Anchoring Corporate Credit Spreads to Firm Fundamentals

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Many studies *test* the significance of credit risk information in a particular variable, controlling for a long list of others.

Do not test, *estimate*.

We explore ways to combine credit risk predictions from a wide range of markets and variables to generate a credit spread estimate that best matches market observations.

We analyze how good this prediction can be.

- Some studies focus on the average bias of a model.
- Our take: Mean bias is not a big deal as long as the predicted ranking matches that of the market.
What we do: Predicting credit risk with firm fundamentals

- Take five-year credit default swap (CDS) spread from Markit as the benchmark for credit spreads for different firms.

- Propose a simple implementation of the Merton model to predict five-year CDS spreads.
  - Analyze the average bias.
  - Analyze the information content:
    - Is the Merton prediction, after bias-adjustment, correlated with observed CDS?
    - When Merton prediction deviates from Markit observation, who is going to be right (in the future)?

- Consider the additional information content of other variables:
  - Alternative measures of leverage.
  - Other accounting ratios on profitability, investment, growth, liquidity, ...
  - Information from stock and options market: size, book to market, momentum, option implied volatility, ...
Data collection and sample construction

- Create a weekly (Wednesday) sample date list from January 8, 2003 to September 30, 2009, 351 weeks.

- At each date, identify a list of U.S. non-financial, public companies with:
  - Five-year CDS observation from Markit.
  - Total debt from Capital IQ.
  - One year stock market history from CRSP.

- Most analyses are cross-sectional.

- 579 companies are selected, with 138,200 week-company observations.
Financial ratios

- For this list of companies, collect/compute the following additional variables when available:
  - The ratio of (current liability + 0.5 long-term liability) to market capitalization (LM)
  - Debt to asset ratio (DA)
  - EBIT to Interest expense ratio (EE)
  - Working capital to total asset ratio (WA)
  - EBIT to total asset (EA)
  - Retained earning to total asset (RA)
  - Log market capitalization (MC)
  - One-year option implied volatility to realized volatility ratio (IV)
  - One year stock return (MM).

- Timing: We use a 45-day rule to match the quarterly financial statement information with market data.
  - Example: Match market data between May 15 to August 14 with the Q1 balance sheet, market data between August 15 to November 14 with Q2 balance sheet, ...
## Summary statistics

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CDS</strong></td>
<td>20.16</td>
<td>39.76</td>
<td>69.25</td>
<td>148.31</td>
<td>665.45</td>
</tr>
<tr>
<td><strong>TD/MC</strong></td>
<td>0.21</td>
<td>0.34</td>
<td>0.41</td>
<td>0.61</td>
<td>3.28</td>
</tr>
<tr>
<td><strong>RV</strong></td>
<td>0.23</td>
<td>0.27</td>
<td>0.32</td>
<td>0.39</td>
<td>0.61</td>
</tr>
<tr>
<td><strong>LM</strong></td>
<td>0.27</td>
<td>0.41</td>
<td>0.48</td>
<td>0.65</td>
<td>2.75</td>
</tr>
<tr>
<td><strong>DA</strong></td>
<td>0.23</td>
<td>0.26</td>
<td>0.27</td>
<td>0.31</td>
<td>0.45</td>
</tr>
<tr>
<td><strong>EE</strong></td>
<td>25.19</td>
<td>14.34</td>
<td>13.47</td>
<td>9.86</td>
<td>3.78</td>
</tr>
<tr>
<td><strong>WA</strong></td>
<td>0.13</td>
<td>0.12</td>
<td>0.14</td>
<td>0.13</td>
<td>0.13</td>
</tr>
<tr>
<td><strong>EA</strong></td>
<td>0.04</td>
<td>0.03</td>
<td>0.03</td>
<td>0.02</td>
<td>0.01</td>
</tr>
<tr>
<td><strong>RA</strong></td>
<td>0.43</td>
<td>0.31</td>
<td>0.28</td>
<td>0.19</td>
<td>-0.08</td>
</tr>
<tr>
<td><strong>MC</strong></td>
<td>10.02</td>
<td>9.16</td>
<td>8.90</td>
<td>8.49</td>
<td>7.61</td>
</tr>
<tr>
<td><strong>IV</strong></td>
<td>0.14</td>
<td>0.09</td>
<td>0.07</td>
<td>0.06</td>
<td>0.06</td>
</tr>
<tr>
<td><strong>MM</strong></td>
<td>0.17</td>
<td>0.16</td>
<td>0.10</td>
<td>0.08</td>
<td>-0.12</td>
</tr>
</tbody>
</table>
**MCDS**: A simple implementation of the Merton model

- **Inputs**: total debt ($TD$), the one-year realized volatility on the stock return ($RV$), and the market capitalization ($MC$):

  - **Outputs**: Firm value ($FV$) and firm volatility ($\sigma_F$):

    \[
    MC = FV \cdot N(d + \sigma_F \sqrt{T}) - TD \cdot N(d), \quad RV = N(d + \sigma_F \sqrt{T}) \sigma_F FV / MC, \]

- **Compute the standardized leverage (moneyness) — distance to default**:

  \[
  d = \frac{\ln(FV/TD) - \frac{1}{2} \sigma^2 F T}{\sigma_F \sqrt{T}}. \]

- **Convert the distance to default into a CDS spread**, \(MCDS = -10000 \cdot (1 - R) \cdot \ln(N(d))/T, \quad R = 40\%.

  (1)

- **Comments**:
  - The model provides a function to combine two inputs ($TD/MC$ & $RV$).
  - Maturity $T$ controls the relative contribution of the two elements: Intrinsic value versus time value.
The mapping is established by performing a *local quadratic* regression cross-sectionally each day:

\[
\ln(CDS) = f(\ln(MCDS)) + R.
\]
WCDS: Additional contributions from other variables

- Define the LCDS’ deviation from market as $R = \ln(CDS) - \ln(LCDS)$.
- Orthogonalize each variable $F$ of its contribution to LCDS:
  
  $$F_k = f^k(\ln(LCDS_t)) + x_t^k, \quad k = 1, 2, \ldots, K.$$ 

- Map the deviation to each orthogonalized variable $x$,
  
  $$R_t = f^k(x_t^k) + e_t^k, \quad k = 1, 2, \ldots, K.$$ 

- Stack the contribution from all variables, $X_t = [\hat{R}_t^1, \hat{R}_t^2, \ldots, \hat{R}_t^K]$, $R = X_t B_t + e$.
  
  - Replace missing values with the average prediction from other variables.
  
  $$R_{ij}^t = \sum_{k=1}^{K} w^k \hat{R}_{ij}^k, \quad w^k = e^\top(ee' + \text{diag}(1 - R^2))^{-1},$$

  - Bayesian regression to maintain intertemporal stability of weights,
    
    $$\hat{B}_t = (X_t^\top X_t + P_{t-1})^{-1} \left( X_t^\top R_t + P_{t-1} \hat{B}_{t-1} \right), \quad P_t = \text{diag}(\langle X_t^\top X_t + P_{t-1} \rangle),$$

  - Generate the WCDS prediction: $\ln(\text{WCDS})_t = \ln(\text{LCDS})_t + X_t \hat{B}_t$. 

Summary statistics on market CDS and model predictions

<table>
<thead>
<tr>
<th>Statistics</th>
<th>ln(CDS)</th>
<th>ln(MCDS)</th>
<th>ln(LCDS)</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>—</td>
<td>0.7633</td>
<td>0.8417</td>
<td>0.8969</td>
</tr>
</tbody>
</table>

Statistics are on pooled data (both cross section and time series), 138,200 observations for each series.
Merton model (MCDS) under-predicts credit spreads for high credit quality (low spread) companies, but the bias declines as the spread level increases.
The average biases are large and positive during booming economies, but disappear (and even become negative) during recessions.

Merton prediction varies more than the market observation.
Does Merton rank companies’ credit quality correctly?

- An average bias is easy to remove ...
- Can the model rank the credit quality of different companies correctly based on the companies fundamentals?
- The appropriate performance measure: cross-sectional correlation

MCDS: Average 0.76, std 0.04, a minimum of 0.69 and a maximum of 0.85.
LCDS: Average 0.81, std 0.05, a minimum of 0.71 and a maximum of 0.88.
When model deviates from market, who is right?

- In-sample fitting (correlation) can be as good as it gets.

When model deviates from market, several possibilities exist:

1. **Model deficiency**: The model does not include all credit-informative variables.
   - Add enough variables ($F$), the deviation will go away.

2. **Information asymmetry**: CDS market investors know more (faster) about credit risk than the stock market, upon which Merton model is based.
   - Current deviation predicts future change in model value.
     
     \[
     CDS_t > LCDS_t \implies LCDS_{t+1} \uparrow,
     \]
     
     \[
     \Rightarrow \text{Corr}(\ln(CDS_t/LCDS_t), \ln(LCDS_{t+1}/LCDS_t)) > 0.
     \]

3. **Information asymmetry**: Stock market investors respond to credit risk information faster than the CDS market (Markit).
   - Current deviation predicts future change in market CDS.
     
     \[
     CDS_t > LCDS_t \implies \Delta CDS_{t+1} \downarrow,
     \]
     
     \[
     \Rightarrow \text{Corr}(\ln(CDS_t/LCDS_t), \ln(CDS_{t+1}/CDS_t)) < 0.
     \]
Forecasting correlations

There is two-way information flow between Markit CDS quotes and the stock market (Merton model).

These are purely out of sample.
VECM and price discovery

- A vector error-correction model (VECM) of Engle and Granger (1987):

\[
\begin{bmatrix}
\Delta \ln(CDS_{t+1}) \\
\Delta \ln(LCDS_{t+1})
\end{bmatrix}
=\begin{bmatrix}
\alpha_1 \\
\alpha_2
\end{bmatrix}
+\begin{bmatrix}
\beta_1 \\
\beta_2
\end{bmatrix} \ln(CDS_t/LCDS_t) + \begin{bmatrix}
e_{1,t+1} \\
e_{2,t+1}
\end{bmatrix},
\]

- Composition of a permanent component:

\[
\begin{pmatrix}
w_1 \\
w_2
\end{pmatrix}
= \frac{1}{\beta_1 - \beta_2}
\begin{pmatrix}
-\beta_2 \\
\beta_1
\end{pmatrix}
= \begin{pmatrix}
9.44\% \\
90.56\%
\end{pmatrix}.
\]

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Adding additional variables not only improve the in-sample fitting, but also reduces its intertemporal variation.

The out-of-sample forecasting performance also improves uniformly.
What others?

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Very positive results in the sea of negative findings

- Bias & credit risk premium puzzles (Huang & Huang...)
  - Cremers, Driessen, and Maenhout: Credit risk premium is consistent with option risk premium.
  - Carr & Wu: DOOM puts are priced similar to CDS.
- A more important question: *Which* fundamentals matter for credit risk?
- Fundamentals do not matter much for monthly changes (Collin-Dufresne, Goldstein, Martin)
  - Fundamentals may not be highly correlated with monthly changes, but they predict monthly changes!
- CDS is more efficient than bond spreads.
  - What bond? What spread?
    - There are tens of thousands of bonds outstanding. Only a small proportion trades actively.
    - Institutional and retail trades happen at very different prices.
  - What is a CDS quote worth?
    - CDS is an OTC contract. Most quotes are indicative quotes.
    - Markit CDS data: Survey several data contributors, take an average.
Concluding remarks

In extracting credit risk information,

- Fundamentals matter.
- Merton model provides a simple yet quite effective way of summarizing the fundamental information.
- In proposing new models, one shall focus less on the functional forms, more on the model’s implications on what/how other fundamental variables/accounting ratios can matter for credit risk.