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The Evolution of Non-Performing Credit Limits During Crisis Period, Using Unique Accounting Data

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Abstract

The purpose of this paper is to study the effect of independent variables in identifying non-performing loans during crisis period, using a binomial logistic regression. We use a unique data of small business loans granted by one of the four systemic banks of Greece. Specifically we study a sample of credit limits granted to micro and small enterprises. Non-performing loans significantly increased as the recession of Greek economy deepens. Moreover we find that in general the variables affect in the same way the creation of non-performing loans during the studied period. Specifically, binomial logistic regression shows a positive correlation between non-performing loans and factors "Adverse" and "Age". In contrast, we find a negative correlation between the probability of classifying a loan as non-performing and the independent variables "Collateral", "Own Facilities", "Property" and "Years of operation". Finally the predicted performance of the binomial logistic regression reduced as the crisis deepens.

Keywords: Banks; Non-performing loans; Micro and small enterprises; Credit scoring; Binomial logistic regression; Economic crisis

JEL Classification: G21, C23

Introduction

The control of non-performing loans is a vital priority and necessity for the proper operation of financial institutions. The necessity of reduction of non-performing loans expressed supremely in the recent global financial crisis, which began in the U.S. in 2006 and spread to the rest of the world - especially in European Union, where it evolved into a sovereign debt crisis. As was expected, the transmitted financial crisis, received large dimensions, due to the fact that large credit institutions was exposed in the so-called "junk bonds." The financial crisis reached the threshold of Greece in the last quarter of 2008 [1]. Especially in the case of Greece, the crisis was denatured extensively to debt crisis and received great proportions due to the extremely high public debt, thereby plunging the economy into great recession. Unlike the public debt, private debt in Greece is lower than that of other European countries, as a result of, in general, conservative credit policies of the Greek banks (Table 1).

Country	Private debt as percentage of GDP	Public debt as percentage of GDP	Total public & private debt
United Kingdom	281,00%	68,60%	349,60%
Denmark	238,00%	33,70%	271,70%
Luxembourg	553,00%	15,00%	568,00%
Malta	433,00%	68,50%	501,50%
Cyprus	321,00%	53,20%	374,20%
Ireland	259,00%	65,80%	324,80%
Portugal	169,00%	77,40%	246,40%
Holland	185,00%	59,80%	244,80%
Spain	181,00%	54,30%	235,30%
Italy	115,00%	114,60%	229,60%
Austria	149,00%	69,10%	218,10%
Belgium	117,00%	97,20%	214,20%
Greece	92,00%	112,60%	204,60%
Germany	129,00%	73,10%	202,10%
France	117,00%	76,10%	193,10%
Finland	89,60%	41,30%	130,90%
Slovenia	93,00%	35,10%	128,10%
Slovakia	47,40%	34,60%	82,00%

Table 1: The public and private debt in Europe in 2009.

The main predictive credit scoring models are distinguished on statistical models (linear discriminant analysis, logistic regression analysis, multivariate adaptive regression splines, etc) and artificial intelligent models (artificial neural networks, decision trees, case based reasoning, support vector machines, etc). The purpose of this paper is to study the behavior of a sample of credit limits granted by one of four systemic banks in Greece in a period of growth (01-12/2005), during the recent financial crisis and the recession in the Greek economy (12/2010-12/2011). The Greek economy till 2008 showed positive growth rates but then sank into recession. So we use a dataset of loans granted during an expansion period and study their behavior during the recession period.

In our paper we find a positive correlation between non-performing loans and factors "Adverse" and "Age". In contrast, we prove that the independent variables "Collateral", "Own Facilities", "Property", "Residence" and "Years of operation" negatively affect the probability of default. Moreover we prove that in general the variables still affect in the same way the creation of non-performing loans as the recession deepens. Finally the predicted performance of the binomial logistic regression reduced as the crisis deepens.

The rest of the paper is structured as follows. In section 2 we provide a literature review for credit scoring models. In section 3 we present the data and the employed variables. In section 4 we demonstrate the research methodology followed by a presentation of the applicable credit scoring model. In section 5 we provide the empirical results of this research, while section 6 concludes the paper and discusses future research.

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Literature Review

In the past, many researchers have developed a variety of traditional statistical methods for credit risk prediction, with utilization of linear discriminant analysis and logistic regression analysis being the two most commonly used statistical methods in building credit risk prediction models [2].

The first credit scoring models were developed around 1950 and 1960, and the methods applied in this kind of problem referred to methods applied in this kind of problem referred to methods of discrimination suggested by Fisher [3], where the models were based on his discriminant function [4]. Possibly the earliest use of applying linear discriminant analysis to credit risk prediction is the work by Durand [5], who was the first one which mentioned that the discriminant analysis technique, invented by Fisher in 1936, could be used to separate good credits from the bad ones [6]. However, Karels and Prakash [7] and Reichert et al. [8] pointed that the application of linear discriminant analysis has often been challenged owing to its assumption of the categorical nature of the corporate credit data and the fact that the covariance matrices of the credit risk and non-risk classes are unlikely to be equal.

In addition to the linear discriminant analysis approach, logistic regression analysis is another commonly used alternative to conduct corporate credit risk prediction tasks. Thomas [6] and West [9] indicated that both linear discriminant analysis and logistic regression analysis are intended for the case when the underlying relationship between variables are linear and hence are reported to be lacking in sufficient prediction accuracy.

As Louzada et al. [4] mentioned, thus Fisher's approach can be seen as the starting point for developments and modifications of the methodologies used for granting of credit until today, where statistical techniques, such as discriminant analysis, logistic regression analysis (logit analysis), probit analysis, naïve logistic regression and multivariate adaptive regression splines, have been used and examined [10-14].

In the recent past, Louzada et al. [4] studied the impact of disproportional sample in credit scoring models, using a Brazilian bank data. They revealed that there is no statistically significant difference in terms of predictive capacity between the naive logistic regression models and the logistic regression with state-dependent sample selection models. However, the naive logistic regression models always underestimating the estimated default probabilities, particularly in the presence of balanced samples.

In order to improve the prediction accuracy of logistic regression, Dong et al. [15] proposed a logistic regression with random coefficients. They claim that the proposed model can improve prediction accuracy of logistic regression without sacrificing desirable features. Twala [16] explores the predicted behaviour of five classifiers – three supervised learning (artificial neural network, decision trees and naive Bayes classifier) and two statistical techniques (k-nearest neighbour and logistic discrimination) for different types of noise in terms of credit risk prediction accuracy, and how such accuracy could be improved by using classifier ensembles. Comparing all considered multiple classifiers together, the find that none of the multiple classifiers is the best for all datasets. Each of the classifiers has its own area of superiority.

Marshall et al. [17] used the bootstrap variable reduction technique, in order to reduce the probability of default for a large data set drawn from a major UK retail bank. The result shows a statistically significant correlation between the loan approval and performance processes.

Shu Ling Lin [18] used a new two stage hybrid approach of logistic regression and artificial neural network. In the prediction of financially distressed, two stage hybrid model giving the best performance of 80% using cross-validation approach and demonstrates stronger prediction power than conventional logistic regression, logarithm logistic regression and artificial neural network approaches.

Abdou et al. [19] evaluate credit risk in Egyptian banks using credit scoring models. Especially they use three statistical techniques: discriminant analysis, probit analysis and logistic regression. The credit scoring task is performed on one bank's personal loans data-set. The results so far revealed that all proposed models gave a better average correct classification rate than the one used by the bank. Also both type I and type II errors had been calculated in order to evaluate the misclassification costs.

Hu and Ansell [20] propose a theoretical framework for predicting financial distress based on Hunt's [21]. "Resource-Advantage Theory of competition. They compare five credit scoring methodologies – Naïve Bayes, Logistic Regression, Recursive Partition, Artificial Neural Network and Sequential Minimal Optimization – with Moody's rankings, for the US retail market. It is found that both Sequential Minimal Optimization and Logistic Regression are better than the Neural Network model in terms of similarity with Moody's ranking, with Sequential Minimal Optimization being slightly better than the Logistic Model.

Crook et al. [22] reviewed a selection of current research topics in consumer credit risk assessment. The claim that the training of a classifier on a sample of accepted applicants rather than on a sample representative of the applicant population seems not to result in bias though it does result in difficulties in setting the cut-off point.

The Data Set and the Employed Variables

The data set is collected manually from the internal Management Information System (MIS) of the bank under study and contains a very wide loan portfolio consisting of micro businesses and small enterprises as defined by the EU. The data set contained 1,884 applications for credit limits of micro and small enterprises spread across Greece granted in the late expansion period (2005). Specifically we study credit limits granted in order to cover working capital needs of the enterprises. The present study is based on a joint project between academic researchers with previous professional banking experience and the top level lending management of the bank under investigation. This was carried out due to the necessity of identifying important drivers of credit risk related to borrowers' characteristics and re-evaluating the existing internal credit scoring model of the bank under study during recession.

Table 2 presents the main descriptive statistics of the dataset. Almost 53.3% of the data are unsecured loans. Moreover 42.3% of loans were granted to businesses operating for 5-9 years. Considering the bank relationship, 524 loans (27.1%) were granted to new customers and only 165 loans (8.76%) were granted to customers that already had deposit collaboration with the bank. Regarding the performance of loans on December 2010, 90.23% were performed loans and 9.77% were NPLs. The percentage of NPLs rise to 18.47% on December 2011.

In our analysis, we set as a dependent variable the 'performance of the loan' during the studied period. For the definition of a loan as non-performing, we use the basic rules of Basel I & II, where NPLs are those loans that are up to ninety days past due. As a time frame for the identification of the behavior of a NPL, empirical studies [23,24] specify either the performance of loans in a specific month or the performance

Collateral		Years in same subject		Property		Bank Relationship	
Mortgage	430	0-4	241	Yes	1472	Deposit relationship	165
No collateral	1004	9-May	797	No	412	Loan relationship	685
Checks	364	19-Oct	574			Deposit & Loan relat.	510
Cash collateral	86	20+	272			New costumer	524
Total	1884	Total	1884	Total	1884	Total	1884
-	-	-	-	-	-	-	-
Own Facilities		**Adverse**		**Performance Dec 2010**		**Performance Dec 2011**	
Yes	869	Yes	154	Performing Loans	90,23%	Performing Loans	81,53%
No	1015	No	1730	NPL	9,77%	NPL	18,47%
Total	1884	Total	1884	Total	100%	Total	100%

Table 2: Descriptive Statistics.

of loans during a specific period, usually 12 months. In our analysis we check the performance of loan on December 2010 and December 2011.

As independent variables we use quantitative and qualitative loan characteristics derived from the loan application at the time of evaluation. In particular, qualitative information (such as the age of the borrower, the type of the loan etc.) is significant in explaining a firm's credit risk [25,26] justified by the "Five Cs of Credit" and used by lenders for credit worthiness evaluation of potential borrowers. In our research analysis, we utilize the nine main characteristics of the credit scoring model used by the bank under study as independent variables (loan characteristics). Table 3 summarizes the definition of these independent variables.

Methodology

The logistic regression analysis was introduced by Joseph Berkson [27], who coined the term. The term was borrowed by analogy from the very similar probit model developed by Chester Ittner Bliss [28] G.A. Barnard [29] coined the commonly used term log-odds; the log-odds of an event is the logit of the probability of the event [30].

Logistic regression analysis is widely used statistical modeling technique in which the response variable, the outcome (non-performing loans), is binary (0, 1) and can thus be used to describe the relationship between the occurrence of an event or interest and a set of potential predictor variables. In the context of credit scoring, the outcome corresponds to the credit performance of a client during a given period of time, in our case 24 months. A set of individual characteristics, such as age, years of experience, residence status, as well as information about his credit behavior, such as relationship with the bank, purpose, are observed at the time the clients apply for the credit.

A logistic regression model with random coefficients is applied, where the coefficients follow multivariate normal distribution. Here, the event $Y_t = 1$ represents a bad credit, while the complement $Y_t = 0$ represents a good credit. In the model, the probability of individual being "bad" is expressed as follows [31]:

$$P_i = \frac{\exp(\sum_{k=1}^{n}\beta_k x_{ik})}{1+\exp(\sum_{k=1}^{n}\beta_k x_{ik})} = \frac{e^{(\sum_{k=1}^{n}\beta_k x_{ik})}}{1+e^{(\sum_{k=1}^{n}\beta_k x_{ik})}} \quad (1)$$

Where

P_i = the probability of i th loan being non-performing

β_k = the coefficient of the k th independent variable

x_i = the k th independent variable of i th loan

The objective of the logistic regression model in credit scoring is to determine the conditional probability of a specific client belonging to a class, given the values of the independent variables of that credit applicant [32].

Our binomial logistic regression is as follows:

log (Yi) = βo + β1 * log (ADVESE) + β2 * log (AGE) + β3 * log (BANKREL) + β4

* log (COLLATERAL) + β5 * log (LTT) + β6 * log (OWFAC) + β7

* log (PROPERTY) + β8 * log (RESIDENCE) + β9 * log (YEARS) (2)

Results

In our paper, using as independent variable the performance of loans, as defined above, we try to identify the relative importance of each independent variable as well as the relative influence of each factor in the creation of non-performing loans during the early recession of the Greek economy (December 2010, December 2011). Below, using the binomial logistic regression, we tried to identify the effects of the independent variables in the determination of non-performing loans as well as to track changes in the effects of variables as the recession of the Greek economy deepens.

Table 4 shows that the effect of the independent variables on December 2010. We note that the variables associated with the welfare of borrowers (existence of own facilities, existence of sufficient property free of liabilities, existence of home ownership) as well as years of operation of borrower's business, have a negative effect on the formation of non-performing loans. On the other side the factor of the borrower's age is positively correlated with the probability of classifying a loan as non-performing. Similarly, borrowers who had experienced adverse elements before granting the loan, are more likely not to pay their loan obligations. Regarding the factor "loan amount to company's turnover ratio", there is no correlation with the probability of the loan to be classified as non-performing.

Regarding the factor of previous collaboration between the client and the bank, we observe that customers without a pre-existing deposit collaboration with the bank behave better than those who have no collaboration with the bank. On the other hand, customers who had already loans, performed worse than new customers. Regarding the factor of the collateral of the loan, we observe that the better the collateral the lower the probability of default.

Number	NPL determinant	Definition	Type of characteristic
1	Adverse	Borrowers who experienced adverse at the time of assessing the application	Character
2	Age	The age of the borrower	Character
3	Bankrel	Four indicators for the type of banking relationship: 1. no customer, 2. only loans, 3. only deposits 4. deposits and loans	Capital
4	Collateral	Four indicators for the type of collateral: 1. no collateral", 2. securities (checks-exchange), 3. "mortgage on the property" 4. Cash collateral cover (deposits, bancassurance and investment savings products)".	Collateral
5	LTT	Loan to turnover ratio.	Economic Conditions
6	Owfac	dummy variable taking the value 0 if the borrower had not owned facilities and the value 1 if the borrower had owned facilities at the time of assessing the application.	Capacity
7	Property	dummy variable taking the value 0 if the borrower and the guarantor meet the criterion of real estate, or the value 1 otherwise.	Capital
8	Residence	Three indicators for the type of residence: 1. "rented house", 2. "live with parent" and 3. private residence".	Capacity
9	Years	The years of vocational experience.	Economic conditions

Table 3: The association of micro and small firms idiosyncratic features with the formation of NPL's.

Dec-10			B	S.E.	Wald	df	Sig.	Exp(B)
Step 1ᵃ		Years	-,025	,014	2,979	1	,084	,976
		Owfac	-1,420	,214	44,243	1	,000	,242
	Bank Relationship	No Customer			33,279	3	,000	
		Deposits and Loans	-1,018	,272	13,964	1	,000	,361
		Deposits	-1,697	,544	9,729	1	,002	,183
		Loans	,219	,200	1,199	1	,273	1,245
	Residence Status	With Parents			10,926	2	,004	
		Home Owner	,356	,252	2,008	1	,156	1,428
		Rental	,901	,284	10,063	1	,002	2,462
		Age	,002	,011	,024	1	,876	1,002
		Adverse	1,074	,274	15,421	1	,000	2,927
		Property	-,565	,193	8,529	1	,003	,569
		LTT	,000	,000	,854	1	,355	1,000
		Collateral	-,027	,104	,067	1	,795	,973
		Constant	-1,435	,489	8,626	1	,003	,238

a. Variable(s) entered on step 1: Years, Owfac, Bankrel, Residence, Age, Adverse, Property, LTT, Collateral.

Table 4: Binomial Logistic Regression – December 2010.

Table 5 presents the binomial logistic regression's results on December 2011. In most cases, the effect of independent variables remain stable. Specifically the variables associated with the welfare of borrowers (existence of own facilities, existence of sufficient property free of liabilities, existence of home ownership) have a negative effect on the formation of non-performing loans. Moreover regarding the years of operation of borrower's business, the more years a company operates, the less the probability of default.

On the other hand the borrower's age is positively correlated with the probability of classifying a loan as non-performing. Similarly, businesses which had experienced adverse elements before granting the loan are more likely to be characterized as bad borrowers. Regarding the factor "loan amount to company's turnover ratio", there is no correlation with the probability of the loan to be classified as non-performing.

Regarding the factor of previous collaboration between the client and the bank, we observe that customers without a pre-existing deposit collaboration with the bank behave better than those who have no collaboration with the bank. Customers who retained only loan collaboration have the worst performance. Concerning the collateral of the loan, we find that unsecured or low covered credit limits had higher probability of being classified as NPLs.

Table 6 shows the average accuracy and the estimated misclassification cost of the binomial logistic regression both on December 2010 and December 2011. We find that the predicted performance of the binomial logistic regression reduced as the recession deepens. Specifically the average accuracy reduced from 90.5% (December 2010) to 81.9% (December 2011). On the other hand the estimated misclassification cost increased form 0.0455 (December 2010) to 0.1568 (December 2011).

Discussion and Conclusions

This paper studies the effect of factors that characterize a credit line as non-performing, as well as the effectiveness of the binomial logistic regression during the early recession period of the Greek economy. The main studies related to credit scoring models, used up in creating the most comprehensive and effective model, concerning the predictive ability to identify non-performing loans.

Regarding the factors that affect the classification of a loan as non-performing, the conclusions are broadly expected. Particularly, binomial logistic regression shows a positive correlation between non-performing loans and factors "Adverse" and "Age". Regarding the variable "Adverse", the positive correlation between the probabilities of a loan not be served and prior misbehavior borrower is demonstrated. An enterprise that has demonstrated bad trading behavior either to the

			B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]		Years	-,013	,010	1,648	1	,199	,987
		Owfac	-,227	,137	2,722	1	,099	,797
	Bank Relationship	No Customer			28,905	3	,000	
		Deposits and Loans	,029	,196	,022	1	,882	1,030
		Deposits	-,093	,311	,089	1	,766	,911
		Loans	,719	,171	17,736	1	,000	2,051
	Residence Status	With Parents			19,223	2	,000	
		Home Owner	-,246	,183	1,814	1	,178	,782
		Rental	,528	,217	5,936	1	,015	1,695
		Age	,001	,009	,025	1	,874	1,001
		Adverse	,956	,213	20,089	1	,000	2,601
		Property	-,697	,145	23,041	1	,000	,498
		LTT	,000	,000	2,343	1	,126	1,000
		Collateral	-,088	,076	1,335	1	,248	,916
		Constant	-,947	,379	6,232	1	,013	,388

a. Variable(s) entered on step 1: Years, Owfac, Bankrel, Residence, Age, Adverse, Property, LTT, Collateral

Table 5: Binomial Logistic Regression – December 2011.

Metric	Dec-10	Dec-11
Average Accuracy	90.50%	81.90%
Estimated misclassification cost	0.0455	0.1568

Notes: The average accuracy is calculated by the equation: AC = (TP+TN)/Total, where: AC: Average Accuracy; TP: True Positive (Predicted Performing Loans); TN: True Negative (Predicted Non-Performing Loans); Total: Total Loans. The estimated misclassification cost is calculated by the equation: EMC = (PL/Total)*Type Error 1 + (NPL/Total)*Type Error 2, where EMC: Estimated Misclassification Cost; Type Error 1 = FN/(TP+FN); Type Error 2 = FP/(TN+FP); PL: Performing Loans; NPL: Non-Performing Loans; FN: False Negative (Predicted Non-Performing Loans); TP: True Positive (Predicted Performing Loans); FP: False Positive (Predicted Performing Loans); TN: True Negative (Predicted Non-Performing Loans); Total: Total Loans

Table 6: Predictive Performance.

public sector or to third banks, either to suppliers or customers, has many more chances not to serve the loan. In addition, the older the borrower, the higher the probability of the loan to be classified as bad.

In contrast, we find a negative correlation between the probability of classifying a loan as non-performing and the independent variables, “Own Facilities”, “Property”, “Residence” and “Years of operation”. Specifically, the existence of private facilities reduce the probability that a loan be classified as non-performing, since the fixed obligations of businesses is smaller, giving them the opportunity to be more competitive. The existence of property also negatively associated with non-performing loans, precisely because of the financial standing of borrowers. Finally, years of operation, also negatively correlated with the appearance of non-performing loans.

Regarding the evolution of the effect of independent variables to identify additional non-performing, we observe that, in general, the intensity of the effect of independent variables is reduced as the recession deepens. This observation indicates that, when the whole economy is in a recession, the characteristics of each business continue to influence the trading behavior but at a decreasing rate. Additionally, since the percentage of non-performing loans increased significantly for all categories of borrowers, it turns out that the importance of exogenous factors increases drastically. In other words the effect of independent variables reduced during recession, as the likelihood of the borrower to default largely influenced by the unfavorable economic conditions.

Our findings suggest that bank managers should focus on lending SMEs that had not bad demonstrated bad trading behavior either to the public sector or to third banks. Moreover they should focus on granting secured loans, in order to minimize the expected loss in case of default. In addition bank managers should focus on the welfare of borrowers, as it is proved that generally performed better even during crisis periods.

This study highlighted the evolution of the importance of those factors that determine the likelihood of a loan not repaid at the current recession of the Greek economy, using data for one of the four systemic banks. It would be of particular interest to study whether there are common characteristics with other European countries in the south Europe (Italy, Spain, Portugal, France) in order the ECB to define a representative joint surveillance platform based on the specific and the common characteristics of countries-states of the European Union.

References

1. Aggelopoulos E, Georgopoulos A (2017) Bank branch efficiency under environmental change: A bootstrap DEA on monthly profit and loss accounting statements of Greek retail branches. Eur Operational Res 261: 1170-88.
2. Wang G, Ma J (2011) Study of corporate credit risk prediction based on intedrating boosting and random subspace. Expert Systems with Applications 38: 13871-78.
3. Fisher RA (1936) The Use of Multiple Measurements in Taxonomic Problems. Annals of Eugenic 7: 179-188.
4. Louzada F, Ferreira-Silva PH, Diniz CAR (2012) On the impact of disproportional samples in credit scoring models: An application to a Brazilian Bank data. Expert Systems with Applications 39: 8071-78.
5. Durand D (1941) Risk Elements in Consumer Instalment Financing. National Bureau of Economic Research New York.
6. Thomas LC (2000) A survey of credit and behavioural scoring; forecasting financial risk of lending to consumers. Int J Forecasting 16: 149-172.
7. Karels G, Prakash A (1987) Multivariate normality and forecasting of business bankruptcy. J Business Finance Acc 14: 573-93.
8. Reichert AK, Cho CC, Wagner GM (1983) An examination of the conseptual issues involved in developing credit-scoring models. J Business and Eco Stat 1: 101-114.
9. West D (2000) Neural Network Credit Scoring Models. Computers & Operations Res 27: 1131-1152.

10. Banasik J, Crook J, Thomas L (2001) Scoring by usage. J Operational Res Society 52: 997-1006.
11. Boyes WJ, Hoffman DL, Low SA (1989) An econometric analysis of the bank credit scoring problem. J Econometrics 40: 3-14.
12. Sarlija N, Bensic M, Bohacek Z (2004) Multinomial Model in Consumer Credit Scoring. 10th International Conference on Operational Research Trogir: Croatia.
13. Steenackers A, Goovaerts MJ (1989) A credit scoring model for personal loans. Insurance Math Eco 8: 31-34.
14. Friedman HJ (1991) Multivariate Adaptive Regression Splines. The Annals of Statistics 19: 1-67.
15. Dong G, Keung Lai K, Yen J (2010) Credit scorecard based on logistic regression with random coefficients. Procedia Computer Science 1: 2463-68.
16. Twala B (2010) Multiple classifier application to credit risk assessment. Expert System with Applications 37: 3326-36.
17. Marshall A, Tang L, Milne A (2010) Variable reduction, sample selection bias and bank retail credit scoring. J Empirical Fin 17: 501-12.
18. Shu Ling Lin (2009) A new two stage hybrid approach of credit risk in banking industry. Expert Systems with Applications.. 36: 8333-41.
19. Abdou H, El-Masry A, Pointon J (2007) On the applicability of credit scoring models in Egyptian Banks. Banks and Bank Systems.. 2: 4-20.
20. Yu-Chiang H, Ansell J (2007) Measuring Retail Company Performance Using Credit Scoring Techniques. Eur J Operational Res 183: 1595-1606.
21. Hunt SD (2000) A General Theory of Competition. Sage Publications Inc California.
22. Crook JN, Edelman DB, Thomas LC (2007) Recent developments in consumer credit risk assessment. Eur J Operational Res 183: 1447-65.
23. Makri V, Tsagkanos A, Bellas A (2014) Determinants of Non-Performing Loans: The case of Eurozone Panoeconomicus 2: 193-206.
24. Louzis D, Vouldis A, Metaxas V (2012) Macroeconomic and bank specific determinants of non-performing loans in Greece: A comparative study of mortgage business and consumer loan portfolios. J Banking and Fin 36: 1012-27.
25. Artavanis N, Morse A, Tsoutsoura M (2016) Measuring income tax evasion using bank credit: Evidence from Greece. The Quarterly J Eco 131: 739-98.
26. Gupta J, Gregoriou A, Healy J (2015) Forecasting bankruptcy for SMEs using hazard function: To what extent does size matter? Review of Quantitative Finance and Acc 45: 845-69.
27. Berkson J (1944) Application of the Logistic Function to Bio-Assay. J Am Statistical Ass 39: 357-65.
28. Bliss Chester Ittner (1934) The method of probits. Science 79: 38-9.
29. Barnard GA (1949) Statistical Inference. J Royal Statistical Society 11: 115-149.
30. Cramer JS (2003) Logit Models from Economics and Other Fields. Published by Cambridge University Press Cambridge United Kingdom.
31. Hosmer DW, Lemeshow S (1989) Applied Logistic Regression. Published by John Wiley & Sons Inc New York USA.
32. Lee C, Chen WJ (2005) Management in the information technology industry. Int J Management p: 22.