Estimating the probability of default for Indian firms

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Importance of the field

1. Corporate bond market, credit derivatives: active speculative trading on credit risk

2. In banking: When Basle 1 was used for banks, measuring risk was not important; fixed rules sufficed. Shift towards Basle 2: greater emphasis on genuinely understanding risk: quantitative measurement becomes key.
The three key questions

I. What is the probability that firm X will default on a stated horizon?
II. What is the loss given default?
III. How do we analyse credit portfolios?
There is no well-defined data release which takes place when default happens.

The loss given default is not observed.

Difficulties of non-comparability across firms and across time of accounting data.
Models of default based on accounting data
Approach 1: Altman and others

- Probit models explaining default in terms of accounting information.
- Project for CMIE by Subrata Sarkar, Susan Thomas.
- CMIE built a unique defaults database.
- CMIE has normalised accounting data.
- We did the models.
- The output of the models is the probability of default for a firm over a one-year horizon.
Choosing the best model using a power curve

The power curve is a graph which answers the simple diagnostic about a model:

- How many firms that the model categorised as having a relatively high probability of default have actually defaulted?
Dataset: we have 20 firms (named **A-T**). We observe that four of them have defaulted (**B, J, M, N**). Models: we have two candidate models **M1, M2** and their output probability of default for all the firms.

Model performance:

<table>
<thead>
<tr>
<th>Model</th>
<th>Decreasing order of Probability of Default (PoD)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1 2 3 4 5 6 7 8 9 10</td>
</tr>
<tr>
<td><strong>M1</strong></td>
<td><strong>B T M S R Q N J A C</strong></td>
</tr>
<tr>
<td><strong>M2</strong></td>
<td><strong>O P L D E F H G I K</strong></td>
</tr>
<tr>
<td></td>
<td>11 12 13 14 15 16 17 18 19 20</td>
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<td><strong>L M N D E F H G I K</strong></td>
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Example of two models and their output

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</tr>
<tr>
<td>M2</td>
<td>B    S    T    R    Q    J    A    C    O    P</td>
</tr>
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An example of the power curve

Model with no prediction capability
Model with perfect prediction capability

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Interpreting the power curve

- The $45^\circ$ line is the line of zero prediction.
- The step line close to the y-axis is the line of perfect prediction.
- The closer the model’s power curve is to the $45^\circ$ line, the worse the model is.
- Accuracy ratio is a relative and quantitative measure of the performance of one model compared to another model.
- The closer the model’s power curve is to the $45^\circ$ line, the closer the accuracy ratio is to 0.
- The larger the accuracy ratio, the better the model.
Replication of standard models

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Our innovations

- Examined all data for all accounting parameters from scratch.
- Estimated a threshold probit model.
- In addition, the best model also incorporates
  1. Ownership structure
  2. Industry effects
  3. Macro-economic effects
- We adapted the standard probit model to suit the credit problem better.
Value of our innovations

- CMIE Credit Model
- Moody’s proxy
- Altman’s Z-score 1
- Altman’s Z-score 2

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Models of default based on stock market data
Background

- Falls out as a consequence of the Black/Scholes option pricing formula
- Published by Merton in 1974
- Rediscovered in the late 1990s and operationalised by a firm called KMV
- Project for ICICI by Rajeeva Karandikar, Ajay Shah, Susan Thomas.
Shareholders have a residual claim on cash after debtholders have been paid.

The equity share is a “call option” - it gets the upside after debt has been serviced.

The market’s stock price and stock volatility is used to uncover $V_t$, the value of assets of the all-equity company.

This is used to compute the probability that debtholders might not get paid.
Why is this attractive?

- The stock market is a great processor of information.
- It looks at all the accounting data - and a lot else - and collapses it into visible data.
- Data is processed in realtime; you are not waiting for accounting data releases.
- As long as there is active trading, and speculative price discovery, this is interesting information.
The stock market had the Enron stock price down to $3 while it was still investment grade.

In India, share prices of ICICI, IDBI, IFCI, etc. crashed in the mid-1990s, reflecting their internal difficulties, well ahead of their distress becoming common knowledge.
Our testing strategy

- What happens to the Merton/KMV “Distance from Default” prior to the date of a credit rating agency upgrade/downgrade?
Key result

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Does the stock market get it before the rating agencies?, Rajeeva Karandikar, Ajay Shah, Susan Thomas, 2002.
The failure probability of banks
A natural application

- Apply the KMV/Merton model to measuring the failure probability of listed banks.
Example of results

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Example of results

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Systemic fragility in Indian banking: Harnessing information from the equity market, Ajay Shah and Susan Thomas, 2000
In later years

- We were pioneers in looking at bank fragility through stock prices.
- In following years, many people are doing weighted averages of bank-level DfDs, and interpreting them as a measure of the fragility of the banking system of a country.
Example of using KMV: Banks in S. Asian countries, IMF paper

Estimated One-Year Default Probability 1/
(In percent)

- India
- Malaysia
- Thailand
- South Asia
- Southeast Asia

May-02 to May-07
Example of using KMV: Indian banks, IMF paper

Distribution Quartiles of the Estimated One-year Default Probability 2/

(In percent)

75th percentile
50th percentile (median)
25th percentile
Where we stand
CMIE model: lack of traction with banks
CMIE has discontinued updating the defaults database.
There is no source of data on either defaults or loss given defaults.
Hence, there is no field of research on credit risk in India, either in academics or in industry.
Banks are only mechanically obeying RBI regulations, not thinking about risk.
The only thing feasible is to model the credit rating.
Neither supply nor demand for sophistication in credit risk modeling.
Only two rays of hope

- The stock market works, and it makes possible KMV-type models
- The CDS market (outside India) seems to be working.
Example of using CDS: ICICI Bank stock and CDS price
New lines of attack on data

- Can a liquid and transparent corporate bond market arise?
- Can a liquid and transparent credit derivatives market arise?
- These would produce information which can go into models.
- New players on these markets would demand analytical support.
- These two new markets would attack both the supply side and the demand side.
KMV/Merton strategy can be utilised for monitoring banks as well as monitor the banking system.

A sound reason for forcing banks to always have 50% of the shares with the general public!

Additional information would come out of a rule which forced banks to raise (say) 20% of their assets through non-insured bond issuance.

(Only works if these bonds are liquid and transparent as with equities).