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Credit default swap spreads and variance risk premia

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ABSTRACT

We find that the firm-level variance risk premium has a prominent explanatory power for credit spreads in the presence of market- and firm-level control variables established in the existing literature. Such predictability complements that of the leading state variable—the leverage ratio—and strengthens significantly with a lower firm credit rating, longer credit contract maturity, and model-free implied variance. We provide further evidence that (1) the variance risk premium has a cleaner systematic component than implied variance or expected variance, (2) the cross-section of firms' variance risk premia capture systematic variance risk in a stronger way than firms' equity returns in capturing market return risk, and (3) a structural model with stochastic volatility can reproduce the predictability pattern of variance risk premia for credit spreads.

1. Introduction

It has long been recognized in the literature that a critical component of systematic economic risk may be missing in credit risk modeling (Jones et al., 1984; Elton et al., 2001; Collin-Dufresne et al., 2001; Huang et al., 2003), which is the main cause of the so-called credit spread puzzle. The relatively larger spikes of high investment-grade credit spreads than speculative-grade during the recent financial crisis highlight a possible systematic shock that tends to explain the low-frequency cyclical movements of credit spreads. In this paper, we try to explain individual firms' credit spreads by the variance risk premium (hereafter, VRP) and relate the VRP component of the credit spread to the exposure to systematic variance or economic uncertainty risk (Bollerslev et al., 2009; Drechsler and Yaron, 2011).

VRP is defined as the difference between expected variance under the risk-neutral measure and expected variance under the objective measure (see among others Britten-Jones and Neuberger, 2000; Jiang and Tian, 2005; Carr and Wu, 2008). Theoretically, the variance risk premium isolates only firms' exposure to systematic variance risk that must be priced in all risky assets since, by construction, the risk-neutral and objective expectations of firms' idiosyncratic variance risk cancel out with each other. Empirically, we estimate VRP as the difference between the model-free option-implied variance and the expected variance based on the realized measures estimated from high-frequency equity return data.

We present robust evidence that firm-level VRP is the most prominent predictor for credit default swap (CDS) spread variations relative to the other macroeconomic and firm-specific credit risk determinants identified in the existing literature: VRP by itself predicts 29% of credit default spread variation. This finding echoes the recent studies that recognize the linkage among

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macroeconomic conditions, the equity risk premium, and credit risk pricing (see, e.g., David, 2008; Bhamra et al., 2009; Chen et al., 2009; Chen, 2010), but our paper focuses on providing cross-sectional evidence of individual firms. We also find that model-free implied variance is valid as long as the underlying stock price follows a jump-diffusion process (Carr and Wu, 2008). In practice, the numerical integration scheme can be set accordingly to a limited number of strike prices to ensure that the discretization errors have a minimal effect on the estimation accuracy of model-free implied variance.[3] The model-free implied variance could be more informative than the implied variances using only at-the-money (out-of-the-money or in-the-money) options, as the model-free approach incorporates the option information across different moneyness (Jiang and Tian, 2005).

In order to define the realized variance that we use in estimating the expected variance, let $s_{i,t}$ denote the logarithmic stock price of firm i. The realized variance over the $[t-1, t]$ time interval may be measured as

$$RV_{i,t} \equiv \sum_{j=1}^{n}\left[s_{i,t-1+\frac{j}{n}} - s_{i,t-1+\frac{j-1}{n}}\right]^2 \rightarrow \text{Variance}_i(t-1,t), \tag{2}$$

where the convergence relies on $n \rightarrow \infty$; i.e., an increasing number of within-period price observations.[4] As demonstrated in the literature (see, e.g., Andersen et al., 2001a; Barndorff-Nielsen and Shephard, 2002), this ''model-free'' realized variance measure based on high-frequency intraday data can provide much more accurate ex-post observations of the ex-ante return variation than those based on daily data.

For a monthly horizon and monthly data frequency, where $IV_{i,t}$ is the end-of-month risk-neutral expected variance for firm i of the next month, and $RV_{i,t}$ is the realized variance of the current month, we adopt a linear forecast of the objective or statistical expectation of the return variance as $RV_{i,t+1} = \alpha + \beta IV_{i,t} + \gamma RV_{i,t} + \epsilon_{i,t+1}$, and the expected variance is simply the time t forecast of realized variance from t to $t+1$ based on estimated coefficients $\hat{\alpha}$ and $\hat{\beta}$ in the linear regression,

$$EV_{i,t} \equiv E_t^P[\text{Variance}_i(t,t+T)] \equiv \widehat{RV}_{i,t+1} = \hat{\alpha} + \hat{\beta} IV_{i,t} + \hat{\gamma} RV_{i,t}, \tag{3}$$

where $\widehat{RV}_{i,t+1}$ is the forecasted realized variance of firm i of the next month.

We use this particular projection because the model-free implied variance from the options market is an informationally more efficient forecast for the future realized variance than the past realized variance (see, e.g., Jiang and Tian, 2005); while the realized variance based on high-frequency data also provides additional power in forecasting the future realized variance (Andersen et al., 2001b). Therefore, a joint forecast model with one lag of implied variance and one lag of realized variance seems to capture the most forecasting power from the time-t available information (Drechsler and Yaron, 2011).

The variance risk premium of an individual firm, or $VRP_{i,t}$, underlying our key empirical findings is defined as the difference between the ex-ante risk-neutral expectation and the objective expectation of future return variation over the $[t, t+1]$ time interval,

$$VRP_{i,t} \equiv IV_{i,t} - EV_{i,t}. \tag{4}$$

Such a construct at the market level has been shown to possess remarkable capability in forecasting the aggregate credit spread indices (Zhou, 2009). Here we investigate in detail how the VRP of individual firms can help us understand the cross section of individual firms' CDS spreads.

2.2. Empirical implementation strategy

We examine the relationship between the panels of CDS spreads and VRPs in the presence of market- and firm-level credit risk determinants suggested by theory and empirical evidence. We focus on monthly data to avoid picking up the market microstructure noise induced by high-frequency comovements between option and credit markets. For spreads and implied variance, we use only the matched last-available end-of-month (daily) observations. Because missing dates and stale quotes signify that daily or even weekly data quality is not reliable, and if we just ignore the daily missing values, we will introduce a serial-dependent error structure in the independent variable CDS spread, which may artificially increase the prediction R^2 or significance. Monthly data will give us a more conservative but reliable estimate and is typically the shortest horizon—compared with quarterly or annual data—for picking up the low-frequency risk premium movement.

CDS spreads should also be influenced by the leverage ratio of the underlying firm and the risk-free spot rate. As suggested by the structural form credit risk models (e.g., Merton, 1974), leverage is the most important credit risk determinant—all else being equal, a firm with higher leverage has a higher likelihood of default (Collin-Dufresne and Goldstein, 2001). The leverage ratio, denoted by $LEV_{i,t}$, is computed as the book value of debt over the sum of the book value of debt and market value of equity. Moreover, structural models predict that risk-free interest rates negatively influence the credit spread (Longstaff and Schwartz, 1995)—when the risk-free rate is increasing, it typically signifies an improving economic environment with better earning growth opportunity for the firms, therefore a lower default risk premium. Alternatively, when the short rate is rising, inflation risk is also increasing, and nominal asset debt becomes less valuable compared to real asset equity (Zhang et al., 2009). We define the risk-free rate variable to be the 1-year swap yield, denoted by r_t.

Empirical research also shows that in practice, CDS spreads contain compensation for non-default risks as well as risk premiums, which may be difficult to identify without the aggregate macro variables. Henceforth, we will not limit our analysis to the traditional theoretically motivated regressors but augment our set of variables by the following market variables: (1) the market variance risk premium based on the S&P 500 denoted by $MVRP_t$ to measure systemic variance or macroeconomic uncertainty risk—all else equal, high market VRP leads to high credit spreads (Zhou, 2009);[5] (2) the S&P 500 return, denoted by $S\&P_t$ to proxy for the overall state of the economy—when the economy is improving, the credit spread should be lower as profit is rising (Zhang et al., 2009); (3) Moody's default premium slope, denoted by DPS_t, is computed as *Baa* yield spread minus *Aaa* yield spread to capture the default risk premium in the corporate bond market—the coefficient of the default premium slope should be positive, consistent to the notion that CDS and corporate bond markets are cointegrated (Blanco et al., 2005; Ericsson et al., 2004; Zhu, 2006); and (4) the difference of the 5-year swap rate and the 5-year Treasury rate, denoted by STS_t, as a proxy for fixed-income market illiquidity, which is expected to move positively with CDS spreads (Tang and Yan, 2008).

For firm characteristic variables, besides leverage ratio, we include the following controls: (1) asset turnover, denoted by $ATO_{i,t}$, is computed as sales divided by total assets; (2) price-earnings

[3] We set the grid number in the numerical integration at 100, although with a reasonable parameter setting a grid number of 20 is accurate enough (Jiang and Tian, 2005).

[4] In practice, we use 15-min returns, although for a similar sample of 307 US firms using 5-min returns produces a similar quality estimation of realized variances (Zhang et al., 2009).

[5] The market variance risk premium is defined as the difference between the risk-neutral and objective expectations of the S&P 500 index variance (Zhou, 2009), where the risk-neutral expectation of variance is measured as the end-of-month observation of VIX-squared and the expected variance under the objective measure is a forecasted realized variance with an AR(12) process. Realized variance is the sum of squared five-minute log returns of the S & P 500 index over the month. Both variance measures are in percentage-squared format on a monthly basis.

ratio denoted by $PE_{i,t}$; (3) market-to-book ratio, denoted by $MB_{i,t}$; (4) return on assets, denoted by $ROA_{i,t}$, computed as earnings divided by total assets; (5) the natural logarithm of sales, denoted by $SALE_{i,t}$. As a proxy for firm size, $SALE_{i,t}$ should influence CDS spread negatively—as larger and more mature firms tend to be investment grade in our sample, all else being equal. Firm asset turnover, market-book ratio, and return on assets are all expected to be negatively related to CDS spreads, because firms of high profitability and future growth tend to have lower credit risk. The price-earnings ratio may have two opposite effects on CDS spreads: on the one hand, a high price-earnings ratio implies high future asset growth that reduce the likelihood of financial distress and credit risk; on the other hand, high growth firms tend to have high return volatilities that increase credit risk. These hypothesized signs of regression coefficients are consistent with the basic Merton (1974) model's implications and are largely confirmed by the empirical literature (see, e.g., Collin-Dufresne et al., 2001).

Given the nature of our cross-sectional and time-series data, we adopt the robust standard error approach of Petersen (2009) to account for both firm and time effects in large panel data sets. Therefore, the above discussions suggest the following one-month ahead forecasting regression

$$\begin{aligned} CDS_{i,t+1}, = \alpha &+ \beta_1 VRP_{i,t} + \beta_2 MVRP_t + \beta_3 LEV_{i,t} + \beta_4 S\&P_t + \beta_5 r_t \\ &+ \beta_6 DPS_t + \beta_7 STS_t + \beta_8 ATO_{i,t} + \beta_9 PE_{i,t} + \beta_{10} MB_{i,t} \\ &+ \beta_{11} ROA_{i,t} + \beta_{12} SALE_{i,t} + \varepsilon_{i,t+1}, \end{aligned} \tag{5}$$

and our focus is the relation between a firm's CDS spread and its VRP.

3. Data description and summary statistics

To conduct the empirical study, we collect data on credit default swap (CDS) spreads, equity option prices, macroeconomic variables, firm equity, and balance sheet information from various sources. The summary statistics of CDS spreads, variance risk premiums, and other market wide or firm-specific controls, are discussed here to set the background for examining the critical link between CDS spreads and VRPs.

3.1. Data sources

Under a CDS contract, the protection seller promises to buy the reference bond at its par value when a predefined default event occurs. In return, the protection buyer makes periodic payments to the seller until the maturity date of the contract or until a credit event occurs. This periodic payment, which is usually expressed as a percentage (in basis points) of the bonds' notional value, is called the CDS spread. By definition, a credit spread provides a pure measure of the default risk of the reference entity. We use CDS spreads as a direct measure of credit spreads. Compared with corporate bond yield spreads, CDS spreads are not subject to the specification of the benchmark risk-free yield curve and are less contaminated by non-default risk components (Longstaff et al., 2005; Ericsson et al., 2006).

Our single-name CDS spreads are obtained from a database compiled by the Markit group. The data set also reports average recovery rates, used by data contributors in pricing each CDS contract, which center around 0.4 without much variation. The sample period covers January 2001 to December 2011. We restrict our sample to US dollar-denominated CDS written on US entities that are not in the government, financial, or utility sectors. We further eliminate the subordinated class of contracts because of its small relevance in the database and its unappealing implications for credit risk pricing. The maturities of Markit CDS contracts range between 6 months and 30 years. We focus on the most popular and liquid 5-year CDS contracts with modified restructuring clauses in our benchmark analysis. CDS spreads of other contract maturities ranging between 1 and 10 years are relatively liquid and are used for robustness checks. After cleaning and matching the CDS data with reliable options, equity, and balance sheet information, we are left with 31,411 monthly observations of 382 entities in our study. For each entity, the monthly CDS spreads are matched with the monthly VRPs.

The option data is obtained from Ivy DB OptionMetrics. We keep only the options whose last trade dates match the record dates and whose option price dates match the underlying security price dates. We further eliminate the option prices that violate arbitrage boundaries ($C \leqslant S - Ke^{-r_T T}$). Stock dividend information is acquired from CRSP and taken into account when applying the CRR model to extract the implied volatility surface.

We compute high-frequency realized variances using information in TAQ database that contains the intraday equity trading data spaced by 15 min during trading hours. Following the method outlined in the previous section, we first calculate the daily variance based on the high-frequency data, then aggregate it to construct monthly realized variance. Next, we estimate expected variance that is of the same maturity as the implied variance. All types of VRPs are then matched with CDS spreads on a firm-month basis.

Market and firm control variables are the most recently available monthly or quarterly variables. Firm quarterly balance-sheet data are acquired from COMPUSTAT. Market variables—the swap rates, constant maturity Treasury yields, and Moody's *Aaa* and *Baa* yields are acquired from the Federal Reserve Board's public website. S&P 500 index returns come from CRSP. The market VRP is from Zhou (2009).

3.2. Summary statistics

Table 1 presents the summary statistics—the average across the 382 firms—of the 5-year CDS spreads and our benchmark VRP measure (Panel A), model-free implied variances and expected variances (Panel B). The average Moody's and S&P ratings of the CDS reference entities range between AAA and CCC. A majority of the CDS ratings are A, BBB, and BB (19%, 37%, and 25% respectively, in total 81%). The average of CDS spreads in our sample is 149 basis points. They increase monotonically from 27 to 589 basis points as the credit ratings of the CDS reference entities deteriorate from AAA to CCC. The difference between the average CDS spreads for AAA grade and AA grade is 10 basis points, whereas the difference between those for CCC grade and B grade is 189 basis points. The CDS spreads display positive skewness of around 1.27 and leptokurtosis of 5.21.

Similar to the CDS spreads, the VRP displays significant variations across rating groups. The average of the benchmark VRP measure for the full sample is 34.73 (monthly percentage squared), increasing from 9.43 to 103.50 as CDS reference entities' credit ratings drop from AAA to CCC. High credit risk entities tend to be associated with high VRPs. The variance risk premia display positive skewness of 1.44 and leptokurtosis of 7.17.

As shown in Panel B of Table 1, the means and standard deviations of model-free implied variances are much higher than those of expected variances, but the skewness and kurtosis are similar. The results suggest that implied variance could contain a larger idiosyncratic component than expected variance. The AR(1) coefficients for VRP, model-free implied, and expected variances are 0.75, 0.93, and 0.93 respectively, suggesting that VRP is less persistent compared with model-free implied variances and expected variances.

We group our sample into three sub-samples by CDS ratings. The first group contains CDS of AAA, AA and A grades, the second

Table 1

Descriptive statistics – CDS spreads, variance risk premium, implied variance and expected variance. This table presents the summary statistics—average across the 382 firms—of the 5-year CDS spreads and our benchmark Variance Risk Premium (VRP) measure (Panel A), model-free implied variances and expected variances (Panel B). The CDS spreads are in basis points. The VRP is computed as the spread between model-free implied variance and expected variance. The implied variance is the model-free implied variance. The expected variance is the linear forecast of realized variance by lagged implied and realized variance. The average Moody's and S&P ratings of the CDS reference entities range between AAA and CCC. The numbers of firms in each rating category are reported in the second column in Panel A. AR(1) denotes autocorrelation with one lag.

Rating	Firm number	CDS spread					VRP				
		Mean	SD	Skew.	Kurt.	AR(1)	Mean	SD	Skew.	Kurt.	AR(1)
Panel A: The means of the statistics of CDS spreads and VRP across individual firms											
AAA	7	27.10	21.70	2.07	9.44	0.96	9.43	11.21	1.89	11.12	0.53
AA	17	37.16	22.98	1.54	6.17	0.98	11.24	12.40	1.54	7.29	0.62
A	101	45.53	29.18	1.46	6.09	0.99	19.86	19.24	1.72	8.10	0.69
BBB	199	98.77	55.41	1.23	4.98	0.98	29.72	25.04	1.38	6.54	0.74
BB	133	251.33	105.11	0.90	4.05	0.98	48.70	32.35	0.96	4.97	0.77
B	65	400.04	132.04	0.30	2.81	0.99	67.64	40.83	0.50	3.70	0.81
CCC	14	588.79	137.37	−0.64	4.81	0.96	103.50	43.14	0.24	2.49	0.88
Total	382	149.12	79.98	1.27	5.21	0.98	34.73	28.13	1.44	7.17	0.75

Rating	Implied variance					Expected variance				
	Mean	SD	Skew.	Kurt.	AR(1)	Mean	SD	Skew.	Kurt.	AR(1)
Panel B: The means of the statistics of IV and EV across individual firms										
AAA	46.64	34.84	2.26	9.56	0.90	37.14	26.74	2.53	11.78	0.92
AA	56.29	40.23	1.94	7.01	0.91	45.03	32.85	1.94	7.01	0.91
A	81.85	59.75	2.08	8.38	0.92	61.92	46.20	2.45	11.18	0.94
BBB	111.38	73.48	1.81	7.02	0.92	81.46	55.18	1.99	8.28	0.93
BB	175.16	91.71	1.38	5.22	0.95	127.14	72.59	1.49	5.68	0.94
B	226.28	109.97	0.99	3.53	0.98	156.87	82.72	1.03	3.84	0.97
CCC	316.37	102.60	0.71	3.26	0.95	211.16	74.88	0.99	4.10	0.94
Total	127.94	84.16	1.93	7.37	0.93	73.21	64.97	2.21	9.40	0.93

group contains CDS of BBB grade, and the third group contains CDS of speculative grades ranging between BB and CCC. The three sub-samples contain 8750, 11,911, and 6180 firm-month observations, respectively. Fig. 1 plots the time-series of the 5-year CDS spreads of a whole sample and three sub-groups. The CDS spreads decrease gradually from the peaks in late 2002, then increase again as the financial crisis approaches in mid-2007 and reaches peaks in early 2009. The spreads of CDS in year 2009 are higher than those in year 2002, more so for investment grades. This pattern highlights the systematic nature of the recent financial crisis, which is mainly fueled by the heightening of systematic risk or economic uncertainty and affects disproportionately the high investment-grade

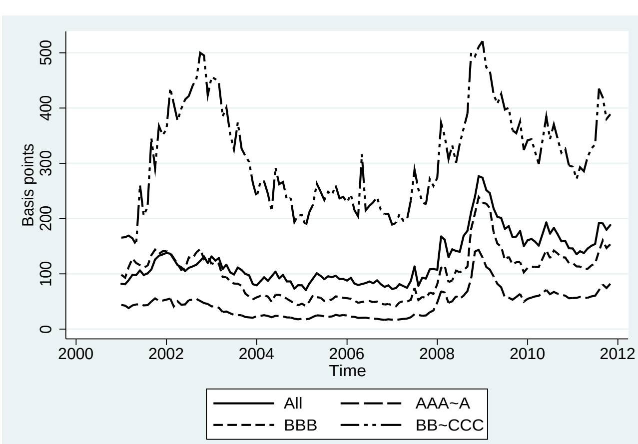


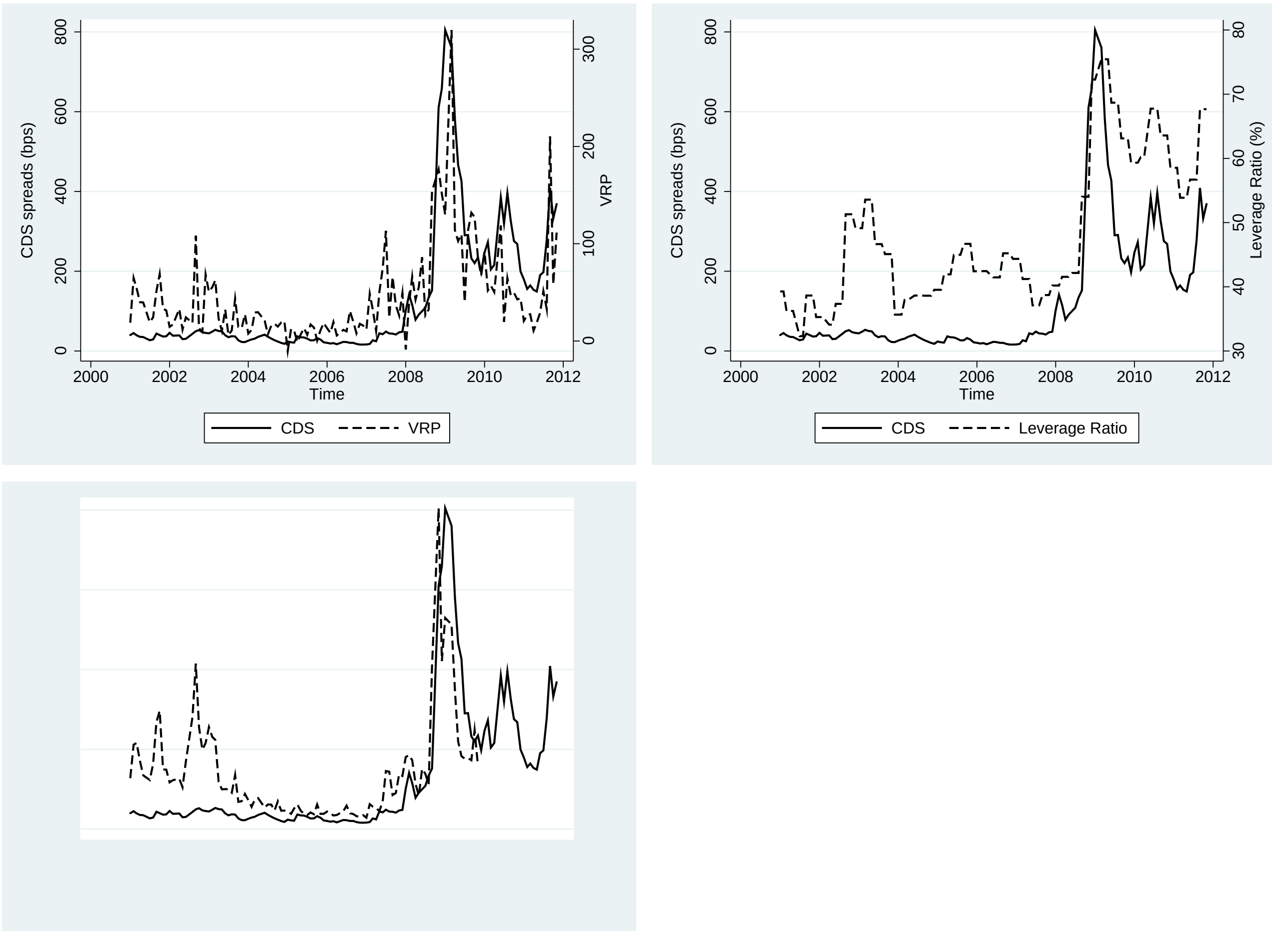
Fig. 1. Time series of 5-year CDS spreads. This figure plots the 5-year CDS spreads of full sample and three sub-samples. We group the CDS spreads into three sub-samples by CDS ratings. The first group contains CDS of AAA, AA and A grades. The second group contains CDS of BBB grade. The third group contains CDS of speculative grades ranging between BB and CCC. The three sub-samples contain 8750, 11,911 and 6180 observations respectively.

credit spreads. The difference between the investment-grade and speculative-grade CDS spreads, however, widened during the period of 2007–2009, potentially because the "flight-to-quality" effect during the financial crisis that drove up the compensation for credit risk.

Fig. 2 further illustrates the dynamic relationships among CDS spreads, VRP, market VRP, and the leverage ratio for a representative firm in our sample: Aloca. The CDS spread line and VRP line resemble each other closely over time. In particular, the two lines move closely in the recent financial crisis. In addition, the CDS spreads tend to comove with the firm's leverage ratio. A visual examination of the relationship between CDS spreads and market VRP suggests that market risk premium, market VRP in particular, may not provide a powerful prediction about Alcoa's credit spreads. For instance, the two lines move in exactly opposite directions in late 2009.

Table 2 reports the descriptive statistics for our market- and firm-level control variables; the latter are averaged across 382 entities. The average monthly market VRP is 16.94 (percentage-squared). The average 1-year swap rate is 2.88%. The firms in our sample have an average leverage ratio of 42% with a standard deviation of 8%. For simplicity, we omit the discussion of other control variables, given that they are similar to those reported in literature.

Table 3 reports the univariate correlations of the regression variables and shows that the CDS spread is positively correlated to VRP, implied variance (IV) and expected variance (EV). VRP is significantly correlated to IV (0.82), and less correlated to EV (0.63). Such a pattern suggests that VRP and EV may capture different risk components embedded in IV. Among credit risk determinants, VRP, and leverage have high correlations with CDS spreads, whereas other variables exhibit lower correlations, suggesting that the two variables may possess significant explanatory power for credit risk. CDS spreads are positively correlated with market VRP (0.30), but the coefficients of market VRP turn out to be insignificant in the presence of firm-level VRP in the multivariate regressions in the next section.



4. Empirical results and analysis

In this section, we show that firm-level VRP displays a significant predictive power for CDS spreads in the presence of all other credit risk determinants. In particular, VRP complements the firm leverage ratio that has been shown as the leading explanatory variable for credit spreads by Collin-Dufresne and Goldstein (2001) within the Merton (1974) framework. VRP crowds out the market-level variation risk measure—market VRP—in capturing the systematic variance risk embedded in CDS spreads. The predictive power of VRP for CDS spreads is unchanged before and after the sub-prime crisis, and increases as firm credit quality deteriorates. Model-free VRP performs better than the VRP implied from call or put options of different moneyness.

Further robustness checks suggest that VRP and expected variance are two indispensable components of the option-implied variance in predicting the individual firms' credit spreads. In addition, VRP seems to possess more forecasting power at monthly and quarterly horizons while implied variance possesses more at weekly horizons, and in aggregate, the market VRP Granger-causes implied and expected variances. Furthermore, the firm-level VRP measure contains a cleaner systematic factor component than either implied variance or expected variance, and the systematic variance risk seems to be priced by the cross-section of firm-level VRPs in a stronger way than the market return risk by firm equity returns. Finally, our empirical finding can be qualitatively justifiable by simulation evidence from a structural model with stochastic asset variance risk.

Table 3

Univariate correlations of the regression variables. This table reports the univariate correlations of the regression variables. *CDS* denotes 5-year maturity CDS spread. *VRP* denotes firm level variance risk premium constructed with model free implied variance *IV* minus expected variance *EV* estimated with high frequency equity returns. *MVRP* represents market variance risk premium. *S&P* and *r* denote S&P 500 return and swap rate of 1-year maturity respectively. *DPS* represents default risk premium measured as the spread between Moody's *Baa* and *Aaa* rates. *STS* is the spread between 5-year swap and constant maturity Treasury rates. *LEV* denotes market leverage. *ATO*, *PE*, *MB* and *ROA* denote asset turnover, price-earnings ratio, market-book ratio and return on assets respectively. *SALE* is the natural logarithm of annual sales.

	CDS	*VRP*	*IV*	*EV*	*MVRP*	*S&P*	*r*	*DPS*	*STS*	*LEV*	*ATO*	*PE*	*MB*	*ROA*	*SALE*
CDS	1.00														
VRP	0.48	1.00													
IV	0.66	0.82	1.00												
EV	0.64	0.63	0.97	1.00											
MVRP	0.30	0.41	0.49	0.46	1.00										
S&P	−0.47	−0.42	−0.65	−0.65	−0.33	1.00									
r	−0.49	−0.29	−0.29	−0.24	−0.23	0.04	1.00								
DPS	0.65	0.40	0.73	0.75	0.28	−0.73	−0.29	1.00							
STS	0.11	0.13	0.34	0.39	0.19	−0.42	0.33	0.28	1.00						
LEV	0.58	0.33	0.43	0.37	0.18	−0.32	−0.46	0.43	−0.03	1.00					
ATO	−0.21	−0.06	−0.04	−0.03	−0.02	0.01	0.24	−0.03	0.17	−0.35	1.00				
PE	−0.18	−0.09	−0.16	−0.15	−0.06	0.12	0.10	−0.17	−0.01	−0.23	0.01	1.00			
MB	−0.43	−0.27	−0.38	−0.33	−0.14	0.28	0.32	−0.34	0.05	−0.79	0.23	0.18	1.00		
ROA	−0.30	−0.12	−0.15	−0.11	−0.07	0.08	0.25	−0.06	0.09	−0.55	0.45	0.02	0.46	1.00	
SALE	0.04	0.00	0.02	0.04	0.08	0.07	−0.02	0.11	0.11	−0.05	0.60	−0.08	0.37	0.34	1.00

4.1. The benchmark regressions

Table 4 reports the regression results of the relationship between 5-year CDS spreads and benchmark VRP computed with model-free implied variance *minus* expected variance estimated from lagged implied and realized variances (see Section 2). Regression 1 reports that CDS spreads are positively related to VRP in the univariate regression. The *t*-statistic is a significant 14.01. In terms of economic significance, one standard deviation increase in VRP (28.13) will increase CDS spreads by 60.76 basis points. Regression 2 shows that leverage ratio is indeed highly significant, as the leading determinant of credit spread levels and changes (Collin-Dufresne and Goldstein, 2001; Collin-Dufresne et al., 2001); however, including leverage ratio in the regression still preserves the high significance of the VRP measure (regression 3).

Regression 4 indicates that market VRP positively predicts CDS spreads. However, regression 5 shows that the relationship between CDS spreads and VRP remains intact in the presence of market VRP. More important, market VRP is insignificant, suggesting firm VRP subsumes market VRP in terms of capturing the exposure to systematic variance risk in predicting CDS spreads. This fact remains true with the control of leverage ratio (regression 6). As indicated in Zhou (2009) and Buraschi et al. (2009), market VRP predicts a significant positive risk premium in market credit spreads, which is consistent with our firm level evidence here.

Regression 7 reports the full-scale regression results after including all control variables. The coefficient of VRP decreases slightly from 2.16 in the univariate regression to 1.38 but remains statistically significant at the 1% level with a robust *t*-statistic of 9.08. Among the market level control variables, the S&P 500 return,

Table 4

The CDS spreads and VRP. This table reports the regression results of 5-year CDS spreads on the VRP computed with model free implied variance *IV* minus expected variance *EV* estimated with high frequency equity returns. Regression (1) is the univariate regression of VRP; regression (2) is the univariate regression of leverage; regression (3) shows the relationship between CDS spreads and VRP in the presence of leverage only; regression (4) is the univariate regression of market VRP; regression (5) shows the relationship between CDS spreads and VRP in the presence of market VRP; regression (6) further includes leverage into regression (5); and regression (7) includes all other control variables. We adjust two-dimensional (firm and time) clustered standard errors in the regressions as in Petersen (2009). The numbers in the brackets are *t*-statistics.

Independent variable	Regression						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VRP	2.16		1.64		2.16	1.63	1.38
	(14.01)		(11.56)		(13.66)	(11.25)	(9.08)
Leverage		4.69	3.62			3.63	3.30
		(11.90)	(11.61)			(11.59)	(9.73)
Market VRP				0.83	0.01	0.06	0.06
				(3.25)	(0.03)	(0.22)	(0.28)
S&P 500 return							0.94
							(4.36)
Swap rate (1 year)							−1.98
							(−1.08)
Baa – *Aaa*							37.88
							(4.12)
Swap – CMT (5 year)							39.81
							(3.31)
Asset turnover ratio							7.78
							(1.36)
Price-earnings ratio							−0.01
							(−1.21)
Market/book ratio							0.00
							(2.56)
Return on assets							−190.2
							(−3.63)
Log sales							−19.84
							(−5.38)
Adjusted R^2	0.29	0.31	0.47	0.02	0.29	0.47	0.51

the spread between Baa and Aaa indexes, and the market illiquidity measure are statistically insignificant. For firm-level controls, return on assets and log sales are statistically significant at the 1% level. The results support the intuition behind the structural-form credit risk models in that firms with higher profitability tend to have a relatively smaller chance of default, hence a lower credit risk premium.

The adjusted R^2 for the univariate regression of VRP indicates that 29% of the variation in CDS spreads can be accounted for by the firm-specific VRP, which may capture a firm's exposure to systematic variance risk. In comparison, the adjusted R^2 for the univariate regression of leverage is 31%, while the adjusted R^2 for market VRP is 0.02. Adding market VRP to the regression has no effect on the adjusted R^2, which remains at 29%. This result suggests that firm-level variation risk measure has much stronger explanatory power for individual firm's CDS spreads compared with the well-documented market-level variation risk measure. Including leverage ratio in the regression increases the adjusted R^2 to 0.47, possibly capturing the firm-specific default risk on top of systematic risk in the spirit of Merton (1974). Adding all other control variables increases the adjusted R^2 sightly to 0.51. It appears that, among all variables, firm-level VRP and leverage ratio are the two most powerful explanatory variables affecting CDS spreads.

The 2007–2008 sub-prime credit crisis significantly changed the landscape of the CDS markets. We, therefore, divide our sample into pre- and post-sub-prime crisis periods to examine whether the predictability of VRP on CDS spreads holds strong during both periods. Table 5 reports that during both periods, VRP positively and significantly predicts subsequent CDS spreads. Its predictive power is pretty much unchanged, evidenced by the t-statistics and R^2's reported in Columns (1) and (4). The results reported in (3) and (6) confirm VRP's strong predictive power on credit spreads in the presence of the control variables. Interestingly, some of the control variables become significant after the sub-prime crisis. For example, the S&P 500 return, the aggregate credit price index ($Baa - Aaa$

Table 6

CDS spreads and VRP by CDS rating. This table reports the regression results of CDS spreads on VRP for three sub-samples: AAA-A, BBB, BB-CCC. The ratings are the average of Moody's and S&P ratings. Two-dimensional (firm and time) clustered standard errors in the regressions are adjusted as in Petersen (2009). The group AAA-A has 8750 observations. The group BBB has 11,911 observations. The group BB-CCC has 6180 observations. The first three regressions are the regressions of VRPs and leverage. The second three regressions are the multivariate regressions with all the control variables. The numbers in the brackets are t-statistics.

Independent variable	Regression by ratings					
	AAA-A	BBB	BB-CCC	AAA-A	BBB	BB-CCC
VRP	0.66	0.94	1.28	0.37	0.66	1.01
	(5.98)	(8.80)	(8.36)	(3.97)	(6.46)	(6.05)
Leverage	0.89	1.57	5.89	0.91	1.23	5.83
	(5.61)	(7.75)	(12.11)	(5.40)	(5.40)	(10.43)
Market VRP				0.12	0.14	0.43
				(1.41)	(1.13)	(1.28)
S&P 500 return				0.29	0.07	0.63
				(2.74)	(0.31)	(1.59)
Swap rate (1 year)				−4.22	−7.39	−9.23
				(−5.31)	(−5.10)	(−2.57)
Baa – Aaa				29.77	30.86	35.92
				(5.91)	(3.23)	(2.13)
Swap – CMT (5 year)				21.59	24.89	98.20
				(3.44)	(2.89)	(5.03)
Asset turnover ratio				1.30	6.80	−13.72
				(0.63)	(1.39)	(−1.00)
Price-earnings ratio				−0.00	−0.01	−0.01
				(−2.04)	(−1.54)	(−0.69)
Market/book ratio				0.00	0.00	0.00
				(3.95)	(0.14)	(2.37)
Return on assets				51.07	−59.42	−173.40
				(2.29)	(−0.94)	(−2.71)
Log sales				−2.63	−2.73	−7.46
				(−2.22)	(−0.76)	(−0.80)
Adjusted R^2	0.26	0.24	0.47	0.43	0.32	0.51

Table 7

The CDS spreads of different maturity terms and VRP. This table reports the regression results of CDS spreads of all maturities on the VRP computed with model free implied variance IV minus expected variance EV estimated with high frequency equity returns. We adjust two-dimensional (firm and time) clustered standard errors in the regressions as in Petersen (2009). The numbers in the brackets are t-statistics.

Independent variable	CDS spreads					
	1-year	2-year	3-year	5-year	7-year	10-year
Panel A: Univariate regressions						
VRP	1.64	1.85	2.03	2.16	2.19	2.18
	(14.15)	(14.16)	(14.43)	(14.01)	(13.66)	(13.20)
Adjusted R^2	0.28	0.29	0.30	0.29	0.29	0.29
Panel B: Multivariate regressions						
VRP	0.96	1.13	1.28	1.38	1.41	1.40
	(8.56)	(8.60)	(8.90)	(9.08)	(8.98)	(8.82)
Leverage	1.88	2.32	2.71	3.30	3.36	3.47
	(8.16)	(8.43)	(9.00)	(9.73)	(9.51)	(9.71)
Market VRP	0.02	0.03	0.03	0.06	0.09	0.11
	(0.13)	(0.15)	(0.13)	(0.28)	(0.45)	(0.54)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.46	0.48	0.50	0.51	0.51	0.51

firm-level VRP and leveraged ratio. The t-statistics confirm that the firm-level VRPs perform much better than the market-level VRP in predicting individual firm credit spreads.[6] In general, the longer the maturity of a CDS contract, the more significant the economic effect of firm-level VRP on CDS spreads with larger slope coefficients and higher adjusted R^2s. It is intuitive that a CDS contract of longer maturity is relatively more exposed to the variance uncertainty risk and hence requires a larger spread compensation.

To check the extent to which the significance of the explanatory power of VRP on credit spreads depends on different methods of constructing VRP, we carry out a regression analysis of CDS spreads on VRPs constructed with various option features. Besides the benchmark model-free implied variance, we use implied variances computed from out-of-the-money, at-the-money, and in-the-money put/call options. As reported in Table 8, all VRP measures display consistently significant predictability for CDS spreads in the presence of other credit risk predictors. Among them, the VRPs constructed with model-free implied variance displays the strongest predicting power on CDS spreads, reflected in both t-statistics and adjusted R^2s. The model-free implied variance is informationally more efficient than the implied variance from at-the-money (out-of-the-money or in-the-money) options alone, as it incorporates by construction the option information across all moneyness.

[6] In another robustness check, we substitute VIX (monthly squared in percentage) for the market-level VRP in the regressions. The unreported results show that the strong predictability of VRP on CDS spreads remains intact in the presence of VIX. Importantly, CDS spreads are negatively correlated to VIX with near zero adjusted R^2. This result is different from previous research that finds a positive relationship between CDS spreads and VIX (Ericsson et al., 2006) in the absence of firm-level VRP.

4.3. Implied variance, expected variance, and VRP

Previous studies find that an individual firm's CDS spread is strongly related to the option-implied volatilities, which is consistent with the information efficiency argument for the options market (see, e.g., among others Cao et al., 2010). However, in this subsection, we try to argue from several empirical angles that the explaining power of VRP for credit spread comes mainly from capturing a systematic risk component and tends to be long run. Also on the market level, VRP Granger causes implied variance but not the other way around.

To investigate this issue, we first carry out regressions in which VRP competes against implied variance and expected variance. Table 9 reports the results of regressing CDS spreads on those variables. The results of regression (1)–(3) indicate that with all control variables, VRP, implied variance, and expected variance explain 51%, 59%, and 56% of the variations in CDS spreads, respectively. In regression (4) and (5), we test the predictability of VRP or expected variance on CDS spreads in the presence of implied variance. The coefficient of VRP remains positive, while that of expected variance turns negative. In regression (6), we regress CDS spreads simultaneously on VRP and expected variance. The coefficients of both VRP and expected variance are positive and statistically significant at the 1% level, suggesting that VRP and expected variance are two important components in implied variance that help to explain individual firm credit spreads.

If VRP better captures a systematic risk factor than implied variance, we might observe that the explanatory power of VRP on CDS spreads increases as data frequency becomes lower, since systematic risk tends to be long term yet information shocks to the options market tend to be short lived. Panel A of Table 10 confirms such intuition by showing that, in univariate regressions, the t-statistics of VRP increases monotonically from 6.44 to 10.41 as the sample frequency changes from weekly to monthly then to quarterly. In the presence of implied variance, the t-statistics of VRP increase consistently, while the t-statistics of implied variance keep decreasing as the sampling frequency lowers. In both sets of regressions, the adjusted R^2 increases for lower data frequency. Finally, at weekly frequency, implied variance improves the predict-

Table 10

Different data frequency analysis and Granger Causality. This table reports the results of different data frequency analysis and Granger Causality tests. Panel A shows the regression results of CDS on VRP, in the absence/presence of IV for weekly, monthly and quarterly data frequency. Panel B reports the Granger Causality tests result for market level VRP, IV, and EV. We use three lags in the regressions as R^2 stops increasing significantly at three lags. The numbers in the brackets are t-statistics.

Independent variable	Frequency					
	Weekly		Monthly		Quarterly	
Panel A: Data frequency analysis						
VRP	1.39	−0.24	2.78	0.06	2.57	0.68
	(6.44)	(-1.43)	(10.03)	(2.41)	(10.14)	(3.00)
IV		0.10		1.08		0.95
		(10.71)		(7.46)		(6.41)
Constant	70.49	0.24	28.00	−13.20	29.71	−7.14
	(9.24)	(0.03)	(5.89)	(−1.63)	(6.83)	(−0.95)
Adjusted R^2	0.14	0.26	0.34	0.39	0.35	0.40

Dependent variable	Independent variable							R^2
Panel B: Granger Causality analysis								
IV_t	*Cont*	VRP_{t-1}	VRP_{t-2}	VRP_{t-3}	IV_{t-1}	IV_{t-2}	IV_{t-3}	0.74
	6.33	−0.17	−0.29	0.06	0.94	0.03	0.01	
	(2.49)	(−1.36)	(−2.42)	(0.48)	(7.47)	(0.17)	(0.08)	
VRP_t	*Cont*	IV_{t-1}	IV_{t-2}	IV_{t-3}	VRP_{t-1}	VRP_{t-2}	VRP_{t-3}	0.31
	2.98	0.10	0.23	0.02	−0.04	−0.09	0.11	
	(1.20)	(0.79)	(1.45)	(0.12)	(−0.28)	(−0.79)	(0.93)	
EV_t	*Cont*	VRP_{t-1}	VRP_{t-2}	VRP_{t-3}	EV_{t-1}	EV_{t-2}	EV_{t-3}	0.58
	3.36	0.71	−0.40	−0.06	0.84	−0.20	−0.01	
	(1.32)	(5.40)	(−2.56)	(−0.44)	(6.65)	(−1.24)	(−0.04)	

Furthermore, we apply the Granger causality tests on market-level VRP, implied variance (IV), and expected variance (EV) as specified in the following regression:[7]

$$Y_t = \phi + \sum_{i=1}^{m}\kappa_i X_{t-i} + \sum_{j=1}^{n}\theta_j Y_{t-j} + \varepsilon_t, \tag{6}$$

and the null hypothesis is $\kappa = 0$. We set both m and n equal to 3.[8] We find evidence that VRP significantly Granger causes both IV and EV, but not vice versa. Panel B of Table 10 shows that IV and EV are significantly correlated with VRP lags, while VRP is not significantly explained by either lag IV or lag EV. The results suggest that, being potentially a cleaner measure of systematic risk, VRP helps to predict future variations in IV and EV that are more likely to be contaminated with idiosyncratic risks.

Finally, we carry out a principal components analysis on VRP, IV, and EV. As reported in Table 11, the first principal component explains 79% of the total variation in VRP, while it only explains 58% in IV. And the first four principal components cumulatively explain 94% of VRP variation versus only 74% of implied variance. In other words, VRP is likely a cleaner measure of firms' exposure to systematic variance or economic uncertainty risk relative to the IV or EV, which is consistent with the finding that a missing systematic risk factor may hold the key to explaining the credit spread puzzle(s) (Collin-Dufresne et al., 2001).

4.4. Cross-sectional validation of market VRP

To examine how much firm-level VRP captures the exposure to a systematic variance risk factor, we compare the relationship between firm and market VRPs to the relationship between firm and market equity returns in our sample. Following the standard approach of testing CAPM (e.g., Lintner, 1965), we carry out two-stage regressions. In the first stage, we run time-series regressions for each firm i to estimate its β_i^{VRP} and β_i^{CAPM}, respectively:

$$\begin{cases} VRP_{it} = \alpha_i^{VRP} + \beta_i^{VRP} \times VRP_t^{MKT} + \varepsilon_{it}^{VRP}, \\ R_{it} = \alpha_i^{CAPM} + \beta_i^{CAPM} \times R_t^{MKT} + \varepsilon_{it}^{R}. \end{cases} \tag{7}$$

We then compute each firm's average VRP, $\overline{VRP_i}$, and average equity return, $\overline{R_i}$, respectively. The second-stage cross-sectional regressions are as follows:

$$\begin{cases} \overline{VRP_i} = \lambda_0^{VRP} + \lambda_1^{VRP} \times \widehat{\beta^{VRP}}_i + u_i^{VRP}, \\ \overline{R_i} = \lambda_0^{CAPM} + \lambda_1^{CAPM} \times \widehat{\beta^{CAPM}}_i + u_i^{R}. \end{cases} \tag{8}$$

The fundamental hypotheses being tested are $\lambda_1^{VRP} = $ mean market VRP and $\lambda_1^{CAPM} = $ mean market Return.[9] For completeness, we also carry out the same two-stage regressions of

Table 11

Principal component analyses of CDS spreads, VRP, IV and EV. This table reports the principal component analysis of CDS spreads, VRP, implied and expected variances. We select firms with 48 monthly observations starting in January 2004. The sample contains 225 firms. VRP is explained mostly by first three components (91.74% cumulatively), whereas IV and EV are driven marginally by several components. Robustness checks with various samples show that sample selection does not change the results qualitatively. E: explained. C: cumulative.

Component	CDS spreads		VRP		IV		EV	
	E. %	C. %	E. %	C. %	E. %	C. %	E. %	C. %
1	69.20	69.20	78.51	78.51	58.48	58.48	65.26	65.26
2	6.94	76.14	9.00	87.51	8.89	67.37	12.58	77.84
3	6.43	82.57	4.22	91.74	3.95	71.33	6.41	84.25
4	3.70	86.27	1.93	93.67	2.74	74.06	2.47	86.72
5	2.79	89.05	1.31	94.97	2.54	76.60	2.03	88.75
6	1.80	90.85	1.03	96.00	2.34	78.95	1.43	90.19
7	1.39	92.24	1.00	97.00	2.18	81.13	1.20	91.39
8	1.12	93.36	0.52	97.51	1.86	82.99	1.03	92.42
9	0.91	94.27	0.44	97.96	1.69	84.68	0.94	93.36
10	0.63	94.90	0.34	98.30	1.57	86.24	0.70	94.06

[7] We also perform the Granger causality tests on individual firms' VRP, IV, and EV. The results are noisy and insignificant, which cannot support any clean causality pattern.

[8] The selection of number of lags in a Granger causality test balances the trade off between eliminating autocorrelation in residuals and maintaining testing power. We report the results with m,n = 3 since the regression R^2s stop changing significantly at three lags.

[9] In the CAPM test the intercept λ_0^{CAPM} is restricted by the risk-free rate, while in the VRP cross-sectional test, the intercept λ_0^{VRP} may be restricted to zero. In our limited exercise, we focus on the interpretation of slope coefficients λ_1^{CAPM} and λ_1^{VRP} as the market prices of risks.

Table 12
VRP and CAPM. This table reports the results of comparing the relationship between firm and market VRPs to the relationship between firm and market equity returns with matched sample. Two-stage regressions are carried out, following the standard approach of testing CAPM. Panel A reports the summary statistics of the time-series regressions. Panel B shows the cross-sectional regression results. The numbers in the brackets are t-statistics.

Regression	VRP on Mkt VRP			Return on Mkt return			VRP on Mkt return			Return on Mkt VRP		
Percentile	beta	t-statistic	r-square	beta	t-statistic	r-square	beta	t-statistic	r-square	beta	t-statistic	r-square
Panel A: Summary statistics of the first-stage time-series regressions												
1	−1.10	−6.44	−0.04	0.14	0.47	−0.02	−0.74	−5.06	−0.04	−9.03	−7.29	−0.04
5	−0.19	−1.65	−0.01	0.41	1.81	0.05	−0.43	−4.57	−0.02	−4.67	−6.04	−0.01
10	0.03	0.28	0.00	0.58	2.41	0.08	−0.29	−3.92	−0.01	−3.44	−5.47	0.01
25	0.19	1.99	0.06	0.83	3.89	0.17	−0.18	−3.10	0.00	−2.45	−4.26	0.05
50	0.42	3.83	0.17	1.16	5.33	0.26	−0.10	−2.04	0.04	−1.66	−3.13	0.10
75	0.79	5.85	0.29	1.56	7.72	0.40	−0.04	−0.84	0.10	−1.09	−2.08	0.16
90	1.33	7.23	0.39	2.04	9.63	0.49	0.00	0.07	0.15	−0.68	−1.21	0.25
95	1.79	8.70	0.47	2.43	10.55	0.53	0.06	0.92	0.20	−0.39	−0.73	0.30
99	3.29	11.05	0.58	3.25	12.72	0.63	0.25	3.72	0.32	1.47	0.69	0.40

Dependent	VRP		Equity return	
Independent	$\beta^{VRPonMKTVRP}$	$\beta^{VRPonMKTRET}$	$\beta^{RETonMKTRET}$	$\beta^{RETonMKTVRP}$
Panel B: The second-stage cross-sectional regressions				
λ_0	9.09	16.60	5.20	−0.91
	(6.05)	(8.73)	(3.98)	(−0.91)
λ_1	29.26	13.75	8.17	15.19
	(19.10)	(5.16)	(4.46)	(14.74)
Adjusted R^2	0.09	0.17	0.04	0.00

firm VRP on market return and firm equity return on market VRP, respectively.

Panel A of Table 12 reports the summary statistics of β_i for the four sets of regressions. As indicated by percentile, the t-statistics of $\beta_i^{VRPonMKTVRP}$ are relatively more dispersively distributed and more significant in the percentiles between 50% and 99%. The R^2's of the VRP regressions are comparable their counterparts in the CAPM regressions. The evidence suggests that VRP captures systematic risk strongly as the well-documented equity returns do. Panel B shows that VRP is significantly related to $\beta^{VRPonMKTVRP}$ with a t-statistic of 19.10, but equity return is less significantly related to $\beta^{RETonMKTRET}$. The VRP regression has an adjusted R^2 of 9%, compared with an adjusted R^2 of 4% for the equity return regression. Fig. 3 visualizes the fitted VRPs (equity returns) versus the observed VRPs (equity returns). In the cross-regressions, VRP is significantly related to $\beta^{VRPonMKTRET}$ with a t-statistic of −5.18, whereas equity return is insignificantly related to $\beta^{RETonMKTVRP}$. The VRP on market return regression has an adjusted R^2 of 17%, compared with an adjusted R^2 of zero for the equity return on market VRP regression. The above evidence further indicates that firm-level VRPs are not only able to price the systematic variance risk factor, but also are stronger than firm-level equity returns to price the systematic return risk factor, as advocated in standard asset pricing models.

4.5. A structural model with stochastic variance risk

The main finding that VRP emerges as a leading explanatory variable for credit spread suggests that there are two default risk drivers in the underlying firm asset dynamics. A structural model with stochastic volatility, as in Zhang et al. (2009), can generate the stylized fact that VRP is intimately related to credit spreads, in addition to the powerful leverage ratio (Collin-Dufresne and Goldstein, 2001).

Assume the same market conditions as in Merton (1974), and one can introduce stochastic variance into the underlying firm-value process:

$$\frac{dA_t}{A_t} = (\mu - \delta)dt + \sqrt{V_t}dW_{1t}, \tag{9}$$

$$dV_t = \kappa(\theta - V_t)dt + \sigma\sqrt{V_t}dW_{2t}, \tag{10}$$

where A_t is the firm value, μ is the instantaneous asset return, and δ is the asset payout ratio. The asset return variance, V_t, follows a square-root process with long-run mean θ, mean reversion κ, and volatility-of-volatility parameter σ. Finally, the correlation between asset return and return volatility is corr $(dW_{1t}, dW_{2t}) = \rho$.

With proper bankruptcy assumptions, we can solve the equity price, S_t, as a European call option on firm asset A_t with maturity T: $S_t = A_tF_1^* - Be^{-r(T-t)}F_2^*$, with r being the risk-free rate. F_1^* and F_2^* are the so-called risk-neutral probabilities. Therefore, the debt value can be expressed as $D_t = A_t - S_t$, and its price is $P_t = D_t/B$, where B is the face value of debt. The credit spread, CS_t, is given by

$$CS_t = -\frac{1}{T-t}\log(P_t) - r. \tag{11}$$

The structural credit risk model presented here also implies the following equity variance process: $V_t^s = \left(\frac{A_t}{S_t}\right)^2\left(\frac{\partial S_t}{\partial A_t}\right)^2 V_t + \left(\frac{\sigma}{S_t}\right)^2 \left(\frac{\partial S_t}{\partial V_t}\right)^2 V_t + \frac{A_t}{S_t^2}\frac{\partial S_t}{\partial A_t}\frac{\partial S_t}{\partial V_t}\rho\sigma V_t$. Inside the simulation, we can examine the relationship between credit spread CS_t and VRP:

$$VRP_t = E_t^Q(RV_{t+1}) - E_t^P(RV_{t+1}) \tag{12}$$

where RV_{t+1} is the realized variance from five-minute equity returns. The risk-neutral expectation $E_t^Q(\cdot)$ and physical expectation $E_t^P(\cdot)$ of equity realized variance are not available in closed form, but are approximated using the risk adjustment implied by the asset volatility dynamics in Eq. (10). See Bollerslev et al. (2011) for the result on risk-neutral and physical expectations of realized variance.

Using a calibrated parameter setting for a BBB firm as in Zhang et al. (2009), we simulate 120 months of data of credit spreads, VRP, expected variances, and leverage ratios for both a Merton (1974) model and a stochastic volatility model (as above). Table 13 reports the OLS regressions on explaining credit spreads with those proxies for underlying risk factors in asset value and volatility dynamics. For the Merton (1974) model, leverage ratio drives expected variance to be statistically insignificant, even though variance itself has a significant positive effect on credit spread. Note that for the Merton model, although the asset volatility is constant, the equity volatility is time varying because asset value is time varying and equity volatility is approximately leverage-adjusted asset volatility. Therefore equity volatility does explain credit spread, to certain degree, but its effect is mostly subsumed when leverage ratio is included in the regression.

However, for the two-factor stochastic volatility model, not only do expected variance, VRP, and leverage ratio all have significant positive effects on credit spreads; but also any two variables combined together would both remain statistically significant with positive signs. In particular, the powerful leverage ratio cannot crowd out VRP or expected variance. These patters are due to the fact that both asset value and asset volatility are time-varying and priced risk factors, and VRP or expected variance is not redundant to leverage ratio as in the case of the one-factor Merton model. This result is qualitatively consistent with the empirical relationship we have discovered here for a large cross-section of individual firms' CDS spreads and VRPs.

5. Conclusions

Investors demand VRP as a compensation for firms' exposures to a systematic risk factor. Such a risk premium may arise from the time-varying economic uncertainty in the underlying cash flow or consumption volatility (Bansal and Yaron, 2004; Bollerslev et al., 2009). Recent studies suggest that market VRP constitutes a critical component in explaining the aggregate credit spread indices (Zhou, 2009; Buraschi et al., 2009). In this paper, we carry out a comprehensive investigation of the relationship between the firm-level VRPs and credit spreads and find empirically that VRP provides a risk-based explanation for the credit spread variations.

We illustrate that VRPs of individual firms possess a significant explanatory power for CDS spreads. Importantly, such a predictability cannot be substituted by market- and firm-level credit risk factors identified in previous research. In addition, firm-level VRP dominates the well-documented market-level VRP or VIX in capturing the macroeconomic uncertainty or systematic variance risk exposure embedded in CDS spreads. The predictive power of VRP increases as the credit quality of CDS entities deteriorates and as the maturity of CDS contracts increases. VRP and leverage ratio emerge as two leading predictors of firms' credit spreads, pointing to time-varying asset value and stochastic volatility as two underlying risk drivers.

Empirical evidence also suggests that the superior explanatory power of VRP for CDS spreads tends to be stronger over monthly and quarterly horizons, while that of implied variance tends to be stronger over weekly horizons. Also, the aggregate VRP Granger causes implied and expected variances, but not vice versa. A principle component analysis indicates that firms' VRPs have a much larger systematic component relative to implied and expected varieconomic uncertainty factor, which is consistent with the fact that the cross-section of firm's VRPs can be used to validate the market VRP correctly. Finally, the stylized predictability pattern of VRP for credit spreads can be reproduced in a simulation by a structural model with stochastic variance.

References

Andersen, Torben G., Bollerslev, Tim, Diebold, Francis X., Ebens, Heiko, 2001a. The distribution of realized stock return volatility. Journal of Financial Economics 61, 43–76.

Andersen, Torben G., Bollerslev, Tim, Diebold, Francis X., Labys, Paul, 2001b. The distribution of realized exchange rate volatility. Journal of the American Statistical Association 96, 42–55.

Bansal, Ravi, Yaron, Amir, 2004. Risks for the long run: a potential resolution of asset pricing puzzles. Journal of Finance 59, 1481–1509.

Barndorff-Nielsen, Ole, Shephard, Neil, 2002. Econometric analysis of realised volatility and its use in estimating stochastic volatility models. Journal of Royal Statistical Society Series B 64, 253–280.

Berndt, Antj, Lookman, Aziz A., Obreja, Iulian, 2006. Default Risk Premia and Asset Returns. Carnegie Mellon University, Working Paper.