Anchoring Credit Default Swap Spreads to Firm Fundamentals*

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Abstract

This paper examines the capability of firm fundamentals in explaining the cross-sectional variation of credit default swap (CDS) spreads. The paper constructs a fundamental-based CDS valuation by combining the Merton distance-to-default measure with a long list of firm fundamental characteristics. Regressing market CDS quotes against the fundamental valuation cross-sectionally generates an average R-squared of 77%. The cross-sectional explanatory power is stable over time, and robust in out-of-sample tests. Deviations between market quotes and the fundamental valuation predict significantly future market movements. The results highlight the important role of firm fundamentals in differentiating the credit quality of different firms.

JEL classification: C11, C13, C14, G12, G13.

Keywords: Credit default swaps; firm fundamentals; cross-sectional variation; structural models.

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I. Introduction

The literature has examined the performance of structural models and firm fundamentals from several different perspectives. Huang and Huang (2012) and Eom, Helwege, and Huang (2004) focus on the average bias of structural models, and show that different structural models generate different average biases. Collin-Dufresne, Goldstein, and Martin (2001) regress monthly changes in credit spreads on monthly changes in firm fundamentals, and find that the time-series regressions generate low R-squares. On the other hand, Ericsson, Jacobs, and Oviedo (2009) show that inputs of the Merton model, e.g., financial leverage, volatility, and the riskfree interest rate, can explain a substantial proportion of the time-series variation in the credit default swap (CDS) spreads. This paper examines the capability of structural models, and more generally firm fundamental characteristics, in explaining the cross-sectional variation of CDS spreads.

An important objective of building structural models such as Merton (1974) is to link a firm's credit risk to its structural characteristics, such as financial leverage and business risk. Accordingly, a simple, intuitive way of analyzing the structural model's implication is to examine whether firms with different structural characteristics show different credit risk. It is this intuition that motivates our focus on the cross-sectional explanatory power of firm fundamentals. Time series regression on monthly changes can be useful in many other applications, but it is not particularly suited for identifying the linkage between firm structural characteristics and credit risk, simply because firms tend to be structurally stable over time in terms of the type of business they are in and the level of financial leverage they target,[1].When a structural characteristic for a company does not fundamentally vary over time, time series regressions on its monthly changes capture nothing but noise. In such scenarios, the low explanatory power says more about the poor empirical design than about the importance of the characteristic on credit risk. By focusing on the cross-sectional relation, this paper strives to determine *how much* one can use firm structural characteristics to differentiate their credit qualities and *what structural characteristics* are particularly useful in this differentiation. The findings shall provide future guidance for developing new structural models.

[1]Lemmon, Roberts, and Zender (2008) find that high (low) levered firms tend to remain as such for over two decades, suggesting that variation in capital structures is primarily determined by factors that remain stable for long periods of time.

To synthesize firm fundamental information for CDS valuation, we start with the classic Merton (1974) model, which combines two major credit risk determinants, financial leverage and asset return volatility, into a standardized distance-to-default measure. We map this measure to the market CDS observation via a cross-sectional nonparametric regression to generate a Merton-based CDS valuation (MCDS). In addition, we collect a long list of firm fundamental characteristics that are not included in the Merton model implementation but have been shown to be informative about a firm's credit spread. We propose a Bayesian shrinkage method to combine the Merton-based valuation with the information from this long list of fundamental characteristics to generate a weighted average CDS valuation (WCDS). The Merton distance-to-default measure has been used as an input for credit risk prediction in many practical and academic implementations.[2] The Bayesian shrinkage methodology allows us to incorporate additional information while addressing practical issues such as possible nonlinearities, missing observations, and potential multi-collinearity among different proxies of the same variable.

We examine the cross-sectional explanatory power of the fundamental CDS valuation based on six and a half years of data on 579 U.S. non-financial public firms from January 8, 2003 to September 30, 2009. At each date, we perform three sets of cross-sectional regression. The first is a benchmark bivariate linear regression of market CDS quotes on the two inputs of the Merton model: the total debt to market capitalization ratio and stock return volatility. The second and third regress the market CDS quotes against the MCDS and WCDS valuation, respectively. The R-squared estimates from the bivariate linear regression average at 49%, similar to the regression findings in, for example, Ericsson, Jacobs, and Oviedo (2009). By comparison, the R-squared estimates average at 65% for MCDS and 77% for WCDS.

The comparative analysis highlights the two important roles played by a structural model: (i) identifying structural characteristics of a firm relevant for its credit risk and (ii) proposing a functional form that combines and converts these characteristics into a credit risk measure. The Merton model is highly successful in these two roles. Simply taking Meron's suggestion in selecting the financial leverage and stock return volatility as the two explanatory variables, one can explain about

[2]See for example, Bharath and Shumway (2008), Crosbie and Bohn (2003), Duan, Sun, and Wang (2012), and Duan and Wang (2012).

half of the cross-sectional CDS variation via a linear regression. Applying the model's structural relation to convert these two inputs into a CDS measure further increases the explanatory power by 16 percentage points, raising the average R-squared to 65%.

One can do even better. By incorporating a long list of additional firm characteristics that have been shown to be informative about the firm's credit risk, the WCDS explains 77% of the cross-sectional variation, another 11 percentage point improvement. The list includes the various fundamental ratios used in Atlman's Z-score (Altman (1968, 1989)), the company's size (Fama and French (1993)), past stock returns (Duffie, Saita, and Wang (2007)), and option implied volatility (Collin-Dufresne, Goldstein, and Martin (2001), Berndt and Ostrovnaya (2007), Cremers, Driessen, Maenhout, and Weinbaum (2008), Wang, Zhou, and Zhou (2009), Berndt and Obreja (2010), Cao, Yu, and Zhong (2010), and Carr and Wu (2010, 2011). For future structural model development, it is important to think of ways to incorporate these firm structural characteristics and combine them into a credit risk measure.

In addition to the high average R-squared, the performance of WCDS also shows high stability over time. The cross-sectional R-squared estimates for WCDS have a low time-series standard deviation of merely 4%, with a narrow range from a minimum R-squared of 67% to a maximum R-squared of 85%. The time-series standard deviation of the performance is larger at 8% for MCDS and 10% for the bivariate linear regression.

To gauge the out-of-sample stability of the valuation methodology, we randomly select half of the universe each day to perform the model estimation and then generate out-of-sample valuation on the other half. The out-of-sample performance for WCDS experiences little deterioration as the average cross-sectional explanatory power goes from 77% in sample to 74% out of sample. By contrast, the bivariate linear regression shows severe out-of-sample deterioration as the average R-squared declines from 51% in sample to 25% out of sample.

The high and robust cross-sectional explanatory power suggests that the methodology can be used to generate reasonable CDS valuation on companies with firm fundamental information but without valid market CDS quotes. In the United States, thousands of publicly traded companies have the relevant fundamental information for the CDS valuation, but only hundreds of them have reliable market CDS quotes. The proposed fundamental-based CDS valuation method can be used to greatly expand the CDS quote universe.

Furthermore, since the fundamental-based CDS valuation captures the cross-sectional market CDS variation well, the remaining deviation between the market quote and our valuation is likely driven by non-fundamental factors such as supply-demand shocks. If these shocks are transitory, the current market-fundamental deviation will predict future market movements. When we analyze the time-series behavior of these deviations, we find that they are indeed much more mean-reverting than the original CDS time series. The annualized mean reversion speeds for the market CDS series average at 1.52, corresponding to a time line of seven to eight months. By contrast, the average mean reversion speed for the market-fundamental deviation is much higher at 3.47, corresponding to a time line of about a quarter. When we estimate the forecasting correlation between the current market-fundamental deviation and future CDS changes, we obtain statistically significant estimates, averaging at -7% at weekly horizon and -12% at a four-week horizon. The negative sign of the correlation estimates suggests that when the market observation deviates from the fundamental-based valuation, the market tends to revert back to the fundamental valuation in the future, highlighting the role of firm fundamentals as an anchor for market CDS movements.

To gauge the economic significance of the forecasting power, we also perform an out-of-sample investment exercise, by paying the premium and buying CDS protection when the market CDS quote is narrower than the fundamental-based valuation and selling CDS protection and receiving the premium when the quoted CDS spread is higher than the fundamental-based valuation. The investment exercise generates high excess returns and low standard deviations, with an annualized information ratio of 2.26 with weekly rebalancing and 1.50 with monthly rebalancing. The high information ratio highlights the economic significance of the CDS forecasts based on the fundamental-based valuation. Firm fundamentals are useful, not only for generating CDS valuations in the absence of market quotes, but also for anchoring market CDS movements.

In related literature, Bharath and Shumway (2008) examine the performance of the Merton distance-to-default measure in forecasting actual default probabilities, and find that even though the measure does not produce a sufficient statistic, its functional form is useful for forecasting defaults. Schaefer and Strebulaev (2008) show that, even though structural models may not be able to match observed bond prices well, they provide quite accurate predictions of the sensitivity of cooperate bond returns to changes in the value of equity and thus provide useful guidance for hedging credit risks. More recently, Huang and Shi (2013) explore ways to reconcile the usefulness of firm characteristics and their low explanatory power in time series regressions.

The rest of the paper is structured as follows. The next section describes the data sources and sample construction. Section III introduces the methodologies for constructing firm fundamental-based CDS valuations. Section IV analyzes the performance of the fundamental-based CDS valuations in explaining the cross-sectional variation of market CDS observations. Section V explores the application of using the fundamental-based CDS valuation as an anchor for relative valuation and examines the forecasting power of the market-fundamental deviation on future market CDS movements. Section VI provides concluding remarks.

II. Data collection and sample construction

We collect data on U.S. non-financial public corporations from several sources. We start with the universe of companies with CDS records in the Markit database. Then, we retrieve their financial statement information from Capital IQ, the stock option implied volatilities from Ivy DB Option-Metrics, and the stock market price information from the Center for Research in Security Prices (CRSP).

At a given date, a company is included in our sample if we obtain valid observations on (i) a five-year CDS spread quote on the company, (ii) balance sheet information on the total amount of book value of debt in the company, (iii) the company's market capitalization, and (iv) one year of daily stock return history, from which we calculate the one-year realized stock return volatility. We perform fundamental-based CDS valuation weekly on every Wednesday from January 8, 2003 to September 30, 2009. The sample contains 351 active weeks and a total of 579 companies that satisfy our data selection criteria. All together, we have 138,200 week-company observations, with an average of 394 companies selected per day and 239 days selected per company.

The credit default swap is an over-the-counter contract that provides insurance against credit events of the underlying reference entity. The protection buyer makes periodic coupon payments to the protection seller until contract expiry or the occurrence of a specified credit event on the reference entity, whichever is earlier. When a credit event occurs within the contract term, the protection buyer delivers an eligible bond issued by the reference entity to the protection seller in exchange for its par value. The coupon rate, also known as the CDS rate or CDS spread, is set such that the contract has zero value at inception.[3] In this paper, we take the five-year CDS spread as the benchmark for corporate credit spread and analyze its linkage to firm fundamentals.

While we use the five-year CDS spread as a measure of a firm's credit quality, many studies choose to use credit spreads on corporate bonds.[4] Both choices shall lead to similar conclusions, but using corporate bonds faces several practical complications. First, credit spreads tend to have a strong term structure effect. With CDS, we can easily control this effect by choosing the over-the-counter quote on the five-year contract for each firm. Controlling the maturity effect is not as straightforward for corporate bonds with fixed expiration dates. One either needs to add maturity (or duration) as an explicit factor to control for the term structure effect, or to choose bonds within a maturity range to mitigate the term structure effect. Second, transaction prices on corporate bonds can vary significantly with the trading size and trading liquidity of the bond, creating a liquidity component in the credit spreads that is driven less by firm characteristics but more by security and trading characteristics. By contrast, the over-the-counter CDS contracts are between institutional players and with zero net supplies. While the bid-ask spread can vary, the mid CDS quote is less affected by the trading liquidity of the contract.[5] Due to these reasons, analysis based on CDS spreads tends to generate cleaner results on the credit risk determinants.[6]

[3]Currently, the North America CDS market is going through structural reforms to increase the fungibility and to facilitate central clearing of the contracts. The convention is switching to fixed premium payments of either 100 or 500 basis points, with upfront fees to settle the value differences between the premium payment leg and the protection leg.

[4]See, for example, Avramov, Jostova, and Philopov (2007), Bao and Pan (2012), Campbell and Taksler (2003), Chen, Lesmond, and Wei (2007), Collin-Dufresne, Goldstein, and Martin (2001), and Cremers, Driessen, Maenhout, and Weinbaum (2008).

[5]For example, Bongaerts, de Jong, and Driessen (2011) show that the effect of liquidity risk on CDS pricing is economically small.

[6]Several studies, e.g., Blanco, Brennan, and Marsh (2005), Longstaff, Mithal, and Neis (2005), Ericsson, Reneby, and Wang (2005), and Zhang, Zhou, and Zhu (2009), show empirically that CDS spreads are cleaner measures of credit risk than corporate bond yield spreads.

Our CDS data come from the Markit Inc., which collects CDS quotes from several contributors (banks and CDS brokers) and performs data screening and filtering to generate a market consensus for each underlying reference entity. To minimize measurement errors, we exclude observations with CDS spreads larger than 10,000 basis points because these contracts often involve bilateral arrangements for upfront payments.

We use a 45-day rule to match the financial statements with market pricing data, assuming that the end-of-quarter balance sheet information becomes available 45 days after the last day of each quarter. For example, we match CDS spread and stock market variables between May 15 to August 14 with Q1 balance sheet, market data between August 15 to November 14 with Q2 balance sheet, market data between November 15 to February 14 with Q3 balance sheet, and market data between February 15 to May 14 with Q4 balance sheet information. When we examine the balance sheet filing date in Capital IQ, we find that almost all firms electronically file their 10Q forms within 45 days after the end of each quarter. The 45-day rule guarantees that the accounting information is available at the date of CDS valuation.

To implement the Merton (1974) model, we use the ratio of total debt to market capitalization and the one-year realized return volatility as inputs. We also consider additional contributions from other credit informative firm characteristics:

- **Leverage**, for which we consider two alternative measures, the ratio of current liability plus half of long-term liability to market capitalization and the ratio of total debt to total asset.
- **Interest Coverage**, computed as the ratio of earnings before interest and tax (EBIT) to interest expense. The ratio measures the capability of a company in covering its interest payment on its outstanding debt with its ongoing earnings.
- **Liquidity**, captured by the ratio of working capital to total asset. Working capital, defined as current assets minus current liabilities, is used to fund operations and to purchase inventory.
- **Profitability**, captured by the ratio of EBIT to total asset.
- **Investment**, captured by the ratio of retained earnings to total asset. Retained earnings are net

earnings not paid out as dividends, but retained by the company to invest in its core business or to pay off debt.

- **Size**, measured by the logarithm of the market capitalization.
- **Stock market momentum**, measured by the stock return over the past year.
- **Options information**, captured by the log ratio of the one-year 25-delta put option implied volatility to the one-year realized volatility.

KMV uses current liability plus half of long-term liability as the proxy of the debt level in its Merton model implementation for the one-year default probability prediction (Crosbie and Bohn (2003)). Altman (1968, 1989) uses total debt to total asset, the interest coverage ratio, the working capital to total asset ratio, the EBIT to total asset ratio, and the retained earnings to total asset ratio to form the well-known Z-score for predicting corporate defaults. The company size has been used as a classification variable for credit risk prediction, as small companies are often required to have a larger coverage ratio for the same credit rating. Du and Suo (2003) find firm value as a strong predictor of credit risk in addition to the distance to default measure. Fama and French (1993) have also identified firm size as a risk factor that can predict future stock returns. Duffie, Saita, and Wang (2007) have used the past stock returns to predict firm default probabilities. We label the past return variable as the stock market momentum because of the evidence that past stock returns predict future stock returns (Jegadeesh and Titman (1993, 2001)). To the extent that stock market momentum predicts future stock returns, we conjecture that it can predict future financial leverage and hence credit risk. Finally, several studies show that stock put options contain credit risk information. See, for example, Collin-Dufresne, Goldstein, and Martin (2001), Berndt and Ostrovnaya (2007), Cremers, Driessen, Maenhout, and Weinbaum (2008), Cao, Yu, and Zhong (2010), and Carr and Wu (2010, 2011). In a recent working paper, Wang, Zhou, and Zhou (2009) highlight the credit risk information in the difference between implied volatility and realized volatility. Under the jump-to-default model of Merton (1976), the difference between the option implied volatility and the pre-default historical volatility is approximately proportional to the default arrival rate (Carr and Laurence (2006)). Furthermore, Berndt and Obreja (2010) show that CDS spreads price economic catastrophe risk and Zhang, Zhou, and Zhu (2009) show that a jump risk measure constructed from high-frequency returns can predict CDS variations. We use the implied to realized volatility ratio as an options market indicator on the firm's crash risk.

Table 1 reports the summary statistics of firm fundamental characteristics. For each characteristic, we pool the 138,200 firm-week observations, and compute their sample mean on the pooled sample. We also divide each characteristic into five groups based on the CDS spread level, and compute its sample average under each CDS quintile. The CDS spreads have a grand average of 188.57 basis points. The average CDS levels at the five quintiles are 20.16, 39.76, 69.25, 148.31, and 665.45 basis points, respectively. The fact that the average CDS is even higher than the fourth quintile level suggests that the distribution of the CDS spreads is positively skewed. The skewness estimate for the pooled CDS sample is highly positive at 8.51. Only when we take natural logarithm on the CDS, do we obtain a much smaller skewness estimate at 0.57, suggesting that the log CDS sample is closer to be normally distributed. Hence, we perform most of our analyses on the logarithm of the CDS spreads for better distributional behaviors.

[Table 1 about here.]

Inspecting the average levels of firm characteristics at different CDS quintiles reveals a monotonic increase in both the total debt to market capitalization ratio and the one-year realized return volatility with increasing CDS levels. The increase is particularly strong from the fourth to the fifth quintile. Similar patterns appear for the two alternative financial leverage measures: the ratio of total liability to market capitalization and the ratio of total debt to total asset. The interest coverage ratio declines with increasing CDS spread. The working capital to asset ratio does not show an obvious relation with the CDS quintiles. The EBIT and retained earnings to total asset ratios both decline with increasing CDS spread. Small companies, measured by log market capitalization, tend to have wider CDS spreads. Companies with declining stock market performance during the previous year tend to have higher CDS spreads. The implied volatility to realized volatility ratio show a slight decline as the CDS spread increases.

To understand how the firm characteristics differ across different firms and how they vary over time, the last four columns of Table 1 report four sets of standard deviation estimates reflecting variations along different dimensions: (i) Pooled — We estimate standard deviation on the pooled sample, which reflects the joint variation both across firms and over time; (ii) XS — We estimate the cross-sectional standard deviation at each date and the entries report the time-series averages of the cross-sectional estimates; (iii) TS — We estimate the time-series standard deviation for each firm and report the cross-sectional average of these estimates; and (iv) TSC — We take weekly changes on each characteristic for each firm and compute the time-series standard deviation for the weekly changes for each firm, with the column reporting the cross-sectional averages of the time-series standard deviation estimates on the changes.

The average cross-sectional (XS) estimates show how much the characteristics can differ across different firms whereas the average time-series (TS) estimates show how much the characteristics can vary over time for a given firm. For most of the firm characteristics, the cross-sectional variation is much larger than the time-series variation. For CDS spreads, the average cross-sectional standard deviation at 345.71 is more than twice as large as the average time-series standard deviation at 154.55. The standard deviation on the weekly changes averages at 34.27, just one-tenth of the cross-sectional standard deviation. The same observation applies to the firm fundamental characteristics. Take the total debt to market capitalization ratio as an example. The cross-sectional standard deviation averages at 3.4, which is three times as large as the average time-series standard deviation at 1.19. The standard deviation for weekly changes averages just about one-ninth of the cross-sectional standard deviation at 0.38. These statistics are consistent with the findings by Lemmon, Roberts, and Zender (2008) that the majority of variation in leverage ratios is driven by an time-invariant effect that generates “surprisingly stable capital structures.”

The large difference between the cross-sectional and the time-series variation is quite understandable. At any given date, companies can differ dramatically in their credit qualities from companies with the safest AAA rating to ones that are on the brink of bankruptcy. Meanwhile, the credit rating for a given company can stay at the same level for many years. The fact that our sample includes the financial crisis period of 2008 makes the time-series variation larger, but it remains much smaller than the corresponding cross-sectional variation on average for most firm characteristics. Even smaller is the time-series variation in the weekly changes on these characteristics. Indeed, many of the characteristics are derived from the financial statements, which are updated quarterly.

Thus, even though they can differ widely from firm to firm, fundamental characteristics do not vary much over a short sample period. The variation difference across different dimensions has important implications for empirical analysis attempting to link firm characteristics to their credit risk. The much larger cross-sectional variation dictates that only through cross-sectional comparative analysis can one most effectively identify the fundamental linkages.

III. Valuing CDS spreads based on firm fundamentals

To generate valuations on the five-year CDS spread, we start with the classic structural model of Merton (1974). We compute Merton's distance-to-default measure using the total debt to market capitalization ratio and the stock return realized volatility as inputs and convert this measure into a bias-corrected CDS valuation. In addition, we collect a long list of firm fundamental characteristics that are not included in the Merton model implementation but have been shown to be informative about a firm's credit spread. We propose a Bayesian shrinkage method to combine the Merton-based valuation with the information from this long list of additional fundamental characteristics to generate a weighted average CDS valuation.

A. MCDS: Merton-based CDS valuation

Merton (1974) assumes that the total asset value (A) of a company follows a geometric Brownian motion with instantaneous return volatility σ_A, the company has a zero-coupon debt with principal D and time-to-maturity T, and the firm's equity (E) is a European call option on the firm's asset value with maturity equal to the debt maturity and strike equal to the debt principal. The company defaults if its asset value is less than the debt principal at the debt maturity. These assumptions lead to the following two equations that link the firm's equity value E and equity return volatility σ_E to its asset value A and asset return volatility σ_A,

$$E = A \cdot N(d + \sigma_A \sqrt{T}) - D \cdot N(d), \tag{1}$$

$$\sigma_E = N(d + \sigma_A \sqrt{T}) \sigma_A A / E. \tag{2}$$

Equation (1) is the European call option valuation formula that treats the equity as a European call option on the company's asset value with strike equal to the debt principle D and expiration equal to the debt maturity date T. Equation (2) is derived from equation (1) and provides a link between the equity return volatility (σ_E) and the asset return volatility (σ_A). In the two equations, $N(\cdot)$ denotes the cumulative normal density and d is a standardized measure of *distance to default*,

$$d = \frac{\ln(A/D) + (r - \frac{1}{2}\sigma_A^2)T}{\sigma_A \sqrt{T}}, \tag{3}$$

with r denoting the instantaneous riskfree rate.

The Merton model is highly stylized in its assumptions on both the asset value dynamics and the capital structure. For asset value dynamics, well-documented discontinuous price movements and stochastic volatilities are ignored. For the capital structure, most companies have more than just a zero-coupon bond. Despite its stylized nature, the model captures two major determinants of credit risk — financial leverage and business risk — and combines them into a standardized distance-to-default measure in (3), which normalizes the financial leverage (log asset to debt ratio, $\ln(A/D)$) by the asset return volatility over the maturity of the debt ($\sigma_A\sqrt{T}$). It is well known that given the same financial leverage, firms with riskier business operations can have a higher chance of default. The distance-to-default measure in (3) normalizes the financial leverage by the business risk so that it reflects the number of standard deviations that the asset value is away from the debt principal.[7] The standardized measure becomes comparable across different firms that have different types of business and hence different levels of business risk. We regard the distance to default measure as the key contribution of the Merton model.[8]

To compute a firm's distance to default, we take the company's market capitalization as its equity value E, the company's total debt as a proxy for the principal of the zero-coupon bond D, and the one-year realized stock return volatility as an estimator for stock return volatility σ_E. We further

[7]Under the assumed dynamics, the log asset value $\ln A_T$ has a normal distribution with a risk-neutral mean of $\mu = \ln A_t + (r - \frac{1}{2}\sigma_A^2)T$ and a variance of $V = \sigma_A^2 T$. Hence, the negative of the distance to default $-d = (\ln D - \mu)/\sqrt{V}$ can be formally interpreted as the number of standard deviations by which the log debt principal exceeds the mean of the terminal log asset value.

[8]The approach of using distance-to-default to predict default probabilities was originally developed by KMV and discussed in Crosbie and Bohn (2003) and Kealhofer (2003), among others. It has also been widely adopted in the academic literature, e.g., Bharath and Shumway (2008), Duan, Sun, and Wang (2012), and Duan and Wang (2012).

assume zero interest rates ($r = 0$) and fix the debt maturity at $T = 10$ years for all firms. Since our focus is on the cross-sectional difference across firms, choosing any particular interest rate level for r or simply setting it to zero generates negligible impacts on the cross-sectional performance.

By regarding equity as an option on the asset, the Merton model uses the option maturity T to control the relative contribution of asset volatility to the equity value and hence default probability. We choose a relatively long option maturity to give more weight to the asset volatility in the determination of the default probability. Appendix A reports additional results regarding the impact of the maturity choice on the model's performance in capturing the cross-sectional variation of the market CDS observations.

We solve for the firm's asset value A and asset return volatility σ_A from the two equations in (1) and (2) via an iterative procedure.[9] With the solved asset value and asset return volatility, we compute the distance to default measure according to equation (3). Furthermore, although the model takes three inputs, (E, D, σ_E), the distance-to-default measure is scale free and does not depend on the firm's size. As a result, we can normalize the equity value to one and replace debt with the debt-to-equity ratio (D/E). Therefore, the distance-to-default measure is essentially computed with two inputs: the debt-to-equity ratio and stock return volatility.

We regard the distance-to-default measure as the final output of the Merton model. To generate a CDS spread valuation, we step away from the Merton model and construct a raw credit default spread (RCDS) measure according to the following transformation,

$$RCDS = -6000 \cdot \ln(N(d))/T, \tag{4}$$

where we treat $1 - N(d)$ as the risk-neutral default probability and transform it into a raw CDS spread with the assumption of a constant hazard rate and a 40% recovery rate. The step-away from the Merton model after the distance-to-default calculation is a common maneuver to retain the key contribution of the Merton model while avoiding its limitations in predicting actual defaults. If one were to take the Merton model assumption literally that default were not to happen before

[9] Appendix A discusses and compares other methods for solving for the asset return volatility and asset value based on return histories.

debt maturity, a five-year CDS contract would never pay out and hence would have zero spread for a company with only a ten-year zero-coupon bond. By switching to a constant hazard rate assumption, we acknowledge that default can happen at any time unexpectedly, with the expected default arrival rate determined by the distance to default. The fixed 40% recovery rate is a standard simplifying assumption in the CDS literature. To the extent that the recovery rate can also vary across firms, this simple transformation does not capture such variation.

To explain the cross-sectional variation of market CDS observations, at each date we estimate the raw CDS valuation (RCDS) on the whole universe of chosen companies, and map the RCDS to the corresponding market CDS observation via a cross-sectional local quadratic regression,

$$\ln(CDS) = f(\ln(RCDS)) + R, \tag{5}$$

where *CDS* denotes the market observation, $f(\cdot)$ denotes the local quadratic transformation of the RCDS value, and R denotes the regression residual from this mapping. Appendix B discusses the technical details on the nonparametric regression.

Had the RCDS valuation represented an unbiased estimate of the market observation, we would expect the two to have a linear relation with an intercept of zero and a slope of one. Nevertheless, the average bias of the Merton model valuation is well-documented (e.g., Huang and Huang (2012)), and we do not expect our simple constant hazard rate transformation in (4) to be bias free. Thus, we use the local quadratic regression to remove the average bias of the RCDS valuation at different risk levels. In performing this local bias removal transformation in (5), we take the natural logarithm on the CDS spread to create finer resolution at lower spread levels and to make the spread distribution closer to a normal distribution. We choose the local quadratic form based on our observation of the general relation between $\ln(CDS)$ and $\ln(RCDS)$. We choose a Gaussian kernel for the local quadratic regression and set the bandwidth to twice as long as the default choice to reduce potential overfitting. Appendix B provides additional robustness analysis on the impact of bandwidth choice on the in-sample and out-of-sample performance of the CDS valuations.

One can in principle choose a different structural model to mitigate the average bias, thus reducing the need for this bias-removal step; however, the prevailing evidence (see for example, Eom, Helwege, and Huang (2004)) is that most existing structural models are biased, even though the behavior of the average bias differs from model to model. Thus, the need for this bias correction step is likely to remain regardless of which structural model one chooses as the starting point.

On the other hand, given the nonparametric transformation to accommodate the nonlinearity between RCDS and market CDS observation, one can in principle skip the transformation in equation (4) and use the distance-to-default measure (d) directly as the explanatory variable in the local quadratic regression in (5).[10] We retain the transformation in (4) because it moves the distance-to-default measure closer to the actual CDS observation, and the local quadratic regression in (5) becomes more stable numerically when the inputs and outputs share similar magnitudes. We label the local-quadratic transformed Merton model CDS valuation as MCDS, $\ln(MCDS) = \widehat{f}(\ln(RCDS))$, with "M" denoting the Merton model origin.

B. WCDS: Capturing contributions from additional firm characteristics

The MCDS implementation accounts for information in the total debt to market capitalization ratio and the one-year realized stock return volatility. Many other firm characteristics have been shown to be informative about the firm's credit risk. Directly including all these characteristics into one multivariate linear regression is not feasible for several reasons. First, a characteristic may have a nonlinear effect on the credit spread. Second, some of these characteristics measure similar information, creating potential multi-collinearity issues for the regression. Third, some characteristics are measured with large errors. These errors can bias the regression estimates. Fourth, not all measures are available for all firms. Missing observations on firm characteristics can create problems for multivariate regressions. This paper proposes a methodology based on Bayesian shrinkage principles to overcome all these limitations in constructing a weighted average CDS valuation that incorporates the information from a long list of firm characteristics.

The approach uses the MCDS as the base valuation and estimates the additional contribution from each firm characteristic. These contributions are then combined via a stacking regression, with

[10]For example, Bharath and Shumway (2008) and Duan, Sun, and Wang (2012) directly use the distance-to-default measure as a predictive variable in their default probability specifications.

a Bayesian updating procedure that adds intertemporal stability. Formally, let F_t denote an $(N \times K)$ matrix for N companies and K additional credit-risk informative firm fundamental characteristics at date t. At each date, we first regress each characteristic cross-sectionally against MCDS to orthogonalize its contribution from the Merton prediction,

$$F_t^k = f^k(\ln(MCDS_t)) + x_t^k, \quad k = 1, 2, \cdots, K, \tag{6}$$

where $f^k(\cdot)$ denotes a local linear regression mapping and x_t^k denotes the orthogonalized component of F_t^k. Second, we regress the Merton prediction residual, $R_t = \ln(CDS_t/MCDS_t)$, cross-sectionally against each of the K orthogonalized characteristic x_t^k via another local linear regression,

$$R_t = f^k(x_t^k) + e_t^k, \quad k = 1, 2, \cdots, K. \tag{7}$$

Through this local linear regression, we generate a set of K residual predictions, $\widehat{R}_t^k$, $k = 1, 2, \cdots, K$, from the K characteristics.

Intuitively, we are explaining the CDS variation via a sequential regression approach. In the first step, we explain the CDS variation using the Merton model prediction (RCDS) in equation (5). In the second step, we explain the remaining CDS variation, i.e., the regression residual R_t from equation (5), by a list of additional variables F. Furthermore, instead of directly regressing R_t on F_t, we first remove the dependence of F_t on the Merton model prediction in equation (6) as a way of orthogonalizing the regressor and then regress R_t on the ortogonalized variable x_t in equation (7).

In all three equations (5)-(7), we could have run simple linear regressions if we think the relations are linear. Instead, we perform nonparametric regressions for all three equations to accommodate potential nonlinearities in the relations. For each nonparametric regression, we choose a large bandwidth to avoid overfitting. Furthermore, we choose a local quadratic form for the nonparametric regression in equation (5) to better capture the observed convex relation between $\ln(CDS)$ and $\ln(RCDS)$, and a local linear form for regressions in (6) and (7) for parsimony and stability. See Appendix B for more detailed discussions and robustness analysis regarding bandwidth and basis functional form choices.

Third, we stack the K predictions to an $N \times K$ matrix, $X_t = [\widehat{R}_t^1, \widehat{R}_t^2, \cdots, \widehat{R}_t^K]$, and estimate the weights among them via the following linear cross-sectional relation,

$$R_t = X_t W_t + e, \tag{8}$$

with W_t denoting the weights on the K predictions at time t.

For a given company, it is possible that only a subset of the K characteristics, and hence only a subset of the K predictions, are available. We fill the missing predictions with a weighted average of the other predictions on the firm, where the relative weights are determined by the R-squared of the regressions in (7) for each available variable,

$$R_t^{ij} = \sum_{k=1}^{\widetilde{K}} w^k \widehat{R}_t^{i,k}, \quad w^k = \mathbf{e}^\top (\mathbf{ee}' + \mathsf{diag}\langle 1 - R^2 \rangle)^{-1}, \tag{9}$$

where R_t^{ij} denotes the missing residual prediction on the ith company from the jth variable, which is replaced by a weighted average of the residual predictions on the subsect of $\widetilde{K}$ available residual predictions on the firm. The weighting is motivated by the Bayesian principle, where we set the prior prediction to zero and the relative magnitude of the measurement error variance for each available residual prediction proportional to one minus the R-squared of the regression.

Equations (6) and (7) each contains K separate univariate local linear regressions on the cross section of N firms at date t. The cross section can be smaller than N when there are missing values for a variable. Once the missing values are replaced by a weighted average, the time-t weighs (W_t) among the K predictions in equation (8) can be estimated in principle via a simple least square regression; however, to reduce the potential impact of multi-collinearity and to increase intertemporal stability to the weight estimates, we perform a Bayesian regression update by taking the previous day's estimate as the prior,

$$\widehat{W}_t = (X_t^\top X_t + P_{t-1})^{-1} \left(X_t^\top R_t + P_{t-1} \widehat{W}_{t-1} \right), \quad P_t = \mathsf{diag}\langle (X_t^\top X_t + P_{t-1}) \phi \rangle, \tag{10}$$

where ϕ controls the degree of intertemporal smoothness that we impose on the weights. We start with a prior of equal weighting and choose $\phi = 0.98$ for intertemporal smoothing.

The "stacking" of multiple predictors in equation (8) has been used in the the data mining literature, e.g., Wolpert (1992). In the econometric forecasting literature, Bates and Granger (1969) propose to apply equal weighting to K predictors. This simple suggestion has been found to be quite successful empirically (e.g., Stock and Watson (2003)). In constructing the Bayesian estimates for the weights on the K predictors in (10), we start with equal weighting as a prior at time 0. Equation (10) provides an average between the regression estimate $(X_t^\top X_t)^{-1} X_t^\top R_t)$ and the prior, with the coefficient ϕ controlling the relative weight for the prior. Furthermore, by setting the prior precision matrix P_{t-1} to a diagonal matrix, we reduce the impact of potential multi-collinearity. The diagonalization is related to the ridge regression literature (Hoerl and Kennard (2000)) if we set the prior coefficient to zero.

In the final step, we add the weighted average prediction of the residual back to the MCDS valuation to generate a new CDS valuation, which we label as WCDS:

$$\ln(WCDS)_t = \ln(MCDS)_t + X_t \widehat{W}_t. \tag{11}$$

In constructing the WCDS, we could have treated MCDS as just one of the firm characteristics. Instead, we separate its effect by treating MCDS as the benchmark CDS valuation and choose other firm characteristics based on their additional contribution to the CDS valuation. MCDS represents a good benchmark because its two inputs are readily available for virtually all publicly traded companies and our later analysis shows that it can explain a large proportion of the market observed CDS variation across firms.

IV. Explaining cross-sectional CDS variation with firm fundamentals

To investigate how much the fundamental-based CDS valuation can explain the cross-sectional variation of market CDS observations, we perform three sets of cross-sectional regression at each date,

$$\ln CDS_t^i = a_t + b_t (D/E)_t^i + c_t (\sigma_E)_t^i + e_t^i, \tag{12}$$

$$\ln CDS_t^i = \ln MCDS_t^i + e_t^i, \tag{13}$$

$$\ln CDS_t^i = \ln WCDS_t^i + e_t^i. \tag{14}$$

All regressions are on the logarithms of CDS for better distributional behaviors. The bivariate linear regression (BLR) in (12) creates a benchmark by taking the two Merton model inputs directly as explanatory variables. The univariate regressions in (13) and (14) measure the cross-sectional explanatory power of MCDS and WCDS valuation, respectively.

A. Cross-sectional explanatory power

Figure 1 plots the time series of the cross-sectional R-squared estimates from the three sets of cross-sectional regressions. The dash-dotted line at the bottom represents the R-squared estimates from the bivariate linear regression, the dashed line represents the cross-sectional explanatory power of MCDS, and the solid line represents the cross-sectional explanatory power of WCDS. The rankings of the R-squared estimates stay the same across all days, with the bivariate linear regression generating the lowest R-squared estimates and WCDS generating the highest R-squared estimates at all times.

[FIGURE 1 about here.]

The universal outperformance of MCDS over the bivariate linear regression suggests that in addition to pointing out the main determinants of credit spreads, the Merton model also provides a useful way of combining the two input variables into a standardized distance-to-default measure that becomes more cross-sectionally comparable. The further performance enhancement from MCDS to WCDS highlights the contribution of the long list of additional firm fundamental characteristics.

The Merton (1974) model predicts that the credit spread is dictated by financial leverage and stock return volatility. The MCDS implementation uses the ratio of total debt to market capitalization as a measure of financial leverage and uses the realized volatility over the past year as a measure for stock return volatility. The WCDS construction includes two alternative measures of financial leverage and an alternative measure of stock return volatility implied from stock options. Furthermore, it includes firm characteristics that are not in the Merton model but have been shown to be informative about the credit risk of a company. Combining all these characteristics through our Bayesian shrinkage methodology generates a sizable improvement over the MCDS.

The dash-dotted line and the dashed line in Figure 1 show that the R-squared estimates from BLR and MCDS are higher during the two recessions in our sample, but lower during the economic expansion period between 2006 and 2007. The time variation in performance suggests that during recessions, the two Merton-suggested characteristics can explain a large portion of the cross-sectional variation; however, when the economy is booming and the overall credit concern is less severe, other firm characteristics can play a larger role in differentiating the CDS spreads across firms. By combining the contribution from a wide range of firm characteristics, the WCDS valuation not only performs better than MCDS at all times, but also generates much more stable performance across different time periods.

Table 2 reports the summary statistics of the R-squared estimates. Panel A reports the statistics based on the full-sample estimation. The R-squared estimates from the bivariate linear regression average at 49%, similar to results reported in the literature from cross-sectional linear regressions.[11] By comparison, the R-squared estimates from regressing on MCDS average at 65%, a 16 percentage point increase. The t-statistic on the average R-squared difference (MCDS-BLR) is estimated at 13.57, suggesting that the MCDS valuation generates strongly significant improvement over the bivariate linear regression, even though the input variables are the same.

[Table 2 about here.]

[11] Ericsson, Jacobs, and Oviedo (2009) regress the CDS spreads on three determinants of the Merton model (financial leverage, volatility, and a riskfree rate), and obtain an R-squared of 46.0-48.4% from a panel regression with quarter dummies.

By incorporating a long list of firm characteristics via a Bayesian shrinkage method, the WCDS can explain 77% of the cross-sectional market CDS variation on average, representing an additional 11 percentage point improvement over the MCDS valuation. The average performance difference between WCDS and MCDS generates a high t-statistic at 6.41, showing the strong significance of the contribution from the additional firm characteristics.

The WCDS valuation generates not only the highest average cross-sectional explanatory power, but also the most stable performance over time. The R-squared estimates for WCDS show a small standard deviation of merely 4%, compared to 8% for the MCDS regression and 10% for the bivariate linear regression. The R-squared estimates for WCDS stay within a narrow range from a low of 67% to a high of 85%.

The high and stable cross-sectional explanatory power suggests that the WCDS can be quite effective in differentiating the credit qualities of different firms based on their differences in firm fundamental characteristics. In the U.S., thousands of publicly-traded companies have publicly available firm fundamental data, but only hundreds of them have reliable CDS quotes. Thus, an important practical application for the WCDS methodology is to generate CDS valuations on firms without reliable CDS quotes, thereby vastly expanding the universe of companies with CDS valuations. Broker dealers and investors can use the fundamental-based WCDS valuation to expand their universe of CDS marks for both market making and marking to market of their CDS positions.

Such an application requires that the WCDS model be calibrated to the universe of companies with reliable CDS marks and then extrapolated to companies without CDS marks. To gauge the robustness of this extrapolation, we perform an out-of-sample exercise each day by randomly selecting half of the universe for model calibration while generating CDS valuations on the whole universe.

Table 2 reports the in-sample performance for the half of the universe used for model calibration in Panel B and the out-of-sample performance for the other half of the universe in Panel C. For the bivariate linear regression, the average R-squared is 51% on the in-sample half of the universe, but it is reduced to 25% for the out-of-sample half of the universe. Furthermore, some of the out-of-sample R-squared estimates are highly negative, suggesting a complete breakdown of the linear extrapolation.

By contrast, the out-of-sample performance of MCDS is largely comparable to its in-sample performance, with the mean R-squared declining mildly from 65% in sample to 64% out of sample. Therefore, while the linear additive regression on the financial leverage and realized volatility can become unstable out of sample, the Merton model approach of combining the two input variables generates a stable output that experiences little out-of-sample deterioration.

The WCDS valuation involves serval layers of local linear nonparametric regressions and a linear combination of several univariate predictors; nevertheless, it shows remarkable out-of-sample stability, with the average R-squared at 77% for the in-sample half of the universe and 74% for the out-of-sample half of the universe. The out-of-sample stability comes from our choice of a large bandwidth for the nonparametric regressions (See Appendix B for more detailed analysis) and the Bayesian shrinkage methodology for combining the multiple predictors. Overall, the out-of-sample exercise shows that the WCDS methodology can be used successfully in expanding the CDS universe based on firm fundamental characteristics.

B. Contributions from additional firm fundamental characteristics

The superior performance of WCDS over MCDS highlights the aggregate contribution from the long list of additional firm fundamental characteristics that we incorporate via the Bayesian shrinkage method. To understand the contribution of each characteristic, Figure 2 plots the mapped relation between each orthogonalized characteristic x^k and the Merton model prediction residuals $\ln(CDS/MCDS)$. All characteristics are first orthogonalized against the contribution of MCDS, and the relations are estimated on the pooled data across 351 weeks and 579 firms. For ease of comparison across different characteristics, we use the percentiles of each characteristic as the x-axis and use the same scale for the y-axis for the predicted market-Merton deviation $\ln(CDS/MCDS)$.

[FIGURE 2 about here.]

The two financial leverage measures in the first two panels generate similar prediction patterns as higher leverage predicts higher additional CDS spread (in addition to the MCDS prediction). The interest coverage ratio in Panel (3) can be regarded as an alternative measure of leverage by comparing the interest payment to the operating income. The higher the coverage ratio, the lower the leverage, and the lower the CDS spread.

Panels (4) to (6) capture the additional contributions from the liquidity measure (the ratio of working capital to total asset), the profitability measure (the ratio of EBIT to total asset), and the investment measure (the ratio of retained earnings to total asset), respectively. The contribution of the liquidity measure is small except at the tails of the deciles. Profitability and investment ratios show similar contributions as both increased profitability and increased investment help reduce the CDS spreads. In particular, a lower or even negative retained earning often leads to a much wider CDS spread.

Panels (7) to (9) show the contributions from three firm risk characteristics: size, momentum, and crash risk. All three characteristics show large contributions, with large size, positive momentum, and low implied-to-realized volatility ratio contributing to lower CDS spreads.

The univariate local linear mapping between each firm characteristic and the market-MCDS deviation $\ln(CDS/MCDS)$ measures the marginal contribution of each characteristic, but does not adjust for the interaction between the different characteristics. The multivariate linear regression in the last step of WCDS construction accommodates such interactions, with the regression coefficients capturing the relative weight from each contribution. Figure 3 plots the time series of the relative weights across our sample period. The time series of the coefficient estimates are quite stable over time, as a result of the intertemporal Bayesian smoothing applied in our methodology.

[FIGURE 3 about here.]

If the nine univariate predictions were mutually orthogonal, we would expect all coefficients on the stacked relation to be positive and the multivariate prediction to be an average of the univariate predictions. Some of the weight estimates in Figure 3 turn negative, showing the effect of multivariate interactions. The highest positive weights come from the size of the company, the retained earnings to total asset ratio, and the option implied-to-realized volatility ratio, suggesting that these characteristics capture rather independent contributions to the credit risk measures. On the other hand, contributions from the two financial leverage measures and the interest coverage ratios are small and can even turn negative during some time periods.

Fundamentally, a structural model plays two important roles in linking a firm's structural characteristics to its credit risk. First, it hypothesizes what types of structural characteristics affect the firm's credit risk. Second, it provides a functional form that combines and converts these characteristics into a credit risk measure. Take the Merton (1974) model as an example. It identifies financial leverage and firm business risk as the two key determinants of credit risk, and proposes to combine the two into a distance to default measure. Our analysis shows that the Merton model, at least our implementation of it, does a good job on both fronts. Simply taking Meron's suggestion in selecting the financial leverage and stock return volatility as the two explanatory variables, the bivariate linear regression can explain about half of the cross-sectional CDS variation. Applying the model's internal structure to convert these two inputs into a credit riskmeasure further raises the average cross-sectional explanatory power to 65%, while also drastically enhancing the out-of-sample stability of the explanatory power. Indeed, Merton's distance to default measure has been well recognized in the industry as a good predictor of the company's credit risk (e.g., Crosbie and Bohn (2003)).

Meanwhile, the superior performance of the WCDS valuation highlights where the Merton (1974) model can be improved upon. The WCDS methodology does not fully replace the need for a better structural model; nevertheless, it represents a stable approach to investigate the additional contributions from a long list of firm characteristics, thus providing guidance for future structural model development. To successfully capture the cross-sectional credit spread difference, a structural model must find ways to ccommodate the contribution from the list of characteristics that we identify. Some of the characteristics are included to address data and definition issues. For example, while the Merton model is implemented using the total debt as the debt principal and market capitalization as the equity value, we also include current liability plus half of long-term liability over the market capitalization ratio as an alternative measure of financial leverage. On the other hand, several of the characteristics suggest that it is important to not only capture the current leverage situation, but also predict its future path. Specifically, the analysis shows high contribution weights on the retained earnings to total asset ratio, the stock market momentum, and the option implied volatilities. A high retained earnings ratio predicts increased future financing flexibility. A high stock market momentum predicts future increase in market capitalization and accordingly reduction in leverage. The option implied volatility has been shown to be an efficient predictor of future realized volatilities and hence predicts future business risk. Finally, the analysis also shows that the firm size can be a strong predictor of credit spread, potentially due to its relation to funding capability, among other considerations.

C. Reconciling with the low R-squared from time-series change regressions

The fundamental-based WCDS valuation can explain a large proportion of the cross-sectional variation in market CDS observations. This high cross-sectional explanatory power forms a contrast with the low explanatory power one often obtains from time-series regressions of changes in credit spreads against changes in firm fundamentals.[12] These two sets of findings, however, are not conflicting with each other, but rather represent different aspects of the data behavior. Although WCDS explains a large proportion of the cross-sectional CDS variation across all days in our sample period, it remains possible that changes in WCDS for a given firm only explain a small proportion of changes in the market CDS observation for that firm, especially when the firm's fundamentals do not vary much over the sample period. Indeed, as we have shown in Table 1, most of the selected firm characteristics vary much more cross-sectionally than over time. If fundamentals do not vary for a given firm, one cannot expect changes in the firm's fundamentals to explain much of its CDS variation, regardless of how strong the linkage between the two is.

To verify this conjecture, we form log CDS spread changes over different horizons from one to four weeks. For each firm with over one year of observations, we perform linear regressions of the market CDS changes against the corresponding changes in (A) the two Merton inputs, D/E ratio and equity return volatility (σ_E), (B) the logarithm of MCDS, and (C) the logarithm of WCDS, respectively. The three time-series change regressions are constructed in parallel with the three

[12] See, for example, Collin-Dufresne, Goldstein, and Martin (2001) and Avramov, Jostova, and Philopov (2007), who regress changes in corporate bond spreads, and Blanco, Brennan, and Marsh (2005), who regress changes in CDS spreads, on changes in economic variables. Ericsson, Jacobs, and Oviedo (2009) and Zhang, Zhou, and Zhu (2009) consider regressions both on CDS spread levels and changes, whereas Campbell and Taksler (2003) and Cremers, Driessen, Maenhout, and Weinbaum (2008) analyze levels of bond spreads. The general finding is that regressions on spread levels generate high R-squared than regressions on changes in spreads. More recently, Huang and Shi (2013) explore ways to reconcile the usefulness of firm characteristics and their low explanatory power in time series regressions.

cross-sectional regressions in (12)-(14). Table 3 reports the cross-sectional averages and standard deviations (in parentheses) of the coefficients estimates and the R-squared (R^2) of the time-series regressions. Each panel reports results from one set of regression. For the bivariate linear regression in panel A, the R-squared estimates average merely at 6% for weekly changes and 12% for four-week changes. The average R-squared estimates are about twice as high for the regression on MCDS and WCDS changes, but they are still much lower than those from the cross-sectional regressions in Table 2. Thus, the high cross-sectional explanatory power is completely compatible with the low time-series R-squared from time-series change regressions. The high cross-sectional R-squared suggests that one can use firm fundamentals to effectively differentiate the credit spread levels of different companies. On the other hand, for a given firm, if its fundamental characteristics do not vary much during the sample period, most of the short term time-series variations of its CDS spreads are likely driven by non-fundamental factors.

[Table 3 about here.]

A related conjecture is that the time-series change regression generates higher R-squared estimates if the firm's CDS levels and fundamental characteristics experience larger variations during the sample period. To test this hypothesis, we measure the time series standard deviation of the log CDS and the regressors for each firm, and then measure the cross-sectional correlation between the time-series regression R-squared and the standard deviation estimates. The columns on the right side of each panel in Table 3 report the correlation estimates. The correlation estimates are strongly positive in all cases, validating our conjecture that when the underlying firm characteristic does experience large variations, a time-series change regression can also identify the relation. Nevertheless, since most firm's structural characteristics such as business types and capital structures are stable over time, a cross-sectional analysis is in general more effective in identifying the structural linkage.

This comparative analysis highlights the general principle that if one intends to identify the impact of a certain variable, it is important to construct a sample in which this variable shows significant variation. By choosing a sample/dimension in which the targeted variable does not vary much, the observed variation is bound to be dominated by other factors.

It is also important to appreciate that different economic objective ask for different types of analysis. A structural model links a firm's structural characteristics to its credit risk. Since these structural characteristics tend to be quite stable for a firm but can vary greatly across firms, it is natural to use cross-sectional analysis to gauge the effectiveness of the proposed linkage. On the other hand, a time-series analysis can be more suitable for analyzing the variations of common risk factors and risk premiums. Indeed, the large common principal component in the residuals of the time-series change regressions by Collin-Dufresne, Goldstein, and Martin (2001) likely reflects variations in common risk factors and the market pricing of these common risks.

V. Forecasting the future based on market-fundamental deviations

Since the WCDS valuation incorporates information from a long list of firm fundamental characteristics, the deviation of market CDS observations from this fundamental-based valuation is most likely driven by non-fundamental factors, such as supply-demand shocks. If such non-fundamental shocks are transitory and tend to dissipate over time, the fundamental-based WCDS valuation can be used as a relative valuation tool in separating the fundamental value from transitory supply-demand shocks in the market observations. In this section, we examine the forecasting power of the market-fundamental deviations on future market CDS movements. First, we examine whether the market-fundamental deviations are more mean-reverting than the original CDS series. Second, we estimate the forecasting correlation between current market-fundamental deviations and future market CDS movements. Finally, we gauge the economic significance of the forecasting power through an out-of-sample investment exercise based on market-fundamental CDS deviations.

A. Mean reversion speeds

We estimate the mean reversion speeds of the log market CDS observations and the market-fundamental CDS deviations from the different valuation methods, which are captured by the residuals e from the cross-sectional regressions in (12)-(14). For each series x, we estimate the mean reversion speed through the following regression,

$$x_{t+h} - x_t = a - \kappa x_t h + \varepsilon_{t+h}, \tag{15}$$

where $h = 1/52$ denotes the weekly sampling frequency and κ measures the annualized mean reversion speed of the series. The reciprocal of κ has the unit of time and intuitively measures the time it takes for the series to revert back to its mean level. The larger the κ estimate, the more mean reverting the series is, and the faster the series reverts back to its mean level. A random walk (with no mean reversion) would generate a κ estimate of zero.

For each firm with more than one year of observation, we estimate the mean reversion speed via a time-series regression in the form of equation (15). Table 4 reports the sample mean and standard deviation of the mean reversion speed estimates across different firms. The market log CDS observation has an average mean reversion speed estimate of 1.52, corresponding to a time line of seven to eight months. The mean reversion speeds from the market-fundamental deviations are higher. The highest average mean reversion estimate comes from the deviation between market CDS and WCDS at 3.47, corresponding to a time line of less than a quarter. The estimates confirm our conjecture that the WCDS valuation separates the market observation into two components, a fundamental-driven component and a more mean reverting component driven by non-fundamental related factors.

[Table 4 about here.]

The mean reversion speed estimates for the market-MCDS deviation average at 1.99, higher than the average mean reversion speed of the original CDS time series, but significantly lower than that from the market-WCDS deviation.[13] By using the distance-to-default measure as the single input, the MCDS valuation does not account for all fundamental information. As a result, the MCDS is not as effective as the WCDS valuation in separating out the transitory components in market CDS observations. Worse still is the bivariate linear regression, which generates regression residuals that are more mean reverting than the original CDS series, but less than that from the market-MCDS

[13]The average mean reversion difference between the two residual series (WCDS and MCDS) is 1.48, with a t-statistic of 13.99.

deviation.

Kapadia and Pu (2012) analyze the co-integrating relation between the stock market and the CDS market. Our finding on the strongest co-integration between CDS and WCDS suggest that the co-integrating relation is more complicated than a simple linkage between the two markets. Only by integrating a long list of firm characteristics can fully extract the underlying co-integrating relation.

B. Cross-sectional forecasting correlations

The more mean-reverting nature of the market-fundamental deviation suggests that one can potentially use the market-fundamental deviation to predict future market movements. When the market CDS observation deviates from the fundamental-based valuation, chance is that the market CDS quote will revert back to the fundamental valuation in the future.

To gauge this forecasting capability, at each date, we measure the cross-sectional forecasting correlation between market-fundamental deviations at that date and future changes in the market observation,

$$\rho_{t,h} = Corr\left(\ln(CDS^i_{t+h}/CDS^i_t), \ln(CDS^i_t/\widehat{CDS}^i_t)\right), \tag{16}$$

where $\ln(CDS^i_{t+h}/CDS^i_t)$ measures the log change from time t to $t+h$ on the market CDS observation for firm i and $\ln(CDS^i_t/\widehat{CDS}^i_t)$ denotes the time-t deviation between the market CDS observation on this firm and the corresponding fundamental-based valuations, $\widehat{CDS}^i_t$. We consider deviations generated from the three sets of the cross-sectional regressions in (12)-(14), i.e., the bivariate linear regression (BLR), MCDS, and WCDS. If the deviation reveals the transitory component of the market observation, we would expect the correlation estimates to be negative as a result of mean reversion on the transitory component. In particular, if the current market observation is higher than the fundamental-based valuation and hence the deviation is positive, we would expect the market CDS spread to decline in the future to converge toward the fundamental valuation.

Table 5 reports the summary statistics of the forecasting correlation estimates. The two panels are for two forecasting horizons h: one week in panel A and four weeks in panel B. For each time series of correlation estimates, we report the sample mean, the standard deviation, and also the t-statistics on the significance of the mean estimate. In computing the t-statistics, we adjust for the serial dependence according to Newey and West (1987) with the lag optimally chosen according to Andrews (1991).

[Table 5 about here.]

The mean correlation estimates are negative over both horizons and for all three sets of deviations, consistent with our conjecture that market-fundamental deviations predict future market reversions to the fundamental valuation. The more negative the correlation estimates are, the stronger the prediction. Deviations from WCDS generates the most negative mean correlation estimates, -7% and -12% at one-week and four-week horizon, respectively, whereas the bivariate linear regression generates the least negative mean correlation estimates at -5% and -9% at one-week and four-week horizon, respectively. The last two columns report statistics on the pair-wise correlation differences. In particular, the difference between WCDS and MCDS averages at negative two percentage points. The average is highly significant statistically, underlining the significance of the contribution from the long list of additional firm fundamental characteristics.

C. An out-of-sample investment exercise

To gauge the economic significance of the forecasting power, we perform a simple out-of-sample CDS investment exercise based on deviations between market observations and the fundamental-based valuations.

At each date t, we measure the deviation between the market CDS observation and the fundamental-based valuation, and we invest in a notional amount in each CDS contract i, n_t^i, that is proportional to this deviation,

$$n_t^i = c_t \left(\widehat{CDS}_t^i - CDS_t^i \right). \qquad (17)$$

Intuitively, if the market observation is lower than the fundamental-based valuation, the market CDS will go up in the future, and it is beneficial to go long on the CDS contract and pay the lower-than-predicted premium. We normalize the proportionality coefficient c_t each day such that we are long and short one dollar notational each in aggregation. The universe that we invest in at time t includes all firms in our sample that have valid CDS quotes and fundamental valuations at that time. The forecasting correlation estimates reported in Table 5 are small in absolute magnitude, although they are strongly significant statistically. By investing in all firms at each point in time, we enhance the prediction by diversifying the prediction errors across different firms. Furthermore, by taking equal dollar notional on long and short positions, we strive to cancel out exposures to market movements so that the movements of the portfolio value are mainly driven by the convergence movements.

We hold the investment for a fixed horizon h. If the company does not default during our investment horizon, we calculate the profit and loss (PL) assuming a flat interest rate and default arrival rate term structure. Since initiating the contract at time t costs zero, the PL is given by the time-$(t+h)$ value of the CDS contract initiated at time t. For a one-dollar notational long position on the i-th contract, the PL is given by

$$PL_{t,h}^{i} = LGD\left(\lambda_{t+h}^{i} - \lambda_{t}^{i}\right)\frac{1 - e^{-(r_{t+h}+\lambda_{t+h}^{i})(\tau-h)}}{r_{t+h} + \lambda_{t+h}^{i}}, \tag{18}$$

where LGD denotes the loss given default, which we assume fixed at 60% for all contracts, r denotes the continuously compounded benchmark interest rate, which we use the five-year interest-rate swap rate as a proxy, and λ^i denotes the default arrival rate for the ith-company, which we infer from the corresponding CDS rate by assuming a flat term structure, $\lambda_t^i = (CDS_t^i/LGD)/10000$. In case the company defaults during our investment horizon, the payout for a one-dollar notional long position is given by the loss given default $PL = LGD$. In aggregate, we can regard the dollar profit and loss from the total investment at each date as excess returns on a one-dollar notional long and one-dollar notional short investment. The investment exercise is purely out-of-sample as the fundamental-based valuations at time t only use information up to time t.

We consider investments horizons from one to four weeks. Table 6 reports the summary statistics of the excess returns from the investment exercise. Panel A shows the result when the investment decisions are based on the residuals from the bivariate linear regression of log market CDS on the total-debt-to-market capitalization ratio and the one-year realized volatility. The investments do generate positive returns on average, but the standard deviations of returns are large, resulting in low information ratios, defined as the ratio of the annualized mean return over the annualized standard deviation. Thus, the linear regression approach is largely ineffective in generating consistently good investment opportunities.

Panel B shows the results when the investment decisions are based on market deviations from the MCDS valuation. At weekly rebalancing, the investments generate an average annualized excess return of 25.25%, and an annualized standard deviation of 16.76%, resulting in a very high information ratio of 1.51. The investments generate positive skewness and positive kurtosis. As the rebalancing frequency declines from weekly to monthly (every four weeks), the average annualized excess return declines to 14.3% and information ratio declines to 0.80, suggesting that the convergence of market observations to the fundamental valuation is reasonably fast.

[Table 6 about here.]

Panel C reports the investment results based on the WCDS valuation. By incorporating information from a long list of additional firm fundamental characteristics, the investments generate both higher average excess returns and lower standard deviation. At weekly rebalancing, the average annualized excess return is 21.14% and the standard deviation is 14.22%, leading to an information ratio of 2.26. The average excess return declines as we reduce the rebalancing frequency. Still, even at 4-week rebalancing frequency, the average annualized excess return is over 20% and the information ratio as high as 1.5.

We do not treat our investment exercise as a realistic backtest for an actual investment strategy and refrain from further exploration on potential refinement of the investment strategy. Realistic backtesting on CDS investment faces several difficulties. First, the CDS spreads that we obtain from Markit are not executable quotes from a broker dealer, but rather some filtered averages of multiple broker-dealer contributions. While the average does present an estimate for the market consensus on the CDS price for a reference entity, it may not represent exactly where transactions can happen.[14]

[14]Markit implements various mechanisms in the data collection procedure to guarantee that the dealer contributions represent where the dealers truly want to trade.

Second, the CDS is an over-the-counter contract, where the transaction cost can vary significantly depending on the institution that initiates the transaction. As a result, some institutions that can initiate CDS transactions with low costs can potentially implement similar strategies as profitable investment opportunities, whereas other institutions may not be able to overcome the transaction cost to profitably explore the deviations between the market observation and the fundamental-based valuations.

Nevertheless, the investment exercise highlights the economic significance of the fundamental-based CDS valuation and shows the importance of incorporating a long list of firm fundamental characteristics in order to effectively separate fundamental-based CDS variations from transitory supply-demand shocks. Even if the market consensus observations are meant only for marking to market, our exercise shows that one can potentially improve the marks by moving them closer to the fundamental-based valuation. Since the market observations revert to the fundamental-based valuations, using the fundamental-based valuations for marking can potentially reduce the transitory movements of the portfolio value and reflect more of the actual credit risk exposure of the institution's position. Finally, the poor investment performance from the bivariate linear regression highlights the economic importance of constructing a structural model that incorporates the many firm characteristics that we have identified via the WCDS methodology.

VI. Conclusion

A well-developed structural model can play important economic roles by linking a firm's structural characteristics to its potential credit risk. Since these structural characteristics tend to be stable over time but can differ widely across firms, it is important to perform cross-sectional comparative analysis to examine the effectiveness of such models. In this paper, we perform cross-sectional analysis of CDS spreads on U.S. non-financial firms and show that a simple structural model like Merton (1974), when well implemented, can go a long way in explaining the cross-sectional differences in CDS spreads. Our analysis also highlights where the simple model can be improved. Via a Bayesian shrinkage methodology, we combine the Merton valuation with a long list of additional firm structural characteristics to generate a weighted average CDS valuation (WCDS), and show that the WCDS explains a much larger cross-sectional variation of the market CDS. Furthermore, when the market CDS quotes deviate from the WCDS valuation, the market quotes tend to move toward the valuation in the future. Our results provide guidance for future structural model developments: A successful structural model must find ways to incorporate the contribution from this long list of firm structural characteristics.

Historically, results from empirical studies have had large impacts on subsequent theoretical efforts. For example, early findings on the average biases of structural models (Huang and Huang (2012)) lead to theoretical efforts in reducing the average biases. As an example, Cremers, Driessen, and Maenhout (2008) introduce jumps to the asset value dynamics and link the jump risk premium to those implied from the equity index options market. By so doing, they find that the average credit spread level is consistent with how equity options are priced. Their findings highlight the inherent awkwardness of using structural models to explain/reconcile the average size of risk premiums. Structural models like Merton (1974) are built on the principles of no-arbitrage trading and relative pricing, rather than risk-return tradeoff. As such, these models do not have much to say about the "appropriate levels" of risk premiums. They merely identify a linkage between the pricing of one security to the pricing of other securities via dynamic no-arbitrage trading arguments. Instead, the sources and size of risk premiums are often the focus of general equilibrium models on the aggregate markets.

Similarly, when Collin-Dufresne, Goldstein, and Martin (2001) show that the time-series change regressions generate low R-squares and that the regression residuals share a large single principal component, much research is directed to the search of this common missing variable that explains the common variation of credit spreads. Intuitively, firms can differ structurally (e.g., in their type of business and level of financial leverage) and hence in their credit risk, but the market pricing per unit of risk should be universal for internal consistency. Thus, the common variation in the regression residuals likely reflects the common variation of risk premiums, again the focus of general equilibrium models rather than firm-level structural models.

While it is possible for a structural model to accommodate a common risk factor, the key strength of such models is to link a firm's structural characteristics to its credit risk. Given the structural stability of firms, our cross-sectional analysis is more likely to identify firm structural characteristics that can be embedded fruitfully in future structural model developments.

Appendix

A. Variations in structural model implementations

The Merton (1974) model has been implemented in several variations in the literature. This section investigates the effects of these variations on the cross-sectional-explanatory power of the resulting MCDS and WCDS. First, the KMV implementation as documented in Crosbie and Bohn (2003) sets the maturity T to one year, matching their default probability forecasting horizon. In Panel A of Table 7, we show how the maturity choice affects the cross-sectional explanatory power of the model on the five-year CDS spread. As in the main text of the paper, each date, we use a random half of the universe to calibrate the model and generate CDS valuations on the whole universe. The left side in the panel reports the time-series average of the cross-sectional R-squared estimates on the in-sample half of the universe for both MCDS and WCDS valuation. The right side reports the corresponding average R-squared estimates on the out-of-sample half of the universe.

[Table 7 about here.]

The results in panel A of Table 7 show that choosing a short maturity such as one year in the Merton model can generate significantly lower cross-sectional explanatory power on the five-year CDS spreads. The performance improves and reaches a plateau once the chosen maturity is five years or longer.

Intuitively, the Merton model predicts that a company's default probability is determined by both the degree of its financial leverage and the volatility in its business (σ_A). Furthermore, by treating equity as a European option on the asset, the model controls the relative importance of the two determinants through the option maturity. As the maturity increases, the equity valuation becomes more sensitive to the asset volatility, and the volatility level plays a larger role in determining the default probability. Our analysis suggests that the market valuation of five-year CDS assigns a higher weight to the volatility consideration than suggested by the one-year maturity assumption used in the KMV implementation.

Second, KMV proposes to approximate the debt principal by the firm's current liabilities plus one half of its long-term debt, but we find that using total debt generates slightly better performance than the KMV choice for explaining the cross-sectional variation of the five-year CDS. Nevertheless, we accommodate alternative leverage measures in our WCDS construction. In panel B of Table 7, we compare our implementation ("Total Debt") with the implementation of using current liability plus half of long-term liability ("CL+LL/2"). In the latter case, we use the ratio of total debt to market capitalization to replace the ratio of current liability plus half of long-term liability to the market capitalization as the alternative leverage measure. The results show that using current liability plus half of long-term liability generates lower cross-sectional explanatory power for MCDS; however, by accommodating the other measure as an alternative leverage measure in the WCDS construction, the two choices generate similar performances for WCDS.

Third, to solve for the firm's asset value and asset return volatility, several studies, e.g., Crosbie and Bohn (2003), Vassalou and Xing (2004), Duffie, Saita, and Wang (2007), and Bharath and Shumway (2008), propose a more computationally intensive iterative approach that involves the time series history: Starting with an initial guess on asset return volatility σ_A, they solve for the history of the firm's asset value based on the firm's equity value history and equation (1). Then, they estimate the asset return volatility σ_A from log changes on the solved asset value series. Duan (1994) and Ericsson and Reneby (2005) propose to embed this iterative procedure into a maximum likelihood framework. However, computing σ_A from the asset value time series can be problematic when changes in the asset value are induced by financing or investment decisions instead of operating activities. In such cases, returns on assets, upon which the asset return volatility σ_A should be measured, can be quite different from log changes in the asset value series. Duan, Sun, and Wang (2012) propose to scale the asset value by the corresponding book value as an approximate correction for this issue. Directly solving the two equations (1) and (2) completely circumvents this scaling issue.

In panel C of Table 7, we analyze the effect of different asset return volatility calculation methods. We label our method as the two-equations-two-unknowns (TETU) approach, and we consider two alternative approaches based on asset value history (AVH). In AVH-I, we take the suggestion from Duan, Sun, and Wang (2012) and scale the extracted asset value by the corresponding book value of total asset. We compute log returns on this scaled asset value and estimate the sample standard deviation of the return series over the past year as the asset return volatility. The cross-sectional explanatory power of MCDS computed from this approach averages around 57% and 55% for the two sub-samples, respectively, markedly lower than the average performance of the MCDS computed from our TETU approach at 65% and 64%.

Scaling the asset value by its book value removes the impact of financing activities such as mergers and issuance or retirement of stocks or debt, but it also has the un-intended effect of mitigating the operating activities because the book value of equity can change due to both financing activities (e.g., issuing or retiring stock) and operating activities (retained earnings). The latter should not be excluded from the asset value change as it is an integral part of the return on asset. As a result, the sample standard deviation computed from the scaled asset value time series may not accurately reflect the true asset return volatility.

In AVH-II, we do not use the asset value history directly, but rather rely on the stock return history and adjust the stock return by the asset-stock sensitivity. Specifically, at each date, we first compute the daily stock total return based on the adjusted stock price series (adjusted for splits and dividend payments), and then convert this stock return into asset return based on the hedge ratio implied by the Merton model:

$$R_{t+1}^{A} = \left[R_{t+1}^{E}\right]\left[\frac{E_t}{A_t}\cdot\frac{1}{N(d_t+\sigma_A\sqrt{T})}\right], \quad (19)$$

where R_{t+1}^{E} in the first bracket denotes the daily stock return, and the second bracket contains the hedge ratio from the Merton (1974) model. We compute the asset return volatility σ_A from this asset return (R_{t+1}^{A}) time series. The return relation in (19) is analogous to the volatility relation in (2) used in our TETU approach. Had the hedging ratio (the second bracket in equation (19)) been a constant, this AVH-II approach would have generated the same result as the TETU approach. The fact that the hedging ratio varies over time can lead to some differences. The last row in panel C of Table 7 shows that with the AVH-II approach, the the cross-sectional explanatory power for MCDS becomes 65% for the in-sample half, and 63% for the out-of-sample half, very close to our TETU approach. Given the similar performance, we choose the TETU approach because it is much less computationally intensive and it fits our cross-sectional focus better.

Finally, a commonly proposed alternative to the Merton (1974) model is to assume as in Leland (1994) and Leland and Toft (1996) that the firm can default any time before the debt maturity when the firm's asset value falls below a certain threshold. In this case, equity becomes a call option on the firm's asset value with a knock-out barrier. If one sets the barrier to the debt principal value and assumes zero rates, the model implies that the equity value is equal to the intrinsic value of the knock-out barrier option, $E = A - D$, and the market value of debt is equal to its principal value. Equity return volatility no longer plays a role in determining the firm's asset value. The "naive" Merton alternative proposed in Bharath and Shumway (2008) can be justified under this barrier option assumption. In panel D of Table 7, we compare the Merton model performance with this alternative on the simple implementation of the Leland model. This simple alternative performs better than the Merton model implementation with $T = 1$, but worse than our Merton model implementation with $T = 10$.

B. Local polynomial regressions and bandwidth choice

In constructing MCDS and WCDS, we have used local polynomial regressions to capture the potentially nonlinear relations between two variables x and y,

$$y = f(x) + e, \tag{20}$$

where $f(\cdot)$ denotes the local polynomial form and e denotes the regression error.

To illustrate the specifics of the regression, suppose that we have N observations of the pair $(y_i, x_i)_{i=1}^N$ and we intend to generate an estimate for $\hat{y}_k$ at $x = x_k$. The estimate $\hat{y}_k$ is obtained from a weighted least square regression,

$$\hat{y}_k = X_k (X^\top W_k X)^{-1} X^\top W_k y, \tag{21}$$

where y denotes the $N \times 1$ vector of the dependent variable observations and X is a matrix made of polynomials of x. Our MCDS construction involves a local quadratic regression, in which case $X = [1, x, x^2]$ is an $N \times 3$ matrix. Our WCDS construction involves many local linear regressions, in which case $X = [1, x]$ is an $N \times 2$ matrix. To construct the weighting matrix W_k, we use a Gaussian kernel, with W_k being a diagonal matrix with the ith diagonal element given by,

$$W_k^i = \exp\left(-\frac{(x_i - x_k)^2}{2h^2}\right), \tag{22}$$

where h is the bandwidth that controls the relative weighting of different observations. Intuitively, observations that are closer to x_k obtain higher weights. The weight declines as the distance $|x_i - x_k|$ increases, with the declining speed controlled by the bandwidth h. A higher bandwidth assigns more uniform weights across observations and thus generates more smoothing. In the limit of $h \to \infty$, W_k becomes an identity matrix and we are essentially running just one global regression.

Under normal distribution assumptions on x and the Gaussian kernel, textbooks, e.g., Simonoff (1996), often propose a default optimal bandwidth choice that balances between smoothing and fitting,

$$\hat{h} = (4/3)^{(1/5)} \sigma_x / N^{(1/5)}, \tag{23}$$

where σ_x denotes the standard deviation of x.

To show how the bandwidth choice affects the cross-sectional performance both in sample and out of sample, we repeat the exercise under different bandwidth choices while setting the maturity to ten years. Table 8 shows the effects of the bandwidth choice on the cross-sectional explanatory powers of MCDS and WCDS. When we set the bandwidth to half of the default choice, the in-sample fitting for both MCDS and WCDS becomes better, but the out-of-sample becomes worse, showing signs of out-of-sample instability. The default bandwidth choice generates both good in-sample and out-of-sample performances. As we set the bandwidth to twice the default bandwidth or higher, the in-sample and out-of-sample performance becomes very much similar to each other. In our main text analysis, we set the bandwidth to twice the default choice.

[Table 8 about here.]

A related choice for the local polynomial regression is the order of the polynomial. If the relations are reasonably flat, one can choose an order of zero and essentially perform local averages around each target region. However, when the relation has a steep slope, a local average regression can generate biases at the boundaries when the averaging can only use data from one side. In this case, a local linear regression can help reduce the bias at the boundaries. We use the local linear regression to link $\ln(CDS/MCDS)$ to each additional firm characteristic. When we map $\ln(RCDS)$ to the market observation $\ln(CDS)$, we choose a local quadratic regression because the observed relations between the two often show a convex shape. The second-order polynomial helps capture this observed curvature well even with a large bandwidth.

References

Altman, E. I. “The Prediction of Corporate Bankruptcy: A Discriminant Analysis.” *Journal of Finance*, 23 (1968), 193–194.

Altman, E. I. “Measuring Corporate Bond Mortality and Performance.” *Journal of Finance*, 44 (1989), 909–922.

Andrews, D. W. K. “Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation.” *Econometrica*, 59 (1991), 817–858.

Avramov, D.; G. Jostova; and A. Philopov. “Understanding Changes in Corporate Credit Spreads.” *Financial Analysts Journal*, 63 (2007), 90–105.

Bao, J., and J. Pan. “Relating Equity and Credit Markets through Structural Models: Evidence from Volatilities.” Working paper, Ohio State University and MIT (2012).

Bates, J. M., and C. W. J. Granger. “The Combination of Forecasts.” *Operations Research Quarterly*, 20 (1969), 451–468.

Berndt, A., and I. Obreja. “Decomposing European CDS Returns.” *Review of Finance*, 14 (2010), 189–233.

Berndt, A., and A. Ostrovnaya. “Do Equity Market Favor Credit Market News Over Options Market News?” Working paper, Carnegie Mellon University (2007).

Bharath, S. T., and T. Shumway. “Forecasting Default with the Merton Distance to Default Model.” *Review of Financial Studies*, 21 (2008), 1339–1369.

Blanco, R.; S. Brennan; and I. W. Marsh. “An Empirical Analysis of the Dynamic Relationship Between Investment-Grade Bonds and Credit Default Swaps.” *Journal of Finance*, 60 (2005), 2255–2281.

Bongaerts, D.; F. de Jong; and J. Driessen. “Derivative Pricing with Liquidity Risk: Theory and Evidence from the Credit Default Swap Market.” *Journal of Finance*, 66 (2011), 203–240.

Campbell, J. Y., and G. B. Taksler. "Equity Volatility and Corporate Bond Yields." *Journal of Finance*, 63 (2003), 2321–2349.

Cao, C.; F. Yu; and Z. Zhong. "The Information Content of Option-Implied Volatility for Credit Default Swap Valuation." *Journal of Financial Markets*, 13 (2010), 321–343.

Carr, P., and P. Laurence. "Implied Volatility Approximation In the Black-Scholes Model with Possible Jump to Default." Working paper, New York University and University of Rome 1 (2006).

Carr, P., and L. Wu. "Stock Options and Credit Default Swaps: A Joint Framework for Valuation and Estimation." *Journal of Financial Econometrics*, 8 (2010), 409–449.

Carr, P., and L. Wu. "A Simple Robust Link Between American Puts and Credit Protection." *Review of Financial Studies*, 24 (2011), 473–505.

Chen, L.; D. A. Lesmond; and J. Wei. "Corporate Yield Spreads and Bond Liquidity." *Journal of Finance*, 62 (2007), 119–149.

Collin-Dufresne, P.; R. S. Goldstein; and J. S. Martin. "The Determinants of Credit Spread Changes." *Journal of Finance*, 56 (2001), 2177–2207.

Cremers, M.; J. Driessen; and P. J. Maenhout. "Explaining the Level of Credit Spreads: Option-Implied Jump Risk Premia in a Firm Value Model." *Review of Financial Studies*, 21 (2008), 2209–2242.

Cremers, M.; J. Driessen; P. J. Maenhout; and D. Weinbaum. "Individual Stock Options and Credit Spreads." *Journal of Banking and Finance*, 32 (2008), 2706–2715.

Crosbie, P., and J. Bohn. "Modeling Default Risk." Working paper, Moodys KMV (2003).

Du, Y., and W. Suo. "Assessing Credit Quality from Equity Markets: Is Structural Approach a Better Approach?" Working paper, Queen's University (2003).

Duan, J.-C. "Maximum Likelihood Estimation Using Price Data of the Derivative Contract." *Mathematical Finance*, 4 (1994), 155–167.

Duan, J.-C.; J. Sun; and T. Wang. "Multiperiod Corporate Default Prediction — A Forward Intensity Approach." *Journal of Econometrics*, 170 (2012), 191–209.

Duan, J.-C., and T. Wang. "Measuring Distance-to-Default for Financial and Non-Financial Fimrs." *Global Credit Review*, 2 (2012), 95–108.

Duffie, D.; L. Saita; and K. Wang. "Multi-period Corporate Default Prediction with Stochastic Covariates." *Journal of Financial Economics*, 83 (2007), 635–665.

Eom, Y. H.; J. Helwege; and J. Huang. "Structural Models of Corporate Bond Pricing: An Empirical Analysis." *Review of Financial Studies*, 17 (2004), 499–544.

Ericsson, J.; K. Jacobs; and R. Oviedo. "The Determinants of Credit Default Swap Premia." *Journal of Financial and Quantitative Analysis*, 44 (2009), 109–132.

Ericsson, J., and J. Reneby. "Estimating Structural Bond Pricing Models." *Journal of Business*, 78 (2005), 707–735.

Ericsson, J.; J. Reneby; and H. Wang. "Can Structural Models Price Default Risk? New Evidence from Bond and Credit Derivative Markets." Working paper, McGill University and Stockholm School of Economics (2005).

Fama, E. F., and K. R. French. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics*, 33 (1993), 3–56.

Hoerl, A. E., and R. W. Kennard. "Ridge Regression: Biased Estimation for Nonorthogonal Problems." *Technometrics*, 42 (2000), 80–86.

Huang, J., and Z. Shi. "Revisiting the Equity-Credit Market Integration Anomaly." Working paper, Penn State University and Ohio State University (2013).

Huang, J.-z., and M. Huang. "How Much of the Corporate-Treasury Yield Spread is Due to Credit Risk?" *Review of Asset Pricing Studies*, forthcoming (2012).

Jegadeesh, N., and S. Titman. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *Journal of Finance*, 48 (1993), 65–91.

Jegadeesh, N., and S. Titman. "Profitability of Momentum Strategies: An Evaluation of Alternative Explanations." *Journal of Finance*, 56 (2001), 699–720.

Kapadia, N., and X. Pu. "Limited Arbitrage between Equity and Credit Markets." *Journal of Financial Economics*, 105 (2012), 542–564.

Kealhofer, S. "Quantifying Credit Risk I: Default Prediction." *Financial Analysts Journal*, 59 (2003), 30–44.

Leland, H. E. "Risky Debt, Bond Covenants and Optimal Capital Structure." *Journal of Finance*, 49 (1994), 1213–1252.

Leland, H. E., and K. B. Toft. "Optimal Capital Structure, Endogenous Bankruptcy and the Term Structure of Credit Spreads." *Journal of Finance*, 51 (1996), 987–1019.

Lemmon, M. L.; M. R. Roberts; and J. F. Zender. "Back to the Beginning: Persistence and the Cross-Section of Corporate Capital Structure." *Journal of Finance*, 63 (2008), 1575–1608.

Longstaff, F. A.; S. Mithal; and E. Neis. "Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit-Default Swap Market." *Journal of Finance*, 60 (2005), 2213–2253.

Merton, R. C. "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates." *Journal of Finance*, 29 (1974), 449–470.

Merton, R. C. "Option Pricing When Underlying Stock Returns Are Discontinuous." *Journal of Financial Economics*, 3 (1976), 125–144.

Newey, W. K., and K. D. West. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica*, 55 (1987), 703–708.

Schaefer, S. M., and I. A. Strebulaev. "Structural Models of Credit Risk are Useful: Evidence from Hedge Ratios on Corporate Bonds." *Journal of Financial Economics*, 90 (2008), 1–19.

Simonoff, J. S. *Smoothing Methods in Statistics*. Springer-Verlag, New York (1996).

Stock, J. H., and M. W. Watson. "Forecasting Output and Inflation: The Role of Asset Prices." *Journal of Economic Literature*, 41 (2003), 788–829.

Vassalou, M., and Y. Xing. "Default Risk in Equity Returns." *Journal of Finance*, 59 (2004), 831–868.

Wang, H.; H. Zhou; and Y. Zhou. "Credit Default Swap Spreads and Variance Risk Premia." Working paper, Tsinghua University, Federal Reserve Board and University of Oklahoma (2009).

Wolpert, D. H. "Stacked Generalization." *Neural Networks*, 5 (1992), 241–259.

Zhang, B. Y.; H. Zhou; and H. Zhu. "Explaining Credit Default Swap Spreads With the Equity Volatility and Jump Risks of Individual Firms." *Review of Financial Studies*, 22 (2009), 5099–5131.

TABLE 1

Summary statistics of firm fundamental characteristics at different CDS quintiles

Entries report the sample statistics of firm characteristics for 579 U.S. non-financial firms over 351 weeks from January 8, 2003 to September 30, 2009, a total of 138,200 firm-week observation for each variable. Panel A reports the average of each firm characteristic on both the pooled sample and at each CDS quintile. Panel B reports four sets of standard deviation estimates: (i) Pooled — standard deviation on the pooled sample; (ii) XS — time-series averages of the cross-sectional standard deviation estimates on each date; (iii) TS — cross-sectional averages of the time-series standard deviation estimates for each firm; and (iv) TSC — cross-sectional averages of the time-series standard deviation estimates on weekly changes of each characteristic for each firm.

	A. Mean at CDS Quintiles						B. Standard Deviation			
Characteristics	Pooled	1	2	3	4	5	Pooled	XS	TS	TSC
CDS (bps)	188.57	20.16	39.76	69.25	148.31	665.45	439.46	345.71	154.55	34.27
Total Debt/Market Cap.	0.98	0.21	0.34	0.41	0.61	3.28	5.25	3.40	1.19	0.38
Realized Volatility	0.36	0.23	0.27	0.32	0.39	0.61	0.23	0.16	0.15	0.01
Liability/Market Cap.	0.93	0.27	0.41	0.48	0.65	2.75	3.65	2.39	0.94	0.30
Total Debt/Total Asset	0.30	0.23	0.26	0.27	0.31	0.45	0.21	0.19	0.05	0.01
EBIT/Interest Expense	13.22	25.19	14.34	13.47	9.86	3.78	26.25	25.71	8.24	1.92
Working Capital/Total Asset	0.13	0.13	0.12	0.14	0.13	0.13	0.17	0.17	0.05	0.01
EBIT/Total Asset	0.03	0.04	0.03	0.03	0.02	0.01	0.02	0.02	0.01	0.00
Retained Earnings/Total Asset	0.22	0.43	0.31	0.28	0.19	-0.08	0.40	0.38	0.07	0.01
ln(Market Cap.)	8.83	10.02	9.16	8.90	8.49	7.61	1.36	1.33	0.34	0.06
Stock Market Momentum	0.08	0.17	0.16	0.10	0.08	-0.12	0.39	0.32	0.32	0.08
ln(Implied/Realized Vol.)	0.08	0.14	0.09	0.07	0.06	0.06	0.23	0.17	0.21	0.06

TABLE 2

Summary statistics of cross-sectional explanatory powers

Entries report the summary statistics of the weekly R-squared estimates from the cross-sectional regressions of the log market CDS against three sets of fundamental-based valuations: (i) a bivariate linear regression (BLR) on debt to equity ratio and realized volatility, (ii) log MCDS, and (iii) log WCDS. We also report the statistics on the pair-wise R-squared differences between these valuations. The t-statistics are computed as the ratio of the mean estimate to its Newey and West (1987) serial-dependence adjusted standard error. The R-squared in Panel A are computed from cross-sectional regressions on the whole universe of companies, where the MCDS and WCDS are also calibrated to the whole sample. The R-squared in Panel B are computed from cross-sectional regressions on a random half of the universe, with MCDS and WCDS calibrated to the same half universe. In Panel C, we compute the out-of-sample R-squared on the remaining half of the universe based on the regression and calibration results from the other half.

	Cross-sectional R^2			R^2 differences	
Statistics	BLR	MCDS	WCDS	MCDS-BLR	WCDS-MCDS
A. In-sample performance from full-sample estimation					
Mean	0.49	0.65	0.77	0.16	0.11
Std	0.10	0.08	0.04	0.04	0.05
Minimum	0.22	0.50	0.67	0.08	0.05
Maximum	0.64	0.78	0.85	0.33	0.23
t-stats	14.75	22.53	54.46	13.57	6.41
B. In-sample performance from half-sample estimation					
Mean	0.51	0.65	0.77	0.15	0.12
Std	0.10	0.09	0.05	0.06	0.05
Minimum	0.19	0.44	0.62	0.00	0.03
Maximum	0.67	0.81	0.88	0.34	0.29
t-stats	26.27	32.13	84.62	22.99	8.84
C. Out-of-sample performance from half-sample estimation					
Mean	0.25	0.64	0.74	0.39	0.10
Std	0.96	0.09	0.06	0.95	0.06
Minimum	-13.24	0.26	0.59	0.04	-0.01
Maximum	0.67	0.80	0.86	13.95	0.37
t-stats	4.79	31.75	83.50	7.41	7.86

TABLE 3
The explanatory power of time-series change regressions

Entries report the cross-sectional mean and standard deviation (in parentheses) of the coefficients and R-squared estimates from three sets of time-series change regressions for each firm i. Firms with less than one year of data are excluded from the regressions. The horizon of the change h is in weeks. Each panel represents one set of regression. Within each panel, the columns on the right report the cross-sectional correlation between the R-squared of each regression and the time-series standard deviation of that firm's log CDS spreads (σ_{CDS}) and the corresponding regressors.

A.	$\Delta\ln(CDS)^i_{t+h} = \alpha_i + \beta_i\Delta(D/E)^i_{t+h} + \gamma_i\Delta(\sigma_E)^i_{t+h} + e^i_{t+h}$								Correlation of R^2 with		
h	α		β		γ		R^2		σ_{CDS}	$\sigma_{D/E}$	σ_{σ_E}
1	0.00	(0.01)	0.43	(0.94)	1.22	(1.59)	0.06	(0.07)	0.31	0.17	0.21
2	-0.00	(0.01)	0.54	(1.16)	1.49	(1.63)	0.09	(0.08)	0.38	0.17	0.31
3	-0.00	(0.02)	0.65	(1.35)	1.66	(1.75)	0.11	(0.10)	0.41	0.16	0.35
4	-0.00	(0.02)	0.70	(1.45)	1.70	(1.79)	0.12	(0.11)	0.39	0.15	0.35

B.	$\Delta\ln(CDS)^i_{t+h} = \alpha_i + \beta_i\Delta\ln(MCDS)^i_{t+h} + e^i_{t+h}$						Correlation of R^2 with	
h	α		β		R^2		σ_{CDS}	σ_{MCDS}
1	0.00	(0.00)	0.47	(0.36)	0.15	(0.13)	0.36	0.14
2	0.00	(0.01)	0.53	(0.37)	0.19	(0.16)	0.39	0.16
3	0.00	(0.01)	0.56	(0.37)	0.22	(0.17)	0.41	0.17
4	0.00	(0.02)	0.58	(0.38)	0.24	(0.18)	0.42	0.18

C.	$\Delta\ln(CDS)^i_{t+h} = \alpha_i + \beta_i\Delta\ln(WCDS)^i_{t+h} + e^i_{t+h}$						Correlation of R^2 with	
h	α		β		R^2		σ_{CDS}	σ_{WCDS}
1	0.00	(0.00)	0.34	(0.26)	0.13	(0.12)	0.36	0.36
2	0.00	(0.01)	0.41	(0.29)	0.18	(0.15)	0.39	0.39
3	0.00	(0.01)	0.47	(0.30)	0.21	(0.17)	0.42	0.41
4	0.00	(0.02)	0.50	(0.31)	0.24	(0.19)	0.44	0.42

TABLE 4

Comparing the mean reversion speeds of market CDS and market-fundamental deviations

Entries report the summary statistics of the annualized mean-reverting speeds for different data series. For a given series x, the mean-reverting speed is estimated from the following regression,

$$x_{t+h} - x_t = a - \kappa x_t h + \varepsilon_{t+h},$$

where κ denotes the annualized mean reversion speed and $h = 1/52$ denotes the weekly data sampling frequency. We estimate the mean reversion speed for each firm with more than one year of observations and report the sample mean and standard deviation of the estimates across different firms.

Statistics	Original series $\ln(CDS)$	Market-fundamental deviations, e		
		BLR	MCDS	WCDS
Mean	1.52	1.88	1.99	3.47
Std	3.70	1.83	1.94	2.89

TABLE 5

Forecasting correlation between market-fundamental deviations and future market movements

Entries report the summary statistics of the weekly estimates on the forecasting cross-sectional correlation between current market-fundamental deviations e_t and future market CDS movements over different horizons: one week in panel A and four weeks in panel B. We generate market-fundamental deviations from three sets of cross-sectional regressions: (i) a bivariate linear regression (BLR) of log market CDS on debt to equity ratio and realized volatility, (ii) the log deviation between market CDS and MCDS, and (iii) the log deviation between market CDS and WCDS. Entries on the right side report the statistics on the pair-wise correlation differences between the two sets of deviations. The t-statistics are computed as the ratio of the mean estimate to its Newey and West (1987) serial-dependence adjusted standard error.

	Forecasting Correlations			Differences	
Statistics	BLR	MCDS	WCDS	MCDS-BLR	WCDS-MCDS
	A. Forecasting horizon: one week				
Mean	-0.05	-0.06	-0.07	-0.01	-0.02
Std	0.10	0.08	0.08	0.06	0.04
t-stats	-7.11	-10.08	-15.89	-2.26	-5.51
	B. Forecasting horizon: four weeks				
Mean	-0.09	-0.10	-0.12	-0.01	-0.02
Std	0.12	0.10	0.09	0.07	0.05
t-stats	-6.15	-7.55	-11.96	-1.33	-3.79

TABLE 6

Summary statistics of excess returns from an out-of-sample investment exercise

Entries report the annualized mean excess return (Mean), annualized standard deviation(Std), skewness, excess kurtosis, and the information ratio (SR), defined as the ratio of the annualized mean excess return to the annualized standard deviation, from an out-of-sample investment exercise over different horizons (in number of weeks h). At each date, we invest in the CDS contracts based on the deviations between the market CDS quotes and fundamental-based CDS valuations.

Horizon, h Weeks	Mean %	Std %	Skewness	Kurtosis	SR
	A. Investments based on BLR valuation				
1	6.76	52.74	-2.22	23.35	0.13
2	11.05	49.05	-1.38	12.60	0.23
3	9.55	41.42	-0.91	10.59	0.23
4	13.88	43.20	-0.30	5.90	0.32
	B. Investments based on MCDS valuation				
1	25.25	16.76	3.06	21.01	1.51
2	19.06	16.19	1.68	7.59	1.18
3	12.56	14.96	1.16	5.43	0.84
4	14.30	17.92	2.99	20.13	0.80
	C. Investments based on WCDS valuation				
1	32.14	14.22	2.87	17.51	2.26
2	27.68	13.98	2.27	8.28	1.98
3	21.60	12.50	1.72	4.98	1.73
4	20.55	13.72	1.02	6.21	1.50

TABLE 7

Variations in structural model implementations and cross-sectional explanatory power

Entries report the time-series averages of the R-squared estimates from cross-sectional regressions of log market CDS quotes on the logarithm of MCDS and WCDS, respectively. Each day, we take a random half of the universe for calibration and generate predictions on the whole universe. The left side reports the average R-squared on the in-sample half of the universe whereas the right side reports the average R-squared on the out-of-sample half of the universe. Panel A shows the effect of maturity choice in the Merton model implementation. Panel B shows the effect of debt principal choice either as total debt or current liability (plus half of long-term liability (CL+LL/2). Panel C shows the effect of different asset return volatility calculation methods. Our default implementation solves the asset return volatility together with the asset value from two equations implied by the Merton model. We label it as the two-equations-two-unknowns (TETU) approach. We also consider two alternative approaches, where the asset return volatility is estimated as the sample annualized standard deviation of daily log returns on the extracted asset value over the past year. We label them as asset-value-history (AVH) approaches I and II. Finally, panel D compares the CDS computed from the Merton model to that from a simplified version of the Leland model, where equity is a barrier option on the asset and is valued as the difference between the asset value and the debt principal.

Choices	In-sample R^2		Out-of-sample R^2	
	MCDS	WCDS	MCDS	WCDS
A. Maturity choice				
1	0.40	0.71	0.37	0.66
3	0.58	0.75	0.56	0.71
5	0.62	0.76	0.61	0.73
10	0.65	0.77	0.64	0.74
15	0.66	0.78	0.65	0.75
20	0.66	0.78	0.65	0.75
B. Debt principal choice				
Total Debt	0.65	0.77	0.64	0.74
CL+LL/2	0.62	0.77	0.62	0.75
C. Asset return volatility estimation method choice				
TETU	0.65	0.77	0.64	0.74
AVH-I	0.57	0.74	0.55	0.70
AVH-II	0.65	0.77	0.63	0.73
D. Different model assumptions				
Merton	0.65	0.77	0.64	0.74
Leland	0.63	0.75	0.61	0.70

TABLE 8

Bandwidth choice in local polynomial regressions and the cross-sectional explanatory power

Entries report the time-series averages of the R-squared estimates from cross-sectional regressions of log market CDS quotes on the logarithm of MCDS and WCDS, respectively. Each day, we take a random half of universe for calibration and generate predictions on the whole universe. The left side reports the average R-squared on the in-sample half of the universe whereas the right side reports the average R-squared on the out-of-sample half of the universe. The performance shows the effects of bandwidth choice for the local quadratic and local linear regressions in the MCDS and WCDS construction, with $\hat{h}$ denoting the textbook default choice.

Bandwidth	In-sample R^2		Out-of-sample R^2	
Choice	MCDS	WCDS	MCDS	WCDS
$.5\hat{h}$	0.67	0.81	0.63	0.71
$1\hat{h}$	0.66	0.79	0.64	0.74
$2\hat{h}$	0.65	0.77	0.64	0.74
$3\hat{h}$	0.65	0.76	0.64	0.74

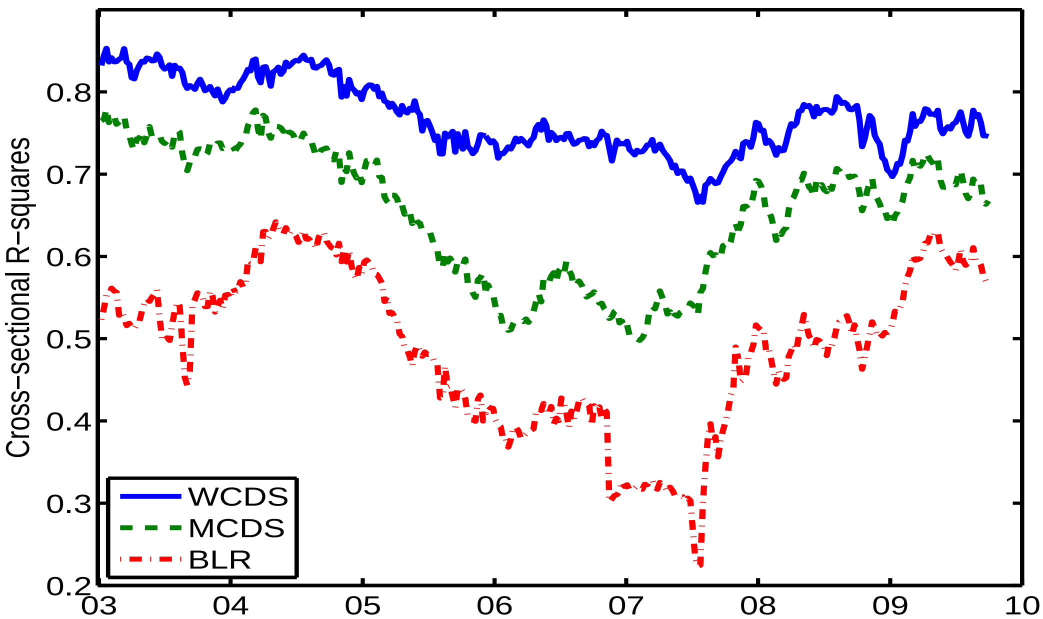

FIGURE 1
The time series of R-squared estimates from cross-sectional regressions.

The three lines denote the time-series of the R-squared estimates from three sets of cross-sectional regressions. The dash-dotted line denotes the R-squared estimates from a bivariate linear regression (BLR) of the log CDS spread on the debt-to-equity ratio and the realized stock return volatility. The dashed line and the solid line represent the cross-sectional explained variation of MCDS and WCDS, respectively.

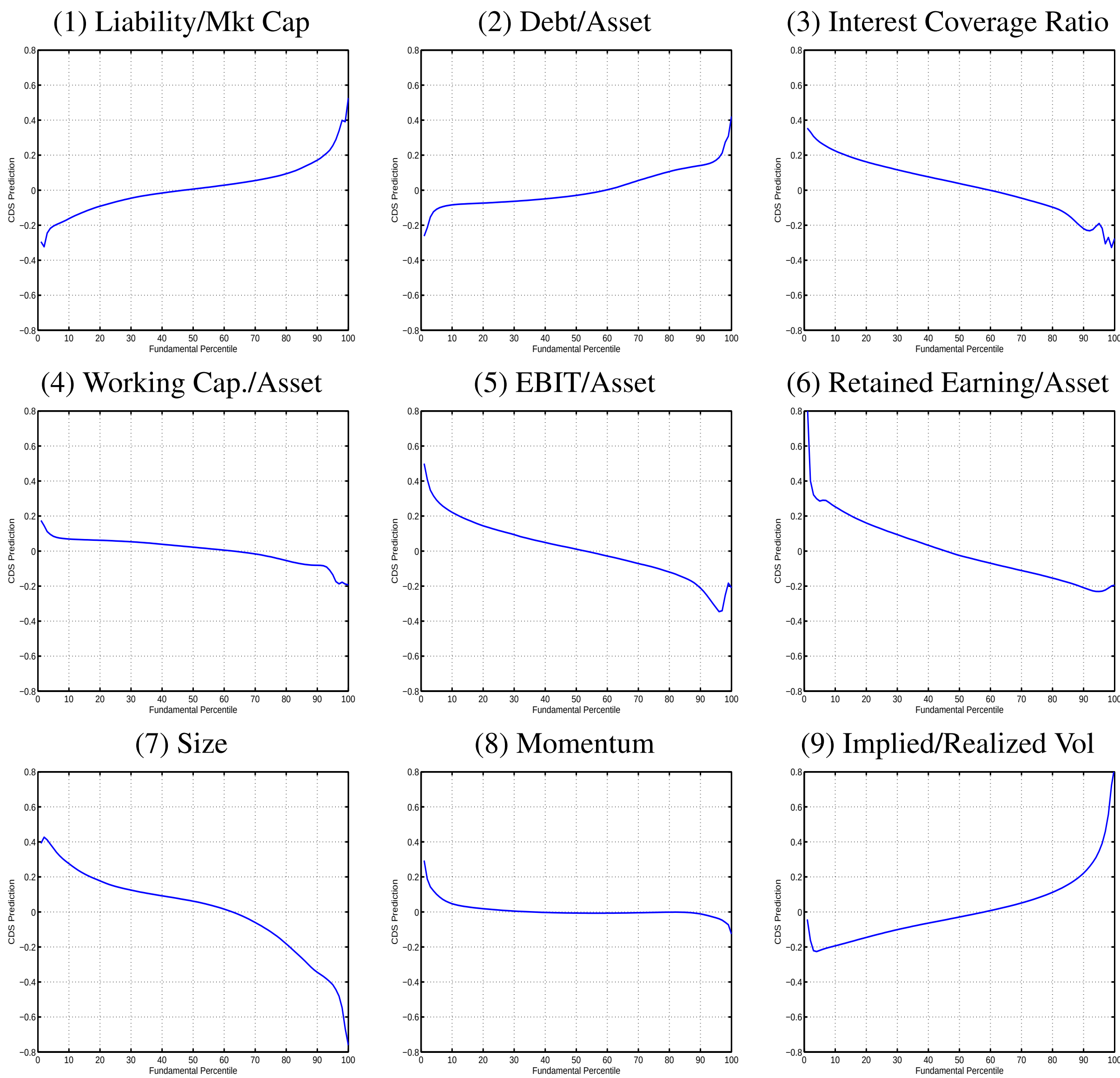

FIGURE 2
Additional contributions from firm fundamental characteristics.

The line in each panel represents the average contribution of one firm characteristic to the $\ln(CDS/MCDS)$ deviation. The x-axis denotes the percentiles of each firm characteristics. The relations are estimated via a local linear regression on the pooled data over 351 weeks and 579 companies.

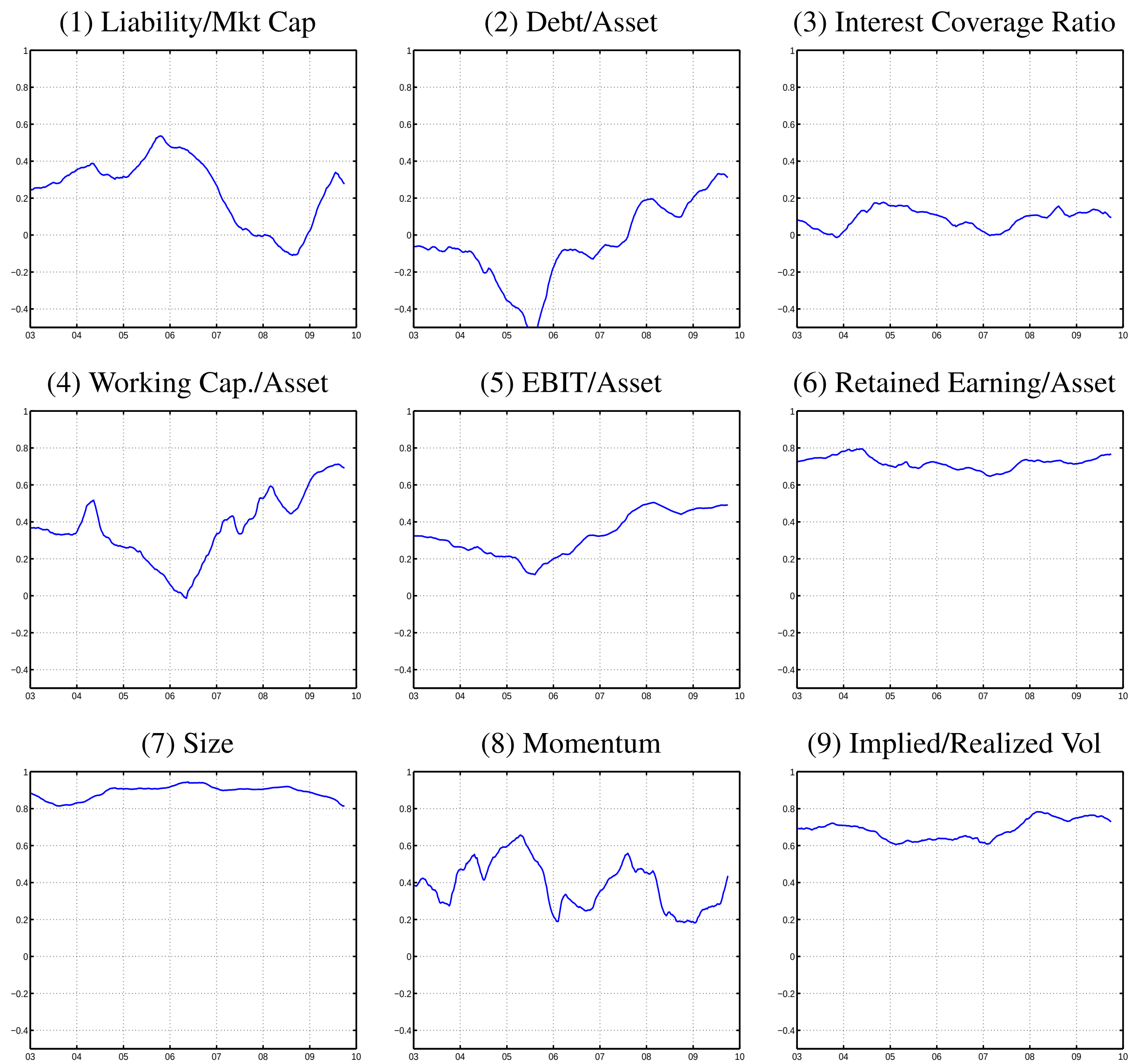

FIGURE 3
Time-varying weights on each firm characteristic.

The line in each panel plots the time series of the relative weight for each firm characteristic in predicting the CDS deviation: $\ln(CDS/MCDS)$. The weights are estimated via Bayesian update of a stack regression.