Anchoring Credit Default Swap Spreads to Firm Fundamentals

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Abstract

This paper examines the capability of structural models, and more generally firm fundamental characteristics, in explaining the cross-sectional variation of five-year credit default swap spreads. The paper starts with a new implementation of the Merton (1974) structural model, highlighting its cross-sectional explanatory power, and then proposes a Bayesian shrinkage method to combine the additional predictions from a long list of firm fundamental variables. A comprehensive analysis based on 579 U.S. non-financial public firms over a period of 351 weeks shows that, with the new implementation, the structural model can explain over 66% of the cross-sectional variation on average. Incorporating additional fundamental variables can increase the average cross-sectional explanatory power to 77% while also making the performance more uniform over time. Furthermore, deviations between market observations and fundamental-based predictions generate statistically and economically significant forecasts on future market credit default swap spread movements.

JEL Classification: C11, C13, C14, G12.

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1. Introduction

This paper examines the capability of structural models, and more generally firm fundamental characteristics, in explaining the cross-sectional variation of five-year credit default swap (CDS) spreads. The performance of structural models and firm fundamentals has been examined from many different perspectives. For example, Huang and Huang (2003) and Eom, Helwege, and Huang (2004) focus on the average bias of structural models, and show that different structural models generate different average biases. Collin-Dufresne, Goldstein, and Martin (2001) regress monthly changes in credit spreads on monthly changes in firm fundamentals, and find that the time-series regressions generate low R-squares. Neither findings, however, tell us much about the capability of firm fundamentals in explaining the cross-sectional variation of credit spreads. When one regresses market observations against fundamental-based predictions, the intercept and slope estimates reflect the average bias of the predictions whereas the R-squared of the regression captures the explanatory power. If the predictions are biased but with high explanatory power, one can easily remove the bias statistically via a cross-sectional regression fitting while exploiting the high explanatory power in differentiating the credit spreads of different companies based on their differences in fundamental characteristics.

Furthermore, short-term changes in credit spreads for a given company can be driven by both permanent credit risk variations and transitory supply-demand shocks. If the fundamental-based predictions capture the cross-sectional difference of the credit spreads well, the low explanatory power on monthly change regressions would imply that a large proportion of the short-term credit spread movements are due to transitory supply-demand shocks. In this case, the fundamental-based prediction can become a useful anchor for market movements. Deviations between market observations and fundamental-based predictions can be used to forecast future market movements.

We examine the cross-sectional explanatory power of firm fundamental characteristics using data on 579
U.S. non-financial public firms over a period of 351 weeks from January 8, 2003 to September 30, 2009. We start with a new implementation of the Merton (1974) structural model, highlighting its cross-sectional exploratory power on the five-year CDS spreads. Similar to the literature, we use the model to infer a company’s asset value and asset return volatility from observations on the company’s market capitalization, debt, and stock return volatility. Deviating from the literature practice, we use a cross-sectional local quadratic regression to remove the average bias and nonlinearity in the relation between market CDS observations and the model’s raw predictions. Through this transformation, we generate an unbiased Merton model CDS prediction, MCDS. With the average bias removed across different credit risk levels, we focus on the performance of MCDS in explaining the cross-sectional variation of market CDS observations.

Over our data sample, the MCDS explains over 66% of the cross-sectional variation in market CDS observations on average. The cross-sectional explanatory power is higher during recessions than during economic booming periods. The average explanatory power is markedly higher than those reported in the literature based on different implementations of the Merton model. We attribute the superior performance of MCDS to differences in our implementation details in inferring the firm’s asset value and asset return volatility and to our nonlinearity correction via the local quadratic regression.

To explain the remaining cross-sectional variation, we collect a long list of firm fundamental variables that are not included in the MCDS implementation, but have been shown to be informative about a firm’s credit spread. We propose a Bayesian shrinkage method to combine the predictions from this long list of variables on the remaining CDS variation. By combining the Merton model prediction with these additional contributions, we generate a new weighted average CDS prediction, WCDS. Compared to MCDS, WCDS not only explains a significantly larger proportion of the cross-sectional CDS variation on average at 77%, but the cross-sectional explanatory power also becomes more uniform over different sample periods. The explanatory power from WCDS is universally higher than that from MCDS, and their average performance
difference is highly statistically significant.

To gauge the robustness of the cross-sectional explanatory power, we also perform an out-of-sample exercise, in which we calibrate the model each day using half of the universe and generate out-of-sample predictions on the other half. Compared to the explanatory power from the full-sample estimation, the out-of-sample prediction shows little performance deterioration.

The high cross-sectional explanatory power of our fundamental-based predictions MCDS and WCDS forms a sharp contrast with the low time-series explanatory power in monthly change regressions by Collin-Dufresne, Goldstein, and Martin (2001). We conjecture that the contrast is partly induced by short-term supply-demand shocks in the market CDS observation. To test this hypothesis, we measure the forecasting correlation between current market-fundamental deviations and future market movements. If our fundamental-based predictions capture the permanent component of the CDS movements and short-term market movements contain a large proportion of transitory supply-demand shocks, we would expect this correlation to be negative due to the mean-reverting behavior of the transitory shocks. At weekly forecasting horizon, the cross-sectional forecasting correlation estimates average at $-6\%$ for MCDS and $-7\%$ for WCDS. At four-week horizon, the average is at $-10\%$ and $-12\%$, respectively. The $t$-statistics on the average forecasting correlation estimates show that the averages are highly significant. The negative sign confirms our hypothesis that short-term market CDS movements contain transient shocks and the fundamental-based predictions can be used as an anchor to filter out these transient components. The more negative estimates for WCDS highlights its increased information content by embedding information from a long list of variables. The average forecasting performance different between WCDS and MCDS is highly significant statistically.

By treating market observations and the fundamental-based predictions as co-integrating fairs, we estimate a vector error correction model (Engle and Granger (1987)) between the CDS-MCDS pair and the CDS-WCDS pair, respectively. The coefficient estimates show two-way information flow between market
observations and the fundamental-based predictions, with the fundamental-based predictions contributing a larger proportion to the permanent component.

To gauge the economic significance of the forecasting power, we also perform a simple 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 prediction and go short when the observed premium is higher than the fundamental-based prediction. The exercise generates high annualized returns with low standard deviations, highlighting the economic significance of the CDS forecasts. Comparing the investments based on the two fundamental-based predictions shows that investment returns based on WCDS not only average higher, but also show lower intertemporal variations.

The virtue of a model can be analyzed from several different perspectives. Traditional analysis in Huang and Huang (2003) and Eom, Helwege, and Huang (2004) focuses on the average bias of structural model predictions. Despite the average bias, Schaefer and Strebulaev (2008) show that structural models can provide accurate predictions on the sensitivity of corporate bond returns to changes in the value of equity. Thus, these models can still be useful for risk management on corporate bond portfolios and capital structure arbitrage investments. Ericsson, Jacobs, and Oviedo (2009) show that inputs of the Merton model, e.g., financial leverage, volatility, and riskfree interest rate, can explain a substantial proportion of the time-series variation in the CDS spreads in a linear regression setting. Bharath and Shumway (2008) examine the forecasting power of the distance to default measure computed from the Merton (1974) 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.

In this paper, we show that structural models, and more generally firm fundamentals characteristics, can be quite capable of explaining the cross-sectional variations in corporate credit default swap spreads. This capability has at least two important practical applications. First, it allows investors to gauge the credit
spread of a company even if CDS contracts are not actively traded on the company. Thousands of companies have firm fundamental information publicly available, yet only hundreds of them have reliable CDS quotes. The WCDS methodology can be used to generate CDS predictions on the thousands of companies without reliable CDS quotes. Our out-of-sample prediction statistics highlight the robustness of the fundamental-based WCDS predictions for this extrapolation purpose. Second, within the universe of companies with reliable CDS quotes, investors can use the fundamental-based WCDS predictions as a relative valuation tool to form CDS portfolios. Our simple investment analysis highlights the economic significance of such an application.

The rest of the paper is structured as follows. The next section describes the data sources and sample construction details. Section 3 introduces the methodology in generating the CDS predictions based on firm fundamentals. Section 4 compares the cross-sectional behavior of the CDS predictions with the corresponding market observations over different sample periods. Section 5 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, with 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.\(^1\) 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 contact 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 payments.

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.

\(^1\)Currently, the North America CDS market is going through structural reforms to increase the fungibility and to facilitate central clearing of the contracts. The convention is switching to fixed premium payments of either 100 or 500 basis points, with upfront fees to settle the value differences between the premium payment leg and the protection leg.
We use a 45-day rule to match the financial statements with the market data, assuming that 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 quarterly 10K forms within 45 days after the end of each quarter. In so doing, we guarantee all fundamental 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 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.

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 contribution of credit-risk informative variables that span the following dimensions of a company:

- **Leverage**, for which we consider two alternative measures, the ratio of total liability to market capitalization and the ratio of total debt to total asset.
• **Interest Coverage**, captured by 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.

• **Options information**, captured by the log ratio of the one-year 25-delta put option implied volatility to the one-year realized volatility.

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

In addition to financial leverage, Altman (1968, 1989) also use 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 his well-known Z-score for predicting corporate defaults. The company size has often been used as a classification variable for credit risk prediction. For example, small companies are often required to have a larger coverage ratio for the same credit rating. To the extent that stock market momentum predicts future
stock returns (Jegadeesh and Titman (1993, 2001)), we conjecture that it can predict future financial leverage and hence credit risk. Finally, the credit risk information in stock put options is well documented in several recent studies, e.g., 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)).

Table 1 reports the summary statistics on the different financial variables. For each variable, we pool the 138,200 firm-week observations, and compute their sample mean and standard deviation. We also divide each variable into five groups based on the CDS spread level, and compute the sample average of each variable under each CDS quintile. The CDS spreads average at 188.57 basis points, with a standard deviation of 439.46 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 mean CDS is even higher than the 4th quintile level suggests that the distribution of the CDS spreads is positively skewed. When we measure the skewness of the pooled CDS sample, we obtain an estimate of 8.51. The skewness estimate for the natural logarithm of the CDS spreads reduces to 0.57, suggesting that the log CDS series are much closer to normally distributed than are the CDS series. Thus, our cross-sectional regressions are performed on the logarithm of the CDS spreads. The prediction errors are also measured in log deviations.

Inspecting the average levels of firm characteristics at each CDS quintile, we observe a monotone 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. We observe similar monotone increases 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. Interestingly, the implied volatility to realized volatility ratio, which can be regarded as a volatility risk premium measure, declines as the CDS spread increases. The last row shows that companies with declining stock market performance during the previous year tend to have higher CDS spreads.

[Table 1 about here.]

3. Generating CDS Prediction Based on Firm Fundamentals

At each date, we construct two predictions on a company’s five-year CDS spread based on the company’s fundamental characteristics. The first prediction is based on a new implementation of the Merton (1974) model, in which we highlight the model’s cross-sectional explanatory power by correcting for the average bias of the raw model prediction via a cross-sectional local quadratic regression of market observations on the raw model predictions. The second prediction combines the Merton model prediction with contributions from a long list of additional firm fundamental variables via a Bayesian shrinkage methodology. We use the Merton model prediction as a benchmark to gauge the additional information content in the chosen list of firm fundamental characteristics.

3.1. MCDS: A bias-corrected implementation of the Merton model

Merton (1974) assumes that the total asset value of a company ($A$) follows a geometric Brownian motion with instantaneous return volatility $\sigma_A$, 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 $\sigma_E$ to its asset value $A$ and asset return volatility $\sigma_A$,

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

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

where $N(\cdot)$ 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.

To implement the Merton model, we take a company’s market capitalization (MC) as its equity value $E$, take its total debt (TD) as the principal for the zero-coupon bond $D$, and take the one-year realized stock return volatility ($RV$) as an estimator for the equity return volatility $\sigma_E$. We further assume zero interest rates ($r = 0$) for simplicity and fix the debt maturity at $T = 10$ for all firms. With these assumptions, we solve for the firm’s asset value $A$ and asset return volatility $\sigma_E$ from the two equations in (1) and (2) via an iterative procedure, starting at $A = E + D$.

After solving for the firm’s asset value and asset return volatility, we compute the distance to default in equation (3) and convert it into a raw credit default spread (RCDS) measure according to,

\[
RCDS = -6000 \cdot \ln(N(d))/T, \quad (4)
\]
where 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.

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

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

where \(CDS\) denotes the market observation, \(f(\cdot)\) denotes the local quadratic transformation of the RCDS value to match the observed CDS value, and \(R\) denotes the residual from this mapping.

Had the raw model prediction RCDS 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 prediction is well-documented. We use the local quadratic functional form to accommodate the average bias and potential nonlinearity in the relation. In equation (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. We label the local-quadratic transformed CDS prediction as MCDS, \(\ln(MCDS) = \hat{f}(\ln(RCDS))\), with “\(M\)” denoting the Merton model origin.

Our implementation differs from the general practice in the existing literature in several aspects. The literature often follows the Moody’s KMV implementation of the Merton (1974) model for predicting future

\footnote{See Simonoff (1996) for a general reference on nonparametric smoothing methods.}
default probabilities, as documented in Crosbie and Bohn (2003). First, Crosbie and Bohn propose to set the maturity $T$ to one year, matching their default probability forecasting horizon. We have experimented with this variation and find that for the purpose of explaining the cross-sectional variation of the five-year CDS spreads, setting $T = 1$ generates much worse performance. Conceptually, we also think that the time to maturity $T$ in the Merton model is closer to the average maturity of a firm’s debt than to the forecasting horizon for default probability.

Second, KMV proposes to approximate the debt principal by the firm’s current liabilities plus one half of its long-term debt. We find that using total debt instead slightly increases the model prediction’s cross-sectional explanatory power.

Third, to predict actual default probabilities, KMV modifies the distance to default measure in equation (3) by replacing the risk-neutral drift $r$ with an estimator for the actual mean return on the asset value ($\mu_A$). We retain the risk-neutral distance to default definition for pricing credit default swaps. Furthermore, since our focus is on the cross-sectional variation, the choice of a fixed interest rate value at any given point in time does not have any material impact on the performance. We set the interest rate to zero for simplicity.

Fourth, to solve for the firm’s asset value and asset return volatility, several studies, e.g., Crosbie and Bohn (2003), Vassalou and Xing (2004), and Bharath and Shumway (2008), propose a more computationally intensive iterative approach: Starting with an initial guess on asset return volatility $\sigma_A$, they solve for the history of the firm’s asset value based on the firm’s equity value history and equation (1). Then, they estimate the asset return volatility $\sigma_A$ (and the mean asset return $\mu_A$) from log changes on the solved asset value series. Duan (1994) and Ericsson and Reneby (2005) propose to embed this iterative procedure into a maximum likelihood framework. However, computing $\sigma_A$ from the asset value time series can be problematic when changes in the asset value are induced by financing or investment decisions instead of operating activities. In such cases, returns on assets, upon which the asset return volatility $\sigma_A$ should be measured, can be quite
different from log changes in the asset value series. Duan, Sun, and Wang (2011) propose to scale the asset value by the corresponding book value to partially correct for this issue. Directly solving the two equations (1) and (2) completely circumvents this scaling issue and it also better matches our cross-sectional focus.

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

Finally, the local quadratic transformation in (5) is new to the literature of structural model implementation. The transformation highlights our focus on explaining the cross-sectional variation of the CDS spreads rather than measuring the absolute bias of a prediction. Intuitively, if a model prediction matches the average CDS spread level observed in the market but cannot distinguish the differences of different firms, this local quadratic regression would have no explanatory power on the market observation. On the other hand, if the model prediction ranks the CDS spreads of different firms the same as the market CDS does, the regression will generate a very high R-squared, regardless of whether the model predictions are biased or not. Therefore, through this cross-sectional local quadratic transformation, our MCDS measure retains the differentiating information from the Merton model but removes the average bias of the model prediction.

Given the flexible local quadratic transformation in the last step, we can in principle skip the transfor-
information 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) allows us to compare the market observation with the raw model prediction in the same unit, and allows us to verify the literature findings on the average bias of the Merton model based on our implementation.

### 3.2. WCDS: A weighted average of additional contributions from other variables

The MCDS accounts for information in total debt, market capitalization, 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 address these concerns in constructing a weighted average credit default swap spread (WCDS) that incorporates the information from a long list of variables.

Formally, we use \( F_t \) to denote an \( (N \times K) \) matrix for \( N \) companies and \( K \) additional credit-risk informative firm fundamental variables at date \( t \). At each date, we first regress each variable cross-sectionally against MCDS to orthogonalize its contribution from the Merton prediction,

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

where \( f^k(\cdot) \) denotes a local linear regression mapping and \( x_t^k \) denotes the orthogonalized component of \( F_t^k \).
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 variable \( x_t^k \) via another local linear regression,

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

Through this local linear regression, we generate a set of \( K \) residual predictions, \( \hat{R}_t^k, k = 1, 2, \cdots, K \), from the \( K \) variables. The two local linear regressions in (6) and (7) remove the potential nonlinearity in the relations and orthogonalize each variable’s contribution to the original Merton prediction.

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

\[
R_t = X_t B_t + e, \tag{8}
\]

with \( B \) denoting the weights on the \( K \) predictions. This “stacking” approach is first proposed by Wolpert (1992) as a way of combining multiple predictors in the data mining literature.

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 \( K \) variables, 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-squares of the regressions in (7) for each available variable,

\[
R_t^{ij} = \sum_{k=1}^{K} w_k^j \hat{R}_t^{ij,k}, \quad w_k^j = e^T (ee^T + \text{diag}(1 - R^2_k))^{-1}, \tag{9}
\]

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 subsect 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,

$$
\hat{B}_t = \left( X_t^\top X_t + P_{t-1} \right)^{-1} \left( X_t^\top R_t + P_{t-1} \hat{B}_{t-1} \right), \quad P_t = \text{diag}((X_t^\top X_t + P_{t-1})\phi),
$$

where $\phi$ controls the degree of intertemporal smoothness that we impose on the weights. We choose $\phi = 0.98$, corresponding to a half life of about 37 weeks.

In the 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), among others, find continuing support for this proposal. In constructing the Bayesian estimates for the weights on the $K$ predictors in (10), we are mindful of the success story of the equal-weighting simple average. If we start with equal weights as the 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 $\phi$ 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. In particular, equation (10) is also 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 prediction to generate a new CDS prediction, which we label as WCDS:

\[
\ln(WCDS)_t = \ln(MCDS)_t + X_t \tilde{B}_t.
\] (11)

In constructing the WCDS, we could have treated MCDS as just one of the firm variables. Instead, we separate its effect by treating MCDS as the benchmark CDS prediction and choose other firm variables based on their additional contribution to the CDS prediction. 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. When no distinctions are necessary, we use FCDS to denote the two fundamental-based predictions, MCDS and WCDS.

3.3. Performance measures and inference

To gauge the performance of MCDS and WCDS in explaining the cross-sectional variation of market CDS observations, we mainly use two measures: (i) the cross-sectional correlation between market observation and model prediction and (ii) root mean squared prediction error (RMSE). If we perform a cross-sectional regression of the market observation on the model prediction, the \(R^2\) of the regression is equal to the squared of the cross-sectional correlation estimate. Thus, the correlation squared measures the proportion of cross-sectional CDS variation that can be explained by the prediction. The RMSE is more of an absolute measure, and we use the difference in RMSE between the two fundamental-based predictions to gauge the statistical significance of the additional firm fundamental variables.

We compute the two measures both in sample and out of sample. While out-of-sample performance measures should be the more relevant measures, comparing the in-sample measures with the corresponding
out-of-sample estimates allows us to gauge the stability of the predictions. We consider two types of out-of-sample analysis, corresponding to two potential applications of the CDS prediction. One application is to generate CDS predictions for companies that do not have reliable vendor CDS quotes. Once we calibrate our model using the universe of companies with CDS quotes, the model can be used to generate CDS values for all companies with the relevant firm fundamental information. On any given date, thousands of publicly traded non-financial firms in the United States have the relevant firm data for our construction of MCDS and WCDS, but less than 500 of these companies have five-year CDS quotes (Figure 1). Thus, if the model predictions capture the cross-sectional variation well, broker dealers can use the predictions to vastly expand the CDS quote universe. For this application, it is important that the fitted relation extend well from the fitted universe to the universe without CDS quotes. To gauge this type of out-of-sample robustness, we divide our sample universe randomly each day into two half samples. We use one half of the universe to calibrate the relation and use the other half to test the out-of-sample stability of the model prediction.

The other application is to predict future market movements based on current deviations between market observations and the fundamental-based predictions. If the fundamental-based predictions explain the cross-sectional variation of the market observations well, the predictions can form a co-integrating relation with the market observations. Deviations between the two can potentially be used to predict future market movements. We use the cross-sectional correlation between current market-fundamental deviations and future market movements as an out-of-sample performance measure. Our fundamental-based predictions are based mainly on cross-sectional regressions. Historical estimates are used for Bayesian smoothing in equation (10), but our model calibration never uses future information. Thus, this forecasting correlation estimate is purely out of sample.

When comparing the performance difference between WCDS and MCDS, we compute the $t$-statistics on the time series average of the performance measure differences between the two models in terms of both the
correlation estimates and the root mean squared prediction errors. The $t$-statistics are computed as the mean difference divided by its standard error estimate, adjusted for serial dependence according to Newey and West (1987) with the number of lags optimally chosen according to Andrews (1991).

We also measure the statistical significance of the performance difference at each date in terms of two $Z$-statistics. For the correlation difference, we construct the $Z$-statistic as,

$$ Z = \frac{\zeta_{WCDS} - \zeta_{MCDS}}{\sigma_Z}, \quad (12) $$

where $\zeta_{WCDS}$ and $\zeta_{MCDS}$ denote the Fisher $Z$-transformation of the corresponding correlation ($\rho$) estimates,

$$ \zeta = \frac{1}{2} \ln \left( \frac{1 + \rho}{1 - \rho} \right), \quad (13) $$

and $\sigma_Z = \sqrt{2/(N-3)}$. For the RMSE difference, we construct the $Z$-statistic as,

$$ Z = \sqrt{N} \frac{\bar{\delta}}{\sigma_\delta}, \quad (14) $$

where $\delta$ denotes the squared error difference between the two model predictions, $\delta = e_{MCDS}^2 - e_{WCDS}^2$, with $e = \ln(CDS/FCDS)$ denoting the log percentage prediction error, and $(\bar{\delta}, \sigma_\delta)$ denoting the sample mean and standard deviation of the squared error difference.

### 4. Comparing Market CDS with Fundamental-Based Predictions

Table 2 reports the summary statistics on market CDS observations and the fundamental-based predictions. 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 raw Merton model prediction RCDS is markedly lower at 3.1532, consistent with the commonly found average bias in the Merton model. Through the local quadratic transformation, the MCDS completely removes this mean bias.

[Table 2 about here.]

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

In what follows, we first measure the performance of MCDS and WCDS in explaining the cross-sectional variation of the market CDS observations. Then, we analyze whether and how much current deviations between the market observations and the fundamental-based predictions can predict future market movements. We conclude the section by discussing the relative contribution of each firm characteristic to the WCDS prediction.

4.1. Explaining the cross-sectional CDS variation with fundamental predictions

At each date, we measure the cross-sectional correlation between the market observations and the model predictions and we also compute the root mean squared prediction error (RMSE) for the two predictors MCDS and WCDS. For better distributional behaviors, we measure the correlations and the RMSE on the natural logarithms of the CDS estimates. Figure 2 plots the time series of the cross-sectional correlation estimates in
Panel A and the RMSE estimates in Panel B, where the solid lines denote the estimates for WCDS and the dashed lines for MCDS. From the dashed line in Panel A, we observe that our new implementation of the Merton model does a reasonably good job in explaining the cross-sectional variation. The cross-correlation estimates between market observation and MCDS range from 71% to 88%, with an average of 81%. The correlation is higher during the two recessions at the beginning and the end of our sample, but lower during the booming period between 2006 and 2007.

By regressing the CDS spreads directly on the 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.\(^3\) 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 and it increases to 38% when they replace the Merton model with their “naive” barrier-option alternative. By comparison, the average of the cross-sectional correlation estimates for MCDS at 81% corresponds to an R-squared of 66%, and the correlation estimate on the pooled sample at 84% (Table 2) corresponds to an R-squared of 71%. The much better performance for MCDS is a result of the differences in our implementation details, mostly notably the choice of a longer maturity closer to the average maturity of corporate debt and the local quadratic transformation to remove nonlinearities in the relation.

\(^3\)They also perform time-series regressions, which generate an average R-squared of 61.4%. The panel regression with quarter dummies is closest to a cross-sectional regression.
cross-correlation estimates between the market and WCDS are not only higher at all times, but also become more uniform across different time periods. The estimates vary within a narrower range from 81.60% to 92.38%, with an average of 87.68%, corresponding to an R-squared of 77% from a cross-sectional regression. The two lines in Panel B shows the extent to which the root mean squared prediction error has been reduced from MCDS to WCDS. The RMSE for WCDS is smaller than that for MCDS for all days. The average RMSE is 0.6247 for MCDS and reduces by more than 10 percentage points to 0.5126 for WCDS.

Table 3 reports the summary statistics on the two weekly performance measures. We start with Panel A, where the statistics are computed on the whole universe, upon which the models are calibrated. Comparing the cross-correlation estimates, we observe that the estimates for WCDS not only average seven percentage points higher than that for MCDS, but also show much smaller time series variation. The sample average of the correlation estimates is 0.88 for WCDS versus 0.81 for MCDS, and the standard deviation of the weekly estimates is merely 0.02 for WCDS compared to 0.05 for MCDS. The statistics on the root mean squared errors tell similar stories. The sample average of the RMSE estimates is 0.51 for WCDS versus 0.62 for MCDS, which is 11 percentage points higher. The standard deviation of the RMSE estimates is also smaller for WCDS at 0.05 than for MCDS at 0.07.

For each measure, Table 3 also reports the statistics on the performance difference between WCDS and MCDS under the columns titled “Diff.” The differences are universally positive for correlations and universally negative for RMSE, showing that WCDS outperforms MCDS at every single week of our sample period. The high estimates for the $t$-statistics of the performance difference further show that on average these performance differences are highly statistically significant.

To gauge the statistical significance of the performance difference at each week, we also compute standardized $Z$-statistics for the performance difference according to (12) and (14), respectively, for the two performance measures, which are asymptotically normally distributed with zero mean and unit variance. The
Z-statistics for the correlation difference has a minimum of 1.44 and a maximum of 5.77. The statistics are greater than 1.64 for 344 out of the 351 weeks. The Z-statistics estimates for the mean squared error difference have a maximum of $-3.55$, suggesting that WCDS generates significantly smaller prediction errors than MCDS at each of 351 weeks in our sample. Overall, the summary statistics show that the WCDS significantly outperforms MCDS in explaining the cross-sectional variation of the CDS spread.

To gauge the robustness of the performance out of sample, we perform an out-of-sample exercise each day by randomly choosing half of the universe for model calibration while generating CDS predictions on the whole universe. Table 3 reports the in-sample performance for the half of the universe used for model estimation in Panel B and the out-of-sample performance for the other half of the universe in Panel C. Comparing the statistics in the two panels, we observe little deterioration in the out-of-sample performance for both MCDS and WCDS. The average cross-correlation decline from 0.81 in sample to 0.80 out of sample for MCDS and from 0.88 in sample to 0.86 out of sample for WCDS. The root mean squared prediction error increases from 0.62 in sample to 0.64 out of sample for MCDS and from 0.51 in sample to 0.54 out of sample for WCDS. For both measures, the out-of-sample performance deterioration is negligible. The average out-of-sample performance difference between MCDS and WCDS remains highly significant.

In summary, our analysis shows that a simple implementation of the Merton model can explain a large proportion of the cross-sectional variation of five-year CDS spreads for U.S. non-financial companies. The explanatory power is higher during recessions than during economic booms. The average explanatory power is higher than those found in the literature, due to the differences in implementation details and our explicit adjustment for the nonlinearity in the relation between raw model predictions and market observations. Furthermore, by incorporating information from a long list of firm fundamental variables via a Bayesian shrinkage method, we have created a weighted average CDS prediction, WCDS, that explains a markedly higher proportion of the cross-sectional CDS variation. Compared to the Merton model prediction, the per-
formance of WCDS is not only better across all days, but also becomes more stable across both recessions and economic booms. The outperformance of WCDS over MCDS is highly statistically significant, both in sample and out of sample.

4.2. Forecasting future CDS movements with current market-fundamental deviations

The previous subsection shows that fundamental-based CDS predictions can explain a large proportion of the cross-sectional variation in market CDS observations; yet, Collin-Dufresne, Goldstein, and Martin (2001) show that monthly changes in fundamental variables can only explain a small portion of the changes in credit spreads for a given company. To verify their findings in our context, we regress changes in market CDS observations on changes in the two fundamental-based predictions MCDS and WCDS, respectively. Table 4 reports the regression results for changes over different horizons from one week to 13 weeks (about a quarter). At each horizon and for each of the two predictions MCDS and WCDS, we perform a time-series regression on each firm that has over two years of observations. Entries in the table report the cross-sectional mean and standard deviation of the slope (β) and R-squared ($R^2$) estimates. 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 average R-squared is merely 15% for MCDS and 13% for WCDS. The average R-squared increases to 35% for MCDS and 39% for WCDS at quarterly horizon. Not only are the R-squared estimates low, but also the average R-squared estimates for WCDS are even lower than that for MCDS at short horizons, even though WCDS performs significantly better than MCDS does in explaining the cross-sectional variation.

To reconcile the high cross-sectional explanatory power of the fundamental-based CDS predictions on the CDS levels of different firms with the low time-series explanatory power of these predictions on short-term CDS movements of a given firm, we conjecture that market CDS observations contain both a persistent credit risk component and a transitory component that is mainly driven by supply and demand shocks. Fundamental-
based predictions capture reasonably well the different credit risk levels across different firms, but they do not capture the short-term, transitory CDS movements due to supply-demand shocks.

If our conjecture is correct, the fundamental-based predictions can be used to separate the permanent credit risk movements from the transitory supply-demand shocks in the market CDS observation. Deviations of market observations from the fundamental-based predictions are transitory and can thus be used to predict future market CDS movements. We test our hypothesis by examining the forecasting power of the market-fundamental deviations on future market CDS movements. First, we estimate the cross-sectional forecasting correlation between current market-fundamental deviations and future market CDS movements. Second, we formulate the forecasting relation in the vector error-correction model (VECM) of Engle and Granger (1987) and estimate the impulse-response function on shocks from both market observations and fundamental-based predictions. The analysis reveals the percentage of shocks from each source that becomes permanent. Third, we gauge the economic significance of the forecasting power through an out-of-sample investment exercise.

4.2.1. Cross-sectional forecasting correlations

At each date $t$, we measure the cross-sectional forecasting correlation between market-fundamental deviations at that date and future changes in the market observation,

$$\rho_{t,h} = Corr(\ln(CDS_t / FCDS_t), \ln(CDS_{t+h} / CDS_t)),$$

(15)

where $\ln(CDS_t / FCDS_t)$ measures the log deviation between the market observation $CDS_t$ and the fundamental-based prediction $FCDS_t$, which can be either MCDS or WCDS, and $\ln(CDS_{t+h} / CDS_t)$ measures the log changes in the market CDS observation over the next $h$ weeks. If the deviations between the market observation and the model valuation $\ln(CDS_t / FCDS_t)$ reveal 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 CDS will decline in the future if it is wider than the fundamental-based prediction now.

Panel A of Table 5 reports the summary statistics of the forecasting correlation over different horizons $h$ and for the two fundamental-based predictions MCDS and WCDS. Consistent with our conjecture, the average estimates for the forecasting correlations on future changes are negative for both MCDS and WCDS, and the estimates become more negative as the forecasting horizon increases. The $t$-statistics show that the average correlation estimates are highly significant statistically.

Compared to the forecasting correlation estimates on MCDS, the forecasting correlation estimates on WCDS not only average more negative, but also show smaller time variation. Although the average difference between WCDS and MCDS is small at about $-2\%$, the time-series variation of the difference is also small. As a result, the $t$-statistics for the average correlation differences are highly negative. On average, WCDS generates significantly better forecasting performance than MCDS does.

We can also interpret the negative forecasting correlation estimates based on the story of information asymmetry across different markets. The two predictions MCDS and WCDS rely mainly stock market information, in terms of market capitalization and one-year realized volatility for MCDS, and also stock return momentum and stock option implied volatility for WCDS.\footnote{The predictions also rely on information from quarterly financial statements such as total debt, total asset, EBIT, interest expense, working capital, and retained earnings. Nevertheless, we do not expect these quarterly statements to lead the CDS market in information flow.} If the stock market and the stock options market contain credit risk information not yet fully embedded in the market CDS observation, the deviations between the market observation and the fundamental-based valuations will be able to forecast future movements in the market CDS.

The information flow can also go the other way. When the market observations deviate from the fundamental-based predictions, it is also possible that the deviations come from mis-valuation in MCDS and WCDS due
to delayed information in the input variables such as those from the quarterly financial statements. Lagged inputs can generate predictions that lag behind the market. In this case, one can also use the current market-fundamental deviations to forecast future movements in the fundamental-based predictions as the lagged predictions will catch up with the market in the future.

To examine this hypothesis, we also measure the forecasting cross-sectional correlation between current market-fundamental deviations and future movements in the predictions. Panel B of Table 5 reports the summary statistics of the forecasting correlation estimates. The average correlation estimates are all significantly positive, confirming our hypothesis of two-way information flow. The absolute magnitudes of the average estimates are smaller than the corresponding forecasting correlation estimates for future market movements. Therefore, when market observation is wider than the fundamental prediction, the market CDS moves down more than the fundamental-based prediction moves up in the future.

Comparing the estimates on MCDS and WCDS shows that the average forecasting correlation on WCDS movements is more positive than that on MCDS movements. Thus, the WCDS prediction based on a long list of variables is more responsive to market movements than does the MCDS prediction.

To examine the time variation of the two-way predictions, we plot the time-series of the forecasting correlation estimates on one-week ahead movements in Figure 3, with Panel A for the forecasting correlation on future market changes and Panel B for future model valuation changes. Since the weekly forecasting correlation estimates are noisy, we apply an exponential smoothing on the estimates to obtain a clearer picture of time variation,

$$\bar{\rho}_{t+1} = \phi \rho_t + (1 - \phi)\bar{\rho}_t,$$

where $$\rho_t$$ denotes the raw correlation estimates and $$\bar{\rho}_t$$ denotes the smoothing average. We set $$\phi = 0.97$$, corresponding to a half life of about 24 weeks. The smoothed estimates in Panel A are all negative and that
in Panel B are all positive, in line with our hypothesis for two-way information flow.

[Figure 3 about here.] 

The time series from Panel A show that the predictions on future market movements are strong at the beginning of the sample, become weaker in the middle of the sample in 2006 and 2007, and start to become stronger again in 2008 and 2009. We conjecture that at least two factors affect the strength of the prediction on future market movements. First, it is possible that the quality of the CDS observations in the early years of 2003 and 2004 are not as good and possibly contain a larger element of staleness and/or data noise. Thus, deviations of the observations from fundamental-based predictions can generate strong predictions that the market will revert back to the prediction in the future. Second, it is also possible that the model works better when the average credit concerns are higher during the two recessions than when credit concerns are less when the economy is booming. When credit is less of a concern, market CDS variations are driven more by supply and demand shocks, model predictions on credit risk may not be as informative about the short-term market CDS variation.

Panel B of Figure 3 shows the time variation of the forecasting correlation on future model valuation changes. Due to the different compositions, the time variations of the predictability on MCDS and WCDS are not always the same. Still, the predictability is strong for both valuations in 2006 during the height of the housing bubble and between 2008 and 2009 in the middle of the financial crisis.
4.2.2. A vector error-correction model

A formal way of analyzing the two-way information flow is through the vector error-correction model of Engle and Granger (1987):

\[
\begin{bmatrix}
\ln(CDS_{t+1}/CDS_t) \\
\ln(FCDS_{t+1}/FCDS_t)
\end{bmatrix} =
\begin{bmatrix}
\alpha_1 \\
\alpha_2
\end{bmatrix}D_t +
\begin{bmatrix}
\beta_1 \\
\beta_2
\end{bmatrix}
\ln\left(\frac{CDS_t}{FCDS_t}\right) +
\begin{bmatrix}
e_{1,t+1} \\
e_{2,t+1}
\end{bmatrix},
\] (17)

where we regard \((\ln CDS, \ln FCDS)\) as a co-integrating pair and use the co-integration error to predict future changes in each of the two elements. We annualize the weekly return and estimate the model using the pooled data with time dummies for both the CDS-MCDS pair and the CDS-WCDS pair. Table 6 reports the \(\beta\) coefficient estimates and their standard errors (in parentheses). As expected from the two-way information flow, the estimates for \(\beta_1\) are significantly negative and that for \(\beta_2\) are significantly positive for both co-integrating pairs.

Based on the error-correction specification, Harris, McInish, and Wood (2002) and Gonzalo and Granger (1995) identify a permanent component from the two series with the following properties: (1) This permanent component is a linear combination of the two series, and (2) the permanent component is not Granger-caused in the long run by the stationary linear combinations of the two series. Given the estimates for the error correction coefficient \(\beta_1\) and \(\beta_2\), the normalized loading of this common factor on the two series is given by

\[
\begin{bmatrix}
w_1 \\
w_2
\end{bmatrix} = \frac{1}{\beta_1 - \beta_2}
\begin{bmatrix}
-\beta_2 \\
\beta_1
\end{bmatrix},
\] (18)

with \(w_1\) denoting the normalized loading contribution from the market CDS observation. Plugging in the coefficient estimates, we obtain a loading of \(w_1 = 32.06\%\) from the CDS-MCDS pair and \(w_1 = 44.72\%\) from the CDS-WCDS pair. If we regard this permanent component as representing the “true” value of the CDS
spread, a larger proportion of it comes from the fundamental-based predictions.

By assuming that the fundamental value follows a random walk, Hasbrouck (1995) proposes an information share measure based on the VECM estimates. The estimates for information share are not unique but present a range. The range for the market CDS is from 9.15% to 35.89% from the CDS-MCDS pair, and from 36.61% to 43.88% for the CDS-WCDS pair. Again, a larger proportion of the CDS information is discovered from the fundamental-based predictions than from the market CDS observation.

Given the estimated model, we calculate the impulse-response functions over multiple periods. Figure 4 plots the impulse response functions, with Panel A for the CDS-MCDS pair and Panel B for the CDS-WCDS pair. In each panel, column (i) plots the responses to a unit shock in the market CDS and column (ii) plots the responses to a unit shock in the fundamental-based prediction MCDS or WCDS. The impulse-response functions from the two sets of VECM estimates share similar features: From both models, shocks from the market CDS have a lower percentage of permanent component than do shocks from the corresponding fundamental-based predictions.

[Figure 4 about here.]

The co-integrating relation between CDS and WCDS also shows some differences from the co-integrating relation between CDS and MCDS. First, the market CDS contributes to a larger proportion to the common factor in the CDS-WCDS pair. Second, shocks converge to the co-integrating long-run relation faster from the CDS-WCDS pair than that from the CDS-MCDS pair. By incorporating more variables, WCDS becomes more responsive to market movements than does MCDS. As a result, WCDS shows stronger co-movement with the market observation. This shows up both in the higher percentage for the market observation in the common factor and in the faster convergence to the co-integrating relation.
4.2.3. 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 predictions.

At each date $t$, we measure the deviation between the market CDS observation and the fundamental-based prediction MCDS or WCDS, and we invest in a notional amount in each CDS contract $i$, $n^i_t$, that is proportional to this deviation,

$$n^i_t = c_t \left( FCDS^i_t - CD^i_t \right). \quad (19)$$

Intuitively, if the market observation is lower than the fundamental-based prediction, 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 $c_t$ such that we are long and short one dollar notational each in aggregation. The universe that we invest in at time $t$ include all firms in our sample that have valid CDS quotes and MCDS/WCDS estimates 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

$$PL^{i}_{t,h} = LGD \left( \lambda^{i}_{t+h} - \lambda^{i}_{t} \right) \frac{1 - e^{-\left(r_{t+h}+\lambda^{i}_{t+h}\right)(\tau-h)}}{r_{t+h} + \lambda^{i}_{t+h}}, \quad (20)$$

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 $\lambda_i^t$ denotes the default arrival rate for the $i$-th company, which we infer from the corresponding CDS rate by assuming a flat term structure, $\lambda_i^t = (CDS_i^t/LGD)/10000$. In case the company defaults during our investment horizon, the payout for a one-dollar notional long position is given by the loss given default $PL = LGD$. In aggregate, we can regard the dollar profit and loss from the total investment at each date as 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 predictions at time $t$ only use information at time $t$ and earlier.

We consider investments horizons from one to four weeks. Table 7 reports the summary statistics from the investment exercise, with Panel A reporting results from MCDS-based predictions and Panel B reporting results from WCDS-based predictions. When investing based on deviations between market CDS and MCDS, we obtain an average annualized return of 25.25% for the weekly investment horizon and 12.63% for the four-week investment horizon. The per-period mean return increases with the holding period length, but the speed of increase declines. The investment returns generate positive skewness, and the information ratios are reasonably high, from 1.5 for the weekly investment to 0.73 from the four-week investment. The high information ratio estimates highlight the economic value of the Merton model in separating the permanent credit risk component from the transitory supply-demand shocks.

The results in Panel B show that the investment performance becomes significantly better when the investments are based on the market-WCDS deviations. Compared to the results in Panel A, the average annualized returns are six to eight percentage points higher, whereas the standard deviation estimates are 14-16% lower. As a result, the information ratios from the WCDS-based investments are 50-77% higher than that from the MCDS-based investments. Thus, the outperformance of WDS over MCDS is significant not only statistically but also economically.

We do not treat our investment exercise as a realistic back test for an actual investment strategy and refrain from further exploration on potential refinement of the investment strategy to achieve better return-
risk tradeoffs. Realistic back testing 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 average of multiple broker-dealer contributions. While the average presents an estimate for the market consensus on where the CDS market should be for a reference entity, it may not represent exactly where transactions can happen. 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 predictions.

Nevertheless, the investment exercise highlights the economic significance of the fundamental-based predictions. 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 predictions. Since the market observations revert to the fundamental-based predictions, using the fundamental-based predictions for marking can potentially reduce the transitory movements of the portfolio value and reflects more on the actual credit risk exposure of the institution’s position.

### 4.3. Contributions from the additional firm fundamental variables

Our analysis shows that, by incorporating a long list of additional variables via a Bayesian shrinkage method, the WCDS significantly outperforms MCDS in terms of both its cross-sectional explanatory power and its forecasting capability of future market movements. To understand the contribution of each additional fundamental variable, Figure 5 plots the mapped relation between the Merton model prediction errors $\ln(CDS/MCDS)$
and each orthogonalized variable $x^k$. All variables 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 variables, we use the percentiles of each variable as the x-axis and use the same scale for the y-axis for the predicted market-Merton deviation $\ln(CDS/MCDS)$. The top panels contain the relations for two leverage measures, the ratio of total liability to market capitalization and the ratio of total debt to total asset, as well as the information from the option market (the ratio of implied volatility to realized volatility). All three measures add additional information as they both predict wider CDS spreads with increasing deciles. The volatility ratio shows a stronger contribution than leverage ratios, especially at the right tail.

[Figure 5 about here.]

The middle panels group the 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). The contribution of the liquidity measure is small except at the tails of the deciles. Both probability and investment measure 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.

The bottom panels shows the contributions from the size of the company (log market capitalization), interest coverage ratio (EBIT to interest expense), and the stock market momentum. Both interest coverage ratio and firm size show strong contributions. A large company size and a high interest coverage ratio both predict a much narrower CDS spread. Good stock performance over the past year can also lead to a narrower spread, but to a much smaller degree.

The univariate local linear mapping between each variable and the CDS prediction $\ln(CDS/MCDS)$ measures the marginal contribution of each variable, but does not adjust for the interaction between the different
variables. The multivariate linear regression in the last step accommodates such interactions, with the regression coefficients capturing the relative weight from each contribution. Figure 6 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.

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 6 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 variables capture rather independent contributions to the credit risk measures. On the other hand, the contributions from the two financial leverage measures and the interest coverage ratios are small and can even turn negative in certain time periods.

5. Conclusion

The literature has shown that structural models tend to generate biased credit spread predictions on average and short-term changes in firm fundamentals do not explain much of short-term changes in credit spreads. In this paper, we explore the capability of structural models, and more generally firm fundamentals, in explaining the cross-sectional variation of credit default swap spreads across different firms. We find that a new implementation of the Merton (1974) structural model can on average explain 66% of the cross-sectional variation in market CDS. By incorporating a long list of additional firm fundamental variables via a Bayesian shrinkage method, we also construct a weighted average CDS prediction, WCDS, that can further improve
the average explanatory power to 77%, while also making the explanatory performance more stable over different sample periods.

When the market CDS observation deviates from the fundamental-based prediction, the deviation forecasts future market CDS movements as the market CDS converges to the fundamental-based prediction in the future. By estimating a vector error correction model, we show that the fundamental-based prediction contributes to a larger proportion of the permanent CDS movements than does the market observation. Through an out-of-sample investment analysis, we further show that the predictions are not only statistically significant, but also economically important.
References


Huang, J.-z., and M. Huang, 2003, “How Much of the Corporate-Treasury Yield Spread is Due to Credit Risk?,” working paper, Penn State University.


Table 1
Summary statistics of firm fundamentals at different CDS quintiles
Entries report the sample average of each firm characteristic at each CDS quintiles. The sample averages are computed on the pooled data on 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.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Mean</th>
<th>Std</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>CDS (bps)</td>
<td>188.57</td>
<td>439.46</td>
<td>20.16</td>
<td>39.76</td>
<td>69.25</td>
<td>148.31</td>
<td>665.45</td>
</tr>
<tr>
<td>Total Debt/Market Cap.</td>
<td>0.98</td>
<td>5.25</td>
<td>0.21</td>
<td>0.34</td>
<td>0.41</td>
<td>0.61</td>
<td>3.28</td>
</tr>
<tr>
<td>Realized Volatility</td>
<td>0.36</td>
<td>0.23</td>
<td>0.23</td>
<td>0.27</td>
<td>0.32</td>
<td>0.39</td>
<td>0.61</td>
</tr>
<tr>
<td>Total Liability/Market Cap.</td>
<td>0.93</td>
<td>3.65</td>
<td>0.27</td>
<td>0.41</td>
<td>0.48</td>
<td>0.65</td>
<td>2.75</td>
</tr>
<tr>
<td>Total Debt/Total Asset</td>
<td>0.30</td>
<td>0.21</td>
<td>0.23</td>
<td>0.26</td>
<td>0.27</td>
<td>0.31</td>
<td>0.45</td>
</tr>
<tr>
<td>Working Capital/Total Asset</td>
<td>0.13</td>
<td>0.17</td>
<td>0.13</td>
<td>0.12</td>
<td>0.14</td>
<td>0.13</td>
<td>0.13</td>
</tr>
<tr>
<td>EBIT/Total Asset</td>
<td>0.03</td>
<td>0.02</td>
<td>0.04</td>
<td>0.03</td>
<td>0.03</td>
<td>0.02</td>
<td>0.01</td>
</tr>
<tr>
<td>Retained Earnings/Total Asset</td>
<td>0.22</td>
<td>0.40</td>
<td>0.43</td>
<td>0.31</td>
<td>0.28</td>
<td>0.19</td>
<td>-0.08</td>
</tr>
<tr>
<td>log(Market Cap.)</td>
<td>8.83</td>
<td>1.36</td>
<td>10.02</td>
<td>9.16</td>
<td>8.90</td>
<td>8.49</td>
<td>7.61</td>
</tr>
<tr>
<td>log(Implied Vol./Realized Vol.)</td>
<td>0.08</td>
<td>0.23</td>
<td>0.14</td>
<td>0.09</td>
<td>0.07</td>
<td>0.06</td>
<td>0.06</td>
</tr>
<tr>
<td>Stock Market Momentum</td>
<td>0.08</td>
<td>0.39</td>
<td>0.17</td>
<td>0.16</td>
<td>0.10</td>
<td>0.08</td>
<td>-0.12</td>
</tr>
</tbody>
</table>

Table 2
Summary statistics on market CDS and model predictions
Entries report the summary statistics of the logarithm of market CDS and model predictions. Statistics for the CDS values include the sample mean, standard deviation (Std), minimum, maximum, and the cross-correlation between market observations and model predictions. 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.

<table>
<thead>
<tr>
<th>Statistics</th>
<th>ln(CDS)</th>
<th>ln(RCDS)</th>
<th>ln(MCDS)</th>
<th>ln(WCDS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>4.3968</td>
<td>3.1532</td>
<td>4.3950</td>
<td>4.4163</td>
</tr>
<tr>
<td>Std</td>
<td>1.1772</td>
<td>2.4030</td>
<td>1.0135</td>
<td>1.0745</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.9145</td>
<td>0.0000</td>
<td>2.6056</td>
<td>1.5658</td>
</tr>
<tr>
<td>Correlation</td>
<td>1.0000</td>
<td>0.7633</td>
<td>0.8417</td>
<td>0.8969</td>
</tr>
</tbody>
</table>
Table 3  
**Summary statistics on weekly performance measures for MCDS and WCDS**

Entries report the summary statistics of the weekly estimates on (i) the cross-sectional correlation between market observations and model predictions on the logarithm of CDS and (ii) the root mean squared prediction error (RMSE) on the log CDS. For each measure, we also report the summary statistics on the performance difference between the two model predictions MCDS and WCDS, with “Diff” denoting the performance difference between WCDS and MCDS and \(Z\) denoting a standardized \(Z\)-statistic for the performance difference at each date, defined according to equation (12) for the correlation difference and according to equation (14) for the RMSE difference. For each measure, we also report a \(t\)-statistic, computed as the ratio of the mean estimate to its Newey and West (1987) serial-dependence adjusted standard error.

<table>
<thead>
<tr>
<th>Statistics</th>
<th>(i) Correlation</th>
<th>(ii) RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MCDS</td>
<td>WCDS</td>
</tr>
<tr>
<td>Mean</td>
<td>0.81</td>
<td>0.88</td>
</tr>
<tr>
<td>Std</td>
<td>0.05</td>
<td>0.02</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.71</td>
<td>0.82</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.88</td>
<td>0.92</td>
</tr>
<tr>
<td>(t)-stats</td>
<td>44.43</td>
<td>109.58</td>
</tr>
</tbody>
</table>

**Panel A: In-sample performance from full-sample estimation**

| Mean       | 0.81  | 0.88  | 0.07  | 2.40 | 0.62  | 0.51  | -0.12 | -4.26 |
| Std        | 0.05  | 0.03  | 0.04  | 0.86 | 0.08  | 0.05  | 0.04  | 0.79 |
| Minimum    | 0.67  | 0.78  | 0.02  | 0.71 | 0.45  | 0.38  | -0.24 | -6.40 |
| Maximum    | 0.90  | 0.94  | 0.19  | 4.82 | 0.81  | 0.67  | -0.03 | -2.57 |
| \(t\)-stats | 63.10 | 169.54 | 7.91  | 12.36 | 30.19 | 41.93 | -11.53 | -34.81 |

**Panel B: In-sample performance from half-sample estimation**

| Mean       | 0.80  | 0.86  | 0.06  | 1.95 | 0.64  | 0.54  | -0.10 | -3.71 |
| Std        | 0.06  | 0.03  | 0.04  | 0.88 | 0.08  | 0.06  | 0.05  | 1.23 |
| Minimum    | 0.57  | 0.78  | -0.01 | -0.23 | 0.47  | 0.41  | -0.23 | -7.18 |
| Maximum    | 0.90  | 0.93  | 0.23  | 4.44 | 0.87  | 0.68  | 0.01  | 0.66 |
| \(t\)-stats | 61.26 | 163.39 | 6.98  | 10.03 | 32.33 | 48.19 | -10.42 | -27.95 |
Table 4

Regressing changes in market CDS to changes in fundamental-based predictions

Entries report the mean and standard deviation (in parentheses) of the slope ($\beta$) and R-squared ($R^2$) estimates of the following time-series regressions for each firm $i$,

$$CDS_{i,t+h} - CDS_{i,t} = \beta_i (FCDS_{i,t+h} - FCDS_{i,t}) + e_{i,t+h},$$

where $FCDS$ denotes the fundamental-based CDS predictions MCDS and WCDS, respectively. Firms with less than two years of data are excluded from the regressions. The horizon of the change $h$ is in weeks.

<table>
<thead>
<tr>
<th>$h$</th>
<th>$\beta$</th>
<th>$R^2$</th>
<th>$\beta$</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.49 (0.35)</td>
<td>0.15 (0.13)</td>
<td>0.35 (0.26)</td>
<td>0.13 (0.12)</td>
</tr>
<tr>
<td>2</td>
<td>0.55 (0.36)</td>
<td>0.20 (0.15)</td>
<td>0.44 (0.29)</td>
<td>0.18 (0.15)</td>
</tr>
<tr>
<td>3</td>
<td>0.58 (0.36)</td>
<td>0.23 (0.16)</td>
<td>0.49 (0.29)</td>
<td>0.22 (0.17)</td>
</tr>
<tr>
<td>4</td>
<td>0.60 (0.36)</td>
<td>0.25 (0.17)</td>
<td>0.53 (0.30)</td>
<td>0.25 (0.18)</td>
</tr>
<tr>
<td>5</td>
<td>0.62 (0.37)</td>
<td>0.27 (0.18)</td>
<td>0.56 (0.31)</td>
<td>0.27 (0.19)</td>
</tr>
<tr>
<td>6</td>
<td>0.63 (0.37)</td>
<td>0.28 (0.19)</td>
<td>0.59 (0.32)</td>
<td>0.30 (0.20)</td>
</tr>
<tr>
<td>7</td>
<td>0.65 (0.37)</td>
<td>0.30 (0.19)</td>
<td>0.61 (0.32)</td>
<td>0.32 (0.21)</td>
</tr>
<tr>
<td>8</td>
<td>0.66 (0.37)</td>
<td>0.31 (0.20)</td>
<td>0.63 (0.33)</td>
<td>0.33 (0.22)</td>
</tr>
<tr>
<td>9</td>
<td>0.66 (0.37)</td>
<td>0.32 (0.20)</td>
<td>0.65 (0.33)</td>
<td>0.35 (0.22)</td>
</tr>
<tr>
<td>10</td>
<td>0.67 (0.37)</td>
<td>0.33 (0.20)</td>
<td>0.67 (0.33)</td>
<td>0.37 (0.23)</td>
</tr>
<tr>
<td>11</td>
<td>0.68 (0.37)</td>
<td>0.34 (0.21)</td>
<td>0.68 (0.33)</td>
<td>0.38 (0.23)</td>
</tr>
<tr>
<td>12</td>
<td>0.68 (0.37)</td>
<td>0.35 (0.21)</td>
<td>0.69 (0.34)</td>
<td>0.38 (0.23)</td>
</tr>
<tr>
<td>13</td>
<td>0.68 (0.37)</td>
<td>0.35 (0.21)</td>
<td>0.70 (0.34)</td>
<td>0.39 (0.23)</td>
</tr>
</tbody>
</table>
Table 5
Forecasting correlation between current deviations and future movements
Entries report the summary statistics of the weekly estimates on the forecasting cross-sectional correlation between current market-fundamental deviations and future movements over the next week in market CDS (Panel A) and the fundamental-based predictions (Panel B) For each measure, we also report the summary statistics on the performance difference between the two model predictions MCDS and WCDS, with “Diff” denoting the correlation difference between WCDS and MCDS and $Z$ denoting a standardized $Z$-statistic for the correlation difference at each date, defined according to equation (12). For each measure, we also report a $t$-statistic, computed as the ratio of the mean estimate to its Newey and West (1987) serial-dependence adjusted standard error.

<table>
<thead>
<tr>
<th>Horizon</th>
<th>MCDS</th>
<th>WCDS</th>
<th>WCDS-MCDS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std</td>
<td>$t$-stats</td>
</tr>
<tr>
<td>$h$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-0.06</td>
<td>0.08</td>
<td>-12.46</td>
</tr>
<tr>
<td>2</td>
<td>-0.08</td>
<td>0.09</td>
<td>-15.36</td>
</tr>
<tr>
<td>3</td>
<td>-0.09</td>
<td>0.10</td>
<td>-17.12</td>
</tr>
<tr>
<td>4</td>
<td>-0.10</td>
<td>0.10</td>
<td>-18.53</td>
</tr>
<tr>
<td>5</td>
<td>-0.11</td>
<td>0.11</td>
<td>-19.39</td>
</tr>
<tr>
<td>6</td>
<td>-0.12</td>
<td>0.11</td>
<td>-20.18</td>
</tr>
<tr>
<td>7</td>
<td>-0.13</td>
<td>0.11</td>
<td>-20.96</td>
</tr>
<tr>
<td>8</td>
<td>-0.13</td>
<td>0.11</td>
<td>-21.63</td>
</tr>
</tbody>
</table>

Panel A: $\text{Corr}(\ln(CDS_t/FCDS_t), \ln(CDS_{t+h}/CDS_t))$

<table>
<thead>
<tr>
<th>Horizon</th>
<th>MCDS</th>
<th>WCDS</th>
<th>WCDS-MCDS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std</td>
<td>$t$-stats</td>
</tr>
<tr>
<td>$h$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.04</td>
<td>0.06</td>
<td>11.45</td>
</tr>
<tr>
<td>2</td>
<td>0.05</td>
<td>0.06</td>
<td>16.33</td>
</tr>
<tr>
<td>3</td>
<td>0.07</td>
<td>0.06</td>
<td>19.46</td>
</tr>
<tr>
<td>4</td>
<td>0.08</td>
<td>0.06</td>
<td>21.85</td>
</tr>
<tr>
<td>5</td>
<td>0.08</td>
<td>0.07</td>
<td>23.55</td>
</tr>
<tr>
<td>6</td>
<td>0.09</td>
<td>0.07</td>
<td>25.10</td>
</tr>
<tr>
<td>7</td>
<td>0.10</td>
<td>0.07</td>
<td>26.51</td>
</tr>
<tr>
<td>8</td>
<td>0.11</td>
<td>0.07</td>
<td>27.68</td>
</tr>
</tbody>
</table>
Table 6
Vector error correction model estimates
Entries report the coefficient estimates and standard errors (in parentheses) of the vector error correction model between market CDS observations and the two fundamental-based predictions MCDS and WCDS. $w_1$ measures the normalized loading of the market CDS observation on the common factor, with $(1 - w_1)$ being the loading from the fundamental-based prediction. $IS$ denotes the Hasbrouck information share, which is defined as a range by the minimum and maximum estimate.

<table>
<thead>
<tr>
<th>VECM pair</th>
<th>$\beta_1$</th>
<th>$\beta_2$</th>
<th>$w_1$</th>
<th>min $IS_1$</th>
<th>max $IS_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>CDS-MCDS</td>
<td>-0.4165</td>
<td>0.1965</td>
<td>0.3206</td>
<td>0.0915</td>
<td>0.3589</td>
</tr>
<tr>
<td></td>
<td>(0.0194)</td>
<td>(0.0126)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CDS-WCDS</td>
<td>-0.6257</td>
<td>0.5063</td>
<td>0.4472</td>
<td>0.3661</td>
<td>0.4388</td>
</tr>
<tr>
<td></td>
<td>(0.0238)</td>
<td>(0.0220)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 7
Summary statistics on an out-of-sample investment exercise

Entries report the annualized mean return (Annual. Mean), mean return per investment period (Mean), standard deviation per period (Std), skewness, excess kurtosis, and the information ratio (SR), defined as the ratio of the annualized mean to the annualized standard deviation, from an out-of-sample investment exercise over different horizons (in number of weeks \( h \)). When the investment is over multiple \( h \) weeks, we start the investment at \( h \) different Wednesdays to generate \( h \) time series of non-overlapping \( h \)-period returns. The statistics in the table represent the average statistics on these non-overlapping series. Panel A reports the results from investments based on the deviations between market observation and Merton model prediction. Panel B reports results based on the WCDS prediction.

<table>
<thead>
<tr>
<th>Horizon, ( h ) Weeks</th>
<th>Annual. Mean %</th>
<th>Mean %</th>
<th>Std %</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>SR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A. Investments based on MCDS prediction</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>25.25</td>
<td>0.49</td>
<td>2.32</td>
<td>3.06</td>
<td>21.01</td>
<td>1.51</td>
</tr>
<tr>
<td>2</td>
<td>19.11</td>
<td>0.74</td>
<td>3.14</td>
<td>1.59</td>
<td>7.57</td>
<td>1.19</td>
</tr>
<tr>
<td>3</td>
<td>14.64</td>
<td>0.84</td>
<td>3.87</td>
<td>1.11</td>
<td>5.55</td>
<td>0.91</td>
</tr>
<tr>
<td>4</td>
<td>12.63</td>
<td>0.97</td>
<td>4.84</td>
<td>1.66</td>
<td>8.76</td>
<td>0.73</td>
</tr>
<tr>
<td></td>
<td>B. Investments based on WCDS prediction</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>32.08</td>
<td>0.62</td>
<td>1.97</td>
<td>2.86</td>
<td>17.43</td>
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<td>1.44</td>
<td>4.05</td>
<td>1.14</td>
<td>6.27</td>
<td>1.29</td>
</tr>
</tbody>
</table>
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.

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A. Cross-correlation between log market CDS and model predictions

The time series of cross-sectional correlations between market CDS and Merton model predictions. The solid line represents the time series of the cross-sectional correlation estimates between ln(CDS) and ln(WCDS). The dashed line represents the correlation estimates between ln(CDS) and ln(MDS).

B. Root mean squared prediction error in the logarithm of CDS spreads

Figure 2

The time series of cross-sectional correlations between market CDS and Merton model predictions. The solid line represents the time series of the cross-sectional correlation estimates between ln(CDS) and ln(WCDS). The dashed line represents the correlation estimates between ln(CDS) and ln(MDS).
A. Predicting future market CDS movements with current deviations from fundamental prediction

B. Predicting future model valuation changes with current deviations from market observation

Figure 3
The time series of cross-sectional forecasting correlations.
Panel A plots the time series of the cross-sectional correlation estimates between the current deviations of market CDS from fundamental-based predictions, $\ln(CDS_t/FCDS_t)$, and the future movement in the market CDS over the next week, $\ln(CDS_{t+1}/CDS_t)$. Panel B plots the time series of the cross-sectional correlation estimates between the current market-fundamental deviations $\ln(CDS_t/FCDS_t)$ and the future movement in the fundamental-based prediction over the next week, $\ln(FCDS_{t+1}/FCDS_t)$. The lines represent the exponential smoothing moving average of the correlation estimates, with smoothing coefficient of 0.97. The solid lines are for WCDS and the dashed lines are for MCDS.
A. VCEM between CDS and MCDS
(i) Responses to a unit shock from CDS
(ii) Responses to a unit shock from MCDS

B. VCEM between CDS and WCDS
(i) Responses to a unit shock from CDS
(ii) Responses to a unit shock from WCDS

Figure 4
Impulse response functions on unit shocks in market CDS and Merton model valuation.
Lines plot the impulse-response functions from the VECM models between CDS and MCDS in Panel A and between CDS and WCDS in Panel B. The shocks are from the market CDS observation in column (i) and from the fundamental-based predictions in column (ii).
Figure 5
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 6

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.