ESTIMATING STRESSED PD TO BANK LOSSES WITH A MODEL OF BEHAVIOURAL AND SOCIOECONOMIC VARIABLES THE CASE OF GREECE

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Abstract

Stress testing refers to a range of techniques used to assess the behavior of a credit portfolio to changes in the economic environment. Basel II framework requires banks to use stress tests to measure credit risk and evaluate portfolio's vulnerability to economic downturns. This paper proposes a single-equation regression model to estimate stressed probability of default (PD) to Bank default losses that incorporates both Behavioral (e.g. behavioral score, days past due, etc) and Socioeconomic variables (e.g. geographic region, type of employment, etc).

By incorporating all stress factors into an aggregate stress-model, various scenarios can be developed by adjusting the weights of the coefficients of the model in order to reflect generic stress factors (e.g. transition from higher behavioral scores to lower behavioral score, etc), as well as, socioeconomic stress factors (e.g. northern Greece PD, agricultural profession PD, etc). Product specific stress-models have been developed (mortgages, consumer loans, credit cards, etc) that reflect the exposure of each particular retail portfolio to the properly selected stress factors. Recent performance indicators and trends confirm that the weighting of the stress-factors in each model is consistent with expectations and the relevant analytical framework. Also, various stress scenarios are developed based on recent trends and historical data of unemployment rates and G.D.P. growth in Greece over the past 10 years.

By developing relevant models, Banks and other financial institutions can easily identify overall exposure to risk as well as the risk concentration to specific regions and professions. Empirical results illustrate the impact of the stressed PD on expected losses and potential minimum capital requirements. The proposed model with its generality, conformity with theory and simplicity of structure provides a vehicle for testing, expanding and improving conventional stress – testing and can assist managers and decision makers in addressing relevant issues.

CONTENTS

1. Introduction

Nowadays, it is more than obvious that banking becomes more demanding each day that passes. In the context of stability in the banking industry as well as in the framework of safety and profitability, an international set of regulations, known as *Basel II*, have been developed in order to ensure the prosperity of the global network of banks. The main aim of this accord is to better align and clarify the association between banks' capital requirements and risk probability.

In essence, it establishes asset management regulations, which attempt to coordinate the total amount of capital reserves a bank possesses in relation with the actual risk the bank is exposed to. In short, the main aims of the final form of the *Basel II* accord are firstly to ensure that capital allocation is more receptive to risk and secondly, to detach the operational risks from the credit risks and make sure to quantify them accordingly. This, mentality was adopted in order to avoid the eminent procyclicality. In simple words, if a trend was introduced that dictated less assets and the *Basel II* accordance did not exist, then subsequently each bank would minimize the capital requirements in order to acquire the maximum possible input but with extreme risk rates. Therefore, what the agreement stipulates is that in order to prevent any unnecessary turbulences in the banking system, all banks should follow the protocol to both safeguard their individual fertility and the systems rigidity.

Though the level of provisions required to be held in stable macroeconomic periods under the Bank's provisioning calculation methodology might be sufficient , there may be an issue with excess capital requirements during a recession that could amplify the severity of the downturn. The procyclicality issue has already been identified by BIS:

"*The measurement difficulties often lead to risk being underestimated in booms and overestimated in recessions. In a boom, this contributes to excessively rapid credit growth, to inflated collateral values, to artificially low lending spreads, and to financial institutions holding relatively low capital and provisions. In recessions, when risk and loan defaults are assessed to be high, the reverse tends to be the case. In some, although not all, business cycles these financial developments are powerful amplifying factors, playing perhaps the major role in extending the boom and increasing the severity and length of the downturn. We argue that the worst excesses of these financial cycles could be mitigated by increased recognition of the build up of risk in economic booms and the recognition that the materialization of bad loans in recessions need not imply an increase in risk*."

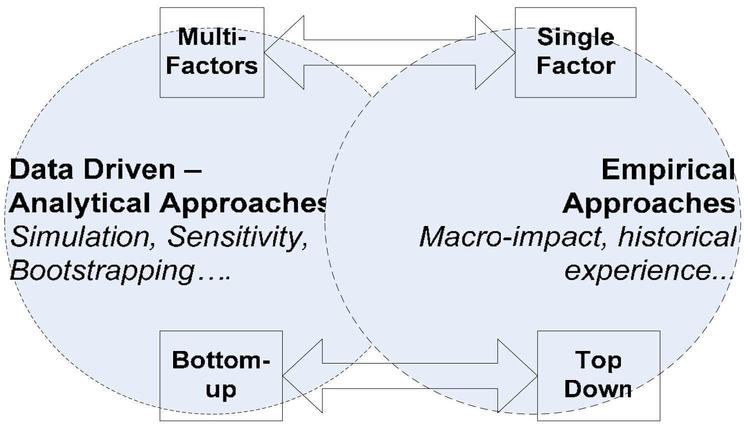
In the context of this process, *Basel II* framework proposes that each bank should calculate and predict possible alternative scenarios that represent not only the positive or the average profitability and capital reserve expectations but also in addition to that, banks must be aware of the worst – case scenario. For instance, under the first pillar of *Basel II*, if a bank is using the I.R.B.A. or Internal Ratings Based Approach then it should 'consider at least the effect of mild recession scenarios'. In order to materialize this action, banks are supposed to run frequent stress tests on their future portfolios and minimum capital requirements. The methods and the form of the tests are entirely dependent on the banks' decision. However, this is a subject for supervision.

According to the BIS survey (Jan 05) on stress testing practice: "*Stress tests generally fall into two categories: scenario tests and sensitivity tests. In scenarios, the source of the shock, or stress event, is well defined, as are the financial risk parameters which are affected by the shock. In contrast, while sensitivity tests specify financial risk parameters, the source of the shock is not identified. Moreover, the time horizon for sensitivity tests is generally shorter - often instantaneous - in comparison with scenarios.*"

BIS, Committee of the Global Financial System, January 2005: "*Stress testing at major financial institutions: survey results and practice*."

The following paper incorporates a variety of ways that illustrate the plausible scenarios of future behavior based on the "bottom-up" approach (see graph 1). There is usage of both risk factor shock approach as well as external factor shock. To explain, when we use the term risk factor shock we signify an alteration in the variables of risk by a specific amount defined by the analyst. Moreover, when we refer to the external factor shock we indicate the usage of a method that involves the alteration of macroeconomic data such as unemployment rates or GDP expectations. In reality, it is logical to assume interaction of external factors and risk factors (*transition from lower to higher delinquencies etc, increase in unemployment rates per region, etc*) under macroeconomic stress situations. However, it is difficult to link the effect of external factors into a bank's specific portfolio. In summary, this paper summons most of the effective and fruitful methods in order to exhibit the practice of accurate and precise risk management and portfolio manipulation through stress testing.

In the remainder of this paper, we present a framework that links the probability of default (PD) with macro-economic and behavioral variables. The following methodology also provides a systematic way of estimating expected credit losses for various scenarios.



Graph 1: Summary of Stress Testing Approaches

2. Modeling Framework

'*Stress testing is a risk management tool used to evaluate the potential impact of a firm of specific event and/or movement in a set of financial variables.*'

BIS Working group report Jan 2005

The purpose of this section is to prove that there is a strong relationship between credit risk and socioeconomic/behavioral parameters. In detail, the methodology proposes a stress model that includes the following independent variables:

- Bucket (days in arrears/delinquent grouped into bands (bucket 1: '1-29 days', bucket 2: '30-59 days', etc)
- Behavior Score[1]
- Geographic Area
- Profession

The stress model is a logistic model that predicts the dependent Good/ Bad variable (probability of default over a 12-month outcome) using the abovementioned variables.

The following quality definition was used in order to characterize an account as good or bad.

"**Bad**"	Defaulted in 12 Months
"**Defaults**"	According to Basel II definition days in arrears >=90 and the delinquent amount above 90 days should be greater than the maximum between 50 € and 2% of the Applied Limit or 5% of the Instalment.

Through the stress test process, a number of scenarios were created in order to calculate the impact of different levels of economic crisis to the probability of default. These scenarios refer to different impact that an economic crisis would have to Piraeus Bank's customers. In order to measure the impact of each stress scenario to each product the following process was followed:

I. *PD Model Development*: Develop a stress model (one for each product). The model contains the variables above and it predicts the probability of

[1] A behaviour score includes characteristics representing the borrower's own payment pattern on the loan. Low scores show high probability of a customer to reach 'higher' delinquencies in the next 6 months.

default during the next 12 months.

II. *Scale the Model:* Scale the stress-model in a meaningful way e.g. at 100 points 1:1 odds and 20 points to double odds so that stress scenarios across variables and attributes can be easily translated into PD effects.

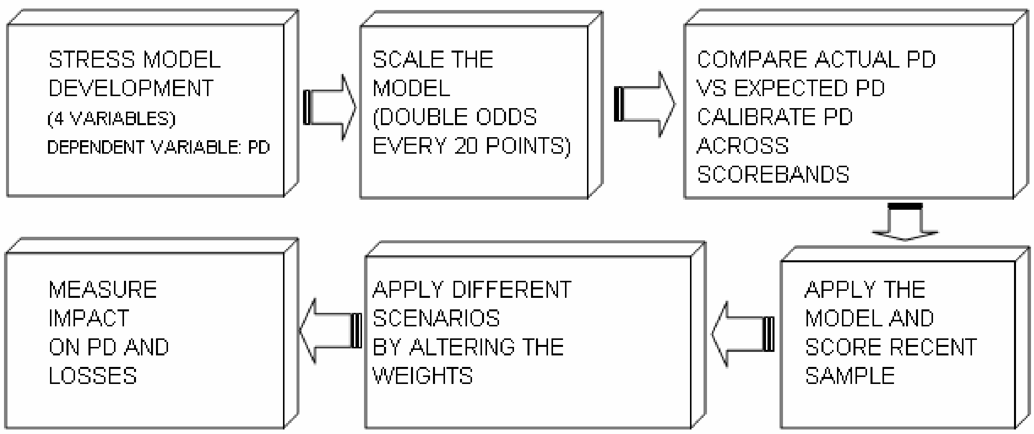
III. *Calibrate PD*: Compare Actual PD versus Expected PD and calibrate PD across scorebands to avoid reversals in monotonous PD trend per score.

IV. *Apply the Model:* Score a through the door sample (sample of June 2009) with the above model and calculation of the probability of default of the portfolio.

V. *Apply stress scenarios:* Creation of different scenarios and simulation of the portfolio in a crisis situation. Each scenario has an effect in one or more characteristics of the model. As a result the stressed accounts score lower than the unstressed and thus have a higher probability of default.

VI. *Measure the impact:* Calculation of the Expected Loss based on the stressed Probability of Default.

The proposed framework is presented below graphically.



3. Model Development

Logistic Model Development

While developing the model, the aim was the scorecard to be optimum in the sense that it will relate as accurately as possible the dependent variable, i.e. Good/

Bad variable, using the minimum number of independent variables. The final goal is to build a scoring model that will be able to distinguish between good and bad clients as much as possible.

For each variable, a preliminary analysis based on the Good/ Bad performance was conducted. More specifically, each variable was segmented into groups using the maximum information value criterion, i.e.

$$IV = \sum_{i=1}^{j} 100 * \left[\frac{G_i}{Goods} - \frac{B_i}{Bads} \right] * \ln \left[\frac{G_i / Goods}{B_i / Bads} \right]$$

It is worth noting that the variables falling under occasion a) above are easier to be handled, since they are a priori grouped. Turning to b) besides the maximum information value, we have also used business–wise rationale, so as to ensure that the finally derived groups have a meaningful result.

Once the candidate variables for inclusion were selected, we examined the importance of each variable separately so as to decide whether it should be included into the model or not. In order to perform this analysis, two different approaches have been used:

- Pearson's chi–squared statistic
- Univariate logistic regression (likelihood ratio)

All variables that were found to be statistical significant were included into the model. All tests were conducted taking 95% significance level.

Once the candidate variables were selected, stepwise (forward selection) logistic regression was carried out. This procedure was selected because it is based on the creation of an optimal model using an iterative algorithm, which examines the importance of a certain variable – with the simultaneous presence of other variables. More specifically, the steps comprising this algorithm are briefly described hereunder:

Step 1: The initial model contains only the constant factor and the likelihood ratio of the model is calculated.

Step 2: The significance of each variable (based on the likelihood ratio) is calculated.

Step 3: The variable with the highest contribution is added (should certain conditions, entry probability are met) to the model.

Step 4: The significance of each variable following the inclusion of the variable in step 3 is calculated.

Step 5: If the significance that was calculated in Step 4 is less than the probability of removal, then the algorithm continues to the next variable. If there is no change compared to the previous model, then the algorithm terminates. Otherwise, the current model is modified by removing the variable.

Step 6: The significance of each variable is calculated again and we return to step 3.

Once we determined the variables to be included in the scorecard, we also examined possible existence of correlations. In case of correlation this means that the effect of a certain variable of the model depends on the levels of another variable. It is stressed that careful attention has been paid so as to ensure that interaction have business justification.

Model Performance

As described above, the first step in the stress test process was the development of a model predicting the probability of default in the next 12 months. For each credit product was developed a different model, all of them containing the same variables, since they seem to be very representative and sensitive to economic changes.

The model's performance was evaluated with a statistic measure called divergence. It is the squared difference between the mean score of the good accounts and the mean score of the bad accounts divided by their average variance. Divergence is used to assess how well scorecards are separating the good and bad accounts in the development sample. The higher the divergence, the larger the separation of scores between good and bad accounts.

The weight associated with each characteristic attribute is chosen to optimize the scorecard divergence. The attribute weights are developed in a series of steps.

Once the model was estimated was transformed the score to a linear scale. To do this, we multiplied the score by 20 and then we divided by ln(2). By multiplying the score by 20 we defined that the odds of going bad are expected to double each time the score increases 20 points.

Below we can see the scorecard developed for one product:

Model Summary

	Char / Bin	Weight
INTERNAL FACTORS	**Bucket**	
	1. 0	144
	2. 1	96
	3. 2	33
	4. 3	41
	5. 4+	19
	Behavior Score	
	Below 522.0	18
	522.0-<586.0	32
	586.0-<609.0	52
	609.0-<647.0	53
	647.0-<High	58
EXTERNAL FACTORS	**Region**	
	1. ATTICA	40
	2. THESSALONIKI	43
	3. PELOPONNHSOS	51
	4. MAIN_GREECE	45
	5. NORTHWESTERN_GREECE	53
	6. NORTH_ESTERN_GREECE	37
	7. AIGAIO_ISLANDS	50
	8. KRHTH	38
	Profession	
	A. PUBLIC SECTOR	29
	B. DOCTOR	28
	C. PRIVATE SECTOR	24
	D. LAWYER	28
	E. FARMER	19
	F. OTHER	46

Results

We have used three statistics to determine the effectiveness of the final scorecard produced, score separation (KS) statistic, Gini coefficient and ROC Curve.

Separation statistic is a number that measures the discrimination that the scorecard achieves, and is defined as the maximum absolute cumulative difference between the inferred good and bad distributions.

The Gini coefficient takes into account the difference between the percentage cumulative good and the percentage cumulative bad. The higher the Gini coefficient, the stronger the score.

The Receiver Operating Curve (ROC) is the area under the curve generated when the cumulative bads are plotted against the cumulative goods (Lorenz Curve).

The difference between separation and the Gini coefficient is that, instead of looking at the maximum cumulative good and bad, the Gini compares the difference between both distributions of cumulative good and bad, across the entire distribution.

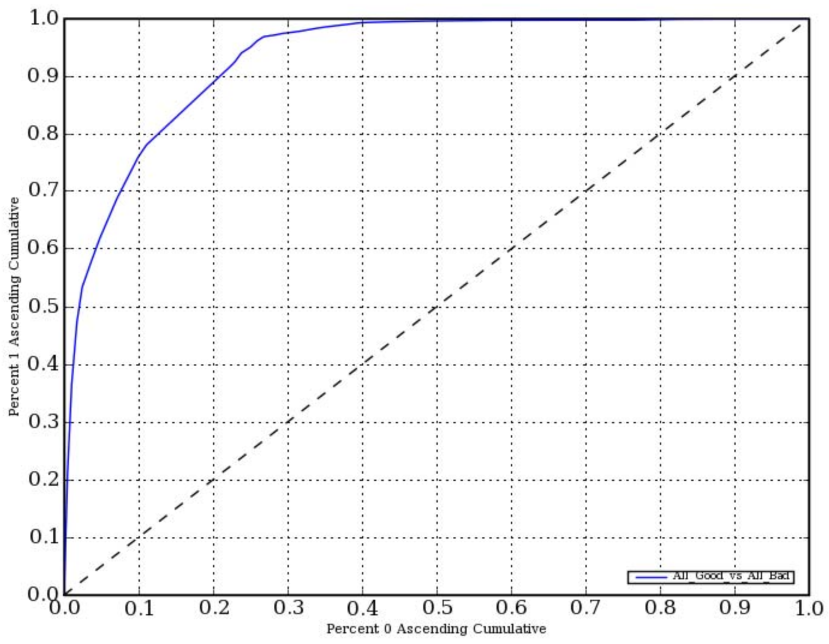
The final score produced the following statistics:

Summary Score Statistics

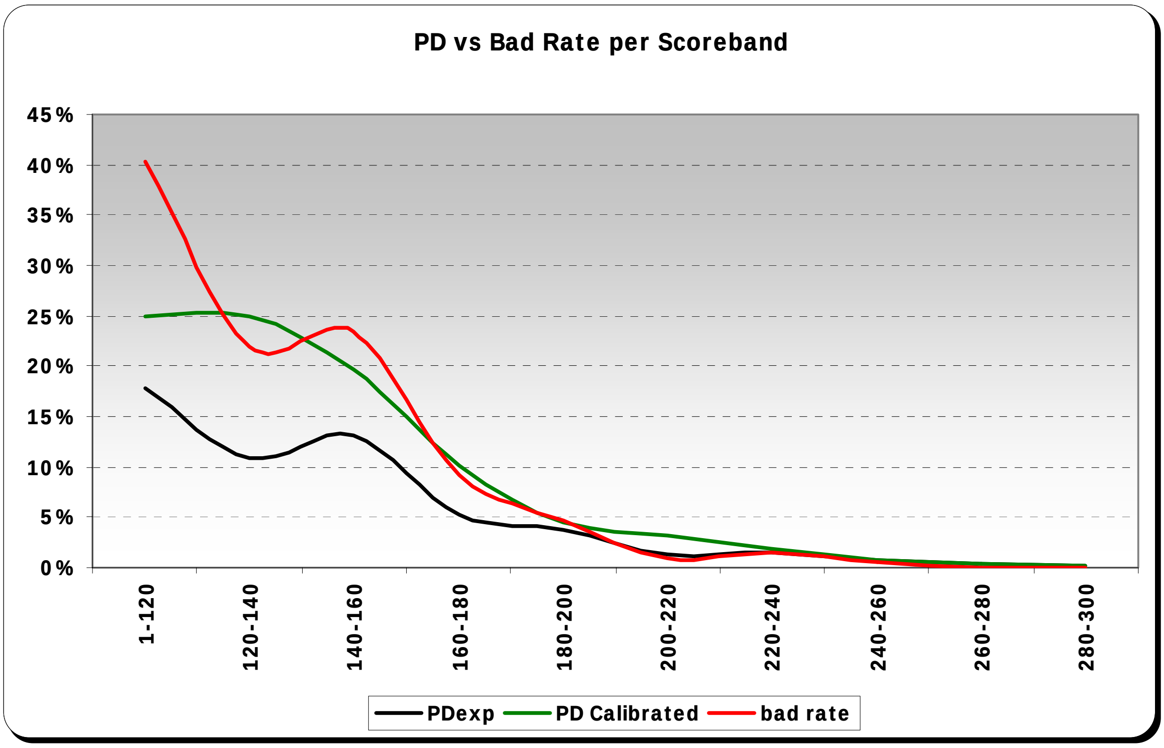
Statistic	All Good	All Bad	Total
Population Odds			16107
Minimum Score	79	83	79
Max Score	301	268	301
Mean Score	237.107	130.054	230.85
Variance Score	2,245.13	1,320.47	2,821.84
Standard Deviation Score	47.383	36.338	53.121
Divergence			6428
KS			75,96%
ROC Area			0.935
Gini			95%

**Full separation table can be found in Appendix I.*

ROC Curve



Since the actual Bad Rate is higher than the Modeled Expected PD, it was necessary to calibrate PD. Also, due to the small number of loans in low score bands, the calibrated PD is not as strict as actual bad rate.



Calibrating PD according to recent bad rate data leads to the following results.

Scoreband	Calibrated PD
1-120	25,00%
120-140	25,00%
140-160	19,72%
160-180	10,20%
180-200	4,42%
200-220	3,13%
220-240	1,82%
240-260	0,67%
260-280	0,33%
280-300	0,17%

Through the door sample

A next step would be to examine a most recent sample. In that way we can calculate the score of the recent population and then simulate the recent sample to a crisis situation. After scoring the recent population we applied the above PD.

After scoring the data of June 2009 we end up to the following:

TTD Sample (June 2009)		
Scenario	**Pd**	**Exp Loss / Balance**
Base	1,43%	0,99%

4. Stress Test Scenarios

Methodology

After developing the models and calibrating the probability of default, the next step is to create different stress scenarios and then measure their effect to the portfolio. By incorporating all stress factors into an aggregate stress-model, various scenarios can be developed by adjusting the weights of the coefficients of the model in order to reflect generic stress factors (e.g. transition from higher behavioral scores to lower behavioral score, etc), as well as, socioeconomic stress factors (e.g. northern Greece PD, agricultural profession PD, etc). Product specific stress-models have been developed (mortgages, consumer loans, credit cards, etc) that reflect the exposure of each particular retail portfolio to the properly selected stress factors. Recent performance indicators and trends confirm that the weighting of the stress-factors in each model is consistent with expectations and the relevant analytical framework. Also, various stress scenarios are developed based on recent trends and historical data of unemployment rates and G.D.P. growth in Greece over the past 10 years.

There were developed eight different scenarios, but the particular process and methodology gives the opportunity to create easily different stress scenarios and measure the effect that each new scenario will have to probability of default.

As shown in past section the model consists of two sets of variables, one of internal variables (bucket, behavior score) and another of external variables (profession, geographic area). The first set is more linked to behavioral characteristics and how customers behave within bank's borders. By altering the weights of the first set of variables, the entire population is affected equally. The second set is more related to demographic profile and indirectly to macro-economic elements that can affect the behavior of certain areas or professions. For example, an economic downturn expressed by a wave of unemployment can affect severely some tourism-related professions (high risk professions) or even some certain areas like islands (high risk areas). On the other hand, some professions or areas may not be altered (low risk).

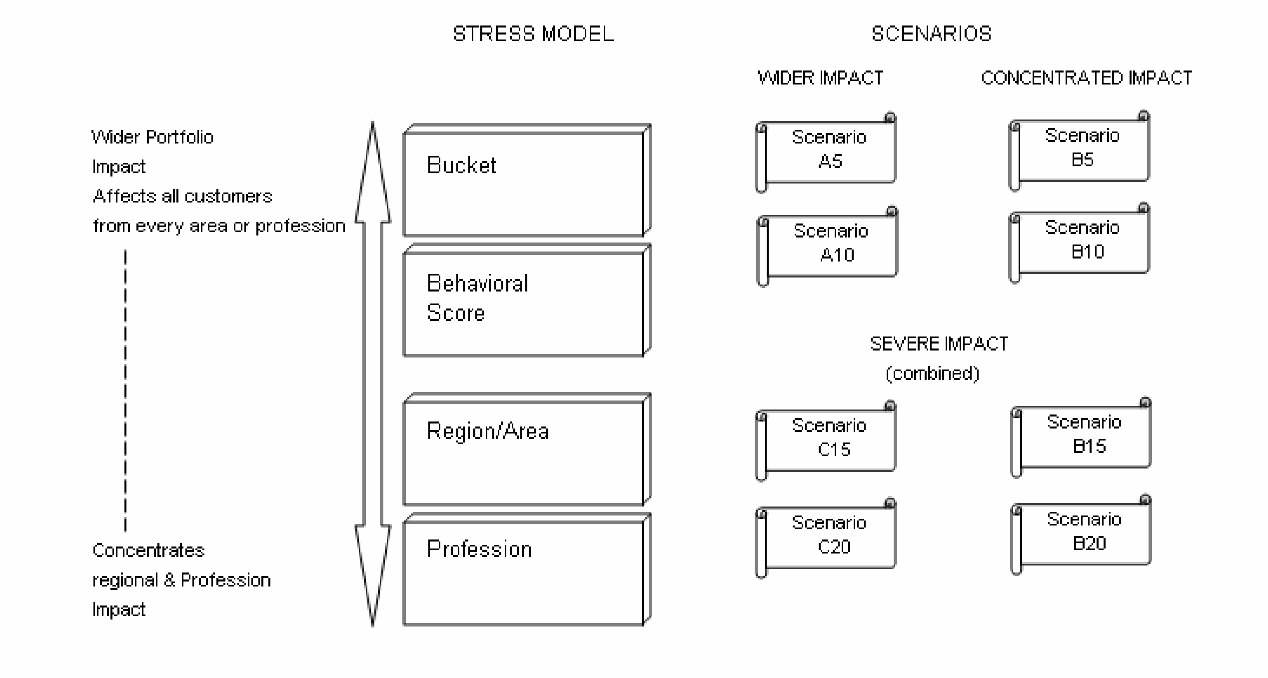
Scenarios that can be found below are coded by a letter that denotes which set of variables is affected and a number that illustrates the maximum points subtracted.

Scenarios A refer to all variables
Scenarios B refer only to the second set of external variables

Scenarios C refer to all variables and especially to high risk segments from external variables

When points are subtracted, a higher PD rate is automatically allocated on the affected segment according to the rule of every 20 points good/bad odds are doubled.

Graphical Illustration



Scenarios in detail

Analytically, the following scenarios were developed:

<u>Scenario A5:</u> It is assumed that an economic crisis will affect all four factors of stress model. Therefore, 5 points of the score of each characteristic is subtracted. As a result each loan has a new score which is 20 points lower than the actual score and this corresponds to a higher probability of default.

<u>Scenario A10:</u> 10 points of each characteristic's score are subtracted.

<u>Scenario B5:</u> It is assumed that an economic crisis will affect mainly the unemployment ratio and the employments' financial rewards. In order to consider the fact that unemployment will also affect different areas, in this scenario there are subtracted 5 points from area's weight and other 5 points from profession's weight.

<u>Scenario B10:</u> 10 points of area's weight and other 10 points of profession's weight are subtracted.

Scenario B15: In this scenario it is assumed that an economic crisis will not affect equally all areas and all professions. It is assumed that certain areas and certain professions are more sensitive to an economic crisis and will appear higher unemployment. Therefore, there were subtracted 15 points from the weight of certain professions and certain areas and 10 points of the rest of the professions and areas. The selection of the areas is based on historical unemployment analysis of National Statistical Office and Eurostat.

Highest Unemployment Ratio per region (in hundreds basic points)		
Region	Time	Maximum (in hundreds
East Macedonia & Thrace	1st Q 2004	14,2
Central Macedonia	4th Q 1999	12,7
West Macedonia	1st Q 2005	18,8
Epirus	1st Q 1998	14,7
Thessaly	4th Q 2001	14,5
Ionian Islands	1st Q 2004	19,3
West Greece	4th Q 1998	13,1
East Central Greece	1st Q 2001	15,6
Attica	4th Q 1999	13,1
Peloponnesus	1st Q 2004	10,2

As a result as high risk regions and professions were selected the following:

High Risk Regions:
Ionian Islands
Aegean Islands
North Western Greece

High Risk Professions:
Private Employee
Lawyer/Businessman/Sailor/Waiter etc.
Farmer/Artist/Dealer etc.

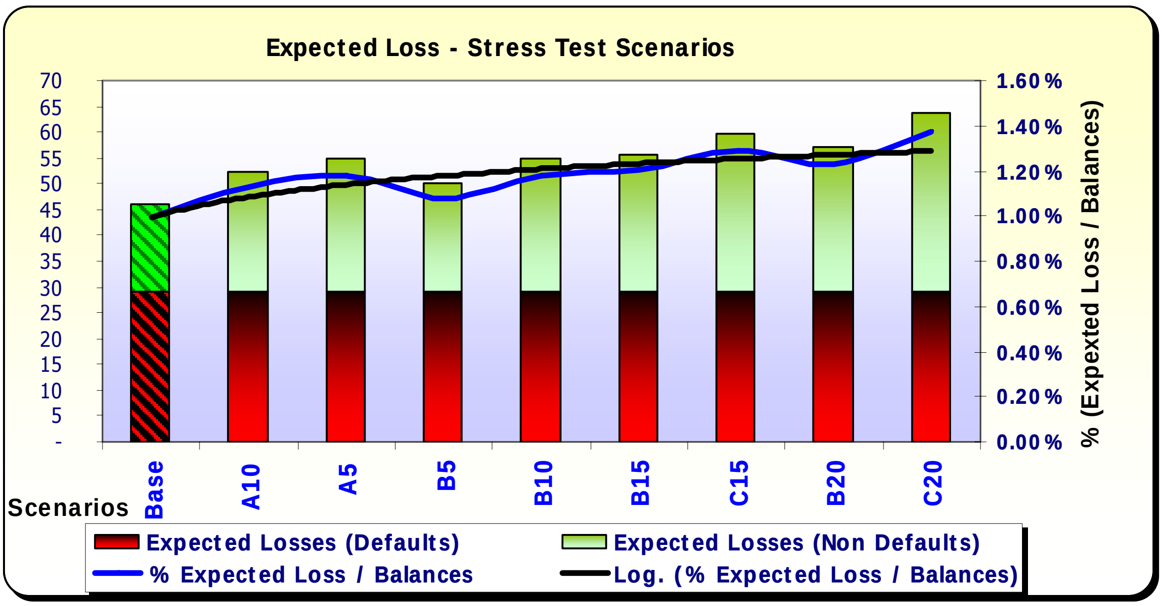
Scenario B20: 20 points from the weight of high risk regions and professions were subtracted and 10 points from the weight of the rest of regions and professions.

Scenario C15: 15 points of the weight of high risk regions and professions were subtracted, 10 point of the weight of the rest of the regions and the weight and 5 points of the rest of the characteristics (bucket, behavior score).
Scenario C20: 20 points of the weight of high risk regions and professions were subtracted, 10 point of the weight of the rest of the regions and the weight and 5 points of the rest of the characteristics (bucket, behavior score).

The various stress scenarios[2] were applied to the total portfolio and finally the total impact to the portfolio was measured.

- A5 : 54% increase of PD
- B5: 25% increase of PD
- B10: 54% increase of PD
- A10: 55% increase of PD
- B15: 60% increase of PD
- B20: 68% increase of PD
- C15: 86% increase of PD
- C20: 104% increase of PD

Scenario	Pd	Exp Loss / Balance
Base	1,43%	0,99%
B5	1,78%	1,08%
A5	2,20%	1,18%
B10	2,21%	1,18%
A10	2,25%	1,19%
B15	2,28%	1,20%
B20	2,40%	1,23%
C15	2,65%	1,29%
C20	2,91%	1,37%



[2] In the results, all figures are fictional. Real figures can be sent upon request.

5. Conclusion

Recent developments in the financial system can amplify swings in the macroeconomy and cause widespread financial instability. The expansion of coverage and use of stress testing reflects the growing demands of senior management, business units and third parties such as investors. In an increasingly complex financial environment where Banks are facing new risks and markets are becoming more global, stress testing benefits from its flexibility, comprehensibility and the insights that it puts on management to discuss the risks that a Bank is currently running.

In this paper, we have provided a practical and meaningful framework under which a Bank's management can understand and quantify stress impact on Retail credit portfolios. Moreover, the discussed approach increases integration of stress testing into risk management frameworks.

This exercise provides insights to the Bank's management in relation to the concentration risk the bank faces under stress scenarios. Although stress situations affect the total portfolio, historical experience reveals that certain regions or professions are more severely affected. Thus, the bank management can take action in limiting exposure on concentration risk under stress factors so as to reduce overall impact of adverse scenarios.

Apart from evaluating the impact of various stress scenarios to the Bank's provisioning levels, the process of applying different stress scenarios through a model helps improve active portfolio management through asking relevant questions such as how the flow rate between buckets could be stabilised or how actual PD per behavioural score will perform in stress scenarios e.g. affect decisions on collections intensity, limit management, pricing etc. In other words, it helps focus management efforts in dealing with the most significant risk drivers under stress scenarios

As a next step, banks could add and test more macro-economic variables (GDP, interest rates etc) and attempt to incorporate them to a simple model. In that way, simulation can be performed in different samples to illustrate impacts on concentrational credit risk.

6. Appendix

Descending Score Distribution					
All_Good_vs_All_Bad					
			ks	Cumulative	Cumulative
	Good	Bad			Bad
	Percent	Percent		Percent	Prob
Score Range	Descending	Descending		Descending	Descending
Low -< 105.00	100.00%	100.00%	0.00%	100.00%	0.058
105.00 -< 115.00	99.19%	79.26%	19.93%	98.03%	0.047
115.00 -< 119.00	98.15%	64.34%	33.81%	96.17%	0.039
119.00 -< 123.00	96.72%	53.29%	43.43%	94.18%	0.033
123.00 -< 127.00	95.93%	49.81%	46.12%	93.24%	0.031
127.00 -< 131.00	93.53%	36.82%	56.71%	90.21%	0.024
131.00 -< 138.00	91.88%	27.13%	64.75%	88.09%	0.018
138.00 -< 165.00	90.09%	21.90%	68.19%	86.10%	0.015
165.00 -< 178.00	88.27%	15.50%	72.77%	84.01%	0.011
178.00 -< 187.00	87.11%	12.79%	74.32%	82.77%	0.009
187.00 -< 193.00	84.42%	8.91%	75.51%	80.00%	0.007
193.00 -< 204.00	82.64%	7.36%	75.28%	78.24%	0.006
204.00 -< 221.00	80.44%	6.78%	73.66%	76.13%	0.005
221.00 -< 226.00	78.41%	5.62%	72.79%	74.16%	0.004
226.00 -< 233.00	77.38%	5.43%	71.95%	73.17%	0.004
233.00 -< 238.00	74.34%	3.88%	70.46%	70.22%	0.003
238.00 -< 240.00	72.43%	3.10%	69.33%	68.38%	0.003
240.00 -< 243.00	71.22%	2.52%	68.70%	67.20%	0.002
243.00 -< 244.00	67.93%	1.94%	65.99%	64.08%	0.002
244.00 -< 247.00	66.91%	1.36%	65.55%	63.08%	0.001
247.00 -< 249.00	63.65%	1.36%	62.29%	60.01%	0.001
249.00 -< 251.00	61.92%	0.97%	60.95%	58.36%	0.001
251.00 -< 252.00	60.65%	0.97%	59.68%	57.17%	0.001
252.00 -< 255.00	58.39%	0.78%	57.61%	55.02%	0.001
255.00 -< 257.00	55.52%	0.78%	54.74%	52.32%	0.001
257.00 -< 258.00	53.33%	0.58%	52.75%	50.24%	0.001
258.00 -< 259.00	52.10%	0.58%	51.52%	49.09%	0.001
259.00 -< 260.00	49.87%	0.58%	49.29%	46.99%	0.001
260.00 -< 261.00	46.12%	0.19%	45.93%	43.43%	0.000
261.00 -< 263.00	44.10%	0.19%	43.91%	41.53%	0.000
263.00 -< 264.00	41.20%	0.19%	41.01%	38.80%	0.000
264.00 -< 265.00	39.36%	0.19%	39.17%	37.07%	0.000
265.00 -< 266.00	36.47%	0.19%	36.28%	34.35%	0.000
266.00 -< 267.00	35.70%	0.19%	35.51%	33.62%	0.000
267.00 -< 268.00	21.93%	0.19%	21.74%	20.66%	0.001
268.00 -< 269.00	19.96%	0.19%	19.77%	18.81%	0.001
269.00 -< 270.00	17.83%	0.00%	17.83%	16.79%	0.000
270.00 -< 272.00	16.52%	0.00%	16.52%	15.55%	0.000
272.00 -< 273.00	10.85%	0.00%	10.85%	10.22%	0.000
273.00 -< 275.00	10.08%	0.00%	10.08%	9.49%	0.000
275.00 -< 277.00	6.58%	0.00%	6.58%	6.20%	0.000
277.00 -< 281.00	4.64%	0.00%	4.64%	4.37%	0.000
281.00 -< High	2.80%	0.00%	2.80%	2.64%	0.000

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