



## An Approach using Machine Learning and Alternative Data

“ Troubles for India's credit markets kicked off in 2018 when IL&FS Group unexpectedly defaulted on its debt, creating a challenge for many financiers, which are now struggling to roll over borrowings.

”

--Al Jazeera

“ Mounting debt failures in India have been catching rating companies off guard, underscoring continued challenges a year after the landmark failure of shadow bank IL&FS increased scrutiny of the industry.

Defaults at companies including Dewan Housing Finance Corp., Cox & Kings Ltd. and Altico Capital India Ltd. have occurred even as their long-term ratings indicated very low to moderate risk of non-payment.

“Raters have not been able to detect stress in time,” said Ashutosh Khajuria, a chief financial officer at Federal Bank Ltd. “Cutting credit profiles after the defaults are no rocket science.”

There’s a lot at stake as India tries to navigate a shadow-banking crisis and expand its debt market. The lack of more forewarning on payment problems has fueled questions about the quality of ratings and could keep some investors away from corporate bonds, hindering market development.

”

-- [www.business-standard.com](http://www.business-standard.com)



The 3 major impediments to current credit rating procedure or system are

### **Conflict of Interest**

The agency doing the rating is paid by the very entity seeking the rating thereby making the process susceptible to rating shopping etc.

### **Exclusive Reliance on Public Data**

The data sources are largely limited to fundamental data (i.e. P&L and balance sheet data) which is often open to being 'managed' so that it looks acceptable/good.

### **Fragile Design**

The current way of arriving at a credit rating is fragile in the sense that it involves a lot of calls based on human judgement and intuition. It does not always draw upon the entirety of empirical evidence available.



## How we are tackling these challenges



### **Independent Agency**

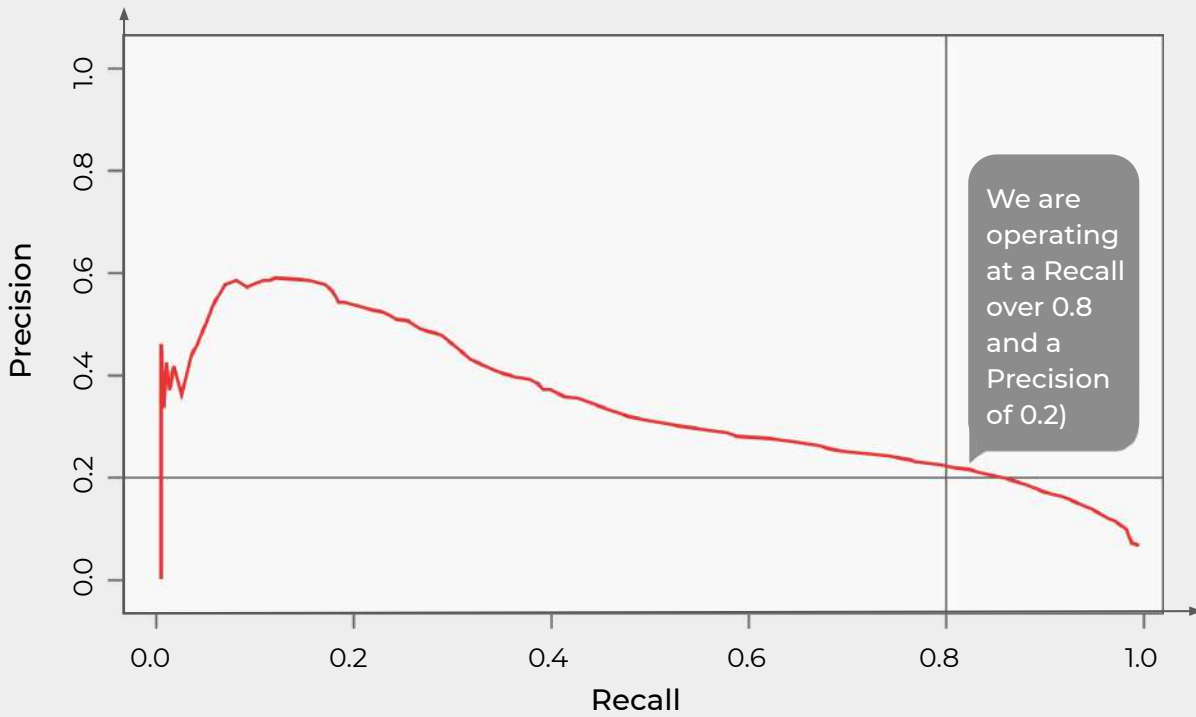
Not paid by the company getting reviewed, which allows for an unbiased approach.

### **Alternate Data Sources**

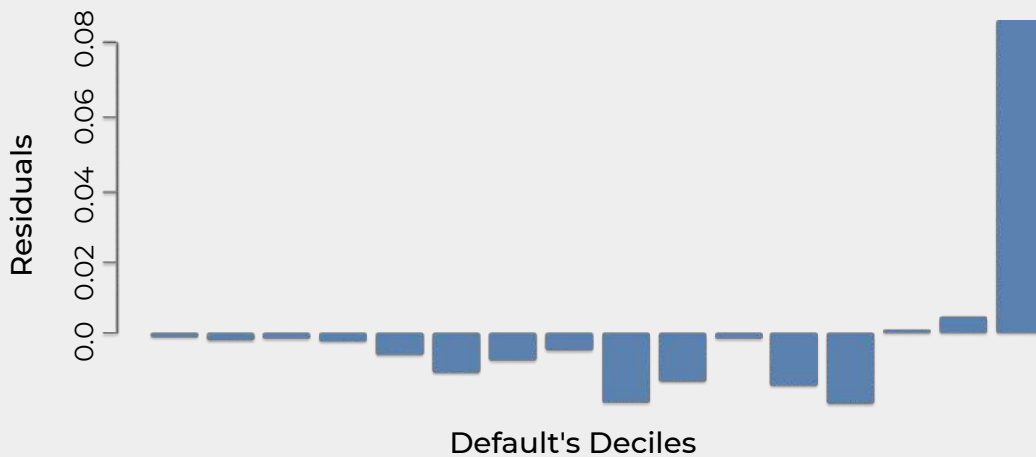
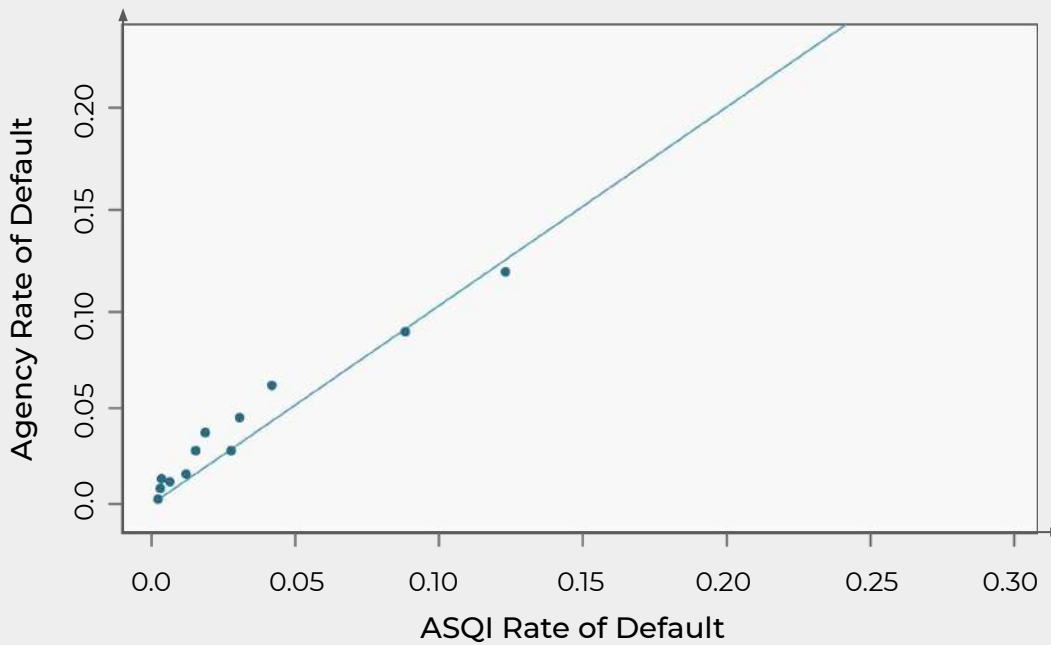
We rely on newer sources of data besides fundamental data giving a faster and different perspective to the incumbent approach.

### **Automated Process**

An automated and reproducible approach which allows us to be objective in how we come with rating or probability of default. Any errors or flaws are systematic in nature which can be improved and worked upon.



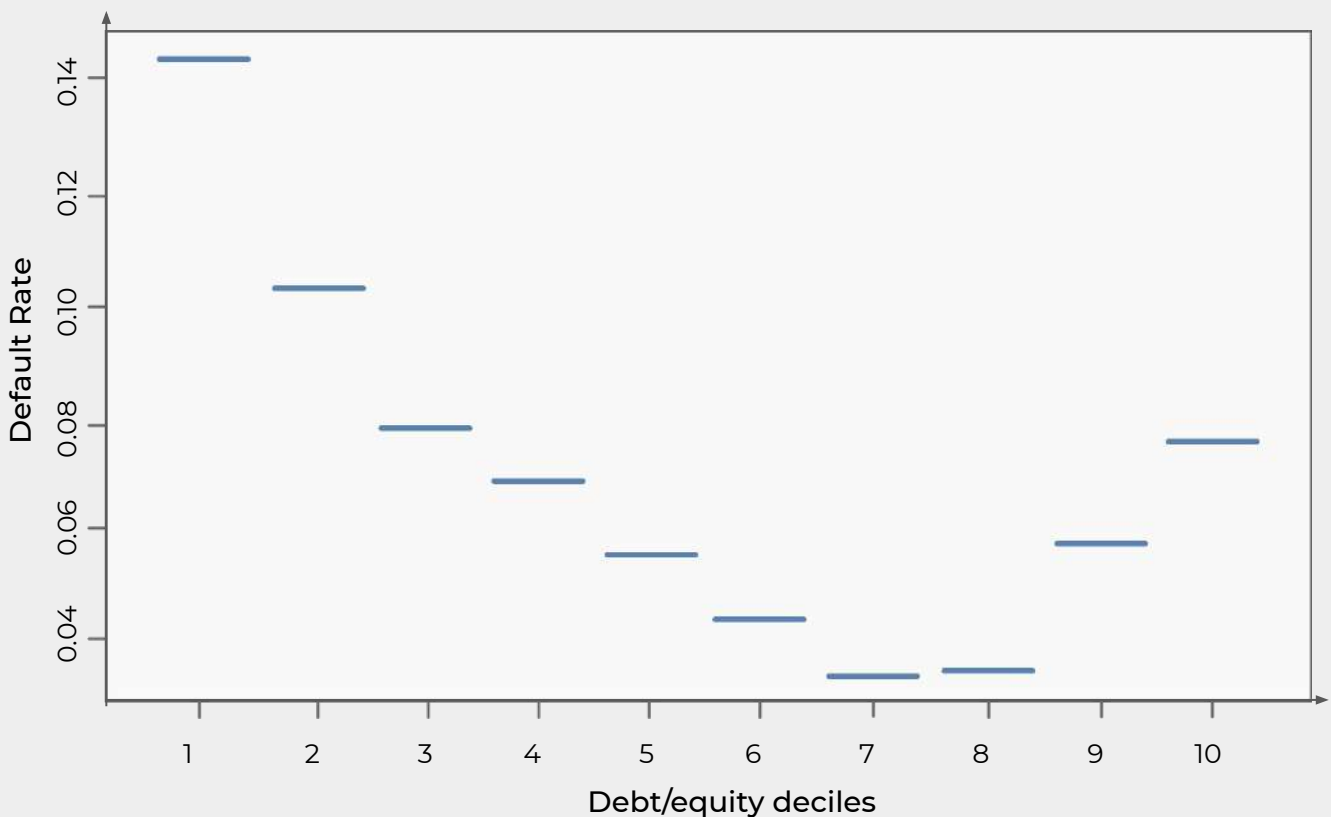
Precision in this context is defined as how many of the defaults we predict, go on to default and recall goes as, how of all defaults, are we able to get in our basket of predictions.



- We have a negative bias in the lower default regions and a positive bias to the default rates in the higher risk areas.
- We expected the divergence to widen as we add more alternate and non-traditional sources of data
- Use of advanced modelling techniques like machine learning and ensemble learning allows being able to capture and model the non-linear aspects and patterns in the data.
- Objective framework based approach makes our approach robust. It can tell us why we got the results we did and why we could get some answers wrong.

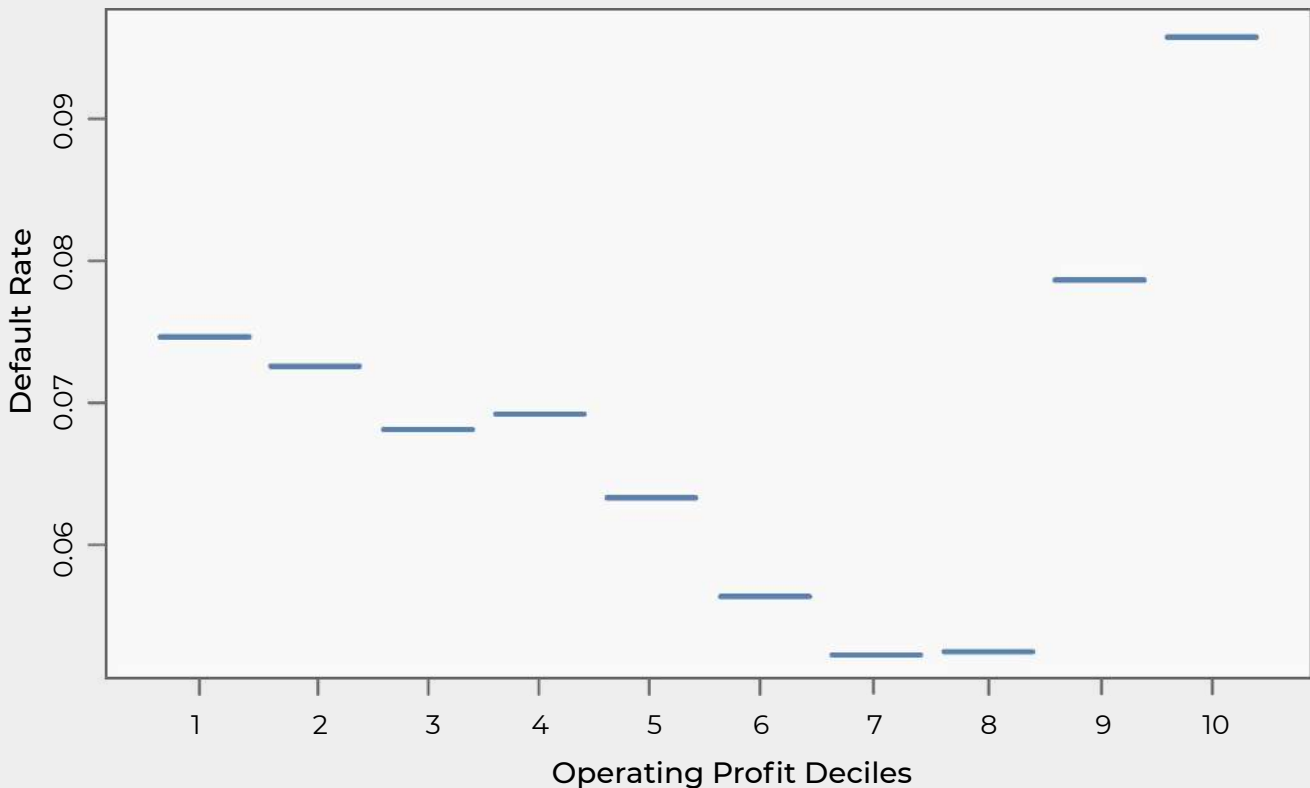
## Debt/Equity Ratio

- The behaviour has very different dynamics than popular perception. There is a right balance between the two which yields the lower default rate compared to spikes for both lower and higher deciles.
- The 10 deciles are ordered in terms of worse to good. Decile 1 has the highest debt to equity ratio. Decile 10 has the lowest.
- Contrary to popular perception, it's not a monotonic fall in default rates with lowering debt/equity ratio.



## Operating Profit

- There is a spike in default rates when we reach the higher deciles? Why there is a good chance, this is due to some amount of management in the numbers for the specific company.
- The 10 deciles are ordered in terms of worse to good. Decile 1 has the lowest operating profit. Decile 10 has the highest operating profit.
- Contrary to popular perception, it's not a completely monotonic fall in default rates with increasing operating profit.





## Current Interesting Lists

"We have only presented a small subset of companies with a moderate probability of default (i.e. the list excludes companies with higher than this and somewhat lower but still significant probabilities of default). For the complete list of companies and their respective probability of default (in next year), reach out to us at [asqi\\_ia@asqi.in](mailto:asqi_ia@asqi.in)"

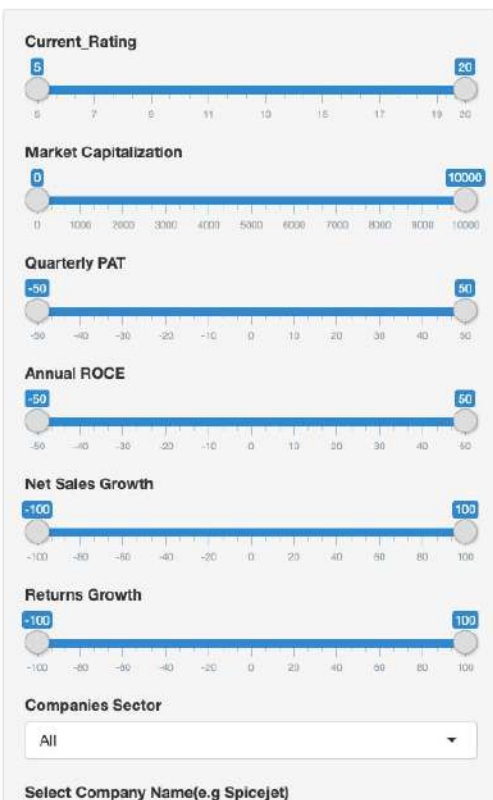
Company_Name	Sector Probabilities	
[REDACTED] Ltd.	Chemicals	19.9
[REDACTED] Ltd.	Chemicals	17.0
[REDACTED] Ltd.	Diamond & Jewellery	14.9
[REDACTED] Ltd.	Agri	12.4
[REDACTED] Ltd.	Diamond & Jewellery	11.8
[REDACTED] Ltd.	Logistics	10.7
[REDACTED] Ltd.	Textile	10.6
[REDACTED] Ltd.	Infrastructure	9.3
[REDACTED] Ltd.	Diversified	9.2
[REDACTED] Ltd.	Power	9.0
[REDACTED] Ltd.	Textile	9.0
[REDACTED] Ltd.	Healthcare	8.8
[REDACTED] Ltd.	Iron & Steel	7.9
[REDACTED] Ltd.	Textile	7.6
[REDACTED] Ltd.	Trading	7.4
[REDACTED] Ltd.	Telecom	6.9

Company_Name	Sector Probabilities	
[REDACTED] Ltd.	Logistics	20.0
[REDACTED] Ltd.	Construction Materials	19.9
[REDACTED] Ltd.	Trading	19.6
[REDACTED] Ltd.	Construction Materials	19.4
[REDACTED] Ltd.	Paper	19.3
[REDACTED] Ltd.	Trading	19.0
[REDACTED] Ltd.	Electricals	18.7
[REDACTED] Ltd.	Consumer Durables	18.6
[REDACTED] Ltd.	Trading	18.4
[REDACTED] Ltd.	Capital Goods	17.7
[REDACTED] Ltd.	IT	17.5
[REDACTED] Ltd.	Inds. Gases & Fuels	17.5
[REDACTED] Ltd.	Chemicals	17.4
[REDACTED] Ltd.	Trading	17.4
[REDACTED] Ltd.	IT	17.4
[REDACTED] Ltd.	Chemicals	17.1
[REDACTED] Ltd.	IT	17.0
[REDACTED] Ltd.	Capital Goods	16.8
[REDACTED] Ltd.	Agri	16.8
[REDACTED] Ltd.	Agri	16.7

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## Credit Explorer



defaults

Show 10 entries Search:

Company Name	Probability of Default(%)	Sector	Class	Current Rating	Market Capitalization	PATM(%)	Gro
1215 [Redacted] Ltd.	96.7	Textile	1	B+	39.7	-676.4	
1094 [Redacted] Ltd.	95.4	Ship Building	1	B	95.3	-676.4	
757 [Redacted] Ltd.	88.9	Infrastructure	1	B	150.8	-281	
71 [Redacted] Ltd.	85.9	Automobile & Ancillaries	1	B-	665	-96.3	
438 [Redacted] Ltd.	85.8	Consumer Durables	1	BB+	437.1	-488.2	
1071 [Redacted] Ltd.	78.9	Realty	1	B	13.8	-363.6	
510 [Redacted] Ltd.	76.2	Electricals	1	BB+	63.9	-536.9	
1364 [Redacted] Ltd.	75.7	Alcohol	1	B-	436.3	-23	
567 [Redacted] Ltd.	74.7	FMCG	1	BB	8.1	-676.4	
[Redacted]		Diamond &					