INTERMEDIATE SUMMARY FOR DISCUSSION

MODELING CREDIT & SAVINGS BEHAVIOUR OF CHIT FUND PARTICIPANTS

A SUMMARY OF THE INTERMEDIATE OUTCOMES

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Small Enterprise Finance Centre, SEFC is a not-for-profit research organisation that combines applied research in economics finance and other behavioural sciences with a focus on persistent problem faced by SMEs in India. We seek to study how SMEs can foster growth and help alleviate poverty. We produce scalable solutions for SMEs by partnering with financial institutions, NGOs, and businesses in India that serve the SMEs.

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Outline
(with links to the slides)

Clicking this button anywhere in the slides will bring you here, outline page

Motivation

- The absence of efficient credit bureaus makes it costly for chit fund industry to collect information on clients' credit-worthiness.
- They rely on relationship with their customers to assess their risk
- From a financial inclusion point of view, these social networks appear to have great value – they inherently reduce the stringency of requirements for borrowers and savers when compared to the formal banking and financial institutions
- This unique feature, however, has not been maximised upon by the chit fund industry due to the heavy reliance on human judgment for decision making including its limitations such as unscientific biases
- A reduction in the risk exposure would very likely result in an increase in the acceptance rate of potential clients of lower income groups and thus the customer base of the company.
- An automated and uniform system of assessing prospective clients is required for supplementing the judgment of company officers and reducing the risk exposure of the company.

Credit Risk and Credit Scores

- **What is credit risk?**
- Credit risk refers to the risk that a borrower will default on any type of debt by failing to make payments
- The risk is primarily that of the lender and include

  lost principal and interest,

  Disruption to cash flows, and

  Increased collection costs

- **What is Credit Score?**
- A credit score represents a number or a grade for the creditworthiness of a person
- Lenders, such as banks and credit card companies, use credit scores to evaluate the potential risk posed by lending money to consumers and to reduce losses due to bad debt
- It based on a statistical analysis of a person's credit repayment behaviour and other characteristics

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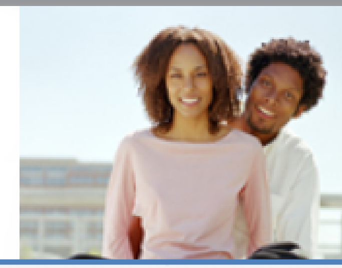
CREDIT REPORTS Printable Page

- Visa's Commitment
- Credit
- **Credit Reports**
- Debit
- Budgeting

Credit Reports

The 3 C's of credit: character, capital, and capacity
The 3 C's of credit refer to character, capital, and capacity. These are areas the creditor generally looks at prior to making a decision.



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The FICO® Score is a number that summarizes your credit risk. Lenders use it to make credit decisions, such as the interest rate you get when you apply for a loan.

Why FICO?

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Credit Score and Banks

- A paper published by Daniel Paravisini and Antoinette Schoar, explores how the introduction of a credit scoring model improves worker productivity at a bank in Colombia.
- It was found that Committees are more likely to make a decision when a credit score is available and improve the productivity of the firm.

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Dear Cardmember,

Nowadays we come across words like 'CIBIL', 'Credit History' etc., in the context of loans/Credit Cards. Citibank and CIBIL together bring you a customer knowledge series to explain these terms.

What is Credit Information Bureau India Limited (CIBIL)?

- CIBIL is India's first credit information company that maintains a centralized information repository on consumers and businesses regarding their credit history, as shared by its member banks and financial institutions.

Risks for the Chit Fund Company

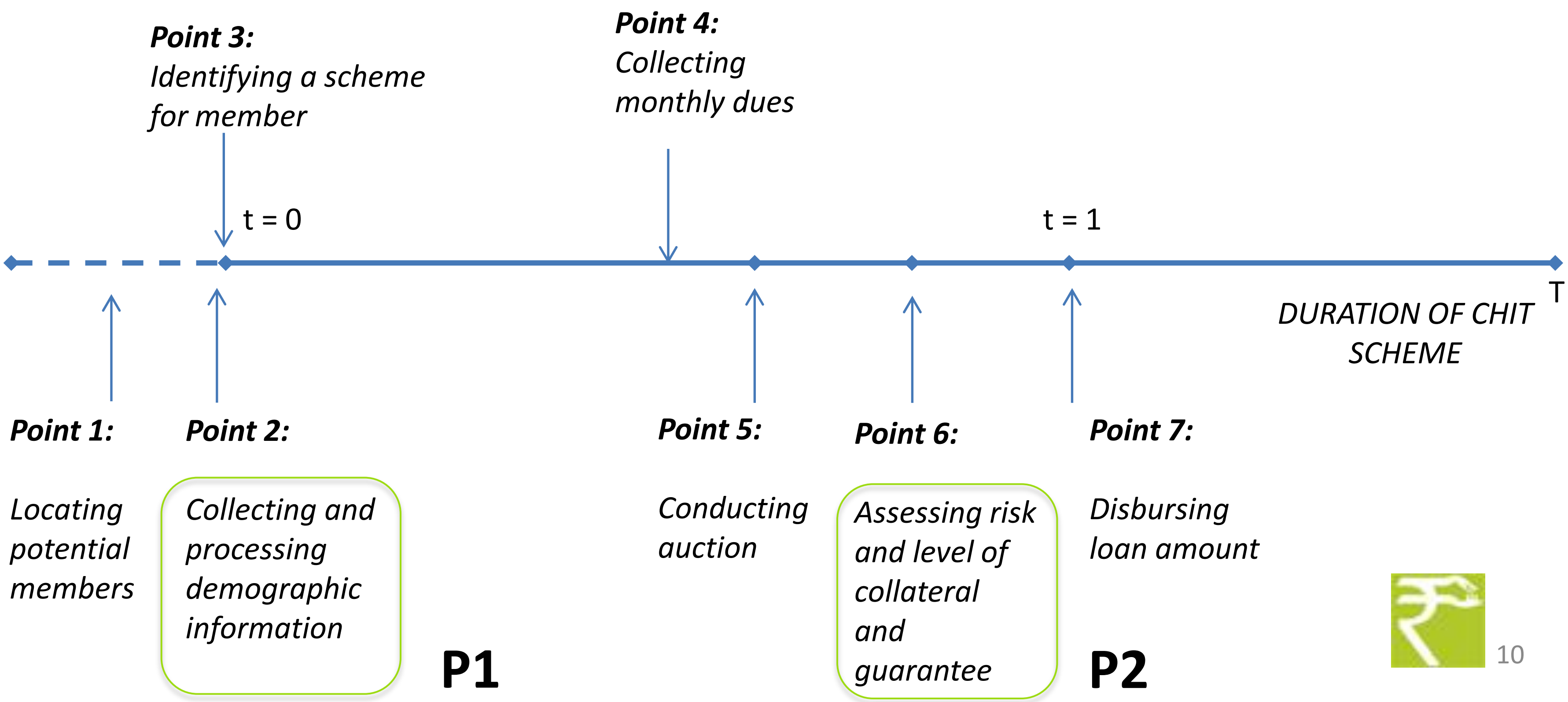
- Chit funds are like the banking industry:
  - Intermediary to mobilize funds from savers and channelize them to borrowers
  - Manage the repayment of loans from the borrowers so that savers may receive their dues when they make a claim

- Chit fund industry faces credit risk as their primary source of risk, much like formal banking

- Currently, chit funds function primarily based on social networks. Each client is introduced by existing clients and assessing credit worthiness or the borrowing or saving nature of the client rely on the relationship the introducer has with the company

Points for Assessing Risk

- Currently risky is identified based on the collection of information at point (2).
- This information is usually incomplete. Further on in the scheme, at point (6), the assessment of risk and the levels of surety or collateral required are again based on the information provided at point (2) – adding to the risks already accrued to the companies at point (2).
- Standardised statistical methods are needed at two points P1 and P2.



Data to Be Used For a Risk Assessing Algorithm

- At P1 Demographic information like age, income, gender, and type of occupation is collected by the companies. This information, coupled with historical information about the member – like whether they were members prior to the current scheme that they are joining, whether they had defaulted in their earlier schemes, how many years have they been part of the company, etc. – can improve the quality of assessing risk of the member.

- At P2, when the member has been participating in a given chit scheme for a certain period of time, and takes part in an auction, wins the auction and is about to claim the prized amount as a loan, another assessment needs to be carried out. At this juncture the transaction history is also available.

Sources of Data

- A large number of companies were willing to share their data
- We collected data from five different companies
- Finally only data from two (unnamed to protect privacy) companies was used for the purpose of modelling based on the criterion of completeness and usefulness

- The data collected for the study, had to be extracted from the documentation created at the four steps outlined before for all the 5 companies
- All physical records were manually entered by data entry operations at the location of the records
- Several tables thus obtained were collated, cleaned, and combined to form the final dataset
- This dataset is in a panel format, where all information is organised by name of chit schemes and by name of members of each scheme

Data: Details and Lessons

Overview

Total Number of Companies	**2**
Total Number of Schemes	274
Total Number of Members	4,936
Total Number of Tickets	9,318
Average Number of Tickets per Member	1.9
Time Period Covered in Dataset	1996 to 2011
Range of Chit Values	Rs.15,000 to Rs.10,00,000
Range of Monthly Contributions	Rs.500 to Rs.25,000
Range of Scheme Duration	20 months to 50 months

Demographics

- The gender ratio of members of the companies maintains an overall approximate average of 60 males for every 40 females. not be truly indicative , since, in the case of many female participants, the tickets were dummy tickets – bought by a male member of the family in the name of female members
- It may be useful to have this distinction, in the future since there may be a difference based on gender

- The average age of the representative population is above 40 years
- According to the demographic trend of the Indian population growth, a majority of the population lies in the age group 15-30; **in future younger populations should be the focus for the chit fund industry**

- The reported incomes of the members appear to be grossly understated. For the future, it might be useful to verify more correct income levels with Income Tax Return documents, or update this field regularly
- **This is important because disposable income of an individual may determine whether an individual can make the monthly contributions**

Occupation

Occupation Type	Number	Percentage
Private Service	2,218	44.9%
Business	770	15.6%
Others/Unstated Occupation	649	13.1%
Housewife	406	8.2%
Small Business Owner	301	6.1%
Government Service	298	6.0%
Retired	214	4.3%
Self-employed Professional	80	1.6%

Member Participation

- Both companies show a significant number of members who have returned to participate in schemes after participating in one scheme.

Number of Schemes taken part	Company 1		Company 2	
	Number of Participants	Percentage of Participants	Number of Participants	Percentage of Participants
1	3017	67.2%	192	43.1%
2	785	17.5%	96	21.6%
3	318	7.1%	56	12.6%
4	157	3.5%	22	4.9%
5+	214	4.8%	79	17.8%

- On an average, members wait for approximately 20 months before joining a new scheme.
- Almost 70% of the members, participate in more than one scheme at the same time.

Defaults and Irregularities

- By definition of the chit industry, defaulters are those individuals who have not paid their dues for more than three months.
- The industry focuses primarily on the group of individuals who default after taking the loan, but defaults before loans also causes the company to lose money, since the company is forced to pool in working capital.

Type of Behavior	By Members			By Total Transactions		
	Overall	Before Winning	After Winning	Overall	Before Winning	After Winning
Defaults	35.1%	20.4%	23.6%	4.0%	2.0%	2.1%
Late Payments	86.2%	66.9%	70.6%	16.3%	6.9%	9.4%
Early Payments	98.6%	95.9%	91.7%	72.3%	38.4%	33.9%
Part Payments	83.3%	60.8%	69.3%	12.0%	4.9%	7.2%
Lump-sum	99.8%	96.3%	89.3%	19.5%	9.4%	10.0%
Note: Defaults by members are calculated as the percentage of members out of the total members, who have defaulted at least once during the time that they participated in schemes. Default by total transactions is calculated as the number of times a member defaults out of all the transactions made by him/her. The same rules apply to the other types of irregular payment behavior that are considered.						

- More than 35% of the members have defaulted at least once nearly 24% of members who have defaulted after taking the loan
- Overall rate of default transactions remains at 4%, and 2% for the period after taking a loan
- These defaults rate are very much in line with what is observed in formal banks.

- Late payments, part payments and lump-sum payments also add to the credit risk
- Extremely high incidence almost 90% of members have made at least one late payment
- Close to 85% of the members have made at least one part payment
- Early and lump-sum payments are made by almost the entire population

- Being able to understand what drives this payment behavior is of central concern to the companies

- **Credit scoring model aims to understand these risks**

Repayment Irregularities

- Longer duration (>30 months) schemes indicate higher rates of default than shorter schemes, around 38% vs. 28%
- But this is not true, when you see the result in a new light:

Default Rates by Monthly Contribution

<table>
<tr><td rowspan="6">By Member</td><td rowspan="3">High Value</td><td>Overall</td><td>31.30%</td></tr>
<tr><td>Before Winning</td><td>18.50%</td></tr>
<tr><td>After Winning</td><td>20.00%</td></tr>
<tr><td rowspan="3">Low Value</td><td>Overall</td><td>34.30%</td></tr>
<tr><td>Before Winning</td><td>20.00%</td></tr>
<tr><td>After Winning</td><td>20.00%</td></tr>
<tr><td colspan="4">Note: High value schemes in terms of monthly contribution are those schemes that have monthly contributions greater than Rs.3,000. Similarly, those schemes with lesser monthly contribution than this benchmark are low value schemes</td></tr>
</table>

Repayment Irregularities

- There is some anecdotal perception in the industry that late payments and defaults increase in frequency around festivals
- No such seasonality in the data for late payments

Explaining Our Model

- Choose a possible dependence of default or late payment
- Check this dependence on a large number of data
- See how much does each parameter effect (coefficient), and if that is true for a good enough number of cases (statistical significance)
- For example default or late payment may have something to do with age, gender, income
- So we make a model, lets say chance of default can be related to age
    - **Chance of default = x*age + other things**
- Which means that as the age increases by one year chance of default in a group will increase or decrease by x%
- Similarly for male/female can be added to this explanation:
    - **Chance of default = x*age + y*male + other things**
- And many more such descriptions such as income, profession, etc.

Model Results and Learning

- If a member participates in an additional scheme, his/her tendency to default **at least once** during the duration of a scheme increases by 12%, and default after winning by 5%
- The longer a person has been a member of a company, the greater the chance of him/her defaulting in the saving period, BUT a lower probability of defaulting as a borrower
- An increase in the age of the member, results in an increase in the total defaults after winning at a decreasing rate
- Male members tend to have a 6% higher rate of defaults after winning than women
- If the duration increases, the probability of an average person defaulting at least once in the scheme increases. It doubles from 25 month schemes to 50 month schemes.

Credit Scores: Predictions of the Algorithms

S. No.	Occupation / Income Category	Score 1 (5)	Score 2 (5)	Total Score at joining (10)
1	Self Employed Prof., High Income	2	0	**2 – least risky**
2	Government Service, Low Income	2	1	3
3	Government Service, Medium Income	3	2	5
4	Government Service, High Income	3	4	7
5	Private Sector, Low Income	5	2	7
6	Housewife, Low Income	6	2	8
7	Private Sector, High Income	5	3	8
8	Private Sector, Medium Income	5	4	9
9	Housewife, High Income	5	5	10
10	Self Employed Professional, Low Income	5	5	10

Credit Scores: Predictions of the Algorithms

S. No.	Occupation / Income Category	Score 1 (5)	Score 2 (5)	Total Score at joining (10)
11	Self Employed Professional, Medium Income	5	5	10
12	Small Business Owner, Low Income	8	2	10
13	Small Business Owner, Medium Income	8	2	10
14	Retired, High Income	10	1	11
15	Housewife, Medium Income	7	5	12
16	Small Business Owner, High Income	7	5	12
17	Retired, Medium Income	10	3	13
18	Business Owner, Low Income	10	4	14
19	Retired, Low Income	9	5	14
20	Business Owner, Medium Income	10	5	**15 – most risky**

Some Real Examples

- **Random Example of Self-Employed "High Income"**
  - Age: 20, Chit Value Rs. 100,000, duration 40 months
    - 35/40 early payments, 5/40 late payments, no default

- **Random Example of Business Owner "Medium Income"**
  - Age: 45, Chit Value Rs. 100,000, duration 40 months
    - 10/40 early payments, 20/40 late payments, 2 default periods

Conclusions

General

- First important step towards better risk mitigation would be collection & updating of comprehensive demographic & background details of members
- There is a need for standardization of collateral & surety requirements
- Chit fund companies can easily expand their business volume if they can operate large no. of low value schemes and focus on getting young members

Before Winning Chit

- Increases bids increases chances of default
- Longer a member has been with a company is also an Indicators of high default at the time of joining
- Demographically most risky groups at time of joining:
  - Middle aged, male business owners
  - Retired individuals with medium and high income

Conclusions

- Demographically least risky groups:
    - Self-employed professionals with high income
    - Government servants with low income

At the Time of Borrowing

- Repeated borrowing at an early stage, large number of late payments, and frequent auction participations increase default risk
- Most risky demographic groups are Business owners with medium and high income
- Least risky groups are self-employed professionals with high income.

Recommendations

- Digitization of older and existing information with chit funds and updating it regularly
- Automation of credit scoring model on existing and prospective clients
- Industry entrepreneurs should take this algorithm and make it into a commercial product
- At a much later stage set-up of a chit fund credit bureau – to share data between chit funds to assess credit worthiness of a client

Thank You

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