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Common risk factors in the cross-section of corporate bond returns[☆]

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ABSTRACT

We investigate the cross-sectional determinants of corporate bond returns 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 factors have economically and statistically significant risk premiums that cannot be explained by long-established stock and bond market factors. We show that the newly proposed risk factors outperform all other models considered in the literature in explaining the returns of the industry- and size/maturity-sorted portfolios of corporate bonds.

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

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We merged the findings of our earlier working paper "Do the distributional characteristics of corporate bonds predict their future returns?" with this paper so that Bai et al. (2016) cited in the paper will remain as a permanent working paper.

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bond returns.[1] Compared to the size of the US equity market ($19 trillion), the corporate bond market is relatively small, 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 US 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 corporate bond returns.

Earlier studies on corporate bonds generally rely on 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 Fama and French (1993), Elton et al. (1995), and Bessembinder et al. (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 poor. In this paper, we show that it is crucial to rely on the prominent features of corporate bonds when constructing 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 investors.

Given these significant differences in market features and the types of investors in the equity and bond markets, we endeavor to identify bond-implied risk factors that provide an accurate characterization of the cross-sectional variation in bond returns. Following Bessembinder et al. (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 2016. Our proxy for downside risk is the 5% value at risk (VaR) estimated from 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 et al. (2011). In addition to these three economically sensible risk characteristics for corporate bonds, we take into account bond exposure to the market risk factor (market beta).

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 11.88% per annum higher return than bonds in the lowest downside risk quintile. After controlling for ten 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: 8.64% per annum with a t-statistic of 2.82, 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 after controlling for bond characteristics. Bivariate portfolio-level analyses indicate that downside risk remains a significant predictor of future bond returns after controlling for credit rating, illiquidity, maturity, and size.

Having established the evidence that downside risk is a strong predictor of future bond returns, we investigate the source of downside risk premium. Specifically, we dissect downside risk into volatility, skewness, and kurtosis components and find that bond return volatility (skewness) is a significantly positive (negative) predictor

[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 2016.

[3] See Feroli et al. (2014) and the Investment Company Institute Annual Report (2014).

[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.

of future bond returns after controlling for skewness (volatility) and kurtosis. Moreover, volatility and skewness contribute strongly to the significance of downside risk in the corporate bond market, whereas kurtosis makes a weak incremental contribution to the downside risk premium after volatility and skewness are controlled for.

Then, we investigate the cross-sectional relation between downside risk and expected returns at the bond level using Fama-MacBeth (1973) regressions in which we control for multiple factors simultaneously. Specifically, we present the time-series averages of the slope coefficients from the regressions of one-month-ahead excess returns on downside risk controlling for past bond risk/return characteristics, including credit rating, illiquidity, market beta, maturity, size, lagged return, and bond exposures to the default and term factors. The results indicate that downside risk remains a strong predictor of future bond returns after controlling for a large number of bond characteristics. Among the control variables, only the short-term reversal effect is found to be strong and robust across different regression specifications. Thus, in addition to the three risk factors (downside, credit, and liquidity risk), we construct a bond return reversal factor and examine its empirical performance in predicting the cross-sectional variation in corporate bonds.

Finally, we introduce novel risk factors based on the above prevalent risk characteristics. In a similar spirit to Fama and French (2015) and Hou et al. (2015), we rely on the independently sorted portfolios using credit rating as the main sorting variable and downside risk, illiquidity, and past one-month return as the other sorting variables when constructing the new bond factors; namely the downside risk factor (DRF), liquidity risk factor (LRF), and return reversal factor (REV). These independent sorts also produce three credit risk factors so that the final credit risk factor (CRF) is defined as the average of the three factors of credit risk. We run time-series 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 using the most general ten-factor model that combines all of the commonly used stock and bond market factors, we find that the alphas for the DRF, CRF, LRF, and REV factors are all economically and statistically significant, indicating that the existing factors are not sufficient to capture the information content in these newly proposed bond factors.

Motivated by the findings in Daniel and Titman (1997) and Brennan et al. (1998), we further examine if the exposures to the new bond factors predict future bond returns. For each bond and each month in our sample, we estimate the factor betas from the monthly rolling regressions of excess bond returns on the DRF, CRF, LRF, and REV factors over a 36-month fixed window while controlling for the bond market factor (MKT^{Bond}). After we obtain the factor exposures, namely, the downside risk beta (β^{DRF}), the credit risk beta (β^{CRF}), the liquidity risk beta (β^{LRF}), and the return reversal beta (β^{REV}), we investigate the significance of the bond factor betas in predicting the cross-sectional differences in corporate bond returns using bond-level cross-sectional regressions. Our results show that all three factor betas (β^{DRF}, β^{CRF}, β^{LRF}) are positively related to future bond returns, lending further support to the finding that the newly proposed factors capture systematic variations in bond returns and common risk premiums in the corporate bond market. However, the bond exposure to the return reversal factor (β^{REV}) turns out to be statistically insignificant with and without controlling for bond characteristics. Thus, we conclude that one-month lagged return (REV) is a strong cross-sectional determinant of future bond returns, but it can be viewed as a nonrisk bond characteristic instead of a common risk factor in the bond market.

One important critique in asset pricing tests, as pointed out by Lewellen et al. (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, Lewellen et al. (2010) suggest that the empirical performance of risk factors should be tested based on alternative test portfolios. Following their insight, we form two sets of test portfolios that do not necessarily relate to the aforementioned risk characteristics: (i) 5×5 independently sorted bivariate portfolios of size and maturity and (ii) 30 industry-sorted portfolios. Then, we examine the relative performance of factor models in explaining the time-series and cross-sectional variations in these test portfolios. We find that the newly proposed four-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.[6]

Specifically, our model produces an average 56% adjusted R^2 for the 25 size/maturity-sorted portfolios of corporate bonds, whereas the existing models can explain up to 18%. Our model also remains its high explanatory power for the 30 industry-sorted portfolios of corporate bonds, with an average adjusted R^2 of 37%, in contrast to the weak performance of existing models with average adjusted R^2 values of only 13% to 18%. Consistent with these findings, the new model has markedly smaller and insignificant alphas in explaining the cross-section of bond returns, generating economically and statistically insignificant alphas for all 25 size/maturity-sorted portfolios of corporate bonds, with an average alpha of 0.04% per month. In contrast, the existing models generate significant alphas for all 25 portfolios, with an average alpha of 0.33% to 0.42% per month. Similarly, the new model generates insignificant alphas for all of the 30-industry portfolios, with an average alpha of 0.14%, whereas the existing models produce significant alphas with a monthly average of 0.41% to 0.55%. These results indicate that the new factors of corporate bonds significantly outperform

[6] Note that the test portfolios constructed based on size, maturity, and industry characteristics do not have a direct link to downside risk, credit risk, or illiquidity. At an earlier stage of the study, we form test portfolios based on downside risk, credit risk, and illiquidity, and, as anticipated, the empirical performance of the newly proposed four-factor model is even higher in predicting the time-series and cross-sectional variations in the returns of the downside risk/credit risk/illiquidity-sorted portfolios.

all existing factor models, and hence the new model serves as a proper and higher benchmark in evaluating the risk-return tradeoff in the corporate bond market.

This paper proceeds as follows. Section 2 sets forth a literature review. Section 3 describes the data and main variables. Section 4 examines the cross-sectional relation between downside risk and expected returns of corporate bonds. Section 5 introduces new risk factors for corporate bonds and compares their relative performance with long-established stock and bond market factors. Section 6 conducts a battery of robustness checks and Section 7 concludes the paper.

2. Literature review

Our empirical findings contribute to the literature in several important ways. The foremost contribution is to identify bond-implied new risk factors that significantly predict the cross-sectional variation 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 et al., 1991).[7] Subsequent studies have investigated the bond returns at the firm level, mainly with quoted price data (see, e.g., Kwan, 1996; Gebhardt et al., 2005)[8] and recently with transaction data (see, e.g., Bessembinder et al., 2009; Lin et al., 2011; Acharya et al., 2013; Jostova et al., 2013; Chordia et al., 2017; Choi and Kim, 2018).[9] 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 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 et al., 2005; Chen et al., 2007). In a recent paper, Culp et al. (2018) show that a risk premium for idiosyncratic tail risk is the primary determinant of corporate spreads, whereas bond market illiquidity, investors' overestimation of default risks, and corporate frictions do not explain credit spreads. The main theme, focus, and methodological approaches of all these papers, however, are very different from ours, as we do not use any parametric/structural model or option data to back out our risk measures. More importantly, our paper differs from earlier studies by analyzing the cross-section of future corporate bond returns (not yield spreads) and introducing a novel risk factor model that measures abnormal returns on corporate bond portfolios.

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 that 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.

Our work is also related to Lettau et al. (2014) who show that downside risk capital asset pricing model (DR-CAPM) can price the cross-section of currency returns and several other assets' returns, but they find no evidence that downside beta is positively related to corporate bond returns (see pp. 222–223). Our work is different from Lettau et al. (2014) by focusing on the extreme total downside risk as measured by value at risk, instead of systematic downside risk as measured by downside beta along the lines of Bawa and Lindenberg (1977) and Ang et al. (2006).

The use of VaR techniques in risk management has exploded over the past two decades. Financial institutions now routinely use VaR and expected shortfall in managing their risk, and nonfinancial firms adopt this technology for their risk management as well. There is an extensive literature on 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 et al., 2009; Huang et al., 2012). The predictive power of VaR or expected shortfall has not been investigated for alternative asset classes. This paper provides the first evidence on the theoretically consistent positive and significant relation between left-tail risk and future corporate bond returns.

[7] 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.

[8] Gebhardt et al. (2005) test the cross-sectional predictive power of default and term spread beta and find that they are significantly related to corporate bond returns.

[9] 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 et al. (2011) construct the market liquidity risk factor and show that it is priced in the cross-section of corporate bond returns. Acharya et al. (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 et al. (2017) and Choi and Kim (2018), that examine whether equity market predictors are priced in the cross-section of corporate 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 TRACE for the sample period July 2002 to December 2016. 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 that are not provided in such datasets as the Lehman Brothers fixed income database, Datastream, or Bloomberg.[10] Therefore, we focus on the TRACE dataset that 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 Internet Appendix, we also expand the TRACE data by including alternative bond datasets, mainly those containing quoted prices, for a longer sample period starting from January 1977. 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 Internet Appendix.

For TRACE intraday data, we adopt the following filtering criteria:

1. Remove bonds that are not listed or traded in the US 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 nonconvertible bonds.[11]
4. Remove bonds that trade under \$5 or above \$1000.
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 the 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; thus, 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.
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.[12]

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 et al. (2009). We then convert the bond prices from daily to monthly frequency. Specifically, our method identifies two scenarios for a return to be realized at the end of month t: (i) from the end of month $t-1$ to the end of month t and (ii) from the beginning of month t to the end of month t. We calculate

[10] 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.

[11] 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 bonds with any option feature. The main findings remain robust.

[12] Bessembinder et al. (2009) test the power of test statistics to detect abnormal bond returns and suggest that eliminating noninstitutional 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.

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% VaR), illiquidity (ILLIQ), and the CAPM beta based on the corporate bond market return, 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% 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 bond exposure to the excess corporate bond market return, constructed using the value-weighted average return of all corporate bonds in our sample. The betas are estimated for each bond from the time-series regressions of bond excess returns on the excess bond market return using a 36-month rolling window estimation. Panel B reports the time-series average of the cross-sectional correlations. The sample period is from July 2002 to December 2016.

Panel A: Cross-sectional statistics over the sample period of July 2002–December 2016

					Percentiles					
	N	Mean	Median	SD	1st	5th	25th	75th	95th	99th
Bond return (%)	1,243,543	0.68	0.50	3.13	−7.46	−3.66	−0.68	1.86	5.59	10.33
Rating	1,243,543	8.32	7.65	4.05	1.56	2.25	5.52	10.35	16.30	19.09
Time to maturity (maturity, year)	1,243,543	9.49	6.60	8.26	1.11	1.51	3.59	12.81	26.69	31.63
Amount out (size, $million)	1,243,543	393.73	269.59	478.63	1.60	5.17	76.99	504.15	1353.24	2480.32
Downside risk (5% VaR)	579,333	5.84	4.08	5.78	0.70	1.17	2.46	6.96	16.75	29.42
Illiquidity (ILLIQ)	977,011	2.14	0.46	5.17	−1.17	−0.23	0.07	1.99	10.16	24.13
Bond market beta (β^{bond})	584,223	1.12	1.01	1.15	−0.24	0.15	0.58	1.67	3.72	5.38

Panel B: Average cross-sectional correlations

	Rating	Maturity	Size	VaR	ILLIQ	β^{Bond}
Rating	1	−0.138	−0.021	0.383	0.117	0.089
Maturity		1	−0.042	0.171	0.106	0.356
Size			1	−0.108	−0.160	0.076
VaR				1	0.323	0.195
ILLIQ					1	0.098
β^{Bond}						1

monthly returns for both scenarios, where the end (beginning) of month refers to the last (first) five trading days within each month. If there are multiple trading records in the five-day window, the one closest to the last trading day of the month is selected. If a monthly return can be realized in both scenarios, the realized return in scenario one (from month-end $t-1$ to month-end t) is selected.

Our final sample includes 38,957 bonds issued by 4079 unique firms, for a total of 1,243,543 bond-month return observations during the sample period July 2002 to December 2016.[13] On average, there are approximately 7147 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 0.68%. The sample contains bonds with an average rating of 8.32 (i.e., BBB+), an average issue size of 393 million dollars, and an average time to maturity of 9.49 years. Among the full sample of bonds, 75% are investment-grade and the remaining 25% are high-yield bonds.

3.3. Cross-sectional bond risk characteristics

The literature that investigates the cross-section of corporate bond returns relies on commonly used stock market factors. This is a natural starting point since the rational asset pricing models suggest that risk premiums 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,

[13] Our key variable of interest, downside risk proxied by the 5% VaR is estimated using monthly returns over the past 36 months. A bond is included in VaR calculation if it has at least 24 monthly return observations in the 36-month rolling window before the test month. Thus, the final sample size that involves downside risk reduces from 1,243,543 to 579,333 bond-month return observations for the period July 2002–December 2016.

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 premiums between equity and corporate bond markets (e.g., Chordia et al., 2017; Choi and Kim, 2018), 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 nonfinancial 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 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 downside risk is 5.84% in the whole sample, implying that there is only a 5% probability that an average corporate bond would lose more than 5.84% over the next one month (or the maximum loss expected on a typical bond, at the 95% confidence level, is 5.84% over the next month).

VaR as a risk measure is criticized for not being subadditive. To alleviate this problem, Artzner et al. (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 Internet 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 that 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 S&P'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 Fixed Income Securities Database (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-). Noninvestment-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 Standard & Poor (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 studies also use other credit risk proxies such as the distance-to-default measure developed by KMV or the credit default spread (Longstaff et al., 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 Internet 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 (2016) and show that our main findings are not sensitive to the choice of a credit quality measure.

3.3.3. Bond illiquidity

The literature shows the importance of illiquidity and liquidity risk in the corporate bond market. For example,

[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.

[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.

the empirical results in Chen et al. (2007) and Dick-Nielsen et al. (2012) establish the relation between corporate bond yield spreads and bond illiquidity. Using transactions data from 2003 to 2009, Bao et al. (2011) show that the bond-level illiquidity explains a substantial proportion of cross-sectional variations in bond yield spreads. Lin et al. (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.[17] 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

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

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

3.3.4. Bond market β

We compute the bond market excess return (MKT^{Bond}) as the value-weighted average returns of all corporate bonds in our sample minus the one-month Treasury bill rate.[18] 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 market beta has a wide range from 0.15 in the 5th percentile to 3.72 in the 95th percentile, with a mean (median) of 1.12 (1.01).

3.3.5. Summary statistics

Table 1 presents the correlation matrix for the bond-level characteristics and risk measures. As shown in Panel B, downside risk is positively associated with β^{bond}, illiquidity, and rating, with respective correlations of 0.195, 0.323, and 0.383. The bond market beta, β^{bond}, is also positively associated with rating and illiquidity, with respective correlations of 0.089 and 0.098. 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 VaR and ILLIQ, indicating that bonds with smaller size have higher VaR and higher ILLIQ. The correlations between size and rating and between size and maturity are economically weak.

4. Downside risk and expected corporate bond returns

We investigate the distributional characteristics of corporate bonds and find that the empirical distribution of bond returns is skewed, peaked around the mode, and has fat tails, implying that extreme returns occur much more frequently than predicted by the normal distribution. Hence, ignoring nonnormality features of the return distribution significantly understates downside risk in bond portfolios, potentially posing a solvency risk for bond investors. We argue for a pricing framework for corporate bonds that builds in nonnormality up front because, beyond its pure statistical merit, the framework offers a significant, practical benefit for investors: the potential to improve portfolio efficiency and reduce its risk relative to unpredictable, extreme negative events.

In this section, we first present the empirical results from testing whether the time-series and cross-sectional returns of corporate bonds are normally distributed. Then, we provide comprehensive empirical evidence supporting the positive relation between downside risk and the cross-section of future bond returns.

4.1. Normality test for corporate bond returns

For each bond in our sample from July 2004 to December 2016, we compute the volatility, skewness, and kurtosis of monthly returns. Panel A of Table A.1 in the online Internet Appendix shows their summary statistics. Panel A tests whether these high-order moments are significantly different from zero based on the time-series distribution of bond returns. Among 38,957 bonds, 84.6% of them have significant volatility at the 10% level or better. In addition, 19,548 bonds exhibit positive skewness, and 19,409 bonds exhibit negative skewness. Among the bonds with positive (negative) skewness, 48.0% (49.5%) are statistically significant at the 10% level or better. Finally, the majority of bonds (26,493) exhibit positive excess kurtosis, and among these bonds, 67.7% are statistically significant at the 10% level or better. We also conduct the Jarque-Bera (JB) normality test, and the last column of Panel A shows that 79.9% of the bonds in our sample exhibit significant JB statistics, rejecting the null hypothesis of normality at the 10% level or better.[19]

Panel B of Table A.1 tests whether these high-order moments are significantly different from zero based on the cross-sectional distribution of bond returns. For each month from July 2004 to December 2016, we compute the volatility (%), skewness, and excess kurtosis of the cross-sectional observations of bond returns and test whether these distributional moments are significantly different from zero. We find that the JB statistics are significant for all months in the sample period, rejecting the null hypothesis of normal distribution of the cross-sectional bond returns.[20]

[17] Choi and Kronlund (2018) examine reaching for yield by corporate bond mutual funds and find that reaching for yield is stronger for retail-oriented mutual funds when corporate bond liquidity is high.

[18] We also consider alternative bond market proxies such as the Barclays Aggregate Bond Index and Merrill Lynch Bond Index. The results from these alternative bond market factors turn out to be similar to those reported in our tables.

[19] For 68% of the corporate bonds in our sample, the JB statistics are significant at the 5% level or better, rejecting the null hypothesis of normality.

[20] Bai et al. (2016) test, for the first time in the literature, nonnormality of the return distribution of corporate bonds and also investigate whether

Table 2
Univariate portfolios of corporate bonds sorted by downside risk.
Quintile portfolios are formed every month from July 2004 to December 2016 by sorting corporate bonds based on the 5% VaR, 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. Quintile 1 is the portfolio with the lowest VaR and Quintile 5 is the portfolio with the highest VaR. The portfolios are value weighted using amount outstanding as weights. Table reports the average VaR, the next-month average excess return, the five-factor alpha from stock market factors, the five-factor alpha from bond market factors, and the ten-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 five-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^{Stock}), and the stock liquidity factor (LIQ^{Stock}). The five-factor model with bond market factors includes the excess bond market return (MKT^{Bond}), the default factor (DEF), the term factor (TERM), the bond momentum factor (MOM^{Bond}), and the bond liquidity factor (LIQ^{Bond}). The ten-factor model combines the five stock and five 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	Five-factor stock	Five-factor bond	Ten-factor	Average portfolio characteristics				
	VaR	return	alpha	alpha	alpha	β^{Bond}	ILLIQ	Rating	Maturity	Size
Low VaR	1.59	0.21	0.19	0.03	0.03	0.55	0.57	7.02	4.43	0.56
		(1.10)	(1.28)	(1.05)	(1.09)					
2	2.95	0.34	0.30	0.04	0.05	0.82	1.15	7.69	7.07	0.46
		(2.99)	(2.78)	(1.17)	(1.35)					
3	4.38	0.44	0.37	0.04	0.04	1.06	1.82	7.91	10.39	0.43
		(2.77)	(2.58)	(0.65)	(0.79)					
4	6.71	0.62	0.54	0.17	0.19	1.44	2.72	8.64	13.26	0.41
		(3.02)	(3.32)	(1.82)	(1.98)					
High VaR	15.72	1.20	0.99	0.81	0.75	2.52	5.20	12.16	12.15	0.34
		(4.18)	(4.41)	(4.32)	(3.16)					
High - Low	14.13***	0.99***	0.79***	0.78***	0.72***					
Return/Alpha diff.	(9.94)	(3.95)	(3.82)	(3.90)	(2.82)					

Since the empirical distribution of bond returns is skewed, peaked around the mode, and has fat tails, downside risk—defined as a nonlinear function of volatility, skewness, and kurtosis—is expected to play a major role in the cross-sectional pricing 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 2016, 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. The portfolios are value weighted using amount outstanding as weights. Table 2 shows the average 5% VaR of bonds in each quintile, the next-month value-weighted 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 and West (1987) adjusted *t*-statistics are reported in parentheses.

Moving from quintile 1 to quintile 5, the average excess return on the downside risk portfolios increases monotonically from 0.21% to 1.20% per month. This indicates a monthly average return difference of 0.99% between quintiles 5 and 1 with a Newey-West *t*-statistic of 3.95, showing that this positive return difference is economically and statistically significant. This result also indicates that corporate bonds in the highest-VaR quintile generate 11.88% 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^{Stock}), and a liquidity risk factor (LIQ^{Stock}), following Fama and French (1993), Carhart (1997), and Pastor and Stambaugh (2003).[21] The third column of Table 2 shows that, similar to the average excess returns, the five-factor alpha on the downside risk portfolios also increases monotonically from 0.19% to 0.99% per month, moving from the low-VaR to the high-VaR quintile, indicating a positive and significant alpha difference (downside risk premium) of 0.79% per month (*t*-stat.= 3.82). 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 risk), we also test whether the significant return difference between high-VaR bonds and low-VaR bonds can be explained

the higher order moments of corporate bonds predict their future returns. In this paper, we merge the main findings of Bai et al. (2016) with our empirical analyses on downside risk so that Bai et al. (2016) remains a permanent working paper.

[21] 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/.

by prominent bond market factors. Following Fama and French (1993), Elton et al. (1995), 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 value-weighted average return of all corporate bonds in our sample in excess of the one-month T-bill return. The default factor (DEF) is defined as the difference between the return on a market portfolio of long-term corporate bonds (the composite portfolio on the corporate bond module of Ibbotson Associates) and the long-term government bond return. The term factor (TERM) is defined as the difference between the monthly long-term government bond return (from Ibbotson Associates) and the one-month Treasury bill rate. In addition to MKT^{Bond}, DEF, and TERM, we 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). We also use the liquidity risk factor (LIQ^{Bond}) of Lin, Wang, and Wu (2011), constructed for the corporate bond market. Specifically, we follow Lin, Wang, and Wu (2011) and estimate the liquidity beta over a five-year rolling window for each individual bond. We then sort individual bonds into ten decile portfolios each month by the preranking liquidity beta. The liquidity factor used in Lin, Wang, and Wu (2011) is defined as the average return difference between the high liquidity beta portfolio (decile 10) and the low liquidity beta portfolio (decile 1).[22]

Similar to our earlier findings from the average excess returns and the five-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 five-factor alpha from bond market factors increases monotonically from 0.03% to 0.81% per month. The corresponding five-factor alpha difference between quintiles 5 and 1 is positive and highly significant; 0.78% per month with a t-statistic of 3.90.

The fifth column of Table 2 presents the ten-factor alpha for each quintile from the combined five stock and five bond market factors. Consistent with our earlier results, moving from the low-VaR to the high-VaR quintile, the ten-factor alpha increases monotonically from 0.03% to 0.75% per month, generating a positive and highly significant risk-adjusted return spread of 0.72% per month with a t-statistic of 2.82.

Finally, we examine the average bond characteristics of VaR-sorted portfolios. As shown in the last five columns of Table 2, bonds with high downside risk have a 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 sections, 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. Bivariate portfolio analysis

Table 3 presents the results from the bivariate sorts of VaR and bond characteristics. Quintile portfolios are formed every month from July 2004 to December 2016 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 subquintiles based on their VaR. This methodology, under each characteristic-sorted quintile, produces subquintile portfolios of bonds with dispersion in downside risk but that have nearly identical characteristics, such as rating, maturity, size, and illiquidity. The portfolios are value weighted using amount outstanding as weights. 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 3 shows that the ten-factor alpha increases monotonically from VaR,1 to VaR,5 quintile. More importantly, after controlling for credit rating, the ten-factor alpha difference between high- and low-VaR bonds remains positive, 0.46% per month, and highly significant with a t-statistic of 2.60. We further investigate the interaction between VaR and credit rating by sorting investment-grade and noninvestment-grade bonds separately into bivariate quintile portfolios. As expected, the positive relation between VaR and expected returns is stronger for noninvestment-grade bonds with the alpha spread of 0.78% per month (t-stat.= 3.38), but the positive downside risk premium remains significant for investment-grade bonds even after controlling for credit ratings, with the alpha spread of 0.38% per month (t-stat.= 2.46).

Panel B of Table 3 reports the results from the bivariate sorts of downside risk and maturity. After controlling for bond maturity, the ten-factor alpha difference between high- and low-VaR bonds remains positive, 0.91% per month, and highly significant with a t-statistic of 4.10. We further examine the interaction between VaR and maturity by sorting short-maturity bonds (one year $\leq$ maturity $\leq$ five years), medium-maturity bonds (five years $<$ maturity $\leq$ ten years), and long-maturity bonds (maturity $>$ ten 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 0.64% per month (t-stat.= 2.66) for short-maturity bonds, 0.81% per month (t-stat.= 2.88) for medium-maturity bonds, and 0.99% per month (t-stat.= 4.59) 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.

[22] We thank Junbo Wang for providing us with the data on LIQ1 and LIQ2 used by Lin, Wang, and Wu (2011). The monthly data on LIQ1 and LIQ2 are available from January 1999 to March 2009. We extend their liquidity risk factors up to December 2016 and use LIQ1 to calculate the risk-adjusted returns (alpha) of VaR-sorted portfolios. The results from LIQ2 are very similar to those reported in Table 2.

Table 3

Bivariate portfolios of corporate bonds sorted by downside risk controlling for bond characteristics.

Quintile portfolios are formed every month from July 2004 to December 2016 by first sorting corporate bonds based on credit rating (Panel A), maturity (Panel B), size (Panel C), or illiquidity (Panel D). Then, within each control quintile, corporate bonds are further sorted into subquintiles 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. The portfolios are value weighted using amount outstanding as weights. Table shows the ten-factor alpha for each quintile. The last row shows the differences in alphas with respect to the ten-factor model, which combines the five stock and five 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	Noninvestment grade	All bonds	Short maturity	Medium maturity	Long maturity
VaR,1	0.04	0.02	0.32	−0.05	−0.08	−0.06	0.01
	(1.07)	(0.96)	(3.01)	(−1.19)	(−1.22)	(−1.34)	(0.44)
VaR,2	0.11	0.05	0.31	−0.02	−0.14	−0.01	0.07
	(3.75)	(2.25)	(3.15)	(−0.57)	(−2.47)	(−0.35)	(3.06)
VaR,3	0.12	0.03	0.43	0.12	0.08	0.11	0.18
	(3.11)	(1.23)	(3.68)	(3.23)	(1.37)	(2.03)	(4.73)
VaR,4	0.18	−0.03	0.42	0.20	0.16	0.23	0.27
	(3.02)	(−1.16)	(2.61)	(2.67)	(1.42)	(1.71)	(3.77)
VaR,5	0.51	0.40	1.10	0.86	0.56	0.74	1.00
	(3.41)	(1.39)	(4.46)	(4.36)	(2.78)	(2.91)	(4.83)
VaR,5 - VaR,1	0.46**	0.38**	0.78***	0.91***	0.64***	0.81***	0.99***
Return/Alpha diff.	(2.60)	(2.46)	(3.38)	(4.10)	(2.66)	(2.88)	(4.59)

	Panel C: Controlling for size			Panel D: Controlling for illiquidity		
	All bonds	Small bonds	Large bonds	All bonds	Investment grade	Noninvestment grade
VaR,1	0.06	0.04	0.05	−0.01	−0.01	0.13
	(0.96)	(0.55)	(0.96)	(−0.20)	(−0.28)	(1.15)
VaR,2	0.08	0.18	0.06	0.07	0.02	0.30
	(1.20)	(1.94)	(1.57)	(2.69)	(0.89)	(2.54)
VaR,3	0.19	0.38	0.08	0.09	0.03	0.39
	(4.16)	(4.09)	(1.63)	(1.98)	(1.41)	(3.03)
VaR,4	0.26	0.49	0.10	0.19	0.01	0.65
	(3.10)	(3.05)	(1.56)	(2.50)	(0.45)	(3.43)
VaR,5	0.71	0.83	0.65	0.72	0.37	1.29
	(4.17)	(2.77)	(3.50)	(4.26)	(2.03)	(4.46)
VaR,5 - VaR,1	0.65***	0.79**	0.60***	0.72***	0.38**	1.16***
Return/Alpha diff.	(3.48)	(2.37)	(3.08)	(3.90)	(2.48)	(3.55)

This result makes sense because longer term bonds usually offer higher interest rates but may entail additional risks.

Panel C of Table 3 presents the results from the bivariate sorts of downside risk and bond size measured by bond outstanding value. After controlling for size, the ten-factor alpha difference between high- and low-VaR bonds remains positive, 0.65% 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 positive link remains strong for bonds with high market value as well.

Panel D of Table 3 demonstrates the results from the bivariate sorts of downside risk and bond illiquidity defined in Eq. (2). After controlling for illiquidity, the ten-factor alpha difference between high- and low-VaR bonds remains positive, 0.72% per month, and statistically significant. In the same panel, we further investigate the interaction between VaR and bond illiquidity by sorting investment-grade and noninvestment-grade bonds separately into bivariate quintile portfolios. As expected, the positive relation between VaR and expected returns is stronger for noninvestment-grade bonds, but the significantly positive link remains strong for investment-grade bonds even after controlling for illiquidity.

4.4. Bond-level Fama-MacBeth regressions

We have thus far tested the significance of downside risk (5% VaR) as the cross-sectional determinant of future bond returns based on the univariate and bivariate portfolio-level analyses. 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, β^{Bond} and the control variables, including years-to-maturity (MAT), the natural logarithm of bond amount outstanding (SIZE), lagged excess return (REV), and bond exposure to the default and term factors (β^{DEF}, β^{TERM}). Monthly cross-sectional regressions are run for the following econometric

Table 4
Bond-level Fama-MacBeth cross-sectional regressions.

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 control variables. Bond characteristics include time to maturity (years) and the natural logarithm of amount outstanding (Size). 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 control variables are the default beta (β^{DEF}), the term beta (β^{TERM}), and bond return in previous month (REV). The Fama and MacBeth regressions are run each month for the period from July 2004 to December 2016. Newey and 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 better.

	Intercept	5% VaR	Rating	ILLIQ	β^{Bond}	β^{DEF}	β^{TERM}	Maturity	Size	REV	Adj. R^2
(1)	−0.011	**0.064**									0.086
	(−0.10)	(4.88)									
(2)	0.127	**0.052**				−0.006	0.002	−0.002	−0.012	**−0.122**	0.173
	(0.96)	(4.36)				(−1.03)	(0.23)	(−0.46)	(−0.84)	(−9.24)	
(3)	−0.182		**0.068**								0.054
	(−1.32)		(3.84)								
(4)	−0.130		**0.064**			−0.008	0.018	**0.015**	−0.001	**−0.119**	0.155
	(−1.23)		(2.84)			(−1.46)	(1.28)	(2.12)	(−1.00)	(−9.36)	
(5)	0.463			**0.081**							0.028
	(3.41)			(6.45)							
(6)	0.304			**0.066**		−0.007	0.041	0.007	0.030	**−0.079**	0.152
	(2.68)			(6.32)		(−0.90)	(1.37)	(1.17)	(0.99)	(−5.29)	
(7)	0.209				**0.486**						0.055
	(1.72)				(3.15)						
(8)	0.224				**0.318**	**−0.023**	0.026	0.004	−0.053	**−0.069**	0.156
	(2.50)				(2.14)	(−2.76)	(1.63)	(0.72)	(−1.13)	(−3.27)	
(9)	−0.195	**0.111**	0.031	**0.047**	−0.097						0.144
	(−1.37)	(5.29)	(1.50)	(6.22)	(−0.94)						
(10)	−0.178	**0.106**	0.030	**0.041**	−0.097	−0.002	0.003	0.002	0.000	**−0.132**	0.217
	(−1.55)	(4.72)	(1.48)	(5.25)	(−0.95)	(−0.31)	(0.31)	(0.30)	(3.22)	(−8.51)	

specification and nested versions thereof:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}VaR_{i,t} + \lambda_{2,t}Rating_{i,t} + \lambda_{3,t}ILLIQ_{i,t} + \lambda_{4,t}\beta^{Bond}_{i,t} + \sum_{k=1}^{K}\lambda_{i,k,t}Control_{i,k,t} + \epsilon_{i,t+1}, \quad (3)$$

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

Table 4 reports the time-series average of the intercept and slope coefficients (λ) and the average adjusted R^2 values over the 149 months from July 2004 to December 2016. 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 0.064 with a t-statistic of 4.88. The economic magnitude of the associated effect is similar to that shown in Table 2 for the univariate quintile portfolios of VaR. The spread in average VaR between quintiles 5 and 1 is approximately 14.13 (= 15.72 - 1.59); multiplying this spread by the average slope of 0.064 yields an estimated monthly downside risk premium of 90 basis points.

Regressions (3), (5), and (7) show that the average slopes on credit risk (Rating), bond-level illiquidity (ILLIQ), and the bond market beta (β^{Bond}) from the univariate regressions of excess bond returns on these risk characteristics are all positive and statistically significant.[23] Regression specifications (2), (4), (6) and (8) in Table 4 show that after controlling for maturity, size, lagged excess return, β^{DEF}, and β^{TERM}, 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 individual 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 0.111 (t-stat.= 5.29) and 0.047 (t-stat.= 6.22), respectively. However, the average slope coefficients on rating and β^{Bond} become insignificant in this general specification, implying that credit rating and the market beta lose their predictive power for future bond returns after VaR and ILLIQ are controlled for.

The last specification, Regression (10), presents the results from the multivariate regression with all bond risk proxies (VaR, Rating, ILLIQ, and β^{Bond}) after controlling for maturity, size, lagged bond return, β^{DEF}, and β^{TERM}. 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. Thus, in Section 5, we construct a new bond return reversal factor and investigate its performance in predicting the cross-sectional and time-series variations in future bond returns.

[23] These findings are also consistent with the univariate portfolio results reported in Table A.2 of the online Internet Appendix. The average return and alpha spreads between quintiles 5 and 1 of the rating-, ILLIQ-, and β^{Bond}-sorted portfolios are all positive and highly significant.

Table 5
The source of downside risk premium.

In Panel A, all corporate bonds in the sample are grouped into 27 portfolios based on trivariate dependent sorts of volatility (VOL), skewness (SKEW), and kurtosis (KURT). Panel A reports the next-month average returns and the ten-factor alpha for i) high- minus low-volatility portfolio controlling for skewness and kurtosis, ii) high- minus low-skewness portfolio controlling for volatility and kurtosis, and iii) high- minus low-kurtosis portfolio controlling for volatility and skewness. The portfolios are value weighted using amount outstanding as weights. VOL, SKEW, and KURT are calculated using a 36-month rolling window estimation. Panel B 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 VOL, SKEW, and KURT with and without control variables. The Fama and MacBeth regressions are run each month for the period from July 2004 to December 2016. Newey and 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. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. Numbers in bold denote statistical significance at the 5% level or better.

Panel A: Trivariate dependent-sort portfolios by VOL, SKEW, and KURT

	Average return	Ten-factor alpha		Average return	Ten-factor alpha		Average return	Ten-factor alpha
Low VOL	0.27	0.03	Low SKEW	0.78	0.45	Low KURT	0.49	0.01
	(1.29)	(0.91)		(4.56)	(3.65)		(3.03)	(0.10)
2	0.47	0.05	2	0.65	0.26	2	0.53	0.10
	(2.05)	(0.92)		(3.11)	(2.29)		(3.35)	(1.73)
High VOL	0.91	0.37	High SKEW	0.53	0.23	High KURT	0.55	0.21
	(3.66)	(2.56)		(2.79)	(2.39)		(3.89)	(4.23)
High - Low	0.64***	0.34**	High - Low	−0.25**	−0.22**	High - Low	0.06	0.20**
t-stat	(3.32)	(2.48)	*t*-stat	(−2.47)	(−2.35)	*t*-stat	(0.81)	(2.34)

Panel B: Cross-sectional regressions with VOL, SKEW, and KURT

	Intercept	VOL	SKEW	KURT	Rating	Maturity	Size	β^{DEF}	β^{TERM}	REV	Adj. R^2
(1)	0.231	**0.011**									0.076
	(2.03)	(2.92)									
(2)	0.128	**0.012**			0.025	0.004	−0.011	−0.001	−0.010	**−0.126**	0.180
	(1.15)	(2.66)			(1.22)	(0.84)	(−0.55)	(−0.10)	(−1.06)	(−9.28)	
(3)	0.206	**0.011**	**−0.128**								0.083
	(1.80)	(2.96)	(−2.81)								
(4)	0.127	**0.012**	**−0.099**		0.025	0.005	−0.014	−0.000	−0.010	**−0.125**	0.184
	(1.16)	(2.74)	(−2.88)		(1.21)	(0.85)	(−0.73)	(−0.09)	(−1.01)	(−9.24)	
(5)	0.375			**0.047**							0.012
	(2.26)			(2.73)							
(6)	0.071			**0.016**	**0.052**	**0.012**	−0.034	−0.005	0.013	**−0.108**	0.159
	(0.54)			(2.34)	(1.97)	(2.02)	(−1.13)	(−0.73)	(1.07)	(−7.95)	
(7)	0.214	**0.011**	**−0.102**	−0.001							0.087
	(1.81)	(2.89)	(−2.43)	(−0.05)							
(8)	0.129	**0.012**	**−0.081**	0.002	0.025	0.005	−0.016	−0.000	−0.010	**−0.125**	0.186
	(1.16)	(2.57)	(−2.53)	(0.26)	(1.27)	(0.94)	(−0.86)	(−0.07)	(−1.05)	(−9.36)	

4.5. The source of downside risk premium

Our results thus far show that downside risk is a strong predictor of future bond returns. In this section, we investigate the source of downside risk premium since this measure is a nonlinear function of high-order moments of the return distribution. Specifically, we test if the high-order moments of bond returns—volatility, skewness, and kurtosis—contribute to the predictive power of downside risk. First, we examine the significance of a cross-sectional relation between volatility/skewness/kurtosis and future returns on corporate bonds using portfolio-level analysis. We then investigate the predictive power of volatility, skewness, and kurtosis simultaneously using bond-level cross-sectional regressions.

Table 2 shows that the average return and ten-factor alpha spreads between the high- and low-VaR quintiles are 99 and 72 basis points per month, respectively. To understand the source of downside risk premium, we dissect downside risk into volatility, skewness, and kurtosis components and conduct trivariate dependent-sort portfolio analyses. Specifically, for each month from July 2004 to December 2016, all bonds in the sample are grouped into portfolios based on ascending sorts of volatility, skewness, and kurtosis. To determine the contribution of volatility to the magnitude of downside risk premium, we group all bonds into 27 portfolios using a trivariate dependent-sort on skewness, kurtosis, and then volatility, with the breakpoints for each sort determined by the 33rd and 67th percentile of the sort variable. We then calculate the value-weighted average return for each of the 27 portfolios, as well as the difference in average returns between the high and low (3-1) volatility-sorted portfolio, for each skewness and kurtosis group. To examine the relation between skewness (kurtosis) and future bond returns, we repeat the analysis, sorting first on kurtosis (skewness), then volatility (volatility), and then skewness (kurtosis).[24]

[24] In all analyses, the portfolio sorts are designed to examine the relation between the last sort variable and future bond returns after controlling for the effects of each of the first two sort variables.

Panel A of Table 5 shows that after controlling for skewness and kurtosis, the average return and alpha spreads between the low- and high-volatility sorted tercile portfolios are, respectively, 0.64% and 0.34% per month and highly significant with corresponding *t*-statistics of 3.32 and 2.48. Panel A also provides evidence for significant skewness premium after controlling for volatility and kurtosis; the average return and alpha spreads between the low- and high-skewness sorted tercile portfolios are, respectively, - 0.25% and - 0.22% per month and statistically significant with corresponding *t*-statistics of - 2.47 and - 2.35. After controlling for volatility and skewness, the predictive power of kurtosis turns out to be weak both economically and statistically; the average return and alpha spreads between the low- and high-kurtosis sorted tercile portfolios are, respectively, 0.06% and 0.20% per month with corresponding *t*-statistics of 0.81 and 2.34.[25]

These results indicate that volatility contributes the most to downside risk premiums; 64 basis points out of the 99 basis points per month, and skewness the second; 25 basis points per month, while kurtosis contributes only 6 basis points per month. Consistent with the findings for raw returns, the ten-factor alphas exhibit similar patterns, except that kurtosis contributes somewhat higher, at 20 basis points per month, which is still lower than volatility and skewness premiums. As expected, volatility contributes the most to the alpha spread in VaR-sorted portfolios; 34 basis points out of the 72 basis points per month, and skewness is again the second, 22 basis points per month.[26]

Finally, we examine the cross-sectional relation between volatility, skewness, and kurtosis and expected returns at the bond level using Fama and MacBeth (1973) regressions. Panel B of Table 5 reports the time-series average of the intercept and slope coefficients and the adjusted R^2 values over the 149 months from July 2004 to December 2016. The results show a positive (negative) and statistically significant relation between volatility (skewness) and the cross-section of future bond returns, in both univariate and multivariate regressions. However, the average slope on KURT is not statistically significant after controlling for volatility and skewness, suggesting that kurtosis does not make a robust incremental contribution to predictability. Overall, Table 5 shows that bond return volatility and skewness contribute significantly to the predictive power of downside risk on future bond returns.

5. Common risk factors in the corporate bond market

In this section, we first introduce novel risk factors based on downside risk, credit quality, bond illiquidity, and return reversal and test whether the newly proposed factors are explained by well-established stock and bond market factors. Then, we investigate if the new factors capture systematic variation in bond returns or common risk premiums in the bond market. Finally, we 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.

5.1. New risk factors: DRF, CRF, LRF, and REV

As discussed previously, 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 factors.

We construct the bond factors in a similar vein to Fama and French (2015) and rely on independent sorts. To construct the downside risk factor for corporate bonds, for each month from July 2004 to December 2016, we form bivariate portfolios by independently sorting bonds into five quintiles based on their credit rating and five quintiles based on their downside risk (measured by 5% VaR). The downside risk factor, *DRF*, is the value-weighted average return difference between the highest-VaR portfolio and the lowest-VaR portfolio across the rating portfolios. The credit risk factor, CRF_{VaR}, is the value-weighted average return difference between the lowest-rating (i.e., highest credit risk) portfolio and the highest-rating (i.e., lowest credit risk) portfolio across the VaR portfolios.

The liquidity risk and the return reversal factors are constructed similarly using independent sorts. The liquidity risk factor, *LRF*, is the value-weighted average return difference between the highest-illiquidity and the lowest-illiquidity portfolios across the rating portfolios. The return reversal factor, *REV*, is the value-weighted average return difference between the short-term loser and the short-term winner portfolios (losers-minus-winners) across the rating portfolios.[27] The above independent sorts used to construct *LRF* and *REV* produce two additional credit risk

[25] At an earlier stage of the study, we sort corporate bonds into univariate quintile portfolios based on kurtosis and find that the average return and alpha spreads between the low- and high-kurtosis quintile portfolios are 0.38% (*t*-stat. = 2.56) and 0.32% per month (*t*-stat. = 2.30), respectively. Although kurtosis itself is a significant predictor of future bond returns, its incremental contribution to downside risk premium is much lower after controlling for volatility and skewness.

[26] When we focus on the alpha spreads reported in Table 5, Panel A, the sum of the volatility, skewness, and kurtosis premiums is 0.76% per month (= 0.34% + 0.22% + 0.20%), which is similar to downside risk premium of 0.72% per month reported in Table 2. Similarly, when we focus on the average return spreads reported in Table 5, Panel A, the sum is 0.95% per month (= 0.64% + 0.25% + 0.06%), which is somewhat lower than the downside risk premium of 0.99% per month reported in Table 2. These results indicate that since VaR is a function of volatility, skewness, kurtosis, and even higher order moments of the return distribution, moments higher than kurtosis may contribute (though very small) to downside risk premium.

[27] Table A.3 of the online Internet Appendix reports the average monthly excess returns for the 5 × 5 portfolios independently sorted on *Rating* and *VaR*, *Rating* and *ILLIQ*, and *Rating* and *REV*.

Table 6
Summary statistics for corporate bond factors.

Panel A reports the descriptive statistics for the excess bond market return and the newly constructed bond factors. MKT^{Bond} is the corporate bond market excess return constructed using the value-weighted average return of all corporate bonds in the sample (in excess of one-month T-bill rate). Downside risk factor (*DRF*) is constructed by independently sorting corporate bonds into 5×5 quintiles based on the 5% VaR and credit rating. *DRF* is the value-weighted average return difference between the highest-VaR portfolio minus the lowest-VaR portfolio within each rating portfolio. Liquidity risk factor (*LRF*) is constructed by independently sorting corporate bonds into 5×5 quintiles based on illiquidity and credit rating. *LRF* is the value-weighted average return difference between the highest-illiquidity portfolio minus the lowest-illiquidity portfolio within each rating portfolio. Return reversal factor (*REV*) is constructed by independently sorting corporate bonds into 5×5 quintiles based on the previous month return and credit rating. *REV* is the value-weighted average return difference between the short-term loser and the short-term winner portfolio within each rating portfolio. Credit risk factor (*CRF*) is the average of the *CRF* obtained from forming the *DRF, LRF*, and *REV*, and $CRF = 1/3(CRF_{VaR} + CRF_{ILLIQ} + CRF_{REV})$. Panel B reports the intercepts (alphas) and *t*-statistics (in parentheses) from time-series regressions of the factors on the commonly used stock and bond market factors. Model 1 includes the five stock market factors defined in Table 2. Model 2 includes the five bond market factors defined in Table 2. Model 3 is the ten-factor model that combines the five stock and five bond market factors. DRF and CRF covers the period from July 2004 to December 2016. LRF and REV cover the period from August 2002 to December 2016.

Panel A: Summary statistics on the value-weighted bond factors

	Mean	*t*-stat
MKT^{Bond}	0.39	3.58
Downside risk factor (DRF)	0.70	3.60
Credit risk factor (CRF)	0.43	2.78
Liquidity risk factor (LRF)	0.52	5.02
Return reversal factor (REV)	0.41	4.05

Panel B: Factor alpha from the ten-factor model

	Model 1	Model 2	Model 3
DRF alpha	0.83	0.79	0.80
t-stat	(2.90)	(3.19)	(2.76)
CRF alpha	0.44	0.34	0.35
t-stat	(2.92)	(2.01)	(1.89)
LRF alpha	0.37	0.32	0.32
t-stat	(3.15)	(2.79)	(2.45)
REV alpha	0.48	0.49	0.46
t-stat	(4.10)	(4.46)	(4.74)

factors, CRF_{ILLIQ} and CRF_{REV}. The credit risk factor *CRF* is defined as the average of CRF_{VaR}, CRF_{ILLIQ}, and CRF_{REV}.[28]

Panel A of Table 6 reports the summary statistics for the new bond factors (DRF, CRF, LRF, and REV). Over the period from August 2002 to December 2016, the corporate bond market risk premium, MKT^{Bond}, is 0.39% per month with a *t*-statistic of 3.58. The value-weighted DRF factor has an economically and statistically significant risk premium of 0.70% per month with a *t*-statistic of 3.60. The value-weighted CRF, LRF, and REV factors also have significant premiums of 0.43% per month (*t*-stat.= 2.78), 0.52% per month (*t*-stat.= 5.02), and 0.41% per month (*t*-stat. = 4.05) respectively. Fig. 1 plots the monthly time series of the new factors (DRF, CRF, LRF, and REV).

Since risk premiums are expected to be higher during financial and economic downturns, we examine the average risk premiums for the newly proposed factors, DRF, CRF, LRF, and REV, during recessionary versus nonrecessionary periods, determined by the Chicago Fed National Activity Index (CFNAI).[29] As expected, we find that the average risk premium on the DRF factor is higher at 0.84% per month during recessionary periods (CFNAI $\leq$ - 0.7), whereas it is 0.67% per month during nonrecessionary periods (CFNAI $>$ - 0.7). The average risk premiums on the CRF and LRF factors are 0.75% and 1.17% per month during recessionary periods, and the corresponding values are lower during nonrecessionary periods; 0.36% and 0.40%, respectively. These magnitudes provide clear evidence that the newly proposed DRF, CRF, and LRF risk factors generate economically large risk premiums during economic downturns.[30]

Finally, we examine whether conventional stock and bond market factors explain the newly proposed factors of corporate bonds. For each of the new factors (DRF, CRF, LRF, and REV), Panel B of Table 6 presents the alphas from (i) the five-factor stock market model of Fama-French (1993), Carhart (1997), and Pastor and Stambaugh (2003) with the stock market (MKT^{Stock}), SMB, HML, MOM^{Stock}, and LIQ^{Stock} factors; (ii) the five-factor bond market model of Fama-French (1993), Elton, Gruber, and Blake (1995), Bessembinder et al. (2009), Jostova et al. (2013), and Lin, Wang, and Wu (2011) with the bond market (MKT^{Bond}), DEF, TERM, MOM^{Bond}, and LIQ^{Bond} factors; and (iii) the ten-factor model that combines the aforementioned five stock and five bond market factors.

Table 6, Panel B, shows that the alphas from the five-factor stock market model, the five-factor bond market model, and the combined ten-factor model are all positive and highly significant for the DRF, CRF, LRF, and REV factors. Overall, these results indicate that the existing stock and bond market factors are not sufficient to capture the information content in the newly proposed bond factors so that these novel factors capture an important source of common return variation in corporate bonds missing from long-established stock and bond market factors.[31]

[28] We rely on the independently sorted 5×5 portfolios to construct the factors to be consistent with our univariate and bivariate portfolio results from quintile portfolios. However, we also follow Fama and French (2015) and Hou et al. (2015) and construct 2×3 and $2 \times 2 \times 2 \times 2$ factors. The results are presented in Table A.4. As shown in Panel B of Table A.4, the correlations between different versions of the same factors (5×5, 2×3, and $2 \times 2 \times 2 \times 2$ factors) are very high.

[29] CFNAI is a monthly index designed to assess overall economic activity and related inflationary pressure (see, e.g., Allen et al., 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 (nonrecessionary) period.

[30] Contrary to our findings for the DRF, CRF, and LRF factors, the bond return reversal factor has lower (higher) average return during recessionary (nonrecessionary) periods. Specifically, the average return on the value-weighted REV factor is 0.29% per month during recessionary periods and 0.43% per month during nonrecessionary periods. This result suggests that REV is a nonrisk characteristic of corporate bonds.

[31] Following Fama and French (2015), we also conduct factor spanning tests by running time-series regressions of each of the four factors on the other three factors. Table A.5 of the online Internet Appendix shows that the regression intercepts (alphas) for the DRF and LRF remain economi-

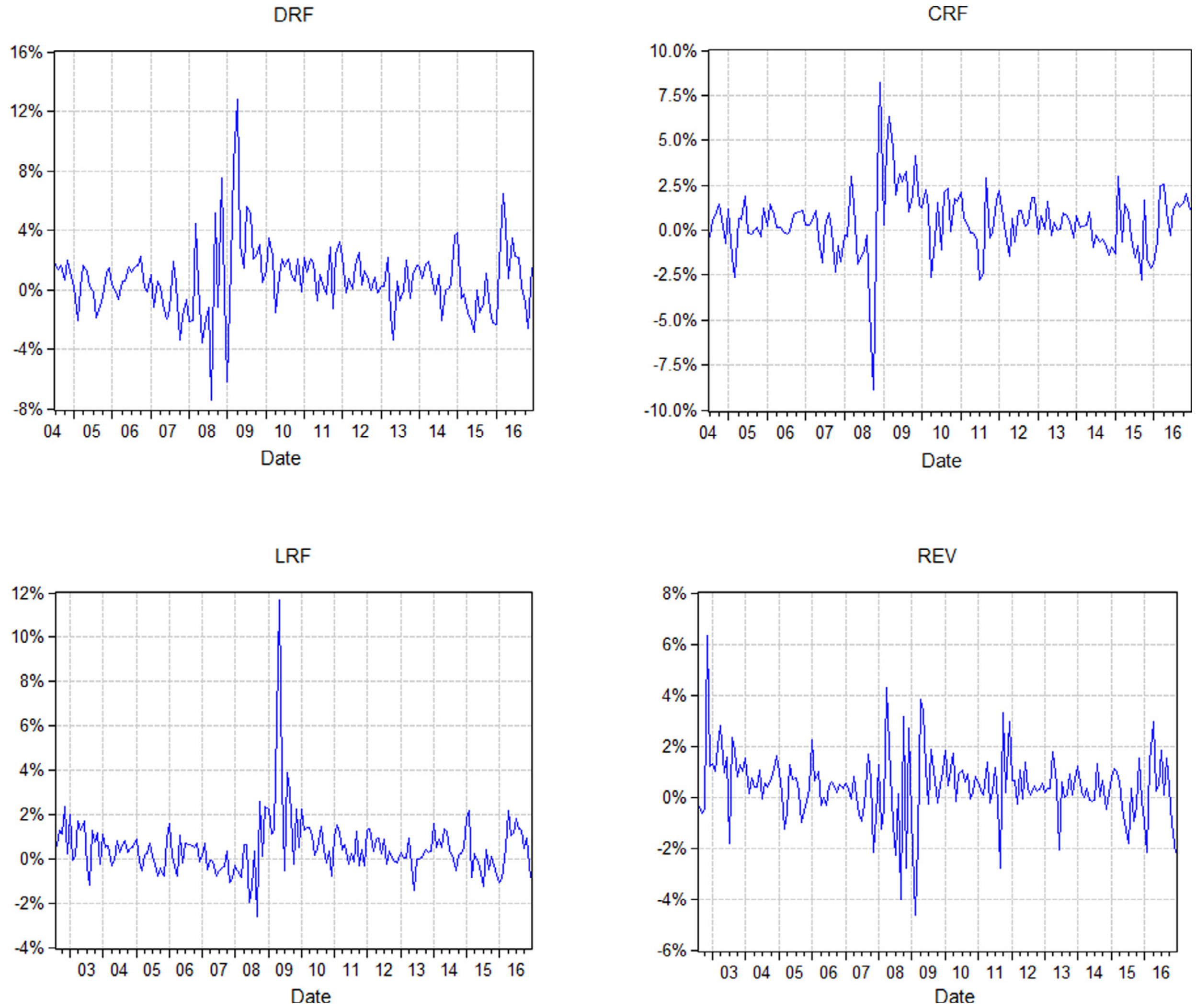

Fig. 1. DRF, CRF, LRF, and REV Factors: 2002–2016. This figure plots the monthly time series of the value-weighted downside risk factor (DRF), credit risk factor (CRF), liquidity risk factor (LRF), and return reversal factor (REV). DRF and CRF cover the period from July 2004 to December 2016. LRF and REV cover the period from August 2002 to December 2016.

5.2. Are exposures to bond risk factors priced?

If the newly proposed DRF, CRF, LRF, and REV factors truly capture systematic variation in bond returns or common risk premiums in the corporate bond market, exposures of corporate bonds to these factors (factor betas) are supposed to predict cross-sectional differences in future bond returns. Motivated by Daniel and Titman (1997) and Brennan et al. (1998), we investigate this issue using bond-level cross-sectional regressions. Specifically, for each bond and each month in our sample, we estimate the factor betas from the monthly rolling regressions of excess bond returns on the DRF, CRF, LRF, and REV factors over a 36-month fixed window after controlling for the bond market factor (MKT^{Bond}):

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} \cdot MKT_t^{Bond} + \beta_{i,t}^{Factor} \cdot Factor_t + \epsilon_{i,t}, \tag{4}$$

where $Factor_t$ is one of the four value-weighted bond market factors: DRF, CRF, LRF, and REV, and $\beta_{i,t}^{Factor}$ is one of the four factor betas: $\beta_{i,t}^{DRF}$, $\beta_{i,t}^{CRF}$, $\beta_{i,t}^{LRF}$, and $\beta_{i,t}^{REV}$ of bond i in month t.

We examine the cross-sectional relation between β^{DRF}, β^{CRF}, β^{LRF}, and β^{REV} and expected returns at the bond level using Fama and MacBeth (1973) regressions. Regression (1) in Table 7 presents positive and statistically significant relations between all three factor betas (β^{DRF}, β^{CRF}, β^{LRF}) and the cross-section of future bond returns, whereas the bond exposure to the return reversal factor (β^{REV}) turns out to be statistically insignificant. The results indicate that the DRF, CRF, and LRF factors capture common risk premiums in the corporate bond market, instead of proxying for bond characteristics. Another notable point in Table 7 is

cally and statistically significant, whereas the CRF alpha becomes smaller and statistically indistinguishable from zero.

Table 7
Are exposures to new bond factors priced?
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 bond market betas, with and without control variables. The bond market betas (β^{Bond}, β^{DRF}, β^{CRF}, β^{LRF}, and β^{REV}) are estimated for each bond from the time-series regressions of bond excess returns on the excess bond market return and the associated bond factors (DRF, CRF, LRF, or REV) using a 36-month rolling window estimation. Bond characteristics include VaR, credit rating, illiquidity (ILLIQ), bond return in previous month (REV), time to maturity (years), and the natural logarithm of bond amount outstanding (Size). Numbers in bold denote statistical significance at the 5% level or better.

	Intercept	β^{Bond}	β^{DRF}	β^{CRF}	β^{LRF}	β^{REV}	VaR	Rating	ILLIQ	REV	Maturity	Size	Adj. R^2
(1)	0.513	**0.301**	**0.399**	**0.816**	**0.267**	−0.174							0.103
	(3.32)	(2.85)	(2.99)	(4.89)	(2.39)	(−1.27)							
(2)	−0.088	**0.202**	**0.275**	**0.118**	**0.272**	−0.049	**0.158**						0.152
	(−0.97)	(2.34)	(2.78)	(2.23)	(2.31)	(−0.54)	(4.61)						
(3)	−0.237	**0.269**	**0.403**	**0.430**	**0.321**	−0.095		**0.095**					0.128
	(−1.74)	(2.63)	(2.37)	(4.36)	(2.74)	(−0.71)		(3.27)					
(4)	0.315	**0.282**	**0.443**	**0.545**	**0.331**	−0.076			**0.095**				0.136
	(2.94)	(2.66)	(2.82)	(3.86)	(2.33)	(−0.54)			(5.59)				
(5)	0.466	**0.261**	**0.321**	**0.627**	**0.162**	−0.234				**−0.035**			0.125
	(3.90)	(2.74)	(2.69)	(4.01)	(2.22)	(−1.91)				(−3.69)			
(6)	0.411	**0.296**	**0.357**	**0.799**	**0.255**	−0.165					0.009		0.129
	(3.12)	(2.71)	(2.75)	(4.83)	(2.28)	(−1.16)					(1.44)		
(7)	0.975	0.318	**0.434**	**0.737**	**0.305**	−0.132						−0.090	0.112
	(2.31)	(1.28)	(2.92)	(4.73)	(2.36)	(−0.93)						(−1.68)	
(8)	−0.346	0.172	**0.351**	**0.493**	**0.289**	−0.102	**0.126**	0.044	**0.055**	**−0.118**	−0.005	0.007	0.234
	(−2.90)	(1.05)	(2.51)	(2.60)	(2.85)	(−1.17)	(5.60)	(1.11)	(6.81)	(−7.40)	(−0.88)	(0.36)	

that β^{REV} does not predict future bond returns in any of the regression specifications with and without controlling for bond characteristics, whereas one-month lagged return (REV) remains a strong cross-sectional determinant of future bond returns. Thus, we conclude that REV is a nonrisk bond characteristic instead of a common risk factor in the bond market.[32]

Brennan et al. (1998) investigate the extent to which expected equity returns can be explained by risk factors (e.g., SMB, HML) rather than by nonrisk firm characteristics (e.g., firm size and book-to-market ratio).[33] Following Brennan et al. (1998), Regressions (2) to (7) in Table 7 control for the risk and nonrisk characteristics of corporate bonds (VaR, rating, illiquidity, lagged return, maturity, and size) one-by-one. Regression (2) shows that downside risk, both as a risk characteristic of individual bonds (VaR) and a common risk factor (DRF), remains a strong predictor of future bond returns because the average slope coefficients on both β^{DRF} and VaR are positive and highly significant with t-statistics of 2.78 and 4.61, respectively.

Regression (8) in Table 7 presents results from the multivariate regression with all factor betas while simultaneously controlling for all risk and nonrisk bond characteristics. Similar to our findings from Regressions (1) through (7), the cross-sectional relations between future bond returns and all three factor betas (β^{DRF}, β^{CRF}, β^{LRF}) are positive and highly significant. Regression (8) provides evidence that the DRF, CRF, and LRF remain significant risk factors along with downside risk, illiquidity, and one-month lagged return as significant characteristics in the cross-section of bond returns.

5.3. Alternative test portfolios

Lewellen et al. (2010) provide evidence that the low power of asset pricing 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, Lewellen et al. (2010) suggest testing risk factors based on alternative test portfolios. Thus, we consider two sets of test portfolios that are not related to the risk characteristics examined in previous sections, that is, downside risk, credit rating and illiquidity.

The first set of test portfolios is based on 5×5 independently sorted bivariate value-weighted portfolios of size and maturity. The second set of test portfolios is based on 30 value-weighted industry-sorted portfolios. We examine the relative performance of factor models in explaining the time-series and cross-sectional variations in the 25 size/maturity-sorted and 30 industry-sorted portfolios of corporate bonds. We investigate the empirical performance of the following five different models:

- Model 1: The five-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^{Stock}), and the stock liquidity risk factor (LIQ^{Stock}).

[32] Bali et al. (2017) propose return-based factors based on the short-term reversal, momentum, and long-term reversal effects in the bond market. They provide an illiquidity-based explanation of the short-term reversal effect, but they do not test whether REV captures systematic variation in bond returns or common risk premiums in the corporate bond market.

[33] Daniel and Titman (1997) show that portfolios of firms that have similar characteristics of size and book-to-market ratio, but different loadings on the SMB and HML factors of Fama-French (1993), have similar average returns. They use this result to conclude that these firm characteristics (size and book-to-market ratio) have an independent influence on expected stock returns.

- Model 2: The five-factor model with the bond market factors of Fama and French (1993), Elton et al. (1995), Bessembinder et al. (2009), Jostova et al. (2013), and Lin et al. (2011), including the bond market factor (MKT^{Bond}), the default factor (DEF), the term factor (TERM), the bond momentum factor (MOM^{Bond}), and the bond liquidity factor (LIQ^{Bond}).
- Model 3: The three-factor model introduced in the paper, including the excess bond market return (MKT^{Bond}), the credit risk factor (CRF), and the bond liquidity risk factor (LRF).
- Model 4: The four-factor model introduced in the paper, including the excess bond market return (MKT^{Bond}), the downside risk factor (DRF), the credit risk factor (CRF), and the bond liquidity risk factor (LRF).
- Model 5: The five-factor model introduced in the paper, including the excess bond market return (MKT^{Bond}), the downside risk factor (DRF), the credit risk factor (CRF), the bond liquidity risk factor (LRF), and the return reversal factor (REV).

Panel A of Table 8 shows that the adjusted R^2, averaged across the 25-size/maturity-sorted portfolios, is only 7% 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 average adjusted R^2 from Model 2 improves to 18% mainly because of the stronger predictive power of the aggregate bond market factor. Compared to the results in Panels A and B, the average R^2 from Model 3 is stronger. As shown in Panel C of Table 8, when we augment MKT^{Bond} with our newly proposed credit and liquidity risk factors (CRF and LRF), the average adjusted R^2 further increases from 18% to 27%, suggesting that these new credit and liquidity risk factors of corporate bonds capture significant cross-sectional information about the portfolio returns that is not fully picked up by the aggregate bond market factor. Moreover, the average alpha of the 25 size/maturity-sorted portfolios reduces from 0.33% per month to 0.14% per month when we replace the existing four bond market factors (DEF, TERM, MOM^{Bond}, and LIQ^{Bond}) with our two new bond factors (CRF and LRF).

We also investigate the relative performance of our CRF and LRF factors with the existing credit and liquidity risk factors proposed by earlier studies. Fama and French (1993) introduce a bond factor to capture the credit risk component of corporate bond returns. In Model 2, we use the default factor (DEF) of Fama-French (1993) defined as the difference between the returns on aggregate corporate bond index and aggregate government bond index. We should note that the average return on the DEF factor is economically and statistically insignificant for the period 2002–2016, 0.03% per month with a t-statistic of 0.19, whereas the average return on the CRF factor is highly significant, both economically and statistically, 0.43% per month (t-stat. = 2.78). These results along with the increase in average R^2 moving from Model 2 (average R^2 = 18%) to Model 3 (average R^2 = 27%) indicate that the DEF factor used in the literature is constructed too coarsely and there is a scope for defining a better credit risk factor, CRF, as the difference between returns on low-rated and high-rated corporate bonds.

The literature has also shown the importance of a liquidity factor in corporate bond returns. Lin et al. (2011) propose a bond factor to capture the liquidity risk component of corporate bond returns. As detailed in Section 4.2, we construct a tradable, return-based liquidity factor following Lin, Wang, and Wu (2011) and find that LIQ^{Bond} has a mean of 0.13% per month (t-stat.= 2.45) over the period from July 2002 to December 2016, whereas the average return on our LRF factor has a higher premium of 0.52% per month with a t-statistic of 5.02. Again, these results along with the improvement in average R^2 moving from Model 2 to Model 3 suggest that there is an opportunity to propose a superior liquidity risk factor, LRF, as the difference between returns on illiquid and liquid corporate bonds.

We now investigate the incremental performance of the DRF in predicting the cross-sectional variation in corporate bond portfolios. Compared to the remarkable results in Panel C obtained from Model 3, the average R^2 from Model 4 is even stronger. As shown in Panel D of Table 8, when we augment Model 3 with our newly proposed DRF, the average adjusted R^2 substantially increases from 27% to 56%, suggesting that the DRF captures significant incremental information about the cross-sectional variation in bond portfolio returns. However, Panel E of Table 8 shows that when we augment Model 4 with the bond REV, the average adjusted R^2 increases only by 1% (from 56% to 57%).[34] Overall, the results in Table 8 indicate that the newly proposed four-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.

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 through 5. Panel A of Table 8 shows that the five-factor model with the stock market factors (Model 1) generates economically significant alpha for all 25 portfolios, ranging from 0.14% to 0.58% per month. Consistent with the economic significance, the alphas are statistically significant for all 25 portfolios. As shown in the last row of Panel A in Table 8, the average alpha across the 25 portfolios is very large, 0.42% per month, and highly significant with a p-value less than 0.01 according to the Gibbons et al. (1989, GRS) test. Panel B of Table 8 shows that the magnitude and statistical significance of the alphas decrease when moving from Model 1 to Model 2. However, the five-factor model with the existing bond market factors (Model 2) still generates economically and statistically significant alphas, ranging from 0.12% to 0.51% per month, for 23 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

[34] This result is consistent with the factor spanning test results in Table A.5 that the REV factor is closely related to the LRF and in line with the illiquidity-based explanation of the short-term reversal effect, proposed by Bali, Subrahmanyam, and Wen (2017).

Table 8
Explanatory power of alternative factor models for 25-size/maturity-sorted bond portfolios.

The table reports the intercepts (alphas), the t-statistics, and the adjusted R^2 values for the time-series regressions of the test portfolios' excess returns on alternative factors. The 25 value-weighted test portfolios are formed by independently sorting corporate bonds into 5×5 quintile portfolios based on size (amount outstanding) and maturity and then constructed from the intersections of the size and maturity quintiles. Five alternative factor models are considered. Model 1 is the five-factor model with stock market factors, including the excess stock market return (MKT^{Stock}), the size factor (SMB), the book-to-market factor (HML), the stock momentum factor (MOM^{Stock}), and the stock liquidity factor (LIQ^{Stock}). Model 2 is the five-factor model with bond market factors: the excess bond market return (MKT^{Bond}), the default spread factor (DEF), the term spread factor (TERM), the bond momentum factor (MOM^{Bond}), and the bond liquidity factor (LIQ^{Bond}). Model 3 is the three-factor model with the excess bond market return (MKT^{Bond}), credit risk factor (CRF), and liquidity risk factor (LRF). Model 4 is the four-factor model with the excess bond market return (MKT^{Bond}), the downside risk factor (DRF), the credit risk factor (CRF), and the liquidity risk factor (LRF). Model 5 is the five-factor model with the excess bond market return (MKT^{Bond}), the downside risk factor (DRF), the credit risk factor (CRF), the liquidity risk factor (LRF), and the return reversal factor (REV). The sample covers the period from July 2004 to December 2016.

Panel A: Model 1

	Alpha (α)						t-statistics						Adj. R^2				
	Short	2	3	4	Long		Short	2	3	4	Long		Short	2	3	4	Long
Small	0.38	0.53	0.58	0.42	0.55	Small	3.44	3.74	3.49	2.63	3.26	Small	0.10	0.09	0.07	0.07	0.09
2	0.31	0.47	0.51	0.52	0.51	2	4.06	4.06	3.60	2.60	3.13	2	0.10	0.10	0.05	0.05	0.07
3	0.24	0.38	0.41	0.43	0.53	3	4.18	4.16	3.25	3.18	3.04	3	0.17	0.13	0.10	0.05	0.01
4	0.23	0.31	0.41	0.37	0.50	4	3.71	3.50	3.15	2.57	2.50	4	0.13	0.08	0.07	0.04	0.02
Big	0.14	0.31	0.40	0.41	0.52	Big	2.30	3.14	2.91	2.70	2.35	Big	0.05	0.04	0.05	0.03	0.02
Average $\|\alpha\|$	**0.42**											Average R^2	**0.07**				
p-GRS	<0.01																

Panel B: Model 2

	Short	2	3	4	Long		Short	2	3	4	Long		Short	2	3	4	Long
Small	0.35	0.48	0.51	0.40	0.49	Small	3.07	3.33	3.03	2.50	2.83	Small	0.13	0.15	0.13	0.15	0.12
2	0.28	0.39	0.42	0.45	0.40	2	3.52	3.38	3.03	2.21	2.39	2	0.17	0.19	0.19	0.07	0.12
3	0.20	0.29	0.27	0.30	0.38	3	3.57	3.32	2.40	2.41	2.24	3	0.30	0.28	0.33	0.24	0.17
4	0.18	0.24	0.28	0.24	0.37	4	3.17	2.98	2.35	1.77	1.86	4	0.30	0.30	0.29	0.20	0.14
Big	0.12	0.28	0.31	0.32	0.39	Big	2.00	2.87	2.27	2.12	1.74	Big	0.13	0.14	0.14	0.11	0.10
Average $\|\alpha\|$	**0.33**											Average R^2	**0.18**				
p-GRS	<0.01																

Panel C: Model 3

	Short	2	3	4	Long		Short	2	3	4	Long		Short	2	3	4	Long
Small	0.15	0.22	0.25	0.14	0.20	Small	1.45	1.65	1.58	0.88	1.21	Small	0.29	0.29	0.22	0.17	0.20
2	0.13	0.17	0.20	0.16	0.18	2	1.90	1.77	1.69	0.82	1.13	2	0.29	0.29	0.22	0.17	0.20
3	0.07	0.12	0.06	0.14	0.24	3	1.38	1.55	0.64	1.11	1.45	3	0.48	0.47	0.50	0.27	0.18
4	0.04	0.08	0.08	0.08	0.18	4	0.79	1.02	0.71	0.56	0.92	4	0.45	0.40	0.41	0.21	0.13
Big	0.02	0.12	0.12	0.17	0.20	Big	0.39	1.29	0.89	1.07	0.87	Big	0.20	0.17	0.21	0.07	0.07
Average $\|\alpha\|$	**0.14**											Average R^2	**0.27**				
p-GRS	0.03																

(*continued on next page*)

Table 8 (*continued*)

Panel D: Model 4																	
	Alpha (α)						t-statistics						Adj. R^2				
	Short	2	3	4	Long		Short	2	3	4	Long		Short	2	3	4	Long
Small	0.02	0.04	0.03	−0.08	−0.02	Small	0.23	0.47	0.28	−0.71	−0.17	Small	0.63	0.64	0.66	0.62	0.61
2	0.05	0.06	0.06	−0.08	−0.03	2	0.88	0.79	0.67	−0.57	−0.21	2	0.65	0.65	0.64	0.56	0.56
3	0.01	0.04	−0.05	0.01	0.06	3	0.37	0.59	−0.57	0.12	0.44	3	0.65	0.64	0.68	0.48	0.46
4	−0.01	0.00	−0.04	−0.06	−0.04	4	−0.32	0.05	−0.45	−0.49	−0.22	4	0.62	0.56	0.61	0.43	0.43
Big	−0.05	0.01	−0.05	−0.02	−0.08	Big	−1.12	0.15	−0.51	−0.15	−0.43	Big	0.55	0.50	0.58	0.45	0.46
Average $\lvert\alpha\rvert$	**0.04**											Average R^2	**0.56**				
p-GRS	0.06																
Panel E: Model 5																	
	Short	2	3	4	Long		Short	2	3	4	Long		Short	2	3	4	Long
Small	0.02	0.05	0.04	−0.06	−0.01	Small	0.26	0.49	0.37	−0.55	−0.05	Small	0.62	0.64	0.66	0.62	0.61
2	0.05	0.06	0.06	−0.07	0.00	2	0.94	0.83	0.68	−0.49	−0.04	2	0.65	0.65	0.64	0.56	0.57
3	0.02	0.04	−0.04	0.02	0.07	3	0.44	0.63	−0.52	0.16	0.50	3	0.65	0.64	0.67	0.48	0.45
4	−0.01	0.01	−0.03	−0.05	−0.02	4	−0.20	0.12	−0.33	−0.42	−0.10	4	0.62	0.56	0.61	0.42	0.43
Big	−0.04	0.02	−0.03	0.01	−0.04	Big	−0.94	0.29	−0.31	0.07	−0.24	Big	0.57	0.50	0.59	0.47	0.48
Average $\lvert\alpha\rvert$	**0.03**											Average R^2	**0.57**				
p-GRS	0.06																

portfolios is large, 0.33% per month, and highly significant according to the GRS test.

Panel D of Table 8 presents substantially different results compared to Panels A and B. The newly proposed four-factor model with DRF, CRF, and LRF (Model 4) generates economically and statistically insignificant alphas for all 25 portfolios. As shown in the last row of Panel D, the average alpha across the 25 portfolios is very low, economically insignificant at 0.04% per month (p-value = 0.06), and it is not statistically significant at the 5% level.[35]

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. Thus, the 4-factor model with DRF, CRF, and LRF factors provides a more accurate characterization of the abnormal returns on portfolios of corporate bonds, which has important practical implications. For example, a typical bond portfolio manager using a traditional factor model (such as Model 1 or 2) thinks that he or she outperforms the standard benchmark with economically large alphas. However, the results in Panel D of Table 8 indicate that these significantly large abnormal returns generated by the existing factor models are in fact compensation for downside, credit, and liquidity risks. Therefore, institutional investors in the corporate bond market should account for bond exposure to the DRF, CRF, and LRF factors to accurately determine the risk-adjusted performance of their bond portfolios.

We also test the relative performance of the factor models using the 30-industry portfolios based on the Fama-French (1997) industry classification. Table 9 shows that the adjusted R^2, averaged across the 30-industry portfolios, is 13% for Model 1, 18% for Model 2, 31% for Model 3, and 37% for Model 4. These results show that the newly proposed four-factor model performs better than the existing stock and bond market factors in explaining the returns of the industry-sorted portfolios of corporate bonds.

We then focus on the magnitude and statistical significance of the alphas for the 30-industry portfolios. As shown in Table 9, Model 1 generates economically significant alphas for 25 out of the 30 portfolios, ranging from 0.28% to 1.33% per month. Consistent with their economic significance, the alphas are also statistically significant for 24 out of 30 portfolios. As shown in the last row of Table 9, the average alpha across the 30 portfolios is very large, 0.55% per month, and highly significant. The results from Model 2 are somewhat better. As shown in Table 9, Model 2 generates economically significant alphas for most of the 30 industry portfolios, ranging from 0.19% to 1.08% per month. As shown in the last row of Table 9, the average alpha across the 30 portfolios is economically large, 0.41% per month, and highly significant.

Similar to our findings from the 25-size/maturity portfolios, Table 9 presents considerably different results from the new four-factor model for the 30-industry portfolios.

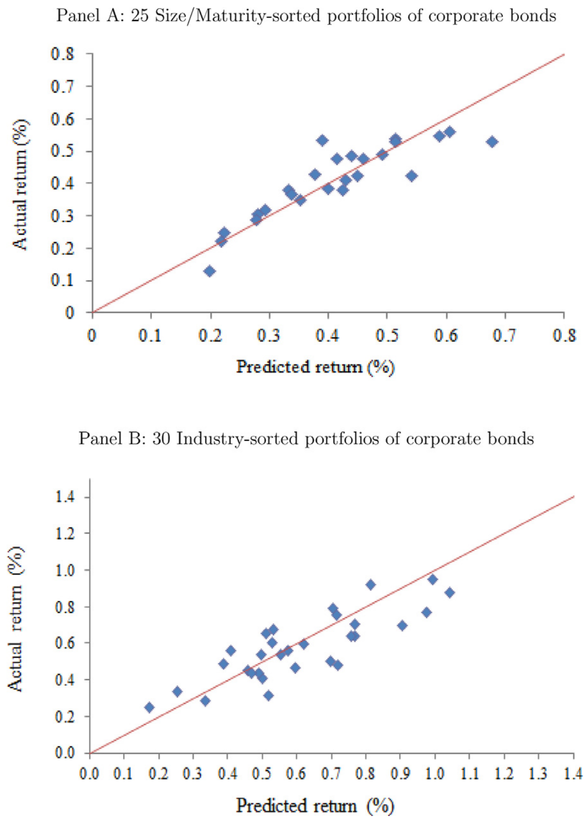

Fig. 2. Average performance of the four-factor model with DRF, CRF, and LRF. The figure plots the monthly mean excess return versus the predicted excess return in percent for the four-factor model with MKT^{Bond}, DRF, CRF, and LRF factors. Test assets are the value-weighted 25 size/maturity-sorted portfolios of corporate bonds in the top panel and the 30 industry-sorted portfolios of corporate bonds in the bottom panel. The sample covers the period from July 2004 to December 2016.

Model 4 with DRF, CRF, and LRF generates statistically insignificant alphas (at the 10% level) for all 30 portfolios, with only one economically significant alpha for one of the 30-industry portfolios. As shown in the last row of Model 4, the average alpha across the 30 portfolios is very low and economically insignificant, at 0.14% per month.[36] 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.[37]

Finally, Fig. 2 plots the monthly mean excess return (i.e., actual return) versus the predicted excess return for the four-factor with MKT^{Bond}, DRF, CRF, and LRF. The test assets are the 25-size/maturity- and 30-industry-sorted portfolios of corporate bonds. Consistent with our earlier findings,

[35] Panel E of Table 8 shows that when we augment Model 4 with the bond REV, the average alpha reduces only by one basis point per month, indicating low incremental contribution of the REV factor to portfolio return predictability over the four-factor model with the DRF, CRF, and LRF factors.

[36] Note that the average alpha is only 14 basis points (bps) per month but is statistically significant with a p-value of 0.03 according to the GRS test.

[37] Tables A.6 and A.7 of the online Internet Appendix report the explanatory power of the 2×3 and $2 \times 2 \times 2 \times 2$ factors for the 25 size/maturity- and 30 industry-sorted bond portfolios, respectively. The results from the 2×3 and $2 \times 2 \times 2 \times 2$ factors are similar to those obtained from the 5×5 factors presented in Tables 8 and 9.

Table 9
Explanatory power of alternative factor models for 30 industry-sorted bond portfolios.

The table reports the intercepts (alphas), the *t*-statistics, and the adjusted R^2 values for the time-series regressions of the test portfolios' excess returns on alternative factors. The value-weighted industry portfolios are formed by sorting corporate bonds into 30 portfolios based on the Fama-French (1997) industry classifications. Five alternative factor models are defined in Table 8.

Industry #	Industry description	Model 1			Model 2			Model 3			Model 4			Model 5		
		Alpha (α)	$t(\alpha)$	R^2	Alpha (α)	$t(\alpha)$	R^2	Alpha (α)	$t(\alpha)$	R^2	(α)	$t(\alpha)$	R^2	(α)	$t(\alpha)$	R^2
1	Food	0.37	3.33	0.10	0.25	2.42	0.23	0.10	0.94	0.25	0.08	0.79	0.27	0.16	1.51	0.30
2	Beer	0.28	3.19	0.05	0.22	2.59	0.14	0.14	1.69	0.18	0.11	1.43	0.30	0.14	1.66	0.30
3	Tobacco	0.43	2.40	0.08	0.39	2.11	0.03	0.21	1.12	0.10	0.14	0.83	0.21	0.24	1.33	0.23
4	Games	0.79	2.24	0.13	0.69	1.92	0.13	0.11	0.33	0.30	0.02	0.05	0.36	0.05	0.15	0.36
5	Books	0.55	1.86	0.38	0.44	1.40	0.32	−0.22	−0.77	0.46	−0.31	−1.17	0.52	−0.22	−0.79	0.53
6	Household	0.45	2.17	0.10	0.39	1.85	0.09	0.22	1.02	0.14	0.14	0.71	0.26	0.18	0.87	0.26
7	Clothes	0.68	2.24	0.26	0.40	1.43	0.37	−0.18	−0.60	0.36	−0.22	−0.78	0.38	0.00	0.01	0.41
8	Health	0.48	2.69	0.02	0.41	2.32	0.09	0.18	1.04	0.16	0.16	0.90	0.17	0.22	1.23	0.18
9	Chemicals	0.52	2.42	0.35	0.40	1.79	0.29	−0.08	−0.37	0.42	−0.17	−0.88	0.54	−0.05	−0.24	0.55
10	Textiles	0.66	1.59	0.03	0.48	1.13	0.04	0.19	0.44	0.05	0.13	0.31	0.07	0.27	0.61	0.07
11	Construction	0.70	3.17	0.17	0.56	2.75	0.31	0.18	0.97	0.47	0.14	0.78	0.50	0.19	0.99	0.49
12	Steel	0.75	2.72	0.18	0.77	2.60	0.09	0.21	0.81	0.32	0.12	0.48	0.42	0.24	0.95	0.43
13	Fabric	1.33	2.49	0.02	1.08	1.97	0.01	0.83	1.48	0.01	0.79	1.40	0.01	0.86	1.46	0.01
14	Electrical equipment	0.65	1.94	0.11	0.38	1.09	0.06	−0.02	−0.06	0.13	−0.05	−0.15	0.14	0.17	0.47	0.16
15	Automobiles	0.76	2.52	0.25	0.54	1.71	0.20	−0.17	−0.68	0.53	−0.24	−1.03	0.57	−0.11	−0.43	0.58
16	Transportation equipment	0.47	1.30	0.03	0.33	0.91	0.03	0.13	0.35	0.06	0.06	0.16	0.10	0.04	0.10	0.09
17	Mines	0.35	1.14	0.06	0.17	0.56	0.10	−0.25	−0.85	0.18	−0.30	−1.00	0.19	−0.08	−0.25	0.22
18	Coal	0.48	1.27	0.02	0.30	0.83	0.10	−0.11	−0.31	0.15	−0.23	−0.67	0.25	−0.12	−0.33	0.25
19	Oil	0.65	1.04	0.01	0.48	0.76	0.02	0.18	0.28	0.04	0.08	0.13	0.06	0.08	0.12	0.06
20	Utilities	0.28	2.42	0.07	0.19	1.95	0.33	0.04	0.37	0.31	−0.01	−0.08	0.46	0.05	0.57	0.47
21	Communication	0.37	2.43	0.13	0.21	1.49	0.30	−0.06	−0.49	0.49	−0.10	−0.90	0.56	−0.03	−0.25	0.57
22	Services	0.43	2.42	0.17	0.28	1.65	0.29	−0.13	−0.96	0.56	−0.17	−1.32	0.60	−0.07	−0.52	0.62
23	Business equipment	0.39	2.59	0.17	0.26	1.83	0.28	0.03	0.22	0.39	−0.02	−0.14	0.47	0.07	0.57	0.49
24	Paper	0.50	2.08	0.24	0.37	1.52	0.24	−0.12	−0.60	0.51	−0.19	−1.01	0.57	−0.06	−0.29	0.59
25	Transportation	0.54	3.40	0.13	0.44	3.10	0.34	0.14	1.11	0.47	0.10	0.80	0.55	0.17	1.35	0.56
26	Wholesale	0.46	2.59	0.12	0.30	1.86	0.28	0.07	0.47	0.43	0.03	0.20	0.48	0.11	0.72	0.49
27	Retail	0.54	2.36	0.12	0.37	1.64	0.17	0.02	0.09	0.34	−0.04	−0.19	0.39	0.02	0.12	0.39
28	Restaurant	0.40	1.55	0.14	0.28	1.09	0.16	−0.25	−1.14	0.43	−0.32	−1.52	0.49	−0.20	−0.92	0.50
29	Finance	0.43	3.30	0.08	0.36	2.85	0.15	0.03	0.30	0.53	−0.01	−0.08	0.61	−0.01	−0.06	0.60
30	Other	0.73	3.27	0.15	0.55	2.55	0.25	−0.05	−0.30	0.53	−0.07	−0.43	0.54	0.03	0.15	0.55
Average $\lvert\alpha\rvert$		**0.55**		**0.13**	**0.41**		**0.18**	**0.15**		**0.31**	**0.14**		**0.37**	**0.12**		**0.38**
p-GRS		$<$ 0.01			$<$ 0.01			0.03				0.03		0.03		

the scatter plots in Fig. 2 are most dense around the 45-degree line, indicating that the newly proposed four-factor model provides a good fit of the actual portfolio returns.

6. Robustness check

In this section, we conduct a battery of robustness checks, but we present and discuss these findings in the online Internet Appendix to save space. As discussed earlier, bond risk characteristics are correlated. To address a potential concern about what unique information each risk characteristic carries, in Section A.1, we construct orthogonalized risk characteristics by running contemporaneous cross-sectional regressions of one risk characteristic on the remaining three variables for each month in our sample.[38] Then, we repeat the Fama-MacBeth regressions in Table A.8 of the online Internet Appendix with the orthogonalized risk characteristics and find that with and without the control variables, the orthogonalized rating and orthogonalized market beta lose their significance, whereas the orthogonalized measures of downside risk and illiquidity remain highly significant in predicting the cross-sectional dispersion of bond returns.

Downside risk has so far been proxied by the 5% VaR. The results remain intact when we use two alternative measures of downside risk: the 10% VaR and the 10% ES that are described in Section A.2 of the online Internet Appendix. Table A.9 of the online Internet Appendix shows that the average returns and alphas on these alternative factors of downside risk, constructed based on the 10% VaR and 10% ES, are positive and highly significant.

We reexamine the properties of the LRF based on two alternative proxies of liquidity: the Roll (1984) and Amihud (2002) illiquidity measures that are described in Section A.3 of the online Internet Appendix. As presented in Table A.10 of the online Internet Appendix, the average returns and alphas on these alternative factors of liquidity risk turn out to be economically and statistically significant.

In Section A.4 of the online Internet Appendix, we provide evidence from alternative measures of credit risk: the distance to default (DD) and implied CDS. Table A.11 of the online Internet Appendix presents Fama-MacBeth regressions using DD and CDS to substitute for credit rating. The results from the firm-level measures of credit risk (DD, CDS) turn out to be similar to those obtained from the bond-level measure of credit risk (rating).

Our empirical analyses are so far based on the Enhanced TRACE transaction data from July 2002 to December 2016. To check whether our results are sensitive to different datasets, we use an extended sample of corporate bonds gathered from a range of data sources covering a longer time period from January 1977 to December 2016. Section A.5 of the online Internet Appendix describes the construction of this comprehensive dataset. As shown in Table A.12 of the online Internet Appendix, our main findings are robust to an extended sample of corporate bond data compiled from different sources including the quoted- and transaction-based bond data.

[38] Each one of these risk characteristics (VaR, Rating, ILLIQ, and β^{Bond}) is orthogonalized with respect to the remaining three variables by running separate contemporaneous cross-sectional regressions for each characteristic so that the results do not depend on the order of orthogonalization.

7. 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 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, and liquidity risk positively predict the cross-sectional variation in future bond returns. We then introduce novel risk factors based on these prevalent bond risk characteristics. We show that all new factors have economically and statistically significant risk premiums, which cannot be explained by the existing stock and bond market factors. We also find a strong short-term reversal effect in the cross-section of corporate bond returns and hence introduce a bond return reversal factor. However, a detailed investigation of the reversal factor indicates that one-month lagged return is a strong nonrisk bond characteristic instead of a common risk factor in the bond market.

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 the four-factor model with the bond market factor and our new factors (DRF, CRF, LRF) outperforms all models considered in the literature in explaining the returns of the industry/size/maturity-sorted portfolios of corporate bonds. The results also indicate that the significantly large abnormal returns (alphas) on corporate bond portfolios, generated by the existing factor models, are in fact compensation for downside, credit, and liquidity risks. Thus, institutional investors in the corporate bond market should account for bond exposure to the newly proposed DRF, CRF, and LRF factors to accurately estimate the risk-adjusted performance of bond portfolios.

References

Acharya, V., Amihud, Y., Bharath, S., 2013. Liquidity risk of corporate bond returns: conditional approach. J. Financ. Econ. 110, 358–386.

Allen, L., Bali, T.G., Tang, Y., 2012. Does systemic risk in the financial sector predict future economic downturns? Rev. Financ. Stud. 25, 3000–3036.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. J. Financ. Mark. 5, 31–56.

Ang, A., Chen, J., Xing, Y., 2006. Downside risk. Rev. Financ. Stud. 19, 1191–1239.

Artzner, P., Delbaen, F., Eber, J.-M., Heath, D., 1999. Coherent measures of risk. Math. Finance 9, 203–228.

Arzac, E.R., Bawa, V.S., 1977. Portfolio choice and equilibrium in capital markets with safety-first investors. J. Financ. Econ. 4, 277–288.

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

Bai, J., Wu, L., 2016. Anchoring credit spreads to firm fundamentals. J. Financ. Quant. Anal. 51, 1521–1543.

Bali, T.G., Demirtas, K.O., Levy, H., 2009. Is there an intertemporal relation between downside risk and expected returns? J. Financial and Quantitative Analysis 44, 883–909.
Bali, T. G., Subrahmanyam, A., Wen, Q., 2017. Return-based factors for corporate bonds. Unpublished working paper,Georgetown University and University of California at Los Angeles.
Bao, J., Pan, J., Wang, J., 2011. The illiquidity of corporate bonds. J. Finance 66, 911–946.
Baumol, W.J., 1963. An expected gain-confidence limit criterion for portfolio selection. Manag. Sci. 10, 174–182.
Bawa, V.S., Lindenberg, E.B., 1977. Capital market equilibrium in a mean-lower partial moment framework. J. Financ. Econ. 5, 189–200.
Bessembinder, H., Kahle, K.M., Maxwell, W.F., Xu, D., 2009. Measuring abnormal bond performance. Rev. Financ. Stud. 22, 4219–4258.
Bessembinder, H., Maxwell, W.F., Venkataraman, K., 2006. Market transparency, liquidity externalities, and institutional trading costs in corporate bonds. J. Financ. Econ. 82, 251–288.
Blume, M., Keim, D., Patel, S., 1991. Return and volatility of low-grade bonds 1977–1989. J. Finance 46, 49–74.
Brennan, M., Chordia, T., Subrahmanyam, A., 1998. Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. J. Financ. Econ. 49, 345–373.
Carhart, M.M., 1997. On persistence in mutual fund performance. J. Finance 52, 57–82.
Chen, L., Lesmond, D., Wei, J., 2007. Corporate yield spreads and bond liquidity. J. Finance 62, 119–149.
Choi, J., Kim, Y., 2018. Anomalies and market (dis)integration. J. Monetary Econ. forthcoming.
Choi, J., Kronlund, M., 2018. Reaching for yield by corporate bond mutual funds. Rev. Financ. Stud 31, 1930–1965.
Chordia, T., Goyal, A., Nozawa, Y., Subrahmanyam, A., Tong, Q., 2017. Are capital market anomalies common to equity and corporate bond markets? J. Financ. Quant. Anal. 52, 1301–1342.
Culp, C., Nozawa, Y., Veronesi, P., 2018. Option-based credit spreads. Am. Econ. Rev. 108, 454–488.
Daniel, K., Titman, S., 1997. Evidence on the characteristics of cross-sectional variation in stock returns. J. Finance 52, 1–33.
Dick-Nielsen, J., Feldhutter, P., Lando, D., 2012. Corporate bond liquidity before and after the onset of the subprime crisis. J. Financ. Econ. 103, 471–492.
Elton, E.J., Gruber, M.J., Blake, C., 1995. Fundamental economic variables, expected returns, and bond fund performance. J. Finance 50, 1229–1256.
Fama, E.F., French, K.R. , 1993. Common risk factors in the returns on stocks and bonds. J. Financ. Econ. 33, 3–56.
Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. J. Financ. Econ. 116, 1–22.
Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: empirical tests. J. Polit. Econ. 81, 607–636.
Feroli, M., Kashyap, A. K., Schoenholtz, K., Shin, H. S., 2014. Market tantrums and monetary policy. Unpublished working paper, New York University and University of Chicago.
Gebhardt, W.R., Hvidkjaer, S., Swaminathan, B., 2005. The cross-section of expected corporate bond returns: betas or characteristics? J. Financ. Econ. 75, 85–114.
Gibbons, M.R., Ross, S.A., Shanken, J., 1989. A test of the efficiency of a given portfolio. Econometrica 57, 1121–1152.
Hong, H., Sraer, D., 2013. Quiet bubbles. J. Financ. Econ. 110, 596–606.
Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies: an investment approach. Rev. Financ. Stud. 28, 650–705.
Huang, W., Liu, Q., Rhee, S.G., Wu, F., 2012. Extreme downside risk and expected stock returns. J. Bank. Finance 36, 1492–1502.
Jostova, G., Nikolova, S., Philipov, A., Stahel, C., 2013. Momentum in corporate bond returns. Rev. Financ. Stud. 26, 1649–1693.
Kwan, S.H., 1996. Firm-specific information and the correlation between individual stocks and bonds. J. Financ. Econ. 40, 63–80.
Lettau, M., Maggiori, M., Weber, M., 2014. Conditional risk premia in currency markets and other asset classes. J. Financ. Econ. 114, 197–225.
Levy, H., Sarnat, M., 1972. Safety first: an expected utility principle. J. Financ. Quant. Anal. 7, 1829–1834.
Lewellen, J., Nagel, S., Shanken, J., 2010. A skeptical appraisal of asset pricing tests. J. Financ. Econ. 96, 175–194.
Lin, H., Wang, J., Wu, C., 2011. Liquidity risk and the cross-section of expected corporate bond returns. J. Financ. Econ. 99, 628–650.
Longstaff, F.A., Mithal, S., Neis, E., 2005. Corporate yield spreads: default risk or liquidity? new evidence from the credit-default-swap market. J. Finance 60, 2213–2253.
Merton, R.C., 1974. On the pricing of corporate debt: the risk structure of interest rates. J. Finance 29, 449–470.
Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.
Pastor, L., Stambaugh, R.F., 2003. Liquidity risk and expected stock returns. J. Polit. Econ. 111, 642–685.
Roll, R., 1984. A simple implicit measure of the effective bid-ask spread in an efficient market. J. Finance 39, 1127–1139.
Roy, A.D., 1952. Safety first and the holding of assets. Econometrica 20, 431–449.