

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 spreads. We start with the Merton (1974) model, which combines two major credit risk determinants into a distance-to-default measure. We convert the distance-to-default measure into a raw CDS valuation based on a constant hazard rate assumption and then map the raw CDS valuation to market observation via a local quadratic regression, removing the average bias of raw valuation at different risk levels. We also collect a long list of firm fundamental characteristics that are not included in the Merton-based valuation but have been shown to be informative about a firm's credit spread, and propose a Bayesian shrinkage method to combine the Merton-based valuation with the information from this long list of fundamental characteristics. Historical analysis on 579 U.S. non-financial public firms over 351 weeks shows that the bias-corrected Merton-based valuation raises the average cross-sectional explanatory power from 49% to 65%. Incorporating additional firm fundamental characteristics further increases the average explanatory power to 77% while also making the performance more uniform over time. Furthermore, deviations between market observations and fundamental-based valuations generate statistically and economically significant forecasts on future market movements in credit default swap spreads.

JEL Classification: C11, C13, C14, G12.

Keywords: firm fundamentals; credit default swaps; cross-sectional variation; relative valuation.

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1. Introduction

This paper examines the capability of firm fundamental characteristics in explaining the cross-sectional variation of credit default swap (CDS) spreads. We start with Merton (1974)'s classic structural model, which combines two major credit risk determinants, financial leverage and business risk, into a distance-to-default measure. We convert the distance-to-default measure into a raw CDS valuation (RCDS) via a constant hazard rate assumption and then map the raw valuation into market CDS observation via a local quadratic regression, removing the average bias of RCDS at different risk levels to generate a bias-corrected Merton-based CDS valuation (MCDS). Next, we collect a long list of firm fundamental characteristics that are not included in the Merton-based valuation 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).

Earlier empirical studies on structural models often focus on the average bias of the model-generated valuations. For example, Huang and Huang (2003) and Eom, Helwege, and Huang (2004) show that different structural models generate different average biases. Given the highly stylized nature of the Merton (1974) model, we do not expect the model to be unbiased or even close to fully capture the CDS behavior. Instead, we exploit the model's key contribution in combining two major credit risk determinants into a distance-to-default measure. The measure normalizes the firm's financial leverage (distance between firm value and debt principal) by the firm's asset return volatility over a horizon defined by the debt maturity. Through this normalization, the measure becomes directly comparable across different firms and can thus be used to differentiate the credit spreads of different companies. On the other hand, although the Merton model captures the two major credit risk determinants, the stylized model naturally misses many other risk factors that also contribute to the credit spread. Through the WCDS valuation, we propose a robust econometric approach to combine the Merton-based valuation with a long list of additional firm characteristics. These characteristics

can include new risk factors missed in the Merton model and/or different measures of the same underlying risk factor, such as different measures of financial leverage and volatility.

We examine the cross-sectional explanatory power of firm fundamental characteristics on corporate credit spreads 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 four sets of cross-sectional regressions. The first is a bivariate linear regression (BLR) of market CDS on the two inputs of the Merton model: the total debt to market capitalization ratio and stock return volatility. The regression serves as a benchmark in assessing the cross-sectional explanatory power of our three sets of CDS valuations: RCDS, MCDS, and WCDS, respectively. Comparing the R-squared estimates from the four sets of regressions highlights the progressive contribution of (1) the two Merton model inputs in a linear, additive framework, (2) the Merton distance-to-default combination of the two inputs via a simple constant hazard rate transformation in RCDS, (3) the MCDS local quadratic bias correction of RCDS, and (4) the information in the long list of additional firm characteristics incorporated in WCDS.

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 univariate regressions on RCDS generate R-squared estimates averaging at 58%, a nine percentage points increase over the bivariate linear regression. The average R-squared increase highlights the contribution of the distance-to-default measure in combining the two Merton model inputs. Accommodating the empirically observed nonlinearity in the relation between market CDS and RCDS via the local quadratic regression in the MCDS construction further improves the average cross-sectional R-squared to 65%. The seven percentage point increase over RCDS shows the contribution of the nonlinearity correction and the importance of building a flexible link between the distance-to-default measure and the CDS spread.

Finally, by including a long list of additional firm fundamental characteristics, the WCDS raises the

average cross-sectional explanatory power to 77%, an 11 percentage point increase over MCDS and a 28 percentage point increase over the bivariate linear regression. In addition to the much higher average R-squared, the performance of WCDS also becomes much more uniform over time than those from other methods. The standard deviation of the cross-sectional R-squared estimates from WCDS is only 4%, compared to 8% from MCDS, 7% from RCDS, and 10% from the bivariate linear regression. The performance differences are highly statistically significant. Therefore, our WCDS valuation methodology improves greatly over both a bivariate linear regression benchmark and the Merton-based valuation in explaining the cross-sectional variation of CDS spreads.

The high cross-sectional explanatory power suggests that the WCDS methodology can be used to generate reasonable CDS valuations 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 a WCDS valuation, but only hundreds of them have valid market CDS quotes. Thus, the WCDS methodology can be used to greatly expand the CDS quote universe. For this application, it is important that the methodology generates stable extrapolations on companies without market CDS quotes. To gauge the stability of the valuation methodology, we perform an out-of-sample exercise. Each day, we randomly choose half of the sample to calibrate the model and generate out-of-sample valuations on the other half. The RCDS generates the same average R-squared estimates at 58% both in sample and out of sample. The out-of-sample performance for MCDS and WCDS only deteriorates slightly as the average cross-sectional explanatory power goes from 65% in sample to 64% out of sample for MCDS, and from 77% in sample to 74% out of sample for WCDS. By contrast, the bivariate linear regression benchmark not only generates the worst in-sample performance at 51%, but its out-of-sample performance also deteriorates the most to merely 25%. Thus, compared to the bivariate linear regression, our WCDS valuation methodology not only generates much higher cross-sectional explanatory power, but also shows greater out-of-sample stability.

Since the fundamental-based WCDS valuation captures the cross-sectional market CDS variation well, the remaining deviation between the market CDS quote and the WCDS valuation is likely driven by non-fundamental factors such as supply-demand shocks. If these non-fundamental-induced variations are transitory, we would be able to use the current market-fundamental deviations to predict future market movements, turning the WCDS valuation into a relative valuation tool. To gauge the performance of the WCDS valuation for this application, we measure the cross-sectional forecasting correlation between the current market-fundamental deviations and future changes in the market CDS quote. At one-week horizon, the forecasting correlation estimates average at -6% for MCDS and -7% for WCDS. At four-week horizon, the average forecasting correlation estimates average at -10% and -12% , respectively. The average forecasting correlations are highly significant. The negative sign confirms our hypothesis that when the market observation deviates from the fundamental-based valuations, the market tends to converge to the fundamental value in the future. The more negative estimates for WCDS highlights its increased forecasting capability. The forecasting performance difference between WCDS and MCDS are highly significant statistically, and both perform significantly better than the bivariate linear regression.

To gauge the economic significance of the forecasting power, we also perform an out-of-sample investment exercise, in which we go long on the CDS contracts (by paying the premium and buying the protection) when the market CDS spread observation is narrower than the fundamental-based valuation and go short when the observed premium is higher than the fundamental-based valuation. Investments based on the bivariate linear regressions generate low average returns and high standard deviations, suggesting that the linear regression approach cannot be effectively used as a relative valuation tool. By contrast, investments based on the WCDS valuation generate 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 excess returns cannot be fully explained by common risk factors. The high information ratio highlights the economic significance of the CDS forecasts based on the WCDS valuation.

Our paper contributes to the literature by providing new evidence on the usefulness of firm fundamentals in two economically important dimensions. First, we show that despite the highly stylized nature and well-documented average bias, the Merton (1974) model provides a good starting point in combining two major determinants of credit spreads into a normalized distance-to-default measure. Ericsson, Jacobs, and Oviedo (2009) show that the inputs of the Merton model can explain a substantial proportion of the time-series variation in the CDS spreads in a linear, additive regression setting. Our analysis shows that the contribution of the Merton model goes far beyond its suggested inputs. Using its distance-to-default measure to combine the inputs while accommodating the empirically observed nonlinear relations can increase the cross-sectional explanatory power from an average of 49% from the bivariate linear regression to an average of 65%, a 16 percentage point improvement. Bharath and Shumway (2008) examine the forecasting power of the distance-to-default measure computed from the Merton model on actual default probabilities, and find that even though the Merton model itself does not produce a sufficient statistic for the probability of default, its functional form is useful for forecasting defaults.

Second, we show that, in addition to the Merton distance-to-default measure, a long list of other firm fundamental characteristics can be used to provide additional information and raise the cross-sectional CDS explanatory power to 77%. While the credit risk information in these variables have been discussed in the literature,¹ we provide a robust econometric approach to combine them and generate a robust and well-performing CDS valuation.

In related literature, 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-squared. We show that the low R-squared from time-series change regressions does not contradict with the

¹The list includes the various fundamental ratios used in Altman'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)).

high R-squared that we have obtained from the cross-sectional regressions. In principle, given the existence of a fundamental relation, the relation can be better identified when the underlying variables show stronger variation relative to other types of variations. In our application, many firm characteristics differ greatly across companies, but they do not vary much over a short period of time for a given company. As a result, the difference in firm characteristics can effectively differentiate credit spread across companies, even though they do not account for much of the short-term credit spread variation for a given firm. The two types of regressions are also used for different economic purposes. Our cross-sectional regression suits the objective of differentiating credit spreads across companies whereas the time-series change regression measures the sensitivity of the credit spread changes over time with respect to a corresponding change in a certain variable. The sensitivity measures from the latter regression can be useful for risk management purpose (Schaefer and Strebulaev (2008)).

The rest of the paper is structured as follows. The next section describes the data sources and sample construction. Section 3 introduces the methodology to construct firm fundamental-based CDS valuations. Section 4 analyzes the performance of the fundamental-based CDS valuation in explaining the cross-sectional variation of market CDS observations over different sample periods. Section 5 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 movements. Section 6 concludes.

2. 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 OptionMetrics, and the stock market

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 sample the data weekly on every Wednesday from January 8, 2003 to September 30, 2009. The sample contains 351 active weeks.

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.² In this paper, we take the five-year CDS spread as the benchmark for corporate credit spread and analyze its linkage to firm fundamentals.

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. The Markit database offers CDS spread consensus estimates in multiple currencies, four types of documentation clause (XR, CR, MR, MM), and a term structure from three months to 30 years. We choose the five-year CDS denominated by the U.S. dollar and with MR type documentation since it is by far the most liquid contract type. 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 pay-

²Currently, 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.

ments.

The Markit CDS database contains CDS spreads for 1695 unique U.S. company names from 2003 to 2009. We exclude financial firms with SIC codes between 6000 and 6999. We match CDS data with the Capital IQ and the CRSP database to identify 579 publicly traded U.S. non-financial companies that satisfy our data selection criteria.

We use a 45-day rule to match the financial statements with the market 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 prediction.

In Figure 1, Panel A plots the number of companies selected at each sample date. The number of selected companies increases over time from 246 on January 8, 2003 to 474 on June 6, 2007, after which the number of selected firms shows a slight decline. The last day of our sample (September 30, 2009) contains 426 companies. Panel B plots the number of days selected for each company. We rank the 579 selected companies according to the number of days they are selected into our sample. Three companies are selected only for one week, and 151 companies are selected for all 351 weeks. All together, we have 138,200 week-company observations, with an average of 394 companies selected per day and 239 days selected per company.

[Figure 1 about here.]

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 the additional contributions of other credit-risk informative firm characteristics that span the following dimensions of a company:

- **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. The lower the ratio, the more the company is burdened by the interest expense.
- **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. With a higher working capital to total asset ratio, a company has better cash-flow health.
- **Profitability**, captured by the ratio of EBIT to total asset. The higher the ratio, the more profit the company generates per dollar 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. The ratio of retained earnings to total asset reflects a company's ability or preparedness in potential investment.
- **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. 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 recent 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. We can regard 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. Most of our analyses in the paper are performed 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, we observe 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 also 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 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 XS estimates show how much the characteristics can differ across different firms whereas the average 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 the 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, which is just about 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.

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. On the other hand, the credit ratings for a given company can stay the same for many years. The fact that our sample includes the financial crisis period of 2008 makes the time-series variation larger, but it remains 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, predicting widely different credit qualities for different firms, these fundamental characteristics do not vary much over a short sample period.

3. 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 the distance-to-default measure from the Merton model using the total debt to market capitalization ratio and the stock return realized volatility as inputs and convert the measure into a raw CDS valuation based on a constant hazard rate assumption. We then remove the average bias of the raw valuation at different risk levels via a local quadratic regression. Next, we collect a long list of firm fundamental characteristics that are not included in the Merton-based valuation 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.

3.1. MCDS: Merton-based valuation with average bias correction

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 a principal value D and time-to-maturity T , and the firm's equity (E) is a call option on the firm's asset value with maturity equal to the debt maturity and strike equal to the principal of the debt. 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 ,

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

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

where 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,

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

with r denoting the instantaneous riskfree rate.

It goes without saying that the Merton model is highly stylized in its assumptions on both the asset value dynamics and the debt structure. For asset value dynamics, well-documented discontinuous price movements and stochastic volatilities are ignored. For the debt structure, most companies have more than just a zero-coupon bond. Despite its stylized nature, the model captures two important determinants of credit risk (financial leverage and business risk) and combines them into a distance-to-default measure in (3), which normalizes the financial leverage (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. Hence, one cannot directly compare the financial leverage of different companies without controlling for their differences in business risk. 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.³ Thus, as in standard industry applications, we regard the distance to default as the key contribution of the Merton model.

³Under the model-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. In the option pricing literature, the distance to default is referred to as a standardized moneyness measure that defines the standardized distance between the strike and spot. Through the standardization, the moneyness measure becomes comparable across different option maturities and different securities with different volatility levels.

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 for the zero-coupon bond D , and the one-year realized stock return volatility as an estimator for stock return volatility σ_E . We further 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 documents 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, starting at $A = E + D$. With the solved asset value and asset return volatility, we compute the standardized distance to default according to equation (3). Furthermore, although the model takes three inputs, (E, D, σ_E) , the distance-to-default measure is actually 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 contributions 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 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,

$$\ln(CDS) = f(\ln(RCDS)) + R, \quad (5)$$

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, 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.

In principle, we can also 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). Nevertheless, the transformation in (4) moves the distance-to-default measure closer to the actual CDS observation so that the local quadratic regression in (5) becomes more stable numerically. We label the local-quadratic transformed Merton model-based CDS valuation as $MCDS$, $\ln(MCDS) = \hat{f}(\ln(RCDS))$, with “M” denoting the Merton model origin.

3.2. WCDS: Capturing contributions from many additional firm characteristics

The MCDS accounts for information in the total debt to market capitalization ratio and the one-year realized stock return volatility. Many other variables have also been shown to explain credit spreads. Directly including all these variables into one multivariate linear regression is not feasible for several reasons. First, a variable may have a nonlinear relation with the credit spread. Second, some of these variables may contain similar information, creating potential multi-collinearity issues for the regression. Third, some variables are measured with large errors, which can bias the regression estimates. Fourth, not all variables are available for all firms. Missing observations on firm characteristics can create problems for multivariate regressions. In this paper, we propose a methodology based on Bayesian shrinkage principles to overcome all the above limitations of a multivariate linear regression in constructing a weighted average credit default swap spread valuation that incorporates the information from a long list of firm characteristics.

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,

$$F_k^k = f^k(\ln(MCDS_t)) + x_t^k, \quad k = 1, 2, \dots, K, \quad (6)$$

where $f^k(\cdot)$ denotes a local linear regression mapping and x_t^k denotes the orthogonalized component of F_t^k . We use the local linear regression to accommodate potential nonlinearities in the relation.

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,

$$R_t = f^k(x_t^k) + e_t^k, \quad k = 1, 2, \dots, K. \quad (7)$$

Through this local linear regression, we generate a set of K residual predictions, \widehat{R}_t^k , $k = 1, 2, \dots, K$, from the K characteristics. The two local linear regressions in (6) and (7) remove the potential nonlinearity in the relations and orthogonalize each characteristic's contribution to the original Merton valuation.

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

$$R_t = X_t B_t + e, \quad (8)$$

with B denoting the weights on the K predictions.

To perform the stacking regression in (8), we need all K predictions available; however, 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,

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

where R_t^{ij} denotes the missing residual prediction on the i th company from the j th variable, which is replaced by a weighted average of the residual predictions on the subset of \tilde{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 weightings (B_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,

$$\widehat{B}_t = (X_t^\top X_t + P_{t-1})^{-1} (X_t^\top R_t + P_{t-1} \widehat{B}_{t-1}), \quad P_t = \text{diag}\langle (X_t^\top X_t + P_{t-1})\phi \rangle, \quad (10)$$

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 also 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.

Stock and Watson (2003) find continuing support for this proposal. 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:

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

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. Our analysis in later sections shows that MCDS represents a good benchmark as it can explain a large proportion of the market observed CDS variation across firms.

4. Explaining Cross-sectional CDS Variation with Firm Fundamentals

Table 2 reports the summary statistics of market CDS observations and the fundamental-based valuations. The statistics are computed on the pooled data over 351 weeks and 579 companies, for a total of 138,200 observations on each series. The logarithm of market CDS has a sample mean of 4.3968. The sample mean of the logarithm of the raw CDS valuation RCDS is markedly lower at 3.1532. Through the local quadratic

bias correction, the MCDS completely removes this mean bias by construction.

[Table 2 about here.]

When we measure the cross-correlation between market CDS observations and fundamental-based valuations on the pooled sample, the correlation estimate with RCDS is 76.33%. Adjusting for nonlinearity of the relation increases the correlation between market and MCDS to 84.17%. Incorporating additional firm characteristics further increases the correlation between market and WCDS to 89.66%. The three correlation estimates correspond to R-squared of 58%, 71%, and 80% from a pooled regression of market observations on each of the three valuations, respectively.

4.1. Cross-sectional explanatory power comparison

To gauge the cross-sectional explanatory performance of the fundamental-based CDS valuations, we perform four sets of cross-sectional regressions on each date,

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

$$\ln CDS_t^i = a_t + b_t \ln RCDS_t^i + e_t^i, \quad (13)$$

$$\ln CDS_t^i = \ln MCDS_t^i + e_t^i, \quad (14)$$

$$\ln CDS_t^i = \ln WCDS_t^i + e_t^i. \quad (15)$$

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, while ignoring the Merton model's suggestion for combining the two variables into a standardized distance-to-default measure. The second regression in (13) takes the RCDS as the explanatory variable, which takes suggestions from the Merton model in both the inputs and the distance-to-default standardization, and

transforms the distance-to-default measure into a CDS value via a simple constant hazard rate assumption. The linear regression removes the potential bias in the RCDS valuation via an intercept term and a linear slope coefficient. The third regression in (14) takes MCDS as the explanatory variable, which removes the average bias of the RCDS valuation at different risk levels via a local quadratic regression. Finally, the last regression in (15) takes the WCDS as the explanatory variable, which combines the MCDS valuation with a long list of additional firm fundamental characteristics. By design, MCDS and WCDS are not biased. Hence, we set the intercept to zero and slope to one for the last two regressions, with the deviations e directly defined as the log difference between the market observation and the model valuation.

By comparing the R-squared from these four regressions, we learn the progressive contribution of (1) the two Merton model inputs (debt-to-equity ratio and stock return volatility) in a linear, additive framework, (2) the Merton distance-to-default combination of the two inputs via a simple constant hazard rate transformation into a raw CDS valuation, (3) the local quadratic bias correction, and (4) the information from the long list of additional firm fundamental characteristics incorporated in WCDS.

Figure 2 plots the time series of the cross-sectional R-squared estimates from the four regressions, where the dotted line at the bottom represents the R-squared estimates from the bivariate linear regression (BLR), the dash-dotted line represents the R-squared estimates from the regression on the RCDS, the dashed line represents the cross-sectional explanatory power of MCDS, and the solid line represents the cross-sectional explanatory power of WCDS. The bivariate linear regression generates the lowest R-squared estimates in most days. Thus, 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 resultant RCDS and MCDS both explain more cross-sectional variation than the bivariate linear regression.

The graph also shows that the cross-sectional explanatory power of MCDS (the dashed line) is universally

higher than that of RCDS (the dash-dotted line). Thus, the simple constant hazard rate assumption used in the RCDS transformation has room for improvement. By accommodating the observed nonlinear relation between market CDS observation and RCDS, the MCDS can explain a higher percentage of the market CDS variation than RCDS does across all days in our sample.

Finally, the solid line on the top shows the improved performance of WCDS, which combines MCDS with a long list of additional firm fundamental characteristics. The Merton model predicts that the credit spread is dictated by financial leverage and stock return volatility. Our MCDS implementation uses the ratio of total debt to market capitalization as a measure of the financial leverage and uses the realized volatility over the past year as a measure for the 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 WCDS methodology generates a sizable improvement over the MCDS.

Inspecting the time-series variations of these R-squared estimates, we also observe that the R-squared estimates from BLR, RCDS, and MCDS are all higher during the two recessions in our sample, but lower during the booming period between 2006 and 2007. By contrast, the performance of WCDS (the solid line) is not only better at all times, but also more uniform across different time periods. The time variation in performance from the Merton-based valuations suggests that during recessions, the two Merton-suggested characteristics (financial leverage and volatility) can explain a large portion of the cross-sectional variation; however, when the economy is good and the overall credit concern is less severe, other firm characteristics can play a larger role in differentiating the CDS spreads across firms.

[Figure 2 about here.]

Table 3 reports the summary statistics of the R-squared estimates. Panel I reports the statistics based on the full-sample estimation. The R-squared estimates from the bivariate linear regression (BLR) average at 49%, whereas the estimates from regressing on RCDS average at 58%. Hence, applying the Merton model distance-to-default standardization and transforming it into a CDS value based on a simple constant hazard rate assumption can generate a nine percentage point R-squared improvement on average over the bivariate linear regression approach. The t -statistic for the average R-squared difference (RCDS-BLR) is estimated at 4.12, suggesting that the even raw CDS valuation generates strongly significant improvement over a simple bivariate linear regression, even though the input variables are the same.

[Table 3 about here.]

By correcting average biases at different risk levels via a local quadratic regression, the MCDS can explain 65% of the cross-sectional variation on average, a seven-percentage-point improvement over the raw CDS valuations and a 16-percentage-point improvement over the bivariate linear regression. The t -statistic for the average performance difference (MCDS-RCDS) is estimated at 4.47, again strongly significant. The strongly significant improvement of MCDS over RCDS shows deficiencies in the RCDS transformation. One can enhance the cross-sectional explanatory power significantly by proposing a transformation that better lines up the distance-to-default measure with the market CDS observation.

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

By regressing the CDS spreads directly on three determinants of the Merton model (financial leverage,

volatility, and a riskfree rate), Ericsson, Jacobs, and Oviedo (2009) obtain an R-squared of 46.0-48.4% from a panel regression with quarter dummies. The estimates are similar to our bivariate linear regression result. Bharath and Shumway (2008) regress the log CDS spreads on the log of the default probability estimate in a panel regression with time dummies. The R-squared is 26% when the default probability is constructed based on the Merton model. These R-squared estimates are both much lower than what we have obtained from our RCDS implementation at 58%. Appendix A shows that the R-squared can be as low as 37% if one uses a one-year option maturity in the Merton model to generate the distance-to-default measure. By further removing nonlinearity and accommodating the contribution of additional firm characteristics, our WCDS can perform dramatically better than either a simple linear regression or a traditional implementation of the Merton model.

With an average cross-sectional R-squared of 77%, the WCDS can be quite effective in differentiating the credit qualities of different firms based on their differences in fundamental characteristics. In the U.S., thousands of publicly-traded, non-financial 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 both for market making and for marking to market of their CDS positions.

For this application, one would need to calibrate the WCDS model coefficients using the universe of companies with reliable CDS marks and then extrapolate the WCDS valuation to companies without CDS marks. To gauge the robustness of this extrapolation, we perform an out-of-sample exercise each day by randomly choosing half of the universe for model calibration while generating CDS valuations on the whole universe. We also perform similar out-of-sample exercises on the linear regressions in BLR and RCDS. The

regression coefficients are estimated based on the first half universe and the valuations are generated on the whole universe.

Table 3 reports the in-sample performance for the half of the universe used for model calibration in Panel II and the out-of-sample performance for the other half of the universe in Panel III. 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. Indeed, some of the out-of-sample R-squared estimates are highly negative, suggesting a complete breakdown of the linear extrapolation.

The RCDS valuation itself does not contain sample calibration and hence does not have extrapolation issues. Nevertheless, to reduce the average bias of RCDS, we perform a univariate linear regression. When we apply the regression coefficients from one half of the universe to the other half of the universe, the average R-squared is the same at 58% for both the in-sample half and the out-of-sample half. Thus, the bias-correction regression on the RCDS is quite stable and does not generate much deterioration for out-of-sample extrapolation.

The MCDS valuation replaces the linear regression in RCDS with a local quadratic nonparametric regression that both removes the average bias and accommodates the nonlinearity in the relation between RCDS and the market observation. The local quadratic regression is much more flexible than the linear regression, but we use a large bandwidth to ensure its stability. Comparing the results in Panels II and III shows that the out-of-sample performance of MCDS is largely comparable to the in-sample performance, with the mean R-squared declining mildly from 65% in sample to 64% out of sample. Therefore, although 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 whether we remove its average bias via a linear regression or a local quadratic regression.

The WCDS valuation involves several 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 and the Bayesian shrinkage methodology for combining multiple predictors. Overall, the out-of-sample exercise shows that the WCDS methodology can successfully expand the CDS universe based on firm fundamental characteristics.

4.2. Contributions from additional firm fundamental characteristics

Our analysis shows that, by incorporating a long list of additional firm fundamental characteristics via a Bayesian shrinkage method, the WCDS significantly outperforms MCDS in terms of its cross-sectional explanatory power. To understand the contribution of each additional firm fundamental characteristic, Figure 3 plots the mapped relation between the Merton model prediction residuals $\ln(CDS/MCDS)$ and each orthogonalized characteristic x^k . 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 $\ln(CDS/MCDS)$. The two financial leverage measures in the first two panels generate similar prediction patterns as higher leverage predicts higher CDS spread. 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 hence the lower the CDS spread.

[Figure 3 about here.]

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 as captured by the difference between option implied volatility and realized volatility. All three characteristics show large contributions, with large size, positive momentum, and low implied volatility contributing to lower CDS spreads.

The univariate local linear mapping between each 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 4 plots the time series of the relative weight estimates across our sample period. The time series of the coefficient estimates are quite smooth, as a result of the Bayesian smoothing applied in our estimation.

[Figure 4 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 4 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 volatility, 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.

4.3. Explaining remaining CDS variation with exposures to common risk factors

Our WCDS methodology includes a long list of firm characteristics that have been shown in the literature to be informative of the firm’s credit risk. Absent from the list, however, are stock return exposure estimates on various common risk factors.⁴ The effects of risk exposure estimates on the credit spreads are also largely absent from the literature. In this section, we examine whether a company’s stock risk exposure estimates provide additional cross-sectional explanatory power to the remaining CDS variation.

At each date and for each company, we estimate its risk exposures (betas) at that time using the following return regression with a three-year rolling window,

$$r_{i,t} = \alpha_i + \sum_{k=1}^K \beta_{i,k} f_{k,t} + \varepsilon_{i,t}, \quad (16)$$

where $r_{i,t}$ denotes the monthly stock return of company i at time t , $f_{k,t}$ denotes the time- t value of the k th common risk factors, and $\beta_{i,k}$ denotes the company i ’s exposure to the k th risk factor. Both the stock returns and the factors are defined over monthly horizons, but the sampling frequency for the regression is weekly to line up with our previous CDS analysis. We consider seven common risk factors: (1) the excess returns on the market portfolio over the Treasury bill rate (MKT), (2) the small minus big (SMB) size portfolio returns and (3) the high minus low (HML) book-to-market portfolio returns constructed by Fama and French (1993), (4) the up minus down (UMD) momentum portfolio returns proposed by Jegadeesh and Titman (1993), (5) the liquidity (LIQ) portfolio returns proposed by Pástor and Stambaugh (2003), (6) excess returns from investing

⁴We thank an anonymous referee for making this suggestion.

in a one-month variance swap contract on the S&P 500 index (VRP), as proposed by Carr and Wu (2009), and (7) a credit risk factor (CSC), computed as monthly changes in the average CDS spreads for all BBB-rated companies in the Markit CDS database. Data and the construction details for the first four factors are publicly available on French's online data library. The liquidity factor returns can be downloaded from the Wharton Research Data Services. They are the value-weighted returns on the ten-minus-one portfolio from a sort on historical liquidity betas. The excess return on the variance swap contract is computed as the log difference between the annualized realized variance on SPX returns over the past 30-days and the 30-day variance swap rate 30 days ago, which is approximated by the VIX index squared. The realized variance is computed using daily returns. The behaviors of the first four risk factors are well documented. We use the excess returns on the variance swap contract to proxy the risk premiums on market crash risk as the VIX index is often regarded as a market fear gauge for potential market crashes. Finally, the average CDS spread change for BBB-rated companies captures the credit risk premium variation over time.

We regress the deviations between market CDS quotes and WCDS, $\ln(CDS_t^i/WCDS_t^i)$, on the seven risk exposure estimates. The multivariate regression on the pooled data generates an R-squared of 1.23%. When we perform the regression cross-sectionally each week, the daily R-squared estimates average at 4.15%. When we apply the WCDS methodology on the risk exposure estimates to accommodate potential nonlinearity, the average R-squared increases only slightly to 5.57%. Overall, these risk exposure estimates do not provide much additional explanatory power on the CDS spreads.

The weak finding is not completely surprising. For stock return predictions, the literature generally finds that the prediction is stronger with the risk characteristics than with the risk exposure estimates, potentially because the risk exposure estimates can be noisy. For example, Daniel and Titman (1997) show that it is the size and book-to-market firm characteristics rather than the risk exposure estimates that explain the cross-sectional variation in stock returns. Similarly, when Ang, Horrick, Xing, and Zhang (2009) include both

the risk exposure estimates and the firm characteristics as risk controls in their Fama and MacBeth (1973) regression, they find that the risk exposure estimates do not significantly predict stock returns in the cross section but the corresponding firm characteristics do. Accordingly, in constructing the WCDS valuation, we focus on firm characteristics instead of risk exposure estimates. Once controlling for the risk characteristics in our WCDS construction, we find little additional explanatory power left in the risk exposure estimates.

4.4. 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. These two sets of findings, however, are not conflicting with each other, but rather represent different aspects of the data behavior. Indeed, 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. 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. Nevertheless, such lower explanatory power does not in any sense discount the fact that credit risk depends crucially on the firm's fundamentals, because if the firm's fundamentals were to deteriorate by a significant amount, its CDS spreads would be bound to rise.

To verify this conjecture, we form log CDS spread changes over different horizons from one to four weeks. Then, for each firm with over two years of observations, we perform a linear regression of the market

CDS changes against the corresponding changes in WCDS,

$$\ln(CDS_{t+h}^i/CDS_t^i) = \alpha_i + \beta_i \ln(WCDS_{t+h}^i/WCDS_t^i) + e_{t+h}^i, \quad h = 1, 2, \dots, 4. \quad (17)$$

Table 4 reports the cross-sectional averages and standard deviations (in parentheses) of the coefficients estimates (α, β) and the R-squared (R^2) of the time-series regressions. The average intercept estimates are close to zero, the average slope estimates are all below one, and the average R^2 estimates are low, especially for changes over shorter horizons. At weekly horizon, the R-squared estimates average at merely 13%. The average R-squared increases to 25% at the four-week horizon, which remains low. Thus, the high cross-sectional explanatory power is completely compatible with the low time-series R-squared from 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 time-series variations of its CDS spreads can be driven by non-fundamental factors.

[Table 4 about here.]

A related conjecture is that the regression in (17) should generate higher R-squared estimates for firms whose CDS levels and fundamental characteristics have experienced larger variations during our sample period. To test this hypothesis, we measure the time series standard deviation of the log CDS and log WCDS for each firm, and then measure the cross-sectional correlation between the time-series regression R-squared and the CDS and WCDS standard deviations. The last two columns in Table 4 report the correlation estimates, which are all positive as predicted by our conjecture.

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 in which the targeted variable does not vary much, the observed variation is bound to be dominated by other factors. Furthermore, it is also important to appreciate that different economic objectives ask for different types of regressions. If the objective is to differentiate the credit spread differences across firms based on their fundamental characteristics, the cross-sectional explanatory power is the natural performance measure. If on the other hand the objective is to determine the sensitivity of the credit spread changes with respect to changes in the underlying stock price for the purpose of hedging the credit risk exposure, the sensitivity coefficient should be estimated from time-series change regressions, and the R-squared of this regression measures the effectiveness of this hedging practice. Schaefer and Strebulaev (2008) find that the hedging ratios implied by structural models match well with those estimated from time-series change regressions.

5. Forecasting CDS Movements with Market-Fundamental Deviations

Another potential application for a good valuation methodology is to separate the fundamental value from transitory supply-demand shocks in the market observations. In this case, deviations of market observations from the fundamental-based valuations are transitory and can thus be used to predict future market movements. In this section, we examine the forecasting power of the market-fundamental CDS deviations on future market CDS movements. First, we examine whether the market-fundamental CDS deviations are indeed more mean-reverting than the original CDS series. Second, we estimate the cross-sectional forecasting correlation between current market-fundamental deviations and future market CDS movements, and compare the forecasting correlation performance between the different valuation methods. Finally, we gauge the economic significance of the forecasting power through an out-of-sample investment exercise based on market-fundamental CDS deviations.

5.1. Mean reversion speeds

We compare the mean reversion behavior of the log market CDS observations with that of the market-fundamental CDS deviations, which are captured by the residuals e from the four sets of cross-sectional regressions in (12)-(15). For each series x , we estimate the mean-reversion speed through the following cross-sectional regression at each date,

$$x_{t+h} - x_t = a - \kappa x_t h + \varepsilon_{t+h}, \quad (18)$$

where $h = 1/52$ denotes the weekly 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 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 of zero.

We estimate the cross-sectional regression each week. Table 5 reports the summary statistics of the mean-reversion speed estimates, including the sample mean, the standard deviation, and the t -statistics of the mean estimate, computed as the ratio of the sample mean to the Newey and West (1987) serial-dependence adjusted standard error. The market log CDS observation has an average mean reversion speed estimate of 0.16, corresponding to a time line of over six years. If one intends to predict future CDS movements based on its mean-reversion behavior, it would take a very long time for the mean reversion to take effect. By comparison, the mean-reversion speeds from the market-fundamental deviations are much higher. The highest average mean reversion estimate comes from the deviation between market CDS and WCDS at 1.18, corresponding to a time line of less than a year. 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 5 about here.]

5.2. 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,

$$\rho_{t,h} = \text{Corr} \left(\ln(CDS_{t+h}^i / CDS_t^i), e_t^i \right), \quad (19)$$

where $\ln(CDS_{t+h}^i / CDS_t^i)$ measures the log change from time t to $t+h$ on the market CDS observation for firm i and e_t^i denotes the time- t deviation between the market CDS observation on this firm and the corresponding fundamental-based valuations, obtained from one for the four cross-sectional regressions in (12)-(15). If the deviation e_t 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. The market CDS spread will decline in the future if it is wider now than what the fundamentals suggest where it should be.

The R-squared estimates from the cross-sectional regressions in (12)-(15) and the forecasting correlation estimates in (19) represent two different aspects of performance for the fundamental-based valuations. If the cross-sectional regression in (12)-(15) generates high R-squared, one can use the valuation methodology to effectively differentiate the credit spread difference across different firms based on their firm character-

istics. One application for such a valuation, as we have discussed in the previous section, is to generate CDS valuations for companies without reliable market CDS quotes. On the other hand, a high forecasting correlation estimate from (19) suggests that the fundamental-based valuation can be used to generate relative value trading opportunities as the deviations of market observation from the fundamental valuation predicts future market reversion to the fundamental valuation. These two aspects of model performance are neither necessarily co-existing nor mutually exclusively. The key for the former application is to match the market as well as possible while also generating stable extrapolation, whereas the key for the latter application is to generate an effective separation of persistent risk from transient movements. Indeed, for the latter application, conditional on the deviation being transient, the larger the deviation, the better it is because larger deviations represent larger investment opportunities.

Table 6 reports the summary statistics of the forecasting correlation estimates. The two panels are for two forecasting horizons h : one week in panel I and four weeks in panel II. 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 6 about here.]

The mean correlation estimates are negative for all models and over all horizons, consistent with our conjecture that the deviations predict future market reversions to the model valuation. The more negative the mean correlation estimates are, the stronger the prediction. Among the four valuation methods, the bivariate linear regression (BLR) and the RCDS regression generate similar mean forecasting estimates, -5% at one week horizon and -9% at four-week horizon. However, the bivariate linear regression is not as stable as the RCDS prediction as the forecasting correlation estimates from BLR show larger time-series variations (Std) than that from RCDS. Over both forecasting horizons, although the mean correlation estimates are about the

same for the two methods, the standard deviation of the correlation estimates from BLR is one percentage point higher than that from RCDS.

By correcting for the nonlinearity in the relation between market CDS and RCDS via a local quadratic regression, MCDS not only explains a higher percentage of the cross-sectional CDS variation, the market deviations from MCDS also generates stronger predictions for future market movements. The forecasting correlation estimates from MCDS average about one percentage point higher at one-week and four-week horizons and two percentage point higher at the eight-week forecasting horizon. The t -statistics suggest that the forecasting performance differences between MCDS and RCDS are statistically significant.

By incorporating a long list of additional firm characteristics via a Bayesian shrinkage method, the WCDS generates even stronger predictions on future market movements. The forecasting correlation estimates average at -7% at one-week horizon and -12% at four-week horizon, about two percentage points higher than that from MCDS. The performance difference between WCDS and MCDS is highly statistically significant over both horizons.

The progressive forecasting performance comparison among the four valuation methods shows the contribution of our WCDS valuation method, which provides a stable framework for effectively differentiating the credit spreads of different firms based on their differences in firm characteristics, and for successfully separating the persistent credit risk component from the more transitory supply-demand shocks in the market CDS quotes.

5.3. An out-of-sample investment exercise

To gauge the economic significance of the forecasting power, we perform a simple out-of-sample investment exercise on the CDS contracts 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 valuations, and we invest in a notional amount in each CDS contract i , n_t^i , that is proportional to this deviation,

$$n_t^i = c_t \left(\widehat{CDS}_t^i - CDS_t^i \right), \quad (20)$$

where \widehat{CDS}_t^i denotes the fundamental-based valuation from one of the four regressions in (12)-(15). 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 the corresponding CDS valuations at that time.

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

$$PL_{t,h}^i = LGD \left(\lambda_{t+h}^i - \lambda_t^i \right) \frac{1 - e^{-(r_{t+h} + \lambda_{t+h}^i)(\tau-h)}}{r_{t+h} + \lambda_{t+h}^i}, \quad (21)$$

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 i th-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 notational 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 the information up to time t .

We consider investment horizons from one to four weeks. Table 7 reports the summary statistics of the excess returns from the investment exercise, where each of the four panels represent results from one of the four valuation methods. In Panel I, 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 excess returns on average, but the standard deviations of returns are very large, resulting in very 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.

[Table 7 about here.]

The investment decisions in Panel II are based on the residuals from a linear regression on the raw CDS valuation RCDS. Compared to Panel I, the RCDS-based investments generate higher average excess returns at shorter horizons (one and two weeks), but lower average excess returns at longer horizons. Nevertheless, the investments generate markedly lower standard deviations. As a result, the information share estimates are much higher, especially at short investment horizons. Thus, even though the linear regression and RCDS generate similar forecasting correlations on average (Table 6), the instability of the linear regression forecast makes it largely ineffective for investment purposes. The enhanced forecasting stability from RCDS generates marked improvement on the stability of the investment returns.

Compared to RCDS, the MCDS-based investments in Panel III generate both higher average excess re-

turns and lower standard deviations over all investment horizons. The information ratio reaches as high as 1.51 at one week horizon, and 0.80 at four-week horizon. Finally, when we base the investment decision on the deviation between market quotes and the WCDS valuation in Panel IV, the average excess returns are the highest and the return standard deviations are the lowest, resulting in the highest information ratio estimates across all investment horizons, from 2.26 at one week horizon to 1.50 at four-week horizon. Thus, the forecasting outperformance of WCDS over all other valuation methods is significant not only statistically but also economically.

To examine whether the CDS investment returns can be explained by common risk factors, we regress the four-week investment returns based on the WCDS valuation on seven common risk factors that we have constructed in Section 4.3. Since these factors are all constructed approximately as monthly investment returns, the slope estimates from the regression can be used to construct a portfolio that are neutral to these risk factors. The intercept of the regression captures the average excess return of this factor-neutral portfolio, whereas the standard deviation of the regression residuals captures the risk of the factor-neutral portfolio return. Table 8 reports the coefficients estimates and *t*-statistics of the coefficient estimates. The last column reports the R-squared of the regression in the first row and the annualized information ratio for the factor-neutralized investment in the second row. The regression estimates suggest that the CDS investment return are positively exposed to the size risk factor, but negatively exposed to the momentum factor and credit spread factor. The factor-neutralized portfolio has an average excess return of 1.88%, higher than the un-neutralized CDS investment return of 1.58%. Furthermore, through factor-neutralization, the portfolio risk is reduced by 31% as shown by the R-squared of the regression. As a result, the factor-neutralized portfolio generates a higher annualized information ratio at 2.14 as compared to the information ratio of 1.50 for the un-neutralized CDS investment return. Overall, the regression shows that the CDS investment returns cannot be fully explained by common risk factors.

[Table 8 about here.]

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.⁵ 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 significance of the fundamental-based CDS valuations. 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 valuations. 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.

⁵Markit implements various mechanisms in the data collection procedure to guarantee that the dealer contributions represent where the dealers truly want to trade.

6. Conclusion

This paper identifies two important economic applications where firm fundamentals can be highly useful. First, we show that, through our WCDS construction methodology, firm fundamentals can explain a large proportion of the cross-sectional variation in the five-year CDS spreads. Second, when market CDS observations deviate from our fundamental-based WCDS valuations, the market observations tend to revert back to the fundamental-based valuations in the future. On the one hand, the high cross-sectional explanatory power suggests that firm fundamentals can be used to differentiate the credit risk of different companies, even when market CDS quotes are not available on these companies. Since firm fundamental information is available for thousands of companies whereas only hundreds of them have market CDS information, one can use the WCDS methodology to generate fundamental-based CDS valuations on companies without market quotes, thus greatly expanding the CDS universe. On the other hand, within the universe of companies with market CDS quotes, one can predict future market CDS movements based on the current deviations between market quotes and the fundamental-based valuations. Thus, the fundamental-based WCDS valuation can be used as a relative valuation tool for profitable CDS investments.

In constructing our fundamental-based CDS valuation, we find that the classic structural model of Merton (1974) provides a good starting point by highlighting two major determinants of credit spreads (financial leverage and asset volatility) and combining them into a normalized distance-to-default measure that is comparable across firms. When we transform this distance-to-default measure to a raw CDS valuation via a simple constant hazard rate assumption and then correct the local bias of this raw CDS valuation at different risk levels via a local quadratic regression, we generate a Merton-based CDS valuation that can explain 65% of the cross-sectional market CDS variation on average. We show that this Merton-based valuation performs much better than a bivariate linear regression on the two Merton model inputs, which generates an average R-squared estimate of 49%. The large performance difference suggests that the Merton model contributes to

the cross-sectional explanatory power not only by pointing out two major credit risk determinants, but also by providing a useful way of combining the two determinants into a standardized credit risk measure.

In addition to the two Merton model inputs, many other firm characteristics can also provide additional information on CDS spreads. The analysis shows that our WCDS construction methodology represents a robust econometric approach for combining the Merton-based valuation with the marginal contributions of a long list of additional firm fundamental characteristics. The WCDS valuation not only improves the average cross-sectional explanatory power to 77%, but also generates much more uniform performance across different sample periods. Furthermore, compared to the Merton-based valuation, the WCDS valuation provides a better separation of fundamental variations and transitory supply-demand shocks in the market CDS variation. As a result, market deviations from the WCDS valuation generates strong forecasting performance on future market CDS movements. A simple investment strategy based on the market-WCDS deviations generate high excess returns and low standard deviations, highlighting the economic significance of the fundamental-based CDS predictions.

When one evaluates the performance of a model, it is important to realize that different applications and objectives ask for different performance metrics. If the purpose is to examine whether the market charges the appropriate amount of risk premium according to theory, one can examine the average bias of a model prediction. Accordingly, the findings in Huang and Huang (2003) and Eom, Helwege, and Huang (2004) are often dubbed as the “credit risk premium puzzle.” Many new structural models have been proposed with the purpose of generating the right magnitude of credit risk premium.⁶

On the other hand, if the purpose is to examine whether and which firm fundamentals matter for credit

⁶Examples include Titman and Torous (1989), Kim, Ramaswamy, and Sundaresan (1993), Leland, Anderson and Sundaresan (1996), Anderson, Sundaresan, and Tychon (1996), Briys and de Varenne (1997), Mella-Barral and Perraudin (1997), Garbade (1999), Fan and Sundaresan (2000), Duffie and Lando (2001), Goldstein, Ju, and Leland (2001), Zhou (2001), Acharya and Carpenter (2002), Collin-Dufresne, Goldstein, and Helwege (2003), Hull, Nelken, and White (2004), Buraschi, Trojani, and Vedolin (2007), Cremers, Driessen, and Maenhout (2008), Chen, Collin-Dufresne, and Goldstein (2009), and Bhamra, Kuehn, and Strebulaev (2010).

spreads, linear regressions can be performed directly on the inputs of a structural model, as in Collin-Dufresne, Goldstein, and Martin (2001) and Ericsson, Jacobs, and Oviedo (2009). In addition, if the purpose is to identify the sensitivity of the credit spread changes to changes in a corresponding underlying variable such as the stock price, the sensitivity coefficient for each firm can be estimated via a time-series regression of changes in credit spreads against changes in stock prices, and the coefficient can be applied for hedging credit risk exposures with the underlying stock, as suggested in Schaefer and Strebulaev (2008). By contrast, if the purpose is to differentiate the credit risk of different companies based on their differences in firm characteristics, a cross-sectional regression makes more economic sense. The identification can also be sharper for characteristics that differ greatly across firms but do not vary much over time for a particular firm.

Furthermore, structural models are useful not just for their implications on the average risk premium or the average credit spread level, but more for their implications on which firm fundamental characteristics matter for credit risk and how they matter. Our analysis shows that with the appropriate choice of maturity as a control coefficient, the Merton distance-to-default measure represents a useful way of combining the two Merton model inputs into one standardized variable that predicts CDS variations.

Finally, while theory provides guidance on which risk factors matter for credit spreads, these risk factors may not have a direct corresponding measurement in observable firm characteristics. Instead, many firm characteristics can only be regarded as approximate and noisy measurements of the underlying risk factors. Thus, a robust econometric approach is needed to extract the credit risk information from the many noisy measurements. Our WCDS valuation methodology represents such an endeavor, and our historical analysis shows that this valuation method can generate robust, stable, and well-performing CDS valuations based on a long list of firm characteristics.

Appendix

A. Maturity choice in the Merton model implementation

The actual implementation of the Merton (1974) model varies across different studies. For example, in the KMV implementation as documented in Crosbie and Bohn (2003), the maturity T is set to one year, matching their default probability forecasting horizon. We have experimented with different maturity choices. Panel I of Table 9 shows how the maturity choice affects the cross-sectional explanatory power of the model on market CDS observation. Each day, 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 on the three fundamental-based valuations (RCDS, MCDS, and WCDS). The right side reports the corresponding average R-squared estimates on the out-of-sample half of the universe.

The results in panel I 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 becomes similar when 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 an option on the asset, the model controls the relative importance of the two determinants through the option maturity. In particular, 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 implied by a one-year maturity assumption used in the KMV implementation.

B. Local polynomial regressions and bandwidth choice

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

$$y = f(x) + e, \quad (22)$$

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,

$$\hat{y}_k = X_k(X^\top W_k X)^{-1} X^\top W_k y, \quad (23)$$

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 i th diagonal element given by,

$$W_k^i = \exp\left(-\frac{(x_i - x_k)^2}{2h^2}\right), \quad (24)$$

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 $(x_i - x_k)^2$ 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 $h \rightarrow \infty$, 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,

$$\hat{h} = (4/3)^{(1/5)} \sigma_x / N^{(1/5)}, \quad (25)$$

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. Panel II of Table 9 shows the effects of the bandwidth choice on the cross-sectional explanatory powers of the three fundamental-based valuations RCDS, MCDS, and WCDS. Since RCDS does not involve a local polynomial regression, its performance is independent of the bandwidth choice. The performance of MCDS and WCDS depends on the bandwidth choice. 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.

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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 I. reports the average of each firm characteristic on both the pooled sample and at each CDS quintile. Panel II. 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.

Characteristics	I. Mean at CDS Quintiles						II. Standard Deviation			
	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 market CDS and fundamental-based valuations**

Entries report the summary statistics of the logarithm of market CDS observations and fundamental-based CDS valuations. Statistics include the sample mean, standard deviation (Std), minimum, maximum, and the cross-correlation between market observations and fundamental valuations. The statistics are computed on the pooled data on 579 U.S. non-financial firms and over 351 weeks from January 8, 2003 to September 30, 2009, a total of 138,200 week-firm observation for each series.

Statistics	$\ln(CDS)$	$\ln(RCDS)$	$\ln(MCDS)$	$\ln(WCDS)$
Mean	4.3968	3.1532	4.3950	4.4163
Std	1.1772	2.4030	1.0135	1.0745
Minimum	0.9145	0.0000	2.6056	1.5658
Maximum	9.1852	8.5688	9.0956	9.1852
Correlation	1.0000	0.7633	0.8417	0.8969

Table 3**Summary statistics of cross-sectional explanatory powers from different valuation methods**

Entries report the summary statistics of the weekly R-squared estimates from the cross-sectional regressions of the log market CDS against four sets of fundamental-based valuations: (i) a bivariate linear regression (BLR) on debt to equity ratio and realized volatility, (ii) RCDS, (iii) MCDS, and (iv) 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 I 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 II 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 III, 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.

Statistics	Cross-sectional R^2				R^2 differences		
	BLR	RCDS	MCDS	WCDS	RCDS-BLR	MCDS-MCDS	WCDS-MCDS
I. In-sample performance from full-sample estimation							
Mean	0.49	0.58	0.65	0.77	0.09	0.07	0.11
Std	0.10	0.07	0.08	0.04	0.07	0.05	0.05
Minimum	0.22	0.48	0.50	0.67	-0.14	0.01	0.05
Maximum	0.64	0.72	0.78	0.85	0.33	0.22	0.23
t -stats	14.75	24.94	22.53	54.46	4.12	4.47	6.41
II. In-sample performance from half-sample estimation							
Mean	0.51	0.58	0.65	0.77	0.07	0.07	0.12
Std	0.10	0.07	0.09	0.05	0.08	0.05	0.05
Minimum	0.19	0.41	0.44	0.62	-0.19	-0.01	0.03
Maximum	0.67	0.75	0.81	0.88	0.33	0.25	0.29
t -stats	26.27	38.67	32.13	84.62	5.54	5.92	8.84
III. Out-of-sample performance from half-sample estimation							
Mean	0.25	0.58	0.64	0.74	0.32	0.06	0.10
Std	0.96	0.08	0.09	0.06	0.96	0.05	0.06
Minimum	-13.24	0.25	0.26	0.59	-0.14	-0.15	-0.01
Maximum	0.67	0.75	0.80	0.86	13.82	0.24	0.37
t -stats	4.79	36.74	31.75	83.50	6.20	4.93	7.86

Table 4**Regressing changes in market CDS to changes in fundamental-based WCDS valuations**

Entries report the cross-sectional mean and standard deviation (in parentheses) of the coefficients (α, β) and R-squared (R^2) estimates from the following time-series regressions for each firm i ,

$$\ln(CDS_{t+h}^i/CDS_t^i) = \alpha_i + \beta_i \ln(WCDS_{t+h}^i/WCDS_t^i) + e_{t+h}^i.$$

Firms with less than two years of data are excluded from the regressions. The horizon of the change h is in weeks. The last two columns 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 and log WCDS spreads, respectively.

h	α		β		R^2		$Corr(R^2, \sigma_{CDS})$	$Corr(R^2, \sigma_{WCDS})$
1	0.00	(0.00)	0.35	(0.26)	0.13	(0.12)	0.33	0.33
2	0.00	(0.01)	0.43	(0.29)	0.18	(0.15)	0.36	0.35
3	0.00	(0.01)	0.49	(0.30)	0.22	(0.17)	0.38	0.37
4	0.00	(0.01)	0.53	(0.30)	0.25	(0.18)	0.40	0.38

Table 5**Comparing the mean-reversion speeds of market CDS and market-fundamental CDS deviations**

Entries report the summary statistics of the weekly estimates on the annualized cross-sectional mean-reverting speeds for different data series. For a given series x , the mean-reverting speed is estimated from the following cross-sectional 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 frequency. Entries report the mean, standard deviation, and the t -statistics of the κ estimates for both the log market CDS series and its regression residuals e against the four sets of valuation methods. The t -statistics are computed as the ratio of the mean estimate to its Newey and West (1987) serial-dependence adjusted standard error.

Statistics	Original series $\ln(CDS)$	Market-fundamental deviations, e			
		BLR	RCDS	MCDS	WCDS
Mean	0.16	0.52	0.52	0.66	1.18
Std	0.54	0.96	0.74	0.79	1.04
t -stats	4.40	8.74	10.69	12.23	21.31

Table 6**Forecasting correlation between current 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 I and four weeks in panel II. We generate market-fundamental deviations from four sets of cross-sectional regressions: (1) a bivariate linear regression (BLR) of log market CDS on debt to equity ratio and realized volatility, (2) a linear regression of log market CDS on log RCDS, (3) the log deviation between market CDS and MCDS, and (4) the log deviation between market CDS and WCDS. Entries on the right side report the statistics on the pair-wise correlation differences between these different 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.

Statistics	Forecasting correlations				Forecasting correlation differences		
	BLR	RCDS	MCDS	(D). WCDS	RCDS-BLR	MCDS-RCDS	WCDS-MCDS
I. Forecasting horizon: one week							
Mean	-0.05	-0.05	-0.06	-0.07	-0.00	-0.01	-0.02
Std	0.10	0.09	0.08	0.08	0.07	0.04	0.04
t -stats	-7.11	-8.44	-10.08	-15.89	-0.38	-3.15	-5.51
II. Forecasting horizon: four weeks							
Mean	-0.09	-0.09	-0.10	-0.12	0.00	-0.01	-0.02
Std	0.12	0.11	0.10	0.09	0.08	0.04	0.05
t -stats	-6.15	-7.21	-7.55	-11.96	0.13	-2.73	-3.79

Table 7**Summary statistics of excess returns from an out-of-sample investment exercise**

Entries report the annualized mean excess return (Annual. 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 four sets of fundamental-based CDS valuations. Each panel represents results from one valuation method.

Horizon, h Weeks	Annual. Mean %	Std %	Skewness %	Kurtosis	SR
I. Investments based on the bivariate linear regression					
1	6.76	7.31	-2.22	23.35	0.13
2	11.05	9.62	-1.38	12.60	0.23
3	9.55	9.95	-0.91	10.59	0.23
4	13.88	11.98	-0.30	5.90	0.32
II. Investments based on RCDS valuation					
1	19.13	2.56	2.40	15.62	1.04
2	14.80	3.63	1.35	5.69	0.80
3	9.61	4.37	0.89	3.06	0.53
4	11.49	5.60	1.84	8.81	0.57
III. Investments based on MCDS valuation					
1	25.25	2.32	3.06	21.01	1.51
2	19.06	3.17	1.68	7.59	1.18
3	12.56	3.59	1.16	5.43	0.84
4	14.30	4.97	2.99	20.13	0.80
IV. Investments based on WCDS valuation					
1	32.14	1.97	2.87	17.51	2.26
2	27.68	2.74	2.27	8.28	1.98
3	21.60	3.00	1.72	4.98	1.73
4	20.55	3.81	1.02	6.21	1.50

Table 8**Explaining CDS investment returns with common risk factors**

Entries report risk exposure estimates and t -statistics of the CDS investment return over four-week horizons. The exposures are estimated by regressing the investment returns against the seven common risk factors, with α measuring the intercept estimate. The last column reports the R-squared of the regression in the first row and the annualized information ratio in the second row.

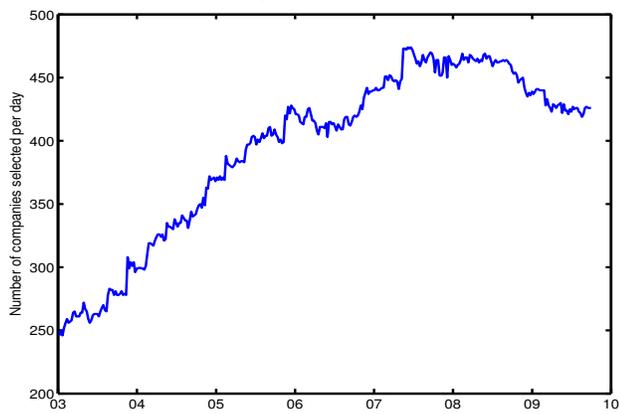
	α	MKT	SMB	HML	UMD	LIQ	VRP	CSC	R^2 /SR
Estimates	1.88	-0.01	0.36	-0.05	-0.16	0.13	0.01	-0.09	0.31
t -statistics	3.88	-0.17	2.05	-0.30	-2.12	1.41	1.19	-2.86	2.14

Table 9**Variations in 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 three fundamental-based valuations (RCDS, MCDS, 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. Panel I shows the effect of maturity choice in the Merton model implementation. Panel II shows the effects of bandwidth choice for the local quadratic and local linear regressions in the MCDS and WCDS construction. The bandwidth choice is $2\hat{h}$ (twice the default) in panel I and the maturity choice is 10 years in panel II.

Choices	In-sample R^2			Out-of-sample R^2		
	RCDS	MCDS	WCDS	RCDS	MCDS	WCDS
T	I. Effects of maturity choice					
1	0.37	0.40	0.71	0.36	0.37	0.66
3	0.54	0.58	0.75	0.54	0.56	0.71
5	0.58	0.62	0.76	0.57	0.61	0.73
10	0.58	0.65	0.77	0.58	0.64	0.74
15	0.58	0.66	0.78	0.57	0.65	0.75
20	0.57	0.66	0.78	0.57	0.65	0.75
h	II. Effects of bandwidth choice					
$.5\hat{h}$	0.58	0.67	0.81	0.58	0.63	0.71
$1\hat{h}$	0.58	0.66	0.79	0.58	0.64	0.74
$2\hat{h}$	0.58	0.65	0.77	0.58	0.64	0.74
$3\hat{h}$	0.58	0.65	0.76	0.58	0.64	0.74

A. Number of companies selected at each date



B. Number of days selected for each company

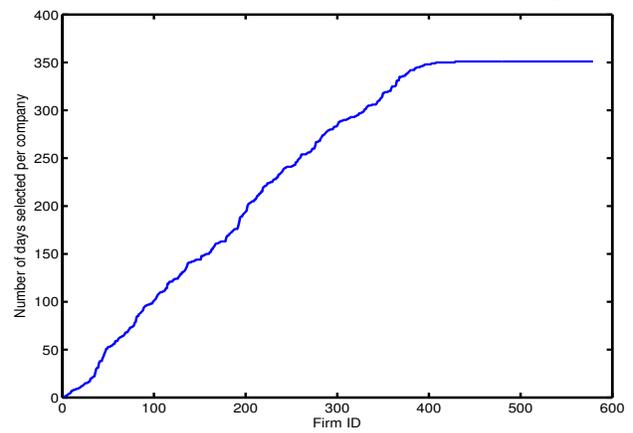


Figure 1

Number of selected companies at different dates and number of days selected for different companies. Panel A plots the number of companies selected at each sample date and Panel B plots the number of days selected for each company.

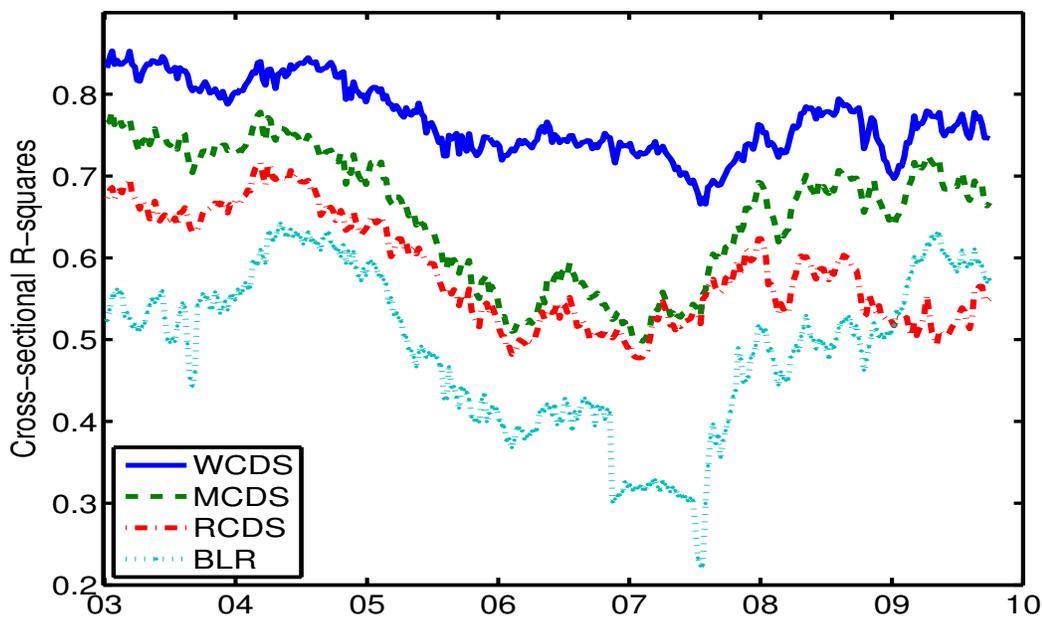


Figure 2

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

At each date, we perform four sets of cross-sectional regressions. The four lines denote the time-series of the R-squared estimates from these regressions. The 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 dash-dotted line is the R-squared estimates from regressions on the RCDS. The dashed line and the solid line represent the cross-sectional explained variation of MCDS and WCDS, respectively.

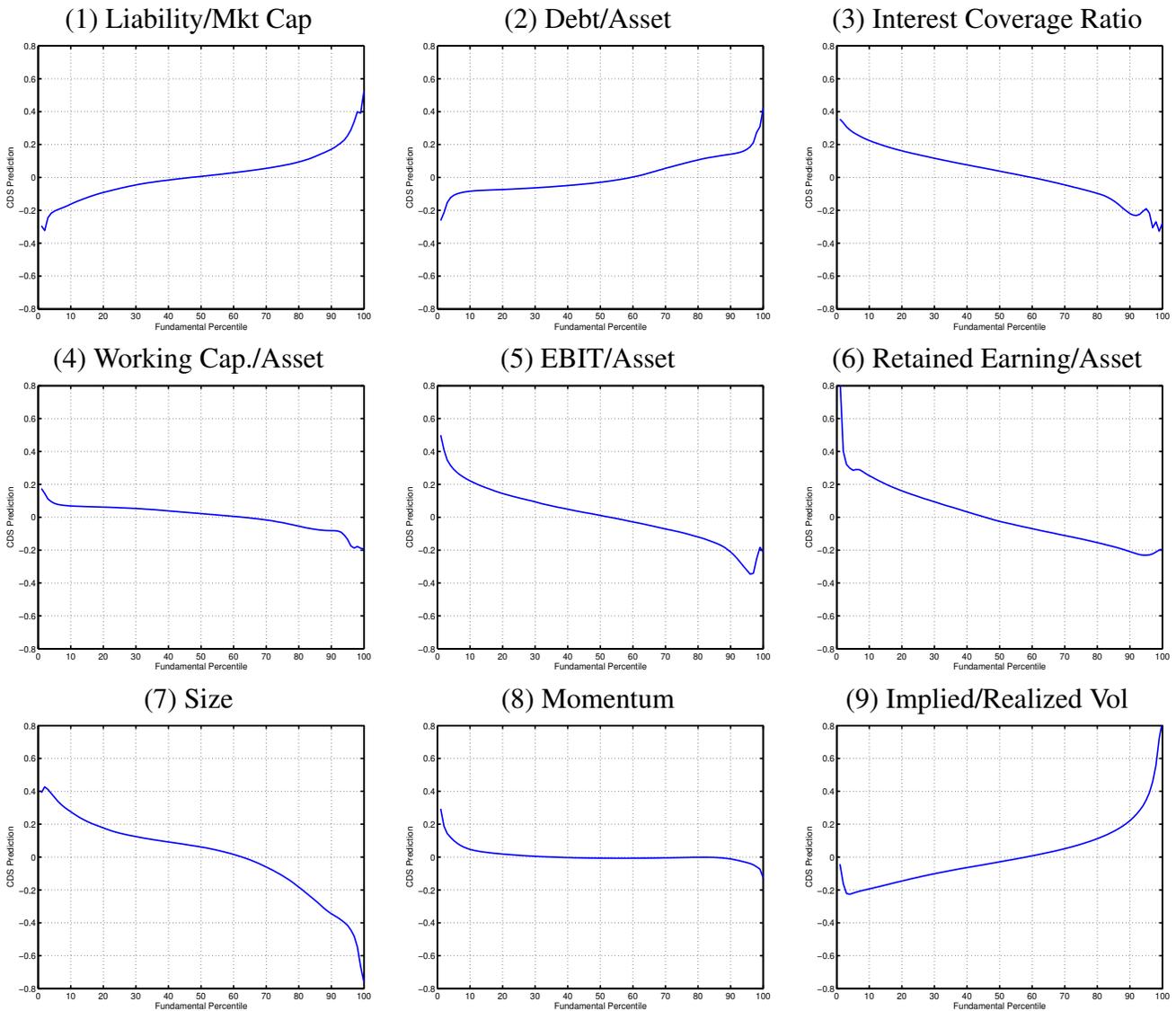


Figure 3

Additional contributions from other firm fundamental characteristics.

The line in each panel represents the average contribution of one firm characteristic to the $\ln(CDS/MCDS)$ prediction. For ease of comparison, we use the percentiles of the firm characteristics for the x -axis and we use the same scale for the y -axis. The relations are estimated via a local linear regression on the pooled data over 351 weeks and 579 companies.

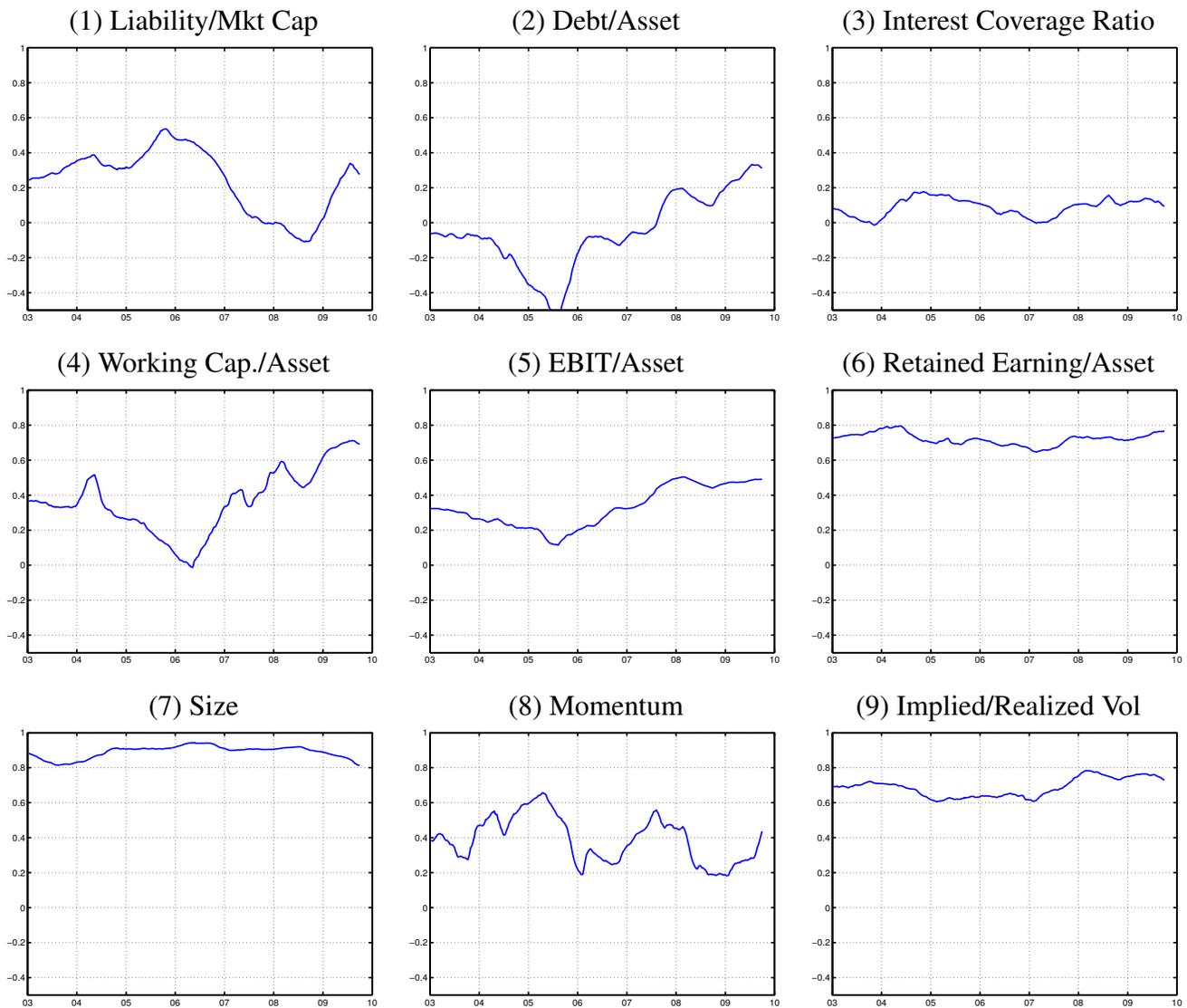


Figure 4

The relative contribution from each firm characteristic to the additional CDS prediction.

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