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EQUITY VOLATILITY COMPONENTS AND CORPORATE CREDIT SPREADS

Amer Demirović [a,1] , Renata Lučić[b,2]

[a] University Teknologi Brunei, Brunei
[b] Faculty of Economics Brcko, University of East Sarajevo, Bosnia and Herzegovina

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ABSTRACT

This paper decomposes equity volatility into the systematic and idiosyncratic components and examines how they affect corporate credit spreads. The relationship between equity volatility and credit spreads is positive only for firms with low credit quality. For high credit quality firms, the effect is negative, suggesting that an increase in equity volatility is associated with a narrower rather than wider credit spread. The positive leg of the relationship is primarily driven by idiosyncratic volatility, while a decrease in credit spreads of high-quality firms is associated with an increase in systematic volatility. The results are robust to controlling for firm size and bond characteristics.

Introduction

The structural model of Merton (1974) provides a theoretical foundation for the analysis of the relationship between the values of equity and debt securities. The model considers the firm's equity and debt as derivatives written on the firm's assets. It implies that the default probability is defined by the gap between the value of assets and the value of debt relative to the volatility of the firm's asset value. As a result, the most important determinants of the difference in yields on corporate and government bonds, known as the credit spread, should include leverage and asset volatility. If the value of debt remains constant, an increase in the value of a firm's assets leads to a decrease in leverage and the default probability. Therefore, the relationship between credit spreads and asset values is expected to be negative. On the other hand, an increase in the asset volatility makes the default more probable and should widen credit spreads.

The structural model utilises asset volatility, which is derived from equity volatility, to estimate credit spreads. It does not differentiate between idiosyncratic and systematic volatilities. The two volatility components are profoundly different. One measures systematic risk, which is priced and therefore related to the firm's value, while another quantifies idiosyncratic risk, which is not expected to be priced in the frictionless markets. Bai et al. (2021) find a significant positive relationship between systematic risk and the expected returns on corporate bonds, but no relationship between idiosyncratic risk and the returns. Bollerslev et al. (2018) emphasise the importance of systematic risk. They show that volatility patterns within and across asset classes are strikingly similar, suggesting that volatilities of equities, bonds and other asset classes are driven by common factors.

Moreover, a burgeoning body of the literature illustrates that the structural model cannot adequately account for systematic risk. Collin-Dufresne et al. (2001) find fractions of credit spreads unexplained by the structural model to be strongly correlated, while Elton et al. (2001) demonstrate that the unexplained

[1] amer.demirovic@staff.utb.edu.bn
[2] renata.lucic@efb.uis.rs.ba

fractions are significantly related to the Fama-French risk factors (Fama and French, 1993) which are known as measures of systematic risk priced in equity returns.

The existing studies focus on the relationship between credit spreads and the total volatility or the idiosyncratic volatility of equity returns estimated as variations in returns over the market return (e.g. Campbell and Taksler, 2003; Cremers et al., 2008). This study contributes to the existing literature by decomposing equity volatility into systematic and idiosyncratic components and examining their relationship with credit spreads. Further, the study controls for credit risk by using a market-based measure of credit risk. This is critical, as the effect of volatility depends on credit risk. Finally, the study utilises a large panel dataset with over seven hundred thousand daily observations at the firm-level. Systematic volatility is estimated as variations in expected equity returns implied by the Fama and French (1993) three-factor model, while the structural model is explicitly estimated to control for credit risk.

The results uncover several intricacies in the relationship between equity volatility and credit spreads. First, the relationship is positive only for firms with low credit quality. As credit quality improves, the positive effect disappears. For high credit quality firms, the effect is negative, suggesting that an increase in equity volatility is associated with narrower rather than wider credit spreads. The positive leg of the relationship is primarily driven by idiosyncratic volatility, while a decrease in credit spreads of high-quality firms is associated with an increase in systematic volatility. This novel result, which is inconsistent with the structural model, provides additional evidence on the flight-to-quality premium investors pay to hold the highest quality assets.

The rest of the paper is organised as follows. The following section reviews the existing literature. Section 2 presents the methodology, specifies empirical models and presents the data set. The empirical results and presented in Section 3 and conclusions are outlined in the final section.

1. Literature review

It is commonly accepted that equity and credit risks are intrinsically linked. In their ground-breaking work, Modigliani and Miller (1958) show that a change in the firm's leverage gives rise to an increase in the expected returns on the firm's equity. This approach recognises that debt and equity securities are different claims on the same firm assets. Building on this insight, Merton (1974) applies the option pricing theory of Black and Scholes (1973) to develop a structural model with analytical formulae for the values of debt and equity. In his seminal work, he shows that the value of equity is equal to the value of a call option, whereas the market value of risky debt exceeds the value of risk-free debt by the value of a put option written on the firm's assets with the exercise price equal to the book value of debt.

An increase in asset volatility implies a higher probability that the value of assets will fall to the value of debt and trigger bankruptcy. As a result, volatility of equity returns and corporate credit spreads should always be positively correlated. It is important to note that total equity volatility, which is influenced by idiosyncratic as well as systematic risks, is relevant in this context. Therefore, both idiosyncratic and systematic risks should be significant determinants of credit spreads.

Campbell and Taksler (2003) focus on idiosyncratic equity volatility, which they estimate as the standard deviation of daily returns over returns on the CRSP value-weighted index of US stocks. It should be noted that calculating excess returns in this way implies that the betas of all firms are set to one. Idiosyncratic equity volatility is reported to account for between six per cent and ten per cent of the variation in credit spreads.

Cremers et al. (2008) use option-based volatility. Following Campbell and Taksler (2003), they calculate idiosyncratic equity volatility as the second moment of excess returns relative to the CRSP value-weighted index. They confirm that the relationship between credit spreads and idiosyncratic equity volatility is positive, but find the coefficient of the S&P 500 index volatility to be negative.

Ericsson et al. (2009) find a positive relationship between total equity volatility and credit default swap premia. Zhang et al. (2009) attempt to explain variations in credit default swap premia using equity volatility and jump measures constructed from high-frequency data. They report that short-run weekly realised volatility and annual historical volatility explain 68 per cent of the variations in default credit swap premia.

The aforementioned studies point to a positive relationship between idiosyncratic (and total) equity volatility and credit spreads. Other researchers focused on systematic risk. Collin-Dufresne et al. (2001)

document that the theoretical variables have limited power in explaining changes in credit spread. They report that leverage, equity returns, changes in the VIX index, S&P 500 index returns, and the risk-free rate explain approximately 20 per cent of credit spread changes. Instead of using an estimate of firm-level equity volatility, the authors use changes in the VIX index. They find leverage and equity returns to be statistically significant, but note that their economic significance is rather limited. In fact, the factor loading on the S&P 500 index returns appears to be significantly larger than the loading on the firm-level equity returns. These findings, together with results of the principal component analysis, showing that the regression residuals grouped into maturity and leverage portfolios are highly correlated over time, lead the authors to conclude that most of the variations in credit spreads is driven by a common factor rather than by firm-specific factors, as implied by the structural model.

The importance of systematic risk is emphasised by Elton et al. (2001) who report that credit spread is strongly related to systematic risk captured by the Fama and French factors commonly associated with equity risk. Cheyette and Tomaich (2003) provide evidence that idiosyncratic and systematic risks may affect credit spread differently. They find the bond yields of high-quality issuers are primarily explained by interest rate factors, while the bond yields of firms with lower credit quality are determined by equity returns. Surprisingly, the bond yields of firms with intermediate credit quality are neither related to interest rate factors nor to equity returns. The only significant determinants for bond yields of these companies appear to be bond-specific factors.

Longstaff et al. (2005) analyse the differences between credit default swap spreads and corporate bond credit spreads. By assuming that credit default swap spreads are a direct measure of credit risk, they find that a major part of bond credit spreads is due to credit risk. However, they also confirm that credit spreads contain a non-default component which is related to market-wide liquidity. The authors interpret this finding as consistent with the findings of Collin-Dufresne et al. (2001). Their analysis shows that firm-specific liquidity variables (such as coupon, bid-ask spread, and the principal amount) explain only approximately 20 per cent of the variations in the non-default component of credit spreads. Interestingly, an indicator variable which takes the value of one if a firm is rated AAA or AA, and zero otherwise, is also statistically significant and is in fact the most economically significant variable. The negative regression coefficient implies bonds issued by AAA/AA rated firms have lower credit spreads after controlling for credit risk. This may be interpreted as a flight-to-quality premium investors are willing to pay to hold the highest quality assets.

The results on the relative importance of idiosyncratic and systematic risks in explaining credit spreads are mixed. Campbell and Taksler (2003) report that idiosyncratic volatility is much more statistically and economically significant than market-wide volatility. The authors note that changes in idiosyncratic risk are more persistent than changes in market risk (Campbell et al., 2001) and thus, lagged idiosyncratic volatility receives a greater weight in predicting total volatility. Cremers et al. (2008) unexpectedly find a significant negative relationship between credit spread and the S&P 500 index volatility. In line with these findings, King and Khang (2005) find that systematic factors are less relevant for bond pricing than idiosyncratic factors. On the other hand, the abovementioned studies of Collin-Dufresne et al. (2001) and Elton et al. (2001) show that systematic risk is a dominant determinant of credit spread. Further, Bai et al. (2021) report that expected bond returns can be explained by their systematic risk, while the relationship between the returns and idiosyncratic risk is not significant.

The structural model implies a non-linear relationship between equity volatility and credit spreads. The importance of equity volatility as a determinant of credit spread should increase, economically and statistically, with the level of credit risk. Campbell and Taksler (2003) use an accounting-based ratio to divide firms in their sample into four leverage groups. Although they do not find a monotonic relationship, their results suggest that equity volatility is more important for firms with higher leverage. Cremers et al. (2008) use credit ratings to classify firms according to their credit risk exposure, and also provide some evidence that the importance of equity volatility increases with credit risk.

2. Methodology and data

Credit spreads are the difference between redemption yields of corporate bonds and redemption yields of equivalent-maturity government bonds referred to as benchmark bonds. A general model for analysis of a panel of credit spreads can be defined as:

$$CS_{it} = \alpha + \beta' x_{it} + \varepsilon_{it,} \qquad \varepsilon_{it} \sim i.i.d.(0, \sigma^2) \tag{1}$$

where CS_{it} is the credit spread of corporate bond i at time t, x_{it} is a $K \times 1$ vector of independent (explanatory) variables for firm i at time t, α is the intercept, β is a $K \times 1$ parameter vector, and ε_{it} is the usual disturbance term.

2.1. Systematic and idiosyncratic equity volatility

A common practice in empirical studies is to consider idiosyncratic returns as returns over the returns on a major equity index (e.g. Campbell and Taksler, 2003; Cremers et al., 2008). This method effectively imposes an assumption that the betas of all firms equal one, which is clearly unrealistic. To avoid this assumption, equity returns are modelled by the widely used three-factors model of Fama and French (1993), which is given in Equation 2.

$$r_{i,t} = r_{f,t} + \beta_{1,i,t}(r_{m,t} - r_{f,t}) + \beta_{2,i,t} r_{smb,t} + \beta_{3,i,t} r_{hml,t} + \varepsilon_{i,t} \tag{2}$$

where $r_{i,t}$ is the equity return of firm *i* at time *t*, $r_{f,t}$ is the risk-free rate, $r_{m,t}$ is the return on S&P 500 index on time *t*, $r_{smb,t}$ is the difference in returns on big and small firms at time *t*, $r_{hml,t}$ is the difference in returns on high and low book-to-market equity firms at time *t*, $\beta_{j,i,t} = \frac{Cov(r_{i,t}, r_{j,t})}{\sigma_{j,t}^2}$ is the sensitivity of return of firm *i* at time *t* to the factor *j* and $\varepsilon_{i,t}$ is the zero-mean idiosyncratic error. Systematic returns are deemed the returns implied by the model above, while the difference between observed and systematic returns (i.e. the residuals) is representing idiosyncratic returns.

In order to consider the time variation in the risk premia, conditional betas are estimated with a bivariate GARCH-in-mean model as described in Bollerslev et al. (1988). The returns are modelled to be proportional to their conditional variances, which are GARCH (1,1) processes. The mean returns, variances and covariances are given in the equations 3, 4 and 5.

$$r_{j,t} = \alpha_1 + \lambda_1 \sigma_{j,t-1}^2 + \varepsilon_{j,t} \tag{3}$$

$$\begin{aligned} \sigma_{j,t}^2 &= \omega_1^2 + \beta_1^2 \sigma_{j,t-1}^2 + \gamma_1^2 \varepsilon_{j,t-1}^2 \\ \sigma_{i,t}^2 &= \omega_2^2 + \beta_2^2 \sigma_{i,t-1}^2 + \gamma_2^2 \varepsilon_{i,t-1}^2 \end{aligned} \tag{4}$$

$$Cov(r_{i,t}, r_{j,t}) = \omega_1 \omega_2 + \beta_1 \beta_2 Cov(r_{i,t}, r_{j,t})_{t-1} + \Upsilon_1 \Upsilon_2 \varepsilon_{j,t-1}^2 \varepsilon_{i,t-1}^2 \tag{5}$$

where $r_{j,t}$ is the return on the Fama and French factor at time t, $r_{i,t}$ is the equity return of firm *i* at time *t.*

Since the Fama and French model has three factors, the auxiliary regressions detailed in Equation 6 are run to estimate equity returns due to each risk factor.

$$\begin{aligned} r_{1,i,t} &= \alpha + \beta_{1,i,t} r_{smb,t} + \beta_{2,i,t} r_{hml,t} + \varepsilon_{1,i,t} \\ r_{2,i,t} &= \alpha + \beta_{1,i,t}(r_{m,t} - r_{f,t}) + \beta_{2,i,t} r_{hml,t} + \varepsilon_{2,i,t} \\ r_{3,i,t} &= \alpha + \beta_{1,i,t}(r_{m,t} - r_{f,t}) + \beta_{2,i,t} r_{smb,t} + \varepsilon_{3,i,t} \end{aligned} \tag{6}$$

Each equation regresses equity returns on two Fama and French model factors. The residuals or returns not explained by the two factors are used in the mean equation of the bivariate GARCH-in-mean model to estimate the correlation of equity returns with a third factor (i.e. the residuals from the first equation with SMB and HML factors as explanatory variables are used for estimation of the conditional correlations with the market factor, and so on).

2.2. Credit Risk and Other Control Variables

In the structural model of Merton (1974), debt and equity are derivative securities for the underlying assets of a firm. The value of the firm's assets represents the underlying assets, the strike price is the book value of the firm's debt, and the value of the firm's equity represents the value of the call option. Mathematically, the relationship can be defined in Equation 7.

$$V_E = V_A N(d_1) - X e^{-rT} N(d_2) \tag{7}$$

where $d_1 = \frac{\ln(\frac{V_A}{X}) + \left(r + \frac{1}{2}\sigma_A^2\right)T}{\sigma_A \sqrt{T}}$, $d_2 = d_1 - \sigma_A \sqrt{T} = \frac{\ln\left(\frac{V_A}{X}\right) + \left(r - \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}}$, r is the risk-free rate, N is the cumulative density function of the standard normal distribution and σ is the volatility of the market value of firm's assets. The variable d_2 is a measure of the distance between the market value of assets and the book value of debt relative to the volatility of the market value of assets. Using the cumulative density function of the standard normal distribution, it is transformed into the default probability.

Market values and volatilities of the firms' assets are not observable. The derivative nature of equity can be exploited to estimate them by simultaneously solving the call pricing formula given in Equation 7 and the following hedge equation (Jones et al., 1984).

$$\sigma_{E,it} = \frac{V_{A,it} N(d_1) \sigma_{A,it}}{V_{E,it}} \tag{8}$$

This appears to be the most frequently used method for the estimation of the unobservable assets' values and volatilities. It is advocated by the seminal texts (e.g. Hull, 2006; Saunders, 1999), and is widely used in academic studies (e.g. Cooper and Davydenko, 2003; Geske and Delianedis, 2001; and Campbell et al., 2008).

Since longer bond maturities imply higher risk, credit spreads on corporate bonds should be also positively correlated with bonds' maturities. Another important bond characteristic which may influence the results is liquidity. Further, existing empirical studies provide ample evidence that firm size is a significant determinant of corporate credit spreads (e.g. Demirovic and Thomas, 2007). To control for these characteristics, the models are augmented with three sets of indicator variables: 1) four variables based on the logarithm of asset values; 2) three variables based on the bond duration, which, as noted by King and Khang (2005), considers the complete set of cash flows and is therefore preferred as a control for bond maturity; and 3) three variables to control for the logarithm of bond issue size, which is commonly used as an indicator of bond liquidity (e.g. Campbell and Taksler, 2003). The riskless rate (annualised 1-month T-Bill rate) is also added as an additional control variable. Finally, a set of 13 annual indicator variables is added to the models to control for common time effects.

2.3. Data

The paper studies firm-level bond and equity data. For a firm to be included in the sample, it must have both publicly traded equity and bonds. Furthermore, the estimation of the structural model and the distance-to-default requires sample firms to have an accounting value for debt. As not all public firms issue bonds, the sample selection process starts with all straight corporate bonds issued by non-financial firms in the US market available in the Refinitiv Datastream database. There are approximately 4,000 straight corporate bonds, but about 800 individual firms because most of the bond issuers issue multiple bonds. Thus, in multiple bond issue cases, the bond with the maximum number of observations is considered for the inclusion in the sample. Alternatively, all bonds could be included in the sample as separate series. That would significantly increase the sample size, but it would also increase the explanatory power of models without introducing much additional information, since credit spreads of different bonds issued by the same firm are highly correlated. As noted by Eberhart and Siddique (2002), this approach would also bias the standard errors downward. Another alternative would be to average the data for different bonds with a common issuer. This approach would involve considering differences between bond issues, such as duration and size, and, as already noted, would not significantly improve the information content of the sample. Therefore, taking one bond issue per issuer appears to be the best approach given the aim of this paper.

The equity, bond and interest rate data are collected from the Datastream database, accounting data is sourced from Compustat, and the Fama and French factors are obtained from Kenneth R. French's website. Bonds with less than 750 observations, asset-backed bonds, bonds with any sort of collateral, or with an average market value of less than $10 million are excluded from the sample. Further, data that appears anomalous, such as series with extremely large positive or negative credit spread observations, are removed from the sample. The remaining bonds are linked carefully to the equity and accounting data of the corresponding firms. The selection process results in a sample of 352 firms with full bond, equity and accounting data, and over 729,000 daily observations. The sample period spans almost 15 years starting on 1st August 1996 and ending on 18th February 2011. It should be noted that the sample is an unbalanced panel, as not all series span the entire sample period. Table 1 presents descriptive statistics for credit spreads, bond values and the five estimated series: idiosyncratic equity volatility, systematic equity volatility, distance-to-default, asset volatility and asset value.

Table 1. Descriptive statistics

Statistics	Credit spread	Bond Issue Value	Distance to Default	Idiosync. Equity Volatility	System. Equity Volatility	Asset Value	Asset Volatility
Mean	279.07	241.88	5.25	0.33	0.21	26,024.51	0.20
Median	185.20	188.38	4.85	0.28	0.16	8,963.24	0.18
Maximum	13,352.40	4,606.11	926.18	9.09	7.01	1.03E+06	7.49
Minimum	-148.10	2.10	-3.71	0.07	0.03	12.95	0.00
Std. Dev.	366.32	270.55	2.88	0.19	0.16	61,434.81	0.13
Skewness	10.38	4.79	30.81	4.56	3.97	8.35	5.53
Kurtosis	205.23	48.73	9,563.06	56.32	37.27	102.48	113.36

Equity volatility is estimated as a GARCH(1,1) process and annualized. Asset values, asset volatilities and the distance-to-default are estimated according to the procedure described in Section 3. Bond issues and asset values are expressed in US$ millions. Credit spread is expressed in basis points.

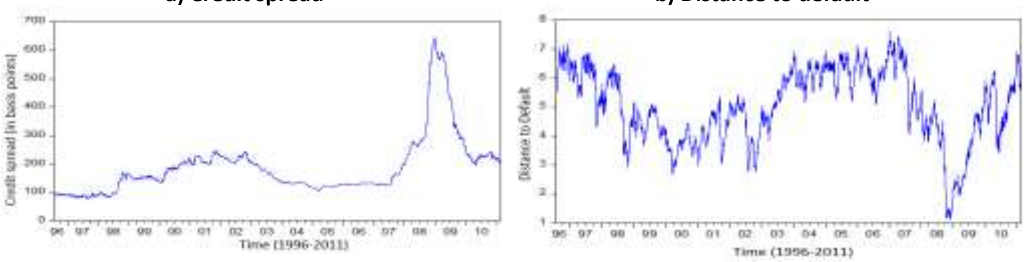
Source: (Prepared by the authors).

Similar to other financial series in the empirical literature, all the series display excess kurtosis, indicating that their empirical distributions have tails which are fatter than those of the normal distribution. The mean of credit spread series is within the BBB rating category while the median credit spread falls within the BB category, according to the mapping of credit spreads presented in Cremers et al. (2008). In a few instances, credit spread is negative. As noted above, series with large negative credit spread observations are excluded from the sample, but series with a few negative credit spread observations at the daily level are technically possible, hence such series remain in the sample.

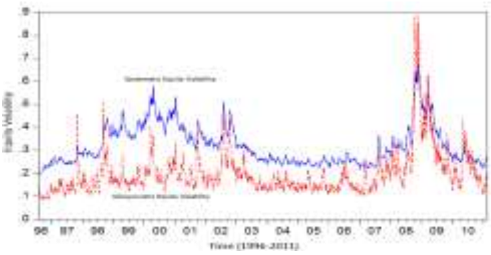
The mean of the distance to default series is 5.25 which effectively means that the average default probability implied by the basic structural model is zero. It should be noted that the mean of the series is influenced by several very high distance-to-default values, which occur when the volatility of assets or leverage is very low. Fig. 1 illustrates the median of credit spread (1.a), distance to default (1.b) and idiosyncratic/systematic equity volatility (1.c) series.

Figure 1. Median values of the main variables

a) Credit spread **b) Distance to default**



c) Systematic and idiosyncratic volatilities



Source: (Prepared by the authors).

The equity volatility series seems to be more volatile than credit spreads, though both appear to follow the same general pattern. The plot of the distance to default series also appears to be consistent with the plots of the other two series, as it is low (i.e. high credit risk) when equity volatility and credit spreads are high. As a risk indicator, the distance to default has an inverse interpretation to that for equity volatility and credit spreads as a lower distance to default implies a higher risk.

3. Results

Credit spreads are regressed on equity volatility, a set of equity volatility – credit risk interaction variables (equity volatility multiplied by an indicator variable taking the value of unity if the distance to default, given by d2 in Equation 7, is within a pre-specified range), the distance to default and the riskless rate (annualised 1-month T-Bill rate). Further, the model is augmented by four sets of indicator variables to control for the firm size, the bond issue size, the bond duration, and the common time effects. The coefficients and t-statistics of the indicator variables (23 in total) are omitted for brevity.

The results are summarised in Table 2 and illustrated in Fig. 2. Model 1 uses total equity volatility; Model 2 employs systematic volatility, and Model 3 utilises idiosyncratic volatility. The effects of total equity volatility and its systematic and idiosyncratic components are significant and strongly depend on credit risk. All coefficients of the equity volatility-distance to default interaction variables covering the distance to default values up to four (four out of six variables covering firms with the highest credit risk) are significant except for one interaction variable in Model 2 which is significant at the 10% level. In all three models, the interaction coefficients monotonically decrease as credit quality improves, i.e. as the distance to default increases.

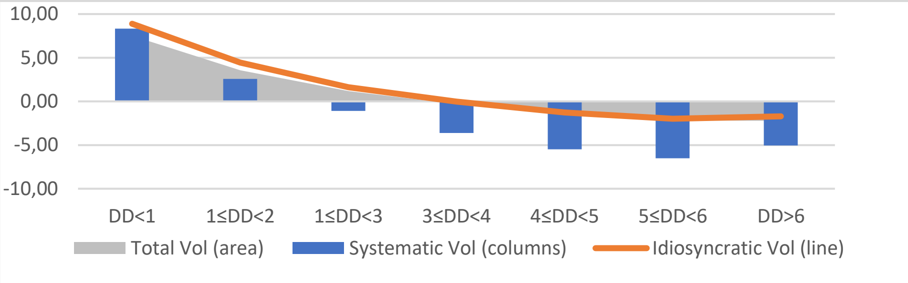
Table 2. Effects of total, systematic and idiosyncratic equity volatilities on credit spreads

Variable	Model 1 Total	Model 2 Systematic	Model 3 Idiosyncratic
Equity Volatility	-222.58	-503.78	-170.19
	[-2.14]	*[-6.74]*	*[-1.97]*
Equity Volatility * I(DD<	973.73	1,335.79	1,058.86
	[10.61]	*[10.11]*	*[10.86]*
Equity Volatility *	577.66	762.58	615.81
	[8.67]	*[9.4]*	*[10.3]*
Equity Volatility *	342.23	393.79	331.08
	[6.77]	*[4.93]*	*[6.89]*
Equity Volatility *	192.32	141.64	166.04
	[4.97]	*[1.92]*	*[4.18]*
Equity Volatility *	75.08	-44.60	41.97
	[2.62]	*[-0.7]*	*[1.31]*
Equity Volatility *	2.35	-147.32	-28.68
	[0.12]	*[-2.99]*	*[-1.17]*
Distance to Default	-14.03	-27.11	-15.13
	[-4.65]	*[-7.3]*	*[-5.49]*
Risk-free Rate	194.00	84.79	-213.98
	[1.19]	*[0.56]*	*[-1.68]*
Intercept	336.07	463.62	328.39
	[7.35]	*[13.82]*	*[9.18]*
Adjusted R-squared	0.50	0.45	0.50

Dependent Variable: Credit Spread; Method: Panel Least Squares; Sample: 8/01/1996 2/18/2011; Periods included: 3,797; Cross-sections included: 352; Total panel (unbalanced) observations: 729,615; White period standard errors and covariance (d.f. corrected); Asset Value Indicator 1 takes the value of 1 if the firm's asset value is up to 2,322 US$ million (178,674 observations); Indicator 2 is up to 4,915 million (177,819 observations); Indicator 3 is up to 10,405 million (231,074 observations); Indicator 4 is up to 22,026 million (207,485 observations) and Indicator 5, which is dropped from the model as the base case, is above 22,026 million (293,065 observations); Bond Value Indicator 1 takes the value of 1 if the bond issue value is up to 54.6 US$ million (151,126 observations); Indicator 2 is up to 148.41 million (154,710 observations); Indicator 3 is up to 403.4 million (358,662 observations) and Indicator 4, which is dropped from the model, is above 403.4 million (111,529 observations); Bond Duration Indicator 1 takes the value of 1 if the bond duration is up to 3 years (133,006 observations); Indicator 2 is between 3 and 6 years (239,872 observations); Indicator 3 is between 6 and 9 years (154,815 observations) and Indicator 4, which is dropped from the model, is above 9 years (248,324 observations); The t-statistics are shown in parentheses.

Source: (Prepared by the authors).

Figure 2. The effects of 1% increase in total, systematic and idiosyncratic equity volatilities on credit spreads conditioned on the distance to default



Source: (Prepared by the authors).

In all three models, equity volatility is positively associated with credit spread for riskier firms. As credit quality improves and firms move away from the theoretical default point, the volatility effect declines and, at some point, turns negative. This suggests that an increase in equity volatility of high-quality firms is associated with a narrower, not wider, credit spread. This holds for all three series, but the effect is more pronounced for systematic volatility, which suggests that the negative impact of equity volatility on credit spread is predominantly driven by its systematic component.

For all but one year, the annual indicator variables are significant. The bond duration and size variables are not significant, while the firm size indicator variables, as expected, indicate a negative relationship between the size of firms and their credit spreads.

3.1. The joint impact of idiosyncratic and systematic volatilities

The models presented in Table 2 regress credit spreads on total equity volatility and its components separately. Model 4, presented in Table 3 and illustrated in Fig. 3, examines the joint impact of systematic and idiosyncratic volatilities. This single model regresses credit spreads on both volatility components, their interactions with the distance to default, the risk-free rate and four sets of control variables (annual, firm size, bond size and bond duration indicator variables – not presented in the table for brevity).

Table 3. Joint effects of systematic and idiosyncratic equity volatilities on credit spreads

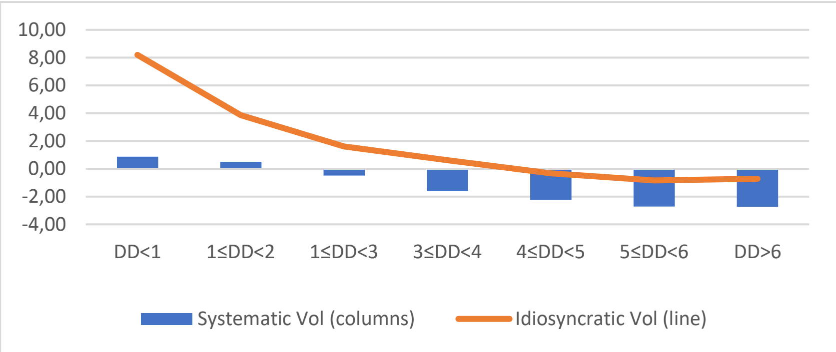
Variable	**Model 4**	
	Systematic	**Idiosyncratic**
Equity Volatility	-275.08	-71.54
	[-3.86]	*[-0.83]*
Equity Volatility * I(DD< 1)	361.04	891.27
	[2.91]	*[6.20]*
Equity Volatility * I(1≤DD<2)	324.88	457.26
	[4.35]	*[5.43]*
Equity Volatility * I(2≤DD<3)	226.78	233.23
	[3.09]	*[3.37]*
Equity Volatility * I(3≤DD<4)	114.55	132.41
	[1.72]	*[2.22]*

Equity Volatility * I(4≤DD<5)	51.22		38.58
	[0.89]		*[0.74]*
Equity Volatility * I(5≤DD<6)	2.23		-12.45
	[0.05]		*[-0.28]*
Distance to Default		-15.44	
		[-5.47]	
Risk-free Rate		-136.17	
		[-1.17]	
Intercept		351.18	
		[9.05]	
Adjusted R-squared	0.50		

Dependent Variable: Credit Spread; Method: Panel Least Squares; Sample: 8/01/1996 2/18/2011; Periods included: 3,797; Cross-sections included: 352; Total panel (unbalanced) observations: 729,615; White period standard errors and covariance (d.f. corrected); Asset Value Indicator 1 takes the value of 1 if the firm's asset value is up to 2,322 US$ million (178,674 observations); Indicator 2 is up to 4,915 million (177,819 observations); Indicator 3 is up to 10,405 million (231,074 observations); Indicator 4 is up to 22,026 million (207,485 observations) and Indicator 5, which is dropped from the model as the base case, is above 22,026 million (293,065 observations); Bond Value Indicator 1 takes the value of 1 if the bond issue value is up to 54.6 US$ million (151,126 observations); Indicator 2 is up to 148.41 million (154,710 observations); Indicator 3 is up to 403.4 million (358,662 observations) and Indicator 4, which is dropped from the model, is above 403.4 million (111,529 observations); Bond Duration Indicator 1 takes the value of 1 if the bond duration is up to 3 years (133,006 observations); Indicator 2 is between 3 and 6 years (239,872 observations); Indicator 3 is between 6 and 9 years (154,815 observations) and Indicator 4, which is dropped from the model, is above 9 years (248,324 observations); The t-statistics are shown in parentheses.

Source: (Prepared by the authors).

Figure 3. The joint effects of 1% increase in systematic and idiosyncratic equity volatilities on credit spreads conditioned on the distance to default



Source: (Prepared by the authors).

The results provide further support for the implications of the results presented in Table 2. The positive part of the relationship between equity volatility and credit spreads is driven entirely by the idiosyncratic volatility component. The idiosyncratic equity volatility variable is not significant, while only the first four idiosyncratic volatility/distance to default interaction variables are significant. This implies that idiosyncratic volatility is significant in explaining credit spreads of bonds issued by firms with relatively low credit quality.

The systematic volatility variable and all its interaction variables are significant. As illustrated in Fig. 3, an increase in systematic volatility is associated with a wider credit spread for low credit quality firms only. This effect is dramatically smaller than the effect of idiosyncratic volatility. As credit quality improves, the systematic volatility effect becomes negative (i.e. an increase in systematic volatility is associated with a decrease in credit spread) and larger than the effect of idiosyncratic volatility.

Conclusions

The structural model of Merton (1974) implies that an increase in asset volatility increases the default probability and, as a result, widens credit spreads on corporate bonds. The existing studies, which use the volatility of equity returns over a benchmark index as a measure of equity volatility (e.g. Campbell and Taksler, 2003), find a statistically and economically positive relationship between credit spreads and idiosyncratic equity volatility. The existing evidence on the importance of systematic equity volatility as a determinant of credit spreads is less conclusive. Campbell and Taksler (2003), for example, report that the market-wide volatility has a positive but drastically smaller effect than idiosyncratic volatility. Cremers et al. (2008), on the other hand, find that the relationship between the market-wide volatility and credit spreads is negative and call it surprising.

This paper uses the Fama-French three-factor model to estimate idiosyncratic and systematic equity volatilities and examine their relationship with credit spreads. The systematic and idiosyncratic equity volatilities are positively related to credit spreads of low credit quality firms. The idiosyncratic volatility effect is larger than the effect of its systematic counterpart. As credit quality improves, the volatility effect shrinks and then turns positive. This implies that an increase in equity volatility of high credit quality firms is associated with a narrower, not wider, credit spread. The negative leg of the relationship between equity volatility and credit spread is driven by systematic volatility. This seemingly surprising result is consistent with the evidence that investors are willing to pay a premium for high-quality bonds. The results are robust to controls for firm size and bond issue size and duration.

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