}}$	0.08%	0.20%	0.10%	0.25%
t-stat$_c$	[0.66]	[1.61]	[1.00]	[2.39]
t-stat$_m$	[0.64]	[1.60]	[0.98]	[2.23]
$\gamma^{\bar{z}^{Log(Mat)}}$		-0.10%		-0.11%
t-stat$_c$		[-3.26]		[-7.84]
t-stat$_m$		[-3.23]		[-4.82]
$\gamma^{\bar{z}^{CRV}}$		0.14%		0.02%
t-stat$_c$		[4.26]		[5.29]
t-stat$_m$		[4.34]		[3.71]
$\gamma^{\bar{z}^{R_{6M}^{equity}}}$		0.29%		0.01%
t-stat$_c$		[8.68]		[2.00]
t-stat$_m$		[8.71]		[1.23]
R^2	0.025	0.798	0.002	0.203
B. 5 ratings, 5 maturity, 10 OAS and 10 sector sorted portfolios				
γ^0	-0.05%	-0.08%	0.03%	0.00%
t-stat$_c$	[-0.92]	[-1.30]	[3.02]	[0.00]
t-stat$_m$	[-0.93]	[-1.30]	[2.28]	[0.00]
$\gamma^{\beta^{MKT^{credit}}}$	0.15%	0.18%	0.05%	0.09%
t-stat$_c$	[1.22]	[1.43]	[0.56]	[0.88]
t-stat$_m$	[1.22]	[1.39]	[0.56]	[0.83]
$\gamma^{\bar{z}^{Log(Mat)}}$		-0.07%		-0.05%
t-stat$_c$		[-2.39]		[-4.32]
t-stat$_m$		[-2.33]		[-3.73]
$\gamma^{\bar{z}^{CRV}}$		0.09%		0.11%
t-stat$_c$		[2.21]		[8.38]
t-stat$_m$		[2.19]		[7.16]
$\gamma^{\bar{z}^{R_{6M}^{equity}}}$		0.19%		0.24%
t-stat$_c$		[0.75]		[1.83]
t-stat$_m$		[0.69]		[1.33]
R^2	0.731	0.864	0.002	0.601

Note: Panel A contains result for 54 portfolios that are formed by independently sorting bonds and forming terciles using maturity, credit relative value and equity momentum in investment grade and high yield separately. Panel B contains the results for 5 rating, 5 maturity, 10 OAS and 10 sector portfolios in spirit of Dickerson, Robotti and Mueller (2023). The exposures to MKT^{credit} are obtained by regressing the full sample time-series of test asset credit returns on MKT^{credit}. Characteristics are the time-series averages of each test-asset's weighted average bond level cross-sectional characteristic z-score. t-stat$_c$ is the t-statistic under correctly specified models, t-stat$_m$ is the model misspecification robust t-statistic of Kan, Robotti and Shanken (2013). Period January 1994 to June 2022.

Appendix A

Table AI: Sorting characteristics

A. Bond			
Name	*Characteristic*	*Definition*	*Reference*
Credit rating	CR	The middle of bond i's credit rating at time t provided by Standard & Poor (S&P), Moody's and Fitch, if all three are available, the worst if two are available, or the rating provided by one of the three rating agencies if only one is available, and converted to numerical scores where 1 refers to AAA and 21 refers to C.	Fama and French (1993) Bai et al. (2019)
Time-to-maturity	$M_{i,t}$	Bond i's time-to-maturity at time t.	Fama and French (1993)
Duration-times-spread	$DTS_{i,t}$	The product of bond i's option-adjusted-spread-duration and option-adjusted-spread at month t, $OASD_{i,t} \times OAS_{i,t}$.	Ben Dor et al. (2007)
5% value-at-risk	VaR	The negative of bond i's second worst monthly total return over the past 36 months, which corresponds to the 5% value-at-risk (VaR).	Bai et al. (2019)
Carry	OAS	Carry is the option-adjusted-spread of bond i at month t	Koijen et al. (2018)
Value	CRV	Credit relative value is the relative mispricing $CRV_{i,t} = \ln\left(\frac{OAS_{i,t}}{\widehat{OAS}_{i,t}}\right)$, where $OAS_{i,t}$ is the observed market option-adjusted-spread at month t for bond i. $\widehat{OAS}_{i,t}$ is the expected (fitted) option-adjusted-spread, as a function of credit rating, maturity and distance-to-default: $\widehat{OAS}_{i,t} = f_t(CR_{i,t}, M_{i,t}, DtD_{j,t})$. Specifically, to obtain the expected spread, at every month t, for financials and non-financials separately, within each rating category, we regress credit spreads on the Nelson-Siegel term structure factors and distance-to-default: $OAS_{i,t}^{public} = \gamma_t^0 + \gamma_t^1 NS^{st}(M_{i,t}) + \gamma_t^2 NS^{mt}(M_{i,t}) + \gamma_t^3 DtD_{j,t} + \varepsilon_{i,t}$	Correia, Richardson and Tuna (2012) Houweling and van Zundert (2017)
Credit momentum	ER_{7-1M}^{bond}	Bond i's cumulative credit return from month $t-7$ to $t-2$.	Jostova et al. (2013)

Short-term reversal	$-R_{1M}^{bond}$	The negative of bond i's total return from month: $-R_{i,t-1}$	Bai et al. (2019)
Long-term reversal	$-R_{48-12M}^{bond}$	The negative of bond i's cumulative total return from month $t-48$ to $t-13$.	De Bondt and Thaler (1985) Bali et al. (2021)
Illiquidity	$LR_{i,t}$	The negative of the serial covariance in daily price changes, $-Cov(\Delta p_{t,d}, \Delta p_{t,d+1})$. Following Bao et al. (2011), liquidity risk is calculated when bond i is traded on at least 75% of the business days in month t, and at least 10 paired price changes are available. Price changes may be between multiple days, but are never more than one week apart.	Bao et al. (2011) and Bai et al. (2019)

B. Issuer

Name	*Symbol*	*Definition*	*Reference*
Bond size	$MV_{j,t}^{bond}$	The sum of the market value of firm j's corporate bonds at month t.	Houweling and van Zundert (2017)
Equity size	$MV_{j,t}^{equity}$	Firm j's stock price times total shares outstanding at month t.	Fama and French (1993)
Equity value	$B/M_{j,t}$	Firm j's book common equity for the fiscal year ending in the previous calendar year, divided by market equity at the end of past December, available from the end of June.	Fama and French (1993)
Operating profitability	$OP_{j,t}$	Firm j's total revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses in the previous fiscal year, divided by book common equity at the end of the previous fiscal year, available from the end of June.	Fama and French (2015)
Investments	$INV_{j,t}$	Firm j's previous fiscal year percentage change in total assets, available from the end of June.	Fama and French (2015) Choi and Kim (2018)
Equity momentum	$MOM_{j,t}^{equity}$	Firm j's cumulative equity return from month $t-6$ to $t-1$.	Gebhardt et al. (2005)
Accruals	$WCA_{j,t}$	$WCA_{j,t} = (\Delta CA_{j,t} - \Delta Cash_{j,t}) - (\Delta CL_{j,t} - \Delta STD_{j,t} - \Delta TP_{j,t}) - Dep_{j,t}$	Sloan (1996) Bhojraj and Swaminathan (2009)