

# 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 the 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, consequently, spreads. In credit markets it is total (i.e., both systematic and idiosyncratic) asset volatility that is relevant for security prices (Campbell and Taksler, 2003). 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. Importantly, we show that regressing credit spreads onto a constrained non-linear function of asset volatility and leverage – the credit spread implied by the Merton model – performs significantly better than regressing onto these variables linearly and independently. 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 24.4%, 23.9%, and 19.0% 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.

Prior studies have documented an association between idiosyncratic equity (Campbell and Taksler, 2003) and bond (Gemmil and Keswani, 2011) volatility and credit spreads at an aggregate and issuer level. Taking these findings into account and

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. This finding is consistent with the two different sources of firm-level return volatility identified by (Vuolteenaho 2002), cash flow news, which are largely firm-specific, and expected return news, with a stronger systematic component. 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). 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 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 daily stock returns over the past 252 days,  $\sigma_E$ .

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 short term debt plus half of the book value of long term debt (e.g., Bharath and Shumway, 2008).

Our second estimate of historical asset volatility,  $\sigma_A^\omega$ , 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,  $\sigma_D$  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 12 month period. 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.

In untabulated robustness tests, we also examine a Merton distance to default model estimate of asset volatility, following Bharath and Shumway (2008). This volatility is computed by simultaneously solving the Black-Scholes-Merton system of equations, using a numerical algorithm with historical volatility as a starting point.

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  $\sigma_A^\omega$  at the 1<sup>st</sup> and 99<sup>th</sup> percentile values of their respective distribution.

The Appendix defines these variables, as well as other variables used in the paper, in more detail.

### 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.<sup>1</sup> We average the implied volatility for a 91-day put and call option. Based on this implied equity volatility,  $\sigma_I$ , we compute two asset volatility estimates,  $\sigma_{AI}^{NAIVE}$  and  $\sigma_{AI}^W$ , using the approaches in (1) and (2), respectively. We winsorize  $\sigma_{AI}^{NAIVE}$  and  $\sigma_{AI}^W$  at their respective 1<sup>st</sup> and 99<sup>th</sup> percentile values. Option implied volatility has been shown to have incremental power with respect to historical volatility in explaining time-series and cross-sectional variation in credit spreads (Cremers et al., 2008; Cao et al., 2010).

### 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*.

#### 2.3.3.1 Quantile regression approach

This approach consists of using quantile regressions to estimate the quantiles and conditional moments of the *RNOA* distribution. 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  $t$ :

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<sup>1</sup> The standardized implied volatilities are calculated by OptionMetrics using linear interpolation from their Volatility Surface file.

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

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 ( $\Delta$ 'ACTQ'- $\Delta$ 'CHEQ'-( $\Delta$ 'LCTQ'- $\Delta$ 'DLCQ'- $\Delta$ '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)  $\beta_1^{50}$  is 0.94 consistent with mean reversion in accounting rates of return (e.g., Penman, 1991, and Fama and French, 2000), (ii)  $\beta_2^{50}$  is -0.01 consistent with loss makers having lower levels of future profitability (e.g., Hou, Van Dijk, and Zhang, 2012), (iii)  $\beta_3^{50}$  is -0.14 consistent with faster mean reversion in profitability for loss making firms (e.g., Beaver, Correia and McNichols, 2012), (iv)  $\beta_4^{50}$  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)  $\beta_5^{50}$  is 0.02 consistent with dividend paying firms having higher levels of future profitability (e.g., Hou, Van Dijk, and Zhang, 2012), and (vi)  $\beta_6^{50}$  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,  $\mathbf{B}_t^q = \beta_{0,t}^q, \dots, \beta_{6,t}^q$  to obtain out-of-sample estimates of the percentiles for the year t+1. In particular, we obtain a vector of coefficient estimates,  $\widehat{\mathbf{B}}_t^q$ , for each percentile and sample quarter. Based on this vector, we estimate the expected value of each of the 100 percentiles as  $E(\widehat{q_{t+1}}|X_t) = \widehat{\mathbf{B}}_t^q X_t$ .

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,  $\sigma_F = Std(E(\widehat{q_{t+1}}|X_t))$ ,  $q=1, \dots, 100$ , and the difference between the predicted value of the 95<sup>th</sup> percentile and the predicted value of the 5<sup>th</sup> 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*,  $\sigma_F^{NAIVE}$ , 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<sup>2</sup>:

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

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,  $\sigma_F^{NAIVE}$  and  $\sigma_F$ , 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.

Panel D of Table 1 reports the average monthly pairwise correlations across volatility measures. Historical equity volatility,  $\sigma_E$ , is highly correlated with implied volatility,  $\sigma_I$ , [0.8822 (0.9013) Pearson (Spearman) correlation]. The Pearson (Spearman) correlation between these equity volatility measures and debt volatility,  $\sigma_D$ , 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 ( $\sigma_F$ ,  $\sigma_F^{NAIVE}$ , and *P95P5*) and market based asset volatility measures ( $\sigma_A^W$ ,  $\sigma_A^{NAIVE}$ ,  $\sigma_{AI}^W$  and  $\sigma_{AI}^{NAIVE}$ ) are much lower. The

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<sup>2</sup> 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:  $RNOA_t = \beta_0 + \beta_1 RNOA_{t-1} + \sum_{q=2}^4 \beta_q I_{qt} + \varepsilon_t$ .

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)<sup>3</sup>; 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 approach.<sup>4</sup> We convert the different scores into probabilities as follows:  $\text{Prob} = e^{\text{score}} / (1 + e^{\text{score}})$ .

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

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<sup>3</sup> 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).

<sup>4</sup> 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.

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:

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

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 a 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:

$$OAS_t = \alpha_1 \ln\left(\frac{V_t}{X_t}\right) + \alpha_2 Exret_t + \alpha_3 \ln(E_t) + \sum_{k=1}^K \alpha_{k+3} \sigma_{k,t} + \Gamma Control_t + \varepsilon_t \quad (7)$$

$OAS_t$  is the option adjusted spread for the respective bond as reported in the Barclays Index. An intercept is not reported as we include time fixed effects. 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  $E(PD_{it}^k)$ . We estimate this physical bankruptcy probability for each of our asset volatility measures according to equation (8) below:

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

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  $E(PD_{it}^k)$  by cumulating survival probabilities over the relevant number of periods. In particular,  $CPD_{i,t}^k = 1 - \left(1 - E(PD_{it}^k)\right)^T$ . 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):

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

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  $\lambda$ ), 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,  $\lambda$ , 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:

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

$R_{i,t}$  is expected recovery rate conditional on bankruptcy, which we set equal to 0.4 for all firms. While we assume  $R_{i,t}$  to be a constant, it is possible that recovery rates exhibit systematic time-variation (Bruche and Gonzales-Aguado, 2009). While this could affect the gap between theoretical and observed credit spreads, we have no reason to believe it will present a concern to our analysis, given that we do not examine this gap directly.

For the constrained approach, we then estimate the following regression model:

$$OAS_t = \alpha_1 Exret_t + \alpha_2 \ln(E_t) + \sum_{k=1}^K \alpha_{k+2} CS_{\sigma_{k,t}} + \Gamma Control_t + \varepsilon_t \quad (11)$$

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. Correlations between accounting based ( $CS_{\sigma_F}$ ,  $CS_{P95P5}$ ,  $CS_{\sigma_F^{NAIVE}}$ ) and market based ( $CS_{\sigma_A^{NAIVE}}$ ,  $CS_{\sigma_A^W}$ ,  $CS_{\sigma_{AI}^{NAIVE}}$ ,  $CS_{\sigma_{AI}^W}$ ) credit spreads are substantially higher than correlations between the corresponding volatility measures, reported in Panel D. In particular, accounting based credit spreads exhibit an average Pearson (Spearman) correlation of 0.8966 (0.7204), which contrasts with an average Pearson (Spearman) correlation of 0.1921(0.2962) between the respective volatility measures. The reported difference in the magnitude of correlations is as expected given that theoretical credit spreads embed common additional information such as leverage.

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 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  $\sigma_E$  is 0.0256. This means that a one standard

deviation change in  $\sigma_E$  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  $\sigma_I$  (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  $\sigma_E$  and  $\sigma_I$  in the same specification due to multicollinearity (panel D of Table 1 shows that  $\sigma_E$  and  $\sigma_I$  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  $\sigma_I$ . We then add a measure of volatility from the credit markets,  $\sigma_D$ . Combining market based measures of asset volatility from the equity and credit markets is superior to examining equity market information alone (the pseudo-R<sup>2</sup> increases from 29.35 percent in model (2) to 29.78 percent in model (6)). Panel B of Table 2 shows that the scaled marginal effect for  $\sigma_D$  is 30 percent as large as that for  $\sigma_I$ . In model (7) when we add our first measure of fundamental volatility,  $\sigma_F$ , we find that all three component measures of volatility are significantly associated with bankruptcy. In terms of relative economic significance,  $\sigma_D$  is 30 percent as large as that for  $\sigma_I$ , and  $\sigma_F$  is 46 percent as large as that for  $\sigma_I$ . 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. In untabulated robustness analysis, we document further that our fundamental volatility measures also improve the

explanatory power of a bankruptcy prediction model that includes Merton-based volatility and leverage measures (see e.g., Bharath and Shumway, 2008).

### *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 component 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. In unreported analysis, we find that our inferences of the combined information content of market and accounting

based information to measure asset volatility is unaffected by the inclusion of  $Rating_t$ .

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 (ii) 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 (ii) 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  $\sigma_D$  is included the relation turns negative).

Models (1) to (6) 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  $\sigma_I$  (marginal effect of 0.6262 is the largest in the first 6 columns of panel B of Table 3).

Models (7) to (10) in Table 3 combine different component measures of asset volatility. As in Table 2, we do not include  $\sigma_E$  and  $\sigma_I$  in the same specification due to multi-collinearity concerns. In model (7) we add a measure of volatility from the credit markets,  $\sigma_D$ . 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 (the  $R^2$  increases from 67.0 percent in model (2) and 67.1 percent in model (6) to 72.3 percent in model (7)). Panel B of Table 3 shows that the scaled marginal effect for  $\sigma_D$  is 81 percent as large as that for  $\sigma_I$ . In model (8) when we add our first measure of fundamental volatility,  $\sigma_F$ , we find that all three component measures of volatility are significantly associated with bankruptcy, but that the relative importance of  $\sigma_F$  is quite low. In terms of relative economic significance,  $\sigma_D$  is 81 percent as large as that for  $\sigma_I$ , and  $\sigma_F$  is only 4 percent as large as that for  $\sigma_I$ . Using alternative measures of fundamental volatility in models (9) and (10) we find similar results: combining measures of volatility from market and accounting sources improves explanatory power of credit spreads. In untabulated sensitivity tests, we document further that this finding is robust to the use of a Merton-based volatility measure estimated following Bharath and Shumway(2008).

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,  $\sigma_E$  and  $\sigma_I$ , 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,  $\sigma_F^{NAIVE}$ , is significant across models (8) to (10) 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)  $CS_{\sigma_E}$  which is based on historical equity volatility alone, (ii)  $CS_{\sigma_i}$  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)  $CS_{\sigma_F}$  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 retain the same set of controls and explanatory variables to allow comparability of explanatory power between equation (7) and 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 71.5 percent of the variation in credit spreads, and the regression coefficient on  $CS_{\sigma_E}^{BASE}$  is 0.567. A regression coefficient less than one may suggest that our measure of theoretical credit spread is larger than the actual market spread. This is not the case as our regression model includes an intercept (via time fixed effects). In unreported analysis, if we exclude fixed effects, and other control variables, we find that the regression coefficient on  $CS_{\sigma_E}^{BASE}$  is statistically greater 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, thus 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 multiply 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 a noticeable change in explanatory power. The  $R^2$  in model (2) increases to 76.6 percent from 71.5 percent for model (1).

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. For the sake of brevity, we do not report regression results using credit spreads based on our naïve delivered measures of asset volatility (i.e.,  $CS_{\sigma_A^{NAIVE}}$  and  $CS_{\sigma_{AI}^{NAIVE}}$ ), as we find that these are strictly dominated by credit spreads based on the weighted measures of asset volatility (i.e.,  $CS_{\sigma_A^\omega}$  and  $CS_{\sigma_{AI}^\omega}$ ).

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.

The last four rows of Table 5 contain summary information based on estimating the unconstrained regression equation (7) for the same sample of 55,431 bond-months. The sample we use in Table 5 is smaller than that in Table 3 as we require an initial out-of-sample period to empirically calibrate our distance to default to a physical bankruptcy probability. Across all of the models in Table 5 we see that the constrained regression specification results in a statistically and economically significant increase in the ability to explain cross-sectional variation in spread levels. The regression specifications are identical except for how we combine leverage and volatility. The constrained specification combines leverage and volatility consistent with the Merton model, and this generates a significant improvement in explanatory power.

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  $CS_{\sigma_F}$ . 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 with respect to the theoretical credit spread measures. 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 respective interaction terms.

### *3.3 Systematic vs. idiosyncratic volatility*

The empirical analysis thus 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,  $E(PD_{it}^k)$ . Equation (8) shows that total asset volatility is a key determinant of  $E(PD_{it}^k)$ . Thus, estimates of total volatility, and not just systematic volatility, are relevant for understanding credit spreads. Accordingly, an association between idiosyncratic equity (Campbell and Taksler, 2003) and bond (Gemmill and Keswani, 2011) volatility and credit spreads has been documented empirically at both the issuer and aggregate level.

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 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  $133 \times 132 / 2 = 8,778$  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,  $\sigma_A^\omega$ , and one accounting based measure,  $\sigma_F$ , 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,  $\sigma_A^\omega$  and  $\sigma_F$ , again into terciles. 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  $HML_{\sigma_F}$  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  $HML_{\sigma_F}$  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  $HML_{\sigma_A^\omega}$  ( $HML_{\sigma_F}$ ) 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  $HML_{\sigma_F}$  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 and robustness tests

#### 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:

$$CDS5Y_t = \alpha_1 Exret_t + \alpha_2 \ln(E_t) + \sum_{k=1}^K \alpha_{k+2} CS_{\sigma_{k,t}} + \Gamma Control_t + \varepsilon_t \quad (12)$$

Our sample size decreases from 55,431 bond-months examined in Table 5 to 29,557 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 53.6 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 65.3 percent for model (6)). Strikingly, our measure of theoretical spread using fundamental volatility alone can explain 64.1 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 69.5 percent in models (8) and (10). Similar to the analysis in Table 5, at the bottom of Table 9 we also report the  $R^2$  of the equivalent unconstrained regression on the CDS sample. Across all of the specifications, with the exception of model (1), we see statistically significant increases in explanatory power when we constrain asset volatility and leverage, consistent with the Merton model, as compared to including these variables linearly and independently.

### *3.4.2 Alternative specifications*

In untabulated analysis, we expand the bankruptcy forecasting model to control for average accounting profitability over the previous four quarters, cash holdings, market to book ratio and price, following Campbell, Hilscher and Szilagyi (2008). We choose not include these variables in our main specification, which only includes (albeit linearly), the main determinants of probability of default as per the Merton model. Specifically, we add the following variables to the analysis reported in Table 3 (variables are defined and labelled consistently with Campbell, Hilscher and Szilagyi, 2008): (i) NIMTAAVG, a geometrically weighted average level of net income scaled by market value of total assets, which places higher weight on more recent quarters, (ii) CASHMTA, cash and short term investments scaled by the market value of assets, (iii) MB, the market to book ratio, and (iv) PRICE the natural logarithm of the firm's stock price. The sample size does not change significantly as a result of the inclusion of these additional control variables (reduced from 67,373 bond-month to 67,124 bond-month observations). Our measures of fundamental

volatility continue to be significant, both when included individually and together with implied volatility and debt volatility.

We also re-estimate the unconstrained and constrained credit spread regressions adding the control variables in Campbell and Taskler (2003). In particular, we control for operating income and long term debt to total assets. The sample size for the unconstrained analysis is reduced from 67,117 to 62,146 bond-month observations. Consistent with our main analysis, we continue to find that fundamental volatility is significant both when included individually and when considered incrementally to debt volatility and implied volatility. Similarly, in the constrained analysis, credit spreads based on fundamental volatility remain both individually and incrementally significant.

#### **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.

## References

- Arora, N., J. Bohn and F. Zhu (2005). Reduced form vs. structural models of credit risk: a case study of 3 models. *Journal of Investment Management* 3 (4): 43-67.
- Beaver, W.H., M. Correia and M. McNichols (2012). Do differences in financial reporting attributes impair the predictive ability of financial ratios for bankruptcy. *Review of Accounting Studies* 17 (4): 969-1010.
- Beaver, W. H., M. McNichols, and J. Rhie (2005). Have financial statements become less informative? Evidence from the ability of financial ratios to predict bankruptcy. *Review of Accounting Studies* 10: 93-122.
- Bharath, S. and T. Shumway (2008). Forecasting default with the Merton distance to default model. *Review of Financial Studies* 21: 1339-1369.
- Bruche, M., C. Gonzales-Aguado (2009). Recovery rates, default probabilities, and the credit cycle. CEMFI Working Paper.
- Campbell, J. and G. Taksler (2003). Equity volatility and corporate bond yields. *The Journal of Finance* 58 (6): 2321-2349.
- Cao, C., F. Yu and Z. Zhong (2010). The information content of option-implied volatility for credit default swap valuation. *Journal of Financial Markets* 13: 321-343.
- Chang, W., S. Monahan and A. Ouazad (2013). The Higher Moments of Future Return on Equity. Working Paper.
- Chava, S., and R. Jarrow (2004). Bankruptcy prediction with industry effects. *Review of Finance* 8: 537-569.
- Correia, M., S. Richardson and I. Tuna (2012). Value Investing in Credit Markets. *Review of Accounting Studies* 17 (3): 572-609.
- Cremers, M., J. Driessen, P. Maenhout and D. Weinbaum (2008). Individual stock-option prices and credit spreads. *Journal of Banking & Finance* 32(12): 2706-2715.
- Crouhy, M, D. Galai and R. Mark (2000). A comparative analysis of current credit risk models. *Journal of Banking & Finance* 24: 59-117.
- Fama, E., and K. French (2000). Forecasting profitability and earnings. *Journal of Business* 72: 161-175.
- Gemmill, G. and A. Keswani (2011). Downside risk and the size of credit spreads. *Journal of Banking and Finance* 35 (8): 2021-2036.
- Goodman, T., M. Neamtiu and F. Zhang. (2012). Fundamental Analysis and Option Returns. Working Paper. [http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=1974753](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1974753)

- Haesen D. P. Howeling and V. Van Zundert (2012). Equity Momentum for Corporate Bonds: Identifying, Understanding and Reducing Time-Varying Factor Exposures. Working Paper. [http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=2131032](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2131032)
- Helwege, J., and C. M. Turner (1999). The slope of the credit yield curve for speculative grade issuers. *Journal of Finance*, 54, 1869-1884.
- Kealhofer, S.( 2003). Quantifying Credit Risk II: Debt Valuation. *Financial Analysts Journal*, May/June: 78-92.
- Konstantinidi, T. and P. Pope (2012). Forecasting Risk in Earnings. Working paper. [http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=1903378](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1903378).
- Hou, K., M.A. Van Dijk and Y. Zhang (2012). The Implied Cost of Capital: A New Approach. *Journal of Accounting and Economics* 53(3): 504-526.
- Lok, S. and S. Richardson (2011). Credit markets and financial information. *Review of Accounting Studies* 16: 487-500.
- Merton, R. (1974). On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance* 29: 449-470.
- Penman, S. H. (1991). An Evaluation of Accounting Rate-of-Return. *Journal of Accounting, Auditing and Finance* Spring: 233-255.
- Penman, S.H., F. Reggiani, S. A. Richardson and I. Tuna (2013). An accounting'based characteristic model for asset pricing. Working paper. [http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=1966566](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1966566)
- Richardson, S. A., R. G. Sloan, M. T. Soliman and I. Tuna (2006). The implications of accounting distortions and growth for accruals and profitability. *The Accounting Review* 81(3): 713-743.
- Richardson, S.A., R.G. Sloan and H. You (2012). What makes stock prices move? Fundamental vs. investor recognition. *Financial Analysts Journal* 68(2)
- Schaefer, S. and I. Strebulaev (2008). Structural models of credit risk are useful: evidence from hedge ratios on corporate bonds. *Journal of Financial Economics*: 1-19.
- Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *Journal of Business* 74: 101-124.
- Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings?. *The Accounting Review* 81 (3): 289-315.
- Sridharan, S. (2012) Volatility Forecasting using Fundamental Information. Working Paper. [http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=1984324](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1984324)
- Vuolteenaho, T. (2002) What drives firm-level stock returns? *The Journal of Finance* 57(1): 233-264.

## Appendix: Variable Definitions

Compustat mnemonics in parenthesis

### Panel A: Volatility Measures

Variable	Description
$\sigma_E$	Historical equity volatility, the annualized standard deviation of realized daily stock returns over the previous 252 days.
$\sigma_I$	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).
$\sigma_D$	Debt volatility, the standard deviation of total monthly bond returns, computed over the previous 12 months (computed based on Barcap total return).
$\sigma_A^{NAIVE}$	Naively deleveraged historical equity volatility, $\sigma_E \frac{E}{E+X}$ .
$\sigma_A^W$	Weighted historical volatility, $\sqrt{\omega^2 \sigma_E^2 + (1 - \omega)^2 \sigma_D^2 + 2\rho_{D,E} \sigma_E \sigma_D}$ .
$\sigma_{AI}^{NAIVE}$	Naively deleveraged implied equity volatility, $\sigma_I \frac{E}{E+X}$ .
$\sigma_{AI}^W$	Weighted implied volatility, $\sqrt{\omega^2 \sigma_I^2 + (1 - \omega)^2 \sigma_D^2 + 2\rho_{D,E} \sigma_I \sigma_D}$ .
$\sigma_F$	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 95 <sup>th</sup> and 5 <sup>th</sup> percentiles of the RNOA distribution.
$\sigma_F^{NAIVE}$	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).
$\omega$	$\frac{E}{E+X}$ , 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).
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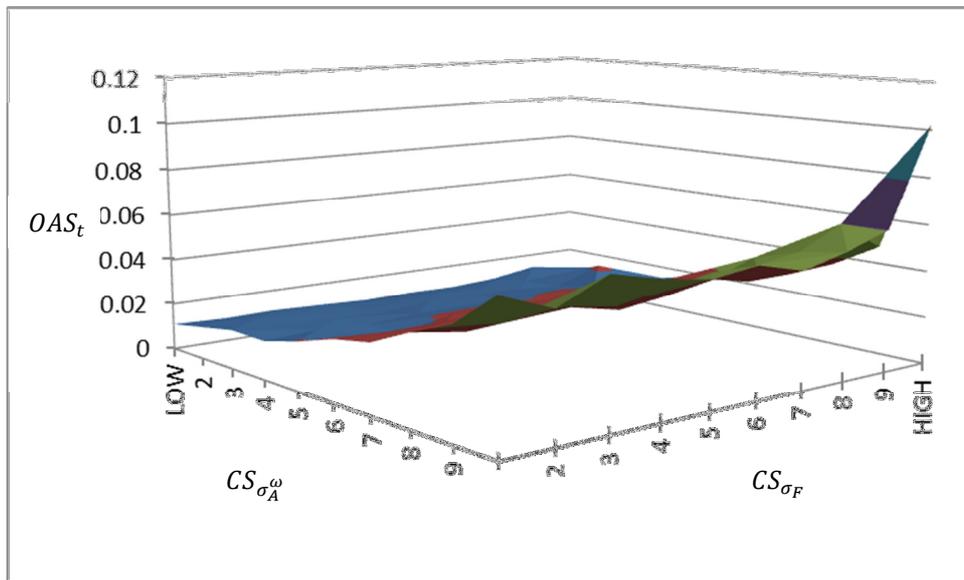
*Panel C: Fundamental volatility estimation*

Variable	Description
<i>RNOA</i>	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).
<i>NOA</i>	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'.
<i>Accruals</i>	Accruals scaled by the average of the opening and closing balance of NOA, with accruals calculated as $\Delta$ 'ACT'- $\Delta$ 'CHE'-( $\Delta$ 'LCT'- $\Delta$ 'DLC'- $\Delta$ '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.
<i>Loss Payer</i>	An indicator variable equal to 1 if RNOA<0, 0 otherwise.
<i>Payout</i>	Dividends paid, 'DVPSX_F', scaled by the average opening and closing balances of RNOA.

*Panel D: Credit Spreads*

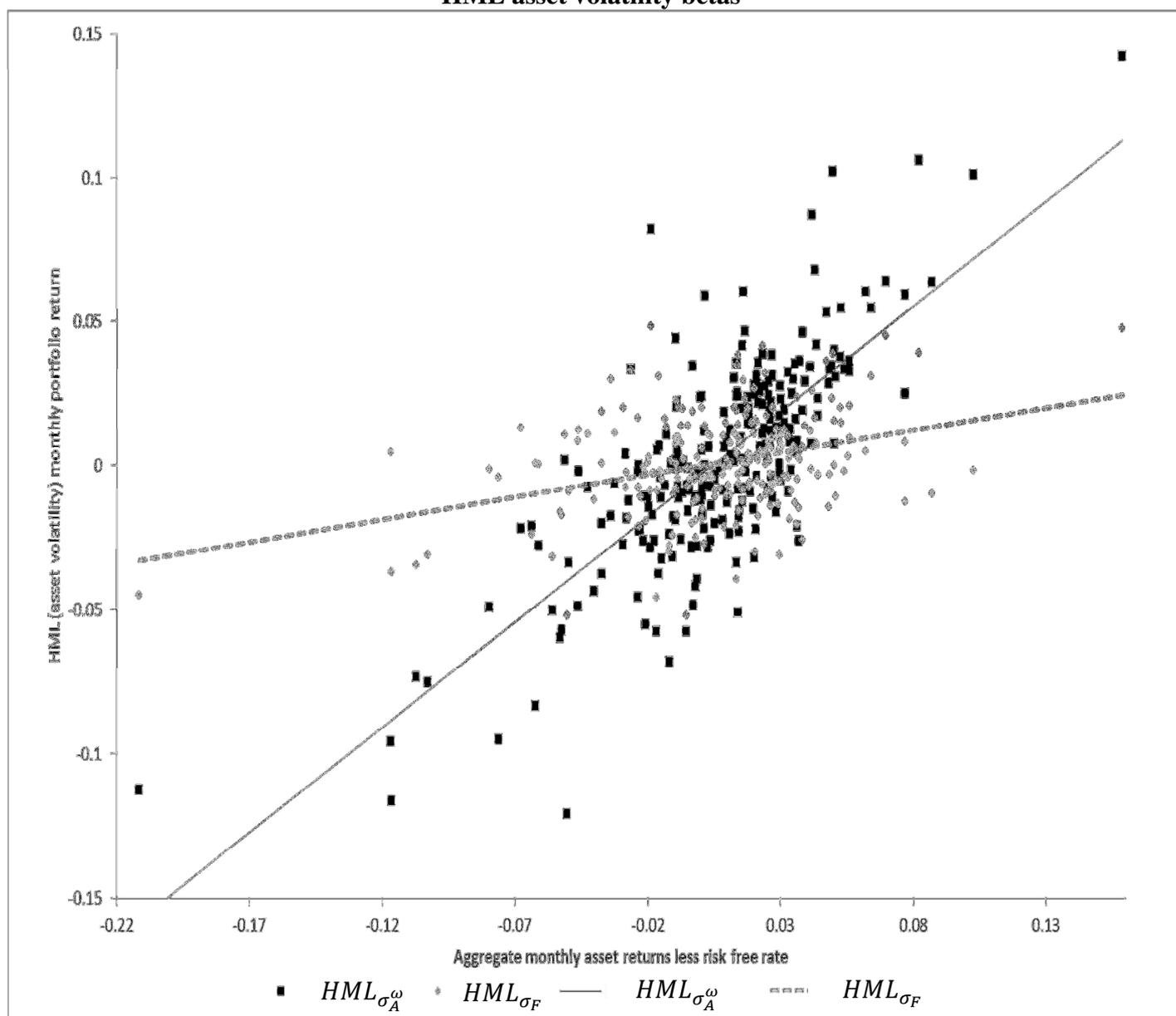
Variable	Description
$CS_{\sigma_E}^{BASE}$	$CS_{\sigma_E}^{BASE} = -\frac{1}{T} [1 - (1 - R)CQDF]$ , where $CQDF = N[N^{-1}(CPD) + \lambda\sqrt{r^2}\sqrt{T}]$ and $CPD = 1 - (1 - PD)^T$ and PD is the empirically fitted physical probability of default, resulting from the estimation of the following logistic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

**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  $CS_{\sigma_A^\omega}$  and  $CS_{\sigma_F}$ . 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)  $\sigma_A^\omega$  a measure of asset volatility using market data, and (ii)  $\sigma_F$  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  $HML_{\sigma_A^\omega}$  and  $HML_{\sigma_F}$  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  $HML_{\sigma_A^\omega}$  ( $HML_{\sigma_F}$ ) 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
$\omega$	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
$\sigma_E$	120,157	0.4088	0.2387	0.1312	0.2498	0.3446	0.4887	1.3034
$\sigma_I$	93,152	0.3906	0.1910	0.1433	0.2605	0.3449	0.4653	1.0850
$\sigma_D$	92,786	0.0905	0.1151	0.0133	0.0429	0.0582	0.0877	0.6353
$\sigma_A^{NAIVE}$	120,055	0.2753	0.1365	0.0722	0.1825	0.2492	0.3365	0.7564
$\sigma_A^W$	93,113	0.2832	0.1216	0.0909	0.2002	0.2632	0.3413	0.6908
$\sigma_{AI}^{NAIVE}$	92,159	0.2912	0.1510	0.0929	0.1904	0.2574	0.3494	0.8580
$\sigma_{AI}^W$	71,424	0.2925	0.1293	0.0993	0.2049	0.2678	0.3509	0.7346
$\sigma_F$	118,162	0.0584	0.1494	0.0142	0.0319	0.0447	0.0596	0.2573
$\sigma_F^{NAIVE}$	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

	$\sigma_E$	$\sigma_I$	$\sigma_D$	$\sigma_A^{NAIVE}$	$\sigma_{AI}^{NAIVE}$	$\sigma_A^W$	$\sigma_{AI}^W$	$\sigma_F$	P95P5	$\sigma_F^{NAIVE}$
$\sigma_E$	1	0.8822	0.3769	0.6335	0.6073	0.7873	0.7543	0.0515	0.0433	0.1643
$\sigma_I$	0.9013	1	0.4732	0.5439	0.6566	0.6820	0.8016	0.0884	0.0803	0.1661
$\sigma_D$	0.2662	0.3381	1	-0.0022	0.0780	0.2813	0.3265	0.0463	0.0397	0.0714
$\sigma_A^{NAIVE}$	0.6868	0.6218	0.0151	1	0.8984	0.9102	0.8376	0.1551	0.1538	0.2121
$\sigma_{AI}^{NAIVE}$	0.6563	0.7204	0.0910	0.9007	1	0.8451	0.9272	0.1745	0.1708	0.2491
$\sigma_A^W$	0.8038	0.7228	0.1750	0.9246	0.8574	1	0.9030	0.1764	0.1736	0.2131
$\sigma_{AI}^W$	0.7605	0.8284	0.2115	0.8537	0.9473	0.9036	1	0.1932	0.1879	0.2451
$\sigma_F$	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
$\sigma_F^{NAIVE}$	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	$CS_{\sigma_E}^{BASE}$	$CS_{\sigma_E}$	$CS_{\sigma_i}$	$CS_{\sigma_A}^{NAIVE}$	$CS_{\sigma_{AI}}^{NAIVE}$	$CS_{\sigma_A^\omega}$	$CS_{\sigma_{AI}^\omega}$	$CS_{\sigma_F}$	$CS_{P95P5}$	$CS_{\sigma_F}^{NAIVE}$
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
$CS_{\sigma_E}$	0.7186	0.9987	1	0.9756	0.8445	0.9138	0.9816	0.9731	0.9440	0.9434	0.9383
$CS_{\sigma_i}$	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
$CS_{\sigma_F}$	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**

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

*Panel A: Regression analysis*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-0.189 (-0.20)	-1.957* (-1.82)	1.095 (1.48)	1.105 (1.50)	0.878 (1.18)	-1.987* (-1.84)	-1.942* (-1.78)	-1.940* (-1.78)	-1.935* (-1.77)
$\ln \left( \frac{V}{X} \right)$	-2.151*** (-3.00)	-1.776*** (-2.58)	-2.446*** (-3.39)	-2.447*** (-3.39)	-2.516*** (-3.41)	-1.645** (-2.39)	-1.713** (-2.42)	-1.713** (-2.42)	-1.819** (-2.45)
Exret	-1.103** (-2.15)	-0.591 (-1.54)	-0.947* (-1.67)	-0.947* (-1.67)	-0.845 (-1.55)	-0.823** (-2.28)	-0.817** (-2.26)	-0.817** (-2.26)	-0.757** (-2.11)
$\ln(E)$	-0.433*** (-3.36)	-0.333** (-2.58)	-0.512*** (-3.73)	-0.512*** (-3.73)	-0.482*** (-3.47)	-0.341*** (-2.61)	-0.343*** (-2.60)	-0.343*** (-2.60)	-0.327** (-2.45)
$\sigma_E$	1.001** (2.18)								
$\sigma_I$		2.233*** (4.03)				1.866*** (3.43)	1.787*** (3.26)	1.791*** (3.27)	1.699*** (3.08)
$\sigma_F$			1.600*** (3.84)				1.290*** (3.37)		
$P95P5$				0.459*** (3.95)				0.370*** (3.41)	
$\sigma_F^{NAIVE}$					4.232*** (4.29)				3.042** (2.51)
$\sigma_D$						1.107* (1.94)	1.057* (1.85)	1.058* (1.85)	0.966 (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)
<i>Effect of a one standard deviation change on the probability of bankruptcy scaled by the unconditional probability of bankruptcy one year ahead</i>									
$\ln\left(\frac{V}{X}\right)$	-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
$\sigma_E$	0.0256								
$\sigma_I$		0.0624				0.0562	0.0513	0.0514	0.0458
$\sigma_F$			0.0195				0.0238		
P95P5				0.0194				0.0237	
$\sigma_F^{NAIVE}$					0.0274				0.0294
$\sigma_D$						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**

$$OAS_t = \alpha_1 \ln\left(\frac{V_t}{X_t}\right) + \alpha_2 Exret_t + \alpha_3 \ln(E_t) + \sum_{k=1}^K \alpha_{k+3} \sigma_{k,t} + \Gamma Control_t + \varepsilon_t \quad (7)$$

*Panel A: Regression analysis*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\ln\left(\frac{V}{X}\right)$	-0.004*** (-8.91)	-0.004*** (-9.53)	-0.004*** (-6.15)	-0.004*** (-6.13)	-0.004*** (-6.60)	-0.001** (-2.36)	-0.002*** (-6.07)	-0.002*** (-6.39)	-0.002*** (-6.37)	-0.002*** (-6.58)
<i>Exret</i>	-0.008* (-1.96)	0.005 (1.61)	-0.002 (-0.25)	-0.002 (-0.26)	-0.001 (-0.20)	-0.012*** (-2.70)	-0.004 (-1.46)	-0.004 (-1.44)	-0.004 (-1.44)	-0.004 (-1.40)
$\ln(E)$	-0.003*** (-5.97)	-0.002*** (-4.69)	-0.003*** (-6.07)	-0.003*** (-6.06)	-0.003*** (-6.13)	-0.004*** (-8.90)	-0.003*** (-7.79)	-0.003*** (-7.84)	-0.003*** (-7.84)	-0.003*** (-7.91)
<i>Rating</i>	0.002*** (8.64)	0.002*** (7.69)	0.004*** (17.18)	0.004*** (17.17)	0.004*** (17.17)	0.002*** (12.73)	0.001*** (6.19)	0.001*** (6.10)	0.001*** (6.10)	0.001*** (5.72)
<i>Age</i>	0.000** (2.42)	0.000*** (3.21)	0.000*** (2.89)	0.000*** (2.89)	0.000*** (2.98)	0.000 (1.50)	0.000** (2.04)	0.000** (2.00)	0.000** (2.00)	0.000** (2.05)
<i>Duration</i>	0.000 (1.49)	0.000 (1.24)	0.000** (2.30)	0.000** (2.31)	0.000** (2.38)	-0.001*** (-5.25)	-0.001*** (-4.24)	-0.001*** (-4.28)	-0.001*** (-4.28)	-0.001*** (-4.25)
$\sigma_E$	0.067*** (10.85)									
$\sigma_I$		0.095*** (14.49)					0.065*** (11.97)	0.065*** (11.97)	0.065*** (11.97)	0.064*** (11.90)
$\sigma_F$			0.012*** (2.89)					0.004** (2.49)		
<i>P95P5</i>				0.003*** (2.93)					0.001** (2.39)	
$\sigma_F^{NAIVE}$					0.038*** (2.82)					0.015 (1.53)
$\sigma_D$						0.149*** (8.48)	0.104*** (6.89)	0.104*** (6.88)	0.104*** (6.88)	0.104*** (6.92)
Month FE	Yes									
Nobs	67,117	67,117	67,117	67,117	67,117	67,117	67,117	67,117	67,117	67,117
R2	0.630	0.670	0.538	0.538	0.542	0.671	0.723	0.723	0.723	0.724

*Panel B: Marginal effects*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\ln\left(\frac{V}{X}\right)$	-0.1188	-0.1188	-0.1188	-0.1188	-0.1188	-0.0297	-0.0594	-0.0594	-0.0594	-0.0594
<i>Exret</i>	-0.0318	0.0199	-0.0079	-0.0079	-0.0040	-0.0477	-0.0159	-0.0159	-0.0159	-0.0159
$\ln(E)$	-0.1497	-0.0998	-0.1497	-0.1497	-0.1497	-0.1998	-0.1497	-0.1497	-0.1497	-0.1497
<i>Rating</i>	0.2576	0.2576	0.5152	0.5152	0.5152	0.2579	0.1288	0.1288	0.1288	0.1288
<i>Age</i>	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
<i>Duration</i>	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0768	-0.0767	-0.0767	-0.0767	-0.0767
$\sigma_E$	0.4903									
$\sigma_I$		0.6262					0.4284	0.4284	0.4284	0.4218
$\sigma_F$			0.0506					0.0169		
<i>P95P5</i>				0.0439					0.0146	
$\sigma_F^{NAIVE}$					0.0890					0.0351
$\sigma_D$						0.4950	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)	(10)
<i>HY</i>	0.026*** (3.76)	0.002 (0.30)	0.090*** (10.09)	0.090*** (10.10)	0.087*** (10.04)	0.065*** (9.98)	0.011** (2.19)	0.011** (2.26)	0.011** (2.26)	0.013*** (2.60)
$\ln\left(\frac{V}{X}\right) * HY$	-0.009*** (-7.55)	-0.006*** (-6.12)	-0.015*** (-8.38)	-0.015*** (-8.36)	-0.016*** (-8.98)	-0.006*** (-4.91)	-0.003*** (-3.42)	-0.003*** (-3.50)	-0.003*** (-3.50)	-0.004*** (-4.60)
<i>Exret</i> * <i>HY</i>	-0.010** (-2.43)	0.001 (0.23)	0.006 (0.96)	0.006 (0.96)	0.007 (1.02)	-0.011*** (-2.67)	-0.009*** (-2.88)	-0.009*** (-2.88)	-0.009*** (-2.88)	-0.008*** (-2.82)
$\ln(E) * HY$	-0.002*** (-3.05)	-0.001 (-1.13)	-0.006*** (-6.01)	-0.006*** (-6.01)	-0.006*** (-5.86)	-0.005*** (-6.93)	-0.002*** (-2.71)	-0.002*** (-2.76)	-0.002*** (-2.76)	-0.002*** (-2.82)
$\sigma_E * HY$	0.045*** (7.56)									
$\sigma_I * HY$		0.064*** (10.49)					0.047*** (7.78)	0.047*** (7.75)	0.047*** (7.76)	0.044*** (7.58)
$\sigma_F * HY$			0.030** (2.04)					0.004 (0.97)		
<i>P95P5</i> * <i>HY</i>				0.008** (2.05)					0.001 (0.93)	
$\sigma_F^{NAIVE} * HY$					0.088*** (3.68)					0.034* (1.94)
$\sigma_D * HY$						0.037 (1.46)	0.005 (0.19)	0.005 (0.18)	0.005 (0.18)	0.004 (0.16)
Time FE	Yes									
Nobs	67,117	67,117	67,117	67,117	67,117	67,117	67,117	67,117	67,117	67,117
R2	0.656	0.697	0.562	0.562	0.575	0.684	0.740	0.740	0.740	0.742

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**

$$OAS_t = \alpha_1 Exret_t + \alpha_2 \ln(E_t) + \sum_{k=1}^K \alpha_{k+2} CS_{\sigma_{k,t}} + \Gamma Control_t + \varepsilon_t \quad (11)$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Exret	-0.004 (-1.19)	-0.001 (-0.28)	0.001 (0.39)	-0.001 (-0.20)	0.000 (0.05)	0.001 (0.38)	0.004 (0.93)	0.002 (0.65)	0.003 (0.68)	0.002 (0.59)	0.003 (0.55)	0.002 (0.65)
ln(E)	-0.002*** (-5.63)	-0.002*** (-4.91)	-0.002*** (-4.79)	-0.002*** (-4.78)	-0.002*** (-5.45)	-0.002*** (-5.64)	-0.003*** (-6.90)	-0.002*** (-5.75)	-0.004*** (-7.25)	-0.002*** (-5.83)	-0.004*** (-7.51)	-0.002*** (-5.95)
Rating	0.003*** (13.94)	0.003*** (13.46)	0.003*** (13.38)	0.003*** (13.69)	0.002*** (12.90)	0.002*** (13.05)	0.003*** (13.88)	0.002*** (12.93)	0.003*** (13.88)	0.002*** (12.93)	0.003*** (13.05)	0.002*** (12.69)
Age	0.000 (1.23)	0.000 (0.96)	0.000 (0.65)	0.000 (0.90)	0.000 (0.75)	0.000 (0.57)	0.000* (1.72)	0.000 (0.65)	0.000* (1.80)	0.000 (0.62)	0.000*** (2.94)	0.000 (0.86)
Duration	0.000 (0.13)	-0.000 (-0.11)	-0.000 (-0.80)	-0.000 (-0.22)	-0.000 (-0.87)	-0.000 (-0.89)	0.000 (0.55)	-0.000 (-0.85)	0.000 (0.99)	-0.000 (-0.82)	0.000 (0.74)	-0.000 (-0.94)
$CS_{\sigma_E}^{BASE}$	0.567*** (14.07)											
$CS_{\sigma_E}$		0.659*** (17.83)		0.590*** (6.43)								
$CS_{\sigma_I}$			0.750*** (16.33)	0.083 (0.85)								
$CS_{\sigma_A}^{\omega}$					0.729*** (19.61)	0.359*** (3.41)		0.284*** (2.75)		0.301*** (2.92)		0.299*** (2.89)
$CS_{\sigma_{AI}}^{\omega}$						0.375*** (3.42)		0.353*** (3.29)		0.354*** (3.30)		0.342*** (3.17)
$CS_{\sigma_F}$							0.680*** (17.76)	0.122*** (3.06)				
$CS_{P95P5}$									0.629*** (12.07)	0.103*** (3.03)		
$CS_{\sigma_F}^{NAIVE}$											0.707*** (14.31)	0.153*** (4.55)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	55,431	55,431	55,431	55,431	55,431	55,431	55,431	55,431	55,431	55,431	55,431	55,431
R2	0.715	0.766	0.754	0.767	0.785	0.788	0.730	0.790	0.709	0.790	0.697	0.792
R2(U)	0.632	0.632	0.680	0.681	0.587	0.609	0.538	0.610	0.538	0.609	0.542	0.611
Included $\sigma$	$\sigma_E$	$\sigma_E$	$\sigma_I$	$\sigma_E, \sigma_I$	$\sigma_A^{\omega}$	$\sigma_A^{\omega}, \sigma_{AI}^{\omega}$	$\sigma_F$	$\sigma_A^{\omega}, \sigma_{AI}^{\omega}, \sigma_F$	$\sigma_A^{\omega}, \sigma_{AI}^{\omega}$	$\sigma_A^{\omega}, \sigma_{AI}^{\omega}, P95P5$	$\sigma_F^{NAIVE}$	$\sigma_A^{\omega}, \sigma_{AI}^{\omega}, \sigma_F^{NAIVE}$
Vuong Z	19.783	18.355	13.779	13.451	24.308	22.758	21.591	21.969	16.468	22.071	17.805	21.566
p-value	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

Variable definitions provided in Appendix. Standard errors clustered by firm and month. R2(U) is the R-square from the estimation of equation (7) with the volatility measures included in each of the constrained specifications (Included  $\sigma$ ).

**Table 6**  
**Cross-sectional partitions: constrained analysis**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
HY	0.028*** (4.96)	0.019*** (3.28)	0.024*** (4.14)	0.021*** (3.69)	0.020*** (3.67)	0.022*** (4.12)	0.033*** (5.17)	0.022*** (4.05)	0.038*** (5.54)	0.023*** (4.19)	0.043*** (7.14)	0.022*** (4.16)
$CS_{\sigma_E}^{BASE} * HY$	0.342*** (5.99)											
$CS_{\sigma_E} * HY$		0.346*** (5.28)		0.830*** (4.40)								
$CS_{\sigma_i} * HY$			0.397*** (5.69)	-0.510** (-2.57)								
$CS_{\sigma_A}^{\omega} * HY$					0.270*** (3.95)	0.257 (1.57)		0.115 (0.73)		0.144 (0.90)		0.184 (1.15)
$CS_{\sigma_{AI}}^{\omega} * HY$						0.003 (0.01)		-0.065 (-0.39)		-0.049 (-0.29)		-0.050 (-0.30)
$CS_{\sigma_F} * HY$							0.607*** (11.16)	0.300*** (4.37)				
$CS_{P95P5} * HY$									0.647*** (11.78)	0.235*** (3.89)		
$CS_{\sigma_F}^{NAIVE} * HY$											0.659*** (12.25)	0.199*** (3.65)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	55,431	55,431	55,431	55,431	55,431	55,431	55,431	55,431	55,431	55,431	55,431	55,431
R2	0.710	0.761	0.750	0.763	0.780	0.783	0.735	0.787	0.723	0.787	0.715	0.789

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*

Industry	N pairs	N firms	Mean		
			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		Medium		High	
$\sigma_A^W$	Low	$\mu$	0.0979	$\mu$	0.0745	$\mu$	0.0430
		SR	0.9196	SR	0.8473	SR	0.4500
	Medium	$\mu$	0.1010	$\mu$	0.1053	$\mu$	0.0560
		SR	0.7598	SR	0.7632	SR	0.3656
	High	$\mu$	0.0931	$\mu$	0.0935	$\mu$	0.1042
		SR	0.4677	SR	0.5198	SR	0.5002
	HML		$\mu$	0.0251			
			SR	0.2028			

*Panel B: Fundamental Asset Volatility*

		Leverage					
		Low		Medium		High	
$\sigma_F$	Low	$\mu$	0.0917	$\mu$	0.0831	$\mu$	0.0607
		SR	0.6582	SR	0.6586	SR	0.4657
	Medium	$\mu$	0.0999	$\mu$	0.0920	$\mu$	0.0700
		SR	0.7228	SR	0.7072	SR	0.4893
	High	$\mu$	0.1008	$\mu$	0.0982	$\mu$	0.0723
		SR	0.6793	SR	0.6754	SR	0.4030
	HML		$\mu$	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)  $\sigma_A^W$  a measure of asset volatility using market data, and (ii)  $\sigma_F$  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**

$$CDS5Y_t = \alpha_1 Exret_t + \alpha_2 \ln(E_t) + \sum_{k=1}^K \alpha_{k+2} CS_{\sigma_{k,t}} + \Gamma Control_t + \varepsilon_t \quad (12)$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Exret	-0.003 (-0.40)	-0.003 (-0.56)	-0.002 (-0.36)	-0.001 (-0.11)	0.003 (0.44)	0.003 (0.44)	0.007 (1.14)	0.006 (1.00)	0.007 (1.15)	0.006 (1.00)	0.007 (1.11)	0.006 (0.85)
ln(E)	-0.000 (-0.08)	0.001 (1.41)	0.001* (1.76)	0.001 (1.64)	-0.001 (-1.43)	-0.001 (-1.64)	0.001 (1.10)	-0.000 (-0.21)	0.001 (1.08)	-0.000 (-0.21)	-0.000 (-0.20)	-0.001 (-0.88)
Rating	0.004*** (7.50)	0.003*** (7.29)	0.003*** (7.56)	0.003*** (7.73)	0.004*** (9.25)	0.004*** (8.89)	0.004*** (8.13)	0.004*** (8.20)	0.004*** (8.11)	0.004*** (8.19)	0.004*** (8.46)	0.004*** (8.34)
$CS_{\sigma_E}^{BASE}$	1.217*** (7.68)											
$CS_{\sigma_E}$		1.728*** (7.90)		-1.416** (-2.43)								
$CS_{\sigma_I}$			1.667*** (8.46)	2.906*** (4.68)								
$CS_{\sigma_A}^{\omega}$					0.910*** (8.24)	0.917*** (7.56)		0.563*** (3.34)		0.557*** (3.27)		0.612*** (3.07)
$CS_{\sigma_{AI}}^{\omega}$						-0.129 (-0.48)		-0.470 (-1.44)		-0.463 (-1.40)		-0.180 (-0.52)
$CS_{\sigma_F}$							1.888*** (9.04)	1.066*** (5.39)				
$CS_{P95P5}$									1.891*** (9.04)	1.072*** (5.29)		
$CS_{\sigma_F}^{NAIVE}$											1.426*** (6.15)	0.649** (2.55)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	29,557	29,557	29,557	29,557	29,557	29,557	29,557	29,557	29,557	29,557	29,557	29,557
R2	0.404	0.505	0.530	0.536	0.653	0.653	0.641	0.695	0.643	0.695	0.622	0.676
R2(U)	0.423	0.423	0.486	0.487	0.345	0.345	0.344	0.346	0.340	0.346	0.340	0.347
Included $\sigma$	$\sigma_E$	$\sigma_E$	$\sigma_I$	$\sigma_E, \sigma_I$	$\sigma_A^{\omega}$	$\sigma_A^{\omega}, \sigma_{AI}^{\omega}$	$\sigma_F$	$\sigma_A^{\omega}, \sigma_{AI}^{\omega}, \sigma_F$	$\sigma_A^{\omega}, \sigma_{AI}^{\omega}$	$\sigma_A^{\omega}, \sigma_{AI}^{\omega}, P95P5$	$\sigma_F^{NAIVE}$	$\sigma_A^{\omega}, \sigma_{AI}^{\omega}, \sigma_F^{NAIVE}$
Vuong Z	-5.6358	8.0274	5.9347	6.2172	5.4388	5.4525	12.6666	8.2671	12.3688	8.3368	9.354	7.7629
p-value	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

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