AN APPROACH TO BUILDING

AN EARLY WARNING SIGNALS (EWS) FRAMEWORK

CONSIDERING MARKET-SPECIFIC ANTECEDENTS
FOR INDIAN CORPORATE CREDIT DEFAULTS

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LIST OF ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
AIF	Alternate Investment Funds
CDS	Credit Default Swap
CDSL	Central Depository Services Limited
CEO	Chief Executive Officer
CFO	Chief Finance Officer
CLO	Collateralized Loan Obligations
CoB	Cost of Borrowing
DLT	Distributed Ledger Technology
EBIDTA	Earnings before interest depreciation and tax
EBIT	Earnings before interest and tax
EWS	Early Warning Signals
FCF	Free Cash Flow
G Sec	Government Security
Holdco	Holding Company
IL & FS	Infrastructure Leasing and Financial Services
IND AS	Indian Account Standards
KMP	Key Managerial Personnel
MDS	Multiple Discriminant Analysis
ML	Machine Learning
NSDL	National Securities Depository Limited
PE	Private Equity
PSA	Professional Scepticism Alerts
SD	Standard Deviation
SEBI	Securities and Exchange Board of India
SPV	Special Purpose Vehicle

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Chapter 1

INTRODUCTION

Several defaults in Indian markets between 2018 and 2021 have been high-impact defaults that caused significant damage to financial wealth and businesses built over many years as well as damage to investor trust and confidence. Some of the defaulters have been highly rated issuers and credible institutions. With their downfall came the ripple effect of liquidity constraints, cautious disbursements and a pessimistic lending sentiment. The genesis of this study emanates from these defaults, in particular from the surprise element in the defaults and the (in) effectiveness of the current early warning signal frameworks. The warning signal frameworks in place could not trigger timely alerts that could prompt adequate interventions to minimize the damage. One such default incident was that of Infrastructure Leasing & Financial Services (IL & FS) which experienced its first default in September 2018 followed by a series of defaults that ultimately led to its collapse. Other issuers followed suit in subsequent months and the Indian credit markets witnessed a difficult period, placing an estimate of exposure at stake for credit defaults that occurred between 2018 and 2021 at more than INR 150,000 crores. It is to be noted that the exposure was spread over different categories of lenders and included smaller retail investors as well.

The problem remains relevant and is a critical area of interest for regulators, intermediaries such as rating agencies as well as institutional lenders. The risk–reward models missed interventions that could have pre-empted the damage. Subsequently, regulators have made efforts to introduce triggers and safety mechanism measures in the monitoring within these early warning signal frameworks. Over time, the market should start seeing the effects of the new measures that have been rolled out.

The idea for the present study was based on the following premise. What went missing? With so much academic research available as well as sophisticated lenders with expertise in risk assessment, with disclosure requirements that are at par with the international standards, with corporate governance frameworks that replicate best practices in the form of Companies Act 2013. The dichotomy is not just the downfall of the largest institutions but also the surprise element or weak interventions preceding the downfall. This study attempts to identify the missing pieces through conversations with senior practitioners who understand the Indian credit well and facilitate measures for solving the problem. At the current stage of India's economic growth, it is important to be patient, knowing fully well that these 'accidents' or undesirable effects put the market back by many years, and also destroyed the economic wealth and business expertise that took the country many years to build.

> The study identifies the gap, suggests a framework and tests the suggested framework for generalized implementation.

1.1 A Systematic Early Warning Signal Framework Vs a Quantitative Model of Probability of Default

An analysis of existing literature reveals that literature on credit defaults and bankruptcy prediction is extensive. There are two broad categories of models—market-based and accounting-based. The most widely cited work within market-based models is the Merton model and the KMV-Merton model based on Merton (1974).

In the Indian context, Arindam Bandyopadhyay discusses a Black-Scholes-Merton (BSM)-based market approach to quantify the default risk of publicly listed individual companies. In the companion article *(Mapping corporate drift towards default II: a hybrid credit scoring model)*,[4,5] the author discusses the inclusion of accounting-based and other firm-specific information to improve the model created in the companion article.

The available literature in the Indian context, however, does not consider market-specific antecedents relevant for an early warning signal (EWS) framework for Indian markets. In essence, there is ***no*** paper that considers the qualitative underlying subtle themes at play within the Indian market.

The limitations of the traditional approach and benefits of using additional qualitative market specific variables are:

- Pure quantitative models are not able to attribute default to any factor(s) other than bring out significant quantitative factors that breach thresholds.
- The predictability of these models is less than perfect.
- There is a lot of privately placed debt out of the total debt. Because of data constraints, simple ratios and factors such as Altman Z-score are not available for several private companies. At the same time, some of the qualitative variables such as ratings are available in the public domain. Two agencies with access to significant information are, therefore, the rating agencies and the auditors. Because rating and auditor reports are publicly available even for private companies, the qualitative variables bring significant information within the domain of publicly available information. When used effectively, they can lead to valuable early warning signals.
- These qualitative variables can reflect transitions with more clarity. During the period of distance to default, interventions in markets like India where interventions for promoter-driven organizations need reasonable professional conviction, these qualitative variables add the conviction for initiating interventions during the very valuable period of distance to default.

The aim of this study is to capture the Indian market-specific antecedents at play and an early warning signal (EWS) model that considers the impact of antecedents. The antecedents are identified based on conversations with CXOs and market participants conversant with the credit ecosystem of the country. The EWS model considers the existing models and attempts to improve the results and effectiveness of the existing models for generate alerts and triggers referred to as the professional scepticism alerts (PSA). The study proposes that the EWS framework helps generate PSA values. The PSA values above a certain threshold are a clear signal for a scepticism alert.

Ideally, a high PSA should lead to any one of the three interventions:

(i) evaluate the condition of the borrower in greater depth to ascertain whether the deterioration is temporary or not. The evaluator might consider no action having convinced himself or herself that the PSA alert is temporary;

(ii) the evaluator might conclude interventions are required to minimize damage;

(iii) the evaluator might conclude that default is imminent and try the best possible preparation to minimize/remedy the damage.

The market-specific antecedents have further been validated through quantitative testing.

The study combines the current academic literature, especially the work done on India-specific credits with field perspectives. I have considered the predictability of traditional methods such as Altman Z and financial ratios as per the academic literature. I then collected insights from senior practitioners involved with markets or lending firms who have been active in their roles. The profiles have mostly been CXOs, heads of credit and heads of investments, etc. I collated common themes from these conversations. Common themes were then run on different software for quantitative validation. I then measured precision and got improved results vis-à-vis both the traditional methods.

A key contribution of this study is that it tries to formalize an EWS framework in terms of an approach. The steps of the methodology followed are:

Step 1: Identify antecedents relevant to Indian credit markets.

Step 2: Apply traditional models that are widely used, i.e., Altman Z model and traditional ratio analysis.

Step 3: Conduct conversations with senior practitioners, understand the factors that they consider relevant and significant in their play and collate the themes

Step 4: Test the themes collated from conversations for data validation, wherever possible, and assess the improvement impact of qualitative themes.

Step 5: Propose an approach based on the results of the EWS framework, and accordingly initiate interventions (or not). The conclusions provide avenues for designing a more effective solution to minimize damage.

The results reflect an improvement in predictability through the PSA scores in addition to the traditional quantitative models. The study also concludes the design of a default predictor for generating a PSA score. This PSA score can capture the underlying qualitative themes relevant in a market scenario. At higher scores, a PSA alert signals a case of a very high risk of default. At medium PSA scores, the default predictor highlights an urgent need for interventions as this could be the delicate period of distance to default during which interventions are most effective. At lower PSA scores, the credit is in a good shape and no intervention is required.

For instance, a PSA score of 4 or 5 across quantitative tests is statistically significant and is indicative of credit transitioning into higher risk zones, increasing the probability of default.

1.2 Introducing the EWS Framework

The construct of the EWS framework considers market-specific antecedents (basically qualitative themes), traditional default predictor models and generates a score to help deal with a specific market situation.

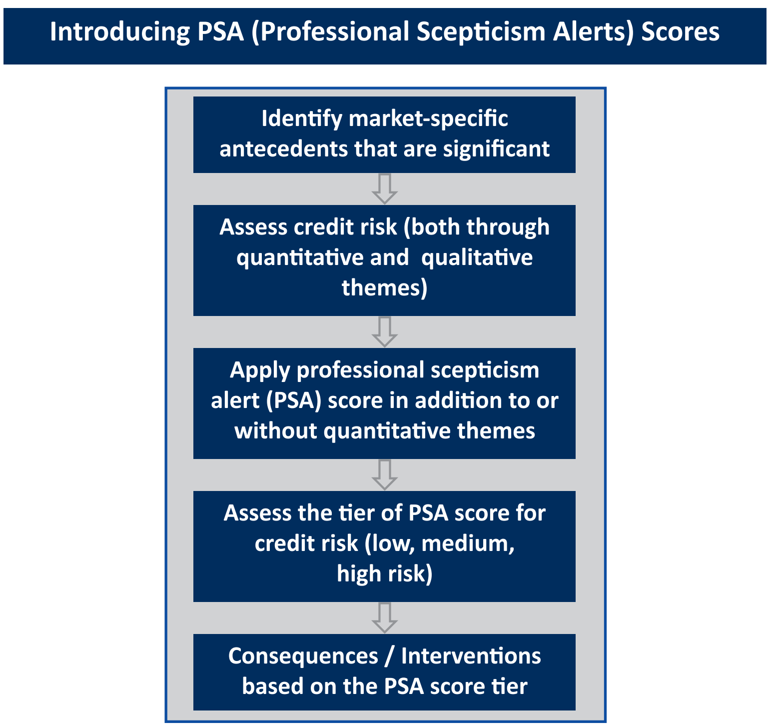

Figure 1.1: Introduction to the PSA Score

- ***Genesis credit:*** The PSA score is based on a conversation with one of the senior practitioners as a part of the interviews. This is with the understanding of **how the professional scepticism of a lender during the period of distance to default was critical** and how cultural dimensions come into play.
- I, therefore, coined the sense-making of the trends of qualitative factors that the chosen practitioner managers who were interviewed thought were the key themes.
- A deterioration in credit within an identified theme (for instance rating downgrade was given a PSA score of 1). PSA score remains unchanged when there is no deterioration or the previous PSA score is maintained.

Figure 1.2: Definition of the PSA Score

1.3: Perspectives of Field Practitioners

For the identification of antecedents that could be significant in their play, the enquiry was designed to include senior CXOs and other market participants within Indian credit/corporate/market/another ecosystem in interviews, each of which lasted around 20–30 minutes. The questionnaire included four broad-based questions around the research hypothesis. The insights from the practitioners revealed some very interesting perspectives that existing literature on Indian corporate default models did not address.

The contribution of this study is in developing a comprehensive framework that outlines remedial steps based on an early warning signals construct. This is achieved with the ability to consider multiple themes at one go and analyse credit from the perspective of multiple dimensions including market-specific factors. The helps overcome constraints of traditional ratio analysis that present a disparate and modular view of credit without factoring in market-specific antecedents.

Stakeholders need conviction to formulate interventions and take concrete remedial actions. The breach of just one or two ratios at times may not be enough for the lender to be convinced that the credit risk has significantly increased. What helps place credit more clearly and with conviction is viewing it from a lens of traditional ratios combined with the relevant PSA scores. Our analysis, for instance, indicates that PSA scores of 4 and 5 across tests are significant as those are the points when credit transitions towards rapid deterioration.

Chapter 2

THE RESEARCH OBJECTIVES

The risk of credit defaults by entities has been long acknowledged as a part and parcel of the financial system which leads to the failures of financial institutions. It is also a risk that can lead to systemic crises depending on the size and systemic importance of the institution. The rate, size and impact of these defaults determine how vulnerable the markets are to these defaults. The impact that these defaults have on lender institutions, retail investors, shareholders and numerous other stakeholders varies. In the past, however, we have seen defaults in Indian credit markets that can be classified as high-impact defaults. These defaults have shaken the stakeholder confidence quotient for lending.

2.1 Research Gap

Indian markets have many peculiarities like a limited number of issuers, limited depth of the markets, a limited number of options for long-term papers that can be matched for long-term assets, etc. There is limited literature dealing with these peculiarities. Existing literature does not fully cover the presence of market-specific antecedents at play and the process of early warning signals framework. What we have largely are default-predicting quantitative models that do not consider market peculiarities in the Indian context.

2.2 Research Problem

In order to figure out if the assessment of the research problem was directionally well placed or not, initial conversations were carried out on sense-making from market participants on whether or not the hypothesis resonated with them. The group that was covered comprised people embedded in the operating environment and included CEOs, CROs and CIOs of well-known financial institutions in the Indian markets.

The problem statement resonated with the group and it bothered the interview group that credit defaults happen like accidents without adequate flagging off of early warning signals / appropriate interventions. The group also pointed out during initial conversations some of the factors that they thought had a correlation potential of an Indian entity to default on credit obligations.

The statement of research problem was stated as:

To study the Indian market-specific antecedents at play and propose an EWS framework that incorporates these antecedents to understand early warning signals to improve the predictability quotient of existing credit default models/framework. The results of the framework are expected to help determine to the nature of interventions/alarms/triggers for interventions.

The design of this study hypothesizes that there are market-linked contexts that are significant in their play. These could cause information asymmetry that prevents predictors of default as per existing models to throw early warning signals and also predict distance to default with reasonable accuracy. The study is designed to explore if and what these factors are. The existing academic papers in their attempt to make theoretical contributions broad-based and generalist in this space miss addressing the subtle contexts that are significant. The question being explored is if a periodic qualitative study can be attempted to incorporate these market-specific contexts and factors that appear significant but are not captured in existing models. If room can be created within the existing models to consider these specific factors that come into play over time and be added to existing models, the predictability of models could improve.

2.3 Research Objectives

Objective 1:

Examine the predictability quotient of existing credit default model / framework to determine corporate default of Indian companies

This objective is achieved with the help of collecting data on Indian companies (listed as well as unlisted) for about a period of five years (2016–2021). The existing models for predicting credit default are tested for the selected companies. The accuracy of the existing models is tested for a few selected case studies.

Objective 2:

Study the Indian market-specific antecedents at play and propose an EWS framework that incorporates these antecedents to understand early warning signals to improve the predictability quotient of existing credit default models/framework. The results of the framework are expected to lead to alerts on the nature of interventions/alarms/triggers for interventions.

This objective is achieved with the help of taking interviews with senior industry executives and market participants. A qualitative approach is applied to the interview transcripts and thereafter thematic analysis, sentiment analysis, content analysis and text mining are applied.

Chapter 3

LITERATURE REVIEW

The literature on credit risk models goes back a long way. The theoretical models in the existing literature fall into the following categories.

- Structural models
  - Merton model (1974)
  - KMV-Merton model
- Reduced-form models
- Accounting / Financial Statements-based models
  - Altman's *Z*-score (1968)
  - Logistic regression
- Hybrid Models

  Several papers have explored hybrid models that combine structural models and accounting-based models with certain firm-specific factors.

3.1 Structural Models

Merton Model

Leland (2002) examined the differences in default probabilities generated by two types of structural models. In the first group, called the 'exogenous default threshold' approach, Merton's (1974) and Black and Scholes's (1973) models are used. The authors proposed a calibration approach based on historical data on defaults. Vassalou and Xing (2004), as a way to realize the effect that the default risk has on stock returns, conducted a study to assess default probabilities for individual companies using the Merton (1974) model. They concluded that both the size and the book-to-market have a strong impact on default risk. Hamilton, Sun and Ding (2011) compare point-in-time (PIT) and through-the-cycle (TTC) structural models.

Empirical studies, such as Kealhofer (2003), Delianedis and Geske (2003), Leland (2002), Vassalou and Xing (2004), document that the theoretical probability measures estimated from structural default risk models have good predictive power over credit ratings and rating transitions.

Then there are multivariate credit scoring models that have been and are used as internal credit assessment models within financial institutions and credit rating agencies. The limitations of ratio-based models with financial statements as their base have been pointed out by many researchers as backwards-looking and accounting data-based.

Merton's KMV Model

One of the most widely used forecasting models which have been applied in both practice and academic research is a particular application of Merton's model (Merton, 1974) that was developed by the KMV Corporation, and is therefore referred to as the KMV-Merton model by some of the academicians and practitioners. The KMV-Merton model applied the framework of Merton (1974), in which the equity of a firm is a call option on the underlying value of the firm with a strike price equal to the face value of the firm's debt. The model recognized that neither the underlying value of the firm nor its volatility is directly observable. Under the model's assumptions, both can be inferred from the value of equity, the volatility of equity and several other observable variables by solving two nonlinear simultaneous equations. After inferring these values, the model specified that the probability of default is the normal cumulative density function of a *Z*-score depending on the firm's underlying value, the firm's volatility and the face value of the firm's debt.

Among other things, the model assumed that the underlying value of each firm follows geometric Brownian motion and that each firm issued just one zero-coupon bond.

Bharath and Shumway (2008) examined the accuracy and the contribution of the distance to the default model (DD) and concluded that this model is useful in default predictions but they stated that it is not statistically sufficient.

Considering the peculiarities of emerging markets, specifically credit assessment practices in markets like India, Arindam Bandyopadhyay discussed a Black-Scholes-Merton (BSM)-based market approach to quantify the default risk of publicly listed individual companies. He used a contingent claim approach to present a framework to optimally use the stock market and balance sheet information of a company to predict its probability of failure as well as ordinal risk ranking over a horizon of one year. The option model that was constructed of 150 Indian corporates from 1998 to 2005 gave the probability of default that provided ordinal rankings of companies based on their default risk which had good early warning predictability. The application of option-based default probability estimation to emerging markets was an innovative approach in that sense.

The market value of assets is a very powerful default predictor since it is an indicator of either a firm's economic prosperity or its distress (Black and Cox, 1976; Leland, 1994).

In the companion article (Mapping corporate drift towards default II: a hybrid credit scoring model), Arindam Bandyopadhyay discussed the inclusion of accounting-based and other firm-specific information to improve the model created in the companion paper further to get more accurate prediction of default in a hybrid type model.

3.2 Reduced-form Models

Reduced-form models originated with Jarrow and Turnbull (1992) and were subsequently studied by Jarrow and Turnbull (1995), and Duffie and Singleton (1999) among others. These models are viewed as competing models (Bielecki and Rutkowski, 2002). The aspects of the model have been further statistically analysed and justified by Lando (2003). Additionally, there is a heated debate in the professional and academic literature as to which class of models is best (see Jarrow 2003, and references therein). This debate usually revolves around default prediction and/or hedging performance.

Jarrow and Philip Protter (2012) in their paper *'Structural Versus Reduced Form Models: A New Information Based Perspective'*[21] compare structural versus reduced-form credit-risk models from an information-based perspective. Structural models assume that the modeller has the same information set as the firm's manager—complete knowledge of the entire firm's assets and liabilities. In most situations, this knowledge leads to a predictable default time. In contrast, reduced-form models assume that the modeller has the same information set as the market—incomplete knowledge of the firm's condition. In most cases, this imperfect knowledge leads to an indeterminable default time. As such, the key distinction between structural and reduced-form models is not whether the default time is predictable or indeterminable, but whether the information set is observed by the market or not. Consequently, for pricing and hedging, reduced-form models are the preferred methodology. The informational perspective of the present paper implies that to pick which credit risk model is applicable, (structural or reduced form), one needs to understand which information set is available to the modeller. Structural models assume that the information available is that the same as the one held by the firm's managers, while reduced-form models assume that it is the information observable to the market. Given this perspective, the defining characteristics of these models are not the property of the default time, but rather the information structure of the model itself. If one is interested in pricing a firm's risky debt or related credit derivatives, then reduced-form models are the preferred approach. Indeed, there is a consensus in the credit risk literature that the market does not observe a firm's asset value continuously in time. This implies, then, that the simple form of structural models illustrated in Section 3.1 does not apply. In contrast, reduced-form models have been constructed, purposefully, to be based on the information available to the market.

Other authors, such as Lando (1998), Jarrow et al. (1997), Duffie and Singleton (1999), have extended these types of models using market prices of companies, i.e., bonds or credit default swaps (CDS), to extract both the probability of default and credit risk dependencies.

Jarrow (1997) has provided descriptions of the Markov model and has claimed that the processes of this model can be estimated through observations and data collections. On the other hand, it has been observed that reduced-form models have been assumed to be convenient and involve various aspects of corporate bonds (Duffie and Singleton 1999).

They assume that the market is the only source of useful information to structure credit risk companies.

3.3 Accounting-based Models

Altman's (1968) accounting analysis model is one of the most popular. He used five financial ratios to measure the probability of a company entering into bankruptcy, through Multiple Discriminant Analysis (MDA). According to Ohlson (1980), the MDA presents some problems in predicting business failures: the need for equality of variance–covariance matrices of the predictors of the two groups of companies; intuitive interpretation of the *Z*-score and the arbitrary nature of the process of matching the sample, since 'failed and non-failed companies are categorized according to criteria such as size and industry.' (Ohlson 1980) Other methodologies have been addressed in the analysis of financial ratios.

The final discriminant function obtained was as follows: $Z = 1.2\, X_1 + 1.4\, X_2 + 3.3\, X_3 + 0.6\, X_4 + 1.0\, X_5$

Where:

X_1 represents the Liquidity Ratio (Working Capital / Total Assets)

X_2 represents the Profitability Ratio (Retained Earnings / Total Assets)

X_3 represents the Solvency Ratio (EBIT / Total Assets)

X_4 represents the Solvency Ratio (Market Value of Equity / Book Value of Total Debt)

X_5 represents the Activity Ratio (Sales / Total Assets)

Z represents Altman's *Z*-score

After estimating the discriminant function, the value of Z is quantified and companies supposedly entering bankruptcy are compared to the ones that failed. In the initial study in 1968, the author used a *Z*-score cut-off of 2,675 (A *Z*-score of a company being assessed below this value was considered bankrupt, while any score with a *Z*-score above this value was not.)

One of the advantages of the Logit model is the possibility of categorizing the independent variables, admitting not only the economic and financial ratios or metric variables, but allowing the use of non-financial or qualitative information.

Some models are more robust than the others for the purposes of parameter estimation. Nevertheless, under certain distributional assumptions, both procedures yield consistent estimates. Discriminant analysis has been regarded as one of the widely accepted models that have the potential to predict insolvency (Prado *et al.* 2019). Furthermore, some models have simpler representation and mathematical treatment compared to the others.

3.4 Hybrid Models

Sobehart and Stein (2000) use financial statements and market information to build a hybrid model to predict the failure of public companies based on methods of nonlinear regression. Tudela and Young (2003) developed a hybrid approach to evaluate the default risk of listed companies through a version of Merton's (1974) model with the use of accounting data. Benos and Papanastasopoulos (2007) combine fundamental analysis with structural analysis in a hybrid model for measuring credit risk.

Chapter 4

RESEARCH METHODOLOGY

The study was conducted in a discovery-driven approach in three phases. The phases are:

1. Conducting initial conversations with practitioners on developing the initial construct of the EWS framework;
2. Developing, qualitative testing and revising a preliminary model of the EWS framework wherein practitioners identified antecedents; and
3. Quantitatively testing the EWS conceptual framework

In the discovery-driven approach, the existing literature findings were used extensively and supplemented with insights of the practitioners to factor in India-specific antecedents. Findings of existing literature were used to run quantitative tests of early warning signals, then qualitative methods were used for theory construction of a set of antecedents followed by testing the qualitative theory through quantitative validations.

For summarizing the research methodology, it is important to reiterate the construct of the EWS framework that comprises the following steps:

Step 1: Identify antecedents relevant to Indian credit markets.

Step 2: Apply traditional models that are widely used, i.e., the Altman Z-score model and traditional ratio analysis.

Step 3: Conduct conversations with senior practitioners and understand the factors that they consider relevant and significant in their play. Collate the themes from interviews on NVivo (software).

Step 4: Test the themes collated from conversations and validate the data .

Step 5: Use annual reports, rating rationales and other publicly available information to analyse and collate events of deterioration year-wise for 3–5 years (about 2016−2021) across themes highlighted as significant by practitioners. Each event of deterioration theme by theme year by year is classified as '1' and each non-event as '0'. Each of these values are used as an increase in the PSA score.

Step 6: Propose an approach as a result of studying the consequences of the EWS framework for initiating interventions or not.

The identification of practitioners with whom qualitative discussions were conducted was done based on the candidate's profile in terms of the experience in the Indian credit markets and the seniority of roles to be able to understand the depth of the research topic and role entailing handling of credit or business risk. The practitioners shortlisted for conversations were very senior with most of them in the capacity of CXOs. The questionnaire basically comprised four broad questions (discussed in detail in Chapter 5). The thematic analysis, text mining and sentiment analysis were performed on the qualitative data collected during the interviews.

The intent of this step was to explore the context-based significance of factors that are prevalent over a period of time and are seen as significant by market participants. These could be qualitative or quantitative. As the factors are embedded in context and are not captured in existing frameworks, they were evaluated through machine learning and regression-based models to ascertain if capturing them improves the predictability of existing models.

4.1 Statistical Methods for Research Objective 1

To examine the predictability quotient of the existing credit default models /framework for the corporate default of Indian companies.

Statistical Tests Applied:

Quantitative tests of financial ratios for 5 years backward from March 2021

4.2 Statistical Methods for Research Objective 2

To study the market-specific antecedents at play in the Indian markets and propose an EWS framework that incorporates these antecedents to understand early warning signals to improve the predictability quotient of existing credit default models/framework. The results of the framework are expected to lead to alerts on the need for interventions/alarms/triggers for interventions.

Statistical Tests Applied:

1. From the interviews, I extracted word frequency to come up with a word cloud and conducted sentiment analysis for extraction of key themes and sub-themes through thematic analysis.
2. Once independent variables/key themes had been listed from NVivo, I proceeded with quantitative testing.
3. I then used logistic regression for running tests of precision, recall and accuracy. This is described in full detail in Chapter 7 Data Collection and Processing.

Chapter 5

METHODOLOGY—INTERVIEWS, THEMES, TESTS AND ANALYTICS

5.1 Interview Methodology

Identification of interviewees:

The identification of practitioners with whom qualitative discussions were conducted was done basis profiling in terms of the experience in Indian credit markets, seniority of roles to be able to understand the depth of the research topic and role entailing handling of credit or business risk. The practitioners shortlisted for conversations were experienced senior professionals, with most in the capacity of CXOs.

Designing the questionnaire:

The questionnaire was broad-based comprising four broad questions as under:

1. What are the primary reasons that contribute towards the surprise elements in Indian credit defaults leading to stressed assets or bankruptcies?
2. Are the tools/models available with the participants in the Indian debt market adequate to predict corporate default with reasonable confidence levels?
3. Is there a level playing field that pertains to the extent and timing of availability of material information among market participants and issuers in the Indian debt market or are information asymmetries significant?
4. Could you enumerate the critical qualitative and quantitative factors that can be added to the existing models to enable building an improved forward-looking predictor of corporate credit defaults?

Methodology of conducting Interviews:

1. The interviews were conducted through Teams/Zoom/Phone and the transcript was written by hand. As most interviewees were very senior CXOs, I did not want to make them uncomfortable by approaching the question of recording their conversations. I, therefore, made notes of the discussions by hand and then made soft copies.
2. A total of 9 respondents were chosen and interviewed for this study.
3. From the interviews, I extracted word frequency to come up with a word cloud, performed sentiment analysis, and then manually extracted key themes and sub-themes.
4. Once independent variables/key themes had been listed from NVivo, I proceeded with the quantitative testing.

5.2 Key Themes and Sub-themes

Theme 1: Asset–Liability Mismatches

- Short-term funds for funding long-term assets – dependence on bank funding
- Mismatches in tenor as well as the cost of liabilities and assets
- Infrastructure funding—a typical case

Asset–liability mismatches as an early warning signal was a theme pointed out by many of the managers (Marozva & Makina 2020). These were a consequence of the absence of institutions making long-term loans available leading to banks as the lenders for even assets with long gestations. In terms of the linkage of assets being built with sources of funds, some managers pointed out that both costs of assets and the tenor of assets are a challenge on account of long-term money not being available which is especially relevant for infrastructure assets.

Theme 2: Absence of CDS Market/Independent Spread Validation

- No independent validation of the spread
- Absence of CDS market

Another theme that came out repeatedly was an absence of a mechanism of independent spread validations, a function normally carried out by CDS markets. In most markets, CDS markets help with price discovery (Hilscher *et al.* 2015). Several practitioner managers spoke about the pricing of credit instruments not being verifiable and being an independent assessment of the respective lender. Some of the managers mentioned that price adjustments with increasing stress in credit were not being carried out appropriately. Mispricing of loans came out as a theme from many practitioners. Practitioners attributed this mispricing for delayed interventions on defaults. Damage could be minimized if only loans could be priced right at the right time and incorporate a deteriorating credit position.

Theme 3: Changes in the Last Six Quarters

- Auditors' qualifications / matters of emphasis
- Change in auditors
- Steep increase in CFO/CEO compensation
- KMP resignations
- Steep increase in CoB
- Steep increase in security placed with lenders

Some of the practitioner managers pointed out that changes over the past few quarters could give out early warning signal triggers if studied carefully. For instance, one of the managers who has a book to his credit on a similar subject felt that there could be a correlation between credit default stress and an increase in the auditor's remuneration or with the change of auditors. He also reflected that there could be a correlation between the steep increase in compensation of key managerial personnel and credit default stress. Another practitioner reflected that changes during quarters preceding a default are the distance to default which is a very valuable period to understand signals. He said at times preceding a default, they see corporate offices generally outside the purview of lender security suddenly being placed as enhanced security.

The market must go deeper into these as it is not normal for a borrower who keeps the corporate office outside the purview of security to place added amounts of security all of a sudden. Similarly, auditor's qualifications came out as a key sub-theme. A spike in the cost of borrowing for incremental or same borrowings could signal additional risk and deteriorating position of the borrower as perceived by the lender. As per another practitioner's perspective, regulators had tried to improve the structural issues post a series of defaults. They had an increased scope of monitoring for intermediaries such as trustees and credit rating agencies. However, the practitioner felt that the responsibility of monitoring was placed on intermediaries who were not equipped to carry out the monitoring functions.

Theme 4: Consideration of Free Cash Flow

- Not enough emphasis on free cash flow
- Uses of cash by a mature and steady business
- Most lenders do not look closely at cash flows. For example, if the cash flow from operations is going down, it is a concern even if EBIDTA is not decreasing at the same rate.

Free cash flow is the first metric to reflect movements in business and is not given enough consideration by lenders and monitoring agents for assessing a deterioration in operating business. There is a need for deeper analysis of cash flow movements even if profits look healthy to catch first reflections of a potential problem.

Theme 5: Corporate Governance and Complex Structure/Layering of Debt

- Layering of debt
- Holdco borrowing for operating business of SPV
- Structure complexity
- Promoter-driven with a weak governance structure
- Board composition (common span, independent passive)
- Complex flow of funds, a maze of transactions, significant influence to mobilize funds at a level different from where they should be
- Aggressive accounting

Some practitioners spoke about weak corporate governance and the existence of complex layered debt structures as being important themes for alerts on debt stress. This was typical in holding companies enjoying certain ratings borrowing at the holding company level or through guarantees, etc., and creating layers and complex structures of subsidiaries. This keeps the borrowing costs down. Corporate governance issues assume more risk in promoter-driven organizations (Yermack 2017). In promoter-driven entities, the board composition, experts at the helm of management, etc., remained a risk. A maze of corporate structures with a common span of control either through common board members or through common management is a signal to be noted and be weary of. Managers also spoke about the use of aggressive accounting techniques wherein an important signal, again to be weary of, could be auditors and management disclosures. They thought these were especially important during the period of distance to default with the intent to wrap up a problem in the short run. The other response was not paying enough attention to consolidated financial statements and cash flow.

Theme 6: Criminalization of Bankruptcy Lead to Efforts to Suppress Bad News

- The approach to bankruptcy is the criminalization of failure.
- Why would you throw away something that has been built over years and destroy all of its value just because it went bankrupt? The value of building the same thing in present times would be at least ten times.

A subtle theme that some managers pointed out was the criminalization of bankruptcy and the absence of a bankruptcy framework in case of business failures. According to them, the fear of bankruptcy can then lead to desperate efforts to hide business failure till things cannot be sustained any further.

Theme 7: Information Asymmetry

- Information is a big theme for lenders, esp. the ones that are unlisted
- Borrowers tend to hide, esp. shocks; independent sources are a challenge
- Information not shared between lenders regulators

Information asymmetry was a theme that most managers emphasized. One of the managers reflected on the predicaments of the rating agencies. According to him, the rating agencies were completely dependent on the information given by the management of the issuer companies. Many managers across tiers spoke about information unavailability. At a minimum level of basic financial information, entities with neither debt nor equity listed were the most chronic problems (Elbadry *et al.* 2015). At another tier, one practitioner manager spoke about shocks as they happen. The information about certain moving parts that are significant in terms of stress of potential default as events unfold remains a challenge. Another practitioner manager spoke about how the challenge of information availability has been significantly solved by the private equity industry because they acknowledged it and started using independent firms to take care of information collation. Some of the managers also spoke about how regulators had been trying to solve the information and disclosure issues.

For instance, the move to IND AS was a step in the direction of disclosure improvements. Similarly, the annual report disclosure requirements and guidelines on the responsibility of the statutory auditors covered a significant distance. SEBI had increased the monitoring responsibilities of intermediaries. Notwithstanding all of this, information availability remained one of the biggest themes for not being able to see early warning signals. Some of the practitioners also spoke about the sharing of available information. For instance, the Reserve Bank of India (RBI) collects a lot of information as a part of their regulatory requirements but there is no sharing of information framework with the lenders. There was also a reflection on information available to institutional investors versus retail investors. One of the managers also spoke about how lenders sometimes don't get into details of the true value of the security. Also, if stakeholders want to collate information through derivations from independent sources of information, then independent sources are not easily and readily available.

Some practitioners felt strongly about the use of technology to generate triggers as credit situation for a borrower changes. They felt the surprise element in defaults could go down with more and more use of technology. The practitioners emphasized that credit monitoring and default assessment were very good cases for use of artificial intelligence (AI) and that was the only way to deal with multiple variables at play here. Also, with machine learning (ML), the accuracy of what is known about a borrower could go up exponentially. One of the practitioners briefly touched upon how China was able to generate deep insights about borrowers to use them for lending cases by using AI and ML.

Theme 8: Lack of Liquidity

- Very difficult to exit when the market gets a warning of a default
- Limited willingness to trade on price. The approach is that I should not have a default and should get > G Sec yield. Liquidity not available below certain ratings
- Both width and depth are limited despite efforts from regulators
- Because debt is not traded, no way to tell whether something is close to default or not

Liquidity in trading was pointed out as an issue especially once information about a problem in a specific firm started to be known in information circles. Deterioration is sometimes amplified simply because liquidity dries up for the firm facing the perceived or actual problems.

Theme 9: Lender Monitoring and Lender Culture

- Incorrect pricing of loans
- Bias on making things 'look good'.

The role of lenders was brought out as another important theme. Managers especially those familiar with culture of the lender organizations felt it was an important theme. Business acquisition targets could dwarf credit quality. Security value assumes importance in regular monitoring and remediation (Choy *et al.* 2021). One practitioner mentioned that if the lenders simply brought down the value of security to reflect deterioration in credit promptly, effective remediation could help in preventing damages. Many managers spoke about perception-based lending and credit models being tweaked to accommodate credit decisions. It was also felt that lenders are often able to look reasonably well on income statements but are not able to identify other stress factors on a balance sheet. Managers also spoke about the pricing angle. One manager specifically pointed out that when banks are printing money, they tend to take their eyes off where the default factor could occur. There was also a lot of emphasis on mispricing. One manager said mispricing is one of the main reasons we default. The markets should use pricing as a means of protection for what is structurally weak.

Theme 10: Overreliance on Financial Numbers

- Overreliance on backwards-looking financial numbers
- Need to use both quantitative and qualitative possibilities of AI for mass customization and behaviour analysis

Another theme that came out as important was an overreliance on financial numbers

It was pointed out that financial numbers are backward looking. As firms enter problem zones, many a times the distance to default is a limited window. Objective projections based on independent metrics like inventory, GST, sale, etc., need to be relied on adequately to identify a problem before it reflects in financial statements, which typically that happens much later.

Theme 11: Over-reliance on Rating Agencies

- Heavy dependence on rating agencies for lending and monitoring
- Conflict of interest for rating agencies for more business

Ratings are one of the most important metrics for lending transactions. Ratings are one of the most important metrics for lending transactions. It was felt that ratings had become sole factor to rely on for assessing a credit. While rating transitions remained extremely important, independent monitoring and assessments of credit were important. One of the interviewees also spoke about rating transitions speed being slower than the actual deterioration in some cases purely on account of rating being a periodic exercise (as opposed to being monitored constantly).

Theme 12: Structural Issues in Business Models:

- Structural issues in models that are different. For instance, infrastructure.
- Trends that help predict default

Theme 13: Valuation of Equity

- For listed entities, price volatility in equity markets can give signals.
- Assets created as security need to be valued periodically and the price of the loan adjusted.

Theme 14: Miscellaneous

There were other themes that were mentioned in conversations that have been clubbed under the category ‘Miscellaneous’ here. Factors like resignations of key managerial personnel were mentioned as themes to watch out for. Higher than normal pledge of promoter shares, block sale of pledged shares by lenders, news in informal channels, markdowns of privately placed debt by a lender like a mutual fund, were some of the signals that were mentioned as signals to watch out for. There was also a mention of unavailability of technically trained resources in the market. In its own way, a sub optimal and inadequately trained talent could lead to inaccurate reading of signals as well as other related financial functions.

Table 5.1: Themes and Sub-themes

1. Asset–Liability Mismatches • Short-term funds for funding long-term assets. Unavailability of long-term money for long-term assets • Dependence on bank funding	***2. Absence of CDS Market/ Independent spread Validation*** • No independent validation of the spread • Absence of CDS Market	***3. Changes in the last Six Quarters*** • Auditors' qualifications/ matters of emphasis • Change in auditors • Steep increase in CFO/CEO compensation • KMP resignations • Steep increase in CoB • Steep increase in security placed with lenders
4. Consideration of Free Cash Flow • Not enough emphasis on FCF • If a business has been there for a long time and has been at mid-level, are they using cash for the level of business? • Most lenders do not look closely at cash flows. For example, if cash flow from operations is coming down, it is a concern even if EBIDTA is not decreasing at the same rate. • Uses of cash by a mature and steady business	***5. Corporate Governance and Complex Structure/Layering of Debt*** • Layering of debt • Holdco borrowing for operating business of underlying subsidiaries Structure complexity • Promoter-driven with a weak governance structure • Board composition (common span, independent, passive) • Complex flow of funds, a maze of transactions, significant influence to mobilize funds at a level different from where they should be • Aggressive Accounting	***6. Criminalization of Bankruptcy Leads to Efforts to Suppress Bad News*** • The approach to bankruptcy is the criminalization of failure • Why would you throw away something that has been built over years and destroy all of its value just because it went bankrupt? The value of building the same thing in present times would at least be ten times.
7. Information Asymmetry • Information is a big theme for lenders, esp. the unlisted ones. • Borrowers tend to hide, esp. shocks; independent sources are a challenge. • Information not shared between lenders and regulators	***8. Lack of Liquidity*** • Very difficult to exit when the market gets a warning of a default. • Limited willingness to trade on price. The approach is that I should not have a default and should get > G Sec yield. Liquidity not available below certain ratings. • Both width and depth are limited despite efforts from regulators. • Because debt is not traded, no way to tell whether something is close to default or not.	***9. Lender Monitoring and Lender Culture*** • Incorrect pricing of loans • Bias on making things 'look good'.
10. Overreliance on Financial Numbers • Overreliance on backwards-looking financial numbers • Need to use both quantitative and qualitative analysis • Possibilities of AI for mass customization and behaviour analysis	***11. Overreliance on Rating Agencies*** • Heavy dependence on rating agencies for lending and monitoring. • Conflict of interest for rating agencies for more business.	***12. Structural Issues in Business Models*** • Structural issues in models that are different. For instance, infrastructure. • Trends that give predictability of default
13. Valuation of Equity • For listed firms price volatility in equity markets can give signals. • Assets created as security need to be valued periodically and the price of the loan adjusted.	***14. Miscellaneous*** • Higher than normal pledge of promoter shares • Block sale of pledged shares by lenders • News in informal channels • Markdown of privately placed debt • Unavailability of technically trained resources in the market.	

5.3 Word Frequency

The most frequently used words in the interview transcripts were analysed. The list of the top 50 words is shown in Table 5.2.

Table 5.2: Word Frequency

Word	Length	Count	Weighted Percentage (%)
Default	7	23	1.12
India	5	18	0.87
Models	6	18	0.87
Factors	7	17	0.83
Monitoring	10	16	0.78
Rating	6	16	0.78
Credit	6	15	0.73
Banks	5	13	0.63
Debt	4	12	0.58
Market	6	12	0.58
Model	5	12	0.58
Business	8	11	0.53
Markets	7	11	0.53
Asymmetry	9	10	0.49
Data	4	10	0.49
Lenders	7	10	0.49
Bank	4	9	0.44
Cash	4	9	0.44
Loans	5	9	0.44
Money	5	9	0.44
Term	4	9	0.44
Understand	10	9	0.44
Lending	7	8	0.39
Liquidity	9	8	0.39
Price	5	8	0.39
Risk	4	8	0.39
Assets	6	7	0.34
Board	5	7	0.34
Corporate	9	7	0.34
Financial	9	7	0.34

Word	Length	Count	Weighted Percentage (%)
Level	5	7	0.34
Long	4	7	0.34
Management	10	7	0.34
Signals	7	7	0.34
Auditors	8	6	0.29
Funding	7	6	0.29
Lender	6	6	0.29
Loan	4	6	0.29
People	6	6	0.29
Quantitative	12	6	0.29
Agencies	8	5	0.24
Analysis	8	5	0.24
CDS	3	5	0.24
Check	5	5	0.24
Company	7	5	0.24
Defaults	8	5	0.24
Difficult	9	5	0.24
Equity	6	5	0.24
Important	9	5	0.24
Independent	11	5	0.24

5.4 Word Cloud

In a visual representation of qualitative data (refer to Fig. 5.1), the most frequently used words reflected are: default, models and factors related to default in the debt market.

Figure 5.1: Word Cloud

5.5 Sentiment Analysis

Sentiment analysis is done on the qualitative data (as shown in Table 5.3). The results of the sentiment analysis are shown Fig. 5.2.

The results reported that most of the respondents are moderately negative about the defaulters.

Table 5.3: Sentiment Analysis

	A: Very negative	B: Moderately negative	C: Moderately positive	D: Very positive
Interview Transcripts	7	38	11	5

The sentiments are visualized in Fig. 5.2:

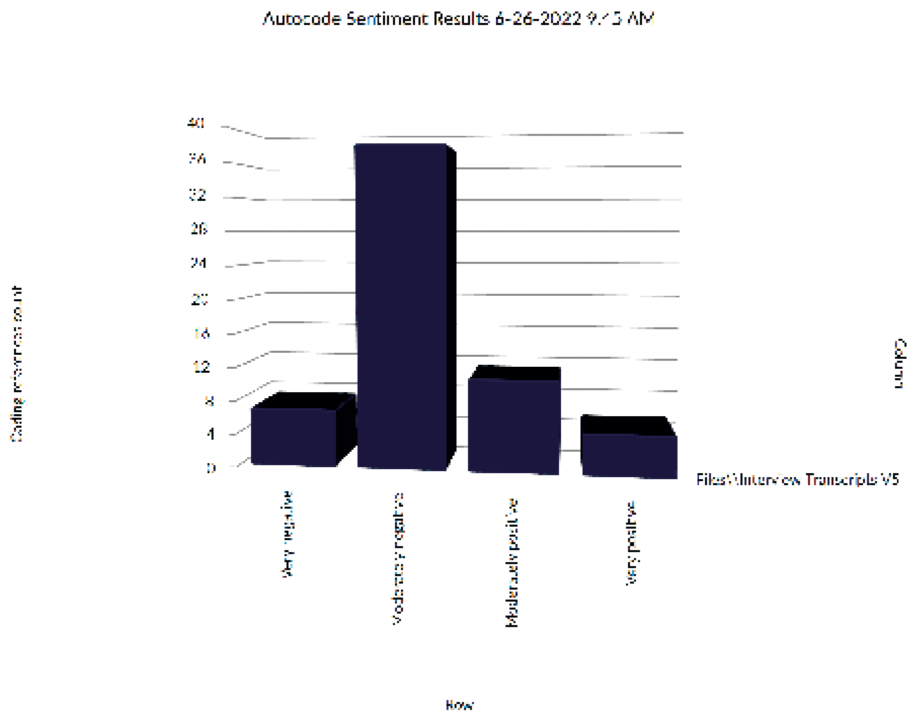

Figure 5.2: Result of Sentiment Analysis

Respondent-wise Sentiment Analysis

Table 5.4: Respondent-wise sentiment analysis

	A: Very negative	B: Moderately negative	C: Moderately positive	D: Very positive
Respondent 1	0	4	0	0
Respondent 2	0	1	0	0
Respondent 3	1	10	2	2
Respondent 4	1	4	3	1
Respondent 5	1	1	0	0
Respondent 6	2	3	3	1
Respondent 7	1	6	1	0
Respondent 8	0	3	0	0
Respondent 9	1	6	2	1

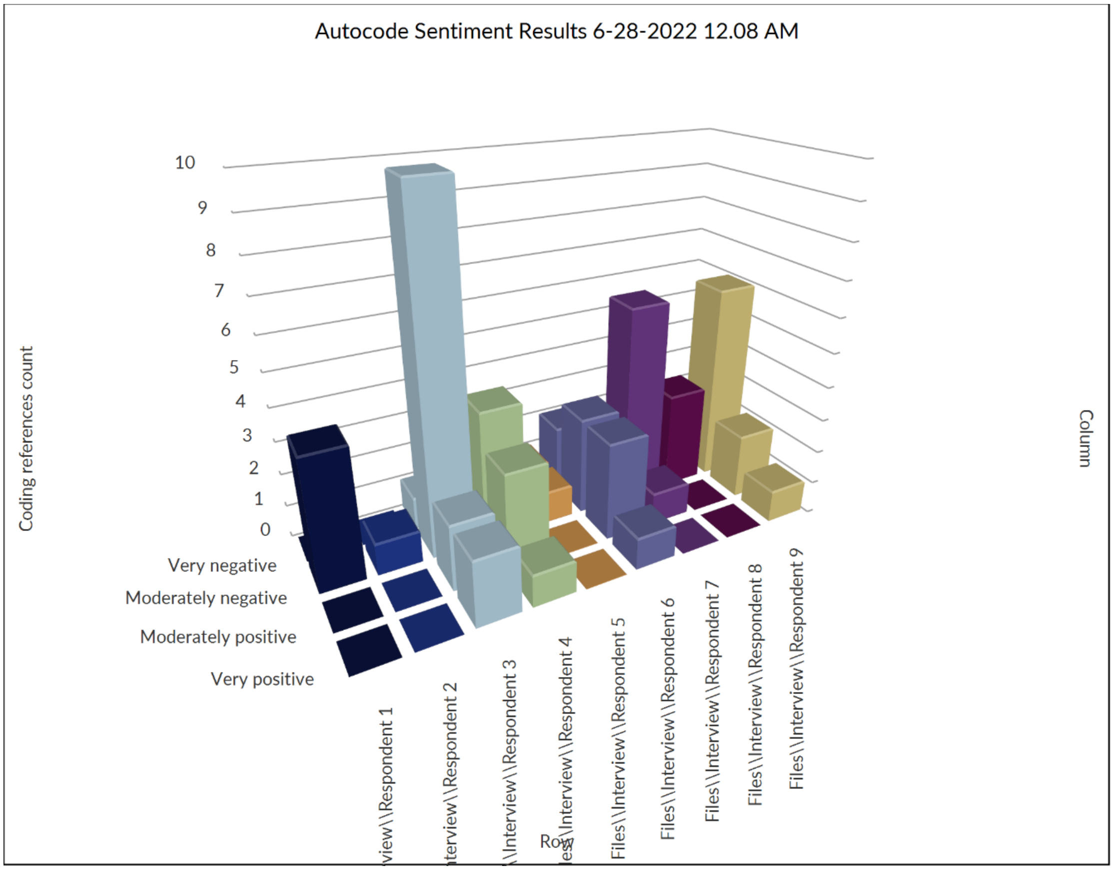

Figure 5.3: Autocode Sentiment Results

5.6 Thematic Analysis

Theme 1: Asset–Liability Mismatches

Table 5.5: Analysis of Theme 1

Key Words and Key Phrases
Long-term money for long-term assets is not available.
Right ALM matches
ALM mismatches Undeveloped credit markets offering long-term money
Asset–liability mismatch
Dependence on bank funding – short-term funds for funding long-term assets
Linkage of assets being built with the sources of funds – tenor as well as the cost of funds. Long-term money not available in the market
Asset Financing For infrastructure funding, the models are now using extensive modelling before funding and building up discount rates scientifically
ALM Mismatches
Infrastructure funding – long-term assets funding through short-term bank loans
ALM Mismatches

Theme 2: Absence of CDS Market /Independent Spread Validation

Table 5.6: Analysis of Theme 2

Key Words and Key Phrases
No independent benchmark of spread. We don't have a CDS market. SEBI over the last few months has tried to correct the situation with new regulations. But there also, I don't understand how trustees can fulfil the role of acting as early warning signals as they're not equipped to run these kinds of responsibilities. This is leading to its issues and delaying issuances (#2)
Development of CDS markets and allowing exposure is one such thing that can help
Absence of a CDS market

Theme 3: Changes in the Last Six Quarters

Table 5.7: Analysis of Theme 3

Key Words and Key Phrases
The pace of up and down – has it changed? That is what will tell us whether the company is going up or down. Check signals – qualifications of auditors, change in auditor's fee, senior management change, auditor change
CoB of the next borrowing should be higher
Higher security (case of allied – why will a borrower give his corporate office to a banker?)
Change in management
Higher security
Higher CoB
Can only come down with the use of more and more technology. Abroad, tech is being used much more
Indicators – increase in audit fees (#8)
Technology – pedictive analysis

Theme 4: Consideration of Free Cash Flow

Table 5.8: Analysis of Theme 4

Key Words and Key Phrases
• The third factor which is completely ignored and is very crucial is cash flow. Somewhere we're not giving importance to FCF. Ability and desire to look at free cash flow as an indicator of business. If a business has been there for a long time and has been at mid-level, how is the cash being used? • Quality of cash flow – efficiency
Another dimension in India is that Financials are structured and there is a heavy dependence on financial parameters.
Most lenders do not look closely at cash flows. For example, if cash flow from operations is going down, it is a concern even if EBIDTA is not decreasing at the same rate. Liquidity is an important parameter and we must shift our focus from EBIDTA to cash.

Theme 5: Corporate Governance and Complex Structure / Layering of Debt

Table 5.9: Analysis of Theme 5

Key Words and Key Phrases
Layering of debt
Structure complexity – Hold Co borrowing so much money and putting it into SPV. Stretch in operating models of SPV
Cannot be mitigated
Ideally, Hold Co should be able to borrow at the SPV level
When projects have a worse rating than Hold Co, you tend to borrow so keep the CoB down. In IL&FS, the structure was a problem.
Structural problem
Internal factors would include factors like mismanagement, fraud risk and weak corporate governance. Surprise element
In promoter-driven organizations, there is always the risk of straddling money
Board composition is also very important. The more independent the board, the better it is. There has to be a focus on the independence of the board.
Corporate Governance
They are not often able to understand balance sheet structures /complexities very well. The rate of deterioration is very high. These kinds of obligations are difficult to identify.
Corporate Structure One should always be cautious of a maze of holdings, subsidiary and SPV structures without clearly delineated roles, responsibilities and focus areas.
Board composition / management structure Extreme caution needs to be exercised when the maze of corporate structure has a common span of control either through the board or management structure.
Sources and uses of funds/resources The moment a maze of complex corporate structures with common control or significant influence is used to mobilize funds at a level different than where the funds are ultimately used, it gives the flexibility of multiple-level leveraging and the seeds of an aggressive business model are sown (Bodie 2015).
Aggressive accounting and governance issues
Using aggressive accounting techniques helps in camouflaging the true and fair picture and in the near term suppresses the underlying simmering risks.
Not paying enough attention to the consolidated financial position and a detailed granular cash flow and fund flow analysis on a standalone and consolidated basis prevents early detection.
There is also an effort to comply with the governance issues in the letter but circumvent the spirit of the regulations.
Over-optimistic business plan falling apart
Usually, such conglomerates are perplexed with aggressive business plans based on unrealistic assumptions reflecting the extreme optimism and over-enthusiasm of the management.
The business plans do not have rigorous sensitivities to test the assumptions and create what-if scenarios for mid-term course correction.
Also in most cases, there are no scenario analyses backed up by plan B or plan C with a hard stop benchmark and plans for reversal or retrievals.
Over-ambitious, aggressive and over-enthusiastic management is saddled with grossly misplaced overconfidence where their view becomes the world's view and they tend to gloss over many ground realities which do not conform to their way of thinking.

Theme 6: Criminalization of Bankruptcy Leads to Efforts to Suppress Bad News

Table 5.10: Analysis of Theme 6

Key Words and Key Phrases
Why in India does it get highlighted so much – the criminalization of failure / bankruptcy is an accepted phenomenon outside India? In India, it is considered a failure of the business. The approach is wrong. One event gets blown out of proportion. Highlighted much more
Another lens to look at this is the right pricing of risk. Typically, good lenders will have around 1–2% of loans going bad whereas bad lenders will have up to 10% of loans going bad. Smart lenders price their risk appropriately. Risk-based pricing is the right framework and approach to lending (#10)
Bankruptcy / Resolution enablement
The approach is that when something goes wrong, build a rule that applies to everyone without understanding all the implications (Wijayati *et al.* 2021). Band-Aid solutions. For example, build a speed breaker after an accident even if cars get damaged.
Why would you throw away something that has been built over years and destroy all of its value just because it went bankrupt? The value of building the same thing in present times would be at least ten times

Theme 7: Information Asymmetry

Table 5.11: Analysis of Theme 7

Key words and Key phrases
Course Corrections – SEBI has come up with new guidelines requiring intermediaries to undertake to monitor and send alerts if the sign of deterioration is there. But the responsibility is misplaced on the trustees. Trustees do not have the infrastructure
Information Asymmetry In recent times, we're seeing detailed models that attempt to capture cash flows in detail through sectoral models. These models generally provide good guidance on the credit model.
Rating agencies typically receive information from management and place reliance on that information. There is no way to check misstatements, incompleteness or inaccuracy of information.
Guidelines on detailed disclosures in financial statements from management have been helpful
Statutory Auditors Revamp of responsibility of statutory auditors Information asymmetry being solved
Lack of Disclosures / Information
Information asymmetry plays a major role. The shock that only I as a promoter know – I will try to deal with it. Signals when the entity is trying to deal with shocks. Direct ways and indirect ways.
The big challenge is unlisted companies because the information is not available. Feeds into the instability of data. Can I build – a project basis say a listed entity in the same sector? First order change, second order change
Information asymmetry is big for retail investors
Asymmetry of information
We don't get into details of the true value of the security. We don't question numbers reported to exchanges that look too good to be true (#5)

Information Asymmetry: • borrowers tend to hide as much as they can • Among the lenders, there is no way to get info that is available from other lenders • Regulatory (it is now compulsory for lenders to come together) • Stressed special mention accounts • Banks reporting not seen by NBFCs and vice versa • It is time that information barriers are removed
Principle for all of the above – Independent sources Access to information – legislation / consent How should we go about default predictors – Set a model / put ranges on acceptable values
The weakness in current models is that they are backwards-looking. Rolling indicators are not there. The model should not be static.
Information usage and sharing The RBI collects all the information but the sharing of data does not happen (#5)
Information Asymmetry Information is on paper, there is always a question on the depth of the audit, information which is provided after the audit. This creates an information asymmetry. The loan is sanctioned as the promoter exists. Even if the information is there, no actions are taken which creates stress. And there is no process in the banking system to detect this early. Again, even if we detect it, round-tripping is done; some malpractices are carried out after some conversation with the promoters to keep the books of banks clean.
Information asymmetry is a big theme.
Frequency and seriousness of how you get the data
Maybe a relevant model for some learning is the PE model. I created a budget and asked the investee to give a budget and fund an agency. The PE appoints its agency. Control and appointment of the agency that collects information is with the lender/investor.
To summarize, maybe information asymmetry is the largest theme.
We also need to look at how good we are at signal reading. For instance, even if servicing is happening, is the credit really on track? Or is the credit just being serviced somehow in terms of managing from multiple sources.

Theme 8: Lack of Liquidity

Table 5.12: Analysis of Theme 8

Key Words and Key Phrases
Lack of liquidity – very difficult to exit when the market gets a warning of a default
Liquidity mismatch
Developed markets – deeper bond markets, far more institutions of market makers
Willingness to trade on price. In India, the approach is that I should not have a default and should also get > G Sec. At levels below a certain rating, liquidity is not available.
Also, the CDS market is a huge lead indicator. Because it's a liquid market, the bid offer is very low. Willing to pay 10/20/30 bps and you can hedge. Exit / but if yields move, things difficult
In India, the RBI has tried but we need players willing to operate at that scale. If I have liquidity, my capacity to take defaults is higher. Width and depth need to be there.
You can do models only at AAA/ G Sec

In terms of ratings, AAA-rated entities are very few. In India, at BBB, there is no trading or liquidity. In other markets, junk bonds are also tradable.
Indian debt doesn't trade – the amount of analysis and how spreads are computed are, therefore, not as rigorous as listed firms.
There are no derivatives in the market. In 2005–06, Tata Motors could issue their CDS/CLOs and buy CLOs. I went to Ishaat Hussain and said your CFO doesn't understand that market is expecting you to default. Spread on CLO is high.
Lesson – less traded / low liquidity. No way to tell whether a firm is close to default or not.
The industry doesn't understand its debt and default rates
Because we don't trade, we don't understand transition rates. Many times, the lag between actual transition and its default characteristics occur so fast that the deterioration happens much before a machine predicts a default. It has been observed that transition of ratings has been faster in India. Many times, there are not enough alerts generated preceding a default.

Theme 9: Lender Monitoring and Lender Culture

Table 5.13: Analysis of Theme 9

Key Words and Key Phrases
Message – monitoring tends to lose basics and becomes routine
If you monitor and bring down the value at regular intervals, you can remediate, say, for instance through a price increase (#14) redraw the balance sheet
For monitoring – there is no single parameter. It needs to be constantly done.
The art of monitoring is being lost
The culture of the lending organization is also a significant factor in monitoring. Current cultures have become so number and sales aggressive that lenders have become more salespeople than lenders. Monitoring has to be a culture within the lender organization.
Professional scepticism – weak in India. Problem is that as Indians, our respect is high. We feel uncomfortable with difficult conversations. Elephant in the room – not questioned. We accept explanations. We can't document. In the case when verbal assurances on businesses are given, can you get us a guarantee paper? Confirmation bias – lender doesn't face the possibility that things could be going wrong (#10).
Credit decision – certain elements are ignored. Perception-driven lending. Models are changed to perception.
Lending monitoring – has to be used properly. Monitoring to have a grip on cash flows. Order book reasonableness.
Monitoring After the sanction of the loan, there is no monitoring of its use of it, and no discussion with the promoters. Banks don't have industry experts to check the purposes like new products or innovations for which the loans are taken. So, as a part of monitoring, there should be regular talks between promoters, banks and subject experts of the banks.
Banks should have their representatives on the Board of Directors at least for some companies having some certain threshold amount of loan. The representatives should not be the bank's employees. A professional who can be responsible for reporting to banks what is happening in the company.
To avoid the NPAs or to avoid 40–60% of haircuts, banks restructure within the realms of the RBI policies. Half of the loan gets converted into equity making it feel that the bank got an exit.
The sanctioning models should focus on the key operating metrics as they are important indicators of credit positions.

Sanctioning models in India have a lot of noise in them. Reasons: (i) People use judgment / overrides in the sanctioning model / political pressure (ii) Models often are not able to account for or identify other stress factors on the balance sheet. Can look reasonably well on income statements and coverage.
There is a pricing angle. They're not adjusted sufficiently for macro conditions. Banks are printing money right now. Interest rates are running up – they're sitting on this book – when you start printing that much money in the near term – what is the underlying impact. Interest rates are high. When banks are making so much money, they tend to take their eyes off where the default will occur. Part of Predictive – India operates at three different levels Large – lots of data available and data is reliable SME – lots of data available but data is unreliable. Data created for Taxman. Real Earnings are different. In SMEs, the decision to sanction at the right price – use of collateral to bring down loans prices that are mispriced. Mispricing is one of the reasons we default. Capital productivity dropped with higher-priced loans. Use pricing as a means of protection for what is structurally weak. As our corporates get bigger / as they use debt more diversely, the ability of people to understand operating risks goes down Big side – you don't understand the nature of the issue
Another lens to look at this is the right pricing of risk. Typically, good lenders will have around 1–2% of loans going bad whereas bad lenders will have up to 10% of loans going bad. Smart lenders price their risk appropriately. Risk-based pricing is the right framework and approach to lending (#10)
Lending models created to fit the parameters
Lender culture
Pricing for complex structures
Having uniform rules for lending pools irrespective of whether they're bonds, bank loans or debentures (e.g. RHF)

Theme 10: Reliance on Financial Numbers

Table 5.14: Analysis of Theme 10

Key Words and Key Phrases
Overreliance on financial numbers – EBIDTA, capex, debt capacity. Financial metrics will present what has happened in the past.
Using financial and non-financial metrics
An important limitation in 1968 when Altman Z-score was used was that machine learning was not there. Now artificial intelligence is available. We have 140 indicators. Predictive analysis is a must in addition to Z-score (#7)
Mass customization which is possible through AI is not possible through statistics. Energy should go into industry factors. Z-score has its value. Only quantitative analysis is not enough. The model has to combine quantitative with qualitative. Factors like ISO certification, quality of the board, changes in the board, and changes in management / CFO. AI can combine qualitative and quantitative.
Integration of qualitative and quantitative (#7)

Theme 11: Over-reliance on Rating Agencies

Table 5.15: Analysis of Theme 11

Key Words and Key Phrases
Heavy dependence on rating agencies. Considering that most lending is done looking at the rating of the issuer, it is most important to track changes in ratings as these are the first signals of stress. Even regulated investment portfolios like insurance portfolios mandate ratings as one of the tools to regulate investments of public money.
Overreliance on rating agencies – conflict of interest for more businesses

Theme 12: Structural Issues in Business Models

Table 5.16: Analysis of Theme 12

Key Words and Key Phrases
Structural issues in infrastructure models of private participation
Quantitative and qualitative factors. Trends that give predictability of default. Not related to and linked with bond prices.

Theme 13: Valuation of Security / Value of Equity

Table 5.17: Analysis of Theme 13

Key Words and Key Phrases
Assets created as security are overvalued
For listed – price volatility in equity markets can give you signals. get info on how the stock is performing.
Context of business failure / bankruptcy / liquidity
Modelling credits
One important thing to consider in my personal opinion is share price. It is critical in developing a model. Equity valuation generally considers events.
Incorporation of stock price
Detecting and dealing with large-scale defaults of the kind of IL&FS.
Systemic and non-systemic risks
Fertile breeding ground
Perpetuates the issues/problems
Tunnelling effect
Failure to detect/notice early warning signals
Risks to endemic levels
Stretched efforts spinning out of control
Stage of no return

Theme 14: Miscellaneous

Table 5.18: Analysis of Theme 14

Key words and Key phrases
• Trained manpower – regulator / auditors – other than the top firms, the kind of training that should go in doesn't get done • upgrade – focused training/lenders/credit risk management courses. domain expertise / functional expertise / understanding of typical business nuances • quality of manpower is different (#10)

CHAPTER 6

THE PSA SCORE AS AN INDEPENDENT VARIABLE

The professional scepticism alert (PSA) highlights how the professional scepticism of a lender during the period of distance to default was critical and how cultural dimensions came into play. If professional scepticism is at appropriate levels, alerts generated could lead to interventions that are remedial in nature.

I, therefore, coined the sense-making (giving meaning to collective experiences) of trends of qualitative factors that practitioners brought out as key themes as professional scepticism alert (PSA) scores. Every deterioration in credit within an identified theme (for instance, rating downgrade) was given a PSA score of 1. A PSA score of 0 was for no deterioration or maintenance of the last PSA score.

6.1 Objective of PSA

> The objective of PSA is simply to generate a parameter on questioning a certain credit situation and cause alerts.

A PSA score by itself does not predict a default; it simply reflects a credit situation that may need a review and subsequent remedial actions.

6.2 The PSA as an Independent Variable

The PSA score is a variable that can be looked at independently for assessing the direction of credit or can be used in conjunction with other independent variables to assess the predictability of default for a credit.

6.3 Defining the Datasets

Dataset Composition:

Three datasets were used for quantitative analysis. Composition of each dataset was asunder

- Dataset #1 = 230 firms. Traditional ratio tests carried out on dataset #1, defined further in this chapter (number of firms = 230).
- Dataset #2 = 63 firms. PSA Scores computed manually for all companies in dataset #2 (number of observations = 63, of which 38 firms are randomly chosen from among defaulted ones, 25 non-defaulted firms are chosen through stratified sampling.)
- Dataset #3 = 50 firms (created from dataset #2). Out of 38 firms (defaulted ones) that form part of dataset #2, traditional ratios were available for 22. Out of 25 firms (non-defaulted) that form part of dataset #2, limited ratios were available for 3 firms so these were dropped and 5 firms were added wherein both traditional ratios were available and the PSA score was computed manually in dataset #3.

Traditional tests plus PSA scores as additional dependent variables for tests carried out (number of observations = 50 with 22 defaulted (34% of 63 defaulted companies) and 28 non-defaulted companies).

6.4 Snapshots of PSA Computation Methodology and Output

Table 6.1 gives an illustration of PSA computed from base documents such as annual reports. The period considered is around 2016–2021, N is the year of default. Mostly, the values three years prior to the default and two years after the default have been considered. Table 6.2 provides the basis for theme-wise computation of the PSA scores.

Table 6.1: Illustration of PSA

	Theme – Changes within 6–8 Quarters (Rating Downgrades)					
	Date of Default					
		N–3	N–2	N–1	N	N+1
Reliance Home Finance Limited	Sept 9, 2019	2016–17	2017–18	2018–19	2019–20	2020–21
LT – CARE		No Change	AA+	A+/PP MLD A+	Default	Default
LT – Brick work		No Change	AA+	AA/PP MLD AA	Default	Default
ST – ICRA		No Change	A+	A2	Default	Default
ST – Brickwork		No Change	A+	A1+	Default	Default
PSA Threshold		1 or more transition downwards = +1; No change = +0				
PSA Score		0	0	1	2	2

Table 6.2: Basis for theme-wise computation of the PSA scores

	The theme for sense-making on PSA scores	Data relied upon in the event of an alert	Why the PSA score is high (1) or low (0)
Theme # 1	ALM Mismatches (includes stressed liquidity)	LM statements if available in financial statements / public news of liquidity stress / rating information	For every year reviewed, if deterioration from previous year is observed, then PSA rating is 1 and no change was rated as 0
Theme # 2	Rating Transitions (downward)	Rating Information	For every transition that is downward, PSA if rated 1.
Theme # 3	Reduction in Promoter Holdings (mostly lender pledge invocations)	Financial Statements	For reductions in excess of 20% or explicit information in the invocation of the pledge of promoter shares by lenders.
Theme # 4	Statutory Auditor's Qualifications / Matter of Emphasis	Auditors Report	Qualifications or Matter of Emphasis = 1
Theme # 5	Change in Auditor's Remuneration	Financial Statements	For one time increase of > 50% or explicit sense-making that remuneration has increased on account of growing stress in financial conditions
Theme # 6	Others (Frauds/KMP resignations/Investor alerts)	News/Public Domain/ Investor statements	For every explicit event of news, PSA = 1

Testing Output for the PSA Score (Qualitative Factors only) as an Independent Variable

For each company, theme-wise PSA scores were computed. These were then added to generate the total PSA score and year-wise PSA score across themes. The company-wise total PSA score is given in Fig. 6.1. The top 5 companies with the highest PSA score were Il&FS Transportation Networks Limited (score = 25), Ashiana Landcraft Realty Private Limited (score = 22), Bhanshali Infrastructure Projects Ltd, D S Kulkarni Limited and SREI Infrastructure Finance (each with a score = 19).

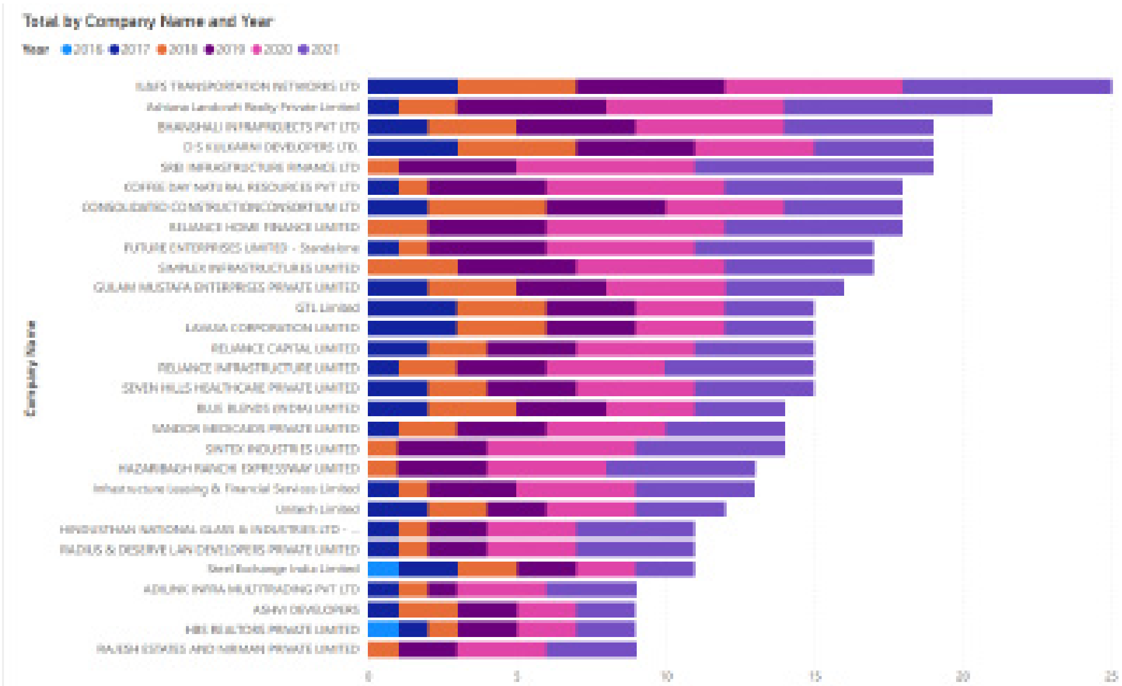

Figure 6.1: Testing Output for the PSA score (Qualitative Factors Only) as an Independent Variable

6.5 View of the PSA Score Transitions

Table 6.3 gives an overall view of the transitions in the PSA score for defaulted companies in dataset #2 roughly over the period 2016–2021. The values in red are marked for the year when the particular company defaulted.

Table 6.3: View of the PSA Score Transitions for Defaulted Companies in Dataset #2

	2013	2014	2015	2016	2017	2018	2019	2020	2021	Grand Total (cumu-lative)	Year of Default
Adilink Infra Multitrading Pvt. Ltd					1	1	1	3		6	2020
Adriti Estate Developers Private Ltd						0	0	0	0	0	2021
Ansal Urban Condominium Pvt Ltd	2	2	2	2							
Aristo Realtors Infrastructure Pvt Ltd			0	0	0	1					
Ashiana Landcraft Realty Private Limited						2	5	6	7	20	2021
Ashvi Developers						2	2	2	3	9	2021
Bhanshali Infraprojects Pvt Ltd						1	1	1	1	4	2021
Blue Blends (India) Limited					4	5	6	6		21	2020
Champalalji Finance Pvt Ltd Champalalji Finance Pvt Ltd					2	2	2	2		8	2020
Coffee Day Natural Resources Pvt Ltd					1	2	5	5		13	2020
Concrete Lifestyles & Infrastructure Pvt Ltd						0	0	0	0	0	2021
Consolidated Construction Consortium	2	2	3	2						9	2016
D S Kulkarni Developers Ltd			2	2	5	5				14	2018
Future Enterprises Limited (Standalone)					1	1	4	5		11	2020
Gulam Mustafa Enterprises Private Limited					2	3	3	4		12	2020
Hazaribagh Ranchi Expressway Limited					0	1	3	4		8	2020
HBS Realtors Private Limited		2	2	1	1					6	2017
Hindusthan National Glass & Industries Ltd (Standalone)						1	2	3	4	10	2021

Il&Fs Transportation Networks Ltd				1	3	4	5			13	2019
Infrastructure Leasing & Financial Services Limited				1	1	1	3			6	2019
Jai Maharashtra Nagar Development Private Limited	3	3	3	3						12	2016
Krishna Enterprises Housing Infrastructure Pvt. Ltd						0	0	1	2	3	2021
Kumar Urban Development Pvt. Ltd			0	0	0	0				0	2018
Lavasa Corporation Limited						3	3	3	3	12	2021
Manyata Developers Private Limited						0	0	1	2	3	2021
Meeti Developers Private Limited						0	0	1	1	2	2021
Mireya Realty Private Limited						0	0	2	3	5	2021
Orissa Stevedores Limited						1	2	2	2	7	2021
Radius & Deserve Lan Developers Private Limited					1	1	2	3		7	2020
Rajesh Estates and Nirman Private Limited						1	2	3	3	9	2021
Reliance Capital Limited					2	2	3	4		11	2020
Reliance Home Finance Limited					1	2	4	6		13	2020
Reliance Infrastructure Limited					1	2	3	4		10	2020
Sandor Medicaids Private Limited					1	2	3	4		10	2020
Seven Hills Healthcare Private Limited						2	3	4	4	13	2021
Simplex Infrastructures Limited					0	3	4	5		12	2020
Sintex Industries Limited					0	1	3	5		9	2020
Srei Infrastructure Finance Ltd						1	4	6	8	19	2021

6.6 Theme-wise Comparisons of PSA Scores for Defaulted Vs Non-Defaulted Companies Computed for Companies in Dataset #2

A theme-wise comparison of the PSA scores of defaulted companies versus non-defaulted companies is asunder in Fig. 6.2. The theme compared asunder is Changes over 6–8 Quarters (Changes in Statutory Auditors Qualifications or Matters of Emphasis).

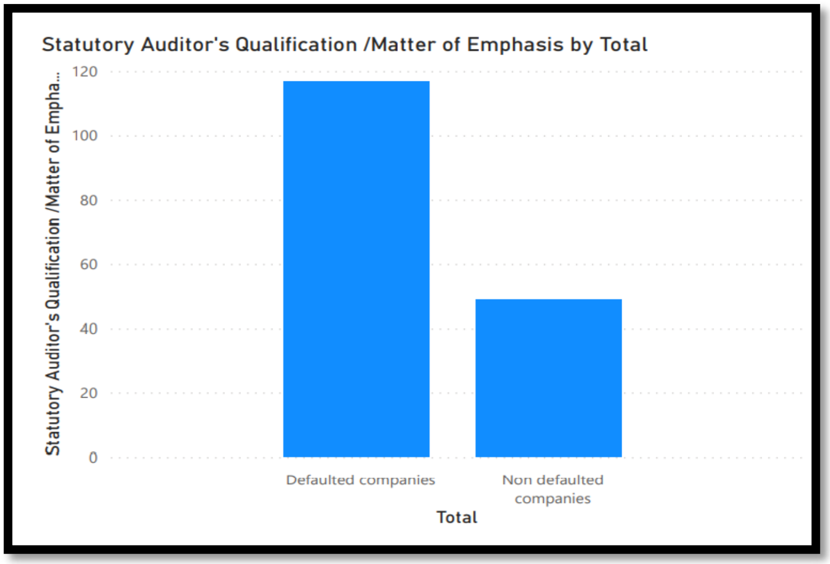

Figure 6.2: Statutory Auditor's Qualification/Matter of Emphasis by Total

The bar chart in Fig. 6.2 shows the total score of the Statutory Auditor's Qualification / Matter of Emphasis for defaulted and non-defaulted companies. The total number of defaulted companies is 117, which is 2.3877551 times the non-defaulted companies whose total is 49.

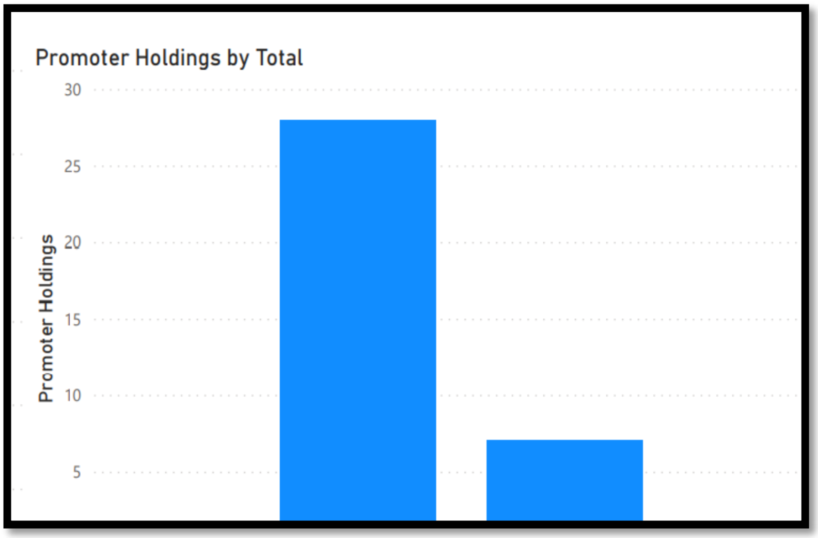

Figure 6.3: Promoter Holdings by Total

The bar chart in Fig. 6.3 shows the total score of promoter holdings for defaulted and non-defaulted companies. The total of defaulted companies is 28, which is four times the non-defaulted companies whose total is 7.

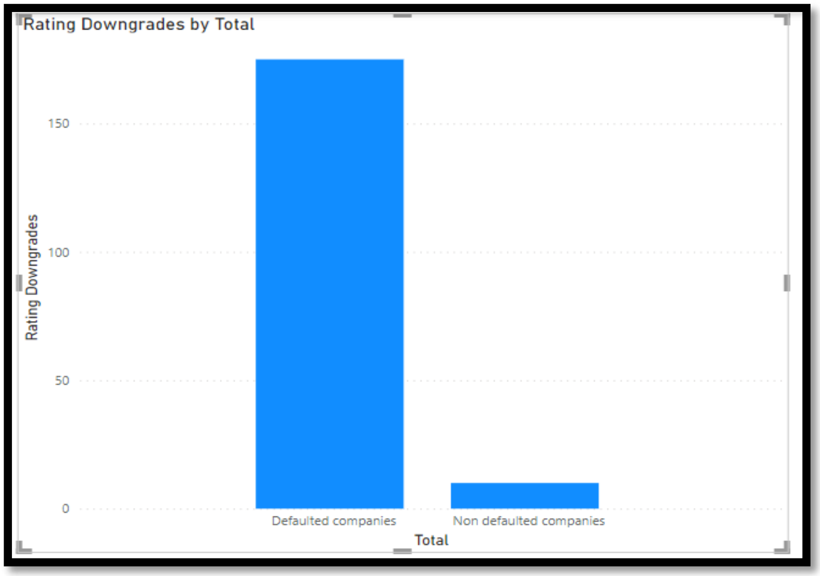

Figure 6.4: Rating Downgrades by Total

The bar chart in Fig. 6.4 shows the total score of rating downgrades for defaulted companies and non-defaulted companies. The total of defaulted companies is 175, which is 17.5 times the non-defaulted companies whose total is 10.

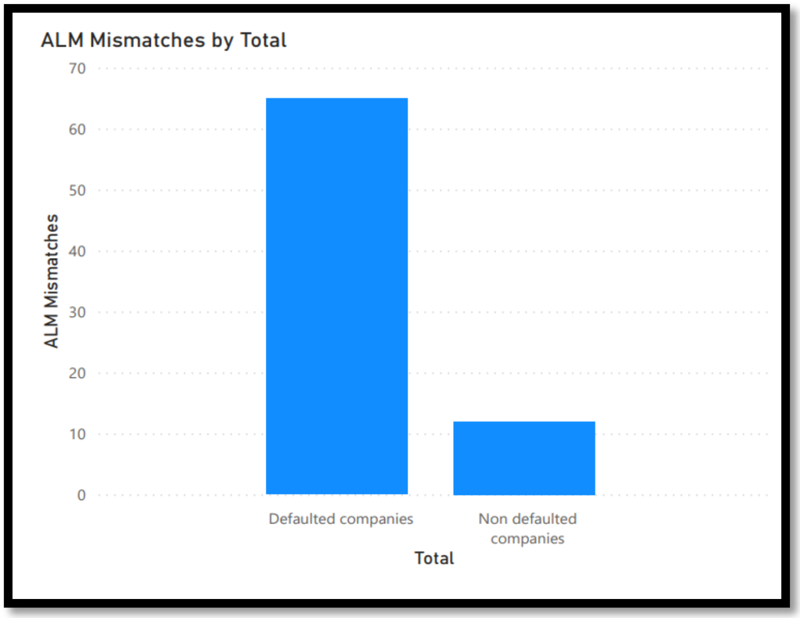

Figure 6.5: ALM Mismatches by Total

The bar chart in Fig. 6.5 shows the total PSA score of ALM mismatches for defaulted and non-defaulted company. The total of defaulted companies is 65, which is 5.4166667 times the non-defaulted companies whose total is 12.

Chapter 7

DATA COLLECTION AND PROCESSING

7.1 Data Collection

Composition of datasets

1. Dataset #1 = 230 firms. Traditional ratio tests carried out on dataset #1, defined further in this chapter (number of firms = 230).
2. Dataset #2 = 63 firms. PSA Scores computed manually for all companies in dataset #2 (number of observations = 63, of which 38 firms are randomly chosen from among defaulted ones, 25 non-defaulted firms are chosen through stratified sampling.)
3. Dataset #3 = 50 firms (created from dataset #2). Out of 38 firms (defaulted ones) that form part of dataset #2, traditional ratios were available for 22. Out of 25 firms (non-defaulted) that form part of dataset #2, limited ratios were available for 3 firms so these were dropped and some firms were added wherein both traditional ratios were available and the PSA score was computed manually in dataset #3.

Traditional tests plus PSA scores as additional dependent variables for tests carried out [number of observations = 50 with 22 defaulted (34% of 63 defaulted companies) and 28 non-defaulted companies]

7.2 Summary and Reconciliation for Dataset #1

Dataset	Sources
Dataset #1 – Start point = 277 companies with debt and equity listed at Stock Exchanges. Final considered = 230 companies.	Capital IQ, Prowess DX and Money Control
Financial ratios for quantitative tests as per traditional methods	Capital IQ, Prowess DX and Money Control

A	Extract from Capital IQ—Total number of companies with debt and equity listed at the stock exchange	
	Number of data items	277
	There were only three defaulted companies in the database that came out and the dataset was primarily non-defaulted companies.	
	Non-defaulted companies	274
	Defaulted companies	3

B	Additions to dataset #1	
	Defaulted companies (unlisted from dataset 2)	15
C	Deletion from dataset #1	
	Companies with information incompleteness of more than 40% were removed	62
D	Number of companies in dataset #1	230

7.3 Summary and Reconciliation for Dataset #2

Dataset	Sources
Dataset #2 – The PSA scores computed for a list of 38 companies randomly chosen from a universe of 63 companies that defaulted on corporate debt. For these 38 companies, the PSA scores were computed manually. The PSA scores were computed for themes where quantitative or qualitative validations were possible.	Defaulted ISIN (unique identifier for each firm) list from CDSL and NSDL
Dataset #2 – The PSA scores computed for a list of 25 non-defaulted companies with debt issued.	Stratified sample base from dataset #1 Total sample size = 38+25=63 The process of stratified sampling is explained at the end of this chapter.
Qualitative testing for the PSA scores	Annual reports, rating rationale and other publicly available information of all Companies in dataset #2. Extraction of themes from financial statements and rating rationales

A	Extract from NSDL and CDSL website of all companies that stand as defaulted as of July 15, 2022	63
	Composition of 63 is as follows:	
B	I added the list of non-defaulted companies that were extracted based on the stratified sample module from the software Orange	25
C	Considered as a part of dataset #2	
	The PSA scores computed manually for defaulted companies	38

7.4 Summary and Reconciliation for Dataset #3

Dataset	Sources
Dataset #3 – The start point is dataset #2 comprising 63 companies with debt and equity listed at Stock Exchanges. Finally, a list of 50 companies was considered.	Capital IQ, Prowess DX and Money Control

A	Closing balance of number of firms in dataset #2 Number of firms that defaulted = 38 Number of non-defaulted firms = 25	63
	Deletion of firms from the list of firms that had defaulted on account of unavailability of traditional ratios. (Addition of 1 defaulted firm to improve the sample.)	16
	Balance firms that had defaulted included in dataset #3	22

B	Non-defaulted firms considered as a part of dataset #2	25
	Deletions of firms from the list of firms that had defaulted on account of unavailability of traditional ratios.	3
C	Addition of 6 firms wherein the PSA scores were computed for dataset #3 to offset deleted firms on account of B.	6
D	Total non-defaulted firms that form part of dataset #3	28
E	Total firms that form part of dataset #3	50

The PSA score is like any other independent variable akin to the financial ratios which when combined with the traditional financial ratios leads to improvement in the dependent variable(s) for determining probability of default. And hence using PSA becomes a more holistic approach to predict defaults and initiate remedial measures.

7.5 Processes Carried Out on Datasets

Process carried out on dataset #1

Financial ratio file of dataset #1 comprised the following ratios. In this input file, uploaded data comprised financial ratios as per traditional methods.

Ind	Year	t	Company Name	Tag 1 Default=1/ NonDefault=0	Tag 2 N= Default, N+=post default, N = pre default	Tag 3 Deafult + post default=1, else 0	Return on Assets %	Return on Equity %	Gross Margin %	EBIT Margin %	Total Asset Turnover	Current Ratio	Quick Ratio	Total Debt/Equity %	Total Liabilities/Total Assets %	EBIT / Interest Exp.
1	2016	1	PTC India Fincial Services Limited	0	0	0	5.02	24.6	99.7	87.5093581	0.076	3.91	3.91	392.8	80.3	2.080765
1	2017	2	PTC India Fincial Services Limited	0	0	0	3.53	16.6	99.6	87.86356777	0.059	3	3	335.8	77.5	1.88691
1	2018	3	PTC India Fincial Services Limited	0	0	0	0.869	4.6	99.5	44.47463233	0.044	2.58	2.57	527.8	84.3	0.778582
1	2019	4	PTC India Fincial Services Limited	0	0	0	1.44	9.19	99.2	90.24481489	0.032	3.5	3.45	528.3	84.3	1.305403
1	2020	5	PTC India Fincial Services Limited	0	0	0	0.886	5.26	98.5	80.54040636	0.02	5.32	5.09	438.6	81.8	1.187238
1	2021	6	PTC India Fincial Services Limited	0	0	0	0.221	1.21	97.7	74.6362054	0.013	4.06	3.85	432.8	81.6	1.145198
2	2016	1	NTPC Limited	0	0	0	3.63	12.3	37	17.6	0.331	0.921	0.636	108.1	58.9	3.94
2	2017	2	NTPC Limited	0	0	0	4.09	11.2	35	18.9	0.347	0.778	0.474	115.3	60.3	4.17
2	2018	3	NTPC Limited	0	0	0	3.76	10.3	39.4	18.1	0.332	0.86	0.461	124.4	63	3.62
2	2019	4	NTPC Limited	0	0	0	3.63	12.8	40.5	18.2	0.319	0.646	0.358	151.5	67	3.27
2	2020	5	NTPC Limited	0	0	0	3.87	10.1	43	20.5	0.302	0.876	0.606	164.2	67.7	2.75
2	2021	6	NTPC Limited	0	0	0	3.5	11.9	45.2	19.5	0.287	0.799	0.55	162.6	67.6	2.26
4	2016	1	Power Grid Corporation of India Limited	0	0	0	4.52	14.5	98	59.6	0.121	0.389	0.337	246.9	75.5	2.58
4	2017	2	Power Grid Corporation of India Limited	0	0	0	5.03	15.9	97.8	58.7	0.137	0.434	0.385	238.6	74.5	2.56
4	2018	3	Power Grid Corporation of India Limited	0	0	0	5.11	15.7	97.9	57.5	0.142	0.433	0.375	241.6	75.8	2.46
4	2019	4	Power Grid Corporation of India Limited	0	0	0	5.33	17.7	97.6	57.5	0.148	0.542	0.487	253.6	76.1	2.46
4	2020	5	Power Grid Corporation of India Limited	0	0	0	5.5	17.9	98	58.8	0.15	0.602	0.541	234.6	74.8	2.44
4	2021	6	Power Grid Corporation of India Limited	0	0	0	5.84	17.9	98.1	60.4	0.155	0.831	0.553	209.8	72.7	3.12
7	2016	1	Centrum Capital Limited	0	0	0	0.221	1.21	5.49	42.7504465	0.013	1.75	1.29	79.9	55.3	1.50629
7	2017	2	Centrum Capital Limited	0	0	0	4.44	10.2	6.04	47.05882353	6.74	1.85	1.33	84.3	57.2	2.13162
7	2018	3	Centrum Capital Limited	0	0	0	2.64	8.32	4.72	68.16487018	6.22	1.62	1.41	226.3	74.4	3.02861
7	2019	4	Centrum Capital Limited	0	0	0	5.81	24.1	99	47.62862939	0.084	1.61	1.61	293.1	76.9	5.71905
7	2020	5	Centrum Capital Limited	0	0	0	0.025	0.097	99.5	54.99215891	0.097	1.22	1.22	230.3	72.1	2.62453
7	2021	6	Centrum Capital Limited	0	0	0	1.37	5.25	99.5	43.80818549	0.081	1.52	1.52	274.3	75.4	0.86657
11	2016	1	RELIANCE HOME FINCE LIMITED	1	N4	0	1.31	15	99.9	81.77488915	0.051	3.12	3.11	1116.4	91.9	1.4184
11	2017	2	RELIANCE HOME FINCE LIMITED	1	N3	0	1.81	10.7	96.7	81.0466284	0.049	3.65	3.65	877	90	1.71895

Figure 7.1: Financial ratios as per traditional methods

Step 1: The significance of the variables was extracted.

Step 2: The logistic regression model was run after the pre-processing.

Step 3: The accuracy of the model was recorded.

Step 4: All excel files were stored and sanitized for being submitted as a part of category II.

Process carried out on dataset #2

Step 1: List of Companies from NSDL and CDSL with their ISINs as of July 15, 2022 was considered.

Step 2: From the database, a list of companies that had defaulted was extracted.

> Default by NSDL and CDSL is defined as default on the principal instalment due.

Step 3: From this list, the PSA scores were computed manually. The sources were annual financial statements, rating rationales and information in the public domain.

Step 4: The PSA scores for non-defaulted companies were computed. A program of stratified sample was run on Software Orange on dataset #1. The process of running a stratified sample is provided at the end of this chapter. Thematic data was computed for working out the PSA scores.

Step 5: From the annual reports, the data for the selected themes was interpreted as under. The metric of PSA was computed year on year for every company from the annual report / rating information / publicly available news (Lorenzo *et al.* 2016). The reason that PSA was defined was the intent to identify events that must raise the professional scepticism alert. During the course of interviews that were conducted as part of the study, one of the respondents had opined that Indians are culturally inclined to believe more and that their professional scepticism was found to be on the lower side in some stress situations pertaining to credit. The study, therefore, simply raises professional scepticism alerts that stakeholders can respond to as deemed most appropriate in their respective situations. The PSA alerts are generated that stakeholders can consciously respond to. These alerts are related mostly to transitions in conditions. 1 is denoted as a deteriorating condition or existing stress at the start of the review period. 0 is denoted as no explicit signal of stress. Once the score of 1 has been given, it remains at 1 or increases with further deterioration.

Step 6: Calculate the cumulative PSA score.

- Once the PSA scores are arrived at for every company, these were added year-wise and theme-wise.
- These were arranged as N = Year of Default, N−1=One year before default, N−2 = Two years before default, N−3 = Three years before default and so on.
- The transition of the PSA scores (PSA score transition) during distance to default for defaulted companies was tabulated.
- The PSA score for non-defaulted companies over a window of time is also captured.
- An overview of the pivot table with the PSA scores of defaulted companies forms part of table in chapter 6.

Table 7.1: PSA score computation for non-defaulted firms in dataset #2

	2016	2017	2018	2019	2020	2021	Grand Total (cumulative)
Aavas Financiers Limited	0	0	0	0	0	0	0
AU Small Finance Bank Limited	0	0	0	0	0	0	0
CG Power and Industrial Solutions Limited	0	0	0	1	1	1	3

Dabur India Limited	0	0	0	0	0	0	0
DCM Shriram Limited	0	0	0	0	0	0	0
DCW Limited	0	1	1	1	1	1	5
Edelweiss Financial Services Limited	0	0	0	0	0	0	0
EPL Limited	0	0	0	0	0	0	0
GTL Limited	0	3	3	3	3	3	15
Hindustan Zinc Limited	0	0	0	0	0	0	0
Kotak Mahindra Bank Limited	0	0	0	0	0	0	0
Macrotech Developers Limited	0	0	0	0	0	0	0
Nuvoco Vistas Corporation Limited	0	0	0	0	0	0	0
Peninsula Land Limited	0	0	1	1	3	3	8
QGO Finance Limited	0	0	0	0	0	0	0
Rashtriya Chemicals and Fertilizers Limited	0	0	1	1	1	1	4
Safari Industries (India) Limited	0	0	0	0	0	0	0
Southern Petrochemical Industries Corporation Limited	0	1	1	1	1	2	6
Steel Authority of India Limited	0	1	1	1	1	1	5
Steel Exchange India Limited	1	2	2	2	2	2	11
Sterlite Technologies Limited	0	1	1	1	1	1	5
Tata Communications Limited	0	0	0	0	1	1	2
Tata Steel Limited	0	0	0	0	1	1	2
Uflex Limited	0	0	0	0	0	0	0
Unitech Limited	0	2	2	2	3	3	12

Process carried out on dataset #3

Figure 7.2 shows the data file containing dataset #3. Testing of dataset #3 was done in Software Orange. The steps followed in Orange are:

Year	Company me	Tag 1 Default=1/ NonDefault=0	Tag 2 N= Default, N+=post default, N = pre default	Tag 3 Deafult + post default=1 , else 0	Return on Assets %	Return on Equity %	Gross Margin %	EBIT Margin %	Total Asset Turnover	Current Ratio	Quick Ratio	Total Debt/Equity %	Total Liabilities /Total Assets %	EBIT / Interest Exp.	PSA Score
2020	Uflex Limited	0	0	0	4.67	8.24	41.9	9.2	0.812	1.41	0.875	77.2	53.1	3.45	0
2021	Uflex Limited	0	0	0	7.53	16.5	46.4	15.1	0.799	1.55	0.974	73	53	6.62	0
2016	Unitech Limited	0	0	0	1.68	8.72	21	39.3	0.068	1.42	0.214	66.5	65.7	0.022166396	0
2017	Unitech Limited	0	0	0	0.521	4.62	1	13.1	0.063	1.38	0.203	70.1	67.2	0.201517657	2
2018	Unitech Limited	0	0	0	0.149	15.6	17.4	3.01	0.079	1.37	0.185	81.2	71.2	0.074044948	2
2019	Unitech Limited	0	0	0	0.473	11.3	8.97	15.2	0.05	1.25	0.071	100.3	76.7	0.693504847	2
2020	Unitech Limited	0	0	0	1.12	28.8	10.9	27.8	0.065	1.14	0.132	151.7	82	1.32478043	3
2021	Unitech Limited	0	0	0	0.254	41.5	13.4	19.2	0.021	1.07	0.131	234.9	88.1	1.32478043	3
2016	RELIANCE HOME FINCE LIMITED	1	N-4	0	1.31	15	99.9	81.774889	0.051	3.12	3.11	1116.4	91.9	1.418399815	0
2017	RELIANCE HOME FINCE LIMITED	1	N-3	0	1.81	19.7	96.7	81.046628	0.049	3.65	3.65	877	90	1.718952114	0
2018	RELIANCE HOME FINCE LIMITED	1	N-2	0	1.25	11.3	97.1	76.294333	0.046	4.89	4.86	722.6	88.2	1.250412296	2
2019	RELIANCE HOME FINCE LIMITED	1	N-1	0	0.402	3.68	97	71.265711	0.036	3.5	3.39	865.7	89.8	1.079832028	4
2020	RELIANCE HOME FINCE LIMITED	1	N	1	2.22	22.7	97	48.483735	0.036	2.01	1.94	906.7	90.7	0.582617809	6
2016	RELIANCE INFRASTRUCTURE LIMITED	1	N-4	0	2.81	3.99	35.6	14.7	0.305	0.664	0.21	149.6	76.9	1.13	0
2017	RELIANCE INFRASTRUCTURE LIMITED	1	N-3	0	2.02	5.8	34.6	13.2	0.246	0.632	0.234	120.4	74.6	0.906	1
2018	RELIANCE INFRASTRUCTURE LIMITED	1	N-2	0	1.62	1.54	36.4	14.4	0.18	0.589	0.26	117.2	74.8	0.982	2
2019	RELIANCE INFRASTRUCTURE LIMITED	1	N-1	0	2.35	30.5	35.7	16.5	0.228	0.508	0.303	112	76.8	1.42	3
2020	RELIANCE INFRASTRUCTURE LIMITED	1	N	1	2.17	6.61	30.2	12.3	0.283	0.548	0.323	147.5	82.1	1.17	4
2016	RELIANCE CAPITAL LIMITED	1	N-4	0	4.94	8.55	69.9	45.7	0.173	0.967	0.456	182.9	76.8	1.92	0
2017	RELIANCE CAPITAL LIMITED	1	N-3	0	3.83	7.67	46.2	26	0.235	0.976	0.436	232.8	79.5	1.69	2
2018	RELIANCE CAPITAL LIMITED	1	N-2	0	3.03	46.5	56.1	24	0.202	4.13	3.28	1757.2	96.8	1.08	2
2019	RELIANCE CAPITAL LIMITED	1	N-1	0	2.33	86.2	40.8	17.5	0.213	2.64	1.72	6180.2	99.1	0.771	3
2020	RELIANCE CAPITAL LIMITED	1	N	1	1.81	163	18.4	14.7	0.197	1.27	0.786	517	102.6	1.41754386	4
2016	Ashiana Landcraft Realty Private Limited	1	N-5	0	8.1%	1.5%	100.0%	24.828263	0.00239	1.31	0.25	18.15	0.76	1.0x	0
2017	Ashiana Landcraft Realty Private Limited	1	N-4	0	5.3%	1.1%	100.0%	24.828263	0.00308	1.78	0.34	16.32	0.47	1.0x	1
2018	Ashiana Landcraft Realty Private Limited	1	N-3	0	0.0%	2.4%	100.0%	26.765432	0.00219	1.69	0.41	19.06	0.43	0.00	2
2019	Ashiana Landcraft Realty Private Limited	1	N-2	0	0.0%	0.1%	100.0%	1.9740901	0.00201	1.54	0.16	17.58	0.37	0.00	5

Figure 7.2: Data file containing dataset #3

Step 1: The input data was uploaded in the software and then the relevant rows were selected for the target variable and feature variable. The parameter selections were asunder (See Fig. 7.3).

Name	Type	Role
Return on Equity %	N numeric	feature
Gross Margin %	N numeric	feature
EBIT Margin %	N numeric	feature
Total Asset Turnover	N numeric	feature
Current Ratio	N numeric	feature
Quick Ratio	N numeric	feature
Total Debt/Equity %	N numeric	feature
Total Liabilities/ Total Assets %	N numeric	feature
EBIT / Interest Exp.	N numeric	feature
Altman Z Score	N numeric	feature
PSA Score	**C categorical**	**feature**

Figure 7.3: Parameter selection of input data

Step 2: The significance of the variables was extracted.

Interpretation: The PSA score comes up as significant for improvement in information gain.

Step 3: The logistic regression model was run after the pre-processing.

Step 4: The accuracy of the model was recorded.

Interpretation: The PSA scores of 4 and 5 come up as significant. This comes up as a transition score for predicting the default.

Process For Running Stratified Sample

Sampling Process:

Using the stratified random sampling technique, I arrived at a sample of 25 companies out of a total of 277 companies that were debt-listed public companies and would be tested for qualitative themes outlined by practitioners.

Method: Stratified Random Sampling

Universe: 277 Debt-listed Companies

Platform: Orange (Orange is an open-source comprehensive component-based software suite for machine learning and data mining.)

Component/Functionality: Data Sampler (Fixed Sample size of 25, deterministic and stratified) The Data Sampler widget gave as output a sampled data set with predefined conditions. The output is processed after the input dataset is provided and sample data is processed. A fixed sample size returns a selected number of data instances with a chance to set sample with replacement, which always samples from the entire dataset with replacement. I can generate more instances than available in the input dataset. Replicable sampling maintains sampling patterns that can be carried across users, while stratified sample mimics the composition of the input dataset.

Figure 7.4: Stratified Sampling Process

Chapter 8

DATA ANALYSIS AND INTERPRETATION

8.1 Overview

This section discusses the findings and interpretations of the statistical results applied to the ratios collected by various sources to study the significance of the prediction of default. The data was collected from various sources—Capital IQ, Prowess IQ, Prowess DX and Money Control. The primary as well as the secondary data were analysed with the help of different statistical methods applied in the study. The frequency distribution and descriptive analysis were applied. This included the estimation of the mean score of the ratios, variation as measured with the help of standard deviation (SD), and symmetry of the distribution as measured with the help of skewness.

Figure 8.1 shows an Extract of Orange data structure table for running tests of regression on dataset #1 of 230 companies.

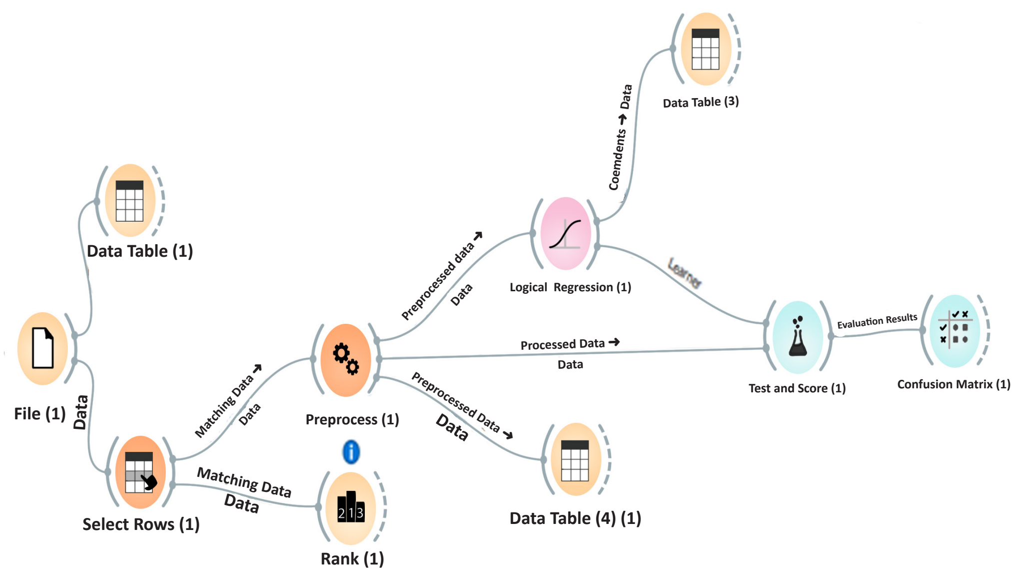

Figure 8.1: Extraction from Software Orange

8.2 Descriptive Statistics of Dataset #1 and Output Parameters

Table 8.1: Descriptive statistics of dataset #1

	Number of observations	Minimum	Maximum	Mean	Standard Deviation
Return on Assets %	1341	−26.16	117.80	4.36	5.26
Return on Equity %	1341	−44.13	2498.70	27.38	131.81
Gross Margin %	1342	−159.77	257.60	49.33	29.31
EBIT Margin %	1343	−5100.00	6072.88	25.72	234.52
Total Asset Turnover	1342	0.00	5100.00	6.01	143.70
Current Ratio	1342	0.00	126.70	2.53	7.55
Quick Ratio	1341	0.00	125.40	1.76	6.96
Total Debt/Equity %	1342	−203.00	23327.90	237.89	1010.09
Total Liabilities/Total Assets %	1341	0.02	7956.10	76.08	234.72
EBIT / Interest Exp.	1337	−66.10	979.85	15.06	67.77
PSA Score	1345	0	8	1.44	1.246

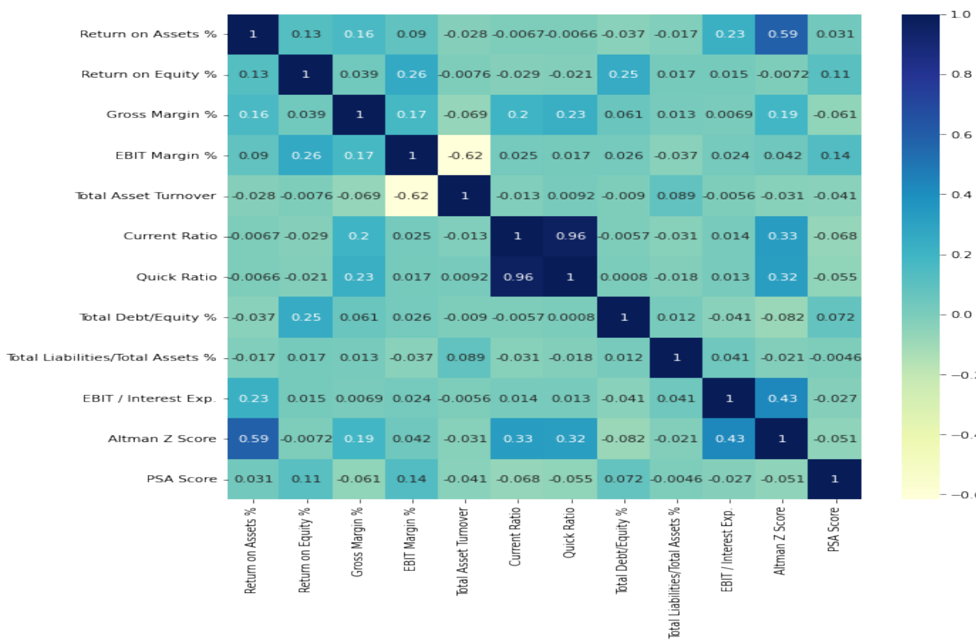

Figure 8.2: Correlation among the variables

Interpretation of the output: The heat map in Fig. 8.2 shows the correlation among the ratios. Dark colour represents a high correlation. When the colour is lighter, the correlation among the variables is low, and it is clear that the current ratio is highly correlated with the quick ratio. There exists a correlation between the Altman Z-score and the percentage return on assets.

Regression coefficients on input of dataset #1:

The inputs include financial ratios and exclude the PSA scores. To reiterate, this dataset has 230 companies.

Table 8.2: Regression coefficients on input of dataset #1

	Without the PSA score
Intercept	−4.292
Return on Assets %	0.250
Return on Equity %	0.235
Gross Margin %	−0.195
EBIT Margin %	0.984
Total Asset Turnover	1.854
Current Ratio	0.368
Quick Ratio	−0.331
Total Debt/Equity %	−0.030
Total Liabilities/Total Assets %	−0.032
EBIT / Interest Exp.	0.108

8.3 Descriptive Statistics of Dataset #2 and Output Parameters

Dataset #2 comprising 63 companies on which tests of regression were run includes the PSA scores for only the defaulted and non-defaulted companies.

The objective is to identify themes from the PSA scores that appear as significant predictors of default.

Table 8.3: Descriptive statistics of dataset #2

Dependent Variable: Default

Method: ML—Binary logit (quadratic hill climbing)

Variable	**Coefficient**	**Std. Error**	**Z-Statistic**	**Probability**
ALM_mismatches	0.100	0.355	0.282	0.777
Changes_in_auditors_remuneration	−0.045	0.511	−0.089	0.928
Miscellaneous_fraud__investor_alerts _KMP resig	0.998	0.508	1.962	0.049
Promoter_holdings	0.217	0.399	0.544	0.586
Rating_downgrades	0.994	0.181	5.487	0.000
Statutory_auditor_s_qualification	1.384	0.326	4.246	0.000
The results of regression that were run on the qualitative themes and were tested for statistical significance within dataset #2.	−2.702	0.267	−10.10	0.000

R-squared = 0.256

LR statistic = 106.589

Prob. (LR statistic) = 0.000

Interpretation of the output: Out of the themes that were extracted as significant from text analytics of interviews of practitioners, the themes that could be tested with quantitative methods were used for testing. The PSA scores were computed for each theme. Out of the themes that were tested, the significant themes with a probability score of under 0.05 were:

- Miscellaneous – fraud filings, lender/investor alerts/KMP resignations
- Statutory Auditors Qualifications/ Matter of emphasis transitions
- Rating transitions

As more and more live data is fed into the PSA scorer, the significance of the other themes is expected to improve.

8.4 Descriptive Statistics of Dataset #3 and Output Parameters

Figure 8.3 shows the results of the tests of logistic regression that were carried out for the 50 firms comprising dataset #3.

Significance of variables

In dataset #3, running the data in Software Orange including the PSA score as one of the independent variables, shows the significance of using the PSA scores. See Fig. 8.3.

Variable	Coefficient	Std. Error	z-Statistic	Prob.
CURRENT_RATIO	0.561439	0.228252	2.459738	0.0139
EBIT__INTEREST_EXP_	-0.398744	0.115501	-3.452300	0.0006
EBIT_MARGIN__	0.006957	0.004616	1.507311	0.1317
GROSS_MARGIN__	0.003700	0.005394	0.685871	0.4928
PSA_SCORE	0.495574	0.122336	4.050927	0.0001
QUICK_RATIO	-0.704526	0.266386	-2.644754	0.0082
RETURN_ON_ASSETS__	0.006145	0.022322	0.275276	0.7831
RETURN_ON_EQUITY__	0.000841	0.000982	0.856704	0.3916
TOTAL_DEBT_EQUITY__	-0.000115	6.93E-05	-1.664439	0.0960
TOTAL_LIABILITIES_TOTAL_ASSETS__	-0.004346	0.005475	-0.793788	0.4273
C	-0.468009	0.582444	-0.803526	0.4217

McFadden R-squared	0.292969	Mean dependent var	0.379310
S.D. dependent var	0.486148	S.E. of regression	0.411763
Akaike info criterion	1.022840	Sum squared resid	42.38726
Schwarz criterion	1.173069	Log likelihood	-122.4806
Hannan-Quinn criter.	1.083227	Deviance	244.9612
Restr. deviance	346.4647	Restr. log likelihood	-173.2324
LR statistic	101.5035	Avg. log likelihood	-0.469274
Prob(LR statistic)	0.000000		

Obs with Dep=0	162	Total obs	261
Obs with Dep=1	99		

Figure 8.3: Outcomes of Orange for Dataset #3

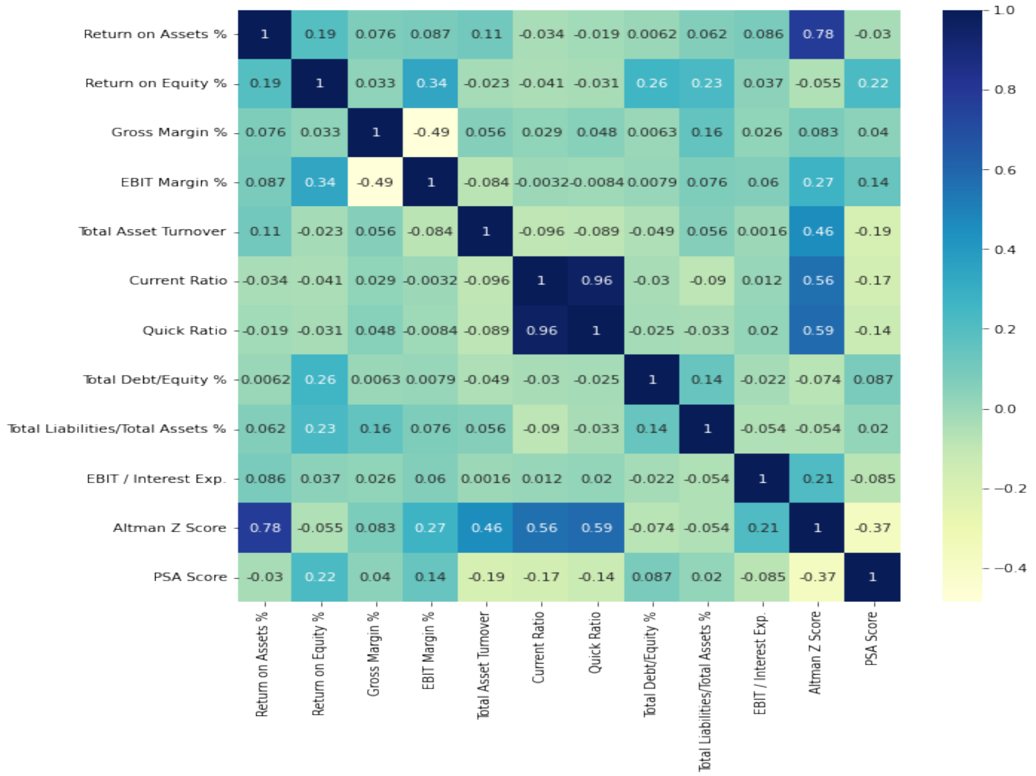

Figure 8.4: Correlation among the variables

Interpretation of the output: The heat map in Fig. 8.4 shows the correlation among the ratios. Dark colour represents a high correlation. When the colour is lighter, the correlation among the variables is low, it is clear that the current ratio is highly correlated with the quick ratio. There exists a correlation between the Altman Z-score and the percentage return on assets.

The information gained on input of dataset #3

The inputs include financial ratios and exclude the PSA scores. To reiterate, this dataset comprises 50 companies. The information gain of the variables was measured with and without the PSA scores as tabulated in Table 8.4.

Table 8.4: Information gain on input of dataset #3

	Information Gain with the PSA score	**Information Gain without the PSA score**
Return on Assets %	0.117	0.117
Return on Equity %	0.083	0.083
Gross Margin %	0.048	0.048
EBIT Margin %	0.002	0.002
Total Asset Turnover	0.088	0.088
Current Ratio	0.007	0.007
Quick Ratio	0.006	0.006
Total Debt/Equity %	0.087	0.087
Total Liabilities/Total Assets %	0.107	0.107
EBIT / Interest Exp.	0.142	0.142
Altman Z-score	0.042	0.042
PSA score	0.152	-

Interpretation of the output: As I add another variable, i.e., the PSA score, to the model and the information gained from the variable is measured, the output depicts that the PSA score improves the explanation of the dependent variables.

The PSA score is like any other independent variable akin to the financial ratios which when combined with the traditional financial ratios leads to improvement in the dependent variable(s) for determining probability of default. And hence, using PSA becomes a more holistic approach to predict defaults and initiate remedial measures.

Table 8.5 shows the results and information gained from the tests of logistic regression with and without the PSA score on dataset #3.

Table 8.5: Regression parameters as under for dataset #3

	With the PSA score	**Without the PSA score**
Intercept	0.141	−0.734
Return on Assets %	−0.011	0.000
Return on Equity %	0.096	0.135
Gross Margin %	−1.062	−1.255
EBIT Margin %	0.515	0.552
Total Asset Turnover	−0.772	−0.968
Current Ratio	0.751	0.629
Quick Ratio	−1.395	−1.421
Total Debt/Equity %	−0.120	−0.111
Total Liabilities/Total Assets %	−0.074	0.034
EBIT / Interest Exp.	−2.218	−2.427
Altman Z-score	0.510	0.514
PSA score = 0	−1.244	-
PSA score = 1	−1.080	-
PSA score = 2	−0.571	-
PSA score = 3	−0.562	-
PSA score = 4	1.466	-
PSA score = 5	0.853	-
PSA score = 6	0.822	-
PSA score = 7	0.294	-
PSA score = 8	0.023	-

Confusion matrix from Software Orange for dataset #3

Table 8.6 provides the data in the confusion matrix from Software Orange for dataset #2 with the PSA score included as a variable in addition to financial ratios.

Table 8.6: Confusion matrix from Orange for dataset #3

Model	AUC	Precision	Recall	Log loss	Specificity
Logistic regression	0.790	0.699	0.704	0.619	0.607

Table 8.7: Predicted and actual outcomes

		PREDICTED		
		0 (non-default)	1 (default)	∑ (Aggregate number of observations)
ACTUAL	0 (non-default)	71.5 %	32.6 %	3327
	1 (default)	28.5 %	67.4 %	2073
	∑	4030	1370	5400

Interpretation of the output: The model when trained and tested on Software Orange could correctly predict 71.5% times for the non-defaulted firms and 67.4% times for the defaulted firms.

The total of observations in Orange pursuant to the machine training and testing the model aggregated to 5400 comprising 4030 aggregate observations in the category of defaults and 1370 in the category of non-defaults.

Chapter 9

CONCLUSIONS OF THE STUDY

9.1 Contribution of the Study

Starting from the point of the gap in research that outlined the inadequacy of existing models to predict corporate credit defaults, the study proposed a framework of the EWS construct that considers antecedents for Indian markets.

The critical component of the EWS framework proposed is the consideration of market antecedents that are reflected in the measure of the PSA score as an independent variable.

Conceptualization of the PSA score is significant in terms of contribution to the existing methods. The PSA scores represent themes that do not find their way in the modular format of financial ratios and give completeness to the assessment of a particular credit situation of a particular borrower. Themes could be macro but are relevant for a specific borrower and their credit situation. They are also flexible in terms of market context. The composition of the PSA score could, therefore, be derived from the actual context of any market.

The most significant contribution is that it proposes a structured comprehensive framework that first identifies alerts including market-specific antecedents and then categorizes the results into risk zones. This leads to the conviction to initiate interventions or not after analysing the triggers.

The framework moves beyond the modular financial ratio-based results. The PSA scores, therefore, contribute to strengthening conviction when there is need for intervention. From a point where lenders or regulators remain in doubt about the need for intervention just because some of the financial ratios breach thresholds to a point where the PSA scores too are at higher levels along with ratios that breach thresholds, the PSA framework lends the necessary conviction that is needed for further remedial interventions.

> The PSA scores add an additional layer of sense-making to the results conveyed only by the breach of financial ratios to assess a particular credit situation.

The existing models present a modular picture of a specific credit based on financial ratios. When I add a PSA score that represents a collation of qualitative or quantitative themes that practitioners hold as significant, it provides improved information and strengthens lender conviction that the time during the period when alerts start to signal deterioration is critical for interventions.

The PSA score as an independent variable contributes to the predictability of default compared to traditional methods as stated earlier. The themes outlined in Chapter 5 came out as significant from the text analytics of interviews with practitioners. Thereafter, the PSA was computed. The PSA score is significant with the most important one to be 4 and by extension 4 and 5.

Post the computation of the PSA scores and quantitative testing, a narrowed down list of the following themes emerged as significant in regression models:

1. Fraud filings, investor write-downs/provisions/KMP resignations
2. Rating transitions
3. Statutory Auditor qualifications / Matters of emphasis

9.2 Limitations of the Study

The limitations of these findings were that these were run on a dataset ***only*** at a point in time. As live data is fed into the PSA scorer, more and more information could be relevant in terms of the significance of themes outlined by practitioners.

The other limitation is that all of the themes could not be tested using quantitative methods. But considering that qualitative tests applied were rigorous, they can be tested on live data at future points in time.

9.3 Recommendations Based on the Study

The study establishes that in an EWS construct, the factors in a qualitative metric such as the PSA score add value to traditional quantitative ratios that are modular in their results. It is recommended that the EWS construct with PSA scores as independent variables representative of market-specific antecedents be developed further on live date and put to use by practitioners for their credit assessments (Alaa *et al.* 2017). This would lead to greater conviction in how the practitioners assess a specific credit situation. This also adds conviction for further actions and interventions.

> The PSA score is like any other independent variable akin to the financial ratios which when combined with the traditional financial ratios leads to improvement in the dependent variable(s) for determining probability of default. And hence using PSA becomes a more holistic approach to predict defaults and initiate remedial measures.

It is also recommended that the study be discussed with stakeholders like SEBI who are already on a path to improve debt markets. Although the EWS construct was originally a part of the SEBI rollout, the framework incorporating financial ratios that the present study points out as significant along with the PSA scores could add value to the EWS construct for the Indian markets.

9.4 Scope for Future Research

The model has been created on past data with existing data constraints on the available information. I intend to set up the PSA score default predictor based on machine learning and feeding it live data so that the model can keep learning from in the coming times.

- Future research potential is promising for unsolved problems. For instance, the model should form a part of blockchain-based DLT platforms that regulators have made live and wherein extensive data would be available over a period of time. The model can similarly be used for exposures of multiple vehicles such as AIFs.
- Themes such as deepening of India's credit markets, bond pricing framework and development of effective CDS markets can also be covered along the way.
- There is tremendous scope for combining behavioural models with quantitative models to further this study.
- Ideally, experiments like these should pave the way to have a mechanism for active bridging between practitioners and academicians. Actual unsolved problems of the industry and regulators, for instance, can be considered for a meaningful collaboration between practitioners and academicians. In this manner, the academicians can help in solving the problems of practitioners and propose efficient solutions for the practitioners who can then live test these solutions. It is hoped that this will be an effective way to standardize the proposed solutions.

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ANNEXURES

Dataset 1

PTC India Financial Services Limited
NTPC Limited
Power Grid Corporation of India Limited
Centrum Capital Limited
RELIANCE HOME FINANCE LIMITED
Coromandel International Limited
Sundaram Finance Limited
Zydus Wellness Limited
Satin Creditcare Network Limited
Patel Engineering Limited
JSW Energy Limited
NHPC Limited
UGRO Capital Limited
Supra Pacific Management Consultancy Limited
MAS Financial Services Limited
RELIANCE CAPITAL LIMITED
Shah Alloys Limited
SREI INFRASTRUCTURE Finance LTD
Zuari Agro Chemicals Limited
Aavas Finciers Limited
Torrent Power Limited
G R Infraprojects Limited
Hindustan Petroleum Corporation Limited
Poonawalla Fincorp Limited
Reliance Industries Limited
Manappuram Finance Limited
Zuari Industries Limited
Force Motors Limited
BEML Limited
FUTURE ENTERPRISES LIMITED
JSW Steel Limited
Andrew Yule & Company Limited
Tata Steel Limited
Motilal Oswal Financial Services Limited
Raymond Limited
Kings Infra Ventures Limited
SPML Infra Limited
Oil and tural Gas Corporation Limited
Adani Ports and Special Economic Zone Limited
NLC India Limited
HT Media Limited
Welspun Corp Limited
Centerac Technologies Limited
Nuvoco Vistas Corporation Limited
Arman Financial Services Limited
Welspun Enterprises Limited
Dhanvarsha Finvest Limited
CSL Finance Limited
RattanIndia Power Limited
Essar Shipping Limited
Home First Finance Company India Limited
Inox Wind Limited
Poddar Housing and Development Limited
SIMPLEX INFRASTRUCTURES LIMITED
The Ramco Cements Limited
Apollo Tyres Limited
Coforge Limited
Sagar Cements Limited
Zee Learn Limited
Richa Industries Limited
Richa Industries Limited
Southern Petrochemical Industries Corporation Limited
Ramasigns Industries Limited
Titan Company Limited
Vodafone Idea Limited
Puravankara Limited

Piramal Enterprises Limited
Indiabulls Real Estate Limited
Coffee Day Enterprises Limited
Macrotech Developers Limited
Chalet Hotels Limited
Wockhardt Limited
Uflex Limited
Seya Industries Limited
PG Electroplast Limited
Vedanta Limited
SJVN Limited
Anant Raj Limited
Jindal Steel & Power Limited
UltraTech Cement Limited
Blue Star Limited
UPL Limited
Jagran Prakashan Limited
EPL Limited
SEPC Limited
Reliance val and Engineering Limited
Shree Rama Newsprint Limited
Reliance Communications Limited
Greenlam Industries Limited
HDFC Life Insurance Company Limited
Tata Chemicals Limited
IIFL Wealth Magement Limited
Tata Communications Limited
Dilip Buildcon Limited
Varroc Engineering Limited
Tata Coffee Limited
Oberoi Realty Limited
Capri Global Capital Limited
Lloyds Metals and Energy Limited
Aditya Birla Fashion and Retail Limited
Parag Milk Foods Limited
Sobha Limited
Bharat Forge Limited
Future Supply Chain Solutions Limited
Crompton Greaves Consumer Electricals Limited
Cochin Shipyard Limited
QGO Finance Limited
Capital India Finance Limited
CG Power and Industrial Solutions Limited
Udaipur Cement Works Limited
Bajaj Hindusthan Sugar Limited
Future Lifestyle Fashions Limited
Lloyds Steels Industries Limited
Jaiprakash Associates Limited
Future Consumer Limited
Walchandgar Industries Limited
Godrej Properties Limited
RELIANCE INFRASTRUCTURE LIMITED
NMDC Limited
Prestige Estates Projects Limited
Ashiana Housing Limited
Finkurve Financial Services Limited
Trident Limited
Marathon Nextgen Realty Limited
Safari Industries (India) Limited
Jain Irrigation Systems Limited
CEAT Limited
Sintercom India Limited
Parsvnath Developers Limited
Vardhman Textiles Limited
Zen Technologies Limited
JK Paper Limited
Sanghi Industries Limited
Muthoot Capital Services Limited
Precot Limited
Century Enka Limited
Hindustan Unilever Limited
Capital Trust Limited
Steel Exchange India Limited
SRF Limited
Ganesh Housing Corporation Limited
Balkrishna Industries Limited
H.G. Infra Engineering Limited
Bombay Rayon Fashions Limited
Vindhya Telelinks Limited
India Power Corporation Limited
SundaramClayton Limited
Genesys International Corporation Limited
Hindalco Industries Limited
Mangalore Refinery and Petrochemicals Limited

Unitech Limited
Adani Enterprises Limited
Viceroy Hotels Limited
Ashok Leyland Limited
Torrent Pharmaceuticals Limited
Arvind Limited
Ind-Swift Laboratories Limited
The Indian Hotels Company Limited
Dabur India Limited
Nagarjuna Fertilizers and Chemicals Limited
Sadbhav Engineering Limited
CESC Limited
National Aluminium Company Limited
Hindustan Zinc Limited
Shalimar Paints Limited
Future Retail Limited
MSP Steel & Power Limited
Rashtriya Chemicals and Fertilizers Limited
Tata Motors Limited
Prism Johnson Limited
CreditAccess Grameen Limited
Britannia Industries Limited
PVR Limited
DCW Limited
Ramkrishna Forgings Limited
Kirloskar Ferrous Industries Limited
Grasim Industries Limited
Trent Limited
Jindal Saw Limited
Indian Oil Corporation Limited
GIC Housing Finance Limited
Sterlite Technologies Limited
Godrej Industries Limited
Shriram City Union Finance Limited
TVS Motor Company Limited
Edelweiss Financial Services Limited
Edelweiss Financial Services Limited
Tourism Finance Corporation of India Limited
The Great Eastern Shipping Company Limited
Steel Authority of India Limited
Birla Corporation Limited
Shriram Transport Finance Company Limited

LIC Housing Finance Limited
Zee Media Corporation Limited
Mercator Limited
Adani Transmission Limited
Ravindra Energy Limited
DLF Limited
Yaari Digital Integrated Services Limited
PVP Ventures Limited
Peninsula Land Limited
DCM Shriram Limited
Kesoram Industries Limited
Nilkamal Limited
KoltePatil Developers Limited
Vascon Engineers Limited
Arihant Superstructures Limited
Reliance Power Limited
Jaypee Infratech Limited
Mphasis Limited
Jindal Stainless Limited
Raghav Productivity Enhancers Limited
Sical Logistics Limited
Dewan Housing Finance Corporation Limited
Srei Equipment Finance Limited
CONSOLIDATED CONSTRUCTIONCONSORTIUM LTD
Reliance Commercial Finance Ltd.
IL&FS Financial Services Limited
BLUE BLENDS (INDIA) LIMITED
Sintex Industries Limited
HINDUSTHAN NATIONAL GLASS & INDUSTRIES LTD Standalone
Ashiana Landcraft Realty Private Limited
Ansal Urban Condominium Pvt Ltd
ARISTO REALTORS INFRASTRUCTURE PVT LTD
D S KULKARNI DEVELOPERS LTD.
CONCRETE LIFESTYLES & INFRASTRUCTURE PVT LTD
SANDOR MEDICAIDS PRIVATE LIMITED
ORISSA STEVEDORES LIMITED
KUMAR URBAN DEVELOPMENT PVT LTD
HAZARIBAGH RANCHI EXPRESSWAY LIMITED
Infrastructure Leasing & Financial Services Limited
IL&FS TRANSPORTATION NETWORKS LTD

Dataset 2

RELIANCE HOME FINANCE LIMITED

RELIANCE INFRASTRUCTURE LIMITED

RELIANCE CAPITAL LIMITED

Ashiana Landcraft Realty Private Limited

ADRITI ESTATE DEVELOPERS PRIVATE LTD

ADILINK INFRA MULTITRADING PVT LTD

Ansal Urban Condominium Pvt Ltd

ARISTO REALTORS INFRASTRUCTURE PVT LTD

ASHVI DEVELOPERS

BHANSHALI INFRAPROJECTS PVT LTD

BLUE BLENDS (INDIA) LIMITED

CONSOLIDATED CONSTRUCTION CONSORTIUM LTD

D S KULKARNI DEVELOPERS LTD.

CHAMPALALJI FINANCE PVT LTD

COFFEE DAY NATURAL RESOURCES PVT LTD

CONCRETE LIFESTYLES & INFRASTRUCTURE PVT LTD

FUTURE ENTERPRISES LIMITED - Standalone

HINDUSTHAN NATIONAL GLASS & INDUSTRIES LTD - Standalone

SANDOR MEDICAIDS PRIVATE LIMITED

RAJESH ESTATES AND NIRMAN PRIVATE LIMITED

RADIUS & DESERVE LAN DEVELOPERS PRIVATE LIMITED

ORISSA STEVEDORES LIMITED

MIRAYA REALTY PRIAVTE LIMITED

MEETI DEVELOPERS PRIVATE LIMITED

MANYATA DEVELOPERS PRIVATE LIMITED

LAVASA CORPORATION LIMITED

KUMAR URBAN DEVELOPMENT PVT LTD

KRISHNA ENTERPRISES HOUSING INFRASTRUCTURE PVT LTD

GULAM MUSTAFA ENTERPRISES PRIVATE LIMITED

HAZARIBAGH RANCHI EXPRESSWAY LIMITED

HBS REALTORS PRIVATE LIMITED

JAI MAHARASHTRA NAGAR DEVELOPMENT PRIVATE LIMITED

SREI INFRASTRUCTURE FINANCE LTD

SINTEX INDUSTRIES LIMITED

SIMPLEX INFRASTRUCTURES LIMITED

Infrastructure Leasing & Financial Services Limited

IL&FS TRANSPORTATION NETWORKS LTD

SEVEN HILLS HEALTHCARE PRIVATE LIMITED

Aavas Financiers Limited

AU Small Finance Bank Limited

CG Power and Industrial Solutions Limited

Dabur India Limited

DCM Shriram Limited

DCW Limited

Edelweiss Financial Services Limited

Kotak Mahindra Bank Limited

EPL Limited

GTL Limited

Hindustan Zinc Limited

Rashtriya Chemicals and Fertilizers Limited

Macrotech Developers Limited

Nuvoco Vistas Corporation Limited

Peninsula Land Limited

QGO Finance Limited

Safari Industries (India) Limited

Southern Petrochemical Industries Corporation Limited

Steel Authority of India Limited

Steel Exchange India Limited

Sterlite Technologies Limited

Tata Communications Limited

Tata Steel Limited

Uflex Limited

Unitech Limited

Dataset 3

Aavas Financiers Limited

CG Power and Industrial Solutions Limited

Dabur India Limited

DCM Shriram Limited

DCW Limited

Edelweiss Financial Services Limited

EPL Limited

Hindustan Zinc Limited

Rashtriya Chemicals and Fertilizers Limited

Macrotech Developers Limited

Nuvoco Vistas Corporation Limited

Peninsula Land Limited

QGO Finance Limited

Safari Industries (India) Limited

Southern Petrochemical Industries Corporation Limited

Steel Authority of India Limited

Steel Exchange India Limited

Sterlite Technologies Limited

Tata Communications Limited

Tata Steel Limited

Uflex Limited

Unitech Limited

RELIANCE HOME Finance LIMITED

RELIANCE INFRASTRUCTURE LIMITED

RELIANCE CAPITAL LIMITED

Ashiana Landcraft Realty Private Limited

ARISTO REALTORS INFRASTRUCTURE PVT LTD

BLUE BLENDS (INDIA) LIMITED

CONSOLIDATED CONSTRUCTION CONSORTIUM LTD

D S KULKARNI DEVELOPERS LTD.

CONCRETE LIFESTYLES & INFRASTRUCTURE PVT LTD

FUTURE ENTERPRISES LIMITED

HINDUSTHAN TIOL GLASS & INDUSTRIES LTD Standalone

SANDOR MEDICAIDS PRIVATE LIMITED

ORISSA STEVEDORES LIMITED

KUMAR URBAN DEVELOPMENT PVT LTD

HAZARIBAGH RANCHI EXPRESSWAY LIMITED

SREI INFRASTRUCTURE Finance LTD

SINTEX INDUSTRIES LIMITED

SIMPLEX INFRASTRUCTURES LIMITED

Infrastructure Leasing & Financial Services Limited

IL&FS TRANSPORTATION NETWORKS LTD

PTC India Financial Services Limited

Centrum Capital Limited

Sundaram Finance Limited

Satin Creditcare Network Limited

Essar Shipping Limited

IL&FS Financial Services Limited

Reliance Commercial Finance Ltd.

Power Grid Corporation of India Limited