Same Firm, Two Volatilities: How Variance Risk is priced in Credit and Equity Markets[☆]

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Abstract

Variance risk premia (VRP) based on equity and credit market information for the same firm differ substantially in magnitude. VRP is strongly dependent on firm characteristics. Higher-leveraged and larger firms have lower VRP. The smirk in the plot of VRP vs. leverage is higher for low-levered firms than for high-levered firms. This smirk is more pronounced in the credit market than in the equity market. VRP, and especially credit VRP, correlates with higher future returns and is a priced source of risk in both markets.

Keywords: Variance Risk Premia, Implied Volatility, Realized Volatility, CDS, Stocks

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1. Introduction

Based on the seminal work of Merton (1973) - the Intertemporal Capital Asset Pricing Model (ICAPM) – and its extension to include stochastic volatility - Campbell et al. (2018) – asset pricing theory has established the desire of investors to hedge news about future uncertainty. Consequently, investors should be willing to pay premia for insurance against volatility shocks. Much recent empirical work has focused on the measurement of variance risk premia and the ability of these measures to explain variations in equity returns and bond yields.

While much of the literature studies firm equity variance risk premia, less attention has been paid to the connection between the firm's equity risk premia (EVRP) and its corresponding credit variance risk premia (CVRP), implied from the credit default swap market. Since Merton (1974), structural models connect variations in equity and credit spreads to variations in the value of a firm's underlying assets. An implication of this approach is that, for a given firm, credit and equity volatility should move together, and therefore, credit variance risk premia and equity variance risk premia should also closely co-move. Additionally, factors which influence equity variance risk premia should impact credit variance risk premia. One would thus expect a close relationship between these quantities. Failure to find these links not only has substantial implications for asset pricing theory but also poses practical challenges for risk management.[1]

Recent work has also made the connection between structural models of credit risk and models where future uncertainty is a priced risk factor. For example, (Huang and Huang, 2012) stresses the importance of including in structural credit models features which allow states of high default probability to be enhanced by high market risk premia. One such class of models allows for the firm value process to have stochastic volatility (Huang et al., 2020; Du et al., 2019), as opposed to a constant asset volatility assumption, and demonstrate that such models help resolve the credit spread puzzle. Coupling this assumption with

[1]Many investors take positions in the equity market and use the credit market to hedge their downside risk. Much of these positions in the credit market are held in open-ended funds that allow investors to exit overnight, posing additional challenges for hedging. This practice has led to an increased trading volume in the credit market, where much of such trading is speculative (Oehmke and Zawadowski, 2017).

Epstein-Zin preferences, as in Campbell et al. (2018), where the stochastic discount factor (SDF) depends not only on current consumption growth but also on lifetime utility, allows news about future volatility to raise the SDF, and therefore investors are willing to pay a premium to hedge this volatility risk. Our paper informs this literature by implying this uncertainty premium, VRP, based on equity and credit market information for the same underlying firm.

Our contribution to the literature has three important aspects. First, by basing our measure of future uncertainty on credit and equity market information of the same underlying firm we test the predictions of structural models which predict a close relationship between these two quantities. Second, we test the implication of asset pricing theory that investors desire to hedge news about future uncertainty measured across different markets. Specifically, we test the implication of this theory that future uncertainty should not only contain useful information in predicting expected returns, but it should also be a priced source of risk in these markets. We therefore jointly examine the implications of structural credit risk models and an influential asset pricing theory. Finally, we provide results from a novel credit market estimate of variance risk premia based on actuarially fair CDS prices. By studying the transformation effects from physical to risk-neutral probability measures we advance our understanding of variance risk premia which have traditionally just been implied from equity and Treasury securities. As such, our approach enables us to inform our understanding of volatility risk premium dynamics jointly in credit and equity markets and, consequently, also provide insight on differences in investor risk aversion across these two markets.

The predictions of structural credit models and asset pricing theory are tested using a unique data set of high-frequency CDS and equity returns for the same 88 companies over a period of four years.[2] We imply our measure of the cost of hedging future uncertainty, the variance risk premium, as the difference in risk-neutral expectations and the objective (physical) expectation of the return variance over the next month, similar to Bollerslev et al. (2009) and Drechsler and Yaron (2011). The equity VRP is estimated as the difference between option-implied volatility and realized volatility. Similarly, the credit market-based

[2]The selection of data was dictated by several criteria, including the availability of sufficiently long time series of high-frequency CDS and equity prices, large capitalization, liquidity, and representation of a broad range of sectors.

uncertainty risk premium is implied as the difference between CDS-implied credit volatility and realized CDS return volatility. The CDS-implied volatility measure is backed out from the no-arbitrage fair value CDS prices implied by an extension of the Merton (1974) model. Realized volatilities are obtained from high-frequency CDS and equity returns. The high-frequency data are advantageous because they allow for obtaining a high statistical precision of volatility risk, which recent reports in the literature refers to as a main source of compensation risk demanded in the credit market (Kelly et al., 2019).

Our findings of positive CVRP and EVRP confirm that markets value insurance against volatility shocks, consistent with predictions of asset pricing models with Epstein-Zin utility. When we pool all observations, we find variance risk premia implied from both markets to be strongly connected with leverage in support of the structural model predictions. However, this relationship is weaker when we control for time invariant firm characteristics. In addition, when we examine the correlation across firms of CVRP and EVRP we find a time-varying and, at times, surprisingly weak relationship between the two. These finding pose a challenge to classic structural models of credit risk.

As structural models rely on leverage to predict default probabilities, we pay particular attention to this factor in our analysis. Different leverage levels represent different "moneyness" of the put options implicit on firms' debt. Consequently, we carry out empirical tests for different levels of leverage separately. In doing so we find that low-levered firms carry a higher variance risk premium in both markets, but this premium is more pronounced in the credit market. This result is congruent with the notion that bondholders are the insurance writers on the firm's assets, and therefore they require a higher risk premium as compensation. We show that the smirk slope in the plot of firms' credit variance risk premium against their leverage levels is more pronounced for low-levered firms than its equity counterpart, in support of the assumption that the credit VRP is a catastrophic risk premium.[3] For the high-levered entities, on the other hand, the smirk slope implied from credit and equity markets is similar, indicating that the credit market contains superior information, relative to the equity market, on only the low levered firms' future crash risk. The strong

[3]The smirk slope of the variance risk premium is obtained by sorting firms on equally-weighted constant-leverage portfolios: and calculating the difference in VRP between firms at 10% and 90% leverage, 10% and 50% leverage, and 50% and 90% leverage.

association of the VRP with the low-levered firms also suggest that the variance risk can shed new light on the low-leverage puzzle debate.[4]

Given that the VRP is significantly time-varying, we further explore what drives changes in the variance risk premium across firms and time in both the equity and credit markets. Specifically, it is important to understand whether the variance risk premium relates to asset volatility, asset beta, and business risk.

We show that the credit variance risk premium increases with the firm's idiosyncratic asset volatility but decreases with the firm's systematic asset risk. The negative relation between the exposure to systematic factors and variance risk premium is statistically significant for the credit market, although this finding does not extend to the equity market. An interesting finding is that this negative relation is particularly robust for the non-financial entities.

Our second key line of inquiry is to test predictions of asset pricing models with Epstein-Zin style preferences which imply that investors desire to hedge news about future uncertainty. According to these models, the variance risk premium is a market risk that should not only contain information useful in predicting future returns but also should be a market priced source of risk. Our finding that CVRP is correlated with future equity returns indicates that credit and equity volatility risks are important risk factors in these markets. Since leverage represents the moneyness of the put option implicit on firm's debt, leverage should interact with measures of variance risk premia. In extensive empirical tests, we show that the VRP associates strongly with returns of low-leverage firms and the investment graded entities, and this association is stronger in the credit market. This result is substantiated by the fact that uncertainty based on the credit market information provides superior predictive ability for future returns than the equity market based VRP, indicative of the notion that the credit market contains improved information on firms' prospects. Furthermore, we show via formal asset pricing tests that firm-specific future uncertainty is a priced source of risk in both equity and credit markets even when we control for the typical risk factors. These results are consistent with investors' desires to hedge news about future uncertainty.

[4] See Du et al. (2019) for recent discussion.

Finally, this paper furthers our understanding on the relationship between risk aversion and the VRP. We find that risk aversion implied from VRP measures are more pronounced in the market for credit risk. To a certain extent then, this paper sheds new light in understanding how well the credit and equity markets are integrated and the implications of such an integration for the theory of capital structure.[5]

This work relates to several recent papers in the literature. Bollerslev et al. (2009) and Zhou (2018) demonstrate that equity variance risk premia measured from S&P 500 and VIX implied volatility has significantly large predictive power for future stock returns. Han and Zhou (2011) examines the ability of firm-level equity VRP to explain the cross-section of stock returns and find that firms with high VRP have high expected returns. Choi et al. (2017) characterize the term structure of variance risk premia. Sabtchevsky et al. (2017) construct variance risk premia for Treasury securities and the S&P 500 index. They find that these premia co-move although the sign of co-movement is time-varying and is often negative. Additionally, they find that VRPs on long-term bonds behave similarly to equity. Our paper complements the work of Kelly et al. (2019) by looking at a wide range of firm-specific factors and their relation with the credit and equity variance risk premia.

While these papers imply the VRP from the Treasury bond market, the present study takes a different approach by combining firm-level information from both equity and credit markets on the same underlying entity. The approach adopted in this study gives insight into volatility risk premiums that one cannot gain from other credit instruments, for example Treasury securities. The value of using CDS over Treasury bonds occurs because treasuries contain very low default risk, higher liquidity and tax advantages, which renders the VRP noisy. Also, credit spreads are the market's assessment of the credit risk of the underlying entity whose pricing dynamics reflect more clearly the changes in the market's assessment of the credit risk and changes in investors' demand for compensation for bearing that risk. Furthermore, by using high-frequency credit and equity data one achieves a superior statistical measure of the volatility risk in a completely model-free fashion. By combining information from both equity and credit markets one acquires additional

[5]See Titman (2002) who suggests that results in Huang and Huang (2012) imply that equity and credit markets are not integrated. We thank an anonymous referee for pointing out on this important issue.

insights into the dynamics of the variance hedging demand of the same underlying firm, providing useful insights for asset pricing and risk management.

The remainder of the paper is organized as follows. Section 2 discusses the method used to imply the variance risk premium, and presents the data set. The empirical results are reported in Section 3, and Section 4 concludes.

2. Estimation of Expected Variance and Data

This section begins by briefly describing the methods used to estimate the variance risk premium and concludes by discussing the data. For more detail on the method used in estimating the expected risk-neutral variance in the equity and credit market we refer the reader to Appendix A.

2.1. Estimation of the Expected Variance

Following Bollerslev et al. (2009) and Drechsler and Yaron (2011), the variance risk premium for a given credit spread/stock i in month t is defined as the difference between the risk-neutral expectation and the objective (physical) expectation of its return variation over the next month.

The risk-neutral expectation of return variation for stocks is estimated as in Jiang and Tian (2005), by implying volatility from one-month call option prices. The risk-neutral expectation of return variation of the corresponding credit default swaps spreads is estimated based on Merton (1974). We obtain the risk-neutral CDS prices from the Bloomberg system and refer the reader to Appendix A for the technical details of their calculation.

To compute the model-free estimate of the realized variance RV_t of stock/credit spread i in month t, Bloomberg's reported five-minute interval intraday equity/CDS prices are used. Denoting by p^i_j the logarithmic price of stock/CDS i at the end of the j^{th} five-minute interval in the month t the realized variance for month t is measured as

$$RV^i_t = 12\sum_{j=1}^{n}[p^i_j - p^i_{j-1}]^2. \tag{1}$$

In the empirical analysis the percentage changes in the credit spreads are used as the credit protection return, and an annualized variance estimate that is comparable to the option-implied variance.[6]

Following Drechsler and Yaron (2011), a linear forecast model is used to estimate the expected variance under the physical measure with lagged risk-neutral expected variance and historical realized variance. For each stock/credit spread i, we run the following regressions

$$RV_t^i = \alpha + \beta IV_{t-1}^i + \nu RV_{t-1}^i + \epsilon_t^i, \tag{2}$$

and take physical expected variance EV_t^i as the fitted value from the regression

$$EV_t^i \equiv \widehat{RV_t^i} = \widehat{\alpha} + \widehat{\beta} IV_{t-1}^i + \widehat{\nu} RV_{t-1}^i. \tag{3}$$

Finally, the empirical estimate of the firm-specific variance risk premium is the difference between the risk-neutral expected variance inferred from equity options and model implied credit prices and the physical expected variance

$$VRP_t^i = IV_t^i - EV_t^i. \tag{4}$$

This measure of the variance risk premium is similar to Drechsler and Yaron (2011) and Wang et al. (2013). Bollerslev et al. (2009) measure the variance risk premium as the difference between model-free implied variance inferred from the option prices and the realized variance based on high frequency return data.

Here we follow Bollerslev et al. (2009) and calculate our expected variance based on the full sample, as opposed to using rolling regressions. We do this for three reasons. First, given our short sample, rolling regressions would be very noisy. Secondly, RV is close to a random walk so agents essentially forecast RV with current RV. Finally, we expect market expectations to be fairly accurate as they are only one month

[6]Consider a strategy that purchases a CDS contract at date t and sells an offsetting CDS contact at date t' divided by the insurance premium. This is a credit protection agreement with an upfront insurance premium equal to the discounted present value of the credit spread, which is approximated by the percentage change in the quoted credit spreads. This is the excess return on a "fully collateralized" CDS contract– which makes the CDS returns comparable in magnitude to the bond returns– and is similar to the specification of absolute changes in spreads of Bongaerts et al. (2011); Hilscher et al. (2015). Longstaff et al. (2011) discount each cash flow by the risk-free rate plus the CDS spread only. We thank the anonymous referee for pointing out on this issue.

ahead expectations and we therefore want to proxy expectations with something that is not too far off from the truth.

2.2. Data Set

The data set comes from Bloomberg and spans June 1, 2012 to June 1, 2016 for all 88 entities for which Bloomberg reports high-frequency CDS and equity prices as well as option and risk-neutral CDS prices. Equity option prices reported by Bloomberg ensure against the violation of obvious no-arbitrage conditions such as $S \geq C \geq max(0, S - Ke^{-rT})$ for a call option C where S is the underlying stock price, K is the strike price of the option, T is the time to maturity of the option, and r is the risk-free rate.

The data set consists of five-minute intra-day values for the five-year CDS spreads and stock prices for 88 constituents of the CDX NA IG index. The credit default swap prices come from Credit Market Analysis Ltd (CMA) DataVision via the Bloomberg data service. CMA is the most widely used database among financial market participants and it is the principal data source for Bloomberg-disseminated CDS prices; thus these data also contain fewer errors.[7] In fact, as noted in the CMA factsheet they "source information on executable and indicative prices from the largest and most active credit investors ..." and "our automated data collection, cleansing and aggregate modelling combines real-time quotes observed in the market with a market standard curve modelling process to calculate full credit term structures." Additionally, as pointed out by Mayordomo et al. (2014): CMA collects its data from around 40 institutions that are active participants in the CDS market. These participants receive tens of thousands of Bloomberg formatted pricing messages which are included in the CMA database. Consequently, these prices are very likely to be tradeable. They also find that these prices lead the price discovery process.

Given that we are interested in constructing volatility measures from these CDS data, we take steps consistent with the literature to ensure that our results are not driven by microstructure noise (e.g., concerns such as stale prices, discreteness of prices, and bid-ask spreads). First, we use the CMA

[7]CMA quotes provided by Bloomberg have been extensively used in the literature; for example, Das et al. (2009), Saretto and Tookes (2013), and Boehmer et al. (2015).

data, which are aggregated across individual dealers, to average out some of this noise. Secondly, we sample at the five-minute frequency because many studies find a five-minute sampling frequency is a well-founded strategy to manage the effect of microstructure noise on volatility estimates ((Hansen and Lunde, 2006)). Additionally, Bandi and Russell (2006) calculate optimal sampling intervals in the presence of microstructure noise and find that "since many optimal sampling intervals are near 5 min, the loss is not substantial when a 5-min interval is used." Similarly, Ait-Sahalia and Mykland (2005) show that more data do not necessarily lead to better estimates of the realized volatility, exactly because of the presence of market microstructure noise. Finally, we eliminate trading days with less than 40 observations of five-minute returns. Repeated observations, and obviously misreported prices are also deleted. Model-implied CDS daily prices also come from Bloomberg.

The 88 matched entities come from nine sectors. Consumer non-cyclical and consumer cyclical each have 17 and 18 entities. There are 16 industrial entities, and 15 financial firms. Communications have seven entities and basic materials have five entities, while technology and energy each have four entities. Finally, utilities have two entities. The sampled firms are divided into four credit rating categories as reported by S&P (Moody's) credit rating of the last quarter. The four credit ratings are divided into AA-, A-, BBB-, and BB- credit-rated entities each having five, twenty-five, fifty and eight entities.

The strong link between asset volatility and systematic risk for the firm's capital structure has been frequently emphasized in the literature with recent reports suggesting that average asset volatility is lower for low-levered entities (Choi and Richardson, 2016) and that high-levered entities have lower asset beta (Schwert and Strebulaev, 2014). Appendix B discusses the importance of asset volatility as a driving factor for equity and credit pricing dynamics of the same firm, and given the importance of systemic risk in asset pricing, the empirical analysis controls for these risk factors. Firm-specific asset volatility is estimated as in Kelly et al. (2019), and the asset beta is estimated similarly to Schwert and Strebulaev (2014). The data used to estimate these quantities come from Bloomberg.

Other balance-sheet control variables employed in this study include the return on equity (ROE), the dividend payout ratio estimated as total dividend divided by total net income (DIVIDEND), the leverage ratio – the sum of current- and long-term debt divided by the sum of total equity and current- and long-term debt – (LEVERAGE), and the firm size measure, proxied as the log of market capitalization (SIZE). To gauge the role of a firm's business risk for the variance risk premium we use: Tobin's Q, PROFITABILITY, estimated as a ratio of net income over net revenue, TANGIBILITY calculated as a ratio of tangible equity over tangible assets, OPERATING LEVERAGE estimated as a ratio of earnings before interests and taxes, and EBIT earnings growth over revenue growth. Further, we estimate net debt and equity issuance of a firm, NDI and NEI, as $\frac{NDI}{A_{j,t-1}}$ and $\frac{NEI}{A_{j,t-1}}$, respectively. NDI is the net debt issuance of firm j in month t, NEI is the net equity issuance of firm j in month t, and $A_{j,t}$ is the book value of total assets of firm j in month t. The data to estimate these variables also come from Bloomberg.

An additional control variable is Bloomberg's estimate of ANALYST RECOMMENDATIONS. The rating scales range between '1' and '5' where return of '5' is the strongest ranking (buy or similar), while a return of '1' is the weakest (sell or similar). We aim to enhance the measure of expectations of future uncertainty contained in the VRP with the subjective expectations captured by analyst recommendations.

Finally, Fama-French bond factors used in this paper are TERM (the difference between the returns on 10-year- and 3-month Treasury securities), the default risk factor DEF – the difference between the return on a market portfolio of long-term corporate bonds (the composite portfolio on the corporate bond module of the Morningstar/Ibbotson Associates index) and the returns on long-term government bonds, and finally the SHORT RATE (3-month Treasury yields). This data comes from the Federal Reserve Economic Database (FRED) and Bloomberg.

3. Empirical Results

To interpret the empirical magnitudes of the variance risk premiums in equity and credit markets one needs a theoretical understanding of the relation between asset, equity, and credit volatilities. Appendix B provides discussion on these theoretical linkages. Specifically, the structural models predict a close relationship between the same firm's equity and credit volatilities.

3.1. *Preliminary findings*

Table 1 reports summary statistics for the credit and equity physical and risk-neutral volatility estimates. The reported values are annualized and reported in percentages. Risk neutral volatilities are on average higher than realized volatilites indicating positive and substantial VRP in both markets. Both series report highly persistent realized volatility measures, as indicated by the AR(1) coefficient which is 0.77 (0.97) for the equity (credit) market. The credit risk-neutral measures of volatility report substantially higher persistence than the respective equity risk-neutral volatilities, AR(1), of 0.84 and 0.66, respectively.

Figure 1 in the top panel plots the time series of the cross-sectional average of expected physical realized volatility of equity and credit spreads for the sampled companies. Consistent with the existing literature and the theoretical prediction discussed in Appendix B, the magnitude of equity volatility is substantially larger than in the credit market. However, the credit volatility exhibits larger variation in the time series.

The bottom panel of Figure 1 plots the average time series of the expected risk-neutral volatilities. As from the findings in the previous figure the magnitude of the equity risk-neutral volatility is larger than in the credit market. Different from the previous figure, it is the equity risk-neutral volatility that exhibits greater time variation than the respective credit volatility. The difference across these two markets can potentially be ascribed to the larger trading volumes in the equity options market– and also to a substantial increase in "naked" trading in the market for credit risk implying larger volatility in the physical measure of the credit volatility– than in the model-implied risk-neutral credit spreads.[8] However, the difference can also be credited to the different levels of risk aversion of investors in these two markets. Indeed, estimates of the risk-aversion coefficient across the markets, discussed later in the paper, reveal that credit investors are substantially more risk-averse.

Figure 2 plots the average monthly time-series of the variance risk premium, annualized and in squared

[8] The naked use of CDSs consists of speculators buying protection against a default without owning the underlying credit or bond. On February 4, 2016, the *Financial Times* reported, "A record $15.7bn in gross notional outstanding positions of single name CDS was cleared by investors during January according to the Intercontinental Exchange, the largest credit derivative clearing house" (https://www.ft.com/content/c47dce8e-ca9f-11e5-be0b-b7ece4e953a0).

percentage points. The series display co-movement although there are times of dislocation. The magnitude of the variance premium in the credit market is similar to that in the equity market, consistent with the results in Table 2. However the magnitudes do exhibit times of significance divergence. The persistence of the variance risk premium is evident in both markets. In the credit market it is marginally larger than that in the equity market as suggested by the AR(1) coefficients of 0.93 and 0.89.

To explore in more detail the co-movements between the two series, for each month, Figure 3 plots the conditional correlation across firms between the equity and credit variance risk premia. This correlation changes frequently, indicative of the fact that there is a large time-variation in relative hedging demand for second moments in equity and bond markets. To the extent that the credit market serves as a hedging instrument in the equity market, these results suggests that the credit market appears to be an imperfect time-varying hedge. Specifically, we do not observe a consistently close relationship between EVRP and CVRP. This finding is at odds with the structural models which link both default probability and variance in the firm's equity valuation to the volatility of the firm's assets.

3.2. Variance Risk Premium and Firm-specific Characteristics

Given that our preliminary results show a substantial divergence between the equity and credit variance risk premia, we now explore if there is a systematic relationship between firm-specific characteristics and these variance risk premia. Since the VRP captures the premium investors are willing to pay to insure against future volatility risk, and because default probability drives volatility in both markets, we therefore examine the relationship between VRP and firm characteristics to which credit risk models relate firm default probability, e.g., leverage.

Table 3 presents the results from regressing the credit and equity VRPs on firm-specific characteristics. Model (1) contains no fixed effects and Model (2) contains firm- and month-fixed effects. The first control variable we employ is firm leverage. In structural models for credit risk, default occurs when the firm's asset value falls below the face value of its debt. Therefore, the firm's leverage ratio defines the "moneyness" of the put option implicit in its debt. This put option gains more in value in times of high distressed periods for the firm with low expected growth rates and increased uncertainty. Consequently, we control how firm's leverage interrelates with the variance risk premia. Controlling for other firm characteristics, results show that, in the cross-section of firms, more levered firms have higher variance risk premiums. This result is sensible since one would expect that more levered firms are seen as riskier and lay support to the structural models of credit risk modeling. However, once the fixed effects are accounted for, this result is no longer significant. This may be due to statistical reasons as time-series variation in leverage is small relative to the cross-sectional variance, highlighting the additional insights one gets from looking at firm-level data as opposed to aggregated time-series level data. However, it also calls for more careful analysis on the relation between leverage and the cost of hedging the future uncertainty, motivating our following empirical analysis.

We include analyst recommendations to capture changes in subjective expectations unrelated to the other control variables. Analysts recommendations are correlated with higher credit VRPs and lower equity VRPs. These results are striking and suggest that analyst recommended stocks may have overlooked credit risk. Higher credit ratings lower credit variance risk premia, which is not surprising, but they tend to raise equity VRP. Financial firms tend to have lower credit variance risk premia but higher equity variance risk premia perhaps because, to function as a financial firm, one must not be seen as too risky in the credit market. But this lack of perceived riskiness allows firms to increase leverage which leads to more volatile equity returns. Net debt issuance lowers VRP but once one controls for the fixed effects new debt raises variance risk premia. This result suggests that high levels of debt are not necessarily a risk factor, but increases in debt within a firm over time are seen as quite risky. Net equity issuance is seen consistently as increasing variance risk premia. This result is consistent with investors viewing these firms as over-valued.

Panel B of Table 3 restricts the results to non-financial firms. Leverage still tends to positively affect VRPs but the results are weaker. The effects of return on equity and analyst recommendations are the same as for the main sample, as are the effects of increased credit ratings. In many ways the effect of new debt and net equity are the same across the samples of financial and non-financial firms.

Results reported above suggest that leverage affects the firms' variance risk premia. Leverage is important in amplifying the firm's asset volatility which is then reflected in the firm's equity and credit price dynamics, as discussed in Appendix B. However, we also note from our preliminary analysis that the equity and credit variance risk premia do not consistently co-move. In addition, even though when we pool all the data together we find a positive relation of leverage and VRP, once we look closely within firm this relationship no longer holds.

Therefore, to gain a deeper understanding of leverage's relation with variance risk, Table 4 reports time series means for the VRPs of equally-weighted portfolios. These portfolios are formed by sorting firms monthly based on their leverage. As discussed earlier, the leverage can be characterized as the "moneyness" of the implicit put option on firm's debt. Therefore, high- levered firms have a ratio of debt to assets close to one, leaving little buffer between asset value and the default boundary. On the other hand, low-leveraged firms would need to suffer catastrophic deterioration of its assets before reaching default.[9]

The results reported in Table 4 suggest a monotonically decreasing pattern of VRP with an increase of leverage in both markets. These results suggest that investors are willing to pay higher premiums to hedge variance risk for low-leveraged firms. The uncertainty risk is thus more expensive for low-levered firms, suggesting that the VRP is a catastrophic risk premium. Further, Table 4 reports firm asset volatility and asset beta.[10] Asset volatility is higher for low-leveraged firms. Asset beta decreases with an increase in leverage. These finding are consistent with those reported by Schwert and Strebulaev (2014) who find that high-leveraged firms have lower asset beta, and with the findings reported by Choi and Richardson (2016) who find that high-leveraged firms have lower average asset volatility. Their inverse relation with leverage is evident from Table 4; asset volatility and asset beta decrease with the leverage.

Next, Table 4 reports firm size. Larger firms have higher leverage. This is because larger firms are better diversified and have lower default probabilities and lower associated bankruptcy costs, which in turn

[9]In the equity option literature this relationship can be characterized as at-the-money for the high-levered entities and deep-out-of-the-money for the low-levered entities.

[10]Asset volatility is estimated as in Kelly et al. (2019) while asset beta is estimated as in Schwert and Strebulaev (2014) as a weighted average of the firms debt and equity betas. The average asset volatility for our sample is 0.26. Schaefer and Strebulaev (2008) reports an average of 0.22 while Schwert and Strebulaev (2014) report a figure of 0.35. The average asset beta for our sampled firms is 0.52, similar to Schwert and Strebulaev (2014).

allows them to take on more leverage. Firm size is, therefore, commonly assumed as an inverse proxy for the expected cost of bankruptcy (Rajan and Zingales, 1995).

Additional insights on the relation between leverage and the VRP can be gained by plotting the time-series of the credit and equity VRP within constant leverage portfolio buckets (Figure 4). This figure provides new evidence on the magnitude of the smirk slope by ploting the magnitude of the smirk slope of the variance risk premium for varying degrees of leverage.[11] These results substantiate the findings reported in Tables 3 and 4 that leverage is a strong factor in explaining VRP for all firms and in particular for the low-levered ones, as suggested by substantially dearer premias for these type of firms

In addition, since the smirk reflects the risk-neutral distribution of the underlying asset volatility over different leverage levels, results reported in Figure 4 show the differences between the credit and equity markets in processing information embedded in the smirks. The CVRP smirk slope steepens more at the low-end of the leverage levels than the EVRP does, indicating the presence of a substantial mass in the left tail of the risk-neutral return distribution. The CVRP thus embeds additional information on the variance hedging demand and provides insights into the regions of the asset distribution that are impossible to infer from equity market information. This analysis extends the work of Kelly et al. (2019) by comparing the credit-market based information with the equity market estimates.

An important theoretical implication of these results is that in Merton's model one needs to assume excessively high asset volatility to match the credit spreads of the low-levered entities, highlighting the limitations of the constant asset volatility models in favor of the stochastic asset volatility models (Huang and Huang, 2012). As discussed in Huang and Huang (2012) structural models of credit risk should include time-varying market risk premia in addition to the features of high default probabilities to match the observed large credit spreads especially for the investment-grade entities. Results reported in this section provide initial support for these predictions and suggest that an important market risk premium is the one stemming from the cost of hedging future uncertainty and this information is better captured in the market for credit

[11]The smirk slope is the differences between the bottom and top leverage deciles, bottom and median deciles (50-60 percentile), and median and top leverage deciles.

risk.

To further explore possible explanations for these divergent findings in credit and equity markets we examine the role that differential risk aversion may play in explaining these results. Specifically, it is important to understand whether investors in the credit and equity markets are systematically different in their risk preferences. To investigate this question we use the GMM estimation method of Bollerslev et al. (2011) based on moment conditions from their structural VRP model to estimate a risk-aversion coefficient on each market.[12] Results suggest that indeed investors in the credit market are substantially more risk-averse than those in the equity market. This finding to a certain extent bares support to Goldstein et al. (2017) who find that equity and bond investors have different risk levels and appetites for investments. These differences appear to be captured by our VRP estimates.

3.3. Variance Risk Premium and Business Risk

As discussed in the previous section, the literature has shown that stochastic asset volatility improves the ability of structural models to match observed credit spreads. The same literature also invokes market risk premia features in the modeling of credit risk to match the observed spreads. Our results in Table 4 and Figure 4 have show that the our measure of the cost of hedging future uncertainty is strongly associated with firm leverage. Consequently, we conjecture that the cost of hedging future uncertainty (i.e. the variance risk premium) is the variable invoked by the literature on the structural modeling of credit risk needed to match observed credit spreads. As such, this hypothesis warrants further investigation into the relationship between VRP and business risk. Understanding this relationship is of primary importance for modeling credit risk since credit spreads and equity returns are cyclical, and by extension the costs of hedging the future uncertainty in both these markets should also relate with business risk. The extent and the nature to which our measure of uncertainty based on the credit or equity market information is associated with business risk is an empirical question with practical implications for hedging practices. We address this question next.

[12] The implementation details of this method can be found in Appendix C.

Table 5 explores the relationship between business risks and the variance risk premium. Tests involve regressing credit and equity VRPs on lagged asset beta, asset volatility and a set of firm-specific control variables– firm's size, Tobin's Q, profitability, tangibility and operating leverage. Industry dummies control for the unobserved industry characteristics that may impact the VRP. The empirical analysis therefore controls for both systematic and total business risk.

Results reported in Table 5 suggest that asset beta is significantly negatively related to the credit variance risk premium but positively related to the equity credit variance risk premium, albeit statistically insignificant. This result is somewhat consistent with the initial findings on the relation between the firm's systematic risk and the leverage sorted portfolios reported in Table 4. This relation is both statistically and economically important. To gauge the economic significance, these changes represent about a 10% of reduction in average of monthly CVRP. The coefficients of asset beta are half the size of the asset volatility, consistent with the notion that a firm's systematic risk is an important determinant in variance hedging demand even after controlling for the firm's total risk. Systematic risk thus increases the VRP in the equity market but depresses the credit VRP as the investors increase their hedging demand in the credit market. This finding is further substantiated once the financial firms are excluded from the analysis as reported in Panel B of Table 5.

We also find in the same table that asset volatility is a significant and important determinant of the VRP in both markets. This finding is consistent when financial firms are excluded from the analysis. Additionally, Size is negatively related to VRP, providing further evidence that larger firms have lower variance risk premium. Tobin's Q reduces the VRP while asset tangibility consistently increases the VRP in both markets.

These results suggest that the variance risk premium relates strongly with a firm's characteristics and its business risk. One should therefore take these results as a symptom of a strong relationship between the variance hedging demand and firm's systematic risk and corporate financial decisions.

3.4. Variance Risk Premium and Equity Predictability

We now turn our attention to asset pricing theory with Epstein-Zin preferences. This theory predicts that investors desire to hedge news about future uncertainty. Therefore, if our measure of the costs of hedging of the future uncertainty is a market state variable, then it should predict returns and be a priced source of risk in the market. In this and in the following sections we investigate these predictions: does the variance risk premium predict future returns and if so, is it a priced source of risk?

Our empirical approach is motivated by structural credit models and asset pricing theory. In the structural models, as discussed, the leverage level is the key driver of future uncertainty. In addition, asset pricing models with Epstein-Zin preferences view the SDF's as dependent not only on current consumption growth but also on news about future volatility and therefore predict that investors are willing to pay a premium to hedge this volatility risk.

Initially we pool all our data and run simple predictive regressions of the variance risk premium on future equity returns over a range spanning from one to twelve months. First, we document that the credit VRP has a more consistent relationship with future equity returns than the equity VRP. Table 6 displays the results from regressing future returns on the CVRP, EVRP and a variety of firm characteristics. The first four columns use one-month ahead returns and the last four columns use three-month ahead returns. We see that the CVRP is significant in every specification while the EVRP is significant in only one-third of them. Furthermore, the EVRP is not significant when included in the regression on its own. It does not appear that CVRP simply proxies for other observable firm characteristics because even after including leverage, ROE, analyst recommendations, credit rating, log assets, and Tobin's q in the regressions CVRP is still highly significant.

Next in table 7 we repeat the previous analysis but with returns at six and twelve-month horizons. We find similar results. Again the CVRP is consistently positive and significant. The EVRP is significant, only on occasion. The sign of the EVRP coefficient also changes depending on the specification. Again, even after controlling for a wide variety of characteristics the CVRP is still highly significant. Therefore we conclude that the CVRP contains important information that relates to future expected returns. We find similar results when forecasting credit returns, as reported in the internet appendix.

Since the horse-race predictive regressions show that CVRP contains predictive value above that in EVRP, we explore what additional information might be captured by CVRP. We specifically relate this question to our previous findings that leverage is a key factor relating to VRP, consistent with the structural models. Therefore, we sort firms into quartiles based on their full sample mean of leverage and into categories based on their credit rating in the last month of the sample. The leverage results are contained in Table 8. This table re-runs our horse-race regression (the regression including both credit and equity VRP and no other firm characteristics) by leverage quartile. Panel A presents results for one to three-month returns and panel B present results for six and twelve-month returns. What we see is that the firms for which the credit VRP is significant, but the equity VRP is not, are the lower leverage quartile firms. For example, CVRP is significant for quartile 2 (25% to 50% leverage) for one-month returns and quartile 1 and 2 (<25% and 25% to 50% leverage, respectively) for three month returns, while the EVRP is not significant. Similarly, CVRP is significant for quartile 1 (<25% leverage) and 3 (50% to 75% leverage) for six-month returns and quartile 1 (<25% leverage) for twelve month returns, while the EVRP is not significant. It appears then that CVRP adds information for the lower-levered firms. These are firms that may, on their face, not appear very risky. However the credit risk market provides information on underlying risks that may not be apparent otherwise. Notably, the coefficient on the CVRP is consistently positive showing that the riskier firms earn an above average risk premium over the next one to twelve months.

Now in Table 9, we repeat the analysis but by credit rating. Again for the highest credit rated firms, CVRP is significant for three out of the four return horizons. While EVRP is only significant in one of these specifications. These results are again consistent with the theory that CVRP contains important information about the riskiness of firms that do not appear very risky by other conventional measures. Another implication of studying predictability by leverage and credit rating is to demonstrate the robustness of our results across different samples. Moreover, this strategy allows us to relate the implications of asset pricing models (variance risk and return predictability) and structural models (the importance of leverage).

3.5. Variance Risk Premium Asset Pricing

The previous section reported that the variance risk premium is strongly associated with firm characteristics, firm capital structure, systematic and total firm risk, and business risk. An interesting result from the previous section is that the VRP can predict future returns over different horizons providing support for the structural models' predictions and the asset pricing theory with Epstein-Zin preferences. However, it is important to investigate whether variance risk and realized volatility risks are priced in the cross-section of credit and equity returns. Since both these risks are sources of uncertainty it is an empirical issue to determine whether investors pay a premium to hedge this uncertainty and if the magnitude of the premium differs between the credit and equity markets. This cross-sectional approach allows us to test whether the variance risk premium is a source of risk in the credit and equity markets and compare these findings with common risk/reward studies in the literature.

For this purpose, the tests employ portfolio sorts of equity/credit returns as in Ang et al. (2006a), Bali and Hovakimian (2009), and Cremers et al. (2015) where, starting at the individual firm credit/equity returns, the factor loadings are estimated over a given period and then credit/equity returns are sorted directly on their estimated factor loadings. For robustness, Fama–MacBeth firm-level second-stage regressions of spread returns on factor loadings that are estimated in first-stage regressions are calculated as well.

For each firm return j, factor loadings at the individual firm level using daily data over rolling annual periods are estimated from the regressions

$$R_t^j = \alpha_0^j + \beta_{RV_t}^j \cdot RV_t + \beta_{RV_{t-1}}^j \cdot RV_{t-1} + \beta_{VRP_t}^j \cdot VRP_t + \beta_{VRP_{t-1}}^i \cdot VRP_{t-1} + \epsilon_t^i, \tag{5}$$

where RV and VRP are firm-specific volatility and variance risk premia estimated as in Section 2. To address potential issues due to infrequent trading, the risk measures are lagged and the sum of their risk factors (contemporaneous and lagged by one period) is included. Other factors that may influence returns, such as Fama–French equity and bond factors, are not modeled in estimating the beta values to avoid adding noise in the estimations and to follow the literature (Ang et al., 2006b; Cremers et al., 2015).

At the beginning of each year, spreads/stocks are sorted into quartiles based on their β^{j}_{VRP} (i.e., based on credit or equity VRP) beta loadings estimated over the next 12 months, from equation (5), similar to Ang et al. (2006a), Bali and Hovakimian (2009), and Cremers et al. (2015). To mitigate potential moving average effects in the empirical setup, due to the overlapping information induced by the 12-month estimation intervals while the evaluation is carried out on annual spread returns at a monthly frequency, the reported t-statistics are computed using 12 Newey–West lags. Since other factors are known to affect credit spreads, the market-level risk premium (alphas) using the Fama–French equity and bond factor model computed in the following regression ensures unbiased estimations.

$$R_t = \alpha + \beta_1 \cdot MKT_t + \beta_2 \cdot SMB_t + +\beta_3 \cdot HML_t + \beta_4 \cdot DEF_t + \beta_5 \cdot TERM_t + \epsilon_t, \tag{6}$$

where R_t is the return of a quartile portfolio in year t; and *MKT SMB* and *HML* are, respectively, the excess return on the market portfolio and the return on two long/short portfolios that capture size and book-to-market effects. The default risk factor DEF captures the default risk premium in the credit market. TERM is the term premium risk in the credit market, defined in Section 2.

Table 10 reports the results of testing whether volatility and variance risk are priced risk factors in the cross-section of returns through portfolio sorts.[13] For the volatility risk factor, Panel A reports the average credit returns, variance and realized volatility factor loadings. The same panel also reports the results for a high-low portfolio (going long spreads with the highest 25% of loadings, quartile four, and going short spreads with the lowest 25% of loadings, quartile one). Since higher returns on portfolios exposed to variance risk can be compensation for holding variance risk or compensation for exposure to other risk factors, it is important to examine whether variance risk is a uniquely priced source of risk. To this end, this study adopts the approach of Carr and Wu (2009) in examining the Fama–French three-factor and bond-factor alphas for equally weighted quartile portfolios to see whether variance risk is priced above and beyond what would be expected given its correlation with other risk factors.

[13] At the beginning of each 12-month period, returns are sorted into quartiles based on their realized betas with respect to the variance risk factors over the next 12 months. The contemporaneous average portfolio characteristics over the same 12 months are similarly computed.

Panel A of Table 10 reports the results of equally weighted portfolio sorts based on the credit-implied variance beta loadings, while Panel B reports the statistics for portfolio characteristics sorted by the equity variance beta loadings. Results suggest that variance risk is a priced risk factor in both markets although it appears that expected volatility is somewhat more significantly priced in the equity market than it is in the credit market. Conversely, the variance hedging demand appears to be larger in the credit market than in the equity market.

Results reported in Table 10 suggest that the average future stock return increases with the variance risk premium in both markets. This result is stronger for the credit market (Panel A). The portfolio that is long quartile four credit and short quartile one credit has a Fama–French three-factor and bond factor alpha (t-statistic = 1.48) that is insignificant, suggesting that in the credit market the VRP premium is a compensation for standard risk factors. The difference in average return of the high and low VRP credit portfolios is positive and statistically significant. Similarly, Panel B of the same table reports results for the stock sorts. The variance risk premium appears to be a priced factor while the expected volatility seems to be a higher-risk priced source in the equity market. The Fama–French three-factor and bond-factor alphas for equally weighted quartile portfolios are significantly priced in the equity market.[14]

In addition, Table 11 reports the two-step regressions of a Fama–MacBeth analysis of individual spread returns on realized betas with respect to the volatility and variance factors. As in the portfolio sort analysis, the credit returns are again regressed on the contemporaneously realized betas obtained for each spread in equation (5). An interesting finding is that variance and volatility risk factors are negatively related to returns in the credit market. One interpretation is that the higher risk increases the companies' insolvency risk and diminishes the credit returns. In Model (2), the variance risk premium and volatility risk are statistically significant for both credit and equity markets. Once the regression specification controls for Fama-French 5 factors, the variance risk remains statistically significant in the credit and equity markets, however, the

[14] As reported in the literature the performance measures such as the Sharpe ratio change significantly if returns are non-Gaussian. Table I.A.1 in the internet appendix reports the studentized 10,000 bootstrapped repetitions to estimate 95% confidence intervals on the mean, Sharpe ratio, and Fama-French equity and bond risk factor alphas of the trading strategies. The confidence intervals do not include zeros suggesting that the average returns for the variance risk premiums trading strategies, the Sharpe ratios and Fama-French-5 alphas are all significantly different from zero.

expected volatility risk appears to be priced more strongly in the equity market.

3.6. Additional Results and Robustness Checks

We also re-run the analysis reported in Table 4 by dividing firms on their credit rating categories. Results are reported in Table I.A.2 in internet appendix and corroborate the main findings reported in Table 4; higher credit ratings associate with lower variance risk premia, high-VRP quartile portfolios have lower leverage levels, net debt issuance, Tobin's Q and return on equity. Consistent with findings reported in Table 4, high-VRP quartile portfolios have higher asset beta, asset volatility and investments.

Further, we also run the predictive regressions concerning the ability of the variance risk premia to predict future credit returns as opposed to equity returns as reported in Tables 6 and 7. Results reported in Table I.A.3 in the internet appendix show fairly consistently that credit variance risk premia predict future credit returns at the one-month and one- to three-month horizons. These results hold even when one controls for the equity risk premia and firm characteristics similar to the covariates employed in Tables 6 and 7. We also, re-estimate Tables 6 and 7 by using the Fama-MacBeth approach to cluster the standard errors. We find our main results to be unaffected by the type of choices for clustering standard errors. We thank an anonymous referee for pointing out on this additional robustness check.

Finally, we examine the ability of the variance risk premia to predict returns out-of-sample. These results are reported in Table I.A.4 in the internet appendix. For monthly data from 2013 through 2015 expected returns are calculated by regressing future returns on the credit and equity variance risk premia using a rolling regression up until the period before the return we are trying to forecast. Then the correlation between these expected returns and the actual returns is examined. There is some evidence of out-of-sample predictability. Equity returns at the six-month and 12-month horizon are predictable with these expected returns as are the CDS returns at three, six and 12-month horizons.

4. Conclusions

In this paper we calculate a novel firm-level measure of the credit variance risk premium based on physical and risk-neutral CDS spreads. We then match credit VRP with the firm's equity VRP and a large number of firm characteristics. This approach establishes several new facts about variance risk premia.

First, credit variance risk premia are substantial suggesting that investors pay a premium to hedge future uncertainty in the credit market. Additionally, while credit VRP and equity VRP co-move over time, they are less tightly linked within the same firm, providing a challenge to structural models linking equity and credit volatility to the underlying firm's asset volatility. To a certain extent, this paper sheds light on the level of integration between the credit and equity markets and therefore has important implications for the theory of capital structure.

We also confirm that our measure of credit VRP has the expected relationship with variables that measure credit risk. In the cross-section, consistent with the predictions of the structural models of credit risk, we find that the CVRP is correlated with firm leverage and the credit rating. Additionally, we find that credit VRP is also correlated in an expected way with the business risk of the firm. Higher levels of asset volatility raise credit VRP while increased size and Tobin's Q lowers credit VRP. Therefore, we conclude that in the cross-section our results lend support to structural models predictions.

However, more detailed tests into the relationship between the VRP and the firm leverage reveal that it is low-levered firms who have higher VRPs, and this relation appears stronger in the credit market. Further, exploring the information content of the leverage– as an implicit put option on firms debt– for the VRP we find that the smirk slope of the credit variance risk premium is more pronounced for the low-levered firms and it steepens more for credit than for equity VRP, indicating presence of a substantial mass in the left tail of the credit return distribution. The substantially dearer variance risk premium for the low-levered entities is indicative of the notion that the VRP is a catastrophic risk premium which is better captured by the information deriving from the credit market than the equity market. These results also indicate that the variance risk premium has potential to resolve the low leverage puzzle as it supports the theory that firms do not increase leverage as doing so incurs a market risk premium.

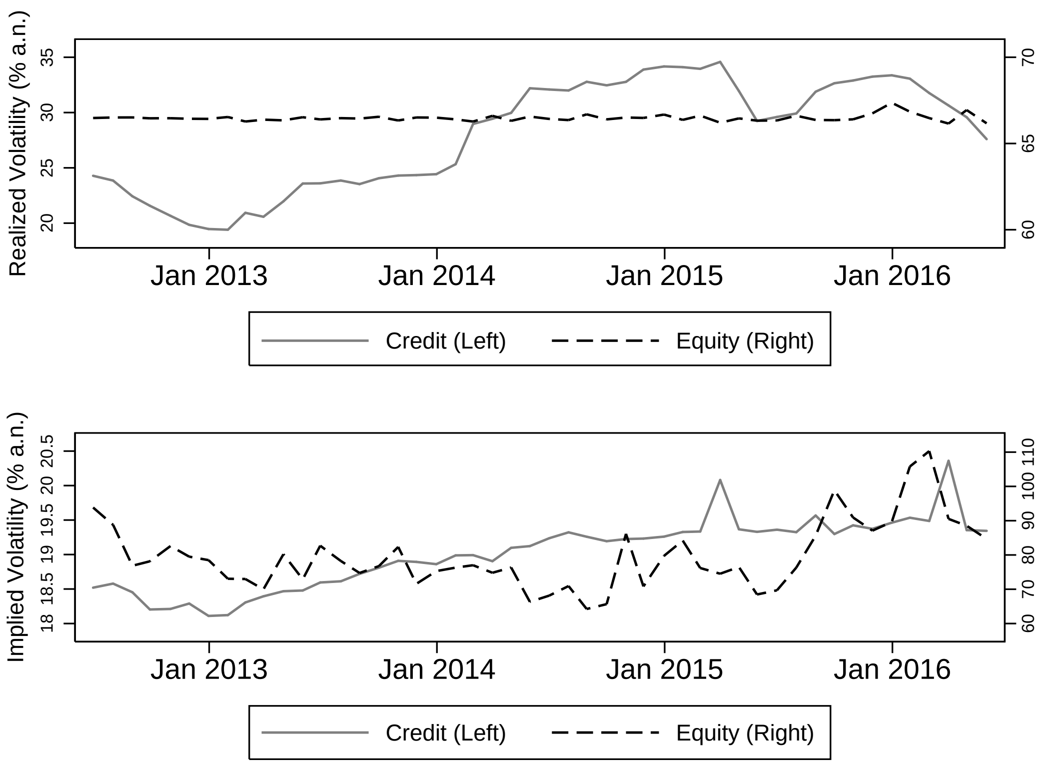
Further, by documenting with extensive predictive regression analysis the VRPs correlation with future returns, we show that our measure of the cost of hedging future uncertainty indeed captures the market's assessment of firms future uncertainty risk. We found that CVRP is positively correlated with future equity returns, even when controlling for the firm's EVRP and other firm characteristics. Turning our attention to why CVRP forecasts future equity returns better than EVRP we found that CVRP was especially useful in forecasting returns for low-leverage and high-credit rating firms. We concluded that CVRP contains information about the credit risk of firms that do not look risky by conventional measures used in the equity market. Additionally, we showed that the long-short portfolio that is long CVRP gives positive returns to investors. We found positive alphas for these portfolios even after controlling for the typical risk factors.

Our results have several important implications for structural models of credit risk and asset pricing. First, the relationship between credit and equity volatility risk does not appear to be as close as structural models imply. Second, the recent push in the structural credit modeling to include stochastic volatility in the determination of credit spreads is well founded as investors are willing to pay a premium to hedge future volatility. Finally, asset pricing models with Epstein-Zin utility, i.e. those that allow the stochastic discount factor to depend on future levels of uncertainty, receive support here as we find that higher levels of credit VRP, the cost to hedge against future uncertainty, imply higher expected equity returns.

Finally, our results also shed light on the low-leverage puzzle debate. Our findings that low-levered firms have a higher cost of hedging future uncertainty risk, the steeper smirk slope, and that the VRP has higher predictive power for these low-levered firms, suggest that the variance risk premium is an important factor to help resolve this puzzle.

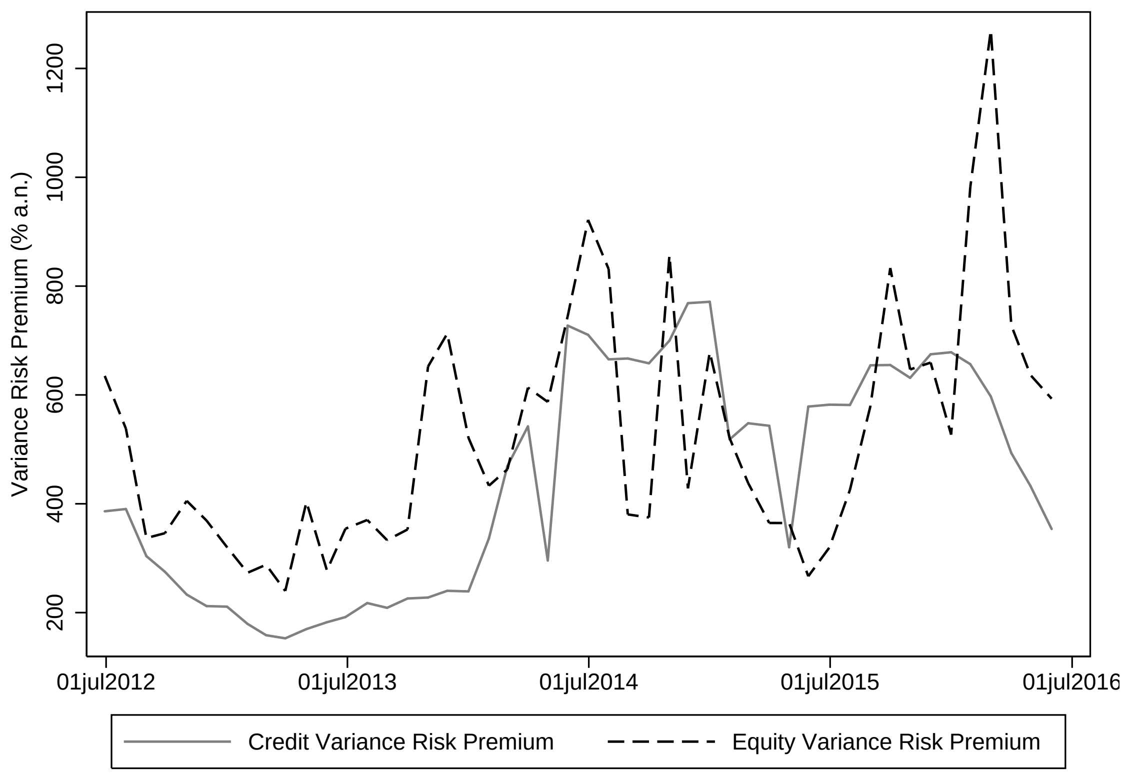
5. Figures and Tables

Figure 1. Credit and Equity Realized and Implied Volatility



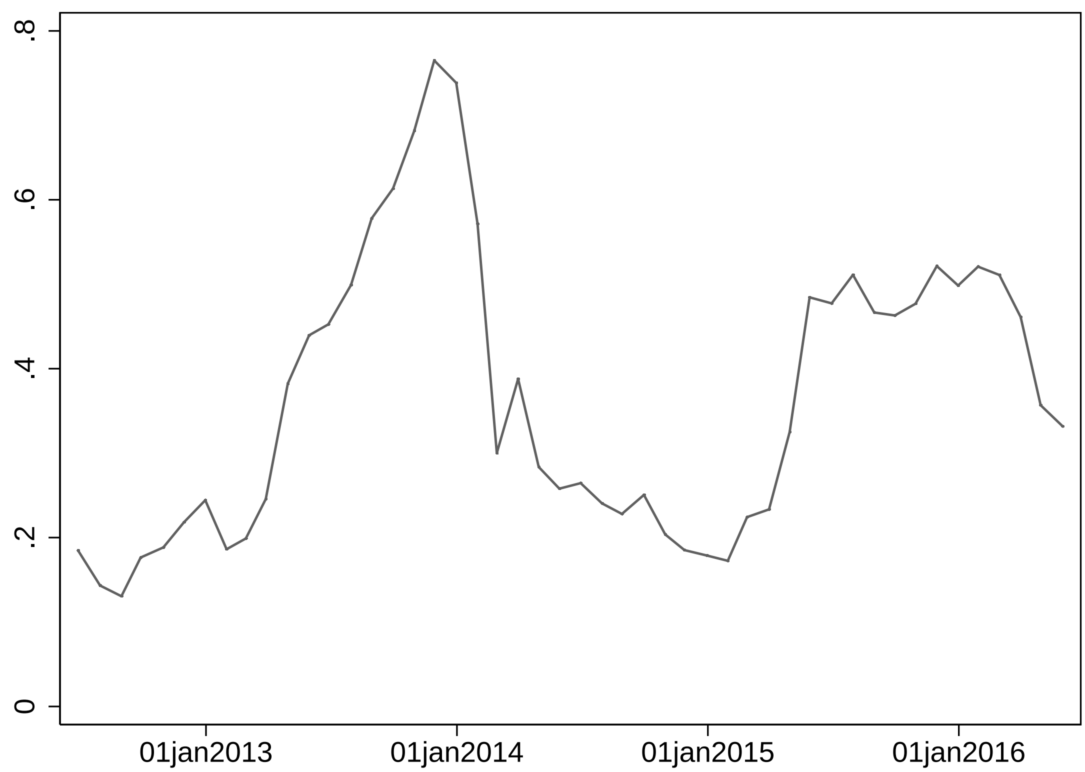
This figure plots the monthly time-series of average annualized credit and equity realized volatility (variance) and implied volatilities in percentage points. The realized volatility of 88 entities is implied from high-frequency credit and equity returns. Implied credit and equity volatility of the 88 entities is estimated from the risk-neutral CDS prices reported by Bloomberg and the corresponding 30-day equity option prices respectively. The time period spans June 1, 2012 to June 1, 2016.

Figure 2. Credit and Equity Variance Risk Premium



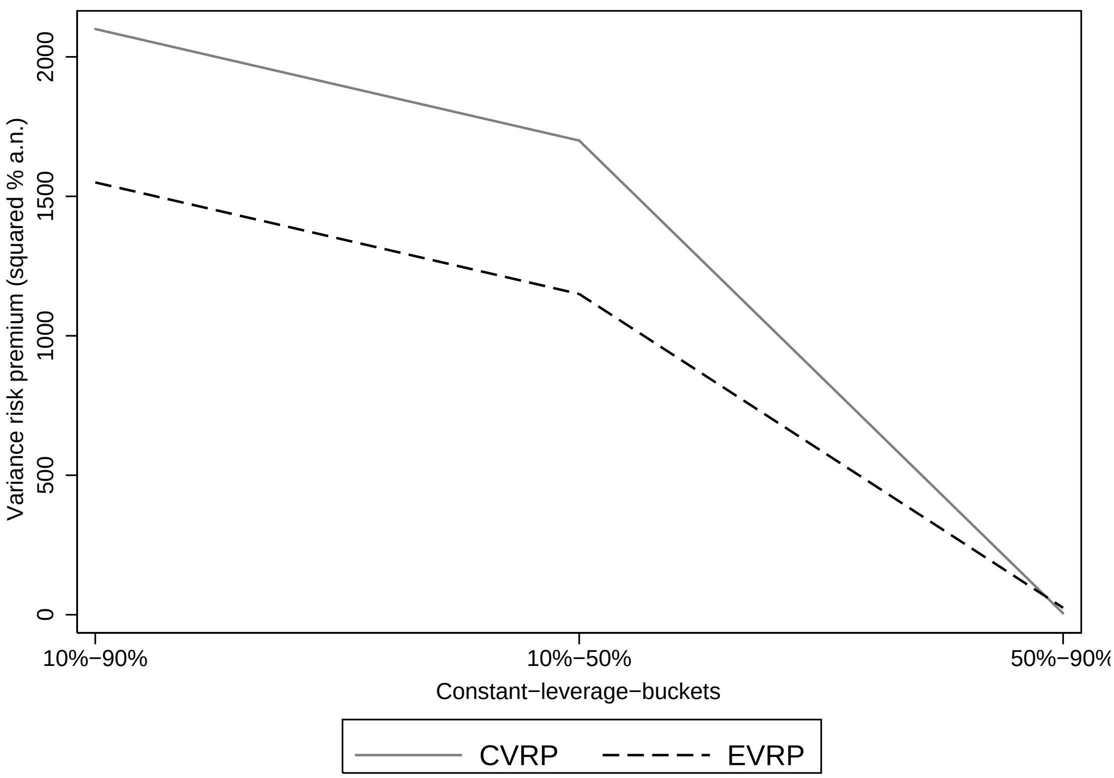
This figure plots the monthly time-series of average annualized credit and equity variance risk premium squared in percentage points. VRP of the 88 entities is the difference between the risk-neutral and physical realized volatility. The physical realized volatility of 88 entities is implied from high-frequency credit and equity returns. Risk-neutral (implied) credit and equity volatility of the 88 entities is estimated from the risk-neutral CDS prices reported by Bloomberg and the corresponding 30-day equity option prices respectively. The time period spans June 1, 2012 to June 1, 2016.

Figure 3. Conditional Correlations of Credit and Equity VRP



This figure plots, for each month, the correlation across firms of the credit and equity variance risk premium. VRP is the difference between the risk-neutral and physical realized volatility. The physical realized volatility of 88 entities is implied from high-frequency credit and equity returns. Risk-neutral (implied) credit and equity volatility of the 88 entities is estimated from the risk-neutral CDS prices reported by Bloomberg and the corresponding 30-day equity option prices respectively. The time period spans June 1, 2012 to June 1, 2016.

Figure 4. VRP Moneyness



This figure plots the magnitude of the smirk slope of the variance risk premium for varying degrees of leverage. The smirk slope is the difference between average VRP for observations in the bottom and top leverage deciles, bottom and median deciles (50-60 percentile), and median and top leverage deciles. VRP is the difference between the risk-neutral and physical realized volatility. The physical realized volatility of 88 entities is implied from high-frequency credit and equity returns. Risk-neutral (implied) credit and equity volatility of the 88 entities is estimated from the risk-neutral CDS prices reported by Bloomberg and the corresponding 30-day equity option prices respectively. The time period spans June 1, 2012 to June 1, 2016.

Table 1. Summary Statistics of Realized and Implied Volatility

	AA	A	BBB	BB	All
	Panel A: Credit Realized Volatility				
Mean	10.858	15.120	76.778	21.410	27.978
Median	10.870	13.329	30.767	15.934	15.359
Std Dev	2.412	7.575	44.186	21.803	53.936
Skew	-0.083	1.918	4.918	6.994	11.296
Kurt	1.610	7.681	30.615	69.559	72.510
AR(1)	0.92	0.88	0.95	0.97	0.97
	Panel B: Equity Realized Volatility				
Mean	64.745	65.580	68.563	66.467	66.479
Median	64.672	65.225	67.351	65.888	65.679
Std Dev	0.893	1.531	5.920	2.604	3.277
Skew	0.810	1.482	1.759	1.824	3.110
Kurt	3.543	8.443	6.246	9.432	18.017
AR(1)	0.12	0.32	0.87	0.63	0.77
	Panel C: Credit Implied Volatility				
Mean	18.014	18.597	19.566	19.150	19.014
Median	17.902	18.530	19.511	19.256	19.054
Std Dev	0.694	1.285	1.370	1.725	1.567
Skew	0.474	1.941	1.971	12.553	9.011
Kurt	3.444	23.261	15.742	307.930	233.498
AR(1)	0.74	0.91	0.73	0.75	0.84
	Panel D: Equity Implied Volatility				
Mean	56.798	70.879	103.081	78.834	79.659
Median	54.654	68.655	91.302	76.818	74.318
Std Dev	10.129	16.511	86.795	29.747	43.039
Skew	0.911	0.964	2.059	0.614	3.831
Kurt	3.647	4.878	9.277	7.965	32.285
AR(1)	0.75	0.63	0.42	0.73	0.66

This table reports the summary statistics of annualized realized and implied volatilities of 88 matched entities for each credit rating, AA-, A-, BBB-, and BB and the full sample All. The realized volatility of 88 entities is implied from high-frequency credit and equity returns. Implied credit and equity volatility of the 88 entities is estimated from the risk-neutral CDS prices reported by Bloomberg and the corresponding 30-day equity option prices respectively. Panels A and C report summary statistics for credit realized and implied volatilities while Panels B and D report the summary statistics for the equity market. AR(1) denotes the first-order autocorrelation coefficient. The sample runs from June 1, 2012, to June 1, 2016.

Table 2. Summary Statistics of Variance Risk Premium

	AA	A	BBB	BB	All
		Panel A: Credit Variance Risk Premium			
Mean	16.306	20.416	7017.004	137.630	1192.023
Std Dev	9.760	33.653	37441.350	1153.595	15160.220
Min	3.270	0.000	0.001	0.000	0.000
Max	39.332	297.573	310928.500	16985.240	310928.500
Skew	0.466	5.365	7.141	13.022	18.209
Kurt	2.124	38.677	54.326	178.331	347.857
AR(1)	0.77	0.88	0.92	0.91	0.93
		Panel B: Equity Variance Risk Premium			
Mean	47.423	81.904	2270.199	273.405	525.009
Std Dev	44.914	178.372	6888.913	690.979	2893.677
Min	0.058	0.000	0.005	0.000	0.000
Max	206.972	3078.037	72012.430	12609.320	72012.430
Skew	1.313	6.964	5.839	7.735	14.219
Kurt	4.442	81.748	44.060	92.393	256.905
AR(1)	0.63	0.70	0.91	0.82	0.89

This table reports the summary statistics of annualized variance risk premium of 88 matched entities for which Bloomberg reports high-frequency CDS and equity prices. The estimates are reported for each credit rating, AA-, A-, BBB-, and BB for which Bloomberg reports S&P or Moody's ratings. VRP is the difference between the risk-neutral and physical realized volatility. The physical realized volatility of 88 entities is implied from high-frequency credit and equity returns. Risk-neutral (implied) credit and equity volatility of the 88 entities is estimated from the risk-neutral CDS prices reported by Bloomberg and the corresponding 30-day equity option prices respectively. Panels A reports the summary statistics for the credit market while Panel B reports the summary statistics for the equity market. AR(1) denotes the first-order autocorrelation coefficient. The sample runs from June 1, 2012, to June 1, 2016.

Table 3. VRP and Firm Characteristics

	Credit VRP		Equity VRP	
	(1)	(2)	(1)	(2)
	Panel A: All firms			
LEVERAGE	4.749***	0.596	3.092***	0.523
	(1.635)	(1.196)	(0.595)	(0.352)
ROE	0.0486***	0.0323***	-0.0696***	-0.0258***
	(0.00760)	(0.00950)	(0.00811)	(0.00847)
ANALYST RECOMM.	4.341***	0.232	-8.047***	-1.031***
	(0.588)	(0.558)	(0.623)	(0.388)
CREDIT RATING	-0.682***		0.795***	
	(0.102)		(0.132)	
FINANCIAL	-9.345***		0.896*	
	(1.314)		(0.457)	
NET DEBT ISSIUANCE	-11.51**	37.89*	-5.083***	12.41***
	(4.807)	(20.81)	(1.309)	(2.453)
NET EQUITY ISSUANCE	1.725	14.79**	13.37***	12.76**
	(3.261)	(6.304)	(1.471)	(5.017)
Constant	-16.37***	-13.01**	29.96***	-1.035
	(3.524)	(5.233)	(2.801)	(3.306)
Firm FE	No	Yes	No	Yes
Month FE	No	Yes	No	Yes
Observations	4,224	4,224	4,224	4,224
R-squared	0.067	0.589	0.323	0.807
	Panel B: Non-Financial Firms			
LEVERAGE	0.0701	1.103***	3.741***	-0.268
	(0.237)	(0.274)	(0.703)	(0.319)
ROE	0.0418***	0.0178***	-0.0676***	-0.0222***
	(0.00634)	(0.00632)	(0.00814)	(0.00826)
ANALYST RECOMM.	5.298***	0.778***	-8.633***	-1.667***
	(0.552)	(0.286)	(0.647)	(0.443)
CREDIT RATING	-0.489***		0.941***	
	(0.0980)		(0.140)	
NET DEBT ISSUANCE	-7.457***	-15.30***	-11.56***	40.78***
	(1.180)	(4.359)	(1.947)	(5.518)
NET EQUITY ISSUANCE	-8.987***	6.462***	14.20***	19.88***
	(1.196)	(2.006)	(1.910)	(4.763)
Constant	-15.92***	-0.428	33.08***	-7.986**
	(2.380)	(1.718)	(3.196)	(3.490)
Firm FE	No	Yes	No	Yes
Month FE	No	Yes	No	Yes
Observations	3,504	3,504	3,504	3,504
R-squared	0.243	0.645	0.373	0.815

This table reports the results of VRP and firm characteristics. Panel A reports the results for the full sample while Panel B reports results for non-financial firms only. Model (1) does not contain fixed effects while Model (2) contains firm- and month–fixed effects. The covariates include firm-specific balance sheet variables; namely, return on equity (ROE) and the leverage ratio (the sum of current and long-term debt divided by the sum of total equity and current and long-term debt, LEVERAGE). Bloomberg's estimates of ANALYST RECOMMENDATIONS ratings scales between '1' and '5' where return of '5' is the strongest ranking (buy or similar), whereas a return of '1' is the weakest (sell or similar). CREDIT RATING and FINANCIAL contain the credit rating and financial firm dummies. The last two control variables are the net long-term debt issuance ($\Delta NDI/A_{j,t-1}$) and net equity issuance ($\Delta NEI/A_{j,t-1}$), where *NDI* denotes net debt issuance of firm *j* in month *t*, *NEI* denotes net equity issuance of firm *j* in month *t*, and $A_{j,t}$ is the book value of total assets of firm *j* in month *t*. Robust standard errors in parentheses. The superscripts $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample runs from June 1, 2012, to June 1, 2016.

Table 4. Portfolio Sorts on Leverage

	EQUITY VRP	CREDIT VRP	σ_A	β_A	LEVERAGE	SIZE
			Panel A: All firms			
Low	28.019	79.745	0.440	0.682	0.233	7.892
2	9.847	69.770	0.246	0.703	0.384	8.475
3	8.229	33.797	0.206	0.493	0.516	8.595
High	7.130	11.251	0.169	0.259	0.749	8.764
			Panel B: Non-Financial firms			
Low	15.456	79.388	0.592	0.592	0.264	8.935
2	9.949	71.685	0.254	0.683	0.402	9.543
3	3.487	28.460	0.228	0.483	0.521	9.878
High	0.891	5.573	0.212	0.259	0.909	10.254

This table reports the full-sample mean of the listed variables for equally-weighted portfolios constructed by sorting firms each month based on their leverage quartile. VRP is the difference between the risk-neutral and physical realized volatility. The physical realized volatility of 88 entities is implied from high-frequency credit and equity returns. Risk-neutral (implied) credit and equity volatility of the 88 entities is estimated from the risk-neutral CDS prices reported by Bloomberg and the corresponding 30-day equity option prices respectively. Panel A reports the summary statistics for the credit and equity markets implied variance risk premiums in the first two columns for all firms. Columns three and four report the asset volatility σ_A and asset beta β_A. Firm leverage and the firm size measure the log of market capitalization (SIZE) are reported in columns four and five. Panel B reports the same statistics but excludes financial firms. The sample runs from June 1, 2012, to June 1, 2016.

Table 5. VRP and Business Risk

	Credit VRP		Equity VRP	
	(1)	(2)	(1)	(2)
Panel A: All firms				
$\beta_{A_{t-1}}$	-0.104*	-0.114**	0.168	0.175
	(0.059)	(0.057)	(0.128)	(0.128)
$\sigma_{A_{t-1}}$	0.259**	0.258***	0.384***	0.391***
	(0.103)	(0.099)	(0.146)	(0.149)
$SIZE_{t-1}$	-2.497***	-2.488***	-1.260***	-1.264***
	(0.327)	(0.324)	(0.135)	(0.134)
$TOBIN'S\,Q_{t-1}$	-1.685***	-1.677***	-0.651***	-0.664***
	(0.204)	(0.203)	(0.120)	(0.120)
$PROFITABILITY_{t-1}$	0.039	0.042	-0.097***	-0.098***
	(0.043)	(0.043)	(0.018)	(0.018)
$TANGIBILITY_{t-1}$	0.018***	0.018***	0.023***	0.022***
	(0.003)	(0.003)	(0.003)	(0.003)
OPERATING LEVERAGE$_{t-1}$	-0.000***	-0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm FE	No	Yes	No	Yes
Month FE	No	Yes	No	Yes
Constant	29.723***	30.822***	17.452***	16.892***
	(3.445)	(3.818)	(1.369)	(1.382)
R-squared	0.04	0.04	0.13	0.13
Panel B: Non-Financial Firms				
$\beta_{A_{t-1}}$	-0.067***	-0.065***	0.181	0.187
	(0.022)	(0.023)	(0.136)	(0.136)
$\sigma_{A_{t-1}}$	0.255**	0.258**	0.381***	0.388***
	(0.106)	(0.106)	(0.143)	(0.146)
$SIZE_{t-1}$	-1.408***	-1.410***	-1.299***	-1.304***
	(0.148)	(0.148)	(0.150)	(0.149)
$TOBIN'S\,Q_{t-1}$	-0.566***	-0.571***	-0.636***	-0.647***
	(0.089)	(0.089)	(0.138)	(0.138)
$PROFITABILITY_{t-1}$	-0.111***	-0.111***	-0.098***	-0.099***
	(0.030)	(0.030)	(0.020)	(0.020)
$TANGIBILITY_{t-1}$	0.012***	0.012***	0.025***	0.024***
	(0.003)	(0.003)	(0.004)	(0.004)
OPERATING LEVERAGE$_{t-1}$	-0.000**	-0.000**	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm FE	No	Yes	No	Yes
Month FE	No	Yes	No	Yes
Constant	16.376***	16.597***	17.910***	17.369***
	(1.423)	(1.405)	(1.519)	(1.534)
R-squared	0.16	0.16	0.13	0.14

This table reports the results of VRP and business risk. Panel A reports the results for the full sample while panel B reports results for non-financial firms only. Model (1) does not contain fixed effects while Model (2) contains firm and month fixed effects. The covariates include asset beta $\beta_{A_{t-1}}$ estimated similarly to Schwert and Strebulaev (2014), asset volatility $\sigma_{A_{t-1}}$ estimated as in Kelly et al. (2019), firm's size proxied as the log of market capitalization (SIZE), Tobin's Q, profitability margin estimated as ratio of net income over net revenue (PROFITABILITY), the asset tangibility proxy estimated as a ratio of tangible equity over tangible assets (TANGIBILITY), and the OPERATING LEVERAGE estimated as EBIT Growth over the Revenue Growth. The time subscripts *t-1* indicates lag one in variables. Robust standard errors in parentheses. The superscripts $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample runs from June 1, 2012, to June 1, 2016.

Table 6. Equity Predictability (1 and 3 months)

	One-month ahead				Three-months ahead			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CVRP	0.00932*		0.0114**	0.0120**	0.00910***		0.0108***	0.0109***
	(0.00541)		(0.00539)	(0.00525)	(0.00282)		(0.00289)	(0.00266)
EVRP		0.00689	0.0119	0.0286*		0.00503	0.00981	0.0243***
		(0.0130)	(0.0132)	(0.0170)		(0.00652)	(0.00654)	(0.00790)
LEVERAGE				-0.0141				0.0853
				(0.303)				(0.165)
ROE				-0.00161				0.000877
				(0.00320)				(0.00139)
ANALYST				0.478**				0.465***
				(0.193)				(0.103)
CREDIT RATING				0.0222				-0.00955
				(0.0883)				(0.0529)
LOG ASSETS				-0.0834				-0.0823*
				(0.102)				(0.0477)
PROFITABILITY				0.0179*				0.00776
				(0.00964)				(0.00520)
TOBIN'S Q				-0.0286				-0.0181
				(0.142)				(0.0823)
SENTIMENT				0.262				0.427**
				(0.330)				(0.200)
Constant	0.271	0.221	0.232	-1.010	0.205**	0.163*	0.173*	-0.972
	(0.193)	(0.184)	(0.185)	(1.369)	(0.0963)	(0.0932)	(0.0935)	(0.677)
Observations	4,136	4,136	4,136	4,070	3,960	3,960	3,960	3,896
R-squared	0.001	0.000	0.001	0.006	0.003	0.000	0.004	0.013

This table reports the results from regressing CVRP and EVRP on future equity returns. The first four columns report the one-month ahead return regressions and the last four columns report the three-month ahead return regressions. Control variables include the sum of current and long-term debt divided by the sum of total equity and current and long-term debt (LEVERAGE), return on equity (ROE), Bloomberg's estimates of analyst ratings scales between '1' and '5' where return of '5' is the strongest ranking (ANALYST), credit rating dummies (CREDIT RATING), log of book value of assets (LOG ASSETS), margin estimated as ratio of net income over net revenue (PROFITABILITY), Tobin's Q, and Bloomberg's estimate of news sentiment, scale -1 to 1, 1 most positive sentiment (SENTIMENT). Robust standard errors clustered by month in parentheses. The superscripts $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample runs from June 1, 2012, to June 1, 2016.

Table 7. Equity Predictability (6 and 12 months)

	Six-months ahead				Twelve-months ahead			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CVRP	0.00945***		0.0100***	0.0102***	0.00867***		0.00839***	0.00834***
	(0.00193)		(0.00226)	(0.00213)	(0.00117)		(0.00112)	(0.00120)
EVRP		-0.000782	0.00369	0.0186***		-0.00559**	-0.00198	0.00842**
		(0.00355)	(0.00388)	(0.00511)		(0.00239)	(0.00217)	(0.00362)
LEVERAGE				0.0193				0.0115
				(0.0801)				(0.0613)
ROE				0.00329***				0.00480***
				(0.000693)				(0.000414)
ANALYST				0.432***				0.374***
				(0.0631)				(0.0574)
CREDIT RATING				-0.00524				-0.0329
				(0.0353)				(0.0361)
LOG ASSETS				-0.0692**				-0.0865***
				(0.0316)				(0.0232)
PROFITABILITY				0.00410				-0.00509
				(0.00412)				(0.00327)
TOBIN'S Q				0.0105				0.00667
				(0.0561)				(0.0459)
SENTIMENT				0.389**				0.269***
				(0.149)				(0.0984)
Constant	0.157**	0.136**	0.146**	-1.041**	0.122***	0.118***	0.127***	-0.488
	(0.0637)	(0.0644)	(0.0635)	(0.484)	(0.0268)	(0.0260)	(0.0258)	(0.406)
Observations	3,696	3,696	3,696	3,649	3,168	3,168	3,168	3,127
R-squared	0.006	0.000	0.006	0.022	0.011	0.001	0.011	0.036

This table reports the results from regressing CVRP and EVRP on future equity returns. The first four columns report the six-month ahead return regressions and the last four columns report the twelve-month ahead return regressions. Control variables include the sum of current and long-term debt divided by the sum of total equity and current and long-term debt (LEVERAGE), return on equity (ROE), Bloomberg's estimates of analyst ratings scales between '1' and '5' where return of '5' is the strongest ranking (ANALYST), credit rating dummies (CREDIT RATING), log of book value of assets (LOG ASSETS), margin estimated as ratio of net income over net revenue (PROFITABILITY), Tobin's Q, and Bloomberg's estimate of news sentiment, scale -1 to 1, 1 most positive sentiment (SENTIMENT). Robust standard errors clustered by month in parentheses. The superscripts $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample runs from June 1, 2012, to June 1, 2016.

Table 8. Predictability by Leverage Quartile Buckets

	One-month ahead				Three-months ahead			
	<25%	25%-50%	50%-75%	>75%	<25%	25%-50%	50-75%	>75%
CVRP	0.0288	0.0772**	0.00535	0.0431	0.0323*	0.0790***	0.00487*	0.0319
	(0.0276)	(0.0300)	(0.00558)	(0.0387)	(0.0164)	(0.0169)	(0.00253)	(0.0267)
EVRP	0.00482	0.0239	0.0913*	0.0368	0.00810	0.0148	0.0757**	0.0407**
	(0.0181)	(0.0440)	(0.0663)	(0.0259)	(0.0104)	(0.0244)	(0.0351)	(0.0159)
Constant	0.477**	0.327	-0.0982	0.0504	0.431***	0.230	-0.110	0.0178
	(0.220)	(0.322)	(0.221)	(0.200)	(0.114)	(0.186)	(0.129)	(0.114)
Observations	1,034	1,034	1,034	1,034	990	990	990	990
R-squared	0.003	0.009	0.012	0.005	0.010	0.029	0.024	0.013

	Six-months ahead				Twelve-months ahead			
	<25%	25%-50%	50%-75%	>75%	<25%	25%-50%	50-75%	>75%
CVRP	0.0314***	0.0783***	0.00456**	0.0411*	0.0277***	0.0606***	0.00476***	0.0267
	(0.00852)	(0.00955)	(0.00178)	(0.0240)	(0.00788)	(0.00791)	(0.00132)	(0.0234)
EVRP	0.00787	-0.0216*	0.0430	0.0494***	0.00613	-0.0384***	-0.0319***	0.0488***
	(0.00510)	(0.0117)	(0.0339)	(0.0102)	(0.00465)	(0.00970)	(0.00980)	(0.00575))
Constant	0.451***	0.290**	-0.0940	-0.0211	0.435***	0.286***	-0.0363	-0.0284
	(0.0753)	(0.117)	(0.107)	(0.0732)	(0.0428)	(0.0692)	(0.0936)	(0.0379)
Observations	924	924	924	924	792	792	792	792
R-squared	0.018	0.076	0.015	0.035	0.028	0.074	0.029	0.062

This table reports the results from regressing CVRP and EVRP on future equity returns by equally-weighted leverage quartiles. Less than 25% is the quartile of firms with the lowest average level of leverage, 25%-50% is the quartile of firms with the second lowest average level while 50%-75% is the quartile of second highest average levels of leverage and finally, the fourth quartile above 75% is the quartile of firms with the highest average level of leverage. Panel A contains the results for one-month forecasting regressions are the three-month forecasting regressions. Panel B contains the results for six-month are the twelve-month forecasting regressions. Robust standard errors clustered by month in parentheses. The superscripts *** , ** , * represent significance at the 1, 5 and 10% levels respectively. The sample runs from June 1, 2012 to June 1, 2016.

Table 9. Predictability by Credit Rating

	One-month ahead				Three-months ahead			
	AA	A	BBB	BB	AA	A	BBB	BB
CREDIT VRP	0.750	0.0915	0.000160	0.0874***	1.054***	0.105***	-0.000384	0.0874***
	(0.672)	(0.0697)	(0.00514)	(0.0255)	(0.333)	(0.0376)	(0.00192)	(0.0177)
EQUITY VRP	-0.0708	0.0448	-0.0123	0.0884***	0.0166	0.0688**	-0.00961**	0.0705***
	(0.186)	(0.0633)	(0.00875)	(0.0291)	(0.0768)	(0.0305)	(0.00417)	(0.0133)
Constant	-2.043	0.241	-0.158	0.0913	-2.674***	0.184*	-0.315*	0.0883
	(1.822)	(0.215)	(0.346)	(0.199)	(0.836)	(0.0951)	(0.170)	(0.108)
Observations	94	1,316	658	2,068	90	1,260	630	1,980
R-squared	0.016	0.003	0.002	0.018	0.086	0.019	0.004	0.039

	Six-months ahead				Twelve-months ahead			
	AA	A	BBB	BB	AA	A	BBB	BB
CVRP	1.013***	0.112***	0.000301	0.0903***	0.592***	0.0943***	0.00244*	0.0873***
	(0.227)	(0.0298)	(0.00131)	(0.0114)	(0.126)	(0.0263)	(0.00129)	(0.0168)
EVRP	0.0372	0.0676***	-0.00811***	0.0476***	0.0592**	0.0636***	-0.00673***	0.0206***
	(0.0632)	(0.0215)	(0.00229)	(0.0109)	(0.0275)	(0.0111)	(0.00112)	(0.00641)
Constant	-2.609***	0.170**	-0.382***	0.130*	-1.727***	0.185***	-0.369***	0.141***
	(0.581)	(0.0682)	(0.112)	(0.0717)	(0.255)	(0.0474)	(0.0690)	(0.0274)
Observations	84	1,176	588	1,848	72	1,008	504	1,584
R-squared	0.199	0.035	0.005	0.056	0.271	0.051	0.012	0.048

This table reports the results from regressing CVRP and EVRP on future equity returns by firm credit rating. The estimates are reported for each credit rating, AA-, A-, BBB-, and BB for which Bloomberg reports S&P or Moody's ratings. Panel A contains the results for one- and three-months ahead forecasting regressions. Panel B contains the results for six- and twelve-months ahead forecasting regressions. Robust standard errors clustered by month in parentheses. The superscripts *** , ** , * represent significance at the 1, 5 and 10% levels respectively. The sample runs from June 1, 2012 to June 1, 2016.

Table 10. Average Returns of Portfolios Sorted by β_{VRP}

	Return	β_{VRP}	β_{RV}	FF-5 α	β_{MKT}	β_{SMB}	β_{HML}	β_{TERM}	β_{DEF}	Sharpe
Portfolio sorts by Credit VRP										
Low	0.03873	-0.00202	-0.00036	0.04528	0.56936	-0.28758	-0.20393	-0.43580	-0.01351	1.23
2	-0.00258	-0.00022	-0.00007	-0.01589	0.77931	-0.25366	-0.33369	-0.43417	-0.01221	-0.18
3	0.00019	0.00029	0.00001	-0.09316	1.04037	-0.06869	-0.45890	-0.13886	-0.01084	0.01
High	0.20173	0.00293	0.00034	0.15796	1.14431	-0.09008	-0.13015	-0.16139	-0.01308	2.17
High-Low	0.16300	0.00495	0.00070	0.11268	0.57495	0.19750	0.07378	0.27441	0.00043	0.93
t-stats	-1.62	16.18	2.83	1.48	3.40	1.71	0.76	2.45	0.35	
Portfolio sorts by Equity VRP										
Low	0.02778	-0.02172	0.00478	0.00029	0.98152	-0.10244	-0.30149	-0.06215	-0.01153	2.70
2	0.02992	-0.00065	0.00231	0.00051	0.92229	-0.22548	-0.22915	-0.33972	-0.01273	2.94
3	0.03779	0.01094	0.00020	0.00039	0.82957	-0.20386	-0.30206	-0.36176	-0.01326	3.38
High	0.04673	0.03272	-0.00342	0.00000	0.79996	-0.16822	-0.29396	-0.40660	-0.01211	4.27
High-Low	0.01895	0.05444	-0.00820	-0.00029	-0.18155	-0.06578	0.00753	-0.34445	-0.00058	1.57
t-stats	1.23	7.79	17.33	4.11	1.08	0.56	-0.08	2.91	0.47	

This table reports the results of quartile portfolio sorts by variance risk premium beta of credit and equity returns and the average returns of the portfolio that is long the high-VRP quartile and the short low-VRP quartile. The table reports Fama–French equity and bond alphas and (β_{MKT},β_{SMB} and β_{HML} reported in columns five to six) and Fama–French bond factors (β_{TERM} and β_{DEF} reported in the eighth and ninth columns, respectively). The 'term risk factor' is the difference between the monthly long-term government bond return (Morningstar/Ibbotson Associates index) and the three-month Treasury bill return measured at the end of the previous month, TERM and the default risk factor is the difference between the return on a market portfolio of long-term corporate bonds (the composite portfolio on the corporate bond module of the Morningstar/Ibbotson Associates index) and the long-term government bond return, DEF. The last column reports annualized Sharpe ratios. The sample runs from June 1, 2012, to June 1, 2016.

Table 11. Fama–MacBeth Regressions

	Credit Market			Equity Market		
	(1)	(2)	(3)	(1)	(2)	(3)
β_{VRP}	-0.47605	-0.20699	-0.82406	0.25544	0.87612	1.01693
	(-2.76)	(-1.63)	(-2.08)	(1.24)	(3.00)	(3.59)
β_{RV}		-0.70689	-0.73969		5.47498	4.57635
		(-4.05)	(-2.72)		(7.18)	(6.78)
β_{MKT}			-0.00070			0.01856
			(-3.27)			(2.17)
β_{HML}			-0.00061			-0.00008
			(-1.18)			(-0.01)
β_{SMB}			-0.00018			-0.00125
			(-1.42)			(-0.22)
β_{DEF}			0.00001			0.00003
			(1.16)			(0.09)
β_{TERM}			-0.00044			-0.05346
			(-3.06)			(-7.45)
Constant	0.00066	0.00061	-0.00078	0.00036	0.00028	0.00016
	(1.93)	(2.02)	(-1.31)	(6.29)	(5.34)	(1.94)

This table reports the results on the monthly cross-sectional regressions of beta VRP and RV. Fama–MacBeth regressions of monthly credit/equity returns are regressed on contemporaneous realized betas. Standard errors are adjusted by using 12 Newey–West lags. RV and VRP factor loadings are calulated at the firm level using daily return data over rolling annual periods. The table includes Fama–French equity and bond alphas and (β_{MKT},β_{SMB} and β_{HML} reported in columns five to six) and Fama–French bond factors (β_{TERM} and β_{DEF} reported in the eighth and ninth columns, respectively). The 'term risk factor' is the difference between the monthly long-term government bond return (Morningstar/Ibbotson Associates index) and the three-month Treasury bill return measured at the end of the previous month, TERM and the default risk factor is the difference between the return on a market portfolio of long-term corporate bonds (the composite portfolio on the corporate bond module of the Morningstar/Ibbotson Associates index) and the long-term government bond return, DEF. The sample runs from June 1, 2012, to June 1, 2016.

Appendix A

In this section we discuss the methods used in estimating the risk-neutral volatility measures in equity and credit markets. The risk-neutral expectation of return variation for stocks is estimated as follows. On the last trading day of each month t, the implied volatilities for one-month call options are translated into call option prices using the Cox et al. (1979) binomial lattice model. Following Jiang and Tian (2005), the one-month model-free implied variance is

$$IV_t^i = 2\int_0^\infty \frac{C_t^i(t+T,K)/B(t,t+T) - max[0, S_t^i/B(t,t+T) - K]}{K^2} dK. \tag{A.1}$$

S_t^i denotes the stock price of firm i at t, T is one-month, $C_t^i(t+T,K)$ is the call option price with time-to-maturity T and strike price K. Finally, $B(t,t+T)$ represents the present value of a zero-coupon bond that pays off one dollar at time $t+T$.

Since risk-neutral, model-implied credit default swaps are not commonly discussed in the literature, the following paragraphs dedicate some time to describe the details of their estimation. First, we aim to calculate a credit variance risk premium (CVRP) based on CDS return data. While credit spreads under the physical measure are directly observable, credit spreads under the risk neutral measure are not. To overcome this difficultly, we use model implied risk-neutral credit spreads calculated by Bloomberg. This section reports for the reader's convenience the method used by Bloomberg to calculate risk-neutral CDS prices.

The Bloomberg method uses a variant of Merton (1974) to predict a firm's default probability. Conditional on this probability, one can calculate the risk neutral CDS spread as the actuarial fair price of CDS insurance. Under the Merton model the equity of the firm can be viewed as a call option on the total assets of the firm where the strike price is equal to its liabilities. This allows to infer the level and volatility of the firm's assets from the observed equity values using the Black and Scholes (1973) option pricing approach. However, Merton's model assumes that default can occur only at the maturity of the firm's liabilities, which is only an approximation of the reality in which defaults occur at any time. To overcome this limitation the Merton model is extended to treat equity as 1-year barrier call option, explicitly incorporating the possibility that the firm can default before the maturity of its liabilities. Under this assumption the firm's equity value E is given by:

$$E_t = E^p[max(V_T - D, 0)]I_{min(V_t)>D}, \tag{A.2}$$

where I is an indicator function, V_t is the firm's asset value and D is the value of the firm's debt. This formulation allows default to take place any time from t to T.

Now assuming that the firm's assets evolve according to equation (B.1) in appendix B and the model relationship between stock return volatility and firm asset volatility is given by (B.4), one can calculate the firm's asset level and volatility by matching the firm's observed equity value under equation (A.2).[15] This matching implies the following formula for the main output of Merton's model, the firm's distance to default:

$$DD = \frac{ln(\frac{V_0}{D}) + (\mu - \frac{\sigma_A^2}{2})T}{\sigma_A \sqrt{T}}. \tag{A.3}$$

here V_0 is the total assets of the firm at time 0, σ_A is the asset volatility, μ is the asset drift, D is the debt liabilities of the firm and T is the time to maturity.

However, it is well known that the default probabilities obtained by the basic Merton model underestimate the true default likelihood over short horizons and for safer firms (higher DDs). Therefore, Bloomberg estimates a non-linear mapping f between the DD and the actual default probability, i.e. $\widehat{DD}= f(DD)$, where f is a nonlinear function. This formulation implies that $\widehat{DD}$ and default likelihoods are largely driven by changes in the market capitalization and equity volatility, making the implied credit default swap spreads responsive to real-time changes in a firm's prospects. This dependency also makes the implied spreads cyclical.

Finally, as shown by Bharath and Shumway (2008) $\widehat{DD}$ is a significant predictor of default but not a sufficient statistic. Therefore, the $\widehat{DD}$ is enhanced by information related to the credit health of the firms.[16] These adjustments ensure unbiased estimates of the default probability. Based on these, Bloomberg estimates

[15]The Bloomberg model abstracts from jump and stochastic volatility.

[16]This information, for example, includes claims and reserves for insurance firms, non-performing loans for banks, and other financial fillings such as accounting adjustments, operating leases, pension adjustments etc.

the model-implied risk-neutral credit default swap spreads as the actuarial fair value of CDS insurance. We obtain these risk-neutral CDS data from the Bloomberg system and use the non-overlapping forward-looking daily standard deviation of these five-year CDS returns to estimate the risk-neutral expectation (implied volatility) of the return variation.

Appendix B

To have a sense of how to interpret the empirical magnitudes of the variance risk premiums in equity and credit markets one needs to have a theoretical understanding on the associations among asset-equity-credit volatilities. Let us consider a reference company with a positive probability of defaulting; the company's underlying asset value process under $\mathbb{Q}$ measures is

$$\frac{dA_t}{A_t} = (\mu - \delta - \lambda\mu_J)dt + \sqrt{V_t}dW_{1t} + J_t dq_t \tag{B.1}$$

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

where A_t is the firm value, μ is the instantaneous asset return, δ is the dividend payout ratio and λ denotes the risk-neutral arrival rate of the default event. Asset jump has Poisson $dq_t \sim Poisson(\lambda \mathrm{dt})$ and Gaussian $log(1 + J_t) \sim Normal(log(1 + \mu_J) - \frac{1}{2}\sigma_J^2, \sigma_J^2)$ distribution. The asset return volatility follows a square root process with long-run mean θ, a mean reversion κ and a variance σ. $\rho = (dW_{1t}, dW_{2t})$ denotes the correlation between the asset return and the return volatility.

The volatility risk premium is given by ξ_v where $\kappa = \kappa^* + \xi_v$ and $\theta = \frac{\theta^* \xi_v}{\kappa*}$ where κ^* and θ^* are the corresponding parameters for the physical volatility measure. The jump intensity risk premium is ξ_λ such that $\lambda = \lambda^* + \xi_\lambda$, while the jump size risk premium is ξ_J such that $\mu_J = \mu_J^* + \xi_J$.

A. Linking asset volatility and equity volatility

This stochastic volatility jump diffusion model ((B.1)-(B.2)) of the asset value and volatility processes implies the following specification of equity price, by applying the Itô's Lemma,

$$\frac{dS_t}{S_t} = \frac{1}{S_t}\mu_t(\cdot)dt + \frac{A_t}{S_t}\frac{\partial S_t}{\partial V_t}\sigma\sqrt{V_t}dW_{2t} + \frac{1}{S_t}[S_t(A_t(1 + J_t), V_t) - S_t(A_t, V_t)]dq_t \tag{B.3}$$

where $\mu_t(\cdot)$ is the instantaneous equity return, A_t and V_t are asset and volatility processes, and $S_t \equiv S_t(A_t, V_t)$.

The instantaneous volatility Σ_t^2 and the jump size J_t^s are

$$\Sigma_t^s = \sqrt{\left(\frac{A_t}{S_t}\right)^2 \left(\frac{\partial S_t}{\partial A_t}\right)^2 V_t + \left(\frac{\sigma}{S_t}\right)^2 \left(\frac{\partial S_t}{\partial V_t}\right)^2 V_t + \frac{A_t}{S_t^2}\frac{\partial S_t}{\partial A_t}\frac{\partial S_t}{\partial V_t}\rho\sigma V_t} \tag{B.4}$$

$$J_t^s = log[S_t(A_t(1 + J_t), V_t)] - log[S_t(A_t, V_t)], \tag{B.5}$$

where μ_J^s is the unconditional mean of the J_t^s with a standard deviation σ_J^s unknown due to nonlinear functional form of $S_t(A_t, V_t)$. If asset volatility (V) is constant Equation (B.4) reduces to standard Merton (1974) $\Sigma_t^s = \sqrt{V\frac{\partial S_t}{\partial A_t}\frac{A_t}{S_t}}$. The equity jump process is the same as the asset jump and has the same intensity function.

B. Linking asset volatility and credit spread volatility

The finance literature has studied the relation between the asset value process and equity volatility extensively and, yet, the relation between the asset value process and credit spreads has not attracted the same attention. This section begins by discussing the importance of the introduction of jumps in the asset value process for credit spreads in the short end. This is followed by providing theoretical intuition on the sensitivities of the changes of spreads and their volatilities contingent on changes in the asset value.

As in Lando (2004), assuming the asset value process evolving as in Equation (B.1) and letting the price of the risky bond with face value B maturing at T be

$$\begin{aligned} D(0,T) &= e^{-rT}E\left[B1_{(A\geq B)} + A_T1_{(A_T<B)}\right] \\ &= e^{-rT}\left[B(A \geq B) + E\left[A_T|A_T < B\right](A_T < B)\right] \\ &= Be^{-rT}\left[1 - (A_T < B) + \frac{1}{B}E[A_T|A_T < B](A_T < B)\right] \\ &= Be^{-rT}\left[1 - (A_T < B)\left(1 - \frac{E[A_T|A_T < B]}{B}\right)\right], \end{aligned} \tag{B.6}$$

one can express the yield spread limit for spread s maturing at T, as $T \to 0$, as

$$\lim_{T\downarrow 0} s(T) = \lim_{T\downarrow 0}\left[\frac{(A_T < B)}{T}\left(1 - \frac{E[A_T|A_T < B]}{B}\right)\right]. \tag{B.7}$$

As $T \to 0$, at most one jump can occur. The jump intensity is λ but the probability of a jump being sufficiently large for $A_T < B$ has a lower intensity; $\lambda = \lambda * [(1+\epsilon)A_0 < B]$.[17] The second term in the expression is the expected loss given default; thus, we have

$$\lim_{T \downarrow 0} s(T) = \lambda E[L(A_0)].^{18} \tag{B.8}$$

Therefore, an increase in the overall jump intensity is followed by a proportional increase in the instantaneous spread. Furthermore, a higher mean jump size should typically lead to higher spreads.

The relation between the asset value process and its effects for equity and credit spreads is evident from the above equations. An increase in the overall jump intensity is followed by a proportional increase in the instantaneous spread. Furthermore, a higher mean jump size should typically lead to higher spreads. High asset volatility, V, and jump intensity, λ, increase credit spreads. Also, the equity volatility would typically increase the credit spreads, although in a convex pattern, due to the leverage effect (equity volatility is higher than asset volatility). Since the equity jump intensity is the same as the asset it will thus have similar linear effects on the credit spreads. It follows that both variance rates and the default arrival rates are stochastic in both markets. Empirically their physical counterparts are discussed in Section 2.

Theoretical predictions therefore suggest that one should expect a close relation among these quantities. Failure to empirically confirm this has important implications for asset pricing and risk management practices.

Appendix C

This section outlines the method of Bollerslev et al. (2011) for estimating risk aversion coefficients from realized and implied volatility. They begin with the stock price process:

$$dp_t = \mu_t dt + \sqrt{V_t} dB_{1t} dV_t = \kappa(\theta - V_t)dt + \sigma_t dB_{2t} \tag{C.1}$$

[17] ϵ denotes a sequence of independent jump sizes with distribution $[-1, \infty)$.

[18] Where $\mathrm{L(A_0)} = 1 - \frac{E[A_0(1+\epsilon)|A_0(1+\epsilon)<B]}{B}$.

where $corr(dB_{1t}, dB_{2t}) = \rho$ and the corresponding risk-neutral process

$$dp_t = r_t dt + \sqrt{V_t} dB^*_{1t} dV_t = \kappa^*(\theta^* - V_t)dt + \sigma_t dB^*_{2t}. \tag{C.2}$$

Next they define the variance risk premium $\lambda = \kappa^* - \kappa$ and show that $\theta^* = \frac{\kappa\theta}{\kappa+\lambda}$.

Relying on previously derived results for the stock price model, they first note that:

$$E(RV_{t+1}) = \alpha E(RV_t) + \beta$$

where $\alpha = \exp^{-\kappa}$ and $\beta = \theta(1 - \exp^{-\kappa})$.

Next they point out that previous work with this model also implies that:

$$E(RV_{t+1}) = A * IV_{t+1} + B$$

where $A = \frac{(1-\exp^{-\kappa})/\kappa}{(1-\exp^{-\kappa^*})/\kappa^*}$ and $B = \theta[1 - (1 - \exp^{-\kappa})/\kappa] - A\theta^*[1 - (1 - \exp^{-\kappa^*})/\kappa^*]$.

They then suggest estimating the underlying structural parameters $\xi = (\kappa, \theta, \lambda)'$ by GMM using the following four moment conditions:

$$E\begin{bmatrix} RV_{t+1} - \alpha E(RV_t) - \beta \\ (RV_{t+1} - \alpha E(RV_t) - \beta)RV_{t-1} \\ RV_{t+1} - A * IV_{t+1} - B \\ (RV_{t+1} - A * IV_{t+1} - B)RV_{t-1} \end{bmatrix} = 0 \tag{C.3}$$

Finally, they show that under standard power utility the risk aversion coefficient $\gamma = \frac{\lambda}{\rho\sigma}$. To estimate ρ, σ we approximate the stock price process using monthly changes.

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