Anchoring Corporate Credit Spreads to Firm Fundamentals

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Two stylized facts:


2. Firm fundamentals only explain a small portion of movements in changes in credit spreads. Collin-Dufresne, Goldstein, and Martin (2001),...

What do these facts mean?

- Structural models are bad?

The two facts do *not* say much about the virtue of a model or fundamentals.
Focus not on average bias, but on cross-sectional differentiation

- An average bias is easy to remove empirically.
- What matters more is whether model predictions can differentiate the relative credit quality of different firms.
  - Cross-sectionally, do model predictions and market observations generate similar relative credit risk rankings?
- Which of the following two models do you want?
  - Model A: iid numbers with mean equal to the mean observed credit spread.
    ⇒ It gets the average right, but does not tell you anything about which firm has better or worse credit quality.
  - Model B: Market = A + BModel. (A ≠ 0, B ≠ 1, but high $R^2$).
- Focus not on the average bias, but on the differentiation (relative prediction) power.
  ⇒ The power can be measured by the cross-sectional correlation or the $R^2$ of the cross-sectional regression.
Regress not on model changes, but on model deviations

- Regressing price/yield changes on fundamentals artificially discounts the usefulness of fundamentals.
  - All security prices contain transient noise (think of bid-ask bounce).
  - In the long run, these noises are just noises. In a very short horizon, all that moves is bid-ask bounce.
  - Think of days with no news but just bid-ask bounces.
    - The changes are purely noise and thus not related to fundamentals.
    - But fundamentals do matter: They tell you that all moves are transient and hence you can buy low and sell high.

- Don’t regress on model changes:
  \[ \Delta \text{Market}_t = \alpha + \beta \Delta \text{Model}_t + e_t. \] — Low \( R^2 \) does not mean anything. Even with the right model, \( R^2 \) will decline as horizon \( \Delta \) shrinks.

- Regress on model deviations from market:
  \[ \Delta \text{Market}_{t+1} = \alpha + \beta (\text{Market}_t - A - B \text{Model}_t) + e_{t+1}. \]

- A good model is not a model without errors, but rather a model with large (hopefully), transient errors.
What we do: Predicting credit risk with firm fundamentals

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

- Propose a simple implementation of the Merton model to predict five-year CDS spreads, and remove the average bias via a cross-sectional nonparametric regression.

  - Analyze the *information content*.

    - Is the Merton prediction correlated with observed CDS?
    - When Merton prediction deviates from Markit observation, which one is going to be right (in the future)?

- Propose a Bayesian methodology to combine a long list of financial variables with the Merton prediction.

  - Analyze the *additional information content* of these 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.
  - Each day, the number of available firms ranges from 246 to 474.
Financial ratios

- For this list of companies, collect/compute the following additional variables when available:
  - Leverage: (i) The ratio of (current liability + 0.5 long-term liability) to market capitalization (LM), (ii) Debt to asset ratio (DA)
  - Coverage: EBIT to Interest expense ratio (EE)
  - Liquidity: Working capital to total asset ratio (WA)
  - Profitability: EBIT to total asset (EA)
  - Investment: Retained earning to total asset (RA)
  - Size: Log market capitalization (MC)
  - Options: One-year option implied volatility to realized volatility ratio (IV)
  - Momentum: 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, ...
**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 metric — distance to default**: 

  
  $$DD = \ln \left( \frac{FV}{TD} \right) - \frac{1}{2} \sigma_F^2 T \sigma_F \sqrt{T}.$$ 

  
  
  The model is extremely stylized, no need to take it literally.

  - It provides a simple function to combine two inputs ($TD/MC \& RV$) into one metric (DD) for credit prediction.

  - Maturity $T$ can be used as a control coefficient to adjust the relative weighting between the two inputs.

- **Other models**: variations in inputs and functional form.

  Example: In a particular barrier model, $FV = TD + MC$. 
**MCDS**: A simple implementation of the Merton model

- Convert the distance to default into a raw CDS spread, $RCDS$,

\[
RCDS = -10000 \cdot (1 - R) \cdot \ln(N(DD))/T, \quad R = 40\%.
\]  

(1)

- Remove systematic bias in the raw model prediction via cross-sectional monotone, local quadratic regression,

\[
\ln(CDS) = f(\ln(RCDS)) + R.
\]

We label the bias-corrected Merton model prediction as **MCDS**:

\[
\ln(MCDS) = \hat{f}(\ln(RCDS)).
\]

- Comments:

  - Average biases are well-documented; we'll skip that part.
  - By removing the average bias and nonlinearity via the regression, we focus on the model’s capability in differentiating (ranking) the relative credit quality of different firms.
  - The regression does not change the ranking of DD or RCDS.
Define the MCDS’ deviation from market as $R = \ln(CDS) - \ln(MCDS)$.

Orthogonalize each variable $F$ of its contribution to MCDS:

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

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, $X_t = [\hat{R}_t^1, \hat{R}_t^2, \ldots, \hat{R}_t^K]$.

Replace missing values with the average prediction from other variables.

$$R_t^{ij} = \sum_{k=1}^{\tilde{K}} w^k \hat{R}_t^{i,k}, \quad w^k = e^\top (ee^\top + \text{diag}(1 - R^2))^{-1},$$

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: $\ln(WCDS)_t = \ln(MCDS)_t + X_t \hat{B}_t$. 

Merton model under-predicts market CDS, especially for investment-grade companies and under booming market conditions.

The mean biases are much smaller during recessions and for high-yield companies.

Similar to literature findings.
Does Merton rank companies’ credit quality correctly?

- Cross-sectional correlation between model predictions & market observations:

  ![Graph showing cross-sectional correlation between RCDS and MCDS]

  - **RCDS**: Average 0.76, std 0.04, min 0.69, max 0.85.
  - **MCDS**: Average 0.81, std 0.05, min 0.71, max 0.88.

- The increase in correlation from RCDS (red line) to MCDS (blue line) is due to nonlinearity correction.

- Nonlinearity effect is larger but correlation is higher during recessions when
  - Overall credit concern is more prominent.
  - Cross-sectional difference in credit quality is larger.
The extrapolation stability

- In the U.S., thousands of companies are publicly traded, but less than 500 of them have market CDS quotes.
- Can the Merton model be used to do the extrapolation? Calibrate the relation to companies with market quotes and extend the predictions to companies without market quotes.
- Out-of-sample stability test: Each day, randomly draw half of the companies as in sample, with which MCDS is calibrated. The other half is used for out of sample test.

There is virtually no difference between in-sample and out-of-sample correlations.
When model deviates from market, which one is right?

- When model deviates from market, several possibilities exist:

  1. **Model deficiency:** The model does not include all credit-informative variables.
  
  2. **Information asymmetry:** CDS market investors know more (faster) about credit risk than the stock market, upon which Merton model is based.

      \[ \Rightarrow \text{Current deviation predicts future change in model value.} \]
      \[ \text{Corr}(\ln(CDS_t/MCDS_t), \ln(MCDS_{t+1}/MCDS_t)) > 0. \]

  3. **Information asymmetry:** Stock market investors respond to credit risk information faster than the CDS market (Markit).

      \[ \Rightarrow \text{Current deviation predicts future change in market CDS.} \]
      \[ \text{Corr}(\ln(CDS_t/MCDS_t), \ln(CDS_{t+1}/CDS_t)) < 0. \]

  4. **Permanent v. transient shocks:** Firm fundamentals (leverage/volatility) capture the permanent component of the credit risk. Deviations from fundamentals are mainly driven transient supply/demand shocks.

      \[ \Rightarrow \text{Current deviation predicts future change in market CDS.} \]
      \[ \text{Corr}(\ln(CDS_t/MCDS_t), \ln(CDS_{t+1}/CDS_t)) < 0. \]
Forecasting correlations

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

These are purely out of sample estimates — estimation of $MCDS_t$ does not depend on any information at time greater than $t$. 

\[ \text{Corr} = -0.0551(0.005) \]

\[ \text{Corr} = 0.0355(0.004) \]
VECM and price discovery

- A vector error-correction model (VECM) of Engle and Granger (1987):
  \[
  \begin{bmatrix}
  \Delta \ln(CDS_{t+1}) \\
  \Delta \ln(MCDS_{t+1})
  \end{bmatrix} = \begin{bmatrix}
  \alpha_1 \\
  \alpha_2
  \end{bmatrix} + \begin{bmatrix}
  \beta_1 \\
  \beta_2
  \end{bmatrix} \ln \left( \frac{CDS_t}{MCDS_t} \right) + \begin{bmatrix}
  e_{1,t+1} \\
  e_{2,t+1}
  \end{bmatrix},
  \]

- Composition of a permanent component:
  \[
  \begin{pmatrix}
  w_1 \\
  w_2
  \end{pmatrix} = \frac{1}{\beta_1 - \beta_2} \begin{pmatrix}
  -\beta_2 \\
  \beta_1
  \end{pmatrix} = \begin{pmatrix}
  9.44\% \\
  90.56\%
  \end{pmatrix} \leftarrow Markit \leftarrow Merton
  \]

Graphs showing impulse response for unit shocks to CDS and MCDS.
Adding additional variables not only improves the cross-sectional correlation, but also reduces its intertemporal variation.

The forecasting performance also improves uniformly.
Time-varying relative contributions

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**Graphs**

1. **Graph 1**
   - Title: Time-varying relative contributions
   - Graphs showing time series data with lines for LM, DA, EE, WA, MC, IV, MM.
   - X-axis: 03 04 05 06 07 08 09 10
   - Y-axis: Values ranging from -0.8 to 0.8

2. **Graph 2**
   - Graph showing time series data with lines for EE, WA.
   - X-axis: 03 04 05 06 07 08 09 10
   - Y-axis: Values ranging from -0.1 to 0.9

3. **Graph 3**
   - Graph showing time series data with lines for EA, RA.
   - X-axis: 03 04 05 06 07 08 09 10
   - Y-axis: Values ranging from 0.1 to 1.0

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**WCDS**

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Concluding remarks

- Despite the average bias, the Merton model generates credit spread predictions that are strongly correlated with market observations.
  - We propose a simple cross-sectional local quadratic regression approach to remove the average bias in the raw Merton prediction across different credit risk levels.

- When the market deviates from the model prediction, it is much more likely that the future market price reverts back to the model than the other way around.
  - The bias-corrected Merton model provides an informative anchor for credit spread movements.

- A long list of financial variables are found to contribute to the informational discovery of credit risk on top of the Merton model prediction.
  - We propose a Bayesian approach to combine the predictions from this long list of variables with the Merton prediction.
After thoughts: What is the purpose of a model?

- To reveal average bias and risk premium puzzles (Huang & Huang...)
  - What risk premiums are we not puzzled by?
  - Cremers, Driessen, and Maenhout: Credit risk premium is consistent with option risk premium.
  - Carr & Wu: DOOM puts are priced similar to CDS.
- To show why & which fundamentals matter.
  - Fundamentals do not matter much for monthly changes (Collin-Dufresne, Goldstein, Martin).
  - Market level deviations from fundamentals predict monthly changes!
- To provide an informative anchor for market prices.
  - Faster is not always better.
    - The fastest movement is bid-ask bounce/noise.
  - Perfectly matching market prices is not always the goal of modeling.
    - Provided that the model pricing errors (deviations from market) are highly transient, the larger the error, the better!