Academy of Economic Studies
Doctoral School of Finance and Banking

CREDIT SCORING MODELING -A MICRO MACRO APPROACH-

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Bucharest,July 2010

Topics

1. Motivation
2. Objectives
3. Literature Review
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1.Motivation

- Classification models in the form of scorecards, use predictor variables (or characteristics) from credit application forms and other sources to yield estimates of the probability of default.

- Banks and financial institutions play an important role in the economy as providers of credit. Beside government supervision and other regulatory conditions, capital requirements limit risks for depositors, and reduce insolvency and systemic risks. Unnecessary capital requirements restrain credit provision needlessly, whereas inadequate capital requirements may lead to undesirable levels of systemic risk.

2.Objectives

- Estimation of probabilities of default ;
- Event Trigger for Retail Credit Risk, financial vs. socio-demographic variables ;
- Including of a macroeconomic indicator at level client;
- Minimizing the loss function for the analyzed models;
- Stressing the client’s income due to cutting-off wages for public sector employers.

3.Literature Review

- In 1997, Hand and Henley made a comparison among logistic regression ,neural networks and other techniques and in their paper also present the Information Value criterion of selection variables;
- West(2000) investigates the credit scoring accuracy of five neural network models and compared them with other techniques such as logistic regression, decision trees etc and the results demonstrate that although neural networks have better results logistic regression is a good alternative to them;
- Komorád (2002) investigated credit scoring prediction accuracy and the methods, namely the logistic regression and multi-layer perceptron (MLP) give very similar results, however the logit model seems to perform marginally better;
- Bellotti and Crook (2007)show that survival analysis is competitive for prediction of default in comparison with logistic regression and also they included macroeconomic variables and a cost decision matrix. Malik and Thomas(2008) incorporated both consumer specific ratings and macroeconomic factors in the framework of Cox proportional hazard model.
- Rommer(2005) come to idea that there is no major difference between logit and probit regression models.
- Rauhmeier(2006) analyzed the validation process for probabilities of default and includes also the concept of “rolling window 12 months “ and in 2010,Sabato also presents the importance of the model’s validation and how back testing is the essential part of this process.

4.Methodology and data input

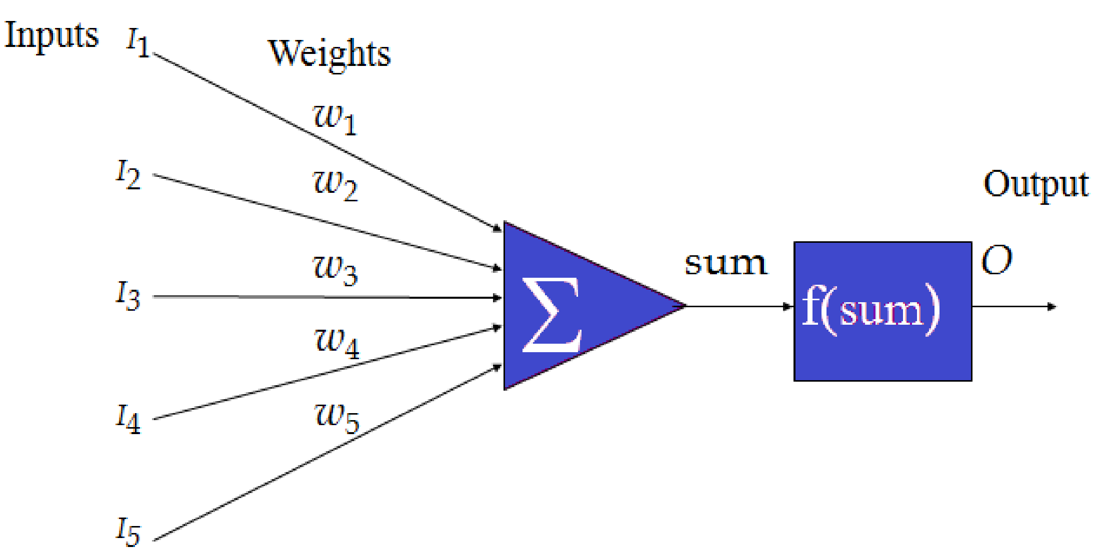
•Logit Model

$$\log\left(\frac{p_i}{1-p_i}\right) = w_0 + w_1x_1 + w_2x_2 + \cdots w_px_p = w \cdot x^T$$

•Probit Model

$$N^{-1}(p_i) = w_0 + w_1x_1 + w_2x_2 + \cdots w_px_p = w \cdot x^T$$

•Neural Networks



4.Methodology and data input

A multilayer perceptron is composed of an input layer of signals, an output layer and a number of layers of neurons between, called hidden layers.

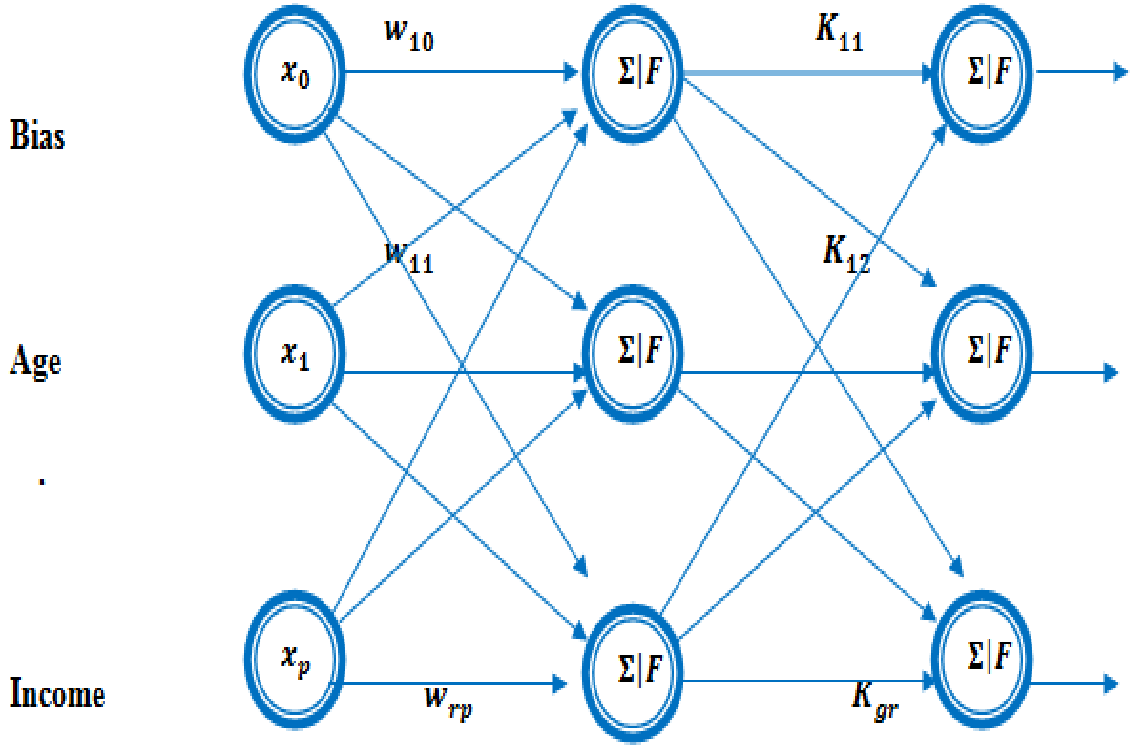
F=activation function

•Hyperbolic tangent

$$F(u) = 1 - \frac{2}{1 + e^{2u}}$$

•Logistic

$$F(u) = \frac{1}{1 + e^{-au}}$$



4.Methodology and data input

- The default definition is set according to Basel II (90 days overdue);
- The data base consists of 33,321 observations representing private individuals that have been granted a loan between January 2006 and December 2008;
- Each client has been observed for the first 12 months after the approval so the period of observation is January 2007 –December 2009.
- The realized default rate for portfolio is 14.81%
- Based on year of approval , data have been split up in three sub – samples.

Performance Measures

The requirements of the IRB approach is that "the institution shall have a cycle of model validation that includes monitoring of model performance and stability"

		Actual	
		Defaulter	Non-Defaulter
Predicted	Defaulter	A	C
	Non-Defaulter	B	D

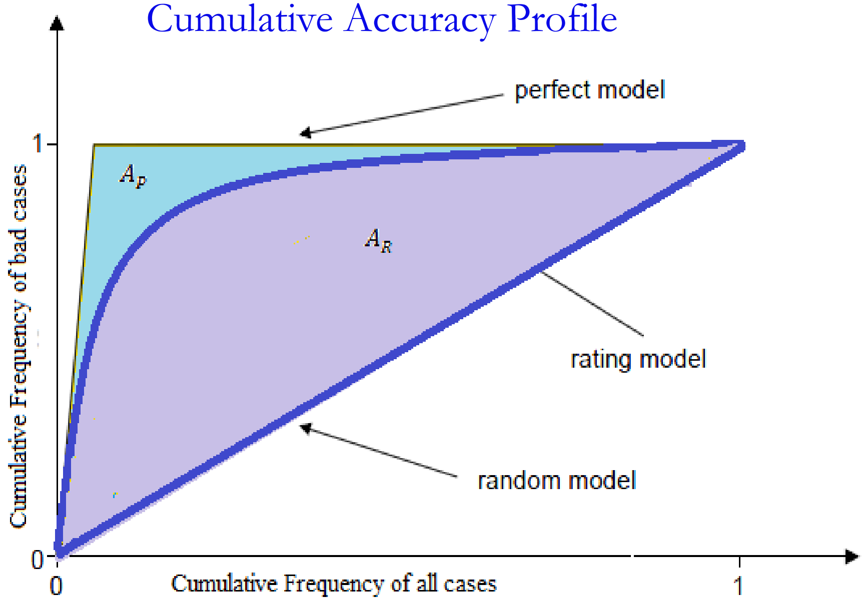
$$Sensitivity = \frac{A}{B + A}$$

$$Specificity = \frac{D}{C + D}$$

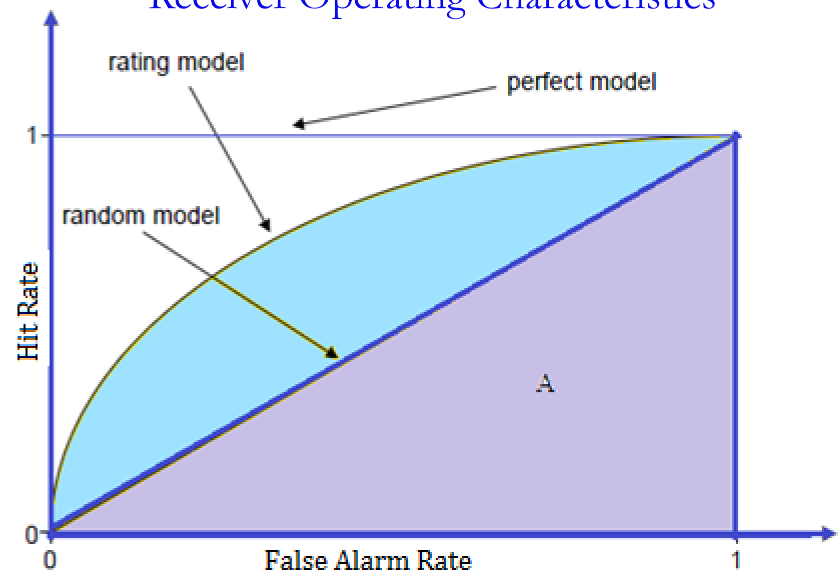
$$AR = \frac{A_R}{A_P}$$

$$AR = 2A - 1$$

Cumulative Accuracy Profile



Receiver Operating Characteristics



Performance Measures

- **Brier Score** $$BS = \frac{1}{n}\sum_{n=1}^{n}\left(p_n{}^{forecast} - \theta_j\right)^2 \qquad \theta_j = \begin{cases} 1, & if\ obligor\ j\ defaults \\ 0, & otherwise \end{cases}$$

- **Spiegelhalter test** $$Z = \frac{BS - E[BS]}{\sqrt{Var[BS]}} \sim N(0,1)$$

$$Var[BS] = \frac{1}{N^2}\sum_{i=1}^{N}(1 - 2p_i^{forecast})^2 \cdot p_i^{forecast} \cdot (1 - p_i^{forecast})$$
$$E[BS] = \frac{1}{N}\sum_{i=1}^{N} p_i^{forecast} \cdot (1 - p_i^{forecast})$$

- **Kuiper Score** $$KS = Hit\ Rate - False\ Alarm\ Rate$$

- **Granger-Pesaran Test** $$GP = \frac{\sqrt{N}KS}{\sqrt{\frac{p_f(1-p_f)}{p_a(1-p_a)}}} \sim N(0,1)$$

Indicator of Macroeconomic Vulnerability

- With the advent of the Basel II banking regulation it is just not enough to correctly rank customers according to their default risk but also to have an accurate probability of default for each client as these predicted values are used to determine the minimum capital requirement for the portfolio of the retail sector.

- In order to incorporate the changes in economic conditions and to observe the modifications of the quality of the portfolio, variables that catch up the macroeconomic vulnerabilities have been introduced in model.

$$IMV_G = \Delta\%UR - \Delta\%NS + \Delta\%IR - \Delta\%IPI + \Delta ER - \Delta\%BET + \Delta\%CPI$$

$$IMV_{client} = IMV_G \cdot DTI \cdot Spread$$

$$DTI = \frac{Monthly\ Payment}{Income - Expenses}$$

$$Spread = Interest\ Rate - Benchmark\ Rate$$

UR–unemployment rate
NS=net average salary
IR-reference interest rate
IPI=index of industrial production
ER=exchange rate
BET=Stock Market Index
CPI=consumer price index.

Variable Selection

- **Stepwise selection-**it is starting with a forward selection and then continues with a backward selection in this way a variable could enter and could be removed from the model several times until no further effect can be added to the model or if the effect just enter into the model is the only effect removed in the subsequent backward elimination

- **Information Value**

$$WOE_c = \ln\left(\frac{\%Non-defaulters}{\%Defaulters}\right)$$

$$IV(c) = (\%Non-defaulters - \%Defaulters) * WOE_c$$

$$Information\,Value = \sum_{i=1}^{k} IV(k)$$

Variable Selection

Information Value			
Variable	2006	2007	2008
AGE	0.39398	0.47938	0.44900
BANK_R	0.24589	0.00696	0.05127
CCY	0.01337	0.02158	0.00689
COUNTY_ID	0.00014	0.00124	0.01049
EDUCATION	1.06506	0.22236	0.20623
EXPENSES	0.78089	0.62239	0.33262
INCOME	0.87698	0.27902	0.13908
INDUSTRY	0.39440	0.49011	0.16557
INTEREST_RATE	0.31112	0.16148	0.12133
LOAN_VALUE	0.67563	0.26445	0.25619
MARITAL_STATUS	0.52518	0.33669	0.52125
PAYMENT	0.59730	0.31969	0.11234
PHONE_ID	0.03745	0.00665	0.04046
PRODUCT_ID	0.13533	0.17437	0.09027
PROFESSION	0.39685	0.07986	0.01145
REPAYMENT	1.18685	1.49617	1.15581
RESIDENCE	0.87919	0.37306	0.72286
SENIORITY	0.17727	0.66712	0.45028
SEX	0.00116	0.00792	0.00299
TERM	0.44065	0.18200	0.26365

***The red colour is for values < 0.1 ,yellow is for values between 0.1 and 0.2 and green otherwise**

5.Empirical Results: A multi-year analysis

2007 Neural Networks	Tanh	Logistic
Train: Akaike's Information Criterion	4121.68000	3953.43000
Train: Schwarz's Bayesian Criterion	4992.89000	4824.64000
Train: Average Error Function	0.19598	0.18748
Train: Error Function	3879.68000	3711.43000
Train: Misclassification Rate	0.07234	0.07254
Train: Number of Wrong Classifications	716.00000	718.00000
Valid: Average Error Function	0.21115	0.20798
Valid: Error Function	1194.24000	1176.34000
Valid: Mean Squared Error	0.05944	0.05800
Valid: Misclassification Rate	0.07284	0.07178
Valid: Number of Wrong Classifications	206	203
Test: Average Error Function	0.20589	0.19242
Test: Error Function	582.25500	544.16500
Test: Mean of Squared Error	0.05774	0.05252
Test: Misclassification Rate	0.07497	0.07143
Test: Number of Wrong Classifications	106	101

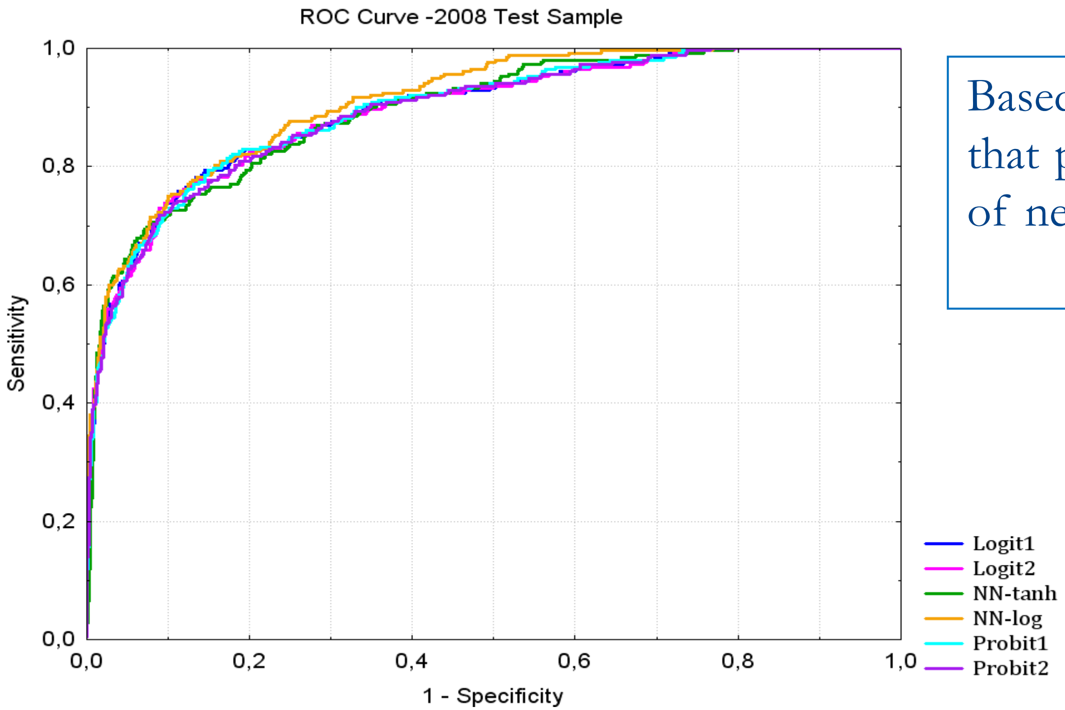
2006 Analysis of Maximum Likelihood Estimates Logit

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-3.0700	1.6965	3.2700	0.0704
Expenses	1	0.0066	0.0008	66.9300	<.0001
Income	1	-0.0024	0.0004	36.4400	<.0001
Interest_rate	1	0.1465	0.0568	6.6500	0.0099
Loan_Value	1	0.0000	0.0000	6.3200	0.0119
Payment	1	0.0030	0.0006	24.4200	<.0001

2008 Analysis of Maximum Likelihood Estimates Probit(1)

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-2.3134	0.4657	24.6800	<.0001
Age	1	-0.0072	0.0030	5.7500	0.0165
Expenses	1	0.0006	0.0000	198.3700	<.0001
Income	1	-0.0002	0.0000	269.6700	<.0001
Interest_rate	1	0.1963	0.0255	59.4200	<.0001
loan_value	1	2.52E-06	6.91E-07	13.2800	0.0003
Payment	1	0.0002	0.0001	5.5000	0.0190

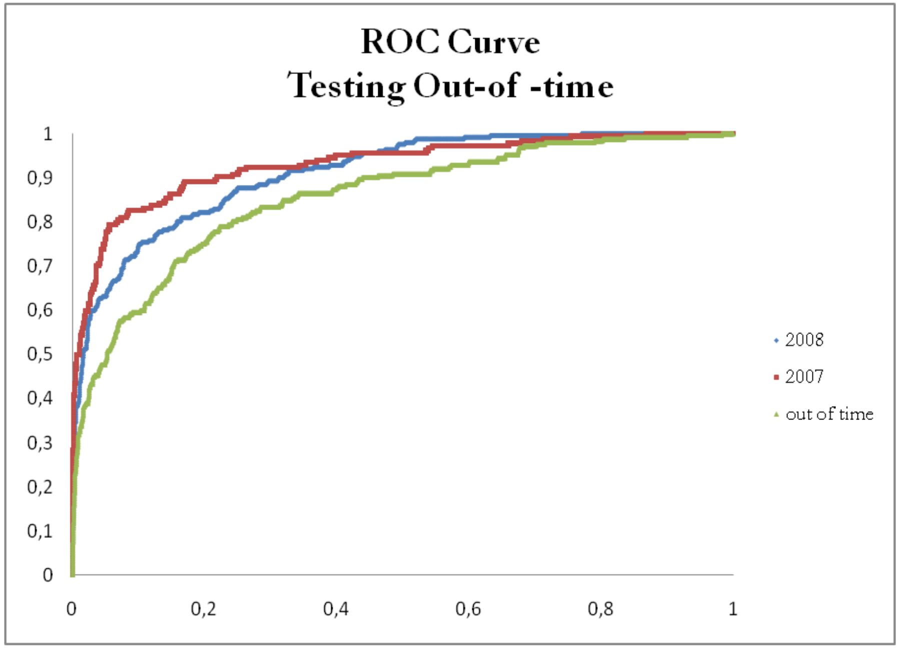
2008-Performance



Based on sample test results the model that performed better is the architecture of neural networks with logistic function

2008		Confusion Matrix				Goodness of Fit						
Model	Sample	TN	FN	TP	FP	Sensitivity	Specificity	Misclass Rate	KS	AUROC	AR	Brier Score
Logit1	test	1200	104	148	49	0.5873	0.9608	0.1019	0.6480	0.8956	0.7913	0.0785
Logit 2	test	1196	102	150	53	0.5952	0.9576	0.1033	0.6427	0.8936	0.7872	0.0790
Probit 1	test	1204	109	143	45	0.5675	0.9640	0.1026	0.6439	0.8961	0.7921	0.0794
Probit2	test	1204	109	143	45	0.5675	0.9640	0.1026	0.6316	0.8935	0.7870	0.0798
NN1	test	1212	102	150	37	0.5952	0.9704	0.0926	0.6279	0.8957	0.7914	0.0763
NN2	test	1199	95	157	50	0.6230	0.9600	0.0966	0.6499	0.9104	0.8208	0.0754

Out of sample -out of time



One important aspect, when validate a model is that the performance should be also tested on different sample on a different scale of time;

- 2006 → 2007
- 2007 → 2008

Confusion Matrix								Goodness of Fit				
Model	Sample	TN	FN	TP	FP	Sensitivity	Specificity	Misclass Rate	KS	AUROC	AR	Brier Score
NN2_2008	test	1199	95	157	50	0.6230	0.9600	0.0966	0.6499	0.9104	0.8208	0.0754
NN2_07_08	test	1230	162	90	19	0.3571	0.9848	0.1206	0.5679	0.8550	0.7100	0.0978
NN2_2007	test	1203	74	110	27	0.5978	0.9780	0.0714	0.7415	0.9290	0.8580	0.0525
NN2_06_07	test	1180	134	50	50	0.2717	0.9593	0.1301	0.4618	0.7945	0.5891	0.1096

Portfolio Analysis

- Portfolio results pointed out that the model with minimum prediction error is the neural network with logistic function

Analysis of Maximum Likelihood Estimates-Logit (1)

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-3.2254	1.3597	5.63	0.0177
Age	1	-0.015	0.00418	12.94	0.0003
Expenses	1	0.00201	7.4E-05	744.3	<.0001
Income	1	-0.001	3.8E-05	684.55	<.0001
Interest_rate	1	0.0697	0.0272	6.58	0.0103
loan_value	1	-5.36E-06	8.55E-07	39.31	<.0001
Payment	1	0.00317	0.00014	490.89	<.0001

Analysis of Maximum Likelihood Estimates-Probit (1)

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-1.9537	0.7119	7.53	0.0061
Age	1	-0.00726	0.00216	11.3	0.0008
Expenses	1	0.000876	3.1E-05	808.89	<.0001
Income	1	-0.00044	1.7E-05	718.17	<.0001
Interest_rate	1	0.0415	0.0144	8.32	0.0039
loan_value	1	-2.71E-06	4.28E-07	40.11	<.0001
Payment	1	0.00148	6.8E-05	473.58	<.0001

Analysis of Maximum Likelihood Estimates-Logit (2)

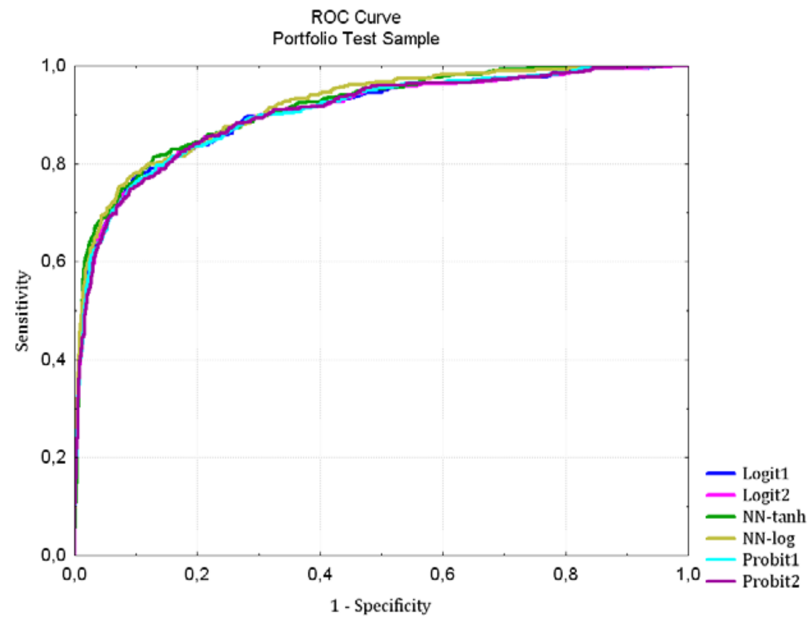
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-1.8361	1.3083	1.97	0.1605
Age	1	-0.0152	0.00415	13.46	0.0002
Expenses	1	0.002	0.000073	748.71	<.0001
Income	1	-0.00099	0.000038	694.92	<.0001
Interest_rate	1	-0.0287	0.0176	2.66	0.1027
loan_value	1	-2.49E-06	1.05E-06	5.66	0.0173
Payment	1	0.00275	0.000166	276.42	<.0001
Term	1	-0.00006	0.000015	16.08	<.0001

Analysis of Maximum Likelihood Estimates-Probit (2)

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-1.2039000	0.6881000	3.06	0.0802
Age	1	-0.0074700	0.0021500	12.03	0.0005
Expenses	1	0.0008770	0.0000310	818.61	<.0001
Income	1	-0.0004500	0.0000160	734.89	<.0001
Interest_rate	1	-0.0142000	0.0093800	2.29	0.1298
loan_value	1	-0.0000014	0.0000005	7.13	0.0076
Payment	1	0.0013000	0.0000800	264.94	<.0001
Term	1	-0.0000300	0.0000079	15.29	<.0001

Portfolio Analysis

Neural Networks	Tanh	Logit
Train: Akaike's Information Criterion	10510.42	10046.78
Train: Schwarz's Bayesian Criterion	11678.73	11215.09
Train: Average Error Function	0.21909	0.20915
Train: Error Function	10220.420	9756.780
Train: Misclassification Rate	0.07893	0.07631
Train: Number of Wrong Classifications	1841	1780
Valid: Average Error Function	0.22910	0.22547
Valid: Error Function	3053.480	3005.10
Valid: Mean Squared Error	0.06530	0.06478
Valid: Misclassification Rate	0.08178	0.08373
Valid: Number of Wrong Classifications	545	558
Test: Average Error Function	0.23237	0.23123
Test: Error Function	1548.52	1540.89
Test: Mean of Squared Error	0.06500	0.06497
Test: Misclassification Rate	0.07743	0.08103
Test: Number of Wrong Classifications	258	270



Benchmark Study(Accuracy ratio)	Logit	Probit	NN
Baesens (2005)	68.60-78.24		66.93-78.58
Galindo and Tamayo (2000)		84.87	89.00
West(2000)	76.30-87.25		74.60-87.14
Martens(2007)	85.7-96.4		

Confusion Matrix						Goodness of Fit						
Model	Sample	TN	FN	TP	FP	Sensitivity	Specificity	Misclass	KS	AUROC	AR	Brier Score
Logit1	test	2755	224	295	58	0.5684	0.9794	0.0846	0.6739	0.9042	0.8084	0.0694
Logit 2	test	2751	229	290	62	0.5588	0.9780	0.0873	0.6608	0.9034	0.8067	0.0704
Probit 1	test	2763	249	270	50	0.5202	0.9822	0.0897	0.6658	0.9038	0.8075	0.0712
Probit2	test	2758	253	266	55	0.5125	0.9804	0.0924	0.6569	0.9030	0.8061	0.0720
NN1	test	2742	187	332	71	0.6397	0.9748	0.0774	0.6844	0.9129	0.8259	0.0650
NN2	test	2740	197	322	73	0.6204	0.9740	0.0810	0.6851	0.9157	0.8314	0.0650

Portfolio with Macroeconomic Variable

Logit

The analysis is done on the same samples of portfolio ,adding the macroeconomic indicator and the model is estimated on training sample with validation on test sample.

[1] Likelihood Ratio Test for Global Null Hypothesis: BETA=0				
-2 Log Likelihood		Likelihood Ratio	DF	Pr > ChiSq
Intercept Only	Intercept & Covariates	Chi-Square		
19352.26	10622.993	8729.2664	51	<.0001

Likelihood Ratio Test for Global Null Hypothesis: BETA=0				
-2 Log Likelihood		Likelihood Ratio	DF	Pr > ChiSq
Intercept Only	Intercept & Covariates	Chi-Square		
19352.26	10758.365	8593.8942	47	<.0001

Analysis of Maximum Likelihood Estimates –Logit (1)					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-3.6365	1.4412	6.3700	0.0116
Age	1	-0.0184	0.0044	17.8900	<.0001
Expenses	1	0.0018	0.0001	552.9500	<.0001
Income	1	-0.0007	0.0000	387.6800	<.0001
Interest_rate	1	0.1146	0.0279	16.8800	<.0001
Loan Value	1	0.0000	0.0000	27.7500	<.0001
Payment	1	0.0023	0.0001	250.6900	<.0001
IMV_cust	1	5.1807	0.3196	262.7200	<.0001

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-3.4977	1.3938	6.3	0.0121
Age	1	-0.0148	0.00422	12.3	0.0005
Expenses	1	0.00175	7.4E-05	558.23	<.0001
Income	1	-0.00075	3.8E-05	393.64	<.0001
Interest_rate	1	0.0298	0.018	2.73	0.0983
loan_value	1	-2.26E-06	1.04E-06	4.74	0.0294
Payment	1	0.00198	0.00017	139.54	<.0001
Term	1	-0.00004	1.5E-05	8.11	0.0044
IMV_cust	1	5.2456	0.3172	273.46	<.0001

Portfolio with Macroeconomic Variable

Probit

[1] Likelihood Ratio Test for Global Null Hypothesis: BETA=0				
-2 Log Likelihood		Likelihood Ratio	DF	Pr > ChiSq
Intercept Only	Intercept & Covariates	Chi-Square		
19352.26	10832.701	8519.5583	51	<.0001

[2] Likelihood Ratio Test for Global Null Hypothesis: BETA=0				
-2 Log Likelihood		Likelihood Ratio	DF	Pr > ChiSq
Intercept Only	Intercept & Covariates	Chi-Square		
19352.26	10964.259	8388.0004	47	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-2.1725	0.7504	8.38	0.0038
Age	1	-0.00888	0.00225	15.59	<.0001
Expenses	1	0.000745	0.000031	564.52	<.0001
Income	1	-0.00033	0.000017	369.32	<.0001
Interest_rate	1	0.0636	0.0148	18.58	<.0001
loan_value	1	-2.41E-06	4.32E-07	31.25	<.0001
Payment	1	0.00108	0.000072	227.57	<.0001
IMV_cust	1	2.8377	0.1702	278.12	<.0001

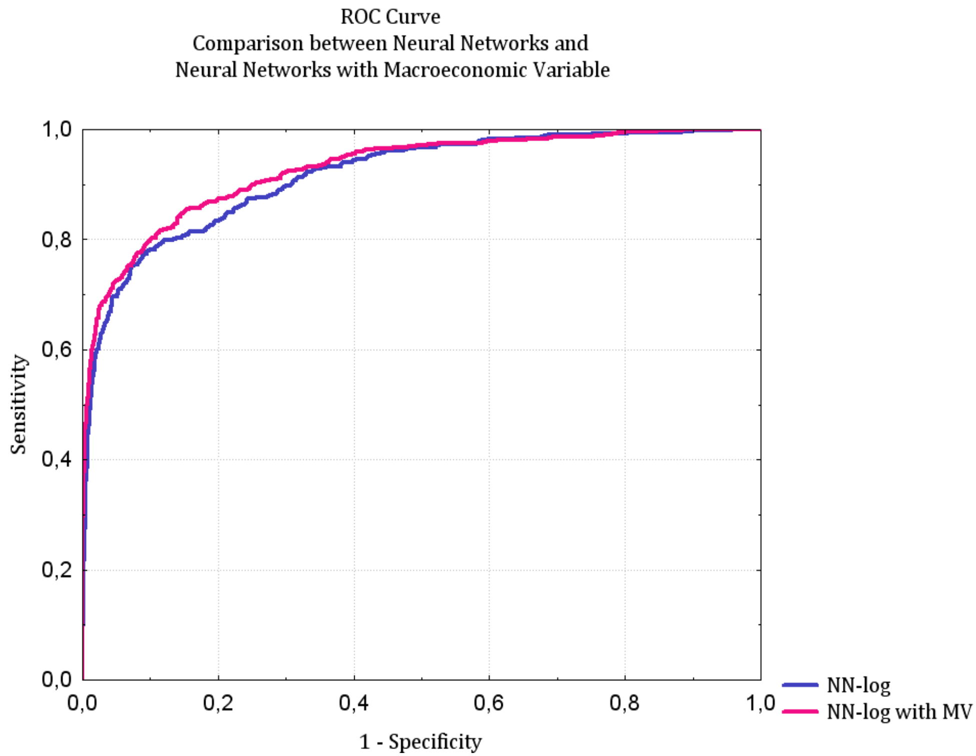
Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-2.0873	0.73	8.18	0.0042
Age	1	-0.00684	0.00218	9.79	0.0018
Expenses	1	0.000749	3.1E-05	573.46	<.0001
Income	1	-0.00033	1.7E-05	382.87	<.0001
Interest_rate	1	0.0157	0.00963	2.65	0.1034
loan_value	1	-1.44E-06	5.27E-07	7.49	0.0062
Payment	1	0.000946	8.3E-05	130.31	<.0001
Term	1	-0.00002	8.02E-06	6.21	0.0127
IMV_cust	1	2.8475	0.1693	282.97	<.0001

Portfolio with Macroeconomic Variable

Neural Networks

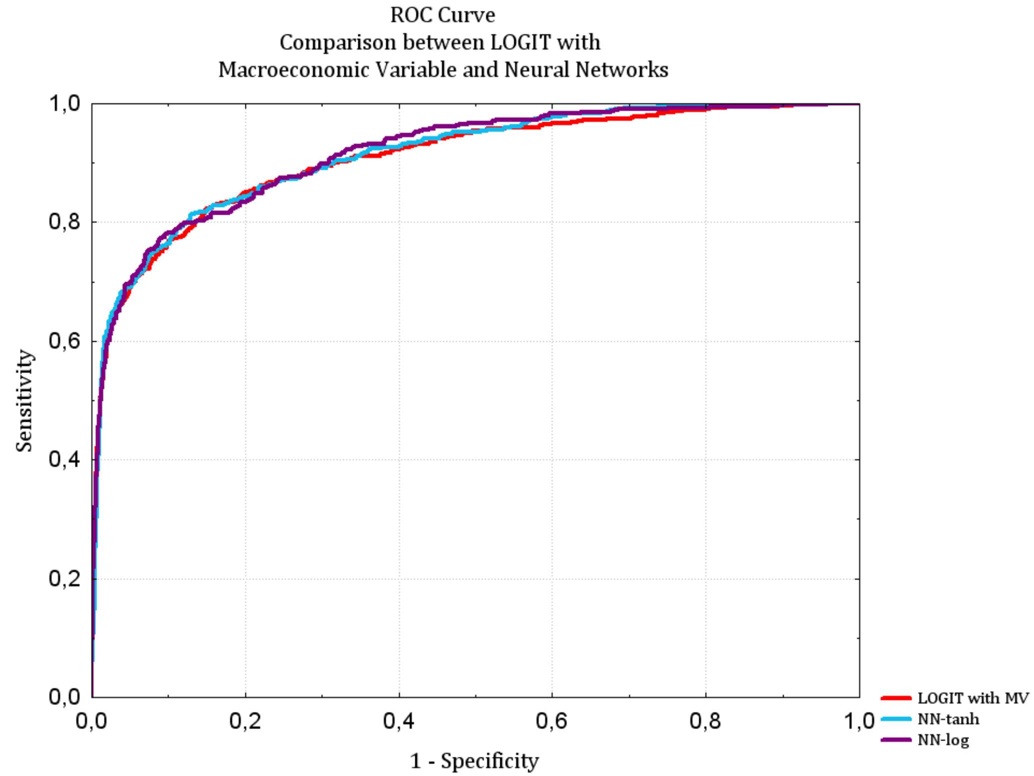
Neural Networks	Tanh	Logit
Train: Akaike's Information Criterion	9381.67	9337.05
Train: Schwarz's Bayesian Criterion	10574.14	10529.53
Train: Average Error Function	0.19476	0.19381
Train: Error Function	9085.67	9041.05
Train: Misclassification Rate	0.07374	0.07117
Train: Number of Wrong Classifications	1720.	1660
Valid: Average Error Function	0.21533	0.21072
Valid: Error Function	2869.89	2808.47
Valid: Mean Squared Error	0.06174	0.06047
Valid: Misclassification Rate	0.08013	0.07773
Valid: Number of Wrong Classifications	534	518
Test: Average Error Function	0.21861	0.20920
Test: Error Function	1456.78	1394.12
Test: Mean of Squared Error	0.06138	0.05939
Test: Misclassification Rate	0.07713	0.07593
Test: Number of Wrong Classifications	257	253



	Macro Result s	Confusion Matrix				Goodness of fit						
Model	Sample	TN	FN	TP	FP	Sensitivity	Specificity	Misclass	KS	AUROC	AR	Brier Score
Logit1	test	2757	214	305	56	0.5877	0.9801	0.0810	0.6741	0.9084	0.8168	0.0666
Logit 2	test	2757	221	298	56	0.5742	0.9801	0.0831	0.6700	0.9072	0.8144	0.0677
Probit 1	test	2764	235	284	49	0.5472	0.9826	0.0852	0.6671	0.9079	0.8159	0.0682
Probit2	test	2765	236	283	48	0.5453	0.9829	0.0852	0.6664	0.9069	0.8138	0.0693
NN1	test	2747	196	323	66	0.6224	0.9765	0.0786	0.7042	0.9201	0.8401	0.0615
NN2	test	2754	181	338	59	0.6513	0.9790	0.0720	0.7037	0.9278	0.8556	0.0587

Model Improvement

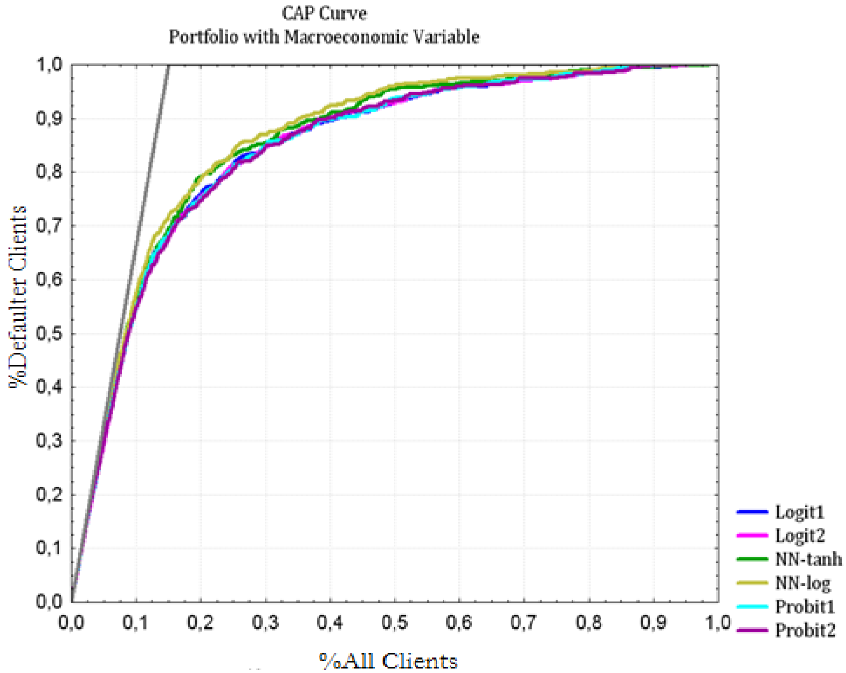
- The results of regression logistic with macroeconomic variable incorporated are comparable with neural networks;

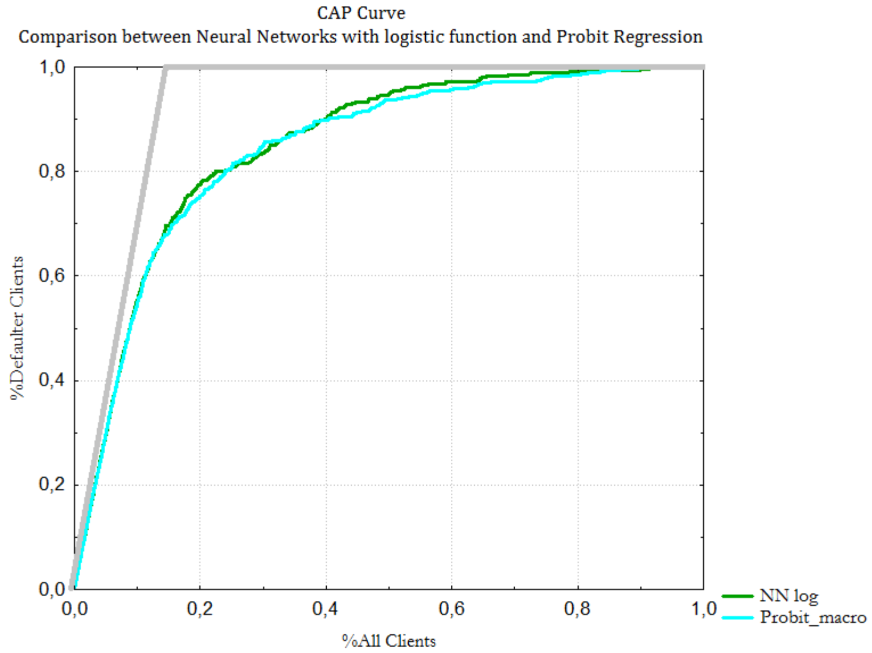


Improvement		Confusion Matrix				Goodness of Fit						
Model	**Sample**	**TN**	**FN**	**TP**	**FP**	**Sensitivity**	**Specificity**	**Misclass**	**KS**	**AUROC**	**AR**	**Brier Score**
Logit 2	test	0.22%	-3.49%	2.76%	-9.68%	2.76%	0.22%	-4.81%	1.40%	0.43%	0.96%	-3.72%
Logit1	test	0.07%	-4.46%	3.39%	-3.45%	3.39%	0.07%	-4.26%	0.03%	0.47%	1.04%	-4.01%
Probit 1	test	0.04%	-5.62%	5.19%	-2.00%	5.19%	0.04%	-5.02%	0.21%	0.46%	1.03%	-4.22%
Probit2	test	0.25%	-6.72%	6.39%	-12.73%	6.39%	0.25%	-7.79%	1.44%	0.43%	0.96%	-3.81%
NN1	test	0.18%	4.81%	-2.71%	-7.04%	-2.71%	0.18%	1.55%	2.88%	0.78%	1.73%	-5.39%
NN2	test	0.51%	-8.12%	4.97%	-19.18%	4.97%	0.51%	-11.11%	2.72%	1.32%	2.91%	-9.63%

Model Improvement

•Detection accuracy of *bad* customers increases on average with 5.85% for probit regressions and with 3% for logistic regressions, neural networks instead recorded an increase of only 1.13%.;





Model Improvement

Spiegelhalter Test	LOGIT1	LOGIT2	PROBIT1	PROBIT2	NN1	NN2
Port	0.7605	0.7330	0.1932	0.1773	0.8992	0.2235
Macro	0.7852	0.6458	0.1626	0.1133	0.2602	0.5743

P-values

•The Spiegelhalter Test indicates that, by accepting the null hypothesis on both portfolios with and without the macroeconomic variable, the observed default rates are close to the estimated probabilities of default

	Kuiper	
Model	Portfolio	Macro
Logit1	0.5478	0.567761
Logit 2	0.5367	0.554274
Probit 1	0.5025	0.529787
Probit2	0.4930	0.528216
NN1	0.6145	0.598888
NN2	0.5945	0.630278

•*Kuiper Score* is the difference between hit rate and false alarm rate and the grater the difference the better the classification between defaulters and non-defaulters

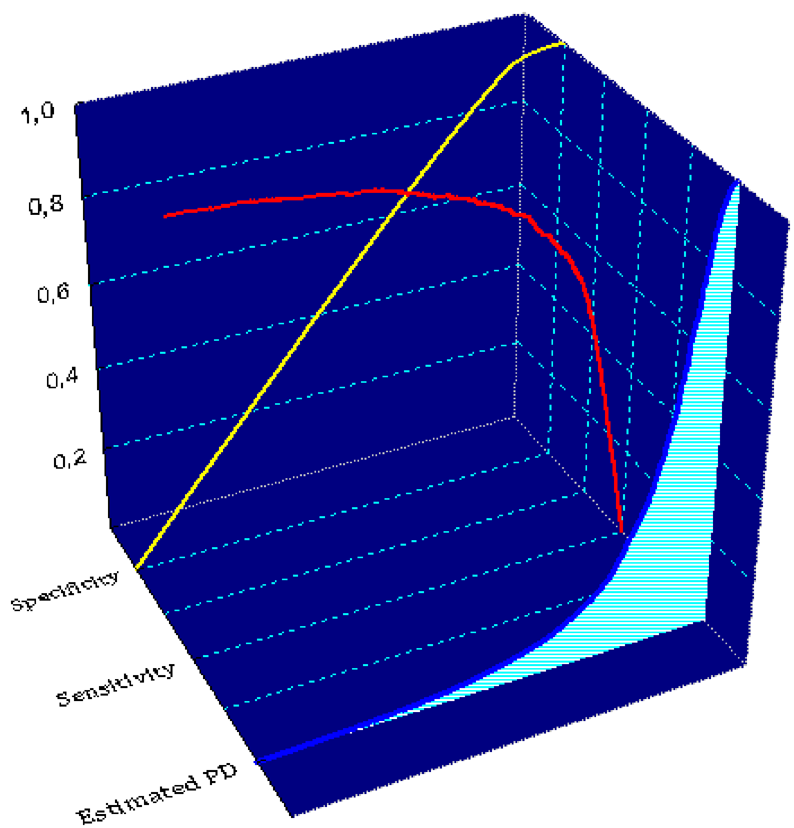
•The models that have the higher score are neural networks and from regressions class the stepwise logistic is the one that discriminates better.

Setting the optimal Cut-off

This issue of acceptance rate is a trade-off between the higher acceptance rate as profit generator and lower acceptance rate as loss in market share.

Confusion Matrix								Misclass
Model	Sample	TN	FN	TP	FP	Sensitivity	Specificity	Rate
Logit1	test	2350	88	431	463	0.83044	0.83541	0.16537
Logit 2	test	2327	91	428	486	0.82466	0.82723	0.17317
Probit 1	test	2349	92	427	464	0.82274	0.83505	0.16687
Probit2	test	2328	93	426	485	0.82081	0.82759	0.17347
NN1	test	2391	85	434	422	0.83622	0.84998	0.15216
NN2	test	2404	79	440	409	0.84778	0.85460	0.14646

Cut-off Dynamic
Portfolio with Macroeconomic Variable



Misclassification Cost

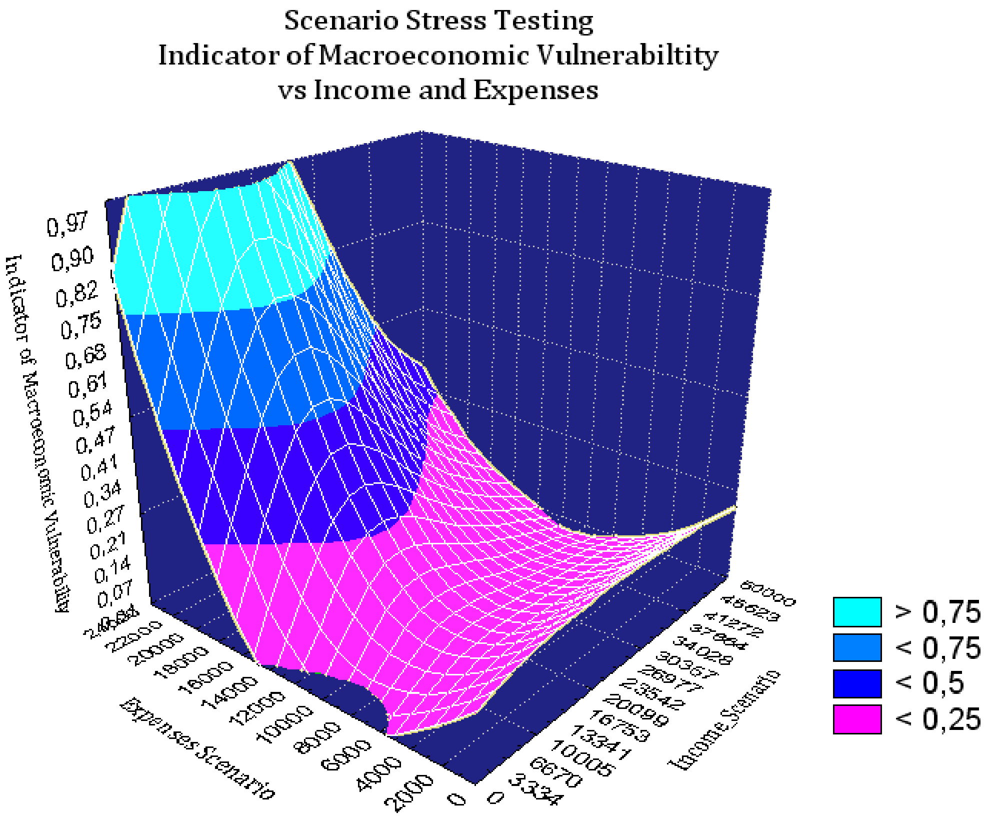
The model that minimizes the expected future loss is an optimal model of classification and considering the fact that there are two classes of customers, the future loss depends on the two types of misclassification errors.

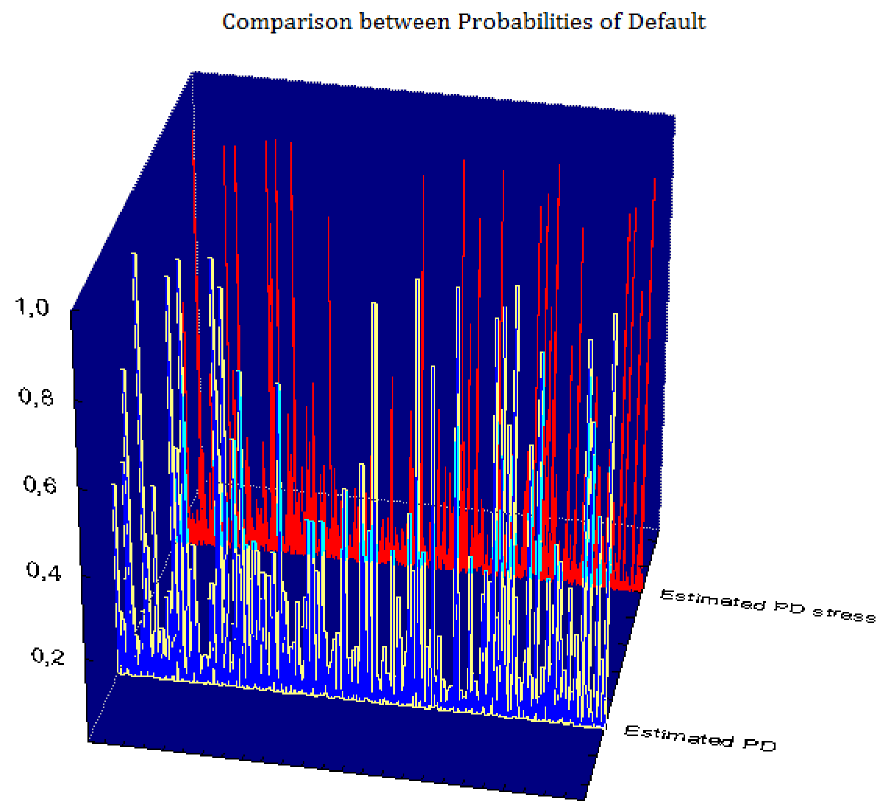
$$Expected\ Loss = P_B Cost_{Type\ I} Error\ Rate\ Type\ I + P_G Cost_{TypeI\ I} Error\ Rate\ Type\ II$$

Cost comparison		Confusion Matrix				Goodness of Fit				
Model	Sample	TN	FN	TP	FP	Sensitivity	Specificity	Kuipers Score	Granger Pesaran	p-value
Logit1	test	2758	212	307	55	0.5915	0.9804	0.5720	38.47	0.000
Logit 2	test	2755	216	303	58	0.5838	0.9794	0.5632	37.93	0.000
Probit 1	test	2762	228	291	51	0.5607	0.9819	0.5426	37.42	0.000
Probit2	test	2765	234	285	48	0.5491	0.9829	0.5321	37.13	0.000
NN1	test	2741	186	333	72	0.6416	0.9744	0.6160	39.46	0.000
NN2	test	2753	193	326	60	0.6281	0.9787	0.6068	39.69	0.000
Logit1	test	2750	234	285	63	0.5491	0.9776	0.5267	36.05	0.000
Logit 2	test	2755	216	303	58	0.5838	0.9794	0.5632	37.93	0.000
Probit 1	test	2767	234	285	46	0.5491	0.9836	0.5328	37.28	0.000
Probit2	test	2765	234	285	48	0.5491	0.9829	0.5321	37.13	0.000
NN1	test	2740	186	333	73	0.6416	0.9740	0.6157	39.40	0.000
NN2	test	2749	191	328	64	0.6320	0.9772	0.6092	39.58	0.000
Logit1	test	2758	212	307	55	0.5915	0.9804	0.5720	38.47	0.000
Logit 2	test	2755	216	303	58	0.5838	0.9794	0.5632	37.93	0.000
Probit 1	test	2762	228	291	51	0.5607	0.9819	0.5426	37.42	0.000
Probit2	test	2765	234	285	48	0.5491	0.9829	0.5321	37.13	0.000
NN1	test	2744	184	335	69	0.6455	0.9755	0.6209	39.82	0.000
NN2	test	2749	191	328	64	0.6320	0.9772	0.6092	39.58	0.000

6.Stress Testing

- **Scenario-** income decreasing with 25% for public sector employers and increasing of Expenses with 4.5% for the whole portfolio
- This scenario impacts the average default probability with an increase of 1% on the public employers sector.





7.Conclusions

- Portfolio results concluded that neural networks have a higher accuracy than regressions;

- After including the macroeconomic variable, results showed that models like logistic regressions have accuracy as high as one of the neural network architectures.

- Minimizing misclassification cost improves probit regressions by reducing the error of prediction with 8% and for logistic regressions and neural networks with 5%

- The indicator of macroeconomic vulnerability could be part of a development model for credit risk based on a scorecard where the capacity of a client would be aligned to the macroeconomic conditions;

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Thank you!