The Cross-Section of Corporate Bond Returns: Evidence from an Elusive Past[*]

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Abstract

Using novel hand-collected data of a preeminent bond market in the pre-OTC era, I provide, for the first time, out-of-sample evidence on cross-sectional determinants of corporate bond returns. I demonstrate that credit quality, short-term reversal, momentum, and book-to-market have significant explanatory power with respect to the cross-section of realized returns for the period 1868 through 1939. In contrast, there is no reliable relation between downside risk, illiquidity, or long-term reversal, and returns. In spanning regressions, factors constructed from credit-quality, illiquidity, short-term reversal, momentum, and book-to-market improve the mean-variance efficient tangency portfolio, but the downside risk and long-term reversal factors do not. Credit factor premiums are generally unrelated to market risks. In all, the findings suggest that most claimed anomalies are a robust and persistent feature of credit returns rather than statistical artifacts resulting from data mining.

Keywords: Corporate Bonds, Return Anomalies, Factors, Return Predictability

JEL Codes: G11, G12, N23, N24

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I. Introduction

What factors explain the cross-section of expected corporate bond returns? Research on the drivers of variation in the cross-section of corporate bond returns has attracted growing interest over the past decade (see Huang and Shi (2021) and references cited therein), as has the importance of corporate bonds in firm financing and investor portfolios. As of July 2022, the market for corporate bonds represents approximately $41 trillion in market value outstanding according to the 2022 *SIFMA Research Capital Markets Fact Book*. Corporate bonds are an important financing channel for corporations, accounting for 78% of debt financing on the aggregate balance sheet of nonfinancial US businesses and between 21.8% (Japan) and 29.6% (China) for nonfinancial businesses located in international markets. Corporate bonds represent about 25% of the Bloomberg Barclays US Aggregate Bond Index, a key benchmark for fixed income portfolio allocations. Understanding the determinants of corporate bond returns is therefore of foremost importance.

A key challenge for researchers and investment professionals lies in the dearth of high-quality corporate bond data due to the over-the-counter (OTC) market structure and complex features of corporate bonds as a more bespoke security as compared to stocks. This has resulted in a comparatively much more scarcer literature base where studies rely on the very same public datasets. Most notable the Trade Reporting And Compliance Engine (TRACE) database — collecting and disseminating corporate bond transaction details for the US bond market since its inception in July 2002 — which plays a defining role in the accreditation of corporate bond anomalies (Bai, Bali, and Wen, 2019; Bessembinder, Kahle, *et al.*, 2009). Fama (1998) suggests that spurious anomalies can be anticipated when return data are examined in such repeated fashion. No study, however, has analyzed the pervasiveness of corporate bond anomalies across time and space. This is an important gap in our understanding of the cross-section of expected corporate bond returns given the size and importance of the corporate bond market and the importance placed on the replication crisis in empirical asset pricing (Harvey, 2017; Hou, Xue, and Zhang, 2020).[1] Consequently, Bekaert and De Santis (2021), Chordia, Goyal, *et al.* (2017), and Huang and Shi (2021) argue that an open challenge in empirical asset pricing is to produce new evidence of cross-sectional pricing efficiency within the corporate bond market.

In this paper, I fill this gap by undertaking a large, out-of-sample investigation of cross-sectional predictability of corporate bond returns in a hitherto unexplored empirical setting. The backbone of this study is a newly compiled and unique dataset of corporate bonds listed on the Brussels Stock Exchange (henceforth BSE) between 1868 and 1939 that has never been studied before. Brussels ranked as one of the leading international financial centers during this period (Cassis, 2010; Kuvshinov and Zimmermann, 2022). More than 180,000 bond-month observations were hand-collected

[1]See Hou, Xue, and Zhang (2020, p. 3–6) for an exposition on the importance of *scientific replication* studies for critical evaluation of published results on the identification of anomalies in cross-sectional tests of asset pricing models. *Scientific replication* uses "different sample, different population and perhaps similar, but not identical model." This in contrast to *pure replication* which consists of "checking on others' published papers using their data and code." I focus on *scientific replication* in this study.

from the Official Quotation Lists of the Brussels Stock Exchange (*Cours Authentique de la Bourse de Bruxelles Seul Officiel Publié par La Commission Instituée en Vertu de la Loi*) — the main datasource of the BSE as declared by Belgian law. This historic record covers the entire domestic Belgian corporate bond market and is remarkable for its large cross-section (more than 1,000 unique bonds) and long time-series (72 years). As such, it rivals other novel bond market history projects such as Meyer, Reinhart, and Trebesch (2022) in terms of scale and it more than triples the period over which corporate bond returns are typically observed within cross-sectional asset pricing studies. Hence, I overcome the lack of credible, high quality corporate bond data over the long run that has resulted in a gap within the literature on factor premia of corporate bond returns (Baltussen, Swinkels, and Van Vliet, 2021, p. 1132).

The present study considers a pre-specified set of seven prominent corporate bond anomalies and examines their pervasiveness within my independent sample of Belgian bonds. The anomalies come from the return drivers compiled by Huang and Shi (2021, p. 7–11). I select those based upon price, market information, and bond characteristics: Downside risk, credit quality, illiquidity, short-term reversal, momentum, and long-term reversal. I further include the bond book-to-market effect as recently discovered by Bartram, Grinblatt, and Nozawa (2021). I focus on these factors because of their prominence in recent corporate bond asset pricing literature.

An alternative to using a historical sample is to look at a cross-section of countries. Putting this idea into practice is not as easy as it might seem, however. Data for most countries typically span relatively short time periods. These sample periods utilized in pricing cross-sectional premia within extant literature have been relatively unique as the macroeconomic environment is characterized by a structurally declining Treasury yield level from the early 1980s onwards. This secular decline in discount rates has resulted in major valuation windfalls for corporate bonds (Binsbergen and Schwert, 2022). Major credit events have also become more infrequent and less severe as compared to early market history (Giesecke *et al.*, 2011).[2] The typically studied recent period was thus favorable historically as it severely limits the number of bad states.[3] The issue of whether samples obtained for international markets in a more contemporary setting are truly independent compared to the US therefore remains.

I propose that data dating back to the early origins of the corporate bond market grant a unique opportunity for empirically understanding the cross-section of corporate bond returns. The period under study before WWII experienced a secular rise and decline in interest rates. In particular, the second half of the nineteenth century experienced declining sovereign bonds yields, a trend which ceased in 1897 as interest rates rose again (see Homer and Sylla (2005)). Additionally, the occurrence of corporate default increased substantially and consistently from the 1860s onward.

[2] Bali, Subrahmanyam, and Wen (2021) and Bali, Goyal, *et al.* (2022, p. 12) specifically highlight the absence of default events in their post-July 2002 sample of the US corporate bond market.

[3] This has a direct effect on realized returns given that corporate bonds trade among investors and dealers in secondary markets at prices that depend on: (i) market-wide interest rates and (ii) market perceptions regarding the likelihood that issuing firms will make the promised payments.

Most notable are the 1870s during which we observe the largest clustering of defaults ever recorded in corporate bond market history as close to a third of the aggregate market went into default in both the US and Belgium (Annaert, Deloof, and Van Mencxel, 2022; Giesecke *et al.*, 2011). I provide descriptive evidence of these events for the study period in Internet Appendix Figure A.2. An additional motivation for this article is that it therefore provides a natural robustness test of the influence of secular yield trends and default experience on corporate bond factor premiums. Such comparison across market states is unavailable for modern empirical settings.

An additional motivation of the historical context is that my inference is not clouded by the potential channels of alpha decay. Recent research has stressed the role of mispricing and arbitrage activity on abnormal returns found in return predictability (Chordia, Subrahmanyam, and Tong, 2014; Jones and Pomorski, 2016; Linnainmaa and Roberts, 2018; McLean and Pontiff, 2016; Pénasse, 2022). These considerations do not play a role as the empirical setting of this study takes place *prior* to the public dissemination of the initial findings of factor premia within the corporate bond market. They would, in comparison, cloud estimates in contemporary settings going forward. Given that arbitrageurs are unable to destroy predictability in returns this study can therefore be considered to be a pure test of the data-snooping hypothesis.

The context that I consider differs from today in two key dimension: prior to the Second World War, (1) liquidity had not migrated towards an OTC market structure and (2) institutional investors did not dominate the Belgian corporate bond market.[4] This means that (1) the bond prices I observe are actual transaction prices rather than matrix prices and that (2) institutional investor trading activities played a marginal role in corporate bond pricing in contrast to the influence that institutional herding excerpts upon bond prices in today's bond market (Cai *et al.*, 2019; Jiang *et al.*, 2022).[5] Rather than a weakness, I see this as a strength of the paper. On the one hand, the observed returns are not susceptible to mismeasurement due to proclaimed bond dealer valuations, while on the other hand there was significant institutional variation in the types of participating traders potentially subject to behavioral biases.

Despite the appeal of out-of-sample tests using data sourced from early financial market history to improve our understanding of whether anomalies might be expected to persist, a major challenge is that available datasets often lack dimensions that are crucial for performing rigorous asset pricing tests. The Belgian corporate bond market presents a compelling empirical laboratory in so far it

[4]In comparison to British and American banks, Belgian banks and investment trusts had a fundamentally different investment policy concentrating much more on holding stocks and government bonds rather than corporate bonds (Valk, 1932; Chlepner, 1943, p. 45-46, 62). Anecdotal evidence suggest that all strata of the population were active on the stock exchange during Belle Époque Belgium (Meynen, 1910; Chlepner, 1930, p. 92).

[5]Matrix prices are set by bond dealers using proprietary algorithms based on the quoted prices of alternative benchmark bond issues with similar characteristics. Such matrix prices are less reliable than actual transaction prices (Gehr and Martell, 1992; Nunn, Hill, and Schneeweis, 1986; Warga and Welch, 1993). However, discarding matrix-priced bonds significantly curtails the cross-section of bonds (see Binsbergen and Schwert (2022, p. 6)). This is especially a problem for international corporate bond markets for which a centralized transaction price database equivalent to TRACE is still in development (Li *et al.*, 2022). A case in point is the European Securities and Markets Authority (ESMA) Markets in Financial Instruments Directive (MiFID II) program since its implementation in January 2018.

helps to address four key challenges to assess the behavior of historical bond returns. First, historical data sources typically vary across sample periods and offer a type of security identification that is ambiguous (Rajan and Zingales, 2003, p. 46; Grossman and Shore, 2006, p. 276–277). Second, when bond data do exist, it is difficult to determine whether bonds' interest or amortization payments are guaranteed or not (Baskin, 1988; Baskin, Miranti Jr, and Miranti, 1997). Third, bond characteristics as specified in a bonds' name, such as coupon rates, tend to capture *contractual* instead of *realized* characteristics.[6] Fourth, corporate default data, especially missed coupon payments, are notoriously elusive outside of a modern setting despite their key role in bond pricing (Muir, 2017).

The unique features of my empirical setting address these challenges. First, the Official Quotation Lists, a datasource of notarial origin, allows for the clear identification of corporate bonds without interference of other types of securities such as stocks or sovereign bonds. Second, the Exchange Commission reported state-owned or state-guaranteed bonds within the section of sovereign bonds allowing for clear disentanglement of bond types. The same holds for the observation of fixed coupon versus floating rate coupon bonds. Third, key bond characteristics such as coupon rates, payment and reimbursement dates, bond quantities, and face values, are reported based upon information extracted by the Exchange Commission from data that companies were required to disclose as a result of their public listing. This helps me to incorporate updated bond characteristics rather than initial values stated upon bond IPO. Fourth, and most uniquely, the BSE reports missed coupon payments from 1873 onwards as a separate section (*obligations des compagnies qui ont des coupons en souffrance ou des coupons suspendus provisoirement*) at the end of each daily record. To the best of my knowledge, no other historic corporate bond market offers these elements.

I start my empirical analysis by testing the significance of a cross-sectional relation between the set of seven bond characteristics and future returns on corporate bonds using portfolio-level analysis. I closely follow the variable definitions from the original studies and make use of value-weighted portfolios to prevent an undue impact of smaller bonds. Further, I construct novel Fama and French (1993) and Carhart (1997) bond and stock factors for my historical sample to study risk-adjusted returns. Specifically, I collect sovereign bond data that allow for the construction of the term premium (TERM) and default premium (DEF) and stock data to construct the well-established Fama-French-Carhart four-factor stock model composed of the stock market factor (MKT^{Stock}), size factor (Smal-Minus-Big, SMB), value factor (High-Minus-Low, HML), and momentum factor (Up-Minus-Down, UMD^{Stock}).[7]

First, I sort bonds in quintiles based on their 5% Value-at-Risk, defined as the second lowest return over the last 36 months following Bai, Bali, and Wen (2019). The six-factor risk-adjusted

[6] It is not uncommon for characteristics to be quite noisy within a historic bond market setting as exact coupon payment dates or reimbursement dates are typically unavailable (see, for example, Bernstein, Frydman, and Hilt (2022)). It is also an open question whether changes in set characteristics are reported. Related, bond quantities are typically unavailable to researchers. The lack of bond characteristics, and the degrees of freedom that ensue for the researcher in their estimation, have a direct effect on the ex-post performance of the asset class (Asvanunt and Richardson, 2017; Hallerbach and Houweling, 2013).

[7] I refer the reader to Internet Appendix A and Internet Appendix B for additional details.

return difference between the lowest and highest VaR quintiles is insignificant, taking on a value of 0.30% per month with a t-statistic of 1.31. Second, I sort bonds in quintile portfolios using credit spreads to test the credit quality premium. Given the lack of credit ratings outside of the US before 1970, I rely on credit spreads as credit quality signal. I find that the credit quality effect survives risk-adjustment, with a highly significant monthly alpha of 0.48% (t-stat. = 4.92). Third, I test for an illiquidity premium by sorting bonds using bond age as the sorting variable of choice. I find a six-factor 0.08% monthly alpha that barely makes the cut to be considered statistically significant at conventional levels (t-stat. = 1.86). Fourth, to test for the short-term reversal (STR) effect, I sort bonds using their previous month' return (i.e., $t-1$). The return difference between the lowest and highest short-term reversal quintiles is economically large, 1.50% per month, and highly significant (t-stat. = 21.80). Fifth, the momentum (MOM) effect is tested using the cumulative return over the past 11 months between $t-12$ and $t-2$, skipping the short-term reversal months (i.e., month $t-1$). The risk-adjusted return difference between the highest and lowest MOM quintiles is economically large, 0.43% per month, and is highly significant (t-stat. = 3.91). Sixth, to make an inquiry in the long-term reversal (LTR) effect, I sort bonds using their previous 36 month' return between $t-48$ and $t-13$ thereby skipping the previously highlighted MOM and STR effects. The spread between lowest and highest LTR quintiles amounts to 0.12% per month, yet statistically insignificant at conventional levels (t-stat. = 1.65). Seventh, I test the value effect in corporate bond returns. I sort bonds in quintiles based on book-to-market ratios, defined as the reciprocal of the dirty price-to-face value ratio. Its risk-adjusted return difference between the lowest and highest book-to-market quintiles taking on a value of 0.40% per month with a t-statistic of 4.72. Bivariate portfolio sorts indicate that, importantly, the observed return spreads are large and significant in all size terciles but that of high-LTR, which indicates that anomaly variable effects are not confined to the dusty corners of the bond market.

Then, I estimate cross-sectional Fama and MacBeth (1973) regressions using weighted-least-squares (WLS) to investigate the cross-sectional relationship between the seven main predictors and expected returns at the bond level. Herein I control for multiple factors simultaneously. Specifically, I present the time-series averages of the slope coefficients from the regressions of one-month-ahead excess returns on downside risk, credit quality, illiquidity, short-term reversal, momentum, long-term reversal, and book-to-market, controlling for past bond risk/return characteristics, bond market beta, maturity, size, and bond exposures to the term and default factors. The results indicate that credit quality, short-term reversal, momentum, long-term reversal, and book-to-market remain strong predictors of future bond returns after controlling for a large number of bond characteristics. Combined, the 12 bond characteristics can explain on average up to 36% of the variation in corporate bond returns.

Finally, I introduce novel risk factors based on the above prevalent risk characteristics. In a similar spirit to Davis, Fama, and French (2000), I rely on the dependent sorted tercile portfolios to accommodate smaller historical cross-sections. Following Bai, Bali, and Wen (2019), I use credit spreads as the main sorting variable and downside risk, illiquidity, and past one-month return as the other sequential sorting variables when constructing the new downside risk factor (DRF), liquidity risk factor (LRF), and short-term return reversal factor ($SREV$). Similar to Jostova *et al.* (2013), I construct the bond momentum factor (UMD^{Bond}) by first sorting on credit spreads and momentum as the other sequential sorting variable. To construct the long-term return reversal factor ($LREV$), I follow Bali, Subrahmanyam, and Wen (2021) and form trivariate portfolios using credit spreads as the first sorting variable, time to maturity as the second sorting variable, and the LTR as the third sorting variable. The bond book-to-market factor ($BHML$) follows the methodology of the Fama and French (1993) equity HML factor as employed by Bartram, Grinblatt, and Nozawa (2021). Each month, bonds are divided into one of six portfolios based on two bond market capitalization categories and three book-to-market (BTM) categories.

I find that CRF, $SREV$, UMD^{Bond}, and $BHML$ generate significantly positive return premia, with Sharpe ratios that are significantly above that of the aggregate corporate bond market portfolio based on the Ledoit and Wolf (2008) block-wise bootstrap procedure. Next, I test if the newly created bond factor premiums can be reconciled with macroeconomic risks. Testing for differences across market states I find no supporting evidence for bond factors varying due to macroeconomic risks. Most importantly for investors, the performance of bond factors is remarkably pervasive and stable across the different scenarios, including recessions and expansions, financial crises, bull and bear markets for both equity markets and bond markets, as well as rising and declining sovereign bond yields.

Motivated by Barillas and Shanken (2017) in seeing the value of spanning regressions over the use of test assets to evaluate the pricing ability of different models, I next run spanning regressions to test the predictive power of the new bond risk factors. The intercepts (alphas) from the regressions represent the abnormal returns not explained by remaining bond and stock market factors. Using the full set of risk factors comprised of the seven new factors and the six established Fama-French-Carhart factors, I find that the alphas for the CRF, LRF, $SREV$, UMD^{Bond}, and $BHML$ factors are all economically and statistically significant, indicating that the factors are largely uncorrelated and do not span each other.

My findings are robust to a wide range of alternative specifications. First, I document that the main findings are robust to correcting delisting returns for bonds that default before leaving the sample. In addition, I obtain consistent results when I adjust excess returns using duration-matched risk-free returns. Third, downweighting the most volatile bonds does not alter my results. Fourth, portfolio returns remain economically large and statistically significant after adjusting for transaction costs. Fifth, portfolio analysis results are robust to using industry-adjusted signals. Sixth, I obtain consistent results when adjusting for multiple bonds outstanding per firm. Seventh, a panel regression controlling for bond, firm, and industry fixed-effects, and clustering at the firm-level shows that the Fama-MacBeth results remain significant. Eighth, a subsample analysis that removes the Great War subperiod or corporate bonds from the financial sector does not affect the baseline results. Neither do more opaque private firms drive my main results. Anomalies are not priced solely in microcaps, meaning that the main results are not simply a "microcap phenomenon".

Overall, the unique empirical setting of Belgium delivers an interesting set of results relevant for the multi factor pricing literature and investment practitioners. The robust set of factors found in this paper can be used as a benchmark model for future research and in performance evaluation. Furthermore, investors in corporate bond markets can build on my findings to implement the most promising factor-investing strategies.

Related Literature. The results of the paper contribute to three ongoing debates. First, my efforts relate most strongly to a rapidly growing literature that studies the behavior of corporate bond returns (Bai, Bali, and Wen, 2019, 2021; Bali, Subrahmanyam, and Wen, 2021; Bartram, Grinblatt, and Nozawa, 2021; Choi and Kim, 2018; Chordia, Goyal, *et al.*, 2017; Chung, Wang, and Wu, 2019; Jostova *et al.*, 2013) and that extends an earlier literature on corporate bonds that found no evidence of mispricing under the CAPM or similar models (e.g., Elton, Gruber, and Blake (1995), Fama and French (1989, 1993), and Gebhardt, Hvidkjaer, and Swaminathan (2005)). Common among these recent studies is the observation of corporate bond return drivers through their singular focus on the US credit market in the post-1980 era relying on corporate bond data sourced from TRACE, DataStream, Mergent FISD/NAIC, or Bank of America Merrill Lynch (BofAML). The robust features of cross-sectional variability in corporate bond returns due to repeated use of the initial estimation sample has not yet been explored. To my knowledge, the present study differentiates itself by being the first to establish robustness and instill beliefs in the accretion of corporate bond anomalies by conducting an out-of-sample analysis through the introduction of novel, unique data that takes the corporate bond market back to its origins. As such, this study links, for the first time in case of corporate bonds, to other empirical asset pricing studies for which the use of historical settings containing pre-sample evidence has proved fruitful. A non-exhaustive list includes Davis (1994), Davis, Fama, and French (2000), Goetzmann and Huang (2018), Grossman and Shore (2006), Linnainmaa and Roberts (2018), and Wahal (2019).

Second, and equally crucial, this paper builds on the emerging strand of literature that tests whether anomalies are the result of statistical biases that do not persist out-of-sample (Chen and Zimmermann, 2020, 2022; Harvey, 2017; Harvey, Liu, and Zhu, 2016; Hou, Xue, and Zhang, 2020; Jensen, Kelly, and Pedersen, 2022; McLean and Pontiff, 2016). The common intent of this emerging literature is the search for new methods and higher statistical hurdle rates to characterize the cross-section of returns. In response, a nascent literature has centered around the development of more rigorous tools to make statistical inferences, including tools imported from machine learning in artificial intelligence and computer science (Bali, Goyal, *et al.*, 2022) and principal component analysis (Kelly, Palhares, and Pruitt, 2022). Where Bali, Goyal, *et al.* (2022) and Kelly, Palhares, and Pruitt (2022) focus on internal validity through the implementation of new modeling frameworks, this study follows the *scientific replication* approach proposed by Hou, Xue, and Zhang (2020) to use data samples previously not yet available to the original study whilst relying on the same testing method. My findings suggesting that the majority of corporate bond factors do hold up out-of-sample and are externally valid, thereby providing fresh evidence on the replicability of corporate bond anomalies, accord well with the implications of these studies. Hence, the present paper complements Jensen, Kelly, and Pedersen (2022) who through the study of equity anomalies in the global market argue that numerous broadly acknowledged equity anomalies are internally and externally valid.

Third, my paper supplements an emerging literature on international corporate bond markets. Recent work by Bekaert and De Santis (2021) and Li *et al.* (2022) step in the debate as to whether global, regional, or local factor models are more useful in explaining local bond returns. They contribute to previous studies testing international integrated asset pricing (e.g., Fama and French (2012)). Rather than focusing on market integration, this paper instead provides a unique inquiry into the factor structure of corporate bond returns that focusses on the veracity of corporate bond anomalies by deviating from the large and persistent US (home) bias in academic research in finance as documented by Karolyi (2016, p. 2075–2076). Such an international out-of-sample test relying on comprehensive data from an important international market can help to provide novel insights to enrich or challenge understanding of bond price formation documented in earlier research.

Finally, my empirical findings may offer industry professionals important insights into ways to optimize their investment process. Investment managers argue that the paucity of long-run studies on corporate bonds as compared to the large body of work on risk factors that explain the cross-sectional variation in stock returns is one of the major reasons why the take-up of factor-based investing has been much slower in the corporate bond market.[8] This study comes at an opportune time as corporate bonds are seen as the new frontier of factor-based investing strategies by investment managers.[9] Related, recent survey evidence suggests the need for, and ample interest in, research of systematic investing in the corporate bond market by the very same professionals (e.g., Axthelm and Haghbin (2021) and Le Sourd and Martellini (2019)).

Outline. The paper proceeds as follows. Section II describes the historical background of the Belgian corporate bond market. Section III presents the data and its sources and provides preliminary descriptive statistics. Section IV and Section V report the main empirical asset pricing results and robustness checks, respectively. Finally, Section VI concludes. The Internet Appendix contains a variety of additional supporting material.

II. Historical Background

This section provides necessary background information on the historical setting I analyze in the paper. I first describe the historical account of the Belgian corporate bond market and how developed it was. Then, I provide an overview of relevant institutional details useful for understanding the market's modus operandi, summarizing how the assets were traded, and how news was transmitted to investors.

[8] See "Buzz around factor investing in fixed income is growing", *Financial Times* on 23 September 2019.

[9] See "The New Quant Billions Are Hiding in the Bond Market", *Bloomberg* on 9 July 2019 and "The Next Quant Revolution: Shaking Up the Corporate Bond Market", *Financial Times* on 6 December 2021.

A. Brussels as a Financial Center

In the nineteenth century, Belgium was the first country in continental Europe to industrialize and to become a major player in the world market (Cameron, 1967; Chlepner, 1943). At the eve of the Second World War, Belgium still ranked as fifth in terms of industrial output per capita (Bairoch, 1982). It has been argued that the financial markets, especially Brussels, played a key role in the industrialization of Belgium (Chlepner, 1930; Van Nieuwerburgh, Buelens, and Cuyvers, 2006).

As the Belgian economy developed, demand for and supply of corporate financing grew rapidly. The historical record indicates that capital was raised by securities with features similar to modern financial instruments: common (*actions ordinaires*) and preferred equity (*actions privilégiées*), and secured (*obligation garantie*) and non-secured (*obligation non garantie*) coupon-bearing debt. This gave rise to a liquid and active market for corporate securities. Consequently, there was a continuing shift in dominance towards the stock exchange in Brussels during the nineteenth century as it further cemented its role as stronghold of financial transactions by focusing on the growing importance of the stocks and corporate bonds segment following the industrial revolution in Belgium. Hence, while Belgium housed several stock exchanges, the scene was dominated by Brussels as it took on the role of the main exchange for industrial securities (Veraghtert, 1992; Willems, 2006).

In terms of market capitalization, international comparison shows that during the nineteenth century and first half of the twentieth century, Brussels was the preeminent corporate bond market in the world on a relative basis, together with the US and the UK (Van Mencxel, Annaert, and Deloof, 2022). The Brussels bond market grew substantially from the mid nineteenth century onwards. In terms of issues, the market grew from 19 bonds concurrently listed in the 1850s to over 550 issues in the 1920s, but in terms of market capitalization to GDP, the market increased almost tenfold from a level of 2.5% to a level of almost 25%. Growth of the corporate bond market was driven on the demand side by a growing number of increasingly prosperous middle-class investors looking for alternative investments to low-yielding government debt (Van de Velde, 1944).[10] The historical record (e.g., Van de Velde (1944, p. 100–101)) and numerous testimonies (e.g., *Bulletin de la Chambre de Commerce Française et d'Industrie de Bruxelles* in 1880 (Van de Velde, 1944, p. 143), *Moniteur des Intérêts Matériels* on 17 May 1863, and Théate (1905)) indicate that investors were actively in search for corporate bonds, mainly for three reasons: (1) preference for assured profits; (2) higher ex-ante expected returns compared to sovereign bonds, and (3) diversification benefits. On the supply side, growth of the corporate bond market was stimulated by the liberalization of Belgian stock exchange- and incorporation law following the Liberal party's rise to power in 1857. Universal banks provided supplementary aid in the issuance of corporate bond securities (Van Schoubroeck, 1951).[11] Not coincidentally, this period spans the rise of capital-intensive infrastructure projects

[10] As the yields on government securities of Belgium and other great European powers steadily declined, it became much more interesting for investors to invest in higher yielding corporate securities.

[11] The world's first joint-stock universal bank originated in Belgium with the founding of the *Société Générale des Pays-Bas pour favoriser l'Industrie nationale* on 28 August 1822. Universal banks played a pivotal role in the industrialization of Belgium and international finance (Cameron, 1967; Da Rin and Hellmann, 2002).

such as railways, coke companies, electricity-utilities, and chemical companies, which attracted and circulated significant capital via the securities market. Where other corporate bond markets were dominated by railroad issues, this was not the case for Brussels as it housed as more diversified corporate bond market relative to other financial centers (Van Mencxel, Annaert, and Deloof, 2022). Global competitors such as New York and London were constrained by restrictive domestic laws that prohibited the free issuance of corporate bonds (Baskin, 1988). In Belgium, the only legal binding constraint in place was on bonds with redemptions above par while in practice bonds were almost exclusively issued and repaid at par (Théate, 1905; Vaes, 1929).

B. Market Structure

In Belgium, only Brussels was in the possession of a *parquet* or *marché au comptant*, a delimitation in the stock exchange based upon the French stock exchange system where brokers met in public to establish the prices of treated titles. The existence of such a *parquet* was certainly in the second half of the nineteenth century an important indication of a liquid and active secondary market for stocks and other securities, like corporate bonds.[12]

Trade took place in a centralized location. Around noon two and a half official trading hours were held in the entrance hall of the Exchange building (François-Marsal, 1931). There were unofficial market makers (*teneurs du marchés* or *teneurs de carnets*) — brokers (*agents de change*) who specialized in individual securities. Trade was based upon limit orders; a large crowd of sworn and free brokers and their delegates (*délégués*) convened to the spot market to execute their principals' orders. Following the Law of 1867, these brokers were no longer prohibited from trading on their own account.[13] Transactions were conducted through open outcry (*à haute voix* or *à la criée*) or *feuilles papier et argent*. These *feuilles papier et argent* were standard slips whose model had been fixed by the Exchange Commission (*la Commission de la Bourse*) and that were to be filed ad hoc in the bond "cabinets" or "ledgers" (*dépôt des fiches de cotation*). A collection of eight such "cabinets" or "ledgers" was known as the "box" in stock exchange circles. Multiple "boxes" were placed on the trading floor, each specializing in a distinct type of security. This was, in effect, a limit order book collecting buy and sell orders and enforcing time and price priority (Bastiné, 1876; L'Amicale Saint-Mathieu, 1938). As noted by Biais and Green (2019), apart from the manual technology, the workings of the "bond cabinet" are very similar to those of electronic order books in the 21st century, such as Euronext, Xetra, Sets, or Inet. This new method of conducting transactions led to a substantial increase in trading volume and liquidity as it made possible to optimally handle the increasing number of listed securities (Willems, 2006). Consequently, the number of sworn brokers (and an unknown number of

[12] The BSE has its roots in the French era which started with the incorporation of the Belgian territories in the French Republic in 1795. It was established by Decree in 1801 (15 messidor year IX (2 July 1801)) by Napoléon Bonaparte.

[13] Following the law of 30 December 1867, brokers were no longer required to pay their annual fee (*patente*) to obtain privileges of the brokerage profession. Brokers which still upheld the *patente* payment were known as sworn brokers. Brokers that did not pay the *patente* were known as free brokers (*agents de change marrons*). See Willems (2006, p. 71–73) for a detailed description.

clerks and free brokers) at the BSE rose in likewise fashion: 224 in 1874, 248 in 1889, 386 in 1896, 895 in 1901, around 900 in 1914, and 913 in 1920. There were 1,800 sworn brokers in 1931, of which 225 market makers, at the apex of the exchange's importance (Lamal, 1934; Van de Velde, 1944).[14]

C. Information Flow

Successful development of a financial market requires access to information. In the second half of the nineteenth century, a sizeable industry of financial analysts providing second-hand assessment of the development of financial markets and investment advice developed quickly and was not dissimilar to what we observe today. Picard (1902, p. 34–36), a contemporary observer, maintained that market participants were perfectly aware of these outlets. The financial press and financial market commentators were centralized in Brussels whereas outlets in Antwerp focused on commercial affairs and political news coverage. Daily and weekly dissemination of information was provided by *Journal de Bruxelles*, *La cote libre*, *L'indépendence Belge*, *Le messager de Bruxelles* and *L'Echo de la bourse*. The *Moniteur des Intérêts Matériels* was generally perceived to be the most complete source of corporate financial information and stock exchange coverage providing announcements of annual shareholder meetings, initial listings of securities, as well as detailing the contract terms of securities next to their potential changes (Van Bocxlaer, 1966). Weekly bulletin of all the recorded prices and annual supplements (e.g., *Titres à Revenu Fixe: Fonds Publics, Emprunts et Obligations* for fixed income securities) which listed all the major issuers — sovereign, municipal, and corporate — and gave detailed information on securities issued by them were made available. Investors therefore had full and timely information on the distribution of asset pay-offs.

III. Data and Anomalies

This section outlines the data and variables used in this study. First, I present the data sources and sample preparation methods. Next, I explain the calculations of my primary return predicting variables. Finally, I summarize the other control variables employed in this study.

A. Data Collection

A.1. Corporate Bond Data

I have compiled my data from several sources in order to obtain a reliable and historically extensive dataset. The following is a brief introduction to my data sources and methodology. Internet Appendix A contains a more detailed description of all data, including sources, and their construction.

My deep historical sample covers 72 years of hand-collected data on corporate bond prices, coupon payments adjusted for defaults and taxes, face values, number of bonds outstanding, maturities, and market capitalizations for bonds traded on the BSE. The sample spans the period from

[14]During the pre-1867 period (the so-called *old regime* or *l'ancien régime*) when Napoleon's strictly regulated stock exchange policy still stood firmly only 25 brokers were allowed on the trading floor.

January 1868 through December 1939 and is at a monthly frequency. The logic behind this choice of period is based on stock exchange regulation and market development. First, 1868 is the first full year following the enactment of the liberalization of the BSE, thereby representing something of a regime shift in Belgian financial history.[15] Second, the period 1868–1939 closely follows the great reversal pattern observed for major corporate bond markets as the first era of corporate bond financing when corporate bond market size against GDP attained levels we see once again in today's leading markets (Goldsmith, 1985; Baron, Verner, and Xiong, 2021, p. 58). Consequently, the sample period starts on January 1868 and ends on December 1939.

Whereas today bonds are traded OTC, during my sample period they were listed on the BSE and traded on the centralized exchange. This historical feature allows me to observe prices for actual transactions. I employ one main archival data source of notarial origin to construct corporate bond returns, the Official Quotation Lists of the Brussels Stock Exchange as published by the Exchange Commission (*Cours Authentique de la Bourse de Bruxelles Seul Officiel Publié par La Commission Instituée en Vertu de la Loi*) which was the official authorative price list for the BSE. For listed securities, the Official Quotation Lists reported transaction prices — both current (*cours faits*) and previous period (*cours précédents*) — coupon rates (*intérets*), ex-coupon dates (*échéance des intérets*), face values (*valeur nominal*), number of bonds admitted (*titres admis*), and number of bonds outstanding (*titres en circulation*).[16] Taxation rates (*taux de taxation*) become available following the enactment of the Law of 29 October 1919 which took effect in January 1920. By considering only one stock exchange and one data source over the long term, I mitigate concerns that my findings are affected by temporal changes in the nature of the price data. Moreover, Thiebauld (1905) details in his study of official reporting by major contemporary financial centers that the reporting by the BSE was characterized as one of the best in the world, which reduces worries about erroneous prices or errors in bond descriptions.[17] For illustration, Internet Appendix Figure A.1 shows an example of how the Official Quotation List looks like.

Identification of corporate bonds is done through the fixed coupon corporate bond subsection (*obligations à revenu fixe*) in each daily record of the Official Quotation Lists. This allows for the clear disentanglement of corporate bonds from bonds that were guaranteed by the Belgian sovereign state. The latter were depicted under the title of *Rentes d'État* in earlier editions and *Rentes Belges Directes*

[15]Following the Royal Decree of 13 August 1855, the Commission for Reforming the Code de Commerce (*Commission pour la revision du Code*) was installed to prepare new legislation. The liberalization of Belgian financial markets (*liberté du courtage*) to intensify financial trade and encourage corporate capitalism occured through a tripartite: (1) The Law of 5 May 1865 on the free-floating of interest rates overturned the usury law of 1807, (2) the Law of 30 December 1867 de facto abolished the statutory provisions introduced in the Code de Commerce during the Napoleonic reign of 1795–1814 thereby removing all restrictions that prohibited speculation outside of governmental oversight, and (3) the Company Reform Act of 18 May 1873 abolished the requirement of government authorization to set up a limited liability company leading to an unprecedented liberalization of the market whereby free incorporation intensified market competition.

[16]The *titres en circulation* series take into account the role of debt buybacks and exchange offers as any difference between the respective series and the *titres admis*.

[17]The government had every interest in being able to attain the highest quality of price reporting possible for inheritance tax was calculated based on these figures. Following the Royal Decree of 29 December 1843, a copy of the official price list was published in Belgium's official journal, the *Moniteur Belge*, for this specific purpose.

et Indirectes in later editions placed at the very start of each daily record, allowing me to screen out state-owned firms.[18] Mergers and take-overs by the State were also reported in *Les Dossiers Financiers: Sociétés Disparues* ("delisted companies") and the *Moniteur Belge*, allowing for cross-checking of the segmentation as proposed by the Official Quotation Lists. Explicit mentioning of the bond type within the Official Quotation Lists further allows for the focus on fixed coupon bonds seeing that floating rate bonds (*obligations à revenu variable*) were listed in a separate subsection of each daily record, as were bonds issued by foreign firms (*obligations à revenu fixe étrangères*).

Unique for my empirical setting is that the Official Quotation Lists identify missed or delayed coupon payments starting from 1873. The identification of coupon defaults is of great importance given its leading role in observing corporate bond defaults (Azizpour, Giesecke, and Schwenkler, 2018) and its effect on long-term bond returns (Meyer, Reinhart, and Trebesch, 2022; Van Mencxel, Annaert, and Deloof, 2022). Each daily record of the Official Quotation Lists contains a separate subsection, *obligations des compagnies qui ont des coupons en souffrance ou des coupons suspendus provisoirement*, that identifies each bond within a state of coupon default. To fill gaps in the earlier years of the sample period, I retrieve retrospective information on interest servicing from Demeur (1870, 1874, 1876, 1879, 1885) and the *Moniteur des Intérêts Matériels*. For the period surrounding the First World War, I make further use of relevant coupon information extracted from the *Recueil Financier* and the corporate appendix of the *Moniteur Belge* (*Annexes au Moniteur Belge: Recueil Spécial des Actes des Sociétés*). In addition, these sources allow me to incorporate coupon arrears when coupon payments were once again being honored. In case I do not find any indication that coupons are missed, I assume that they are paid in full.

Maturity or redemption dates (*dates des remboursements*) are sourced from the *Moniteur des Intérêts Matériels*, the corporate appendix of the *Moniteur Belge* (*Annexes au Moniteur Belge: Recueil Spécial des Actes des Sociétés*), and the *Recueil Financier*. If I cannot define maturity in this way, I instead look for the last date at which the bond was listed in the dataset. Since bonds almost always appear every month this gives an alternative way to roughly capture maturity. In case the redemption date can not be determined, I instead rely on the drawing date for reimbursement (*dates des tirages*).[19]

The data collection described above produces an initial dataset of close to 320,000 bond-month observations of which a considerable amount is dropped following multiple data quality screens. The construction thereof is described in extensive detail in Internet Appendix A.1. I then narrow the data further in accordance with standard practices in the corporate bond literature to reduce

[18]Notable examples include bonds issued by state-owned railroad firms — which would eventually become known as monopolist *Société Nationale des Chemins de fer belges* starting from 1926 (and which still exists today) — and bonds issued by the *Crédit Communal* for statesponsered infrastructure and utility works.

[19]Most bonds in history are not due and payable at maturity (that is, so-called bullet bonds), but have stretched out amortization across its lifespan, often in the form of so-called sinking fund arrangements. The debt service was used to amortize bonds either by redemption at par to bondholders or via repurchases on the secondary market. Redemption at par is attractive to investors because bonds typically trade at prices below par. For this reason, the allocation of repayments from the sinking funds were often assigned via lottery (*amortissable par tirage au sort*). The date whereupon bonds were drawn for reimbursement were very close, if not equal, to the actual reimbursement date. Customarily these dates coincided with the coupon payment date.

the sensitivity of my return estimates to extreme outliers. Specifically, I follow Kelly, Palhares, and Pruitt (2022) and Gilchrist and Zakrajšek (2012) and discard bond-month observations with extreme bond spreads (that is, less than 5 basis points or greater than 3,500 basis points against duration-matched sovereign bond). I also exclude bonds maturing in less than a year and ensure a (Macaulay) duration of at least 0.25 years (Kelly, Palhares, and Pruitt, 2022).

Place Table I about here.

Panel IA of Table I provides an overview of the cleaned, final dataset after these adjustments in comparison to the initial version as obtained through the Official Quotation Lists. Overall my corporate bond universe covers 181,379 bond-month observations and 27,679 coupon payments by 1,010 corporate bonds. Corporate bonds were issued by 632 unique firms. The cross-section starts with 49 bonds in 1868 and ends with 152 bonds in 1939. After the data quality checks, the sample covers 74.5% of firms and 67.11% of the corporate bonds that were listed on the Belgian corporate bond market between 1868 and 1939. There is no potential survivorship in my sample as I do not exclude bonds of firms that have gone bankrupt or bonds that have matured.

Panel IB of Table I shows that the Belgian corporate bond market was diversified, both geographically and across industries. Internet Appendix Figure A.3 presents a more granular breakdown of the relative importance of regions and industries on a monthly basis throughout my entire sample. Time-series evidence per Panel A.3A and Panel A.3B highlights that the overall majority of bonds in my sample were issued by Belgian firms with main activity in Belgium (i.e., *Belgium*). Belgian firms held a long-term average of 73.70% in terms of issues and 73.04% in terms of market capitalization between 1868 and 1939. However, from 1875 onwards there is a remarkable increase in foreign direct investments until 1912 when, at the height of its importance, Belgian firms with main activity in foreign countries (i.e., *Abroad*) held a market share of 45.3% in terms of issues and 53.4% in terms of market capitalization. This pattern is consistent with the dating of the first era of financial globalization and Belgium's role as one of the top five foreign investors. Belgian firms with their main activity located in the colony (i.e., *Colony*) rose in importance as the share of *Abroad* securities diminished. This boom in capital export towards colonial industrial activity took place only after the rebuilding of the economic landscape in native Belgium following the turmoil of WWI.[20] Interestingly, only a limited amount of FDI in the form of bond listings is allocated to the colony. At the height of its importance in 1931, Belgian firms with main activity in the colony accounted for 3.75% of issues and 22.6% of market capitalization. Looking at the industrial breakdown per Panel A.3C and Panel A.3D, I find that the financial industry achieved its zenit in the Belgian corporate bond market in 1879 with a relative market capitalization of 22.3% against the aggregate corporate bond market. This greatly exceeds its long-term average of 9.67% over the entire sample period from 1868 to 1939. Non-financials attain a long-term average of 90.33%. I formally test the influence of industry effects as a robustness exercise at the end of paper.

[20]During the pre-WWI period, Congo was exploited under the dictatorial regime of King Leopold II.

A.2. Risk-Free Proxy Data

While the Belgian government issued Treasury bills as of 1833, this rate did not move much in the pre-World War I period, indicating that it did not fully reflect money market evolution (Nicolai, 1922). I therefore obtain data on the rate on Belgian commercial paper (*taux de l'escompte hors banque du papier commercial*) seeing it was recognized as the best money market rate for this period (Dupriez, 1930, p. 124). These short-term securities usually had a maturity of one to three months with a maximum maturity of 100 days. Commercial paper rates before 1918 come from the Official Quotation Lists of the Antwerp Stock Exchange (*Cours Authentique de la Bourse d'Anvers*) and were cross-checked with data sourced from the *Journal du Commerce d'Anvers*, *L'Avenir*, *Moniteur des Intérêts Matériels*, and *Het Handelsblad*. For the period 1919–1939, I source data on the commercial paper rate from the National Bank of Belgium.

B. Measuring Corporate Bond Returns

The monthly gross corporate bond total return at time t is computed as:

$$r_{i,t}^{tot} = \frac{P_{i,t} + AI_{i,t} + C_{i,t}}{P_{i,t-1} + AI_{i,t-1}} - 1 \tag{1}$$

where $P_{i,t}$ is the clean price reported at end-of-month t, $AI_{i,t}$ is the accrued interest, and $C_{i,t}$ is the coupon payment obtained by the holders, if any, of bond i. The prices of corporate bonds are shown as "clean" prices (*intérêts non compris dans le cours* or *intérêts au dehors*) except from May 1923 onward due to a change in the way bond prices are reported in the Official Quotation Lists. I thus have to adjust for accrued interest (*intérêts à bonifier*) accumulated in month t from the last coupon payment onwards to reflect the full or "dirty" price, $DP_{i,t}$, paid at settlement. I use the standard convention for coupon accrual, meaning that I calculate the accrued interest as the coupon rate multiplied by the fractional coupon period between current month-end t and the last payment date.[21] Defaulted bonds trade "dirty," thereby obviating the need for Equation (1)'s accrued interest adjustments to convert "clean" prices into prices paid. Moreover, the coupons promised by defaulted bonds are never realized in month $t+1$.

To eliminate possible data entry errors, I look for extreme price reversals. I perform a similar screen as the one used by Bessembinder, Kahle, *et al.* (2009), defined as 20% or greater returns in month t followed by 20% or greater returns of the opposite sign in month $t+1$, or vice versa. This screening procedure involved examining the data on bonds that had unusually high pricing errors with the daily records of the Official Quotation Lists for mistakes in recording the data indicated as *cours modifié* (i.e., "adjusted price") or *hier cours nul* (i.e., "wrong price") on the days following the

[21] Historical examples of interest tables that served to provide financial literacy to investors made use of the 30/360 day count convention, which assumes 30 days in each month, when calculating interest (e.g., p. 185 of the stock exchange manual "*Beurshandboek — Practische Raadgevingen en Nuttige Werken omtrent het Financiewezen en Beurszaken aan Renteniers, Kapitalisten, Industriëlen, en Handelaars*" published by *Financiënblad* in 1902.). I therefore make use of a 30/360 day count convention.

end-of-month price. If such referencing was found, the bond price was changed accordingly.

I denote $R_{i,t}$ as bond i's excess return, $R_{i,t} \equiv r^{tot}_{i,t} - r_{f,t}$, where $r_{f,t}$ is the risk-free rate proxied by Belgian commercial paper. To construct a series of contemporaneous monthly risk-free returns, $r_{f,t}$, I need to compute prices from the quoted discount rates and assume that the investor buys at the end of month t and sells in the following month $t+1$. The monthly price, P^{rf}_t, is calculated using the bank discount rate formula:

$$P^{rf}_t = 100 \cdot \left(1 - y_t \cdot \left(\frac{d}{360}\right)\right), \tag{2}$$

where y_t denotes the discount rate (in decimals) at time t and d equals the days to maturity. I assume that an investor buys a bill at 100 days maturity and sells in the following month at 70 days of maturity. For each month, t, an acquisition price, $P^{rf,A}_t$, was calculated along with a sale price, $P^{rf,S}_t$. The monthly return is calculated as $P^{rf,S}_t / P^{rf,A}_{t-1} - 1$.

C. Defining Candidate Anomalies

I consider a comprehensive list of established return predictors for the cross-section of corporate bond returns as documented in the broad survey of corporate bond asset pricing studies by Huang and Shi (2021). Among these, I select all characteristics that can be directly constructed using information on price, market capitalization, and book values. I focus on these factors because of their prominence in recent empirical asset pricing work. Additionally, financial and accounting data needed to test whether issuer-level characteristics can explain the cross-section of corporate bonds are either not readily available or not applicable within a historical setting.[22] Using the set of most prominent corporate bond factors listed by Huang and Shi (2021, p. 7–11) provides discipline against the critique of picking and choosing factors that suit the paper. I further augment this list of anomalies with the value effect found by Bartram, Grinblatt, and Nozawa (2021). Although I vary the methods in forming portfolios and in performing cross-sectional regressions, I closely follow the variable definitions in the original studies.

Place Table II about here.

Below I briefly describe each anomaly, relegating additional details on variable construction to Internet Appendix B. For each anomaly, there is a corresponding long–short trading strategy that goes long in the bonds that earn high returns (that is, the long leg) and short in those that earn low returns (that is, the short leg). The relationship between the subsequent bond performance and the ranking variable is positive for some anomalies and negative for others. Table II summarizes the characteristics of bonds in the long and short legs for each anomaly.

Anomaly 1: *Downside risk.* As documented by Bai, Bali, and Wen (2019), bonds with higher downside risk earn on average higher returns than bonds with lower downside risk. Follow-

[22] I refer the reader to Internet Appendix B for specific details.

ing Bai, Bali, and Wen (2019), I measure downside risk as a bond its 5% *VaR*, which is the second-lowest monthly return observation over the past 36 months. Seeing that the 5% *VaR* is obtained from the left tail of the return distribution of bond i, I multiply the original VaR measure by -1 for the ease of interpretation as a positive return spread in downside risk portfolios can then be interpreted as indicating that downside risk is positively related to cross-sectional bond returns. A bond is included in the VaR calculation if it has at least 24 monthly return observations in the 36-month rolling window.

Anomaly 2: *Credit quality.* It is well documented that expected returns decrease as credit quality increases (Asvanunt and Richardson, 2017; Fama and French, 1993; Kelly, Palhares, and Pruitt, 2022). I use credit spreads, defined as the spread between the yield-to-maturity of corporate bonds and duration-matched sovereign bonds, as proposed by Nozawa (2017) to measure credit quality.

Anomaly 3: *Illiquidity.* Bongaerts, De Jong, and Driessen (2017) find a strong effect of the liquidity level on expected bond returns. Specifically, amount issued and bond age have been shown to be good proxies of liquidity as a bond characteristic by Houweling, Mentink, and Vorst (2005) and Bongaerts, De Jong, and Driessen (2017). In accordance with Israel, Palhares, and Richardson (2018), I define bond age as a percentage obtained by relating the time passed since issuance to the original maturity.

Anomaly 4: *Short-term reversal.* Bai, Bali, and Wen (2019) find that bonds with low prior month returns outperform bonds with high prior month returns. Following Bai, Bali, and Wen (2019), I measure the short-term reversal of bond i for month t using its return during the previous month $t-1$.

Anomaly 5: *Momentum.* The momentum effect in bond refers to the phenomenon where bonds with higher past recent returns ("winners") continue to outperform bonds with lower past recent returns ("losers"). I employ the conventional definition of momentum, the past 11-month cumulative return from month $t-12$ to $t-2$, skipping the short-term reversal month $t-1$ (Bali, Subrahmanyam, and Wen, 2021; Jostova *et al.*, 2013). The holding period is from month $t-1$ to t.

Anomaly 6: *Long-term reversal.* The long-term reversal effect is a contrarian strategy takes a longer-term view of winners and losers than does momentum. As documented by Bali, Subrahmanyam, and Wen (2021), bonds with the lowest past performance over the last three to five years produce higher returns than do bond with superior performance over the same period. I measure long-term reversal with the past 36-month cumulative returns from month $t-48$ to $t-13$. A bond is included if it has at least 24 months of return observations during the 36-month window.

Anomaly 7: *Book-to-market.* The value effect is one of the most prominent anomalies in asset pricing. Bartram, Grinblatt, and Nozawa (2021) find that bonds with lower prices compared to book value earn higher subsequent returns. I measure the book-to-market of bond i in month t as the ratio of notional amount to market value (i.e., the reciprocal of the dirty price of the bond per unit of face value).

D. Summary Statistics

PLACE TABLE III ABOUT HERE.

Table III reports summary statistics of the panel data on bond returns and characteristics. In my sample, the average bond has a monthly total (excess) return of 0.40% (0.12%) with a return volatility of 5.81%. While the average rate of return is lower than average bond returns using modern samples (e.g., approximately 0.70% per month found by Bai, Bali, and Wen (2019) and Bali, Subrahmanyam, and Wen (2021)), bond volatility at 5.81% is almost twice as large as modern levels. This can in part be explained by the longer duration of bonds in my sample. Time to maturity is on average 26.17 years whereas bond age and duration amount to 13.86 years and 12.86 years, respectively. Hence, firms were much more active on the long-end of the maturity spectrum during my sample period. While this contrasts on a first view with the average maturity of less than 10 years for the typical bond today, long-term maturity bonds still account for a significant proportion of corporate debt financing (Badoer and James, 2016).

Bonds have on average an amount outstanding of 5.92 BEF million and a market capitalization of 5.15 BEF million. The distribution of these values showcase a significant positive skew, with the range running from 171.5 BEF thousand to almost 44 BEF million for the amount outstanding and from 142 BEF thousand to 39.5 BEF million in terms of market capitalization.[23] The coupon rate is on average 4.48% on an annual basis. The yield-to-maturity is on average 6.02%. The mean credit spread amounts to 395 basis points vis-à-vis a duration-matched sovereign bond.

I also consider characteristics of the issuers of bonds. I define a bond issuing firm as public when the firm has its stock concurrently listed with its bonds. I find that 83% of bonds are issued by publicly listed firms. Of these publicly traded bonds, 59% are issued by big firms as defined by a stock market size above the median market capitalization in month t. The remainder is made up by 25% small firms, defined as having a stock market capitalization between the 20th and 50th percentile, and 16% micro firms with a stock market capitalization below the 20th percentile. This strongly contrasts with the dominant role of big firms, accounting for 80.03% between 1973 and 2014, in issuing corporate bonds in the modern bond market (Chordia, Goyal, *et al.*, 2017). This result therefore shows that smaller firms were much more able to issue corporate bonds in the early

[23]In terms of 2022 Euro, this equates to an average amount outstanding of mio. €28 and a market capitalization of mio. €25. The 99th percentile equates to approximately mio. €285 in amount outstanding and mio. €240 in market capitalization. The largest bond issue had an amount outstanding of around mio. €602.

history of the corporate bond market.[24]

IV. Results

A. Portfolio Sorts

A.1. Univariate Portfolio Analysis

I first examine the significance of a cross-sectional relation between characteristics and future corporate bond returns using portfolio-level analysis. For each month from January 1868 to December 1939, I form quintile portfolios where quintile 1 contains bonds with the lowest value of the sorting variable and quintile 5 contains bonds with the highest value of the sorting variable. The portfolios are value-weighted using market capitalization as weights and rebalanced monthly. Importantly, in the construction of portfolios, I do not use any information that would be unavailable to the investor at the time the portfolio decisions are made. This means that all portfolios are constructed using historically available data that is available to investors in month $t-1$ to prevent any problems associated with look-ahead bias.

In addition to measuring excess returns, I also examine whether profits accrued by anomaly strategies compensate for systematic risk. I therefore regress portfolio returns on bond and equity risk factors previously found to be priced in the cross-section of corporate bond returns (Elton, Gruber, Agrawal, *et al.*, 2001; Fama and French, 1989, 1993; Gebhardt, Hvidkjaer, and Swaminathan, 2005). Using ordinary least squares (OLS) regression with Newey and West (1987) adjusted standard errors, I estimate abnormal returns (i.e., alphas) from the following benchmark model:

$$R_{p,t} = \alpha_p + \boldsymbol{\beta}_p^{\prime} \boldsymbol{F}_t + \epsilon_{p,t}, \tag{3}$$

where $R_{p,t}$ is the portfolio excess return over the risk-free asset proxied by three-month Belgian commercial paper, and $\boldsymbol{F}_t$ contains combinations of bond factors such as the term factor ($TERM$) and the default factor (DEF), and equity factors such as the value-weighted stock market factor (MKT^{Stock}), the size factor (SMB), the value factor (HML), and the momentum factor (UMD^{Stock}). This means I employ the same factor models to estimate risk-adjusted returns of corporate bond portfolios as Jostova *et al.* (2013).

Following the historic setting of this study, a comment regarding the construction of the standard bond pricing factors is in order. Given the lack of standard bond- and stock-factor data for Belgium's early market history, I construct Fama and French (1993) and Carhart (1997) factors specifically for the purpose of this study.[25] The stock and goverment bond data are described in Internet Ap-

[24] I test the robustness of my results by checking whether corporate bond anomalies are a "microcap phenomenon" in Internet Appendix Table A.XXII.

[25] Note that this is not unique however. The construction of Fama and French (1993) stock market factors for the pre-CRSP era (that is, pre-1926) for the US market has only very recently been carried out (see Baltussen, Vliet, and Van Vliet (2022)). Likewise, to the best of my knowledge, there exists no study of the Fama and French (1993) two-factor bond model in an out-of-sample setting pre-dating the original study.

pendix A. Following Fama and French (1993), the term risk factor, $TERM$, is the difference between the monthly value-weighted long-term government bond market return, comprised of sovereign bonds with at least 10 years of maturity, and the one-month return on Belgian commercial paper. The default risk factor, DEF, is the difference between the monthly value-weighted corporate bond market return and the monthly value-weighted long-term government bond market return. To construct equity market factors, I follow Fama and French (1993) and Carhart (1997) and construct standard 2x3 portfolios sorted on size and a characteristic. To construct the 2x3 portfolios, every month all stocks in my database are classified as either large or small, using the median cross-sectional market capitalization as breakpoint. Next, stocks are sorted on their factor variable within both of these size groups and split in three portfolios (Low, Medium, and High) based on the 30% and 70% percentiles. "High" always refers to the favorable factor characteristic, conversely "Low" always refers to the unfavorable characteristic. This methodology is applied to construct the Carhart (1997) four factor model comprised of the value-weighted stock market factor (MKT^{Stock}), the size factor (SMB), the value factor (HML), and the momentum factor (UMD^{Stock}).

Table IV provides summary statistics on the risk factors. The stock market outperformed the risk-free asset by 21 basis on average on a monthly basis. Consistent with previous literature on individual stock factors in other historical markets, I find a significant momentum effect but an insignificant value and size effect (e.g., Grossman and Shore (2006) and Goetzmann and Huang (2018), among many others). I find an average term premium ($TERM$) of 0.05% per month. This is consistent with the maturity premia of 0.06% found by Fama and French (1993) and the annual premium of 0.70% found by Dimson, Marsh, and Staunton (2002). The default premium (DEF) was on the order of 0.03% per month during the period of study. This estimate is surprisingly similar to 0.02% default premium found by Fama and French (1993) and the annual default premium of 48 basis points reported by Dimson, Marsh, and Staunton (2002).[26]

Place Table IV about here.

Table V shows the average characteristic of bonds in each quintile, the next month value-weighted average excess return, and the alphas for each quintile from regressing portfolio excess returns on the two bond market factors (2F α), on the four stock market factors (4F α), and on the six bond and stock market factors (6F α), respectively. The last row displays the differences of average returns and the alphas between quintile 5 and quintile 1. Average excess returns and alphas are defined in terms of monthly percentages. Newey and West (1987) adjusted t-statistics are reported in parentheses.

[26] Asvanunt and Richardson (2017) and Hallerbach and Houweling (2013) have critiqued the results of Fama and French (1993) due to its use of Ibbotson's historical bond indices which, as shown by the authors, has significant maturity and credit quality biases. Given the positive maturity premium, the default premium is therefore underestimated by taking the simple difference between the corporate bond market return and the long-dated government bond return without incorporating any maturity or duration adjustment. I test the robustness of my main results in Internet Appendix Table A.IX and Internet Appendix Table A.X by looking at duration-adjusted returns in accordance with Kelly, Palhares, and Pruitt (2022) and Binsbergen and Schwert (2022).

On average, the portfolios contain 38 securities in each quintile.[27]

Place Table V about here.

Panel A of Table V studies the cross-sectional relation between VaR and future corporate bond returns. For each month from January 1868 to December 1939, I form quintile portfolios by sorting corporate bonds based on their downside risk (5% VaR), where quintile 1 contains bonds with the lowest downside risk and quintile 5 contains bonds with the highest downside risk. Moving from quintile 1 to quintile 5 in Panel A, the average excess return on the downside risk portfolios increases monotonically from 0% to 0.14% per month. This indicates a monthly average return difference of 0.14% between quintiles 5 and 1 with a Newey-West t-statistic of 1.71, showing that this positive return difference is statistically significant, albeit only on a 10% level. The third column of Panel A shows that, in contrast to the average excess returns, the two-factor bond alpha does not change monotonically moving from the low-VaR quintile to the high-VaR quintile, yielding a positive yet non-significant alpha difference of 0.10 (t-stat. = 1.26). The four-factor stock alpha is, however, significant with a positive alpha difference of 0.14 (t-stat. = 1.81). Combining both models into a six-factor pricing model attains the same conclusion as for the two-factor bond model, showing an insignificant alpha difference for the downside risk anomaly variable. These results indicate that after I control for well-known bond and equity market factors, the return difference between the high- and low-VaR bonds does not remain positive and statistically significant. Consequently, I find little evidence of a downside risk premium in corporate bond returns between 1868 and 1939. This results therefore contrasts with the main finding of Bai, Bali, and Wen (2019).[28]

Next, I test the significance of a cross-sectional relation between credit quality and future bond returns using portfolio sorts on credit spreads. Quintile 1 contains the bonds with the lowest spread (i.e., high credit quality), and quintile 5 contains the bonds with the highest spread (i.e., lowest credit quality). Panel B shows spreads in excess returns and alphas between low and high credit quality are positive, with a monthly outperformance of 0.41% in terms of excess return and an alpha spread between 0.41% and 0.48% per month. These differences are the result of an monotonical increase across quintile portfolios and highly statistically significant, with t-statistics ranging between 3.97 (for the two-factor bond alpha) and 5.18 (for the four-factor stock alpha). This result indicates that corporate bonds in the highest-credit spread quintile generate 5.16% per annum higher return than do bonds in the lowest-credit spread quintile. The outperformance of high-credit risk bonds vis-à-vis low-credit risk bonds confirms the outperformance of junk bonds against investment grade bonds as originally found by Hickman (1958) for the US over the 1900–1944 period. My results thus allow for a rebuttal of the critique by Fraine and Mills (1961) that the results of Hickman (1958) are

[27]In the early part of my study period quintile portfolios contain 7 bonds whilst this increases upwards to 80 bonds per quintile portfolio at the zenith of the bond market's importance in the early 1920s. See Internet Appendix Figure A.6 for time-series evidence on the average and minimum number of bonds included within quintile portfolios.

[28]Yet, I do showcase the non-normality of corporate bond returns in Internet Appendix Table A.VI and Internet Appendix Figure A.5, echoing the conclusion of Bai, Bali, and Wen (2019).

due to sample selection choices rather than true statistical facts observed in the data.[29] In fact, the outperformance of Belgian "junk" bonds greatly exceeds Hickman's (1958) 3.5% difference found between BB to C bonds and AAA bonds. This is an important insight in financial history given the influence that the original Hickman study holds within the fixed income sphere, most notably motivating Michael Milken in cultivating the junk bond market at Drexel Burnham Lambert in the 1980s.

Illiquidity portfolios are sorted by bond age, where quintile 1 contains bonds with the highest liquidity (or conversely, the least illiquid; youngest bonds) and quintile 5 contains bonds with the lowest liquidity (or conversely, the most illiquid; oldest bonds). The conclusion for illiquidity-sorted portfolios shown in Panel C is comparable to that of the downside risk-sorted in Panel A. While I do find that most of those portfolios earned positive average returns, these positive average returns are indistinguishable from zero (t-stat. = 1.86). That is to say, I find no statistically significant difference between the most extreme quintile portfolios apart from the two-factor bond model alpha in column 2. Hence, I do not find any meaningful illiquidity premia in my historical bond sample. This result is consistent with Richardson and Palhares (2018) finding little evidence of a liquidity premium in corporate bond returns.

To examine the significance of a cross-sectional relation between short-term reversal and future corporate bond returns, I form portfolios based on a bond its previous month total return (i.e., R_{t-1}; STR). Panel D shows that moving from quintile 1 to quintile 5, the average excess return on the STR-sorted portfolios decreases from 0.61% to -0.90% per month. This result produces a monthly average return difference of -1.51% between quintiles 5 and 1 with a Newey-West t-statistic of -21.40, indicating that corporate bonds in the lowest STR quintile generate an economically and statistically significant 18% per annum higher return than bonds in the highest STR quintile. The third column of Panel D shows that, similar to the average excess returns, the two-factor alpha on the STR portfolios also decreases from 0.52% to -0.98% per month, moving from the low-STR to the high-STR quintile, yielding a significant alpha difference of -1.50% per month (t-stat. = -21.77). Similar to my earlier findings for the average excess returns and the two-factor alphas from bond market factors, the fourth column of Panel D shows that, moving from the low- to the high-STR quintile, the four-factor alpha from stock market factors decreases from 0.63% to -0.89% per month. The corresponding four-factor alpha difference between quintiles 5 and 1 is negative and significant; -1.52% per month with a t-statistic of -20.11. The fifth column of Panel D presents the six-factor alpha for each quintile from the combined two bond and four stock market factors. Consistent with my earlier results, moving from the low- to the high-STR quintile, the six-factor alpha decreases from 0.52% to -0.98% per month, providing a significant alpha spread of -1.50% per month (t-stat. = -21.80). These results indicate that after I control for well-known bond and equity market factors, the return difference between the high- and low-STR bonds remains negative and highly significant, consistent with Bai,

[29] One key argument raised by Fraine and Mills (1961) was the effect of declining interest rates for the outperformance of junk bonds. Correcting for interest rate effects in Internet Appendix Table A.IX, I show that that my main result still holds, and, in fact, even increases to an annual outperformance of 6.84% with a t-statistic of 5.26.

Bali, and Wen (2019).

Table V presents a positive and statistically significant return difference between momentum winners and losers. I form quintile portfolios by sorting corporate bonds based on their past 11-month cumulative returns (MOM) from $t-12$ to $t-2$ (skipping month $t-1$), where quintile 1 contains the bonds with the lowest MOM (medium-term losers), and quintile 5 contains the bonds with the highest MOM (medium-term winners). As shown in Panel E, the monthly average return difference between quintiles 5 and 1 is economically and statistically significant 0.45% per month with a Newey-West t-statistic of 4.59. In other words, corporate bonds in the lowest MOM quintile generate 75.4% per annum higher returns than bonds in the highest MOM quintile do. The two-factor (four-factor) alpha difference between quintiles 5 and 1 is 0.48% (0.40%) per month with a Newey-West t-statistic of 4.98 (4.57), indicating that corporate bonds in the highest MOM quintile significantly outperform those in the lowest MOM quintile. Interestingly, Panel E shows that the two-, four-, and six-factor alphas of bonds in both quintile 5 (momentum winners) and quintile 1 (momentum losers) are positive, respectively negative, as well as economically and statistically significant. In comparison, Jostova *et al.* (2013) finds that bond momentum profits are primarily driven by momentum winners for the modern US bond market. I instead find that more than two-thirds of raw returns (that is, 31 bps. out of 45) of the zero-cost momentum portfolio is obtained through quintile 1 (momentum losers), a result that is in line with Avramov *et al.* (2007) showing that equity momentum is predominantly driven by losers rather than winners.

Panel F tests the significance of a long-term reversal effect in corporate bond returns. For each month between January 1868 and December 1939, I form quintile portfolios by sorting corporate bonds based on their past 36-month cumulative returns (LTR) from months $t-48$ to $t-13$. Quintile 1 contains the bonds with the lowest LTR (long-term losers), and quintile 5 contains the bonds with the highest LTR (long-term winners). When moving from quintile 1 to quintile 5, the average excess return on the LTR portfolios generally decreasing from 0.20% to 0.05%, producing a monthly average return difference of -0.15% with a Newey-West t-statistic of -1.93. The six-factor alpha also decreases from 0.11% in quintile 1 to -0.01% in quintile 5, showing a weak significant negative alpha difference of -0.12% per month (t-stat. = -1.65). These results indicate that after I control for well-known bond and stock market factors, the return difference between high-LTR and low-LTR bonds remains negative, yet not statistically different from zero at conventional levels of significance. Consequently, I do not find the same outspoken effect for long-term reversals in corporate bond returns as do Bali, Subrahmanyam, and Wen (2021).

To test the value effect in corporate bond returns, I sort bonds into quintiles according to their book-to-market ratio (BTM) by relating a bond's face value to its dirty price. Quintile 1 contains the bonds with the lowest BTM (most expensive bonds), and quintile 5 contains the bonds with the highest BTM (cheapest bonds). Panel G shows that the value portfolios' average excess returns are monotonically increasing with BTM, with the most cheap bonds earning 0.41% per month higher average returns than the most expensive bonds, with a test-statistic of 3.91. The third column of Panel G shows that, similar to the average excess returns, the two-factor alpha on the book-to-market portfolios also increases monotonically from -0.09% to 0.20% per month, moving from the low-BTM to the high-BTM quintile, indicating a positive and significant alpha difference (value premium) of 0.34% per month (t-stat. = 3.60). Similar to my earlier findings from the average excess returns and the two-factor alphas from bond market factors, the fourth column of Panel G shows that, moving from the low-BTM to the high-BTM quintile, the five-factor alpha from stock market factors increases monotonically from -0.09% to 0.37% per month. The corresponding four-factor alpha difference between quintiles 5 and 1 is positive and highly significant; 0.46% per month with a test-statistic of 5.40. Consistent with my earlier results, moving from the low-BTM to the high-BTM quintile, the six-factor alpha increases monotonically from -0.15% to 0.25% per month, generating a positive and highly significant risk-adjusted return spread of 0.40% per month with a t-statistic of 4.72. This confirms the recent evidence presented by Bartram, Grinblatt, and Nozawa (2021) on the presence of a significant value effect in expected corporate bond returns.

Importantly, it is worth noting that the t-statistics of spread portfolios formed on credit quality, short-term reversal, momentum, and book-to-market are relatively high. This holds true even though the number of assets in the historic cross-section is incomparably lower than in usual bond-level studies for the modern US credit market. The results are therefore consistent with the much higher acceptable standard for empirical finance argued by Harvey, Liu, and Zhu (2016) given the recent explosion in studies of the cross-section of return as well as the associated risk of data snooping. Indeed, the mean returns and alpha shown in Table V considerably clear the single test hurdle of the absolute t-statistic of 3.0.

A.2. Bivariate Portfolio Analysis

Place Table VI about here.

Having established the essential cross-sectional relationship between characteristics and future returns, I continue with bivariate sorts. I want to ascertain that the effects found using univariate portfolio sorts are independent asset pricing phenomena. Table VI presents the results from the bivariate sorts of key anomaly variables and a number of potential bond return predictors. I follow Davis, Fama, and French (2000) and form 3x3 portfolios to accommodate the number of bonds within the cross-section. Tercile portfolios are formed every month from January 1868 to December 1939 by first sorting corporate bonds into three terciles based on their bond market beta (β^{Bond}), maturity, or size; then within each tercile portfolio of a control variable, bonds are sorted further into three sub-terciles based on their anomaly variable. I make use of dependent sorting to alleviate the problem of sparse portfolios by sequentially stratifying bonds into portfolios. The use of successive subportfolios is a common strategy to circumvent the problem of empty portfolios when using independent sorting, especially in international or smaller samples (see, for example, Daniel, Grinblatt, *et al.* (1997), Novy-Marx (2013), and Wahal and Yavuz (2013)). For brevity, I do not report six-factor alpha returns for all nine (that is, 3x3) portfolios. Instead, the first row of each panel of Table VI presents alpha returns averaged across the three control terciles to produce tercile portfolios with dispersion in the sorting variable, but which contain all levels of the control variable. This procedure creates a set of anomaly portfolios with similar levels of the control variable and, thus, these anomaly portfolios control for differences in the control variable. The table reports the alpha return based on the six-factor risk model, which exhibited the more conservative alpha estimates in the previous section.

Comparing the results of the bivariate portfolio analysis to the univariate results in Table V shows that most firm characteristics have only limited impact on the magnitude of the return spread between high- and low-anomaly variable bond. Panel A of Table VI reports the results from the bivariate sorts of downside risk on, respectively, bond market beta, maturity, and size. After controlling for bond market beta, the six-factor alpha difference between high-VaR and low-VaR bonds is insignificant with a t-statistic of 0.74. Yet, after controlling for maturity and size, the six-factor alpha difference between high-VaR and low-VaR bonds is positive (equating to 0.09 in both cases) and significant with a t-statistic of 1.84 for the maturity corrected tercile portfolios and 2.34 for the size corrected porfolios. In both scenarios it is the high-VaR tercile portfolio that drives the result, a finding that is consistent with Bai, Bali, and Wen (2019).

Panel B of Table VI shows that the value-weighted average six-factor alpha increases monotonically from the low-credit quality to high-credit quality tercile. The alpha return difference between tercile 3 (high credit spread) and tercile 1 (low credit spread) ranges between 0.32% (t-stat. = 4.90) and 0.39% (t-stat. = 5.94) per month. These results indicate that after controlling for bond market beta, maturity, and size, the alpha spreads between high- and low-credit quality bonds remain positive and highly statistically significant.

I find only consistent results for the illiquidity effect when correcting for bond market beta and size. Panel C of Table VI shows that the alphas after controlling for these predictors amount to 0.10% (t-.stat = 2.88) and 0.08% (t-stat. = 3.19), respectively. In both instances it are the high-illiquidity bonds that drive the results. However, I do not find an alpha spread distinguishable from zero when correcting for maturity.

The short-term reversal effect in Panel D of Table VI shows a monotonically decreasing six-factor alpha return across STR terciles. The monthly alpha return difference between the high-STR and low-STR tercile amounts to -1.15% when correcting for bond market beta (t-stat. = -21.86) and size (t-stat. = -26.97). The monthly alpha difference is -1.19% (t-stat. = -26.24) when correcting for maturity.

As shown in the last column of Panel E of Table VI, the difference in alphas between the high MOM and low MOM portfolios is approximately 0.41% per month with a Newey–West t-statistic of between 4.82 (corrected for maturity) and 7.12 (corrected for size). This difference is economically significant and statistically significant at all conventional levels.

I find only consistent results for the long-term reversal effect when correcting for bond market beta and maturity. Panel F of Table VI shows that the alphas after controlling for these predictors amount to -0.13% (t-.stat = -2.29) and -0.11% (t-stat. = -2.09), respectively. In both instances it are the long-term losers that drive the results. However, I find no alpha spread distinguishable from zero when correcting for size.

Looking at book-to-market portfolios in Panel G, the average six-factor alpha spread between the high- and low-BTM terciles ranges from 0.32% to 0.46% per month and is significant at the 1% level in all cases.

In sum, credit quality, short-term reversal, momentum, and book-to-market remain robust and strong even after controlling for the other popular return predictors. Importantly, the return spread is large and significant in all size terciles but that of high-LTR, which indicates that anomaly variable effects are not confined to the dusty corners of the bond market.

B. Return Premia over Time

B.1. Performance Across Subperiods

Place Figure 1 about here.

I now investigate the significance of anomaly returns over time. Figure 1 shows the performance over time of the anomaly strategies presented in Table V. The figure shows the strategy's realized annual Sharpe ratio over the preceding five years at the end of each month between January 1873 and December 1939.

The figure shows that while anomaly strategies generally performed well over the sample, every single strategy except short-term reversal had significant periods in which they lost money. Downside risk had the most frequent negative episodes. It performed poorly during the 1875-1876 financial crisis, from the mid 1880s to the mid 1890s, the early 1900s, right after the Great War, and during the Great Depression. Credit quality performed poorly from the late 1880s to the late 1890s and over the first five years of the twentieth century. Illiquidity generally performed well in the periods when downside risk performed poorly. There are six episodes when the Sharpe ratio comes into negative territory for the illiquidity strategy: (1) the late 1860s going into the early 1870s, (2) the late 1880s, (3) late 1890s going into the twentieth century, (4) post-Great War period, (5) the Great Depression, and (6) two years during the recession leading up to the Second World War. Downside risk and illiquidity are too volatile to attain but fleeting periods of statistical significance. Momentum only had two distinct periods of poor performance, the first being the roaring 1920s and the second being the mid 1930s. Long-term reversals exhibit negative Sharpe ratios during the mid 1880s, the Great War period, and the post-war period until the mid 1920s. The value strategy performed poorly in the late 1870s and early years of the 1900s.

Consistent with the visual evidence provided by Figure 1, Table VII reports the frequency of positive Sharpe ratios across 5-year rolling subperiods. All corporate bond anomaly strategies display consistent premiums over time, with frequencies significantly above 50%. Overall, the general consistency of performance over time further strengthens my empirical evidence for the existence of most of the corporate bond factor premiums I examine.

Place Table VII about here.

B.2. Seasonal Patterns

Figure 1 and Table VII show consistent performance over time of anomaly returns. To address a potential concern of seasonality in corporate bond returns, I follow Keloharju, Linnainmaa, and Nyberg (2016) and compare expected returns across the full sample with returns obtained from the non-January sample.[30]

Place Table VIII about here.

The first two columns in Table VIII report the average monthly returns for the market and the anomalies and the t-statistics associated with these averages. These are the same estimates obtained in Table IV. The p-value in the next column is from the test that the average returns are the same in every calendar month. Consistent with Keloharju, Linnainmaa, and Nyberg (2016) I find that all bond anomalies, as well as the market portfolio, show considerable seasonal variation in their profitability. I reject the null of constant expected returns with p-value < 0.001 when I use all months of the year. Return seasonalities are highly significant in joint tests of the complete set of seven anomalies. These tests reject the no-seasonality null hypothesis in both the full and the non-January data with p-value < 0.001. Some anomaly strategies display significant seasonalities even though their unconditional average returns are not statistically different from zero on a 5% level (t-stat. < 1.96). These include downside risk, illiquidity, and long-term reversal. These anomalies earn relatively high returns in some months and low returns in other months, so that, over the calendar year, the abnormal returns almost perfectly offset each other. Visual evidence thereof can be found in Figure 2.

Place Figure 2 about here.

C. Cross-Section Regressions

I have so far tested the significance of characteristics as the cross-sectional determinant of future bond returns at the portfolio level. This portfolio-level analysis has the advantage of being non-parametric, in the sense that I do not impose a specific functional form on the relation between characteristics and future bond returns. However, the portfolio-level analysis also has two potentially significant disadvantages. First, aggregating bonds into portfolios leads to a loss of information because it conceals differences across bonds in characteristics other than those used for sorting. Second, it is a difficult setting in which to control for multiple effects or bond characteristics simultaneously.

[30] I perform a test of the January effect in Internet Appendix Table A.VII, detailing month-by-month returns. The results indicate a significant January effect in anomaly returns.

Consequently, in this section, I now examine the cross-sectional relation between risk characteristics and expected returns at the bond level using the two-pass methodology of Fama and MacBeth (1973).

The first pass of the bond-level Fama-MacBeth regressions is a time-series regression of individual asset returns on the proposed factors to estimate factor loadings, or betas. The second pass regresses the cross-section of asset returns on betas obtained from the first-pass regression. Specifically, every month I conduct a Fama and MacBeth (1973) cross-sectional regression of individual bond returns that take the following form and nested versions thereof:

$$R_{i,t} = \lambda_{0,t-1} + \sum_{f=1}^{F} \lambda_{i,f,t-1} Factor_{i,f,t-1} + \sum_{k=1}^{K} \lambda_{i,k,t-1} Control_{i,k,t-1} + \epsilon_{i,t}, \tag{4}$$

where $R_{i,t}$ denotes the excess return of corporate bond i at month t, *Factor* denotes the collection of main variables of interest (downside risk, credit quality, illiquidity, short-term reversal, momentum, long-term reversal, and book-to-market) measured at the end of month $t-1$. $\lambda_{i,f,t-1}$ are the corresponding slope coefficients. I test the time-series averages of the estimated slope coefficients from the first step and use autocorrelation and heteroskedasticity consistent standard errors (HAC) (Newey and West, 1987). The average slopes and their t-statistics determine whether a characteristic, on average, has a non-zero premium over the sample period. Different from portfolio sorts, this analysis allows for extensive controls of variables that have been found to have predictive power for bond returns. *Control* denotes bond characteristics at each month $t-1$. Following Bai, Bali, and Wen (2019) and Bali, Subrahmanyam, and Wen (2021), I make use of TERM beta (β^{TERM}), DEF beta (β^{DEF}), maturity, and the log of amount outstanding as bond controls. The TERM and DEF betas are estimated through the two-factor model of Gebhardt, Hvidkjaer, and Swaminathan (2005) which takes the following form:

$$R_{i,t} = \alpha_i^{2F} + \beta_{1,i}^{2F} TERM_t + \beta_{2,i}^{2F} DEF_t + \epsilon_{i,t}^{2F}, \tag{5}$$

where $\beta_{1,i}^{2F}$ denotes the sensitivity of bond i to the TERM factor and $\beta_{2,i}^{2F}$ denoted the sensitivity of bond i to the DEF factor. In accordance with Bai, Bali, and Wen (2019), I estimate the betas on a rolling-window of 36 months with a minimum of 24 observations.

PLACE TABLE IX ABOUT HERE.

Table IX reports the time-series average of the intercept and slope coefficients (λ) and the average adjusted R-squared values ($\overline{R^2}$) over the 864 months from January 1868 to December 1939. The Newey-West adjusted t-statistics are reported in parentheses. All independent variables are standardized by the cross-sectional standard deviation each month, so that the regression coefficients can be interpreted as the premiums per unit of standard deviation. I value-weight each bond-month observation to prevent my results to be skewed to smaller bonds, especially the bonds trading for a few cents on the franc. The process of minimizing the sum of squared errors may allocate a higher weight to outliers with extreme returns and characteristics. Notably, these companies are likely to be tiny firms, thereby emphasizing microcaps' significance.[31] Harvey and Liu (2021) indicate that value-weighted estimates from WLS regressions effectively capture their economic importance. Value-weighting is also shown to be an effective procedure to mitigate the upward biases in regression estimates arising from noise in security prices (Asparouhova, Bessembinder, and Kalcheva, 2013).

Consistent with the univariate quintile portfolios of downside risk in Table V, regression (1) shows that the average slope from univariate cross-sectional regressions of excess bond returns on 5% VaR is positive, 0.06, and insignificant with a t-statistic of 1.27. Likewise, the average slope from univariate cross-sectional regressions of excess bond returns on bond age is positive, 0.01, and insignificant with a t-statistic of 0.54 according to the output of regression (5). As shown in regressions (2) and (6), these results hold after controlling for β^{TERM}, β^{DEF}, maturity, and size.

Regressions (3), (7), (9), (11), and (13) in Table IX show that the average slopes on credit spread (Spread), short-term reversal (STR), momentum (MOM), long-term reversal (LTR), and book-to-market (BTM) from the univariate regressions of excess bond returns on these risk characteristics are all significantly positive at 0.22 (t-stat. = 5.03), -0.69 (t-stat. = -17.75), 0.16 (t-stat. = 3.49), -0.10 (t-stat. = 2.76), and 0.45 (t-stat. = 4.41), respectively. These findings are consistent with the univariate portfolio results reported previously in Table V.

Regression specifications (4), (8), (12), and (14) after controlling for β^{TERM}, β^{DEF}, maturity, and size, the average slope coefficients on Spread, STR, LTR, and BTM remain positive and statistically significant. Their respective average slope are 0.23 (t-stat. = 4.49), -0.70 (t-stat. = -15.21), -0.09 (t-stat. = -2.76), and 0.39 (t-stat. = 4.05). In other words, controlling for bond characteristics and other risk factors does not affect the positive cross-sectional relation between the individual risk proxies and future bond returns. The effect of MOM, with a slope of 0.06 (t-stat. = 1.24), as shown in regression (10) does lose it significance once bond characteristics and other risk factors are included.

Regression (15) tests the cross-sectional predictive power of VaR, Spread, Age, STR, MOM, LTR, and BTM simultaneously. The average slopes on Spread and STR are significantly positive at 0.10 (t-stat. = 2.35) and significantly negative at -0.80 (t-stat. = -19.15), respectively. However, the average slope coefficients on VaR, Age, LTR, and BTM become insignificant in this general specification, implying that downside risk, liquidity risk, momentum, and long-term reversals lose their predictive power for future bond returns after credit spread and short-term reversal are controlled for.

The last specification, Regression (16), presents the results from the multivariate regression with all bond risk proxies (VaR, Spread, Age, STR, MOM, LTR, and BTM) after controlling for β^{TERM}, β^{DEF}, maturity, and size. Similar to my findings in Regression (15), the cross-sectional relation between future bond returns and Spread are positive (0.13) and highly significant (t-stat. = 2.64), whereas the relation between future returns and STR are negative (-0.74) and highly significant (t-stat. = -12.98). However, the predictive power of VaR, Age, MOM, and LTR disappears, indicating that credit quality and short-term reversal have a more pervasive effect on future bond returns than

[31]See Internet Appendix Figure A.4 on the importance of micro and small firms in terms of issues as compared to their importance in terms of market capitalization.

downside risk, liquidity risk, and medium- to long-term return signals when bond controls are included. In total, these seven characteristics in combination with the five bond controls explain 36% of the cross-sectional variation in bond returns.

D. Asset Pricing Tests

In this section, I first introduce novel risk factors based on downside risk, credit quality, bond illiquidity, short-term return reversal, momentum, long-term return reversal, and book-to-market, and test their economic and statistical significance. Then, I investigate factor performance across different market states. Finally, I examine factor redundancy by running spanning tests on the complete collection of well-established and newly constructed risk factors.

D.1. Factor Definitions and Summary Statistics

PLACE TABLE X ABOUT HERE.

I construct the bond factors in a similar vein as done previously for the bivariate portfolio analysis in Section A.2 and rely on dependent sorts to accommodate the size of the cross-section within my historic setting. Consistent with Davis, Fama, and French (2000), I create sequential 3x3 tercile portfolios. As before, portfolios are formed every month and rebalanced monthly.

To construct the downside risk factor for corporate bonds, for each month from January 1868 to December 1939, I form bivariate portfolios by dependently sorting bonds into three terciles based on their credit spread and sequentially three subterciles based on their downside risk (measured by 5% VaR). The downside risk factor, DRF, is the value-weighted average return difference between the highest-VaR portfolio and the lowest-VaR portfolio across the credit spread portfolios (Bai, Bali, and Wen, 2019). The credit risk factor, CRF, is the value-weighted average return difference between the highest-credit spread (i.e., highest credit risk) portfolio and the lowest-credit spread (i.e., lowest credit risk) portfolio across the bond illiquidity (measured by bond age) portfolios (Bai, Bali, and Wen, 2019). The liquidity risk and the short-term return reversal factors are constructed similarly using dependent sorts. The liquidity risk factor, LRF, is the value-weighted average return difference between the highest-illiquidity portfolio and the lowest-illiquidity portfolio across the credit spread portfolios (Bai, Bali, and Wen, 2019). The short-term return reversal factor, $SREV$, is the value-weighted average return difference between the short-term loser and the short-term winner portfolios ("losers-minus-winners") across the credit spread portfolios (Bai, Bali, and Wen, 2019). The bond momentum factor, UMD^{Bond}, is the value-weighted average return difference between the medium-term winner and the medium-term loser portfolios ("up-minus-down") across the credit spread portfolios (Bali, Subrahmanyam, and Wen, 2021; Jostova *et al.*, 2013). The long-term return reversal factor, $LREV$, is the value-weighted average return difference between the long-term loser and the long-term winner portfolios ("losers-minus-winners") across credit spread and maturity portfolios (Bali, Subrahmanyam, and Wen, 2021). The bond high-minus-low factor, $BHML$ is the value-weighted average return difference the lowest-BTM portfolio and the highest-BTM portfolio across market capitalization portfolios (Bartram, Grinblatt, and Nozawa, 2021).

Table X reports the summary statistics for the downside risk factor (DRF), credit risk factor (CRF), liquidity risk factor (LRF), short-term return reversal factor ($SREV$), bond momentum factor (UMD^{Bond}), long-term return reversal factor ($LREV$), and bond high-minus-low facor ($BHML$) over the period from January 1868 to December 1939. The value-weighted DRF, LRF and LREV factors have a statistically insignificant risk premium. The risk premium of DRF is 0.07% per month (t-stat. = 1.15). The LRF factor has a monthly mean of 0.03% (t-stat. = 0.66), while the LREV factor has a monthly risk premium of 0.02% (t-stat = 0.74). The value-weighted CRF, $SREV$, UMD^{Bond}, and $BHML$ factors all have an economically and statistically significant risk premium. The monthly CRF premium is 0.34% (t-stat. = 4.46). The $SREV$ factor premium is 1.09% per month (t-stat. = 19.35). Finally, the UMD^{Bond} and $BHML$ are, respectively, 0.44% (t-stat. = 6.28) and 0.46% (t-stat. = 4.87) per month. Their annualized Sharpe ratios are all higher than than the Sharpe ratios for the aggregate bond and stock market. The difference in Sharpe ratios is statistically significant with a p-value of < 0.05 using block-wise bootstrapping with random block length procedure introduced by Ledoit and Wolf (2008) with 10,000 runs. Over the same period of January 1868–December 1939, the bond market risk premium, MKT^{Bond}, is 0.08% per month with a t-statistic of 1.59, yielding an annualized Sharpe ratio of 0.23 for the aggregate bond market factor. For the same period, the stock market risk premium, MKT^{Stock}, 0.21% per month with a t-statistic of 1.36, yielding an annualized Sharpe ratio of 0.20 for the aggregate stock market factor.

D.2. The Risk of Factor Returns

Risk-based explanations of asset pricing anomalies argue for time variation in their expected returns related to time variation in their risks or risk premiums, aspects that can be expected to relate to macroeconomic or market conditions (Fama and French, 1989; Lin, Wu, and Zhou, 2018). If cross-sectional predictability in bonds arises from risk premia that are related to business-cycle risk, then the characteristic premiums should vary with the state of the business cycle and with variables that vary with business cycles.

Place Table XI about here.

I consider the time variation in factor premia by considering several market states based upon the GDP growth, the indication of financial crises, aggregate stock market return, change in sovereign bond yields, and the aggregate corporate bond market filtered for termstructure effects. To test if the mean returns are equal to zero in each state respectively, I regress the time-series of zero-cost factor portfolio returns on an state dummy variable, with no intercept. To test if the mean strategy profits following bad and good states are equal, I regress the time-series of high-minus-low returns on a bad state dummy variable and an intercept. These approaches preserve the full time-series of returns and allow me to reliably estimate the standard errors under serial correlation. Table XI presents the results.

Overall, most corporate bond return factors do not display stronger returns during bad states (that is, recessions, crises, bear markets, rising yields, or increasing default risk). The most notable exceptions are illiquidity which has higher returns during recessions, bear markets, and increasing yields. Hence, based on this evidence, the factor returns of corporate bonds cannot be explained by poor performance in bad states. From this, we can conclude that a macroeconomic risk-based explanation for the factor premiums seems unlikely. Perhaps most importantly for investors, the performance of bond factors is stable across the different scenarios, including, for example, falling or rising equity markets (thereby providing evidence of added value over equity markets). Interestingly, performance is good regardless of yields rising or falling, nor do increasing of decreasing defaults have any effect.[32] My deep historical sample makes it possible to make such a statement because it also contains multi-year periods with rising yields, unlike a sample that covers only post-1980 data. Likewise, the same argument holds for the incidence of default clusterings which were much more prevalent in the pre-WWII era (see Internet Appendix Figure A.2).

D.3. Spanning Tests

In this section, I conduct factor spanning tests to examine factor redundancy. I perform redundancy tests that use factor returns directly by regressing each individual factor return onto the set of other remaining factor returns. Each test shows how much additional return is captured by each factor return after other factors are accounted for. Put differently, redundancy tests investigate whether any factor effects are subsumed by the other factor returns, as the regression intercepts (i.e., alphas) measure the average return of the portfolios that is not compensation for exposure to the other risk factors considered. This allows me to test whether we truly need all of the newly proposed factors in the corporate bond asset pricing literature.

PLACE TABLE XII ABOUT HERE.

Table XII show regressions of one factor on the remaining factors. The results show that DRF has a negative intercept of -0.06% that is insignificant (*t*-stat. = -0.88), akin to the portfolio sorts and Fama-MacBeth results. CRF alpha has a high magnitude (0.13%) with a *t*-statistic of 2.14. Thus, CRF is not explained by other factors, consistent with evidence of an anomaly premium that is economically and statistically significant in portfolio sorts and Fama-MacBeth regressions. Interestingly, regressions for LRF indicate that LRF produces a large positive alpha of 0.24% with a *t*-statistic of 5.07. This shows that LRF improves the mean-variance-efficient tangency portfolio produced by combining the risk-free asset, CRF, $SREV$, UMD^{Bond}, $BHML$, $TERM$, DEF, MKT^{Stock}, and UMD^{Stock}. All other newly constructed bond risk factors show an alpha that is consistent with

[32] I perform an additional test based upon default clusterings using the definition of Giesecke *et al.* (2011, 2014) and obtain the same results as the last column in Table XI (unreported).

the previous evidence of portfolio sorts and Fama-MacBeth regressions, with the exception of $LREV$. This underlines their respective importance in cross-sectional corporate bond asset pricing. $SREV$ has a positive intercept of -0.88% with a t-statistic of 14.36. Bond momentum, UMD^{Bond}, has a significant alpha of 0.44, with a t-statistic of 4.43. $LREV$ is insignificantly positive with an intercept of 0.05% (t-stat. = 1.11). The bond value factor, $BHML$, has an alpha of 0.13% with a t-statistic of 2.09. Out of the well-established bond and stock factors, only the stock market factor and stock momentum factor attain a statistically significant intercept. The stock market factor has an alpha of -0.29% with a t-statistic of -2.16 while the stock momentum factor has an alpha of 1.08% with a t-statistic of 5.86.

V. Robustness Checks and Subsample Analyses

In this section, I present a battery of robustness checks and subsample analyses corresponding to the main results in Section A and Section C. Specifically, I test whether defaulting returns, risk-free rate choice, bond volatility, the inclusion of transaction costs, industry signals, multiple bond issues per firm, regression specifications, or different bond samples yield a similar impact of the return drivers as previously shown for the main results. Where the findings of these robustness checks are discussed below, I relegate the presentation of the outputs to the Internet Appendix to save space.

A. Defaulting Bond Returns

Corporate bonds occasionally delist prior to reaching maturity or buyback operations effected on secondary markets. If delisting returns are simply treated as missing observations, return estimates can be overstated, particularly for high-yield bonds and long-term losers. Sadly no information is readily available that allows to compute a composite delisting return for defaulting bonds.[33] I perform three robustness checks regarding bond default returns. First, to address the potential return bias, I follow Bali, Subrahmanyam, and Wen (2021) and use a -40% return for issues that default as exit path out of the sample. This correction enables me to avoid the delisting bias shown in previous research on stock returns (Shumway, 1997). Related to Goetzmann and Huang (2018), I perform a second robustness check regarding bond default returns under the assumption that exit bonds following a default event all have –100% returns. Despite the elusive past of corporate bond defaults in early bond market history (Muir, 2017), my empirical setting allows for clear disentanglement of default events. To identify defaulting issues, I make use of Moody's definition. Specifically, I flag any bond that delists within three months following (i) a missed coupon payment, (ii) a change in face value or coupon rate, (iii) a distressed exchange, or (iv) either a bankruptcy filing or creditor composition. This means that I adjust the delisting return of 114 defaulting issues (out of 1,010 in the full sample). Third, I eliminate bonds with a clean price below 40% of face value in the formation

[33] Such lack of post-delisting information also plagues equity research that makes use of early financial market settings. See, for example, Goetzmann and Huang (2018) and Grossman and Shore (2006).

month following Binsbergen and Schwert (2022). This concerns a typical signal of default in modern bond markets (Jankowitsch, Nagler, and Subrahmanyam, 2014).

Overall, the results in Internet Appendix Table A.VIII show that accounting for defaulting returns and the highest credit risk bonds only alters the main results for the long-term reversal premium. In Table IV, I concluded that the significantly negative alpha spread between high- and low-LTR bonds is due to the outperformance of long-term losers but not to the underperformance of long-term winners. However incorporating defaulting returns renders the excess return and alpha difference of the long-term losers statistically insignificant from zero. Yet, introducing a price floor of 40% of face value further enhances the LTR premium from -0.15% to 0.18% per month in terms of excess return (t-.stat. = -2.99) and from -12% to -0.15% (t-.stat. = -2.62) in terms of six-factor alpha.

B. Alternative Risk-Free Asset

Throughout the paper I follow standard practice and measure bond excess return as the difference between the corporate bond return and the risk-free asset. The risk-free asset is proxied by the three-month Belgian commercial paper return. I provide robustness check of the main results using duration-matched Treasury returns to calculate bond excess returns. This ensures that the performance I measure is actually related to corporate bond market characteristics, that is, foremost credit risk, liquidity, and further bond-specific return components, and not linked to interactions with government bond markets, that is, changes in the risk-free yield curve. This approach is in accordance with Asvanunt and Richardson (2017), Kelly, Palhares, and Pruitt (2022), and Binsbergen and Schwert (2022).

Since the duration-adjusted corporate bond excess returns are already cleansed from total return components related to interest rate risk, I do not include a factor representing interest rate risk into the regression models. Thus, the Fama and French (1993) two-factor bond model as employed in Table V is replaced by a single-factor model, the duration-adjusted bond CAPM model of Kelly, Palhares, and Pruitt (2022) and Binsbergen and Schwert (2022). The duration-adjusted bond market factor is the value-weighted average return of all corporate bonds in the sample in excess of the duration-matched sovereign bond return.

The result is shown in Internet Appendix Table A.IX for the portfolio analysis and Internet Appendix Table A.X for the cross-sectional regressions. Overall, I find very consistent results for both the portfolio analysis as the Fama-MacBeth regressions using duration-adjusted returns compared to the standard definition of excess returns used in the main analyses of the paper. Two results are worth noting. First, regression (5) of the Fama-MacBeth cross-sectional regressions now shows a significant relation liquidity and expected bond returns compared to evidence using standard excess returns in Table IX. This effect is consistent with duration-adjusted corporate bond returns showing a higher percentage of total returns as compensation to investors for bearing credit and liquidity risk (Binsbergen and Schwert, 2022).[34] Yet, this effect does not uphold in regression (6) when I

[34]See Internet Appendix Table A.V for detailed decomposition of standard excess returns compared to duration-adjusted

include bond characteristics. Second, regression (10) now shows a persistent momentum effect in cross-sectional regressions when using duration-adjusted returns, compared to the insignificant effect of momentum as a risk characteristic in Table IX.

C. Bond Volatility

Table III shows that the cross-sectional variation in bond returns is substantial. Corporate bond returns can have vastly different levels of risk depending on the credit quality of the issuer and the macroeconomic environment. Following Kelly, Palhares, and Pruitt (2022), I make use of asset-specific volatility to test whether the results are robust or being dominated by the most volatile assets only. I adjust bond returns to have similar ex-ante volatility by scaling returns by the previous month's "Duration times Spread (DtS)," following Ben Dor *et al.* (2007) who derive DtS as an analytical, accurate, and forward-looking approximation of bond return volatility. In particular, I define:

$$R_{i,t}^{scaled} = \frac{R_{i,t}}{max\left(DtS_{i,t}, \underline{DtS}\right)}, \tag{6}$$

where $R_{i,t}$ is the raw excess credit return, $DtS \equiv Duration_{i,t} \cdot Spread_{i,t}$, and $\underline{DtS}$ is set at 0.30.[35] Approximately 35% of bonds have a DtS less than $\underline{DtS}$ and therefore these low-volatility bonds are essentially unadjusted (being all divided by the same number). This highlights that the role of DtS-scaling is to downweight high volatility bonds. In essence, the return transformation in Equation (6) is designed to reduce the degree of heteroskedasticity in corporate bond returns. I further introduce the same logical in the Fama-MacBeth regression cross-sectional regression approach to account for high volatility bonds that unduly affect least squares estimation.

Internet Appendix Table A.XI and Internet Appendix Table A.XII show the result for the portfolio analysis and cross-sectional regressions, respectively. Using volatility-scaled returns does not alter the main results of the paper. Additionally, I test the robustness of my main results for the Great Depression era of 1929–1939, shown to have been a unique period in various economic time-series data. This includes corporate bond return volatility (Van Mencxel, Annaert, and Deloof, 2022). Internet Appendix Table A.XIII shows that my results still hold up after excluding the high volatility regime of the Great Depression.

D. Transaction Costs

To assess the real-world practicality and economic significance of portfolios' performance, I ultimately have to include transaction costs in my analysis. This issue is crucial from a practical perspective. Many anomalies are characterized by a great deal of turnover, leading to elevated trading costs. Most recently, Novy-Marx and Velikov (2016) observe that while returns to low turnover strategies are robust to adjustments for trading costs, many higher turnover strategies are not. Fur-

returns for the Belgian bond market between 1868–1939.

[35]In my data, DtS has a mean of 0.39, a median of 0.36, a minimum of 0.001, and a maximum of 1.60.

thermore, trading in the corporate bond market is well known to be costly due to its microstructure nuances and general illiquidity.

To test the impact of trading fees on portfolio strategy returns, I make use of three estimates of transaction costs ranging from a lower bound (10 bps.), over a mid-range estimate (19 bps.), to an upper bound (44 bps.). These estimates are based upon contemporaneous inner workings of the BSE as well as estimates obtained through modern OTC market data. Bastiné (1876, p.296) documents a transaction cost of 10 basis points set by brokers at the eve of the *nouveau régime* as the liberalization of the BSE took effect. Findings based on OTC market data showcase a much more expensive market setting in comparison with a strong dependence of transaction costs on trade size. For example, Choi, Huh, and Shin (2022) recommend a one-way cost of 19 basis points. This estimate is intringuingly similar to estimated trading costs of US bonds during the 1940s at the eve of the modern OTC market (Biais and Green, 2019). To be conservative, I further include the average trading cost of 40 basis points set by brokers operating at the BSE during the 1930s, increased by an additional 10% stamp duty on brokerage commissions put in place by the exchange commission (François-Marsal, 1931, p. 588). This is comparable with the one-way costs reported by Bessembinder, Jacobsen, *et al.* (2018) using TRACE data for the institutional bond market. I define net portfolio returns, $R^{net}_{p,t}$, at time t as

$$R^{net}_{p,t} = \underbrace{\sum_i w_{i,t-1} R_{i,t}}_{\text{gross return}} - \underbrace{\sum_i c_{t-1} |w_{i,t-1} - w_{i,t-2}|}_{\text{transaction cost adjustment}}, \tag{7}$$

where $w_{i,t-1}$ and $w_{i,t-2}$ is the weight of bond i at time $t-1$ and $t-2$, respectively. The single-counted turnover from month $t-2$ to $t-1$ is subsequently determined as the sum of all weight increments across portfolio constituents. Portfolio transaction costs are then obtained by relating turnover to one-way transaction costs, c_{t-1}, at time $t-1$.

Deducting these transaction cost estimates from the return and alpha spreads reported in Internet Appendix Table A.XIV, provide clear evidence that after accounting for transaction costs the main results remain economically and statistically significant. This even holds for the high turnover strategies as indicated by the average absolute change in monthly weights ($|\Delta w|$); short-term reversal, momentum, and long-term reversal. These results indicate that key characteristics of corporate bonds are strong determinants of the cross-sectional dispersion in future returns, even after controlling for transaction costs.

E. Industry-Adjusted Signals

One might argue that characteristics are industry specific. The unconditional predictive power of bond characteristics may therefore stem from their inter-industries component or from their firm-specific (intra-industries) component. Surprisingly, previous research on the cross-sectional predictability of corporate bond returns has not tested this possibility. Daniel, Mota, *et al.* (2020) shows that sorting stocks tends to pick-up unintended (industry) risks, generating portfolios that are no longer mean-variance efficient. Sector-concentrated portfolios are more volatile because assets within the same sector tend to be more highly correlated than assets across industries. Adding industry constraints in the portfolio construction processes can therefore help to avoid concentration risks. This is especially true for a historical bond market context given the role of railroad bonds in effectively creating the bond market during the nineteenth century (see Van Mencxel, Annaert, and Deloof (2022) and references cited therein).

I construct industry-hedged anomaly portfolios by normalizing the sorting characteristic into an industry-adjusted characteristic as follows:

$$S^{*}_{i,t} = S_{i,j,t} - S^{Avg}_{j,t}, \tag{8}$$

where $S^{*}_{i,t}$ denoted the industry-adjusted characteristic obtained by subtracting the cross-sectional mean, $S^{Avg}_{j,t}$, of the sorting characteristic S of industry j from the unadjusted characteristic, $S_{i,j,t}$, of bond i belonging to set industry j. When building industry portfolios, I require that an industry has at least 500 total bond-month observations to be included, and that an industry-month is non-missing if it has at least three bonds present. These requirements leave me with 12 industry portfolios, amounting for a total of 179,414 bond-month observations. Hence, 1,965 bond-month observations are discarded from the original sample due to the enforcement of industry restrictions. Summary statistics are provided in Internet Appendix Table A.XV.

The results using industry-adjusted signals are shown in Internet Appendix Table A.XVI. I find that the credit quality, short-term reversal, momentum, long-term reversal, and book-to-market effect in returns is mostly an intra-industry phenomenon. More importantly, these results show that controlling for industry effects does not alter my main portfolio results of Table V. Yet, comparing the standard to industry-hedged anomaly portfolios shows that industry adjustment often improves anomaly performance. This is especially the case for the downside risk premium which now becomes statistically significant with a t-statistic of 2.14 for its raw return (compared to 1.71 in Table V) and 1.94 for its six-factor alpha (compared to 1.31 in Table V). Obtaining a stronger result is not uncommon when adjusting signals for industry peer effects. See, for example, Novy-Marx (2013).

F. Firm-Level Evidence

Throughout the paper, my empirical analyses have thus far been based on bond-level data since I test whether characteristics of *individual* bonds predict future returns. However, firms often have *multiple* bonds outstanding at the same time. One concern is that firms with large numbers of distinct bond issues can have a material impact on the cross-sectional relations that I am testing. In my historical sample, 19.40% of firm-month observations (that is, 28,205 out of a total of 145,415) are populated by firms with multiple bonds concurrently outstanding. The time-series of firms with multiple bonds outstanding shows significant variation over time. On average, 18.8% of firms have multiple bonds outstanding at any given moment. This fraction ranges from a minimum of 12.4% to a high of 31.2%, with a monthly standard deviation 4.94%.

To control for the effect of multiple bonds issued by the same firm, I follow Chordia, Goyal, *et al.* (2017) and choose one of outstanding bond issues by using three different methods. Each month, I (1) pick one bond issue of the largest size, (2) choose an issue with the shortest remaining maturity as long as it is more than one year, and (3) choose the most recently issued bond, as representative of the firm and replicate my portfolio-level analysis and cross-sectional regressions using this firm-level dataset. The portfolio sorts are shown in Internet Appendix Table A.XVII. The Fama-MacBeth cross-sectional regressions are subdivided across selection method to avoid clutter, with Internet Appendix Table A.XVIII using the largest bonds (i.e., subsample (1)), Internet Appendix Table A.XIX using the shortest maturity bonds (i.e., subsample (2)), and Internet Appendix Table A.XX using the most recent bonds (i.e., subsample (3)).

Overall, the results are consistent and similar to those reported in the main body of the paper. Thus, firms with multiple bonds in the market do not yield the results.

G. Panel Regressions

Harvey and Liu (2021) argue that it might be more appropriate to employ panel regressions than Fama-MacBeth cross-sectional regressions. They state that panel regressions allow asset-specific intercepts to absorb idiosyncrasies that are unrelated to the regressors of interest, thereby mitigating the impact of extreme observations and model misspecification. Using a simulation study, the authors show that panel regressions are more powerful than cross-sectional regressions. In Internet Appendix Table A.XXI, I therefore present robustness of Equation (4) excess bond returns on anomaly variables using panel regressions. Internet Appendix Table A.XXI reports the coefficients for individual bond characteristics using different specifications of panel regressions. The first column reports the estimates with no fixed-effects. The second column includes bond-level fixed effects and month-year fixed effects which aims to control for unobserved heterogeneity for each bond in the sample and time-variation. The third column control for unobserved heterogeneity at firm-level in the sample and also time fixed effect. Last column control for heterogeneity at the industry level using four-digit NACE Codes as created by Annaert, Buelens, and De Ceuster (2012) for Belgium's early financial market. All specifications are clustered at the month-year and firm level. Each of the panel regressions includes bond controls as done for the Fama-MacBeth regressions in Table IX: bond market beta (β^{Bond}), bond term beta (β^{TERM}), bond default beta (β^{DEF}), time-to-maturity, and size.

Again, similar to the results reported in Table IX, the anomaly signals generally are associated with significant coefficients holding consistent signs. The relationship is statistically significant in all the specifications for credit quality, short-term reversal, and book-to-market. Yet, the first regression specification using no fixed-effects shows no significant effect for momentum and long-term reversal. Downside risk is significant in all regression specifications but when I include industry fixed effects in model (4).

H. Subsample Analysis

I continue the robustness checks with subsample analyses. The Great War of 1914–1918 was a period characterized by a large number of corporate bond defaults (Annaert, Deloof, and Van Mencxel, 2022; Giesecke *et al.*, 2011) and substantial price volatility in financial markets (Anarkulova, Cederburg, and O'Doherty, 2022). To ensure my results are not driven by the effects of this period, I remove from my sample observations from the war period. Specifically, I remove return months, t, from July 1914 through December 1918 inclusive. The results of the tests with the Great War removed, shown in Panel A of Internet Appendix Table A.XXII, are qualitatively the same as those in the main paper. There is no evidence that my results are driven by the Great War.

To avoid the possibility that financial firms drive the results, I exclude from the sample all bonds from all financial firms using the industry classification as previously shown in Table I and Internet Appendix Figure A.3. The results shown in Panel B of Internet Appendix Table A.XXII are qualitatively the same as those in the main paper. There is no evidence that my results are influenced by financial firms.

Table III shows that a considerable amount of bonds are issued by private firms. Indeed, approximately one out of five bonds are issued by private firms. The cost of debt of privately owned firms is higher, driven mainly by the poorer information environment in which these firms operate. This is especially the case for the time period under study given the lack of disclosure rules concerning firms' financial accounts. The model of Duffie and Lando (2001) predicts higher spreads associated with such imperfect information and observes that the price and term structure of debt should be affected by the completeness of information. In order to make sure that my results are not driven by the risk premium of private firms, I exclude from the sample all bonds from all private firms using the classification of Table III. The results are shown in Panel C of Internet Appendix Table A.XXII and reflect that my results are not influenced by private firms.

An intruiging finding of Table III is that a considerable amount of bonds are issued by microcap firms, defined as public firms with an equity market capitalization between the 20th percentile as in Fama and French (2008). Microcaps represent on average 15.76% of total issues for the 1868-1939 study period compared to the 6% as shown by Chordia, Goyal, *et al.* (2017) for the modern bond market between 1973–2014. Microcaps can potentially inflate the magnitude of anomalies (Fama and French, 2008; Hou, Xue, and Zhang, 2020). In order to make sure that my results are not driven by microcap firms, I exclude from the sample all bonds issued by microcap firms using the classification of Table III. The results are shown in Panel D of Internet Appendix Table A.XXII and reflect that my conclusions are not influenced by the smallest size of firms.

VI. Conclusion

In this paper, I study the pervasiveness across time and space of seven premier cross-sectional corporate bond anomalies. Specifically, the present study serves to underscore the question about the potential influence of data snooping given the opaque nature of the modern OTC-based corporate bond market that has resulted in excessive familiarity with the same bond samples obtained from a very limited number of public datasets from one particular country, the US.

I solve the lack of high-quality deeper historical corporate bond data by turning to the bond market's early history pre-dating its modern OTC market structure to solve any transparency issues that plague more modern work and that are detrimental for performing rigorous asset pricing tests. I construct a novel dataset of more than 1,000 bonds across 72 years from the archives of the Brussels Stock Exchange — one of the world's preeminent corporate bond markets during the period of study — for the purpose of this study. It offers, for the first time, a genuine out-of-sample perspective on corporate bond return predictability by overcoming all major problems that plague the asset class's elusive past. Hence, my analysis allows me to reassess previous results on the performance of systematic trading strategies within the credit market.

I demonstrate credit quality, short-term reversal, momentum, and book-to-market profitability using data from 1868 through 1939. The returns to these anomaly strategies are economically and statistically significant, highly persistent over time, and cannot be explained by common risk factors from the bond- and stock market. Nor are the results conditional on macroeconomic effects. Not so reassuringly, downside risk, long-term reversal, and illiquidity are absent. It is highly unlikely that this is due to low power seeing that the study period is trice as long as the typical timespan studied using modern bond data. The cross-section is also quite complete, rivaling the overall size of other major bond markets. Yet, spanning regressions show that the illiquidity factor increases the mean-variance efficient tangency portfolio.

Taken in their entirety, my findings show a strong, robust, and persistent presence of economically important credit factor premiums. This study is thus consistent with the notion that the majority of recent revelations concerning the cross-sectional predictability of corporate bond returns ought to be considered true effects rather than statistical artifacts due to the continuing, repeated use of correlated bond samples.

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Tables

Table I: Composition of Corporate Bond Dataset

Panel A – Distribution over Decades

	# Firms			# Bonds			# Bond-Month Obs.		
Year	Collected	Included	Included (%)	Collected	Included	Included (%)	Collected	Included	Included (%)
1870	68	46	67.65	85	55	64.71	970	634	65.36
1880	90	56	62.22	127	70	55.12	1,393	777	55.78
1890	159	102	64.15	216	124	57.41	2,450	1,384	56.49
1900	334	241	72.16	434	280	64.52	4,998	3,190	63.83
1910	392	286	72.96	543	342	62.98	6,223	3,944	63.38
1920	444	326	73.42	634	423	66.72	7,303	4,694	64.27
1930	358	200	55.87	565	273	48.32	6,415	2,988	46.58
1939	230	115	50.00	392	152	38.78	4,591	1,752	38.16
Total	848	632	74.53	1,505	1,010	67.11	318,553	181,379	56.94

Panel B – Distribution over Geography and Industry Type

	Financials	Non-Financials	Total
Abroad	4,052	54,666	58,718
Belgium	8,519	111,211	119,730
Colony	0	2,931	2,931
Total	12,571	168,808	181,379

Notes: This table shows the number of firms, the number of corporate bonds, and the number of bond-month observations included within the dataset in Panel IA. These descriptive statistics are obtained following numerous screening procedures as described in Internet Appendix A.1. The sample, depicted as *Total* in the table, runs from January 1868 through December 1939 (864 months) and comprises all corporate bonds issued by Belgian firms on the Brussels Stock Exchange. Panel IB shows the number of bond-month observations per geography and industry type. The geography is defined as the geographical location of Belgian companies' main activity. *Abroad* denotes bonds issued by Belgian companies with main economic activity abroad, conditional on being outside of the Belgian Congo. *Belgium* denotes bonds issued by Belgian companies whose main economic activity is in Belgium. *Colony* denotes bonds issued by Belgian colonial companies. *Financials* comprise banks, insurance companies, trusts, investment funds, and holding companies. *Non-Financials* comprise any industry other than *Financials*.

Table II: Return Anomaly Definitions

#	Anomaly	Variable	Bonds in Long Leg	Bonds in Short Leg
1	Downside risk	$VaR5$	High downside risk	Low downside risk
2	Credit quality	$Spread$	Low credit quality	High credit quality
3	Illiquidity	Age	Young bonds	Old bonds
4	Short-term reversal	STR	Low past return	High past return
5	Momentum	MOM	High past return	Low past return
6	Long-term reversal	LTR	Low past return	High past return
7	Book-to-market	BTM	Low price to book value	High price to book value

Notes: This table provides brief descriptions of the main anomalies examined in this study. It summarizes the characteristics of bonds in the long leg (that is, the highest performing group) and those in the short leg (that is, the lowest performing group) for the seven anomalies. More details on construction can be found in Internet Appendix B.

Table III: Summary Statistics

Variable	N	Mean	SD	Percentiles 1st	25th	50th	75th	99th
Return (%)	181,379	0.40	5.81	−13.13	−0.55	0.36	1.29	14.04
Excess Return (%)	181,379	0.12	5.80	−13.46	−0.81	0.08	1.02	13.70
Amt. Outst. (thou., BEF)	181,379	5,920.09	10,585.74	171.50	1,100.00	2,714.50	6,500.00	43,750.00
Mkt. Value (thou., BEF)	181,379	5,152.46	9,581.37	142.10	988.24	2,251.00	5,369.84	39,590.63
Maturity (years)	181,379	26.17	19.34	1.50	12.08	22.00	34.25	85.76
Age (years)	181,379	13.86	11.76	0.00	5.00	11.00	19.00	59.00
Duration (years)	181,379	12.86	5.92	1.47	8.62	12.92	16.67	27.05
Coupon (%)	181,379	4.48	0.85	3.00	4.00	4.50	5.00	7.00
Yield (%)	181,379	6.02	3.65	3.01	4.34	5.05	6.30	25.23
Spread (bps.)	181,379	394.83	386.14	37.27	223.62	309.09	418.32	2,420.45
VaR5 (%)	148,586	5.00	5.35	0.00	2.08	3.12	5.78	28.57
STR (%)	180,397	0.39	5.88	−13.22	−0.56	0.36	1.29	14.06
MOM (%)	169,652	4.00	15.89	−39.38	0.76	3.91	6.68	48.57
LTR (%)	137,496	13.83	24.29	−56.57	6.62	13.07	18.85	88.02
BTM	181,379	1.23	0.65	0.86	0.99	1.06	1.22	4.55
BETA	159,249	0.90	2.54	−4.18	0.00	0.68	1.48	10.38
Public	181,379	0.83	0.38	0.00	1.00	1.00	1.00	1.00
Micro	150,469	0.16	0.37	0.00	0.00	0.00	0.00	1.00
Small	150,469	0.25	0.43	0.00	0.00	0.00	0.00	1.00
Big	150,469	0.59	0.49	0.00	0.00	1.00	1.00	1.00

Notes: This table reports the summary statistics of the main variables used in the paper at the bond-month level for the sample from January 1868 through December 1939. The table includes the number of bond-month observations, the cross-sectional mean, median, standard deviation and monthly return percentiles of corporate bonds, and bond characteristics. *Return* (in percentage) is the total return of the bond. *Excess Return* is the bond total return in excess of the risk-free asset proxied by three-month Belgian commercial paper. *Amount Oustanding* (in thousands of BEF) is the offering amount of the bond. *Market value* (in thousands of BEF) is defined as the product of the dirty price and the number of bonds outstanding on the stock exchange. *Maturity* (in years) is the time to maturity of the bond. *Age* (in years) is the time passed since initial issuance. *Duration* (in years) is a bond's Macauley duration. *Coupon* (in percentage) is the annual coupon rate. *Yield* (in percentage) is the bond's yield-to-maturity. *Spread* (in basis points) is the bond's credit spread based on the difference between the bond's yield-to-maturity and the yield on a duration-matched sovereign bond. Downside risk ($VaR5$, in percentage) is the 5% VaR of the monthly corporate bond return, defined as the second-lowest monthly return observation over the past 36 months. STR (in percentage) is the short-term reversal effect defined as the past month, $t-1$, corporate bond return. MOM (in percentage) is bond momentum defined as the cumulative return between $t-12$ and $t-2$, skipping the short-term reversal month. LTR (in percentage) is the long-term reversal defined as the past 36-month cumulative returns from $t-48$ to $t-13$, skipping the 12-month momentum and the short-term reversal month in $t-1$. BTM is the bond's book-to-market ratio defined as the ratio of face value to the dirty price. β^{Bond} is the bond exposure to the excess corporate bond market return, constructed using the value-weighted average return of all corporate bonds in my sample. It is estimated for each bond from the time-series regressions of bond excess returns on the excess bond market return using a 36-month rolling window estimation with a minimum of 24 observations, accounting for the nonsynchronous trading problem of Scholes and Williams (1977) using the correction of Dimson (1979), by calculating beta as the sum of the slope coefficients on the market's contemporaneous return and its one- and two-month lagged returns. *Public* indicates whether the issuing firm has a public listing on the stock market. *Micro*, *Small*, and *Big* are dummies that equal to one if a firm belongs to the respective stock market capitalization group. I follow Fama and French (2008) and assign firms to size groups at the end of December each year. *Micro* firms are below the 20th percentile of BSE's stock market capitalization at the end of December, *Small* firms are between the 20th and 50th percentiles, and *Big* firms are above the BSE median.

Table IV: Summary Statistics of Risk Factors

		Dispersion		
	Mean	SD	Min	Max
Market (MKT^{Stock})	0.21	3.69	−13.25	22.17
Small-Minus-Big (SMB)	0.10	2.01	−12.08	12.27
High-Minus-Low (HML)	0.01	2.24	−12.76	10.76
Momentum (UMD^{Stock})	1.10	3.91	−21.30	23.79
Term ($TERM$)	0.05	1.92	−13.05	22.10
Default (DEF)	0.03	1.61	−14.88	10.05

Notes: This table reports average monthly percentage returns, the associated volatilities, and minimum and maximum returns for risk factors, MKT^{Stock}, SMB, HML, UMD^{Stock}, $TERM$, and DEF for the full sample period between January 1868 through December 1939. MKT^{Stock}, SMB, HML, UMD^{Stock} are the Carhart (1997) four stock factors. The market (MKT) factor is the value-weighted monthly percent return of common stocks listed on the Brussels Stock Exchange in excess of the risk-free asset, the return on 3-month commercial paper. The size (SMB) and value (HML) factors sort stocks into six portfolios by size and dividend-to-price at the end of each December and hold the value-weighted portfolios from the December of year t to the December of year $t+1$. These sorts use the median breakpoint for size and the 30th and the 70th percentile breakpoints for dividend-to-prize. SMB is the average return on the three small-stock portfolios minus the average return on the three big-stock portfolios. HML is the average return on the two high-divided-to-prize portfolios minus the average return on the two low-dividend-to-price portfolios. The momentum factor, UMD, uses size as a first sorting variable and the 11-month cumulative return from $t-12$ to $t-2$ as the second sorting variable. Both these sorts are updated monthly. UMD is the average return on the two high-prior-return portfolios minus the average return on the two low-prior-return portfolios. $TERM$ and DEF are the Fama and French (1993) two bond factors. The term factor ($TERM$) is the difference between the long-term government bond return and the one-month commercial paper return. The default factor (DEF) is the difference between the return of a value-weighted portfolio of corporate bonds in the sample and the return of long-term government bonds.

Table V: Returns on Univariate-Sorted Portfolios of Corporate Bonds

Panel A: Downside Risk

Quintile	Avg. VaR	$\mathbb{E}[R]$	2F α	4F α	6F α
Low	1.84	0.00	−0.05	0.02	−0.04
		(0.01)	(−1.88)	(0.71)	(−1.47)
2	2.57	0.07	0.00	0.07	0.00
		(1.42)	(0.09)	(1.65)	(−0.17)
3	3.25	0.13	0.07	0.14	0.06
		(2.98)	(3.67)	(2.98)	(2.75)
4	4.38	0.14	0.06	0.16	0.07
		(2.35)	(2.69)	(2.73)	(2.60)
High	8.92	0.14	0.04	0.16	0.06
		(1.54)	(0.65)	(1.89)	(0.82)
High-Low	7.08	0.14	0.10	0.14	0.10
Return/α diff.	(3.04)	(1.71)	(1.26)	(1.81)	(1.31)

Panel B: Credit Quality

Quintile	Avg. Spread	$\mathbb{E}[R]$	2F α	4F α	6F α
Low	121.51	−0.09	−0.17	−0.09	−0.18
		(−1.54)	(−5.87)	(−1.48)	(−7.69)
2	221.94	0.11	0.03	0.12	0.02
		(2.26)	(1.46)	(2.09)	(0.90)
3	298.72	0.17	0.10	0.18	0.10
		(3.11)	(2.99)	(3.69)	(3.07)
4	384.84	0.20	0.13	0.22	0.14
		(3.65)	(3.85)	(4.41)	(4.27)
High	665.97	0.34	0.24	0.39	0.29
		(3.32)	(2.99)	(4.47)	(3.72)
High-Low	544.47	0.43	0.41	0.48	0.48
Return/α diff.	(7.39)	(4.36)	(3.97)	(5.18)	(4.92)

Panel C: Illiquidity

Quintile	Avg. Age	$\mathbb{E}[R]$	2F α	4F α	6F α
Low	8.34	0.07	−0.03	0.09	−0.02
		(1.11)	(−1.36)	(1.30)	(−1.08)
2	20.11	0.06	−0.02	0.09	−0.01
		(1.06)	(−0.72)	(1.70)	(−0.22)
3	30.71	0.10	0.04	0.11	0.03
		(1.99)	(1.81)	(2.49)	(1.45)
4	42.01	0.08	0.02	0.09	0.02
		(1.89)	(0.84)	(2.03)	(0.63)
High	60.59	0.11	0.06	0.11	0.05
		(3.11)	(2.08)	(3.39)	(1.82)
High-Low	52.25	0.04	0.09	0.02	0.08
Return/α diff.	(5.56)	(0.76)	(2.12)	(0.40)	(1.86)

Panel D: Short-Term Reversal

Quintile	Avg. STR	$\mathbb{E}[R]$	2F α	4F α	6F α
Low	−2.94	0.61	0.52	0.63	0.52
		(7.74)	(9.50)	(7.47)	(10.38)
2	−0.38	0.39	0.32	0.40	0.32
		(6.43)	(10.76)	(6.49)	(10.35)
3	0.38	0.24	0.13	0.24	0.13
		(4.27)	(3.93)	(4.57)	(3.50)
4	1.13	0.04	−0.03	0.05	−0.03
		(0.69)	(−0.99)	(0.93)	(−0.78)
High	3.81	−0.90	−0.98	−0.89	−0.98
		(−15.23)	(−28.35)	(−16.81)	(−25.94)
High-Low	6.76	−1.51	−1.50	−1.52	−1.50
Return/α diff.	(23.52)	(−21.40)	(−21.77)	(−20.11)	(−21.80)

Panel E: Momentum

Quintile	Avg. MOM	$\mathbb{E}[R]$	2F α	4F α	6F α
Low	−4.59	−0.31	−0.41	−0.25	−0.36
		(−3.48)	(−6.25)	(−3.09)	(−4.70)
2	2.27	−0.06	−0.14	−0.05	−0.15
		(−0.97)	(−5.69)	(−0.75)	(−5.57)
3	4.50	0.18	0.11	0.17	0.09
		(2.91)	(3.75)	(3.08)	(2.87)
4	6.66	0.30	0.24	0.30	0.23
		(6.83)	(8.63)	(6.68)	(8.90)
High	13.64	0.14	0.08	0.15	0.07
		(2.09)	(2.03)	(2.50)	(1.52)
High-Low	18.23	0.45	0.48	0.40	0.43
Return/α diff.	(7.69)	(4.59)	(4.98)	(4.57)	(3.91)

Panel F: Long-Term Reversal

Quintile	Avg. LTR	$\mathbb{E}[R]$	2F α	4F α	6F α
Low	0.03	0.20	0.11	0.21	0.11
		(2.14)	(1.82)	(2.51)	(1.68)
2	11.87	0.13	0.06	0.16	0.08
		(2.38)	(1.70)	(2.95)	(2.19)
3	16.13	0.08	0.01	0.10	0.02
		(1.69)	(0.44)	(2.29)	(0.54)
4	20.20	0.05	−0.02	0.05	−0.03
		(1.02)	(−0.70)	(1.09)	(−1.07)
High	32.13	0.05	−0.01	0.06	−0.01
		(1.16)	(−0.30)	(1.38)	(−0.34)
High-Low	32.11	−0.15	−0.12	−0.15	−0.12
Return/α diff.	(6.58)	(−1.93)	(−1.73)	(−1.91)	(−1.65)

Panel G: Book-to-Market

Quintile	Avg. BTM	$\mathbb{E}[R]$	2F α	4F α	6F α
Low	0.95	−0.09	−0.14	−0.09	−0.15
		(−2.31)	(−5.42)	(−2.73)	(−6.24)
2	1.06	−0.03	−0.10	−0.02	−0.11
		(−0.49)	(−2.87)	(−0.41)	(−3.48)
3	1.13	0.13	0.05	0.14	0.05
		(2.07)	(1.74)	(2.45)	(1.75)
4	1.24	0.16	0.06	0.17	0.05
		(2.44)	(2.43)	(2.37)	(1.89)
High	1.58	0.32	0.20	0.37	0.25
		(2.85)	(2.52)	(4.17)	(3.37)
High-Low	0.63	0.41	0.34	0.46	0.40
Return/α diff.	(6.48)	(3.91)	(3.60)	(5.40)	(4.72)

Notes: This table reports monthly raw excess returns and alphas for quintile portfolios formed on the anomaly variables, constructed as explained in Table II, Table III, and Internet Appendix B. Quintile portfolios are formed every month from January 1868 to December 1939 by sorting corporate bonds on their downside risk (Panel A), credit quality (Panel B), illiquidity (Panel C), short-term reversal (Panel D), momentum (Panel E), long-term reversal (Panel F), and book-to-market (Panel G). Credit quality ($Spread$, in basis points) is the bond's credit spread based on the difference between the bond's yield-to-maturity and the yield on a duration-matched sovereign bond. Downside risk ($VaR5$, in percentage) is the 5% VaR of the monthly corporate bond return, defined as the second-lowest monthly return observation over the past 36 months. STR (in percentage) is the short-term reversal effect defined as the past month, $t-1$, corporate bond return. MOM (in percentage) is bond momentum defined as the cumulative return between $t-12$ and $t-2$, skipping the short-term reversal month. LTR (in percentage) is the long-term reversal defined as the past 36-month cumulative returns from $t-48$ to $t-13$, skipping the 12-month momentum and the short-term reversal month in $t-1$. BTM is the bond's book-to-market ratio defined as the ratio of face value to the dirty price. All portfolios are rebalanced at the end of the next month, and their realized return is recorded. For each quintile portfolio, I report the value-weighted average monthly excess return, two-factor alpha obtained from the Fama and French (1993) bond model (composed of $TERM$, and DEF), four-factor alpha obtained from the Carhart (1997) stock model (composed of MKT^{Stock}, SMB, HML, and UMD^{Stock}) and six-factor alpha obtained from combining the Fama and French (1993) and Carhart (1997) models. The last row reports differences in returns and alphas between quintile 5 ("High") and quintile 1 ("Low"). Corresponding t-statistics in parentheses are based on Newey and West (1987) standard errors. The sample includes all corporate bonds listed on the Brussels Stock Exchange at portfolio formation.

Table VI: Returns on Bivariate-Sorted Portfolios of Corporate Bonds

	Panel A: Downside Risk				Panel B: Credit Quality				Panel C: Illiquidity			
Control	Low	2	High	High-Low	Low	2	High	High-Low	Low	2	High	High-Low
β^{Bond}	−0.01	0.03	0.03	0.04	−0.10	0.08	0.22	0.32	−0.03	0.01	0.06	0.10
	(−0.36)	(1.61)	(0.61)	(0.74)	(−4.66)	(3.45)	(3.91)	(4.90)	(−1.32)	(0.58)	(2.36)	(2.88)
Maturity	−0.01	0.05	0.08	0.09	−0.17	0.13	0.21	0.39	0.01	0.02	0.04	0.03
	(−0.51)	(3.39)	(1.73)	(1.84)	(−8.81)	(8.00)	(4.18)	(5.94)	(0.68)	(1.00)	(1.44)	(0.78)
Size	−0.01	0.06	0.08	0.09	−0.16	0.08	0.21	0.37	−0.02	0.03	0.05	0.08
	(−0.68)	(3.49)	(2.12)	(2.34)	(−7.70)	(5.28)	(5.35)	(7.03)	(−1.05)	(1.55)	(3.02)	(3.19)

	Panel D: Short-Term Reversal				Panel E: Momentum				Panel F: Long-Term Reversal			
Control	Low	2	High	High-Low	Low	2	High	High-Low	Low	2	High	High-Low
β^{Bond}	0.53	0.10	−0.62	−1.15	−0.25	0.06	0.15	0.41	0.13	−0.01	0.00	−0.13
	(13.52)	(4.19)	(−19.78)	(−21.86)	(−5.19)	(3.78)	(4.29)	(6.79)	(2.53)	(−0.36)	(0.16)	(−2.29)
Maturity	0.49	0.21	−0.70	−1.19	−0.30	0.13	0.11	0.41	0.10	0.05	0.00	−0.11
	(13.18)	(8.88)	(−26.48)	(−26.24)	(−5.43)	(7.68)	(3.38)	(4.82)	(2.19)	(1.97)	(−0.20)	(−2.09)
Size	0.51	0.21	−0.64	−1.15	−0.27	0.11	0.15	0.42	0.07	0.05	0.01	−0.06
	(13.82)	(9.72)	(−25.44)	(−26.97)	(−6.89)	(6.92)	(5.04)	(7.12)	(1.71)	(2.73)	(0.63)	(−1.39)

	Panel G: Book-to-Market			
Control	Low	2	High	High-Low
β^{Bond}	−0.13	0.01	0.19	0.32
	(−5.83)	(0.58)	(3.51)	(5.06)
Maturity	−0.16	0.04	0.30	0.46
	(−6.72)	(2.23)	(5.30)	(6.60)
Size	−0.14	0.05	0.20	0.34
	(−5.91)	(3.39)	(3.94)	(5.04)

Notes: This table reports monthly 6-factor alphas and corresponding Newey-West t-statistics (in parentheses) from the long-short bivariate portfolios by first sorting corporate bonds based on bond market beta (β^{Bond}, 1st row), maturity (2nd row), or size (3rd row) into tercile portfolios, then within each control portfolio, corporate bonds are sorted into sub-terciles based on each anomaly variable as defined in Table II. A total of nine two-way sorted value-weighted portfolio are formed. Finally, I calculate average value-weighted returns on the three portfolios from sorts on anomaly variables across the terciles from sorts on the control variables. All corporate bonds are sorted at the end of each month using signals dated month $t-1$. Portfolios are value-weighted using market capitalization and rebalanced monthly. The 6-factor model combines two bond market factors ($TERM$ and DEF) and 4 stock market factors (MKT^{Stock}, SMB, HML, UMD^{Stock}). Alphas are defined in monthly percentage terms. The "High-Low" column provides the alpha spread of the strategy that buys the winner tercile and sells the loser tercile within each anomaly variable-return tercile (across each row). The sample period from January 1868 through December 1939 for all anomalies.

Table VII: Sub-Period Performance of Corporate Bond Anomaly Strategies

	5% VaR	Spread	Age	STR	MOM	LTR	BTM
P($Sharpe_{5y} > 0$)	71.93%	77.89%	62.86%	100.00%	81.37%	70.68%	89.07%
p-Value	[0.00]	[0.00]	[0.03]	[0.00]	[0.00]	[0.00]	[0.00]

Notes: The table summarizes the historical sub-period performance of the return anomalies. The strategies are long–short extreme value-weighted quintiles from univariate sorts and correspond to the strategies considered in Table V. Shown per anomaly is the percentage of rolling 5-year period with positive Sharpe ratios, P($Sharpe_{5y} > 0$). The sample starts in January 1873 and ends December 1939 and is at the monthly frequency. Numbers in brackets indicate p-values (based on Newey and West (1987) to account for 5-year overlapping observations).

Table VIII: Seasonal Variation in Expected Corporate Bond Anomaly Returns

		All Months			Excluding January		
#	Strategy	Mean	t-Stat.	$\overline{R}_{\text{Jan}} = \overline{R}_{\text{Feb}}$ $\ldots = \overline{R}_{\text{Dec}}$, p-Value	Mean	t-Stat.	$\overline{R}_{\text{Feb}} = \overline{R}_{\text{Mar}}$ $\ldots = \overline{R}_{\text{Dec}}$, p-Value
1	Market	0.082	1.59	0.000	−0.018	−0.33	0.000
2	Downside Risk	0.143	1.71	0.011	0.116	1.41	0.007
3	Credit Quality	0.430	4.36	0.006	0.417	4.11	0.004
4	Illiquidity	0.039	0.76	0.018	0.022	0.40	0.016
5	Short-Term Reversal	−1.514	−21.40	0.000	−1.523	−21.08	0.000
6	Momentum	0.451	4.59	0.005	0.509	4.80	0.043
7	Long-Term Reversal	−0.148	−1.93	0.007	−0.082	−1.07	0.058
8	Book-to-Market	0.409	3.91	0.023	0.355	3.20	0.072
2-8	Joint Seasonality Test			0.000			0.000

Notes: This table reports average monthly returns for the corporate bond market portfolio over the one-month commercial paper return and seven anomalies as defined in Table II. I sort all corporate bonds at the end of each month using signals dated at month $t-1$. Portfolios are value-weighted using market capitalization and rebalanced monthly. Anomaly strategies are zero-cost portfolios that are long the top tercile and short the bottom tercile. Column $\overline{R}_{\text{Jan}} = \ldots = \overline{R}_{\text{Dec}}$, p-value reports the p-value from the test that the average return is the same in every calendar month. The last row reports p-values from joint tests that the anomalies in rows 2 through 9 show no seasonalities in their average returns based upon seemingly unrelated regressions (SUR) of anomaly returns on calendar month indicators. Tests of statistical significance make use of Newey and West (1987) standard errors. The sample period is from January 1868 through December 1939 for all anomalies.

Table IX: Bond-Level Fama-MacBeth Cross-Sectional Regressions

	Int.	5% VaR	Spread	Age	STR	MOM	LTR	BTM	β^{Bond}	β^{TERM}	β^{DEF}	Maturity	Size	Adj. $\overline{R}^2$	T	N
(1)	0.10	0.06												0.04	864	148,586
	(1.95)	(1.27)														
(2)	0.10	0.08							0.02	0.11	−0.04	−0.05	0.01	0.21	864	148,586
	(2.10)	(1.55)							(0.57)	(1.78)	(−0.63)	(−2.80)	(0.91)			
(3)	0.16		0.22											0.03	864	179,702
	(3.02)		(5.03)													
(4)	0.12		0.23						0.01	0.12	−0.07	0.03	0.03	0.20	864	157,636
	(2.48)		(4.49)						(0.17)	(2.26)	(−1.34)	(1.46)	(2.24)			
(5)	0.09			0.01										0.01	864	180,397
	(1.83)			(0.54)												
(6)	0.08			0.00					0.04	0.11	−0.03	−0.04	0.00	0.18	864	158,316
	(1.83)			(0.23)					(1.06)	(1.84)	(−0.44)	(−2.14)	(−0.25)			
(7)	0.08				−0.69									0.09	864	180,397
	(1.55)				(−17.75)											
(8)	0.09				−0.70				0.05	0.10	−0.02	−0.05	0.00	0.24	864	158,316
	(1.90)				(−15.21)				(1.08)	(1.52)	(−0.31)	(−2.24)	(0.32)			
(9)	0.06					0.16								0.04	864	169,652
	(1.12)					(3.49)										
(10)	0.08					0.06			0.05	0.07	0.01	−0.05	0.01	0.20	864	158,261
	(1.75)					(1.24)			(1.38)	(1.35)	(0.10)	(−2.61)	(0.63)			
(11)	0.10						−0.10							0.03	864	137,496
	(1.95)						(−2.76)									
(12)	0.10						−0.09		−0.01	0.13	−0.01	−0.05	0.00	0.21	864	137,496
	(2.38)						(−2.76)		(−0.36)	(2.16)	(−0.19)	(−2.79)	(−0.23)			
(13)	0.15							0.45						0.04	864	181,379
	(2.49)							(4.41)								
(14)	0.13							0.39	0.04	0.14	−0.11	−0.08	0.03	0.21	864	158,321
	(2.52)							(4.05)	(1.15)	(2.47)	(−2.01)	(−3.53)	(2.22)			
(15)	0.15	0.05	0.10	0.00	−0.80	0.00	0.00	0.04						0.24	864	136,806
	(3.18)	(1.34)	(2.35)	(−0.22)	(−19.15)	(0.00)	(0.01)	(0.78)								
(16)	0.14	0.03	0.13	−0.01	−0.74	−0.03	0.01	0.01	0.01	0.10	−0.07	0.00	0.02	0.36	864	136,806
	(3.10)	(0.82)	(2.64)	(−0.44)	(−12.98)	(−0.60)	(0.46)	(0.20)	(0.31)	(1.77)	(−1.24)	(−0.03)	(1.16)			

Notes: This table reports average intercept and slope coefficients from Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead corporate bond excess returns against a constant and a series of bond characteristics. Bond characteristics are measured at the end of month t over my sample period from January 1868 to December 1939. All independent variables are defined in Table III and are standardized to have zero mean and unit variance in each month to ease the interpretation of the estimated coefficients. The table presents the time-series averages of the cross-sectional regression coefficients; intercept and slope coefficients (both multiplied by 100). The corresponding t-statistics in parentheses are based on Newey and West (1987) standard errors to determine the statistical significance of the average intercept and slope coefficients. The last columns report the average adjusted cross-sectional coefficient of determination, $\overline{R}^2$, of the regressions, the number of time periods, T, and the number of observations, N, respectively.

Table X: Summary Statistics for Corporate Bond Factors

	Mean	SD	t-Stat.	Sharpe
Downside Risk Factor (DRF)	0.07	1.58	1.15	0.15
Credit Risk Factor (CRF)	0.34	1.69	4.46	0.70**
Liquidity Risk Factor (LRF)	0.03	1.29	0.66	0.07
Short-Term Reversal Factor ($SREV$)	1.09	1.53	19.35	2.48***
Momentum Factor (UMD^{Bond})	0.44	1.63	6.28	0.93***
Long-Term Reversal Factor ($LREV$)	0.02	1.03	0.74	0.08
Bond High-Minus-Low Factor ($BHML$)	0.46	1.68	4.87	0.94***

Notes: This table reports descriptive statistics for bond factors. The downside risk factor (DRF) is constructed by dependently sorting corporate bonds into 3x3 terciles based on the 5% VaR and credit spread. DRF is the value-weighted average return difference the highest-VaR portfolio and the lowest-VaR portfolio across credit spread tercile portfolios. The credit risk factor (CRF) is constructed by dependently sorting corporate bonds into 3x3 terciles based on bond-level illiquidity (Age) and credit spread. CRF is the value-weighted average return difference the highest-$Spread$ portfolio and the lowest-$Spread$ portfolio across illiquidity tercile portfolios. The liquidity risk factor (LRF) is constructed by dependently sorting corporate bonds into 3x3 terciles based on credit spread and bond-level illiquidity (Age). LRF is the value-weighted average return difference the highest-illiquidity portfolio and the lowest-illiquidity portfolio across credit spread tercile portfolios. The short-term reversal factor ($SREV$) is constructed by dependently sorting corporate bonds into 3x3 terciles based on previous month's return (STR) and credit spread. $SREV$ is the value-weighted average return difference the lowest-STR portfolio and the highest-STR portfolio across credit spread tercile portfolios. The momentum factor (UMD^{Bond}) is constructed by dependently sorting corporate bonds into 3x3 terciles based on previous 11 month cumulative return (MOM) and credit spread. UMD^{Bond} is the value-weighted average return difference the highest-MOM portfolio and the lowest-MOM portfolio across credit spread tercile portfolios. The long-term reversal factor ($LREV$) is constructed by dependently sorting corporate bonds into 2x2x2 trivariate portfolios based on long-term reversal (LTR) between month $t-48$ and $t-36$, time-to-maturity (TTM), and credit spread. $LREV$ is the value-weighted average return difference between the lowest-LTR minus the highest-LTR portfolio across the credit spread and maturity portfolios. The book-to-market factor ($BHML$) follows the methodology of the equity HML factor. Each month, bonds are divided into one of six portfolios based on two bond market capitalization categories and three book-to-market (BTM) categories. $BHML$ is the value-weighted average return difference the lowest-BTM portfolio and the highest-BTM portfolio across market capitalization portfolios. The block-wise bootstrapping with random block length procedure introduced by Ledoit and Wolf (2008) is used with 10,000 runs to test for the statistical significance of the difference between the Sharpe ratios of individual risk factors and the aggregate corporate bond market portfolio. The sample period runs from January 1868 through December 1939. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table XI: Expected Factor Returns Across States

	Economic State			Financial Crisis			Market Return			Yield Curve			Default Risk		
	Rec.	Exp.	Diff.	Crisis	Non-Crisis	Diff.	Bear	Bull	Diff.	Up	Down	Diff.	Incr.	Decr.	Diff.
Downside Risk	0.01	0.12	−0.12	0.01	0.08	−0.07	−0.10	0.16	−0.26	0.02	0.10	−0.09	0.07	0.05	0.02
	(0.10)	(1.66)	(−1.04)	(0.11)	(1.21)	(−0.51)	(−1.06)	(2.29)	(−2.17)	(0.24)	(1.31)	(−0.79)	(1.42)	(0.30)	(0.13)
Credit Quality	0.24	0.44	−0.21	0.14	0.40	−0.25	0.07	0.49	−0.42	0.45	0.26	0.20	0.34	0.37	−0.03
	(2.21)	(4.35)	(−1.55)	(0.89)	(4.74)	(−1.43)	(0.55)	(5.16)	(−2.73)	(4.67)	(2.47)	(1.49)	(5.26)	(1.47)	(−0.14)
Illiquidity	0.10	−0.04	0.14	0.14	0.00	0.14	0.20	−0.07	0.27	0.14	−0.06	0.20	−0.02	0.21	−0.22
	(1.59)	(−0.83)	(1.65)	(1.29)	(−0.07)	(1.21)	(2.47)	(−1.48)	(2.86)	(1.75)	(−1.02)	(1.76)	(−0.42)	(1.70)	(−1.61)
Short-Term Reversal	1.03	1.15	−0.12	0.98	1.12	−0.15	1.02	1.13	−0.12	1.09	1.09	0.00	1.10	1.06	0.04
	(12.83)	(14.82)	(−1.08)	(10.24)	(16.64)	(−1.25)	(10.91)	(15.35)	(−1.00)	(13.98)	(16.16)	(−0.01)	(24.03)	(5.45)	(0.21)
Momentum	0.51	0.36	0.15	0.47	0.43	0.04	0.53	0.39	0.14	0.36	0.49	−0.13	0.48	0.24	0.24
	(6.00)	(3.89)	(1.24)	(2.77)	(5.73)	(0.21)	(4.17)	(4.58)	(0.91)	(4.51)	(4.73)	(−1.17)	(8.07)	(1.01)	(0.95)
Long-Term Reversal	−0.01	0.05	−0.06	−0.04	0.04	−0.08	−0.04	0.06	−0.10	0.05	0.00	0.05	0.05	−0.07	0.12
	(−0.23)	(1.06)	(−1.07)	(−0.62)	(1.09)	(−1.15)	(−0.84)	(1.37)	(−1.57)	(1.02)	(0.07)	(0.72)	(1.46)	(−0.85)	(1.39)
Book-to-Market	0.30	0.60	−0.29	0.28	0.50	−0.22	0.22	0.58	−0.35	0.45	0.46	−0.01	0.43	0.57	−0.15
	(2.91)	(4.90)	(−2.01)	(1.46)	(4.87)	(−1.01)	(2.13)	(4.65)	(−2.29)	(4.66)	(3.89)	(−0.12)	(6.42)	(2.06)	(−0.61)

Notes: This table reports the average monthly return spreads and their Newey-West t-statistics (in parentheses) from the factor portfolios of corporate bonds sorted by seven anomaly variables as defined in Table X. I sort all corporate bonds at the end of each month using signals dated month $t-1$. Portfolios are value-weighted using market capitalization and rebalanced monthly. Anomaly strategies are zero-cost portfolios that are long the top tercile and short the bottom tercile. The sample period from January 1868 through December 1939 for all anomalies is broken into two categories based on economic state, financial crisis, market return, yields, or default risk. Recessions are dated based upon turning points in real GDP per capita identified by the Bry and Boschan (1971) algorithm. Recessions start one year after the dating of a peak until the eve of the next trough. The years 1872–1873, 1875–1876, 1885–1886, 1900–1901, 1914, 1925, 1929–1931, 1934, and 1939 are denoted as financial crisis following Baron, Verner, and Xiong (2021) and Buyst and Maes (2008). Market return states are based on return (including dividends) on the Brussels' stock market. Consistent with Cooper, Gutierrez Jr, and Hameed (2004), negative (non-negative) returns of the value-weighted BSE stock index over months $t-12$ to $t-1$ define down (up) markets. Default risk states are based on the duration-adjusted corporate bond market return following Kelly, Palhares, and Pruitt (2022) and Binsbergen and Schwert (2022). Consistent with stock market down states, I define negative (non-negative) returns of the value-weighted BSE duration-adjusted corporate bond index over months $t-12$ to $t-1$ as down (up) markets. The column "Diff." contains the differential factor returns between bad and good states.

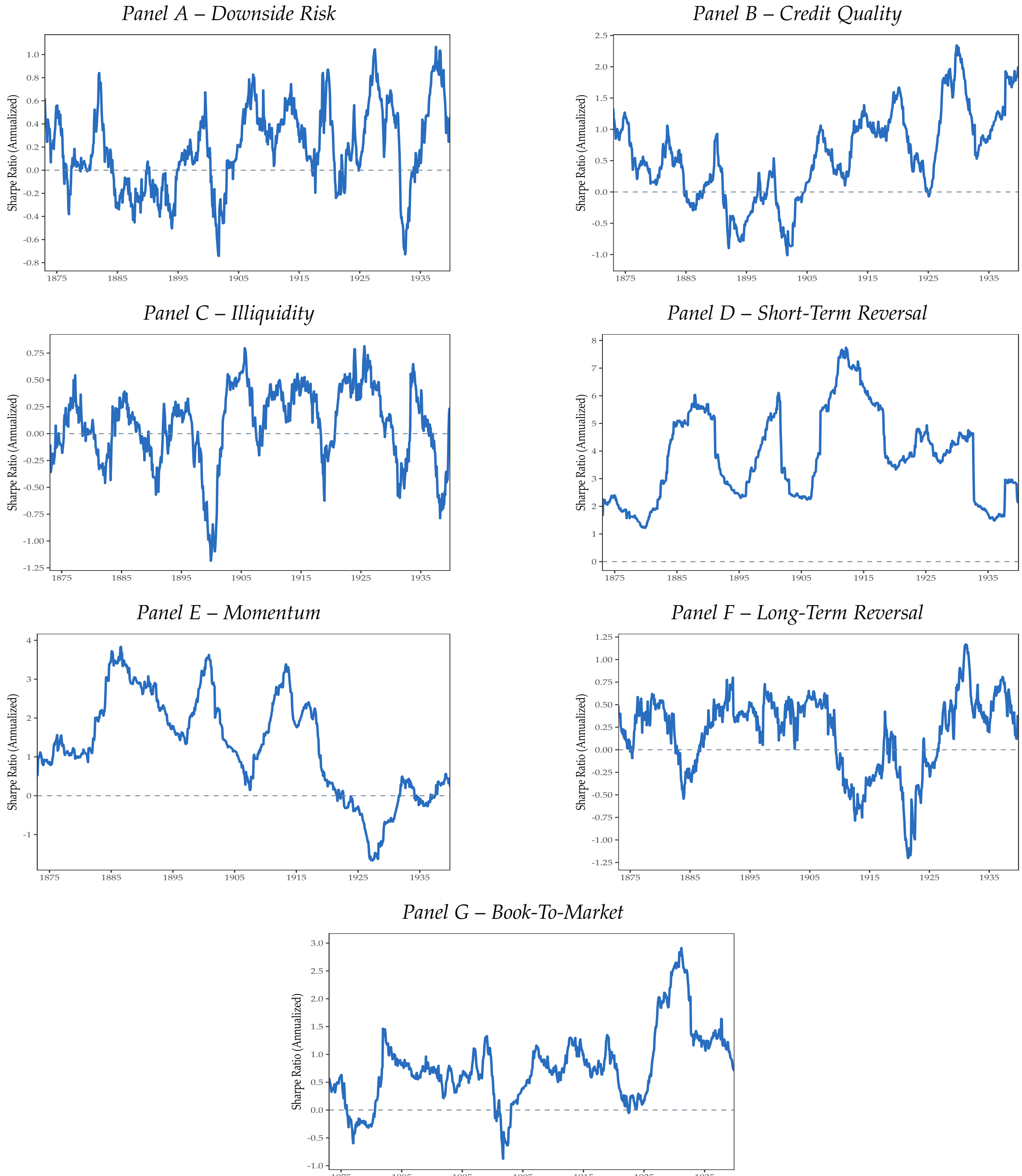
Table XII: Spanning Regressions of One Factor on The Remaining Twelve Factors

	Int.	*DRF*	*CRF*	*LRF*	*SREV*	UMD^{Bond}	*LREV*	*BHML*	*TERM*	*DEF*	*MKT*	*SMB*	*HML*	UMD^{Stock}	Adj. R^2	$s(e)$
DRF	−0.06		23.48	4.43	−12.68	1.09	18.81	31.05	24.22	22.86	4.51	1.44	−0.78	0.07	0.45	1.17
	(−0.88)		(3.77)	(0.75)	(−3.01)	(0.24)	(2.44)	(5.82)	(4.58)	(4.37)	(3.48)	(0.59)	(−0.43)	(0.06)		
CRF	0.13	22.57		−27.50	8.52	−11.91	17.15	45.51	−38.04	−31.19	2.40	5.07	−1.47	−2.40	0.54	1.15
	(2.14)	(3.80)		(−4.17)	(2.01)	(−2.97)	(2.74)	(7.47)	(−5.23)	(−4.96)	(2.00)	(1.51)	(−0.61)	(−1.68)		
LRF	0.24	3.40	−21.92		−14.53	3.82	5.29	6.65	−48.17	−45.75	−2.89	−3.04	−3.96	1.61	0.37	1.03
	(5.07)	(0.83)	(−4.68)		(−3.66)	(1.13)	(0.92)	(1.43)	(−10.07)	(−9.41)	(−2.05)	(−1.44)	(−2.72)	(1.65)		
SREV	0.88	−17.24	12.06	−25.79		12.41	−27.71	30.30	−3.42	−12.84	1.20	−3.26	0.99	0.72	0.20	1.37
	(14.36)	(−2.37)	(1.90)	(−2.94)		(2.49)	(−5.04)	(5.98)	(−0.40)	(−1.49)	(0.78)	(−1.09)	(0.54)	(0.59)		
UMD^{Bond}	0.44	1.72	−19.45	7.83	14.33		10.11	−23.28	−16.19	−27.39	5.81	6.52	0.74	−0.01	0.19	1.47
	(4.43)	(0.24)	(−3.12)	(1.07)	(2.10)		(1.17)	(−3.11)	(−1.71)	(−3.25)	(2.90)	(1.36)	(0.25)	(−0.01)		
LREV	0.05	11.93	11.32	4.38	−12.93	4.09		11.22	0.83	1.59	−0.31	0.53	1.17	−0.45	0.18	0.93
	(1.11)	(2.75)	(2.52)	(0.91)	(−4.22)	(1.20)		(2.22)	(0.18)	(0.30)	(−0.31)	(0.28)	(0.80)	(−0.49)		
BHML	0.13	25.37	38.68	7.09	18.20	−12.12	14.45		30.44	28.49	3.08	0.66	0.62	−0.74	0.60	1.06
	(2.09)	(5.86)	(9.51)	(1.28)	(3.64)	(−2.45)	(2.37)		(4.96)	(6.30)	(2.19)	(0.30)	(0.37)	(−0.67)		
TERM	0.11	15.62	−25.52	−40.54	−1.62	−6.65	0.85	24.03		−94.27	3.21	2.02	1.81	−1.32	0.76	0.94
	(1.73)	(4.04)	(−4.32)	(−5.04)	(−0.38)	(−1.80)	(0.18)	(5.30)		(−22.74)	(2.79)	(0.43)	(0.74)	(−0.94)		
DEF	0.13	11.86	−16.83	−30.97	−4.90	−9.05	1.30	18.09	−75.82		2.72	2.48	1.93	−0.42	0.73	0.84
	(2.96)	(4.23)	(−4.01)	(−5.60)	(−1.59)	(−3.32)	(0.31)	(6.11)	(−20.94)		(2.82)	(0.94)	(1.04)	(−0.36)		
MKT^{Stock}	−0.29	32.18	17.81	−26.93	6.29	26.44	−3.53	26.90	35.50	37.46		−62.78	−24.86	13.84	0.28	3.13
	(−2.16)	(3.63)	(1.98)	(−1.87)	(0.78)	(3.08)	(−0.31)	(2.43)	(3.19)	(3.35)		(−3.42)	(−2.54)	(1.60)		
SMB	−0.04	3.49	12.78	−9.62	−5.80	10.06	2.04	1.95	7.59	11.58	−21.29		2.42	12.71	0.18	1.82
	(−0.35)	(0.62)	(1.41)	(−1.36)	(−1.15)	(1.46)	(0.27)	(0.29)	(0.44)	(0.99)	(−4.19)		(0.34)	(2.43)		
HML	0.01	−2.73	−5.35	−18.08	2.56	1.64	6.45	2.67	9.80	13.06	−12.19	3.50		−0.86	0.04	2.19
	(0.04)	(−0.44)	(−0.61)	(−2.95)	(0.57)	(0.26)	(0.85)	(0.38)	(0.73)	(0.99)	(−2.50)	(0.34)		(−0.18)		
UMD^{Stock}	1.08	0.67	−25.39	21.39	5.42	−0.07	−7.15	−9.16	−20.77	−8.14	19.71	53.39	−2.49		0.09	3.74
	(5.86)	(0.06)	(−1.88)	(1.75)	(0.59)	(−0.01)	(−0.47)	(−0.67)	(−0.97)	(−0.38)	(1.95)	(3.09)	(−0.20)			

Notes: The table contains regression of each factor (in the first column) on the remaining twelve factors. Their construction is detailed in Internet Appendix B. The sample runs from January 1868 to December 1939 and is at the monthly frequency. Shown are slope coefficients and intercepts (expressed in percentages). The associated t-statistics with Newey and West (1987) standard errors are given in parentheses. The last two columns report the adjusted coefficient of determination, R^2, of the regressions, and residual standard errors from each spanning regression, $s(e)$, respectively.

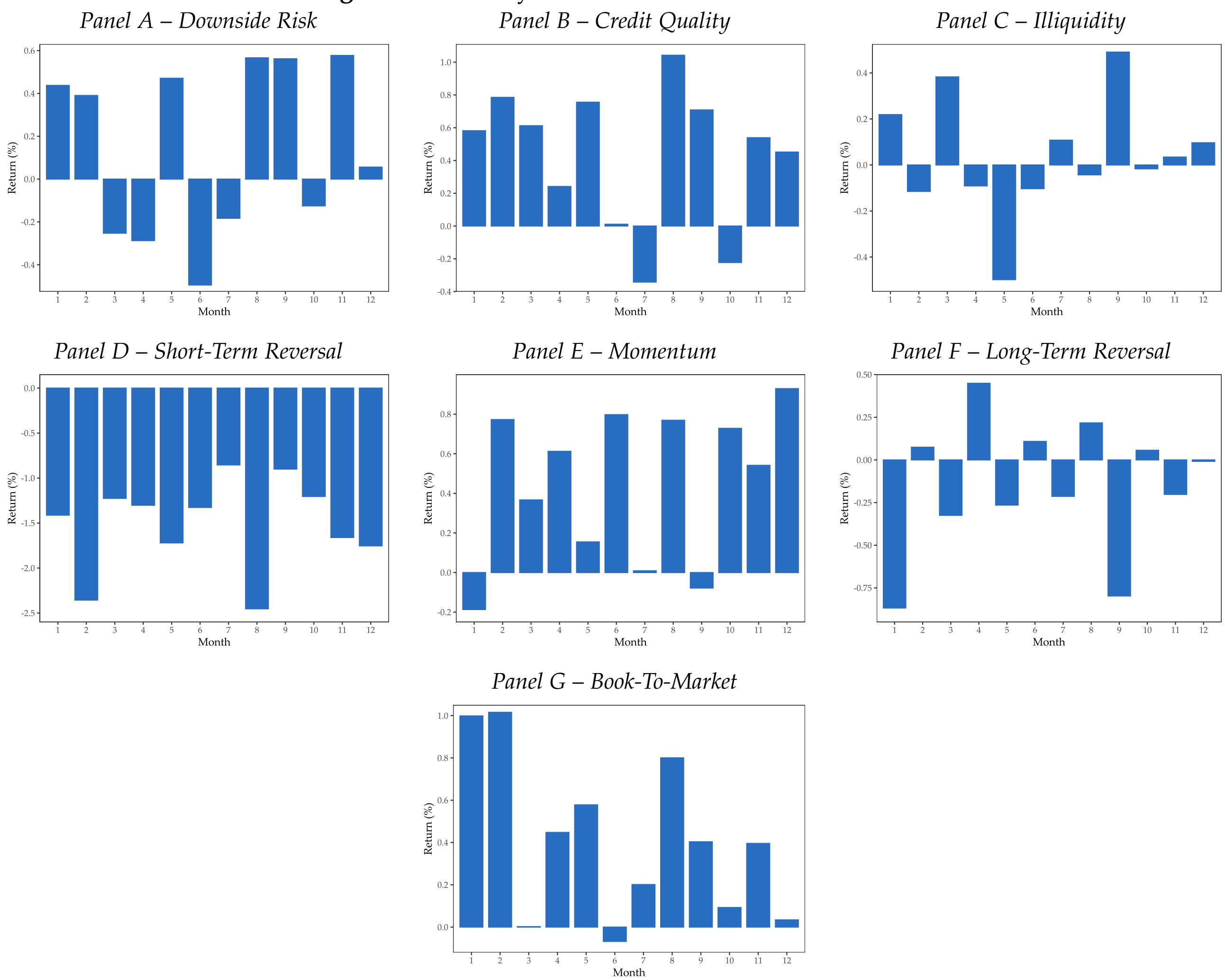
Figures

Figure 1: Performance Over Time of Anomaly Strategies



Notes: The figure shows the trailing five-year Sharpe ratios of downside risk (Panel 1A), credit quality (Panel 1B), illiquidity (Panel 1C), short-term reversal (Panel 1D), momentum (Panel 1E), long-term reversal (Panel 1F), and book-to-market (Panel 1G). The strategies are long–short extreme value-weighted quintiles from univariate sorts and correspond to the strategies considered in Table V. The sample covers January 1868 through December 1939 inclusive.

Figure 2: Anomaly Returns Across Calendar Months



Notes: The figure displays the mean returns on anomaly strategies in different calendar months. The strategies analyzed are zero-investment portfolios that go long (short) in the highest (lowest) quintile and correspond to the strategies considered in Table V. Quintile portfolios are formed every month from January 1868 to December 1939 by sorting corporate bonds on their downside risk (Panel 2A), credit quality (Panel 2B), illiquidity (Panel 2C), short-term reversal (Panel 2D), momentum (Panel 2E), long-term reversal (Panel 2F), and book-to-market (Panel 2G). All portfolios are rebalanced at the end of the next month, and their realized return is recorded.

The Cross-Section of Corporate Bond Returns: Evidence from an Elusive Past

Internet Appendix

Kevin Van Mencxel

Internet Appendix A. Data Appendix

This section provides a detailed description of the construction of the final datasets used for the empirical analysis.

A.1. Corporate Bond Data

I have compiled my data from several sources in order to obtain a reliable and historically extensive dataset. My sample covers 72 years of data on monthly corporate bond prices, realized coupon payments, and market capitalizations for all bonds issued by domestic firms traded on the Brussels Stock Exchange (BSE). The sample spans the period from January 1868 through December 1939 and is at a monthly frequency. I build my dataset from the Official Quotations Lists of the Brussels Stock Exchange (*Cours Authentique de la Bourse de Bruxelles Seul Officiel Publié par La Commission Instituée en Vertu de la Loi*) — the official datasource of notorial origin for Belgian corporate securities. For illustration, Internet Appendix Figure A.1 shows an example of how pages of this source look like. Below I further outline the steps taken to obtain the final dataset.

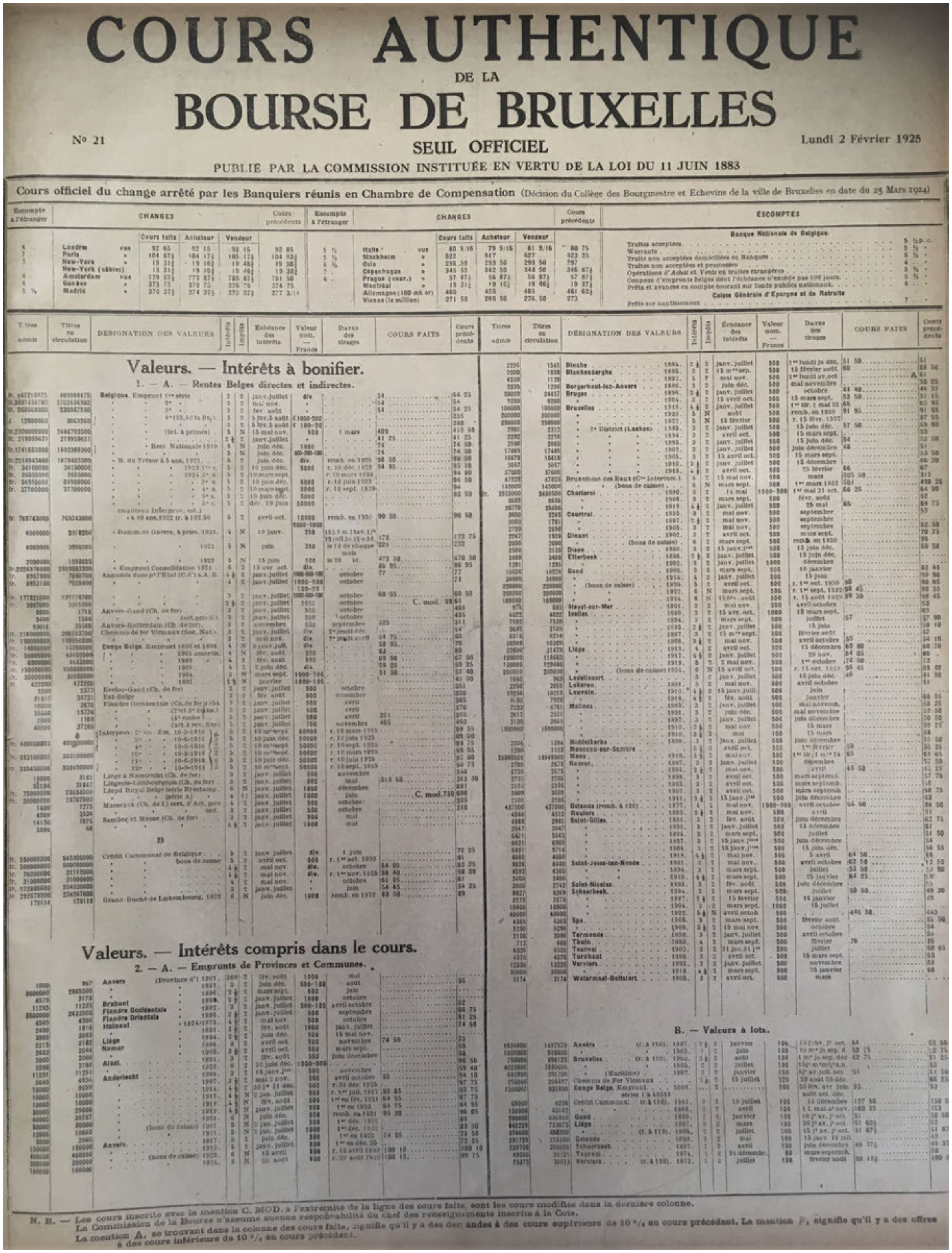
Obtaining information from earlier versions of the Official Quotation Lists has two caveats. Specifically, I make use of several secondary sources to fill gaps in the observation of bond quantities (that is, pre-1878) and coupon defaults (that is, pre-1873) to support the empirical analysis. In the earlier years, the numbers of bonds outstanding are not reported. Before 1878, I collect data on the number of bonds admitted to the stock exchange. Information on bond quantities was extracted by the Exchange Commission from the transcripts of general meetings, lists of bonds to be drawn or redeemed, and balance sheets which companies were obligated to disclose as part of its listing requirements (Thiebauld, 1905). However, the use of *titres en circulation* rather than *titres admis* is important seeing that the former bond quantity series take into account the role of debt buybacks and exchange offers as any difference between the respective series. The quantities reported also correct for amount by which the issue's amount outstanding was adjusted through multiple successive series or tranches (the so-called process of *à la souche*). I therefore rely on the number of bonds *outstanding* rather than the number of bonds *admitted* from 1878 onwards to construct value-weighted portfolio returns.

The original historical database contains 318,553 monthly bond hand-collected price quotes of 1,505 corporate bonds traded in Brussels. Upon closer inspection, I drop a considerable number of these observations, so as to get to a homogenous sample of corporate bonds issued by Belgium firms, irrespective where their main economic activity takes place, denoted in Belgian franc or Belga, and whose interest payment nor amortization is not guaranteed by the Belgian state.[1] The main steps taken to clean the initial data collection effort is shown in Internet Appendix Table A.I.

[1]Belgium left the Latin Monetary Union at the end of 1925 following the constant devaluation of its members' currencies. The Belgian franc was stabilized at one-seventh of former parity. One of the measures taken in the decree of October 25 1926 was the establishment of a new currency, the Belga, worth 5 francs. This new unit was to replace the Belgian franc on the international exchange market. In this way, Belgium distanced itself from the French franc which was in turmoil at the time.

Figure A.1: Example of Data

Panel A – Excerpt of the Official Quotation Lists: Example of Historical Sovereign Bond Data



COURS AUTHENTIQUE
DE LA
BOURSE DE BRUXELLES

Nº 21 — SEUL OFFICIEL — Lundi 2 Février 1925

PUBLIÉ PAR LA COMMISSION INSTITUÉE EN VERTU DE LA LOI DU 11 JUIN 1883

Cours officiel du change arrêté par les Banquiers réunis en Chambre de Compensation (Décision du Collège des Bourgmestre et Echevins de la ville de Bruxelles en date du 25 Mars 1924)

Valeurs. — Intérêts à bonifier.

1. — A. — Rentes Belges directes et indirectes.

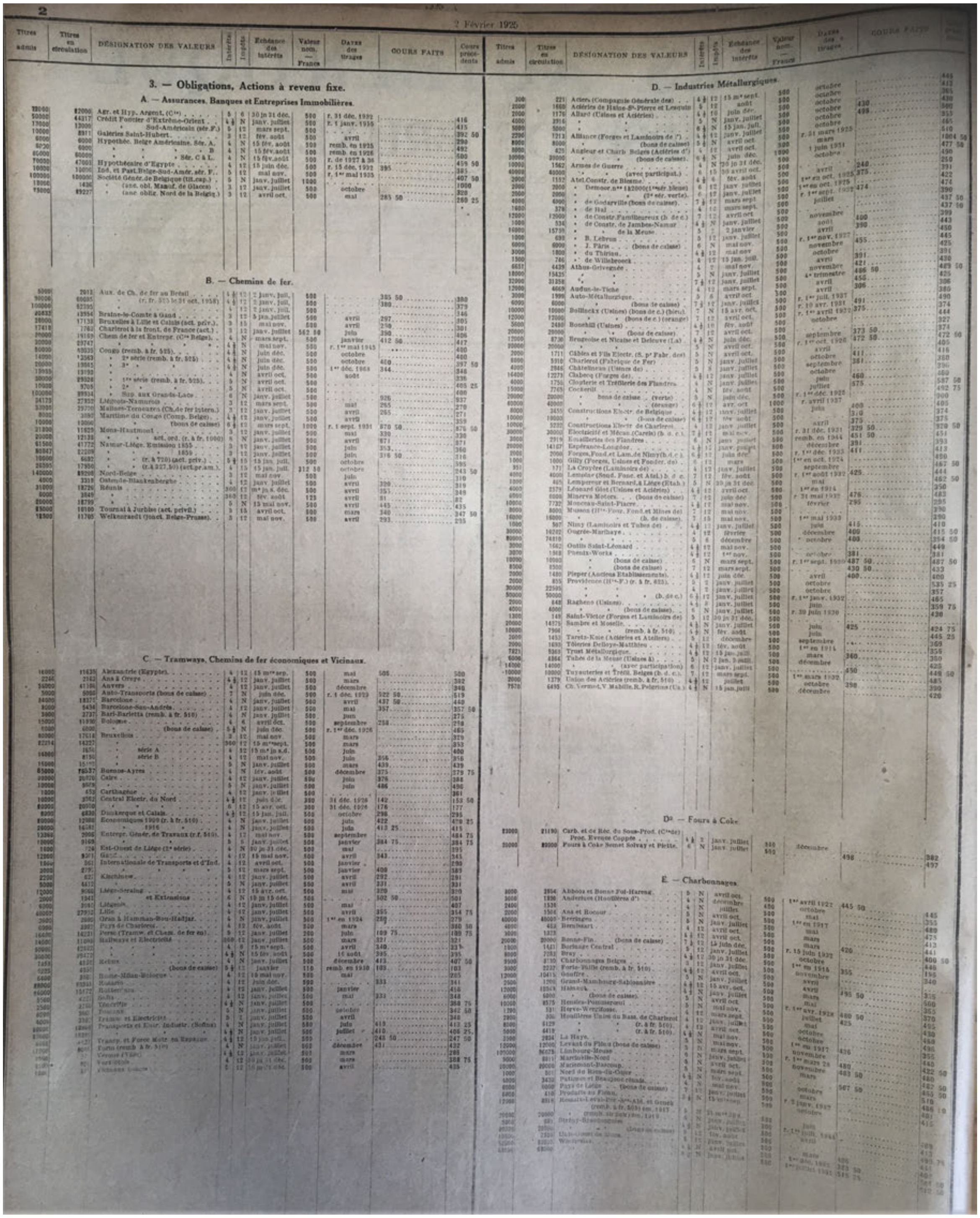
Valeurs. — Intérêts compris dans le cours.

2. — A. — Emprunts de Provinces et Communes.

B. — Valeurs à lots.

N. B. — Les cours inscrits avec la mention C. MOD. à l'extrémité de la ligne des cours faits, sont les cours modifiés dans la dernière colonne. La Commission de la Bourse n'assume aucune responsabilité du chef des renseignements inscrits à la Cote. La mention A, se trouvant dans la colonne des cours faits, signifie qu'il y a des demandes à des cours supérieurs de 10 °/o au cours précédent. La mention P, signifie qu'il y a des offres à des cours inférieurs de 10 °/o au cours précédent.

Panel B – Excerpt of the Official Quotation Lists: Example of Historical Corporate Bond Data



Notes: This figure illustrates my data collection by showing an example of the original records used to construct the historical corporate bond dataset. Panel A.1A from the Official Quotation Lists of February 2, 1925 shows the organization of the records and the typical information that is included. It entails the reporting of Belgian sovereign bonds and municipality bonds in separate sections. Panel A.1B shows the page that follows suit upon Panel A.1A as it details the recording of Belgian fixed-coupon corporate bonds. Note that for this particular day, corporate bonds are reported in one more additional page worth of data before floating rate bonds and stock data are shown. The very last page of the daily record details bonds — sovereign as well as corporate — that are in a state of coupon default (not shown).

Table A.I: Sample Exclusion Criteria

No.	Exclusion Criteria	Description
1.	Domestic bonds only	If one bond is not issued by a Belgian firm, it is excluded from the sample.
2.	Domestic currency only	If one bond is denominated in a currency other than Belgian franc or Belga, it is excluded from the sample.
3.	Fixed coupon bonds only	If one bond is not adherend to a fixed coupon payment schedule, it is excluded from the sample.
4.	Qualified bonds only	If one bond has less than 11 monthly return observations, it is discarded from the sample. Additionally, bonds that are different from plain vanilla corporate bonds are excluded from the sample. Instruments excluded include: bonds holding a profit clause, bonds with detached coupons, bonds with multiple price lines in the Official Quotation Lists, and bonds whose interest or redemption is guaranteed by the state.
5.	Bonds with face value only	If one bond does not have data on face value that allows for the estimation of its amount outstanding, it is excluded from the sample.

Notes: This table outlines the filters that have been applied to the initial corporate bond data set as obtained from the Official Quotations Lists of the Brussels Stock Exchange (*Cours Authentique de la Bourse de Bruxelles Seul Officiel Publié par La Commission Instituée en Vertu de la Loi*).

Specifically, I drop:

1. 93,054 observations of bonds issued by companies domiciled abroad (that is, cross-listed issues).

2. 2,230 observations for bonds denominated in foreign currencies (that is, not in Belgian francs or Belga).

3. 7,168 observations of bonds that had a floating rate coupon (*obligations à revenu variable*).

4. 16,862 observations for bonds that had a too short listing period, were issued or explicitly guaranteed by the Belgian or Belgian Congo state, next to bonds that exhibit exotic characteristics compared to plain-vanilla bonds. Notable examples of the first category include railroads owned by the Belgian state or Intercommunal companies created for the purpose of performing a public service such as water, gas and electricity distribution, and public transport. Such bonds are commonly referred to as "sovereigns, supranationals and agencies (SSA) bonds." The second category includes bonds that had a profit-sharing clause or were equity-linked (*obligations avec participation dans le bénéfice* and *obligations avec un droit d'option de convertibilité*), bonds that had detached coupons (*obligations avec des coupons détaché*), and bonds that

had multiple price lines in the Official Quotation Lists therefore rendering pricing of the bond ambiguous.

5. 350 observations by bonds for which I did not find basic information on their face value.

A.2. Sovereign Bond Data

The Official Quotation Lists contain bond prices and information that characterize different bond issues sold by the Belgian government in the nineteenth and twentieth century. These individual bond issues were placed under the *Fonds de l'État* for the early part of the sample and *Rentes Belges Directe et Indirecte*. The annual *Titres à Revenu Fixe — Fonds Publics, Emprunts, et Obligations* supplement found within the *Moniteur des Intérêts Matériels* allows for cross-checking their identification.

The most notable issue was the "Belgian Outstanding Debt 2.5%" (*Dette Active Belge 2.5%*). This was coincidentally the first listed bond issue by the Belgian state in 1831 following its declared independence from The Netherlands. In terms of amount borrowed it was a large issue compared to standard emissions in the nineteenth century. Yet, Homer and Sylla (2005) argue that because of the noteworthy variety in simultaneous yields in long-term *rentes*, "it should illustrate the caution with which the yield calculations on any one security should be treated as representing a whole market". Accordingly, for all long-term bonds issued by the Belgian government with a maturity of at least 10 years, I collect data on bond prices, coupon rates, coupon payment dates, number of bonds issued, number of bonds listed, and taxation rates. This is consistent with the portfolio approach of Kelly, Palhares, and Pruitt (2022).

The historical dataset of Belgian sovereign bonds covers 4,231 monthly prices and 683 coupon payments of 20 unique sovereign bonds.

A.3. Stock Data

I construct stock return data following Annaert, Buelens, and De Ceuster (2012) and Annaert, Buelens, and Deloof (2015). The collected stock data includes end-of-month stock prices, dividends, ex-dividend day, the number of stocks admitted to the BSE, and taxation rates. The Official Quotation Lists serve as the main data source. Importantly, stock returns are adjusted for important capital operations (e.g., mergers and demergers, splits and reverse splits, bonus stocks, inscription rights and attribution rights, exchanges, liquidations, and delistings). To attain a comparable sample with my corporate bond dataset, I focus on stocks issued by Belgian firms and exclude foreign firm stocks. Next, I only select stocks that were traded on the spot market.[2] Stocks with a listing period less than 11 months were excluded since it is doubtful whether these companies really got off the ground. I focus on common stocks, thus excluding all other stock types as described by Annaert, Buelens, and De Ceuster (2012, p. 191). Finally, in order to emphasize economic importance and statistical reliability (see, e.g., Fama (1998), Fama and French (2008), and Soebhag, Van Vliet, and

[2] Note that the forward market was comprised nearly exclusively of coss-listed stocks.

Verwijmeren (2022)), I control for microcap stocks by discarding observations with prices below 5 BEF. These data enable me to construct a value-weighted total return index of the Belgian stock market and equity factor returns for the entire sample period.

Using the filters described above, I collect 373,573 monthly prices and 19,309 dividend payments of 1,658 unique stocks. These 1,653 stocks were issued by 1,489 unique firms between January 1868 through December 1939.

Internet Appendix B. Variable Definitions and Portfolio Construction

B.1. Corporate Bond Anomaly Variables

Downside risk Bond downside risk is proxied by its 5% *VaR*, which is the second-lowest monthly return observation over the past 36 months. A bond is included in the VaR calculation if it has at least 24 monthly return observations in the 36-month rolling window.

Credit quality The credit quality of bonds is typically observed through credit ratings provided by rating agencies such as Moody's and S&P's. However, credit ratings were introduced by John Moody in 1909, in the US. It was only in the 1970s that credit ratings were introduced worldwide (Sylla, 2002). It is therefore impossible to rely upon credit ratings to gauge credit quality at the bond level for my historical setting between 1868 and 1939. Neither other widely used credit risk proxies such as distance-to-default and credit default swap spreads are available for early financial market settings. The latter derivative security was only created in 1994, with Blythe Masters from JP Morgan & Co. being credited with its invention. Neither is accurate and systematic accounting information available in the pre-WWII period that would allow for the construction of distance-to-default. This is not specific to Belgium (Van Overfelt, Deloof, and Vanstraelen, 2010) but rather holds for all major financial centers, such as the US (Cohen, Polk, and Vuolteenaho, 2003; Linnainmaa and Roberts, 2018; Wahal, 2019), the UK (Arnold, 1996, 1997), and the Netherlands (van den Brand, 2005). Instead, I rely on credit spreads, defined as the spread between the yield-to-maturity of corporate bonds and duration-matched sovereign bonds, as signal of credit quality at the bond level. The high degree of transparency of the centralized limit-order book within my empirical setting where bond trading was centered around an organized exchange alleviates information asymmetries between brokers and investors and reduces the cross-sectional variation in the extent to which investors are informed about bond prices.[3] Credit spreads are therefore an ideal candidate to signal information about future defaults as these reflect the market consensus view of the credit worthiness of the underlying firm to meet its financial commitments in transparent markets (Badoer and

[3] The bond market enjoyed a high degree of pre- and post-trade transparency. All brokers could observe the book of recent orders and inform their customers. Investors could use this information to monitor their brokers ex-post. The public also had the possibility to directly converse with its broker as they were separated from the trade by a wooden boarding (*la barre*). They were however also able to directly observe bond quotations as the official price list was shown per chalk board at the entrance of the Stock Exchange. The workings of the pre-OTC era were voiced by Chester Spratt in 2006, then chief economist of the SEC, when discussing the quest for increasing transparency of the US corporate bond market. See https://www.sec.gov/news/speech/spch010606css.htm.

Demiroglu, 2019). Accordingly, the higher the credit spread, the higher the probability of default of the company. The predictive power of credit spreads has previously been shown for modern markets providing further motivation for my choice of credit spreads as default risk signal (Abinzano *et al.*, 2020; Norden and Weber, 2004).

To provide some additional descriptive evidence on my choice of credit spreads as sorting variable, Table A.II presents characteristics on corporate bonds sorted into value-weighted portfolios by credit spread quintile. Consistent with their lower default risk, the annual default rate and standard deviation of returns is lower for bonds with lower credit spreads. Duration is decreasing monotonically in credit quality, with higher-quality bonds having longer duration due to their longer maturities and lower coupon rates.

Table A.II: Additional Summary Statistics of Credit Spread-Sorted Portfolios

Quintile	Default Rate	SD	Duration	Maturity	Coupon
Low	0.32	10.82	18.81	41.48	3.90
2	0.95	10.56	14.94	29.44	4.34
3	1.97	11.53	12.34	23.03	4.56
4	1.97	12.71	9.98	17.89	4.78
High	5.64	29.29	8.20	18.75	4.82

Notes: This table reports average characteristics of corporate bond portfolios sorted by previous month's credit spread as defined in Table III. Following Altman (1989) and Giesecke *et al.* (2011), *Default Rate* is the value-weighted annual default rate defined as the fraction of the total par value of corporate bonds defaulting during each year in the sample period. The specific data used in calculating the default rate consists of two time series. The first is the total par value of a snapshot of all corporate bonds included in the portfolio at the beginning of each year. The second is the total par amount of the subset of bonds in the annual snapshot of the portfolio defaulting each year. The default rate is simply the ratio of the latter to the former. As is standard in the corporate bond default literature, default events are identified by adopting Moody's definition: (1) a missed interest payment, (2) a bankruptcy filing or creditor compensation, (3) a distressed exchange wherein debt holders receive a new security or package of securities that amount to a diminished financial obligation, and (4) an unfavorable change in the payment terms of a credit contract that results in a diminished financial obligation (i.e., a change in face value or coupon rate). *SD* is the annualized volatility of value-weighted portfolio returns. The standard deviation is annualized by multiplying the monthly volatility by the square root of 12. *Duration* (in years) is a bond's Macauley duration. *Maturity* (in years) is the time to maturity of the bond. *Coupon* (in percentage) is the annual coupon rate. The sample period runs from January 1868 through December 1939.

Illiquidity Studies using modern trade-based bond data beyond July 2002 from TRACE typically proxy illiquidity through the Roll (1984) illiquidity measure as employed by Bao, Pan, and Wang (2011) by estimating the covariance of adjacent returns, or the Amihud (2002) illiquidity measure incorporating daily trading volume data. Since detailed high-frequency trade (and volume) data are not available for my sample period, I rely upon alternative liquidity proxies used in empirical asset pricing. Amount issued and bond age have been shown to be good proxies of liquidity by Houweling, Mentink, and Vorst (2005) and Bongaerts, De Jong, and Driessen (2017). I define bond age as a percentage obtained by relating the time passed since issuance to the original maturity (Israel, Palhares, and Richardson, 2018).

Short-term reversal I measure the short-term reversal of bond i for month t using its return during the previous month $t-1$.

Momentum Bond momentum is defined as the past 12-month cumulative return from month $t-12$ to $t-2$, skipping the short-term reversal month $t-1$.

Long-term reversal I calculate long-term reversal with the past 36-month cumulative returns from month $t-48$ to $t-13$. A bond is included in the LTR calculation if it has at least 24 months of return observations during the 36-month window.

Book-to-market I measure the book-to-market of bond i in month t as the ratio of notional amount to market value (i.e., the reciprocal of the dirty price of the bond per unit of face value).

B.2. Corporate Bond Factor Portfolio Construction

Bond market The corporate bond market factor, MKT^{Bond}, in month t is defined as a value-weighted average constructed from the individual corporate bond returns of month t in excess of the risk-free asset. The risk-free asset is proxied by monthly return in month t on Belgian commercial paper (*taux de l'escompte hors banque du papier commercial*). Market capitalization is the bond price times the number of bonds listed on the stock exchange.

Term Following Fama and French (1993), the term factor, $TERM$, is the difference between the monthly value-weighted long-term government bond market return, comprised of sovereign bonds with at least 10 years of maturity, and the one-month return on Belgian commercial paper.

Default Following Fama and French (1993), the default factor, DEF, is the difference between the monthly value-weighted corporate bond market return and the monthly value-weighted long-term government bond market return.

Downside risk The downside risk factor, DRF, is the difference between the average returns of the highest-VaR portfolios and the lowest-VaR portfolios across the credit spread tercile portfolios. I form the value-weighted bivariate portfolios by dependently sorting bonds into three portfolios based on their credit spreads, and three portfolios based on their downside risk estimates (Bai, Bali, and Wen, 2019).

Liquidity risk The liquidity risk factor, LRF, is the difference between the average returns of the highest-$ILLIQ$ portfolios and the lowest-$ILLIQ$ portfolios across the credit spread tercile portfolios. I form the value-weighted bivariate portfolios by dependently sorting bonds into three portfolios based on their credit spreads, and three portfolios based on their bond-level illiquidity ($ILLIQ$) estimates (Bai, Bali, and Wen, 2019).

Credit risk The credit risk factor, CRF, is the difference between the average returns of the highest-$SPREAD$ portfolios and the lowest-$SPREAD$ portfolios across the illiquidity tercile portfolios. I form the value-weighted bivariate portfolios by dependently sorting bonds into three portfolios based on their bond-level illiquidity ($ILLIQ$), and three portfolios based on their credit spreads ($SPREAD$) estimates (Bai, Bali, and Wen, 2019).

Short-term reversal The short-term reversal factor, SRF, is the difference between the average returns of the short-term loser portfolios and the short-term winner portfolios across the credit spread tercile portfolios. I form the value-weighted bivariate portfolios by dependently sorting bonds into three portfolios based on their credit spread, and three portfolios based on their short-term reversal (Bai, Bali, and Wen, 2019).

Momentum The momentum factor, UMD, is the difference between the average returns of the highest-momentum portfolios and the lowest-momentum portfolios across the credit spread tercile portfolios. I form the value-weighted bivariate portfolios by dependently sorting bonds into three portfolios based on their credit spreads, and three portfolios based on their momentum (Bali, Subrahmanyam, and Wen, 2021; Jostova *et al.*, 2013).

Long-term reversal The long-term reversal factor, LRF, is the difference between the average returns of the lowest-long-term reversal portfolios and the highest long-term reversal portfolios across the credit spread and maturity portfolios. I form the value-weighted $2x2x2$ portfolios by first sorting bonds into two portfolios based on their credit spread, next into another two portfolios based on their time-to-maturity, and finally into two portfolios based on their long-term reversal (Bali, Subrahmanyam, and Wen, 2021).

Book-to-market The book-to-market factor, $BHML$, follows the methodology of Fama and French (1993) for the stock value factor. Each month, we divide bonds into one of six portfolios based on two bond size categories (that is, bond market capitalization) and three BTM categories. Within each of the two bond size categories (that is, Big and Small), I compute each month's return spread between a value weighting of the top- and bottom-third BTM bonds. Averaging the Big and Small bond return spreads generates that month's Bond HML factor, $BHML$ (Bartram, Grinblatt, and Nozawa, 2021).

B.3. Stock Factor Portfolio Construction

Stock market The stock market factor, MKT^{Stock}, in month t is defined as a value-weighted average constructed from the individual stock returns of month t in excess of the risk-free asset. The risk-free asset is proxied by monthly return in month t on Belgian commercial paper (*taux de l'escompte hors banque du papier commercial*).

Size and Value The construction of the Small-Minus-Big (SMB) and High-Minus-Low (HML) portfolios follows Fama and French (1993). I first split the universe of stocks into two categories (Small and Big) by using the median market capitalization of stocks at December each year as the breakpoint. Next, stocks are sorted on their value characteristic within both of these size groups. I make use of dividend yield as proxy for the value signal, as in the nineteenth century dividends were widespread, strongly associated with earnings (Braggion and Moore, 2011; Turner, Ye, and Zhan, 2013), and seen as an important information communication and valuation tool for stocks (Baskin, 1988; Baskin, Miranti Jr, and Miranti, 1997; Poitras, 2010). Seeing earnings and book values are not available during my sample period, I construct High, Neutral, and Low portfolios using the 30th and the 70th percentiles of the dividend-to-price ratio, (D/P), or dividend yield, at December as the breakpoints. The extreme portfolios contain 30% of the stocks (High and Low), the remaining 40% are in the middle group (Neutral). The dividend-to-price ratio is calculated as the sum of dividend paid in the year divided by the current stock price. Zero-yielding stocks are excluded when constructing the SMB and HML factors. Following Baltussen, Vliet, and Van Vliet (2022), I rely upon dependent rather than independent sorting to guard against the occurence of empty portfolios, especially in the early part of the sample period. From this procedure, the dependent $2x3$ sorting, I get six intersection portfolios, namely, Small High, Small Neutral, Small Low, Big High, Big Neutral, and Big Low as shown in Internet Appendix Table A.III:

Table A.III: Defining SMB and HML Factors

	Dividend-to-Price		
Size	Low	Neutral	High
Small	Small Low	Small Neutral	Small High
Big	Big Low	Big Neutral	Big High

Notes: This table presents the sorting procedure used to create three size and dividend-to-price portfolios which are the building blocks of the SMB and HML factors.

Holding these portfolios fixed from December of year t to the end of December of year $t+1$, I compute the value-weighted monthly returns to each of the six portfolios. Returns are value-weighted given the influence of microcap stocks in equally-weighted portfolio returns (Hou, Xue, and Zhang, 2020; Soebhag, Van Vliet, and Verwijmeren, 2022; Walter, Weber, and Weiss, 2022). SMB is the average return on the three small portfolios minus the average return on the three big portfolios,

$$SMB = 1/3\,(Small\ Low + Small\ Neutral + Small\ High) - 1/3\,(Big\ Low + Big\ Neutral + Big\ High)\,. \tag{A.1}$$

HML is the average return on the two high portfolios minus the average return on the two low portfolios,

$$HML = 1/2\,(Small\ High + Big\ High) - 1/2\,(Small\ Low + Big\ Low)\,. \tag{A.2}$$

Momentum The Up-Minus-Down (UMD) portfolio is defined similarly to HML, except it is updated monthly instead of annually. I repeat the first sort based upon market capitalization. For the second dependent sort, at each month t, I follow Jegadeesh and Titman (1993), Fama and French (1996), and Grinblatt and Moskowitz (2004) and construct Winner and Loser portfolios based on the 30th and 70th breakpoint of the past 11-month return between months $t-12$ and $t-2$, skipping the most recent month $t-1$:

Table A.IV: Defining UMD Factor

	Momentum		
Size	Low	Neutral	High
Small	Small Low	Small Neutral	Small High
Big	Big Low	Big Neutral	Big High

Notes: This table presents the sorting procedure used to create three size and dividend-to-price portfolios which are the building blocks of the UMD factor.

Individual stocks returns are value-weighted to obtain portfolio returns given the influence of microcap stocks in equally-weighted portfolio returns (Hou, Xue, and Zhang, 2020; Soebhag, Van Vliet, and Verwijmeren, 2022; Walter, Weber, and Weiss, 2022). UMD is the average return on the two high prior return portfolios (that is, Small High and Big High) minus the average return on the two low prior return portfolios (that is, Small Low and Big Low),

$$UMD = 1/2\left(Small\ High + Big\ High\right) - 1/2\left(Small\ Low + Big\ Low\right). \tag{A.3}$$

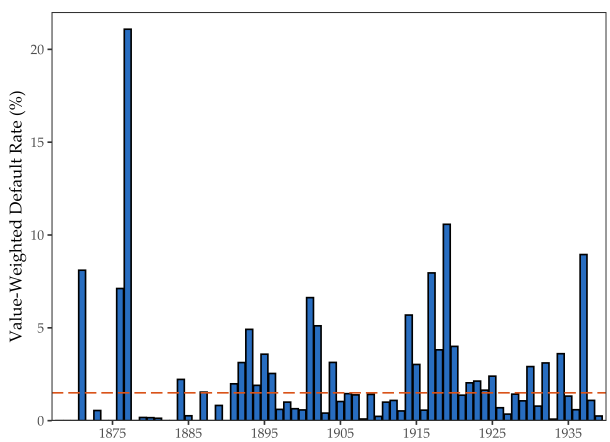
Internet Appendix C. Additional Results

C.1. Belgian Interest Rates and Default Rates

Figure A.2: Historical Interest Rates and Default Rates

Panel A – Historical Long-Run Sovereign Bond Yields

Panel B – Historical Default Rates



Notes: The figure plots historical value-weighted yields of the Belgian long-run sovereign bond market and value-weighted corporate bond default rates, respectively. Internet Appendix Figure A.2A estimates the monthly value-weighted average yield-to-maturity of all long-term bonds issued by the Belgian government with a maturity of at least 10 years collected from the *Rentes Belges Directe et Indirecte* section of the Official Quotation Lists. The period starts from the enactment of the Treaty of London in April 1839, as it recognzed and guaranteed the independence of the newly created Belgian state, until December 1939 to give a full perspective of 19th century and early 20th century secular rate trends. The grey dashed vertical line shows the international hinge point, 1897, documented by Homer and Sylla (2005) as the point in time when the secular trend of declining interest rates during the 19th century turned its course. Following Altman (1989) and Giesecke *et al.* (2011), Internet Appendix Figure A.2B depicts the annual value-weighted default rate defined as the fraction of the total par value of corporate bonds defaulting during each year in the studied period from January 1868 until December 1939. The specific data used in calculating the default rate consists of two time series. The first is the total par value of a snapshot of all corporate bonds included in the portfolio at the beginning of each year. The second is the total par amount of the subset of bonds in the annual snapshot of the portfolio defaulting each year. The default rate is simply the ratio of the latter to the former. As is standard in the corporate bond default literature, default events are identified by adopting Moody's definition: (1) a missed interest payment, (2) a bankruptcy filing or creditor compensation, (3) a distressed exchange wherein debt holders receive a new security or package of securities that amount to a diminished financial obligation, and (4) an unfavorable change in the payment terms of a credit contract that results in a diminished financial obligation (i.e., a change in face value or coupon rate). The orange dashed horizontal line is set at 1.5%, the average value-weighted annual default rate over the *longue durée* for the US corporate bond market between 1866 and 2008 as reported by Giesecke *et al.* (2011).

C.2. *Return Decomposition*

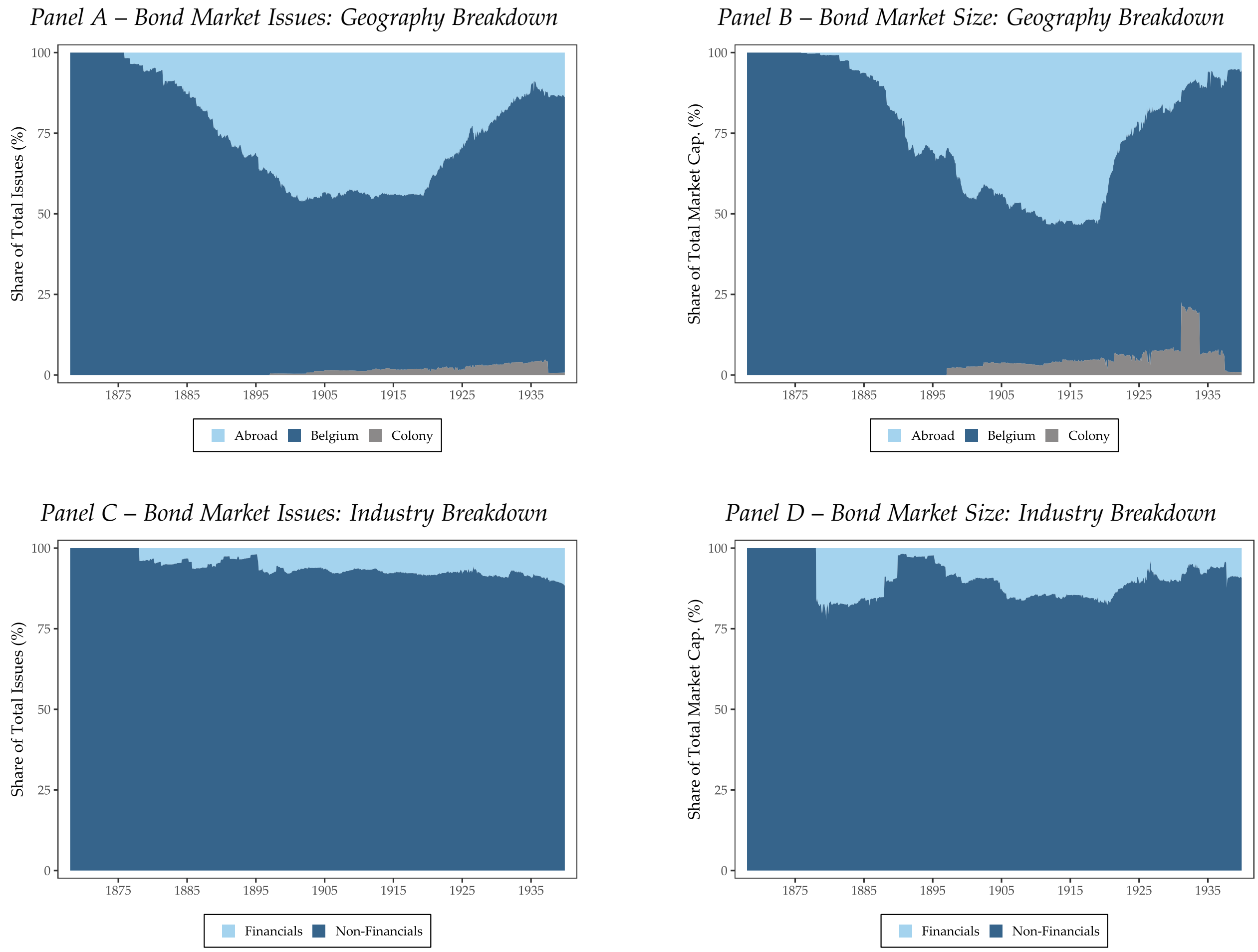
Table A.V: Decomposition of Corporate Bond Returns

		Standard Approach		Duration-Adjusted Approach		
	Return	C. Paper	Excess	Sovereign	Excess	Log(Excess)
Portfolio	$r_{p,t}^{tot}$	$r_{f,t}$	$r_{p,t}^{tot} - r_{f,t}$	$r_{p,t}^{sov}$	$r_{p,t}^{Dur\ Adj}$	$\log(1 + r_{p,t}^{Dur\ Adj})$
Spread1	0.169	0.261	−0.091	0.236	−0.067	−0.075
Spread2	0.373	0.261	0.112	0.197	0.176	0.168
Spread3	0.430	0.261	0.169	0.164	0.265	0.257
Spread4	0.459	0.261	0.199	0.116	0.343	0.334
Spread5	0.599	0.261	0.339	0.098	0.501	0.474
Market	0.342	0.261	0.082	0.184	0.158	0.152

Notes: This table summarizes the decomposed monthly returns of corporate bond portfolios sorted by credit spread. The aggregate market portfolio is also shown. The sample consists of 864 monthly observations from January 1868 to December 1939. From left to right, the columns contain the average monthly total return for each corporate bond portfolio; the one-month return on Belgian commercial paper, and the standard excess corporate bond return; the duration-matched sovereign bond return and the duration-adjusted excess corporate bond return; and the log duration-adjusted excess corporate bond return (to account for compounding).

C.3. Geography and Industry Breakdown of Corporate Bond Market

Figure A.3: Composition of Corporate Bond Market in Geography and Industry

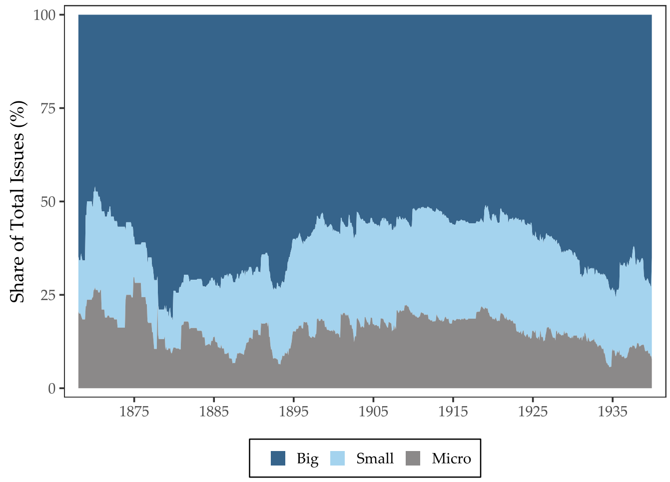


Notes: The figure plots the breakdown of corporate bonds traded on the Brussels Stock Exchange in terms of geography (Panel A.3A and Panel A.3B) and industry (Panel A.3C and Panel A.3D). The relative importance is shown in terms of number of bond issues (Panel A.3A and Panel A.3C) and in terms of relative market capitalization (Panel A.3B and Panel A.3D). *Abroad* denotes bonds issued by Belgian companies with main economic activity abroad, but different from Belgian Congo. *Belgium* denotes bonds issued by Belgian companies whose main economic activity is in Belgium. *Colony* denotes bonds issued by Belgian colonial companies. *Financials* comprise bonds issued by banks, insurance companies, trusts, investment funds, and holding companies. *Non-Financials* comprise bonds issued by companies active in any industry other than *Financials*. The sample period runs from January 1868 through December 1939.

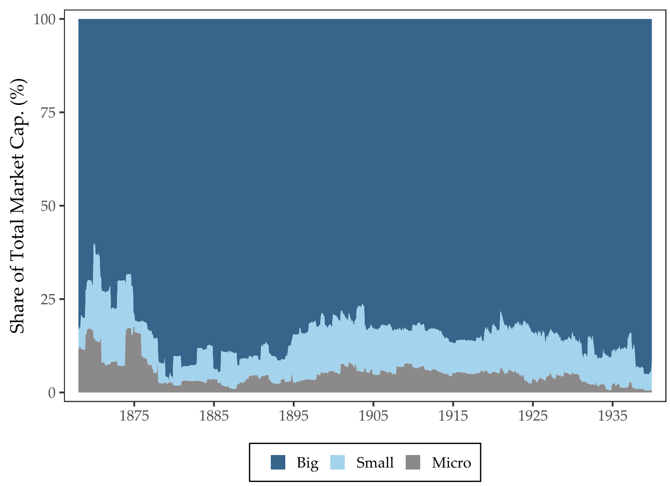
C.4. Firm Size Breakdown of Corporate Bond Market

Figure A.4: Composition of Corporate Bond Market in Firm Size

Panel A – Bond Market Issues: Firm Breakdown



Panel B – Bond Market Size: Firm Breakdown



Notes: The figure plots the breakdown of corporate bonds issued by public firms traded on the Brussels Stock Exchange in terms of firm size. The relative importance is shown in terms of number of bond issues (Panel A.4A) and in terms of relative market capitalization (Panel A.4A). *Micro*, *Small*, and *Big* are dummies that equal to one if a firm belongs to the respective stock market capitalization group. I follow Fama and French (2008) and assign firms to size groups at the end of December each year. *Micro* firms are below the 20th percentile of BSE's stock market capitalization at the end of December, *Small* firms are between the 20th and 50th percentiles, and *Big* firms are above the BSE median. The sample period runs from January 1868 through December 1939.

C.5. *Normality Test of Corporate Bond Returns*

Table A.VI: Normality Test for Corporate Bond Returns

	Skewness		Kurtosis		Normality
	Positive	Negative	Positive	Negative	JB-Stat.
Panel A – Time-Series Distribution of All Corporate Bond Returns					
Total # of Bonds	589	421	954	56	1010
% of Bonds Significant	69.95	63.42	90.46	14.29	84.16
Median p-value	0.00	0.00	0.00	0.00	0.00
% of Bonds Insignificant	30.05	36.58	9.54	85.71	15.84
Panel B – Cross-Sectional Distribution of Monthly Corporate Bond Returns					
Total # of Months	440	424	858	6	864
# of Months Significant	382	375	830	1	836
Median p-value	0.00	0.00	0.00	0.03	0.00
# of Months Insignificant	58	49	28	5	28

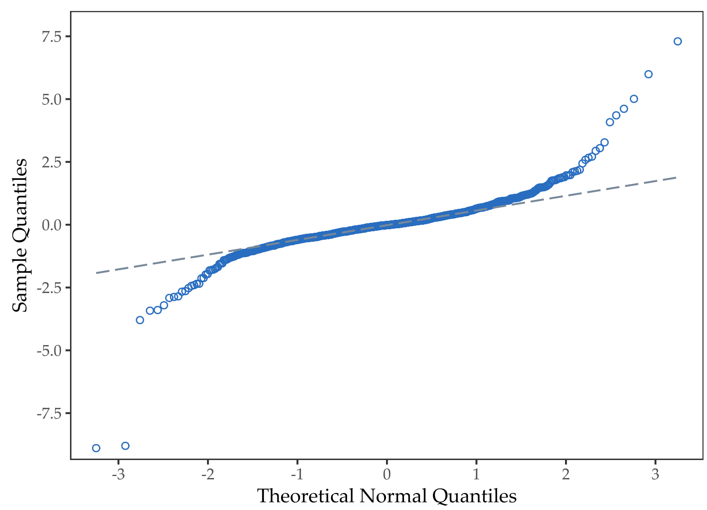
Notes: This table reports normality tests for corporate bond returns. Panel A reports the total number of bonds and the percentage of bonds with significant and insignificant return moments, for the time-series distribution of all corporate bond returns. For each bond in the sample from January 1868 to December 1939, I compute the skewness and excess kurtosis of monthly returns, and then test whether these high-order moments are significantly different from zero. Panel B reports the total number of months and the number of months with significant and insignificant return moments for the cross-sectional distribution of monthly corporate bond returns. For each month from January 1868 to December 1939, I compute the return moments including skewness and kurtosis using the cross-section of bond returns, and test whether these distributional moments are significantly different from zero. The table also reports the Jarque-Bera (JB) statistics for the normality test of the distribution of corporate bond returns. The median p-value is reported to test the statistical significance of the return moments and the significance of the JB statistics.

I explore the normality assumption for my historical bond sample in Internet Appendix Table A.VI. For each bond in the sample from January 1868 to December 1939, I compute the skewness and kurtosis of monthly returns. Skewness measures the asymmetry in return distributions. A positively (negatively) skewed distribution has more large positive (negative) outliers than large negative (positive) outliers of a similar magnitude. Excess kurtosis measures the extent to which we observe extreme realizations in both directions. Under normality, skewness and excess kurtosis equal zero. Panel A of Internet Appendix Table A.VI shows the summary statistics. Panel A tests whether these high-order moments are significantly different from zero based on the time-series distribution of bond returns. Among 1,010 bonds, 589 bonds exhibit positive skewness and 421 bonds exhibit negative skewness. Among the bonds with positive (negative) skewness, 69.95% (63.42%) are statistically significant at the 10% level or better. In addition, the majority of bonds (954 out of 1,010) exhibit positive excess kurtosis, and among these bonds, 90.46% are statistically significant at the 10% level or better. I also conduct the Jarque-Bera (JB) normality test, and the last column of Panel A shows that 84.16% of the bonds in my sample exhibit significant JB statistics, rejecting the null hypothesis of normality at the 10% level or better.

Panel B of Internet Appendix Table A.VI tests whether these high-order moments are significantly different from zero based on the cross-sectional distribution of bond returns. For each month from January 1868 to December 1939, I compute the skewness and excess kurtosis of the cross-sectional observations of bond returns and test whether these distributional moments are significantly different from zero. I find that the JB statistics are significant for 836 out of 864 months in the sample period, rejecting the null hypothesis of normal distribution of the cross-sectional bond returns.

I confirm these result by documenting the lack of normality of corporate bond market returns. Internet Appendix Figure A.5 shows the quantile-quantile plot of value-weighted bond market returns between January 1868 and December 1939. I use the full sample to standardize the market returns. The resulting standardized returns are reflected on the y-axis. The x-axis correspond to the quantiles of a standard normal random variable, depicting how frequently we expect to see an observation of that magnitude on a normal distribution. It is clear that many observations in the tails deviate than what the normality assumption would dictate. Specifically, we see that there is a concentration of normalized returns that are below (above) the 45-degree line, for the lowest (highest) quantiles, indicative of extreme tails in bond returns.

Figure A.5: QQ-Plot of Corporate Bond Market Index

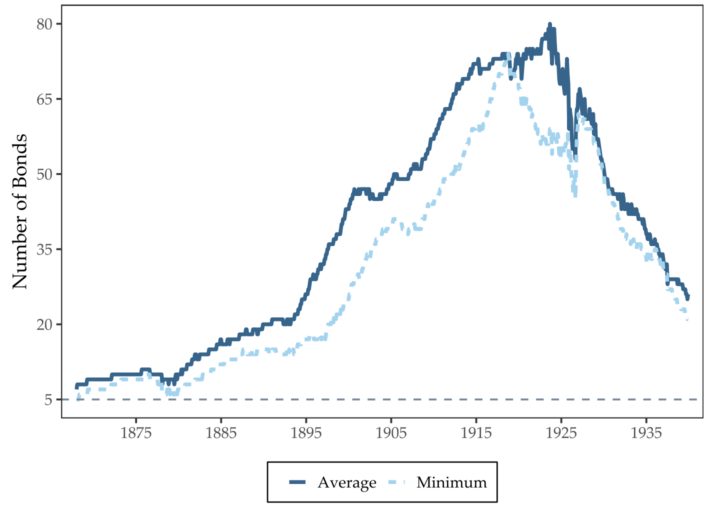


Notes: The figure shows the quantile–quantile (QQ) plot with standard normal random variable on the x-axis and normalized monthly value-weighted returns of the corporate bond market on the y-axis. Normalized returns are returns divided by full period realized volatility. Deviation from the 45-degree line represents deviation from the normal distribution.

Together, these results present novel evidence that corporate bond return distributions deviate significantly from normality.

C.6. Portfolio Size

Figure A.6: Time-Series of the Number of Bonds per Quintile



Notes: The figure plots the average and minimum number of bonds included within univariate quintile portfolios across the main anomaly variables described in Table II. The sample period runs from January 1868 through December 1939.

C.7. *Returns by Calendar Month*

Table A.VII: Anomaly Returns by Calendar Months

	5% VaR	Spread	Age	STR	MOM	LTR	BTM
Jan.	0.44	0.58	0.22	−1.41	−0.19	−0.87	1.00
	(1.33)	(1.98)	(1.28)	(−7.13)	(−0.95)	(−2.77)	(3.46)
Feb.	0.39	0.79	−0.11	−2.36	0.77	0.07	1.02
	(1.43)	(2.60)	(−0.65)	(−11.58)	(2.80)	(0.24)	(3.57)
Mar.	−0.25	0.61	0.38	−1.23	0.37	−0.32	0.00
	(−0.82)	(2.21)	(1.78)	(−5.27)	(1.22)	(−1.25)	(0.01)
Apr.	−0.29	0.24	−0.09	−1.30	0.61	0.45	0.45
	(−1.21)	(0.90)	(−0.56)	(−5.37)	(3.48)	(1.83)	(1.62)
May	0.47	0.76	−0.50	−1.72	0.15	−0.26	0.58
	(1.93)	(2.76)	(−2.35)	(−10.25)	(0.58)	(−1.18)	(2.15)
Jun.	−0.49	0.01	−0.10	−1.33	0.80	0.11	−0.07
	(−2.38)	(0.06)	(−0.63)	(−7.07)	(3.43)	(0.64)	(−0.36)
Jul.	−0.18	−0.34	0.11	−0.85	0.01	−0.21	0.20
	(−0.86)	(−1.87)	(0.80)	(−4.13)	(0.04)	(−1.12)	(0.97)
Aug.	0.57	1.04	−0.04	−2.45	0.77	0.22	0.80
	(2.96)	(4.97)	(−0.28)	(−17.30)	(3.76)	(1.16)	(3.88)
Sep.	0.56	0.71	0.49	−0.90	−0.08	−0.80	0.40
	(1.84)	(2.17)	(2.74)	(−3.87)	(−0.29)	(−2.85)	(1.29)
Oct.	−0.12	−0.22	−0.02	−1.20	0.73	0.06	0.09
	(−0.49)	(−0.65)	(−0.08)	(−4.52)	(3.02)	(0.20)	(0.32)
Nov.	0.58	0.54	0.03	−1.66	0.54	−0.20	0.40
	(2.20)	(1.72)	(0.28)	(−7.93)	(2.39)	(−1.01)	(1.59)
Dec.	0.06	0.45	0.10	−1.75	0.93	−0.01	0.03
	(0.19)	(1.97)	(0.55)	(−9.37)	(3.07)	(−0.03)	(0.11)
Feb.-Dec.	0.12	0.42	0.02	−1.52	0.51	−0.08	0.35
	(1.36)	(4.17)	(0.41)	(−20.84)	(4.89)	(−1.09)	(3.35)
F-Stat.	2.24	2.39	2.10	5.74	2.44	2.35	2.03
	[0.01]	[0.01]	[0.02]	[0.00]	[0.01]	[0.01]	[0.02]

Notes: This table reports monthly raw excess returns for quintile portfolios formed on anomaly variables by calendar month. Quintile portfolios are formed every month from January 1868 to December 1939 by sorting corporate bonds on their downside risk (5% VaR), credit quality (credit spread), illiquidity (bond age), short-term reversal (STR), momentum (MOM), long-term reversal (LTR), and book-to-market (BTM). All sorting variables are defined in Table III. All portfolios are rebalanced at the end of the next month, and their realized return is recorded. Corresponding t-statistics in parentheses are based on Newey and West (1987) standard errors. The F-statistics are computed under the hypothesis that the mean return in January is equal to the mean return in February through December. p-values are in brackets. The sample includes all corporate bonds listed on the Brussels Stock Exchange at portfolio formation. The sample period is January 1868 to December 1939.

C.8. Robustness Checks

Table A.VIII: Returns on Univariate-Sorted Portfolios Using Alternative Measures of Defaulting Bond Returns

	5% VaR		Spread		Age		STR		MOM		LTR		BTM	
Quintile	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α
Panel A – Delisting Return Adjustment of -40%														
Low	−0.02	−0.06	−0.11	−0.20	−0.02	−0.06	0.60	0.51	−0.35	−0.40	0.14	0.06	−0.12	−0.18
	(−0.33)	(−1.86)	(−1.78)	(−7.48)	(−0.33)	(−1.86)	(7.72)	(10.21)	(−3.94)	(−5.25)	(1.46)	(0.80)	(−2.81)	(−6.12)
2	0.06	−0.01	−0.11	0.00	0.06	−0.01	0.35	0.28	−0.07	−0.16	0.10	0.05	−0.03	−0.12
	(1.26)	(−0.51)	(−1.78)	(−0.12)	(1.26)	(−0.52)	(5.04)	(6.04)	(−1.13)	(−5.83)	(1.80)	(1.17)	(−0.65)	(−3.54)
3	0.13	0.05	0.13	0.07	0.13	0.05	0.22	0.10	0.17	0.08	0.06	2.16	−0.03	0.04
	(2.86)	(2.51)	(2.23)	(1.80)	(2.85)	(2.51)	(3.70)	(2.58)	(2.76)	(2.81)	(1.31)	(0.00)	(−0.65)	(1.26)
4	0.12	0.05	0.18	0.12	0.12	0.05	0.03	−0.03	0.30	0.23	0.03	−0.04	0.15	0.04
	(2.08)	(1.85)	(3.29)	(3.70)	(2.08)	(1.85)	(0.59)	(−0.95)	(6.79)	(8.79)	(0.74)	(−1.47)	(2.31)	(1.58)
High	0.05	−0.03	0.28	0.24	0.05	−0.04	−0.93	−1.00	0.09	0.01	0.03	−0.03	0.24	0.18
	(0.49)	(−0.40)	(2.77)	(3.01)	(0.44)	(−0.45)	(−16.05)	(−25.76)	(1.14)	(0.20)	(0.66)	(−1.13)	(2.21)	(2.22)
High-Low	0.07	0.02	0.39	0.43	0.06	0.02	−1.53	−1.51	0.44	0.42	−0.11	−0.09	0.36	0.36
Return/α diff.	(0.68)	(0.27)	(3.95)	(4.50)	(0.63)	(0.23)	(−21.56)	(−21.92)	(4.32)	(3.59)	(−1.32)	(−1.13)	(3.47)	(3.94)
Panel B – Delisting Return Adjustment of -100%														
Low	−0.04	−0.08	−0.13	−0.22	−0.04	−0.08	0.58	0.49	−0.41	−0.47	0.05	−0.02	−0.16	−0.22
	(−0.74)	(−2.21)	(−2.02)	(−6.28)	(−0.74)	(−2.21)	(7.46)	(9.78)	(−4.52)	(−5.80)	(0.44)	(−0.24)	(−3.05)	(−4.88)
2	0.05	−0.02	−0.13	−0.04	0.05	−0.02	0.29	0.23	−0.09	−0.17	0.06	0.01	−0.05	−0.13
	(1.00)	(−0.94)	(−2.02)	(−0.87)	(1.01)	(−0.94)	(2.72)	(2.59)	(−1.37)	(−5.90)	(0.87)	(0.14)	(−0.88)	(−3.73)
3	0.12	0.05	0.08	0.03	0.12	0.05	0.18	0.07	0.16	0.07	0.04	−0.03	−0.05	0.02
	(2.66)	(2.08)	(0.99)	(0.48)	(2.66)	(2.07)	(2.69)	(1.32)	(2.54)	(2.38)	(0.70)	(−0.66)	(−0.88)	(0.73)
4	0.10	0.03	0.15	0.09	0.10	0.03	0.02	−0.04	0.29	0.23	0.02	−0.06	0.14	0.03
	(1.59)	(0.83)	(2.68)	(2.53)	(1.59)	(0.83)	(0.43)	(−1.19)	(6.71)	(8.62)	(0.33)	(−1.92)	(2.07)	(1.04)
High	−0.09	−0.16	0.20	0.16	−0.09	−0.17	−0.97	−1.04	0.00	−0.08	0.00	−0.07	0.13	0.08
	(−0.57)	(−1.24)	(1.87)	(1.89)	(−0.59)	(−1.27)	(−16.03)	(−23.42)	(−0.03)	(−0.83)	(−0.05)	(−1.94)	(0.97)	(0.65)
High-Low	−0.05	−0.09	0.32	0.37	−0.05	−0.09	−1.55	−1.53	0.41	0.39	−0.05	−0.04	0.29	0.30
Return/α diff.	(−0.33)	(−0.67)	(3.25)	(3.80)	(−0.37)	(−0.70)	(−20.92)	(−21.23)	(3.53)	(2.99)	(−0.49)	(−0.41)	(2.16)	(2.37)
Panel C – Price Floor of 40% of Face Value														
Low	0.02	−0.02	−0.09	−0.18	0.02	−0.02	0.68	0.59	−0.21	−0.27	0.25	0.16	−0.09	−0.15
	(0.44)	(−0.78)	(−1.50)	(−7.24)	(0.45)	(−0.77)	(9.27)	(12.14)	(−2.70)	(−4.67)	(3.10)	(3.33)	(−2.21)	(−5.95)
2	0.06	−0.01	−0.09	0.02	0.06	−0.01	0.41	0.33	−0.02	−0.11	0.17	0.12	−0.04	−0.12
	(1.38)	(−0.42)	(−1.50)	(0.81)	(1.38)	(−0.42)	(7.16)	(11.69)	(−0.39)	(−4.01)	(3.27)	(3.53)	(−0.71)	(−3.57)
3	0.14	0.06	0.18	0.11	0.14	0.06	0.28	0.17	0.21	0.12	0.09	0.03	−0.04	0.05
	(3.08)	(2.93)	(3.26)	(3.32)	(3.08)	(2.93)	(5.24)	(5.28)	(3.53)	(3.92)	(1.98)	(0.93)	(−0.71)	(1.96)
4	0.14	0.07	0.22	0.16	0.14	0.07	0.05	−0.02	0.30	0.24	0.05	−0.03	0.15	0.05
	(2.51)	(2.95)	(4.04)	(4.86)	(2.51)	(2.95)	(1.02)	(−0.50)	(7.07)	(9.09)	(1.17)	(−1.03)	(2.38)	(1.82)
High	0.29	0.19	0.58	0.52	0.29	0.19	−0.88	−0.96	0.18	0.10	0.08	0.02	0.48	0.40
	(3.95)	(4.05)	(6.69)	(8.02)	(3.95)	(4.05)	(−15.13)	(−26.32)	(2.81)	(2.74)	(1.92)	(0.72)	(4.88)	(6.57)
High-Low	0.27	0.21	0.66	0.69	0.27	0.21	−1.56	−1.55	0.38	0.36	−0.18	−0.15	0.56	0.55
Return/α diff.	(4.55)	(4.00)	(7.87)	(8.08)	(4.55)	(3.99)	(−23.57)	(−23.38)	(4.67)	(4.56)	(−2.99)	(−2.62)	(6.05)	(7.55)

Notes: This table reports monthly raw excess returns and alphas for quintile portfolios formed on anomaly variables. Quintile portfolios are formed every month from January 1868 to December 1939 by sorting corporate bonds on their downside risk (5% VaR), credit quality (credit spread), illiquidity (bond age), short-term reversal (STR), momentum (MOM), long-term reversal (LTR), and book-to-market (BTM). All sorting variables are defined in Table III. All portfolios are rebalanced at the end of the next month, and their realized return is recorded. Panel A uses default returns of -40% for bonds that default in the formation month t. Panel B uses default returns of -100% for bonds that default in the formation month t. I follow Moody's corporate bond default definition and flag any bond that delists within three months following (i) a missed coupon payment, (ii) a change in face value or coupon rate, (iii) a distressed exchange, or (iv) either a bankruptcy filing or creditor composition. Panel C of the table eliminates all bonds priced below 40% of face value in the formation month t. For each quintile portfolio, I report the value-weighted average monthly excess return and six-factor alpha obtained from combining the Fama and French (1993) bond model (composed of $TERM$, and DEF) and Carhart (1997) stock model (composed of MKT^{Stock}, SMB, HML, and UMD^{Stock}). The construction of set factors is explained in Internet Appendix B. The last row reports differences in returns and alphas between quintile 5 ("High") and quintile 1 ("Low"). Corresponding t-statistics in parentheses are based on Newey and West (1987) standard errors. The sample includes all corporate bonds listed on the Brussels Stock Exchange at portfolio formation.

Table A.IX: Duration-Matched Returns on Univariate-Sorted Portfolios of Corporate Bonds

	Panel A: Downside Risk				Panel B: Credit Quality				Panel C: Illiquidity			
Quintile	$\mathbb{E}[R]$	1F α	4F α	5F α	$\mathbb{E}[R]$	1F α	4F α	5F α	$\mathbb{E}[R]$	1F α	4F α	5F α
Low	0.07	−0.05	0.08	−0.05	−0.07	−0.22	−0.09	−0.25	0.07	−0.05	0.08	−0.05
	(2.24)	(−1.86)	(2.26)	(−1.46)	(−1.56)	(−7.72)	(−1.91)	(−10.09)	(2.24)	(−1.86)	(2.26)	(−1.46)
2	0.14	0.00	0.13	−0.01	0.18	0.02	0.16	0.01	0.14	0.00	0.13	−0.01
	(5.60)	(0.13)	(4.46)	(−0.43)	(5.51)	(0.93)	(4.11)	(0.34)	(5.60)	(0.13)	(4.46)	(−0.44)
3	0.21	0.08	0.19	0.07	0.27	0.13	0.26	0.13	0.21	0.00	0.19	0.07
	(7.39)	(4.18)	(6.83)	(2.69)	(7.31)	(4.51)	(7.12)	(3.97)	(7.39)	(0.13)	(6.83)	(2.69)
4	0.21	0.06	0.21	0.07	0.34	0.22	0.36	0.24	0.21	0.06	0.21	0.07
	(5.75)	(2.69)	(5.43)	(2.62)	(7.84)	(6.19)	(8.69)	(6.61)	(5.75)	(2.69)	(5.43)	(2.62)
High	0.23	0.03	0.23	0.04	0.50	0.33	0.54	0.38	0.23	0.03	0.23	0.04
	(2.79)	(0.43)	(3.09)	(0.63)	(5.31)	(3.94)	(6.81)	(4.95)	(2.74)	(0.37)	(3.06)	(0.59)
High-Low	0.16	0.08	0.15	0.09	0.57	0.55	0.63	0.63	0.16	0.08	0.15	0.09
Return/α diff.	(1.95)	(1.02)	(2.07)	(1.16)	(5.26)	(5.75)	(6.81)	(6.63)	(1.89)	(0.97)	(2.02)	(1.12)

	Panel D: Short-Term Reversal				Panel E: Momentum				Panel F: Long-Term Reversal			
Quintile	$\mathbb{E}[R]$	1F α	4F α	5F α	$\mathbb{E}[R]$	1F α	4F α	5F α	$\mathbb{E}[R]$	1F α	4F α	5F α
Low	0.70	0.54	0.70	0.54	−0.22	−0.43	−0.19	−0.39	0.27	0.10	0.26	0.10
	(11.08)	(11.51)	(10.90)	(10.45)	(−3.03)	(−5.83)	(−2.83)	(−5.06)	(3.60)	(1.53)	(3.64)	(1.48)
2	0.46	0.33	0.45	0.33	0.02	−0.14	0.01	−0.15	0.20	0.06	0.21	0.07
	(11.57)	(10.46)	(11.33)	(10.32)	(0.49)	(−5.13)	(0.26)	(−5.06)	(5.42)	(1.59)	(5.74)	(2.04)
3	0.31	0.13	0.29	0.12	0.26	0.12	0.23	0.10	0.15	0.01	0.15	0.01
	(6.66)	(3.16)	(5.84)	(3.31)	(5.93)	(4.49)	(4.91)	(3.43)	(4.98)	(0.41)	(4.08)	(0.36)
4	0.11	−0.03	0.11	−0.03	0.37	0.25	0.36	0.24	0.13	0.00	0.11	−0.02
	(3.06)	(−1.04)	(2.65)	(−0.93)	(10.40)	(8.34)	(9.35)	(7.73)	(4.09)	(−0.15)	(3.30)	(−0.72)
High	−0.82	−0.99	−0.83	−0.99	0.22	0.09	0.21	0.08	0.13	0.00	0.11	−0.01
	(−18.44)	(−26.52)	(−17.36)	(−23.92)	(4.15)	(1.95)	(3.90)	(1.87)	(3.29)	(−0.03)	(2.71)	(−0.32)
High-Low	−1.52	−1.52	−1.53	−1.54	0.44	0.52	0.39	0.47	−0.15	−0.10	−0.15	−0.11
Return/α diff.	(−20.58)	(−20.96)	(−19.94)	(−19.08)	(4.58)	(6.31)	(4.60)	(4.35)	(−1.94)	(−1.31)	(−1.95)	(−1.38)

	Panel G: Book-to-Market			
Quintile	$\mathbb{E}[R]$	1F α	4F α	5F α
Low	0.01	−0.10	0.00	−0.11
	(0.51)	(−4.02)	(−0.04)	(−4.26)
2	0.08	−0.05	0.07	−0.06
	(2.23)	(−1.66)	(1.60)	(−2.01)
3	0.20	0.05	0.20	0.05
	(4.72)	(1.72)	(4.62)	(1.76)
4	0.21	0.03	0.19	0.02
	(4.73)	(1.19)	(4.08)	(0.57)
High	0.38	0.15	0.41	0.20
	(4.20)	(1.91)	(5.29)	(2.79)
High-Low	0.36	0.25	0.41	0.31
Return/α diff.	(3.64)	(2.74)	(4.95)	(3.88)

Notes: This table reports monthly raw excess returns and alphas for quintile portfolios formed on anomaly variables, after adjusting for duration-matched Treasury returns. Quintile portfolios are formed every month from January 1868 to December 1939 by sorting corporate bonds on their downside risk (Panel A), credit quality (Panel B), illiquidity (Panel C), short-term reversal (Panel D), momentum (Panel E), long-term reversal (Panel F), and book-to-market (Panel G). All sorting variables are defined in Table III. For each quintile portfolio, I report the value-weighted average monthly excess return, one-factor alpha obtained from the Kelly, Palhares, and Pruitt (2022) and Binsbergen and Schwert (2022) duration-adjusted bond CAPM model (composed of $MKT^{Bond}_{Dur.adj.}$), four-factor alpha obtained from the Carhart (1997) stock model (composed of MKT^{Stock}, SMB, HML, and UMD^{Stock}) and five-factor alpha obtained from combining the respective models. The last row reports differences in returns and alphas between quintile 5 ("High") and quintile 1 ("Low"). Corresponding t-statistics in parentheses are based on Newey and West (1987) standard errors. The sample includes all corporate bonds listed on the Brussels Stock Exchange at portfolio formation.

Table A.X: Bond-Level Fama-MacBeth Cross-Sectional Regressions Using Duration-Matched Returns

	Int.	5% VaR	Spread	Age	STR	MOM	LTR	BTM	$\beta^{Bond}_{Dur.adj.}$	Maturity	Size	Adj. $\overline{R^2}$	T	N
(1)	0.17	0.07										0.04	864	148,586
	(5.34)	(1.55)												
(2)	0.19	0.07							0.03	−0.08	0.01	0.11	864	148,586
	(6.36)	(1.58)							(0.96)	(−4.95)	(0.90)			
(3)	0.26		0.28									0.04	864	179,702
	(7.70)		(6.31)											
(4)	0.23		0.29						0.01	0.01	0.03	0.11	864	157,636
	(7.45)		(5.29)						(0.31)	(0.79)	(2.18)			
(5)	0.17			0.04								0.01	864	180,397
	(6.05)			(2.17)										
(6)	0.18			0.00					0.07	−0.07	−0.01	0.08	864	158,316
	(6.40)			(0.11)					(2.13)	(−3.45)	(−0.49)			
(7)	0.16				−0.70							0.09	864	180,397
	(4.91)				(−17.68)									
(8)	0.19				−0.74				0.09	−0.07	0.00	0.16	864	158,316
	(6.68)				(−17.26)				(2.13)	(−3.75)	(−0.16)			
(9)	0.14					0.15						0.04	864	169,652
	(4.20)					(3.33)								
(10)	0.18					0.14			0.09	−0.09	0.00	0.11	864	158,261
	(6.19)					(2.50)			(2.53)	(−4.60)	(0.07)			
(11)	0.17						−0.10					0.03	864	137,496
	(5.52)						(−2.83)							
(12)	0.20						−0.09		0.04	−0.08	0.00	0.11	864	137,496
	(6.89)						(−2.83)		(1.29)	(−4.52)	(0.15)			
(13)	0.22							0.44				0.04	864	181,379
	(6.30)							(4.34)						
(14)	0.23							0.42	0.01	−0.11	0.02	0.11	864	158,321
	(7.27)							(4.25)	(0.23)	(−5.24)	(1.52)			
(15)	0.25	0.04	0.18	0.02	−0.80	0.00	0.00	0.01				0.24	864	136,806
	(7.83)	(1.19)	(3.99)	(0.98)	(−19.12)	(0.02)	(0.12)	(0.17)						
(16)	0.25	0.03	0.19	0.01	−0.80	0.00	0.01	0.01	0.03	0.00	0.00	0.29	864	136,806
	(8.10)	(0.79)	(3.71)	(0.69)	(−16.87)	(−0.06)	(0.25)	(0.16)	(1.03)	(−0.16)	(0.39)			

Notes: This table reports average intercept and slope coefficients from Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead corporate bond excess returns after adjusting for duration-matched Treasury returns against a constant and a series of bond characteristics. Bond characteristics are measured at the end of month t over my sample period from January 1868 to December 1939. All independent variables are defined in Table III and are standardized to have zero mean and unit variance in each month to ease the interpretation of the estimated coefficients. The table presents the time-series averages of the cross-sectional regression coefficients; intercept and slope coefficients (both multiplied by 100). The corresponding t-statistics in parentheses are based on Newey and West (1987) standard errors to determine the statistical significance of the average intercept and slope coefficients. The last columns report the average adjusted cross-sectional coefficient of determination, $\overline{R^2}$, of the regressions and the number of observations, N, respectively.

Table A.XI: Returns on Univariate-Sorted Portfolios Using Volatility-Scaled Bond Returns

	5% VaR		Spread		Age		STR		MOM		LTR		BTM	
Quintile	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α
Low	0.02	−0.01	−0.06	−0.11	0.02	−0.01	0.38	0.33	−0.18	−0.22	0.12	0.07	−0.04	−0.08
	(0.62)	(−0.53)	(−1.54)	(−7.69)	(0.62)	(−0.53)	(7.69)	(9.78)	(−3.38)	(−4.94)	(2.17)	(1.79)	(−1.71)	(−5.82)
2	0.05	0.00	0.07	0.01	0.05	0.00	0.25	0.20	−0.03	−0.08	0.10	0.06	−0.01	−0.06
	(1.65)	(0.34)	(2.26)	(0.90)	(1.65)	(0.34)	(7.19)	(11.28)	(−0.72)	(−4.98)	(2.99)	(2.96)	(−0.25)	(−3.02)
3	0.09	0.05	0.11	0.06	0.09	0.05	0.16	0.09	0.13	0.07	0.06	0.03	0.09	0.04
	(3.26)	(3.34)	(3.11)	(3.07)	(3.26)	(3.34)	(4.45)	(4.52)	(3.49)	(3.91)	(2.26)	(1.49)	(2.43)	(2.13)
4	0.11	0.06	0.12	0.09	0.11	0.06	0.03	−0.01	0.20	0.16	0.04	−0.01	0.11	0.05
	(3.18)	(4.42)	(3.65)	(4.27)	(3.18)	(4.42)	(0.95)	(−0.36)	(7.69)	(10.98)	(1.28)	(−0.61)	(2.69)	(2.53)
High	0.09	0.03	0.21	0.18	0.09	0.03	−0.54	−0.59	0.11	0.07	0.06	0.02	0.18	0.14
	(1.53)	(0.82)	(3.32)	(3.72)	(1.53)	(0.82)	(−14.25)	(−24.48)	(2.85)	(2.99)	(2.08)	(1.11)	(2.70)	(3.01)
High-Low	0.07	0.04	0.27	0.30	0.07	0.04	−0.92	−0.91	0.30	0.29	−0.06	−0.05	0.22	0.21
Return/α diff.	(1.43)	(0.95)	(4.36)	(4.92)	(1.43)	(0.95)	(−22.49)	(−21.48)	(5.39)	(4.84)	(−1.45)	(−1.24)	(3.71)	(4.07)

Notes: This table reports voltility-scaled monthly raw excess returns and alphas for quintile portfolios formed on anomaly variables. Quintile portfolios are formed every month from January 1868 to December 1939 by sorting corporate bonds on their downside risk (5% VaR), credit quality (credit spread), illiquidity (bond age), short-term reversal (STR), momentum (MOM), long-term reversal (LTR), and book-to-market (BTM). All sorting variables are defined in Table III. All portfolios are rebalanced at the end of the next month, and their realized return is recorded. The volatility-managed portfolio scales the portfolio by scaling individual constituent bonds by the inverse of the bonds' "Duration times Spread (DtS)," in the previous month. DtS is set at a minimum of 0.3, meaning that low volatility bonds are essentially unscaled being all divided by the same number. For each quintile portfolio, I report the value-weighted average scaled monthly excess return and six-factor alpha obtained from combining the Fama and French (1993) bond model (composed of $TERM$, and DEF) and Carhart (1997) stock model (composed of MKT^{Stock}, SMB, HML, and UMD^{Stock}). The construction of set factors is explained in Internet Appendix B. The last row reports differences in returns and alphas between quintile 5 ("High") and quintile 1 ("Low"). Corresponding t-statistics in parentheses are based on Newey and West (1987) standard errors. The sample includes all corporate bonds listed on the Brussels Stock Exchange at portfolio formation.

Table A.XII: Bond-Level Fama-MacBeth Cross-Sectional Regressions Using Volatility-Scaled Returns

	Int.	5% VaR	Spread	Age	STR	MOM	LTR	BTM	β^{Bond}	β^{TERM}	β^{DEF}	Maturity	Size	Adj. $\overline{R^2}$	T	N
(1)	0.07	0.02												0.04	864	147,913
	(2.23)	(0.60)														
(2)	0.06	0.02							0.00	0.07	−0.03	−0.02	0.01	0.21	864	147,913
	(2.21)	(0.85)							(0.14)	(2.07)	(−0.90)	(−2.11)	(1.18)			
(3)	0.10		0.14											0.03	864	179,702
	(3.02)		(5.03)													
(4)	0.08		0.14						0.00	0.07	−0.04	0.02	0.02	0.20	864	157,636
	(2.48)		(4.49)						(0.17)	(2.26)	(−1.34)	(1.46)	(2.24)			
(5)	0.07			0.01										0.01	864	179,702
	(2.31)			(0.65)												
(6)	0.06			0.01					0.01	0.08	−0.04	−0.01	0.00	0.18	864	157,636
	(2.07)			(1.28)					(0.44)	(2.34)	(−1.02)	(−0.69)	(0.38)			
(7)	0.06				−0.42									0.09	864	179,702
	(1.87)				(−18.62)											
(8)	0.06				−0.42				0.02	0.08	−0.04	−0.02	0.01	0.24	864	157,636
	(2.13)				(−15.93)				(0.67)	(2.01)	(−0.98)	(−1.62)	(0.57)			
(9)	0.05					0.11								0.04	864	168,958
	(1.49)					(4.41)										
(10)	0.05					0.06			0.02	0.05	−0.01	−0.02	0.01	0.20	864	157,578
	(1.91)					(2.07)			(0.94)	(1.59)	(−0.32)	(−1.97)	(0.88)			
(11)	0.07						−0.04							0.03	864	136,845
	(2.37)						(−1.98)									
(12)	0.07						−0.03		−0.02	0.09	−0.03	−0.02	0.00	0.21	864	136,845
	(2.55)						(−1.91)		(−0.73)	(2.61)	(−0.72)	(−1.76)	(0.09)			
(13)	0.08							0.13						0.04	864	179,702
	(2.24)							(3.94)								
(14)	0.07							0.12	0.01	0.08	−0.06	−0.03	0.02	0.20	864	157,636
	(2.32)							(3.69)	(0.67)	(2.51)	(−1.77)	(−2.93)	(2.15)			
(15)	0.10	0.03	0.06	0.00	−0.50	8.12	0.00	0.03						0.24	864	136,806
	(3.18)	(1.34)	(2.35)	(−0.22)	(−19.15)	(0.00)	(0.01)	(0.78)								
(16)	0.09	0.02	0.08	−0.01	−0.46	−0.02	0.01	0.01	0.01	0.06	−0.05	0.00	0.01	0.36	864	136,806
	(3.10)	(0.82)	(2.64)	(−0.44)	(−12.98)	(−0.60)	(0.46)	(0.20)	(0.31)	(1.77)	(−1.24)	(−0.03)	(1.16)			

Notes: This table reports average intercept and slope coefficients from Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead corporate bond excess returns against a constant and a series of bond characteristics. Bond characteristics are measured at the end of month t over my sample period from January 1868 to December 1939. All independent variables are defined in Table III and are standardized to have zero mean and unit variance in each month to ease the interpretation of the estimated coefficients. Observations are weighted by the inverse of the bonds' "Duration times Spread (DtS)," in the previous month. DtS is set at a minimum of 0.3, meaning that low volatility bonds are essentially unscaled being all divided by the same number. The table presents the time-series averages of the cross-sectional regression coefficients; intercept and slope coefficients (both multiplied by 100). The corresponding t-statistics in parentheses are based on Newey and West (1987) standard errors to determine the statistical significance of the average intercept and slope coefficients. The last columns report the average adjusted cross-sectional coefficient of determination, $\overline{R^2}$, of the regressions, the number of time periods, T, and the number of observations, N, respectively.

Table A.XIII: Returns on Univariate-Sorted Portfolios Excluding Great Depression

	5% VaR		Spread		Age		STR		MOM		LTR		BTM	
Quintile	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α
Low	0.00	−0.07	−0.06	−0.14	0.07	−0.01	0.55	0.48	−0.35	−0.43	0.18	0.06	−0.07	−0.14
	(−0.09)	(−2.87)	(−1.03)	(−4.74)	(1.18)	(−0.46)	(6.84)	(9.21)	(−3.66)	(−4.87)	(1.84)	(0.88)	(−1.61)	(−5.84)
2	0.07	−0.02	0.11	0.04	0.04	−0.06	0.43	0.36	−0.09	−0.17	0.10	0.03	−0.02	−0.10
	(1.43)	(−0.74)	(2.35)	(1.32)	(0.59)	(−1.98)	(6.88)	(11.34)	(−1.41)	(−6.05)	(1.83)	(1.20)	(−0.46)	(−2.95)
3	0.11	0.04	0.16	0.09	0.10	0.01	0.26	0.16	0.21	0.13	0.07	−0.01	0.13	0.06
	(2.47)	(1.97)	(2.70)	(2.24)	(1.93)	(0.59)	(4.02)	(3.91)	(3.92)	(4.83)	(1.29)	(−0.37)	(2.09)	(1.98)
4	0.12	0.04	0.16	0.09	0.08	0.01	0.08	0.00	0.32	0.24	0.04	−0.04	0.14	0.04
	(2.12)	(1.82)	(2.96)	(2.89)	(1.64)	(0.21)	(1.47)	(−0.06)	(7.69)	(9.43)	(0.76)	(−1.85)	(2.19)	(1.32)
High	0.14	0.02	0.25	0.18	0.09	0.03	−0.94	−1.04	0.16	0.09	0.05	−0.02	0.25	0.16
	(1.37)	(0.31)	(2.32)	(2.43)	(2.77)	(1.26)	(−15.63)	(−29.39)	(2.28)	(1.75)	(1.26)	(−0.57)	(2.24)	(2.30)
High-Low	0.14	0.09	0.31	0.33	0.02	0.05	−1.50	−1.51	0.52	0.52	−0.13	−0.08	0.32	0.30
Return/α diff.	(1.53)	(1.10)	(2.96)	(3.54)	(0.48)	(1.08)	(−19.14)	(−23.97)	(4.70)	(4.18)	(−1.49)	(−0.95)	(2.90)	(3.44)

Notes: This table reports monthly raw excess returns and alphas for quintile portfolios formed on anomaly variables. Quintile portfolios are formed every month from January 1868 to December 1928, exluding the Great Depression era (1929–1939). All sorting variables are defined in Table III. For each quintile portfolio, I report the value-weighted average monthly excess return and six-factor alpha obtained from combining the Fama and French (1993) bond model (composed of $TERM$, and DEF) and Carhart (1997) stock model (composed of MKT^{Stock}, SMB, HML, and UMD^{Stock}). The construction of set factors is explained in Internet Appendix B. The last row reports differences in returns and alphas between quintile 5 ("High") and quintile 1 ("Low"). Corresponding t-statistics in parentheses are based on Newey and West (1987) standard errors. The sample includes all corporate bonds listed on the Brussels Stock Exchange at portfolio formation.

Table A.XIV: Returns on Univariate-Sorted Portfolios Including Transaction Costs

		$\mathbb{E}[R]$ After Trading Cost				α After Trading Cost			
Quintile	$\lvert\Delta w\rvert$	0 bps.	10 bps.	19 bps.	44 bps.	0 bps.	10 bps.	19 bps.	44 bps.
Panel A – Downside Risk									
Low	0.09	0.00	−0.01	−0.02	−0.04	−0.04	−0.05	−0.06	−0.08
		(0.01)	(−0.19)	(−0.37)	(−0.86)	(−1.47)	(−1.79)	(−2.08)	(−2.86)
High	0.11	0.14	0.13	0.12	0.10	0.06	0.05	0.04	0.01
		(1.54)	(1.43)	(1.33)	(1.04)	(0.82)	(0.67)	(0.53)	(0.14)
High-Low		0.14	0.14	0.14	0.14	0.10	0.10	0.09	0.09
Return/α diff.		(1.71)	(1.69)	(1.68)	(1.64)	(1.31)	(1.29)	(1.27)	(1.22)
Panel B – Credit Quality									
Low	0.09	−0.09	−0.10	−0.11	−0.13	−0.18	−0.19	−0.20	−0.22
		(−1.54)	(−1.68)	(−1.82)	(−2.18)	(−7.69)	(−7.96)	(−8.22)	(−8.88)
High	0.17	0.34	0.32	0.31	0.27	0.29	0.28	0.26	0.22
		(3.32)	(3.16)	(3.02)	(2.62)	(3.72)	(3.52)	(3.33)	(2.81)
High-Low		0.43	0.42	0.42	0.40	0.48	0.47	0.46	0.44
Return/α diff.		(4.36)	(4.28)	(4.15)	(3.94)	(4.92)	(4.84)	(4.77)	(4.56)
Panel C – Illiquidity									
Low	0.08	0.07	0.06	0.05	0.03	−0.02	−0.03	−0.04	−0.06
		(1.11)	(0.98)	(0.87)	(0.55)	(−1.08)	(−1.41)	(−1.71)	(−2.54)
High	0.05	0.11	0.10	0.10	0.08	0.05	0.05	0.04	0.03
		(3.11)	(2.97)	(2.84)	(2.49)	(1.82)	(1.66)	(1.51)	(1.11)
High-Low		0.04	0.04	0.04	0.05	0.08	0.08	0.08	0.09
Return/α diff.		(0.76)	(0.82)	(0.87)	(1.02)	(1.86)	(1.93)	(1.99)	(2.16)
Panel D – Short-Term Reversal									
Low	0.87	0.61	0.53	0.45	0.23	0.52	0.44	0.36	0.14
		(7.74)	(6.64)	(5.65)	(2.90)	(10.38)	(8.64)	(7.07)	(2.75)
High	0.85	−0.90	−0.99	−1.06	−1.28	−0.98	−1.06	−1.14	−1.35
		(−15.23)	(−16.62)	(−17.86)	(−21.26)	(−25.94)	(−28.02)	(−30.01)	(−35.01)
High-Low		−1.51	−1.51	−1.51	−1.50	−1.50	−1.50	−1.50	−1.49
Return/α diff.		(−21.40)	(−21.31)	(−21.22)	(−20.97)	(−21.80)	(−21.71)	(−21.63)	(−20.98)
Panel E – Momentum									
Low	0.46	−0.31	−0.35	−0.39	−0.51	−0.36	−0.41	−0.45	−0.57
		(−3.48)	(−4.00)	(−4.46)	(−5.72)	(−4.70)	(−5.26)	(−5.75)	(−7.19)
High	0.49	0.14	0.10	0.05	−0.07	0.07	0.02	−0.02	−0.15
		(2.09)	(1.38)	(0.75)	(−0.98)	(1.52)	(0.45)	(−0.51)	(−3.18)
High-Low		0.45	0.45	0.45	0.44	0.43	0.43	0.43	0.42
Return/α diff.		(4.59)	(4.56)	(4.53)	(4.43)	(3.91)	(3.87)	(3.84)	(3.75)
Panel F – Long-Term Reversal									
Low	0.23	0.20	0.18	0.15	0.10	0.11	0.09	0.07	0.01
		(2.14)	(1.89)	(1.67)	(1.05)	(1.68)	(1.33)	(1.02)	(0.16)
High	0.24	0.05	0.03	0.00	−0.06	−0.01	−0.03	−0.06	−0.12
		(1.16)	(0.61)	(0.11)	(−1.27)	(−0.34)	(−1.21)	(−1.98)	(−4.05)
High-Low		−0.15	−0.15	−0.15	−0.15	−0.12	−0.12	−0.12	−0.13
Return/α diff.		(−1.93)	(−1.94)	(−1.95)	(−1.96)	(−1.65)	(−1.67)	(−1.69)	(−1.73)
Panel G – Book-to-Market									
Low	0.16	−0.09	−0.11	−0.12	−0.16	−0.15	−0.17	−0.18	−0.22
		(−2.31)	(−2.70)	(−3.00)	(−3.90)	(−6.24)	(−6.84)	(−7.38)	(−8.66)
High	0.14	0.32	0.30	0.29	0.26	0.25	0.24	0.22	0.19
		(2.85)	(2.72)	(2.61)	(2.31)	(3.37)	(3.19)	(3.03)	(2.58)
High-Low		0.41	0.41	0.41	0.42	0.40	0.41	0.41	0.41
Return/α diff.		(3.91)	(3.94)	(3.96)	(4.02)	(4.72)	(4.75)	(4.78)	(4.86)

Notes: This table reports average absolute change in monthly weights ($\lvert\Delta w\rvert$), monthly raw excess returns ($\mathbb{E}[R]$), and alphas (α) for the most extreme quintile portfolios when including transaction costs. Quintile portfolios are formed every month from January 1868 to December 1939 by sorting corporate bonds on their downside risk (Panel A), credit quality (Panel B), illiquidity (Panel C), short-term reversal (Panel D), momentum (Panel E), long-term reversal (Panel F), and book-to-market (Panel G). All sorting variables are defined in Table III. I report the effect of four sets of trading costs. The first trading cost of zero bps. represents the base case as used throughout the paper. The 10 bps. trading cost comes from Bastiné (1876, p.296), the 19 bps. from Choi, Huh, and Shin (2022), and the 44 bps. from François-Marsal (1931, p. 588). For each quintile portfolio, I report the value-weighted average monthly excess return and six-factor alpha obtained from combining the Fama and French (1993) bond model (composed of $TERM$, and DEF) and Carhart (1997) stock model (composed of MKT^{Stock}, SMB, HML, and UMD^{Stock}). The construction of set factors is explained in Internet Appendix B. The last row reports differences in returns and alphas between quintile 5 ("High") and quintile 1 ("Low"). Corresponding t-statistics in parentheses are based on Newey and West (1987) standard errors. The sample includes all corporate bonds listed on the Brussels Stock Exchange at portfolio formation.

Table A.XV: Descriptive Statistics for Industry Portfolios

#	Industry Group	Dating			Portfolio Size			Portfolio Return			
		Start	End	Obs.	Mean	Min.	Max.	Mean	SD	Min.	Max.
1	Metals	1868:01	1939:12	34,037	41	3	99	0.33	1.50	−11.54	11.14
2	Mining	1868:01	1939:12	21,436	25	3	57	0.35	1.66	−13.54	9.70
3	Railroads	1868:01	1939:12	26,240	30	9	48	0.29	1.85	−26.03	9.97
4	Utilities	1870:07	1939:12	21,440	26	3	62	0.34	1.66	−11.93	10.62
5	Trams	1876:10	1939:12	35,665	47	3	99	0.29	1.65	−11.49	10.17
6	Glass	1877:06	1929:04	3,986	6	3	11	0.39	1.71	−10.15	12.89
7	Financials	1880:04	1939:12	12,519	17	3	34	0.33	1.38	−12.53	9.65
8	Construction	1880:09	1939:12	4,975	8	3	16	0.18	2.37	−29.44	10.79
9	Transport Misc.	1881:05	1928:12	561	4	3	6	0.02	4.59	−18.87	22.72
10	Textiles	1884:07	1939:12	7,979	12	3	25	0.42	1.80	−6.75	30.97
11	Industrials	1893:05	1939:12	4,715	8	4	15	0.35	2.17	−13.82	20.10
12	Chemicals	1896:10	1939:12	5,861	11	3	19	0.29	2.68	−16.57	16.62
	Total	1868:01	1939:12	179,414	208	39	433				

Notes: This table reports summary statistics for 12 industry portfolios. The value-weighted industry portfolios are formed by sorting corporate bonds into 12 portfolios based on the historical four-digit NACE industry classification of Annaert, Buelens, and De Ceuster (2012). When building industry portfolios, their size is set to a minimum of three corporate bonds concurrently listed in month t and a minimum of 500 bond-month observations ought to be accrued across the entire sample period before the classification thereof is included. The sample includes all corporate bonds listed on the Brussels Stock Exchange at portfolio formation that adhere to these requirements. The final row shows the total sample after the enforcement of these sample requirements, the difference of which with Table III gives indication of the small subset of discarded data.

Table A.XVI: Returns on Industry-Adjusted Univariate-Sorted Portfolios

Quintile	5% VaR		Spread		Age		STR		MOM		LTR		BTM	
	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α
Low	0.01	−0.03	−0.07	−0.15	0.08	−0.02	0.61	0.52	−0.18	−0.24	0.22	0.14	−0.07	−0.14
	(0.17)	(−1.07)	(−1.40)	(−7.49)	(1.28)	(−0.68)	(8.56)	(11.92)	(−2.14)	(−3.94)	(2.43)	(2.00)	(−1.41)	(−3.90)
2	0.09	0.03	0.07	−0.01	0.07	−0.01	0.40	0.32	−0.03	−0.13	0.10	0.04	0.02	−0.04
	(2.45)	(1.43)	(1.34)	(−0.44)	(1.08)	(−0.47)	(6.90)	(12.98)	(−0.42)	(−4.27)	(2.09)	(1.26)	(0.48)	(−1.79)
3	0.10	0.03	0.15	0.08	0.08	0.02	0.22	0.13	0.15	0.07	0.11	0.05	0.04	−0.06
	(1.85)	(1.09)	(2.84)	(3.19)	(1.64)	(1.06)	(3.55)	(4.02)	(2.90)	(3.00)	(2.19)	(1.35)	(0.62)	(−2.05)
4	0.12	0.02	0.23	0.14	0.09	0.02	−0.03	−0.10	0.21	0.12	0.07	0.00	0.20	0.10
	(2.03)	(0.77)	(3.74)	(3.87)	(2.30)	(0.88)	(−0.58)	(−2.88)	(3.82)	(4.21)	(1.42)	(−0.11)	(3.16)	(3.54)
High	0.18	0.10	0.32	0.27	0.09	0.05	−0.87	−0.94	0.14	0.08	0.04	−0.02	0.37	0.29
	(1.99)	(1.55)	(3.65)	(3.74)	(2.54)	(1.65)	(−14.05)	(−24.25)	(1.99)	(1.68)	(0.91)	(−0.90)	(3.48)	(4.26)
High-Low	0.17	0.13	0.39	0.42	0.01	0.06	−1.48	−1.46	0.32	0.32	−0.18	−0.16	0.44	0.43
Return/α diff.	(2.15)	(1.94)	(5.08)	(5.11)	(0.30)	(1.43)	(−22.70)	(−22.40)	(3.49)	(3.43)	(−2.48)	(−2.12)	(4.51)	(5.24)

Notes: This table reports monthly raw excess returns and alphas for quintile portfolios formed on industry-adjusted anomaly variables. Quintile portfolios are formed every month from January 1868 to December 1939 by sorting corporate bonds on their downside risk (5% VaR), credit quality (credit spread), illiquidity (bond age), short-term reversal (STR), momentum (MOM), long-term reversal (LTR), and book-to-market (BTM). All original sorting variables are defined in Table III. I adjust each characteristic to the cross-sectional mean of its industry peers. All portfolios are rebalanced at the end of the next month, and their realized return is recorded. For each quintile portfolio, I report the value-weighted average monthly excess return and six-factor alpha obtained from combining the Fama and French (1993) bond model (composed of $TERM$, and DEF) and Carhart (1997) stock model (composed of MKT^{Stock}, SMB, HML, and UMD^{Stock}). The construction of set factors is explained in Internet Appendix B. The last row reports differences in returns and alphas between quintile 5 ("High") and quintile 1 ("Low"). Corresponding t-statistics in parentheses are based on Newey and West (1987) standard errors. The sample includes all corporate bonds listed on the Brussels Stock Exchange at portfolio formation.

Table A.XVII: Firm-Level Returns on Univariate-Sorted Portfolios

	5% VaR		Spread		Age		STR		MOM		LTR		BTM	
Quintile	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α
Panel A – Largest Bond Issue														
Low	0.01	−0.03	−0.09	−0.18	0.01	−0.04	0.57	0.48	−0.34	−0.40	0.21	0.12	−0.08	−0.15
	(0.30)	(−1.10)	(−1.49)	(−6.31)	(0.12)	(−1.32)	(7.44)	(8.92)	(−3.93)	(−5.01)	(2.24)	(1.87)	(−2.05)	(−5.77)
2	0.06	−0.01	0.12	0.03	0.05	−0.03	0.29	0.23	−0.06	−0.15	0.12	0.07	−0.01	−0.10
	(1.33)	(−0.55)	(2.31)	(1.18)	(1.02)	(−1.19)	(2.81)	(2.72)	(−0.93)	(−5.16)	(2.26)	(2.04)	(−0.17)	(−3.38)
3	0.14	0.06	0.15	0.09	0.15	0.07	0.24	0.13	0.19	0.09	0.06	0.00	0.13	0.05
	(3.04)	(2.67)	(2.78)	(2.93)	(3.24)	(2.96)	(3.78)	(3.10)	(2.96)	(2.38)	(1.23)	(0.02)	(2.01)	(1.60)
4	0.14	0.08	0.20	0.14	0.13	0.06	0.01	−0.06	0.30	0.23	0.07	−0.01	0.14	0.03
	(2.60)	(3.11)	(3.19)	(3.93)	(2.30)	(2.22)	(0.16)	(−1.70)	(7.28)	(9.17)	(1.36)	(−0.37)	(2.17)	(1.14)
High	0.14	0.04	0.31	0.25	0.13	0.04	−0.99	−1.06	0.16	0.09	0.05	−0.02	0.31	0.24
	(1.36)	(0.49)	(2.88)	(3.02)	(1.29)	(0.50)	(−15.59)	(−22.70)	(2.15)	(2.02)	(1.09)	(−0.59)	(2.71)	(3.12)
High-Low	0.12	0.06	0.39	0.43	0.12	0.07	−1.55	−1.54	0.51	0.49	−0.16	−0.14	0.39	0.39
Return/α diff.	(1.36)	(0.81)	(3.81)	(4.33)	(1.31)	(0.90)	(−21.27)	(−21.22)	(4.92)	(4.34)	(−2.02)	(−1.83)	(3.67)	(4.52)
Panel B – Shortest Remaining Maturity														
Low	0.00	−0.04	−0.08	−0.17	0.00	−0.05	0.53	0.45	−0.32	−0.38	0.18	0.10	−0.12	−0.19
	(−0.06)	(−1.60)	(−1.58)	(−6.97)	(−0.10)	(−1.71)	(6.87)	(7.61)	(−3.55)	(−5.28)	(1.89)	(1.44)	(−2.83)	(−7.67)
2	0.06	0.00	0.12	0.03	0.06	−0.01	0.27	0.19	−0.05	−0.13	0.12	0.07	−0.01	−0.10
	(1.38)	(−0.17)	(2.34)	(1.18)	(1.32)	(−0.40)	(2.53)	(2.12)	(−0.82)	(−4.41)	(2.27)	(2.34)	(−0.10)	(−2.90)
3	0.14	0.07	0.12	0.07	0.15	0.07	0.21	0.13	0.18	0.08	0.10	0.03	0.13	0.05
	(3.24)	(3.22)	(2.87)	(2.52)	(3.33)	(3.04)	(3.07)	(1.89)	(2.84)	(2.56)	(2.19)	(0.80)	(2.31)	(1.72)
4	0.12	0.04	0.20	0.13	0.12	0.05	0.02	−0.05	0.30	0.24	0.03	−0.04	0.14	0.04
	(2.13)	(1.57)	(3.03)	(3.70)	(2.14)	(1.82)	(0.40)	(−1.29)	(6.65)	(8.74)	(0.72)	(−1.34)	(2.23)	(1.37)
High	0.15	0.06	0.30	0.26	0.13	0.04	−0.98	−1.06	0.16	0.08	0.04	−0.02	0.33	0.25
	(1.56)	(0.89)	(2.74)	(2.94)	(1.30)	(0.55)	(−15.75)	(−23.10)	(2.25)	(1.58)	(1.00)	(−0.58)	(2.85)	(3.46)
High-Low	0.15	0.11	0.39	0.43	0.13	0.09	−1.52	−1.51	0.48	0.46	−0.14	−0.12	0.45	0.44
Return/α diff.	(1.73)	(1.36)	(3.52)	(4.10)	(1.46)	(1.04)	(−18.82)	(−19.46)	(4.48)	(4.27)	(−1.73)	(−1.49)	(4.00)	(5.27)
Panel C – Most Recent Bond Issue														
Low	0.01	−0.03	−0.09	−0.18	0.01	−0.02	0.53	0.44	−0.35	−0.40	0.19	0.11	−0.07	−0.13
	(0.29)	(−1.07)	(−1.54)	(−6.88)	(0.26)	(−0.83)	(6.60)	(6.91)	(−3.85)	(−4.87)	(2.00)	(1.58)	(−1.75)	(−5.27)
2	0.07	0.00	0.12	0.03	0.07	−0.01	0.33	0.26	−0.07	−0.16	0.13	0.07	−0.01	−0.10
	(1.40)	(−0.17)	(2.33)	(1.21)	(1.40)	(−0.24)	(4.71)	(5.62)	(−0.97)	(−5.38)	(2.42)	(2.01)	(−0.19)	(−3.01)
3	0.12	0.05	0.15	0.08	0.12	0.05	0.26	0.18	0.18	0.09	0.07	0.01	0.14	0.06
	(2.76)	(2.26)	(2.94)	(3.16)	(2.67)	(2.29)	(4.13)	(3.78)	(2.83)	(2.40)	(1.49)	(0.47)	(2.23)	(1.53)
4	0.15	0.08	0.19	0.13	0.14	0.07	−0.01	−0.08	0.30	0.23	0.08	0.01	0.17	0.06
	(2.78)	(3.29)	(2.90)	(3.72)	(2.49)	(2.87)	(−0.12)	(−2.26)	(7.48)	(9.72)	(1.64)	(0.39)	(2.53)	(1.87)
High	0.14	0.05	0.30	0.24	0.12	0.03	−1.00	−1.08	0.18	0.11	0.05	−0.02	0.26	0.20
	(1.40)	(0.72)	(2.71)	(2.84)	(1.11)	(0.37)	(−15.01)	(−21.57)	(2.47)	(2.37)	(1.07)	(−0.49)	(2.23)	(2.39)
High-Low	0.13	0.08	0.39	0.42	0.11	0.05	−1.53	−1.53	0.54	0.51	−0.14	−0.12	0.33	0.33
Return/α diff.	(1.39)	(0.97)	(3.68)	(4.08)	(1.09)	(0.62)	(−22.11)	(−21.12)	(5.03)	(4.40)	(−1.78)	(−1.56)	(2.94)	(3.52)

Notes: This table reports monthly raw excess returns and alphas for quintile portfolios formed on anomaly variables. Quintile portfolios are formed every month from January 1868 to December 1939 by sorting corporate bonds on their downside risk (5% VaR), credit quality (credit spread), illiquidity (bond age), short-term reversal (STR), momentum (MOM), long-term reversal (LTR), and book-to-market (BTM). All sorting variables are defined in Table III. All portfolios are rebalanced at the end of the next month, and their realized return is recorded. To control for bonds issued by the same firm, for each month in my sample, I pick one bond with the largest size (Panel A), the bond with the shortest remaining maturity (Panel B), and the bond with the shortest amount of time passed since issuance (Panel C) as the representative issue for the firm in case of multiple concurrently outstanding issues. For each quintile portfolio, I report the value-weighted average monthly excess return and six-factor alpha obtained from combining the Fama and French (1993) bond model (composed of $TERM$, and DEF) and Carhart (1997) stock model (composed of MKT^{Stock}, SMB, HML, and UMD^{Stock}). The construction of set factors is explained in Internet Appendix B. The last row reports differences in returns and alphas between quintile 5 ("High") and quintile 1 ("Low"). Corresponding t-statistics in parentheses are based on Newey and West (1987) standard errors. The sample includes all corporate bonds listed on the Brussels Stock Exchange at portfolio formation.

Table A.XVIII: Firm-Level Fama-MacBeth Cross-Sectional Regressions Using The Largest Bond Issue

	Int.	5% VaR	Spread	Age	STR	MOM	LTR	BTM	β^{Bond}	β^{TERM}	β^{DEF}	Maturity	Size	Adj. $\overline{R^2}$	T	N
(1)	0.10	0.06												0.04	864	117,485
	(1.95)	(1.23)														
(2)	0.10	0.08							0.02	0.13	−0.05	−0.05	0.01	0.22	864	117,493
	(2.07)	(1.36)							(0.55)	(1.86)	(−0.73)	(−3.04)	(0.70)			
(3)	0.16		0.22											0.04	864	144,082
	(2.87)		(4.72)													
(4)	0.12		0.23						0.00	0.13	−0.07	0.03	0.03	0.21	864	125,266
	(2.37)		(4.21)						(0.06)	(2.10)	(−1.26)	(1.17)	(2.16)			
(5)	0.09			0.01										0.01	864	144,572
	(1.80)			(0.37)												
(6)	0.08			0.00					0.04	0.11	−0.03	−0.04	−0.01	0.18	864	125,768
	(1.77)			(0.13)					(1.08)	(1.72)	(−0.47)	(−2.33)	(−0.46)			
(7)	0.08				−0.69									0.10	864	144,577
	(1.55)				(−18.17)											
(8)	0.08				−0.70				0.06	0.09	−0.02	−0.05	0.01	0.25	864	125,768
	(1.83)				(−15.29)				(1.18)	(1.33)	(−0.31)	(−2.46)	(0.42)			
(9)	0.06					0.16								0.04	864	135,404
	(1.08)					(3.24)										
(10)	0.08					0.07			0.05	0.08	0.01	−0.05	0.01	0.21	864	125,710
	(1.68)					(1.36)			(1.30)	(1.22)	(0.09)	(−2.69)	(0.44)			
(11)	0.10						−0.10							0.03	864	108,117
	(1.97)						(−2.67)									
(12)	0.10						−0.09		−0.02	0.15	−0.01	−0.05	0.00	0.22	864	108,107
	(2.35)						(−2.71)		(−0.55)	(2.17)	(−0.14)	(−2.71)	(−0.22)			
(13)	0.15							0.40						0.04	864	145,415
	(2.42)							(4.24)								
(14)	0.13							0.42	0.04	0.16	−0.12	−0.08	0.04	0.21	864	125,777
	(2.50)							(3.93)	(1.16)	(2.39)	(−1.88)	(−3.75)	(2.11)			
(15)	0.15	0.06	0.09	0.00	−0.81	0.01	0.02	0.04						0.25	864	107,593
	(3.05)	(1.43)	(1.78)	(−0.22)	(−18.58)	(0.24)	(0.57)	(0.70)								
(16)	0.14	0.05	0.12	−0.01	−0.74	−0.02	0.02	−0.02	0.02	0.11	−0.08	0.00	0.01	0.38	864	107,590
	(3.04)	(1.28)	(1.96)	(−0.55)	(−12.39)	(−0.33)	(0.61)	(−0.24)	(0.53)	(1.62)	(−1.30)	(0.15)	(0.66)			

Notes: This table reports average intercept and slope coefficients from Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead corporate bond excess returns against a constant and a series of bond characteristics. To control for bonds issued by the same firm, for each month in my sample, I pick one bond with the largest size as the representative for the firm. Bond characteristics are measured at the end of month t over my sample period from January 1868 to December 1939. All independent variables are defined in Table III and are standardized to have zero mean and unit variance in each month to ease the interpretation of the estimated coefficients. The table presents the time-series averages of the cross-sectional regression coefficients; intercept and slope coefficients (both multiplied by 100). The corresponding t-statistics in parentheses are based on Newey and West (1987) standard errors to determine the statistical significance of the average intercept and slope coefficients. The last columns report the average adjusted cross-sectional coefficient of determination, $\overline{R^2}$, of the regressions, the number of time periods, T, and the number of observations, N, respectively.

Table A.XIX: Firm-Level Fama-MacBeth Cross-Sectional Regressions Using The Shortest Maturity Issue

	Int.	5% VaR	Spread	Age	STR	MOM	LTR	BTM	β^{Bond}	β^{TERM}	β^{DEF}	Maturity	Size	Adj. $\overline{R^2}$	T	N
(1)	0.10	0.07												0.04	864	119,693
	(2.02)	(1.45)														
(2)	0.10	0.08							0.04	0.07	−0.02	−0.05	0.01	0.23	864	119,680
	(2.28)	(1.56)							(1.02)	(1.11)	(−0.24)	(−2.92)	(0.57)			
(3)	0.15		0.21											0.04	864	144,195
	(2.68)		(4.60)													
(4)	0.13		0.24						0.01	0.10	−0.05	0.03	0.02	0.21	864	126,900
	(2.66)		(4.32)						(0.25)	(1.58)	(−0.89)	(1.42)	(1.57)			
(5)	0.09			0.02										0.01	864	144,645
	(1.89)			(1.29)												
(6)	0.08			0.00					0.06	0.07	0.00	−0.04	−0.01	0.19	864	127,354
	(1.94)			(0.21)					(1.43)	(1.05)	(−0.06)	(−2.17)	(−0.64)			
(7)	0.07				−0.66									0.09	864	144,645
	(1.47)				(−17.43)											
(8)	0.09				−0.68				0.07	0.04	0.02	−0.04	0.00	0.25	864	127,348
	(2.08)				(−14.65)				(1.26)	(0.62)	(0.26)	(−2.50)	(−0.18)			
(9)	0.06					0.15								0.04	864	136,242
	(1.11)					(3.04)										
(10)	0.09					0.07			0.07	0.04	0.03	−0.05	0.00	0.21	864	127,311
	(1.96)					(1.19)			(1.85)	(0.59)	(0.48)	(−2.75)	(−0.10)			
(11)	0.10						−0.10							0.03	864	110,888
	(2.01)						(−2.64)									
(12)	0.11						−0.09		−0.01	0.09	0.03	−0.05	0.00	0.22	864	110,896
	(2.56)						(−2.50)		(−0.22)	(1.36)	(0.41)	(−2.91)	(0.02)			
(13)	0.14							0.43						0.05	864	145,415
	(2.32)							(4.33)								
(14)	0.14							0.46	0.04	0.11	−0.09	−0.09	0.03	0.22	864	127,354
	(2.70)							(3.92)	(1.15)	(1.75)	(−1.40)	(−4.12)	(1.94)			
(15)	0.16	0.06	0.13	0.01	−0.77	0.01	0.01	0.06						0.25	864	110,448
	(3.36)	(1.46)	(2.94)	(0.40)	(−18.43)	(0.20)	(0.40)	(1.00)								
(16)	0.15	0.04	0.15	0.01	−0.73	−0.02	0.03	0.01	0.03	0.06	−0.04	0.01	0.02	0.38	864	110,423
	(3.33)	(0.93)	(2.29)	(0.46)	(−13.37)	(−0.39)	(0.88)	(0.20)	(0.60)	(0.93)	(−0.59)	(0.43)	(1.06)			

Notes: This table reports average intercept and slope coefficients from Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead corporate bond excess returns against a constant and a series of bond characteristics. To control for bonds issued by the same firm, for each month in my sample, I pick one bond with the shortest amount of time passed since issuance as the representative for the firm. Bond characteristics are measured at the end of month t over my sample period from January 1868 to December 1939. All independent variables are defined in Table III and are standardized to have zero mean and unit variance in each month to ease the interpretation of the estimated coefficients. The table presents the time-series averages of the cross-sectional regression coefficients; intercept and slope coefficients (both multiplied by 100). The corresponding t-statistics in parentheses are based on Newey and West (1987) standard errors to determine the statistical significance of the average intercept and slope coefficients. The last columns report the average adjusted cross-sectional coefficient of determination, $\overline{R^2}$, of the regressions, the number of time periods, T, and the number of observations, N, respectively.

Table A.XX: Firm-Level Fama-MacBeth Cross-Sectional Regressions Using The Most Recent Bond Issue

	Int.	5% VaR	Spread	Age	STR	MOM	LTR	BTM	β^{Bond}	β^{TERM}	β^{DEF}	Maturity	Size	Adj. $\overline{R^2}$	T	N
(1)	0.10	0.05												0.04	864	115,011
	(1.99)	(1.01)														
(2)	0.10	0.07							0.03	0.10	−0.02	−0.06	0.02	0.23	864	115,006
	(2.12)	(1.35)							(0.80)	(1.54)	(−0.26)	(−2.82)	(1.12)			
(3)	0.16		0.21											0.04	864	143,956
	(2.80)		(4.60)													
(4)	0.12		0.21						0.01	0.10	−0.04	0.04	0.03	0.21	864	123,335
	(2.37)		(3.94)						(0.27)	(1.74)	(−0.80)	(1.47)	(1.80)			
(5)	0.09			0.01										0.01	864	144,476
	(1.85)			(0.77)												
(6)	0.08			0.01					0.05	0.09	−0.01	−0.05	0.00	0.18	864	123,844
	(1.73)			(0.30)					(1.10)	(1.58)	(−0.18)	(−2.34)	(−0.03)			
(7)	0.08				−0.66									0.09	864	144,480
	(1.57)				(−15.38)											
(8)	0.08				−0.67				0.07	0.06	0.01	−0.06	0.01	0.25	864	123,860
	(1.88)				(−13.64)				(1.27)	(0.92)	(0.21)	(−2.57)	(0.54)			
(9)	0.06					0.17								0.04	864	134,355
	(1.05)					(3.43)										
(10)	0.08					0.07			0.06	0.03	0.03	−0.06	0.01	0.21	864	123,804
	(1.65)					(1.26)			(1.46)	(0.65)	(0.60)	(−2.77)	(0.60)			
(11)	0.10						−0.10							0.03	864	105,048
	(2.07)						(−2.67)									
(12)	0.11						−0.10		−0.01	0.13	0.00	−0.06	0.00	0.23	864	105,056
	(2.56)						(−2.63)		(−0.35)	(1.99)	(0.07)	(−3.02)	(−0.15)			
(13)	0.16							0.47						0.05	864	145,415
	(2.58)							(4.08)								
(14)	0.13							0.39	0.05	0.12	−0.08	−0.08	0.03	0.21	864	123,848
	(2.49)							(4.06)	(1.29)	(1.94)	(−1.32)	(−3.19)	(2.20)			
(15)	0.16	0.06	0.08	−0.01	−0.80	0.01	0.01	0.07						0.25	864	104,505
	(3.18)	(1.35)	(1.72)	(−0.42)	(−18.30)	(0.19)	(0.23)	(1.03)								
(16)	0.15	0.04	0.13	0.00	−0.71	−0.06	0.01	−0.01	0.01	0.05	−0.03	0.01	0.01	0.38	864	104,524
	(3.21)	(0.95)	(1.98)	(0.05)	(−12.57)	(−1.20)	(0.47)	(−0.10)	(0.18)	(0.74)	(−0.42)	(0.43)	(0.32)			

Notes: This table reports average intercept and slope coefficients from Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead corporate bond excess returns against a constant and a series of bond characteristics. To control for bonds issued by the same firm, for each month in my sample, I pick one bond with the shortest remaining maturity as the representative for the firm. Bond characteristics are measured at the end of month t over my sample period from January 1868 to December 1939. All independent variables are defined in Table III and are standardized to have zero mean and unit variance in each month to ease the interpretation of the estimated coefficients. The table presents the time-series averages of the cross-sectional regression coefficients; intercept and slope coefficients (both multiplied by 100). The corresponding t-statistics in parentheses are based on Newey and West (1987) standard errors to determine the statistical significance of the average intercept and slope coefficients. The last columns report the average adjusted cross-sectional coefficient of determination, $\overline{R^2}$, of the regressions, the number of time periods, T, and the number of observations, N, respectively.

Table A.XXI: Bond-Level Panel Regressions of Returns on Characteristics

	(1)			(2)			(3)			(4)		
	Coeff.	Adj. R^2	Obs.	Coeff.	Adj. R^2	Obs.	Coeff.	Adj. R^2	Obs.	Coeff.	Adj. R^2	Obs.
5% VaR	0.023	0.00	148,586	0.038	0.08	148,586	0.031	0.09	148,586	0.020	0.08	148,586
	(1.632)			(2.349)			(2.069)			(1.489)		
Spread	0.107	0.00	157,636	0.228	0.11	157,636	0.191	0.11	157,636	0.117	0.10	157,636
	(4.830)			(6.106)			(6.125)			(5.404)		
Age	0.001	0.00	158,316	0.004	0.09	158,316	0.003	0.09	158,316	0.002	0.09	158,316
	(0.769)			(1.888)			(1.727)			(1.676)		
STR	−0.099	0.01	158,316	−0.135	0.11	158,316	−0.134	0.11	158,316	−0.130	0.11	158,316
	(−6.540)			(−8.745)			(−8.746)			(−8.620)		
MOM	0.004	0.00	158,261	−0.006	0.09	158,261	−0.006	0.09	158,261	−0.003	0.09	158,261
	(1.177)			(−3.039)			(−2.745)			(−1.665)		
LTR	−0.003	0.00	137,496	−0.007	0.08	137,496	−0.006	0.08	137,496	−0.005	0.08	137,496
	(−1.496)			(−2.879)			(−2.612)			(−1.980)		
BTM	0.010	0.01	158,321	0.021	0.11	158,321	0.018	0.11	158,321	0.013	0.10	158,321
	(5.000)			(7.268)			(7.092)			(6.094)		
Controls		✓			✓			✓			✓	
Bond FE		–			✓			–			–	
Firm FE		–			–			✓			–	
Industry FE		–			–			–			✓	
Month-Year FE		–			✓			✓			✓	

Notes: This table presents results from panel regressions of one-month-ahead corporate bond excess returns on a set of explanatory variables. Bond characteristics are measured at the end of month t over my sample period from January 1868 to December 1939. All independent variables are defined in Table III. Explanatory variables follow Table IX and include bond market beta (β^{Bond}), TERM beta (β^{TERM}), DEF beta (β^{DEF}), time-to-maturity, and size. Each column reports results for a different fixed-effect specification. Standard errors are clustered at the month-year and firm level for all specifications.

Table A.XXII: Returns on Univariate-Sorted Portfolios Across Subsamples

	5% VaR		Spread		Age		STR		MOM		LTR		BTM	
Quintile	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α	$\mathbb{E}[R]$	6F α
Panel A – Excluding The Great War														
Low	0.00	−0.04	−0.11	−0.20	−0.02	−0.06	0.63	0.54	−0.36	−0.42	0.14	0.07	−0.12	−0.19
	(0.02)	(−1.34)	(−1.73)	(−7.33)	(−0.31)	(−1.74)	(7.66)	(10.30)	(−4.01)	(−5.32)	(1.42)	(0.85)	(−2.67)	(−5.76)
2	0.07	0.00	0.09	0.00	0.06	−0.01	0.36	0.30	−0.04	−0.13	0.11	0.05	−0.03	−0.11
	(1.39)	(−0.05)	(1.69)	(0.07)	(1.23)	(−0.39)	(4.97)	(6.06)	(−0.68)	(−4.77)	(1.71)	(1.17)	(−0.54)	(−3.37)
3	0.14	0.07	0.14	0.08	0.14	0.06	0.20	0.08	0.17	0.07	0.06	0.00	0.12	0.04
	(2.95)	(2.89)	(2.23)	(1.88)	(2.83)	(2.64)	(3.13)	(1.81)	(2.55)	(2.53)	(1.24)	(0.01)	(1.86)	(1.33)
4	0.14	0.07	0.18	0.13	0.13	0.06	0.01	−0.06	0.28	0.21	0.04	−0.04	0.15	0.04
	(2.32)	(2.64)	(3.13)	(3.56)	(2.03)	(1.89)	(0.09)	(−1.82)	(6.09)	(7.92)	(0.71)	(−1.43)	(2.13)	(1.35)
High	0.14	0.05	0.27	0.23	0.03	−0.05	−0.93	−1.01	0.07	−0.01	0.03	−0.04	0.24	0.18
	(1.39)	(0.71)	(2.57)	(2.75)	(0.30)	(−0.55)	(−15.26)	(−24.51)	(0.88)	(−0.10)	(0.56)	(−1.21)	(2.07)	(2.11)
High-Low	0.14	0.09	0.38	0.43	0.05	0.01	−1.56	−1.55	0.44	0.41	−0.12	−0.10	0.36	0.37
Return/α diff.	(1.50)	(1.16)	(3.70)	(4.26)	(0.48)	(0.10)	(−21.29)	(−21.25)	(4.23)	(3.40)	(−1.34)	(−1.20)	(3.29)	(3.83)
Panel B – Non-Financial Firms														
Low	0.00	−0.05	−0.11	−0.20	−0.02	−0.06	0.60	0.50	−0.37	−0.43	0.12	0.04	−0.11	−0.17
	(−0.01)	(−1.33)	(−1.72)	(−7.15)	(−0.37)	(−1.69)	(7.38)	(9.88)	(−4.20)	(−5.47)	(1.21)	(0.46)	(−2.63)	(−5.66)
2	0.06	−0.01	0.10	0.01	0.06	−0.02	0.34	0.27	−0.06	−0.15	0.10	0.04	0.00	−0.07
	(1.39)	(−0.66)	(1.84)	(0.19)	(1.23)	(−0.96)	(4.87)	(5.60)	(−0.91)	(−5.34)	(1.67)	(0.96)	(0.04)	(−2.20)
3	0.12	0.05	0.12	0.06	0.12	0.04	0.22	0.11	0.15	0.04	0.06	−0.01	0.11	0.02
	(2.59)	(2.09)	(2.06)	(1.57)	(2.51)	(1.95)	(3.57)	(2.53)	(2.24)	(1.29)	(1.20)	(−0.23)	(1.83)	(0.66)
4	0.13	0.05	0.17	0.12	0.12	0.04	0.02	−0.05	0.29	0.22	0.03	−0.05	0.13	0.02
	(2.23)	(1.97)	(2.96)	(3.12)	(1.97)	(1.37)	(0.37)	(−1.79)	(6.45)	(8.57)	(0.67)	(−1.65)	(1.91)	(0.72)
High	0.15	0.06	0.25	0.20	0.05	−0.03	−0.92	−1.00	0.08	0.01	0.04	−0.02	0.22	0.15
	(1.52)	(0.84)	(2.45)	(2.48)	(0.45)	(−0.38)	(−15.50)	(−26.38)	(1.07)	(0.10)	(0.92)	(−0.84)	(1.95)	(1.85)
High-Low	0.15	0.11	0.36	0.40	0.07	0.03	−1.52	−1.50	0.46	0.44	−0.08	−0.06	0.34	0.33
Return/α diff.	(1.65)	(1.41)	(3.70)	(4.04)	(0.67)	(0.33)	(−21.07)	(−22.09)	(4.51)	(3.71)	(−0.92)	(−0.71)	(3.14)	(3.56)
Panel C – Public Firms														
Low	0.01	−0.04	−0.09	−0.18	−0.01	−0.05	0.61	0.53	−0.35	−0.40	0.16	0.07	−0.11	−0.18
	(0.12)	(−1.42)	(−1.47)	(−7.22)	(−0.19)	(−1.68)	(7.99)	(9.96)	(−3.97)	(−5.55)	(1.71)	(1.06)	(−2.76)	(−5.38)
2	0.09	0.02	0.13	0.03	0.09	0.02	0.40	0.34	−0.04	−0.12	0.10	0.05	−0.01	−0.09
	(1.92)	(1.02)	(2.33)	(0.89)	(1.83)	(0.84)	(7.80)	(10.79)	(−0.67)	(−3.65)	(1.71)	(1.14)	(−0.26)	(−2.81)
3	0.13	0.06	0.09	0.02	0.13	0.06	0.22	0.11	0.18	0.08	0.08	0.01	0.10	0.02
	(2.92)	(3.15)	(1.53)	(0.54)	(2.75)	(2.78)	(3.27)	(2.44)	(2.94)	(2.11)	(1.71)	(0.51)	(1.90)	(0.68)
4	0.12	0.04	0.23	0.18	0.12	0.03	0.04	−0.03	0.31	0.24	0.05	−0.02	0.15	0.04
	(2.15)	(1.24)	(3.86)	(4.52)	(2.05)	(1.12)	(0.68)	(−1.09)	(6.81)	(8.04)	(1.13)	(−0.73)	(2.17)	(1.39)
High	0.16	0.07	0.30	0.25	0.11	0.02	−0.93	−1.01	0.11	0.02	0.03	−0.04	0.36	0.28
	(1.68)	(1.02)	(2.84)	(3.15)	(1.16)	(0.26)	(−15.37)	(−26.21)	(1.54)	(0.38)	(0.56)	(−1.15)	(3.27)	(4.03)
High-Low	0.15	0.11	0.38	0.43	0.12	0.07	−1.55	−1.54	0.46	0.42	−0.13	−0.12	0.47	0.46
Return/α diff.	(1.75)	(1.46)	(3.89)	(4.62)	(1.36)	(0.89)	(−23.76)	(−22.71)	(4.82)	(3.83)	(−1.70)	(−1.50)	(4.84)	(5.49)
Panel D – Excluding Micro Firms														
Low	0.04	−0.01	−0.10	−0.19	0.09	0.00	0.61	0.52	−0.35	−0.41	0.15	0.08	−0.13	−0.19
	(0.82)	(−0.27)	(−1.64)	(−7.39)	(1.55)	(0.15)	(8.10)	(9.31)	(−4.31)	(−6.65)	(1.77)	(1.45)	(−3.12)	(−6.03)
2	0.09	0.01	0.12	0.04	0.06	−0.02	0.42	0.35	−0.03	−0.12	0.14	0.09	0.00	−0.07
	(1.97)	(0.62)	(2.28)	(1.02)	(1.08)	(−0.75)	(7.28)	(9.91)	(−0.59)	(−3.90)	(2.59)	(2.30)	(−0.09)	(−2.25)
3	0.12	0.06	0.14	0.07	0.06	−0.01	0.23	0.13	0.20	0.11	0.08	0.02	0.08	0.00
	(2.66)	(2.75)	(2.40)	(1.94)	(1.14)	(−0.33)	(4.12)	(3.40)	(3.26)	(2.76)	(1.65)	(0.48)	(1.43)	(−0.04)
4	0.15	0.08	0.18	0.14	0.07	0.01	0.06	−0.02	0.29	0.23	0.05	−0.03	0.12	0.02
	(2.69)	(3.20)	(3.51)	(4.00)	(1.65)	(0.24)	(1.10)	(−0.62)	(6.74)	(7.51)	(1.06)	(−0.88)	(1.82)	(0.65)
High	0.09	0.00	0.26	0.20	0.08	0.04	−0.94	−1.01	0.15	0.07	0.04	−0.03	0.33	0.26
	(1.14)	(−0.03)	(2.71)	(2.85)	(2.21)	(1.06)	(−15.72)	(−26.54)	(2.09)	(1.35)	(0.99)	(−0.77)	(3.59)	(4.86)
High-Low	0.05	0.01	0.35	0.40	−0.01	0.03	−1.55	−1.54	0.50	0.47	−0.11	−0.11	0.47	0.45
Return/α diff.	(0.78)	(0.09)	(4.10)	(4.71)	(−0.28)	(0.69)	(−23.69)	(−21.82)	(5.56)	(4.79)	(−1.62)	(−1.62)	(5.43)	(6.23)

Notes: This table reports monthly raw excess returns and alphas for quintile portfolios formed on anomaly variables. Quintile portfolios are formed every month from January 1868 to December 1939. All sorting variables are defined in Table III. Panel A discards the Great War period from July 1914 through December 1918 inclusive. Panel B uses bonds issued by non-financial firms, following the industry mapping of Table I. Panel C eliminates all bonds issued by private firms. Panel D eliminates micro firms as identified in Table III. For each quintile portfolio, I report the value-weighted average monthly excess return and six-factor alpha obtained from combining the Fama and French (1993) bond model (composed of $TERM$, and DEF) and Carhart (1997) stock model (composed of MKT^{Stock}, SMB, HML, and UMD^{Stock}). The construction of set factors is explained in Internet Appendix B. The last row reports differences in returns and alphas between quintile 5 ("High") and quintile 1 ("Low"). Corresponding t-statistics in parentheses are based on Newey and West (1987) standard errors. The sample includes all corporate bonds listed on the Brussels Stock Exchange at portfolio formation.

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