Asset Volatility

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Abstract

Asset volatility is a primitive variable in structural models of credit spreads. We evaluate alternative measures of asset volatility using information from (i) historical security returns (both equity and credit), (ii) implied volatilities extracted from equity options, and (iii) financial statements. For a large sample of US firms, we find that combining information from all three sources improves explanatory power of corporate bankruptcy models and cross-sectional variation in credit spreads. Market based (accounting) measures of asset volatility appear to reflect systematic (idiosyncratic) sources of volatility and combining both sources of information generates a superior measure of total asset volatility that is relevant for understanding credit spreads.

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1. Introduction

Our objective is to compare and contrast alternative measures of asset volatility in their ability to explain security prices. A seminal paper by Merton (1974) developed structural models as a benchmark to describe credit spreads. In these models asset volatility is arguably the most important primitive variable for determining distance to default and consequent spreads. In credit markets it is total (i.e., both systematic and idiosyncratic) asset volatility that is relevant for security prices. Thus, credit markets are a natural setting to evaluate the relative importance of measures of asset volatility for security pricing.

We examine three primary sources of information to measure asset volatility. First, we extract information from secondary equity and credit markets to measure equity volatility, debt volatility and their correlations. We derive several measures of historical asset volatility ranging from simplistic deleveraging of historical equity volatility to a complete measure that uses historical return volatilities and historical return correlations (see e.g., Schaefer and Strebulaev, 2008). Second, we extract information from equity option markets. Specifically, we use the implied volatility for at the money put and call options. Third, we extract information from firm financial statements about the volatility of firm's unlevered profitability.

We find that combining information about asset volatility from market based (historical and forward looking) and accounting based (historical) information improves estimates of corporate bankruptcy. Using a large sample of firms with liquid corporate bond data, we find that a one standard deviation change in our market (accounting) based component measures of asset volatility translates to an increase of 5.5 (2.5) percent in the conditional probability of bankruptcy. We further find that market based and accounting based estimates of asset volatility improve explanatory power of cross-sectional credit spread regression models. In unconstrained regression analysis, we find that a one standard deviation change in implied credit spreads based on our market (accounting) based component measures of asset volatility translates to an additional 124 (6) basis points of credit spread. In constrained regression analysis where we incorporate component measures of asset volatility into theoretically justified implied spreads, we find that all component measures of asset volatility are relevant. Specifically, historical market, forward looking market, and historical accounting component measures of asset volatility account for 26.7%, 26.0%, and 20.5% of the cross-sectional variation in credit spreads respectively. We also find some evidence that the relative importance of accounting based measures of asset volatility is greatest for high yield corporate bonds relative to investment grade bonds.

Measures of fundamental volatility have recently been examined in the context of equity option markets (see e.g., Goodman, Neamtiu and Zhang, 2012 and Sridharan, 2012). A limitation of these analyses is that fundamental measures of volatility are related to short dated (less than 90 day) straddle returns. Financial statements are released at a quarterly frequency which makes them a slow moving source of information about volatility. The credit instruments we examine (corporate bonds and CDS) have considerably longer duration, thus making credit spreads a more natural setting to examine the relative importance of market and accounting based component measures of asset volatility.

To help better understand the relative importance of market based and accounting based component measures of asset volatility we explore the mapping of these respective measures to systematic and idiosyncratic volatility. We find that average within industry pairwise correlations of market measures of returns (both equity and credit market returns) are significantly larger than within industry pairwise correlations of changes in seasonally adjusted accounting rates of return. This suggests that market based measures of asset volatility are more likely to reflect systematic sources of volatility. To further explore this possibility, we form factor mimicking portfolios based on market and accounting based measures of asset volatility. We find that the market based asset volatility factor mimicking portfolio has a significantly higher beta with respect to aggregate asset returns. Together this evidence suggests that combining measures of asset volatility from market based and accounting based measures yields a superior measure of asset volatility due to a combination of systematic and idiosyncratic measures of asset volatility. As discussed earlier, in the context of credit derivatives total asset volatility is the relevant measure, and not just systematic volatility.

The rest of the paper is structured as follows. Section 2 describes our sample selection and research design. Section 3 presents our empirical analysis and robustness tests, and section 4 concludes.

2. Sample and research design

2.1 Secondary credit market data

Our analysis is based on a comprehensive panel of US corporate bond data, which includes all the constituents of (i) Barclays U.S. Corporate Investment Grade Index, and (ii) Barclays U.S. High Yield Index. The data includes monthly returns and bond characteristics from September 1988 to February 2013. We exclude financial firms, with SIC codes between 6000 and 6999. Table 1, Panel A shows the industry composition of the resulting sample, using Barclays Capital's industry definitions. Approximately 35% of the sample firms are consumer products firms. Capital Goods firms and Basic Industry make up for another 20% of the sample.

2.2 Representative bond

Given that corporate issuers often issue multiple bonds and that our analysis is directed at measuring asset volatility of the issuer, we need to select a representative bond for each issuer. To do this, we follow the criteria in Haesen, Houweling and VanZundert (2012) to select a representative bond for each issuer. We repeat this exercise every month for our sample period. The criteria used for identifying the representative bond are selected so as to create a sample of liquid and cross-sectionally comparable bonds. Specifically, we select representative bonds on the basis of (i) seniority, (ii) maturity, (iii) age, and (iv) size.

First, we filter bonds on the basis of seniority. Because most companies issue the majority of their bonds as senior debt, we select only bonds corresponding to the largest rating of the issuer. To do this we first compute the amount of bonds outstanding for each rating category for a given issuer. We then keep only those bonds that belong to the rating category which contains the largest fraction of debt outstanding. This category of bonds tends to have the same rating as the issuer. Second, we then filter bonds on the basis of maturity. If the issuer has bonds with time to maturity between 5 and 15 years, we remove all other bonds for that issuer from the sample. If not, we keep retain all bonds in the sample. Third, we then filter bonds on the basis of time since issuance. If the issuer has any bonds that are at most two years old, we remove all other bonds for that issuer. If not, we keep all bonds from that issuer in the sample. Finally, we then filter on the basis of size. Of the remaining bonds, we pick the one with the largest amount outstanding.

Our resulting sample includes 121,612 unique bond-month observations, corresponding to 6,084 bonds issued by 1,547 unique firms. Sample bonds have an average option adjusted spread (OAS) of 3.33% over the sample period and an average option adjusted duration (OAD) of 5.16 years (Table 1, Panel B).

2.3 Measures of asset volatility

2.3.1 Historical market data

We calculate historical equity volatility using the annualized standard deviation of CRSP realized monthly daily stock returns over the past 252 days, σ_E.

We use market leverage to de-lever historical equity volatility and obtain our first measure of asset volatility:

$$\sigma_A^{NAIVE} = \sigma_E \frac{E}{E+X} \quad (1)$$

where E is the market value of the firm's equity and X is the book value of long term debt plus half of the book value of short term debt (e.g., Bharath and Shumway, 2008).

Our second estimate of historical asset volatility, σ_A^{ω}, combines historical credit and equity market data:

$$\sigma_A^{\omega} = \sqrt{\omega^2\sigma_E^2 + (1-\omega)^2\sigma_D^2 + 2\rho_{D,E}\sigma_E\sigma_D} \quad (2)$$

where $\omega = \frac{E}{E+X}$ is the fraction of asset value attributable to equity, σ_D is the standard deviation of total monthly bond returns from Barcap and $\rho_{D,E}$ is an estimate of the historical correlation between equity and bond returns. We compute the correlation between equity and bond returns for each bond in the representative sample over a period of 12 months. Note that while our selection of a representative bond can change each month for a given issuer, our correlation and volatility measures hold a given bond fixed when looking back in time.

To mitigate noise in our estimate of historical correlations we shrink our estimate of correlation to the average correlation for a given level of credit risk (see e.g., Lok and Richardson, 2011). Specifically, we compute $\rho_{D,E}$ for each issuer as the average correlation for all firms in the same decile of option adjusted credit spread.

Table 1, Panel B presents descriptive statistics for the variables used to deleverage volatility. Sample firms have an average market leverage of approximately 27% (1-0.7324) and exhibit an average correlation between equity and debt returns $\rho_{D,E}$ of 0.2284. We winsorize $\sigma_E, \sigma_A^{NAIVE}$, and σ_A^{ω} at their respective 1st and 99th percentile values.

2.3.2 Forward looking market data

We obtain implied Black-Scholes volatility estimates for at-the-money 91-day call options from the OptionMetrics Ivy DB standardized database.[1] We average the implied volatility for a 91-day put and call option. Based on this implied equity volatility, σ_I, we compute two asset volatility estimates, σ_{AI}^{NAIVE} and σ_{AI}^{w}, using the approaches in (1) and (2), respectively. We winsorize σ_{AI}^{NAIVE} and σ_{AI}^{w} at their respective 1st and 99th percentile values.

2.3.3 Fundamental data

We use two approaches to compute measures of fundamental volatility. Both approaches are designed to measure volatility of unlevered profitability, *RNOA*. First, we use the quantile regression approach described in Konstantinidi and Pope (2012) and Chang, Monahan and Ouazad (2013). Second, we use a simple approach based on historical volatility of seasonally adjusted *RNOA*.

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[1] The standardized implied volatilities are calculated by OptionMetrics using linear interpolation from their Volatility Surface file.

2.3.3.1 Quantile regression approach

This approach consists of using quantile regressions to estimate the quantiles and conditional moments of the distribution of RNOA. Following Konstantinidi and Pope (2012) and Chang, Monahan and Ouazad (2013), we exclude financial firms with SIC codes 6000 to 6999. We estimate coefficients for each percentile using an expanding window approach starting in 1963. In particular, for each year t, we estimate the following regression, using quarterly data from 1963 to t:

$$QUANT_q\left(RNOA_{i,t}\middle|\cdot\right) = \beta_{0,t}^q + \beta_{1,t}^q RNOA_{i,t-1} + \beta_{2,t}^q LOSS_{i,t-1} + \beta_{3,t}^q \left(LOSS_{i,t-1} \times RNOA_{i,t-1}\right) + \beta_{4,t}^q ACC_{i,t-1} + \beta_{5,t}^q PAYER_{i,t-1} + \beta_{6,t}^q PAYOUT_{i,t-1} \qquad (3)$$

This model is similar to the model in Chang et al. (2013) and Hou, Van Dijk, and Zhang (2012), with the exception that we forecast return on net operating assets (*RNOA*) instead of return on equity (*ROE*) and therefore do not include Leverage as an explanatory variable and scale all variables by the average balance of net operating assets (*NOA*) rather than by the average balance of equity. *RNOA* is operating income ('OIADPQ') scaled by the average balance of *NOA*. *NOA* is defined as the sum of common equity, preferred stock, long term debt, debt in current liabilities and minority interests minus cash and short term investments ('CEQQ'+'PSTKQ'+'DLTTQ'+DLCQ'+'MIBQ'-'CHEQ'). *LOSS* is an indicator variable equal to 1 if RNOA is negative and 0 otherwise. *ACC* are the accruals reported by the firm (Δ'ACTQ'-Δ'CHEQ'-(Δ'LCTQ'-Δ'DLCQ'-Δ'TXPQ')-'DPQ'). *PAYOUT* is the dividends paid by the firm ('DVPSX_F'). *PAYER* is an indicator variable equal to 1 if the firm distributed dividends, i.e. *PAYOUT*>0, 0 otherwise. We compute these variables at the end of each quarter, using the most recent four quarters of data.

In unreported analyses, we find the expected relations between our included explanatory variables and future profitability. Specifically, the median quantile regression generates the following results: (i) β_1^{50} is 0.94 consistent with mean reversion in accounting rates of return (e.g., Penman, 1991, and Fama and French, 2000), (ii) β_2^{50} is -0.01 consistent with loss makers having lower levels of future profitability (e.g., Hou, Van Dijk, and Zhang, 2012), (iii) β_3^{50} is -0.14 consistent with faster mean reversion in profitability for loss making firms (e.g., Beaver, Correia and McNichols, 2012), (iv) β_4^{50} is -0.02 consistent with the well documented negative relation between accruals and future firm performance (e.g., Sloan, 1996, and Richardson, Sloan, Soliman and Tuna, 2006), (v) β_5^{50} is 0.02 consistent with dividend paying firms having higher levels of future profitability (e.g., Hou, Van Dijk, and Zhang, 2012), and (vi) β_6^{50} is 0.26 also consistent with firms with higher dividend payout having higher levels of profitability (e.g., Hou, Van Dijk, and Zhang, 2012).

We combine the values of the independent variables in year t with the vector of coefficients, $Ƀ_t^q = \beta_{0,t}^q, \dots, \beta_{6,t}^q$ to obtain out-of-sample estimates of the percentiles for the year t+1. In particular, we obtain a vector of coefficient estimates, $\widehat{Ƀ_t^q}$, for each percentile and sample quarter. Based on this vector, we estimate the expected value of each of the 100 percentiles as $E(\widehat{q_{t+1}}|X_t) = \widehat{Ƀ_t^q} X_t$.

For purposes of estimation of the vector of coefficient estimates, we delete extreme observations of dependent and independent variables. In particular, we delete all observations with $|RNOA_{i,t}|$>2, $|RNOA_{i,t-1}|$>2, $|ACC_{i,t-1}|$>2, $|PAYOUT_{i,t-1}|$>1, $|PAYOUT_{i,t-1}|$<0.

We focus on two measures of conditional volatility for each firm, and year t. The standard deviation of the distribution of quantile estimates,

$\sigma_F = Std\left(E(\widehat{q_{t+1}}|X_t)\right)$, q=1,…, 100, and the difference between the predicted value of the 95th percentile and the predicted value of the 5th percentile, $P95P5 = E(\widehat{95_{t+1}}|X_t) - E(\widehat{5_{t+1}}|X_t)$.

2.3.3.2 Naïve approach

For each quarter we compute *RNOA* as operating income ('OIADPQ') to average *NOA* during the quarter. We estimate the volatility of *RNOA*, σ_F^{NAIVE}, as the standard deviation of seasonally adjusted *RNOA* over the previous 5 years (20 quarters), requiring at least 10 available quarterly observations. Seasonally adjusted *RNOA* for quarter k in year t is computed as[2]:

$$RNOA_{t,k}^{SA} = RNOA_{t,k} - RNOA_{t-1,k} \quad (4)$$

We then compute the standard deviation of seasonally adjusted RNOA over the previous 5 years, requiring a minimum of 10 quarters of data.

$$\sigma_F^{NAIVE} = Std(RNOA_{t,k}^{SA}) \quad (5)$$

Table 1, Panel C reports descriptive statistics for the different volatility measures. These measures exhibit differences in scale. In particular, volatility measures based on financial statement information, σ_F^{NAIVE} and σ_F, are lower, on average, than asset volatility measures based on naïve or weighted deleveraging of historical equity returns or implied equity volatility. We discuss how we deal with differences in scale below when combining our component measures of asset volatility in section 3.2.2.

[2] As an alternative naïve approach, we estimate a time-series model for RNOA and calculate the time-series volatility only for the residual (the stationary component). In particular, we estimate the following regression for each firm: $RNOA_t = \beta_0 + \beta_1 RNOA_{t-1} + \sum_{q=2}^{4} \beta_q I_{qt} + \varepsilon_t$.

Panel D of Table 1 reports the average monthly pairwise correlations across volatility measures. Historical equity volatility, σ_E, is highly correlated with implied volatility, σ_I, [0.8822 (0.9013) Pearson (Spearman) correlation]. The Pearson (Spearman) correlation between these equity volatility measures and debt volatility, σ_D, ranges between 0.3769 and 0.4732 (0.2662 and 0.3381). As a result, the correlations between weighted asset volatilities and the corresponding equity volatility measures are, on average lower than 0.80.

Correlations between accounting based (σ_F, σ_F^{NAIVE}, and $P95P5$) and market based asset volatility measures ($\sigma_A^w, \sigma_A^{NAIVE}, \sigma_{AI}^w$ and σ_{AI}^{NAIVE}) are much lower. The maximum pairwise Pearson (Spearman) correlation between these two types of measures is 0.2491 (0.4223) and the minimum 0.1538 (0.2201).

2.4 Bankruptcy data and distance to default

We estimate the probability of bankruptcy based on a sample of Chapter 7 and Chapter 11 bankruptcies filed between 1980 and the end of 2012. We combine bankruptcy data from four main sources: Beaver, Correia, and McNichols (2012) (BCM)[3]; the New Generation Research bankruptcy database (bankruptcydata.com); Mergent FISD; and the UCLA-Lo Pucki bankruptcy database.

Following Shumway (2001), we winsorize all independent variables at 1% and 99%. To ensure that prediction is made out of sample and to avoid a potential bias of ex post over-fitting the data, we estimate coefficients using an expanding window

[3] Beaver, Correia, and McNichols (2012) combine the bankruptcy database from Beaver, McNichols, and Rhie (2005), which was derived from multiple sources including CRSP, Compustat, Bankruptcy.com, Capital Changes Reporter, and a list provided by Shumway with a list of bankruptcy firms provided by Chava and Jarrow and used in Chava and Jarrow (2004).

approach.[4] We convert the different scores into probabilities as follows: Prob=$e^{score}/1+e^{score}$.

Following Correia, Richardson and Tuna (2012) we use quarterly financial data to compute the default barrier and update market data on a monthly basis to obtain monthly estimates of the probabilities of bankruptcy. Market variables are measured at the end of each month and accounting variables are based on the most recent quarterly information reported before the end of the month. We ensure that all independent variables are observable before the declaration of bankruptcy. Our dependent variable is equal to 1 if a firm files for bankruptcy within 1 year of the end of the month. Following prior literature, we keep the first bankruptcy filing and remove from the sample all months after this filing.

Following Shumway (2001), we estimate probabilities of bankruptcy by using a discrete time hazard model and including three types of observations in the estimation: nonbankrupt firms, years before bankruptcy for bankrupt firms, and bankruptcy years. All of the models are nonlinear transformations of various accounting and market data.

The primary regression model for estimating bankruptcy over the next twelve months is as follows:

$$\Pr(Y_{t+1} = 1) = f\left[ln\left(\frac{V_t}{X_t}\right), Exret_t, ln(E_t), \sigma_{k,t}\right] \quad (6)$$

[4] In particular, to estimate the probability of bankruptcy for calendar year 2011 (January 2011 to December 2011), we combine all the available accounting and market data from January 1980 to December 2009, use it to predict bankruptcy outcomes for January 1981 to December 2010, retain the coefficients, and use them to estimate the probability of bankruptcy for 2011. To obtain an estimate of the probability of bankruptcy for the period from February 2011 to January 2012, we include one more month in the estimation. In particular, we combine all the available accounting and market data from January 1980 to January 2010, use it to predict bankruptcy outcomes for January 1981 to January 2011, and apply the estimated coefficients to accounting and market data available at January 2011.

The dependent variable is equal to 1 if the firm filed for bankruptcy within the following year. $ln\left(\frac{V_t}{X_t}\right)$ is a measure of dollar distance to default barrier (akin to an inverse measure of leverage). We compute V_t as the sum of the market value of the firm's equity and the book value of debt. We compute our default barrier, X_t, as the sum of short-term debt ('DLCQ') and half of long-term debt ('DLTTQ') as reported at the most recent fiscal quarter (see e.g., Bharath and Shumway, 2008). $Exret_t$ is the excess equity return over the risk free rate for the most recent 12 months. $ln(E_t)$ is the log of the market value of equity measured at the start of the forecasting month. $\sigma_{k,t}$ is the respective measure of asset volatility as defined in section 2.3. We estimate equation (6) using various combinations of our measures of asset volatility over different samples to assess the relative importance of market based and accounting based measures of asset volatility in the context of forecasting bankruptcy.

Our priors for equation (6) are as follows: (i) $ln\left(\frac{V_t}{X_t}\right)$ is expected to be negatively associated with bankruptcy likelihood (the further the market value of assets is from the default barrier the lower the likelihood of hitting that barrier in the next twelve months), (ii) $Exret_t$ is expected to be negatively associated with bankruptcy likelihood (assuming there is information content in security prices, decreases in security prices should be associated with increased bankruptcy likelihood), (iii) $ln(E_t)$ is expected to be negatively associated with bankruptcy likelihood (this is well known empirical relation but the ex-ante justification is less clear, some argue that large firms offer better diversification and better realizations of asset values in the event of default), and (iv) $\sigma_{k,t}$ is expected to be positively associated with bankruptcy likelihood (the greater the volatility of the asset value the greater the chance of passing through the default barrier).

2.5 Theoretical Credit Spreads

Our next empirical prediction is dependent on the success of the respective measures of asset volatility in forecasting bankruptcy in the context of equation (6). Given that a measure of asset volatility is useful in forecasting bankruptcy, and under the assumption that security prices in the secondary market are reasonably efficient, we test whether different combinations of measures of asset volatility are able to better explain cross-sectional variation in credit spreads.

We do this analysis with two approaches. First, we estimate an unconstrained cross-sectional regression where we include multiple measures of determinants of credit spreads in a linear model. Second, we estimate a constrained cross-sectional regression where we combine our various measures of asset volatility into measures of distance to default which are in turn mapped to an implied credit spread. A benefit of the constrained approach is that it combines the dollar distance to default, $ln\left(\frac{V_t}{X_t}\right)$, with measures of asset volatility, $\sigma_{k,t}$, to better identify closeness to the default barrier. An unconstrained regression is unable to capture the inherent non-linearity in distance to default.

For the unconstrained approach we estimate the following regression model:

$$OAS_t = \alpha_0 + \alpha_1 ln\left(\frac{V_t}{X_t}\right) + \alpha_3 Exret_t + \alpha_4 ln(E_t) + \sum_{k=5}^{K} \alpha_k \sigma_{k,t} + \Gamma Control_t + \varepsilon_t \quad (7)$$

OAS_t is the option adjusted spread for the respective bond as reported on the Barclays Index. In addition to the determinants of bankruptcy, i.e., $ln\left(\frac{V_t}{X_t}\right)$, $Exret_t$, $ln(E_t)$, and $\sigma_{k,t}$, which are all issuer level determinants of credit risk, we also include issue specific determinants of credit risk that will influence the level of credit spreads. Specifically, our additional controls include: (i) $Rating_t$ which is the issue specific rating (higher rated issues are expected to have higher credit spreads, given that we code ratings to be increasing in risk), (ii) Age_t is the time since issuance (liquidity is decreasing for progressively 'off the run' securities, so we expect credit spreads to be increasing in time since issuance), and (iii) $Duration_t$ is option adjusted duration of the issue (for the vast majority of corporate issuers the credit term structure is upward sloping so we expect credit spreads to increase with duration, see e.g., Helwege and Turner, 1999).

For our constrained approach, we first combine our measures of the dollar distance to default, $ln\left(\frac{V_t}{X_t}\right)$, and the respective measures of asset volatility, $\sigma_{k,t}$, to construct a measure of expected distance to default. This distance to default is then empirically mapped to our bankruptcy data to generate a forecast of physical bankruptcy probability, labelled as $E\left(PD_{it}^{k}\right)$. We estimate this physical bankruptcy probability for each of our asset volatility measures according to equation (8) below:

$$E\left(PD_{it}^{k}\right) = f\left[\frac{ln\frac{V_{A_{i,0}}}{X_{i.t}}}{\sigma_{A,t}\sqrt{t}}\right] \tag{8}$$

We next convert each physical bankruptcy probability into a risk-neutral measure, following the approach described in Kealhofer (2003) and Arora, Bohn, and Zhu (2005). We first cumulate our physical bankruptcy probability, $CPD_{i,t}^{k}$. It is computed directly from $E\left(PD_{it}^{k}\right)$ by cumulating survival probabilities over the relevant number of periods. In particular, $CPD_{i,t}^{k} = 1 - \left(1 - E\left(PD_{it}^{k}\right)\right)^{T}$. We then convert this cumulative physical bankruptcy probability, $CPD_{i,t}^{k}$, to a cumulative risk neutral bankruptcy probability, $CQDF_{i,t}^{k}$. We use a normal distribution to convert physical probabilities of bankruptcy to risk neutral probabilities, following the approach in Crouhy, Galai, and Mark (2000), Kealhofer (2003); and Arora, Bohn and Zhu (2005):

$$CQDF_{i,t}^{k} = N\left[N^{-1}\left[CPD_{i,t}^{k}\right] + \lambda\sqrt{r_{i,t}^{2}}\sqrt{T}\right] \tag{9}$$

The cumulative physical bankruptcy probability is first converted into a point in the cumulative normal distribution. A risk premium is then added. The risk premium is the product of (i) the issuers sensitivity to the market price of risk, as measured by the correlation between the underlying issuer level asset returns and the market index return, $\sqrt{r_{i,t}^{2}}$, (ii) the market price of risk (i.e. the market Sharpe ratio, measured by λ), and (iii) the duration of the credit risk exposure, *T*. The risk modified physical bankruptcy probability is then mapped back to risk neutral space. We set the market Sharpe ratio, λ, equal to 0.5, consistent with the values observed by Kealhofer(2003). We set $\sqrt{r_{i,t}^{2}}$ equal to the correlation between monthly firm stock returns and monthly market returns using a rolling 60 month window. We impose a floor (ceiling) on the estimated correlation at 0.1 (0.7).Finally, we estimate implied (or theoretical) credit spreads as follows:

$$CS_{i,t}^{k} = -\frac{1}{T}ln\left[1 - \left(1 - R_{i,t}\right)CQDF_{i,t}^{k}\right] \tag{10}$$

$R_{i,t}$ is expected recovery rate conditional on bankruptcy, which we set equal to 0.4 for all firms. For the constrained approach we then estimate the following regression model:

$$OAS_t = \sum_{k=1}^{K} \alpha_k \, CS_{\sigma_{k,t}} + \Gamma Control_t + \varepsilon_t \tag{11}$$

Table 1, Panel E reports the average pairwise correlations between the observed credit spread, OAS_t, and the theoretical credit spreads based on each volatility measure. Theoretical spreads based on historical security data or option implied volatility exhibit higher correlation with observed spreads than theoretical spreads based on accounting data. In particular, OAS_t exhibits an average Pearson (Spearman) correlation with accounting based spreads ($CS_{\sigma_F}, CS_{P95P5}, CS_{\sigma_F^{NAIVE}}$) of 0.7002 (0.5333), and an average Pearson (Spearman) correlation of 0.7704 (0.7230) with market based spreads ($CS_{\sigma_A^{NAIVE}}, CS_{\sigma_A^{w}}, CS_{\sigma_{AI}^{NAIVE}}, CS_{\sigma_{AI}^{w}}$).

3. Results

3.1 Bankruptcy forecasting

Table 2 reports the estimation results of regression equation (6). Across all specifications firms we find expected relations for our primary determinants: bankruptcy likelihood is decreasing in (i) distance to default barrier, $ln\left(\frac{V_t}{X_t}\right)$, (ii) recent equity returns, $Exret_t$, and (iii) firm size, $ln(E_t)$.

To assess the relative importance of our different component measures of asset volatility, we first examine each measure individually after controlling for the same issuer level determinants of bankruptcy. Across models (1) to (5) in Table 2 we find that all of the component measures of asset volatility are significantly positively associated with the probability of bankruptcy. These regression specifications are unconstrained so we include each of the respective component measures of asset volatility separately and do not attempt to combine together different volatility measures. In our constrained specifications later we combine the component measures of asset volatility together.

To provide a sense of the relative economic significance across the component measures of asset volatility, we report in panel B of Table 2 the marginal effects for each explanatory variable. Specifically, we hold each explanatory variable at its average value and report the change in probability of bankruptcy for a one standard deviation change for the respective explanatory variable relative to the full sample unconditional probability of bankruptcy. For example, column (1) in panel B of Table 2 states that the marginal effect of σ_E is 0.0256. This means that a one standard deviation change in σ_E is associated with a 2.56% increase in bankruptcy probability, relative to the full sample unconditional probability of bankruptcy (0.61%). Comparing marginal effects across explanatory variables reveals that distance to default barrier and recent equity returns appear to be the most economically important explanatory variables. Individually, the most important component measure of asset volatility is σ_I (marginal effect of 0.0624 is the largest in the first 5 columns of panel B of Table 2).

Models (6) to (9) in Table 2 combine different component measures of asset volatility. We do not include σ_E and σ_I in the same specification due to multi-collinearity (panel D of Table 1 shows that σ_E and σ_I have a parametric correlation of 0.8822). In model (6) we start with issuer level determinants ($ln\left(\frac{V_t}{X_t}\right)$, $Exret_t$, and $ln(E_t)$) and σ_I. We then add a measure of volatility from the credit markets, σ_D. Combining market based measures of asset volatility from the equity and credit markets is superior to examining equity market information alone. Panel B of Table 2 shows that the scaled marginal effect for σ_D is 30 percent as large as that for σ_I. In model (7) when we add our first measure of fundamental volatility, σ_F, we find that all three component measures of volatility are significantly associated with bankruptcy. In terms of relative economic significance σ_D, is 30 percent as large as that for σ_I, and σ_F is 46 percent as large as that for σ_I. Using alternative measures of fundamental volatility in models (8) and (9) we find similar results: combining measures of volatility from market and accounting sources improves explanatory power of bankruptcy prediction models.

3.2 Cross-sectional variation in credit spreads

3.2.1 Unconstrained analysis

Having established the information content of our candidate component measures of asset volatility for bankruptcy prediction, we now turn to assess the information content of the same measures for secondary credit market prices. As discussed in section 2.5, under the assumption that security prices in the secondary market are reasonably efficient, we expect to see that the determinants of bankruptcy prediction models should also be able to explain cross-sectional variation in credit spreads.

Table 3 reports estimates of equation (7). This is our unconstrained analysis of how, and whether, different measures of asset volatility have information content for security prices. We include month fixed effects to control for macroeconomic factors, and as such we do not report an intercept. As discussed in section 2.5, we include additional issue specific measures ($Rating_t$, Age_t, and $Duration_t$) to help control for other known determinants of credit spreads. Of course, it is possible that we are 'throwing the baby out with the bath water' by including these determinants, especially $Rating_t$. For example, the rating agencies may be using algorithms to assess credit risk that spans accounting and market data sources, and as such included rating categories might subsume the ability of this data to explain cross-sectional variation in credit spreads.

Across all models estimated in Table 3 we find expected relations for our primary determinants. Credit spreads are consistently decreasing in (i) distance to default barrier, $ln\left(\frac{V_t}{X_t}\right)$, and (iii) firm size, $ln(E_t)$. Credit spreads are consistently increasing in (i) credit rating (scaled to take higher values for higher yielding issues),

$Rating_t$, and (iii) time since issuance, Age_t. Recent excess equity returns, $Exret_t$, is usually negative across different models but is rarely significant at conventional levels. Option adjusted duration, $Duration_t$, is either negatively or positively associated with credit spreads: its effect is dependent upon the included explanatory variables (once σ_D is included the relation turns negative).

Models (1) to (5) in Table 3 examine each of our component measures of asset volatility separately. Individually, each of our component measures of asset volatility is significantly positively associated with credit spreads. To provide a sense of the relative economic significance across the component measures of asset volatility, we also report in panel B of Table 3 the marginal effects for each explanatory variable. Similar to the marginal effects reported in Table 2, we report the change in credit spreads for a one standard deviation change for the respective explanatory variable relative to the full sample unconditional mean credit spread. Individually, the most important component measure of asset volatility is σ_I (marginal effect of 0.6262 is the largest in the first 5 columns of panel B of Table 3).

Models (6) to (9) in Table 3 combine different component measures of asset volatility. As in Table 2, we do not include σ_E and σ_I in the same specification due to multi-collinearity concerns. In model (6) we add a measure of volatility from the credit markets, σ_D. Consistent with the results in Table 2, combining market based measures of asset volatility from the equity and credit markets is superior to examining equity market information alone. Panel B of Table 3 shows that the scaled marginal effect for σ_D is 81 percent as large as that for σ_I. In model (7) when we add our first measure of fundamental volatility, σ_F, we find that all three component measures of volatility are significantly associated with bankruptcy, but that the relative importance of σ_F is quite low. In terms of relative economic significanceσ_D, is 81 percent as large as that for σ_I, and σ_F is only 4 percent as large as that for σ_I. Using alternative measures of fundamental volatility in models (8) and (9) we find similar results: combining measures of volatility from market and accounting sources improves explanatory power of credit spreads.

Table 4 reports the results of equation (7) where we allow the regression coefficients to vary for Investment Grade (IG) and High Yield (HY) issuers. For the sake of brevity we only report the differential coefficients for HY issuers. As expected the HY indicator variable is strongly significantly positive reflecting the higher risk of HY issuers relative to IG issuers. Across the various specifications there is consistent evidence that the primary determinants of credit spreads are stronger for HY issuers: credit spreads are more strongly decreasing in firm size, distance to default and recent excess equity returns for HY issuers relative to IG issuers. We find that market based component measures of asset volatility, σ_E and σ_I, are also more strongly associated with credit spreads for HY issuers. Finally, there is only weak evidence that component measures of asset volatility based on fundamentals are more important for HY issuers (only the naïve measure, σ_F^{NAIVE}, is significant across models (7) to (9) in panel A of Table 4).

3.2.2 Constrained analysis

We now assess the relative information content of the different component measures of volatility in a constrained specification. As described in section 2.5 and equation (8), we combine component measures of asset volatility with dollar distance to default to identify a distance to default barrier in standard deviation units. We then calibrate the various distance to default measures to an expected physical default probability which is converted to an implied spread as per equations (9) and (10). We thus generate k different theoretical spreads where the difference is attributable to the use of different component measures of volatility. This approach is arguably superior to the unconstrained analysis discussed in section 3.2.1 because of the inherent non-linearity between dollar distance to default barrier and asset volatility. Two firms could have the same dollar distance to default but typically vary in terms of asset volatility. It is the ratio of these two measures that matters for determining physical bankruptcy probability, not the two measures separately.

An empirical challenge that we face is combining different component measures of volatility that vary in scale. As can be seen from panel C of Table 1, the market based component measures of asset volatility have higher average values and higher standard deviations relative to the accounting based measures of asset volatility. To handle these differences in scale when we combine component measures of asset volatility we first standardize each accounting based component measure and rescale them such that they have the same mean and standard deviation as the market based component measures of asset volatility to which they will be combined with. As a result of this process we end up with seven different measures of theoretical spreads. We have four market based theoretical spreads: (i) CS_{σ_E} which is based on historical equity volatility alone, (ii) CS_{σ_i} which is based on implied equity volatility alone, (iii) $CS_{\sigma_A^\omega}$ which is based on a weighted combination of historical equity volatility and historical credit volatility, and (iv) $CS_{\sigma_{AI}^\omega}$ which is based on a weighted combination of implied equity volatility and historical credit volatility. We have three accounting based theoretical spreads: (i) CS_{σ_F} which is based on a parametric estimate of fundamental volatility, (ii) CS_{P95P5} which is based on a non-parametric estimate of fundamental volatility, and (iii) $CS_{\sigma_F^{NAIVE}}$ which is based on historical fundamental volatility.

Table 5 reports regression results of equation (11). We include a set of month fixed effects and as such do not report a regression intercept. Model (1) shows that theoretical spreads based on a simple measure of historical equity volatility is able to explain 71 percent of the variation in credit spreads, and the regression coefficient is 0.596, which is less than one consistent with the well-known result that structural models tend to under forecast credit spreads (e.g., Huang and Huang, 2008).

Before assessing the incremental improvement in explanatory power from alternative component measures of asset volatility, we first use our secondary credit market data to apply a 'hair-cut' to the book value of debt used as an approximation for the market value of assets. While fixed and floating rate debt is usually issued at par, over time changes in credit risk of the issuer tend to create situations where the market value of debt is below the book value of debt, this our estimate of market value of assets is likely to be too high. A consequence of this is that any implied spread will be too low. To correct for this error we take a fraction of the book value of debt as our approximation for the market value of debt using the current credit spread on the representative bond we have selected for each issuer. Specifically, we multiple the book value of debt by $\frac{1}{(1+OAS)^5}$, which assumes an average duration of around five years which is consistent with the average option adjusted duration for our sample as reported in panel B of Table 1. Model (2) of Table 5 shows that once we incorporate this 'hair-cut' we observe two noticeable and expected changes. First, we see the explanatory power of the regression increase to an R^2 of 76.3 percent. Second, we see the regression coefficient increase to 0.686 which is as expected as by removing an upward bias in our estimate of asset value we under forecast credit spreads to a lesser extent.

Models (3) to (12) in Table 5 consider various combinations of our theoretical spreads. When we include both historical and forward looking equity volatility information in model (4) we find that historical equity dominates. More importantly, in model (6) when we include theoretical spreads based on combined component measures of asset volatility we see that both historical equity volatility and forward looking equity information are important. Models (7) to (12) then add the three different accounting based theoretical credit spread measures. Across all three accounting based measures we see evidence of the joint role of market and accounting based component measures of asset volatility. In all specifications, accounting based volatility measures are statistically significant.

To help visualize the relative importance of component measures of asset volatility for credit spreads, each month we sort issuers into deciles based on $CS_{\sigma_A^{\omega}}$ and CS_{σ_F}. These sorts are independent as the two measures of theoretical spreads are highly correlated (Pearson correlation of 0.93 reported in Panel E of Table 1). We then plot the median credit spread across the resulting 100 cells. It is clear that as we move from the back to the front of Figure 1 (that is increasing theoretical spreads based on market information) we see credit spreads increase. It is also clear that as we move from left to right of Figure 1 (that is increasing theoretical spreads based on accounting information) we see also credit spreads increase. What is most interesting, though, is the increase in credit spreads along the main diagonal: when information from the market and financial statements are suggesting higher asset volatility then credit spreads are indeed higher. A combination of market and accounting based measures of asset volatility is superior to either source alone. We find similar patterns if we instead sort issuers on the basis of $CS_{\sigma_{AI}^{\omega}}$ as an alternative market based measure of theoretical spreads, and either CS_{P95P5} or $CS_{\sigma_F^{NAIVE}}$ as alternative accounting based measures of theoretical spreads. For the sake of brevity we do not show these figures, but they are available upon request.

Table 6 reports the results of equation (7) where we allow the regression coefficients to vary for Investment Grade (IG) and High Yield (HY) issuers. As before in Table 4, for the sake of brevity we only report the differential coefficients for HY issuers. In contrast to the evidence in Table 4, we now find stronger evidence that accounting based component measures of asset volatility are more relevant to explain cross-sectional variation in credit spreads for HY issuers relative to IG issuers. This inference is true for all three theoretical spreads using accounting based component measures of asset volatility: models (8), (10), and (12) in Table 6 all show a statistically significant positive coefficient on the interaction terms.

3.3 Systematic vs. idiosyncratic volatility

The empirical analysis this far suggests that combining market and accounting information generates superior estimates of asset volatility for forecasting bankruptcy and also for explaining cross-sectional variation in credit spreads. To help better understand the relative information content of each component measure of asset volatility we assess the extent to which market and accounting measures of returns are attributable to systematic versus idiosyncratic factors.

As discussed in the introduction, total volatility is the relevant measure of volatility for explaining derivative prices. This is readily apparent from inspection of equations (9) and (10). Equation (10) is a contingent claims representation of credit spreads. Spreads are (i) increasing in the cumulative risk neutral bankruptcy probability, $CQDF_{i,t}^{k}$, and (ii) increasing in the expected loss given bankruptcy, $(1 - R_{i,t})$. As per equation (9), the primary determinant of $CQDF_{i,t}^{k}$ is the cumulative physical bankruptcy probability, $CPD_{i,t}^{k}$, which, in turn, is a function of the expected physical bankruptcy probability, $E\left(PD_{it}^{k}\right)$. Equation (8) shows that total asset volatility is a key determinant of $E\left(PD_{it}^{k}\right)$. Thus, estimates of total volatility, and not just systematic volatility, are relevant for understanding credit spreads. However, in addition to total asset volatility, systematic risk is also relevant for understanding credit spreads. This is because we need to map physical bankruptcy probabilities to risk neutral bankruptcy probabilities. Equation (9) shows one approach to do this which assumes a single factor pricing model. More generally, firm sensitivity to risk and the market price of said risk, will map physical bankruptcy probabilities to risk neutral bankruptcy probabilities. Thus, sources of systematic risk (e.g., correlation of asset returns to aggregate asset returns) represent an additional source of volatility that will be priced in credit spreads. In credit markets both systematic and idiosyncratic sources of asset volatility are relevant for determining credit spreads, and given equations (9) and (10) systematic sources will be relatively more important (as it affects both asset volatility and the risk premium).

It is quite possible that measures of asset volatility extracted from financial statements capture relatively more idiosyncratic information relative to market based measures of asset volatility. Market based measures of asset volatility are based on changes in prices in equity and credit markets, which in turn, are driven by changes in expectations of cash flows and changes in expectations of discount rates. Arguably, the latter component is a larger determinant of changes in security prices, especially as the return interval is shortened (e.g., Richardson, Sloan and Yu, 2012). In contrast, measures of volatility based on changes in accounting rates of return are a direct consequence of applying accounting rules to firm transactions over a given fiscal period. These accounting measures are mostly backward looking in terms of the cash flow generation and are only indirectly capturing changing expectations of discount rates (e.g., Penman, Reggiani, Richardson, and Tuna, 2013).

To assess the difference in the mapping of market and accounting based measures of asset volatility to systematic and idiosyncratic sources, we first examine the strength of commonality across market and accounting based measures of returns. We do this by computing pair-wise correlations between market and accounting based measures of returns for all possible pairs within each Fama-French sector (11 sectors in total excluding financials). We estimate these correlations using return measures over non-overlapping three month intervals, and require at least 20 three month periods for each pair. For example, if there are 500 issuers in the manufacturing sector but only 133 issuers have at least twenty three month periods to compute all three return measures (equity, credit, and accounting), we then compute all 133*132/2 = 8,778 pairs. We end up with fewer than 8,788 pairs, as not all issuers have twenty non-overlapping three month returns for all three return measures. In Table 7 we report the resulting average pairwise correlations. In Panel A we average across all industries and in Panel B we report results by industry. In both panels there is a striking difference in the average pairwise correlation: equity and credit market based return measures have a much higher average pairwise correlation than accounting based measures of returns (between 0.38 and 0.46 for market based for the pooled sample and only 0.09 for accounting based for the pooled sample). This is a necessary condition for accounting and market based return measures to differentially reflect systematic and idiosyncratic sources of risk. In unreported tests, we also identify the first principal component for a balanced panel of 500 issuers that have non-missing credit, equity and accounting rates of return for our time period. We find that the first principal component explains 22.7 (35.3) percent of the cross-sectional variation in equity (credit) returns, but only 13.2 percent for accounting rates of return.

The results in Table 7 suggest that the market based measures are more likely to reflect systematic sources of volatility. To address more directly the extent to which market based measures of asset volatility reflect systematic sources more so than accounting based measures of asset volatility, we perform standard asset pricing tests. First, we construct multiple factor mimicking portfolios on the basis of our component measures of asset volatility. For the sake of brevity we only discuss and tabulate one market based measure, σ_A^ω, and one accounting based measure, σ_F, but results are similar with alternative measures. To abstract away from the effects of leverage, we first sort issuers each month into terciles on the basis of market leverage. Then, within each leverage terciles we sort on the two composite measures of asset volatility, σ_A^ω and σ_F. We then form factor mimicking portfolios each month by equal weighting the difference in asset returns across the top and bottom volatility portfolios across the three leverage terciles, labelled as $HML_{\sigma_A^\omega}$ and HML_{σ_F} respectively. We compute asset returns by weighting the respective equity and credit return each month by the respective weight of equity and credit in the capital structure of the firm. Panel A (B) of Table 8 reports the average annualized asset returns and associated Sharpe ratios across the 9 cells for the market (accounting) based component measure of asset volatility. The resulting $HML_{\sigma_A^\omega}$ and HML_{σ_F} factor mimicking portfolios have similar unconditional Sharpe ratios (about 0.2). We next estimate the asset beta of these two factor mimicking portfolios by projecting the monthly portfolio asset returns onto contemporaneous aggregate asset returns (measured as the equally weighted asset returns for issuers in our sample). The data used for this analysis covers 244 months from August 1992 to November 2012. Figure 2 contains the scatter plots for the two factor mimicking portfolios along with the respective OLS regression line. The bold (shaded) data points and lines represent $HML_{\sigma_A^\omega}$ (HML_{σ_F}) respectively. Tests of difference reveal a strong difference in asset beta: the asset beta for the $HML_{\sigma_A^\omega}$ portfolio is 0.73, and the asset beta for the HML_{σ_F} portfolio is 0.15, test statistic for difference is 11.29 significant at conventional levels). Results are similar if we instead extract a credit or equity return beta as opposed to the asset beta that we show in Figure 2.

The evidence in Tables 7 and 8, and Figure 2, show that market based measures of asset volatility capture relatively more systematic sources of volatility and accounting based measures of asset volatility capture more idiosyncratic sources of volatility. This provides a basis for why both market and accounting based measures were useful in generating estimates of asset volatility for forecasting bankruptcy and also for explaining cross-sectional variation in credit spreads. Further, as equations (9) and (10) note, systematic sources of volatility (and hence risk) are relatively more important as they are relevant for measuring asset volatility (key input to distance to default) and assessing the risk premium to convert risk neutral bankruptcy probabilities to credit spreads.

3.4 Extensions

3.4.1 CDS data

In Table 9 we report regression estimates of a modified version of equation (11) where we use credit spreads from CDS contracts rather than bonds. As with our previous spread level regressions, we include a set of month fixed effects and as such do not report a regression intercept. A benefit of this approach is that the credit spread is a cleaner representation of credit risk, but a disadvantage is the shorter time period for which this data is available (2003 to 2012 only). Because we are examining cross-sectional variation in 5 year CDS spreads, $CDS5Y_t$, we no longer need to control for issue specific characteristics such as Age_t and $Duration_t$. All 5 year CDS contracts have the same seniority, the same time since issuance (we only examine 'on the run' contracts), and the same tenor (5 years). Thus, we estimate the following model:

$$CDS5Y_t = \sum_{k=1}^{K} \alpha_k \, CS_{\sigma_{k,t}} + \varepsilon_t \qquad (12)$$

Our sample size decreases from 57,010 bond-months examined in Table 5 to 30,115 CDS-months examined in Table 9. Despite the smaller sample size, we find striking results with this alternative sample. Models (1) to (4) show that theoretical spreads based on equity market information are able to explain up to 48.5 percent of the cross-sectional variation in credit spreads. Models (5) and (6) show that by combining component measures of asset volatility generates theoretical spreads that can explain a greater fraction of the cross-sectional variation in credit spreads (the R^2 increases to 55.5 percent for model (6)). Strikingly, our measure of theoretical spread using fundamental volatility alone can explain 57.6 percent of the cross-sectional variation in credit spreads (see model (7)). Finally, including both market and accounting based measures of asset volatility yields theoretical spreads that can explain even more of the cross-sectional variation in credit spreads: R^2 of 62.7 percent in model (8) and R^2 of 62.6 percent in model (10).

4. Conclusion

In this paper we evaluate alternative measures of asset volatility using information from (i) historical security returns (both equity and credit), (ii) implied volatilities extracted from equity options, and (iii) financial statements. We find that combining component measures of asset volatility across these three sources generates superior forecasts of bankruptcy, and in turn, is better able to explain cross-sectional variation in corporate bond and corporate CDS spreads for a large sample of US corporate issuers.

We further show that market based component measures of asset volatility have a greater common component to them as evidenced by greater pairwise correlations between market based measures of returns relative to accounting based measures of returns. This greater comovement of market based measures of returns is strongly evident in differential asset betas of factor mimicking portfolios generated on the basis of market versus accounting based component measures of asset volatility. The market based asset volatility factor mimicking portfolio has a much larger beta to aggregate market returns, suggesting that market based measures reflect systematic sources of volatility and accounting based measures reflect idiosyncratic sources of volatility. Thus, combining market and accounting based measures of asset volatility generates a superior measure of total asset volatility that is relevant for understanding credit spreads.

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Appendix: Variable Definitions

Compustat mnemonics in parenthesis

Panel A: Volatility Measures

Variable	Description
σ_E	Historical equity volatility, the annualized standard deviation of realized daily stock returns over the previous 252 days.
σ_I	Implied volatility, the average of implied Black and Scholes volatility estimates for at-the-money 91-day call and put options (source: Option Metrics Iv DB standardized database).
σ_D	Debt volatility, the standard deviation of total monthly bond returns, computed over the previous 12 months (computed based on Barcap total return).
σ_A^{NAIVE}	Naively deleveraged historical equity volatility, $\sigma_E \frac{E}{E+X}$.
σ_A^W	Weighted historical volatility, $\sqrt{\omega^2\sigma_E^2 + (1-\omega)^2\sigma_D^2 + 2\rho_{D,E}\sigma_E\sigma_D}$.
σ_{AI}^{NAIVE}	Naively deleveraged implied equity volatility, $\sigma_I \frac{E}{E+X}$.
σ_{AI}^W	Weighted implied volatility, $\sqrt{\omega^2\sigma_I^2 + (1-\omega)^2\sigma_D^2 + 2\rho_{D,E}\sigma_I\sigma_D}$.
σ_F	Fundamental volatility, the standard deviation of the estimated RNOA percentiles (RNOA is computed for each quarter as the rolling sum of 'OIADP' for the previous 4 quarters, scaled by the average of the opening and ending balance of NOA over this 4 quarter period).
$P95P5$	The difference between the estimated 95th and 5th percentiles of the RNOA distribution.
σ_F^{NAIVE}	The standard deviation of the difference between quarterly RNOA and RNOA for the same quarter of the previous year, computed over the previous 5 years (requiring a minimum of 10 quarters of data).

Panel B: Credit spreads and other variables used in the estimation of asset volatility and theoretical credit spreads

Variable	Description
OAS	Option adjusted spread (source: Barcap).
OAD	Option adjusted duration (source: Barcap).
X	Book value of short term debt ('DLCC')+0.5* book value of long term debt ('DLTTQ').
E	Market capitalization, calculated as |'PRC'|*'SHROUT' (source: CRSP monthly file).
ω	$\frac{E}{E+X}$, the ratio of market capitalization and the sum of market capitalization and the book value of debt.
$r_{i,t}^2$	Correlation between the firm's monthly equity return and the market value weighted return calculated over the prior 5 years (computed based on the CRSP monthly file).

$\rho_{E,D}$	Average correlation of monthly equity and bond returns, calculated over the prior 12 months for all bonds in the same decile of OAS (computed based on the equity returns from the CRSP monthly file and total bond returns from Barcap).

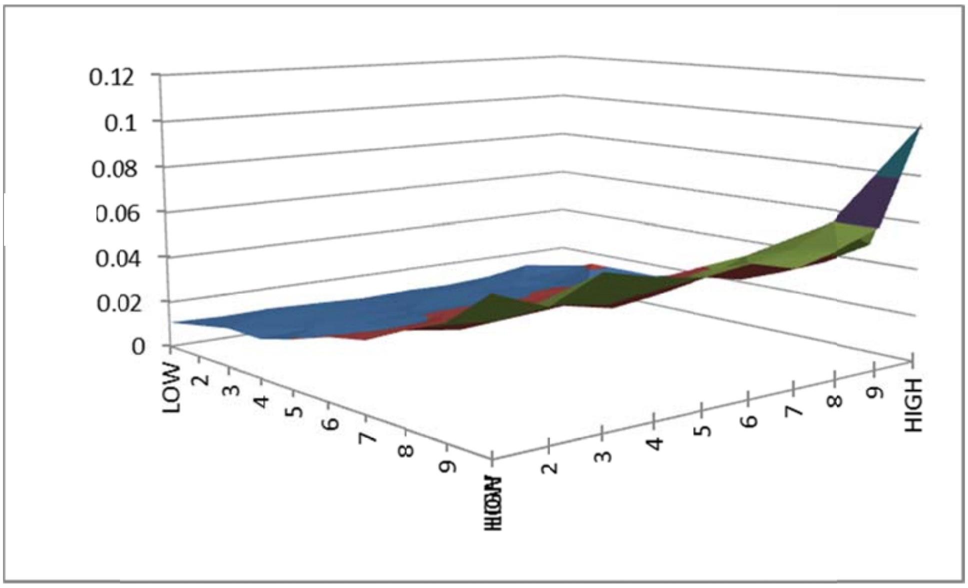
Panel C: Fundamental volatility estimation

Variable	Description
RNOA	Return on net operating assets, defined as the ratio of operating income after depreciation ('OIADP') and the average of the opening and closing balance of net operating assets (NOA).
NOA	Net operating assets, defined as the sum of common equity, preferred stock, long-term debt, debt in current liabilities and minority interests minus cash and short term investments, 'CEQ'+'PSTK'+'DLTT'+'DLC'+'MIB'-'CHE'.
Accruals	Accruals scaled by the average of the opening and closing balance of NOA, with accruals calculated as Δ'ACT'-Δ'CHE'-(Δ'LCT'-Δ'DLC'- Δ 'TXP')-'DP', where 'ACT' are current assets, 'CHE' cash and short term investments, 'LCT' current liabilities, 'DLC' debt in current liabilities, 'TXP' taxes payable and 'DP' depreciation and amortization.
Loss	An indicator variable equal to 1 if RNOA<0, 0 otherwise.
Payer	An indicator variable equal to 1 if Payout>0, 0 otherwise.
Payout	Dividends paid, 'DVPSX_F', scaled by the average opening and closing balances of RNOA.

Panel C: Credit Spreads

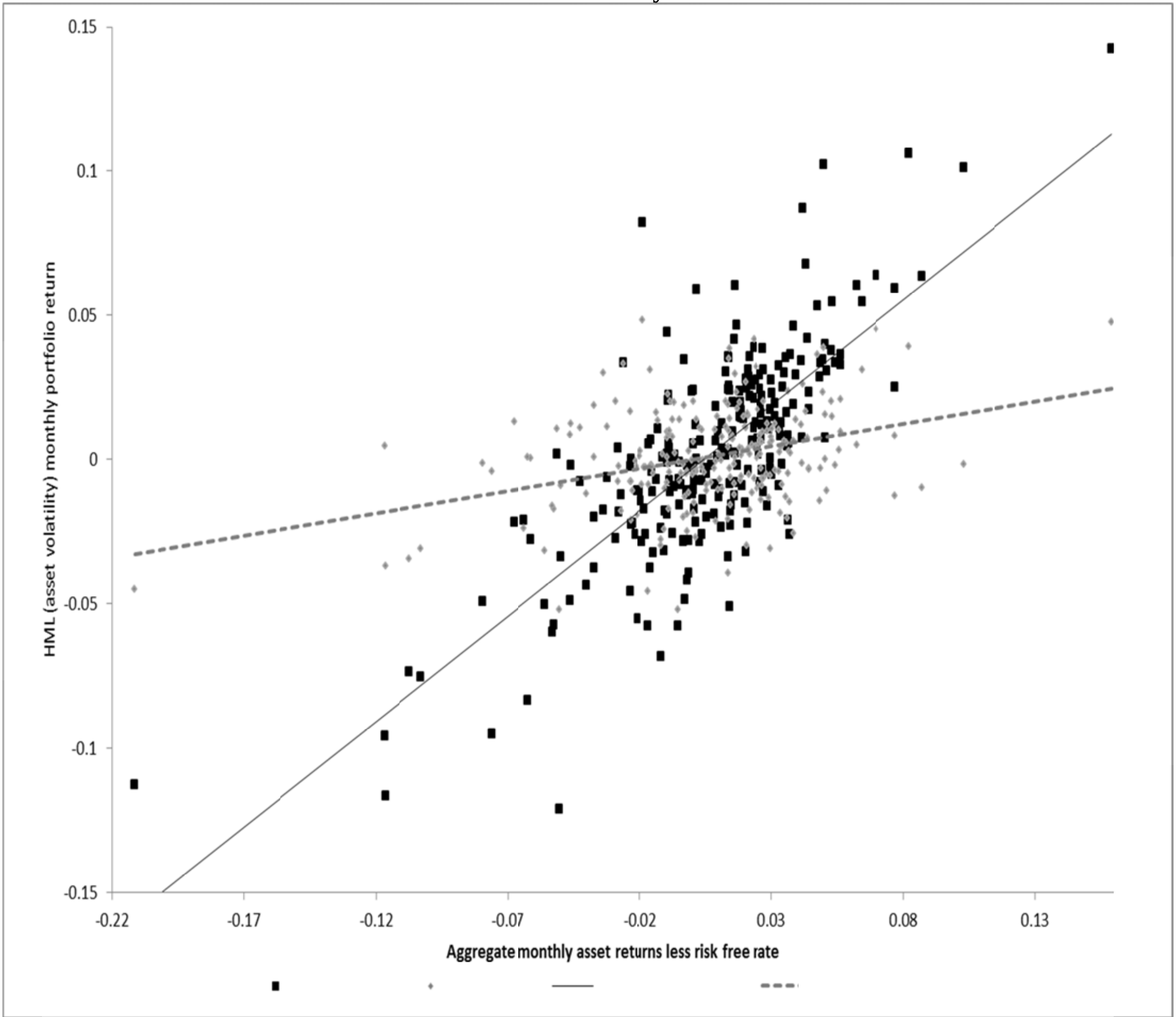
Variable	Description
$CS_{\sigma_E}^{BASE}$	$CS_{\sigma_E}^{BASE} = -\frac{1}{T}[1-(1-R)CQDF]$, where $CQDF = N\left[N^{-1}(CPD) + \lambda\sqrt{r^2}\sqrt{T}\right]$ and $CPD = 1-(1-PD)^T$ and PD is the empirically fitted physical probability of default, resulting from the estimation of the following logistic regression $E(PD) = f\left(\frac{ln\frac{V_A}{X}+\left(\mu-\frac{\sigma_E^2}{2}\right)t}{\sigma_E\sqrt{t}}\right)$.
CS_{σ_K}	Similar to $CS_{\sigma_E}^{BASE}$, except that $E(PD) = f\left(\frac{ln\frac{V_A^{Alt}}{X}+\left(\mu-\frac{\sigma_k^2}{2}\right)t}{\sigma_k\sqrt{t}}\right)$, with $V_A^{Alt} = E + \frac{X}{(1+OAS)^5}$.

Figure 1
Median credit spreads by decile of market based and fundamental based theoretical credit spreads



Each month we sort issuers into deciles based on and . These sorts are independent given that our sorting variables are highly correlated. We then plot the median credit spread across the resulting 100 cells.

Figure 2
HML asset volatility betas



Each month we sort issuers into terciles based on market leverage. Then, within leverage terciles we sort on two composite measures of asset volatility: (i) a measure of asset volatility using market data, and (ii) a measure of asset volatility using accounting data. We form factor mimicking portfolios each month by equal weighting the difference in asset returns across the top and bottom volatility portfolios across the three leverage terciles. We compute asset returns by weighting the respective equity and credit return each month by the respective weight of equity and credit in the capital structure of the firm. In the figure the factor mimicking portfolios are labelled and respectively. We estimate the asset beta of these two factor mimicking portfolios by projecting the monthly returns onto contemporaneous aggregate asset returns (measured as equally weighted asset returns for issuers in our sample). The scatter plots above cover 244 months from August 1992 to November 2012. The bold (shaded) data points represent ( ) respectively.

Table 1
Descriptive statistics

Panel A: Industry composition

	%
Consumer Non-Cyclical	17.40
Consumer Cyclical	17.19
Capital Goods	10.34
Basic Industry	10.17
Energy	9.79
Communications	9.08
Electric	8.12
Technology	6.35
Other Industrial	4.47
Transportation	3.41
Natural Gas	2.52
Other	1.17

Panel B: Bond characteristics

	N	Mean	Std. Dev.	p1	p25	Median	p75	p99
OAS	121,612	0.0333	0.0520	0.0000	0.0096	0.0195	0.0401	0.2454
OAD	121,598	5.1607	2.1992	0.7300	4.0300	5.0000	5.9600	12.5900
X	121,612	2,474	10,689	69	311	744	1,984	21,000
E	121,399	10,971	26,967	36	974	2,978	9,070	146,123
ω	121,399	0.7324	0.2002	0.1081	0.6337	0.7846	0.8847	0.9832
$r_{i,t}^2$	121,612	0.2058	0.1557	0.0005	0.0801	0.1761	0.3023	0.6254
$\rho_{E,D}$	121,612	0.2284	0.1584	0.0500	0.0700	0.2001	0.3556	0.5928

Panel C: Volatility measures

	N	Mean	Std. Dev.	p1	p25	Median	p75	p99
σ_E	120,157	0.4088	0.2387	0.1312	0.2498	0.3446	0.4887	1.3034
σ_I	93,152	0.3906	0.1910	0.1433	0.2605	0.3449	0.4653	1.0850
σ_D	92,786	0.0905	0.1151	0.0133	0.0429	0.0582	0.0877	0.6353
σ_A^{NAIVE}	120,055	0.2753	0.1365	0.0722	0.1825	0.2492	0.3365	0.7564
σ_A^W	93,113	0.2832	0.1216	0.0909	0.2002	0.2632	0.3413	0.6908
σ_{AI}^{NAIVE}	92,159	0.2912	0.1510	0.0929	0.1904	0.2574	0.3494	0.8580
σ_{AI}^W	71,424	0.2925	0.1293	0.0993	0.2049	0.2678	0.3509	0.7346
σ_F	118,162	0.0584	0.1494	0.0142	0.0319	0.0447	0.0596	0.2573
σ_F^{NAIVE}	114,408	0.0306	0.0660	0.0027	0.0087	0.0153	0.0279	0.3625
$P95P5$	118,162	0.1934	0.5242	0.0437	0.1041	0.1468	0.1956	0.8834

Panel D: Correlations across volatility measures

	σ_E	σ_I	σ_D	σ_A^{NAIVE}	σ_{AI}^{NAIVE}	σ_A^W	σ_{AI}^W	σ_F	$P95P5$	σ_F^{NAIVE}
σ_E	1	0.8822	0.3769	0.6335	0.6073	0.7873	0.7543	0.0515	0.0433	0.1643
σ_I	0.9013	1	0.4732	0.5439	0.6566	0.6820	0.8016	0.0884	0.0803	0.1661
σ_D	0.2662	0.3381	1	-0.0022	0.0780	0.2813	0.3265	0.0463	0.0397	0.0714
σ_A^{NAIVE}	0.6868	0.6218	0.0151	1	0.8984	0.9102	0.8376	0.1551	0.1538	0.2121
σ_{AI}^{NAIVE}	0.6563	0.7204	0.0910	0.9007	1	0.8451	0.9272	0.1745	0.1708	0.2491
σ_A^W	0.8038	0.7228	0.1750	0.9246	0.8574	1	0.9030	0.1764	0.1736	0.2131
σ_{AI}^W	0.7605	0.8284	0.2115	0.8537	0.9473	0.9036	1	0.1932	0.1879	0.2451
σ_F	0.0188	0.0806	0.0026	0.2201	0.2725	0.2288	0.2629	1	0.9989	0.4071
$P95P5$	0.0024	0.0603	-0.0104	0.2204	0.2684	0.2255	0.2550	0.9977	1	0.4043
σ_F^{NAIVE}	0.3533	0.3523	0.0856	0.3731	0.4101	0.3956	0.4223	0.2121	0.2087	1

Panel E: Correlations across theoretical measures

	OAS	$CS_{\sigma_E}^{BASE}$	CS_{σ_E}	CS_{σ_i}	$CS_{\sigma_A^{NAIVE}}$	$CS_{\sigma_{Ai}^{NAIVE}}$	$CS_{\sigma_A^{\omega}}$	$CS_{\sigma_{AI}^{\omega}}$	CS_{σ_F}	CS_{P95P5}	$CS_{\sigma_F^{NAIVE}}$
OAS	1	0.7034	0.7395	0.7507	0.7598	0.7775	0.7721	0.7720	0.6970	0.6956	0.7079
$CS_{\sigma_E}^{BASE}$	0.7141	1	0.9811	0.9614	0.8049	0.8635	0.9481	0.9353	0.8977	0.8969	0.8922
CS_{σ_E}	0.7186	0.9987	1	0.9756	0.8445	0.9138	0.9816	0.9731	0.9440	0.9434	0.9383
CS_{σ_i}	0.7158	0.9687	0.9708	1	0.8529	0.9246	0.9567	0.9710	0.9308	0.9304	0.9272
$CS_{\sigma_A^{NAIVE}}$	0.6890	0.9443	0.9465	0.9161	1	0.9408	0.8872	0.8761	0.8232	0.8229	0.8282
$CS_{\sigma_{Ai}^{NAIVE}}$	0.7208	0.9342	0.9367	0.9699	0.9543	1	0.9464	0.9609	0.8985	0.8979	0.8986
$CS_{\sigma_A^{\omega}}$	0.7396	0.9761	0.9774	0.9430	0.9832	0.9554	1	0.9884	0.9310	0.9300	0.9283
$CS_{\sigma_{AI}^{\omega}}$	0.7426	0.9472	0.9495	0.9803	0.9448	0.9955	0.9608	1	0.9344	0.9335	0.9324
CS_{σ_F}	0.5253	0.8075	0.8128	0.8203	0.6930	0.7172	0.7169	0.7308	1	0.9999	0.9709
CS_{P95P5}	0.5222	0.8067	0.8120	0.8196	0.6920	0.7161	0.7155	0.7295	0.9998	1	0.9712
$CS_{\sigma_F^{NAIVE,}}$	0.5523	0.8201	0.8247	0.8335	0.7089	0.7368	0.7363	0.7519	0.9398	0.9405	1

Correlations are computed for each of the months for which we have data. Correlations are based on the largest possible sample size for each pair of default forecasts. Reported correlations are averages across the months in the sample. Average Pearson correlations are reported above the diagonal and average Spearman correlations are reported below the diagonal. Variable definitions are provided in the appendix.

Table 2
Probability of Bankruptcy

$$\Pr(Y_{t+1} = 1) = f\left[ln\left(\frac{V_t}{X_t}\right), Exret_t, ln(E_t), \sigma_{k,t}\right] \quad (6)$$

Panel A: Regression analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-0.189	-1.957*	1.095	1.105	0.878	-1.987*	-1.942*	-1.940*	-1.935*
	(-0.20)	(-1.82)	(1.48)	(1.50)	(1.18)	(-1.84)	(-1.78)	(-1.78)	(-1.77)
$ln\left(\frac{V}{X}\right)$	-2.151***	-1.776***	-2.446***	-2.447***	-2.516***	-1.645**	-1.713**	-1.713**	-1.819**
	(-3.00)	(-2.58)	(-3.39)	(-3.39)	(-3.41)	(-2.39)	(-2.42)	(-2.42)	(-2.45)
Exret	-1.103**	-0.591	-0.947*	-0.947*	-0.845	-0.823**	-0.817**	-0.817**	-0.757**
	(-2.15)	(-1.54)	(-1.67)	(-1.67)	(-1.55)	(-2.28)	(-2.26)	(-2.26)	(-2.11)
$ln(E)$	-0.433***	-0.333**	-0.512***	-0.512***	-0.482***	-0.341***	-0.343***	-0.343***	-0.327**
	(-3.36)	(-2.58)	(-3.73)	(-3.73)	(-3.47)	(-2.61)	(-2.60)	(-2.60)	(-2.45)
σ_E	1.001**								
	(2.18)								
σ_I		2.233***				1.866***	1.787***	1.791***	1.699***
		(4.03)				(3.43)	(3.26)	(3.27)	(3.08)
σ_F			1.600***				1.290***		
			(3.84)				(3.37)		
$P95P5$				0.459***				0.370***	
				(3.95)				(3.41)	
σ_F^{NAIVE}					4.232***				3.042**
					(4.29)				(2.51)
σ_D						1.107*	1.057*	1.058*	0.966
						(1.94)	(1.85)	(1.85)	(1.64)
Nobs	67,373	67,373	67,373	67,373	67,373	67,373	67,373	67,373	67,373
Pseudo-R2	0.2743	0.2935	0.2747	0.2745	0.2817	0.2978	0.3020	0.3019	0.3049

Panel B: Marginal effects

	(1)	(2)	(3)	(4)	(5)	(6)	*(7)*	(8)	(9)
Effect of a one standard deviation change on the probability of bankruptcy scaled by the unconditional probability of bankruptcy one year ahead									
$ln\left(\frac{V}{X}\right)$	-0.2628	-0.2623	-0.2459	-0.2461	-0.2407	-0.2620	-0.2599	-0.2602	-0.2593
Exret	-0.1347	-0.0873	-0.0952	-0.0952	-0.0808	-0.1311	-0.1240	-0.1241	-0.1079
$ln(E)$	-0.0529	-0.0491	-0.0514	-0.0515	-0.0461	-0.0544	-0.0520	-0.0521	-0.0466
σ_E	0.0256								
σ_I		0.0624				0.0562	0.0513	0.0514	0.0458
σ_F			0.0195				0.0238		
$P95P5$				0.0194				0.0237	
σ_F^{NAIVE}					0.0274				0.0294
σ_D						0.0167	0.0152	0.0152	0.0131

Variable definitions are provided in Appendix. Standard errors are clustered by firm and month.
Marginal effects are reported as the marginal increase in the probability of bankruptcy as each of the explanatory variables increases by one standard deviation, scaled by the unconditional probability of bankruptcy one year ahead.

Table 3

Pooled regressions of OAS levels on components of theoretical spreads : unconstrained analysis

$$OAS_t = \alpha_0 + \alpha_1 ln\left(\frac{V_t}{X_t}\right) + \alpha_3 Exret_t + \alpha_4 ln(E_t) + \sum_{k=5}^{K} \alpha_k \sigma_{k,t} + \Gamma Control_t + \varepsilon_t \quad (7)$$

Panel A: Regression analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$ln\left(\frac{V}{X}\right)$	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.002***	-0.002***	-0.002***	-0.002***
	(-8.91)	(-9.53)	(-6.15)	(-6.13)	(-6.60)	(-6.07)	(-6.39)	(-6.37)	(-6.58)
Exret	-0.008*	0.005	-0.002	-0.002	-0.001	-0.004	-0.004	-0.004	-0.004
	(-1.96)	(1.61)	(-0.25)	(-0.26)	(-0.20)	(-1.46)	(-1.44)	(-1.44)	(-1.40)
$ln(E)$	-0.003***	-0.002***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(-5.97)	(-4.69)	(-6.07)	(-6.06)	(-6.13)	(-7.79)	(-7.84)	(-7.84)	(-7.91)
Rating	0.002***	0.002***	0.004***	0.004***	0.004***	0.001***	0.001***	0.001***	0.001***
	(8.64)	(7.69)	(17.18)	(17.17)	(17.17)	(6.19)	(6.10)	(6.10)	(5.72)
Age	0.000**	0.000***	0.000***	0.000***	0.000***	0.000**	0.000**	0.000**	0.000**
	(2.42)	(3.21)	(2.89)	(2.89)	(2.98)	(2.04)	(2.00)	(2.00)	(2.05)
Duration	0.000	0.000	0.000**	0.000**	0.000**	-0.001***	-0.001***	-0.001***	-0.001***
	(1.49)	(1.24)	(2.30)	(2.31)	(2.38)	(-4.24)	(-4.28)	(-4.28)	(-4.25)
σ_E	0.067***								
	(10.85)								
σ_I		0.095***				0.065***	0.065***	0.065***	0.064***
		(14.49)				(11.97)	(11.97)	(11.97)	(11.90)
σ_F			0.012***				0.004**		
			(2.89)				(2.49)		
$P95P5$				0.003***				0.001**	
				(2.93)				(2.39)	
σ_F^{NAIVE}					0.038***				0.015
					(2.82)				(1.53)
σ_D						0.104***	0.104***	0.104***	0.104***
						(6.89)	(6.88)	(6.88)	(6.92)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	67,236	67,236	67,236	67,236	67,236	67,236	67,236	67,236	67,236
R2	0.630	0.670	0.538	0.538	0.542	0.723	0.723	0.723	0.724

Panel B: Marginal effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$ln\left(\frac{V}{X}\right)$	-0.1188	-0.1188	-0.1188	-0.1188	-0.1188	-0.0594	-0.0594	-0.0594	-0.0594
Exret	-0.0318	0.0199	-0.0079	-0.0079	-0.0040	-0.0159	-0.0159	-0.0159	-0.0159
$ln(E)$	-0.1497	-0.0998	-0.1497	-0.1497	-0.1497	-0.1497	-0.1497	-0.1497	-0.1497
$Rating$	0.2576	0.2576	0.5152	0.5152	0.5152	0.1288	0.1288	0.1288	0.1288
Age	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$Duration$	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0767	-0.0767	-0.0767	-0.0767
σ_E	0.4903								
σ_I		0.6262				0.4284	0.4284	0.4284	0.4218
σ_F			0.0506				0.0169		
$P95P5$				0.0439				0.0146	
σ_F^{NAIVE}					0.0890				0.0351
σ_D						0.3451	0.3451	0.3451	0.3451

Variable definitions are provided in Appendix. Standard errors are clustered by firm and month.

Marginal effects are reported as the marginal increase in option adjusted credit spreads as each of the explanatory variables increases by one standard deviation.

Table 4
Cross-sectional partitions : unconstrained analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
HY	0.025***	0.000	0.090***	0.090***	0.087***	0.010**	0.010**	0.010**	0.012**
	(3.72)	(0.04)	(10.38)	(10.39)	(10.36)	(2.05)	(2.12)	(2.12)	(2.49)
$ln\left(\frac{V}{X}\right) * HY$	-0.008***	-0.006***	-0.015***	-0.015***	-0.016***	-0.002***	-0.003***	-0.003***	-0.003***
	(-7.92)	(-6.23)	(-8.68)	(-8.67)	(-9.32)	(-2.81)	(-2.91)	(-2.90)	(-4.04)
Exret$*$ HY	-0.010**	0.001	0.006	0.006	0.007	-0.008***	-0.008***	-0.008***	-0.008***
	(-2.41)	(0.24)	(0.96)	(0.96)	(1.02)	(-2.80)	(-2.80)	(-2.80)	(-2.74)
$ln(E) * HY$	-0.002***	-0.001	-0.006***	-0.006***	-0.006***	-0.002***	-0.002***	-0.002***	-0.002***
	(-2.92)	(-1.16)	(-5.83)	(-5.83)	(-5.67)	(-3.17)	(-3.22)	(-3.22)	(-3.26)
$\sigma_E * HY$	0.045***								
	(7.67)								
$\sigma_I * HY$		0.063***				0.045***	0.045***	0.045***	0.042***
		(10.46)				(7.66)	(7.64)	(7.64)	(7.47)
$\sigma_F * HY$			0.030**				0.004		
			(2.06)				(0.98)		
$P95P5 * HY$				0.008**				0.001	
				(2.07)				(0.93)	
$\sigma_F^{NAIVE} * HY$					0.088***				0.034**
					(3.75)				(1.97)
$\sigma_D * HY$						0.016	0.015	0.016	0.015
						(0.76)	(0.76)	(0.76)	(0.73)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	67,236	67,236	67,236	67,236	67,236	67,236	67,236	67,236	67,236
R2	0.654	0.694	0.559	0.559	0.572	0.736	0.736	0.736	0.738

Standard errors clustered by firm and month. Variable definitions in Appendix.
The full regression includes all the main effects in addition to the reported interaction terms.

Table 5

Pooled regression of credit spreads on theoretical credit spreads : constrained analysis

$$OAS_t = \sum_{k=1}^{K} \alpha_k \, CS_{\sigma_{k,t}} + \Gamma Control_t + \varepsilon_t \qquad (11)$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$CS_{\sigma_E}^{BASE}$	0.596***											
	(14.53)											
CS_{σ_E}		0.686***		0.604***								
		(18.56)		(6.25)								
CS_{σ_i}			0.783***	0.100								
			(16.84)	(0.98)								
$CS_{\sigma_A^{\omega}}$					0.757***	0.410***		0.331***		0.350***		0.357***
					(20.62)	(4.12)		(3.38)		(3.59)		(3.66)
$CS_{\sigma_{AI}^{\omega}}$						0.352***		0.332***		0.333***		0.321***
						(3.41)		(3.28)		(3.29)		(3.15)
CS_{σ_F}							0.702***	0.124***				
							(18.97)	(3.10)				
CS_{P95P5}									0.651***	0.104***		
									(12.53)	(2.93)		
$CS_{\sigma_F^{NAIVE}}$											0.734***	0.141***
											(14.30)	(4.15)
Rating	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.004***	0.003***	0.004***	0.003***	0.004***	0.003***
	(26.02)	(24.32)	(23.68)	(24.86)	(23.79)	(23.83)	(24.33)	(24.00)	(20.64)	(24.04)	(23.53)	(23.73)
Age	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000**	0.000
	(0.76)	(0.46)	(0.19)	(0.40)	(0.24)	(0.07)	(1.18)	(0.16)	(1.21)	(0.12)	(2.40)	(0.33)
Duration	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000
	(-0.22)	(-0.43)	(-1.13)	(-0.55)	(-1.16)	(-1.18)	(0.20)	(-1.14)	(0.59)	(-1.12)	(0.32)	(-1.24)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	57,010	57,010	57,010	57,010	57,010	57,010	57,010	57,010	57,010	57,010	57,010	57,010
R2	0.710	0.763	0.751	0.764	0.783	0.786	0.723	0.788	0.701	0.787	0.683	0.789

Variable definitions provided in Appendix. Standard errors clustered by firm and month.

Table 6
Cross-sectional partitions : constrained analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
HY	0.019***	0.018***	0.017***	0.019***	0.017***	0.017***	0.019***	0.017***	0.019***	0.017***	0.018***	0.016***
	(21.52)	(21.41)	(20.31)	(23.19)	(21.67)	(21.74)	(20.27)	(20.44)	(19.16)	(20.48)	(16.95)	(19.52)
$CS_{\sigma_E}^{BASE} * HY$	0.347***											
	(5.65)											
$CS_{\sigma_E} * HY$		0.306***		0.986***								
		(4.57)		(4.78)								
$CS_{\sigma_i} * HY$			0.362***	-0.712***								
			(5.02)	(-3.38)								
$CS_{\sigma_A^\omega} * HY$					0.225***	0.331**		0.190		0.223		0.257
					(3.20)	(2.00)		(1.18)		(1.37)		(1.59)
$CS_{\sigma_{AI}^\omega} * HY$						-0.115		-0.185		-0.168		-0.168
						(-0.67)		(-1.08)		(-0.99)		(-0.98)
$CS_{\sigma_F} * HY$							0.637***	0.307***				
							(11.58)	(4.78)				
$CS_{P95P5} * HY$									0.705***	0.239***		
									(11.45)	(4.07)		
$CS_{\sigma_F^{NAIVE}} * HY$											0.742***	0.209***
											(12.10)	(3.63)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	57,010	57,010	57,010	57,010	57,010	57,010	57,010	57,010	57,010	57,010	57,010	57,010
R2	0.688	0.747	0.734	0.749	0.767	0.769	0.706	0.773	0.690	0.772	0.677	0.774

Variable definitions are provided in Appendix. Standard errors clustered by firm and month.
The full regression includes all the main effects in addition to the reported interaction terms.

Table 7
Within-industry pairwise correlation of quarterly equity and bond returns and RNOA innovations

Panel A: Pooled sample

	N pairs	N firms	Avg. T	Mean	Std. Dev	Min	Q1	Median	Q3	Max
Equity	24218	783	67.74	0.3878	0.2490	-0.7506	0.2327	0.4125	0.5716	0.9630
Bond	24218	783	67.74	0.4578	0.3395	-0.8593	0.2285	0.5185	0.7384	0.9946
Fundamental	24218	783	67.74	0.0859	0.3385	-0.9710	-0.1284	0.0782	0.3100	0.9902

Panel B: Average by Industry

			Mean		
Industry	N pairs	N firms	Equity	Bond	Fundamental
Consumer non-durables	1037	54	0.2410	0.3507	0.0290
Consumer durables	155	22	0.4858	0.4632	0.0990
Manufacturing	5966	133	0.4058	0.4295	0.0793
Oil, gas and coal extraction	3367	107	0.5360	0.4761	0.2376
Chemicals and allied products	542	38	0.3976	0.4596	0.1260
Business equipment	520	35	0.3705	0.3670	0.0798
Telephone and television transmission	2190	89	0.3065	0.3111	0.0597
Utilities	4828	107	0.4100	0.6807	0.0390
Wholesale, retail and some services	376	30	0.3537	0.4784	0.1384
Healthcare, medical equipment and drugs	950	54	0.2531	0.3456	0.0255
Other	4287	114	0.3287	0.3660	0.0600

The Fama French 12 industry classification is used to identify industries. This results in 11 industries, as we exclude financial firms from the analysis. Correlations are computed based in quarterly equity and bond returns and changes in RNOA. Only the firms with the most common fiscal year within each industry are used in the analysis. Return correlations are computed for all pairs of firms within each industry with a minimum 20 monthly available observations (Avg, T is the average number of months used to compute the correlation in returns between the pairs of firms).

Table 8
Average asset returns and Sharpe ratios within leverage and volatility groups

Panel A: Market Asset Volatility

		Leverage: Low		Leverage: Medium		Leverage: High	
σ_A^W	Low	μ	0.0979	μ	0.0745	μ	0.0430
		SR	0.9196	SR	0.8473	SR	0.4500
	Medium	μ	0.1010	μ	0.1053	μ	0.0560
		SR	0.7598	SR	0.7632	SR	0.3656
	High	μ	0.0931	μ	0.0935	μ	0.1042
		SR	0.4677	SR	0.5198	SR	0.5002

HML	μ	0.0251
	SR	0.2028

Panel B: Fundamental Asset Volatility

		Leverage: Low		Leverage: Medium		Leverage: High	
σ_F	Low	μ	0.0917	μ	0.0831	μ	0.0607
		SR	0.6582	SR	0.6586	SR	0.4657
	Medium	μ	0.0999	μ	0.0920	μ	0.0700
		SR	0.7228	SR	0.7072	SR	0.4893
	High	μ	0.1008	μ	0.0982	μ	0.0723
		SR	0.6793	SR	0.6754	SR	0.4030

HML	μ	0.0120
	SR	0.2040

Each month we sort issuers into terciles based on market leverage. Then, within leverage terciles we sort on two composite measures of asset volatility: (i) σ_A^ω a measure of asset volatility using market data, and (ii) σ_F a measure of asset volatility using accounting data. Each panel contains annualized average asset returns and Sharpe ratios for each of the nine cells, as well as summary information on the respective HML volatility portfolio. We form factor mimicking portfolios each month by equal weighting the difference in asset returns across the top and bottom volatility portfolios across the three leverage terciles. We compute asset returns by weighting the respective equity and credit return each month by the respective weight of equity and credit in the capital structure of the firm.

Table 9

Robustness : 5 year CDS spread analysis

$$CDS5Y_t = \sum_{k=1}^{K} \alpha_k \, CS_{\sigma_{k,t}} + \varepsilon_t \qquad (12)$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$CS_{\sigma_E}^{BASE}$	1.920***											
	(10.01)											
CS_{σ_E}		2.156***		-0.878								
		(10.34)		(-1.56)								
CS_{σ_i}			2.023***	2.804***								
			(10.77)	(4.64)								
$CS_{\sigma_A^{\omega}}$					1.075***	0.987***		0.526***		0.518***		0.566***
					(8.73)	(8.88)		(3.75)		(3.66)		(3.51)
$CS_{\sigma_{AI}^{\omega}}$						1.107***		0.408		0.422		0.862**
						(4.15)		(1.29)		(1.32)		(2.25)
CS_{σ_F}							2.223***	1.347***				
							(10.64)	(6.87)				
CS_{P95P5}									2.226***	1.353***		
									(10.60)	(6.78)		
$CS_{\sigma_F^{NAIVE}}$											1.710***	0.875***
											(6.13)	(3.36)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	30,115	30,115	30,115	30,115	30,115	30,115	30,115	30,115	30,115	30,115	30,115	30,115
R2	0.320	0.455	0.483	0.485	0.539	0.555	0.576	0.627	0.578	0.626	0.535	0.598

Variable definitions provided in Appendix. Standard errors clustered by firm and month.