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Downside Tail Risk and the Cross-section of Corporate Bond Returns in Korea*

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〈Abstract〉

This study investigates the cross-sectional relationship between bond downside risk, quantified by 5% Value at Risk (VaR), and expected returns in the Korean corporate bond market from 2010 to 2019. Based on portfolio analyses and Fama-MacBeth regressions, we find a significant positive relationship between downside risk and subsequent bond returns, notably during economic expansions. The relationship diminishes during economic downturns, potentially influenced by the interaction between the interest rates and bond yields. Our findings hold even after controlling for other risk factors and bond characteristics.

Keywords : Downside Risk, Value at Risk, Corporate Bond Return, Economic Cycle

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Ⅰ. Introduction

The risk-return relationship of financial assets has been a central issue for decades. A substantial portion of the literature has concentrated on equity markets, which are more readily accessible to a wider range of investors. However, as the net influx of bond funds increases, studies on the risk factors and corporate bond returns are drawing increased attention.[1] Specifically, whether the downside risk can explain the cross-section of corporate bond returns and in which countries downside risk is associated with its risk premium are hotly debated topics. We tackle these issues by examining the cross-section of corporate bond returns in Korea.

Empirical evidence on the relationship between downside risk and the expected asset return is inconclusive in the literature. While Bai et al. (2019) showed that downside risk, as measured by a 5% value at risk (VaR), is priced in the cross-section of U.S. corporate bond returns, Dang et al. (2023) report that the downside risk is subsumed by other risk factors such as carry, duration, momentum, and term-structure. Dickerson et al. (2023) find that the multi-factor model proposed by Bai et al. (2019), which incorporates the downside risk factor, does not yield significantly superior performance when compared to a single-factor model with the bond market factor. Dickerson et al. (2023) point out that the credit, downside, and liquidity risk factors used in Bai et al. (2019) contain lead/lag errors in their variable construction. After correcting the dataset, they report that the downside risk premiums lose their statistical significance in the U.S. corporate bond markets.[2] Atilgan et al. (2020) show that the VaR based downside risk is negatively related to the subsequent returns in the U.S. and international stock markets. Bi and Zhu (2020) find that this negative relationship depends on investor sentiment, suggesting that stocks with high tail risk are favored during periods of high investor sentiment, leading to diminished expected returns on these assets. Gui and Zhu (2021) do not observe this negative relationship in the Chinese stock markets, and the cross-sectional relationship

1) According to the Investment Company Fact Book 2022, total net assets in U.S. bond mutual fund have doubled over the past decade, rising from $2.8 trillion in 2011 to $5.6 trillion in 2021.

2) We conducted a thorough examination of our dataset to ensure that it does not exhibit the same issues observed in Bai et al. (2019), and we confirm that our constructed variables are free from time-misalignment problems.

varies with the consumer confidence.

Moreover, despite the rich body of literature on downside risk, much focus has been on stock markets. Notably, studies on emerging markets are even more scarce except Li et al. (2021) who investigated Chinese corporate bond markets. Our study seeks to fill this gap by empirically examining the relationship between downside risk and expected returns in the Korean corporate bond market.

We further place a particular emphasis on this relationship across different phases of the economic cycle, seeking insights into bond investor behaviors. A strand of literature suggests that bond risk premium is time-varying upon business cycle. Acharya et al. (2013) showed that a bond's exposures to stock and bond market illiquidities change over time, revealing that illiquidities produce significant premium in times of stress. Chen and Chiang (2016) found that the relationship between downside risk and expected stock return varies before and after the 2008 global financial crisis. Eriksen (2017) employed the Survey of Professional Forecasters to proxy the expected business condition and found that the business condition explains part of variations in 1-year ahead bond risk premium. Nozawa (2017) decomposed the credit spread into credit risk and discount rate components and showed that the composition of credit spread varies through the business cycle. Boons et al. (2023) empirically showed that macroeconomic shocks, supposedly orthogonal to credit market conditions, contain sizable predictive information on the credit spread. In this regard, we checked whether downside risk affects the cross-section of corporate bond returns conditionally.

Despite a relatively shorter history than the U.S. bond market, the Korean bond market has remarkably enhanced its efficiency and liquidity due to the market transparency policies introduced in the 2000s (Jeong, 2011). After the government bonds market became active, the corporate bond markets have been developed by opening a retail bond market, lowering the unit of volumes, and introducing a well-organized book building system. To the extent that the developed markets shows a similar relationship between risk factors and asset returns, we investigate the Korean corporate bond markets and compare the results with those of the U.S. markets.

We first performed portfolio analyses to examine the relationship between the downside risk and future corporate bond returns. The results show that the portfolio in the highest downside risk quintile generates an average return that is four times higher than that of the portfolio in the lowest quintile, and the average difference between the two portfolios is statistically significant. In our subsample analyses related to economic cycles, we observe a positive relationship between downside risk and expected returns exclusively during periods of economic expansion. We attribute these results to the different interactions between the interest rates and bond yields with a time lag during the economic expansions and contractions.

We conducted Fama-MacBeth regressions with and without controlling for well-known bond risk factors and bond characteristics to examine whether the downside risks have any cross-sectional predictive power for future corporate bond returns. Specifically, we provide the time-series averages of the slope coefficients obtained from the regressions of one-week-ahead bond excess returns on downside risk with credit and illiquidity risk. The set of control variables includes bond exposure to the term and default spreads, lagged returns, time-to-maturity, and size. The two-stage regression results confirm that each risk factor, especially downside risk, has a positive and significant predictive power on the cross-section of corporate bond returns.

This study contributes to the literature by providing empirical evidence on the cross-sectional relationship between downside risk and corporate bond return in Korea. Our findings show that there is a positive relationship between VaR and expected return in the Korean corporate bond markets, results that align closely with those of Bai et al. (2019) in the U.S. corporate bond markets. We further emphasize the important role of the economy cycle in shaping this relationship, revealing the positive VaR-return relationship mainly appear during periods of economic expansion.

Ⅱ. Related Literature

In search of risk factors that explain the cross-section of corporate bond returns, the literature has suggested a number of candidates. Fama and French (1993) two-factor model includes term and default spreads that capture interest rate and credit risk, respectively. Momentum (Jostova et al., 2013) and long-term reversal (Bali et al., 2021a) are suggested as common risk factors of corporate bond returns as in the stock markets.

Lin et al. (2011) investigated whether the exposure to market-wide illiquidity is priced into the corporate bond returns. Israel et al. (2018) showed that carry, defensive (safety/quality), momentum, and value factors explain the cross-section of corporate bond returns, where carry is measured by option-adjusted spread over T-bonds. Chung et al. (2019) employed VIX as a measure of aggregate volatility and showed that volatility has a positive risk premium in corporate bond markets. Bali et al. (2021b) and Tao et al. (2022) showed that macroeconomic uncertainty and economic policy uncertainty are priced, respectively. Kelly et al. (2023) provide a conditional factor model using instrumented principal components analysis to model corporate bond returns.

Among the proposed risk factors, downside risk has drawn increased attention. Ang et al. (2006) suggested downside beta to measure the tail risk of equity returns and showed that the cross-section of stock returns reflects a premium for downside risk. Using value at risk, Bali et al. (2009) examined the intertemporal relationship between downside risk and stock returns. Lettau et al. (2014) suggested the downside risk capital asset pricing model (DR-CAPM). They showed that downside risk is priced in the cross section of currencies, equity portfolios, equity index options, commodities, and sovereign bonds, while they found no evidence in the corporate bond markets. Farago and Tédongap (2018) suggested downstate, market downside, and volatility downside risk as disappointment-related factors to explain the cross-section of stocks, options, and currency returns.

Empirical evidence regarding downside risk and the cross-sectional asset returns remains uncertain. Gemmill and Kaswani (2011) and Bai et al. (2019) showed the existence of downside risk premium in the U.S. corporate bond market. Atilgan et al. (2020) reported that there are negative relationships between downside risk and expected returns in U.S. and international stock markets. Bi and Zhu (2020) argued that this negative relationship is contingent upon investor sentiment, suggesting that stocks with elevated tail risk are favored during periods of high investor sentiment. Gui and Zhu (2021) found no evidence of this negative relationship in the Chinese stock markets.

While much of the literature on downside risk and asset return has focused on the stock markets,[3] a few studies investigate bond markets, although downside risk could

3) See Ang et al. (2006), Bali et al. (2009), Lettau et al. (2014), Farago and Tédongap (2018), Atilgan (2020), Bi and Zhu (2020), Gui and Zhu (2021) among others.

matter more to bond investors than stock investors. Roy (1952) suggested the concept of the safety-first investor, who avoid chances of disaster. The risk averse safety-first investor seeks to maximize expected return while minimizing downside risk.[4] Bond investors typically have a weaker appetite for tail risk (Canner, 1997), and their payoff is usually capped from the above. Thus, bondholders are more exposed to downside losses than speculative opportunities for the upside potential of stockholders. Farago and Tédongap (2018) and Augustin et al. (2020) suggested a model that downside risk explains the cross-section of corporate bond returns. They showed that asymmetric investor preference and aversion to disappointing outcomes induce a linear model of asset returns whose covariates include market return, aggregate volatility, and three downside state-related factors. That is, one can express the expected return on an asset as

$$E[r_{it}] = p_{im} cov(r_{it}, r_{mt}) + p_{iD} cov(r_{it}, I_{\{D_t < b\}}) + p_{mD} cov(r_{it}, r_{mt} I_{\{D_t < b\}})$$
$$+ p_{iX} cov(r, \Delta\sigma^2_{mt}) + p_{XD} cov(r, \Delta\sigma^2_{mt} I_{\{D_t < b\}}),$$

where r_{it} denotes the time-t return of asset i, r_{mt} is the market return, $\Delta\sigma^2_{mt}$ is the change in the market variance, $I_{\{D_t < b\}}$ represents an indicator variable that takes the value of one in the downstate and zero otherwise, and p_{AB} represents the premium on the covariance risk between A and B; see the appendix, for details.

Bai et al. (2019) employed value at risk to measure downside risk of bond returns and showed that U.S. corporate bond markets price downside risk as well as credit and liquidity risk. They also found that the primary sources of downside risk premium are volatility and skewness of corporate bond returns, not kurtosis. Similarly, Li et al. (2021) employed value at risk and semi-variance to investigate the cross-section of bond yields in the Chinese corporate bond markets. They showed that the downside risk is positively related to the subsequent excess bond returns in China, and the relationship is more pronounced for the high-credit rating bonds. Dang et al. (2023) investigated 23 prominent common risk factors of corporate bond returns with Bayesian model selection, and showed that a parsimonious model with a maximum of five factors does not include

4) See, for example, Arzac and Bawa (1997) and references therein.

the downside risk factor of Bai et al. (2019).

Besides the downside risk, credit risk and illiquidity risk have been widely accepted risk factors that affect corporate bond yield spreads (Chen et al., 2007; Huang & Huang, 2012). Ohk and Jung (2013) found evidence of a significant positive relationship between liquidity and expected excess return in the Korean corporate bond market. Shin and Kim (2015) studied the impact of credit and illiquidity risks on corporate yield spreads. They found that illiquidity accounted for a relatively large proportion of the variation in yield spreads before and during the global crisis period, while credit risk became a more influential determinant of yield spreads after the global crisis.

Ⅲ. Data and variables

1. Data

To construct our sample, we collected issuance information and daily transaction records of Korean corporate bonds from the Check Expert database for the sample period from November 2010 to June 2019. The Check Expert provides daily closing price, trading volume, and credit rating of exchange-traded corporate bonds. It also provides bond issuance information such as offering amount, maturity, coupon information, credit rating, and option features.

We mainly referenced the data-filtering procedure of Bai et al. (2019) and adjusted it to fit Korean market particularity with Shin and Kim (2015). We pre-processed dataset as follows: 1) We only used fixed or zero coupons to secure the accuracy of computed bond returns. Our sample only contains publicly listed and Korean-dominated issues. 2) We excluded bonds with guarantees or subordinates. The prices of those bonds are generally dependent on the creditworthiness of the assurer or the priority structure of debt issues but not on the credit quality of the bond issuer (Shin and Kim, 2015). 3) We excluded bonds with embedded options since the prices of those bonds are determined by the option premium rather than the bond's risk factors (Shin and Kim, 2015). 4) We excluded bonds with credit rating lower than BBB- given that the issuance and trading activity of high-yield bond are highly limited in the Korean corporate bond markets due to flight-to-quality (Kim, 2018). To mitigate the possible distortion stemming from liquidity, we removed bonds with time-to-maturity of less than six months or those with transaction observations of less than 24 days. This is due to the fact that bonds with residual maturity less than one year usually suffer from rapid decline of liquidity and therefore excluded in the bond indices calculations. 6) Notably, our sample includes straight corporate bonds issued by financial firms not to dismiss significant role of those firm in the economy.[5] 7) To ensure the consistency of our data, we applied linear interpolation to achieve a uniform weekly frequency throughout the sample period.

2. Variables

We computed the weekly corporate bond return for bond i at time t as follows:

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

where P is the price, AI is the accrued interest, and C represents the coupon payment. The excess weekly return, $\tilde{r}_{i.t}$, is computed by $\tilde{r}_{i.t} = r_{i,t} - r_{f,t}$, where $r_{f,t}$ is the risk-free rate proxied by the 91-days Certificate of Deposit (CD) rate.

To measure the downside risk of bonds, we employ VaR which indicates the potential loss that a bond return could suffer at a given probability. Following Bai et al. (2019), we obtain 5% VaR as the second-lowest weekly return over the past 36 weeks and multiply it by -1 so that the higher value indicates a higher downside risk.[6]

At the bond level, we measure credit risk using the bond's credit rating. Following Covitz and Downing (2007), we mapped the letter grades of credit ratings to ordered

5) Specifically, our sample includes corporate bonds issued by financial firms such as financial holdings and securities companies, but does not include financial bonds issued by banks or other financial companies.

6) We used 36 weeks of bond returns to estimate 5% VaR to reduce estimation errors potentially arising from interpolations. Market practitioners often use 52- or 26-week windows to estimate VaR. However, for example, when using 52 weeks, 5% VaR corresponds to the lowest 2.6th return, which could be obtained by interpolating the second lowest and the third lowest bond returns and it could arise systematic biases upon the choice of interpolation scheme. Additionally, since the exchange-traded corporate bonds in Korea do not have abundant transaction records, requiring a 52-week of persistent bond return series force us to drop non-negligible amount of data.

numbers so that the higher the credit rating, the lower the numerical value: AAA = 1, AA+ = 2, ⋯, and D = 20. Therefore, the numerical rating of investment-grade bonds ranges from 1 (corresponding to AAA) to 10 corresponding to BBB-), and that of high-yield bonds ranges from 11 (corresponding to BB+) to 20 (corresponding to D).

We select the Amihud illiquidity as a measure of liquidity risk, defined as

$$Amihud = \frac{1}{T}\sum_{t=1}^{T}\frac{|r_t|}{V_t},$$

where V_t is the trading volume on week t, and r_t is the average of the returns on a 24-week rolling window before week t. A higher value of the Amihud illiquidity indicates a higher liquidity risk.

<Table 1> reports the summary statistics of our sample. Starting from 7,134 bonds with 204,971 transactions, our final sample includes 356 bonds and 27,795 weekly excess returns from November 2010 to June 2019. The typical bond in our final sample has a time-to-maturity of 2.08 years, credit rating of A-, an excess return of 0.053%, and 5% VaR of 0.798%. The 5% VaR of the average bond is more than 10 times its average excess return.

<Table 1> Descriptive Statistics

This table presents an overview of bond-related metrics in the Korean corporate bond market during the period from November 2010 to June 2019. It reports the number of observations, time-series averages for the cross-sectional mean, standard deviation, and percentile values. The bond characteristics include maturity, time-to-maturity, amount outstanding, and credit rating. Additionally, it reports downside risk (represented by the 5% VaR) and liquidity risk (measured by the Amihud illiquidity). The credit ratings are converted to numerical ratings, where 1 represents an AAA and 20 represents a D. The 5% VaR, a proxy for downside risk, is defined as the second-lowest weekly return observation over the past 36 weeks. The value multiplied by -1 is reported; thus, a higher VaR indicates higher downside risk.

	N	Mean	Standard deviation	Percentile				
				5%	25%	50%	75%	95%
Maturity (year)	27,795	4.08	1.94	2	3	3	5	8
Time-to-Maturity (year)	27,795	2.08	1.64	0.61	0.99	1.58	2.41	5.91
Amount outstanding (billion won)	27,795	117	80	20	50	100	170	250
Credit rating	27,795	6.9	1.54	3	6	7	8	9
Amihud illiquidity (%)	27,795	0.529	0.916	0.066	0.153	0.273	0.544	1.778
Excess return (%)	27,795	0.053	1.028	-0.774	-0.039	0.045	0.151	0.862
Value-at-risk (%)	27,795	0.798	1.115	-0.032	0.094	0.432	1.020	2.941

3. Normality Test for Corporate Bond Returns

Aside from the non-parametric method for estimating VaR we employed, a parametric method, which estimates VaR assuming that asset return follows a normal distribution, is also widely used. To validate our choice of estimation method, we first checked whether the excess bond returns are normally distributed.

<Table 2> reports higher-order moments alongside normality test results for corporate bond returns in our sample. The cross-sectional averages of skewness and kurtosis cast doubt that bond returns in our sample are normally distributed. Specifically, we performed Jarque-Bera and Shapiro-Wilk tests and reported the cross-sectional averages of test results in <Table 2>. At the 1% significance level, 71.1 % of bonds (253 out of 356) rejected the null hypothesis that bond return follows a normal distribution of the Jarque-Bera test. For the Shapiro-Wilk test, 77.8% of all bonds (277 out of 356) rejected the same null hypotheses. The negatively skewed distribution with fat tails suggests a more frequent occurrence of extreme events than predicted under the normal distribution and substantiates our choice of estimation method for VaR.

<Table 2> Normality Test

This table presents the cross-sectional averages of skewness, kurtosis, and normality test results of bond returns. We performed Jarque-Bera and Shapiro-Wilk tests to check whether the bond returns follow normal distributions. The p-value of each test was calculated under the null hypothesis that bond returns are normally distributed. The Ratio of each test indicates the portion of bonds that reject the null hypothesis, at the 1% significance level, out of all bonds in our sample. The numbers in the parentheses indicate t-statistics. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Skewness	Kurtosis	Jarque-Bera Test:			Shapiro-Wilk Test:		
		Test statistic	p-value	Ratio	Test statistic	p-value	Ratio
-0.182* (-1.70)	10.155** (11.67)	2499.551	0.117	0.711	0.7570	0.054	0.778

Ⅳ. Empirical analysis

1. Univariate Portfolio Analysis

We first utilized univariate portfolio analysis to examine the cross-sectional relationship between downside risk and future returns in the Korean corporate bond markets. For each week from November 2010 to June 2019, we constructed quintile portfolios using 5% VaR as a sorting variable. Quintile 1 consists of bonds with the lowest downside risk, whereas quintile 5 consists of bonds with the highest downside risk. <Table 3> reports the time-series averages of 5% VaR, one-week-ahead excess return, and other bond characteristics of each quintile. The portfolio excess returns are value-weighted,

<Table 3> Univariate Portfolio Analysis

This table presents the average values of excess returns, 5% VaR, and other bond characteristics for the portfolios,where 5% VaR is the negative of second-lowest weekly return over the past 36 weeks. Quintile portfolios were formed based on 5% VaR spanning from November 2010 to June 2019. Bonds in Quintile 1 have the lowest downside risk, while those in Quintile 5 possess the highest downside risk. Excess returns are calculated using value weights, whereas other portfolio averages utilize equal weighting. The final row denotes the return difference between the portfolios with the highest and lowest VaR. Parenthetical numbers represent the Newey-West corrected t-statistics with a lag of 4. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Quintile portfolios for 5% VaR: Full sample

Quintiles	VaR (%)	Excess return (%)	Rating	Amihud (%)	Maturity (year)	Size (billion won)
Lowest	-0.003	0.036	5.98	0.207	2.583	116
2	0.171	0.023	6.40	0.288	2.309	115
3	0.478	0.007	6.77	0.420	1.890	130
4	0.955	0.043	7.50	0.627	1.661	118
Highest	2.396	0.133	7.85	1.160	1.710	113
High-Low	2.399***	0.098**				
	(27.04)	(2.86)				

Panel B: Quintile portfolios for 5% VaR: Economic expansion

Quintiles	VaR	Excess return	Rating	Amihud	Maturity	Size
Lowest	0.001	0.032	6.02	0.207	2.615	114
2	0.179	0.024	6.46	0.291	2.401	110
3	0.487	0.013	6.74	0.436	1.928	131
4	0.970	0.047	7.48	0.665	1.738	121
Highest	2.420	0.144	7.86	1.263	1.788	112
High-Low	2.420***	0.112**				
	(20.37)	(2.50)				

Panel C: Quintile portfolios for 5% VaR: Economic contraction

Quintiles	VaR	Excess return	Rating	Amihud	Maturity	Size
Lowest	-0.010	0.043	5.89	0.209	2.535	119
2	0.161	0.029	6.29	0.280	2.129	124
3	0.463	-0.005	6.85	0.388	1.814	127
4	0.926	0.037	7.54	0.552	1.502	112
Highest	2.371	0.092	7.83	0.962	1.556	114
High-Low	2.381***	0.050				
	(20.34)	(1.09)				

and all other values reported are equally weighted. The last row shows the return difference between the highest and lowest VaR portfolios.

Panel A of <Table 3> reports the full sample results of the univariate test. The return difference between the highest and lowest quintile is 0.098% per week (5.23% per annum) with a t-statistic of 2.86, which is economically and statistically significant. The excess return of the quintile portfolio increases as its VaR increases, although the pattern is not monotonic. These results suggest a positive relationship between downside risk and expected return in the Korean corporate bond markets.

We further investigate the average portfolio characteristics to examine if other bond characteristics drive the VaR-return relationship. The last four columns of <Table 3> report the time-series averages of portfolio credit rating, Amihud illiquidity, time-to-maturity, and size. Notably, the credit and liquidity risk increase as VaR increases, while time-to-maturity decreases. We conducted bivariate portfolio analyses to control for these possible concerns and report the results in the subsequent section.

We are also interested in whether the VaR-return relationship varies over the economic cycle. We employ the cyclical component of Composite Leading Indicator (CLI) to divide the sample into economic expansion and contraction periods. The CLI is an aggregate-level index of economic activity providing early signals of turning points, indicating the inflection points for periods of expansion and contraction. The CLID is obtained by detrending the corresponding CLI. The sample with a CLID equal to or greater than 100 is defined as the economic expansion phase, and less than 100 as the economic contraction phase. [Figure 1] illustrates the time evolution of CLID from November 2010 to June 2019. The solid line indicates CLID values, and the dashed line represents the threshold level, 100. The shaded area indicates the economic contraction defined by Statistics Korea, which we will explain in detail in section V. The single-sort results for the sub-samples of economic expansion and contraction phases are reported in Panel B and C of <Table 3>.

Panel B of <Table 3> shows the conditional results of the univariate portfolio analysis during the expansion phase. As shown in the last row, the average high minus low return spread is 0.112% per week (5.99% per annum) with a t-statistic of 2.50, indicating that 5% VaR is positively related to the future return when economic expansion is expected. Panel C of <Table 3>, however, shows that the positive relationship between VaR and expected return diminishes when an economic contraction is expected. The average high minus low spread is 0.050% per week (2.63% per annum) with a t-statistic of 1.09. Both the economic and statistical significance decrease significantly when economic downturn is expected.

According to the behavioral explanation, investors tend to exhibit optimism regarding future asset prices during bullish market conditions, leading them to increase their exposure to riskier assets relative to bearish market periods. For example, Stambaugh et al. (2012) found that some well-known asset pricing anomalies are pronounced during periods of high investor sentiment. Atilgan et al. (2020) argue that investors who have recently suffered substantial losses tend to overprice assets with persistent tail risk. In the same vein, Bi and Zhu (2020) and Gui and Zhu (2021) found that downside risk premia vary with changes in investor sentiment and consumer confidence, respectively.

Given the strong correlation between the business cycle and investor sentiment (Sibley, 2016), our conditional findings on the link between downside risk and bond returns are at odds with the existing literature. We attribute these findings to the intricate interplay between interest rates and corporate bond yields, which occur with some time lag. During economic expansions characterized by rising interest rates, yields-to-maturity of corporate bonds typically increase. Consequently, bonds that had previously experienced significant losses (high VaR) become more appealing to investors, leading to an upswing in subsequent holding period returns. Conversely, during economic contractions, falling interest rates exert downward pressure on corporate bond yields and expected returns to maturity, rendering high-quality bonds less attractive to investors. This phenomenon leads to a decline in bond prices and, as a result, lower holding period returns. Given this pronounced impact on high-VaR bonds, the positive cross-sectional relationship between VaR and expected returns may weaken during periods of economic contraction.

2. Bivariate Portfolio Analysis

As reported in the last four columns of <Table 3>, we observe monotonic patterns between portfolio VaR and bond characteristics such as credit rating, Amihud illiquidity, and time-to-maturity. This observation raises the concern that the positive relationship between downside risk and expected return in <Table 3> may be driven by credit risk, liquidity risk, or the term-structure of yields. To investigate this concern, we performed bivariate portfolio analysis to control for the potential drivers.

To control for rating, liquidity, or size, we first binned the sample by the median of each control variable. Then, within each bintile, we formed quintile portfolios by 5% VaR and compute the value-weighted portfolio excess returns. We use 1-year as a break-point for time-to-maturity when forming bintile portfolios: the bonds with remaining life less than 1-year are labeled as short-term while the others are labeled as long-term. <Table 4> reports the return differences between the highest VaR and lowest VaR portfolios of each control bintile.

<Table 4> Bivariate Portfolio Analysis

This table presents the excess return difference between the highest and lowest VaR portfolios. The sample period is from November 2010 to June 2019. We first brake the sample by the median of each control variable. Then, within each bintile, we formed quintile portfolios by 5% VaR and computed the value-weighted portfolio excess returns. For time-to-maturity, we use 1-year as a breakpoint for bintile portfolios in that the bonds with a remaining life of less than one year are labeled as short-term, while the others are labeled as long-term. Each panel contains full sample and conditional sample results of economic expansion and contraction periods. The numbers in the parentheses indicate the Newey-West corrected t-statistics with a lag of four. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Controlling for rating

	Full sample		Economic expansion		Economic contraction	
	Low	High	Low	High	Low	High
H-L excess return	0.077**	0.121**	0.102*	0.164***	0.025	0.034
	(1.99)	(2.36)	(1.91)	(2.69)	(0.65)	(0.38)

Panel B: Controlling for Amihud illiquidity

	Full sample		Economic expansion		Economic contraction	
	Low	High	Low	High	Low	High
H-L excess return	0.032	0.159***	0.012	0.203**	0.065	0.058
	(1.15)	(2.68)	(0.34)	(2.50)	(1.48)	(0.91)

Panel C: Controlling for size

	Full sample		Economic expansion		Economic contraction	
	Small	Large	Small	Large	Small	Large
H-L excess return	0.085*	0.089**	0.122**	0.087	0.020	0.067
	(1.84)	(2.25)	(2.16)	(1.54)	(0.26)	(1.61)

Panel D: Controlling for time-to-maturity

	Full sample		Economic expansion		Economic contraction	
	Short	Long	Short	Long	Short	Long
H-L excess return	0.119**	0.071**	0.153**	0.060	0.055	0.065
	(2.54)	(2.07)	(2.53)	(1.26)	(0.82)	(1.41)

The first two columns of <Table 4> report the full sample results of the bivariate portfolio analysis. The last rows of each panel report the return difference between the highest and lowest VaR portfolios. As shown in each last row, there is positive relationship between downside risk and corporate bond returns, even after controlling for credit risk, liquidity risk, size, and time-to-maturity. As shown in the first two columns of <Table 4>, the controlled return differences for rating, size, and time-to-maturity range from 0.071% to 0.121% per week, including the univariate result of 0.098% per week.

The remaining four columns of <Table 4> show the bivariate-sort result for conditional samples. As shown in the third and fourth columns of <Table 4>, there is positive relationship between downside risk and corporate bond returns during the expansionary phases. The statistical and economic significance of this conditional sample do not vary much from those of the full sample results. During the contraction phase, however, the relationship diminishes as shown in the last two columns of <Table 4>. Notably, the high minus low excess returns decrease significantly for the high rating, highly illiquid, or small sized bond groups.

3. Bond-level Fama-MacBeth Regression

The cross-sectional relationship between risk factors and the expected returns was tested at the bond-level using Fama-MacBeth (1973) regression. We first regress bond excess return on 5% VaR, credit rating, Amihud illiquidity, and control variables. The control variables include bond exposure to term spread (β_{TERM}), bond exposure to default spread ($\beta_{DEFAULT}$), one-week lagged return (*Reversal*), time-to-maturity (*Maturity*), and log of amount outstanding (*Size*). The time-series averages of the cross-sectional regression coefficients are computed in the second stage. The term spread is computed by the difference between the yields on 10-year and 1-year government bonds, and the default spread is calculated from the difference between the yields on BBB- and AA- rated corporate bonds. We find beta estimates, β_{TERM} and $\beta_{DEFAULT}$, from the time-series regressions of individual bond excess return using a 36-week rolling window. We conduct predictive regressions of the excess return of bond i in week $t+1$ based on the following model specification:

$$\tilde{r}_{i,t+1} = \gamma_{0,t} + \gamma_{1,t} VaR_{5\%,i,t} + \gamma_{2,t} Rating_{i,t} + \gamma_{3,t} Amihud_{i,t} + \sum_{k=1}^{K} \gamma_{k,t} Control_{k,i,t} + \epsilon_{i,t+1}$$

<Table 5> presents the time-series average of the cross-sectional regression estimates, the Newey-West adjusted t-statistics, and the adjusted R-squared of the bond-level Fama-MacBeth regressions. Models (1) through (3) in <Table 5> report univariate regression results of the average slope coefficients on 5% VaR, credit rating, and Amihud illiquidity, respectively. Model (4) tests the average slope coefficients on 5% VaR with control variables, and model (5) shows the results of the full model specification with downside, credit, and liquidity risks with control variables.

Panel A of <Table 5> reports the full sample results. As shown in the first three columns, downside, credit, and liquidity risk have the sole explanatory power on the cross-section of corporate bond returns in Korea. This finding is consistent with the results of uni- and bivariate portfolio analyses in section IV.1 and IV.2. From models (4) and (5), we verify that the average slope coefficient on 5% VaR is significant at the 1% level, even after controlling for rating, illiquidity, and other control variables.

Panel B and C of <Table 5> show the results conditional on economic cycle. During the expansionary phase, the time-series average of slope coefficient on 5% VaR is statistically and economically significant as shown in models (1), (4), and (5). However, as shown in model (1) in Panel C of <Table 5>, 5% VaR loses its explanatory power on the cross-section of corporate bond returns when used as a sole explanatory covariate. The results confirm that the positive relationship between downside risk and corporate bond return is mainly due to the economic expansion phase.

<Table 5> Bond-level Fama-MacBeth Regression

This table reports the time-series averages of the bond-level Fama-MacBeth (1973) cross-sectional regression: $\tilde{r}_{i,t+1} = \gamma_{0,t} + \gamma_{1,t} VaR_{5\%,i,t} + \gamma_{2,t} Rating_{i,t} + \gamma_{3,t} Amihud_{i,t} + \sum_{k=1}^{K} \gamma_{k,t} Control_{k,i,t} + \epsilon_{i,t+1}$, where $VaR_{5\%}$ measures downside risk, $Rating$ is the proxy for credit risk, and $Amihud$ measures bond-level liquidity. Bond characteristics such as time-to-maturity, reversal (one-week lagged return), and size (log of amount outstanding), were controlled. The bond exposures to term spread (β_{TERM}) and default spread ($\beta_{DEFAULT}$) are estimated over 36-week rolling windows. The numbers in the parentheses indicate the Newey-West corrected t-statistics. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from November 2010 to June 2019.

Panel A: Full sample

	(1)	(2)	(3)	(4)	(5)
$VaR_{5\%}$	0.050***			0.043***	0.052***
	(3.68)			(3.39)	(3.66)
Rating		0.010*			-0.012*
		(1.70)			(-1.88)

<Table 5> Bond-level Fama-MacBeth Regression (Continued)

	(1)	(2)	(3)	(4)	(5)
Amihud			0.049** (2.20)		0.003 (0.16)
β_{TERM}				0.009 (0.39)	0.005 (0.20)
β_{DEF}				−0.012 (−0.94)	−0.013 (−1.02)
Reversal				0.013 (0.70)	0.002 (0.11)
Maturity				−0.008* (−1.71)	−0.009* (−1.67)
Size				−0.003 (−0.31)	−0.014 (−1.48)
Intercept	0.004 (0.49)	−0.025 (−0.70)	0.017 (1.52)	0.053 (0.50)	0.262* (1.89)
Num. Obs.	27,314	27,314	27,314	27,314	27,314
Adj. R^2	0.0555	0.0054	0.0946	0.1785	0.2219

Panel B: Economic expansion

	(1)	(2)	(3)	(4)	(5)
$VaR_{5\%}$	0.061*** (3.44)			0.039** (2.40)	0.045** (2.22)
Rating		0.012* (1.71)			−0.010 (−1.16)
Amihud			0.052* (1.78)		0.007 (0.28)
β_{TERM}				−0.005 (−0.19)	−0.009 (−0.33)
β_{DEF}				−0.013 (−0.90)	−0.013 (−0.97)
Reversal				0.018 (0.78)	0.003 (0.13)
Maturity				−0.011* (−1.73)	−0.011 (−1.57)
Size				0.000 (0.01)	−0.014 (−1.34)
Intercept	−0.001 (−0.07)	−0.033 (−0.81)	0.013 (0.81)	0.023 (0.22)	0.250 (1.49)
Num. Obs.	17,964	17,964	17,964	17,964	17,964
Adj. R^2	0.0572	0.0054	0.0998	0.1754	0.2214

<Table 5> Bond-level Fama-MacBeth Regression (Continued)

Panel C: Economic contraction

	(1)	(2)	(3)	(4)	(5)
$VaR_{5\%}$	0.029			0.047^{**}	0.067^{***}
	(1.46)			(2.47)	(4.25)
Rating		0.006			-0.014
		(0.54)			(-1.40)
Amihud			0.038		-0.001
			(1.25)		(-0.04)
β_{TERM}				0.037	0.031
				(0.91)	(0.67)
β_{DEF}				-0.004	-0.004
				(-0.17)	(-0.16)
Reversal				0.015	0.010
				(0.45)	(0.30)
Maturity				-0.003	-0.003
				(-0.46)	(-0.37)
Size				-0.004	-0.012
				(-0.24)	(-0.62)
Intercept	0.016^{*}	-0.002	0.030^{**}	0.070	0.246
	(1.75)	(-0.03)	(2.04)	(0.30)	(0.96)
Num. Obs.	9,350	9,350	9,350	9,350	9,350
Adj. R^2	0.0555	0.0041	0.0881	0.1908	0.2322

Ⅴ. Analyses for Robustness Check

1. Variance-covariance VaR

We checked the robustness of our results by conducting the same set of analyses as in Section Ⅳ based on an alternative measure of downside risk. Although we showed in Section 2 that corporate bond returns do not follow a normal distribution, market practitioners often apply the normality assumption to their VaR calculations. Because of these differences in perception, the relationship between downside risk and return that we have explored may be different up to the estimation scheme. In this regard, we employed variance-covariance VaR (NVaR) as an alternative measure of downside risk and conducted portfolio analyses to check whether our results are robust. Assuming that bond returns follow a normal distribution, we define $NVaR_{\alpha,it}$ at the confidence level α by $NVaR_{\alpha,it} = -\mu_{it} + \sigma_{it}\phi^{-1}(\alpha)$, where μ_{it} is the mean of bond i over $[t-36weeks, t]$,

σ is the standard deviation over the same estimation period, and ϕ is the density function of standard normal distribution. This approach of calculating VaR is known as variance-co-variance method and has been widely accepted by market practitioners to estimate down-side risk.[7)]

<Table 6> presents the single-sort results using 5% NVaR as the sorting variable.[8)] As in <Table 3>, the high minus low excess return is positive and statistically significant for the full sample and the economic expansion subsample. <Table 7> presents the dou-ble-sort results by the set of bond-related variables and 5% NVaR. As in <Table 4>, the high minus low excess return is positive and statistically significant for the full sample and economic expansion subsample. <Table 8> presents the Fama-MacBeth regression result using 5% NVaR. The portfolio analyses and Fama-MacBeth regression results using two different methods of estimating VaR are qualitatively identical.

<Table 6> Univariate Portfolio Analysis: Variance-covariance Method

This table presents the average values of excess returns, 5% NVaR, and other bond characteristics for the portfolios. Assuming that bond returns are normally distributed, 5% NVaR is the value at risk calculated using the variance-covariance method, with the returns over the past 36 weeks to estimate the mean and variance. Quintile portfolios were formed based on 5% NVaR spanning from November 2010 to June 2019. Bonds in Quintile 1 have the lowest downside risk, while those in Quintile 5 possess the highest downside risk. Excess returns are calculated using value weights, whereas other portfolio averages are based on equal weights. The last row denotes the return difference between the portfolios with the highest and lowest NVaR. The numbers in parentheses represent the Newey-West corrected t-statistics with a lag of 4. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Quintile portfolios for 5% NVaR: Full sample

Quintiles	NVaR (%)	Excess return (%)	Rating	Amihud (%)	Maturity (year)	Size (billion won)
Lowest	0.025	0.031	5.92	0.188	2.605	117
2	0.207	0.021	6.37	0.279	2.262	120
3	0.476	0.004	6.87	0.415	1.858	124
4	0.945	0.041	7.60	0.636	1.703	116
Highest	2.557	0.151	7.73	1.186	1.723	114
High-Low	2.533*** (20.16)	0.120*** (3.16)				

7) Since its inception by RiskMetrics in 1994, the variance-covariance method of value-at-risk has been widely used by practitioners as a result of the Basel I Accord in 1996.

8) We also performed the subsequent robustness tests using 1% and 10% NVaR as alternatives to 5% NVaR. The qualitative results are identical and we omit the results to save space. The results are available upon request.

<Table 6> Univariate Portfolio Analysis: Variance-covariance Method(Continued)

Panel B: Quintile portfolios for 5% NVaR: Economic expansion

Quintiles	NVaR	Excess return	Rating	Amihud	Maturity	Size
Lowest	0.028	0.028	5.94	0.188	2.683	116
2	0.214	0.021	6.47	0.279	2.277	114
3	0.476	0.007	6.79	0.421	1.949	126
4	0.955	0.049	7.61	0.666	1.763	120
Highest	2.547	0.161	7.74	1.311	1.794	112
High-Low	2.519*** (15.84)	0.132** (2.57)				

Panel C: Quintile portfolios for 5% NVaR: Economic contraction

Quintiles	NVaR	Excess return	Rating	Amihud	Maturity	Size
Lowest	0.018	0.035	5.89	0.186	2.465	120
2	0.196	0.031	6.18	0.280	2.240	131
3	0.479	-0.005	7.03	0.402	1.666	120
4	0.926	0.032	7.60	0.579	1.582	108
Highest	2.591	0.110	7.70	0.943	1.582	117
High-Low	2.572*** (13.47)	0.075 (1.63)				

<Table 7> Bivariate Portfolio Analysis: Variance-covariance Method

This table presents the excess return difference between the highest and lowest NVaR portfolios. The sample period is from November 2010 to June 2019. We first brake the sample by the median of each control variable. Then, within each bintile, we formed quintile portfolios by 5% NVaR and computed the value-weighted portfolio excess returns. For time-to-maturity, we use 1-year as a breakpoint for bintile portfolios in that the bonds with less than one year to maturity are labeled short-term, while the rest are labeled long-term. Each panel contains full sample and conditional sample results for economic expansion and contraction periods. The numbers in parentheses indicate the Newey-West corrected t-statistics with a lag of four. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Controlling for rating

	Full sample		Economic expansion		Economic contraction	
	Low	High	Low	High	Low	High
H-L excess return	0.076** (1.97)	0.179*** (3.05)	0.090* (1.72)	0.208*** (2.75)	0.046 (1.09)	0.090 (1.00)

Panel B: Controlling for Amihud illiquidity

	Full sample		Economic expansion		Economic contraction	
	Low	High	Low	High	Low	High
H-L excess return	0.024 (0.85)	0.174*** (2.98)	-0.003 (-0.08)	0.235*** (2.90)	0.073* (1.70)	0.036 (0.61)

Panel C: Controlling for size

	Full sample		Economic expansion		Economic contraction	
	Small	Large	Small	Large	Small	Large
H-L excess return	0.105** (2.17)	0.124*** (2.72)	0.146** (2.39)	0.118* (1.86)	0.018 (0.23)	0.100* (1.82)

Panel D: Controlling for time-to-maturity

	Full sample		Economic expansion		Economic contraction	
	Short	Long	Short	Long	Short	Long
H-L excess return	0.141*** (2.82)	0.098** (2.51)	0.162*** (2.81)	0.104** (1.92)	0.093 (1.00)	0.069 (1.44)

<Table 8> Bond-level Fama-MacBeth Regression: Variance-covariance Method

This table reports the time-series averages of the bond-level Fama-MacBeth (1973) cross-sectional regression: $\tilde{r}_{i,t+1} = \gamma_{0,t} + \gamma_{1,t} NVaR_{5\%,i,t} + \gamma_{2,t} Rating_{i,t} + \gamma_{3,t} Amihud_{i,t} + \sum_{k=1}^{K} \gamma_{k,t} Control_{k,i,t} + \epsilon_{i,t+1}$, where $NVaR_{5\%}$ measures downside risk, $Rating$ is the proxy for credit risk, and $Amihud$ measures bond-level liquidity. Bond characteristics such as time-to-maturity, reversal (one-week lagged return), and size (log of amount outstanding) were controlled. The bond exposures to term spread (β_{TERM}) and default spread ($\beta_{DEFAULT}$) are estimated over the 36-week rolling windows. The numbers in the parentheses indicate the Newey-West corrected t-statistics. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from November 2010 to June 2019.

Panel A: Full sample

	(1)	(2)	(3)	(4)	(5)
$NVaR_{5\%}$	0.052***			0.041***	0.047***
	(3.36)			(2.95)	(3.16)
Rating		0.010*			-0.010*
		(1.70)			(-1.72)
Amihud			0.049**		0.009
			(2.20)		(0.46)
β_{TERM}				0.009	0.002
				(0.37)	(0.10)
β_{DEF}				-0.011	-0.013
				(-0.91)	(-1.04)
Reversal				0.008	-0.002
				(0.39)	(-0.09)
Maturity				-0.009*	-0.008*
				(-1.93)	(-1.75)
Size				-0.004	-0.013
				(-0.39)	(-1.42)
Intercept	-0.001	-0.025	0.017	0.063	0.239*
	(-0.05)	(-0.70)	(1.52)	(0.57)	(1.84)
Num. Obs.	27,314	27,314	27,314	27,314	27,314
Adj. R^2	0.0513	0.0054	0.0946	0.1725	0.2172

Panel B: Economic expansion

	(1)	(2)	(3)	(4)	(5)
$NVaR_{5\%}$	0.064***			0.040**	0.042**
	(3.07)			(2.33)	(2.32)
Rating		0.012*			-0.008
		(1.71)			(-1.12)
Amihud			0.052*		0.009
			(1.78)		(0.32)
β_{TERM}				-0.009	-0.014
				(-0.31)	(-0.48)
β_{DEF}				-0.011	-0.012
				(-0.86)	(-1.04)
Reversal				0.011	-0.001
				(0.46)	(-0.04)
Maturity				-0.011*	-0.010
				(-1.94)	(-1.63)
Size				-0.001	-0.013
				(-0.07)	(-1.18)
Intercept	-0.008	-0.033	0.013	0.030	0.222
	(-0.49)	(-0.81)	(0.81)	(0.28)	(1.35)
Num. Obs.	17,964	17,964	17,964	17,964	17,964
Adj. R^2	0.0538	0.0054	0.0998	0.1667	0.2154

<Table 8> Bond-level Fama-MacBeth Regression: Variance-covariance Method (Continued)

Panel C: Economic contraction

	(1)	(2)	(3)	(4)	(5)
$NVaR_{5\%}$	0.026 (1.28)			0.040* (1.71)	0.053** (2.16)
Rating		0.006 (0.54)			-0.012 (-1.02)
Amihud			0.038 (1.25)		0.019 (0.66)
β_{TERM}				0.046 (1.11)	0.036 (0.80)
β_{DEF}				-0.008 (-0.32)	-0.007 (-0.26)
Reversal				0.010 (0.30)	0.007 (0.22)
Maturity				-0.005 (-0.70)	-0.002 (-0.33)
Size				-0.006 (-0.30)	-0.012 (-0.70)
Intercept	0.019** (1.67)	-0.002 (-0.03)	0.030** (2.04)	0.094 (0.38)	0.234 (1.01)
Num. Obs.	9,350	9,350	9,350	9,350	9,350
Adj. R^2	0.0504	0.0041	0.0881	0.1880	0.2276

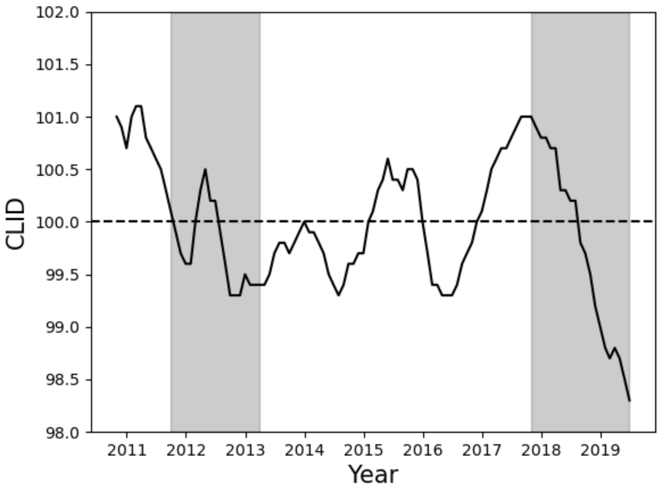
2. Alternative Definition of Economic Cycles

Statistics Korea defines the peaks and troughs of the economic cycle irregularly. They utilize a composite coincident indicator that incorporate GDP and other macroeconomic indicators to assess the overall state of the economy and determine the specific times when economic cycles reach their peaks and troughs. In terms of the Korean economy, a transition from a trough to a peak or vice versa is defined as an economic expansion or contraction, respectively. The shaded area of [Figure 1] illustrates the periods of economic contraction defined by Statistics Korea.[9]

9) According to Statistics Korea (2023), the latest economic trough, the lowest point of the 12th economic cycle, is May 2020. Since Statistics Korea assesses the economic cycle from a long-term perspective and declares turning points in a backward-looking manner, we choose CLID as our primary measure of the economic cycle preferred by market practitioners.

[Figure 1] Economic Cycle

This figure presents the periods of economic expansion and contraction from November 2010 to June 2019. The solid line is the cyclical component of the Composite Leading Indicator (CLI), with values equal to or greater than 100 indicating economic expansion and below 100 indicating economic contraction. The shaded area of the figure is the period of economic contraction as defined by Statistics Korea. Statistics Korea publishes economic cycles based on the composite coincide index and a long-term and comprehensive assessment of macroeconomic conditions. Notably, the period from 2012 to 2013 and 2018 to 2019, when the cyclical component of the CLI is in a long-term decline, overlaps with the periods of economic contraction defined by Statistics Korea.



<Table 9> Univariate Portfolio Analysis: Alternative Economic Cycle Definition

This table presents the average values of excess returns, 5% VaR, and other bond characteristics for the portfolios during the phases of economic expansion and contraction. The alternative economic cycle is defined by the Statistics Korea (Statistics Korea, 2023). 5% VaR is the minus of second-lowest weekly return over the past 36 weeks. Quintile portfolios were formed based on 5% VaR spanning from November 2010 to June 2019. Bonds in Quintile 1 have the lowest downside risk, while those in Quintile 5 possess the highest downside risk. Excess returns are calculated using value weights, whereas other portfolio averages utilize equal weighting. The final row denotes the return difference between the portfolios with the highest and lowest VaR. The numbers in parentheses represent the Newey-West corrected t-statistics with a lag of 4. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Quintile portfolios for 5% VaR: Economic expansion

Quintiles	VaR	Excess return	Rating	Amihud	Maturity	Size
Lowest	−0.003	0.033	6.03	0.201	2.821	118
2	0.194	0.022	6.65	0.313	2.524	105
3	0.547	0.000	6.93	0.472	1.967	131
4	1.068	0.038	7.67	0.701	1.699	115
Highest	2.633	0.161	7.96	1.266	1.899	119
High-Low	2.636***	0.128**				
	(22.17)	(2.52)				

<Table 9> Univariate Portfolio Analysis: Alternative Economic Cycle Definition (Continued)

Panel B: Quintile portfolios for 5% VaR: Economic contraction

Quintiles	VaR	Excess return	Rating	Amihud	Maturity	Size
Lowest	-0.004	0.040	5.91	0.218	2.207	113
2	0.136	0.025	6.00	0.249	1.969	129
3	0.368	0.020	6.54	0.338	1.769	128
4	0.775	0.051	7.22	0.509	1.600	123
Highest	2.021	0.089	7.66	0.993	1.410	102
High-Low	2.025***	0.049				
	(20.50)	(1.43)				

Using the economic cycle data provided by Statistics Korea, we established sub-samples corresponding to periods of economic expansion and contraction. Subsequently, we conducted the portfolio analyses identical to those presented in Section Ⅳ. As reported in <Table 9> and <Table 10>, the positive relationship between downside risk and corporate bond excess return remains consistent within the economic expansion sub-sample. However, except for short-term bonds, this positive association does not reach statistical significance during periods of economic contraction.

<Table 10> Bivariate Portfolio Analysis: Alternative Economic Cycle Definition

This table presents the excess return difference between the highest and lowest VaR portfolios during economic expansion and contraction phases. The alternative economic cycle is defined by the Statistics Korea (Statistics Korea , 2023). The sample period is from November 2010 to June 2019. We first brake the sample by the median of each control variable. Then, within each bintile, we formed quintile portfolios by 5% VaR and calculated the value-weighted portfolio excess returns. For time-to-maturity, we use 1-year as a breakpoint for bintile portfolios in that the bonds with a remaining life of less than one year are labeled as short-term, while the others are labeled as long-term. The numbers in parentheses indicate the Newey-West corrected t-statistics with a lag of four. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Controlling for rating

	Economic expansion		Economic contraction	
	Low	High	Low	High
H-L excess return	0.104*	0.154**	0.034	0.07
	(1.70)	(2.30)	(1.41)	(0.88)

Panel B: Controlling for Amihud illiquidity

	Economic expansion		Economic contraction	
	Low	High	Low	High
H-L excess return	0.034	0.216**	0.029	0.069
	(0.82)	(2.43)	(0.97)	(1.20)

<Table 10> Bivariate Portfolio Analysis: Alternative Economic Cycle Definition (Continued)

Panel C: Controlling for size

	Economic expansion		Economic contraction	
	Small	Large	Small	Large
H-L excess return	0.135** (2.16)	0.105* (1.72)	0.005 (0.08)	0.062 (0.99)

Panel D: Controlling for time-to-maturity

	Economic expansion		Economic contraction	
	Short	Long	Short	Long
H-L excess return	0.131* (1.81)	0.089* (1.77)	0.100** (2.39)	0.043 (1.11)

Ⅵ. Conclusion

This study investigates the significance of the cross-sectional relationship between the downside risk and expected return in the Korean corporate bond markets. Our special focus is on whether the economy cycle affect the downside risk-expected return relationship in the corporate bond markets. For the sample period from November 2010 to June 2019, we found that there is significant positive relationship between 5% VaR and one-week ahead corporate bond returns. Based on the bivariate portfolio analysis and Fama-MacBeth regressions, we confirmed that the positive relationship holds even after controlling for the well-known common risk factors such as credit and liquidity, as well as bond exposure to term spread, bond exposure to default spread, short-term reversal, time-to-maturity, and size.

A sub-sample analysis of business cycles shows that the positive relationship between VaR and returns is driven primarily by periods of economic expansion. On the other hand, this relationship becomes less economically and statistically significant during economic contractions. We suggest that the changing dynamics of VaR and returns may be influenced by the different interactions between interest rates and bond yields, which are particularly pronounced during economic contractions with some time lag.

Despite the remarkable growth of the exchange trading in the Korean corporate bond market, our analysis is limited by the relatively small share of exchange trading relative to OTC trading. According to the Korean Financial Investment Association, corporate bond tradings are notably skewed towards the OTC markets. The trading volume of the OTC market accounted for approximately 72% of the total bond trading activities in 2020. This scarcity of exchange-based trading activities significantly limits our ability to reliably identify common risk factors that govern the corporate bond market. Throughout our sample period, acquiring a persistent series of test portfolio returns with sufficient testing power, such as continuous series of 5-by-5 double-sorted portfolios based on credit and downside risk, remained unattainable. As a result, we believe that further exploration of more robust analyses in this direction is an important avenue for future research.

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<Appendix> Summary of Theoretical Framework

In this appendix, we summarize the generalized disappointment aversion factor model of Farago and Tédongap (2018) and Augustin et al. (2020), which suggest that downside risk explains the cross-section of corporate bond returns.

Consider a representative investor with the Epstein-Zin preference (1989) given by

$$V_{t-1} = \begin{cases} C_{t-1}^{1-\delta}\left[R_{t-1}(V_t)\right]^{\delta} & \text{if} \quad \psi = 1 \\ \left[(1-\delta)\,C_{t-1}^{1-\frac{1}{\psi}} + \delta\left[R_{t-1}(V_t)\right]^{1-\frac{1}{\psi}}\right]^{\frac{1}{1-\frac{1}{\psi}}} & otherwise, \end{cases}$$

where C_{t-1} is the period's consumption, V_{t-1} is the lifetime utility, R_{t-1} is the certainty equivalent, $0 < \delta < 1$ is the time preference, and $\psi > 0$ is the elasticity of inter-temporal substitution. For a CRRA utility U of wealth w given by

$$U(w) = \begin{cases} \ln w & \text{if} \quad \gamma = 1 \\ \dfrac{w^{1-\gamma}-1}{1-\gamma} & otherwise, \end{cases}$$

with a risk-aversion parameter $\gamma \geq 0$, Routldege and Zin (2010) incorporated disappointment aversion into the framework by implicitly defining the certainty equivalent R_{t-1} by

$$U(R_{t-1}) = E_{t-1}\left[U(V_t)\right] - \theta E_{t-1}\left[\left(U(\kappa R_{t-1}) - U(V_t)\right) I_{\{V_t < \kappa R_{t-1}\}}\right]$$

where $\theta \geq 0$ is the degree of disappointment aversion and $0 \leq \kappa \leq 1$ is the ratio of certainty equivalent that outcomes below it are regarded as disappointing. Farago and Tédongap (2018) solved an utility maximization problem with budget constraint $w_t = (w_{t-1} - C_{t-1})(1 + r_{mt})$ to obtain a stochastic discount factor SDF expressed as

$$SDF_{t-1,t} = \delta\left(\frac{C_t}{C_{t-1}}\right)^{-\frac{1}{\psi}}\left(\frac{V_t}{R_{t-1}(V_t)}\right)^{\frac{1}{\psi}-\gamma}\left(\frac{1+\theta I_{\{V_t < \kappa R_{t-1}(V_t)\}}}{1+\kappa^{1-\gamma}\theta E_{t-1}\left[I_{\{V_t < \kappa R_{t-1}(V_t)\}}\right]}\right).$$

Assuming that the market returns are related with the consumption growth and the welfare valuation ratio growth (Epstein and Zin, 1989; Routledge and Zin, 2010), the time-t market return, denoted by r_{mt}, is derived as

$$r_{mt} = -\ln\delta + \ln\frac{C_t}{C_{t-1}} + \left(1-\frac{1}{\psi}\right)\left(\ln\frac{V_t}{C_t} - \ln\frac{R_{t-1}(V_t)}{C_{t-1}}\right).$$

Moreover, assuming that aggregate consumption growth is heteroskedastic, Farago and Tédongap (2018) derive the following linear equation for corporate bond excess return by solving for the Euler equation $E_{t-1}[SDF_{t-t,t}r] = 0$:

$$E[r_{it}] = p_{im}cov(r_{it}, r_{mt}) + p_{iD}cov(r_{it}, I_{\{D_t < b\}}) + p_{mD}cov(r_{it}, r_{mt}I_{\{D_t < b\}})$$
$$+ p_{iX}cov(r, \Delta\sigma^2_{mt}) + p_{XD}cov(r, \Delta\sigma^2_{mt}I_{\{D_t < b\}}),$$

where $\Delta\sigma^2_{mt}$ is the change in market variance, $I_{\{D_t < b\}}$ is an indicator function of downstate with the preference and aggregate consumption process parameters $a > 0$ and b.

Next, consider a portfolio that is long the market portfolio and a times short the market volatility. Then, in this framework, the disappointment event D_t occurs when the portfolio return is below a threshold level b. That is, the likelihood of a disappointment event is related to the measure of downside risk, such as value-at-risk or expected shortfall. Specifically, a one-factor model of downside risk, as introduced in Bai et al. (2019), can be derived as a particular instance of the generalized disappointment aversion factor model (Augustin et al., 2020).

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하방꼬리위험이 국내 회사채 투자수익률 횡단면에 미치는 영향*

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〈요 약〉

본 연구에서는 국내 회사채 시장에서 최대예상손실액(value at risk)으로 측정한 하방위험과 기대수익률 간의 횡단면적 특성을 살펴보았다. 2010년부터 2019년까지의 국내 투자등급 회사채 자료를 바탕으로 포트폴리오 분석과 Fama-MacBeth 회귀분석을 수행한 결과, 하방위험은 회사채의 횡단면 보유기간수익률(holding period return)과 통계적으로 유의미한 양(+)의 관계를 가지며 이는 경기팽창 국면에서 더욱 두드러지게 나타남을 확인하였다. 한편, 경기가 축소될 것으로 예상될 때는 경기주기에 따른 금리변동과 채권 수익률간의 상호작용으로 인하여 위의 유의미한 양(+)의 관계가 더 이상 관찰되지 않았다. 이러한 결과는 신용 및 유동성 위험과 다양한 채권 특성 변수를 통제한 뒤에도 유의한 신뢰수준으로 유지되는 것으로 나타났다.

주제어 : 하방꼬리위험, 최대예상손실액, 회사채 투자수익률, 경기변동

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