Common Risk Factors in the Cross-Section of Corporate Bond Returns*

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Abstract

We investigate the cross-sectional determinants of corporate bonds and find that downside risk is the strongest predictor of future bond returns. We also introduce common risk factors based on the prevalent risk characteristics of corporate bonds – downside risk, credit risk, and liquidity risk – and find that these novel bond market factors have economically and statistically significant risk premia, which cannot be explained by the long-established stock and bond market factors. We further show that these newly proposed risk factors outperform all other models considered in the literature in explaining the returns of the industry-sorted and size/maturity-sorted portfolios of corporate bonds.

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1 Introduction

Over the past three decades, financial economists have identified a large number of risk factors that explain the cross-sectional variation in stock returns. In contrast, far less studies are devoted to the cross section of corporate bond returns.[1] Compared to the size of the U.S. equity market ($19 trillion), the corporate bond market is relatively smaller with a total amount outstanding of $12 trillion.[2] However, the issuance of corporate bonds is at a much larger scale than the issuance of stocks for U.S. corporations: an annual average of $1.3 trillion for corporate bonds compared to $265 billion for stocks since 2010. Moreover, corporate bonds play an increasingly important role in institutional investors' portfolios, evidenced by the recent influx to bond funds.[3] Both corporate bonds and stocks are important financing channels for corporations, and both are important assets under management for fund managers. Thus, it is pivotal to enhance our understanding of the common risk factors that determine the cross-sectional differences in bond returns.

Earlier studies on corporate bonds generally rely on the long-established stock and bond market factors to predict contemporaneous or future bond returns, including the stock market factors of Fama and French (1993), Carhart (1997), and Pastor and Stambaugh (2003): excess stock market return, the size factor (SMB), the book-to-market factor (HML), the momentum factor (MOM), and the liquidity factor (LIQ), along with the bond market factors of Elton, Gruber, and Blake (1995), and Bessembinder, Kahle, Maxwell, and Xu (2009): excess bond market return, the default spread (DEF), and the term spread (TERM). However, these commonly used factors are either constructed from stock-level data or aggregate macroeconomic variables, hence their cross-sectional predictive power is limited for bond-level returns. When we test these existing models in terms of their ability to explain the industry-sorted and size/maturity-sorted portfolios of corporate bonds, their empirical performance turns out to be unsatisfactorily low. In this paper, we show that it is crucial to rely on the prominent features

[1] This is partly because of the dearth of high-quality corporate bond data and the complex features of corporate bonds such as optionality, seniority, changing maturity, and risk exposure to a number of financial and macroeconomic factors.

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

[3] See Feroli, Kashyap, Schoenholtz, and Shin (2014) and the Investment Company Institute Annual Report (2014).

of corporate bonds and to construct bond-implied risk factors to explain the cross-sectional differences in corporate bond returns.

Although corporate bonds and stocks both reflect firm fundamentals, they differ in several key features. First and foremost, bondholders, compared to stockholders, are more sensitive to downside risk.[4] Second, it is well-known that firms issuing corporate bonds suffer from potential default risk given legal requirements on the payment of coupons and principal, whereas firms issuing stocks have relatively lower exposure to bankruptcy. This feature makes credit risk particularly important in determining corporate bond returns. Third, the corporate bond market, due to its over-the-counter trading mechanism and other market features, bears higher liquidity risk. Bond market participants are dominated by institutional investors such as insurance companies, pension funds, and mutual funds.[5] Many bondholders are long-term investors who often follow a buy-and-hold strategy. Therefore, liquidity in the corporate bond market is lower compared to the stock market in which active trading is partially attributable to the existence of individual (retail) investors.

Given these significant differences in market features and the types of investors, we endeavor to identify bond-implied risk factors. We begin with examining the performance of bond risk characteristics—downside risk, credit, and illiquidity—in predicting the cross-sectional dispersion of future bond returns. Following Bessembinder, Maxwell, and Venkataraman (2006) who highlight the importance of using Trade Reporting and Compliance Engine (TRACE) transaction data, we calculate bond returns at the monthly frequency using the intraday transaction records from the Enhanced TRACE data for the period July 2002 to December 2014, yielding about one million bond-month observations. Our proxy for downside risk is the 5% value-at-risk (VaR) estimated based on the lower tail of the empirical return distribution, that is, the second lowest monthly return observation over the past 36 months. Our proxy for credit quality is bond-level credit rating. Our proxy for illiquidity is the bond-level measure of Bao, Pan, and Wang (2011). In addition to these three economically sensible risk characteristics for

[4]Bondholders gain the cash flow of fixed coupon and principal payment, thus hardly benefit from the euphoric news in firm fundamentals. Since the upside payoffs are capped, bond payoffs become concave in the investor beliefs about the underlying fundamentals, whereas equity payoffs are linear in investor beliefs regarding fluctuations in the underlying factors (e.g., Hong and Sraer (2013)).

[5]Source: Financial Accounts of the United States, Release Z1, Table L.213.

corporate bonds, we take into account bond exposure (beta) to the market risk factor.[6]

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 downside risk quintile generate 10.18% per annum higher return than bonds in the lowest downside risk quintile. After controlling for nine well-known stock and bond market factors, the risk-adjusted return difference between the lowest and highest downside risk quintiles (downside risk premium) is economically large and statistically significant: 10.30% per annum with a t-statistic of 4.23, suggesting that loss-averse bond investors prefer high expected return and low downside risk. We also examine the average portfolio characteristics of VaR quintiles, and find that bonds with high VaR have higher market risk, higher credit risk, lower liquidity, longer maturity, and smaller size. Thus, we test whether the positive relation between downside risk and future returns holds controlling for bond characteristics. Bivariate portfolio-level analyses and bond-level cross-sectional regressions indicate that downside risk remains a significant predictor of future bond returns after controlling for market beta, credit rating, illiquidity, maturity, and size.

Second, we examine the cross-sectional relation between credit risk and future bond returns, and find that corporate bonds in the highest credit risk quintile generate 5.57% more risk-adjusted annual return (9-factor alpha) compared to bonds in the lowest credit risk quintile. Examining the average portfolio characteristics, we also find that bonds with high credit risk have higher downside risk, higher market beta, lower liquidity, and shorter maturity, but don't differ significantly in size.

Third, we test the significance of a cross-sectional relation between illiquidity and future returns of corporate bonds and find that bonds in the highest illiquidity quintile generate 6.42% per annum more 9-factor alpha compared to bonds in the lowest illiquidity quintile. Bonds in the high illiquidity quintile also have higher downside risk, higher market beta, higher credit risk, longer maturity, and smaller size.

Fourth, we investigate whether the Capital Asset Pricing Model (CAPM) holds in the cor-

[6] The market risk factor is proxied by the corporate bond market index instead of conventional stock market indices. We also consider alternative measures of downside risk, credit risk, and liquidity risk. As discussed later in the paper, our main findings from these alternative measures of risk remain intact.

porate bond market. Specifically, we test whether the CAPM with the bond market factor explains the cross-sectional differences in bond returns, and we find that the market factor proxied by the Merrill Lynch Aggregate Bond Market Index has significant and positive predictive power. Bonds in the highest bond market beta quintile generate 7.12% more annual risk-adjusted returns compared to bonds in the lowest market beta quintile.[7]

After simultaneously accounting for the aforementioned bond risk characteristics and controlling for other bond characteristics in cross-sectional regressions, downside risk and illiquidity turn out to be the most significant predictor of future returns, whereas the credit and market risk premia either become weak or disappear in the multivariate Fama-MacBeth regressions.

Finally, we introduce novel risk factors based on the above prevalent risk characteristics. We rely on the conditional bivariate portfolios using credit rating as the first sorting variable and downside risk and illiquidity as the second sorting variable when constructing the new risk factors, namely downside risk factor (DRF), credit risk factor (CRF), and liquidity risk factor (LRF). We run time-series factor regressions to assess the predictive power of these new risk factors. The intercepts (alphas) from the regressions represent the abnormal returns not explained by standard stock and bond market factors. When we use the most general 9-factor model which combines all of the commonly used stock and bond market factors, we find that the alphas for the DRF, CRF, ad LRF factors are all economically and statistically significant, indicating that the existing risk factors are not sufficient to capture the information content in these newly proposed bond risk factors.

One important critique in asset pricing tests, as pointed out by Lewellen, Nagel, and Shanken (2010), is that characteristic-sorted portfolios (used as test assets) do not have sufficient independent variation in the loadings of factors constructed with the same characteristics. To improve the power of asset pricing tests, both studies suggest that the empirical performance of risk factors is tested based on alternative test portfolios. Following their suggestion, we consider two distinct sets of test portfolios that do not necessarily relate to the aforementioned risk characteristics. Specifically, we form alternative bond portfolios (i) based on 5×5 inde-

[7] Following the literature, we also use the stock market index to proxy for the market factor. However, the market beta defined as the bond exposure to the Standard and Poor's (S&P) 500 or the CRSP index does not predict the cross-section of future bond returns. Hence, we find that the CAPM with the stock market index fails to explain the cross-sectional differences in corporate bonds.

pendently sorted bivariate portfolios of size and maturity, and (ii) based on 30 industry-sorted portfolios, then we examine the relative performance of factor models in explaining the time-series and cross-sectional variation in these test portfolios. We find that the newly proposed 4-factor model with the market, downside, credit and liquidity risk factors substantially outperforms all other models considered in the literature in predicting the returns of the industry and size/maturity sorted portfolios of corporate bonds.

This paper proceeds as follows. Section 2 sets forth a literature review. Section 3 describes the data and variables used in our empirical analyses. Section 4 examines the cross-sectional relation between downside risk and expected returns of corporate bonds. Section 5 investigates the empirical performance of credit rating, bond illiquidity, and market beta for predicting future bond returns. Section 6 introduces new risk factors for corporate bonds, and compares their relative performance with the long-established stock and bond market risk factors. Section 7 conducts a battery of robustness checks and Section 8 concludes the paper.

2 Literature Review

Our empirical findings contribute to the existing literature in several important ways. The foremost contribution is to identify bond-implied new risk factors that significantly predict the cross-sectional differences in future bond returns. The earlier literature on corporate bond returns focuses on aggregate indices (see, e.g., Fama and French (1993), Elton et al. (1995)), and bond portfolios (e.g., Blume, Keim, and Patel (1991)).[8] Succeeding studies have investigated the bond returns at the firm level, mainly with quoted price data (see, e.g., Kwan (1996), Gebhardt, Hvidkjaer, and Swaminathan (2005)),[9] and recently with transaction data (see, e.g., Bessembinder et al. (2009), Lin, Wang, and Wu (2011), Acharya, Amihud, and Bharath

[8]Fama and French (1993) use five corporate bond indices from the module of Ibbotson for rating groups Aaa, Aa, A, Baa, and LG (low-grade, that is, below Baa). Elton et al. (1995) study 20 bond indices across Treasury bonds, corporate bonds, mortgage securities from Ibbotson, Merrill Lynch, and Lehman Brothers. Blume, Keim, and Pate (1991) study the Salomon (Lehman) Brothers index of corporate bonds, Ibbotson long-term government bond index, as well as bonds below BBB listed in the S&P Bond Guide. Note that quite a few papers, though they study bonds, are indeed limited to Treasury bonds, or a combination of Treasury and corporate bonds.

[9]Gebhardt, Hvidkjaer, and Swaminathan (2005) test the cross-sectional predictive power of default and term spread beta and find that they are significantly related to corporate bond returns, even after controlling for a number of bond characteristics.

(2013), Jostova, Nikolova, Philipov, and Stahel (2013), and Nozawa (2016)).[10] Our paper also uses transaction data, but differs from the literature by deriving bond-implied risk factors. Our downside, credit, and liquidity risk factors together have superior predictive power over the long-established risk factors, outperforming the existing models in explaining the cross-sectional differences in individual bond returns as well as in the industry-sorted and size/maturity-sorted portfolios of corporate bonds.

The idea of linking credit and liquidity to bond pricing is by no means new. Our paper, however, advances the literature by showing that credit risk and liquidity risk have significant pricing power for the cross-section of future corporate bond returns. The literature on the credit spread puzzle well documents the evidence that credit and illiquidity can explain contemporaneous bond yield spreads (see, e.g., Longstaff, Mithal, and Neis (2005), Chen, Lesmond, and Wei (2007)) Our paper further differs from earlier studies by analyzing the cross-section of future corporate bond returns (not yield spreads) through factor models.

The second contribution of this paper is to demonstrate the empirical performance of downside risk in predicting the cross-sectional differences in future returns of corporate bonds. There is a large body of literature on safety-first investors who minimize the chance of disaster (or the probability of failure). The portfolio choice of a safety-first investor is to maximize expected return subject to a downside risk constraint. The safety-first investor in Roy (1952), Baumol (1963), Levy and Sarnat (1972) and Arzac and Bawa (1977) uses a downside risk measure which is a function of value-at-risk. Roy (1952) indicates that most investors are principally concerned with avoiding a possible disaster and that the principle of safety plays a crucial role in the decision-making process. Thus, the idea of a disaster exists and a risk averse, safety-first investor will seek to reduce the chance of such a catastrophe occurring insofar as possible.

The use of value-at-risk (VaR) techniques in risk management has exploded over the past two decades. Financial institutions now routinely use VaR and expected shortfall in managing

[10] Bessembinder et al. (2009) find that using the daily bond returns generated from the TRACE data increases the power of the test statistics designed to detect abnormal bond returns in corporate event studies. 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. Acharya, Amihud, and Bharath (2013) show that corporate bonds are exposed to liquidity shocks in equity and Treasury markets. Jostova et al. (2013) investigate whether the momentum anomaly exists in the corporate bond market. There are also two recent papers, Chordia, Goyal, Nozawa, Subrahmanyam, and Tong (2016) and Choi and Kim (2016), that examine whether equity market predictors can be priced in the cross-section of corporate bond returns.

their trading risk, and non-financial firms adopt this technology for their risk-management purposes as well. There is an extensive literature on financial risk management and VaR per se; however, only a few studies investigate the time-series or cross-sectional relation between VaR and expected returns on individual stocks or equity portfolios (e.g., Bali, Demirtas, and Levy (2009); Huang, Liu, Rhee, and Wu (2012)). The predictive power of VaR has not been investigated for alternative asset classes. This paper generates the first evidence on the theoretically consistent positive and significant relation between VaR and future bond returns.

3 Data and Variable Definitions

3.1 Corporate Bond Data

For corporate bond data, we rely on the transaction records reported in the enhanced version of the Trade Reporting and Compliance Engine (TRACE) for the sample period July 2002 to December 2014. Ideally, we would prefer to investigate the cross-section of corporate bond returns using a longer sample period. However, one critical risk factor of corporate bond returns, illiquidity, requires daily bond transaction prices which are not provided in such datasets as the Lehman Brothers fixed income database, Datastream, or Bloomberg.[11] Therefore, we focus on the TRACE data which offers the best quality of corporate bond transactions with intraday observations on price, trading volume, and buy and sell indicators. We then merge corporate bond pricing data with the Mergent fixed income securities database to obtain 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, we also expand the TRACE data by including alternative bond data sets, mainly containing quoted prices, for a longer sample period starting from January 1973. For this longer sample, we construct downside risk factor and credit risk factor (but not the liquidity risk factor), and replicate our main analysis in the online appendix.

[11] The National Association of Insurance Commissioners (NAIC) database also includes daily prices but given the fact that it covers only a part of the market and it contains more illiquid observations and 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.

For TRACE intraday data, we adopt the filtering criteria proposed in Bai, Bali, and Wen (2016):

1. Remove bonds that are not listed or traded in the U.S. public market, which include bonds issued through private placement, bonds issued under the 144A rule, bonds that do not trade in US dollars, and bond issuers not in the jurisdiction of the United States.

2. Remove bonds that are structured notes, mortgage backed or asset backed, agency-backed or equity-linked.

3. Remove convertible bonds since this option feature distorts the return calculation and makes it impossible to compare the returns of convertible and non-convertible bonds.[12]

4. Remove bonds that trade under five dollars or above one thousand dollars.

5. Remove bonds that have a floating coupon rate, which means the sample comprises only bonds with a fixed or zero coupon. This rule is applied based on the consideration of accuracy in bond return calculation, given the challenge in tracking a floating-coupon bond's cash flows.

6. Remove bonds that have less than one year to maturity. This rule is applied to all major corporate bond indices such as the Barclays Capital Corporate Bond Index, the Bank of America Merrill Lynch Corporate Master Index, and the Citi Fixed Income Indices. If a bond has less than one year to maturity, it will be delisted from major bond indices; hence, index-tracking investors will change their holding positions. This operation will distort the return calculation for bonds with less than one year to maturity; hence, we remove them from our sample.

7. For intraday data, we also eliminate bond transactions that are labeled as when-issued, locked-in, or have special sales conditions, and that have more than a two-day settlement.

[12]Bonds also contain other option features such as being putable, redeemable/callable, exchangeable, and fungible. Except callable bonds, bonds with other option features are a relatively small portion in the sample. However, callable bonds constitute approximately 67% of the whole sample. Hence, we keep the callable bonds in our final sample. As a robustness check, we also replicate our main analyses by using a smaller sample excluding any bond with option features. The main findings remain similar.

8. Remove transaction records that are canceled and adjust records that are subsequently corrected or reversed.

9. Remove transaction records that have trading volume less than \$10,000.[13]

3.2 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 transaction price, $AI_{i,t}$ is accrued interest, and $C_{i,t}$ is the coupon payment, if any, of bond i in month t. We denote $R_{i,t}$ as bond i's excess return, $R_{i,t} = r_{i,t} - r_{f,t}$, where $r_{f,t}$ is the risk-free rate proxied by the one-month Treasury bill rate.

Using TRACE intraday data, we first calculate the daily clean price as the trading volume-weighted average of intraday prices 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 presents a detailed discussion on the conversion methods in the literature. Specifically, our 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

[13] Bessembinder et al. (2009) test the power of test statistics to detect abnormal bond returns and suggest that eliminating non-institutional trades (daily volume smaller than \$100,000) from the TRACE data helps increase the power of the tests to detect abnormal performance, relative to using all trades or the last price of the day. Here we include more bonds with relatively smaller trading volume, which only makes our tests more stringent, that is, it becomes harder to detect abnormal bond alphas. In unreported results, we use two alternative samples, one is smaller by keeping bonds with trading volume larger than \$100,000, following Bessembinder et al. (2009), and the other is larger by keeping all bonds regardless of trading volume (we do apply the rule of using trading-volume-weighted price as the daily price, which vastly mitigates the impact of trades with smaller trading volume, mainly from individual investors). In both of these alternative samples, our main findings remain intact. As expected, the smaller sample gives us greater power to detect significant alphas. To make our results more generally applicable to a wide range of bonds, we adopt the current rule, which is to eliminate bonds with trading volume smaller than \$10,000.

day of the month is 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) is selected.

Our final sample includes 33,309 bonds issued by 3,887 unique firms, for a total of 1,057,436 bond-month return observations during the sample period July 2002 to December 2014. On average, there are approximately 7,002 bonds per month over the whole sample. Panel A of Table 1 reports the time-series average of the cross-sectional bond return distribution and bond characteristics. The average monthly bond return is 0.59%. The sample contains bonds with an average rating of 8.41 (i.e., BBB+), an average issue size of 366 million dollars, and an average time-to-maturity of 9.65 years. Among the full sample of bonds, 78% are investment-grade and the remaining 22% are high-yield bonds.

3.3 Cross-sectional Bond Risk Characteristics

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

However, the corporate bond market has its own unique features. First, credit risk is particularly important in determining corporate bond returns because firms that issue corporate bonds suffer from potential default risk given legal requirements on the payment of coupons and principal. Second, bondholders are more sensitive to downside risk than stockholders. Third, the corporate bond market is less liquid than the equity market, with most corporate bonds trading infrequently. Thus, both the level of liquidity and liquidity risk are serious concerns for investors in the corporate bond market. Fourth, corporate bond market participants have been dominated by institutional investors such as insurance companies, pension funds, and mutual funds, whose attitudes toward risk differ significantly from individual investors.[14] Finally, there is some evidence that shows the discrepancy in return premia between equity and corporate bond markets (e.g., Choi and Kim (2016), Chordia et al. (2016)), suggesting potential market segmentation.

Thus, it is important to identify common risk factors based on the broad risk characteristics of corporate bonds, rather than relying on stock market factors or aggregate bond market factors (e.g., DEF, TERM). As discussed below, we introduce three new risk factors originated from the cross-section of individual bond returns.

3.3.1 Downside Risk

Extraordinary events such as stock market crashes and bond market collapses are major concerns in risk management and financial regulation. Regulators are concerned with the protection of the financial system against catastrophic events, which can be a source of systematic risk. A central issue in risk management has been to determine capital requirement for financial and non-financial firms to meet catastrophic market risk. This increased focus on risk management has led to the development of various methods and tools to measure the risks companies face. A primary tool for financial risk assessment is Value-at-Risk (VaR).

Hence, we measure downside risk of corporate bonds using VaR, which 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 convenience of interpretation.[15] As shown in Table 1, the average

[14] Institutional investors in particular make extensive use of corporate bonds in constructing their portfolios. According to Flow of Fund data during the 1986-2012 period, 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.

[15] 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 and positive return/alpha spreads in portfolios are interpreted as the higher downside risk being related to the higher cross-sectional bond returns.

downside risk is 6.27% in the whole sample, implying that there is only a 5% probability that an average corporate bond would lose more than 6.27% over the next one month (or the maximum loss expected on a typical bond, at the 95% confidence level, is 6.27% over the next month).

VaR as a risk measure is criticized for not being sub-additive. To alleviate this problem, Artzner, Delbaen, Eber, and Heath (1999) introduce an alternative measure of downside risk, "expected shortfall," defined as the conditional expectation of loss given that the loss is beyond the VaR level. In our empirical analyses, we use the 10% expected shortfall (ES) defined as the average of the four lowest monthly return observations over the past 36 months (beyond the 10% VaR threshold). In the online appendix, we reexamine the cross-sectional relation between downside risk and future bond returns using the 10% VaR and 10% ES measures and show that our main findings are not sensitive to the choice of a downside risk measure.

3.3.2 Credit Quality

We measure credit quality of corporate bonds via their credit ratings which capture information on bond default probability and the loss severity. Ratings are assigned to corporate bonds on the basis of extensive economic analysis by rating agencies such as Moody's and Standard & Poor's. Bond-level ratings synthesize the information on both the issuer's financial condition, operating performance, and risk management strategies, along with specific bond characteristics like coupon rate, seniority, and option features, hence making ratings a natural choice to measure credit risk of a corporate bond.

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+, ..., and 21 refers to CCC. Investment-grade bonds have ratings from 1 (AAA) to 10 (BBB-). Non-investment-grade bonds have ratings above 10. A larger number indicates higher credit risk, or lower credit quality. We determine a bond's rating as the average of ratings provided by S&P and Moody's when both are available, or as the rating provided by one of the two rating agencies when only one rating is available.

Although credit rating is the widely-used, traditional measure of credit quality, earlier s-tudies also use other credit risk proxies such as the distance-to-default measure developed by

KMV (Crosbie and Bohn (2003)), or the CDS spread (Longstaff, Mithal, and Neis (2005)). Different from bond-level credit rating, all alternative proxies can only be constructed at the firm level as the calculation requires firm balance sheet information. In addition, the CDS spread is available only for a limited number of firms that are usually large, liquid, and important. Our objective is to investigate the cross-section of corporate bond returns, which differs across firms and even bonds issued by the same firm may have different returns.[16] Therefore, we adopt credit rating to measure bond-level credit risk.

In the online appendix, we reexamine the cross-sectional relation between credit quality and future bond returns using the firm-level distance-to-default and implied CDS measures in Bai and Wu (2015), and show that our main findings are not sensitive to the choice of credit quality measure.

3.3.3 Bond Illiquidity

The literature documentes 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) establish 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 proportion of 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 measure, $ILLIQ$, which aims to extract the transitory component from bond price. Specifically, let $\Delta p_{itd} = p_{itd} - p_{itd-1}$ be the log price change for bond i on day d of month t. Then, $ILLIQ$ is defined as

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

[16] 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.

In the online appendix, we reexamine the cross-sectional relation between illiquidity and future bond returns using two additional proxies of liquidity risk; the Roll (1984) and Amihud (2002) illiquidity measures.

3.3.4 Bond Market β

Following Elton, Gruber, and Blake (1995), we identify the bond market factor as the common variation in corporate bond returns related to the aggregate bond market portfolio. Specifically, we compute the bond market excess return (MKT^{Bond}) as the percentage change in the monthly Merrill Lynch Bond Index values minus the one-month Treasury-bill rate.[17] We estimate the bond market beta, β^{Bond}, for each bond from the time-series regressions of individual bond excess returns on the bond market excess returns using a 36-month rolling window. As shown in Table 1, the bond beta has a wide range from -0.51 in the 5th percentile to 1.89 in the 95th percentile, with an average value of 0.37.

3.3.5 Summary Statistics

Table 1 presents the correlation matrix for the bond-level characteristics and risk measures. As shown in Panel B, the bond market beta, β^{bond}, is positively associated with downside, credit, and liquidity risk measures, with the correlation coefficients ranging from 0.061 to 0.227. As expected, downside risk is also positively associated with β^{bond}, ILLIQ, and rating, with respective correlations of 0.189, 0.349, and 0.385. Bond maturity is positively correlated with all risk measures, except credit rating, implying that bonds with longer maturity (i.e., higher interest rate risk) have higher β^{bond}, higher VaR, higher ILLIQ, and lower rating. Bond size is negatively correlated with β^{bond}, VaR, and ILLIQ, indicating that bonds with smaller size have higher β^{bond}, higher VaR, and higher ILLIQ. The correlations between size and rating and between size and maturity are economically and statistically weak.

[17] We also consider alternative bond market proxies such as the Barclays Aggregate Bond Index, and the equal-weighted and value-weighted average returns of all corporate bonds in our sample. The results from these alternative bond market factors turn out to be similar to those reported in our tables.

4 Downside Risk and Expected Corporate Bond Returns

In this section, we first summarize earlier theoretical evidence indicating a positive cross-sectional relation between downside risk and expected returns. Then, we provide comprehensive empirical evidence supporting the positive relation between downside risk and the cross-section of future bond returns.

4.1 Theoretical Evidence

The mean-variance (MV) portfolio theory of Markowitz (1952) relies on two critical assumptions; either the investors have a quadratic utility or the asset returns are jointly normally distributed (see Levy and Markowitz (1979)). If an investor has quadratic preferences, she cares only about the mean and variance of returns; and the skewness and kurtosis of returns have no effect on expected utility, i.e., she will not care, for example, about extreme losses. The MV theory can be justified if asset returns are jointly normally distributed since the mean and variance completely describe the return distribution. However, as shown by Bai, Bali, and Wen (2016), the empirical distribution of corporate bond returns is skewed, peaked around the mode, and has fat-tails, implying that extreme bond returns occur much more frequently than predicted by the normal distribution. Therefore, traditional measures of risk (e.g., volatility) may not be sufficient to approximate the maximum likely loss of corporate bond portfolios mainly held by institutional investors, especially during extraordinary periods (e.g., market downturns, economic recessions).[18]

To address the concern about the non-normal return distribution of corporate bonds, we assume a loss-averse investor who solves the optimal portfolio selection problem in a Value-at-Risk framework. The loss-averse investor uses a mean-VaR approach to allocate financial assets by maximizing the expected value of a utility function approximated by the expected return and VaR of the portfolio. The focus on VaR as the appropriate measure of portfolio risk allows investors to treat losses and gains asymmetrically.

Based on standard utility functions, Bali, Demirtas, and Levy (2009) show that an increase

[18]Bali (2003) provides evidence that ignoring non-normality features of the interest rate distribution significantly understates downside risk, potentially posing a solvency risk for bond investors.

in downside risk reduces the expected utility of a loss-averse investor who takes into account higher-order moments of the return distribution. Hence, the loss-averse investor uses a VaR-efficient portfolio to solve the following constrained optimization problem:

$$\begin{aligned} &\max_w \; E_t(R_{p,t+\Delta}) \\ &\text{s.t. } VaR_t(w,\alpha,\Delta) \;= VaR_b \end{aligned} \tag{3}$$

where the VaR-efficient allocation depends on the loss probability level α, the benchmark VaR level VaR_b, limiting the authorized risk, the length of investment horizon Δ, and the initial budget w allocated at time t among n financial assets.

It is straightforward to show that as the expected return of a risky portfolio exceeds the risk-free rate, the optimization problem in equation (3) yields a positive relation between the portfolio's expected return and VaR. In the following subsections, we run portfolio-level analyses and cross-sectional regressions to empirically test the significance of a positive relation between VaR and expected return of corporate bonds.

4.2 Univariate Portfolio Analysis

We first examine the significance of a cross-sectional relation between VaR and future corporate bond returns using portfolio-level analysis. For each month from July 2004 to December 2014,[19] we form quintile portfolios by sorting corporate bonds based on their downside risk (5%VaR), where quintile 1 contains bonds with the lowest downside risk and quintile 5 contains bonds with the highest downside risk. Table 2 shows the average 5%VaR of bonds in each quintile, the next month average excess return, and the alphas for each quintile. The last five columns report the average bond characteristics for each quintile including the bond market beta, illiquidity, credit rating, time-to-maturity, and bond size. The last row displays the differences of average returns and the alphas between quintile 5 and quintile 1. Average excess returns and alphas are defined in terms of monthly percentages. Newey-West (1987) adjusted t-statistics are reported

[19] 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, so we report portfolio results starting in July 2004.

in parentheses.

Moving from quintile 1 to quintile 5, the average excess return on the downside risk portfolios increases monotonically from 0.201% to 1.048% per month. This indicates a monthly average return difference of 0.85% between quintiles 5 and 1 with a Newey-West t-statistic of 2.86, showing that this positive return difference is economically and statistically significant. This result also indicates that corporate bonds in the highest VaR quintile generate 10.18% per annum higher return than bonds in the lowest VaR quintile.

In addition to the average excess returns, Table 2 presents the intercepts (alphas) from the regression of the quintile excess portfolio returns on the well-known stock and bond market factors — the excess stock market return (MKT^{Stock}), 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).[20] The third column of Table 2 shows that, similar to the average excess returns, the 5-factor alpha on the downside risk portfolios also increases monotonically from 0.198% to 0.995% per month, moving from the low-VaR to the high-VaR quintile, indicating a positive and significant alpha difference (downside risk premium) of 0.797% per month (t-stat.= 3.10). Consistent with the theoretical evidence summarized in Section 4.1, this result suggests that loss-averse bond investors prefer high expected return and low VaR.

Beyond the well-known stock market factors (size, book-to-market, momentum, and liquidity), we also test whether the significant return difference between high-VaR bonds and low-VaR bonds can be explained by prominent bond market factors. Following Elton et al. (2001) and Bessembinder et al. (2009), we use the aggregate corporate bond market, default spread and term spread factors. The excess bond market return (MKT^{Bond}) is proxied by the Merrill Lynch Aggregate Bond Market Index returns in excess of the one-month T-bill return. The default spread factor (DEF) is defined as the monthly change in the difference between BAA- and AAA-rated corporate bond yields. The term spread factor (TERM) is defined as the monthly change in the difference between 10-year and 3-month constant-maturity Trea-

[20] The factors MKT^{Stock} (excess market return), SMB (small minus big), HML (high minus low), MOM (winner minus loser), and LIQ (liquidity risk) are described in and obtained from Kenneth French's and Lubos Pastor's online data libraries: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/ and http://faculty.chicagobooth.edu/lubos.pastor/research/.

sury yields. In addition to MKT^{Bond}, DEF, and TERM, we also use the momentum factor for the corporate bond market. Following Jostova et al. (2013), the bond momentum factor (MOM^{Bond}) is constructed from 5×5 bivariate portfolios of credit rating and bond momentum, defined as the cumulative returns over months from $t-7$ to $t-2$ (formation period).

Similar to our earlier findings from the average excess returns and the 5-factor alphas from stock market factors, the fourth column of Table 2 shows that, moving from the low-VaR to the high-VaR quintile, the 4-factor alpha from bond market factors increases almost monotonically from 0.142% to 0.968% per month. The corresponding 4-factor alpha difference between quintiles 5 and 1 is positive and highly significant; 0.827% per month with a t-statistic of 4.05. The fifth column of Table 2 presents the 9-factor alpha for each quintile from the combined five stock and four bond market factors. Consistent with our earlier results, moving from the low-VaR to the high-VaR quintile, the 9-factor alpha increases almost monotonically from 0.141% to 0.999% per month, generating a positive and highly significant risk-adjusted return spread of 0.858% per month with a t-statistic of 4.23.

Finally, 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, lower liquidity, 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 several ways to handle this concern. Specifically, in the following subsections, we test whether the positive relation between VaR and the cross-section of bond returns holds once we control for the market beta, credit rating, maturity, liquidity, and size based on bivariate portfolio sorts and Fama-MacBeth (1973) regressions.

4.3 Controlling for Bond Characteristics

Table A.1 of the online appendix presents the results from the bivariate sorts of VaR and bond characteristics. Quintile portfolios are formed every month from July 2004 to December 2014 by first sorting corporate bonds into five quintiles based on their credit ratings (Panel A), maturity (Panel B), size (Panel C), or illiquidity (Panel D); then within each quintile portfolio, bonds are sorted further into five sub-quintiles based on their VaR. This methodology, under each characteristic-sorted quintile, produces sub-quintile portfolios of bonds with dispersion in downside risk but that have nearly identical characteristics, such as rating, maturity, size, and illiquidity. VaR,1 represents the lowest VaR-ranked bond quintiles within each of the five bond characteristic-ranked quintiles. Similarly, VaR,5 represents the highest VaR-ranked quintiles within each of the five bond characteristic-ranked quintiles.

Panel A of Table A.1 shows that the 9-factor alpha increases monotonically from VaR,1 to VaR,5 quintile. More importantly, after controlling for credit rating, the 9-factor alpha difference between high- and low-VaR bonds remains positive, about 0.614% per month, and highly significant with a t-statistic of 4.92. We further investigate the interaction between VaR and credit rating 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 0.711% per month (t-stat.= 4.06), but the positive downside risk premium remains significant for investment-grade bonds even after controlling for credit ratings, with the alpha spread of 0.473% per month (t-stat.= 3.13).

Panel B of Table A.1 presents the results from the bivariate sorts of downside risk and maturity. After controlling for bond maturity, the alpha difference between high- and low-VaR bonds remains positive, 0.774% per month, and highly significant with t-statistic of 4.21. 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 0.646% per month (t-stat.= 2.94) for short-maturity bonds, 0.784% per month (t-stat.= 4.34) for medium-maturity bonds, and about 0.833% per month (t-stat.= 4.06) 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 spread 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.[21]

[21] As the bond's maturity lengthens, there is more time for rates to change and, hence, for the bond price to be affected. Therefore, bonds with longer maturities generally present greater interest rate risk than bonds of

Panel C of Table A.1 presents the results from the bivariate sorts of downside risk and bond size measured by bond outstanding value. After controlling for size, the alpha difference between high- and low-VaR bonds remains positive, about 0.754% 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 remains strong for bonds with high market value.

Panel D of Table A.1 presents the results from the bivariate sorts of downside risk and bond illiquidity measured in equation (2). After controlling for illiquidity, the alpha difference between high- and low-VaR bonds remains positive, approximately 0.683% per month, and statistically significant. In the same panel, we further investigate the interaction between VaR and bond illiquidity 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, but the significantly positive link remains strong for investment grade bonds even after controlling for illiquidity.

5 Credit, Liquidity, Market Risk and Corporate Bond Returns

The credit spread literature has long recognized the importance of credit risk and liquidity risk in explaining the bond yield spread. The asset pricing literature rarely used the bond market factor in explaining the bond portfolio returns (Elton, Gruber, and 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 one million bond-month observations.

5.1 Credit Quality and Expected Corporate Bond Returns

Similar to the investigation in Section 4, we first test the significance of a cross-sectional relation between credit quality and future returns of corporate bonds using portfolio-level analysis. For

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.

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 numerical score in rating (i.e., low credit risk bonds), and quintile 5 contains bonds with the highest numerical 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 alphas for each quintile. When moving from quintile 1 to quintile 5, the average excess return on the rating portfolios increases almost monotonically from 0.315% to 0.937% per month. This indicates a monthly average return difference of 0.62% between quintiles 5 and 1 with a Newey-West t-statistic of 3.00. In other words, corporate bonds in the highest credit risk quintile generate 7.48% per annum higher return than bonds in the lowest credit risk quintile.

The 9-factor alpha also increases from 0.267% in quintile 1 to 0.730% in quintile 5, suggesting a positive and significant alpha difference of 0.46% per month (t-stat.= 2.72). 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. We also 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 market beta, higher downside risk, lower liquidity, and shorter maturity. Bonds in different credit risk quintiles, however, do not seem to have significantly different size.

5.2 Bond Illiquidity and Expected Corporate Bond Returns

As discussed earlier (Section 3.3.3), we use the illiquidity (ILLIQ) measure of Bao, Pan, and Wang (2011), which aims to extract the transitory component from bond price. 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 alphas for each quintile. When moving from quintile 1 to quintile 5, the average excess return on the illiquidity portfolios increases from 0.587% to 1.165% per month. This indicates a monthly average return difference of 0.578% between quintiles 5 and 1, with a Newey-West t-statistic of 3.16, suggesting that this positive return difference is statistically and economically significant. Put differently, corporate bonds in the highest illiquidity quintile (illiquid bonds) generate 6.94% per annum higher return than bonds in the lowest illiquidity quintile (liquid bonds).

The fifth column of Table 4 shows that, similar to the average excess returns, the 9-factor alpha also increases monotonically from 0.489% to 1.024% per month, moving from quintile 1 to quintile 5, indicating a positive and significant alpha difference of 0.535% per month (t-stat.= 3.63). These results indicate that after controlling for the commonly used stock and bond market factors, the alpha difference between Low-illiquidity and High-illiquidity bonds (the illiquidity premium) remains positive and highly significant.

We also compute 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 market beta, higher credit risk, longer maturity, smaller size, and somewhat higher credit risk.

5.3 Market β and Expected Corporate Bond Returns

In testing the empirical validity of the CAPM, the market factor unanimously adopts a stock market index such as the excess returns on the S&P500 or CRSP index which capture the information on public companies that 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 traded in the stock market. Second, firms traded in the stock market may not have public bonds.

In this section, we investigate whether the CAPM holds in the corporate bond market. First, the corporate bond market is proxied by the Merrill Lynch U.S. Aggregate Bond Index. Then, the bond market beta, β^{Bond}, is estimated for each bond using the monthly rolling regressions of individual bond excess returns on the bond market excess returns over the past 36 months requiring at least 24 monthly return observations.[22] Once the market betas are estimated, we

[22] If the monthly return observations are less than 24, 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.

form quintile portfolios for every month from July 2004 to December 2014 by sorting corporate bonds based on their bond market betas. Quintile 1 is the portfolio with the lowest beta, and quintile 5 is the portfolio with the highest beta. The results are presented in Table 5. When moving from quintile 1 to quintile 5, the average bond beta increases monotonically from -0.401 to 1.494, with a cross-sectional spread of 1.895. Consistent with the CAPM's prediction, the average excess return on the highest bond beta quintile (0.848% per month) is significantly higher than the average excess return on the lowest bond beta quintile (0.255% per month). The average return spread between quintiles 5 and 1 is economically and statistically significant: 0.593% per month (t-stat.= 2.88). This result indicates that bonds with high beta earn a market risk premium of 7.07% per annum than bonds with low beta. Moreover, the significantly positive bond market risk premium is driven by bonds with high beta (0.848% per month with t-stat.= 2.25), whereas bonds with low beta have insignificant average return (0.255% per month with t-stat.= 1.07).

Examining the average characteristics of individual bonds in the market beta portfolios, we find that the high beta portfolio has lower liquidity, higher downside risk, lower credit quality, and smaller bond size. However, the average maturity of high-beta vs. low-beta bonds does not significantly differ.

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. Thus, it is essential to use the corporate bond market factor to price the cross-sectional variation in corporate bond returns.

5.4 Fama-MacBeth Regressions

We have thus far tested the significance of downside risk (5% VaR), credit quality (rating), bond illiquidity (ILLIQ), and bond market beta (β^{Bond}) as the determinants of the cross-section of future bond returns at the portfolio level. We now examine the cross-sectional relation between risk characteristics 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 including bond year-to-maturity (MAT), bond amount outstanding (SIZE), bond momentum (MOM^{Bond}), and lagged excess return.[23] Monthly cross-sectional regressions are run for the following econometric specification and nested versions thereof:

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

where $R_{i,t+1}$ is the excess return on bond i in month t+1.

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 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 0.063 with a t-statistic of 2.81. 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 13.44 (= 15.15 − 1.71), multiplying this spread by the average slope of 0.063 yields an estimated monthly downside risk premium of 85 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 0.065 with a t-statistic of 3.12. As reported in the first column of Table 3, the spread in average rating between quintiles 5 and 1 is 11.73 (= 15.24 − 3.52), multiplying this spread by the average slope of 0.065 yields an estimated monthly credit risk premium of 76 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, 0.049, and highly significant with a t-statistic of 4.87. As shown in the first column of Table 4, the spread in average ILLIQ between quintiles 5 and 1 is 9.43 (= 9.23 − (−0.20)). Multiplying

[23] Following Jostova et al. (2013), bond momentum is defined as the cumulative return over months from the formation period of $t-7$ to $t-2$ (skipping the short-term reversal month).

this spread by the average slope of 0.049 yields an estimated monthly illiquidity premium of 47 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 0.281 with a t-statistic of 2.73. As presented in the first column of Table 5, the spread in average β^{Bond} between quintiles 5 and 1 is approximately 1.90 ($= 1.49 - (-0.40)$); multiplying this spread by the average slope of 0.281 yields an estimated monthly market risk premium of 53 basis points.

Regression specifications (2), (4), (6) and (8) in Table 6 show that after controlling for maturity, size, bond momentum, and lagged excess return, the average slope coefficients on VaR, rating, ILLIQ, and β^{Bond} remain positive and statistically significant. In other words, controlling for bond characteristics and other risk factors 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 0.096 (t-stat.$=$ 4.05) and 0.035 (t-stat.$=$ 4.38), respectively. Although the average slope on β^{Bond} is positive, it is not statistically significant in this general specification. Moreover, the average slope on rating becomes insignificant, implying that credit rating loses its predictive power for future bond returns after VaR and ILLIQ are controlled for.

The last specification, Regression (10), presents results from the multivariate regression with all bond risk proxies (VaR, Rating, ILLIQ, and β^{Bond}) after controlling for maturity, size, bond momentum, and lagged bond returns. Similar to our findings in Regression (9), the cross-sectional relations between future bond returns and VaR and ILLIQ are positive and highly significant. However, the predictive power of rating and β^{Bond} disappears, indicating that downside risk and liquidity risk have a more pervasive effect on future bond returns than credit risk and market risk. Among the control variables, only the short-term reversal effect is found to be strong and robust across regression specifications.

6 Common Risk Factors in the Corporate Bond Market

In this section, we introduce novel risk factors based on downside risk, credit quality, and bond illiquidity and test whether the newly proposed factors are explained by the well-established stock and bond market factors. We also form alternative test assets based on the industry and the size/maturity sorted portfolios of corporate bonds, and compare the relative performance of the new factors with the commonly used factor models in predicting the cross-sectional dispersion of corporate bond returns.

6.1 New Risk Factors: DRF, CRF, LRF

As discussed previously (Section 3.3.5), corporate bonds with high credit risk also have higher downside risk and higher illiquidity both at the bond level and portfolio level, indicating a positive cross-sectional relation between credit risk and bond illiquidity and downside risk. More importantly, default/credit risk is one of the most frequently monitored barometers, closely followed by rating agencies, financial regulators, and investors. 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.

To construct the downside risk factor for corporate bonds, for each month from July 2004 to December 2014, we form mimicking portfolios by first sorting bonds into five quintiles based on their credit rating, and 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-weighted average return difference between the highest-VaR portfolio and the lowest-VaR portfolio across the rating portfolios.[24]

The liquidity risk factor is similarly constructed. For each month from July 2002 to December 2014, we form portfolios by first sorting bonds into five quintiles based on their credit rating, and then within each rating portfolio, bonds are sorted further into five sub-quintiles based on their illiquidity (ILLIQ). The liquidity risk factor, LRF, is the equal-weighted average return difference between the highest-illiquidity portfolio and the lowest-illiquidity portfolio

[24] As a robustness check, we also report the value-weighted bond risk factors since bonds with relatively high downside risk, high credit risk, and high illiquidity are smaller in size. To alleviate this concern, we use amount outstanding as a portfolio weight to construct the value-weighted factors. All results remain the same.

across the rating portfolios.

Finally, we construct the credit risk factor of corporate bonds by using 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), and then within each ILLIQ quintile, bonds are sorted further into five sub-quintiles based on their credit rating. The credit risk factor, CRF, is the equal-weighted average return difference between the lowest-rating (i.e., highest credit risk) portfolio and the highest-rating (i.e., lowest credit risk) portfolio across the ILLIQ portfolios.[25]

6.2 Descriptive Statistics of the New Risk Factors

Panel A of Table 7 reports the summary statistics for the new risk factors (DRF, CRF and LRF). Over the period 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 of 0.72% per month, with a t-statistic of 3.58. The equal-weighted CRF and LRF factors also have significant risk premia of 0.62% per month (t-stat.= 3.37) and 0.51% per month (t-stat.= 4.01), respectively. The risk premia on the factors remain qualitatively similar when they are generated from the value-weighted portfolios: 0.57% per month (t-stat.= 3.43) for the DRF factor, 0.54% per month (t-stat.= 2.54) for the CRF factor, and 0.47% per month (t-stat.= 4.88) for the LRF factor.

Since risk premia are expected to be higher during financial and economic downturns, we examine the average risk premia for the newly proposed factors, DRF, CRF, and LRF, during recessionary vs. non-recessionary periods, according to the Chicago Fed National Activity Index (CFNAI).[26] As expected, we find that the average risk premium on the equal-weighted DRF factor is much higher at 1.27% per month during recessionary periods (CFNAI $\leq$ -0.7), whereas it is 0.55% per month during non-recessionary periods (CFNAI $>$ -0.7). The average

[25]Our final sample of corporate bond risk factors, CRF and LRF, covers the period from July 2002 to December 2014, whereas the DRF factor spans a shorter sample period from July 2004 to December 2014, due to the requirement of at least 24 monthly return observations when calculating downside risk based on a 36-month rolling window estimation.

[26]CFNAI is a monthly index designed to assess overall economic activity and related inflationary pressure (see, e.g., Allen, Bali, and Tang (2012)). 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 a recessionary (non-recessionary) period.

risk premium on the equal-weighted CRF factor is 0.66% during recessionary periods and 0.55% during non-recessionary periods. Finally, the average risk premium on the equal-weighted LRF factor is higher at 1.27% per month during recessionary periods, whereas it is 0.32% per month during non-recessionary periods. These magnitudes provide clear evidence that the newly proposed corporate bond risk factors generate economically large risk premia during economic downturns.

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 DRF and the standard stock market factors (MKT^{Stock}, SMB, HML, UMD, and LIQ) are in the range of 0.06 and 0.13 in absolute magnitude. The correlations between the DRF factor and the standard bond market factors (MKT^{Bond}, DEF, TERM, and MOM^{Bond}) are in the range of 0.05 and 0.21 in absolute magnitude. The corresponding correlations are low for the CRF factor as well in the range of 0.01 and 0.10 for the stock market factors and from 0.04 to 0.24 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 0.26 for the stock market factors and range from 0.01 to 0.26 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 the Existing Factor Models Explain the DRF, CRF, and LRF Factors?

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

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

where $Factor_t^{New}$ is one of the three bond market factors: 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, TERM, and MOM^{Bond}.

Equation (5) is estimated separately for 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 reports the regression results using the stock market factors as explanatory variables. As shown in Panel A, all intercepts (alphas) are economically and statistically significant, indicating that the existing stock market factors are not sufficient to capture the information content in these new bond risk factors. Based on the 5-factor model, the alphas for the DRF, CRF and LRF factors are 0.70% per month (t-stat.= 3.47), 0.53% per month (t-stat.= 2.30), and 0.52% (t-stat.= 3.14), respectively. The adjusted-R^2 values from these regressions are in the range of 9.92% to 17.12%, suggesting that the commonly-used stock market factors have low explanatory power for the risk factors of corporate bonds. Overall, these results suggest that the newly proposed bond market factors capture an important source of common return variation in corporate bonds missing from the traditional stock market factors.

Panel B of Table 8 shows the regression results using the standard bond market risk factors (MKT^{Bond}, DEF, TERM, MOM^{Bond}) as explanatory variables. All intercepts are statistically and economically significant, and the magnitudes of the alphas are similar to those reported in Panel A using the stock market factors as explanatory variables. As shown in Panel B, the alphas for the DRF, CRF and LRF factors are 0.73% per month (t-stat.= 4.10), 0.43% per month (t-stat.= 2.35), and 0.45% (t-stat.= 2.96), respectively.

Panel C of Table 8 presents the regression results from the extended 9-factor model, combining all of the stock and bond market factors. The results are consistent with our earlier findings. First, the alphas of all bond risk factors are economically and statistically significant, indicating that the existing stock and bond market factors are not sufficient to capture the information content in these new bond risk factors. Second, the explanatory power of the existing factors is considerably low for the new bond market factors. All factors combined together explain about 55.95% of the DRF factor, 26.65% of the CRF factor, and 55.88% of the LRF factor. 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.

6.4 Alternative Test Portfolios

Lewellen, Nagel, and Shanken (2010) review and criticize the empirical methods and find that asset pricing tests provide weak support for factor models. Specifically, the low power of these tests is driven by characteristic-sorted portfolios (used as test assets) that do not have sufficient independent variation in the factor loadings. To improve the power of asset pricing tests, both studies suggest testing risk factors on alternative test portfolios. Following their suggestion, we consider two sets of test portfolios that do not relate to risk characteristics tested in previous sections, that is, downside risk, credit rating, illiquidity, and market beta.

The first set of test portfolios is based on 5×5 independently sorted bivariate portfolios of size and maturity. The second set of test portfolios is based on 30-industry portfolios. We then examine the relative performance of factor models in explaining the time-series and cross-sectional variation in the 25-size/maturity and 30-industry sorted portfolios of corporate bonds.[27] The monthly returns of the test portfolios cover the period from July 2002 to December 2014. We investigate the empirical performance of the following three factor models:

- Model 1: the 5-factor model with the stock market factors of Fama and French (1993), Carhart (1997), and Pastor and Stambaugh (2003), including the excess stock market return (MKT^{Stock}), the size factor (SMB), the book-to-market factor (HML), the stock momentum factor (MOM), and the Pastor-Stambaugh liquidity factor (LIQ).

- Model 2: the 4-factor model with the bond market factors of Elton et al. (1995) and Bessembinder et al. (2009), including the excess bond market return (MKT^{Bond}), the default spread factor (DEF), the term spread factor (TERM), and the bond momentum factor (MOM^{Bond}).

[27] Before we form 25-size/maturity portfolios, we test the cross-sectional predictive power of size and maturity in univariate portfolios. For each month from July 2002 to December 2014, we sort corporate bonds into 10 size portfolios and find that corporate bonds in size decile 10 underperform those in decile 1 by 0.34% per month with a t-statistic of 2.67. When we sort them into 10 maturity portfolios, corporate bonds in maturity decile 10 outperform those in decile 1 by 0.31% per month with a t-statistic of 2.42. These results indicate that size and maturity characteristics contain significant risk premia in the cross-section of corporate bond returns.

- Model 3: the 4-factor model introduced in the paper, including the excess bond market return (MKT^{Bond}), the downside risk factor (DRF), credit risk factor (CRF), and liquidity risk factor (LRF).

In the time-series regressions, the adjusted R^2 values provide direct evidence on whether different risk factors capture common variation in bond returns. Table 9 reports the adjusted R^2 values from the time-series regressions of the 25-size/maturity sorted portfolios' excess returns on the newly proposed and existing risk factors. Overall, the results indicate that the commonly used stock and bond market factors do not perform as well as the newly proposed factors in explaining the cross-sectional variation in the returns of bond portfolios.

Specifically, Panel A of Table 9 shows that the adjusted R^2, averaged across the 25 portfolios, is only 13% for Model 1, implying that a large proportion of the variance in 25 bond portfolio returns is not explained by the commonly used stock market factors. Panel B shows that the adjusted R^2 values from Model 2 improves to 34% mainly because of the strong predictive power of the bond market factor (MKT^{Bond}). Compared to the results in Panels A and B, the average R^2 from Model 3 is much stronger. As shown in Panel C of Table 9, when we augment MKT^{Bond} with our newly proposed bond risk factors (DRF, CRF and LRF), the average adjusted R^2 significantly increases from 34% to 74%, suggesting that these new risk factors of corporate bonds capture significant cross-sectional information about the portfolio returns that is not fully picked up by the bond market factor. Overall, the results in Table 9 indicate that the newly proposed 4-factor model with the market, downside, credit and liquidity risk factors outperforms the existing factor models in explaining the returns of the size/maturity sorted portfolios of corporate bonds.

We also test the relative performance of the factor models using the 30-industry portfolios based on the Fama-French industry classification. Table 10 shows that the adjusted R^2, averaged across the 30-industry portfolios, is 14% for Model 1, 25% for Model 2, and 41% for Model 3. These results show that the newly proposed 4-factor model performs better than the existing stock and bond market factors in explaining the returns of the industry sorted portfolios of corporate bonds.

As an alternative way of evaluating the relative performance of the factor models, we focus on the magnitude and statistical significance of the alphas on the 25-size/maturity portfolios generated by Models 1, 2, and 3. Panel A of Table A.2 in the online appendix shows that the 5-factor model with the stock market factors (Model 1) generates economically significant alpha for 24 out of 25 portfolios, ranging from 0.34% to 0.76% per month.[28] Consistent with the economic significance, the alphas are statistically significant for 24 out of 25 portfolios. As shown in the last row of Panel A in Table A.2, the average alpha across the 25 portfolios is very large, 0.49% per month, and highly significant with a zero p-value according to the Gibbons, Ross, and Shanken (1989, GRS) test. Panel B of Table A.2 shows that the magnitude and statistical significance of the alphas decrease when moving from Model 1 to Model 2. However, the 4-factor model with the traditional bond market factors (Model 2) still generates economically and statistically significant alphas, ranging from 0.26% to 0.60% per month, for 24 out of 25 portfolios. Similar to our findings in Panel A, the last row of Panel B shows that the average alpha across the 25 portfolios is large, 0.38% per month, and highly significant with a zero p-value according to the GRS test.

Panel C of Table A.2 presents substantially different results compared to Panels A and B. The newly proposed 4-factor model with DRF, CRF, and LRF (Model 3) generates economically and statistically *insignificant* alphas for 23 out of 25 portfolios, ranging from 0.07% to 0.15% per month.[29] As shown in the last row of Panel C, the average alpha across the 25 portfolios is very low, economically insignificant at 0.11% per month.[30] Overall, these results confirm the superior performance of the newly proposed factors in predicting the cross-sectional variation in the returns of the 25-size/maturity sorted portfolios of corporate bonds.

We replicate these analyses for the 30-industry portfolios in Table A.3 of the online appendix. As shown in Panel A of Table A.3, Model 1 generates economically significant alphas for all 30 portfolios, ranging from 0.41% to 1.61% per month. Consistent with their economic significance, the alphas are also statistically significant for 26 out of 30 portfolios. As shown in the last row

[28] There is only one portfolio that contains bonds with large size/short maturity with economically lower alpha, 0.26% per month, but that is still statistically significant with a t-statistic of 2.74.

[29] There are only two portfolios out of the 25-size/maturity sorted portfolios with marginally significant alpha: 0.16% per month (t-stat. = 1.92) and 0.21% per month (t-stat. = 1.92). Although these alphas are statistically significant (marginally), they are economically insignificant.

[30] Although the average alpha is only 11 bps per month, it is statistically significant with a p-value of 0.02 according to the GRS test.

of Panel A, the average alpha across the 30 portfolios is very large, 0.68% per month, and highly significant. The results from Model 2 are somewhat better. As shown in Panel B of Table A.3, Model 2 generates economically significant alphas for 29 out of 30 portfolios, ranging from 0.27% to 1.20% per month. The alphas from Model 2 are also statistically significant for 21 out of 30 portfolios. As shown in the last row of Panel B, the average alpha across the 30 portfolios is economically large, 0.56% per month, and highly significant.

Similar to our findings from the 25-size/maturity portfolios, Panel C of Table A.3 presents considerably different results from the new proposed 4-factor model for the 30-industry portfolios. Model 3 with DRF, CRF, and LRF generates economically and statistically *insignificant* alphas (at the 10% level) for 26 out of 30 portfolios. As shown in the last row of Panel C, the average alpha across the 30 portfolios is very low, economically insignificant, at 0.09% per month.[31] Overall, these results provide supporting evidence for the remarkable performance of the newly proposed factors in predicting the cross-sectional variation in the returns of the 30-industry portfolios of corporate bonds.

7 Robustness Check

7.1 Orthogonalized Risk Characteristics

As discussed earlier (Section 3.3.5), bond risk characteristics are correlated.[32] Bonds with higher downside risk also have lower credit quality and lower liquidity; bonds with higher market beta tend to have lower credit quality and higher downside risk. When putting them jointly in the Fama-MacBeth regressions (see specifications (9) and (10) in Table 6), downside risk and bond illiquidity dominate in predicting the cross-sectional bond returns, while credit rating and market beta lose their predictive power. All these results lead to concern about what unique information each risk characteristic carries. To investigate this issue, we construct

[31] Note that the average alpha is only 9 bps per month, but is statistically significant with a p-value of 0.02 according to the GRS test.

[32] He and Xiong (2012) introduce a theoretical model that demonstrates an interaction between liquidity premium and credit risk premium through rollover risk. Chen, Cui, He, and Milbradt (2016) propose a structural model of credit risk and investigate how the interactions between liquidity and default risk affect corporate bond pricing.

orthogonalized risk characteristics.

For each month, we run the cross-sectional regression of one risk characteristic on the remaining three variables:

$$
\begin{aligned}
VaR_{i,t} &= \lambda_{0,t} + \lambda_{1,t}\beta^{Bond} + \lambda_{2,t}Rating_{i,t} + \lambda_{3,t}ILLIQ_{i,t} + \epsilon_{i,t}^{VaR} \\
Rating_{i,t} &= \lambda_{0,t} + \lambda_{1,t}\beta^{Bond} + \lambda_{2,t}VaR_{i,t} + \lambda_{3,t}ILLIQ_{i,t} + \epsilon_{i,t}^{Rating} \\
ILLIQ_{i,t} &= \lambda_{0,t} + \lambda_{1,t}\beta^{Bond} + \lambda_{2,t}Rating_{i,t} + \lambda_{3,t}VaR_{i,t} + \epsilon_{i,t}^{ILLIQ} \\
\beta_{i,t}^{Bond} &= \lambda_{0,t} + \lambda_{1,t}Rating_{i,t} + \lambda_{2,t}VaR_{i,t} + \lambda_{3,t}ILLIQ_{i,t} + \epsilon_{i,t}^{\beta^{Bond}}
\end{aligned}
$$

Once we generate the residuals from each regression in month t, we label them as orthogonalized downside risk ($\text{VaR}^{\perp}$), orthogonalized credit rating ($\text{Rating}^{\perp}$), orthogonalized illiquidity ($\text{ILLIQ}^{\perp}$), and orthogonalized market beta ($\beta^{Bond,\perp}$). In so doing, we filter out the common information and retain only the unique information contained in each risk characteristic.

Then, we repeat the Fama-MacBeth regressions with orthogonalized risk characteristics and report the results in Table A.4. In the univariate regressions, both with and without control variables, orthogonalized rating and orthogonalized market beta lose their significance, whereas the orthogonalized measures of downside risk and illiquidity remain their strong power in predicting the cross-sectional dispersion of bond returns. Compared to the original (unorthogonalized) estimates of the coefficients, orthogonalized downside risk has even greater economic significance and statistical power, with a coefficient of 0.095 (t-stat. = 4.00) compared to 0.063 (t-stat. = 2.81) in the original univariate regression (1). The multivariate regression results remain the same as those in the original setup of Table 6, that is, only the orthogonalized measures of downside risk and illiquidity have significant predictive power, whereas the orthogonalized measures of rating and market beta do not predict future bond returns. These results are robust after controlling for bond maturity, bond size, bond momentum, and one-month lagged bond returns.

7.2 Alternative Measures of Downside Risk

Downside risk has so far been proxied by the 5% VaR. Our main results remain intact when we use two alternative measures of downside risk: the 10% VaR and the 10% Expected Shortfall (ES) which are introduced in Section A.1 of the online appendix. The 10% VaR is defined as the fourth lowest monthly return observation over the past 36 months. The 10% expected shortfall (ES) is defined as the average of four lowest monthly return observations over the past 36 months (beyond the 10% VaR threshold). The original VaR and ES measures are multiplied by -1 for convenience of interpretation. Panel A of Table A.5 in the online appendix reports the summary statistics for the alternative downside risk factors, constructed based on the 10% VaR and 10% ES. The equal-weighted DRF factor constructed from the 10% VaR has an economically and statistically significant downside risk premium of 0.67% per month with a t-statistic of 3.47. The equal-weighted DRF factor constructed from the 10% ES also has a significant downside risk premium of 0.79% per month with a t-statistic of 3.70. The risk premia on the DRF factors remain qualitatively similar when they are generated from the value-weighted portfolios: 0.51% per month (t-stat.= 3.16) and 0.65% (t-stat.= 3.54), respectively.

Panel B of Table A.5 shows the regression results from the equal-weighted DRF factors based on the extended 9-factor model combining all of the stock and bond market factors. As shown in Panel B, all intercepts (alphas) are economically and statistically significant: the alphas for the DRF factors constructed from the 10% VaR and 10% ES are 0.67% per month (t-stat.= 4.01) and 0.87% per month (t-stat.= 4.37), respectively. Panel C of Table A.5 presents the corresponding regression results from the value-weighted DRF factors. The results are consistent with those reported in Panel B. All intercepts are economically and statistically significant, and the magnitudes of the alphas are similar to those reported in Panel B for the equal-weighted DRF factors.

7.3 Alternative Measures of Bond Illiquidity

We reexamine the properties of the liquidity risk factor (LRF) based on two alternative proxies of liquidity: the Roll (1984) and Amihud (2002) illiquidity measures which are introduced in

Section A.2 of the online appendix. Panel A of Table A.6 shows that the equal-weighted LRF factor constructed from the Roll's measure has an economically and statistically significant liquidity risk premium of 0.43% per month with a t-statistic of 2.94. The equal-weighted LRF factor constructed from the Amihud measure also has a significant liquidity risk premium of 0.40% per month with a t-statistic of 2.82. The risk premia on the LRF factors remain qualitatively similar when they are generated from the value-weighted portfolios: 0.38% per month (t-stat.= 4.24) and 0.33% (t-stat.= 3.32), respectively. Panels B and C of Table A.6 show that all of the intercepts (alphas) are economically and statistically significant, implying that the extended 9-factor model does not explain the returns on the alternative LRF factors.

7.4 Alternative Measures of Credit Risk

In Section A.3 of the online appendix, we construct alternative measures of credit risk: the distance-to-default (DD) and implied credit default spread (CDS). Table A.7 presents the Fama-MacBeth regression results using DD or CDS to substitute for credit rating. The average slope from the univariate cross-sectional regressions of excess bond returns on DD (CDS) is negative (positive) and significant, indicating that higher credit risk is associated with higher future bond returns. However, the multivariate regressions in Table A.7 show that with all bond risk proxies (VaR, rating, ILLIQ, and β^{bond}) and bond characteristics (maturity, size), DD and CDS lose their predictive power, while the slope coefficients on VaR and ILLIQ remain positive and significant. These results are consistent with those reported in Table 6, where credit risk is proxied by rating.

7.5 New Risk Factors Using a Longer Sample

Our empirical analyses are thus far based on the TRACE Enhanced transaction data from July 2002 to December 2014. To further check whether our results are sensitive to different datasets, we also consider an extended sample of corporate bonds gathered from a range of data sources from January 1977 to December 2014. With this longer sample, we replicate our main analysis, except those requiring an illiquidity measure. In Section A.4 of the online appendix, we show that the results are very similar to those reported in the paper. Panel A of Table A.8 shows that the equal-weighted DRF factors have economically and statistically significant downside risk premia, ranging from 0.59% to 0.67% per month. The CRF factor also has a significant credit risk premium of 0.32% per month with a t-statistic of 3.76. The risk premia on the DRF and CRF factors remain qualitatively similar when they are generated from the value-weighted portfolios. Panel B of Table A.8 shows that all of the intercepts (alphas) from the extended 8-factor models are economically and statistically significant, in the range of 0.52% per month (t-stat.= 4.54) and 0.65% per month (t-stat.= 4.53) for the equal-weighted DRF factors. The last row in Panel B shows that the extended 8-factor model does not explain the returns of the CRF factor either. Panel C of Table A.8 presents the corresponding regression results for the value-weighted bond risk factors. The results are consistent with the findings in Panel B for the equal-weighted factors.

Overall, our main findings are not sensitive to the choice of downside risk or liquidity risk measure, and are robust to an extended sample of corporate bond data compiled from different sources including the quoted- and transaction-based bond data.

8 Conclusion

An extensive literature examines the cross-sectional determinants of stock returns. There is, however, surprisingly little research on the common risk factors that explain the cross-section of corporate bond returns. This paper aims to fill this gap by identifying common risk factors that predict the the cross-sectional differences in corporate bonds.

In contrast to the commonly used stock market factors and aggregate macroeconomic variables that have been investigated in the literature for bond returns, the common risk factors we identify are motivated by the unique features of individual corporate bonds. Specifically, we find that downside risk, credit risk, liquidity risk, and market risk positively predict the cross-sectional variation in future bond returns. We then introduce novel risk factors based on the three prevalent measures of downside risk, credit risk, and liquidity risk. We find that all these factors have economically and statistically significant risk premia, which cannot be explained by the existing stock and bond market risk factors.

We further examine the explanatory power of the newly proposed risk factors for alternative test portfolios sorted by bond size, maturity, and industry. We find that a 4-factor model with the bond market factor and our newly proposed three factors outperforms all other models considered in the literature in explaining the returns of the industry and size/maturity sorted portfolios of corporate bonds.

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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). Panel B reports the time-series average of the cross-sectional correlations. 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 (%)	1,057,436	0.59	0.43	4.67	-13.21	-4.47	-0.67	1.75	5.97	15.71
Rating	1,057,436	8.41	7.70	4.13	1.47	2.05	5.64	10.39	16.44	19.09
Time-to-maturity (maturity, year)	1,057,436	9.65	6.77	8.73	1.12	1.55	3.71	13.12	26.54	30.02
Amount Out (size, $million)	1,057,436	366	242	486	1.22	4.24	58.09	462	1258	2407
Downside risk (5% VaR)	501,161	6.27	4.51	5.61	0.81	1.35	2.78	7.69	17.30	26.25
Illiquidity (ILLIQ)	812,152	2.62	0.50	7.21	-1.61	-0.33	0.08	2.14	12.99	32.25
Bond Market Beta (β^{Bond})	501,161	0.37	0.23	0.74	-1.15	-0.51	-0.03	0.61	1.89	2.82

Panel B: Correlations

	Rating	Maturity	Size	VaR	ILLIQ	β^{Bond}
Rating	1	-0.105	0.032	0.385	0.052	0.227
Maturity		1	-0.007	0.176	0.087	0.061
Size			1	-0.119	-0.143	-0.153
VaR				1	0.349	0.189
ILLIQ					1	0.140
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 reports the average VaR, the next-month average excess return, the 5-factor alpha from stock market factors, the 4-factor alpha from bond market factors, and the 9-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 factor models. The 5-factor model with stock market factors includes the excess stock market return (MKT^{Stock}), the size factor (SMB), the book-to-market factor (HML), the momentum factor (MOM), and the stock liquidity factor (LIQ). The 4-factor model with bond market factors includes the excess bond market return (MKT^{Bond}), the default spread factor (DEF), the term spread factor (TERM), and the bond momentum factor (MOM^{Bond}). The 9-factor model combines 5 stock market factors and 4 bond market factors. 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	5-factor stock	4-factor bond	9-factor	Average portfolio characteristics				
	VaR	return	alpha	alpha	alpha	β^{Bond}	ILLIQ	Rating	Maturity	Size
Low VaR	1.707	0.201	0.198	0.142	0.141	0.130	0.566	7.001	4.422	0.538
		(1.26)	(2.47)	(2.00)	(2.11)					
2	3.113	0.287	0.272	0.182	0.177	0.210	1.157	7.717	7.064	0.449
		(2.30)	(2.09)	(1.53)	(1.56)					
3	4.540	0.396	0.372	0.268	0.268	0.274	1.915	8.153	10.369	0.429
		(2.34)	(2.19)	(1.84)	(1.89)					
4	6.899	0.599	0.564	0.442	0.464	0.351	3.231	8.873	13.265	0.391
		(2.57)	(2.65)	(2.46)	(2.56)					
High VaR	15.147	1.048	0.995	0.968	0.999	0.918	8.380	12.656	12.027	0.329
		(3.09)	(3.33)	(4.25)	(4.34)					
High − Low		0.848***	0.797***	0.827***	0.858***					
Return/Alpha diff.		(2.86)	(3.10)	(4.05)	(4.23)					

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 reports the average credit rating, the next-month average excess return, the 5-factor alpha from stock market factors, the 4-factor alpha from bond market factors, and the 9-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 factor models. The 5-factor model with stock market factors includes the excess stock market return (MKT^{Stock}), the size factor (SMB), the book-to-market factor (HML), the momentum factor (MOM), and the stock liquidity factor (LIQ). The 4-factor model with bond market factors includes the excess bond market return (MKT^{Bond}), the default spread factor (DEF), the term spread factor (TERM), and the bond momentum factor (MOM^{Bond}). The 9-factor model combines 5 stock market factors and 4 bond market factors. 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 rating	Average return	5-factor stock alpha	4-factor bond alpha	9-factor alpha	Average portfolio characteristics				
						β^{Bond}	ILLIQ	VaR	Maturity	Size
Low Credit Risk	3.517	0.315	0.320	0.265	0.267	0.135	1.680	3.886	10.564	0.381
		(1.42)	(1.24)	(2.44)	(2.46)					
2	5.996	0.356	0.366	0.296	0.312	0.129	1.828	4.284	10.344	0.357
		(2.61)	(2.50)	(2.44)	(2.61)					
3	7.708	0.436	0.416	0.294	0.292	0.217	2.047	4.854	9.910	0.384
		(3.13)	(2.78)	(2.62)	(2.60)					
4	9.871	0.524	0.475	0.321	0.321	0.351	2.517	5.639	9.367	0.373
		(2.99)	(2.72)	(1.92)	(1.92)					
High Credit Risk	15.242	0.937	0.864	0.716	0.730	0.839	4.413	11.088	7.188	0.366
		(3.81)	(3.84)	(3.71)	(3.67)					
High − Low		0.623***	0.544***	0.451***	0.464***					
Return/Alpha diff.		(3.00)	(2.63)	(2.78)	(2.72)					

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 reports the average illiquidity, the next-month average excess return, the 5-factor alpha from stock market factors, the 4-factor alpha from bond market factors, and the 9-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 factor models. The 5-factor model with stock market factors includes the excess stock market return (MKT^{Stock}), the size factor (SMB), the book-to-market factor (HML), the momentum factor (MOM), and the stock liquidity factor (LIQ). The 4-factor model with bond market factors includes the excess bond market return (MKT^{Bond}), the default spread factor (DEF), the term spread factor (TERM), and the bond momentum factor (MOM^{Bond}). The 9-factor model combines 5 stock market factors and 4 bond market factors. 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	5-factor stock	4-factor bond	9-factor	Average portfolio characteristics				
	ILLIQ	return	alpha	alpha	alpha	β^{Bond}	VaR	Rating	Maturity	Size
Low ILLIQ	-0.202	0.587	0.581	0.470	0.489	0.280	5.328	8.539	7.927	0.667
		(3.64)	(3.97)	(3.85)	(3.99)					
2	0.132	0.324	0.322	0.233	0.237	0.205	3.981	8.285	6.745	0.603
		(3.04)	(2.96)	(2.36)	(2.53)					
3	0.514	0.422	0.408	0.309	0.314	0.284	5.170	8.633	8.745	0.419
		(3.10)	(3.08)	(2.64)	(2.80)					
4	1.654	0.546	0.523	0.407	0.420	0.366	6.521	8.602	10.674	0.294
		(3.07)	(3.22)	(2.98)	(3.07)					
High ILLIQ	9.227	1.165	1.139	0.975	1.024	0.595	9.512	9.338	12.222	0.202
		(3.55)	(4.01)	(4.33)	(4.39)					
High - Low		0.578***	0.558***	0.505***	0.535***					
Return/Alpha diff.		(3.16)	(3.49)	(3.57)	(3.63)					

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 reports the average illiquidity, the next-month average excess return, the 5-factor alpha from stock market factors, the 4-factor alpha from bond market factors, and the 9-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 factor models. The 5-factor model with stock market factors includes the excess stock market return (MKT^{Stock}), the size factor (SMB), the book-to-market factor (HML), the momentum factor (MOM), and the stock liquidity factor (LIQ). The 4-factor model with bond market factors includes the excess bond market return (MKT^{Bond}), the default spread factor (DEF), the term spread factor (TERM), and the bond momentum factor (MOM^{Bond}). The 9-factor model combines 5 stock market factors and 4 bond market factors. 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	5-factor stock	4-factor bond	9-factor	Average portfolio characteristics				
	β^{Bond}	return	alpha	alpha	alpha	ILLIQ	VaR	Rating	Maturity	Size
Low β^{Bond}	-0.401	0.255	0.136	0.124	0.081	2.571	6.332	8.380	10.270	0.485
		(1.07)	(0.55)	(0.72)	(0.47)					
2	0.020	0.226	0.188	0.126	0.111	1.265	3.951	7.489	8.093	0.527
		(1.68)	(1.33)	(0.84)	(0.78)					
3	0.230	0.342	0.310	0.228	0.221	1.575	4.267	7.971	8.492	0.472
		(2.61)	(2.27)	(1.73)	(1.71)					
4	0.523	0.478	0.423	0.319	0.317	2.307	5.576	9.141	9.210	0.376
		(2.52)	(2.19)	(1.77)	(1.76)					
High β^{Bond}	1.494	0.848	0.689	0.720	0.714	5.213	11.281	11.397	10.413	0.260
		(2.25)	(1.82)	(2.22)	(2.07)					
High − Low		0.593***	0.553**	0.595***	0.633**					
Return/Alpha diff.		(2.88)	(2.57)	(2.62)	(2.53)					

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. Other controls include bond momentum (MOM^{Bond}) and bond return in previous month (Lag Return). 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.

	Intercept	5% VaR	Rating	ILLIQ	β^{Bond}	Maturity	Size	MOM^{Bond}	Lag Return	Adj. R^2
(1)	-0.147	**0.063**								0.080
	(-1.37)	(2.81)								
(2)	-0.093	**0.058**				-0.001	0.059	-0.002	**-0.109**	0.157
	(-1.03)	(2.73)				(-0.11)	(1.11)	(-0.24)	(-7.39)	
(3)	-0.142		**0.065**							0.049
	(-0.97)		(3.12)							
(4)	-0.246		**0.058**			**0.015**	0.001	0.004	**-0.153**	0.150
	(-1.95)		(2.41)			(2.16)	(0.78)	(0.62)	(-12.99)	
(5)	0.452			**0.049**						0.023
	(2.90)			(4.87)						
(6)	0.230			**0.039**		0.006	0.081	0.004	**-0.106**	0.126
	(1.72)			(4.03)		(0.99)	(1.91)	(0.46)	(-7.09)	
(7)	0.548				**0.281**					0.024
	(2.65)				(2.73)					
(8)	0.214				**0.223**	0.008	-0.005	0.004	**-0.060**	0.136
	(1.41)				(2.18)	(1.07)	(-0.10)	(0.35)	(-3.43)	
(9)	-0.207	**0.096**	0.016	**0.035**	0.028					0.123
	(-1.24)	(4.05)	(0.78)	(4.38)	(0.45)					
(10)	-0.221	**0.072**	0.018	**0.034**	0.040	0.000	0.006	-0.004	**-0.130**	0.202
	(-1.50)	(2.77)	(0.85)	(4.80)	(0.71)	(0.05)	(0.80)	(-0.53)	(-8.82)	

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

Panel A reports the descriptive statistics for the excess bond market return and the newly constructed bond market risk 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. Panel B reports the correlations among the bond and stock market factors. DRF covers the period from July 2004 to December 2014. CRF and and LRF cover the period from July 2002 to December 2014.

Panel A: Summary statistics

	Equal-weighted		Value-weighted	
	Mean	t-stat	Mean	t-stat
MKT^{Bond}	–	–	0.40	2.86
Downside risk factor (DRF)	0.72	3.58	0.57	3.43
Credit risk factor (CRF)	0.62	3.37	0.54	2.54
Liquidity risk factor (LRF)	0.51	4.01	0.47	4.88

Panel B: Correlations

	MKT^{Bond}	DRF	CRF	LRF	MKT^{Stock}	SMB	HML	MOM	LIQ	DEF	TERM	MOM^{Bond}
MKT^{Bond}	1	0.15	0.16	0.26	0.12	-0.06	0.05	-0.21	0.06	-0.16	-0.56	-0.04
DRF		1	0.31	0.61	0.13	-0.06	0.13	-0.08	0.09	0.05	-0.05	-0.21
CRF			1	0.02	0.08	0.06	0.04	-0.10	-0.01	-0.16	-0.04	-0.24
LRF				1	0.26	-0.09	0.22	-0.09	-0.04	0.10	-0.02	0.01
MKT^{Stock}					1	0.42	0.15	-0.22	0.24	-0.14	0.26	-0.03
SMB						1	0.10	0.07	0.13	-0.07	0.14	-0.10
HML							1	-0.12	0.12	-0.03	0.03	0.05
MOM								1	-0.13	-0.01	-0.02	-0.02
LIQ									1	-0.03	0.00	-0.12
DEF										1	-0.07	-0.05
TERM											1	-0.01
MOM^{Bond}												1

Table 8: **Time-Series Regression of 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 new risk factors on the commonly used stock and bond market factors. The new risk factors include the equal-weighted downside risk factor (DRF), credit risk factor (CRF), and liquidity risk factor (LRF). 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 (MOM), and the Pastor-Stambaugh stock liquidity factor (LIQ). The bond market factors include the excess bond market return (MKT^{Bond}), the default spread factor (DEF), the term spread factor (TERM), and the bond momentum factor (MOM^{Bond}). Newey-West adjusted t-statistics are given in parentheses. Numbers in bold denote statistical significance at the 5% level or below. DRF covers the period from July 2004 to December 2014. CRF and and LRF cover the period from July 2002 to December 2014.

Panel A: Regressions with stock market factors

Dep. Var	α	MKT^{Stock}	SMB	HML	MOM	LIQ	Adj. R^2 (%)
			Model 1: Fama-French (1993), Carhart (1997), Pastor-Stambaugh (2003)				
DRF	**0.70**	0.04	-0.09	0.08	-0.19	0.62	17.12
	(3.47)	(0.59)	(-1.16)	(1.19)	(-2.11)	(0.11)	
CRF	**0.53**	0.14	-0.02	-0.09	-0.07	-5.04	9.92
	(2.30)	(1.61)	(-0.21)	(-0.88)	(-1.76)	(-1.07)	
LRF	**0.52**	0.00	-0.05	0.03	-0.12	-2.54	13.24
	(3.14)	(-0.02)	(-0.85)	(0.47)	(-1.94)	(-0.71)	

Panel B: Regressions with bond market factors

Dep. Var	α	MKT^{Bond}	DEF	TERM	MOM^{Bond}	Adj. R^2 (%)
		Model 2: Elton-Gruber-Blake (1995), Bessembinder et al. (2009), extended with MOM^{Bond}				
DRF	**0.73**	0.20	0.80	1.04	-0.65	51.27
	(4.10)	(1.14)	(0.95)	(1.50)	(-5.46)	
CRF	**0.43**	0.42	-5.06	0.80	-0.21	27.61
	(2.35)	(2.57)	(-4.52	(1.14)	(-1.93)	
LRF	**0.45**	0.28	1.93	1.03	-0.46	53.90
	(2.96)	(2.18)	(2.37)	(1.88)	(-6.00)	

Panel C: Regressions with stock and bond market factors

Dep. Var	α	MKT^{Stock}	MKT^{Bond}	SMB	HML	MOM	LIQ	DEF	TERM	MOM^{Bond}	Adj. R^2 (%)
					Model 3: 9-factor model, combining five stock and four bond market factors						
DRF	**0.76**	0.02	0.05	-0.09	0.08	-0.10	2.16	0.99	0.55	-0.60	55.95
	(4.32)	(0.63)	(0.34)	(-1.83)	(1.41)	(-2.71)	(0.53)	(0.98)	(1.01)	(-6.66)	
CRF	**0.43**	0.04	0.34	0.03	-0.04	-0.03	-3.61	-4.99	0.28	-0.19	26.65
	(2.31)	(0.74)	(2.16)	(0.37)	(-0.50)	(-0.60)	(-0.90)	(-5.15)	(0.33)	(-1.81)	
LRF	**0.48**	-0.04	0.26	-0.02	0.05	-0.05	-1.48	1.80	0.94	-0.44	55.88
	(3.08)	(-0.69)	(2.77)	(-0.56)	(0.76)	(-1.48)	(-0.80)	(2.50)	(1.95)	(-5.29)	

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 three alternative factor models. The 25 test portfolios are formed by independently sorting corporate bonds into 5 by 5 quintile portfolios based on size (amount outstanding) and maturity and then constructed from the intersections of the size and maturity quintiles. Three alternative factor models are considered. Model 1 is the 5-factor model with stock market factors, including the excess stock market return (MKT^{Stock}), size factor (SMB), book-to-market factor (HML), momentum factor (MOM) and Pastor-Stambaugh liquidity factor (LIQ). Model 2 is the 4-factor model with bond market factors: the excess bond market excess return (MKT^{Bond}), the default spread factor (DEF), the term spread factor (TERM), and bond momentum factor (MOM^{Bond}). Model 3 is the 4-factor model including the excess bond market return (MKT^{Bond}), the downside risk factor (DRF), credit risk factor (CRF), and liquidity risk factor (LRF). The sample period starts from July 2004 to December 2014.

Panel A: Model 1

	Short	2	3	4	Long
Small	0.11	0.18	0.10	0.12	0.18
2	0.16	0.20	0.14	0.19	0.14
3	0.29	0.23	0.20	0.09	0.07
4	0.23	0.15	0.17	0.06	0.06
Large	0.04	0.04	0.09	0.03	0.05
Average R^2	**0.13**				

Panel B: Model 2

	Short	2	3	4	Long
Small	0.50	0.50	0.48	0.40	0.31
2	0.45	0.47	0.34	0.47	0.29
3	0.41	0.33	0.37	0.24	0.18
4	0.44	0.31	0.32	0.17	0.13
Large	0.48	0.33	0.35	0.16	0.13
Average R^2	**0.34**				

Panel C: Model 3

	Short	2	3	4	Long
Small	0.78	0.86	0.85	0.82	0.85
2	0.79	0.88	0.82	0.92	0.87
3	0.76	0.80	0.79	0.67	0.64
4	0.73	0.67	0.72	0.55	0.57
Large	0.67	0.64	0.74	0.57	0.60
Average R^2	**0.74**				

Table 10: **Explanatory Power of Alternative Factor Models for Industry-Sorted Bond Portfolios**

The table reports the average adjusted R^2 for the time-series regression of the test portfolios' excess returns on three alternative factor models. The industry portfolios are formed by univariate sorting corporate bonds into 30 portfolios based on the Fama-French industry classifications. Three alternative factor models are considered. Model 1 is the 5-factor model with stock market factors, including the excess stock market return (MKT^{Stock}), size factor (SMB), book-to-market factor (HML), momentum factor (MOM) and Pastor-Stambaugh liquidity factor (LIQ). Model 2 is the 4-factor model with bond market factors: the excess bond market excess return (MKT^{Bond}), the default spread factor (DEF), the term spread factor (TERM), and bond momentum factor (MOM^{Bond}). Model 3 is the 4-factor model including the excess bond market return (MKT^{Bond}), the downside risk factor (DRF), credit risk factor (CRF), and liquidity risk factor (LRF). The sample period starts from July 2004 to December 2014.

Industry #	Industry description	Model 1	Model 2	Model 3
1	Food	0.09	0.22	0.27
2	Beer	0.05	0.11	0.33
3	Smoke	0.08	0.04	0.24
4	Games	0.14	0.30	0.42
5	Books	0.44	0.41	0.59
6	Household	0.10	0.11	0.28
7	Clothese	0.32	0.38	0.44
8	Health	0.01	0.08	0.17
9	Chemicals	0.39	0.37	0.62
10	Textiles	0.04	0.07	0.10
11	Construction	0.18	0.30	0.55
12	Steel	0.17	0.22	0.40
13	Fabric	0.02	0.02	0.01
14	Electrical Equipment	0.25	0.38	0.53
15	Autos	0.25	0.35	0.62
16	Carry	0.02	0.05	0.11
17	Mines	0.14	0.15	0.25
18	Coal	0.02	0.17	0.28
19	Oil	0.00	0.01	0.02
20	Utilities	0.07	0.28	0.45
21	Communication	0.13	0.41	0.61
22	Services	0.18	0.41	0.65
23	Business Equipment	0.17	0.38	0.51
24	Paper	0.26	0.33	0.65
25	Transportation	0.12	0.31	0.53
26	Wholesale	0.12	0.29	0.47
27	Retail	0.12	0.30	0.42
28	Meals	0.14	0.33	0.55
29	Finance	0.09	0.47	0.67
30	Other	0.14	0.40	0.55
Avg. R^2		**0.14**	**0.25**	**0.41**

Common Risk Factors in the Cross-Section of Corporate Bond Returns

Online Appendix

Section A.1 presents the results for downside risk factor constructed from alternative measures of downside risk. Section A.2 presents the results for liquidity risk factor constructed from alternative measures of illiquidity. Section A.3 presents the results for alternative measures of bond credit quality. Section A.4 presents the results for the risk factors constructed using the extended sample from January 1977 to December 2014.

A.1 Alternative Measures of Downside Risk

In addition to the 5% Value-at-Risk (VaR) used in the main tables, we consider two additional measures of downside risk: the 10% Value-at-Risk (VaR) and the 10% Expected Shortfall (ES). The 10% VaR is defined as the fourth lowest monthly return observation over the past 36 months. The 10% expected shortfall (ES) is defined as the average of four lowest monthly return observations over the past 36 months (beyond the 10% VaR threshold). The original VaR and ES measures are multiplied by -1 for the convenience of interpretation. The downside risk factor (DRF) is constructed by first sorting corporate bonds into five quintiles based on their credit rating, and then within each rating portfolio, corporate bonds are sorted into five sub-quintiles based on the 10%VaR and the 10%ES, respectively. DRF is the equal- or value-weighted average return difference between the highest downside risk portfolio minus the lowest downside risk portfolio within each rating portfolio.

A.2 Alternative Measures of Bond Illiquidity

In addition to the ILLIQ measure used in the main tables, we also consider two additional proxies of illiquidity; the Roll (1984) and Amihud (2002) illiquidity measures. The Roll (1984) measure is defined as,

$$\text{Roll} = \begin{cases} 2\sqrt{-\text{cov}(r_t, r_{t-1})} & \text{if cov}(r_t, r_{t-1}) < 0, \\ 0 & \text{otherwise,} \end{cases} \tag{A.1}$$

where r_t is the corporate bond return on day t. Given the fact that corporate bonds do not trade frequently, this measure crucially depends on two conditions. First, a bond is traded for two days in a row so that we can calculate its daily return. Second, a bond has at least a number of daily returns calculated each month so that we can calculate its covariance. We set the threshold equal to five. A bond's monthly Roll measure will be missing if that bond does not have five daily returns calculated that month.

The Amihud illiquidity measure is motivated to capture the price impact. It is defined as,

$$\text{Ami} = \frac{1}{N}\sum_{t=1}^{N}\frac{|r_t|}{Q_t}, \tag{A.2}$$

where N is the number of positive-volume days in a given month, r_t the daily corporate bond return and Q_t the trading volume on day t. Table A.6 presents the results for alternative liquidity risk factor from July 2002 to December 2014.

A.3 Alternative Measures of Bond Credit Quality

In addition to bond-level credit rating, we consider two alternative proxies of credit quality. One is the firm-level distance-to-default measure,[33] and the other is the firm-level raw credit default swap spread developed in Bai and Wu (2014). Both measures are based on the Merton (1974) model which assumes that the total asset value (A) of a company follows a geometric Brownian motion with instantaneous return volatility σ_A, the company has a zero -coupon debt with principal D and time-to-maturity T, and the firm's equity (E) is a European call option on the firm's asset value with maturity equal to the debt maturity and strike equal to the debt principal. The company defaults if its asset value is less than the debt principal at the debt maturity. These assumptions lead to the following two equations that link the firm's equity value E and equity return volatility σ_E to its asset value A and asset return volatility σ_A.

$$\begin{aligned} E &= A\cdot N(d+\sigma_A\sqrt{T}) - D\cdot N(d), \\ \sigma_E &= N(d+\sigma_A\sqrt{T})\sigma_A\, A/E. \end{aligned}$$

In the two equations, $N(\cdot)$ denotes the cumulative normal density and d is a standardized measure of distance to default,

$$d = \frac{\ln(A/D) + (r - \frac{1}{2}\sigma_A^2)T}{\sigma_A\sqrt{T}}, \tag{A.3}$$

with r denoting the instantaneous risk-free rate.

[33] The distance-to-default measure, often used to predict default probabilities, is developed by KMV and discussed in Crosbie and Bohn (2003) among others. It has also been widely adopted in the academic literature, e.g., Bharath and Shumway (2008), Duan, Sun, and Wang (2012), etc.

To compute a firm's distance to default, we follow the procedure in Bai and Wu (2014). We take the company's end-of-month market capitalization as its equity value E, the company's total debt as a proxy for the principal of the zero-coupon bond D, and the one-year realized stock return volatility as an estimator for stock return volatility σ_E. We further assume zero interest rates ($r = 0$) and fix the debt maturity at $T = 10$ years for all firms. Since our focus is on the cross-sectional difference across firms, choosing any particular interest rate level for r or simply setting it to zero generates negligible impacts on the cross-sectional sorting. Bai and Wu (2014) discuss the impact of the maturity choice on the model's performance, and suggest that the relative longer maturity choice $T > 5$ improves the performance in capturing the cross-sectional variation of the credit spreads.

We solve for the firm's asset value A and asset return volatility σ_A via an iterative procedure, then we compute the standardized distance to default according to equation (A.3). To generate a CDS spread valuation, we step away from the Merton model and construct a raw credit default spread (CDS) measure according to the following transformation,

$$CDS = -6000 \cdot \ln(N(d))/T, \tag{A.4}$$

where we treat $1-N(d)$ as the risk-neutral default probability and transform it into a raw CDS spread with the assumption of a constant hazard rate and a 40% recovery rate. By switching to a constant hazard rate assumption, we acknowledge that default can happen at any time unexpectedly, with the expected default arrival rate determined by the distance to default. The fixed recovery rate is a standard simplifying assumption in the credit literature. To the extent that the recovery rate can also vary across firms, this simple transformation does not capture such variation.

A.4 New Risk Factors from Extended Sample: January 1977 to December 2014

Beyond the transaction-based data on corporate bonds from July 2002 to December 2014, we also consider an extended sample of bond data from January 1973 to December 2014. Using a longer sample of bond returns, we are able to construct an extended sample of downside risk factor (DRF) and credit risk factor (CRF). The extended sample is complied from six sources: Lehman Brothers fixed income database (Lehman), Datastream, National Association of Insurance Commissioners database (NAIC), Bloomberg, the 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.

Beyond the TRACE data, the Lehman data covers the period from January 1973 to March 1998; the Datastream reports corporate bond information from January 1990 to June 2014; NAIC reports the transaction information by insurance companies during January 1994 to December 2014; Bloomberg provides daily bond prices during January 1997 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. We adopt the following principle to handle the overlapping observations among different data sets. If two or more data sets have overlapping observations at any point in time, we give priority to the data set that reports the transaction-based bond prices. For example, TRACE will dominate other data sets from July 2002 to December 2014. If there are no transaction data or the coverage of the data is too small, we give priority to the data set that has a relatively larger coverage on bonds/firms, and can be better matched to the bond characteristic data, FISD. For example, Bloomberg daily quotes data are preferred to those of Datastream for the period 1998 to 2002 for its larger coverage and higher percentage of matching rate to FISD. We adopt the same data filtering criteria as in Section 3 for non-TRACE datasets.

Finally, we filter out a few months at the beginning of the sample period during which there are insufficient number of bonds in the sequentially sorted portfolios to construct the risk factors. Our final extended sample of the corporate bond risk factors, DRF and CRF start from January 1977 to December 2014.

Table A.1: **Quintile Portfolios of Corporate Bonds Sorted by VaR Controlling for Bond Characteristics**

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), size (Panel C), or illiquidity (Panel D). 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 9-factor alpha for each quintile. The last row shows the differences in alphas with respect to the 9-factor models, which combines 5 stock market factors and 4 bond market factors. 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			Panel B: Controlling for maturity			
	All bonds	Investment grade	Non-investment grade	All bonds	Short maturity	Medium maturity	Long maturity
VaR,1	0.149	0.136	0.341	0.139	0.191	0.132	0.158
	(1.90)	(2.80)	(1.92)	(1.21)	(1.72)	(2.61)	(1.12)
VaR,2	0.212	0.197	0.437	0.205	0.213	0.143	0.297
	(1.93)	(2.56)	(2.20)	(1.58)	(1.64)	(2.47)	(1.75)
VaR,3	0.318	0.242	0.460	0.288	0.295	0.207	0.410
	(2.13)	(2.21)	(1.99)	(2.00)	(2.17)	(2.67)	(2.45)
VaR,4	0.422	0.346	0.531	0.463	0.508	0.311	0.590
	(2.66)	(2.50)	(1.95)	(2.66)	(2.35)	(2.34)	(2.70)
VaR,5	0.764	0.609	1.052	0.913	0.837	0.917	0.991
	(4.30)	(3.31)	(3.80)	(4.17)	(2.97)	(4.33)	(3.65)
VaR,5 − VaR,1	0.614***	0.473***	0.711***	0.774***	0.646***	0.784***	0.833***
Return/Alpha diff.	(4.92)	(3.13)	(4.06)	(4.21)	(2.94)	(4.34)	(4.06)

	Panel C: Controlling for size			Panel D: Controlling for illiquidity		
	All bonds	Small bonds	Large bonds	All bonds	Investment grade	Non-investment grade
VaR,1	0.132	0.176	0.206	0.154	0.125	0.231
	(1.49)	(2.15)	(3.04)	(1.86)	(2.05)	(1.40)
VaR,2	0.273	0.257	0.301	0.225	0.193	0.336
	(2.27)	(2.20)	(2.91)	(1.95)	(2.26)	(1.63)
VaR,3	0.473	0.420	0.388	0.289	0.240	0.441
	(2.49)	(2.65)	(2.71)	(1.96)	(2.38)	(2.18)
VaR,4	0.751	0.616	0.504	0.399	0.349	0.627
	(2.65)	(3.07)	(2.79)	(2.47)	(2.54)	(2.32)
VaR,5	0.886	0.942	0.889	0.836	0.515	1.124
	(2.60)	(3.57)	(3.32)	(3.97)	(3.28)	(3.72)
VaR,5 − VaR,1	0.754***	0.767***	0.683***	0.683***	0.390***	0.894***
Return/Alpha diff.	(2.67)	(3.54)	(3.17)	(4.22)	(3.41)	(4.18)

Table A.2: **Explanatory Power of Alternative Factor Models for Size and Maturity-Sorted Bond Portfolios - Average Alpha**

The table reports the average alpha and its t-statistic for the time-series regression of the test portfolios' excess returns on four alternative factor models. The 25 test portfolios are formed by independently sorting corporate bonds into 5 by 5 quintile portfolios based on size (amount outstanding) and maturity and then constructed from the intersections of the size and maturity quintiles. Three alternative factor models are considered. Model (1) is the 5-factor model with stock market factors, including the excess stock market return (MKT^{Stock}), size factor (SMB), book-to-market factor (HML), momentum factor (MOM) and Pastor-Stambaugh liquidity factor (LIQ). Model (2) is the 4-factor model with bond market factors: the excess bond market excess return (MKT^{Bond}), the default spread factor (DEF), the term spread factor (TERM), and bond momentum factor (MOM^{Bond}). Model (3) is the 4-factor model including the excess bond market return (MKT^{Bond}), the equal-weighted downside risk factor (DRF), credit risk factor (CRF), and liquidity risk factor (LRF). The sample period starts from July 2004 to December 2014.

Panel A: Model 1

	Alpha (α)					t-statistics $t(\alpha)$				
	Short	2	3	4	Long	Short	2	3	4	Long
Small	0.46	0.50	0.57	0.43	0.46	2.45	2.19	2.32	2.23	1.86
2	0.36	0.51	0.52	0.36	0.55	2.91	2.42	2.21	1.20	2.70
3	0.36	0.47	0.49	0.52	0.66	3.33	2.80	2.32	2.86	3.10
4	0.34	0.43	0.50	0.48	0.64	3.06	3.03	2.31	2.91	2.82
Large	0.26	0.39	0.59	0.53	0.76	2.74	3.12	2.75	3.17	3.10
Average α	**0.49**									
p-GRS	0.00									

Panel B: Model 2

	Short	2	3	4	Long	Short	2	3	4	Long
Small	0.38	0.49	0.5	0.38	0.43	3.18	2.72	2.83	2.34	2.08
2	0.31	0.4	0.39	0.36	0.44	3.59	2.63	1.71	1.37	2.42
3	0.27	0.35	0.29	0.37	0.48	3.32	2.27	1.60	2.27	2.32
4	0.26	0.31	0.33	0.33	0.44	2.89	2.36	1.54	1.81	1.84
Large	0.21	0.33	0.49	0.43	0.6	3.65	3.24	2.81	2.78	2.61
Average α	**0.38**									
p-GRS	0.00									

Panel C: Model 3

	Short	2	3	4	Long	Short	2	3	4	Long
Small	0.12	0.12	0.15	0.11	0.11	1.13	1.12	1.29	1.02	1.06
2	0.10	0.10	0.10	0.07	0.14	0.63	0.56	0.58	0.60	1.10
3	0.08	0.10	0.07	0.12	0.16	0.46	0.80	0.65	1.22	1.92
4	0.07	0.09	0.08	0.09	0.15	0.66	0.68	0.97	1.28	1.42
Large	0.08	0.10	0.15	0.14	0.21	0.91	0.93	0.81	0.83	1.92
Average α	**0.11**									
p-GRS	0.02									

Table A.3: **Explanatory Power of Alternative Factor Models for Industry-Sorted Bond Portfolios - Average Alpha**

The table reports the average alpha and its t-statistic for the time-series regression of the test portfolios' excess returns on three alternative factor models. The industry portfolios are formed by univariate sorting corporate bonds into 30 portfolios based on the Fama-French industry classifications. Three alternative factor models are considered. Model (1) is the 5-factor model with stock market factors, including the excess stock market return (MKT^{Stock}), size factor (SMB), book-to-market factor (HML), momentum factor (MOM) and Pastor-Stambaugh liquidity factor (LIQ). Model (2) is the 4-factor model with bond market factors: the excess bond market excess return (MKT^{Bond}), the default spread factor (DEF), the term spread factor (TERM), and bond momentum factor (MOM^{Bond}). Model (3) is the 4-factor model including the excess bond market return (MKT^{Bond}), the equal-weighted downside risk factor (DRF), credit risk factor (CRF), and liquidity risk factor (LRF). The sample period starts from July 2004 to December 2014.

Industry #	Industry description	Model 1	$t(\alpha)$	Model 2	$t(\alpha)$	Model 3	$t(\alpha)$
1	Food	0.47	(3.78)	0.31	(2.62)	0.18	(1.53)
2	Beer	0.40	(4.20)	0.32	(3.37)	0.23	(2.71)
3	Smoke	0.56	(2.76)	0.56	(2.65)	0.26	(1.33)
4	Games	0.90	(2.17)	0.94	(2.47)	0.01	(0.03)
5	Books	0.65	(1.99)	0.54	(1.57)	-0.30	(-1.02)
6	Household	0.59	(2.42)	0.62	(2.54)	0.25	(1.08)
7	Clothese	0.80	(2.42)	0.45	(1.38)	-0.18	(-0.57)
8	Health	0.63	(3.04)	0.48	(2.34)	0.31	(1.52)
9	Chemicals	0.65	(2.74)	0.56	(2.25)	-0.13	(-0.65)
10	Textiles	0.80	(1.65)	0.75	(1.55)	0.16	(0.32)
11	Construction	0.85	(3.36)	0.62	(2.57)	0.24	(1.22)
12	Steel	0.95	(3.02)	1.04	(3.35)	0.31	(1.13)
13	Fabric	1.61	(2.56)	1.20	(1.86)	1.08	(1.61)
14	Electrical Equipment	0.45	(1.91)	0.29	(1.33)	-0.34	(-1.72)
15	Autos	0.95	(2.70)	0.80	(2.40)	-0.14	(-0.55)
16	Carry	0.68	(1.60)	0.67	(1.56)	0.22	(0.52)
17	Mines	0.54	(2.02)	0.36	(1.30)	-0.02	(-0.08)
18	Coal	0.31	(1.24)	0.09	(0.40)	-0.19	(-0.88)
19	Oil	0.90	(1.27)	0.78	(1.09)	0.46	(0.63)
20	Utilities	0.41	(3.33)	0.27	(2.41)	0.13	(1.36)
21	Communication	0.51	(2.94)	0.38	(2.59)	0.01	(0.06)
22	Services	0.54	(2.65)	0.41	(2.32)	-0.10	(-0.72)
23	Business Equipment	0.51	(2.94)	0.45	(2.97)	0.07	(0.50)
24	Paper	0.70	(2.55)	0.62	(2.32)	-0.07	(-0.33)
25	Transportation	0.73	(4.08)	0.59	(3.64)	0.28	(2.01)
26	Wholesale	0.61	(3.02)	0.49	(2.62)	0.16	(0.99)
27	Retail	0.69	(2.58)	0.64	(2.62)	0.07	(0.31)
28	Meals	0.41	(1.37)	0.40	(1.48)	-0.38	(-1.67)
29	Finance	0.58	(3.94)	0.53	(4.61)	0.10	(1.10)
30	Other	0.94	(3.61)	0.68	(3.07)	0.09	(0.47)
Avg. α		**0.68**		**0.56**		**0.09**	
p-GRS		0.00		0.00		0.02	

Table A.4: **Fama-MacBeth Cross-Sectional Regressions with Orthogonalized 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 orthogonalized VaR (VaR$^{\perp}$), orthogonalized credit rating (Rating$^{\perp}$), orthogonalized illiquidity (ILLIQ$^{\perp}$), and orthogonalized bond market beta ($\beta^{Bond,\perp}$), with and without controls. VaR$^{\perp}$ is the residual VaR from the cross-sectional regression of VaR on the contemporaneous measures of rating, ILLIQ, and bond market beta. Rating$^{\perp}$ is the residual credit rating from the cross-sectional regression of rating on the contemporaneous measures of VaR, ILLIQ, and bond market beta. ILLIQ$^{\perp}$ is the residual ILLIQ from the cross-sectional regression of illiquidity on the contemporaneous measures of VaR, rating, and bond market beta. $\beta^{Bond,\perp}$ is the residual β^{Bond} from the cross-sectional regression of bond market beta on the contemporaneous measures of VaR, rating, and ILLIQ. 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. Other controls include bond momentum (MOM^{Bond}) and bond return in previous month (Lag Return). 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.

	Intercept	5% VaR$^{\perp}$	Rating$^{\perp}$	ILLIQ$^{\perp}$	$\beta^{Bond,\perp}$	Maturity	Size	MOM^{Bond}	Lag Return	Adj. R^2
(1)	0.600	**0.095**								0.039
	(2.50)	(4.00)								
(2)	0.355	**0.067**				-0.001	0.022	0.004	**-0.072**	0.137
	(2.04)	(3.22)				(-0.20)	(0.47)	(0.31)	(-4.23)	
(3)	0.528		0.017							0.021
	(2.43)		(0.92)							
(4)	0.221		0.019			0.012	0.000	0.008	**-0.110**	0.138
	(1.47)		(0.94)			(1.47)	(0.30)	(0.85)	(-7.28)	
(5)	0.595			**0.023**						0.008
	(2.48)			(3.33)						
(6)	0.254			**0.023**		0.008	0.010	0.004	**-0.077**	0.129
	(1.49)			(3.55)		(1.06)	(0.17)	(0.32)	(-4.36)	
(7)	0.746				0.024					0.006
	(2.58)				(0.34)					
(8)	0.279				0.031	0.008	-0.028	0.002	**-0.052**	0.135
	(1.46)				(0.50)	(1.09)	(-0.37)	(0.13)	(-2.78)	
(9)	0.585	**0.153**	0.142	**0.038**	0.311					0.114
	(2.42)	(3.56)	(1.37)	(4.24)	(1.69)					
(10)	0.398	**0.114**	0.111	**0.034**	0.271	0.002	0.000	-0.004	**-0.113**	0.198
	(1.89)	(2.68)	(1.03)	(4.22)	(1.57)	(0.34)	(1.93)	(-0.39)	(-6.70)	

Table A.5: **Downside Risk Factor Constructed from Alternative Measures of Downside Risk**

Panel A reports the descriptive statistics for downside risk factor constructed from alternative measures of downside risk: the 10% Value-at-Risk (VaR) and 10% expected shortfall (ES). 10% VaR is defined as the fourth lowest monthly return observation over the past 36 months. 10% expected shortfall (ES) is defined as the average of the four lowest monthly return observation over the past 36 months. The original VaR and expected shortfall measures are multiplied by -1. 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 10% VaR, 5% ES, and 10% ES, respectively. DRF is the equal- or value-weighted average return difference between the highest downside risk portfolio minus the lowest downside risk portfolio within each rating portfolio. All factors start from July 2004 to December 2014.

Panel A: Summary statistics

Downside risk factor (DRF)	Equal-weighted		Value-weighted	
	Mean	t-stat	Mean	t-stat
Constructed from 10% VaR	0.67	3.47	0.51	3.16
Constructed from 10% Expected Shortfall	0.79	3.70	0.65	3.54

Panel B: Equal-weighted downside risk factors

Dep. Var	α	MKT^{Stock}	MKT^{Bond}	SMB	HML	MOM	LIQ	DEF	TERM	MOM^{Bond}	Adj. R^2 (%)
$DRF^{10\%\ VaR}$	**0.67**	0.03	0.11	-0.09	0.09	-0.08	3.08	1.05	0.42	-0.54	50.39
	(4.01)	(0.74)	(0.74)	(-1.85)	(1.36)	(-2.15)	(0.69)	(0.99)	(0.67)	(-6.29)	
$DRF^{10\%\ ES}$	**0.87**	0.01	0.01	-0.09	0.10	-0.11	0.77	1.07	0.70	-0.65	56.90
	(4.37)	(0.17)	(0.05)	(-1.80)	(1.53)	(-2.94)	(0.20)	(0.92)	(1.23)	(-6.93)	

Panel C: Value-weighted downside risk factors

Dep. Var	α	MKT^{Stock}	MKT^{Bond}	SMB	HML	MOM	LIQ	DEF	TERM	MOM^{Bond}	Adj. R^2 (%)
$DRF^{10\%\ VaR}$	**0.49**	0.02	0.12	-0.11	0.09	-0.03	3.02	0.37	0.11	-0.35	28.38
	(3.11)	(0.41)	(0.89)	(-1.98)	(1.16)	(-0.98)	(0.74)	(0.34)	(0.16)	(-4.67)	
$DRF^{10\%\ ES}$	**0.70**	0.00	0.03	-0.08	0.10	-0.08	0.57	0.02	0.32	-0.47	39.24
	(4.01)	-(0.04)	(0.17)	(-1.27)	(1.32)	(-2.30)	(0.18)	(0.02)	(0.49)	(-5.49)	

Table A.6: **Liquidity Risk Factor Constructed from Alternative Measures of Illiquidity**

Panel A reports the descriptive statistics for liquidity risk factor constructed from alternative measures of bond illiquidity using the Roll (1984) and Amihud (2002) measure. The Roll's measure is defined as $2\sqrt{-cov(r_t, r_{t-1})}$ if $cov(r_t, r_{t-1}) < 0$, and zero otherwise, where r_t is the corporate bond return on day t. The Amihud measure is defined as the average of the absolute value of the daily return-to-volume ratio. The illiquidity measures are calculated for bonds with at least 5 daily returns within a month. 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 the illiquidity measure. LRF is the equal- or value-weighted average return difference between the highest illiquidity portfolio minus the lowest illiquidity portfolio within each rating portfolio. All factors start from July 2002 to December 2014.

Panel A: Summary statistics

Liquidity risk factor (DRF)	Equal-weighted		Value-weighted	
	Mean	t-stat	Mean	t-stat
Constructed from Roll's measure	0.47	3.54	0.43	4.16
Constructed from Amihud measure	0.46	4.01	0.43	4.95

Panel B: Equal-weighted liquidity risk factors

Dep. Var	α	MKT^{Stock}	MKT^{Bond}	SMB	HML	MOM	LIQ	DEF	TERM	MOM^{Bond}	Adj. R^2 (%)
LRF^{Roll}	**0.43**	-0.04	0.24	0.01	0.06	-0.07	-1.71	1.58	0.93	-0.45	60.20
	(2.94)	(-0.83)	(2.53)	(0.34)	(0.97)	(-1.78)	(-0.94)	(2.30)	(1.83)	(-5.85)	
LRF^{Amihud}	**0.40**	-0.01	0.20	0.02	0.09	-0.08	-2.85	1.55	0.84	-0.32	54.92
	(2.82)	(-0.32)	(2.08)	(0.70)	(1.65)	(-1.79)	(-2.30)	(2.20)	(2.05)	(-4.22)	

Panel C: Value-weighted liquidity risk factors

Dep. Var	α	MKT^{Stock}	MKT^{Bond}	SMB	HML	MOM	LIQ	DEF	TERM	MOM^{Bond}	Adj. R^2 (%)
LRF^{Roll}	**0.38**	0.04	-0.01	-0.02	0.09	-0.09	-3.84	-0.34	0.11	-0.19	44.98
	(4.24)	(2.17)	(-0.08)	(-0.51)	(2.31)	(-2.19)	(-3.65)	(-0.58)	(0.26)	(-3.65)	
LRF^{Amihud}	**0.33**	0.03	0.16	0.03	0.07	-0.08	-2.51	1.14	0.46	-0.07	38.82
	(3.32)	(1.17)	(1.95)	(1.05)	(1.69)	(-1.69)	(-2.19)	(1.87)	(1.05)	(-1.18)	

Table A.7: **Fama-MacBeth Cross-Sectional Regressions with Alternative Measures of Credit Risk**

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 two alternative measures of credit risk: distance-to-default (DD) and credit default spread (CDS), at the firm-level, 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.

	Intercept	DD	CDS	5% VaR	ILLIQ	β^{Bond}	Maturity	Size	Adj. R^2
(1)	0.665	**-0.281**							0.046
	(3.90)	(-2.69)							
(2)	0.581	**-0.294**					**0.022**	-0.159	0.077
	(3.50)	(-2.82)					(3.05)	(-1.53)	
(3)	0.288		**0.072**						0.052
	(2.89)		(3.35)						
(4)	0.158		**0.077**				**0.024**	-0.154	0.084
	(1.68)		(3.66)				(3.28)	(-1.18)	
(5)	-0.125	-0.027		**0.101**	**0.029**	0.065			0.122
	(-0.83)	(-0.46)		(3.79)	(2.59)	(1.00)			
(6)	-0.139	-0.020		**0.105**	**0.023**	0.074	-0.004	0.063	0.155
	(-0.87)	(-0.37)		(3.81)	(2.30)	(1.15)	(-0.47)	(0.82)	
(7)	-0.086		0.019	**0.085**	**0.028**	0.028			0.134
	(-0.73)		(0.88)	(3.12)	(2.57)	(0.40)			
(8)	-0.133		0.024	**0.085**	**0.022**	0.043	0.000	0.079	0.167
	(-1.14)		(1.18)	(3.08)	(2.25)	(0.65)	(0.04)	(0.94)	

Table A.8: **Risk Factors from the Extended Sample: January 1977 to December 2014**

This table reports the the descriptive statistics for downside risk factor (DRF) and credit risk factor (CRF) constructed with the extended sample from January 1977 to December 2014. Four measures of downside risk include the 5% Value-at-Risk (VaR), 10% VaR, and 10% expected shortfall (ES). 5% (10%) VaR is defined as the second (fourth) lowest monthly return observation over the past 36 months. 10% expected shortfall (ES) is defined as the average of the four lowest monthly return observation over the past 36 months. The original VaR and expected shortfall measures are multiplied by -1. 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% VaR, 10% VaR, and 10% ES, respectively. DRF is the equal- or value-weighted average return difference between the highest downside risk portfolio minus the lowest downside risk portfolio within each rating portfolio. Credit risk factor (CRF) is constructed by first sorting corporate bonds on the 5% VaR into quintiles, then within each VaR 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 VaR portfolio.

Panel A: Summary statistics

	Equal-weighted		Value-weighted	
	Mean	t-stat	Mean	t-stat
DRF constructed from 5% VaR	0.61	7.33	0.51	6.85
DRF constructed from 10% VaR	0.59	7.26	0.48	6.71
DRF constructed from 10% Expected Shortfall	0.67	7.62	0.58	7.15
CRF (Credit risk factor)	0.32	4.96	0.30	4.41

Panel B: Equal-weighted risk factors

Dep. Var	α	MKT^{Bond}	MKT^{Stock}	SMB	HML	UMD	LIQ	DEF	TERM	MOM^{Bond}	Adj. R^2
$DRF^{5\%\ VaR}$	**0.52**	0.19	0.06	-0.01	0.02	-0.05	-3.71	0.86	-0.47	-0.40	30.04
	(4.79)	(2.49)	(2.25)	(-0.37)	(0.72)	(-1.36)	(-2.16)	(0.62)	(-2.82)	(-2.61)	
$DRF^{10\%\ VaR}$	**0.47**	0.26	0.07	-0.01	0.02	-0.04	-2.70	0.54	-0.46	-0.36	32.92
	(4.51)	(4.03)	(2.52)	(-0.52)	(0.72)	(-0.93)	(-1.61)	(0.42)	(-3.04)	(-2.58)	
$DRF^{10\%\ ES}$	**0.59**	0.22	0.06	-0.02	0.01	-0.04	-4.70	1.02	-0.46	-0.43	30.57
	(4.42)	(2.74)	(1.93)	(-0.81)	(0.21)	(-1.25)	(-2.87)	(0.62)	(-2.69)	(-2.76)	
CRF	**0.33**	-0.08	0.04	0.06	0.01	-0.05	-0.85	-3.15	0.42	-0.07	20.75
	(5.03)	(-1.19)	(2.13)	(2.58)	(0.31)	(-2.40)	(-0.41)	(-3.62)	(4.04)	(-1.16)	

Panel C: Value-weighted risk factors

Dep. Var	α	MKT^{Bond}	MKT^{Stock}	SMB	HML	UMD	LIQ	DEF	TERM	MOM^{Bond}	Adj. R^2
$DRF^{5\%\ VaR}$	**0.42**	0.18	0.07	-0.01	0.03	-0.03	-3.34	0.38	-0.51	-0.25	23.16
	(4.92)	(2.35)	(3.01)	(-0.43)	(1.12)	(-1.08)	(-2.17)	(0.35)	(-3.12)	(-2.27)	
$DRF^{10\%\ VaR}$	**0.37**	0.25	0.07	-0.02	0.02	-0.01	-2.11	0.31	-0.47	-0.24	27.86
	(4.78)	(4.27)	(2.72)	(-0.98)	(0.55)	(-0.36)	(-1.25)	(0.32)	(-3.22)	(-2.37)	
$DRF^{10\%\ ES}$	**0.49**	0.22	0.07	-0.03	0.02	-0.03	-4.22	0.50	-0.49	-0.30	25.13
	(4.74)	(2.65)	(2.97)	(-1.13)	(0.54)	(-0.99)	(-2.57)	(0.39)	(-2.88)	(-2.48)	
CRF	**0.28**	-0.06	0.05	0.05	0.01	-0.03	-0.87	-3.02	0.37	-0.12	16.25
	(4.02)	(-0.79)	(2.71)	(1.93)	(0.35)	(-1.13)	(-0.41)	(-2.82)	(3.38)	(-1.98)	