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Interest-Risk Relationships in Luxury Car Credit Portfolio in India

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Abstract: People with high purchasing power afford to buy luxury cars. However, majority of these people too, make the purchase of these luxury cars through vehicle finance services. These are the people with good credit score and will be granted with credit by vehicle finance service providers. Even though they have good credit score and high purchasing power there is risk involved with these credit portfolios as well. This study deals with data set comprising of luxury car credit portfolio to establish the interest and risk relationship characterized by relevant variables. The main motive of this study is to assess the risk associated with these portfolios and has established the relationship between interest rate and default with the help of regression analysis.

Key words: Comprising, luxury car, credit portfolio, interest rate, established, regression

INTRODUCTION

About until 5 years ago, a long stylish sedan with a logo that has three striking lines in a circle (Mercedes Benz) signified power, royalty and class. But this privilege was restricted to only a few of those belonging to a royal family or business moguls. But the tides have turned. Today, a local farmer from Kolhapur is purchasing a Mercedes, a SME owner from Raipur is buying a BMW, young IT professional from Pune owns an Audi, young industrialist from Delhi is driving a Ferrari-one can see the variance in the customer profile and also their inclination towards luxury cars. Be it the real-estate boom or the growing number of entrepreneurs, purchase of luxury cars remains the symbol of power, recognition, prestige and status and that is driving the numbers in the luxury car space in India. Also the luxury car segment in India is estimated to grow at a CAGR of 25% for the next 8 years to touch 1, 50,000 units by 2020.

Along with the growth, the default rate in the loan portfolio of the luxury car is also gaining momentum. Hence, there is a need for the prediction of defaults in the credit portfolio of luxury cars where there is little works done in India. The objective of the research study is to estimate the factors that determine the default in the luxury passenger car segment. A 50 sample survey was conducted amoung the luxury passenger car customers in India.

Literature review: Joao A. Bastos in his study "Forecasting bank loans loss given default" used the dataset that was provided by the largest private bank in Portugal, Banco Comercial Portugues. The sample contains 374 loans granted to Small and Medium Size Enterprises (SMEs) that defaulted between June 1995 and December 2000. The variables used for the analysis were constant, loan size, collateral, personal guarantee, manufacturing sector, trade sector, services sector, lending rate, age of firm, rating, missing rating and years of relationship. The statistical methods used for the analysis were fractional response regression, regression trees, out of sample predictive accuracy and out of time predictive accuracy:

$$\mathrm{SDR} = \sigma(\mathrm{T}) - \frac{m(\mathrm{T}_1)}{m(\mathrm{T})}\sigma(\mathrm{T}_1) - \frac{m(\mathrm{T}_2)}{m(\mathrm{T})}\sigma(\mathrm{T}_2)$$

where, T is the set of observations in the parent node and T_1 and T_2 are the set of observations in the daughter nodes that result from splitting the parent node according to the optimal attribute. The operatorsm (.) and r (.) represent the mean and standard deviation of the target variable in the set. Starting from the root node, all observations flow down the tree and terminate their path in a leaf. The conclusion of the study was that the regression tree models capture effects on recovery rates due to explanatory variables that are statistically insignificant in the fractional response regression. The forecasting accuracy of these models is evaluated using two different approaches: an out-of-sample estimation using the complete dataset with the help of a 10-fold cross-validation and an out-of-time estimation in which the models are fit using defaults from one period and the accuracy is measured on defaults from the following year. The performance of the models is benchmarked against predicted recoveries given by historical averages. When out-of-sample estimation is considered, the regression

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trees give better results for shorter recovery horizons of 12 and 24 months while the fractional response regression gives better results for longer horizons.

Crook and Banasik (2012) in their research study "Forecasting and explaining aggregate consumer credit delinquency behaviour" used the data from the delinquency rates published on the FRB website for period 1992-2008 for the volume of overdue debt on consumer loans to commercial banks estimated. The variables used in the study were consumer credit total real default volume, credit card default rate, other loans default rate, residential real estate loans default rate, diff in personal loan interest rate, diff in mortgage interest rate, Log diff. in mortgage delinquency rate, delinquency, interest rate %, credit, sentiment index, unemployment % and house price index. The statistical methods used were regression model and ARIMA Model. As per the result different explanations of delinquency are appropriate for different types of debts. For the volume of consumer debt, variations in the quality of debt but not changes in the stigma of default, appear to drive the delinquent volume; while at the level of the household irrationality, adverse income shocks and changes in house prices are at work.

Henley and Hand (1996) in their research paper "A k-nearest-neighbour classifier for assessing consumer credit risk" used sample from the full population of applicants for credit from a large mail order company over a period of year. The 16 variables where used in the analysis out of which one was time on electoral roll. The statistical methods used for analysis were k-nearest, decision tree, linear regression and sensitivity analysis. The study asserted that it is practical to implement k-NN classification rule for credit scoring new applicants in real time.

Andrade and Thomas (2007) in their study "Structural models in consumer credit" used monthly observations of credit bureau scores supplied by Serasa for the Brazilian market. Serasa is the leading credit bureau company in Brazil. The data comprised 37 monthly observations of the individual's scores from January 2000-2003 of 1000 consumers randomly selected from the total number of consumers that had credit activity registered at Serasa. The variables used in the study were default probability, default rate, current score of the consumer, period, default threshold and the statistical method used were likelihood, discriminant analysis and simulation technique. The analysis resulted in a hybrid structural-reduced-form model. And comparisons are made with the Basel II approach. The conclusions partially support that approach for modelling the credit risk of portfolios of retail credit.

Lee *et al.* (2006) in their study "Mining the customer credit using Classification and Regression Tree (CART) and Multivariate Adaptive Regression Splines (MARS)" used credit card data set provided by a local bank in Taipei, Taiwan. There are totally 8000 customers in the data set. Among them, 4000 data sets with respect to the ratio of good and bad credit (the prior probabilities or simply priors) were randomly selected as the training sample (estimating the parameters of the corresponding built scoring model), another 2000 are used to test the model (selecting the final scoring model) and the remaining 2000 are retained for validation (evaluating the classification capability of the built scoring model). The variables used were gender, age, marriage status, educational level, occupation, job position, annual income, residential status and credit limits. The statistical method used discriminant analysis, logistic regression and artificial neural network. Analytic results demonstrate that CART and MARS both have better average correct classification rate in comparison with discriminant analysis, logistic regression, neural networks and Support Vector Machine (SVM). Besides, CART and MARS not only have better credit scoring accuracies but also lower Type II errors associated with high misclassification costs and therefore have better overall credit scoring capabilities. The research findings provide efficient alternatives in conducting credit scoring tasks.

Lee *et al.* (2002) in their research study "credit scoring using the hybrid neural discriminant technique" used one credit card dataset provided by a local bank in Taipei, Taiwan. Six thousand datasets with respect to the ratio of good and bad credits were randomly selected and then used to build the credit scoring models. Among them, 4000 datasets are used as the model building set (training sample) while the remaining 2000 are retained as the validation set (testing sample). The variables in the study are gender, age, marriage status, educational level, occupation, job position, annual income, residential status and credit limits. The statistical methods used are discriminate analysis, logistic regression and artificial neural networks. Analytic results of the study demonstrated that the proposed hybrid model provides a better initial solution and hence, converges much faster than the conventional neural networks model. Besides in comparison with the traditional neural network approach, the credit scoring accuracy increases in terms of the proposed hybrid methodology. Moreover, the superior credit scoring capability of the proposed technique can be observed by comparing the credit scoring results with those using linear discriminant analysis and logistic regression approaches.

Avery *et al.* (2004) in their research study "Consumer credit scoring: do situational circumstances matter?" used the Federal Reserve Board obtained the full credit records (excluding any identifying personal information) for a nationally representative random sample of 248,000 individuals as of June 1999 from one of the national credit reporting agencies. A credit history score was provided for 203,000 individuals in the sample. The paper sample-approximately 1 in 657 individuals from the credit reporting agency records. July 1997 To June 1999 (test period) and prior to July 1997 (base period). The variables in the study are default, unemployment rate, marital status, age, type of account, instalment, mortgage and credit line. The statistical methods used in the study are regression, indirect inferential tests ordinary least squares. In the study, empirical models yield strong inferences that situational circumstances influence an individual's propensity to default on a new loan, holding constant the credit quality of the individual as reflected in an estimated ex-ante credit history score. Also, the study demonstrates that the likelihood that an individual will default on a new loan depends on contemporaneous economic conditions in the area where the individual resides.

Westgaard and van der Wijst (2001) in their study "Default probabilities in a corporate bank portfolio: a logistic model approach" used in the study the data that were collected by Dun and Bradstreet and comprise all Norwegian limited liability companies (AS Companies) from the period 1995-1999. The variables used were operating income plus depreciation to total Debt, financial coverage, current ratio, equity to total capital, age, size, geography and industry. The statistical method used for the study is Logit Model through maximum likelyhood. In this study, one model to estimate probability of bankruptcy is presented. The model combined financial ratios as well as firms fixed data and found a set of co efficient for Logit Model. The main conclusion is that expected default frequency decreases a function of the ratios mentioned as well as with size and age.

Bofondi and Lotti (2006) in their study "Innovation in the retail banking industry: the diffusion of credit scoring" analysed based on the diffusion of credit scoring in Italy on a unique data set that draws information from three different sources. The first is a direct survey, aimed at understanding the technology used by Italian banks to measure credit risk. Addressed to nearly 330 banks, i.e., the universe of Italian commercial banks with the exclusion of mutual banks; 104 of the interviewed answered that they were using credit scoring. The second source of information is a further survey addressed only to those banks that answered positively to the first wave. It turned out that only 77 banks actually adopted automated credit scoring models. Lastly, the study merged this information with bank level data drawn from the supervisory reports at the Bank of Italy, allowing us to focus on the evolution of bank's characteristics over time. The mortgage loans in the period 1995-2003 are also used. The variables used in the study were number of banks, time, number of consumer loans, number of mortgage loans, number small business, network size, market risk , ROE, operating expenses to gross income, number of branches in the local market in which the bank's headquarters are located to the total number of branches, specification, dummy variable. The study used survival analysis, likelihood, duration model, pooled tobit as the statistical method. The conclusion of the study is credit scoring is first introduced by large banks with broad branch networks which are fully able to exploit scale economies.

Lopez and Saidenberg (2000) in their research study "Evaluating credit risk models" used simulated data, using a panel data approach. The variables used are number of credits, present discounted value of these credits, the value of bank credit portfolio, the change in value of credit portfolio, change in value of individual credit, time. The statistical methods used are time-series analysis, likelihood, simulation method, Regressions. The study proposed evaluation methods based on statistical resampling that can provide quantitative measures of model accuracy for credit risk models. These methods provide performance evaluation in a cross-sectional environment.

Bucay and Rosen (2001) in their research study "applying portfolio credit risk models to retail portfolios" presented a simulation-based model to estimate the credit loss distribution of retail loan portfolios and apply the model to a sample credit card portfolio of a North American financial institution. Three variants of the model are presented. They are factor based logit model, sector based logit model and factor based merton model. The data consists of account information for credit cards issued between the last quarter of 1995 and the first quarter of 1999. The sample portfolio consists of half a million to a million cards. The variables required for all the three models are current ratings scores for all the accounts, definition of sectors for sector analysis, definition of default events, default probabilities of each sector, credit exposures and recovery rates. In addition to the above variables for factor model nine macro economic variables are considered. they are Industrial production, stock index, consumer price index, retail sales, unemployment level, 3 months treasury bill at tender, short term government bond yield, medium term government bond yield, long term government bond yield. Monthly data for macroeconomic factors are from December 1982 till March 1999. The study developed a simulation based framework to estimate the one period credit loss distribution of retail loan portfolio and demonstrated the usefulness of the model by estimating one year credit losses for credit card portfolio. While the sector model is purely descriptive the factor models are casual that capture the economic cycle through macroeconomic factors.

Salari *et al.* (2012) in their study "A credit risk model for bank's loan portfolio and optimize the VaR" proposes a method to calculate portfolio credit risk. This

Table 1: Sample characteristics

Variables	N	Min.	Max.	Mean	SD
Age	50	29	66	45.97	9.050
Asset price range	50	2.36E6	7.66E6	3.7750E6	1.16942E6
Down payment	50	0.0%	81.4%	25.930%	17.9071%
Loan amount	50	5.00E5	7.00E6	2.8927E6	1.24446E6
Loan tenure mths	50	36	84	55.68	15.853
EMI amount	50	16560.00	1.71E5	6.2071E4	28161.55750
Interestrate	50	11.50%	15.00%	12.4898%	0.93273%
Approximate total income	50	1.95E5	2.86E7	2.9755E6	5.35424E6

empirical research study attempts to measure credit risk of a bank's corporate loan portfolio including firms from 5 different business sectors. Credit loss distributions for each segment are selected and used in a Monte Carlo simulation process to generate the loss distribution of the portfolios. The samples of agriculture, manufacturing and mining, construction and housing, exports, trade services and miscellaneous are used to obtain efficiency estimates for individual firms in each industry. This period covers 36 monthly observations. Corporate credit risk models split into structural and reduced form modelling. A variety of analytical techniques can be used for credit risk assessment. Examples are linear or quadratic programming, Data Envelopment Analysis (DEA), neural networks models, multivariate discriminant analysis, logistic regression, probit analysis, logit analysis and trait recognition, mixed Logit Model to predict financial distress, discriminant analysis, probit, logit and principal component models, actuarial approach, Markov chain model and static scorecard models. This study used data involving installment loans of corporates. These data were supplied by a major commercial bank in Iran. The data included all the payment behavior registered for these corporates from March 2007 up to 2009 covering a total of 36 months. Sector name and sector number assigned are: agriculture, exports, construction and housing, manufacturing and mining, trade services and miscellaneous. The variables used are the amount of exposition paid days after due date, the interest rate of bank, the penalty rate, number of days after due date of exposition, number of corporates, corporate default rate of month, the amount of exposition of month, sectoral default rate of month. Since, the numbers of historical observations are not sufficient to obtain a smooth probability distribution, the sectoral default rates need to be simulated. Monte Carlo simulation is used as simulation method. Monte Carlo simulation is applied for 1,500 times. Based on the simulated default rates, the mean and the standard deviation of expected sectoral default rates are computed. Then, a credit quality rating scale is fitted into the sectoral default rates distributions. By means of Monte-Carlo simulation, VaR measure for the sample portfolio of loans was proposed. Also, how calculating VaR can enable financial institutions to evaluate alternative lending policies on the basis of their implied credit risks and loss rates was shown. The study attempts to measure the credit risk and capital requirement of a sample bank's corporate loan portfolio using advanced IRB approach. Since, the amounts of historical default rates are limited, the expected sectoral default rates are simulated using Monte Carlo approach. The simulated default rates are then applied to a theoretical bank's corporate loan portfolio in the value of $100 million. The calculation results show that the bank needs to allocate $19.05 million capital for credit risk for its loan portfolio using IRB approach.

Verstraeten and Van (2005) in their research study "The impact of sample bias on consumer credit scoring performance and profitability" used the data of a large Belgian direct mail order company offering consumer credit to its customers. The data use consists of all short-term credit orders placed between July 1st 2000 and February 1st 2002 and their credit repayment information until 9 February 1st 2003. The variables used in the study for analysis is No. of proposals not handled, automatic score value accepted, rejected, override rejected and override accepted and the statistical methods used for analysis were logit analysis, sensitivity analysis and judgemental method. The results of the study indicate that sample bias does appear to have a negative influence on credit-scoring performance and profitability.

In the sample about 50 customers of luxury cars were sampled for their credit portfolios. The sample is composed of 12 ladies and 38 men. The sample was distributed over 22 cities. There were about 5 defaulters in the sample.

The age group of the luxury car customers in the sample is between 29 and 66. The interest rate varies between 11.5-15%. Loan tenure varies between 36-84 months (Table 1).

In order to estimate the impact of the demographic factors on the default, a dichotomous variable called default was created with 0 representing non-default and 1 representing default. Analysis of variance was carried out to estimate if there is a significant influence of the available variables on default.

Analysis of variance indicates that there is a significance of difference in the interest rate paid by the defaulters and non-defaulters. Correlation coeffecients were estimated using carl pearsons partial correlation (Table 2 and 3).

A simple regression analysis was built with the following variables: (Constant), lninterest rate, EMI amount, gender, approximate total income, job type, age,

Table 2: Analysis of variance between defaulters and non-defaulters

Variables	Sum of squares	df	Mean square	F-values	Sig.
Gender					
Between groups	0.009	1	0.009	0.047	0.830
Within groups	9.111	48	0.190		
Total	9.120	49			
Date of birth					
Between groups	3.775E16	1	3.775E16	0.458	0.502
Within groups	3.954E18	48	8.236E16		
Total	3.991E18	49			
Age					
Between groups	37.959	1	37.959	0.458	0.502
Within groups	3975.290	48	82.819		
Total	4013.249	49			
City					
Between groups	2.136	1	2.136	0.056	0.813
Within groups	1819.244	48	37.901		
Total	1821.380	49			
Job type					
Between groups	0.222	1	0.222	1.371	0.247
Within groups	7.778	48	0.162		
Total	8.000	49			
Asset price range					
Between groups	3.911E11	1	3.911E11	0.282	0.598
Within groups	6.662E13	48	1.388E12		
Total	6.701E13	49			
Down payment					
Between groups	174.496	1	174.496	0.539	0.466
Within groups	15538.008	48	323.708		
Total	15712.504	49			
Loan amount					
Between groups	1.665E12	1	1.665E12	1.076	0.305
Within groups	7.422E13	48	1.546E12		
Total	7.589E13	49			
Loan tenure mths					
Between groups	1.280	1	1.280	0.005	0.944
Within groups	12313.600	48	256.533		
Total	12314.880	49			
EMI amount					
Between groups	4.925E8	1	4.925E8	0.616	0.436
Within groups	3.837E10	48	7.993E8		
Total	3.886E10	49			
Interest rate					
Between groups	3.647	1	3.647	4.490	0.039
Within groups	38.983	48	0.812		
Total	42.629	49			
Approximate total income					
Between groups	8.440E12	1	8.440E12	0.290	0.593
Within groups	1.396E15	48	2.909E13		
Total	1.405E15	49			

Table 3: Proximity matrix

	Correlation between vectors of values											
Variables	Gender	Date of birth	Age	City	Job type	Asset price range	Down payment	Loan amount	Loan tenure mths	EMI amount	Interest rate	Approximate total income
Gender	1.00	0.02	-0.02	-0.12	-0.07	0.11	-0.03	0.15	-0.37	0.20	-0.08	0.08
Date of birth	0.02	1.00	-1.00	-0.11	-0.11	0.04	-0.19	0.08	0.41	0.02	0.26	-0.18
Age	-0.02	-1.00	1.00	0.11	0.11	-0.04	0.19	-0.08	-0.41	-0.02	-0.26	0.18
City	-0.12	-0.11	0.11	1.00	-0.03	-0.02	0.15	-0.05	0.07	-0.21	0.34	0.19
Job type	-0.07	-0.11	0.11	-0.03	1.00	-0.26	0.14	-0.27	-0.09	-0.23	0.22	0.09
Asset price range	0.11	0.04	-0.04	-0.02	-0.26	1.00	-0.21	0.85	0.11	0.70	-0.06	-0.11
Down payment	-0.03	-0.19	0.19	0.15	0.14	-0.21	1.00	-0.64	-0.14	-0.57	-0.33	-0.15
Loan amount	0.15	0.08	-0.08	-0.05	-0.27	0.85	-0.64	1.00	0.08	0.82	0.15	0.01
Loan tenure mths	-0.37	0.41	-0.41	0.07	-0.09	0.11	-0.14	0.08	1.00	-0.19	0.19	-0.34
EMI amount	0.20	0.02	-0.02	-0.21	-0.23	0.70	-0.57	0.82	-0.19	1.00	0.02	0.18
Interest rate	-0.08	0.26	-0.26	0.34	0.22	-0.06	-0.33	0.15	0.19	0.02	1.00	0.13
Approximate total income	0.08	-0.18	0.18	0.19	0.09	-0.11	-0.15	0.01	-0.34	0.18	0.13	1.00
Defaulter	0.03	0.10	-0.10	0.03	-0.17	0.08	-0.11	0.15	-0.01	0.11	0.29	-0.08

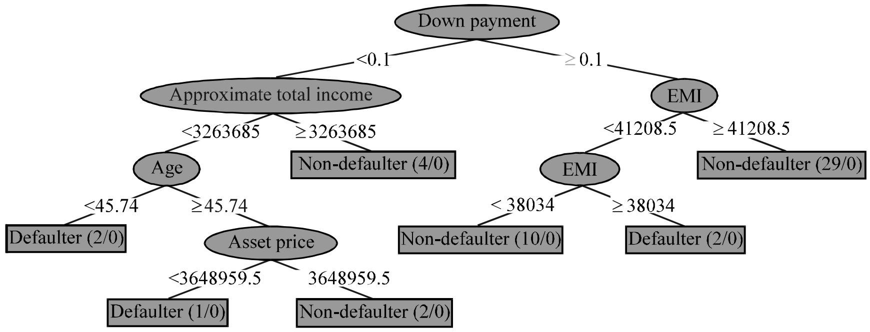

Fig. 1: Decision tree classifier

Table 4: Fit of the regression model

Model	R	R^2	Adjusted R^2	SE of the estimate
1	0.452^a	0.204	-0.054	0.311

Table 5: Regression coefficients

	Unstandardized coefficients		Standardized coefficients		
Coeffecients	B	SE	•	t-values	Sig.
(Constant)	-3.793	2.368		-1.602	0.118
Gender	-0.029	0.118	-0.041	-0.246	0.807
Age	0.000	0.006	-0.024	-0.131	0.896
City	-0.006	0.009	-0.128	-0.680	0.501
Job type	-0.214	0.127	-0.285	-1.684	0.101
Asset price range	8.354E-9	0.000	0.032	0.045	0.964
Down payment	-0.007	0.017	-0.406	-0.393	0.696
Loan amount	-2.010e-8	0.000	-0.083	-0.092	0.927
Loan tenure mths	-0.002	0.004	-0.120	-0.550	0.586
Emi amount	8.964e-7	0.000	0.083	0.244	0.808
Approximate total income	-7.469e-9	0.000	-0.132	-0.755	0.455
Down payment 2	0.000	0.000	0.496	0.721	0.476
Lninterest rate	1.770	0.867	0.415	2.043	0.048

city, loan tenure mths, down payment 2, asset price range, loan amount, down payment. In the model, the log of interest rate was included as there was correlation between the interest rates and other explanatory variables.

The identified regression model did not have a predictive fit, however, it was useful in establishing the causalities between the default and the available variables (Table 4 and 5). The regression results indicate that the job type and the interest rates are the two most important factors that determine the default of the luxury passenger car customers.

DECISION TREE CLASSIFIER

The different variables of the multi-variate data are given as an input to the classifier. The last variable is the class variable. In this study, the variables considered are as discussed in section. The data is divided into two classes namely ‘Defaulters’ and ‘Non-Defaulters’. Thus, the leaves in the decision tree would represent the class labels and the nodes, they are associated with the attributes being classified. On application of the random tree algorithm, a comprehensive decision tree was obtained which is shown in Fig. 1.

Table 6: Decision matrix for random tree classifier

A	B	<=Classified as
5	0	A
0	45	B

Here, ‘Down payment’ is the root node and the best feature that classifies the data into defaulters or non-defaulters. Further, the less important but significant features are ‘Approximate Total Income’, ‘EMI’ and ‘Age’. The classification was done using a full training set. The classification accuracy was 100% and all instances were correctly classified. The decision matrix is shown in Table 6 and clearly signifies that all the instances were correctly. Other classifiers has less classification accuracy.

CONCLUSION

In the sample about 50 customers of luxury cars were sampled for their credit portfolios. The sample is composed of 12 ladies and 38 men. The sample was distributed over 22 cities. There were about 5 defaulters in the sample. The age group of the luxury car customers in the sample is between 29 and 66. The interest rate varies between 11.5-15%. Loan tenure varies between 36-84 months.

Analysis of variance indicates that there is a significance of difference in the interest rate paid by the defaulters and non-defaulters. The proximity matrix was estimated for similarities between variables. The significant correlations between the explanatory variables were among asset price, loan amount and EMI Amount. The regression results indicate that the job type and the interest rates are the two most important factors that determine the default of the luxury passenger car customers. The random decision tree had classified the variables like down payment, approximate total income and the EMI as the key determinants of the default in the luxury passenger car segment. From different types of statistical analysis we can conclude with certainty the variables like interest rate, job type, down payment, approximate total income of the customer and the EMI as the key determinants of the default at the luxury car segment.

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