THE EFFECT OF IDIOSYNCRATIC AND SYSTEMATIC STOCK VOLATILITY ON BOND RATINGS AND YIELDS

by

Xiao Cui
B.Sc., Imperial College London, 2013

and

Li Xie
B.Comm., Saint Mary's University, 2015

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Supervisory Committee:

____

Amir Rubin
Senior Supervisor
Professor, Finance

____

Alexander Vedrashko
Second Reader
Associate Professor, Finance

Date Approved: ____

Abstract

This paper uses Fama-French and Carhart Four-factor Model to compute systematic risk and idiosyncratic risk for firm's equity risk. It then assesses these two equity risk components to bond credit rating and bond yield. The analysis is conducted by applying a multivariate regression model on a universe of US equity and bond data over the last ten years from 2007 to 2016. Our research shows that idiosyncratic risk is an important determinant of both bond rating and yield. Interestingly, while systematic risk seems not to affect the rating, it seems to be an important determinant for bond yields. For low credit rating bonds, yields are mainly driven by idiosyncratic risk; but for high rating bonds, systematic risk is just as important (and sometimes even more important than) as the idiosyncratic risk. Additionally, this relationship varies with the economic condition; for example, the systematic risk was not an important factor during the financial crisis period of 2007-2010.

Keywords: Bond Rating; Bond Yield; Systematic risk; Idiosyncratic risk

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Table of Contents

1. Introduction

According to financial theory, there are commonly two sources of risks: systematic risk and idiosyncratic risk. "Systematic risk is attributable to its sensitivity to the market and persists regardless of the extent of portfolio diversification" (Imazeki, 2012). It provides a measure on how individual firms react to a given movement of the market. In contrast, idiosyncratic risk is diversifiable and independent from the market. While systematic risk is correlated with the expected return, idiosyncratic risk, by definition, is not expected to correlate with the expected return because investors can diversify it away. Over time, research of stock returns has evolved, and it is now rather established that the market is not a good proxy for systematic risk. It is common to consider four or five factors as the sources of systematic risk (Fama and French, 1993; Carhart, 1997; Fama and French, 2015).

Though the relationship between a stock return and risk is well established, the effect of these sources of returns on bond yield is less clear. Over the past few years, some finance studies are working on the relationship between bond yield and equity risk, but the results are somewhat ambiguous. Mainly when people use different models or testing strategies, their results vary from the positive correlation to negative. King and Khang (2005) conclude that systematic risk, which is the beta of the market risk factor, is not a significant factor in explaining the bond yield except with only one exception, the AA-rated bond (highest rated-bond). The t-statistic of systematic risk on other rated-bonds are either insignificant or inaccurate. In contrast, Elton, Gruber, Agrawal, and Mann (2001) run the regression of average bond spread on the systematic risk then provide evidence that systematic risk is an important factor to explain the majority of bonds' yields.

In this paper, we employ the Fama - French and Carhart Four-factor model to estimate the effect of systematic and idiosyncratic risk of equity on bond ratings and yields. In general, one would think that these two sources of risk should be important also for understanding the risk-return trade-off of bonds. Bondholders and equity holders are both affected by the performance of companies. While equity holders are the residual claimants, the bondholders received a fixed amount of cash as long as the firm does not go solvent. As such, one would think that rating agencies and investors would try to assess the probability of bankruptcy of firms. Both systematic risk and idiosyncratic risk should matter for such assessments. However, while idiosyncratic risk is diversifiable, it seems that it may be used as an "unconditional" measure of the probability of bankruptcy, while systematic risk may be used as a "conditional" measure of volatility. Hence, idiosyncratic volatility would not depend on the probability of bankruptcy of other firms, but systematic volatility would depend on the state of the economy. Also, a firm with high systematic risk for its equity, it is expected to have a higher level of bankruptcy probability when the market is a recession and when other firms are going bankrupt. However, whether these predictions are related to bond ratings and yields is an empirical question, that has not thoroughly been addressed yet in the literature. We note that credit rating agencies provide bond ratings based on a broad analysis structure which is probably much more elaborate than just analyzing systematic and idiosyncratic risk. These agencies review the company's business fundamentals and management. It involves factors such as market position and industry risk, as well as the sensitivity analysis to test the capability of the company to adapt or cope with adverse business conditions. Hence, rather than what a rating agency might do when analyzing the bond's risk, we quantify all these factors into two risk components of a firm, following measurement the factor models of Fama, French (1993) and Carhart (1997). The analysis of the correlation between rating changes of bonds and stock risk is crucial for our understanding on both what rating agency do, and for better understanding on the linkage between risk and bankruptcy probability. This is especially important now when current rating agency is under scrutiny after it failed to provide an accurate rating grade in the subprime mortgage crisis in 2008. We describe the modeling and testing strategies in section 3 followed by data selection and empirical results in section 4 and 5. We provide our conclusion of findings and recommendation in section 6.

2. Literature Review

2.1. Bond Credit Rating vs. Equity Volatility

The research that we find attempts to analyze how bond rating changes affect the equity return or volatility, there are many theoretical supports show that credit rating changes will affect the default probability which has a strong relationship to the stock price by using the Merton type model (Jorion and Zhang, 2007). The opposite studies are almost nonexistent. Based on previous research, our analysis focuses on filing this literature gap and finding out whether rating agencies consider firm's market risk and idiosyncratic risk when they make rating decisions.

Many recent studies researched on how credit rating agency rate corporate bonds, but the impacts of systematic risk and idiosyncratic risk of equity return over bond rating has attracted relatively limited attention in literature until recent years. For instance, Ang and Patel (1975) compare the ability of the available bond rating statistical models to duplicate Moody's credit rating as well as the predictability of financial distress over different times. In their models, rating agencies use financial ratios or historical data of the firm, such as debt coverage, debt capacity and variability of earnings. In addition, some papers claim that the rating agencies only summarize public information and there is no valuable information in their rating decisions (e.g., Wakeman, 1984)

Several researchers are investigating the relationship between bond rating changes and stock return. For instance, Schwendiman and Pinches (1975) analyze the relationship between systematic risk of equity beta and rating grade on the US market in 1975. Their results indicate a negative correlation between these two variables. There are a few other studies on bond ratings and systematic risk. For example, Brook, Ingram, and Copeland's (1983) research shows that there is an increase in beta risk when the related bonds are downgraded, while the upgrading on the bonds does not affect the market beta risk. This result also provides empirical evidence of the strong connections between beta return risk and bond credit ratings.

Abad and Robles (2006) analyze the effect of corporate bond credit ratings over stock prices and systematic risk in stock markets, using the beta of CAPM (Capital Asset Pricing Model) as the measure of systematic risk. They report the conclusion that the systematic risk tends to be lower for credit rating changes in both directions. Abad and Robles (2010) analyze the relationship between the rating agency and idiosyncratic risk in Spanish companies listed on the Electronic Continuous Stock Market from 1988 to 2010 by extending the existing research from Abad and robles (2007) on the effect of credit rating changes on stock markets. In their report, the empirical evidence suggests that an upgrade in credit rating causes both lower systematic and idiosyncratic risk, while a downgrade in bond rating will result in a higher beta risk but lower idiosyncratic risk.

2.2. Bond Yield vs. Equity Volatility

A large amount of literature has analyzed the risk factors that influence the bond yield. As studied by the researchers (Fama & French, 1993), the most common risk factor in bond return is TERM, which is the difference between the monthly government long-term bond return and the previous one-month Treasury bill rate. Also, another common risk factor mentioned in their paper is the default risk, which calculates the difference between the yield on the market long-term corporate bond and the long-term government bond. The influence of default risk factor on bond yield is also confirmed by Longstaff, Mithal, and Neis (2005), which indicate that the firm-specific default risk has a significant impact on the majority of bond yields. Even for the most senior rating bonds, default risk plays a significant role in more than 50 percent of corporate bonds. Additionally, Chen, Liao, and Tsai (2011) conclude that the internal (firm-specific) liquidity risk positively and significantly influences the bond yield when other well-known risk factors are fixed. As it is demonstrated by Chen, Liao and Lu (2011), internal liquidity, which is an indicator of a company's funding liquidity, measures the relationship between a firm's available liquidity and debt payment, that is also different from the trading liquidity (external liquidity).

Merton (1973) discusses that a corporate bond is equivalent to a short position on a put option with corresponding underlying assets. He reports that the bond yield is expected to be positively correlated with the firm's equity volatility because the idiosyncratic risk increases the default risk of the company. Campbell and Taksler (2003) analyze the effect of the equity volatility on corporate bond yield by comparing the average spread which is reported by the S&P and Moody credit agencies. Panel data results after the 1990s show that the impacts of equity volatility on the bond yield spread are relatively stronger compared to the credit ratings. Thus, the equity volatility is a crucial determinant of corporate bond yield. Accordingly, they use the cross-sectional dispersion of equity return to measure the idiosyncratic risk and find that the systematic volatility has temporarily fluctuated without increasing trend, while the idiosyncratic volatility has an upward trend since the 1970s. Also, they report that the idiosyncratic risk has supported the equity price but depressed the corporate bond price. The researchers reveal the same results (Jubinski & Lipton, 2011), showing that the bond investors change their decision correspondingly as the equity volatility moves. When the market risk increases, the yield on the senior corporate bonds is expected to fall. However, the spread on the lower quality of the corporate bond is likely to widen since more investors like to invest in the high-quality bond. Gómez-Puig (2009) conducts a panel regression for 15 European countries by using the yield spread as an indicator of idiosyncratic risk or domestic risk. The most striking observation is that idiosyncratic risk dramatically drives the spread difference of Germany in all European countries during the seven years after the European integration.

In recent articles, rather than systematic risk, King and Khang (2005) analyze the importance of systematic risk in explaining the corporate bond yield. They examine a sample of 1,771 U.S. corporate bonds over 1985 to 1998 and find that the beta provides limited explanatory power on the bond yields by using cross-sectional regression of bond spread on systematic volatility factor.

In contrast, Elton, Gruber, Agrawal, and Mann (2001) conclude that the systematic risk is the primary determinant of both the corporate bond yield and government bonds'. Also, they find that the measurement of yield spread on the corporate bond mainly depends on three factors: possible loss default, tax difference between corporate bonds and government bonds, and the equity systematic risk. Their results show that there is 47.8 percent of the spreads between corporate and government bonds could be explained by the systematic risk. However, only 17.8 percent could be explained by the loss default, and 36.1 percent could be explained by the tax difference. Same as the researchers (Collin-Dufresne, Goldstein, & Martin, 2001) illustrate in their paper, the corporate bond cannot be replicated by holding a position of underlying stock and risk-free bond. This approves that standard contingent claim theory does not work and systematic risk affects the bond yield which is an essential role in bond pricing.

3. Methodology

We use statistical tools such as multivariate regression analysis to re-examine the relationship between bond yield and equity risks as well as the connection between credit rating and equity volatility. Our data is collected mostly from WRDS and is analyzed by using Software Stata and Microsoft Excel.

3.1. Fama-French and Carhart Four-factor Model

In our initial part of defining the risks of equity returns, we imply a Fama-French Carhart Four-factor model by using the list of companies corresponding to our bonds. Fama and French (1993) introduce a Three-factor model in which the dependent variable is the expected return of stocks. The independent variables involve excess returns on a small stock portfolio over a large stock portfolio, excess return on a low book-to-market equity portfolio over a high book-to-market equity portfolio and a stock index return. Carhart (1997) further extend this Three-factor model by adding a price momentum factor as the fourth systematic risk factor. This model can be expressed by using the following formula:

$$E(R_i) - R_f = \alpha + \beta_{im}\left(E(R_m) - R_f\right) + \beta_{is}E(SMB) + \beta_{ih}E(HML) + \beta_{im}E(MOM) + \varepsilon_i$$

Where R_f stands for risk-free return rate, R_m is the market return, R_i is the portfolio expected return, α is the abnormal return, ε_i is the error term; SMB stands for the difference between the returns on small stocks and big stocks, HML is high book value to market ratio minus low book value to market ratio, MOM is the difference between the average return on two-high-prior-return portfolios and the average return on two-low-prior-return portfolios.

We run cross-sectional regression for each stock return from 2007 to 2016 based on the Four-factor model. R squared is obtained from the regression, measuring the percent of the variance that can be explained by the factors. The risk of the equity return can be decomposed into two components, and they are the systematic risk and idiosyncratic risk. We use R squared multiplying by equity volatility as a measure of systematic risk, and our measure for Idiosyncratic risk is (1-R squared) multiplied by equity volatility. Compared to the Fama-French Three-factor model, the proportion of idiosyncratic risk to total volatility is smaller with the inclusion of the momentum factor by Carhart (1997).

3.2. Multivariate Regression Model

Multivariate regression is a technique to estimate a single regression model with more than one outcome variables, and the number of predictor variables is greater than one. Moreover, it is an excellent method to investigate the strength of a linear relationship between variables.

3.2.1. Modeling and Testing Strategy

There are two regression models we use in our data analysis and the models that we test are the following:

Model 1: analyze the relationship between the credit rating and equity volatility

$$Rating_{it} = \gamma_0 + \gamma_1(Systematic\ risk_{it}) + \gamma_2(Idiocyncratic\ risk_{it}) + \gamma_3(Duration_{it}) + \varepsilon_{it}$$

$$Rating_{it} = \gamma_0 + \gamma_1(Ratio_{it}) + \gamma_2(Total\ volatility_{it}) + \gamma_3(Duration_{it}) + \varepsilon_{it}$$

In this model, in order to allow the software Stata to process the data, we need to code the credit ratings as integers. All the participating companies are sorted based on their credit ratings each year. The bond rating is equally divided into four rating groups, so the number of observations for each bond rating group is the same in each given year.

Model 2: analyze the relationship between the bond yield and equity volatility

$$Bond\ yield_{it} = \gamma_0 + \gamma_1(Systematic\ risk_{it}) + \gamma_2(Idiocyncratic\ risk_{it}) + \gamma_3(Duration_{it}) + \varepsilon_{it}$$

$$Bond\ yield_{it} = \gamma_0 + \gamma_1(Ratio_{it}) + \gamma_2(Total\ volatility_{it}) + \gamma_3(Duration_{it}) + \varepsilon_{it}$$

where $\gamma_0, \gamma_{1,}\gamma_2, \gamma_3$ are the predictors in the multivariable model, ε_{it} is the error term.

We take a two-step approach in deriving the multivariate regression specification. In the first step, we test for the significance of systematic risk and idiosyncratic risk, respectively. In the second step, we test whether the proportion of the systematic risk out of total volatility is significant after controlling for volatility.

3.2.2. Confidence Level

All the regression analysis was done with 95 percent confidence level, meaning that the level of significance is 5 percent. In our paper, the standard criteria for testing the significance of the independent variables includes P-value, F-statistic and t-statistic.

3.2.3. Control Variable

Apart from systematic risk and unsystematic risk, we include several control variables in the analysis. Firstly, to capture the effect of the bond characteristic on bond yield and credit rating, we include duration which is calculated by using the Excel *MDuration* function. We add the year fixed effect manually by adding ten dummy variables for each year in our regression. Also, the firm fixed effect is captured by including indicators for each company ticker.

4. Data and Summary Statistics

4.1. Data Sources

The primary bond data are drawn from Wharton Research Data Service (WRDS) *Bond and Fixed Income – Trace Bond Summary* Database. The trace Bond Summary database involves the transaction data for investment grade corporate bond, high yield corporate bond, and convertible debt. This database is professional and investors can acknowledge on all the OTC bond activities in more than 99% of U.S. corporate bond markets over 30,000 bonds. Our sample consists of 29,628 U.S. bond transactions with all related bond information including bond symbol, company ticker, CUSIP, price, and yield at the last day of each calendar year over the period between 2007 and 2016. Based on this data set, we use Bloomberg Excel add-in *BDH* function to download the historical bonds' rating information, maturity and coupon rate in the same bond file. We report the bond rating by using the S&P rating agency for notational convenience. The bonds are equally divided into four categories using integers 1 to 4, where bonds in integer category 1 have the highest rating, and integer category 4 represents the lowest bond rating.

Next, we use the bond data to sort, delete the duplicate transactions and export the company's ticker into a text format. By uploading the company's ticker file onto the WRDS' *CRSP Daily Stock* Database, we could obtain the equity data, including the daily price and daily value-weighted return (including distributions) over last ten years. We then calculate the daily standard deviation as a measure of equity volatility of individual companies in each given year. Fama-French and Carhart Four-factor model data is downloaded from the WRDS' *Fama-French Portfolios and Factors* Database. The Four-factor model data covers a daily frequency data during the period of 2007-2016, and it has four variables: HML (High Minus Low), MKTRF (or Rm-Rf), SMB (Small Minus Big) and UMD (Momentum). Next, we calculate the equity risk premium by deducting the risk-free rate by the equity return. Hence, the beta and R-squared can be obtained by regressing the equity risk premium on the market risk premium which is the market return minus the risk-free rate.

After further review, the beta, R-squared from the previous regression are merged to the remaining 25,662 transaction bond data after dropping the duplicated information. The systematic risk is calculated by the equity volatility multiplying the R squared and the idiosyncratic risk is calculated by the equity volatility multiplying 1 minus R squared.

4.2. Summary Statistics

In our research, the bond rating is equally divided into four rating groups, where Rating 1 is the highest rating group and Rating 4 is the lowest rating group. Table 1 summarizes the most frequently occurring rating grade for each rating group. The first three rating groups mostly involve the investment grade bonds while the majority non-investment bonds are lying in the Rating 4 category.

Table 1. The most frequent rating grade in each rating groups

Rating Group	Rating Grade	Number of Observations
Rating1	A	11593
Rating2	BBB+	3074
Rating3	BBB	6565
Rating4	BB	4430

Note: The Stata cannot split bonds with the same rating grade into different rating groups, which results in different number of observations in each rating group

Table 2 summarizes the average corporate bond yields for bonds under rating category from 1 to 4 over past ten years from 2007 to 2016. In general, the first rating group has relatively low average yield, while the fourth rating category has a higher average bond yield. Notably, it reached the highest yield level at approximately 44.24% in 2008. Moreover, it also demonstrates that on average, the bond yields are considerately higher in 2007 and 2008 than in later years.

These statistics economically make sense because there was an economic crisis happening in the U.S. in 2008. Thus, investors require a higher spread to compensate for the higher credit risk.

Table 2. Average corporate bond yield

By using Panel data between 2007 and 2016, the table below lists the average of the corporate bond yields in each given year, in percentages. All bonds are in U.S. dollars and have callable futures.

Year	Rating 1	Rating 2	Rating 3	Rating 4
2007	7.48926	6.37247	9.43720	13.01985
2008	5.87242	6.75938	10.54350	44.23725
2009	4.42750	N.A.	8.03511	9.15409
2010	3.95418	N.A.	4.84116	8.54466
2011	3.31082	N.A.	5.27205	8.24454
2012	2.51770	N.A.	3.33123	6.23509
2013	2.47182	2.76934	3.82095	6.24736
2014	2.32944	2.89616	3.46801	14.07652
2015	2.99046	3.28743	4.76306	15.26702
2016	2.72688	3.23244	3.85644	6.57275

Table 3 provides the mean value, standard deviation and percentile values of idiosyncratic volatility and systematic volatility for each rating group, respectively. Among these four rating categories, we could find that when the rating grade becomes lower, the difference between the systematic risk and idiosyncratic risk becomes larger, which means the idiosyncratic risk has relatively more significant impacts on the bond's credit rating.

Table 3. The magnitude of risk factors in different rating groups

Panel A: Rating 1 Statistic	Idiosyncratic Volatility	Systematic Volatility
Mean	0.0100219	0.0092696
Standard Deviation	0.0088781	0.0078786
P1	0.0034071	0.0006017
P25	0.0059448	0.0044225
P50	0.0077373	0.00664
P75	0.0108015	0.0113819
P99	0.041658	0.0369138

Panel B: Rating 2 Statistic	Idiosyncratic Volatility	Systematic Volatility
Mean	0.0123732	0.0105545
Standard Deviation	0.0114481	0.0097448
P1	0.0037649	0.0003789
P25	0.0070188	0.0042751
P50	0.0088566	0.0076712
P75	0.0123105	0.0124833
P99	0.0744425	0.0421195

Panel C: Rating 3 Statistic	Idiosyncratic Volatility	Systematic volatility
Mean	0.0140587	0.0090881
Standard Deviation	0.0112344	0.0077213
P1	0.0043828	0.0005998
P25	0.0083661	0.0038407
P50	0.0110067	0.0063095
P75	0.0153723	0.0116506
P99	0.0802201	0.0348934

Panel D: Rating 4 Statistic	Idiosyncratic Volatility	Systematic volatility
Mean	0.0223502	0.0082726
Standard Deviation	0.0152838	0.0069255
P1	0.004401	0.0003002
P25	0.0122924	0.0036219
P50	0.0178625	0.0060429
P75	0.0279097	0.0101618
P99	0.0932186	0.0315136

5. Empirical results

5.1. Ratings and Risk

In this section, we run the regression to estimate the relationships between bond ratings and risks of equity return. Bond yields and other bond-related data are measured once at the end of each calendar year (December 31). Bond information including bond symbol, company ticker, CUSIP is downloaded from WRDS under the Trace Daily Summary during the period 2007 to 2016.The historical bonds' credit rating information is obtained from the Bloomberg Terminal by using excel Bloomberg input functions. The S&P rating agency is used in our dataset as it provides credit ratings for more companies, rating from AAA to the lowest rating D. The bond rating is equally divided into four rating categories, expressed as rating category integer from 1 to 4, where 1 is the highest-grade rating group and 4 are the lowest grade rating.

Two primary dependent variables are used in two different regression specifications in our study. The first regression model is to regress the bond rating on both the systematic risk and idiosyncratic risk variables. In the second model, apart from total volatility, we use another variable, which is the ratio of systematic volatility divided by the total volatility. This ratio would be positive and significant if systematic volatility is more significant for the dependent variable than idiosyncratic risk.

Table 4. Regression results for bonds rating and related risk factors

The following table shows the regression results, where the dependent variable is the bond-rating (defined as integer 1-4). The category integer 1 is the highest-grade rating group and category integer 4 is the lowest-grade rating group. The independent variables of the first regression are systematic volatility, idiosyncratic volatility, and duration. The independent variables of second regression are the ratio (systematic volatility / idiosyncratic volatility), duration and total volatility. The bond rating is downloaded from Bloomberg using Excel add-in BDH function. We report the bond rating from S&P rating agency. Total volatility, systematic volatility, and idiosyncratic volatility are on a daily basis.

VARIABLES	(1) Rating Integer	(2) Rating Integer
Ratio		-2.5542***
		(-9.24)
Duration	-0.0065	-0.0073*
	(-1.62)	(-1.85)
Total volatility		17.1134***
		(4.14)
Systematic volatility	-30.6408***	
	(-3.61)	
Idiosyncratic volatility	41.5935***	
	(6.95)	
Constant	2.0688***	3.0665***
	(15.25)	(18.26)
Observations	25,631	25,631
R-squared	0.157	0.198
Adjusted R-squared	0.156	0.197
Fixed Year Effect	Yes	Yes
Fixed Firm Effect	Yes	Yes

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

In the first regression model, we find that there is a negative correlation between idiosyncratic risk and credit rating. This result makes economic sense because idiosyncratic volatility is related to the probability of bankruptcy, and the literature indicates that the idiosyncratic volatility is a major determinant of yields (Merton, 1973). Thus, our finding is that the more volatile a company is, the lower rating of its bond. However, we also find, rather surprisingly, that systematic volatility is positively correlated with rating grade (negatively with the rating integer), reflecting that higher systematic risk is associated with a more senior rating grade. One possible reason for this result is that perhaps the rating agencies are not able to clearly extract probability of bankruptcy arising from systemic risk and movements due to systematic risk are expected. Therefore, when the rating agencies evaluate a bond, they do not consider much the company's performance under specific economic condition. However, even this is the case, it is still hard to conceptualize why a positive relation between the rating and systematic risk exists. The second regression model gives similar results. Therefore, we conclude that rating agencies seem to care much more about idiosyncratic risk than systematic risk. In fact, it seems that systematic risk is not a good measure of bankruptcy probability. Perhaps firms that move with the economy and have a large systematic component are simply more mature and tend to be less subject to bankruptcy risk.

Based on previous data set, we divide the statistics into two groups, one group involves observations from 2007 to 2010 (turbulence time of financial crisis), and the other one has the rest of the observations from 2011 to 2016 (economic recovery time). The results are shown as the follows:

Table 5. Regression results bonds rating and related risk factors during or after crisis

	(1) 2017-2010 (During Crisis)	(2) 2011-2016 (After Crisis)

VARIABLES	Rating Integer	Rating Integer
Systematic volatility	-24.4270***	10.4081***
	(-3.89)	(10.19)
Idiosyncratic volatility	22.6056***	9.1911***
	(4.20)	(10.67)
Duration	-0.0157***	0.0055***
	(-1.83)	(6.26)
Constant	2.2105***	1.9412***
	(15.02)	(143.02)
Observations	8,177	17,454
R-squared	0.098	0.858
Adjusted R-squared	0.0972	0.847
Fixed Firm Effect	Yes	Yes

T-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

During the financial crisis over the period between 2007 to 2010, our regression result is consistent with the result in the first regression, showing that systematic volatility is positively correlated with rating grade (negatively with the rating integer). However, during the economic recovery period between 2011 to 2016, both systematic risk and idiosyncratic volatility are statistically significant and systematic risk is somewhat more important than idiosyncratic risk. This result is in line with the result in Hyleen and Ostlund (2009). They discuss that the relationship between bond rating and equity beta risk in economic recession tends to be worse than in a normal economic climate. They explain that this is because beta always changes faster compared to credit ratings which are a somewhat a lagging indicator.

5.2. Market and Risk

We next analyze the effect of equity risk on bond yield. The data set is the same as the one we used in the previous model, but we run regression separately for each of the four rating categories. For each rating group, the bond yields are regressed on systematic risk, idiosyncratic risk, and duration. In addition to the t-test on the dependent variables, an F-test is used to test whether these two risks are statistically different.

Table 6. Regression Results for bond yield and related risk factors

The table provides the bond yields (dependent variable) across four different rating groups. The independent variables of this regression are systematic volatility, idiosyncratic volatility, and duration, which are measured on a daily basis. We also run F-test to assess whether systematic volatility is equivalent to idiosyncratic volatility.

VARIABLES	(1) Rating 1	(2) Rating 2	(3) Rating 3	(4) Rating 4
Systematic volatility	58.6819***	84.1709***	124.0950***	316.7041
	(3.81)	(4.09)	(2.66)	(0.98)
Idiosyncratic volatility	41.4250***	83.3997***	142.5624***	840.1169***
	(2.92)	(2.98)	(7.17)	(2.59)
Duration	0.1781***	0.1116***	-0.0602	-1.0409***
	(6.09)	(4.30)	(-0.75)	(-3.21)
Constant	1.3404***	1.9735***	2.5968**	-3.8668
	(3.78)	(6.07)	(2.57)	(-0.46)
Observations	11,564	3,073	6,564	4,430
R-squared	0.013	0.137	0.025	0.052
F-test	0.455	0.000349	0.208	6.570 **

Adjusted R-squared	0.0123	0.136	0.0242	0.0513
Fixed Firm Effect	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

As it is shown in Table 6, only the last rating category has a p-value for F-test less than 5%, suggesting that for the non-investment grade bonds, their yields are not correlated with systematic risk. For the other three categories, which are investment grade bonds, both the systematic risk and the idiosyncratic risk are statistically significant. This may imply that for those companies in the lowest rating category, their bonds' yields mainly depend on the general bankruptcy risk, independently of market conditions.

Table 7. Regression results for bonds yield and related ratio

VARIABLES	(1) Rating 1	(2) Rating 2	(3) Rating 3	(4) Rating 4
Total Volatility	51.2189***	67.2624***	120.8290***	442.4302***
	(6.54)	(16.26)	(7.70)	(7.24)
Ratio	1.0160	1.4464**	0.2385	-4.1060
	(1.32)	(2.51)	(0.18)	(-0.60)
Duration	0.1612***	0.1463***	-0.0643	-1.1080***
	(7.64)	(9.79)	(-1.44)	(-3.88)
Constant	0.9409**	1.5145***	2.8654***	5.4468*
	(2.33)	(5.28)	(4.32)	(1.71)
Observations	11,564	3,073	6,564	4,430
R-squared	0.049	0.512	0.225	0.503

Adjusted R-squared	0.0188	0.459	0.145	0.410
Fixed Firm Effect	Yes	Yes	Yes	Yes

T-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

From Table 7, the results show that only the second rating category has a ratio (systematic volatility/ total volatility) which is statistically significant, suggesting that just for group 2 there is evidence that systematic risk is somewhat more important than idiosyncratic risk, though that evidence seems weak in the previous table. In general, the evidence is supportive of the idea that bond yields of high rating companies tend to move with both types of risk, while the low rating companies are mostly driven by idiosyncratic risk.

Similar to the previous case, we conduct regression analysis on two different datasets. The first data set includes bond information over 2007 to 2010, and the other dataset contains observations over the rest six years. The results are demonstrated as the follows:

Table 8

Panel A. Regression results for bonds yield and related factors between 2007-2010

VARIABLES	(1) Rating 1	(2) Rating 2	(3) Rating 3	(4) Rating 4
Systematic volatility	-19.1202	-3.0614	2.0342	272.4846
	(-0.62)	(-0.18)	(0.04)	(1.06)
Idiosyncratic volatility	32.4043	86.6028***	132.6679***	1,133.0124***
	(1.41)	(6.88)	(3.96)	(9.37)
Duration	0.1610**	-0.0179	-0.4589***	-1.3540**
	(2.45)	(-0.47)	(-3.60)	(-2.31)

Constant	3.7382***	5.2168***	8.2800***	-8.8564
	(5.99)	(14.80)	(6.70)	(-1.55)
Observations	3,430	1,294	2,120	1,333
R-squared	0.002	0.056	0.018	0.086
Adjusted R-squared	0.00141	0.0536	0.0166	0.0839

T-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

During the financial crisis over the period between 2007 to 2010, for those companies lying in the highest rating category, both the systematic risk and idiosyncratic risk are statistically insignificant. Perhaps because investors have enough confidence for these companies, and the relatively low default risk will not affect their investments in those bonds. Another possibility is that there is simply a demand shock for these bonds as they are highly rated bonds and investors may have fled to them during these troubled times. Plenty of money flows into these bonds making their equity volatility an insignificant issue for investors.

For the companies have rating grade in the rest three categories, the results show that only the idiosyncratic risk matters as every volatility could lead to bankruptcy and investors have less confidence about the company's' performance in economic conditions.

Panel B. Regression results for bonds yield and related factors between 2011 to 2016

VARIABLES	(1) Rating 1	(2) Rating 2	(3) Rating 3	(4) Rating 4
Systematic volatility	105.1858***	97.8608***	127.1190***	37.9712

	(7.21)	(3.07)	(4.42)	(0.13)
Idiosyncratic volatility	114.8188***	51.9149**	75.9779***	655.8622***
	(4.09)	(2.16)	(3.06)	(4.50)
Duration	0.1732***	0.2202***	0.1070***	-0.9647**
	(14.42)	(22.25)	(4.32)	(-2.34)
Constant	0.0542	0.7290**	1.6920***	0.8590
	(0.21)	(2.28)	(4.21)	(0.19)
Observations	8,134	1,779	4,444	3,097
R-squared	0.132	0.516	0.132	0.103
Adjusted R-squared	0.0976	0.463	0.0197	-0.102

T-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

From Panel B, during the booming economic times, both the systematic risk and idiosyncratic risk are statistically significant for the investment grade bonds. It seems that investors would care both the companies' general performances as well as how these companies react to economic changes, this might be due to the lessons learned from the previous financial crisis.

6. Conclusion & Further Research

In our paper, we have documented the empirical evidence on the relationship between bond yield and equity volatility. Our research shows that only for high-rated bonds, the systematic risk would matter. For those bonds with low credit ratings, especially the non-investment grade bonds, their yields are mainly driven by the idiosyncratic risk. Additionally, this relationship also varies with different economic conditions due to the changes in the investor's confidences.

Nevertheless, compared to the financial market, the bond credit rating provided by the rating agency is less sensitive to the systematic risk of equity returns. Credit rating analysts are criticized for relying too much on the recent past and the classic argument is that they tend to react to yields rather than what affects yields. In addition, Matt Krantz discusses that shortcomings with rating agencies still exist despite the lessons learned from the financial crisis as there is a profit incentive to be uncritical, as well as investors, rely on them too much (Krantz, 2013).

Our results provide evidence on the effect of idiosyncratic and systematic equity risk on bonds, and many additional plans remain for future research. It remains to be investigated why there is a negative correlation between bond yield and beta from Fama- French Carhart Four-factor model during the financial crisis. The results may vary for different industries. Rather than using the U.S. bonds information, classifying all bonds into different categories on industry level would allow for a complementary analysis. Apart from this, we use the classic multivariate regression model in our paper to investigate the linear relationships. However, to prevent our results being overly affected by violations of assumptions used in the underlying data generating process, robust regression could be added to our model, which will allow us to detect outliers and to provide resistant results in the presence of outliers.

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