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

Online Appendix

Section A.1 discusses the results from orthogonalized risk characteristics. Section A.2 reports the results for the downside risk factor constructed from alternative measures of downside risk. Section A.3 shows the results for the liquidity risk factor constructed from alternative measures of bond illiquidity. Section A.4 presents the results for alternative measures of bond credit quality. Section A.5 provides the summary statistics of the risk factors constructed using the extended sample from January 1977 to December 2016.

Table A.1 reports the results from testing whether the time-series and cross-sectional returns of corporate bonds are normally distributed. Table A.2 reports the results from univariate portfolios of corporate bonds sorted by credit ratings, illiquidity, and β^{Bond}. Table A.3 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 A.4 reports the descriptive statistics for the newly constructed bond factors using independent 2×3 and $2 \times 2 \times 2 \times 2$ sorts. Table A.5 conducts factor spanning test and reports the intercept (α) and slope coefficients from time-series regressions of each of the four bond factor (DRF, CRF, LRF, or REV) on the other three factors. Table A.6 reports the explanatory power of the 2×3 and $2 \times 2 \times 2 \times 2$ factors for the 25-size/maturity-sorted bond portfolios. Table A.7 reports the explanatory power of the 2×3 and $2 \times 2 \times 2 \times 2$ factors for the 30-industry-sorted bond portfolios. Table A.8 shows the results from Fama-MacBeth cross-sectional regressions with the orthogonalized measures of VaR, rating, illiquidity, and the bond market beta. Table A.9 presents the results from downside risk factor constructed from alternative measures of downside risk. Table A.10 demonstrates the results from bond liquidity risk factor constructed from alternative measures of bond illiquidity. Table A.11 reports the results from Fama-MacBeth cross-sectional regressions with alternative measures of credit risk. Table A.12 presents the results from downside risk and credit risk factors obtained from a comprehensive dataset covering the extended sample period from January 1977 to December 2016.

A.1. Orthogonalized Risk Characteristics

As discussed earlier, bond risk characteristics are correlated. Bonds with higher downside risk also have lower credit quality and lower liquidity; bonds with higher market beta tend to have lower credit quality and higher downside risk. When putting them jointly in the Fama-MacBeth regressions (see specifications (9) and (10) in Table 4), downside risk and bond illiquidity dominate in predicting the cross-sectional bond returns, while credit rating and market beta lose their predictive power. All these results lead to a concern about what unique information each risk characteristic carries. To investigate this issue, we construct orthogonalized risk characteristics.

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

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

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

Then, we repeat the Fama-MacBeth regressions with orthogonalized risk characteristics and report the results in Table A.8 of the online appendix. In the univariate regressions, both with and without control variables, orthogonalized rating and orthogonalized market beta lose their significance, whereas the orthogonalized measures of downside risk and illiquidity remain highly significant in predicting the cross-sectional dispersion of bond returns. Compared to the original (unorthogonalized) estimates of the coefficients, orthogonalized downside risk has somewhat greater economic significance and statistical power. The multivariate regression results remain the same as those in the original setup of Table 4; that is, only the orthogonalized measures of downside risk and illiquidity have significant predictive power, whereas the orthogonalized measures of rating and market beta do not predict future bond returns. These results are robust to controlling for bond maturity, size, lagged return, and bond exposures to the default and term factors.

A.2. Alternative Measures of Downside Risk

Downside risk has so far been proxied by the 5% VaR. Our main results remain intact when we use two alternative measures of downside risk: the 10% VaR and the 10% Expected Shortfall (ES). The 10% VaR is defined as the fourth lowest monthly return observation over the past 36 months. The 10% expected shortfall (ES) is defined as the average of four lowest monthly return observations over the past 36 months (beyond the 10% VaR threshold). The original VaR and ES measures are multiplied by -1 for convenience of interpretation. Panel A of Table A.9 in the online appendix reports the summary statistics for the alternative downside risk factors, constructed based on the 10% VaR and 10% ES. The equal-weighted DRF factor constructed from the 10% VaR has an economically and statistically significant downside risk premium of 0.81% per month with a t-statistic of 3.10. The equal-weighted DRF factor constructed from the 10% ES also has a significant downside risk premium of 0.86% per month with a t-statistic of 3.08. The risk premia on the DRF factors remain qualitatively similar when they are generated based on the value-weighted portfolios: 0.68% per month (t-stat.$=$ 3.09) and 0.70% (t-stat.$=$ 2.99), respectively.

Panel B of Table A.9 shows the 10-factor alpha of the DRF factors based on the extended 10-factor model combining all of the stock and bond market factors. As shown in Panel B, all intercepts (alphas) are economically and statistically significant: the alphas for the equal-weighted DRF factors constructed from the 10% VaR and 10% ES are 0.68% per month (t-stat.$=$ 3.04) and 0.89% per month (t-stat.$=$ 3.14), respectively. For the value-weighted DRF factors, all intercepts are economically and statistically significant, and the magnitudes of the alphas are similar to those reported for the equal-weighted DRF factors.

A.3. Alternative Measures of Bond Illiquidity

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

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

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

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

$$\text{Ami} = \frac{1}{N}\sum_{d=1}^{N}\frac{|r_d|}{Q_d}, \tag{A.2}$$

where N is the number of positive-volume days in a given month, r_d the daily corporate bond return and Q_d the trading volume on day d. Table A.10 of presents the results for alternative liquidity risk factor from July 2002 to December 2016. Panel A of Table A.10 shows that the equal-weighted LRF factor constructed from the Roll's measure has an economically and statistically significant liquidity risk premium of 0.42% per month with a t-statistic of 2.93. The equal-weighted LRF factor constructed from the Amihud measure also has a significant liquidity risk premium of 0.49% per month with a t-statistic of 3.13. The risk premia on the LRF factors remain qualitatively similar when they are generated from the value-weighted portfolios: 0.35% per month (t-stat.= 3.45) and 0.47% (t-stat.= 4.40), respectively. Panel B of Table A.10 shows that all of the intercepts (alphas) are economically and statistically significant, implying that the extended 10-factor model does not explain the returns on the alternative LRF factors.

A.4. Alternative Measures of Bond Credit Quality

In addition to bond-level credit rating, we consider two alternative proxies of credit quality. One is the firm-level distance-to-default measure,[39] and the other is the firm-level raw credit default swap spread developed in Bai and Wu (2014). Both measures are based on the Merton (1974) model which assumes that the total asset value (A) of a company follows a geometric Brownian motion with instantaneous return volatility σ_A, the company has a zero-coupon debt with principal D and time-to-maturity T, and the firm's equity (E) is a European call option on the firm's asset value with maturity equal to the debt maturity and strike equal to the debt principal. The company defaults if its asset value is less than the debt principal at the debt maturity. These assumptions lead to the following two equations that link the firm's equity value E and equity return volatility σ_E to its asset value A and asset return volatility σ_A.

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

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

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

with r denoting the instantaneous risk-free rate.

To compute a firm's distance to default, we follow the procedure in Bai and Wu (2014). We take the company's end-of-month market capitalization as its equity value E, the company's total debt as a proxy for the principal of the zero-coupon bond D, and the one-year realized stock return volatility as an estimator for stock return volatility σ_E. We further assume zero interest rates ($r = 0$) and fix the debt maturity at $T = 10$ years for all firms. Since our focus is on the cross-sectional differences across firms, choosing any particular interest rate level for

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

r or simply setting it to zero generates negligible impacts on the cross-sectional sorting. Bai and Wu (2014) discuss the impact of the maturity choice on the model's performance, and suggest that the relative longer maturity choice $T > 5$ improves the performance in capturing the cross-sectional variation of the credit spreads.

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

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

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

Table A.11 presents the Fama-MacBeth regression results using DD and CDS to substitute for credit rating. The average slope from the univariate cross-sectional regressions of excess bond returns on DD (CDS) is negative (positive) and significant, indicating that higher credit risk is associated with higher future bond returns. However, the multivariate regressions in Table A.11 show that with all bond risk proxies (VaR, rating, ILLIQ, and β^{bond}) and bond characteristics (maturity, size), DD and CDS lose their predictive power, while the slope coefficients on VaR and ILLIQ remain positive and significant. These results are consistent with those reported in Table 4, where credit risk is proxied by rating.

A.5. New Risk Factors from Extended Sample: January 1977 to December 2016

Beyond the transaction-based data on corporate bonds from July 2002 to December 2016, we also consider an extended sample of bond data from January 1973 to December 2016. Using a longer sample of bond returns, we are able to construct an extended sample of downside risk factor (DRF) and credit risk factor (CRF). The extended sample is complied from six sources: Lehman Brothers fixed income database (Lehman), Datastream, National Association of Insurance Commissioners database (NAIC), Bloomberg, the enhanced version of the Trade Reporting and Compliance Engine (TRACE), and Mergent fixed income securities database (FISD). These datasets together generate the most complete corporate bond data in both the academia and the industry.

Beyond the TRACE data, the Lehman data cover the period from January 1973 to March 1998; the Datastream reports corporate bond information from January 1990 to June 2016; NAIC reports the transaction information by insurance companies during January 1994 to December 2016; Bloomberg provides daily bond prices during January 1997 to December 2016; The two datasets, NAIC and TRACE, provide prices based on the real transactions, whereas other datasets, Lehman, Datastream, and Bloomberg, provide prices based on quotes and matrix calculations. We adopt the following principle to handle the overlapping observations among different datasets. If two or more datasets have overlapping observations at any point in time, we give priority to the dataset that reports the transaction-based bond prices. For example, TRACE will dominate other datasets from July 2002 to December 2016. If there are no transaction data or the coverage of the data is too small, we give priority to the dataset that has a relatively larger coverage on bonds/firms, and can be better matched to the bond characteristic data, FISD. For example, Bloomberg daily quotes data are preferred to those of Datastream for the period 1998 to 2002 for its larger coverage and higher percentage of matching rate to FISD. We adopt the same data filtering criteria as in Section 3 for non-TRACE datasets.

Finally, we filter out a few months at the beginning of the sample period during which there are insufficient number of bonds in the sequentially sorted portfolios to construct the risk factors. Our final extended sample of the corporate bond risk factors, DRF and CRF, start from January 1977 to December 2016.

With this longer sample, we replicate our main analysis, except those requiring an illiquidity measure. Panel A of Table A.12 shows that the equal-weighted DRF factors have economically and statistically significant downside risk premia, ranging from 0.34% to 0.39% per month. The CRF factor also has a significant credit risk premium of 0.29% per month with a t-statistic of 4.37. The risk premia on the DRF and CRF factors remain qualitatively similar when they are generated from the value-weighted portfolios. Panel B of Table A.12 shows that all of the intercepts (alphas) from the extended 9-factor models are economically and statistically significant, in the range of 0.30% per month (t-stat.= 4.14) and 0.34% per month (t-stat.= 5.14) for the equal-weighted DRF factors. The last row in Panel B shows that the extended 9-factor model does not explain the returns of the CRF factor either. Panel B of Table A.12 also shows similar results for the value-weighted bond risk factors.

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

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Table A.1: Normality test for corporate bond returns

Panel A reports the total number of bonds and the percentage of bonds with significant and insignificant return moments, for the time-series distribution of all corporate bond returns. For each bond in our sample from July 2004 to December 2016, we compute the volatility, skewness, and excess kurtosis of monthly returns, and then test whether these high-order moments are significantly different from zero. Panel B reports the total number of months and the number of months with significant and insignificant return moments for the cross-sectional distribution of monthly corporate bond returns. For each month from July 2004 to December 2016, we compute the return moments including volatility, skewness, and kurtosis using the cross-section of bond returns, and test whether these distributional moments are significantly different from zero. Table also reports the Jarque-Bera (JB) statistics for the normality test of the distribution of corporate bond returns. The median p-value is reported to test the statistical significance of the return moments and the significance of the JB statistics.

Panel A: Time-series distribution of all corporate bond returns

		Skewness		Kurtosis		Normality
	Volatility	Positive	Negative	Positive	Negative	JB-stat
Total # of bonds	38,957	19,548	19,409	26,493	12,464	38,957
% of bonds significant	84.57%	48.02%	99.45%	67.65%	52.60%	79.91%
Median p-value	0.00	0.00	0.00	0.00	0.00	0.00
% of bonds insignificant	15.43%	51.98%	0.55%	32.35%	47.40%	20.09%

Panel B: Cross-sectional distribution of monthly corporate bond returns

		Skewness		Kurtosis		Normality
	Volatility	Positive	Negative	Positive	Negative	JB-stat
Total # of months	150	118	32	150	0	150
# of months significant	150	118	32	150	0	150
Median p-value	0.00	0.00	0.00	0.00	0.00	0.00
# of months insignificant	0	0	0	0	0	0

Table A.2: Univariate portfolios of corporate bonds sorted by credit rating, illiquidity, and bond market beta

Quintile portfolios are formed every month from July 2002 to December 2016 by sorting corporate bonds based on their credit rating (Panel A), illiquidity (Panel B), or bond market beta (Panel C). The portfolios are value-weighted using amount outstanding as weights. Ratings are in conventional numerical scores, where 1 refers to an AAA rating and 21 refers to a C rating. Higher numerical score means lower ratings (i.e., higher credit risk). 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 (in excess of one-month Tbill rate). 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. Table reports the next-month average excess return and the 10-factor alpha for each quintile. The 10-factor model combines 5 stock market factors and 5 bond market factors as defined in Table 2. 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.

Panel A: Univariate sort by credit rating

	Rating	Average return	10-factor alpha
Low Credit Risk	3.39	0.37	-0.02
		(1.65)	(-0.73)
2	5.82	0.38	0.06
		(2.12)	(1.00)
3	7.65	0.45	0.05
		(3.31)	(1.47)
4	9.92	0.50	-0.01
		(3.09)	(-0.11)
High Credit Risk	15.14	1.00	0.43
		(4.27)	(4.22)
High − Low	11.75***	0.73***	0.45***
Return/Alpha diff.	(27.17)	(3.41)	(3.84)

Panel B: Univariate sort by illiquidity

	ILLIQ	Average return	10-factor alpha
Low ILLIQ	-0.19	0.53	0.18
		(3.81)	(2.99)
2	0.12	0.39	0.03
		(3.42)	(1.03)
3	0.48	0.52	0.09
		(3.34)	(2.78)
4	1.54	0.69	0.22
		(3.23)	(3.03)
High ILLIQ	8.41	1.14	0.88
		(3.67)	(3.39)
High − Low	8.59***	0.61***	0.69***
Return/Alpha diff.	(8.30)	(3.41)	(3.20)

Panel C: Univariate sort by β^{Bond}

	β^{Bond}	Average return	10-factor alpha
Low β^{Bond}	-0.15	0.30	0.09
		(1.24)	(1.24)
2	0.55	0.33	0.03
		(1.38)	(0.37)
3	0.84	0.42	-0.01
		(2.62)	(-0.06)
4	1.22	0.59	0.08
		(2.92)	(1.12)
High β^{Bond}	2.25	1.03	0.34
		(3.39)	(2.14)
High − Low	2.40***	0.73***	0.42**
Return/Alpha diff.	(20.32)	(2.91)	(2.14)

Table A.3: Average monthly excess returns for portfolios sorted on *Rating* and VaR, *Rating* and $ILLIQ$, *Rating* and REV

Corporate bonds are sorted independently into 5×5 quintiles every month from July 2004 to December 2016 based on credit rating and 5% Value-at-Risk (VaR). The intersections of the two sorts produce 25 value-weighted *Rating*-VaR portfolios in Panel A. Corporate bonds are sorted independently into 5×5 quintiles every month from July 2002 to December 2016 based on credit rating and illiquidity (ILLIQ). The intersections of the two sorts produce 25 value-weighted *Rating*-$ILLIQ$ portfolios in Panel B. Corporate bonds are sorted independently into 5×5 quintiles every month from July 2002 to December 2016 based on credit rating and previous month return (REV). The intersections of the two sorts produce 25 value-weighted *Rating*-REV portfolios in Panel C. The table reports averages of monthly excess returns of the 25 portfolios.

Panel A: Independently sorted 5×5 quintile portfolios of Rating and VaR

	Low VaR	2	3	4	High VaR
Low credit risk	0.17	0.29	0.35	0.45	0.90
2	0.19	0.30	0.38	0.53	1.02
3	0.22	0.35	0.41	0.60	0.84
4	0.23	0.32	0.36	0.53	0.76
High credit risk	0.34	0.39	0.48	0.54	1.15

Panel B: Independently sorted 5×5 quintile portfolios of Rating and ILLIQ

	Low ILLIQ	2	3	4	High ILLIQ
Low credit risk	0.22	0.27	0.35	0.32	0.57
2	0.35	0.29	0.37	0.43	0.68
3	0.45	0.35	0.42	0.46	0.82
4	0.47	0.40	0.47	0.58	0.79
High credit risk	1.22	0.63	0.85	1.14	2.52

Panel C: Independently sorted 5×5 quintile portfolios of Rating and REV

	Low REV	2	3	4	High REV
Low credit risk	0.44	0.33	0.27	0.22	-0.13
2	0.58	0.35	0.30	0.29	0.10
3	0.54	0.44	0.39	0.36	0.22
4	0.65	0.56	0.43	0.46	0.42
High credit risk	1.12	1.10	0.81	0.72	0.57

Table A.4: Summary Statistics for 2×3 and $2 \times 2 \times 2 \times 2$ Corporate Bond Factors

Panel A reports the descriptive statistics for the newly constructed bond factors using independent 2×3 or $2 \times 2 \times 2 \times 2$ sorts. In the 2×3 sorts, downside risk factor (DRF) is constructed by independently sorting corporate bonds into 2×3 portfolios based on the 5% Value-at-Risk (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 2×3 portfolios based on illiquidity (ILLIQ) 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 2×3 portfolios 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 $CRF = 1/3(CRF_{VaR} + CRF_{ILLIQ} + CRF_{REV})$. In the $2 \times 2 \times 2 \times 2$ sorts, corporate bonds are independently sorted into two groups based on credit rating, two groups based on the 5% VaR, two groups based on illiquidity, and two groups based on previous month return. DRF is the value-weighted average return on the eight portfolios of high VaR minus the average return on the eight portfolios of low VaR. LRF is the value-weighted average return on the eight portfolios of high ILLIQ minus the average return on the eight portfolios of low ILLIQ. REV is the value-weighted average return on the eight portfolios of short-term loser minus the average return on the eight portfolios of short-term winner. CRF is the value-weighted average return on the eight portfolios of high credit risk minus the eight portfolios of low credit risk. Panel B shows the correlations of the same factors from different sorts. The bond factors cover the period from July 2004 to December 2016.

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

	2×3			2×2×2×2	
	Mean	t-stat		Mean	t-stat
DRF	0.67	3.43	DRF	0.51	3.59
CRF	0.53	2.53	CRF	0.32	2.76
LRF	0.47	4.93	LRF	0.45	5.14
REV	0.30	3.71	REV	0.36	6.50

Panel B: Correlations between different versions of the same factors

	DRF				CRF		
	5×5	2×3	2×2×2×2		5×5	2×3	2×2×2×2
5×5	1	0.96	0.92	5×5	1	0.97	0.91
2×3		1	0.97	2×3		1	0.93
2×2×2×2			1	2×2×2×2			1

	LRF				REV		
	5×5	2×3	2×2×2×2		5×5	2×3	2×2×2×2
5×5	1	0.96	0.94	5×5	1	0.57	0.51
2×3		1	0.98	2×3		1	0.89
2×2×2×2			1	2×2×2×2			1

Table A.5: Spanning Test on the Bond Factors

This table reports the intercept (α) and slope coefficients from time-series regressions of each of the four bond factor on the other three factors. The bond factors include the value-weighted downside risk factor (DRF), credit risk factor (CRF), liquidity risk factor (LRF), and return reversal factor (REV). Newey-West adjusted t-statistics are given in parentheses. Numbers in bold denote statistical significance at the 5% level or below. DRF and CRF cover the period from July 2004 to December 2016. LRF and REV cover the period from August 2002 to December 2016.

Panel A: Dep.var = DRF

Intercept	CRF	LRF	REV	Adj. R^2 (%)
0.47	**0.54**			17.30
(2.52)	(2.62)			
0.44		**0.53**		9.52
(2.36)		(3.89)		
0.66			0.13	2.98
(2.68)			(0.53)	
0.37	**0.44**	**0.41**	-0.17	20.14
(2.12)	(2.49)	(3.39)	(-0.82)	

Panel B: Dep.var = CRF

Intercept	DRF	LRF	REV	Adj. R^2 (%)
0.19	**0.33**			17.30
(1.38)	(5.33)			
0.20		**0.47**		11.80
(1.15)		(5.14)		
0.38			0.16	0.56
(1.61)			(1.40)	
0.09	**0.27**	**0.35**	-0.07	21.71
(0.61)	(4.41)	(3.68)	(-0.60)	

Panel C: Dep.var = LRF

Intercept	DRF	CRF	REV	Adj. R^2 (%)
0.36	**0.19**			9.52
(2.81)	(2.19)			
0.38		**0.27**		11.80
(2.78)		(2.67)		
0.32			**0.49**	22.95
(2.47)			(3.58)	
0.18	**0.12**	**0.17**	**0.51**	35.95
(2.39)	(2.18)	(2.49)	(3.56)	

Panel D: Dep.var = REV

Intercept	DRF	CRF	LRF	Adj. R^2 (%)
0.26	-0.05			0.56
(2.91)	(-0.90)			
0.24		-0.03		0.05
(2.81)		(-0.98)		
0.28			**0.05**	20.04
(3.18)			(2.60)	
0.24	-0.06	-0.02	**0.09**	22.07
(3.35)	(-1.79)	(-0.82)	(2.14)	

Table A.6: Explanatory Power of 2×3 and 2×2×2×2 Factors 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 by 5 quintile portfolios based on size (amount outstanding) and maturity and then constructed from the intersections of the size and maturity quintiles. The baseline factor model is the 4-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). In Panel A, DRF, CRF, and LRF are constructed base on the independent 2×3 sorts. In Panel B, DRF, CRF, and LRF are constructed base on the independent 2×2×2×2 sorts. The sample covers the period from July 2004 to December 2016.

Panel A: 2×3 factors

	Alpha (α)						t-statistics						Adj. R^2				
	Short	2	3	4	Long		Short	2	3	4	Long		Short	2	3	4	Long
Small	0.05	0.10	0.09	-0.03	0.04	Small	0.70	1.04	0.84	-0.25	0.34	Small	0.58	0.59	0.61	0.60	0.59
2	0.08	0.11	0.11	0.00	0.03	2	1.43	1.38	1.17	-0.02	0.27	2	0.57	0.59	0.59	0.49	0.52
3	0.03	0.07	-0.01	0.06	0.11	3	0.87	1.11	-0.08	0.54	0.82	3	0.52	0.51	0.54	0.45	0.32
4	0.01	0.03	0.00	-0.01	0.03	4	0.17	0.46	-0.02	-0.12	0.19	4	0.49	0.52	0.48	0.40	0.40
Big	-0.03	0.04	-0.01	0.03	0.00	Big	-0.69	0.59	-0.06	0.26	0.01	Big	0.52	0.48	0.47	0.44	0.44
Average $\|\alpha\|$	**0.04**											Average R^2	**0.51**				
p-GRS	0.06																

Panel B: 2×2×2×2 factors

	Short	2	3	4	Long		Short	2	3	4	Long		Short	2	3	4	Long
Small	0.07	0.11	0.12	0.02	0.08	Small	0.85	1.19	1.16	0.18	0.71	Small	0.52	0.53	0.56	0.57	0.55
2	0.07	0.09	0.10	0.01	0.09	2	1.33	1.15	1.02	0.07	0.78	2	0.51	0.54	0.53	0.44	0.49
3	0.02	0.06	-0.01	0.08	0.18	3	0.66	0.95	-0.18	0.79	1.31	3	0.59	0.57	0.58	0.42	0.38
4	0.00	0.03	0.00	0.02	0.12	4	0.00	0.48	-0.01	0.19	0.74	4	0.56	0.50	0.54	0.38	0.37
Big	-0.02	0.07	0.03	0.10	0.11	Big	-0.57	0.90	0.29	0.87	0.66	Big	0.51	0.45	0.51	0.43	0.42
Average $\|\alpha\|$	**0.06**											Average R^2	**0.50**				
p-GRS	0.06																

Table A.7: Explanatory Power of 2×3 and 2×2×2×2 Factors 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. The baseline factor model is the 4-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). In Panel A, DRF, CRF, and LRF are constructed base on the independent 2×3 sorts. In Panel B, DRF, CRF, and LRF are constructed base on the independent 2×2×2×2 sorts. The sample covers the period from July 2004 to December 2016.

		Panel A: 2×3 factors			Panel B: 2×2×2×2 factors		
Industry #	Industry description	Alpha (α)	$t(\alpha)$	R^2	Alpha (α)	$t(\alpha)$	R^2
1	Food	0.08	0.79	0.27	0.06	0.64	0.28
2	Beer	0.10	1.28	0.23	0.14	1.73	0.24
3	Smoke	0.04	0.22	0.25	0.07	0.42	0.22
4	Games	-0.01	-0.02	0.39	-0.09	-0.31	0.36
5	Books	-0.39	-1.53	0.49	-0.51	-2.08	0.50
6	Household	0.17	0.85	0.21	0.15	0.75	0.21
7	Clothese	-0.35	-1.36	0.43	-0.43	-1.68	0.42
8	Health	0.15	0.87	0.18	0.11	0.67	0.19
9	Chemicals	-0.16	-0.86	0.48	-0.20	-1.12	0.49
10	Textiles	0.12	0.28	0.09	0.09	0.22	0.08
11	Construction	0.14	0.80	0.45	0.05	0.30	0.44
12	Steel	0.24	1.00	0.37	0.18	0.76	0.39
13	Fabric	0.82	1.46	0.02	0.86	1.52	0.02
14	Electrical Equipment	-0.08	-0.23	0.16	-0.10	-0.30	0.15
15	Autos	-0.11	-0.52	0.55	-0.20	-0.89	0.50
16	Carry	0.06	0.15	0.07	0.05	0.13	0.07
17	Mines	-0.26	-0.88	0.19	-0.31	-1.05	0.19
18	Coal	-0.19	-0.55	0.19	-0.13	-0.37	0.20
19	Oil	0.11	0.17	0.04	0.10	0.15	0.05
20	Utilities	-0.03	-0.32	0.39	-0.01	-0.07	0.39
21	Communication	-0.08	-0.77	0.53	-0.10	-0.95	0.50
22	Services	-0.13	-1.17	0.60	-0.20	-1.76	0.58
23	Business Equipment	-0.04	-0.35	0.45	-0.08	-0.69	0.45
24	Paper	-0.16	-0.94	0.54	-0.24	-1.32	0.50
25	Transportation	0.10	0.83	0.47	0.07	0.58	0.45
26	Wholesale	0.05	0.32	0.40	0.02	0.10	0.39
27	Retail	0.02	0.09	0.38	-0.05	-0.28	0.37
28	Meals	-0.21	-1.16	0.52	-0.33	-1.87	0.51
29	Finance	0.02	0.28	0.57	0.04	0.55	0.57
30	Other	-0.01	-0.04	0.51	-0.05	-0.31	0.48
Average $\lvert\alpha\rvert$		**0.15**		**0.35**	**0.17**		**0.34**
p-GRS		0.03			0.03		

Table A.8: Fama-MacBeth cross-sectional regressions with orthogonalized VaR, Rating, ILLIQ, and β^{Bond}

This table reports the average intercept and slope coefficients from the Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead corporate bond excess returns on the orthogonalized VaR (VaR$^{\perp}$), orthogonalized credit rating (Rating$^{\perp}$), orthogonalized illiquidity (ILLIQ$^{\perp}$), and orthogonalized bond market beta ($\beta^{Bond,\perp}$), with and without control variables. VaR$^{\perp}$ is the residual VaR from the cross-sectional regression of VaR on the contemporaneous measures of rating, ILLIQ, and bond market beta. Rating$^{\perp}$ is the residual credit rating from the cross-sectional regression of rating on the contemporaneous measures of VaR, ILLIQ, and bond market beta. ILLIQ$^{\perp}$ is the residual ILLIQ from the cross-sectional regression of illiquidity on the contemporaneous measures of VaR, rating, and bond market beta. $\beta^{Bond,\perp}$ is the residual β^{Bond} from the cross-sectional regression of bond market beta on the contemporaneous measures of VaR, rating, and ILLIQ. Bond characteristics include time-to-maturity (years) and the natural logarithm of bond 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 controls include bond momentum (MOM^{Bond}) 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-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$^{\perp}$	Rating$^{\perp}$	ILLIQ$^{\perp}$	$\beta^{Bond,\perp}$	β^{DEF}	β^{TERM}	Maturity	Size	REV	Adj. R^2
(1)	0.690	**0.100**									0.032
	(2.91)	(4.94)									
(2)	0.660	**0.083**				-0.003	**0.038**	0.005	-0.029	**-0.099**	0.147
	(2.50)	(4.37)				(-0.51)	(2.17)	(0.81)	(-1.15)	(-6.14)	
(3)	0.557		0.022								0.022
	(2.74)		(1.25)								
(4)	0.362		0.013			-0.002	**0.035**	0.012	-0.000	**-0.112**	0.142
	(2.69)		(0.90)			(-0.37)	(2.40)	(1.78)	(-0.80)	(-7.85)	
(5)	0.617			**0.058**							0.010
	(2.73)			(6.87)							
(6)	0.379			**0.044**		-0.001	**0.047**	0.009	-0.013	**-0.093**	0.139
	(2.57)			(5.33)		(-0.19)	(2.26)	(1.42)	(-0.32)	(-5.68)	
(7)	0.825				-0.128						0.020
	(2.85)				(-1.25)						
(8)	0.494				-0.046	-0.005	**0.055**	**0.014**	-0.129	**-0.082**	0.134
	(2.73)				(-0.45)	(-0.86)	(2.01)	(2.13)	(-1.73)	(-4.80)	
(9)	0.665	**0.210**	0.142	**0.075**	0.529						0.136
	(3.06)	(4.68)	(1.30)	(6.65)	(1.02)						
(10)	0.652	**0.181**	0.127	**0.064**	0.454	-0.003	0.013	0.003	-0.000	**-0.097**	0.209
	(3.66)	(5.33)	(1.47)	(6.17)	(1.29)	(-0.50)	(1.07)	(0.45)	(-0.16)	(-6.52)	

Table A.9: Downside risk factor constructed from alternative measures of VaR and expected shortfall

Panel A reports the descriptive statistics for downside risk factor constructed from alternative measures of downside risk: the 10% Value-at-Risk (VaR) and 10% expected shortfall (ES). 10% VaR is defined as the fourth lowest monthly return observation over the past 36 months. 10% expected shortfall (ES) is defined as the average of the four lowest monthly return observations over the past 36 months. The original VaR and expected shortfall measures are multiplied by -1. Downside risk factor (DRF) is constructed by independently sorting corporate bonds into 5×5 quintiles based on the 10% VaR or 10% ES and credit rating. DRF is the equal- or value-weighted average return difference between the highest VaR or ES portfolio minus the lowest VaR or ES portfolio within each rating portfolio. Panel B reports the intercepts (alphas) and t-statistics (in parentheses) from time-series regressions of the DRF factor on the 10-factor model that combines the five stock and five bond market factors, defined in Table 2. All factors cover the period from July 2004 to December 2016.

Panel A: Summary statistics

Downside risk factor (DRF)	Equal-weighted		Value-weighted	
	Mean	t-stat	Mean	t-stat
Constructed from 10% VaR	0.81	3.10	0.68	3.09
Constructed from 10% Expected Shortfall	0.86	3.08	0.70	2.99

Panel B: DRF factor alpha from the 10-factor model

	Equal-weighted	Value-weighted
$\text{DRF}^{10\%\ VaR}$ alpha	0.68	0.60
	(3.04)	(3.03)
$\text{DRF}^{10\%\ ES}$ alpha	0.89	0.66
	(3.14)	(3.01)

Table A.10: Liquidity risk factor constructed from alternative measures of illiquidity

Panel A reports the descriptive statistics for liquidity risk factor constructed from alternative measures of bond illiquidity using the Roll (1984) and Amihud (2002) measure. The Roll's measure is defined as $2\sqrt{-cov(r_d, r_{d-1})}$ if $cov(r_d, r_{d-1}) < 0$, and zero otherwise, where r_d is the corporate bond return on day d. The Amihud measure is defined as the average of the absolute value of the daily return-to-volume ratio. The illiquidity measures are calculated for bonds with at least 5 daily returns within a month. Liquidity risk factor (LRF) is constructed by independently sorting corporate bonds into 5×5 quintiles based on illiquidity and credit rating. LRF is the equal- or value-weighted average return difference between the highest illiquidity portfolio minus the lowest illiquidity portfolio within each rating portfolio. Panel B reports the intercepts (alphas) and t-statistics (in parentheses) from time-series regressions of the LRF factor on the 10-factor model that combines the five stock and five bond market factors, defined in Table 2. All factors cover the period from August 2002 to December 2016.

Panel A: Summary statistics

Liquidity risk factor (DRF)	Equal-weighted		Value-weighted	
	Mean	t-stat	Mean	t-stat
Constructed from Roll's measure	0.42	2.93	0.35	3.45
Constructed from Amihud measure	0.49	3.13	0.47	4.40

Panel B: LRF factor alpha from the 10-factor model

	Equal-weighted	Value-weighted
LRF^{Roll} alpha	0.25	0.25
	(2.89)	(2.37)
LRF^{Amihud} alpha	0.38	0.31
	(3.78)	(2.58)

Table A.11: Fama-MacBeth cross-sectional regressions with alternative measures of credit risk

This table reports the average intercept and slope coefficients from the Fama and MacBeth (1973) cross-sectional regressions of one-month-ahead corporate bond excess returns on two alternative measures of credit risk: distance-to-default (DD) and credit default spread (CDS), at the firm-level, with and without control variables. Bond characteristics include time-to-maturity (years) and the natural logarithm of bond 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. The Fama and MacBeth regressions are run each month for the period from July 2004 to December 2016. Newey-West (1987) t-statistics are reported in parentheses to determine the statistical significance of the average intercept and slope coefficients. The last column reports the average adjusted R^2 values. Numbers in bold denote statistical significance at the 5% level or better.

	Intercept	DD	CDS	5% VaR	ILLIQ	β^{Bond}	Maturity	Size	Adj. R^2
(1)	0.778	**-0.300**							0.048
	(4.70)	(-2.90)							
(2)	1.194	**-0.312**					**0.023**	-0.101	0.078
	(5.23)	(-2.96)					(3.32)	(-0.58)	
(3)	0.350		**0.083**						0.053
	(3.53)		(4.11)						
(4)	0.720		**0.086**				**0.025**	-0.098	0.084
	(3.45)		-4.32				(3.48)	(-1.24)	
(5)	-0.021	-0.037		**0.116**	**0.033**	-0.065			0.129
	(-0.15)	(-0.57)		(4.32)	(2.69)	(-1.06)			
(6)	0.037	-0.033		**0.121**	**0.028**	-0.030	-0.005	-0.009	0.150
	(0.13)	(-0.54)		(4.42)	(2.24)	(-0.59)	(-0.58)	(-0.31)	
(7)	-0.018		0.024	**0.094**	**0.029**	-0.036			0.140
	(-0.17)		(1.13)	(3.42)	(2.51)	(-0.58)			
(8)	-0.014		0.025	**0.097**	**0.024**	-0.017	0.001	-0.004	0.159
	(-0.05)		(1.24)	-3.53	(2.00)	(-0.31)	(0.03)	(-0.13)	

Table A.12: Risk Factors from the Extended Sample: January 1977 to December 2016

Panel A reports the descriptive statistics for downside risk factor (DRF) and credit risk factor (CRF) constructed with the extended sample from January 1977 to December 2016. Three measures of downside risk are the 5% Value-at-Risk (VaR), 10% VaR, and 10% expected shortfall (ES). 5% (10%) VaR is defined as the second (fourth) lowest monthly return observation over the past 36 months. 10% expected shortfall (ES) is defined as the average of the four lowest monthly return observations over the past 36 months. The original VaR and expected shortfall measures are multiplied by -1. Downside risk factor (DRF) is constructed by independently sorting corporate bonds into 5×5 quintiles based on the 5% VaR, 10% VaR, or 10% ES and credit rating. DRF is the equal- or value-weighted average return difference between the highest VaR portfolio minus the lowest VaR portfolio within each rating portfolio. CRF is the equal- or value-weighted average return difference between the highest credit risk portfolio minus the lowest credit risk portfolio within each VaR portfolio. Panel B reports the intercepts (alphas) and t-statistics (in parentheses) from time-series regressions of the DRF factor on the 9-factor model that combines five stock market factors (MKT^{Stock}, SMB, HML, MOM^{Stock}, LIQ^{Stock}) and four bond market factors (MKT^{Bond}, DEF, TERM, MOM^{Bond}) defined in Table 2.

Panel A: Summary statistics

	Equal-weighted		Value-weighted	
	Mean	t-stat	Mean	t-stat
DRF constructed from 5% VaR	0.51	5.47	0.45	6.00
DRF constructed from 10% VaR	0.49	5.37	0.44	5.34
DRF constructed from 10% Expected Shortfall	0.51	5.32	0.45	5.25
CRF (Credit risk factor)	0.30	4.76	0.27	4.43

Panel B: Factor alpha

	Equal-weighted	Value-weighted
$DRF^{5\%\ VaR}$ alpha	0.39	0.34
	(4.91)	(5.14)
$DRF^{10\%\ VaR}$ alpha	0.34	0.30
	(4.53)	(4.14)
$DRF^{10\%\ ES}$ alpha	0.39	0.33
	(4.48)	(4.21)
CRF alpha	0.29	0.25
	(4.37)	(3.64)