The Cross-Section of Expected Corporate Bond Returns*

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Abstract

This study constructs risk factors that are important for the pricing of corporate bond. We find that expected corporate bond returns are related cross-sectionally to downside risk, credit risk, liquidity risk, and bond market risk. Based on these risk proxies, we construct three bond-implied risk factors: DRF, CRF, and LRF. Our new factors rely on the unique features of corporate bonds that distinguish from stocks, hence have superior performance in explaining the cross-section of expected bond returns, than all established stock and bond market factor models.

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1 Introduction

In the past three decades, researchers have identified many risk factors in the cross section of stock returns. However, far fewer studies are devoted to the cross section of corporate bond returns. Compared to the size of the U.S. stock market, $29 trillions, the corporate bond market is relatively small with an outstanding of $12 trillions.[1] However, the issuance of corporate bond is in much larger scale than the issuance of stocks for the United States corporations, on average $1,294 billions for corporate bonds compared to $265 billions for stocks since 2010. Both corporate bonds and stocks are important financing channels for corporations, and both are important assets under management for practitioners. It's important to enhance our understanding of the risk-return relationship in the corporate bond market.

Conventional corporate bond studies rely on the long-established stock and bond factors to predict the corporate bond expected returns, including the five factors of Fama and French (1993), Carhart (1997) and Pastor and Stambaugh (2003): the excess stock market return (MKT), the size factor (SMB), the book-to-market factor (HML), the momentum factor (MOM), and the liquidity factor (LIQ), and the excess bond market return (Elton, Gruber, and Blake (1995)), the default spread (DEF) and the term spread (TERM). In this paper, we show that it is crucial to respect the unique features of corporate bonds and construct bond-implied risk factors to explain the cross-section of corporate bond returns.

Although corporate bonds and stocks both reflect firm fundamentals, they differ in several key features. First and foremost, firms issue corporate bonds suffer from the potential default risk given the legal requirement on the payments of coupons and principals, whereas firms issue stocks only have negligible exposure to bankruptcy. This main feature makes credit risk in particular important in determining corporate bond returns.

Second, bondholders compared with stockholders are more sensitive to downside risk. Bondholders gain the cash flow of fixed coupon and principal payment, thus hardly benefit from the euphoric news in the firm fundamentals. Since the upside payoffs are capped, the bond payoffs become concave in the investor beliefs about the underlying fundamental, whereas equity payoffs are linear in the investor beliefs regarding the underlying fundamental.

[1]Source: Table L.213 and L.223 in the Federal Reserve Board's Z1 Flow of Funds, Balance Sheets, and Integrated Macroeconomic Accounts, as of the fourth quarter of 2015.

Third, the corporate bond market, due to its over-the-counter trading mechanism and other market features, bears higher liquidity risk. The bond market participants have been dominated by institutional investors such as insurance companies, pension funds, and mutual funds.[2] Many bondholders are long-term investors who often take the buy-and-hold strategy. Therefore the liquidity in the corporate bond market is lower compared with the stock market in which active trading is partially contributed by the existence of individual (noisy) traders.

Given these special features in the corporate bond market, we endeavor to identify bond-implied risk factors. In particular, we examine the pricing power of downside risk, credit risk, and liquidity risk on the cross-section of expected corporate bond returns. The bond returns are calculated at the monthly frequency using the intraday trasaction records from the enhanced TRACE data from July 2002 to December 2014, a total of 507,714 bond-month observations. Our proxy for downside risk is the 5% Value-at-Risk (VaR) which is based on the lower tail of the empirical return distribuition, that is, the second lowest monthly return observation over the past 36 months. Our proxy for credit risk is bond-level credit rating. Our proxy for liquidity risk is bond-level illiquidity measure following Bao, Pan, and Wang (2011). In the online appendix, we also consider alternative proxies for downside risk, credit risk, and liquidity risk, and results remain robust. In addition to these three bond risk proxies, we further consider the market risk factor based on the corporate bond market index instead of conventional stock market index, and construct the bond market β.

First, we test the significance of a cross-sectional relation between downside risk and future returns on corporate bonds using portfolio-level analysis. We find that bonds in the highest VaR quintile generate 9.43% per annum higher return than bonds in the lowest VaR quintile do. After controlling seven long-established stock and bond factors, the risk-adjusted return premium from the lowest to the highest VaR quintile is still about 8.52% with a t-statistic of 3.85, suggesting that loss-averse bond investors prefer high expected return and low VaR. We investigate the source of the significant return spread between high- and low-VaR bonds, and find that the significantly positive return spread is due to outperformance by high-VaR

[2] According to the balance sheet of corporate bonds in 2014:Q4, reported by the Federal Reserve release, the main holders of corporate bond are insurance industries which hold \$2678 billion, pension and retirement funds which hold \$983 billion, mutual funds, close-end funds and exchange-traded funds which together hold \$2502 billion. Source: the Financial Accounts of the United States, Release Z1, Table L.213, Line 19 – 47.

bonds, but not to underperformance by low-VaR bonds. We also test if the positive relation between downside risk and future returns holds controlling for bond characteristics, and find that downside risk remains a significant predictor after controlling for credit rating, bond maturity and size.

Second, we examine the cross-sectional relation between credit risk, liquidity risk and future bond returns. We find that corporate bonds in the highest credit risk quintile generate 7.80% to 5.09% more raw and risk-adjusted returns per annum compared to bonds in the lowest credit risk quintile. In addition, the significantly positive credit risk premium is driven by bonds with high credit risk, but not by bonds with low credit risk. Examining the portfolio bond characteristics, we also find that high credit risk bonds tend to have higher downside risk, higher illiquidity, shorter maturity, and smaller size, but not significantly different market betas. The results for the cross-sectional relation between liquidity risk and bond returns are similar. Corporate bonds in the highest illiquidity quintile generate 6.42% to 6.35% more raw and risk-adjusted returns per annum compared to bonds in the lowest illiquidity quintile. Bonds in the high illiquidity quintile also tend to have higher downside risk, higher bond market beta, longer maturity, and smaller size, though not significantly different credit risk.

Third, we particularly investigate whether the CAPM holds in the corporate bond market. Specifically, we test if the CAPM with the bond market factor explains the cross-sectional corporate bond returns. We find that the market factor based on the stock market index such as S&P 500 or CRSP cannot explain the cross-section of expected bond returns; however, the market factor based on the Merrill Lynch Aggregate Bond market index has significant and positive predicting power. Bonds in the high bond market beta quintile generates 7.07% to 6.68% higher raw and risk-adjusted returns per annume compared to bonds in the low market beta quintile. Moreover, the significantly positive bond market risk premium is driven by bonds with high beta, whereas bonds with low beta have insignificant average return.

After combining all bond risk proxies and controlling bond characteristics in the Fama-MacBeth regression, downside risk and liquidity risk stand out with significance, whereas the pricing power of credit risk and bond market risk weakens or disappears.

Finally, we propose three novel risk factors based on the aforementioned bond risk proxies: downside risk factor (DRF), credit risk factor (CRF), and liquidity risk factor (LRF), in the similar spirit of Fama and French (1993, 1996) constructing stock market risk factors. We show that when regressing each of new risk factors on long-established stock and market factors, all intercepts (alphas) are statistically and economically significant and the adjusted-R^2 values are relatively low, suggesting that the existing common risk factors are not sufficient to capture the information contained in these new bond risk factors. We further form test portfolios using corporate bond returns and examine the explanatory power of our bond risk factors and that of alternative factor models. Either for the 10 decile portfolios sorted by bond size, or for the 10 decile portfolios sorted by bond maturity, or for the 25 portfolios sorted by size and maturity, our newly proposed bond risk factor model has the greatest explanatory power compared with three benchmark factors models based on the literature. For example, the difference of average R^2 values between our model and the Fama-French five-factor model is 0.80 vs 0.41 for size-sorted 10 portfolios, 0.81 vs 0.47 for maturity-sorted 10 portfolios, and 0.78 vs 0.41 for size and maturity sorted 25 portfolios. These results suggest that the newly proposed bond risk factors capture common variations of the cross-section corporate bond returns, which cannot be fully characterized by the existing stock and/or bond market risk factors.

In the following sections, we describes the data, test the pricing power of bond characteristics, construct three new risk factors and show their superior performance in explaining the cross-section of expected bond returns.

2 Data

2.1 Corporate Bond Data

For corporate bond data, we rely on the transaction records reported in the original and enhanced version of the Trade Reporting and Compliance Engine (TRACE) for the sample period of July 2002 to December 2014. Ideally, we hope to understand the risk-return relationship using a longer sample period; however, one crucial factor to study corporate bond returns, the illiquidity, requires the daily bond transaction prices which are not provided in data sets such as Lehman Brothers fixed income database, Datastream, or Bloomberg.[3] Therefore, we focus on the TRACE data which offers the best quality of corporate bond transactions with intraday observations on price, trading volume, buy and sell indicator. We then merge corporate bond pricing data merged with Mergent fixed income securities database to collect bond characteristics such as offering amount, offering date, maturity date, coupon rate, coupon type, interest payment frequency, bond type, bond rating, bond option features, and issuer information.

In the online appendix A.2, we also expand our dataset to include alternative bond data sets, mainly containing quoted prices, for a longer sample period starting from January 1973. With this longer sample, we replicate our analysis except those requring an illiquidity measure.

For TRACE data, we adopt the filtering criteria proposed in Bai, Bali, and Wen (2016). Concisely, we remove bonds i) that are not listed or traded in the U.S. public market; ii) that are structured notes, mortgage backed or asset backed, agency-backed or equity-linked; iii) that are convertible; iv) that trade under five dollars or above one thousand dollars; v) that have floating coupon rates; and bonds vi) that have less than one year to maturity. For intraday data, we also eliminate bond transactions vii) that are labeled as when-issued, locked-in, or have special sales conditions; viii) that are canceled, x) that have more than two-day settlement, and xi) that have trading volume smaller than \$100,000. We adjust records that are subsequently corrected or reversed.

2.2 Corporate Bond Return

The monthly corporate bond return at time t is computed as

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

where $P_{i,t}$ is the transaction price, $AI_{i,t}$ is accrued interest, and $C_{i,t}$ is the coupon payment, if any, of bond i in month t.

With the TRACE intraday data, we first calculate the daily clean price as the trading

[3] The National Association of Insurance Commissioners database (NAIC) also includes daily prices but given the fact that it covers only part of the market and it is more illiquid, transactions only by the buy-and-hold insurance companies, combining this data with TRACE does not make a compatible sample. For consistency, we focus on the TRACE data.

volume-weighted average of intraday prices in order to minimize the effect of bid-ask spreads in prices, following Bessembinder, Kahle, Maxwell, and Xu (2009). We then convert the bond prices from daily to monthly following Bai, Bali, and Wen (2016) which has a detailed discussion on the conversion methods in the literature. In detail, the method identifies three scenarios for a return to be realized at the end of month t: 1) from the end of month $t-1$ to the end of month t, 2) from the beginning of month t to the end of month t, and 3) from the beginning of month t to the beginning of month $t+1$. We calculate monthly returns for all three scenarios, where the end (beginning) of month refers to the last (first) five trading days within each month. If there are multiple trading records in the five-day window, the one closest to the last trading day of the month will be selected. If a monthly return can be realized in more than one scenario, the realized return in scenario one (from month-end $t-1$ to month-end t) will be selected.

Our final sample includes 13,425 bonds issued by 2,178 unique firms, a total of 507,714 bond-month return observations during the sample period of July 2002 to December 2014. On average, there are about 3,530 bonds per month over the whole sample. Panel A of Table 1 reports the time-series average of the cross-sectional bond returns' distribution and bond characteristics. The average monthly bond return is 0.39%, which corresponds to 4.68% per annum. The sample contains bonds with an average rating of 8.06 (i.e., BBB+), an average issue size of 396 millions of dollars, and an average of time-to-maturity of 12.74 years. Among the full sample of bonds, about 90% are investment-grade and the remaining 10% are high-yield bonds.

3 Cross-sectional Predictors

In this section, we aim to identify several bond risk proxies and evaluate their power to explain the cross-section of bond returns. Corporate bonds provide an attractive setting to study these issues because there are few studies examine the cross-section of corporate bond returns in the empirical asset pricing literature and because the risk factors are easier to identify (Gebhardt, Hvidkjaer, and Swaminathan (2005)). Among these, Fama and French (1993) first show that default and term premia are important risk factors for corporate bond pricing, in addition to the commonly used Fama-French three factors (e.g., the stock market excess returns, the size factor, and the book-to-market factor). Gebhardt, Hvidkjaer, and Swaminathan (2005) test the pricing power of default beta and term beta and find that they are significantly related to the cross-section of bond returns, even after controlling for a large number of bond characteristics. Lin, Wang, and Wu (2011) construct the market liquidity risk factor and show that it is priced in the cross-section of corporate bond returns.

The strand of literature that study the cross-section of corporate bond returns tend to use the commonly used stock market factors. This is a natural starting point since rational pricing suggests that risk premia in the equity market should be consistent with the corporate bond market, to the extent that two markets are integrated. First, because both bond and stock are contingent claims on the value of the same underlying assets, stock market factors such as size and book-to-market equity should share common variations in stock and bond returns (e.g., Merton (1974)). Second, expected default loss of corporate bonds changes with equity price. Default risk decreases as the equity value appreciates, and this induces a systematic factor that affects corporate bond returns.

However, corporate bond market has its unique features. First and foremost, firms that issue corporate bonds suffer from the potential default risk given the legal requirement on the payments of coupons and principals, whereas firms that issue stocks have only negligible exposure to bankruptcy. This main disparity makes *credit risk* particularly important in determining corporate bond returns. Second, bondholders are more sensitive to *downside risk* than stockholders. Bondholders gain the cash flow of fixed coupon and principal payments and, thus hardly benefit from the euphoric news in firm fundamentals. Since the upside payoffs are capped, the bond payoff relation with investor beliefs about the underlying fundamental becomes concave, whereas the equity payoff relation with investor beliefs regarding the underlying fundamental is linear (e.g., Hong and Sraer (2013)).

Third, the corporate bond market is much less liquid than the equity market with most corporate bonds trading infrequently. Thus, both the level of liquidity and *liquidity risk* are serious concern for investors in the corporate bond market. Fourth, the corporate bond market participants have been dominated by institutional investors such as insurance companies, pension funds, and mutual funds, whose attitudes toward risk may differ significantly from individual investors.[4] Lastly, there is abundant evidence that shows the discrepancies in return premia between equity and corporate bond markets (e.g., Choi and Kim (2015); Chordia et al. (2015)), thus suggesting potential market segmentation.

3.1 Downside Risk

We measure downside risk of corporate bonds using Value-at-Risk (VaR). VaR determines how much the value of an asset could decline over a given period of time with a given probability as a result of changes in market rates or prices. For example, if the given period of time is one day and the given probability is 1%, the VaR measure would be an estimate of the decline in the asset's value that could occur with 1% probability over the next trading day. Our proxy for downside risk, 5% VaR, is based on the lower tail of the empirical return distribution, that is, the second lowest monthly return observation over the past 36 months. We then multiply the original measure by -1 for the convenience of interpretation.[5] As shown in Table 1, the average downside risk is 6.43% in the whole sample with a standard deviaion of 3.87%. Section 4 will further discuss the importance of downside risk to bondholders and test their pricing power on the cross-sectional expected corporate bond returns.

3.2 Credit Risk

To measure the credit risk of corporate bonds, we rely on corporate bond credit ratings. Credit ratings capture information on bond default probability, and hence is the benchmark choice to measure the credit risk of corporate bonds. We collect bond-level rating information from Mergent FISD historical ratings. All ratings are assigned a number to facilitate the analysis, for example, 1 refers to a AAA rating, 2 refers to AA+, 21 refers to CCC, and so forth. Investment-grade bonds have ratings from 1 (AAA) to 10 (BBB-). Non-investment-grade bonds have ratings above 10. A larger number suggests higher credit risk, or lower credit

[4] Institutional investors in particular make extensive use of corporate bonds in constructing their portfolios. According to flow of fund data during 1986-2012, about 82% of corporate bonds were held by institutional investors including insurance companies, mutual funds and pension funds. The participation rate of individual investors in the corporate bond market is very low.

[5] Note that the original maximum likely loss values are negative since they are obtained from the left tail of the return distribution. After multiplying the original VaR measure by -1, a positive regression coefficient can be explained as the higher downside risk is related to the higher cross-sectional bond returns.

quality. In section 5.1, we test the pricing power of credit risk, as measured by bond credit rating, in the cross-section of expected corporate bond returns.

3.3 Liquidity Risk

The literature has documented the importance of illiquidity and liquidity risk in the corporate bond market. For example, the empirical results in Chen, Lesmond, and Wei (2007), and Dick-Nielsen, Feldhutter, and Lando (2012) have established the relation between corporate bond yield spreads and bond illiquidity. Using transactions data from 2003 to 2009, Bao, Pan, and Wang (2011) show that the bond-level illiquidity explains a substantial cross-sectional variations in bond yield spreads. Lin, Wang, and Wu (2011) construct a liquidity risk factor for the corporate bond market and show that the market liquidity beta is priced in the cross-section of corporate bond returns. Given the importance of the transaction-based data such as TRACE for measuring bond illiquidity, we follow Bao, Pan, and Wang (2011) to construct bond-level illiquidity. The illiquidity measure, $ILLIQ$, is aimed at extracting the transitory component from bond price. Specifically, let $\Delta p_t = p_t - p_{t-1}$ be the log price change from $t-1$ to t. Then, $ILLIQ$ is defined as

$$ILLIQ = -Cov_t(\Delta p_{itd}, \Delta p_{itd+1}), \tag{2}$$

where Δp_{itd} is the price change for bond i on day d of month t. In section 5.2, we test the pricing power of bond illiquidity in the cross-section of expected corporate bond returns.

3.4 Bond Market β

In the capital asset pricing model test, the market model almost unanimously adopts the excess stock market return as the factor. This is motivated by the observation that if markets are integrated, a single model that explains equity returns should also explain bond returns (Fama and French (1993)). However, as pointed out by Elton, Gruber, and Blake (1995), the best candidate in a single factor model that best explains individual bond returns would be an index of aggregate bond returns. Following Elton, Gruber, and Blake (1995), we identify our first corporate bond risk factor as the excess bond market returns. The bond market factor is designed to mimic the common variation in corporate bond returns related to the aggregate bond market returns. We use the Merrill Lynch U.S. Aggregate Bond Index as a proxy for the corporate bond market factor.[6] Our first bond risk factor, the bond market return (MKT^{Bond}), is computed as the percentage change in the monthly Merrill Lynch Bond Index values. We also estimate bond market beta, β^{Bond}, for each bond from the time-series regressions of bond excess returns on the excess bond market return, with a 36-month rolling window. As shown in Table 1, the bond beta has a wide range from -0.39 in the 1st percentile to 3.20 in the 99th percentile, with an average value of 1.10 over the whole sample. In section 5.3, we investigate whether CAPM holds in the corporate bond market. Specifically, we test if the CAPM with the bond market factor explains the cross-sectional differences in expected returns on corporate bonds.

Panel B of Table 1 presents the correlations between different bond risk proxies and bond characteristics. It is worth noting that bond market beta, β^{Bond}, is positively correlated with all other variables, with correlation coefficients ranging from 0.08 to 0.49. Among them, downside risk has the highest correlation with β^{Bond} with a value of 0.49, implying that bonds with higher downside risk have high market risk as well. Bond maturity has the second highest correlation with β^{Bond} with a value of 0.32. Bond illiquidity is also positively correlated with downside risk, with a value of 0.24. In sum, bonds with higher downside risk tend to be those also having higher credit risk, higher illiquidity, and higher market risk. In the next session, we provide new empirical evidence that downside risk, as measured by Value-at-Risk (VaR), is significantly priced in the cross-section of expected corporate bond returns.

4 Pricing Power of Downside Risk

4.1 Motivation

Downside risk captures the exposure to losses. That is, it is the risk of the actual return being below the expected return, or the uncertainty about the magnitude of that difference. We con-

[6]We also consider alternative proxies such as the Barclays Aggregate Bond Index, the equal-weighted and value-weighted corporate bond market index using the sample in our paper, and the results remain similar.

sider Value-at-Risk (VaR) as the proxy to determines how much the value of a corporate bond could decline over a given period of time with a given probability. Bai, Bali, and Wen (2016) investigate the distributional features of corporate bonds, volatility, skewness, and kurtosis, and find that the empirical distribution of bond returns is skewed, peaked around the mode, and has fat-tails, implying that extreme returns occur much more frequently than predicted by the normal distribution. Downside risk measures, accounting for higher-order moments of the return distribution, provide more accurate estimates of actual losses and produce good predictions of market risk during extraordinary periods such as bond market collapses.

From investors' perspective, investors in the corporate bond market are more cautious than those in the stock market. Bondholders gain the cash fow of fixed coupon and principal payments and, thus hardly benefit from the euphoric news in firm fundamentals. Since the upside payoffs are capped, the bond payoff relation with investor beliefs about the underlying fundamental becomes concave, whereas the equity payoff relation with investor beliefs regarding the underlying fundamental is linear (Hong and Sraer (2013)). Table A.1 of the appendix estimates the risk aversion parameter for the corporate bond and stock markets. Proxies for the corporate bond market are the Merrill Lynch U.S. aggregate bond index, the equal-weighted and value-weighted indexes of all corporate bonds in our sample. Proxies for the stock market are the Standard & Poor's (S&P) 500 index and the value-weighted CRSP index which includes all stocks trading on the NYSE, AMEX, and NASDAQ.

We use both conditional and unconditional approaches to estimate the risk aversion parameter (see Section A.1). Table A.1 shows that the conditional approach based on the GARCH-in-mean model yields the risk aversion parameter for a typical corporate bond market investor in the range of 12.1 to 14.7. The unconditional approach yields similar estimates of risk aversion for an average bond market investor, in the range of 12.3 to 16.6. The risk aversion for a typical stock market investor however is much lower: 5.5 for the S&P500 index and 7.5 for the value-weighted CRSP index if using the conditional approach; and even lower if using the unconditional approach: 3.5 for the S&P500 index and 3.7 for the value-weighted CRSP index.

Overall, these findings provide evidence that corporate bond investors are more risk averse and more sensitive to downside risk. To evaluate the risk-return relationship in the corporate bond market, downside risk is quintessential. We appraise the pricing power of downside risk in the next subsection.

4.2 Univariate Portfolio Analysis

We first examine the significance of a cross-sectional relation between VaR and future corporate bond returns using portfolio analysis. For each month from July 2004 to December 2014, we form quintile portfolios by sorting corporate bonds based on their downside risk (VaR), where quintile 1 contains bonds with the lowest downside risk, and quintile 5 contains bonds with the highest downside risk.[7] Table 2 shows the average VaR values of bonds in each quintile, the next month average excess return, and the 7-factor alpha for each quintile. The last five columns report the average bond characteristics for each quintile including bond beta, illiquidity, creidt rating, time-to-maturity, and bond size. The last row displays the differences of average returns or the alphas between quintile 5 and quintile 1. Average excess returns and alphas are defined in terms of monthly percentage. Newey-West (1987) adjusted t-statistics are reported in parentheses.

Moving from quintile 1 to quintile 5, the average excess return on the downside risk portfolios increases monotonically from -0.137% to 0.649% per month. This indicates a monthly average return difference of 0.786% between quintiles 5 and 1 (i.e., High-VaR quintile vs. Low-VaR quintile) with a Newey-West t-statistic of 3.19, showing that this positive return difference is statistically and economically significant. This result also indicates that corporate bonds in the highest VaR quintile generate 9.43% per annum higher return than bonds in the lowest VaR quintile do.

In addition to the average excess returns, Table 2 also presents the alphas from the regression of the quintile portfolio returns on well-known stock and bond market factors — the excess stock market return (MKT), a size factor (SMB), a book-to-market factor (HML), a momentum factor (MOM), and a liquidity factor (LIQ), following Fama and French (1993), Carhart (1997), and Pastor and Stambaugh (2003), and the default spread factor (DEF) and the term spread factor (TERM), following Elton et al. (2001), and Bessembinder et al. (2009). Similar to

[7] Downside risk is measured by the 5% VaR using a 36-month rolling window. A bond is included in our sample if it has at least 24 monthly return observations in the 36-month rolling window before the test month. Our data start in July 2002 and we report portfolio results starting from July 2004.

the average excess returns, the 7-factor alpha on the downside risk portfolios also increases monotonically from -0.207% to 0.503% per month, moving from the low-VaR to the high-VaR quintile, indicating a positive and significant alpha difference of 0.710% per month (t-statistic = 3.85). This result suggests that loss-averse bond investors prefer high expected return and low VaR.

Next, we investigate the source of significant alpha spread between high-VaR and low-VaR bonds. As reported in Table 2, the alphas in quintile 1 (low-VaR bonds) are statistically insignificant, whereas the alphas in quintile 5 (high-VaR bonds) are economically and statistically positive significant. Therefore, we conclude that the significant and positive alpha spread between high-VaR and low-VaR bonds is due to the outperformance of high-VaR bonds, but not due to the underperformance of low-VaR bonds.

Lastly, we examine the average characteristics of VaR-sorted portfolios. As shown in the last five columns of Table 2, bonds with high downside risk have higher market beta, higher level of trading illiquiduity, higher credit risk, longer time-to-maturity, and smaller size. This creates a potential concern about the interaction between downside risk and bond characteristics. We provide different ways of handling this concern. Specifically, we test whether the positive relation between VaR and the cross-section of bond returns holds once we control for credit rating, maturity, and size based on bivariate portfolio sorts and Fama-MacBeth regressions in the following subsections.

4.3 Controlling for Bond Characteristics

Table A.2 of the online appendix presents the results from the bivariate sorts of VaR and bond characteristics. In Panel A of Table A.2, quintile portfolios are formed by first sorting corporate bonds into five quintiles based on their credit ratings; then, within each rating portfolio, bonds are sorted further into five sub-quintiles based on their VaR. This methodology, under each rating-sorted quintile, produces sub-quintile portfolios of bonds with dispersion in downside risk but have nearly identical ratings. VaR,1 represents the lowest VaR-ranked bond quintiles within each of the five rating-ranked quintiles. Similarly, VaR,5 represents the highest VaR-ranked quintiles within each of the five rating-ranked quintiles.

Panel A of Table A.2 shows that the alphas under 5- and 7-factor model increase monotonically from the VaR,1 to the VaR,5 quintile. More importantly, after controlling for credit rating, the 7-factor alpha differences between high- and low-VaR bonds remain positive, about 0.634% per month, and highly significant with t-statistics of 4.23. We further investigate the interaction between VaR and credit ratings by sorting investment-grade and non-investment-grade bonds separately into bivariate quintile portfolios. As expected, the positive relation between VaR and expected returns is stronger for non-investment-grade bonds with the alpha spread of 0.730% per month (t-stat= 3.88), but the significantly positive relationship remains for investment-grade bonds even after we control for credit ratings, with the alpha spread of 0.463% per month (t-stat= 2.97).

Panel B of Table A.2 presents the results from the bivariate sorts of downside risk and maturity. Quintile portfolios are formed by first sorting corporate bonds into five quintiles based on their maturity; then, within each maturity portfolio, bonds are sorted further into five sub-quintiles based on their VaR. Panel B shows that after controlling for bond maturity, the alpha differences between high- and low-VaR bonds remain positive, 0.661% per month, and highly significant with t-statistics of 4.07. We further examine the interaction between VaR and maturity by sorting short-maturity bonds (1 year $\leq$ maturity $\leq$ 5 years), medium-maturity bonds (5 years $<$ maturity $\leq$ 10 years), and long-maturity bonds (maturity $>$ 10 years) separately into bivariate quintile portfolios based on their VaR and maturity. After controlling for maturity, the alpha spread between the VaR,1 and VaR,5 quintiles is 0.576% per month and marginally significant for short-maturity bonds, 0.615% per month and significant for medium-maturity bonds, and about 0.626% per month and significant for long-maturity bonds. Although the economic significance of these alpha spreads is similar across the three maturity groups, the statistical significance of the alpha differences is greater for medium- and long-maturity bonds. This result makes sense because longer-term bonds usually offer higher interest rates, but may entail additional risks.[8]

Panel C of Table A.2 presents the results from the bivariate sorts of downside risk and

[8]The longer the bond's maturity, the more time there is for rates to change and, hence, affect the price of the bond. Therefore, bonds with longer maturities generally present greater interest rate risk than bonds of similar credit quality that have shorter maturities. To compensate investors for this interest rate risk, long-term bonds generally offer higher returns than short-term bonds of the same credit quality do.

bond size measured by bond outstanding value. Quintile portfolios are formed by first sorting corporate bonds into five quintiles based on their market value (size); then, within each size portfolio, bonds are sorted further into five sub-quintiles based on their VaR. Panel C shows that after controlling for size, the alpha differences between high- and low-VaR bonds remain positive, about 0.692% per month, and statistically significant. In the same panel, we further investigate the interaction between VaR and bond size by sorting small and large bonds separately into bivariate quintile portfolios. As expected, the positive relation between VaR and expected returns is stronger for bonds with low market value, but the significantly positive link remain intact for bonds with high market value.

5 Pricing Power of Credit, Liquidity, and Market Risk

The credit spread literature has long recognized the importance of credit risk and liquidity risk in explaining the bond credit spread.[9] The asset pricing literature ever uses bond market factor in explaining the bond portfolio returns (Elton, Gruber, Blake, 1995). In this section, we formally test the pricing power of credit, liquidity, and market risk in the cross-section of expected bond returns for a large sample of about half million bond-month observations.

5.1 Credit Risk

A good proxy of credit risk should capture both the probability of default and the loss severity. Credit rating is a natural choice to measure the credit risk of corporate bond. Ratings are assigned for each corporate bond on the basis of extensive economic analysis by the rating agencies such as Moody's and Standard & Poor's. Bond-level ratings synthesize the information of both the issuer's financial condition, operating performance, risk management strategies, and the specific bond characteristics like coupon rate, seniority, and option features. Alternative proxies of credit risk, say the distance-to-default measure developed by KMV (Crosbie and Bohn (2003)) to predict default probabilities, or raw credit default swap spread proposed by Bai and Wu (2014), apply only to the firm level since their calculations require firm balance sheet information, thus they don't distinguish the difference of bond-level returns. Our interest

[9] The literature is large, to cite a few,

of study is the cross-section of corporate bond returns, which are different across firms and even bonds issued by the same firm may have different returns.[10] Therefore we adopt credit rating to measure bond-level credit risk.

Similar to the exercise in Section 4, we first test the significance of a cross-sectional relation between credit risk and future returns of corporate bonds using portfolio-level analysis. For each month from July 2002 to December 2014, we form quintile portfolios by sorting corporate bonds based on their credit ratings, where quintile 1 contains bonds with the lowest numeric score in rating (i.e., low credit risk bonds), and quintile 5 contains bonds with the highest numeric score in rating (i.e., high credit risk bonds).

In Table 3 we present the average credit rating in each quintile, the next month average excess return, and the 7-factor alpha values for each quintile. When moving from quintile 1 to quintile 5, the average return on the rating portfolios increases almost monotonically from 0.113% to 0.678% per month. This indicates a monthly average return difference of 0.565% between quintiles 5 and 1 (i.e., high credit risk quintile vs. low credit risk quintile) with a Newey-West t-statistic of 2.59. In other words, corporate bonds in the highest credit risk quintile generate 7.80% per annum higher return than bonds in the lowest credit risk quintile do.

The 7-factor alpha also increases from 0.017% in quintile 1 to 0.440% in quintile 5, suggesting a positive and significant alpha difference of 0.424% per month (t-statistic = 2.65). These results indicate that after controlling for the well-known stock and bond market factors, the return difference between high credit risk and low credit risk bonds, or the credit risk premium, remains positive and highly significant. In addition, the significantly positive return/alpha spread between high- and low-rating bonds is due to outperformance by bonds with high credit risk, but not to underperformance by bonds with low credit risk.

Lastly, we examine the average characteristics of individual bonds in rating portfolios. As presented in the last five columns of Table 3, high credit risk bonds have higher downside risk, higher illiquidity, shorter maturity, and smaller size. Bonds in different credit risk quintiles however does not seem to have significantly different market betas.

[10]Bonds issued by the same firm may have similar probability of default but not necessarily have the same recovery rate, liquidity risk, market risk, or downside risk. Thus bonds issued by the same firm often have different returns.

5.2 Liquidity Risk

Iliquidity is an important issue in the corporate bond market. The role of illiquidity on corporate bond yields or bond returns is well documented in the literature.[11] We employ the illiquidity measure, $ILLIQ$ following Bao, Pan, and Wang (2011), which is aimed at extracting the transitory component from bond price. Specifically, let $\Delta p_t = p_t - p_{t-1}$ be the log price change from $t-1$ to t. Then, $ILLIQ$ is defined as

$$ILLIQ = -Cov_t(\Delta p_{i,t,d}, \Delta p_{i,t,d+1}), \tag{3}$$

where $\Delta p_{i,t,d}$ is the log price change for bond i on day d of month t. It's worth noting that there is no consensus on the best liquidity measure for corporate bonds.

For each month from July 2002 to December 2014, we form quintile portfolios by sorting corporate bonds based on their level of illiquidity, where quintile 1 contains bonds with the lowest illiquidity (i.e., liquid bonds), and quintile 5 contains bonds with the highest illiquidity (i.e., illiquid bonds). Table 4 shows the average illiquidity level ($ILLIQ$), the next month average excess return, and the 7-factor alpha values for each quintile. When moving from quintile 1 to quintile 5, the average return on the illiquidity portfolios increases from 0.228% to 0.762% per month. This indicates a monthly average return difference of 0.535% between quintiles 5 and 1 (i.e., high illiquidity quintile vs. low illiquidity quintile) with a Newey-West t-statistic of 3.25, suggesting that this positive return difference is statistically and economically significant. Alternatively speaking, corporate bonds in the highest illiquidity quintile (illiquid bonds) generate 6.42% per annum higher return than bonds in the lowest illiquidity quintile (liquid bonds) do.

The fourth column of Table 4 shows that, similar to the average excess returns, the 7-factor alpha also increases monotonically from 0.092% to 0.621% per month, moving from quintile 1 to quintile 5, indicating a positive and significant alpha difference of 0.529% per month (t-statistic = 4.13). These results indicate that after controlling for the commonly used stock and bond market factors, the return difference between Low-illiquidity and High-illiquidity bonds

[11] The literature is extensive, to name a few but not limited to, de Jong and Driessen (2006), Chen, Lesmond, and Wei (2007), Lin, Wang, and Wu (2011), Bao, Pan, and Wang (2011), Dick-Nielsen, Feldhutter, and Lando (2012).

(the illiquidity premium) remains positive and highly significant.

Lastly, we examine the average characteristics of individual bonds in liquidity portfolios. As presented in the last five columns of Table 4, illiquid bonds have relatively higher downside risk, higher bond beta, longer maturity, and smaller size. Bonds in different illiquidity quintiles however do not seem to have significantly different credit risk.

5.3 Market β

In the empirical test of the capital asset pricing model , the market factor unanimously adopts the stock market return such as the return on the S&P 500 composite index or the CRSP index. These indices capture the information on public companies which issue common stocks. However, there are two reasons which make the stock market return proxy less appealing in explaining the corporate bond market. First, firms issuing public bonds may not have common stocks trade in the stock market. Second, firms trade in the stock market may not have public bonds. The number of firms in the corporate bond market is often smaller than that in the stock market. Since 2002, the average daily number of firms in the corporate bond market is XX, compared to XX in the stock market. However, one firm may issue multiple bonds.

In this section, we investigate whether the CAPM holds in the corporate bond market. Specifically, we test if the CAPM with the the bond market factor explains the cross-sectional variation in expected corporate bond returns. We use the Merrill Lynch U.S. Aggregate Bond Index as a proxy for the corporate bond market factor.[12] The corporate bond market return is computed as the percentage change in the monthly Merrill Lynch Bond Index values.

To examine the predictive power of the CAPM, we first estimate the exposures (betas) of corporate bonds to bond market factors, denoted by β^{Bond}, which is calculated for each bond based on the monthly rolling regressions of bond excess returns on the bond market excess returns over the past 36 months.[13] Once betas are estimated, we form quintile portfolios every month from January 1975 to December 2014 by sorting corporate bonds based on their bond betas. Quintile 1 is the portfolio with the lowest beta, and Quintile 5 is the portfolio with the

[12]We also consider alternative proxies such as the Barclays Aggregate Bond Index, the equal-weighted and value-weighted corporate bond market index using the sample in our paper, and the results are similar.

[13]If the observations of monthly returns are less than 36, the month t value of β^{Bond} for a given bond is not calculated and this bond-month observation is not used in empirical analyses that require a value of β.

highest beta.

Table 5 presents the results. When moving from quintile 1 to quintile 5, the average bond beta increases monotonically from 0.28 to 2.12, with a cross-sectional spread of 2.40. Consistent with the CAPM prediction, the average return on the highest bond beta quintile (0.568% per month) is significantly higher than the average return on the lowest bond beta quintile (-0.021% per month). The average return spread between quintiles 5 and 1 is economically and statistically significant; 0.589% per month (t-statistics=3.48). That means, high beta bond portfolios earn a market risk premium of 7.068% per annum than low beta bond portfolios. Moreover, the significantly positive bond market risk premium is driven by bonds with high beta (0.438% per month with t-stat = 2.03), whereas bonds with low beta have insignificant average return (-0.119% per month with t-stat = -1.10).

Examining the bond characteristics of individual bonds in beta portfolios, we find that high bond beta portfolio tend to have higher illiquidity, higher downside risk, longer maturity, and larger in size. Credit rating across beta quintiles are not dramatically different from each other, indicating that bond beta is not much relevant to bond rating.

Overall, the results in Table 5 indicate that the bond market beta predicts the cross-sectional differences in expected returns of corporate bonds. The CAPM with the bond market factor not only holds in the corporate bond market, but also generates economically sensible estimates of the bond market risk premium. That's why it is essential to use the corporate bond market factor to price the cross-sectional variation in corporate bond returns.

5.4 Fama-MacBeth Regression

So far we have tested the significance of downside risk (5% VaR), credit risk (rating), illiquidity (ILLIQ), and bond market beta (β^{Bond}) as a determinant of the cross-section of future bond returns at the portfolio level. This portfolio-level analysis has the advantage of being non-parametric, in the sense that we do not impose a functional form on the relation between these risk proxies and future bond returns. The portfolio-level analysis also has two potentially significant disadvantages. First, it throws away a large amount of information in the cross-section via aggregation. Second, it is a difficult setting in which to control for multiple effects or bond characteristics simultaneously. Consequently, we now examine the cross-sectional relation between the risk proxies and expected returns at the bond level using Fama and MacBeth (1973) regressions.

We present the time-series averages of the slope coefficients from the regressions of one-month-ahead excess bond returns on VaR, rating, ILLIQ, and β^{Bond} and the control variables; maturity (MAT) and amount outstanding (SIZE). Monthly cross-sectional regressions are run for the following econometric specification and nested versions thereof:

$$\begin{aligned} R_{i,t+1} &= \lambda_{0,t} + \lambda_{1,t} VaR_{i,t} + \lambda_{2,t} Rating_{i,t} + \lambda_{3,t} ILLIQ_{i,t} \\ &\quad + \lambda_{4,t} \beta^{Bond} + \sum_{k=1}^{K} \lambda_{k,t} Control_{k,t} + \epsilon_{i,t+1} \end{aligned} \tag{4}$$

where $R_{i,t+1}$ is the excess return on bond i in month t+1. The predictive cross-sectional regressions are run on the one-month lagged values of risk proxies and control variables.

Table 6 reports the time series average of the intercept and slope coefficients λ's and the average adjusted R^2 values over the 125 months from July 2004 to December 2014. The Newey-West adjusted t-statistics are reported in parentheses. The univariate regression results show a positive and statistically significant relation between VaR and and the cross-section of future bond returns. In Regression (1), the average slope, $\lambda_{1,t}$, from the monthly regressions of excess returns on VaR alone is 0.068 with a t-statistic of 2.91. The economic magnitude of the associated effect is similar to that documented in Table 2 for the univariate quintile portfolios of VaR. The spread in average VaR between quintiles 5 and 1 is approximately 9.57 (= 12.47 − 2.90), multiplying this spread by the average slope of 0.068 yields an estimated monthly risk premium of 65 basis points.

The average slope, $\lambda_{2,t}$, from the univariate cross-sectional regressions of excess bond returns on rating is positive and statistically significant. Regression (3) shows an average slope of 0.064 with a t-statistic of 2.57. The economic magnitude of the associated effect is similar to that documented in Table 3 for the univariate quintile portfolios of rating. The spread in average rating between quintiles 5 and 1 is approximately 11.48 (= 14.41 − 2.93), multiplying this spread by the average slope of 0.064 yields an estimated monthly risk premium of 73 basis points.

Consistent with the univariate quintile portfolios of illiquidity in Table 4, the average slope, $\lambda_{3,t}$, from the univariate cross-sectional regressions of excess bond returns on ILLIQ is positive, 0.062, and highly significant with a t-statistic of 5.14. As shown in the first column of Table 4, the spread in average ILLIQ between quintiles 5 and 1 is approximately 8.01 (= 7.85 - (-0.16)). Multiplying this spread by the average slope of 0.062 yields an estimated monthly risk premium of 50 basis points.

Regression (7) shows a positive and significant relation between β^{Bond} and future bond returns. The average slope, $\lambda_{4,t}$, from the monthly regressions of excess returns on β^{Bond} alone is 0.280 with a t-statistics of 2.80. The economic magnitude of the associated effect is similar to that documented in Table 5 for the univariate quintile portfolios of β^{Bond}. The spread in average β^{Bond} between quintiles 5 and 1 is approximately 1.84 ($= 2.12 - 0.28$), multiplying this spread by the average slope of 0.280 yields an estimated monthly risk premium of 52 basis points.

Regression specifications (2), (4), (6) and (8) in Table 6 show that after controlling for maturity and size, the average slope on VaR, rating, ILLIQ, and β^{Bond} remains positive and statistically significant. In other words, controlling for bond characteristics does not affect the positive cross-sectional relation between the risk proxies and future bond returns.

Regression (9) tests the cross-sectional predictive power of VaR, rating, ILLIQ, and β^{Bond} simultaneously. The average slopes on VaR and ILLIQ are significantly positive at 0.097 (t-stat. $=$ 3.99) and 0.028 (t-stat. $=$ 3.55), respectively. Although the average slope on β^{Bond} is positive, it is not statistically significant. Moreover, the average slope on rating becomes insignificant and negative, implying that credit rating loses its predictive power for future bond returns after VaR and ILLIQ are controlled for.

The last specification, Regressions (10) presents results from the multivariate regressions with all bond risk proxies (VaR, Rating, ILLIQ, and β^{Bond}) after controlling for bond characteristics. Similar to our findings from univariate regressions, the cross-sectional relation between VaR and ILLIQ and future bond returns is positive and highly significant. However, after controlling for VaR and ILLIQ, the predictive power of rating and β^{Bond} either disappears or becomes weak, indicating that downside risk and liquidity risk have more pervasive effect on future bond returns than credit risk and market risk. Overall, the Fama-MacBeth regression results echo the portfolio-level analyses, indicating that the downside risk, credit risk, liquidity risk, and market risk of corporate bonds contribute significantly to the prediction of cross-sectional variation in future bond returns.

6 Portfolio Returns and Corporate Bond Risk Factors

In previous sections we have shown that downside risk, credit risk, bond-level illiquidity, and bond market beta have significant pricing power for the cross-sectional variations in future corporate bond returns. These results suggest that the aforementioned variables characterize or proxy for common risk factors in bond returns. To investigate this thoroughly, we propose new bond risk factors based on these risk proxies in section 6.1 and examine their empirical properties in section 6.2. These bond risk factors are fully motivated by the unique features of corporate bonds and bond investor risk preference. We then test in section 6.3 on whether these bond-specific risk factors can be explained by the long-established stock and bond market factors. Finally, in section 6.4, we form test portfolios and compare the explanatory power of the bond risk factors with the other commonly used factor models for the cross-section of corporate bond returns.

6.1 New Risk Factors: DRF, CRF, LRF

Following Fama and French (1993, 1996) who form stock market risk factors, we use double sorts to construct common risk factors for corporate bonds. However, we use sequential sorts rather than independent sorts since bond credit risk, downside risk, and liquidity risk are correlated with each other. As expected, corporate bonds with high credit risk have higher downside risk (see Tables 2 and 3); corporate bonds with high credit risk have high illliquidity as well (see Tables 3 and 4). Thus, it is natural to use credit risk (proxied by credit rating) as the first sorting variable in the construction of these new bond market risk factors.

First, to construct the downside risk factor for corporate bond returns, for each month from July 2004 to December 2014, we form portfolios by first sorting corporate bonds into five quintiles based on their credit rating; then within each rating portfolio, bonds are sorted further into five sub-quintiles based on their downside risk (measured by 5% VaR). The downside risk factor, DRF, is the equal- or value-weighted average return difference between the highest-VaR portfolio and the lowest-VaR portfolio within each rating portfolio.[14]. This methodology, under each rating-sorted quintile, produces sub-quintile portfolios of bonds with dispersion in downside risk and nearly identical ratings.

Second, for the liquidity risk factor, for each month from July 2002 to December 2014, we form portfolios by first sorting corporate bonds into five quintiles based on their credit rating; then within each rating portfolio, bonds are sorted further into five sub-quintiles based on their illiquidity (ILLIQ), as defined in section 5.2. The liquidity risk factor, LRF, is the equal- or value-weighted average return difference between the highest-illiquidity portfolio and the lowest-illiquidity portfolio within each rating portfolio.

Finally, to construct the credit risk factor for corporate bond returns, we use a reverse sequential sort. For each month from July 2002 to December 2014, we form portfolios by first sorting corporate bonds into five quintiles based on their illiquidity (ILLIQ); then within each ILLIQ portfolio, bonds are sorted further into five sub-quintiles based on their credit rating. The credit risk factor, CRF, is the equal- or value-weighted average return difference between the lowest-rating (i.e., highest credit risk) portfolio and the highest-rating (i.e., lowest credit risk) portfolio within each ILLIQ portfolio.

Our final sample of corporate bond risk factors CRF and LRF start from July 2002 to December 2014. The DRF factor starts from July 2004 to December 2014 due to the requirement of at least 24 monthly return observations to calculate downside risk for a 36-month rolling window.

6.2 Empirical Properties

Panel A of Table 7 reports the summary statistics for the new risk factors (DRF, CRF and LRF), and the long-established stock and bond market risk factors in the literature. The traditional stock market factors include the five factors of Fama and French (1993), Carhart (1997)

[14]We also report the value-weighted bond risk factors since bonds with relatively high credit risk, downside risk, and liquidity risk are smaller in size. To alleviate this concern, we use amount outstanding as weights to construct the factors

and Pastor and Stambaugh (2003): the excess stock market return (MKT), the size factor (SMB), the book-to-market factor (HML), the momentum factor (MOM), and the liquidity factor (LIQ). The standard bond market factors include the excess bond market return (Elton, Gruber, and Blake (1995)), the default spread (DEF) and term spread (TERM) factors of Fama and French (1993).

Over the period from July 2002 to December 2014, the corporate bond market risk premium, MKT^{Bond}, is 0.40% per month with a t-statistic of 2.86. The equal-weighted DRF factor has an economically and statistically significant risk premium: mean of 0.70% per month with a t-statistic of 4.32. The equal-weighted CRF and LRF factors also have significant risk premia: mean of 0.53% per month (t-stat.= 2.69) and 0.47% per month (t-stat.= 4.37), respectively. The risk premia on the factors remain qualitatively similar when we use value-weighting: 0.59% per month for the DRF factor, 0.51% per month for the CRF factor, and 0.43% per month for the LRF factor. For comparison, Panel A of Table 7 also shows the summary statistics for the commonly used stock market factors. The stock market risk premium, MKT^{Stock} is 0.69% per month with a t-statistic of 1.95. SMB, HML, UMD, and LIQ factors have an average monthly return of 0.23% (t-stat.= 1.21), 0.09% (t-stat. = 0.49), -0.07% (t-stat.= -0.17), and 0.00% (t-stat.= 0.55), respectively.

Since risk premia are expected to be higher during financial and economic downturns, we examine the average risk premia for the newly proposed DRF, CRF, and LRF during recessionary vs. non-recessionary periods, according to the Chicago Fed National Activity Index (CFNAI). The CFNAI index is a monthly index designed to assess overall economic activity and related inflationary pressure (see, e.g., Allen, Bali, and Tang (2012)). The CFNAI is a weighted average of 85 existing monthly indicators of national economic activity. It is constructed to have an average value of zero and a standard deviation of one. An index value below (above) -0.7 corresponds to recessionary (non-recessionary) period. As expected, we find that the average risk premium on the equal-weighted DRF factor is much higher at 1.42% per month (t-stat.= 2.34) during recessionary periods (CFNAI $<$ -0.7), whereas 0.50% per month (t-stat.= 4.45) during non-recessionary periods (CFNAI $>$ -0.7). The average risk premium on the equal-weighted CRF factor is 0.53% (t-stat.= 0.81) during recessionary periods and 0.50% (t-stat.= 2.80) during non-recessionary periods. Finally, the average risk premium on the equal-weighted LRF factor is higher at 1.33% per month (t-stat.$=3.10$) during recessionary periods, whereas 0.26% per month (t-stat.$=3.63$) during non-recessionary periods. These magnitudes provide clear evidence that the newly proposed corporate bond risk factors generates economically large risk premia during downturns of the economy.

Panel B of Table 7 shows that all of these new risk factors have low correlations with the existing stock and bond market factors. Specifically, the correlations between the DRF factor and the standard stock market factors (MKT^{Stock}, SMB, HML, UMD, and LIQ) are in the range of 0.14 and 0.48 in absolute magnitude. The correlations between the DRF factor and the standard bond market factors (MKT^{Bond}, DEF, and TERM) are in the range of 0.01 and 0.48 in absolute magnitude. The corresponding correlations are also low for the CRF factor; in the range 0.06 and 0.62 for the stock market factors and range from 0.04 to 0.47 for the bond market factors in absolute magnitude. Similarly, the corresponding correlations are low for the LRF factor too; in the range 0.04 and 0.53 for the stock market factors and range from 0.03 to 0.32 for the bond market factors in absolute magnitude. These results suggest that the newly proposed risk factors represent an important source of common return variation missing from the long-established stock and bond market risk factors.

6.3 Do Existing Stock and Bond Market Factors Explain the DRF, CRF, and LRF Factors?

To examine whether the conventional stock and bond market risk factors can explain the newly proposed risk factors of corporate bonds, we conduct a formal test using the following time-series regression:

$$Factor_t = \alpha + \sum_{k=1}^{K} \beta_k Factor_{k,t}^{Stock} + \sum_{l=1}^{L} \beta_l Factor_{l,t}^{Bond} + \varepsilon_t, \tag{5}$$

where $Factor_t$ is one of the four bond market factors: MKT^{Bond}, DRF, CRF, and LRF. $Factor_{k,t}^{Stock}$ denotes a vector of stock market factors: MKT^{Stock}, SMB, HML, UMD, and LIQ; and $Factor_{k,t}^{Bond}$ denotes a vector of bond market factors: MKT^{Bond}, DEF, and TERM.

Equation (5) is estimated separately for MKT^{Bond} and each of the newly proposed bond risk factors: DRF, CRF, or LRF on the left hand side. These factor regression results are presented in Table 8. The intercepts (alphas) from these time-series regressions represent the abnormal returns not explained by the standard stock and bond market factors. The alphas are defined in terms of monthly percentage. Newey-West (1987) adjusted t-statistics are reported in parentheses.

Panel A of Table 8 presents the regression results from the bond market excess return factor, MKT^{Bond}, on the 7 commonly used stock and bond market factors. The results show that MKT^{Bond} contains information about bond market returns not captured by the other stock and bond market factors. The intercept (alpha) is statistically and economically significant, 0.30% per month with a t-statistics of 2.64. The adjusted-R^2 values is 56.40%, suggesting that a large fraction of the total variance of MKT^{Bond} is still not explained by the other factors.

Panel B of Table 8 shows the regression results from the equal-weighted bond risk factors on the 7-factor model, as well as the extended 8-factor model combining all of the stock and bond market factors. Our results highlight several findings. First of all, all of the intercepts (alphas) are statistically and economically significant, indicating that the existing stock and bond market factors are not sufficient to capture the information contained in these new bond risk factors. Based on the 7-factor model, the alphas for the DRF, CRF and LRF factors are 0.64% per month (t-stat.= 3.91), 0.36% per month (t-stat.= 2.28), and 0.47% (t-stat.= 4.15), respectively. Second, the adjusted-R^2 values from these regressions are in the range of 26% to 58%, suggesting that the commonly used stock and bond market factors have low explanatory power for the newly proposed risk factors of corporate bonds.

Panel B also shows that adding MKT^{Bond} to the 7-factor model does not explain the returns of DRF, CRF and LRF. The alphas remain statistically and economically significant. Based on the extended 8-factor model, the alphas for the DRF, CRF and LRF factors are 0.46% per month (t-stat.= 3.40), 0.31% per month (t-stat.= 2.26), and 0.41% (t-stat.= 4.10), respectively. Combining all factors together, they explain about 52% of the DRF factor, 58% of the CRF factor, and 28% of the LRF factor. Overall, these findings suggest that our new bond market risk factors represent an important source of common return variation missing from the long-established stock and bond market risk factors.

Panel C of Table 8 presents the regressions results from the value-weighted bond risk factors on the 7- and extended 8-factor model. The results are consistent with our earlier findings. All of the intercepts are statistically and economically significant, and the magnitude of the alphas are similar to those in Panel B for the equal-weighted bond risk factors. Based on the 7-factor model, the alphas for the DRF, CRF and LRF factors are 0.49% per month (t-stat.= 3.17), 0.29% per month (t-stat.= 2.18), and 0.42% (t-stat.= 4.35), respectively. Combining all factors together, the adjusted-R^2 values from the 8-factor model are in the range of 31% to 62%, suggesting that the commonly used stock and bond market factors have low explanatory power for our newly proposed risk factors of corporate bonds.

6.4 Test Portfolios Formed on Size and Maturity

In this subsection, we form test portfolios using corporate bond returns and examine the explanatory power of alternative factor models. First, we form 10 decile portfolios from univariate sort of corporate bonds based on size (amount outstanding), where decile 1 (10) is the portfolio with smallest (largest) size. Second, we form 10 decile portfolios from univariate sort of corporate bonds based on time-to-maturity, where decile 1 (10) is the portfolio with the shortest (longest) time-to-maturity.[15] Finally, we form 25 size and maturity portfolios from independently sorting corporate bonds into 5 by 5 quintile portfolios based on size and time-to-maturity. We use excess returns on the 10 or 25 portfolios as dependent variables in the time-series regressions and investigate the explanatory power of alternative factor models for the test portfolio returns. The returns of the test portfolios start from July 2002 to December 2014.

We examine four alternative factor models on their explanatory power for the time-series of test portfolios' returns. The factors models are:

- Model 1: the Fama-French (1993) 5-factor model, including the excess stock market return (MKT^{Stock}), size factor (SMB), book-to-market factor (HML), default spread factor (DEF), and term spread factor (TERM).

[15] From July 2002 to December 2014, corporate bonds in size decile 10 underperform those in decile 1 by 0.33% per month, with a t-statistics of 2.70; corporate bonds in maturity decile 10 outperform those in decile 1 by 0.36% per month, with a t-statistics of 2.56.

- Model 2: the augmented 7-factor model based on the Fama-French (1993) 5-factor model, with a momentum factor (MOM) and a Pastor-Stambaugh liquidity factor (LIQ) as additional factors.

- Model 3: the bond market factor model with the bond market excess returns (MKT^{Bond}) as the single factor.

- Model 4: the 4-factor model including the bond market excess returns (MKT^{Bond}), the value-weighted downside risk factor (DRF), credit risk factor (CRF), and liquidity risk factor (LRF).

We seek to determine whether our newly proposed bond market risk factors capture common variations in bond returns related to size and maturity, compared with the commonly used factor models.

6.4.1 10 Portfolios Formed on Size and Maturity

In the time-series regressions, the R^2 values are direct evidence on whether different risk factors capture common variation in bond returns. Panel A of Table 9 reports the adjusted R^2 for the time-series regression of the 10 size-sorted portfolios' excess returns on the alternative factor models. The results show that the commonly used stock and bond factors do not have much explanatory for the cross-sectional variation in returns. The first row of Panel A shows the average R^2 based on the Fama-French (1993) 5-factor model is 0.41, suggesting that a large fraction of return variance is not explained by these factors. In the second row, when we augment the 5-factor model with two additional stock market factors with a momentum factor (MOM) and a Pastor-Stambaugh liquidity factor (LIQ), the average R^2 remains to be small with a magnitude of 0.49.

On the contrary, the bond market excess return factor MKT^{Bond} and our newly proposed bond risk factors DRF, CRF and LRF capture much common variation in the size-sorted portfolio returns. In the third row of Panel A, when used alone as the explanatory variable in the time-series regressions, MKT^{Bond} has an average R^2 of 0.68, higher than any of those based on the 5- or 7-factor model. In the last row of Panel A, when we augment MKT^{Bond} with our newly proposed bond risk factors DRF, CRF and LRF, the average R^2 value is further increased, from 0.68 to 0.80, suggesting that these new bond risk factors capture information about return variation that is not contained in MKT^{Bond}. For each size-sorted portfolio, the R^2 values based on the 4-factor model range from 0.58 for small bonds to 0.91 for large bonds.

Panel B of Table 9 shows the results of the 10 maturity-sorted portfolio returns. Consistent with Panel A, the results show that the commonly used stock and bond factors do not have much explanatory for the maturity-sorted portfolio returns. The first and second row of Panel B show that the average R^2 based on the Fama-French (1993) 5- or augmented 7-factor model is 0.47 and 0.50, respectively. By contrast, the average R^2 value for the single bond market factor model is 0.75, and is further increased to 0.81 based on the 4-factor bond market model. For each maturity-sorted portfolio, the R^2 values based on the 4-factor model range from 0.76 for bonds with shorter time-to-maturity, 0.77 for bonds with medium time-to-maturity, and 0.82 for bonds with the longest time-to-maturity.

Overall, the results in Panels A and B suggest that the 4-factor model has the greatest explanatory power for the size- and maturity-sorted corporate bond portfolio returns, compared with the other three factor models.

6.4.2 25 Portfolios Formed on Size and Maturity

In this subsection, we examine the explanatory power of alternative factor models for the 25 size- and maturity-sorted portfolios. Panels C to F of Table 9 report the adjusted R^2 for the time-series regression of the 25 portfolios' excess returns on the alternative factor models. The results show that the commonly used stock and bond factors do not have much explanatory for the size- and maturity-sorted bond portfolio returns. In Panel C, where the benchmark is the the Fama-French (1993) 5-factor model, the average R^2 is 0.41. In Panel D, the average R^2 increases to 0.52 based on the augmented 7-factor model. The low R^2 values thus imply that a large fraction of the 25 portfolio return variance is not explained by the commonly used factors.

By contrast, the bond market excess return factor MKT^{Bond} and our newly proposed bond risk factors DRF, CRF and LRF capture much common variation in the size- and maturity-sorted portfolio returns. In Panel E, when used alone as the explanatory variable in the time-series regressions, MKT^{Bond} has an average R^2 of 0.64, higher than any of those based on the 5- or 7-factor model. In Panel F, when we augment MKT^{Bond} with our newly proposed bond risk factors DRF, CRF and LRF, the average R^2 value is further increased, from 0.64 to 0.78, suggesting that these new bond risk factors capture information about return variation that is not contained in MKT^{Bond}. Overall, the results are consistent with the univariate sort test portfolio and suggest that the 4-factor model performs the best in explaining the size- and maturity-portfolio returns, compared with the other commonly used factor models.

7 Conclusion

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Table 1: **Descriptive Statistics**

Panel A reports the number of bond-month observations, the cross-sectional mean, median, standard deviation and monthly return percentiles of corporate bonds, and bond characteristics including credit rating, time-to-maturity (Maturity, year), amount outstanding (Size, $ million), downside risk (5% Value-at-Risk, VaR), illiquidity (ILLIQ), and CAPM beta based on the corporate bond market index, β^{Bond}. Ratings are in conventional numerical scores, where 1 refers to an AAA rating and 21 refers to a C rating. Higher numerical score means higher credit risk. Numerical ratings of 10 or below (BBB- or better) are considered investment grade, and ratings of 11 or higher (BB+ or worse) are labeled high yield. Downside risk is the 5% Value-at-Risk (VaR) of corporate bond return, defined as the second lowest monthly return observation over the past 36 months. The original VaR measure is multiplied by -1 so that a higher VaR indicates higher downside risk. Bond illiquidity is computed as the autocovariance of the daily price changes within each month, multiplied by -1. β^{Bond} is the corporate bonds beta with respect to the excess corporate bond market return, constructed using the Merrill Lynch U.S. Aggregate Bond Index. The betas are estimated for each bond from the time-series regressions of bond excess returns on the excess bond market return, with a 36-month rolling window (prior 36 months). The sample period is from July 2002 to December 2014.

Panel A: Cross-sectional statistics over the sample of July 2002 - December 2014

					Percentiles					
	N	Mean	Median	SD	1st	5th	25th	75th	95th	99th
Bond return (%)	507,714	0.39	0.30	3.52	-8.30	-4.72	-1.32	1.86	5.77	11.24
Rating	502,646	8.06	7.59	4.04	1.66	1.90	5.55	9.98	16.00	18.52
Time-to-maturity (maturity, year)	510,853	12.74	9.37	9.10	3.19	4.56	6.33	17.92	28.18	35.57
Amount out (size, $million)	505,301	395.62	278.25	465.04	1.62	5.34	80.51	500.78	1270.71	2496.40
Downside risk (5% VaR)	244,754	6.43	5.37	3.87	1.88	2.56	3.90	7.77	14.12	20.56
Illiquidity (ILLIQ)	406,088	2.38	0.60	5.39	-1.31	-0.27	0.11	2.25	11.57	25.38
Bond market beta (β^{Bond})	246,446	1.10	1.02	0.70	-0.39	0.11	0.66	1.44	2.36	3.20

Panel B: Correlations

	Rating	Maturity	Size	VaR	ILLIQ	β^{Bond}
Rating	1	-0.165	0.011	0.382	0.059	0.147
Maturity		1	-0.061	0.161	0.104	0.319
Size			1	-0.081	-0.136	0.080
VaR				1	0.241	0.485
ILLIQ					1	0.117
β^{Bond}						1

Table 2: **Univariate Portfolios of Corporate Bonds Sorted by Downside Risk**

Quintile portfolios are formed every month from July 2004 to December 2014 by sorting corporate bonds based on the 5% Value-at-Risk (VaR), defined as the second lowest monthly return observation over the past 36 months. The original VaR measure is multiplied by -1. Quintile 1 is the portfolio with the lowest VaR, and Quintile 5 is the portfolio with the highest VaR. Table also reports the average VaR, the next-month average excess return, and the 7-factor alpha for each quintile. The last five columns report average portfolio characteristics including bond beta (β^{Bond}), illiquidity (ILLIQ), credit rating, time-to-maturity (years), and amount outstanding (size, in $billion) for each quintile. The last row shows the differences in monthly average returns, the differences in alphas with respect to the 7-factor models. The 7-factor model includes the excess stock market return (MKT), a size factor (SMB), a book-to-market factor (HML), a momentum factor (MOM), a liquidity factor (LIQ), plus two bond market factors: the default spread factor (DEF) and the term spread factor (TERM). Average excess returns and alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Quintiles	Average	Average	7-factor	Average portfolio characteristics				
	VaR	return	alpha	β^{Bond}	ILLIQ	Rating	Maturity	Size
Low VaR	2.90	-0.137	-0.207	0.71	0.78	6.60	8.10	0.53
		(-1.14)	(-2.10)					
2	4.18	-0.022	-0.118	0.93	1.35	7.31	10.49	0.51
		(-0.15)	(-1.01)					
3	5.39	0.044	-0.066	1.06	1.94	7.79	14.11	0.46
		(0.25)	(-0.50)					
4	7.20	0.190	0.076	1.23	2.60	8.72	15.05	0.44
		(0.89)	(0.48)					
High VaR	12.47	0.649	0.503	1.49	5.14	11.31	22.23	0.45
		(2.26)	(2.23)					
High − Low		0.786***	0.710***					
Return/Alpha diff.		(3.19)	(3.85)					

Table 3: **Univariate Portfolios of Corporate Bonds Sorted by Credit Rating**

Quintile portfolios are formed every month from July 2002 to December 2014 by sorting corporate bonds based on their credit rating. Quintile 1 is the portfolio with the lowest credit rating, and Quintile 5 is the portfolio with the highest credit rating. Ratings are in conventional numerical scores, where 1 refers to an AAA rating and 21 refers to a C rating. Higher numerical score means lower ratings (i.e., higher credit risk). Table also reports the average credit rating, the next-month average excess return, and the 7-factor alpha for each quintile. The last five columns report average portfolio characteristics including bond beta (β^{Bond}), illiquidity (ILLIQ), VaR, time-to-maturity (years), and amount outstanding (size, in \$billion) for each quintile. The last row shows the differences in monthly average returns, the differences in alphas with respect to the 7-factor models. The 7-factor model includes the excess stock market return (MKT), a size factor (SMB), a book-to-market factor (HML), a momentum factor (MOM), a liquidity factor (LIQ), plus two bond market factors: the default spread factor (DEF) and the term spread factor (TERM). Average excess returns and alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Quintiles	Average	Average	7-factor	Average portfolio characteristics				
	rating	return	alpha	β^{Bond}	ILLIQ	VaR	Maturity	Size
Low Credit Risk	2.93	0.113	0.017	0.95	2.06	5.14	12.89	0.41
		(0.74)	(0.13)					
2	6.02	0.124	0.037	1.10	1.60	4.91	13.79	0.46
		(0.78)	(0.29)					
3	7.81	0.183	0.100	1.20	2.03	5.81	13.49	0.44
		(1.08)	(0.73)					
4	9.70	0.284	0.156	1.12	2.51	6.36	12.90	0.42
		(1.49)	(1.05)					
High Credit Risk	14.41	0.678	0.440	1.06	3.22	9.66	10.02	0.40
		(2.60)	(2.31)					
High − Low		0.565***	0.424***					
Return/Alpha diff.		(2.59)	(2.65)					

Table 4: **Univariate Portfolios of Corporate Bonds Sorted by Illiquidity**

Quintile portfolios are formed every month from July 2002 to December 2014 by sorting corporate bonds based on the illiquidity measured, $ILLIQ$, in Bao, Pan, and Wang (2011). Table also reports the average illiquidity, the next-month average excess return, and the 7-factor alpha for each quintile. The last five columns report average portfolio characteristics including bond beta (β^{Bond}), VaR, credit rating, time-to-maturity (years), and amount outstanding (size, in $billion) for each quintile. The last row shows the differences in monthly average returns, the differences in alphas with respect to the 7-factor models. The 7-factor model includes the excess market return (MKT), a size factor (SMB), a book-to-market factor (HML), a momentum factor (MOM), a liquidity factor (LIQ), plus two bond market factors: the default spread factor (DEF) and the term spread factor (TERM). Average excess returns and alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Quintiles	Average	Average	7-factor	Average portfolio characteristics				
	ILLIQ	return	alpha	β^{Bond}	VaR	Rating	Maturity	Size
Low ILLIQ	-0.16	0.228	0.092	1.05	5.88	8.49	11.29	0.69
		(1.32)	(0.64)					
2	0.18	0.020	-0.111	0.99	5.13	8.25	10.11	0.64
		(0.14)	(-0.94)					
3	0.61	0.070	-0.067	1.07	5.88	8.33	11.82	0.47
		(0.45)	(-0.54)					
4	1.75	0.219	0.072	1.12	6.60	8.11	13.32	0.35
		(1.19)	(0.49)					
High ILLIQ	7.85	0.762	0.621	1.21	8.10	8.40	14.76	0.25
		(2.51)	(2.57)					
High − Low		0.535***	0.529***					
Return/Alpha diff.		(3.25)	(4.13)					

Table 5: **Univariate Portfolios of Corporate Bonds Sorted by Bond Market Beta**

Quintile portfolios are formed every month from July 2004 to December 2014 by sorting corporate bonds based on their bond market betas. β^{Bond} is the corporate bonds beta with respect to the excess corporate bond market return, constructed using the Merrill Lynch U.S. Aggregate Bond Index. The betas are estimated for each bond from the time-series regressions of bond excess returns on the excess bond market return with a 36-month rolling window (prior 36 months). Quintile 1 is the portfolio with the lowest β^{Bond}, and Quintile 5 is the portfolio with the highest β^{Bond}. Table also reports the average β^{Bond}, the next-month average excess return, and the 7-factor alpha for each quintile. The last five columns report average portfolio characteristics including illiquidity (ILLIQ), VaR, credit rating, time-to-maturity (years), and amount outstanding (size, in $billion) for each quintile. The last row shows the differences in monthly average returns, the differences in alphas with respect to the 7-factor models. The 7-factor model includes the excess market return (MKT), a size factor (SMB), a book-to-market factor (HML), a momentum factor (MOM), a liquidity factor (LIQ), plus two bond market factors: the default spread factor (DEF) and the term spread factor (TERM). Average excess returns and alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Quintiles	Average	Average	7-factor	Average portfolio characteristics				
	β^{Bond}	return	alpha	ILLIQ	VaR	Rating	Maturity	Size
Low β^{Bond}	0.28	-0.021	-0.119	2.00	5.11	8.60	8.94	0.35
		(-0.14)	(-1.10)					
2	0.75	-0.012	-0.113	1.59	5.07	8.09	8.91	0.44
		(-0.08)	(-1.10)					
3	1.03	0.077	-0.017	1.68	5.56	7.95	10.30	0.50
		(0.52)	(-0.16)					
4	1.35	0.211	0.096	2.01	6.71	8.08	13.33	0.54
		(1.21)	(0.72)					
High β^{Bond}	2.12	0.568	0.438	3.41	9.73	9.05	18.01	0.53
		(2.37)	(2.03)					
High − Low		0.589***	0.557***					
Return/Alpha diff.		(3.48)	(3.02)					

Table 6: **Fama-MacBeth Cross-Sectional Regressions with VaR, Rating, ILLIQ, and β^{Bond}**

This table reports the average intercept and slope coefficients from the Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead corporate bond excess returns on the VaR, credit rating, illiquidity (ILLIQ), bond market beta (β^{Bond}) with and without controls. Bond characteristics include time-to-maturity (years) and amount outstanding (size, in $billion). Ratings are in conventional numerical scores, where 1 refers to an AAA rating and 21 refers to a C rating. Higher numerical score means higher credit risk. The Fama and MacBeth regressions are run each month for the period from July 2004 to December 2014. Newey-West (1987) t-statistics are reported in parentheses to determine the statistical significance of the average intercept and slope coefficients. The last column reports the average adjusted R^2 values. Numbers in bold denote statistical significance at the 5% level or below. The sample period is from July 2004 to December 2014.

	Intercept	5% VaR	Rating	ILLIQ	β^{Bond}	Maturity	Size	Adj. R^2
(1)	-0.359	**0.068**						0.042
	(-2.64)	(2.91)						
(2)	-0.359	**0.061**				0.003	-0.029	0.076
	(-3.21)	(2.52)				(0.54)	(-0.87)	
(3)	-0.230		**0.064**					0.042
	(-1.49)		(2.57)					
(4)	-0.326		**0.066**			**0.010**	-0.000	0.073
	(-2.80)		(2.66)			(2.08)	(-0.98)	
(5)	0.096			**0.062**				0.017
	(0.60)			(5.14)				
(6)	0.029			**0.052**		0.003	0.108	0.050
	(0.18)			(5.07)		(0.53)	(1.81)	
(7)	-0.156				**0.280**			0.031
	(-1.01)				(2.80)			
(8)	-0.128				**0.267**	0.001	-0.108	0.058
	(-0.79)				(2.62)	(0.21)	(-1.78)	
(9)	-0.531	**0.097**	-0.004	**0.028**	0.036			0.102
	(-2.74)	(3.99)	(-0.21)	(3.55)	(0.52)			
(10)	-0.562	**0.100**	-0.004	**0.029**	0.023	-0.001	0.001	0.127
	(-3.45)	(4.10)	(-0.19)	(3.73)	(0.37)	(-0.24)	(0.20)	

Table 7: **Summary Statistics for Corporate Bond Risk Factors**

Panel A reports the descriptive statistics for the bond market risk factors and the stock market factors. MKT^{Bond} is the corporate bond market excess return constructed using the U.S. Merrill Lynch Aggregate Bond Index. **Downside risk factor (DRF)** is constructed by first sorting corporate bonds on credit rating into quintiles, then within each rating portfolio, corporate bonds are sorted into sub-quintiles based on the 5% Value-at-Risk (VaR). DRF is the equal- or value-weighted average return difference between the highest VaR portfolio minus the lowest VaR portfolio within each rating portfolio. **Credit risk factor (CRF)** is constructed by first sorting corporate bonds on illiquidity (ILLIQ) into quintiles, then within each ILLIQ portfolio, corporate bonds are sorted into sub-quintiles based on credit rating. CRF is the equal- or value-weighted average return difference between the highest credit risk portfolio minus the lowest credit risk portfolio within each ILLIQ portfolio. **Liquidity risk factor (LRF)** is constructed by first sorting corporate bonds on credit rating into quintiles, then within each rating portfolio, corporate bonds are sorted into sub-quintiles based on illiquidity. LRF is the equal- or value-weighted average return difference between the highest illiquidity portfolio minus the lowest illiquidity portfolio within each rating portfolio. The stock market factors include the excess stock market return (MKT^{Stock}), a size factor (SMB), a book-to-market factor (HML), a momentum factor (UMD), a liquidity factor (LIQ). Panel B reports the correlation values among the bond and stock market factors. MKT^{Bond} and DRF start from July 2004 to December 2014. CRF and and LRF start from July 2002 to December 2014.

Panel A: Summary statistics

Bond market risk factors	Equal-weighted		Value-weighted		Stock market factors		
	Mean	*t*-stat	Mean	*t*-stat		Mean	*t*-stat
MKT^{Bond}	–	–	0.40	2.86	MKT^{Stock}	0.69	1.95
Downside risk factor (DRF)	0.70	4.32	0.59	3.57	SMB	0.23	1.21
Credit risk factor (CRF)	0.53	2.69	0.51	2.30	HML	0.09	0.49
Liquidity risk factor (LRF)	0.47	4.37	0.43	4.03	UMD	-0.07	-0.17
					LIQ	0.00	0.55

Panel B: Correlations

	MKT^{Bond}	DRF	CRF	LRF	MKT^{Stock}	SMB	HML	UMD	LIQ	DEF	TERM
MKT^{Bond}	1	0.63	0.01	0.32	0.26	-0.01	0.06	-0.25	0.16	-0.30	-0.59
DRF		1	0.33	0.70	0.45	0.16	0.19	-0.48	0.14	-0.15	-0.05
CRF			1	0.26	0.62	0.36	0.09	-0.41	-0.06	-0.39	0.48
LRF				1	0.21	0.04	0.10	-0.53	0.03	-0.23	0.03
MKT^{Stock}					1	0.41	0.24	-0.40	0.24	-0.27	0.20
SMB						1	0.15	-0.10	0.05	-0.10	0.17
HML							1	-0.22	0.14	-0.11	-0.01
UMD								1	-0.02	0.11	-0.13
LIQ									1	1	-0.02
DEF										1	-0.02
TERM											1

Table 8: **Time-Series Regression of Equal- and Value-weighted Bond Risk Factors on Stock and other Bond Market Factors**

This table reports the intercept (α) and slope coefficients from time-series regressions of the bond market excess return factor, equal- and value-weighted bond risk factors on the commonly used stock and bond market factors. Bond risk factors including the downside risk factor (DRF), credit risk factor (CRF), and liquidity risk factor (LRF). Panel A reports the results for the bond market excess return factor. Panel B reports the results for the equal-weighted bond risk factors and Panel C reports the results for the value-weighted bond risk factors, using amount outstanding as weights. The stock market factors include the excess stock market return (MKT^{Stock}), the size factor (SMB), the book-to-market factor (HML), the momentum factor (UMD), and the Pastor-Stambaugh stock liquidity factor (LIQ). The bond market factors include the excess bond market returns constructed using the Merrill Lynch U.S. aggregate bond index (MKT^{Bond}), the default spread factor (DEF), and the term spread factor (TERM). Newey-West adjusted t-statistics are given in parentheses. Numbers in bold denote statistical significance at the 5% level or below. MKT^{Bond} and DRF start from July 2004 to December 2014. CRF and and LRF start from July 2002 to December 2014.

Panel A: Bond market excess return factor

Dep. Var	α	MKT^{Stock}	SMB	HML	UMD	LIQ	DEF	TERM	Adj. R^2
MKT^{Bond}	**0.30**	0.11	-0.03	-0.06	-0.08	0.01	-2.72	-3.92	56.40
	(2.64)	(2.97)	(-0.60)	(-0.83)	(-3.21)	(0.01)	(-2.52)	(-6.30)	

Panel B: Equal-weighted bond risk factors

Dep. Var	α	MKT^{Bond}	MKT^{Stock}	SMB	HML	UMD	LIQ	DEF	TERM	Adj. R^2
DRF	**0.64**		0.09	0.03	-0.01	-0.21	-0.10	0.71	-0.63	35.96
	(3.91)		(2.13)	(0.42)	(-0.24)	(-3.77)	(-0.03)	(0.27)	(-0.76)	
CRF	**0.36**		0.17	0.16	-0.07	-0.11	-2.18	-5.82	2.51	58.01
	(2.28)		(3.28)	(2.63)	(-0.63)	(-3.50)	(-0.73)	(-3.61)	(5.03)	
LRF	**0.47**		-0.02	0.06	-0.03	-0.15	-1.12	-0.75	0.19	25.95
	(4.15)		(-0.76)	(1.21)	(-0.77)	(-3.07)	(-0.52)	(-0.41)	(0.45)	
DRF	**0.46**	0.66	0.00	0.08	0.07	-0.14	-0.32	2.23	1.64	52.05
	(3.40)	(4.60)	(-0.01)	(1.56)	(1.68)	(-3.68)	(-0.16)	(1.05)	(1.70)	
CRF	**0.31**	0.17	0.15	0.16	-0.06	-0.09	-2.19	-5.35	3.18	58.37
	(2.26)	(1.15)	(2.74)	(2.85)	(-0.54)	(-2.96)	(-0.74)	(-3.00)	(4.44)	
LRF	**0.41**	0.20	-0.05	0.06	-0.02	-0.13	-1.13	-0.22	0.97	28.30
	(4.10)	(1.47)	(-1.10)	(1.40)	(-0.55)	(-3.20)	(-0.55)	(-0.13)	(1.20)	

Panel C: Value-weighted bond risk factors

Dep. Var	α	MKT^{Bond}	MKT^{Stock}	SMB	HML	UMD	LIQ	DEF	TERM	Adj. R^2
DRF	**0.49**		0.15	-0.01	-0.03	-0.16	1.13	0.15	-0.71	30.82
	(3.17)		(3.15)	(-0.07)	(-0.55)	(-3.08)	(0.32)	(0.07)	(-0.87	
CRF	**0.29**		0.26	0.14	-0.07	-0.10	-6.47	-4.93	3.08	62.10
	(2.18)		(4.77)	(1.81)	(-0.66)	(-2.80)	(-1.98)	(-2.98)	(5.67)	
LRF	**0.42**		-0.01	0.00	-0.02	-0.14	0.27	-1.75	-0.17	28.55
	(4.35)		(-0.41)	(0.01)	(-0.31)	(-3.26)	(0.13)	(-1.28)	(-0.47)	
DRF	**0.26**	0.85	0.03	0.06	0.08	-0.07	0.84	2.09	2.22	56.54
	(2.21)	(6.52)	(0.65)	(1.01)	(1.85)	(-2.13)	(0.43)	(1.16)	(2.51)	
CRF	**0.29**	0.00	0.26	0.14	-0.07	-0.10	-6.47	-4.93	3.08	61.82
	(2.07)	(-0.01)	(4.18)	(1.79)	(-0.66)	(-2.57)	(-1.97)	(-2.96)	(3.84)	
LRF	**0.36**	0.21	-0.04	0.01	0.00	-0.13	0.26	-1.18	0.65	31.31
	(4.21)	(1.79)	(-0.86)	(0.14)	(-0.06)	(-3.37)	(0.13)	(-1.01)	(0.98)	

Table 9: **Explanatory Power of Alternative Factor Models for Size and Maturity-Sorted Bond Portfolios**

The table reports the average adjusted R^2 for the time-series regression of the test portfolios' excess returns on four alternative factor models. Panel A reports the results for the 10 decile bond portfolios sorted on size (amount outstanding). Decile 1 is the portfolio with the smallest size and decile 10 is the portfolio with the largest size of corporate bonds. Panel B reports the results for the 10 decile portfolios sorted on time-to-maturity. Decile 1 is the portfolio with the shortest time-to-maturity and decile 10 is the portfolio with the longest time-to-maturity of corporate bonds. Panel C reports the results for the 25 size and maturity portfolios. The 25 portfolios are formed by independently sorting corporate bonds into 5 by 5 quintile portfolios based on size and maturity and then constructed from the intersections of the size and maturity quintiles. Four alternative factor models are considered. Model (1) is the Fama-French (1993) 5-factor model, including the excess stock market return (MKT^{Stock}), size factor (SMB), book-to-market factor (HML), default spread factor (DEF), and term spread factor (TERM). Model (2) is the augmented 7-factor model based on the Fama-French (1993) 5-factor model, with a momentum factor (MOM) and a Pastor-Stambaugh liquidity factor (LIQ) as additional factors. Model (3) is the bond market factor model using the bond market excess returns (MKT^{Bond}) as the single factor. Model (4) is the 4-factor model including the bond market excess returns (MKT^{Bond}), the value-weighted downside risk factor (DRF), credit risk factor (CRF), and liquidity risk factor (LRF).

Panel A: 10 size-sorted test portfolios

Model	Small	2	3	4	5	6	7	8	9	Large	Average R^2
(1)	0.27	0.29	0.34	0.52	0.47	0.48	0.49	0.43	0.44	0.39	**0.41**
(2)	0.36	0.40	0.42	0.56	0.54	0.59	0.56	0.50	0.51	0.44	**0.49**
(3)	0.47	0.43	0.50	0.68	0.76	0.75	0.80	0.85	0.85	0.76	**0.68**
(4)	0.58	0.62	0.62	0.86	0.89	0.88	0.89	0.91	0.91	0.87	**0.80**

Panel B: 10 maturity-sorted test portfolios

Model	Short	2	3	4	5	6	7	8	9	Long	Average R^2
(1)	0.37	0.42	0.47	0.47	0.50	0.47	0.48	0.51	0.51	0.45	**0.47**
(2)	0.43	0.48	0.51	0.50	0.53	0.49	0.50	0.53	0.53	0.47	**0.50**
(3)	0.66	0.69	0.68	0.67	0.77	0.85	0.78	0.77	0.80	0.78	**0.75**
(4)	0.76	0.78	0.81	0.81	0.86	0.89	0.80	0.79	0.79	0.82	**0.81**

Panel C: Model (1), 25 size- and maturity-sorted portfolios

	Short	2	3	4	Long
Small	0.25	0.20	0.31	0.33	0.29
2	0.52	0.56	0.50	0.46	0.38
3	0.42	0.48	0.50	0.54	0.46
4	0.37	0.47	0.44	0.47	0.40
Large	0.25	0.39	0.41	0.41	0.36
Average R^2	**0.41**				

Panel D: Model (2), 25 size- and maturity-sorted portfolios

	Short	2	3	4	Long
Small	0.52	0.42	0.41	0.44	0.42
2	0.61	0.66	0.59	0.52	0.46
3	0.61	0.64	0.63	0.60	0.50
4	0.52	0.63	0.56	0.52	0.44
Large	0.40	0.51	0.47	0.45	0.39
Average R^2	**0.52**				

Panel E: Model (3), 25 size- and maturity-sorted portfolios

	Short	2	3	4	Long
Small	0.40	0.26	0.46	0.48	0.49
2	0.46	0.48	0.64	0.70	0.76
3	0.59	0.55	0.75	0.79	0.82
4	0.68	0.69	0.84	0.84	0.83
Large	0.63	0.66	0.76	0.74	0.76
Average R^2	**0.64**				

Panel F: Model (4), 25 size- and maturity-sorted portfolios

	Short	2	3	4	Long
Small	0.56	0.49	0.54	0.63	0.60
2	0.77	0.83	0.85	0.77	0.77
3	0.80	0.83	0.91	0.86	0.83
4	0.80	0.87	0.91	0.87	0.85
Large	0.73	0.84	0.86	0.79	0.85
Average R^2	**0.78**				

The Cross-section of Expected Corporate Bond Returns

Online Appendix

To save space in the paper, we present some of our findings in the Online Appendix. Table **??** shows the data filtering process for TRACE, Lehman, and NAIC.

A.1 Estimation of Stock and Bond Investors' Risk Aversion Parameter

In this section, we provide empirical evidence to shed light on the differences between stock and bond investors' attitudes towards risk (and downside risk). Specifically, we describe the estimation methodology and then present the estimated risk aversion parameters for the stock and corporate bond market investors. We use both conditional and unconditional approaches to estimate the risk aversion parameter.

Following Engle, Lilien and Robins (1987), we use the following GARCH-in-Mean model to estimate the risk aversion parameter (γ) of the stock and corporate bond market investors:

$$R_t = \alpha + \tfrac{\gamma}{2} \cdot \sigma^2_{t|t-1} + \varepsilon_t, \tag{A.1}$$

$$E\left(\varepsilon_t^2 | \Omega_{t-1}\right) = \sigma^2_{t|t-1} = \beta_0 + \beta_1 \varepsilon^2_{t-1} + \beta_2 \sigma^2_{t-1}, \tag{A.2}$$

where R_t denotes the return at time t for the stock or corporate bond market, ε_t is the information shock or unexpected news at time t, Ω_{t-1} is the information set up to time t-1 and contains the entire history of returns and unexpected news up to time t-1. The conditional mean of R_t is $E(R_t|\Omega_{t-1}) = \hat{\alpha} + \frac{\hat{\gamma}}{2} \cdot \sigma^2_{t|t-1}$. The current conditional variance of R_t in equation (A.2) is defined as a function of the last period's unexpected news or information shocks (as in Bollerslev (1986)).

Parameters in equations (A.1) and (A.2) are estimated simultaneously using the maximum likelihood methodology. Assuming that R_t is normally distributed, the conditional density function for R_t is:

$$f(R_t; \Theta) = \frac{1}{\sqrt{2\pi\sigma^2_{t|t-1}}} \exp\left\{ -\frac{1}{2} \left(\frac{R_t - \mu_{t|t-1}}{\sigma_{t|t-1}} \right)^2 \right\} \tag{A.3}$$

$\mu_{t|t-1} = \hat{\alpha} + \frac{\hat{\gamma}}{2} \cdot \sigma^2_{t|t-1}$ is the conditional mean of R_t, $\sigma^2_{t|t-1} = \hat{\beta}_0 + \hat{\beta}_1 \varepsilon^2_{t-1} + \hat{\beta}_2 \sigma^2_{t-1}$ is the conditional variance of R_t, and $\Theta \equiv (\alpha,\ \gamma,\ \beta_0,\ \beta_1,\ \beta_2)$ is the parameter vector. Given the initial values of ε_t and $\sigma^2_{t|t-1}$, the parameters can be estimated by maximizing the log-likelihood function over the sample period. The conditional normal density in equation (A.3) yields the following conditional log-likelihood function:

$$LogL(\Theta) = -\frac{n}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{n}\ln\sigma_{t|t-1}^{2} - \frac{1}{2}\sum_{t=1}^{n}\left(\frac{R_t - \mu_{t|t-1}}{\sigma_{t|t-1}}\right)^2 \tag{A.4}$$

where n is the number of time-series observations in the $\{R_t\}$ sequence. Maximizing equation (A.4) with respect to the parameter vector yields the maximum likelihood estimates of α, γ, β_0, β_1, and β_2. Since there is no closed form solution for equation (A.4), we used the Marquardt algorithm to solve it numerically.

As shown in equations (A.1) and (A.2) , when estimating the risk aversion parameters with the GARCH-in-Mean model, we account for time-series variations in both the conditional mean and conditional variance of market returns. Since we use the conditional return distribution in the estimation of risk aversion parameters, we refer to this as the "conditional approach" in the paper.

A.2 Experiments with Longer Sample from 1973 to 2014

We collect corporate bond data from six sources: Lehman Brothers fixed income database (Lehman), Datastream, National Association of Insurance Commissioners database (NAIC), Bloomberg, the original and enhanced version of the Trade Reporting and Compliance Engine (TRACE), and Mergent fixed income securities database (FISD). These datasets together comprise of the most complete corporate bond data in both the academia and the industry. The Lehman data are from January 1973 to March 1998; Datastream reports corporate bond information from January 1990 to June 2014. Both Lehman and Datastream data provide prices based on dealer quotes. NAIC reports the transaction information by insurance companies during January 1994 to July 2013; Bloomberg provides daily bond prices during January 1997 to December 2004; and the enhanced TRACE records the transaction of the entire corporate bond market during July 2002 to March 2014, the original TRACE supplements the bond transaction data from April 2014 to December 2014. The two datasets, NAIC and TRACE, provide prices based on the real transactions, whereas other datasets, Lehman, Datastream, and Bloomberg, provides prices based on quotes and matrix calculations.

The quote-based data sets (Lehman and Datastream) provide month-end prices and returns. NAIC and Bloomberg provide daily prices, and TRACE provides intraday clean prices.

Table A.1: **Risk Aversion of Stock and Corporate Bond Investors**

This table reports the estimated risk aversion parameters for the stock and corporate bond market investors. Three proxies are used for the corporate bond market: the Merrill Lynch aggregate bond index (MKT^{Bond}), the value-weighted corporate bond index (VW index), and the equal-weighted corporate bond index (EW index). Two proxies are used for the aggregate stock market: the S&P500 index and the value-weighted CRSP index including all stocks trading at NYSE, AMEX, and NASDAQ.

	Conditional Approach	Unconditional Approach
Corporate Bond Market	Risk Aversion	Risk Aversion
MKT^{Bond}	14.70	16.55
VW index	12.58	12.29
EW index	12.12	12.63
Stock Market	Risk Aversion	Risk Aversion
S&P 500 index	5.51	3.50
CRSP VW index	7.51	3.71

Table A.2: **Quintile Portfolios of Corporate Bonds Sorted by VaR Controlling for Credit Rating, Maturity, and Size**

Quintile portfolios are formed every month from July 2004 to December 2014 by first sorting corporate bonds based on credit rating (Panel A), maturity (Panel B) or size (Panel C). Then, within each quintile portfolio, corporate bonds are sorted into sub-quintiles based on their 5% VaR, defined as the second lowest monthly return observation over the past 36 months multiplied by -1. "VaR,1" is the portfolio of corporate bonds with the lowest VaR within each quintile portfolio and "VaR, 5" is the portfolio of corporate bonds with the highest VaR within each quintile portfolio. Table shows the average excess return and the 7-factor alpha for each quintile. The last row shows the differences in monthly average returns, the differences in alphas with respect to the 7-factor models. The 7-factor model includes the excess market return (MKT), a size factor (SMB), a book-to-market factor (HML), a momentum factor (MOM), a liquidity factor (ILLIQ), plus two bond market factors: the default spread factor (DEF) and the term spread factor (TERM). Average excess returns and alphas are defined in monthly percentage terms. Newey-West adjusted *t*-statistics are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Controlling for credit rating

	All bonds		Investment-grade		Non-investment-grade	
	Average return	7-factor alpha	Average return	7-factor alpha	Average return	7-factor alpha
VaR,1	-0.131	-0.205	-0.128	-0.188	-0.035	-0.154
	(-1.26)	(-2.47)	(-1.10)	(-1.85)	(-0.14)	(-0.96)
VaR,2	-0.043	-0.140	-0.029	-0.108	0.100	-0.065
	(-0.33)	(-1.41)	(-0.21)	(-0.90)	(0.35)	(-0.37)
VaR,3	0.061	-0.061	0.044	-0.060	0.208	0.021
	(0.39)	(-0.53)	(0.27)	(-0.44)	(0.62)	(0.10)
VaR,4	0.198	0.068	0.141	0.033	0.443	0.246
	(1.07)	(0.49)	(0.68)	(0.21)	(1.10)	(1.02)
VaR,5	0.563	0.429	0.377	0.274	0.771	0.576
	(2.46)	(2.24)	(1.40)	(1.28)	(1.64)	(2.03)
VaR, 5 − VaR,1	0.694***	0.634***	0.505***	0.463***	0.806***	0.730***
Return/Alpha diff.	(4.39)	(4.23)	(2.75)	(2.97)	(3.09)	(3.88)

Panel B: Controlling for maturity

	All bonds		Short-maturity		Medium-maturity		Long-maturity	
	Average return	7-factor alpha	Average return	7-factor alpha	Average return	7-factor alpha	Average return	7-factor alpha
VaR,1	-0.119	-0.214	-0.116	-0.158	-0.117	-0.206	-0.053	-0.183
	(-0.91)	(-2.11)	(-1.10)	(-1.73)	(-0.84)	(-1.68)	(-0.28)	(-1.17)
VaR,2	0.003	-0.099	-0.303	-0.365	-0.028	-0.134	0.094	-0.035
	(0.02)	(-0.92)	(-1.39)	(-1.71)	(-0.18)	(-1.05)	(0.47)	(-0.22)
VaR,3	0.056	-0.044	-0.519	-0.583	0.054	-0.049	0.181	0.049
	(0.37)	(-0.38)	(-1.48)	(-1.78)	(0.32)	(-0.40)	(0.84)	(0.28)
VaR,4	0.174	0.067	0.225	0.138	0.121	0.028	0.265	0.119
	(0.99)	(0.52)	(0.50)	(0.33)	(0.51)	(0.19)	(0.99)	(0.60)
VaR,5	0.593	0.447	0.619	0.369	0.531	0.410	0.631	0.443
	(2.31)	(2.25)	(1.03)	(1.04)	(1.41)	(1.49)	(1.79)	(2.08)
VaR, 5 − VaR,1	0.712***	0.661***	0.791	0.576**	0.648**	0.615**	0.684***	0.626***
Return/Alpha diff.	(3.52)	(4.07)	(1.48)	(1.91)	(2.16)	(2.58)	(2.82)	(4.69)

Table A.2: **(Continued)**

Panel C: Controlling for size

	All bonds		Small bonds		Large bonds	
	Average return	7-factor alpha	Average return	7-factor alpha	Average return	7-factor alpha
VaR,1	-0.117	-0.189	-0.082	-0.171	-0.155	-0.213
	(-1.10)	(-2.06)	(-0.64)	(-1.55)	(-1.33)	(-2.06)
VaR,2	-0.014	-0.110	0.044	-0.061	-0.056	-0.147
	(-0.11)	(-1.07)	(0.28)	(-0.48)	(-0.39)	(-1.20)
VaR,3	0.085	-0.028	0.078	-0.035	0.046	-0.058
	(0.54)	(-0.24)	(0.43)	(-0.27)	(0.25)	(-0.43)
VaR,4	0.177	0.056	0.258	0.125	0.131	-0.005
	(0.94)	(0.38)	(0.95)	(0.63)	(0.57)	(-0.03)
VaR,5	0.649	0.502	0.813	0.679	0.488	0.301
	(2.39)	(2.31)	(1.89)	(2.29)	(1.41)	(1.26)
VaR, 5 − VaR,1	0.766***	0.692***	0.896***	0.850***	0.643**	0.514***
Return/Alpha diff.	(3.58)	(3.81)	(2.70)	(3.54)	(2.41)	(2.78)

Table A.3: **Univariate Portfolios of Corporate Bonds Sorted by Downside Risk**

Quintile portfolios are formed every month from January 1975 to December 2014 by sorting corporate bonds based on the 5% Value-at-Risk (VaR), defined as the third lowest monthly return observation over the past 60 months. The original VaR measure is multiplied by -1. Quintile 1 is the portfolio with the lowest VaR, and Quintile 5 is the portfolio with the highest VaR. Table also reports the average VaR, the next-month average excess return, and the 7-factor alpha for each quintile. The last five columns report average portfolio characteristics including bond beta (β^{Bond}), credit rating, illiquidity, time-to-maturity (years), and amount outstanding (size, in billions of dollars) for each quintile. The last row shows the differences in monthly average returns, the differences in alphas with respect to the 7-factor models. The 7-factor model includes the excess market return (MKT), a size factor (SMB), a book-to-market factor (HML), a momentum factor (MOM), a liquidity factor (LIQ), plus two bond market factors: the default spread factor (DEF) and the term spread factor (TERM). Average excess returns and alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Quintiles	Average	Average	7-factor	Average portfolio characteristics				
	VaR	return	alpha	β^{Bond}	Rating	ILLIQ	Maturity	Size
Low VaR	2.09	0.025	-0.095	0.69	7.15	0.13	10.58	0.26
		(0.24)	(-0.88)					
2	3.18	0.082	-0.054	0.87	6.97	0.18	12.63	0.24
		(0.71)	(-0.46)					
3	4.01	0.177	0.026	1.01	6.89	0.23	14.48	0.25
		(1.35)	(0.20)					
4	4.91	0.205	0.052	1.14	6.96	0.27	17.02	0.25
		(1.45)	(0.36)					
High VaR	7.87	0.614	0.406	1.15	9.48	0.50	17.33	0.24
		(2.69)	(1.83)					
High − Low		0.589***	0.501***					
Return/Alpha diff.		(3.58)	(3.24)					

Table A.4: **Univariate Portfolios of Corporate Bonds Sorted by Credit Rating**

Quintile portfolios are formed every month from January 1975 to December 2014 by sorting corporate bonds based on their credit rating. Quintile 1 is the portfolio with the lowest credit rating, and Quintile 5 is the portfolio with the highest credit rating. Ratings are in conventional numerical scores, where 1 represents a AAA rating and 21 reflects a C rating. Higher numerical score means lower ratings (i.e., higher credit risk). Table also reports the average credit rating, the next-month average excess return, and the 7-factor alpha for each quintile. The last five columns report average portfolio characteristics including VaR, bond beta (β^{Bond}), illiquidity (ILLIQ), time-to-maturity (years), and amount outstanding (size, in billions of dollars) for each quintile. The last row shows the differences in monthly average returns, the differences in alphas with respect to the 7-factor models. The 7-factor model includes the excess market return (MKT), a size factor (SMB), a book-to-market factor (HML), a momentum factor (MOM), a liquidity factor (LIQ), plus two bond market factors: the default spread factor (DEF) and the term spread factor (TERM). Average excess returns and alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Quintiles	Average	Average	7-factor	Average portfolio characteristics				
	rating	return	alpha	VaR	β^{Bond}	ILLIQ	Maturity	Size
Low Credit Risk	3.14	0.148	0.015	3.87	1.03	0.25	16.26	0.27
		(1.38)	(0.15)					
2	5.44	0.150	0.020	3.95	1.06	0.22	15.02	0.27
		(1.42)	(0.20)					
3	6.91	0.172	0.043	4.03	1.00	0.30	14.42	0.25
		(1.67)	(0.43)					
4	8.82	0.204	0.136	4.04	0.99	0.28	14.24	0.24
		(1.97)	(0.95)					
High Credit Risk	14.05	0.472	0.31	6.16	0.81	0.39	12.30	0.24
		(3.48)	(1.68)					
High − Low		0.327***	0.297***					
Return/Alpha diff.		(2.89)	(2.34)					

Table A.5: **Univariate Portfolios of Corporate Bonds Sorted by Bond Market Beta**

Quintile portfolios are formed every month from January 1975 to December 2014 by sorting corporate bonds based on their 36-month rolling betas. β^{Bond} is the corporate bonds beta with respect to the excess corporate bond market return, constructed using the Merrill Lynch U.S. Aggregate Bond Index. The betas are estimated for each bond from the time-series regressions of bond excess returns on the excess bond market return, with a 36-month rolling window period (prior 36 months' returns). Quintile 1 is the portfolio with the lowest β^{Bond}, and Quintile 5 is the portfolio with the highest β^{Bond}. Table also reports the average β^{Bond}, the next-month average excess return, and the 7-factor alpha for each quintile. The last five columns report average portfolio characteristics including downside risk (VaR), credit rating, illiquidity, time-to-maturity (years), and amount outstanding (size, in billions of dollars) for each quintile. The last row shows the differences in monthly average returns, the differences in alphas with respect to the 7-factor models. The 7-factor model includes the excess market return (MKT), a size factor (SMB), a book-to-market factor (HML), a momentum factor (MOM), a liquidity factor (LIQ), plus two bond market factors: the default spread factor (DEF) and the term spread factor (TERM). Average excess returns and alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Quintiles	Average	Average	7-factor	Average portfolio characteristics				
	β^{Bond}	return	alpha	VaR	Rating	ILLIQ	Maturity	Size
Low β^{Bond}	0.35	0.144	0.041	4.10	9.46	0.27	9.92	0.22
		(1.48)	(0.40)					
2	0.76	0.089	0.004	3.74	7.45	0.18	10.85	0.26
		(0.94)	(0.04)					
3	1.01	0.121	-0.009	4.12	6.96	0.18	13.20	0.28
		(1.15)	(-0.09)					
4	1.25	0.128	-0.027	4.66	6.77	0.23	15.64	0.29
		(1.09)	(-0.24)					
High β^{Bond}	1.69	0.342	0.166	5.94	7.02	0.32	19.74	0.30
		(2.33)	(1.14)					
High $-$ Low		0.198*	0.106					
Return/Alpha diff.		(1.82)	(0.93)					