Anchoring Credit Default Swap Spreads to Firm Fundamentals

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Abstract

In this article, we examine the extent to which firm fundamentals can explain the cross-sectional variation in credit default swap (CDS) spreads. We construct a fundamental CDS valuation by combining the Merton distance-to-default measure with a long list of firm fundamentals via a Bayesian shrinkage method. Regressing CDS quotes against the fundamental valuation cross-sectionally generates an average R^2 of 77%. The explanatory power is stable over time and robust in out-of-sample tests. Deviations between market quotes and the valuation predict future market movements. The results highlight the important role played by firm fundamentals in differentiating the credit spreads of different firms.

I.   Introduction

The literature examines the performance of structural credit models and firm fundamentals from several perspectives. Huang and Huang (2012) and Eom, Helwege, and Huang (2004) focus on the average bias of structural models and show that different structural models generate different average biases on credit spreads. 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^2 estimates and that the regression residuals share a large single principal component. In this article, we examine the extent to which structural models, and more generally firm fundamental characteristics, can explain the cross-sectional variation in credit default swap (CDS) spreads.

The main objective of building a structural model such as Merton (1974) is to link a firm's credit risk to its structural characteristics, such as financial leverage and business risk. Accordingly, the most direct way of analyzing the structural model's performance is to examine whether firms with different structural characteristics bear different credit risks as predicted by the model. It is this intuition that motivates our focus on the cross-sectional explanatory power of firm fundamentals. Average bias is an important concern, but it is inherently awkward to use structural models to explain the average size of risk premiums, mainly because most structural models are built on no-arbitrage principles instead of risk–return trade-offs. As such, these models do not have much to say about the appropriate levels of risk premiums; rather, they identify a linkage between the pricing of one security and the pricing of other securities via dynamic no-arbitrage arguments.[1] Similarly, time-series regressions on monthly changes can be useful in many other applications, but they are not particularly suited for identifying the linkage between firm structural characteristics and credit risk, simply because firms tend to be structurally stable over time in terms of the type of business they are in and the level of financial leverage they target. The common variations in the time-series regression residuals likely reflect the common variation of risk premiums, the focus of general equilibrium models rather than firm-level structural models. By focusing on the cross-sectional relation, we strive to determine the extent to which firm structural characteristics can differentiate the credit quality and accordingly credit spreads of different firms and what structural characteristics are particularly useful in this differentiation. The findings provide guidance for developing new structural models.

To synthesize firm fundamental information for CDS valuation, we start with the classic Merton (1974) model, which combines two major credit risk determinants, financial leverage and asset return volatility, into a standardized distance-to-default measure. Mapping this measure to market CDS observations via a cross-sectional nonparametric regression generates a Merton-based CDS (MCDS) valuation. In addition, we collect a long list of firm fundamental characteristics that are not included in the Merton model implementation but have been shown to be informative about a firm's credit spread, and we propose a Bayesian shrinkage method to combine the Merton-based valuation with the information from this list of fundamental characteristics to generate a weighted average CDS (WCDS) valuation. The Merton distance-to-default measure has been used as input for credit risk prediction in many practical and academic implementations (Bharath and Shumway (2008), Crosbie and Bohn (2003), Duan, Sun, and Wang (2012), and Duan and Wang (2012)). The Bayesian shrinkage method incorporates additional information while addressing practical issues such as possible nonlinearities, missing observations, and potential multicollinearity among different proxies of the same variable.

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[1]As an example, Cremers, Driessen, and Maenhout (2008) introduce jumps to the asset value dynamics and link the jump risk premium to those implied from the equity index options market. By doing so, they find that the average credit spread level is consistent with how equity index options are priced. Their analysis does not answer the question of whether the level of risk premium is appropriate given the level of risk but, rather, examines whether the pricing of the same risk is consistent across two markets.

We examine the cross-sectional explanatory power of the fundamental CDS valuation based on 6½ years of data on 579 U.S. nonfinancial public firms from Jan. 8, 2003 to Sept. 30, 2009. On each date, we perform three sets of cross-sectional regressions. The first is a benchmark bivariate linear regression (BLR) of market CDS quotes on the two inputs of the Merton model: the total-debt-to-market capitalization ratio and stock return volatility. The second and third regress the market CDS quotes against the MCDS and WCDS valuations, respectively. The R^2 estimates from BLR average 49%. By comparison, the R^2 estimates average 65% for MCDS valuations and 77% for WCDS valuations.

To gauge the out-of-sample stability of the valuation method, we randomly select half of the universe each day to estimate the model and conduct out-of-sample valuation on the other half. The out-of-sample performance for both MCDS and WCDS valuation deteriorates very little as the average cross-sectional explanatory power goes from 65% in sample to 64% out of sample for MCDS valuation, and from 77% in sample to 74% out of sample for WCDS valuation. By contrast, the BLR approach shows severe out-of-sample deterioration as the average R^2 value declines from 51% in sample to 25% out of sample.

The high and stable cross-sectional explanatory power suggests that the WCDS method can be used to generate reasonable CDS valuations for companies with firm fundamental information but without valid market CDS quotes, effectively expanding CDS market coverage. Furthermore, because the fundamental-based CDS valuation captures the cross-sectional market CDS variation well, the remaining deviation between the market quote and the valuation is likely driven by nonfundamental factors such as supply–demand shocks. If these shocks are transitory, the current market–fundamental deviation will predict future market movements. When we estimate the forecasting correlation between the current market–fundamental deviation and future CDS changes, we obtain statistically significant estimates, averaging −7% at a weekly horizon and −12% at a 4-week horizon. The negative sign of the correlation estimates suggests that when market observations deviate from the fundamental valuation, the market tends to revert to the fundamental valuation in the future, highlighting the role of firm fundamentals as an anchor for market CDS movements.

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

The rest of the article is structured as follows: Section II describes the data sources and sample construction. Section III introduces the method for constructing firm fundamental-based CDS valuation. Section IV examines the performance of the fundamental CDS valuation in explaining the cross-sectional variation in

market CDS observations. Section V applies the fundamental CDS valuation as an anchor for relative valuation and studies the forecasting power of the market–fundamental deviation on future market CDS movements. Section VI concludes.

II.   Data Collection and Sample Construction

Data on U.S. nonfinancial public corporations come from several sources. We start with the universe of companies with CDS records in the Markit database and retrieve their financial statement information from Capital IQ, stock option implied volatilities from OptionMetrics, and stock market price information from the Center for Research in Security Prices (CRSP).

We perform fundamental-based CDS valuation every Wednesday from Jan. 8, 2003 to Sept. 30, 2009. On a given date, a company is included in the sample if data are available on i) a 5-year CDS spread quote on the company, ii) balance sheet information on the total book value of debt in the company, iii) the company's market capitalization, and iv) 1 year of daily stock return history. The sample contains 351 active weeks and a total of 579 companies that satisfy our data selection criteria. All together, we have 138,200 week-company observations.

Whereas we use the 5-year CDS spread as a measure of a firm's credit quality, many researchers choose to use credit spreads on corporate bonds (e.g., Avramov, Jostova, and Philopov (2007), Bao and Pan (2013), Campbell and Taksler (2003), Chen, Lesmond, and Wei (2007), Collin-Dufresne et al. (2001), and Cremers, Driessen, Maenhout, and Weinbaum (2008)). Both choices should lead to similar conclusions, but the use of corporate bonds faces several practical complications. First, credit spreads tend to have a strong term structure effect. With CDS, we can easily control this effect by choosing the over-the-counter quote on a 5-year contract for each firm. Controlling the maturity effect is not as straightforward for corporate bonds with fixed expiration dates. One needs to either add maturity (or duration) as an explicit factor to control for the term structure effect or choose bonds within a maturity range to mitigate the term structure effect. Second, transaction prices on corporate bonds can vary significantly with the trading size and trading liquidity of the bond, creating a liquidity component in credit spreads that is driven less by firm characteristics and more by security and trading characteristics. By contrast, the over-the-counter CDS contracts are between institutional players and with zero net supply. Although the bid–ask spread can vary, the mid-CDS quote is less affected by the trading liquidity of the contract (Bongaerts, de Jong, and Driessen (2011)). For these reasons, analysis based on CDS spreads tends to generate cleaner results on the credit risk determinants (Blanco, Brennan, and Marsh (2005), Longstaff, Mithal, and Neis (2005), Ericsson, Reneby, and Wang (2006), and Zhang, Zhou, and Zhu (2009)).

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

We use a 45-day rule to match the financial statements with market pricing data, assuming that the end-of-quarter balance sheet information becomes available 45 days after the last day of each quarter. For example, we match CDS spread and stock market variables between May 15 and Aug. 14 with the Q1 balance sheet, market data between Aug. 15 and Nov. 14 with the Q2 balance sheet, market data between Nov. 15 and Feb. 14 with the Q3 balance sheet, and market data between Feb. 15 and May 14 with the Q4 balance sheet information. When we examine the balance sheet filing date from 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 on the date of CDS valuation.

To implement the Merton (1974) model, we use the ratio of total debt to market capitalization and the 1-year realized return volatility as inputs. In addition, we consider contributions from other credit-informative firm characteristics:

- *Leverage*, for which we consider two alternative measures: the ratio of current liability plus half of long-term liability to market capitalization and the ratio of total debt to total assets.

- *Interest coverage*, computed as the ratio of earnings before interest and taxes (EBIT) to interest expense. The ratio measures the capability of a company in covering its interest payment on its outstanding debt with its ongoing earnings.

- *Liquidity*, captured by the ratio of working capital to total assets. Working capital, defined as current assets minus current liabilities, is used to fund operations and to purchase inventory.

- *Profitability*, captured by the ratio of EBIT to total assets.

- *Investment*, captured by the ratio of retained earnings to total assets. Retained earnings are net earnings not paid out as dividends but retained by the company to invest in its core business or to pay off debt.

- *Size*, measured by the natural logarithm of market capitalization.

- *Stock market momentum*, measured by the stock return over the past year.

- *Options information*, captured by the natural logarithm of the ratio of the 1-year 25-delta put option implied volatility to the 1-year realized volatility.

Kealhofer, McQuown, and Vasicek (KMV) use current liability plus half of long-term liability as the proxy of the debt level in its Merton (1974) model implementation for the 1-year default probability prediction (Crosbie and Bohn (2003)). Altman (1968), (1989) uses total debt to total assets, the interest coverage ratio, the working-capital-to-total-assets ratio, the EBIT-to-total-assets ratio, and the retained-earnings-to-total-assets ratio to form the well-known Z-score for predicting corporate defaults. Company size has been used as a classification variable for credit risk prediction, as small companies are often required to have a larger coverage ratio for the same credit rating. Du and Suo (2007) find firm value to be a

strong predictor of credit risk in addition to the distance-to-default measure. Fama and French (1993) also identify firm size as a risk factor that can predict future stock returns. Duffie, Saita, and Wang (2007) use past stock returns to predict firm default probabilities. We label past return as stock market momentum because of evidence that past stock returns predict future stock returns (Jegadeesh and Titman (1993), (2001)). To the extent that stock market momentum predicts future stock returns, we conjecture that it can predict future financial leverage and hence credit risk. Finally, several studies show that stock put options contain credit risk information (Collin-Dufresne et al. (2001), Berndt and Ostrovnaya (2014), Cremers et al. (2008), Cao, Yu, and Zhong (2010), Carr and Wu (2010), (2011), and Wang, Zhou, and Zhou (2013)). We use the ratio of implied to realized volatility as an options market indicator of 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 5 groups based on the CDS spread level and compute its sample average for each CDS quintile. The CDS spreads have a pooled average of 188.57 bps. The average CDS levels at the 5 quintiles are 20.16, 39.76, 69.25, 148.31, and 665.45 bps, 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 the natural logarithm of the CDS do we obtain a much smaller skewness estimate at 0.57, suggesting that the natural logarithm of the CDS sample is closer to be normally distributed. Hence, we perform most of our analyses on the natural logarithm of the CDS spreads for better distributional behavior.

Inspecting the average levels of firm characteristics at different CDS quintiles reveals a monotonic increase in both the total-debt-to-market-capitalization ratio and the 1-year realized return volatility with increasing CDS levels. The increase is particularly strong from the fourth quintile to the fifth quintile. Similar patterns

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TABLE 1
Summary Statistics of Firm Fundamental Characteristics and CDS Spreads

Table 1 reports sample statistics of firm characteristics for 579 U.S. nonfinancial firms over 351 weeks from Jan. 8, 2003 to Sept. 30, 2009, a total of 138,200 firm-week observations for each variable. Panel A reports the average of each firm characteristic on both the pooled sample and at each credit default swap (CDS) quintile. Panel B reports four sets of standard deviation estimates: i) standard deviation on the pooled sample, ii) time-series averages of the cross-sectional (XS) standard deviation estimates on each date, iii) cross-sectional averages of the time-series (TS) standard deviation estimates for each firm, and iv) cross-sectional averages of the time-series standard deviation estimates on weekly changes (TSC) of each characteristic for each firm.

Characteristics	Panel A. Mean at CDS Quintiles						Panel B. 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 assets	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 assets	0.13	0.13	0.12	0.14	0.13	0.13	0.17	0.17	0.05	0.01
EBIT/Total assets	0.03	0.04	0.03	0.03	0.02	0.01	0.02	0.02	0.01	0.00
Retained earnings/Total assets	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

appear for the two alternative financial leverage measures. The interest coverage ratio declines with increasing CDS spread. The ratio of working capital to asset does not show an obvious relation with the CDS quintiles. The ratios of EBIT and retained earnings to total assets both decline with increasing CDS spread. Small companies tend to have wider CDS spreads. Companies with declining stock market performance during the previous year tend to have higher CDS spreads. The ratio of implied volatility to realized volatility shows a slight decline as the CDS spread increases.

To examine how firm characteristics differ across firms and vary over time, the last four columns of Table 1 report four sets of standard deviation estimates reflecting variations along different dimensions: i) pooled, where we estimate the standard deviation on the pooled sample; ii) XS, where we estimate the cross-sectional standard deviation for each date and report the time-series averages of the cross-sectional estimates; iii) TS, where we estimate the time-series standard deviation for each firm and report the cross-sectional average of these estimates; and iv) TSC, where we take weekly changes in each characteristic, compute the time-series standard deviation for the weekly changes for each firm, and report the cross-sectional averages of the time-series standard deviation estimates on weekly changes.

The average cross-sectional estimates show the extent to which the characteristics differ across firms, whereas the average time-series estimates show how much the characteristics vary over time for a given firm. For most of the firm characteristics, the cross-sectional variation is much larger than the time-series variation. For CDS spreads, the average cross-sectional standard deviation of 345.71 is more than twice as large as the average time-series standard deviation at 154.55. The standard deviation of the weekly changes averages 34.27, just one-tenth of the cross-sectional standard deviation. The same observation applies to the firm fundamental characteristics. Take the ratio of total debt to market capitalization as an example. The cross-sectional standard deviation averages 3.4, which is 3 times as large as the average time-series standard deviation of 1.19. The standard deviation for weekly changes averages just about one-ninth of the cross-sectional standard deviation at 0.38. These statistics are consistent with the findings of Lemmon, Roberts, and Zender (2008) that the majority of variation in leverage ratios is driven by a time-invariant effect that generates "surprisingly stable capital structures."

The large difference between the cross-sectional and time-series variations is understandable. At any given date, companies can differ dramatically in their credit qualities, from companies with the highest rating to those on the brink of bankruptcy. Yet the credit rating for a given company can stay at the same level for many years. This difference has important implications for empirical analysis attempting to link firm fundamental characteristics to credit risk. The much larger cross-sectional variation dictates that cross-sectional comparative analysis can identify the role of fundamental characteristics much more effectively than time-series regressions, and time-series regressions on short-term changes are the least effective for this purpose.

III.   Value CDS Spreads Based on Firm Fundamentals

To generate valuations on the 5-year CDS spread, we start with the classic structural model of Merton (1974). We compute Merton's distance-to-default measure using the total-debt-to-market-capitalization ratio and the stock return realized volatility as inputs and convert this measure into a bias-corrected CDS valuation. In addition, we collect a long list of firm fundamental characteristics that are not included in the Merton model implementation but have been shown to be informative about a firm's credit spread. We propose a Bayesian shrinkage method to combine the Merton-based valuation with the information from this list of additional fundamental characteristics to generate a weighted average CDS valuation.

A.   MCDS: Merton-Based CDS Valuation

Merton (1974) assumes that the total asset value (A) of a company follows a geometric Brownian motion with instantaneous return volatility σ_A, and the company has a zero-coupon debt with principal D and time to maturity T. The company defaults if its asset value is less than the debt principal at 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:

$$(1) \qquad E = A \times N(d + \sigma_A\sqrt{T}) - D \times N(d),$$
$$(2) \qquad \sigma_E = N(d + \sigma_A\sqrt{T})\sigma_A A / E.$$

Equation (1) is the equity valuation formula that treats equity as a European call option on the company's asset value with strike price 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 equity return volatility (σ_E) and asset return volatility (σ_A). In the two equations, $N(\cdot)$ denotes the cumulative normal density function and d is a standardized measure of distance to default,

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

where r denotes the instantaneous risk-free rate.

The Merton (1974) model captures two major determinants of credit risk, financial leverage and business risk, and combines them into a standardized distance-to-default measure in equation (3), which normalizes the financial leverage ($\ln(A/D)$) by the asset return volatility over the debt maturity ($\sigma_A\sqrt{T}$), and measures the number of standard deviations that the asset value deviates from the debt principal.[2] The standardized measure is comparable across firms that have different levels of business risk. We consider the distance-to-default measure the key contribution of the Merton model.[3]

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

[3]The approach of using the distance to default to predict default probabilities was originally developed by KMV and discussed by Crosbie and Bohn (2003) and Kealhofer (2003), among others. It has

To compute a firm's distance to default, we take the company's market capitalization as its equity value E, the company's total debt as a proxy for the principal of the zero-coupon bond D, and the 1-year realized stock return volatility as an estimator for stock return volatility σ_E. We further assume 0 interest rates ($r = 0$) and set the debt maturity at $T = 10$ years for all firms. Because our focus is on the cross-sectional difference across firms, choosing any particular interest rate level for r or simply setting it to 0 generates negligible impacts on cross-sectional performance. By regarding equity as an option on the asset, the Merton (1974) 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 provide more weight to asset volatility in the determination of the default probability. We solve for the firm's asset value A and asset return volatility σ_A from equations (1) and (2) via an iterative procedure. Because the distance-to-default measure is scale free, it can be computed with two inputs: the debt-to-equity ratio (D/E) and stock return volatility.

We consider the distance-to-default measure the final output of the Merton (1974) model. To generate a CDS spread valuation, we step away from the Merton model and construct a raw CDS (RCDS) measure according to the transformation,

$$(4) \qquad \qquad \text{RCDS} \quad = \quad -6{,}000 \times \ln(N(d))/T,$$

where we treat $1 - N(d)$ as the risk-neutral default probability and transform it into an RCDS spread assuming a constant hazard rate and a 40% recovery rate. Stepping away from the Merton model after the distance-to-default calculation is a common maneuver to retain the key contribution of the Merton model while avoiding its limitations in predicting actual defaults. If one were to take the Merton model assumption literally, that default is not to happen before debt maturity, a 5-year CDS contract would never pay out and hence would have zero spread for a company with only a 10-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 explain the cross-sectional variation of market CDS observations, on each date we estimate the 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,

$$(5) \qquad \qquad \ln(\text{CDS}) \quad = \quad f(\ln(\text{RCDS})) + R,$$

where $\ln(\text{CDS})$ denotes the natural logarithm of market CDS observation, $f(\cdot)$ denotes the local quadratic transformation of the RCDS value, and R denotes the regression residual from this mapping. We label the local-quadratic transformed Merton (1974) model CDS valuation MCDS, $\ln(\text{MCDS}) = \widehat{f}(\ln(\text{RCDS}))$.

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also been widely adopted in the academic literature (e.g., Bharath and Shumway (2008), Duan et al. (2012), and Duan and Wang (2012)).

B.   WCDS: Capturing Contributions from Additional Firm Characteristics

The MCDS implementation accounts for information in the total-debt-to-market-capitalization ratio and the 1-year realized stock return volatility. Many other firm characteristics have been shown to be informative about a firm's credit risk. Directly including all these characteristics into one multivariate linear regression is not feasible for several reasons. First, a characteristic may have a nonlinear effect on the credit spread. Second, some of these characteristics measure similar information, creating potential multicollinearity issues for the regression. Third, some characteristics are measured with large errors. These errors can bias the regression estimates. Fourth, not all measures are available for all firms. Missing observations on firm characteristics can create problems for multivariate regressions. We propose a method based on Bayesian shrinkage principles to overcome all these limitations.

The approach uses the MCDS valuation as the base valuation and estimates the additional contribution of each firm characteristic. These contributions are then combined via a stacking regression, with a Bayesian updating procedure that adds intertemporal stability. Formally, let F_t denote an $(N \times K)$ matrix for N companies and K additional credit-risk-informative firm fundamental characteristics on date t. On each date, we first regress each characteristic cross-sectionally against the MCDS valuation to orthogonalize its contribution from the Merton (1974) prediction,

$$(6) \qquad F_t^k \quad = \quad f^k(\ln(\text{MCDS}_t)) + x_t^k, \quad k \quad = \quad 1, 2, \ldots, K,$$

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

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

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

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

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

where W_t denotes the weights on the K predictions at time t.

For a given company, it is possible that only a subset of the K characteristics, and hence only a subset of the K predictions, are available. We fill the missing predictions with a weighted average of the other predictions on the firm, where the relative weights are determined by the R^2 values of the regressions in equation (7) for each available variable,

$$(9) \qquad R_t^{ij} \quad = \quad \sum_{k=1}^{\tilde{K}} w^k \widehat{R}_t^{i,k},$$

$$(10) \qquad w^k \quad = \quad \mathbf{e}^\top (\mathbf{e}\mathbf{e}' + \text{diag}\langle 1 - R^2\rangle)^{-1},$$

where R_t^{ij} denotes the missing residual prediction on the ith company from the jth variable, which is replaced by a weighted average of the residual predictions on the subset of $\widetilde{K}$ available residual predictions on the firm. The weighting is motivated by the Bayesian principle, where we set the prior prediction to 0 and the relative magnitude of the measurement error variance for each available residual prediction proportional to 1 minus the R^2 value of the regression.

To estimate time t weights (W_t) among the K predictions in equation (8), we perform a Bayesian regression update by taking the previous day's estimate as the prior,

$$(11) \qquad \widehat{W}_t \;\; = \;\; (X_t^\top X_t + P_{t-1})^{-1} \left(X_t^\top R_t + P_{t-1} \widehat{W}_{t-1} \right),$$

$$(12) \qquad P_t \;\; = \;\; \mathrm{diag}\langle (X_t^\top X_t + P_{t-1})\phi \rangle,$$

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.

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:

$$(13) \qquad \ln(\text{WCDS})_t \;\; = \;\; \ln(\text{MCDS})_t + X_t \widehat{W}_t.$$

The literature implements the Merton (1974) model in several variations. We provide an Internet Appendix (available at www.jfqa.org) to discuss the rationale behind our particular implementation choice on the Merton model as well as the WCDS construction.

IV.   Explain Cross-Sectional CDS Variation with Firm Fundamentals

To gauge how much fundamental CDS valuation can explain the cross-sectional variation of market CDS observations, we perform three sets of cross-sectional regressions on each date:

$$(14) \qquad \ln \text{CDS}_t^i \;\; = \;\; a_t + b_t (D/E)_t^i + c_t (\sigma_E)_t^i + e_t^i,$$

$$(15) \qquad \ln \text{CDS}_t^i \;\; = \;\; \ln \text{MCDS}_t^i + e_t^i,$$

$$(16) \qquad \ln \text{CDS}_t^i \;\; = \;\; \ln \text{WCDS}_t^i + e_t^i.$$

All regressions are on the natural logarithms of CDS for better distributional behavior. The BLR in equation (14) creates a benchmark by taking the two Merton model inputs directly as explanatory variables. The univariate regressions in equations (15) and (16) measure the cross-sectional explanatory power of MCDS and WCDS valuation, respectively.

A.   Cross-Sectional Explanatory Power

Figure 1 plots the time series of the cross-sectional R^2 estimates from the three sets of cross-sectional regressions. The dash-dotted line represents the R^2 estimates from BLR, the dashed line represents the cross-sectional explanatory

FIGURE 1

Time Series of R^2 Estimates from Cross-Sectional Regressions

The three lines in Figure 1 denote the time series of the R^2 estimates from three sets of cross-sectional regressions: bivariate linear regression (dash-dotted line), Merton-based credit default swap (dashed line), and weighted average credit default swap (solid line).
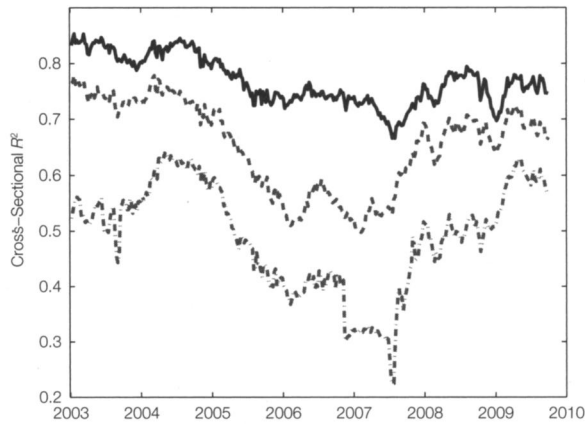
power of MCDS, and the solid line represents the cross-sectional explanatory power of WCDS. The rankings of the R^2 estimates stay the same across all days, with the BLR generating the lowest R^2 estimates and WCDS generating the highest R^2 estimates at all times.

The universal outperformance of MCDS valuation over BLR suggests that, in addition to pointing out the main determinants of credit spreads, the Merton (1974) model also provides a useful way of combining the two input variables into a standardized distance-to-default measure that becomes more cross-sectionally comparable. The further performance enhancement from MCDS to WCDS valuation highlights the contribution of the long list of additional firm fundamental characteristics.

Figure 1 shows that the R^2 estimates from BLR and MCDS valuations are higher during the two recessions in our sample but lower during the economic expansion period between 2006 and 2007. The time variation in performance suggests that during recessions, the two Merton (1974)-suggested characteristics can explain a large portion of the cross-sectional variation; however, when the economy is booming and the overall credit concern is less severe, other firm characteristics can play a larger role in differentiating CDS spreads across firms. By combining the contributions of a wide range of firm characteristics, the WCDS valuation not only performs better than the MCDS valuation at all times, but also generates much more stable performance across different periods.

Table 2 reports the summary statistics of the R^2 estimates. Panel A reports the statistics based on the full-sample estimation. The R^2 estimates from BLR average 49%, similar to cross-sectional linear regression results reported in the

TABLE 2

Summary Statistics of Cross-Sectional Explanatory Powers

Table 2 reports summary statistics of the weekly R^2 estimates from cross-sectional regressions of the natural logarithm of market credit default swap (CDS) against three sets of fundamental-based valuations: i) bivariate linear regression (BLR), ii) Merton-based CDS (MCDS), and iii) weighted average CDS (WCDS). We also report the statistics on the pairwise R^2 differences between these valuations. The statistics in Panel A are computed from cross-sectional regressions on the whole universe of companies. Panel B reports in-sample statistics from cross-sectional regressions on a random half of the universe. Panel C reports out-of-sample statistics on the remaining half of the universe.

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

literature.[4] By comparison, the R^2 estimates from regressing on MCDS average 65%, a 16-percentage-point increase. The t-statistic on the average R^2 difference (MCDS–BLR) is estimated at 13.57, suggesting that the MCDS valuation generates a strongly significant improvement over BLR, even though the input variables are the same.

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

The WCDS valuation generates not only the highest average cross-sectional explanatory power, but also the most stable performance over time. The R^2 estimates for the WCDS valuation show a small standard deviation of merely 4%, compared to 8% for MCDS and 10% for BLR. The R^2 estimates for the WCDS regression remain within a narrow range, from a low of 67% to a high of 85%.

The high and stable cross-sectional explanatory power suggests that the WCDS valuation can be effective in differentiating the credit qualities of different firms based on firm fundamental characteristics. In the United States, thousands of publicly traded companies have publicly available firm fundamental data, but

[4]Ericsson, Jacobs, and Oviedo (2009) regress the CDS spreads on three determinants of the Merton (1974) model (financial leverage, volatility, and a risk-free rate) and obtain an R^2 value of 46.0%–48.4% from a panel regression with quarter dummies.

only a small fraction of them have reliable CDS quotes. Thus, an important practical application for the WCDS method is to generate CDS valuations on firms without reliable CDS quotes, thereby vastly expanding the universe of companies with CDS valuations. Broker dealers and investors can use the fundamental-based WCDS valuation to expand their universe of CDS marks for both market making and marking to market of their CDS positions.

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

Table 2 reports the in-sample performance for the half of the universe used for model calibration in Panel B and the out-of-sample performance for the other half of the universe in Panel C. For BLR, the average R^2 is 51% for the in-sample universe but deteriorates to 25% for the out-of-sample universe. By contrast, the out-of-sample performance of the MCDS valuation experiences little deterioration, with the mean R^2 value declining slightly 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 (1974) model approach of combining the two inputs generates a stable output that experiences little out-of-sample deterioration.

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 an average R^2 value of 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 method for combining the multiple predictors. The out-of-sample exercise shows that the WCDS method can be successfully used in expanding the CDS universe based on firm fundamental characteristics.

B.   Contributions of Additional Firm Fundamental Characteristics

The superior performance of WCDS over MCDS valuation highlights the aggregate contribution of the long list of additional firm fundamental characteristics that we incorporate via the Bayesian shrinkage method. To examine the contribution of each characteristic, Figure 2 plots the mapped relation between each orthogonalized characteristic x^k and the Merton (1974) model prediction residuals ln(CDS/MCDS). All characteristics are first orthogonalized against the MCDS contribution 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 Graphs A and B of Figure 2 generate similar prediction patterns: Higher leverage predicts higher additional CDS spread (in addition to the MCDS prediction). The interest coverage ratio in Graph C can be regarded as an alternative measure of leverage by comparing the interest

FIGURE 2

Additional Contributions from Firm Fundamental Characteristics

Each graph in Figure 2 plots the average contribution of one firm characteristic to the credit default swap (CDS)–Merton-based CDS (MCDS) deviation, ln(CDS/MCDS). The x-axis denotes the percentiles of the characteristic. The relations are estimated via a local linear regression on the pooled data over 351 weeks and 579 companies. EBIT stands for earnings before interest and taxes.
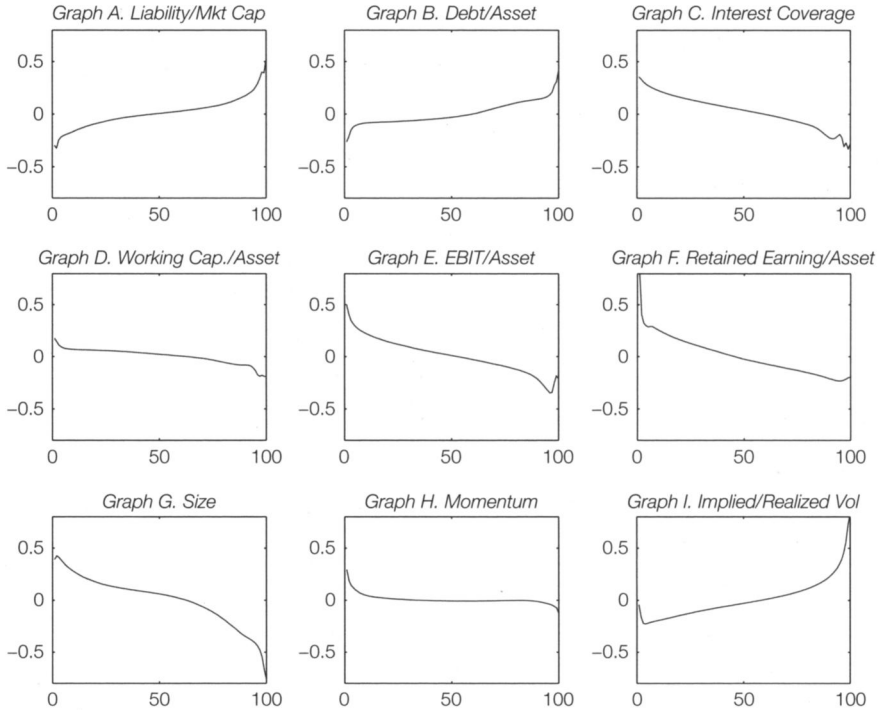
payment to the operating income. The higher the coverage ratio, the lower the leverage, and the lower the CDS spread.

Graphs D to F of Figure 2 capture the additional contributions of the liquidity measure (ratio of working capital to total assets), the profitability measure (ratio of EBIT to total assets), and the investment measure (ratio of retained earnings to total assets), respectively. The contribution of the liquidity measure is small, except at the tails of the deciles. Profitability and investment ratios show similar contributions: Both increased profitability and increased investment help reduce the CDS spreads. In particular, lower or even negative retained earnings lead to a much wider CDS spread.

Graphs G to I of Figure 2 show the contributions from three firm risk characteristics: size, momentum, and crash risk. All three characteristics show large contributions, with large size, positive momentum, and a low ratio of implied to realized volatility contributing to lower CDS spreads.

The univariate local linear mapping between each firm characteristic and the market–MCDS deviation, ln(CDS/MCDS), measures the marginal contribution of each characteristic but does not adjust for the interaction between the dif-

ferent characteristics. The multivariate linear regression in the last step of the WCDS construction accommodates such interactions, with the regression coefficients capturing the relative weight from each contribution. Figure 3 plots the time series of the relative weights across our sample period. The time series of the coefficient estimates are stable over time because of the intertemporal Bayesian smoothing applied in our method.

If the nine univariate predictions were mutually orthogonal, we would expect all the coefficients on the stacked relation to be positive and the multivariate prediction to be an average of the univariate predictions. Some of the weight estimates in Figure 3 become negative, showing the effect of multivariate interactions. The highest positive weights come from company size, the ratio of retained earnings to total assets, and the ratio of option implied to realized volatility, suggesting that these characteristics capture independent contributions to the credit risk measures. Conversely, the contributions from the two financial leverage measures and the interest coverage ratios are small and can even become negative during some periods, mainly because the bulk of the financial leverage information has already been incorporated in the Merton (1974) distance-to-default measure.

FIGURE 3

Time-Varying Weights on Each Firm Characteristic

The line in each graph in Figure 3 plots the time series of the relative weight for each firm characteristic in predicting the credit default swap (CDS)–Merton-based CDS (MCDS) deviation, ln(CDS/MCDS). The weights are estimated via Bayesian update of a stack regression. EBIT stands for earnings before interest and taxes.
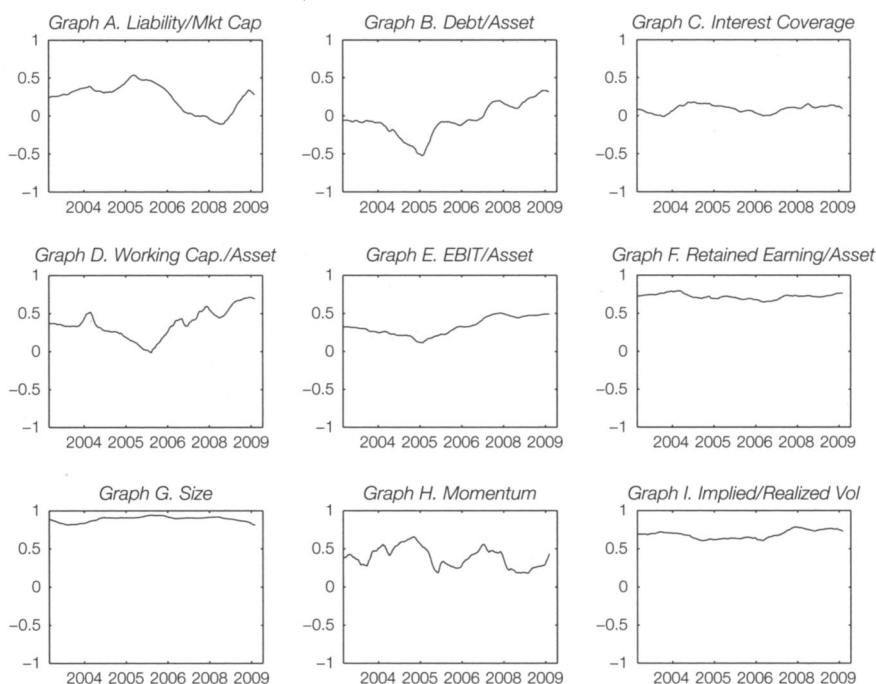
Fundamentally, a structural model plays two important roles in linking a firm's structural characteristics to its credit risk. First, it hypothesizes what types of structural characteristics affect the firm's credit risk. Second, it provides a functional form that combines these characteristics into a credit risk measure. Take the Merton (1974) model as an example. It identifies financial leverage and firm business risk as the two key determinants of credit risk, and proposes to combine the two into a distance-to-default measure. Our analysis shows that the Merton model, at least our implementation of it, does a good job on both fronts. Indeed, Merton's distance-to-default measure is well recognized in the industry as a good predictor of company credit risk.

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

V.   Forecast CDS Movements with Market–Fundamental Deviations

Because the WCDS valuation incorporates information from a long list of firm fundamental characteristics, the deviation of market CDS observations from this fundamental-based valuation is most likely driven by nonfundamental factors, such as supply–demand shocks. If such shocks are transitory and dissipate over time, the fundamental-based WCDS valuation can be used as a relative valuation tool in separating the fundamental value from transitory supply–demand shocks in market observations. In this section, we examine the forecasting power of market–fundamental deviations on future market CDS movements.

A.   Cross-Sectional Forecasting Correlations

When market CDS observations deviate from fundamental-based valuations, chances are that the market CDS quote will revert to the fundamental valuation in the future. To gauge this forecasting capability, on each date, we measure the cross-sectional forecasting correlation between market–fundamental deviations on that date and future changes in market observations,

$$(17) \qquad \rho_{t,h} \quad = \quad \text{corr}(\ln(\text{CDS}^i_{t+h}/\text{CDS}^i_t), \ln(\text{CDS}^i_t/\widehat{\text{CDS}}^i_t)),$$

where $\ln(\text{CDS}^i_{t+h}/\text{CDS}^i_t)$ measures the natural logarithm of the change from time t to $t+h$ on market CDS observations for firm i, and $\ln(\text{CDS}^i_t/\widehat{\text{CDS}}^i_t)$ denotes the time t deviation between market CDS observations on this firm and the corresponding fundamental-based valuations, $\widehat{\text{CDS}}^i_t$. We consider deviations generated from the three sets of the cross-sectional regressions in equations (14)–(16), that is, BLR, MCDS, and WCDS valuations. If the deviation reveals a transitory component of the market observation, we expect the correlation estimates to be negative as a result of mean reversion on the transitory component. In particular, if the current market observation is higher than the fundamental-based valuation and hence the deviation is positive, we expect the market CDS spread to decline in the future to converge toward the fundamental valuation.

Table 3 reports the summary statistics of the forecasting correlation estimates. The two panels are for two forecasting horizons h: 1 week in Panel A and 4 weeks in Panel B. For each correlation estimate time series, we report the sample mean, standard deviation, and t-statistics on the significance of the mean estimate. In computing the t-statistics, we adjust for serial dependence according to Newey and West (1987) with the lag optimally chosen according to Andrews (1991).

The mean correlation estimates are negative over both horizons and for all three sets of deviations, consistent with our conjecture that market–fundamental deviations predict future market reversions to the fundamental valuation. The more negative the correlation estimates are, the stronger the prediction.

TABLE 3

Correlation Between Market–Fundamental Deviations and Future Market Movements

Table 3 reports summary statistics of the weekly estimates on the forecasting cross-sectional correlation between current market–fundamental deviations e_t and future market credit default swap (CDS) movements over different horizons: 1 week in Panel A and 4 weeks in Panel B. Entries on the right side report the statistics on the pairwise correlation differences between the two sets of deviations. BLR stands for bivariate linear regression, MCDS stands for Merton-based CDS, and WCDS stands for weighted average CDS.

Statistics	Forecasting Correlations			Differences	
	BLR	MCDS	WCDS	MCDS–BLR	WCDS-MCDS
Panel A. Forecasting Horizon: 1 Week					
Mean	−0.05	−0.06	−0.07	−0.01	−0.02
Std. dev.	0.10	0.08	0.08	0.06	0.04
t-statistics	−7.11	−10.08	−15.89	−2.26	−5.51
Panel B. Forecasting Horizon: 4 Weeks					
Mean	−0.09	−0.10	−0.12	−0.01	−0.02
Std. dev.	0.12	0.10	0.09	0.07	0.05
t-statistics	−6.15	−7.55	−11.96	−1.33	−3.79

Deviations from the WCDS valuation generate the most negative mean correlation estimates, -7% and -12% at 1-week and 4-week horizons, respectively, whereas the BLR valuation generates the least negative mean correlation estimates at -5% and -9% at 1-week and 4-week horizons, respectively. The last two columns report statistics on the pairwise correlation differences. In particular, the difference between the WCDS and MCDS valuations averages -2 percentage points. The average is highly significant statistically, underlining the significance of the contribution of the long list of additional firm fundamental characteristics.

B.   An Out-of-Sample Investment Exercise

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

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

$$(18) \qquad n_t^i \;\; = \;\; c_t \left(\widehat{\text{CDS}}_t^i - \text{CDS}_t^i \right).$$

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 \$1 notional each in aggregation. The universe that we invest in at time t includes all firms in our sample that have valid CDS quotes and fundamental valuations at that time. The forecasting correlation estimates reported in Table 3 are small in absolute magnitude, although they are strongly significant statistically. By investing in all firms at each point in time, we enhance the prediction by diversifying the prediction errors across different firms. Furthermore, by taking equal dollar notional amounts on long and short positions, we strive to cancel out exposures to market movements so that the movements of the portfolio value are mainly driven by the convergence movements.

We hold the investment for a fixed horizon h. If the company does not default during our investment horizon, we calculate the profit and loss (PL) assuming a flat interest rate and default arrival rate term structure. Since initiating the contract at time t costs 0, the PL is given by the time $(t+h)$ value of the CDS contract initiated at time t. For a \$1 notional long position on the ith contract, the PL is

$$(19) \qquad \text{PL}_{t,h}^i \;\; = \;\; \text{LGD} \left(\lambda_{t+h}^i - \lambda_t^i \right) \frac{1 - e^{-\left(r_{t+h} + \lambda_{t+h}^i \right)(\tau - h)}}{r_{t+h} + \lambda_{t+h}^i},$$

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 5-year interest rate swap rate as a proxy; and λ^i denotes the default arrival rate for the ith company, which we infer from the corresponding CDS rate by assuming a flat term structure, $\lambda_t^i = (\text{CDS}_t^i / \text{LGD})/10{,}000$. In case the company defaults during our investment horizon, the payout for a \$1 notional long position is given by the loss given default $\text{PL} = \text{LGD}$. In aggregate, we can

regard the dollar PL from the total investment on each date as excess returns on a $1 notional long and $1 notional short investment. The investment exercise is out of sample, as the fundamental-based valuations at time t use information only up to time t.

We consider investment horizons from 1 week to 4 weeks. Table 4 reports the summary statistics of the excess returns from the investment exercise. Panel A shows the result when the investment decisions are based on the residuals from the BLR. The investments generate positive returns, on average, but the standard deviations of the returns are large, resulting in low information ratios, defined as the ratio of the annualized mean return over the annualized standard deviation. Thus, the linear regression approach is largely ineffective in generating consistently good investment opportunities.

Panel B of Table 4 shows the results when the investment decisions are based on market deviations from the MCDS valuation. Upon weekly rebalancing, the investments generate an average annualized excess return of 25.25% and an annualized standard deviation of 16.76%, resulting in a very high information ratio of 1.51. The investments generate positive skewness and positive kurtosis. As the rebalancing frequency declines from weekly to once every 4 weeks, the average annualized excess return declines to 14.3% and the information ratio declines to 0.80, suggesting that the convergence of market observations to fundamental valuation is fast.

Panel C of Table 4 reports the investment results based on the WCDS valuation. By incorporating information from a long list of additional firm fundamental characteristics, the investments generate both higher average excess returns and lower standard deviations. Upon weekly rebalancing, the average annualized excess return is 21.14% and the standard deviation is 14.22%, leading to an information ratio of 2.26. The average excess return declines as we reduce the rebalancing

TABLE 4

Summary Statistics of Excess Returns from an Out-of-Sample Investment Exercise

Table 4 reports the annualized mean excess return (Mean), annualized standard deviation (Std. Dev.), 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 credit default swap (CDS) contracts based on the deviations between the market CDS quotes and fundamental-based CDS valuations. BLR stands for bivariate linear regression, MCDS stands for Merton-based CDS, and WCDS stands for weighted average CDS.

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

frequency. Still, even at the 4-week rebalancing frequency, the average annualized excess return is over 20% and the information ratio is as high as 1.5.

We do not treat the investment exercise as a realistic backtest for an actual investment strategy and refrain from overinterpretation. 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 are, rather, the filtered averages of multiple broker–dealer contributions. Although 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 market observations and fundamental-based valuations.

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

VI.   Conclusion

A well-developed structural model can play an important economic role by linking a firm's structural characteristics to its potential credit risk. Because these structural characteristics tend to be stable over time but can differ widely across firms, it is important to perform cross-sectional comparative analysis to examine the effectiveness of such models. We perform cross-sectional analysis of CDS spreads on U.S. nonfinancial firms and show that a simple structural model like Merton (1974), when well implemented, can go a long way in explaining the cross-sectional differences in CDS spreads.

The analysis also highlights areas for potential improvements to the simple model. Via a Bayesian shrinkage method, we combine the Merton valuation with a long list of additional firm structural characteristics to generate a WCDS valuation and show that it explains a much larger cross-sectional variation of the market CDS. When market CDS quotes deviate from the WCDS valuation, they tend to

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

move toward the valuation in the future. These results provide guidance for future structural model development: A successful structural model must find ways to incorporate the contribution of this long list of firm structural characteristics.

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