Lending Technologies

Atul Kedia

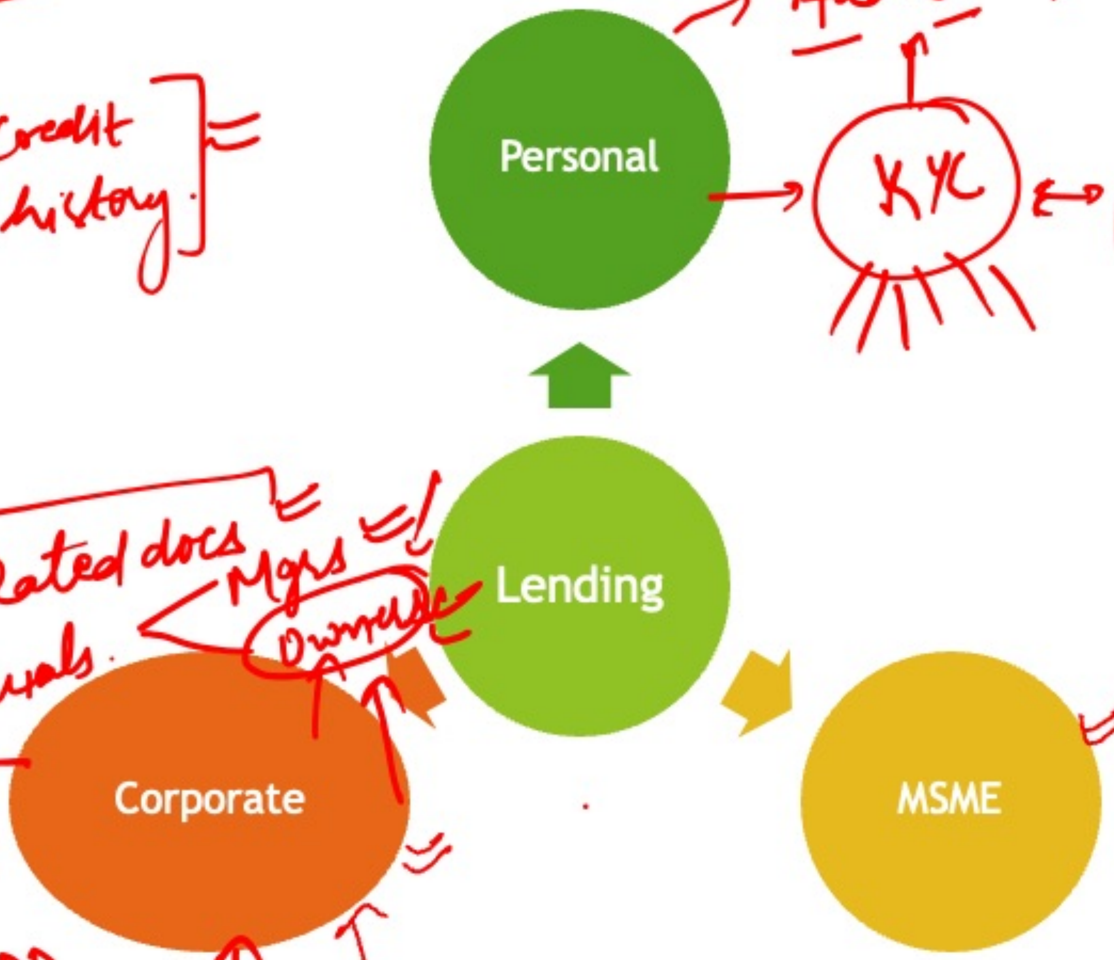
Managing Partner, Light Hill Capital

atul.kedia@iiml.org

Lending

KYC – AML / CFT – International

→ Bkgnd check – ? credit history



→ Aadhaar + CIBIL (PAN)

KYC ↔ Risk Asst.

Credit Risk
Repayment
Delay
Downgrade Rating

CDF
Risk

ABC Ltd
→ Co. related docs
→ Individuals
Mgrs
Ownership

UBO

Amit Kumar

EDD

COF + $\boxed{\text{margin}}$ →
7%

Lending

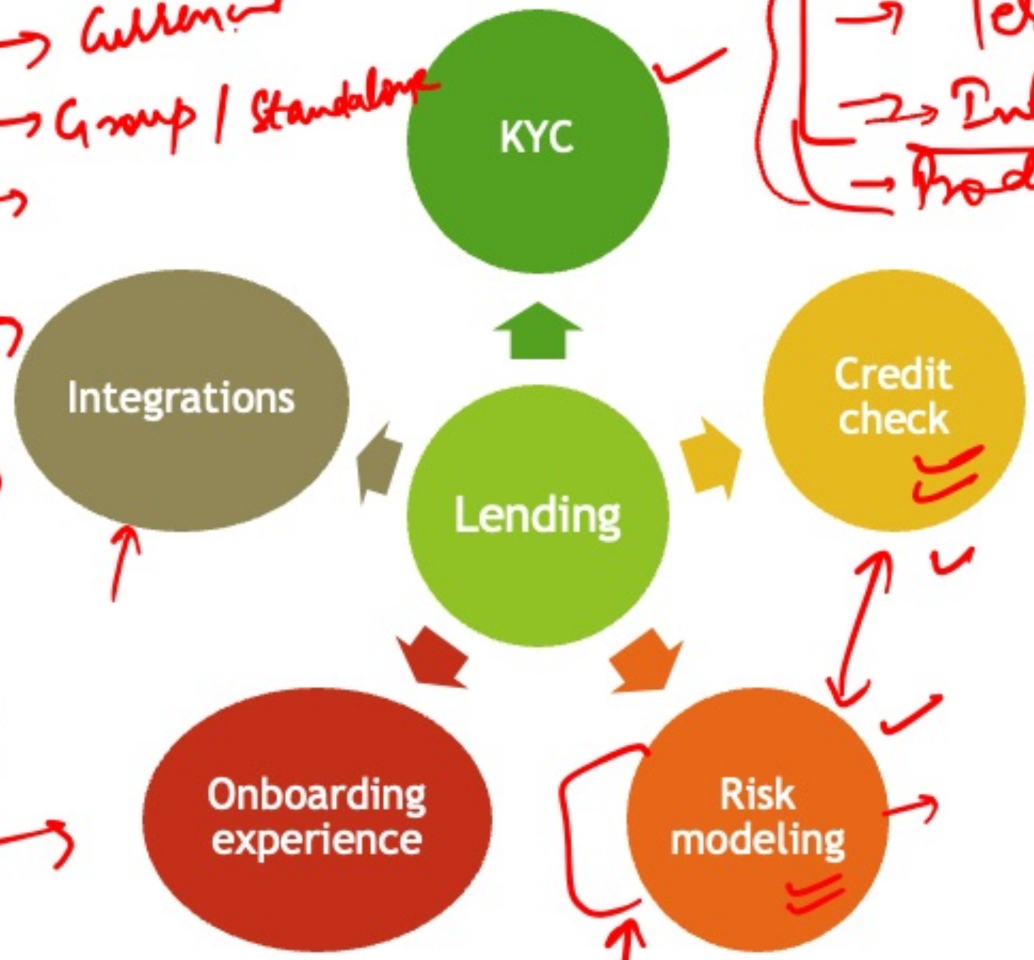
A+ A−
2L 50K
1yr 11m
11% 20%

Cap. Req. = F(RWA)
Expensive

Inputs
→ BS, P&L – Ratios
→ Countries
→ Currencies
→ Group / Standalone
→

Credit Risk model → Output ?
→ Y/N
→ Amount
→ Term
→ Interest rate
→ Products →

CIBIL report
+
Income
+
...... (industry)



→ Initial
Continuous Monitoring

→ Risk of default
↳ Prob. of default.

Variables

Financial (Quant) + Qualitative ⇒ Risk Rating

- Debt / Equity ratio ↑ Risky
- Profit / Sales ↑ Better
- Coverage ratios DSCR
- 10 ratios
- Size 10 Cr / 100 Cr / 1000 Cr

50

B

- Neg. audit 1 → 0, 0 → 5 (2 – 10)
- Currency exposure: Hedge / Unhe.
- Imp. for the country (Scores)
- Default history
- Quality of mgt. → Scores
  - Continuity -- 3 yrs → 5, → 0
  - Total no. of yrs of exp. of BOD →
- Auditors: 1 → 5, 0 → 0
- Group linkages

Adjusted with qual. factors → A-

Risk Rating: A+, A, A-, B+, B, B-, ⋮

Prob. of Default (%)

Scores (Marks) 1-10 (Matrix of scores)

5 Co.	DE	NP	DSCR
A	0.1	10%	
B	0.5	20%	
C	0.9 (2)	25% (6)	(6)
D	1.5	17%	
E	0	30%	

Wts (Weight)	DE	NP	DSCR
	1/3	1/3	1/3
	20%	20%	60%
	50%	10%	40%
	1	0.6	2.4

= 4.0 Total Quant Score (Co. C)

DE		NP		DSCR
≤ 0.1	10	> 40%	10	
0.11 – 0.2	8	30 – 39%	8	
0.21 – 0.3	6	⋮		
⋮	2	⋮		

$\xrightarrow{9m}$ Def

8+ → A+

7+ → A

⋮

4 → B →

Variables ?

'Salary' = Exp. yrs. + Desig. Quant + Age + Cur Sal + M/F + Edu yrs. + Orig exp

VP 10
AVP 8

[Dependent] → Ind. Var. → Data Analysis

Regression

Sal.
- 3L
- 4L
- 5L
- 5.1L
⋮
100

~~Height → Age + Gender + ...~~

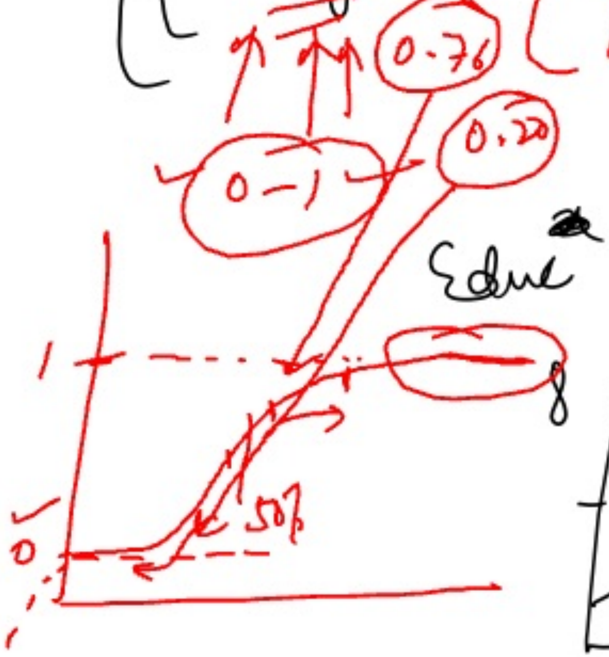
	Sal.	Exp	Desig.	Age	M/F	Edu
E_1	5L	5	6			
E_2	6L	6	7			
E_3	6.5L	7	7			
E_4	4L	6	6			
⋮						

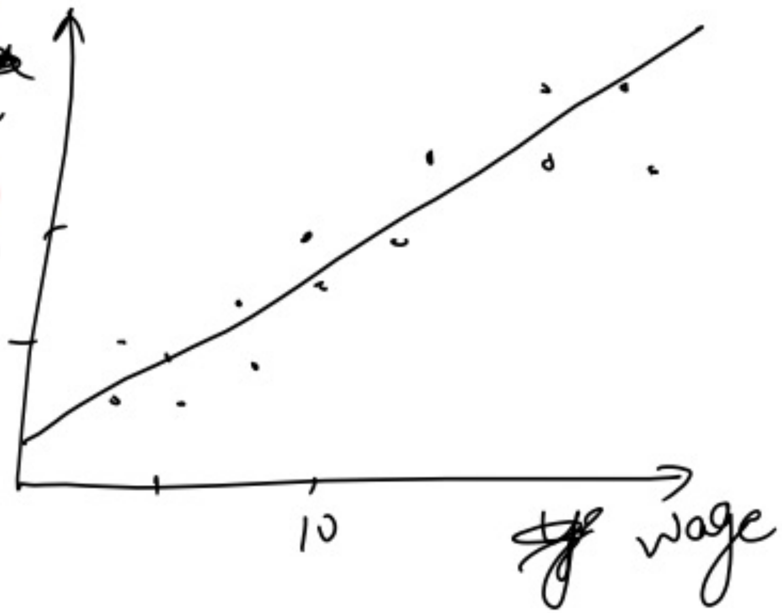
AD % → 0% → 100%

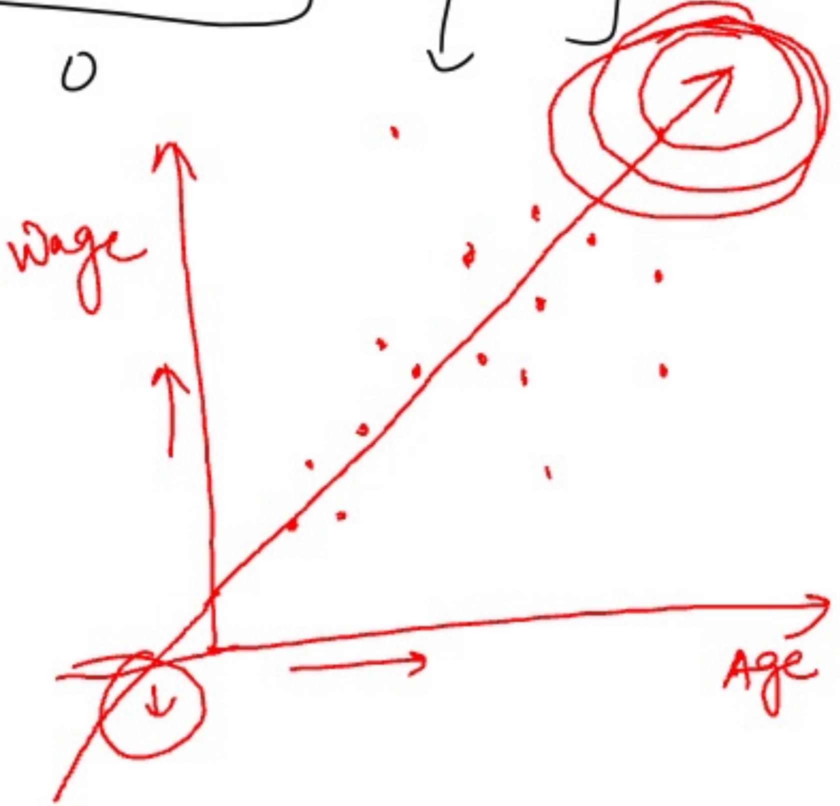
0 – 1 $\quad$ [0, 100%] $\quad$ 0.0001

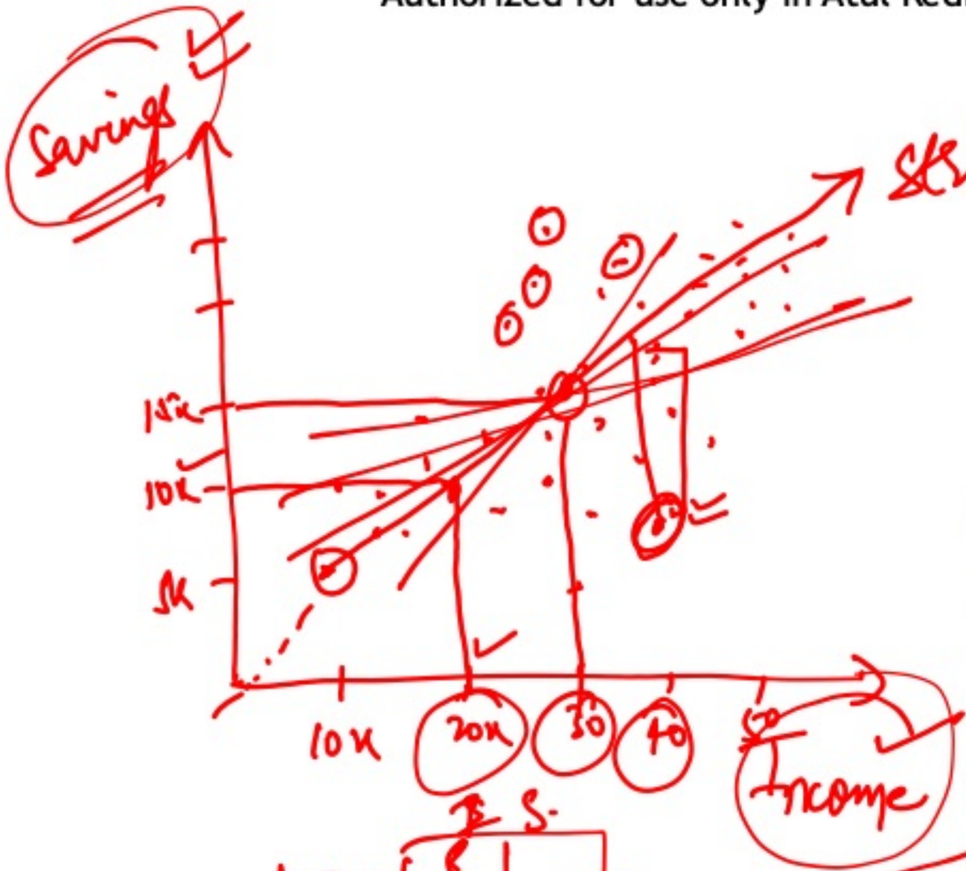
$$\boxed{Wage} = 0.60 \times Educ + 0.064\,Exper - 2.15\,Female + -1.73$$

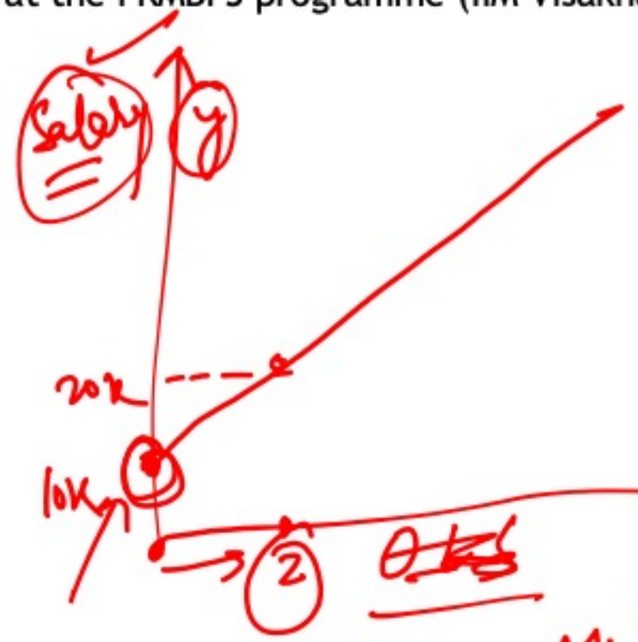
$$wage = \{0.60 \times 10 + 0.064 \times 6 \underbrace{- 2.15 \times 1}_{0} - 1.73\}$$











$y = \alpha + \beta x + e$

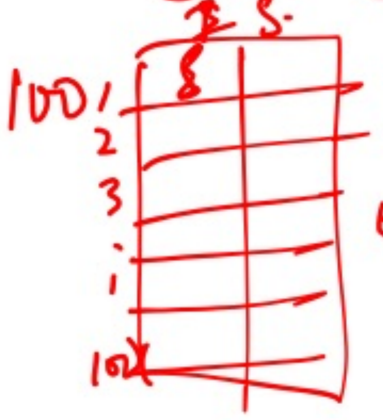
Salary = Intercept coefficient

Savings

Expr (yrs)

x

Min (e^2)



Savings = x% of Income + errors

y (Avg) x

50%

5K = 1 + 50% x 10K

+500Rs. +1K

Savings = ___ + β ~~Consump~~ Expenses ↑

S	Exp
3000	5000
2600	6000

40%

$$y = \alpha + \beta x$$

$$y = \alpha - 40\% \times x$$

→ Sign of coefficient

Marginal Effects ⟶ Magnitude of coefficient (rate of change in simple regs.)

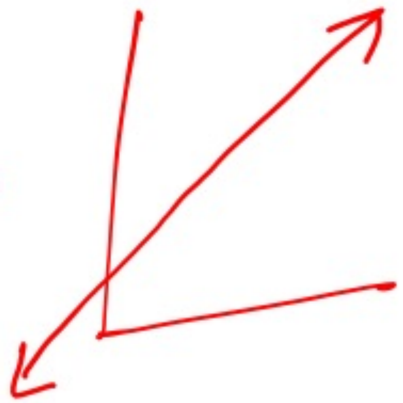
OLS

Dep Var. Ind. Var.

[Salary] → Age, Educ, Expr., M/F, - - - -

Continuous variable

$$y = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \dots + e$$



?

N L

credit risk model

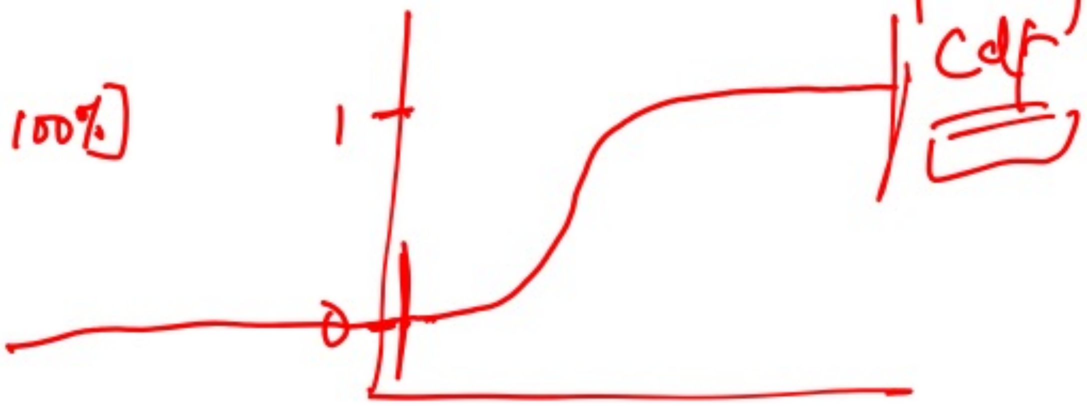
Probit / Logit

[Default] → D/E, Inc, Age, gender, educ, loan amt. - - - -

0 1

=< 0.50 0 [0, 100%]

> 0.50 ≤ 1.0 1



OLS Regress → Coeff = Marginal Effects (Rate of change)

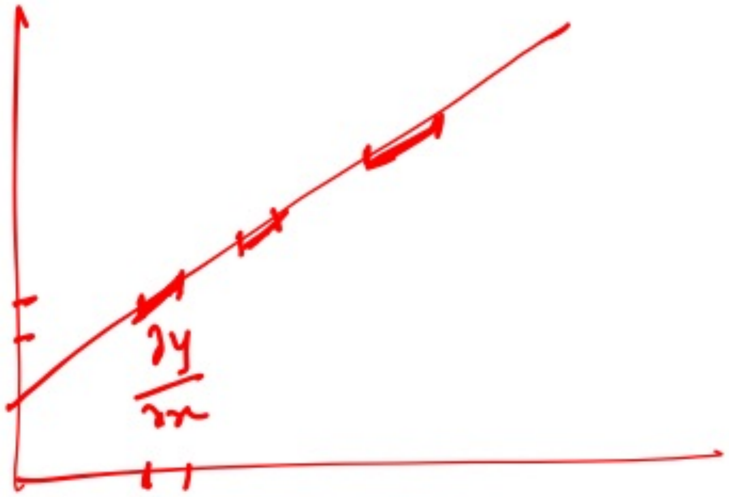
$\frac{\partial Y}{\partial x}$

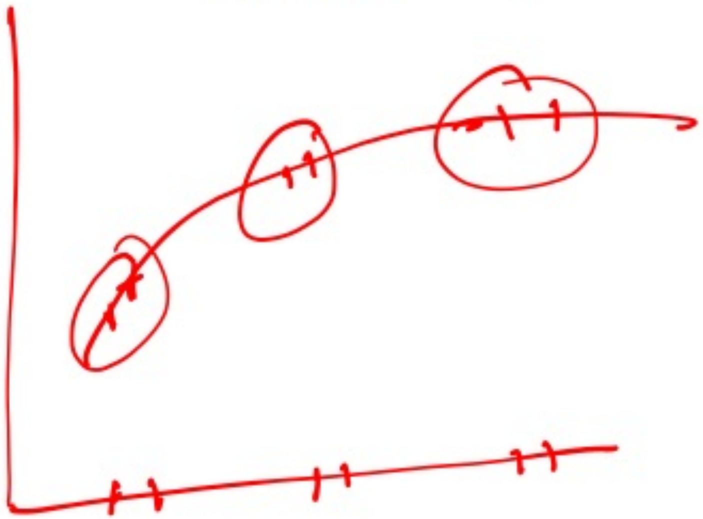
βX

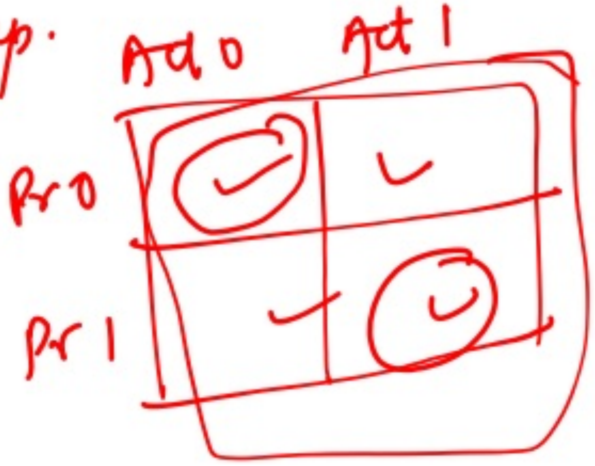
$= \beta$

Probit/Logit → Coeff ≠ ME

need to be calc. sep.







Source	SS	df	MS
Model	1179.73205	1	1179.73205
Residual	5980.68226	524	11.4135158
Total	7160.41431	525	13.6388844

Number of obs	=	526
F(1, 524)	=	103.36
Prob > F	=	0.0000
R-squared	=	0.1648
Adj R-squared	=	0.1632
Root MSE	=	3.3784

wage	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
educ	.5413593	.053248	10.17	0.000	.4367534	.6459651
_cons	-.9048517	.6849678	-1.32	0.187	-2.250472	.4407687

$wage = \alpha + \beta x + e$

$$\boxed{y = -0.90 + 0.54x + e}$$

$4.5 = -.9 + .54 \times 10$

$.54x + 1$ (May diff)

$+ .54$

$= 5.04$

Real data

Predicted data $\rightarrow \hat{y} = \alpha + \beta \bar{x}$

$p < 0.05$

Variable is significant

1, ND = 0

Default   Age   Income   Loan

PD ↑   0.63   = [0.023 × 50 + 0.0012 × 5L + 0.123 × 3L]

PD ↓   0.27

Pricing a loan

$\frac{15\% \text{ RoI}}{x \text{ Advances}}$

Yab. COF + x% 5%

Premium

→ op cost

→ Riskiness

$RWA \times 11.5\% = Cap \uparrow$ (expensive)

Risk of default

Assets [A+ vs B-]

5%	15%
A+	B-

Credit Risk

Ind. Var.

Result (Dependent)

Prob. of default

%

	Amt of loan	Type of loan	Tenure	Age	Default
A	100K	Uns.	1	36	1
B	150K	Sec.	3	38	0
C					
D					
E					

Data

Sec = 1 → Tata Gtee

Unsec = 0

Def = 1

No def = 0

Binary Variables

Dummy

Default = [Amt of Loan + Type + Ten + Age

Past

Digital lending

→ Income (Sal slips, ITR)

→ CIBIL Report — Loans, Repayment

→ Education → PG — IIM, T2, Lower

→ Bank statements

→ SMS → Purchases / Bank transactions / Electricity

Apps installed? → Credit / loan apps / social media / ... (Reminders)

Credit decision?

→ Call history → No. of missed calls?

→ Geo location →

Present + Future

Alternative Data

→ Smm

X

Borr. → App ⟷ NBFC / Bank

2 m

AA / API int

– Aadhar

– CIBIL

College (Var3)

Edu (Var1)

Race (Var2) X

80% B

90% W

85%

95%

Credit checks and risk modelling

- Initial credit checks
- Ongoing credit monitoring
- Sources of data
- Risk and EL modelling
  - PD, LGD, EAD
  - VaR
  - Others
- Impact on balance sheet

10L Investment

Shares

1day (Max loss ?) → 99%

~~Daily Volati~~, Max loss

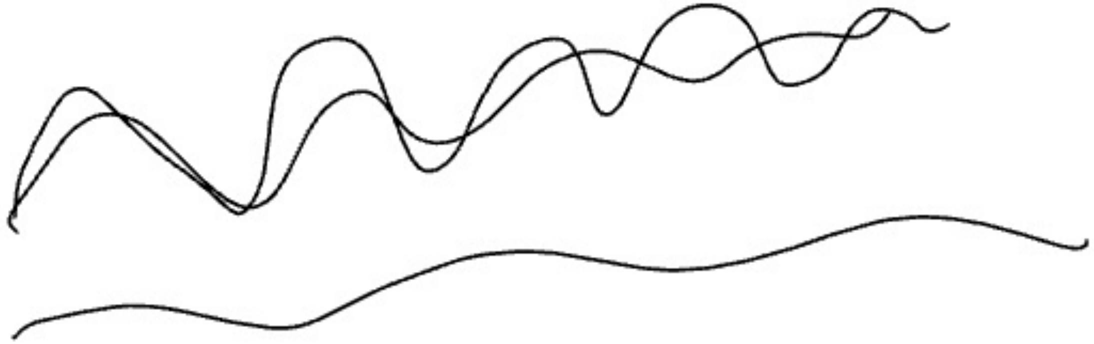
5000

495

Conf Int → 99%

Duration

1d



Bank

6m

93

1yr

95/-

ABC Ltd

85

USDINR

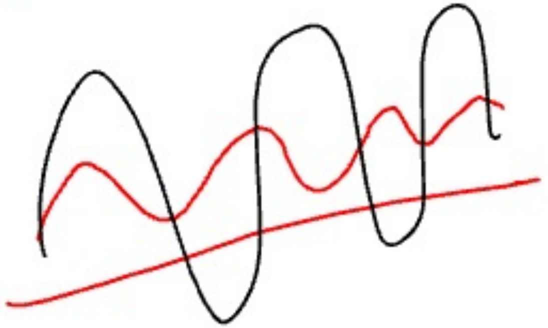
Bank to ABC

1yr $1m

90/-

ABC to Bank

VaR

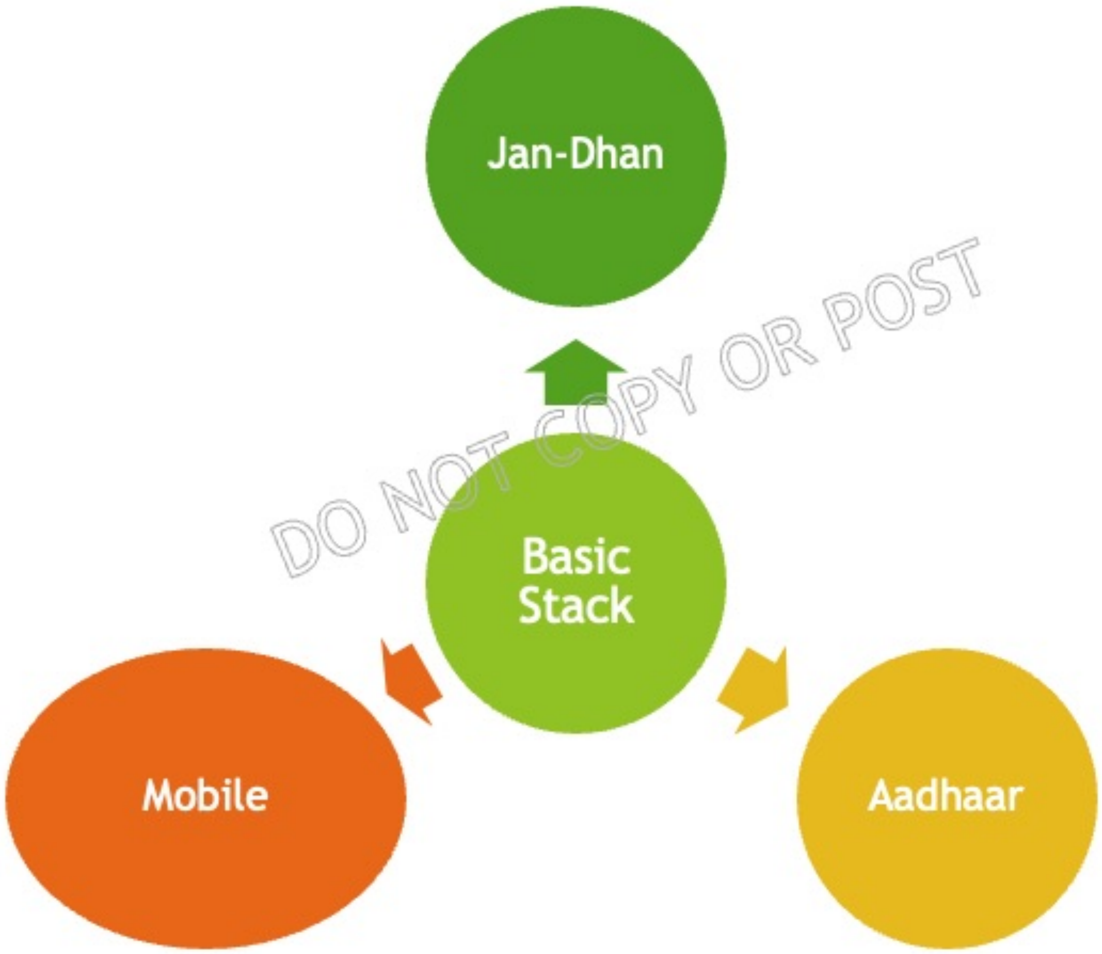


Credit Risk / Default Risk

Lending in personal space - issues

- The issues with KYC
- Cost of acquisition
- Sources of data for credit analysis
  - Reliability on CIBIL
  - No credit history

Tech enablers



Digital Lending

- REs shall ensure that all loan servicing, repayment, etc., shall be executed by the borrower directly in the RE's bank account without any pass-through account/ pool account of any third party. The disbursements shall always be made into the bank account of the borrower except for disbursals covered exclusively under statutory or regulatory mandate (of RBI or of any other regulator), flow of money between REs for co-lending transactions[2] and disbursals for specific end use, provided the loan is disbursed directly into the bank account of the end-beneficiary.
- REs shall capture the economic profile of the borrowers covering (age, occupation, income, *etc.*), before extending any loan over their own DLAs and/or through LSPs engaged by them, with a view to assessing the borrower's creditworthiness in an auditable way.
- REs shall prominently publish the list of their DLAs, LSPs engaged by them and DLAs of such LSPs with the details of the activities for which they have been engaged, on their website.
  - https://personalfinance.adityabirlacapital.com/pages/individual/platform-partners.aspx
- Reporting to Credit Information Companies (CICs)

Digital Lending

- Who regulates lending partners (banks / NBFCs)?
- Who regulates LSPs / DLAs?
- Why were many apps / lending platforms banned recently?

DLG

FLDG

RE ⟷ LSP

default?

Aditya → One97

Birla

→ 100% of respon. X

20cr → One97

limits

10cr

5% Max

SDL

1cr def

→ Cap. Adeq.

→ RBI reg.

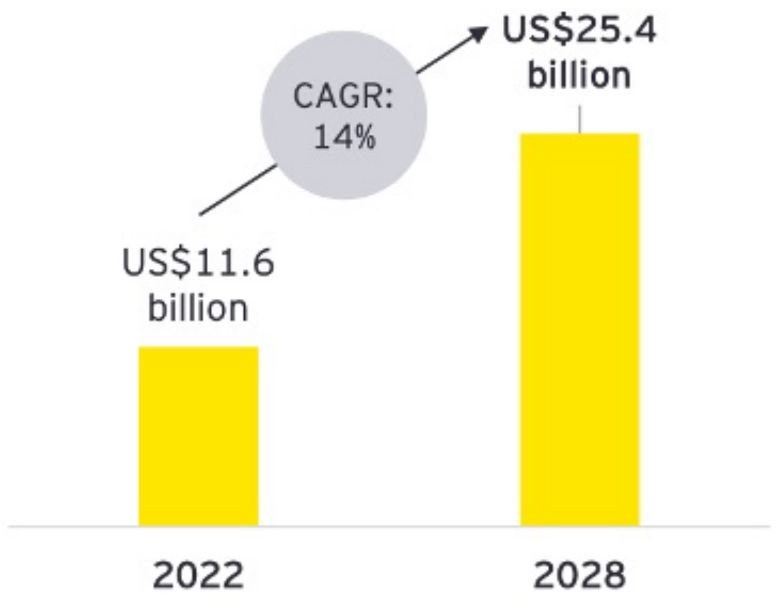
→ Gtee → RBI X

→ Gtee X → Ad. Birla X

5%

BNPL

BNPL Gross Merchandise Value, 2022-2028E



Leading BNPL providers in India

- LAZYPAY
- CAPITAL FLOAT
- OLAMONEY POSTPAID
- Simpl
- Paytm POSTPAID
- zest EMI FOR EVERYONE
- amazon pay
- Bullet UPI Now, Pay Later.
- sezzle

Source: EY

MSME lending – issues

- Majority MSMEs still do not have access to formal credit
- No credit history
- Cost of analysis
- Sources of data
- Cost of collection
- Cashflow lending to MSME – the missing piece
- Small Ticket Short Tenure Loan – practically unthinkable
- High interest cost / no credit

PD

Corporate

Financial Statements

Credit Risk Model

50% p.a. loss

NBFC

QR

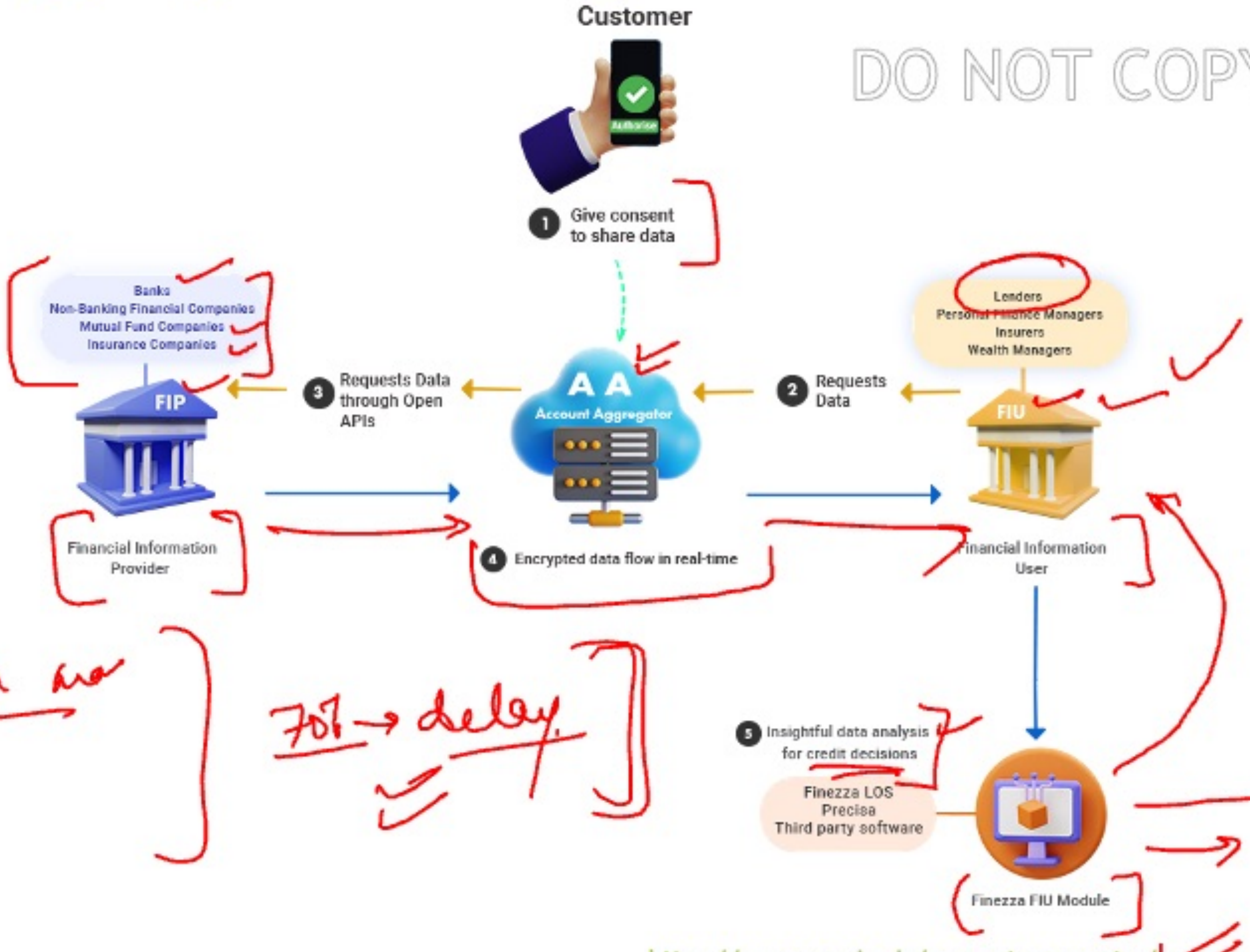
Exp

CF A/c

500 x 100 = 50,000

48%

Account Aggregator Integration



Set ev fun ma

→ 2-3%

70% → delay

https://www.precisa.in/account-aggregator

Account Aggregator Ecosystem

Source: tigerfeathers.substack.com / Sahamati

Information asymmetry

- Suppose a buyer walks into a dealership to buy a used car. Cars can either be high quality or low quality with equal probabilities. The value of a high-quality car is $20,000, and the value of a low-quality car is $10,000.

$E(x) = 15k$

- How much are you willing to pay for the car?
- If the seller can perfectly observe the type of car, but the buyer can not.
  - "How much is the buyer willing to pay for the car?"

Borr.

lender

- Who knows more about the creditworthiness of a borrower: the borrower or the lender?

'Newer' sources of information!

Indian banks are testing out mining customers' cell phones for clues about their creditworthiness in a fast-growing personal-loan market.

Ecommerce activity
Companies can share data on users' purchase and payment history.

SMS
Banks can look at SMS inboxes to analyze messages they get about transactions.

Location
A phone's location can reveal an applicant's address.

Social media
A profile could reveal if an applicant has told the truth about a job or family circumstances.

Call logs
The information shows how many missed calls an applicant has and how often they respond to them.

Phone type
Lenders can see what type of phone or connection an applicant is using.

https://www.wsj.com/articles/are-you-a-credit-risk-indian-banks-dig-deep-in-your-phone-to-find-out-1511433007

Use of Alternative Data

- Alternative data sources for credit analysis

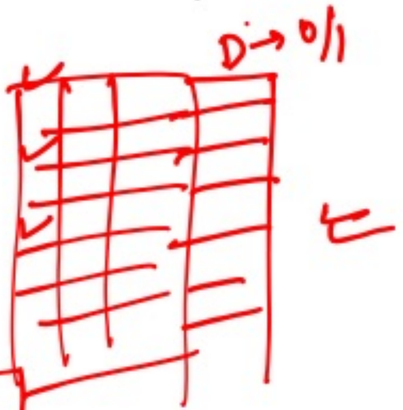
- How and why does alternative data help to mitigate information frictions?

- Is the use of alternative data "fair"?

Is the use of alternative data "fair"?

- Borrowers get expanded access to credit, lenders get better risk assessment. What's the catch?
- Alternative variables used by underwriters may be correlated with ethnicity, race, gender, age, or other protected characteristics that lenders, by law, cannot consider.
- *A borrower's "online footprint" (e.g., device, operating system, time a purchase was made) was correlated with the likelihood of default. Do you think that the use of such data promotes fairness?*

10-11 am] A →
1-2 pm] B →
8-10 pm] C →
HW



Profit → Alt. [illegible]