Pricing and Risk in the Credit Markets: Investigation of Credit Default Swaps

Industry Sponsor: Standard & Poor’s

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Outline

1 Introduction
   - Background
   - Market Derived Signals (MDS) Model

2 Methodology
   - Evaluating MDS Model Performance
   - Multinomial Logit Model
   - Optimal Bond Pricing Curve

3 Conclusions
   - Finishing Remarks
The models and analyses presented here are exclusively part of a research effort intended to better understand the strengths and weaknesses of various approaches to interpreting credit risk implied by financial market pricing data.

No comment or representation is intended or should be inferred regarding Standard & Poor’s ratings criteria or models that are used in the ratings process for any type of security.
Introduction
Problem Statement

- To understand how to best use CDS, bond and equity market data in monitoring the credit quality of bond issuers.
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- Evaluate the effectiveness of the current models used to provide signals on credit quality.
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- Evaluate the effectiveness of the current models used to provide signals on credit quality.

- Determine an optimal credit curve to price bonds.
**Definitions**

- **Credit Quality**: measurement of ability to pay back debt, probability of default and ability to recover given default.

- **Credit Rating**: opinion on the general credit quality of a borrower.

<table>
<thead>
<tr>
<th>Investment Grade Ratings</th>
<th>Non-Investment Grade Ratings</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>BB+</td>
</tr>
<tr>
<td>AA+</td>
<td>BB</td>
</tr>
<tr>
<td>AA</td>
<td>BB-</td>
</tr>
<tr>
<td>AA-</td>
<td>B+</td>
</tr>
<tr>
<td>A+</td>
<td>B</td>
</tr>
<tr>
<td>A</td>
<td>B-</td>
</tr>
<tr>
<td>A-</td>
<td>CCC</td>
</tr>
<tr>
<td>BBB+</td>
<td>CC</td>
</tr>
<tr>
<td>BBB</td>
<td>C</td>
</tr>
<tr>
<td>BBB-</td>
<td>D</td>
</tr>
</tbody>
</table>

**Figure**: S&P’s Rating System
We consider the following three markets:

- Bond market
- Equity market
- Credit Default Swap (CDS) Market
Market Derived Signals (MDS) Model

- It provides signals that indicate changes in credit quality.
CDS MDS Model

Discrepancy = Official S&P Rating - Implied Rating

\(^1\)Provided by S&P
Determine the significant signals from markets for analysts to react upon

- Evaluate Company A’s Credit Quality
- 6 Months
- Re-evaluate
Determine the significant signals from markets for analysts to react upon
Goals

- Determine the significant signals from markets for analysts to react upon

- Evaluate Company A’s Credit Quality
  - 6 Months
  - Re-evaluate

- Evaluate Company A’s Credit Quality
  - 2 Months
  - Re-evaluate

- A large drop in bond price
Goals

- Determine the significant signals from markets for analysts to react upon
  - Evaluate Company A’s Credit Quality
    - 6 Months
    - Re-evaluate
  - Evaluate Company A’s Credit Quality
    - 2 Months
    - Re-evaluate

- Obtain an optimal credit curve for bond pricing

A large drop in bond price
Evaluating MDS Model Performance
Cumulative Accuracy Profile (CAP)

- Visualization validation technique
Cumulative Accuracy Profile (CAP)

- Visualization validation technique
- Fraction of Events Population V.S. Fraction of Entire Population
Cumulative Accuracy Profile (CAP)

- Visualization validation technique
- Fraction of Events Population V.S. Fraction of Entire Population

![CAP Plot]

The CAP plot shows the fraction of events population against the fraction of entire population. The plot demonstrates how the cumulative accuracy profile evolves as the fraction of the population increases.
Cumulative Accuracy Profile (CAP)

- Visualization validation technique
- Fraction of Events Population V.S. Fraction of Entire Population
Cumulative Accuracy Profile (CAP)

- Visualization validation technique
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Cumulative Accuracy Profile (CAP)

- Visualization validation technique
- Fraction of Events Population V.S. Fraction of Entire Population
Accuracy Ratio (AR)

- $a_r$: area between actual model and random model
- $a_p$: area between perfect model and random model
Accuracy Ratio (AR)

- $a_r$: area between actual model and random model
- $a_p$: area between perfect model and random model

$AR = \frac{a_r}{a_p}$
## Data Processing

<table>
<thead>
<tr>
<th>Market</th>
<th>Observations</th>
<th>Companies</th>
<th>Date Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>CDS Market</td>
<td>2,000,000</td>
<td>1370</td>
<td>01.2005 - 06.2012</td>
</tr>
<tr>
<td>Bond Market</td>
<td>500,000</td>
<td>1012</td>
<td>01.2010 - 06.2012</td>
</tr>
<tr>
<td>Equity Market</td>
<td>720,000</td>
<td>1011</td>
<td>01.2009 - 06.2012</td>
</tr>
</tbody>
</table>

Intersect three data sets for valid comparison of model performances. Final sample: 150,000 observations; 281 companies.
Intersect three data sets for valid comparison of model performances.
Intersect three data sets for valid comparison of model performances.

Final sample: 150,000 observations; 281 companies.
Approach

- Assign numerical values to S&P rating and MDS ratings
Approach

- Assign numerical values to S&P rating and MDS ratings
- Calculate daily discrepancy
Approach

- Assign numerical values to S&P rating and MDS ratings
- Calculate daily discrepancy
- Assign numerical values to S&P Credit Watch and Outlook
Approach

- Assign numerical values to S&P rating and MDS ratings
- Calculate daily discrepancy
- Assign numerical values to S&P Credit Watch and Outlook
- Check for subsequent credit status changes
**Simple Moving Average (SMA)**

- **Signaling Period**: Average of discrepancy calculated over time $T$.
- **Gap**: Lag time for analysts to react.
- **Checking Period**: Credit events noted over time $R$. 
Choose parameters:

- $T = 20$, $R = 10$, $Gap = 5$
Choose parameters:
- $T = 20$, $R = 10$, $Gap = 5$

Sort observations based on SMA of discrepancy (x-axis)
Choose parameters:
- $T = 20$, $R = 10$, $Gap = 5$

Sort observations based on SMA of discrepancy ($x$-axis)

Calculate cumulative percentage of credit events ($y$-axis)
Results

CAP Plot Bond-MDS Model

Fraction of Negative Changes

Fraction of all Observations

$AR = 0.262$
**Results**

- **Investment Grades V.S. Non-Investment Grades**

  ![CAP Plot for Bond-MDS Model](image1)

  ![CAP Plot for Bond-MDS Model (Non-Investment Grade)](image2)

  \[ \text{AR} = 0.262 \]

  \[ \text{AR} = 0.432 \]
Density of SMA of Discrepancy

SMA Distributions for Bond (Non-Investment Grade)

- Downgraded
- All Companies
Analysis

- Conjectures on:
  1. Plots over different intervals of SMA
  2. Outstanding peaks

Persistent signal: discrepancy constant over time
Fluctuations of market: High standard deviation of discrepancy
Exclude observations with high standard deviation
Analysis

- Conjectures on:
  1. Plots over different intervals of SMA
  2. Outstanding peaks

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2. Outstanding peaks

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Fluctuations of market: High standard deviation of discrepancy
Analysis

- Conjectures on:
  1. Plots over different intervals of SMA
  2. Outstanding peaks

- Persistent signal: discrepancy constant over time

- Fluctuations of market: High standard deviation of discrepancy

- Exclude observations with high standard deviation
Comparison

- **Bond MDS Model (Non-investment grades)**

  **CAP Plot for Bond–MDS Model (Non–Investment Grade)**

  - AR = 0.432
  - AR = 0.419

  - All observations v.s. Observations with std. < 0.42
  - SMA < 0
Comparison

- CDS MDS Model (Non-investment grades)

\[ \text{AR} = 0.448 \quad \text{AR} = 0.642 \]

- All observations v.s. Observations with std. < 0.25
- SMA \( \leq -2 \)
Comparison

- Test on different of $T$:

  $T = 30$
  Observations with std. < 0.25
  SMA $\leq -2$

  AR = 0.457
  AR = 0.686
Summary

- Bond MDS model has strongest signaling power with an overall higher AR.
Summary

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- MDS models work better with non-investment grade companies.
Summary

- Bond MDS model has strongest signaling power with an overall higher AR.

- MDS models work better with non-investment grade companies.

- Persistent signals with low std. on discrepancy boosts model performance.
Multinomial Logit Model
Multinomial Logit Model

- Mutinomial Logit Model

- Response Vector: $Y = \begin{cases} 1, & \text{if negative status change} \\ 2, & \text{if positive status change} \\ 3, & \text{if no change (reference level)} \end{cases}$

- Predictor Matrix $X$: Official S&P rating, sector, PD, CDS spread, bond yield, etc.
Multinomial Logit Model

- Response Vector.

\[ Y = \begin{cases} 
1, & \text{if negative status change} \\
2, & \text{if positive status change} \\
3, & \text{if no change (reference level)} 
\end{cases} \]
Multinomial Logit Model

Response Vector.

\[ Y = \begin{cases} 
1, & \text{if negative status change} \\
2, & \text{if positive status change} \\
3, & \text{if no change (reference level)} 
\end{cases} \]

Predictor Matrix \( X \)

Official S&P rating, sector, PD, CDS spread, bond yield, etc.
The Multinomial Logit Model

\[ \log \frac{P(Y = j|X)}{P(Y = 3|X)} = X\beta_j + \epsilon \]

where \( j \in \{1, 2\} \)

- \( \beta_j \)'s are regression coefficients to be estimated.
- Take exponential of the log odds ratio to obtain the probabilities.
For our reference category $Y = 3$

$$P(Y = 3|X) = \frac{1}{1 + \sum_{k \in \{1,2\}} \exp (X \beta_k)}$$
For our reference category $Y = 3$

$$P(Y = 3 | X) = \frac{1}{1 + \sum_{k \in \{1, 2\}} \exp(X \beta_k)}$$

For $j \in \{1, 2\}$

$$P(Y = j | X) = \frac{\exp(X \beta_j)}{1 + \sum_{k \in \{1, 2\}} \exp(X \beta_k)}$$

Note: $\sum_{i=1}^{3} P(Y = i | X) = 1$
Effectiveness of MNRFIT and MNRVAL

- Tested the performance of *mnrfit*.
- Random sample of observations, 3 response categories.
- Assigned explicit $\beta$ values.

<table>
<thead>
<tr>
<th>Model 1</th>
<th>Real</th>
<th>Estimated</th>
<th>se</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>intercept</td>
<td>-2</td>
<td>-1.7762</td>
<td>0.2422</td>
<td>0.000</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>0.3</td>
<td>0.6829</td>
<td>0.3319</td>
<td>0.0396</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>-2</td>
<td>-1.9271</td>
<td>0.1857</td>
<td>0.000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model 2</th>
<th>Real</th>
<th>Estimated</th>
<th>se</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>intercept</td>
<td>1</td>
<td>1.0085</td>
<td>0.1113</td>
<td>0.000</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>5</td>
<td>5.0111</td>
<td>0.3269</td>
<td>0.000</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>0.007</td>
<td>-0.0778</td>
<td>0.1037</td>
<td>0.4533</td>
</tr>
</tbody>
</table>

**Table:** Testing *mnrfit*
Testing MNRVAL Function

- Random data, 3 response categories.
- Two generated data types, with and without noise:

<table>
<thead>
<tr>
<th></th>
<th>1.1 $x(y = 1) = 0$</th>
<th>2.1 $x(y = 1) = 0$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1.2 $x(y = 2) = 3$</td>
<td>2.2 $x(y = 2) = 3$</td>
</tr>
<tr>
<td></td>
<td>1.3 $x(y = 3) = 2$</td>
<td>2.3 $x(y = 3) = 2 + Noise$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Data</th>
<th>Correct Predictions</th>
<th>Actual Responses</th>
<th>AR</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Noise</td>
<td>200</td>
<td>200</td>
<td>1</td>
</tr>
<tr>
<td>Noise</td>
<td>164</td>
<td>200</td>
<td>0.82</td>
</tr>
</tbody>
</table>
The Multinomial Logit Model

Results using $T = 15$, $Gap = 15$, $R = 30$:

<table>
<thead>
<tr>
<th></th>
<th>Negative Change Model</th>
<th>Estimated</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>PD</td>
<td>0.9792</td>
<td>0.1118</td>
<td></td>
</tr>
<tr>
<td>CDS Spread</td>
<td>-0.0021</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>CDS Discrep.</td>
<td>0.0066</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>Bond Yield</td>
<td>0.1337</td>
<td>0.0016</td>
<td></td>
</tr>
<tr>
<td>Bond Adj.S.</td>
<td>0.0009</td>
<td>0.0701</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Positive Change Model</th>
<th>Estimated</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>PD</td>
<td>-16.0916</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>CDS Spread</td>
<td>0.0007</td>
<td>0.0008</td>
<td></td>
</tr>
<tr>
<td>CDS Discrep.</td>
<td>-0.0065</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>Bond Yield</td>
<td>0.6788</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>Bond Adj.S.</td>
<td>-0.0045</td>
<td>0.0000</td>
<td></td>
</tr>
</tbody>
</table>
Isolated Effects of CDS Discrepancy & PD

\[ T = 15, \ Gap = 15, \ R = 30 \]
Effect of CDS & Bond Given Correlation

\[ T = 15, \text{ Gap} = 15, R = 30 \]
The Multinomial Logit Model

Results using $T = 15$, $Gap = 10$, $R = 25$:

<table>
<thead>
<tr>
<th>Negative Change Model</th>
<th>Estimated</th>
<th>$p$ value</th>
</tr>
</thead>
<tbody>
<tr>
<td>intercept</td>
<td>-4.8181</td>
<td>0.000</td>
</tr>
<tr>
<td>PD</td>
<td>1.6120</td>
<td>0.0130</td>
</tr>
<tr>
<td>CDS Spread</td>
<td>-0.0025</td>
<td>0.0000</td>
</tr>
<tr>
<td>CDS Discrep.</td>
<td>0.0070</td>
<td>0.0000</td>
</tr>
<tr>
<td>Bond Yield</td>
<td>0.1848</td>
<td>0.0000</td>
</tr>
<tr>
<td>Bond Adj.S.</td>
<td>0.0005</td>
<td>0.2876</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Positive Change Model</th>
<th>Estimated</th>
<th>$p$ value</th>
</tr>
</thead>
<tbody>
<tr>
<td>intercept</td>
<td>-5.6106</td>
<td>0.000</td>
</tr>
<tr>
<td>PD</td>
<td>-15.9469</td>
<td>0.000</td>
</tr>
<tr>
<td>CDS Spread</td>
<td>0.0005</td>
<td>0.0236</td>
</tr>
<tr>
<td>CDS Discrep.</td>
<td>-0.0063</td>
<td>0.0000</td>
</tr>
<tr>
<td>Bond Yield</td>
<td>0.7233</td>
<td>0.0000</td>
</tr>
<tr>
<td>Bond Adj.S.</td>
<td>-0.0048</td>
<td>0.0000</td>
</tr>
</tbody>
</table>
Interpretation

- Compare most probable response to actual response

<table>
<thead>
<tr>
<th></th>
<th>Downgrades</th>
<th>Upgrades</th>
<th>No Change</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted Downgrades</td>
<td>0</td>
<td>0</td>
<td>13</td>
<td>13</td>
</tr>
<tr>
<td>Predicted Upgrades</td>
<td>0</td>
<td>29</td>
<td>6</td>
<td>35</td>
</tr>
<tr>
<td>Predicted No Change</td>
<td>2046</td>
<td>3505</td>
<td>104127</td>
<td>109678</td>
</tr>
<tr>
<td>Total</td>
<td>2046</td>
<td>3534</td>
<td>104127</td>
<td>109726</td>
</tr>
</tbody>
</table>

\[ T = 15, R = 30, \text{Gap} = 15 \]

- Larger Type II Error
Interpretation

- Compare most probable response to actual response

<table>
<thead>
<tr>
<th></th>
<th>Downgrades</th>
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<tr>
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<td>0</td>
<td>29</td>
<td>6</td>
<td>35</td>
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<tr>
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<td>2046</td>
<td>3534</td>
<td>104127</td>
<td>109726</td>
</tr>
</tbody>
</table>

\[ T = 15, \ R = 30, \ Gap = 15 \]

- Larger Type II Error
- Correct prediction of downgrades = 0%
- Correct prediction of upgrades = 0.8%
- Correct prediction of no change > 99%
Interpretation

- Compare relative probability to distinguish larger likelihood for credit events
Interpretation

- Compare relative probability to distinguish larger likelihood for credit events
- Sort prob. of up/downgrade from the highest to lowest (x-axis)
- Calculate cumulative percentage of credit events (y-axis)
Interpretation

- Compare relative probability to distinguish larger likelihood for credit events

\[ T = 15, \ R = 25, \ Gap = 10 \]
Better performance with longer checking period $R$

- Better performance with investment grades companies

$T = 15, R = 25, \text{Gap} = 10, \text{AR is approx. 7\% higher}$

Better performance with upgrades prediction

All else equal, AR is approx. 20\% higher

Issue: Simultaneous high probability of upgrades and downgrades
Better performance with longer checking period $R$

Better performance with investment grades companies

$T = 15, R = 25, Gap = 10$, AR is approx. 7% higher
Interpretation

- Better performance with longer checking period $R$

- Better performance with investment grades companies
  - $T = 15$, $R = 25$, $Gap = 10$, AR is approx. 7% higher

- Better performance with upgrades prediction
  - All else equal, AR is approx. 20% higher
Interpretation

- Better performance with longer checking period $R$

- Better performance with investment grades companies
  - $T = 15$, $R = 25$, $Gap = 10$, AR is approx. 7% higher

- Better performance with upgrades prediction
  - All else equal, AR is approx. 20% higher

- Issue: Simultaneous high probability of upgrades and downgrades
Interpretation

- $T = 15$, $R = 25$, $Gap = 10$; Investment grades companies only.

![CAP Plot for Multinomial Logit Model]

AR = 0.4802
Most probably response for predicting credit status:
- Unbalanced data with less than .05 credit change events
Most probably response for predicting credit status:
  - Unbalanced data with less than .05 credit change events

Relative probability for investigating credit changes
  - Highly dependent on parameters $T, R, Gap$
  - Different predictors used for categories upgrade or downgrade
Remarks

- Most probably response for predicting credit status:
  - Unbalanced data with less than .05 credit change events

- Relative probability for investigating credit changes
  - Highly dependent on parameters $T, R, Gap$
  - Different predictors used for categories upgrade or downgrade

- Predictor matrix $X$
  - Normalizing raw data from markets
  - MDS output: Persistent signals can be considered.
Most probably response for predicting credit status:
- Unbalanced data with less than .05 credit change events

Relative probability for investigating credit changes
- Highly dependent on parameters $T, R, Gap$
- Different predictors used for categories upgrade or downgrade

Predictor matrix $X$
- Normalizing raw data from markets
- MDS output: Persistent signals can be considered.

Comparison with single MDS models can be further made.
Optimal MDS Curve to Price Bonds
How to Price a Bond

Standard Bond Pricing Formula

Bond Price = \frac{FV}{(1 + y)^T} + \sum_{t=1}^{T} \frac{C}{(1 + y)^t}

where,

- \( FV \) = Face Value
- \( C \) = Coupon payments
- \( T \) = Maturity date
- \( y \) = Yield or interest rate

Our focus will be on the bond’s credit risk measured by \( y \) in the previous formula.
Objectives

- Build bond pricing framework that takes as input:
  - Credit spread curves
  - Bond terms and conditions

- Compare accuracy of pricing with CDS-based and bond-based credit curves.

- Conclude an optimal curve from outputs of the MDS models.
Figure: Credit Spreads of Sample of Corporations
To avoid measurement error caused by various options in corporate bonds, we restricted our sample to bonds with:

- No optionality.
- Fixed-term coupon payments.
- Five year maturity.
Figure: Comparison of Yields
Figure: 5-year Spot Rate vs. 5-year Treasury Rate
Our Approach

- We selected a set of bonds that had reported prices in the Trade Reporting and Compliance Engine (TRACE) over the year 2010.
Our Approach

- We selected a set of bonds that had reported prices in the Trade Reporting and Compliance Engine (TRACE) over the year 2010.
- For each selected bond, we found all issuer outputs of the CDS and Bond- MDS models.
Our Approach

Assuming a flat spread term structure,

- We calculated the prices of the selected bond for the period using the 5-year CDS and Option Adjusted Spread (OAS) benchmark.
Our Approach

Assuming a flat spread term structure,

- We calculated the prices of the selected bond for the period using the 5-year CDS and Option Adjusted Spread (OAS) benchmark.
- We validated both price time series with the actual reported price found in TRACE.
Figure: Average Daily Bond Prices Time Series

Results
We can conclude the following observations:

- Bonds spreads seem to be higher than CDS spreads.
- The CDS yield seems to be the closest to the bond’s yield obtained from TRACE prices.
- We can observe that the CDS spread provides a slightly more closer estimate to the real value than the bond spread.
These price discrepancies could be a result of:

- The implementation of our pricing function.
- Information unrelated to the credit risk that is priced in, especially liquidity.
- Counter-party risk, which makes CDS spread of lower value.
Conclusion
Conclusions

Effectiveness of MDS models:
- Bond-MDS model seems to provide the strongest signals.
- Non-investment grade companies provide a higher AR.
- We recommend considering the standard deviation of discrepancies when determining the persistence of signals.
Conclusions

Effectiveness of MDS models:
- Bond-MDS model seems to provide the strongest signals.
- Non-investment grade companies provide a higher AR.
- We recommend considering the standard deviation of discrepancies when determining the persistence of signals.

Our multinomial logit model:
- CAP and AR results indicate the model can predict a significant fraction of credit rating changes.
- The model seems to perform better for positive changes in credit quality compared to negative changes.
Conclusions

Effectiveness of MDS models:
- Bond-MDS model seems to provide the strongest signals.
- Non-investment grade companies provide a higher AR.
- We recommend considering the standard deviation of discrepancies when determining the persistence of signals.

Our multinomial logit model:
- CAP and AR results indicate the model can predict a significant fraction of credit rating changes.
- The model seems to perform better for positive changes in credit quality compared to negative changes.

Optimal credit curve for pricing bonds:
- Our empirical analysis suggests that the CDS spread provides a closer estimate to the real price than the bond spread.
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Q & A