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Conditional Relationship between Distress Risk and Stock Returns

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A B S T R A C T

Purpose: Previous research on the relationship between a firm's distress risk and future stock returns produces inconsistent results. This study attempts to explain the conflicting results of earlier studies by showing that systematic distress risk leads to positive rewards, while unsystematic distress risk leads to low stock returns. In addition, this study intends to elucidate the factors of systematic distress risk and unsystematic distress risk, respectively. In this way, this study informs the rational investor what kind of distress risk they should take.
Design/methodology/approach: This study considers two distress-predictor sets to show a possibility between distress risk and stock returns in both directions. The first set includes profitability ratio, excess returns, and volatility, and the second consists of leverage, firm size, and book-to-market ratio. Similar to the methodology proposed in Campbell et al. (2008), this study measures the distress risk using a dynamic logit model. Depending on which explanatory variables predict the distress risk, the relationship between distress risk and future stock returns could be in both ways.
Findings: This study first shows that systematic and unsystematic distress risk factors are significant in predicting failures. However, the effects of the two distress risk factors on stock returns appear in opposite directions. Precisely, the systematic distress risk is estimated by the debt ratio, company size, and book-to-market ratio. The common factors of Fama and French (1993) explain the positive risk premium due to the systematic distress risk. In contrast, the unsystematic distress risk is predicted by profitability, momentum effect, and firm-specific volatility. The Fama-French common factors do not explain low stock returns due to unsystematic distress risk.
Research limitations/implications: Because of the two different attributes of distress risk, investors must assume systematic distress risk and avoid unsystematic distress risk. Although the results of this study are based on the analysis of the Korean stock market, the main hypotheses can be tested in other countries' stock markets as well.
Originality/value: This study is the first to compromise the inconsistent results of existing studies, and it explicitly shows the factors of systematic and unsystematic distress risk.

Keywords: Distress risk, Failure prediction, Fama-French factors, Systematic distress risk

I. Introduction

Previous research on the relationship between a firm's distress risk and future stock returns produces inconsistent results. For example, Fama and French (1992, 1996) suggest a positive relationship between distress risk and stock returns. They show that value firms proxied by higher book-to-market ratios earn higher stock returns, and they interpret that higher distress risks could drive the higher stock returns

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of the firms with higher book-to-market ratios. However, Campbell et al. (2008) estimate the distress risk using a dynamic logit model and report an anomalously negative relation between distress risk and future stock returns, which is inconsistent with the conjecture by Fama and French.

Also, a recent study, Aretz et al. (2018), measures distress risk using the model in Campbell et al. (2008) but reports that distress risk has a positive effect on stock returns in 14 countries other than the United States. These results show that distress risk can positively affect stock returns even when the distress risk is measured using the model in Campbell et al. (2008). Aretz et al. (2018) interpret it as a result of systematic distress risk. However, it is unclear what constitutes systematic distress risk.

This study attempts to explain the conflicting results of earlier studies by showing that systematic distress risk leads to positive rewards, while unsystematic distress risk leads to low stock returns. In addition, this study intends to elucidate the factors of systematic distress risk and unsystematic distress risk, respectively. In this way, this study informs the rational investor what kind of distress risk they should take.

This study uses a methodology proposed by Campbell et al. (2008) to measure distress risk. But a firm's distress predictors are divided into two sets to distinguish the factors of systematic and unsystematic distress risk. The first set (profitability ratio, excess returns, and volatility) comprises unsystematic distress predictors, which are expected to have the opposite directional effect on the probability of a firm's failure and its stock returns. For example, firms with lower profitability ratios are expected to have higher failure probabilities but lower future stock returns than firms with higher profitability ratios. In contrast, systematic distress predictors in the second set (leverage, firm size, and book-to-market ratio) are expected to have the same directional effect on the probability of failure and future stock returns. For example, smaller firms are expected to have higher failure probabilities and higher future stock returns than larger firms. This study estimates a firm's failure probability based on each set of distress predictors using the dynamic logit model as a proxy for distress risk. When using unsystematic distress predictors, the distress risk is negatively related to future stock returns. On the other hand, the distress risk based on systematic distress predictors is positively associated with future stock returns.

A firm's failure is defined as the firm's delisting event when estimating the dynamic logic model to measure a firm's failure probability. It is shown that unsystematic and systematic distress predictors are significant failure predictors in the sample using the information on companies listed on the Korean stock market from January 1993 to December 2018. It is also essential to examine whether failure prediction models have high predictive power outside the estimation period. Using unsystematic distress predictors, the model predicted 436 failed firms (68.4% of 637 failed firms in total) in a quintile portfolio with the highest failure probability. The model used systematic distress predictors to predict 356 failed firms (55.9% of 637) in a quintile portfolio with the highest failure probability. Thus, the within-sample and out-of-sample predictions suggest that the explanatory variables in both groups are distress risk factors.

Although unsystematic and systematic distress risk factors are good failure predictors, they could affect future stock returns differently. Firms are sorted into quintiles by either unsystematic or systematic distress risk. Then, monthly returns are computed for a long-short portfolio, which buys a quintile portfolio with the highest distress risk and sells a quintile portfolio with the lowest distress risk, to examine how each type of distress risk affects stock return. When estimating the failure prediction model using unsystematic distress predictors, the spread portfolio yields an average return of -1.37% per month (t-stat = -2.89). However, the spread portfolio delivers an average return of 0.88% per month (t-stat = 2.42) when systematic distress predictors are used. Hence, the results suggest that systematic distress risk leads to positive rewards, while unsystematic distress risk leads to low stock returns.

When the Capital Asset Pricing Model (hereafter, CAPM) is used for computing the risk-adjusted returns

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of quintile portfolios, the statistical significance of the above directional effects remains the same. Thus, the market risk factor does not explain the conditional impact of distress risk on future stock returns. However, the positive compensation for taking systematic distress risk becomes insignificant when the common factors of Fama and French (1993) are controlled. In contrast, the negative effect of unsystematic distress risk on future stock returns remains.

Overall, the results confirm that the sources of systematic distress risk are the debt ratio, company size, and book-to-market ratio. The systematic distress risk is consistent with the distress risk explained by Fama and French (1992, 1996). On the other hand, the sources of unsystematic distress risk are profitability, momentum effect, and firm-specific volatility. The unsystematic distress risk leads to anomalously low returns documented in Campbell et al. (2008). Therefore, this study is the first to compromise the conflicting results of existing studies, and it explicitly shows the factors of systematic and unsystematic distress risk.

II. Literature Review

This paper uses two sets of distress predictors to show different directional relationships between distress risk and future stock returns. After estimating the probability of failure using a dynamic logit model for each distress predictor, this study uses it to proxy distress risk. When dividing predictors into two sets, this study considers each predictor's directional expectation on failure probability and its directional expectation on future stock returns. Hence, this study reviews prior studies on those directional expectations of each distress predictor.

This study uses six variables as distress predictors: profitability ratio, excess returns, volatility, leverage, firm size, and book-to-market ratio. Among these variables, profitability ratio, excess returns, volatility, leverage, and firm size are the variables of Shumway (2001), which are commonly used for predicting failures in the prior literature. If a firm has lower profitability, then the firm should have a higher probability of failure than a higher profitability firm because a firm with lower profitability is considered to have lower operational efficiency. If firms come close to failure, equity values decrease because of higher risk. Thus, a firm with lower excess returns is expected to have a higher failure probability than a firm with higher excess returns. The third variable is idiosyncratic volatility. A firm with higher idiosyncratic volatility of stock returns is expected to have a higher failure probability than a firm with lower idiosyncratic volatility. Highly leveraged firms would have a high failure probability because they have an unstable financial structure. As mentioned before, equity values decrease when firms are close to failure. Thus, firm size is also a distress predictor along with the excess returns. Smaller firms are more likely to fail than larger firms. This study also uses a firm's book-to-market ratio to predict the probability of failure. Fama and French (1992, 1996) suggest that book-to-market ratios reflect distress risk, and firms with higher distress risk have a higher book-to-market ratio.

Meanwhile, extensive literature studies the directional expectations on the future stock returns of each of those explanatory variables. Fama and French (2015) show that profitability is positively related to future stock returns. Thus, a firm with a lower profitability ratio is expected to have lower future stock returns than a higher profitability ratio. Jegadeesh and Titman (1993) argue that a firm with lower past returns would have lower future returns than a firm with higher past returns because of a momentum effect. Ang et al. (2006) and Ang et al. (2009) examine the relationship between past idiosyncratic volatility and future stock returns. If a firm has higher idiosyncratic volatility of stock returns, the firm is expected to have lower future stock returns. Bhandari (1988) argues that leverage is positively related to future stock returns. Thus, a firm with higher leverage is expected to have higher future stock returns than a firm with lower leverage. Banz (1981) and Fama and French (1992) show that smaller firms are expected to have higher future stock returns than larger firms.

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Table 1. Literature Reviews

Variables	Expected Sign		Literature Reviews
	Prob. of Failure	Future Stock Returns	
Profitability ratio (NITA)	(-)	(+)	Shumway (2001), Fama and French (2015)
Excess returns (EXRET)	(-)	(+)	Shumway (2001), Jegadeesh and Titman (1993)
Volatility (Sigma)	(+)	(-)	Shumway (2001), Ang et al. (2006), Ang et al. (2009)
Leverage (TLTA)	(+)	(+)	Shumway (2001), Bhandari (1988)
Firm size (Relative size)	(-)	(-)	Shumway (2001), Banz (1981), Fama and French (1992)
Book-to-market ratio (B/M)	(+)	(+)	Fama and French (1996), Fama and French (1992)

Fama and French (1992) find value firms with high book-to-market ratios earn higher stock returns than growth firms with low book-to-market ratios.

Table 1 summarizes the expected effect of each distress predictor on the probability of failure and future stock returns. Profitability ratio (NITA), excess returns (EXRET), and volatility (Sigma) are the variables whose impact on the probability of failure and future stock returns are in the opposite direction. As a result, this study calls the variables unsystematic distress risk factors. In contrast, leverage (TLTA), firm size (Relative size), and book-to-market ratio (B/M) predict failure probability and future stock returns in the same order. This study names the variables as systematic distress risk factors. Then, future stock returns are expected to decrease with higher failure probabilities predicted by unsystematic distress risk factors. On the other hand, future stock returns are expected to increase with higher failure probabilities driven by systematic distress risk factors.

III. Data and Methods on Predicting Failures

A. Data and Sample Statistics

Samples are the common stocks of firms listed on the Korean stock markets, Korea Composite Stock Price Index (KOSPI) and Korean Securities Dealers Automated Quotations (KOSDAQ), from January 1993 to December 2018 and obtained from FnGuide, a data provider in Korea. A dynamic logit model for estimating a firm's probability of failure requires failure indicators. This study defines a firm's failure as the firm's delisting event. Hence, failure indicators are constructed from delisting events. Table 2 reports the number of failures, the total number of listed firms, and the proportion of failures for every year of the sample period. The frequency of delisting events had increased dramatically since the 1997 Asian financial crisis and peaked at 5.17% in 1999. It decreased to below 1% in 2006 and 2007. However, after the 2008 global financial crisis, the failure rate increased significantly to 4.93% in 2010. And then it decreased again. Thus, the number of delisting events sufficiently reflects changes in market conditions, suggesting that delisting events reasonably represent failures.

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Table 2. Number of Delisting per Year

Year	Delisting	All	Proportion
1995	2	647	0.31%
1996	7	677	1.03%
1997	6	889	0.67%
1998	29	996	2.91%
1999	52	1,004	5.18%
2000	33	1,004	3.29%
2001	35	1,187	2.95%
2002	40	1,308	3.06%
2003	33	1,465	2.25%
2004	54	1,520	3.55%
2005	53	1,553	3.41%
2006	9	1,595	0.56%
2007	15	1,627	0.92%
2008	21	1,687	1.24%
2009	75	1,734	4.33%
2010	84	1,768	4.75%
2011	64	1,824	3.51%
2012	57	1,840	3.10%
2013	41	1,813	2.26%
2014	20	1,815	1.10%
2015	28	1,816	1.54%
2016	18	1,880	0.96%
2017	31	1,975	1.57%
2018	38	2,039	1.86%
1995-2018	845	35,663	2.37%

This table reports the number of firms being delisted, the total number of listed firms, and the proportion of delisting for each year.

Monthly stock market data is merged with annual accounting data for creating the variables expected to predict failures. When combining the two datasets, accounting data is merged with monthly stock market data with a lag of three months. This adjustment ensures that accounting data is available when forecasting failures and subsequent stock returns.

This study first constructs the five variables as in Shumway (2001). Profitability ratio (NITA) and leverage (TLTA) are measured as net income to total assets and as total liabilities to total assets, respectively. Each firm's excess returns (EXRET) are calculated as cumulative monthly returns over a month t-12 to t-1 minus cumulative monthly returns of the KOSPI index over the same period. The idiosyncratic volatility (Sigma) of each firm's stock returns is measured by computing the standard deviation of monthly residual returns from the CAPM regression for months t-12 to t-1. The firm size (Relative size) variable is measured relative to the market capitalization of the stock market in month t-1 and takes a logarithm. In addition to the five variables in Shumway (2001), the book-to-market ratio (B/M) is considered the sixth distress predictor. All variables are winsorized at 1st and 99th percentiles to mitigate the impact of outliers.

Table 3 reports summary statistics for the explanatory variables. Panel A summarizes the distribution of the variables for the entire sample, and Panel B provides each variable's mean values across non-failure and failure groups. The t-test of Satterthwaite (1946) is used for testing the significant difference between the two groups. Following Campbell et al. (2008) and Kim (2016), the non-failure months of a failed firm are treated as non-failure observations, and only the failure month of the failed firm is treated as failure observation. Overall, there are significant differences between the non-failure and failure groups. The failure group tends to have lower profitability ratios, lower past returns, and higher leverage than the non-failure group. In addition, the failure group is relatively more volatile and smaller than the non-failure group.

B. Failure Prediction Models

This study uses a dynamic logit model in Campbell et al. (2008) for measuring a firm's failure probability. The probability of a firm i to fail in 12 months, conditional on survival for the previous 11 months, is specified as follows:

$$\Pr_{m-12}(Y_{i,m}=1 | Y_{i,m-1}=0) = \frac{1}{1+\exp\left(-\alpha-\beta' X_{i,m-12}\right)}, \quad (1)$$

where $Y_{i,m}$ is a failure indicator of firm i which

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Table 3. Summary Statistics for Failure Predictors

Panel A: Summary Statistics for Failure Predictor Variables

Variables	Mean	Median	Standard Deviation	Minimum	Maximum
NITA	0.00	0.02	0.16	-0.86	0.30
EXRET	0.05	-0.08	0.72	-1.22	3.66
Sigma	15.40	12.07	11.66	1.41	74.38
TLTA	0.51	0.51	0.25	0.06	1.30
Relative size	-9.02	-9.28	1.52	-11.83	-4.37
B/M	1.31	0.96	1.42	-2.66	8.24

Panel B: Average Values across Non-failure vs. Failure Groups

Variables	Non-failure Group	Failure Group	Difference:(2)-(1)
NITA	0.00	-0.17	-0.17***
EXRET	0.06	-0.26	-0.31***
Sigma	15.39	20.24	4.85***
TLTA	0.51	0.63	0.12***
Relative size	-9.02	-9.68	-0.66***
B/M	1.31	1.27	-0.05
Observations	401,090	715	

This table reports summary statistics for each of the following variables used to predict failure: NITA (net income to total assets), EXRET (annualized stock return of a firm minus value-weighted KOSPI index annualized return), Sigma (idiosyncratic volatility of each firm's monthly returns for 12 months), TLTA (total liabilities to total assets), Relative size (logarithm of each firm's market capitalization relative to the total value of the KOSPI market), B/M (book-to-market ratio of each firm). Panel A reports summary statistics for the failure predictor variables. Panel B reports each variable's mean values across non-failure and failure firm-month groups and results from t-tests to test whether the mean values of each variable are equal. Non-failure months for a failed firm are treated as non-failure firm-month observations. All variables are truncated to the ninety-ninth and first percentiles, so the minimum and maximum are the corresponding percentile values. The reported statistics are from the observations for which all variables are available. The sample period is from 1993 to 2018. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

equals one if the firm fails in month m, and $X_{i,m-12}$ is a vector of explanatory variables measured in month $m-12$. A higher value of $\alpha+\beta' X_{i,m-12}$ implies a higher probability of failure. Therefore, a positive (negative) β means that the failure probability increases (decreases) as the corresponding explanatory variable x goes higher.

Table 4 reports the results from the dynamic logit regressions for two different models. Predictor variables are divided into unsystematic and systematic distress risk factors. Model 1 forecasts failures with unsystematic distress risk factors (NITA, EXRET, Sigma), and Model 2 predicts failures with systematic distress risk factors (TLTA, Relative size, B/M). The regression results show that lower profitability ratio (NITA), lower excess returns (EXRET), higher stock return volatility (Sigma), higher leverage (TLTA), and smaller firm size (Relative size) increase the probability of failure. Overall, the directional effect of each predictor on the failure probability is consistent with the expected sign described earlier.

Table 4. Logit Regression of Failure Indicator on 12-month Lag Predictors

	Model 1	Model 2
NITA	-2.22***	
	(-17.59)	
EXRET	-0.63***	
	(-7.42)	
Sigma	0.02***	
	(6.93)	
TLTA		1.72***
		(10.75)
Relative size		-0.34***
		(-9.92)
B/M		0.01
		(0.35)
Constant	-6.84***	-10.49***
	(-115.93)	(-32.67)
Pseudo-R^2	0.053	0.030

This table reports the results of logit regression of failure indicators for predictors delayed by 12 months. If the company is delisted in month t, the failure indicator will be 1 in month t and 0 in another month. Model 1 predicts failures with unsystematic distress risk factors (NITA, EXRET, Sigma). Model 2 forecasts failures with systematic distress risk factors (TLTA, Relative size, B/M). The sample period is from 1993 to 2018. The table presents estimated coefficients, and t-values are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Pseudo-R^2 is computed according to McFadden (1974).

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C. Out-of-Sample Predictability

This study examines whether failure prediction models have good predictive power outside the sample before investigating the relationship between distress risk and future stock returns. Only past information should be used to avoid look-ahead bias when measuring the likelihood that a firm fails. Therefore, rolling window estimations of dynamic logit models calculate the probability of failure. Then, firms are sorted by the predicted probability.

The first estimation window covers seven years of data until December 1999. Then the probability of failure is computed using the estimated coefficients. At the beginning of January 2000, firms are sorted into quintile portfolios by the predicted chance of failure. The above process is repeated every month until December 2018. Suppose the failure prediction models have good predictive power out-of-sample. In that case, a quintile portfolio with the higher predicted failure probability will include more failed firms than a quintile portfolio with the lower predicted failure probability. If the predicted probability based on each model does not have any predictive power, roughly 20% of failed firms should be expected from each quintile group.

Table 5 examines whether the model has good predictive power outside of the sample. Both Model 1 and Model 2 show reasonably good out-of-sample failure predictability, although the two models predict failures by completely different unsystematic and systematic distress risk factors. In Panel A, 450 failed firms (68.5% of 657) are found in a quintile portfolio with the highest failure probability using Model 1.

Table 5. Out-of-Sample Predictive Power of Failure Prediction Models

		Panel A. Model 1					
		Number of failed firms					
Year	Average number of companies per month	Low distress	Quintile 2	Quintile 3	Quintile 4	High distress	Total
2000	179	3	3	4	3	7	20
2001	204	2	6	4	2	6	20
2002	233	1	2	0	2	27	32
2003	264	1	2	3	5	17	28
2004	280	7	1	3	8	31	50
2005	284	2	3	4	4	35	48
2006	292	1	0	1	2	4	8
2007	305	1	1	1	1	9	13
2008	315	1	1	2	2	15	21
2009	323	1	2	3	1	62	69
2010	318	5	0	2	1	71	79
2011	320	6	4	1	3	38	52
2012	330	2	3	0	3	43	51
2013	330	2	9	5	1	21	38
2014	329	0	2	3	1	11	17
2015	338	2	0	3	4	16	25
2016	353	5	2	0	0	11	18
2017	372	5	7	2	4	12	30
2018	383	4	17	1	2	14	38
Total		51	65	42	49	450	657

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Table 5. Continued

		Panel B. Model 2					
		Number of failed firms					
Year	Average number of companies per month	Low distress	Quintile 2	Quintile 3	Quintile 4	High distress	Total
2000	179	3	3	0	4	10	20
2001	204	1	0	0	4	15	20
2002	233	2	0	3	8	19	32
2003	264	2	1	2	6	17	28
2004	280	2	2	3	10	33	50
2005	284	6	2	2	5	33	48
2006	292	0	1	1	0	6	8
2007	305	2	0	1	3	7	13
2008	315	4	3	3	1	10	21
2009	323	4	8	8	7	42	69
2010	318	6	11	7	12	43	79
2011	320	4	9	12	12	15	52
2012	330	3	4	9	11	24	51
2013	330	3	1	9	7	18	38
2014	329	3	1	3	1	9	17
2015	338	4	3	1	2	15	25
2016	353	1	2	2	4	9	18
2017	372	2	2	1	5	20	30
2018	383	6	2	1	3	26	38
Total		58	55	68	105	371	657

This table reports whether failure prediction models have good predictive power outside of the sample. The failure prediction models are estimated every month using the prior seven years of data, and a firm's probability of failure is measured with the estimated coefficients. Model 1 predicts failures with unsystematic distress risk factors (NITA, EXRET, Sigma). Model 2 forecasts failures with systematic distress risk factors (TLTA, Relative size, B/M). Then, all firms are sorted into quintiles by the predicted chance of failure. After that, failed firms are counted in each quintile from 2000 to 2018.

In Panel B, 371 failed firms (56.5% of 657) are discovered in a quintile portfolio with the highest chance of failure using Model 2. This result indicates that unsystematic and systematic distress risk factors are significant in predicting failures.

IV. Results on the Relationship between Distress Risk and Stock Returns

A. Evidence from Time-series Regressions

This section examines the directional relationship between distress risk and future stock returns. Two types of distress risks are considered. Unsystematic (systematic) distress risk means failure probability predicted by unsystematic (systematic) distress risk factors. All firms are grouped into quintile portfolios by either unsystematic or systematic distress risk. Then, equally-weighted portfolio returns are computed from January 2000 to December 2018.

Monthly average return and risk-adjusted return are computed for examining each portfolio's performance. Alpha is a risk-adjusted return obtained by subtracting factor loadings times returns on common factors. If alpha is insignificant, it is interpreted that common factors explain the performance of a portfolio and

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Table 6. How Distress Risks Affect Future Stock Return: Raw Return & CAPM

	Panel A: Model 1 (Unsystematic Distress Risk)				Panel B: Model 2 (Systematic Distress Risk)			
Portfolios	Raw Return	Alpha	MKTRF	Adj-R^2	Raw Return	Alpha	MKTRF	Adj-R^2
Quin1	1.33	0.87	0.81	0.42	0.62	0.14	0.89	0.48
	(2.58)	(2.21)	(12.92)		(1.17)	(0.38)	(14.57)	
Quin2	1.53	1.06	0.84	0.62	0.87	0.40	0.87	0.52
	(3.46)	(3.91)	(19.41)		(1.75)	(1.16)	(15.68)	
Quin3	1.44	0.95	0.97	0.64	1.26	0.78	0.88	0.49
	(2.88)	(3.14)	(20.01)		(2.40)	(2.09)	(14.85)	
Quin4	1.34	0.85	0.99	0.54	1.36	0.87	0.96	0.58
	(2.39)	(2.21)	(16.21)		(2.62)	(2.58)	(17.81)	
Quin5	-0.04	-0.52	0.90	0.32	1.50	1.02	0.91	0.46
	(-0.06)	(-0.95)	(10.34)		(2.68)	(2.47)	(13.93)	
Q5-Q1	-1.37	-1.39	0.10	0.00	0.88	0.87	0.03	0.00
	(-2.89)	(-2.94)	(1.30)		(2.42)	(2.40)	(0.45)	

This table reports the results of time-series regressions for quintile portfolios sorted by distress risk. In Panel A, Model 1 forecasts failures with unsystematic distress risk factors (NITA, EXRET, Sigma). In Panel B, Model 2 predicts failures by systematic distress risk factors (TLTA, Relative size, B/M). Firms are grouped into quintiles by each type of distress risk. Then, each quintile portfolio return is computed with equal weights. The zero-cost spread portfolio (Q5-Q1) longs a quintile portfolio with the highest distress risk and shorts a quintile portfolio with the lowest distress risk. In the table, raw return and alpha report the average monthly return and the risk-adjusted return obtained from the CAPM regression, respectively. T-statistics are expressed in parentheses under each estimated parameter value. The analysis period is from January 2000 to December 2018.

are related to the sources of distress risk. Furthermore, returns on the zero-cost spread portfolio (Q5-Q1), which longs a quintile portfolio with the highest distress risk and shorts a quintile portfolio with the lowest distress risk, suggest how each type of distress risk affects future stock returns.

Table 6 reports that systematic distress risk leads to positive rewards, while unsystematic distress risk leads to low stock returns. In Panel A, the results show that higher unsystematic distress risks lower stock returns. The spread portfolio's average return and CAPM alpha are significantly negative at -1.37% per month (t-stat = -2.89) and -1.39% per month (t-stat = -2.94). The average return and alpha on the quintile portfolio with the highest failure probability are extremely lower than the others. On the other hand, Panel B indicates a positive relationship between systematic distress risk and stock returns. The spread portfolio's average return and CAPM alpha are significantly positive at 0.88% per month (t-stat = 2.42) and 0.87% per month (t-stat = 2.40). The average returns and CAPM alphas increase monotonically as systematic distress risks increase.

Table 7 reports portfolios' performance after controlling the three factors, the market, size (SMB), and value (HML) factors, in Fama and French (1993). Panel A shows the alpha of the spread portfolio by unsystematic distress risk is still negative at -0.87% per month (t-stat = -1.80). Thus, the results suggest that unsystematic distress risk factors drive the low stock returns of distressed firms documented in Campbell et al. (2008). However, Panel B shows that the three-factor alpha of the spread portfolio becomes insignificant as 0.16% per month (t-stat = 0.44) because the size and value factors explain the positive risk premium due to systematic distress risk. Hence, systematic distress risk is a source of size and value premium presented by Fama and French (1992, 1996). Therefore, this study compromises the conflicting results of previous researches on the relationship between distress risk and future stock returns.

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Table 7. How Distress Risks Affect Future Stock Return: Fama-French Three-Factor Model

	Panel A: Model 1 (Unsystematic Distress Risk)					Panel B: Model 2 (Systematic Distress Risk)				
Portfolios	Alpha	MKTRF	SMB	HML	Adj-R^2	Alpha	MKTRF	SMB	HML	Adj-R^2
Quin1	0.35	0.98	0.95	0.24	0.85	0.26	1.03	0.85	-0.19	0.88
	(1.68)	(30.29)	(25.52)	(4.88)		(1.29)	(33.55)	(24.29)	(-4.28)	
Quin2	0.59	0.98	0.70	0.24	0.94	0.21	1.02	0.88	0.02	0.94
	(4.98)	(53.74)	(33.71)	(9.05)		(1.57)	(49.64)	(37.34)	(0.57)	
Quin3	0.57	1.10	0.73	0.17	0.90	0.37	1.06	0.95	0.17	0.91
	(3.44)	(43.32)	(25.09)	(4.62)		(2.21)	(40.98)	(32.00)	(4.33)	
Quin4	0.65	1.15	0.89	0.02	0.87	0.40	1.11	0.81	0.23	0.88
	(3.06)	(35.17)	(23.90)	(0.44)		(2.11)	(38.10)	(24.21)	(5.23)	
Quin5	-0.52	1.09	1.09	-0.15	0.71	0.41	1.08	0.88	0.31	0.77
	(-1.36)	(18.53)	(16.25)	(-1.74)		(1.45)	(24.54)	(17.41)	(4.71)	
Q5-Q1	-0.87	0.10	0.14	-0.39	0.08	0.16	0.06	0.03	0.50	0.14
	(-1.80)	(1.39)	(1.67)	(-3.50)		(0.44)	(1.04)	(0.47)	(6.16)	

This table reports the results of time-series regressions for quintile portfolios sorted by distress risk. In Panel A, Model 1 forecasts failures with unsystematic distress risk factors (NITA, EXRET, Sigma). In Panel B, Model 2 predicts failures by systematic distress risk factors (TLTA, Relative size, B/M). Firms are grouped into quintiles by each type of distress risk. Then, each quintile portfolio return is computed with equal weights. The zero-cost spread portfolio (Q5-Q1) longs a quintile portfolio with the highest distress risk and shorts a quintile portfolio with the lowest distress risk. In the table, alpha reports the risk-adjusted return obtained from the three-factor model of Fama and French (1993). T-statistics are expressed in parentheses under each estimated parameter value. The analysis period is from January 2000 to December 2018.

Table 8. How Distress Risks Affect Future Stock Return: Cross-Sectional Regressions

	Model 1 (Unsystematic Distress Risk)		Model 2 (Systematic Distress Risk)	
	1-(1)	1-(2)	2-(1)	2-(2)
Distress Risk	-0.29***	-0.47***	0.22**	-0.01
	(-2.86)	(-4.24)	(2.45)	(-0.10)
Relative size		-0.61***		-0.47***
		(-3.72)		(-3.06)
B/M		0.44***		0.45***
		(4.11)		(3.86)
Constant	1.69***	-3.88***	0.14	-3.93***
	(3.35)	(-3.01)	(0.25)	(-3.22)

This table reports the results of the Fama-MacBeth cross-sectional regression. Excess returns are regressed on each type of distress risk and the Fama-French factors (Relative size and B/M) for each month. The time series mean of monthly parameter estimates for each variable is reported with the Newey-West adjusted t-statistic in parentheses. The dependent variable is each stock's monthly return minus the monthly return of a one-year Monetary Stabilization Bond (MSB). Model 1 predicts failures with unsystematic distress risk factors (NITA, EXRET, Sigma). Model 2 forecasts failures with systematic distress risk factors (TLTA, Relative size, B/M). The rank variable of distress risk is measured from 1 to 5. The Fama-French factor variables are measured as described in Table 3. Cross-sectional regressions are run each month from January 2000 to December 2018. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

B. Evidence from Cross-sectional Regressions

This section implements firm-level cross-sectional regressions of Fama and MacBeth (1973) to investigate how robust the results reported in the previous time-series regressions are. The rank variable of distress risk is measured every month, ranging from rank 1 (the lowest distress risk) to rank 5 (the highest distress risk). The excess returns of firms are regressed on the rank variable of distress risk and lagged Fama-French factor variables (firm size and book-to-market ratio) every month. Table 8

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reports the time-series average of the coefficients from the monthly cross-sectional regressions with t-statistics adjusted by the standard errors based on Newey and West (1987).

The cross-sectional regressions confirm that higher unsystematic distress risks lower future stock returns. A firm's future stock returns fall by 0.29% per month (t-stat = -2.86) as its unsystematic distress risk increases by one rank. The effect of unsystematic distress risk on future stock returns is still significantly negative (-0.47, t-stat = -4.24) even when the firm size and book-to-market ratio variables are included in the cross-sectional regression.

In contrast, a firm's future stock returns increase by 0.22% per month (t-stat = 2.45) as its systematic distress risk increases by one rank. However, the positive effect of systematic distress risk on stock returns disappears after controlling the Fama-French factors. Overall, the results from cross-sectional regressions confirm the findings of the previous time-series regressions.

V. Conclusion

Previous research on the relationship between a firm's distress risk and future stock returns produces inconsistent results. This study attempts to explain the conflicting results of earlier studies by showing that systematic distress risk leads to positive rewards, while unsystematic distress risk leads to low stock returns. In addition, this study intends to elucidate the factors of systematic distress risk and unsystematic distress risk, respectively.

Six distress predictors suggested by the prior literature are divided into two sets based on each variable's directional expectation on failure probability and future stock returns. Then, this study shows that systematic and unsystematic distress risk factors are significant in predicting failures both in-sample and out-of-sample. However, the effects of the two distress risk factors on stock returns appear in opposite directions. It is found that the higher the systematic distress risk, the higher the future stock return, while the higher the unsystematic distress risk, the lower the future stock return.

Precisely, systematic distress risk is predicted by the debt ratio, company size, and book-to-market ratio. The size and value factors of Fama and French (1993) explain the positive risk premium due to the systematic distress risk. Thus, the systematic distress risk is consistent with the distress risk proposed by Fama and French (1992, 1996). In contrast, unsystematic distress risk is predicted by profitability, momentum effect, and firm-specific volatility. The unsystematic distress risk leads to anomalously low returns documented in Campbell et al. (2008).

Therefore, this study is the first to compromise the conflicting results of existing studies, and it explicitly shows the factors of systematic and unsystematic distress risk. Because of the two different attributes of distress risk, a rational investor must assume systematic distress risk to earn compensation and avoid unsystematic distress risk. Although the results of this study are based on the analysis of the Korean stock market, the main hypotheses can be tested in other countries' stock markets as well. Therefore, it will be interesting to examine whether the main findings of this study are global phenomena.

References

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *The Journal of Finance, 61*(1), 259-299.

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2009). High idiosyncratic volatility and low returns: International and further US evidence. *Journal of Financial Economics, 91*(1), 1-23.

Aretz, K., Florackis, C., & Kostakis, A. (2018). Do stock returns really decrease with default risk? New international evidence. *Management Science, 64*(8), 3821-3842.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics, 9*(1), 3-18.

Bhandari, L. C. (1988). Debt/equity ratio and expected

www.kci.go.kr

common stock returns: Empirical evidence. *The Journal of Finance, 43*(2), 507-528.

Campbell, J. Y., Hilscher, J., & Szilagyi, J. (2008). In search of distress risk. *The Journal of Finance, 63*(6), 2899-2939.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance, 47*(2), 427-465.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*(1), 3-56.

Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *The Journal of Finance, 51*(1), 55-84.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics, 116*(1), 1-22.

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy, 81*(3), 607-636.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance, 48*(1), 65-91.

Kim, J. M. (2016). Failure Risk and the Cross-Section of Hedge Fund Returns. *Financial Management, 45*(4), 845-876.

McFadden, D. (1974). The measurement of urban travel demand. *Journal of Public Economics, 3*(4), 303-328.

Newey, W. K., & West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica, 55*(3), 703-708.

Satterthwaite, F. E. (1946). An approximate distribution of estimates of variance components. *Biometrics Bulletin, 2*(6), 110-114.

Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *The Journal of Business, 74*(1), 101-124.

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