THE WORRYING TREND OF NON-PERFORMING LOANS IN HIGHER EDUCATION

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DOI: 10.23762/FSO_VOL7_NO3_5

ABSTRACT
The rate of education loans is on the rise in both developed and developing countries, whereby an increasing number of middle and upper middle-income families are resorting to bank loans to send their children to pursue higher education. The accessibility of education is among the Sustainable Development Goals (SDG) of the United Nations, listed as SDG Goal 4. Accordingly, economies around the world are promoting higher education, in spite of the high costs. Hence a bank loan becomes an inevitable part of the equation for most individuals who wish to pursue higher education. However, the rising crisis of non-performing education loans is a worrying international trend. Non-performing education loans are categorised as Non-Performing Assets (NPA) in the Indian Banking System. This paper attempts to study the root cause of this rising crisis and subsequently develop a model utilising the variables from an education loan application form, which can be used to predict potential defaults on higher education loans. Further, the study also attempts to explore whether the institutions which offer higher education have any significant impact on a loan becoming non-performing. Statistical tools including the T test, Chi-square test and Linear Discriminant Function were used to analyse the primary data gathered from banks. The results from the study imply that the annual income and net worth of the loan applicant's parents exhibits a significant relationship with default and non-default on educational loans. This result is connected in turn with the quality of education the candidates receive and the employability of the candidates which various educational institutions produce. Based on the significant findings, the study proposes recommendations which includes advice to banks on being vigilant as regards the repayment ability of the applicant based on certain profiling of the individual, as well as the ability of the education institution and its reputation which affects the employability of the students.

KEY WORDS
Education loans, defaults, NPA, Linear Discriminant Analysis.

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Paper received: 8 June 2019 • Paper revised: 29 August 2019 • Paper accepted: 3 September 2019

Introduction

Education makes a significant contribution to the economic development of a nation, whether developing or developed. One of the most important resources for the development of an economy is its human capital, i.e. the national workforce. Quality education is required to ensure a productive workforce which leads to sustained economic growth and the prosperity of a nation (Zvarikova and Majerova, 2013). However, quality education comes at a price. Mankiw et al. (1992) show that investment in human capital to make education more accessible can lead to a productive work force. Ziderman (2013) states that education loans are a means by which to broaden and deepen accessibility and to ensure retention and successful completion. He goes on to say that easy access to education loans will help make high tuition fees more palatable, both politically and socially.

Financing tertiary education is an ongoing struggle faced by families in many countries throughout the world, be they developed or developing countries. In countries such as Kenya and Ghana, educational loans are available to all students regardless of their needs and ability to repay (Onen, 2013). However, the same is true for most countries and especially rising economies. The default rate of educational loans in developed countries such as the US is equally on the rise as well (Barr et al., 2019). However, there seems to be no short-term solution to this emerging crisis of non-performing education loans. There is also evidence of inadequate profiling and targeting of loan applicants before the loans are approved. Despite the use of rigorous forms to collect various information from applicants, it seems that little is being done to curb the rise of the non-performing loans. Hence, the rising level of education debt is becoming a huge burden to governments across the world. This study focuses on one of the economic giants of Asia, namely India. Among the problems faced by banks in India is the overwhelming number of non-performing education loans which are termed in banks as Non-Performing Assets (NPA). This has been rising consistently over the past few decades. The Net NPAs as a percentage of Net Advances stood at 8% for the financial year 2017-18 compared to 1.3% in 2011-12 (Reserve Bank of India, 2018). The banking industry needs to take affirmative action to stem this crisis and take measures to cut down on default rates on loans. One of the proactive measures that can be taken up by banks is to identify and weed out potential defaulters on loans at the application stage itself through proper profiling of applicants (Thiagarajan et al., 2011).

Priority sector loans (of which educational loans are part) form a considerable proportion of the total NPAs in India. Outstanding education loans amount to 728 billion INR as of 2017-18. Although the share of priority sector NPAs in total NPAs declined marginally during 2017-18, it still constituted one-fifth of the total (Reserve Bank of India, 2018). Education transforms individuals into efficient and effective contributors to the economic activity of a country. The quality of education imparted reflects the future of a country (Karaçor, 2018; Štefko et al., 2007; Plaček et al., 2015). Through education, it is expected that individuals will acquire knowledge and realise their potential to engage in income-generating activity and in turn enjoy a good quality of life (Krawczyk, 2014; Ślusarczyk and Herbuś, 2014). However, tertiary education today has become very cost-prohibitive, and thus requires prospective students to depend heavily on banks for financing higher education.

The employability of an educated individual is not guaranteed by the level of education or degrees earned. This makes it a risky proposition for individuals and institutions funding these endeavours (Sharma and Sharma, 2006).

The demand for higher education has been on the rise over the years, and successive central and state governments have taken multiple initiatives to improve the quality and reach of higher education in India. Since the 1950s, higher education has been significantly financed or subsidised by the state and the union governments. However, after 1991, there was a major shift in the budgetary allocation of the government, which has gradually shifted the financial burden to the individuals seeking education (Agarwal, 2006). The cost of education in both government and private institutions has also increased multi-fold in this period. This has forced individuals to borrow from banks and financial institutions to fund education. The Reserve Bank of India (RBI), for its part, has made education a priority sector, thereby coercing banks to lend more to this sector.

The recovery of loans provided by banks is of crucial importance to their efficient performance (Sadaf et al., 2018). It has been observed that a significant proportion of the educational loans sanctioned by banks turn into NPAs. However, as education is a priority sector, banks are not able to cease giving loans to new applicants. Large numbers of applicants are unaware of the consequences of defaulting on an educational loan (Kliestikova and Misankova, 2016). The study focuses on identifying and evaluating the factors that can give an early indication of whether an educational loan will turn into an NPA and take suitable preventive measures to ensure that defaults are minimised by means of effective screening of the loan applicant and the institution where the applicant plans to pursue higher education at the application processing stage itself (Patra et al., 2017).

The rising cost of education, especially given the proliferation of private educational institutions, has caused a lot of financial stress on parents who fund the education of their wards. Many are forced to take loans from banks and financial institutions with no guarantee that the graduating student will secure a job and be able to pay back his/her loan (Tilak, 2018; Rani, 2018). Through this study we expect to identify the variables from loan applications that can indicate potential warning signs for defaulting on an educational loan, and develop a model for predicting the probability that the applicant will default on an education loan. This study is expected to provide loan application processing officers at banks with a tool to verify loan applications and identify red flags that could indicate probable default on loans. This paper is structured as follows. Section 2 gives the literature review, followed by materials and methodology. The discussion of the findings is given in section 4, which is followed by the conclusions.

1. Literature review

In light of the rising costs of higher education, financial assistance is required to make higher and technical education affordable to the masses. Education loans are prevalent in most developed countries and are seen as one of the primary ways to finance higher education (Britton et al., 2019). However, the practice of financing higher education through educational loans has become popular only in recent years, particularly after the introduction of a model education loan scheme in 2001 by RBI (Patra et al., 2017). The educational loans scheme in India mainly aims to provide financial support to meritorious and deserving students to pursue higher studies in India or abroad. This has enabled students to pursue their dreams by overcoming financial constraints. However, student loans have become a huge burden to the banks, as most of them have turned to be NPAs due to several reasons. Table 1 gives the details of education loans and NPAs for the period 2012-2018.

Table 1. Details of outstanding education loans and increasing NPAs

Year	Outstanding Education Loans	NPAs	NPA – Total Loans
2012-2013	48,382	2,615	5.40%
2013-2014	59,834	3,439	5.75%
2014-2015	62,244	3,385	5.44%
2015-2016	68,133	5,006	7.35%
2016-2017	72,818	5,339	7.33%
2017-2018	71,725	6,434	8.97%

Source: Reserve Bank of India, 2018.

Gross et al. (2009) conducted a meta-analysis of the studies on student loan default. Empirical studies conducted between 1991 to 2007 were examined and identified student characteristics, institution category, level of student debt and student employment, income and total debt position as major factors influencing student loan default. Ionescu (2008) observed that the ability to learn, prior knowledge accumulated and repayment flexibility contribute positively to student enrolment in higher education, but the wealth of parents has a minor effect on enrolment. But the paper is silent on the contribution of these variables towards ensuring prompt repayment and avoiding defaults.

Callender and Mason (2017) analysed the possibilities of student loan debts deterring participation in higher education in England. The results drawn from the study show that lower-class students have more debt-averse attitudes compared to upper-class students. The key results reveal that debt-averse attitudes among the lower-class students deter their participation in higher education. A similar study conducted in England by West et al. (2015) has found that high-income families were able to protect their children from student loan debts in several ways whereas non-affluent parents were not able to support their children, creating a new form of inequality.

A recent study by Bandyopadhyay (2016) on the level of risk of education loans in India found that education loan defaults in India are highly influenced by the period of repayment, borrower margin and security (collateral). The socio-economic background and the location of the borrower are also factors which impact on the level of default. Kaur and Arora (2019) developed a multidimensional scale measuring student attitude towards educational debt for higher studies in India, identifying six variables, namely economic empowerment, social empowerment, utility, procedural requirements, risk and stress as key variables which influence the attitude of students.

The ratio of defaults on education loans is relatively higher than most other categories of loans. Panjali and Kasilingam (2014) identified that the quantum of the loan received, the time taken to sanction and disburse loans, lack of transparency and disclosure, change in interest rates, location and place and adherence to borrower's rights are some of the factors affecting the repayment of bank loans. They employed factor analysis, cluster analysis, discriminant analysis and correspondent analysis to analyse their survey data. They also observed that lack of employment opportunities, low income earned and interest in further/higher studies may also lead to default.

In a 70-nation multinational study on student loan repayment and recovery, Shen and Ziderman (2009) observed that banks benefit from government subsidies and grants to support defaults and administrative costs, but these benefits are not passed on to student borrowers. The study noted that many loan schemes have built-in subsidies of over 40% of the loan value and the default levels were at 40% or less. So, banks were in no way poorer because of these student loans. Ismail et al. (2011) used a SEM-based model to observe that there is a positive relationship between students' attitude and intention to repay education loans. They observed that the media was able to create awareness among parents on the consequence of defaulting on a loan, which in turn prompted them to guide their children on the merits of prompt repayment. This, along with a well-drafted loan agreement, positively influenced the students to make prompt loan repayments, thus ensuring a good quality of life after graduation.

All the above studies were based on questionnaire data. Experience from the banking crisis of the 1980s and early 1990s suggest that prediction models help prevent bank failures and promote economic stability (Pakurár et al., 2019a; Pakurár et al., 2019b). When using secondary data, classification techniques such as discriminant analysis and cluster analysis are more widely used. Glen (2005) used a piecewise-linear function that can approximate nonlinear functions. Swicegood and Clark (2001) compared the ability of discriminant analysis, neural networks, and professional human judgement methodologies in predicting commercial bank underperformance. Linear discriminant analysis (LDA) is a popular technique that works for both dimensionality reduction and classification (Erenguc and Koehler, 1990; Kumar and Bhatttacharya, 2006). Similarly, Shu and Lu (2014) used LDA and detected hidden common characteristics among data samples in their related study. There is, however, a lack of studies in this area in recent times when non-performing loans have been on the rise. Considering this gap, the study aims to contribute relevant information which would be helpful in identifying the factors which are responsible for educational loan defaults and provide a preliminary basis for future studies in this regard.

2. Research methodology

The framework of this paper is based on linear discriminant analysis (LDA). This is a generalisation of Fisher's function used in statistics, pattern recognition and machine learning to identify a linear combination of features that characterises or separates two or more classes of objects or events. The resulting function may be used as a linear classifier or, more commonly, for dimensionality reduction before later classification (Mika et al., 1999). Discriminant Analysis is used primarily to predict membership in two or more mutually exclusive groups. The classifier equation for the Linear Discriminant Function is as below:

$$(\overline{x_1}\text{-}\overline{x_2})' S^{-1}_{pooled} x_0 \text{-} \frac{1}{2}((\overline{x_1}\text{-}\overline{x_2})' S^{-1}_{pooled} (\overline{x_1}+\overline{x_2}) \geq In\left[\left(\frac{c(1|2)}{c(2|1)}\right)\left(\frac{p_2}{p_1}\right)\right]$$

Before using the discriminant function, the chi-squared test is used to determine whether there is a significant difference between the expected frequencies and the observed frequencies in one or more categories. A t-test is also used to compare whether two groups have different average values. The statistical software SPSS has been used to conduct the study.

3.1. Data collection

The data collected for the study comprised the details of the student loan applications submitted in 2015 from Ayyappankavu Branch of Canara Bank, Kottayam, Kerala. The data used was of confidential nature; hence it was formally agreed that it would be used for academic purposes only. 87 duly completed applications were used for the analysis. The loan applications submitted in 2015 were chosen, since the moratorium period for most of the loans had concluded by 2019, which makes it possible to identify whether or not an applicant had defaulted.

3.2. Data analysis

A Chi-Square test and T-test were used to test whether variables such as gender, category, prior education, course studied, parents' occupation, parents' income and parents' net worth are significantly different among defaulters and non-defaulters. The variables which were found to be significant were identified and used in the linear discriminant function to develop a classifier equation.

3.3. Hypotheses

The hypotheses developed to identify the variables that are significant in predicting defaults are as listed below.

Hypothesis 1. *There is a significant difference between the gender, category, course studied, and parents' occupation among defaulters and non-defaulters on education loans respectively.*

Hypothesis 2. *There is a significant difference in the number of years of prior education, duration of the course and marks obtained among defaulters and non-defaulters on education loans respectively.*

Hypothesis 3. *There is a significant difference between parents' income and parents' net worth among defaulters and non-defaulters on education loans respectively.*

Hypothesis 4. *There is a significant difference between the amount of the loan taken out, the cost of the course and repayment periods of loans among defaulters and non-defaulters on education loans respectively.*

4. Research results and discussion

Based on the data collected, Table 2 describes the demographic characteristics of the respondents.

Table 2. Demographic characteristics

Variable	Items	Frequency	Percentage
Gender	Male	41	47.13
	Female	46	52.87
Default	Default	44	50.57
	Non-Default	43	49.43
Community	Backward Caste / Scheduled Caste / Tribe	29	33.33
	Other Backward Caste	25	28.74
	Other Caste	33	37.93
Course for which loan is availed	Professional Course	59	67.82
	Regular Degree	28	32.18
Parents' Occupation	Business / Self Employed	29	33.33
	Salaried	58	66.66

Source: Own elaboration.

The variables given below are tested using Chi-Square as they are categorical variables.

Table 3. Chi-Square test results

Hypothesis	Pearson χ^2	Sig.
Gender Vs. Loan Default	1.381	0.240
Community Vs. Loan Default	4.627	0.099*
Course Vs. Loan Default	0.713	0.399
Parents' Occupation Vs. Loan Default	0.368	0.544

* Significant at 10% significance level

Source: Own elaboration.

From the results given in Table 3, it can be observed that the gender of the loan applicant (0.240), the category of the loan applicant (0.099), course of study (0.399) and parents' occupation (0.544) are not significantly different among defaulters and non-defaulters on loans at the 5% significance level. However, the category of the applicant is significant at 10%. Therefore, it can be concluded that the first hypothesis cannot be rejected and none of the variables given in Table 3 significantly contribute to defaulting on loans. The mean and standard deviation for the variables used in hypotheses 2, 3 and 4 are as tabulated below.

Table 4. Summary statistics for the t-Test

Variable	Mean		Standard Deviation	
	Default	Non-Default	Default	Non-Default
Previous Qualification	12.6512	12.5000	1.2889	1.1102
Qualifying Examination Marks	0.7021	0.7205	0.1025	0.0936
Duration of the Course	3.6512	3.4545	0.7199	0.9512
Parents' Income	234,641	556,818	151,425	263,593
Parents' Net Worth	1,834,366	2,832,961	1,981,563	2,248,128
Loan Amount	328,881	374,259	146,029	298,318
Cost of the Course	354,606	376,453	193,408	232,341
Repayment Tenure	5.30	5.50	1.536	1.210

Source: Own elaboration.

Hypotheses H2, H3 and H4 are tested using a t-test as one of the variables is numeric and the other one (loan default) is categorical.

Table 5. t-Test Results of Items in Hypotheses

Items in hypotheses	t Test	Sig.
Prior Education Vs. Loan Default	-0.586	0.560
Qualifying Exam Marks Vs. Loan Default	0.872	0.386
Course Duration Vs. Loan Default	-1.089	0.280
Parents' Income Vs. Loan Default	7.010	0.000***
Parents' Net Worth Vs. Loan Default	2.199	0.031**
Loan Amount Vs. Loan Default	0.904	0.369
Cost of the Course Vs. Loan Default	0.47	0.635
Repayment Period Vs. Loan Default	0.666	0.507

***Significant at 1% significance level; ** Significant at 5% significance level

Source: Own elaboration.

From the above table, we may observe that the number of years of prior education of the loan applicant (0.560), the marks obtained in the previous highest qualification (0.386), duration of the course (0.280), cost of the course (0.635), repayment period (0.507) and loan amount (0.369) are not significantly different among defaulters and non-defaulters on loans at the 5% significance level.

Furthermore, it can be observed that both parental income (0.000) and parents' net worth (0.031) of the loan applicants are significantly different among defaulters and non-defaulters on loans at 1% and 5% significance levels respectively. It can therefore be concluded that only the null hypothesis H3 can be rejected; the other null hypotheses H2 and H4 cannot be rejected. Hence, parental income and parents' net worth are the only significant variables in predicting default on educational loans; other variables such as prior qualifications, marks in the qualifying exam, length of the course, the amount of loan taken, the cost of the course and the repayment tenure do not seem to be contributing factors.

Linear Discriminant Analysis

The variables that are found to be significant in the hypotheses testing stage are used to develop a classifier function that will discriminate the data set into predefined classes (defaulters and non-defaulters) with a high degree of accuracy. Furthermore, the developed classifier equation can be used to predict a new unlabelled observation.

Based on the literature survey, the Linear Discriminant Function is identified as one of the most powerful classification test measures, and hence is used in the study.

Table 6. Tests of equality of group means

	Wilks' Lambda	F	df1	df2	Sig.
Income	.636	48.566	1	85	.000
Net Worth	.946	4.823	1	85	.031

Source: Own elaboration.

In Table 6, the results of the univariate ANOVA carried out for both the significant independent variables are presented. Here, both parents' income and net worth are significantly different for the two groups.

Table 7. Box's Test of equality of covariance matrices

Box's M	F (Approx.)	df1	df2	Sig.
13.695	4.449	3	1323463.65	.004

Source: Own elaboration.

Further, from the Box's M test (sig.=0.004) we may confirm that both income and net worth differ significantly for the two groups. Since we have unequal sample sizes in the default and the non-default categories, the algorithm computes the prior probabilities based on group sizes.

Table 8. Summary of canonical discriminant functions

Function	Eigen value	% of Variance	Cumulative %	Canonical Correlation
1	.580a	100.0	100.0	.606

Source: Own elaboration.

A large eigen value is associated with a strong function. The eigen value of 0.58 indicates that 58% of the variance is explained by the two variables. The canonical relation is a correlation between the discriminant scores and the levels of the dependent variable. A high correlation indicates a function that discriminates well. The present correlation of 0.606 is moderately high and hence significant.

Table 9. Wilk's Lambda

Test of Function(s)	Wilk's Lambda	Chi-square	df	Sig.
1	.633	38.411	2	.000

Source: Own elaboration.

The ratio of the sum of squares within the group to the total sum of the square is Wilk's Lambda. In other words, Wilk's Lambda is a measure of the amount of the total variance in the computed discriminant scores that is not expounded by differences among the groups. When the observed group mean values are equal, the Lambda value is 1 which means that the factors can explain the variances other than the difference between the mean values. By contrast, if the Lambda value is small, then it means that the within-groups variability is small compared to the total variability or the group means are different. The significance value associated with the Wilk's Lambda reveals whether this difference is significant. In the case of the model used, the Lambda value is 0.633 and this value is significant (Sig. = 0,000); thus, the group means appear to differ.

Table 10. Standardised canonical discriminant function coefficients

Variables	Scores
Income	.969
Net Worth	.123

Source: Own elaboration.

The discriminant function developed using the model will be as below:

$$\boldsymbol{Disc.Score = 0.969\ Inc + 0.123\ NW}$$

Since income has a somewhat higher loading than net worth, it has a greater effect in terms of determining group membership (defaulters and non-defaulters respectively).

Table 11. Classification results

Category	Predicted Group Membership		Total
	Non-Default	Default	
Non-Default	36 (81.8%)	8 (18.2%)	44
Default	6 (14%)	37 (86%)	43

Source: Own elaboration.

From the 44 cases of non-defaulters, 8 were misclassified (18.2%), and of the 43 cases of defaulters, 6 were misclassified (14.0). The overall classification of the linear discriminant model for the given data set is 83.9% given that there were 14 misclassifications out of a total of 87 loan applications. The results imply that parents' income and net worth are two significant variables which can predict the likelihood of defaulting on an educational loan. These findings are in line with the previous studies of Bandyopadhyay (2016) which state that the economic background of the loan applicants has a significant impact on educational loan default. The results of Hillman (2009) also shed light on the finding that the income of the loan applicants has an impact on loan default. The study also shares similar findings given by West et al. (2015) that parents' income is one of the significant factors which impact on the likelihood of defaulting.

Conclusions

Based on the previous studies, approximately 12 variables were investigated in this study and jointly compounded into five hypotheses for empirical testing. These variables were found to be significant in previous studies conducted in other parts of the world. The study aimed to find if these variables were significant in the Indian context, where education loans come under the priority lending sector.

The study examined the data available from the educational loan applications of a leading Public Sector Undertaking (PSU) bank in order to identify and evaluate those variables in the application which are indicative of potential default and non-default on educational loans. From the analysis, it was observed that the annual income and net worth of the loan applicant's parents have a significant association with default and non-default on educational loans. It was also found that loan applicants who belong to socially backward communities also tend to show a higher rate of default. Furthermore, it was observed that variables such as the gender of the applicant, prior education of the applicant, the course studied by the applicant, the institution at which the applicant studied the course, the amount of the loan and finally the proposed repayment period revealed no significant relationship with default and non-default on educational loans.

Only two out of the 12 variables were significant for the study, namely parents' income and net worth. These two variables were used to develop the linear discriminant function which was found to be able to classify 84% of the loans correctly into either of the categories: defaulters or non-defaulters. This function can be used by bankers at the processing stage itself to identify potential defaults.

Based on the above results, it is recommended that the loan processing officer of the bank should be very vigilant in making sure that the loan applicant has completed all relevant documentation. The officer should also place great emphasis on the net worth and annual income of the applicant's parents over other variables in the application. Further, this study is also important from a government policy-making perspective, as a particular category of society has a tendency towards higher default rates. Measures such as directed interest subvention or a longer moratorium could be considered to encourage higher repayment rates.

Among the major findings, parents' ability to repay the loan is highly significant in the study, which is alarming and indicates that perhaps the students are not finding employment at salaries that will help them repay the loans. Given the high level of non-repayment of education loans, this further suggests a possible flaw in the quality of higher education that prepares individuals both for industry and to enter society at large (Nathan, 2013). Institutions of higher learning need to constantly work hard to create highly employable, clear-thinking and problem-solving graduates who will become useful members of industry and the community as a whole. Perhaps institutions ought to also include elements of entrepreneurship and inculcate a start-up mentality among graduates so as to produce graduates who are also job creators themselves, instead of looking for employment with existing companies by themselves.

Education loans in India are one of the enablers for improving the standard of living and also producing qualified individuals who can contribute to the nation's progress. It could be a significant source of return on investment if non-performing loans can be reduced or eliminated. This study had difficulties and limitations in obtaining banking data on non-performing loans as most banks were not willing to share what they have termed as confidential applicant information with the research team. The study had a limited small sample size of 87 observations from which to make statistical analysis and inference, though the insights from this data are still statistically rigorous and meaningful. Given these facts, a larger study including multiple bank branches and banks across the public and private sector would be ideal in order to better generalise these findings. Future studies could also perform comparative analysis between banking data from India and countries from other geographical areas. Additionally, a deeper analysis of academic institutions and their employability drivers could be a further direction for research.

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