Key Indicators Of Banking Behaviour Changes Contributing To The Results Of Regulatory Stress Testing

MSc Reseach Project
Data Analytics

Prasad Pore
x15006298

School of Computing
National College of Ireland

Supervisor: Oisin Creaner

National College of Ireland
Project Submission Sheet – 2015/2016
School of Computing

Student Name:	Prasad Pore
Student ID:	x15006298
Programme:	Data Analytics
Year:	2016
Module:	MSc Reseach Project
Lecturer:	Oisin Creaner
Submission Due Date:	22/08/2016
Project Title:	Key Indicators Of Banking Behaviour Changes Contributing To The Results Of Regulatory Stress Testing
Word Count:	5807

I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution will be fully referenced and listed in the relevant bibliography section at the rear of the project.

ALL internet material must be referenced in the bibliography section. Students are encouraged to use the Harvard Referencing Standard supplied by the Library. To use other author's written or electronic work is illegal (plagiarism) and may result in disciplinary action. Students may be required to undergo a viva (oral examination) if there is suspicion about the validity of their submitted work.

Signature:	
Date:	12th September 2016

PLEASE READ THE FOLLOWING INSTRUCTIONS:
1. Please attach a completed copy of this sheet to each project (including multiple copies).
2. **You must ensure that you retain a HARD COPY of ALL projects**, both for your own reference and in case a project is lost or mislaid. It is not sufficient to keep a copy on computer. Please do not bind projects or place in covers unless specifically requested.
3. Assignments that are submitted to the Programme Coordinator office must be placed into the assignment box located outside the office.

Office Use Only	
Signature:	
Date:	
Penalty Applied (if applicable):	

Contents

Key Indicators Of Banking Behaviour Changes Contributing To The Results Of Regulatory Stress Testing

Prasad Pore
x15006298
MSc Reseach Project in Data Analytics

12th September 2016

Abstract

Global Financial Crisis (GFC) of 2007-2011 resulted in failure of many financial institutions like Lehman Brothers and Washington Mutual. After GFC, Basel Committee on Banking Supervision (BCBS) and many worldwide regulatory/governing authorities focused on the implementation of a standardized framework for enhancing the ability of banking sector to withstand financial or economic crisis. This standardized framework, Third Basel Accord (Basel III), mainly concerns with stress testing, capital adequacy requirement and market liquidity risk. With the help of different financial indicators like capital, risk profile etc., regulatory stress testing assesses the ability of financial institutions to withstand financial and economic crisis. Changes in these indicators show certain banking behavior in anticipation of regulatory stress testing. This study tries to find such key indicators of banking behavioral changes contributing to the results of EU wide regulatory stress testing conducted in 2014. To understand similar problems and methodologies to solve such problems, literature in the field of data mining, statistics and finance has been reviewed in this paper.

1 Introduction

Due to the GFC of 2007-2011, banks such as Lehman Brothers (USA), Dexia (Belgium), Northern Rock (UK) failed severely and number of other banks had to recapitalize themselves. Failure of such banks and recapitalization of others, exposed great buildup of risk within worldwide financial system. In order to bring overall financial system to normalcy, governing/regulatory authorities across the world along with Basel Committee on Banking Supervision focused on implementation of a standardized framework, Basel III, for enhancing the ability of banking sector to withstand financial or economic crisis. From regulatory point of view, Basel III prescribes specific measures necessary for keeping financial system stabilized and resilient to financial crisis. The aftermath of GFC made governments and regulatory authorities all over the world to plan and conduct regulatory stress tests on all significant banks under their regulation. The key goal of regulatory stress test is to conduct standardized evaluation of capability of individual banks and overall financial system to withstand severe financial and economic crisis. Focus of regulatory stress test is stability and regulatory capital adequacy. Cihak (2007) mentions that regulatory stress testing is a famous and helpful method to assess resilience of financial systems to worst economic events. Regulatory stress test applies various methods to assess stability of financial companies and banks under the scope using different financial indicators. There are four chronological stages of regulatory stress test: 1. Stress test announcement 2. Clarification 3. Methodology 4. Results. Neretina et al. (2015)

This study is stimulated by research discussion in Glasserman and Tangirala (2015) while explaining potential hazards of prediction of stress test results that banks will optimize their financial settings for particular regulatory hurdle and will cause new hard to detects risks. Also, its a general view that if banks possibility of failing the stress tests is substantial, bank will change its financial settings to cross the hurdle of regulatory stress test. Which means, bank will exhibit behavioral change in anticipation of stress test. Present study will assess such behavioral changes with the help of respective financial indicators of banks and try to identify key behavioral change indicators contributing to the results of regulatory stress testing.

Author proposes following research hypothesis along with set of proposed behavioral change indicators listed in Appendix D

"H0: Among the proposed financial behavioral change indicators, there are certain statistically significant financial behavioral change indicators which contributes to the results of regulatory stress testing conducted in EU in 2014.

H1: There are no statistically significant financial behavioral change indicators which contributes to the results of regulatory stress testing conducted in EU in 2014."

This study will attempt to identify key behavioral changes exhibited by sample of EU banks assessed by the European Banking Authority (EBA) in 2014 regulatory stress test. Study will help to identify and understand important decisions with respect to capital and risk, taken by different EU banks. And it will stimulate policy markets to utilize this cognizance to direct the banks in their regulatory authority to follow similar financial decisions aimed at enhanced solvency position. Eventually, it will contribute to overall financial system stability.

In this paper, initially relevant literature review is conducted to build the knowledge base, then selected research methodology and implementation is explained in detail and finally results have been evaluated and research is concluded with future scope discussion.

2 Related Work

This section is an extension of previous work done by author, Pore (2016), in Research in Computing module.

2.1 Stress Testing

Assuring a stable, reliable and efficient financial system is one of the key responsibilities of regulatory authorities Marcelo et al. (2008). Though there is absence of universally accepted definition of financial stability, it can be defined as a state of financial system (for a given economy) which ensures that efficiency of intermediation between fund buyer and fund suppliers will not be impacted significantly by adverse economic or financial shocks. Effective supervision and prudential regulation are foundational elements of stable and efficient financial system. Stress tests are useful in effective supervision and its development and implementation as a prudential approach is supplementing existing regulatory practices. Marcelo et al. (2008) defines stress test as "a set of techniques, tools or, in general, procedures used by either individual institutions or supervisory authorities to gauge as objectively as possible the financial condition of the system under examination."This paper precisely describes stress testing process in a systematic way. Though it covers theoretical aspect of stress testing, it can be improved by adding case study of an individual bank that went under stress testing.

In his study, Worrell (2008) focuses on interpretation of stress test results when a financial system is stressed to extreme. He analyses effects of shocks on capital adequacy ratio (CAR) and rate of downfall of CAR to a minimum limit required by regulatory authorities. He applies exchange rate stress (particularly, depreciation percentage) from -15% to 50% on sample of six banks A, B, C, D, E, F and finds out F has highest position in net foreign liability. It makes bank F a prime candidate for both loss and gain i.e. higher suffering in CAR due to depreciated exchange rate as well as higher gains due to appreciated exchange rate. CAR deteriorates from 18.6% to slightly above minimum required i.e. 8% when stress increased from 0% to 50%. Due to balanced exposure position, banks A, B, C remains unaffected whereas banks D and E become high gainer under 50% stress due to positive net foreign asset position and suffer under -15% stress. This study used realistic data of six banks and hypothetical scenario of extreme stress. This generalized approach of changing various parameters systematically helps to easily understand the results of study.

As this study try to identify key indicators of banking behavior changes contributing to stress test results, it is necessary to find out feasibility of prediction of stress test results. Glasserman and Tangirala (2015) state that regulatory stress testing processes have been matured over the period since its inception and the predictability of stress test results have been increased. They compare results of Dodd-Frank Act Stress Test (DFAST) 2014 using different scenarios and sample of 19 big American Bank Holding Companies (BHCs). Using regression analysis, they determine predictability of loss rates and loss levels. They conclude their research with findings that US regulatory stress test shows clear trend towards greater predictability. While discussing concerns about predictability Glasserman and Tangirala (2015) say, "The main concern with a routinized stress test is the danger that it will lead banks to optimize their choices for a particular supervisory hurdle and implicitly create new, harder to detect risks in doing so."This discussion stimulates author to analyze such banking behavior in anticipation of regulatory stress test and overall research gives support for feasibility of stress test result predictability and identification of contributing factors.

2.2 Data Mining

As analysis of financial data to find contributing factor of stress test results is core of this research, it is important to understand various data mining methodologies and approaches to solve similar problems. Data mining is defined by Frawley et al. (1992) as - "the nontrivial extraction of implicit, previously unknown, and potentially useful information from data."Due to expeditious evolution in data mining since a decade, lot of industrial and academic efforts have been invested in systematize overall data mining process. In their comparative study, Azevedo and Santos (2008), explain, compare and contrast three main types of data mining methodologies: 1. KDD (Knowledge discovery in databases) 2. SEMMA (Sample, Explore, Modify, Model, Assess) 3. CRISP-DM (CRoss-Industry Standard Process for Data Mining). Five step KDD process is iterative and generic in nature where data mining step mainly focuses on modelling and patterns discovery. Business goal setting and business understanding are prerequisite for KDD. SEMMA process has five steps and it is designed by SAS Institute. Although generic in nature and independent of data mining tools, SEMMA has links with SAS tools. CRISP-DM is six stage iterative process of data mining where order of stages is not rigid as user can switch back and forth as per the need of refinement in the project. It is a complete design and independent of data mining tools. It is a well documented process and has linkage to SPSS Clementine. In conclusion, KDD is a generic process and SEMMA and CRISP-DM are standardized implementations of it to solve real world problems.

While researching on problem of bankruptcy prediction with data mining algorithms, Olson et al. (2012) summarize that logistic regression method is more accurate than radial basis but less accurate than decision trees. Though Artificial Neural Network (ANN) and Support Vector Machine (SVM) fit data correctly, they are black box techniques due to lack of comprehensibility of results and transparency in internal logic. Decision trees are easy to understand but increased number of rules add complexity in understanding them. They can be optimized and constrained to minimum levels of support to enhance understandability. This study has explained technicalities of different approaches and results in depth. It can be improved by adding interpretation of results from business perspective.

2.3 Statistical Modelling

In this study, as response variable is dichotomous (pass/fail), it is a classification problem. As generally classification problems are solved using logistic regression (Salehi et al. (2016)), it is important to understand logistic regression modelling techniques and possible problems in it. Chao-Ying et al. (2002) explain logistic regression or logit using example of remedial reading instruction recommendation problem. Using regression coefficient and regression equation, gender based recommendation can be predicted. When response variable is dichotomous (sigmoid function), liner regression fails to describe it but logistic regression describes it using logit (log of odds) of predictors. Authors suggest to incorporate sufficient information including evaluation logistic regression model, goodness of fit tests, statistical tests of predictors and output probabilities. This study has explained and exemplified logistic regression in detail and suggested best practices of analysis reporting. It can be improved by adding information about general problems that may occur due to data issues.

Logistic regression is used in different fields of study and it has pivotal importance in financial analytics. Zaghdoudi (2013) study bankruptcy prediction using logistics regression and generalized liner model (GLM). First, financial data of 14 Tunisian banks is collected from annual reports of 2002-2010 published by Central Bank of Tunisia and association of Tunisia banks. Then predictor variables are chosen to build logistic regression model. The study summarizes that profitability measure of bank has high odds ratio i.e. there are high chances of bankruptcy. Another study of Indian share market stock prediction i.e. good/bad stock depending on rate of return, is conducted by Dutta et al. (2012). If stock price outperforms NIFTY index, it is good otherwise it is bad. Sixteen financial ratios of 30 companies are used as predictors to find probability of performance of stock using logistic regression. After dimensionality reduction, 6 predictors and 118 observations are used to build logistic regression model. Goodness of fit of model is tested with Chi-square test ($p<0.05$) and Hosmer-Lemeshow test ($p<0.01$). Study concludes that there is no significant difference in predicted and actual observations and model fits the data appropriately. Many times, logistic regression modelling faces problems of convergence failure. Mostly these failures arise due to quasi-complete or complete separation problem where maximum likelihood does not exist. Allison (2008) explains why these problems arise and how they can be fixed. When some of the predictors clearly classify the response variable or linear function of some predictors correctly predict response variable, then convergence failure occurs. There are two solutions to this problem: 1. Reduce the model by deleting problematic predictor variable 2. Penalized likelihood method. Hui and Hastie (2005) propose an advanced regularization and variable selection method, called elastic net which is a combination of ridge and lasso regression where it combines L1 and L2 penalties. It is specifically used when predictors are more in comparison with observations. They discuss that it produces better accuracy and encourage grouping effect. Empirically, it shows superiority over lasso regression.

2.4 Data Mining Tools

When selecting programming tool for statistical modelling, Matloff (2011) explains why one should use R. R is open source project which is extended from widely accepted S statistical language. It is a de facto standard in industry and comparable to enterprise tools. Apart from statistical operations it can perform general operations like Extract-Transform-Load (ETL) tasks, automation and visualization. It has object oriented and functional structure and support for Linux, Mac and Windows. It has big user community and prominent contributors. In survey of open source tools, Landset et al. (2015) says that there are many tools for machine learning; each has advantages, disadvantages and many overlaps. H2O is open source framework which provides wide range of advanced machine learning and statistical libraries with web UI and support for Scala, Java, Python and R.

3 Methodology

In data mining projects, applying different models and tools is common practice but it causes switching between the tasks and processes. This requirement makes it really important to choose a methodology which is iterative and agile. From industry perspective, data mining process should be proven, stable and robust in nature. As CRISP-DM has all above features and explicitly considers the importance of business understanding and deployment phases (Azevedo and Santos (2008)), author finds it suitable for this industry focused study.

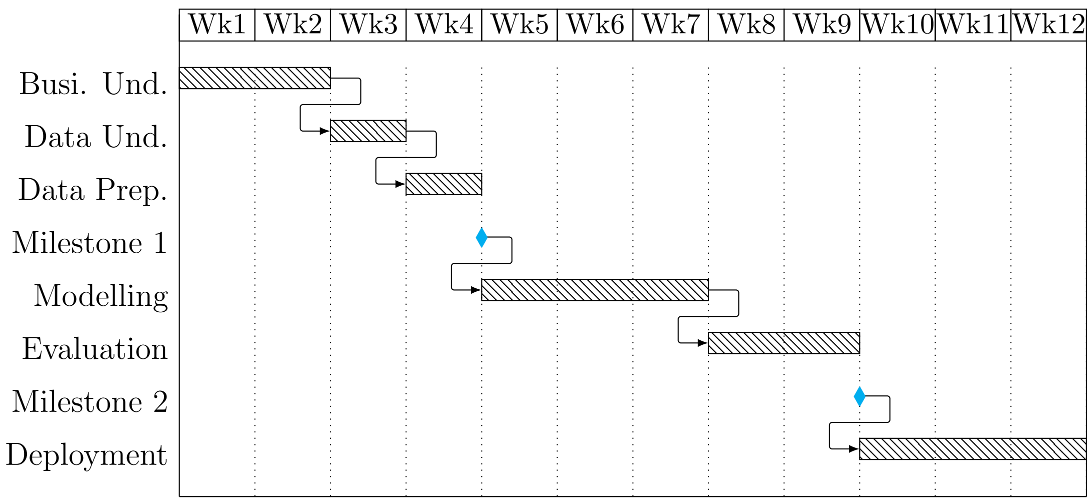
CRISP-DM lifecycle consists of six steps as shown in Fig.1.:

3.1 Business Understanding

This step deals with defining clear business requirements, objectives and project plans. In this step, author defines research hypothesis based on his previous study and available data. As this topic is very niche, author discusses and validates his hypothesis with

Figure 1: CRISP-DM (Image Source: Wikipedia)

three industry experts with more than 15 years of experience in finance and regulatory stress testing. During discussions, author gains insights about stress testing process and different banking behaviors. After analyzing amount of publicly available data and validating its usefulness for this study with two experts, author finalizes 13 banking behavior indicators, listed in Appendix D, for this study. Also author prepares project plan of 12 weeks as shown in gantt chart below:



In 2014, EBA carried out stress testing exercise across 123 top EU wide banks based on a common methodology and macroeconomic scenarios. In this test, 24 out of a total of 123 banks failed; specifically, the 24 banks failed to meet the minimum capital requirements based on the transitional Capital Requirement Regulation (CRR), which was set at ratio 5.5% and 8.0% of Common Equity Tier 1 under the stress and baseline scenarios respectively. As data used for this study is public data published by EBA, there are no privacy or legal issues associated with it.

3.2 Data Understanding

The data of the financial year ended 2013 for all 123 banks is provided as a part of 2014 stress test result on EBA website Appendix E. However, data for the financial year ended 2012 is only available for 63 banks out of 123, as a part of 2013 transparency exercise conducted by EBA. When metadata and data dictionaries for 2012 and 2013 data are compared, it is observed that there is difference in conventions used in them e.g. different field ids and bank codes. Further data analysis confirmed that data is of good quality as there are no duplicates, missing values or errors in the data. All variables in data are real numbers representing different financial indicators. It is also observed that there is no explicit response variable that represent stress test results (pass/fail) of the banks. It indicates the need of generation of response variable from available financial indicators using the rule provided by EBA.

3.3 Data Preparation

Due to data limitation discussed above, this analysis is based on data of 63 EU banks across 21 jurisdictions out of 123 EU banks. As per empirical rule of thumb of sample size, all 63 observations are used in sample because of small population size (<100). The initial sample analysis shows that selected sample is appropriately stratified sample as it maintains relatively similar ratio of banks that passed and failed the stress test compared to total population of 123 banks. Please see Appendix A for total banks in the sample, Appendix C for total population and selected sample breakdown by Pass/Fail and Appendix B for the breakdown of the sample by jurisdiction and outcome.

Data preparation involves ETL tasks to prepare final dataset for modelling purpose. As data contains different conventions for field id and bank codes, appropriate field mapping is conducted manually to create mapping file. After that, all available data is loaded into the system memory and performed filter operations using R to get required subset of data representing 13 behavioral indicators. R is capable of doing ETL and visualization tasks along with statistical modelling (Matloff (2011)). Once data is selected, all data from different data frames merged into single data frame. Then transformations required for finding relative change in predictors is performed. Also dichotomous response variable is generated by applying calculation rules of stress test result for transitional scenario. As the sample size is small and data itself is diverse from different countries and regimes, non-random holdout sample method of validation is selected (Keane and Wolpin (2007)) and data is split between training and test dataset in 70:30 proportion.

3.4 Modelling

Author has decided to use statistical logistic models due to the reasons: 1. Kwak et al. (2014) says "from data mining models outputs, we cannot tell which factor contributed to the prediction rates due to the black box process. However, the logit analysis can show which factors are contributing to improving the prediction rates and it is easy for managers or other decision makers to focus on their companies financial factors. Logit model is the preferred choice in most accounting or finance literature."2. As mentioned by Kwak et al. (2014), Ohlson (1980) applied logistic regression model which does not require assumptions of prior probability of event or distribution of predictors. 3. As per empirical insights from finance industry experts, statistical models are used, tested and proven since a century and corporate decision makers prefer statistical results and confidence while taking financial decisions compared to new machine learning methods.

Before logistic regression modelling, it is important to perform required checks (Pallant (2007)) 1. Sample size should be sufficiently large w.r.t. no. of predictors. 2. Predictors should not be multicolinear. 3. Outliers should be detected and treated appropriately. Initially sample analysis indicates that there are relatively more no. of predictors compared to sample size; which may lead to convergence failure in modelling. Correlation analysis is performed to find the multicolinearity between the predictor variables. Multicollinearity causes increase in standard errors of coefficients, which in turn lead to making some variables statistically insignificant even if they are significant in absence of multicollinearity.

Initial sample analysis and correlation analysis suggest that there is need to address problems w.r.t assumptions of logistic regression. Also, initial logistic regression modelling identifies underlying problem of complete separation and convergence failure, which is attributable to presence of variable that perfectly classifies the data. As explained by Allison (2008), above problems can be solved in two ways:
1. Reduce the model by deleting problematic predictor variable and/or stepwise regression by adding/removing variables to find best model with minimum number of contributing variables and minimum Akaike Information Criterion (AIC) [1] value.
2. Penalization/Regularization using ridge regression, lasso regression or elastic net regression. Elastic net performs better than other and internally uses ridge and lasso regression where it combines L1 and L2 penalties (Hui and Hastie (2005)).

From above solutions, deletion of problematic variables, automatic stepwise regression, logistic regression and elastic net regression modelling techniques are selected to find behavioral change indicators contributing to stress test results. Using one by one deletion of predictors, problematic variables are identified and deleted from the model. When logistic analysis is applied with remaining predictors, it converges for the first time but reports only one significant contributing predictor. When stepwise regression algorithm is applied on same set of predictors using forward, backward and both directions, it selected a model with five predictors. Then logistic regression algorithm is applied on set of five predictors finalized in last step; which showed four significant predictors contributing to stress test results. To analyze deviance table, ANOVA tests are conducted and to test Goodness of Fit, Pseudo R-Square and Hosmer-Lemeshow tests are conducted. After confirmation of model fitment, model is validated against holdout test dataset using validation measures: accuracy, precision, recall, specificity, AUC and ROC. As elastic net algorithm is capable of penalization and regularization, it is applied on all predictors. The results showed eight significant predictors contributing to stress test results. Model is then validated against holdout test dataset with same set of validation measures above.

3.5 Evaluation

It is important to evaluate built models from data analytics and business perspective. Using various statistical tests, built models are tested and evaluated to find contributions of predictors to the stress test results. Then models are compared with each other using

[1] AIC = -2log-likelihood + 2p, a measure of relative quality of models

validation measures selected. Final results (set of contributing predictors) are validated against proposed hypothesis to make sure that goals are achieved. Finally, results are validated, interpreted and understood from business perspective by discussing it with industry experts and then reported appropriately.

3.6 Deployment

In general, deployment phase involves deployment of built application/software into decision support system of organization. Due to pure analytical nature of this study, it does not have major deployable artifacts but automation of ETL and modelling tasks, visualization in Tableau and detail report generated using Latex.

4 Implementation

This project is implemented using R programming, H2O api, Tableau and Latex.

4.1 Architecture

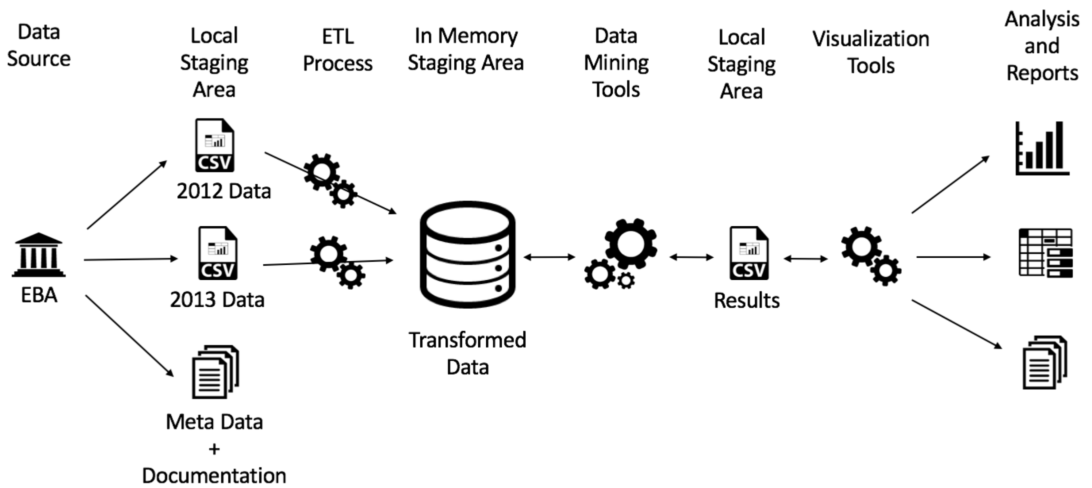


Figure 2: System Architecture

Fig.2 shows technical architecture of this project. Main components of the architecture are data source, local staging area (local file system), ETL process, in memory staging area, data mining tools e.g. R and statistical modelling api, visualization tools e.g. Tableau. Data is first downloaded from EBA and stored in local file system. Details of staging area structure and file paths can be seen in Appendix E. Staged data then utilized by ETL programs written in R to perform extraction-transformation-loading activities. Once data is ready for mining, it is loaded into in-memory staging area (R data frame). Then various statistical modelling algorithms are used to build best model and results of modelling are saved in CSV files for visualization. Results CSV is imported in Tableau to create graphs and dashboard for business analysis. General reporting/documentation is done using Latex tool.

4.2 Extract-Transform-Load (ETL)

Initially, BankNamesMapping.csv file is created manually to map same banks with different field ids from two different datasets. Also other financial indicator fields are mapped manually. There is one 2012 data file, EBA_DISCLOSURE_EXERCISE_2013.csv and two 2013 data files, Credit_risk.csv and Other_templates_v2.csv. BankNamesMapping.csv file is loaded into the memory using etl.R program as data frame and other CSV files are loaded using individual ETL subprograms written for each. Once loaded as R data frame, required data is filtered from whole data, using various filtering criteria based on business rules. All required 13 predictor variables (v1, v2, . . . , v13) and one response variable (t_pass_overall) is generated using appropriate criteria and formulas mentioned in Appendix F and stored into in-memory data frame. Then three data frames are merged into one using BankNamesMapping data frame. Merged data contains two columns for each predictor variables because of data of two different years. Relative change is calculated using formula ((2013 data value - 2012 data value)/2012 data value) %100. Final data frame is saved as df_ready.csv on local file system.

4.3 Modelling

R subprogram, model.R is created for all statistical modelling tasks. Initially correlation function cor() is called to generate correlation matrix and graph is plotted. Then df_ready data frame is divided approximately into 70:30 proportion to create train and test data frames. Then glm() function with parameters family=binomial, link=logit and all 13 predictors is used to build first logistic regression model. It does not converge because of complete separation problem. Problematic predictors are detected and removed manually. Glm() is again used with remaining predictors to build better model. It converges properly but shows less contributing variables. The step() function is used with null and full model to do stepwise regression. It selects best model with minimum AIC value. Then again glm() function is used with variables v2,v3,v7,v8,v9 to build logit and it showed four statistically significant contributing variables. Statistical tests are performed using function pR2(), anova(), hoslem.test(). Using predict() function, model is validated against test data and validation measures are calculated and plotted. For elastic net regression model, H2O api are used and model is built using function h2o.glm() with all predictors. Built model is validated against test data and validation measures are calculated and plotted. Finally, all results are saved in RESULTS.csv and COEF_TABLE.csv for visualization.

4.4 Visualization

Initially, df_ready.csv, RESULTS.csv and COEF_TABLE.csv data files are loaded into Tableau. Then Pie chart, geographic map and bar charts, these simplest but intuitive forms of visualization are used for explanatory analysis. For pass and fail categories of response variable, contrasting colors green and red are used and for model comparison, blue and orange contrasting pair of colors is used.

5 Evaluation

All analyses conducted in this study are evaluated by appropriate statistical tests at statistical significance level of $p<0.05$. All built models are validated using holdout sample with validation measures: accuracy, precision, recall, specificity, AUC and ROC. Final models are compared using validation measures and analyzed for commonality of major contributing predictors.

5.1 Correlation Analysis

The relationship among all predictor v1, v2, ... v13 was investigated using Pearson product-moment correlation coefficient. Preparatory checks were performed to make sure no violation of the assumptions of normality, linearity and homoscedasticity. A review of correlation between predictors shows strong correlation at sig. level $p<0.05$ between predictors shown in Table 1. For complete correlation matrix, please refer Appendix G

Variables	v1, v3	v1, v6	v3, v5	v3, v6	v8, v9
Correlation Coefficient, r	-0.58	-0.89	-0.73	0.72	0.68

Table 1: Strongly correlated predictors

5.2 Logistic regression analysis with all predictors

When logistic analysis is applied first time with all predictors, it does not converge because of complete separation problem. It indicates that logistic regression model with all predictors is not significant. One by one predictor deletion analysis indicates that predictors v5,v11,v13 causes complete separation problem.

5.3 Logistic regression analysis after removing problematic predictors

Result of this model indicates that there is only one statistically significant predictor at sig. level $p<0.05$. When we analyze this result (Appendix H), along with correlation result, it is clear that due to multicollinearity among predictors there is increase in standard errors of coefficients, making some predictors statistically insignificant even if they are significant in absence of multicollinearity.

5.4 Stepwise regression analysis

It selects best model which has minimum AIC value. Results in Appendix I indicate that there is significant drop in AIC in stepwise procedure and final model has minimum AIC value and five predictors (v2,v3,v7,v8,v9) with maximum explanatory power.

5.5 Logistic regression analysis

As shown in Appendix J, results of logistic regression with five predictors (v2,v3,v7,v8,v9) indicates that there are four statistically significant predictors (v2,v3,v7,v9) which contributes to stress test results at sig. level $p<0.05$. Results of ANOVA test in Appendix

J, indicates that wider gap between null deviance and residual deviance (42.51 to 18.07) suggests that this model is better than null model. Also step wise addition of predictors show significant drop in deviance. In Pseudo R-Square test (Appendix J), as value of McFadden R-Square (0.57) is close to 1, indicates that model has fare predictive power. In Hosmer-Lemeshow test (Appendix J), p-value > 0.05 indicates that model is a good fit. Fig.3 lists all validation measures. For confusion matrix please refer Appendix J.

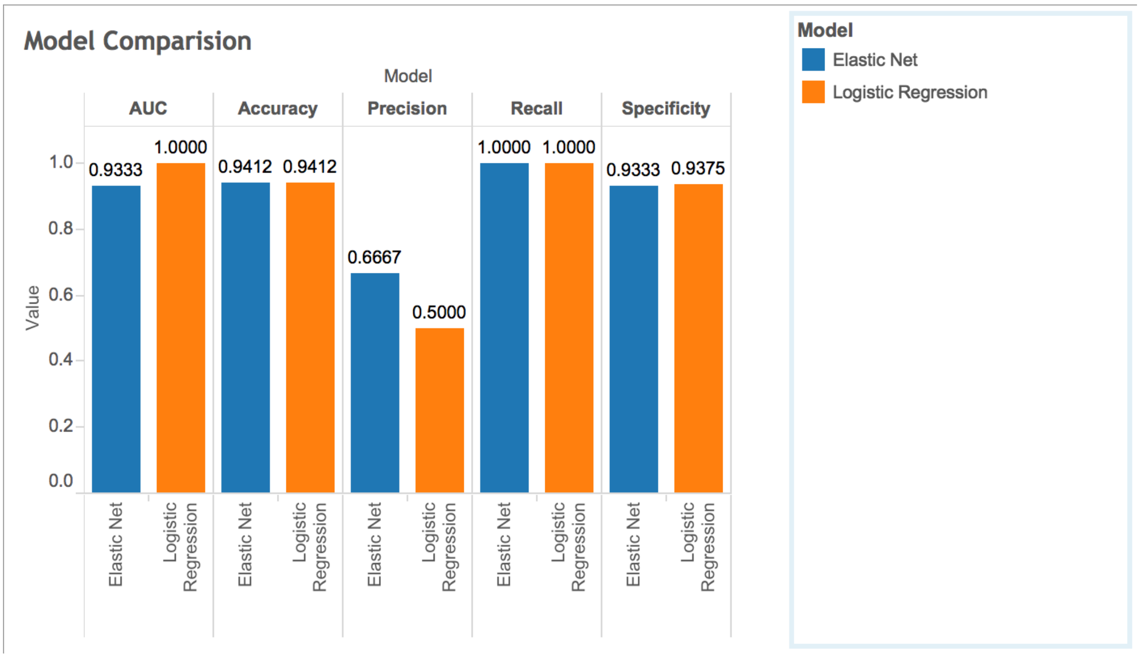


Figure 3: Model comparison with validation measures

5.6 Elastic net regression analysis

As shown in Appendix K, results of elastic net regression with all predictors indicates that there are eight significant predictors (v2,v3,v5,v7,v9,v10,v11,v13) which contributes to stress test. Wider gap between null deviance and residual deviance (42.51 to 14.38) suggest that model is better than null model. Value of R-Square (0.68) is close to 1 which indicates, model has good predictive power. Fig.3 lists all validation measures. For confusion matrix please refer Appendix J.

5.7 Discussion

Simple logistic regression model has four statistically significant predictors at sig. level $p<0.05$ and elastic net regression has eight significant predictors. Elastic net documentation states that p-values are currently not supported[2].

It can be observed from Fig.4, that v2,v3,v7,v9 are the common contributing predictors among both models with statistical confidence explained by simple logistic regression. Also Fig.3 shows, both models are equally good in terms of accuracy, recall and specificity but simple logistic regression is better in terms of AUC and explainable statistical confidence, and weak in terms of precision in comparison with elastic net. In both models,

[2] http://www.h2o.ai/product/faq/

intercept values are high compared to all predictors which indicates that it is important to consider starting position while interpreting the results.

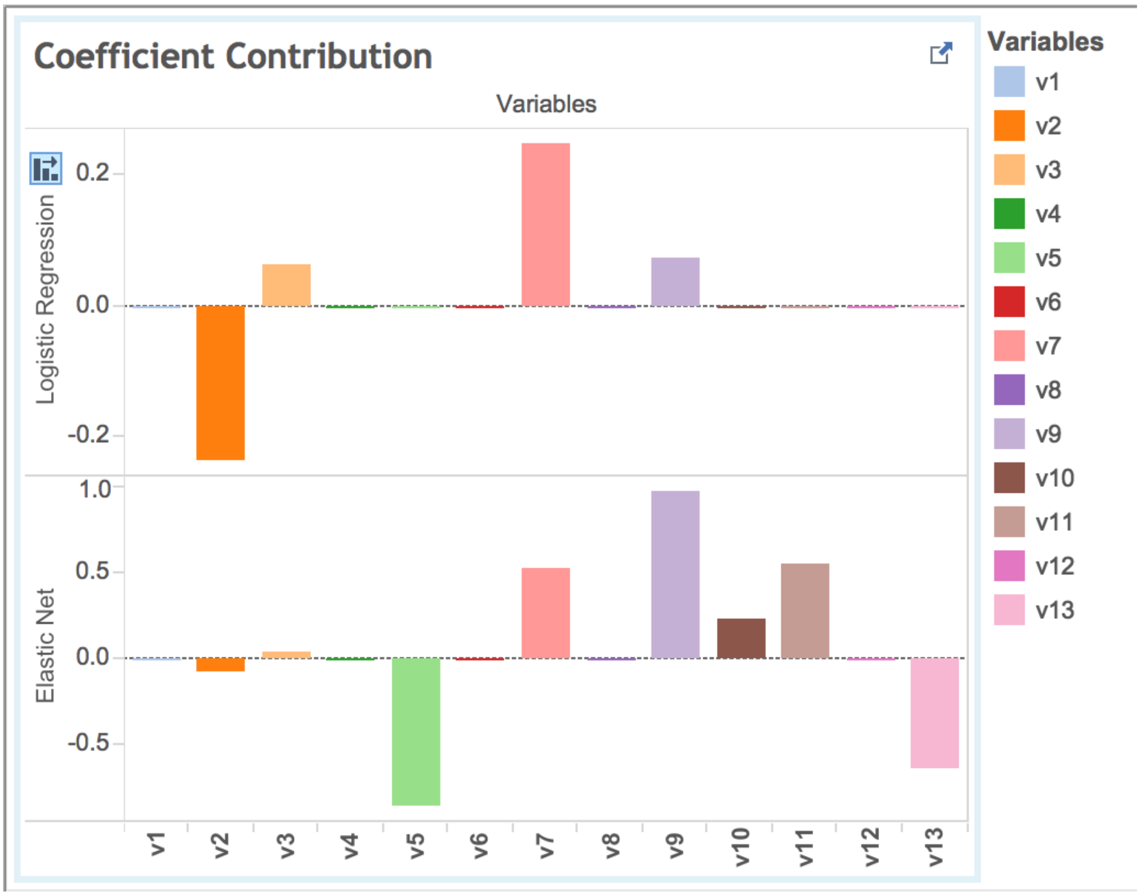


Figure 4: Coefficient contribution

This study is more focused on identifying contributing behavioral change indicators rather than identifying best model for prediction purpose. In sum, there are main four statistically significant contributing predictors (v2,v3,v7,v9) and four other supplementary predictors (v5,v10,v11,v13) which contribute to results of stress test. Interpretation of these contributing variables from business perspective is listed below:

Change in the risk profile of the bank (v2): It includes reducing the level of risk of its underlying exposures and consequently the portfolio level average risk weights. This is possible by way of shifting into higher credit quality exposures and particular those with either higher ratings by the External Credit Rating Agencies, lower internally estimated Probabilities of Default (PD) or lower Loss Given Default (LGD).

Deleveraging of the non-performing portfolio and overall deleveraging (v3, v7): This finding is supportive of the need for implementation of appropriate balance sheet management and repair strategies prior to the stress testing exercise by those banks facing potential solvency challenges.

Flight to quality (v9): It includes changing the treatment of the sovereign exposures; particularly the proportion of the sovereign exposures under the standardized approach to total sovereign exposures. It strongly indicates to inability of the supervisory stress testing to act as a constraint to the optimization of risk weighted assets. In particular, the results indicate that banks can essentially pass the supervisory stress testing by moving their sovereign exposures from the Internal Rating Based Approach (IRBA) to the Standardized Approach (SA).

Change in the structure and risk profile of the credit portfolio (v5): This is possible through implementation of specific strategies that would result in the reduction of the banks overall RWAs; particularly; 1. rebalancing portfolio with the aim of reducing the risk profile, 2. change in the approach to calculation of RWA including potential rollout of RWA optimization strategies such as reverting to the standardized approach for exposures to sovereign entities which reduces RWAs to zero.

Change in overall balance sheet management resulting in changes in the provision level (v11): This could be possible through implementation of debt restructuring strategies. The potential debt restructuring strategies may include loan modification arrangements such as: term extensions, split the mortgages, voluntary surrenders, interest only facilities, etc.

Changes in securitization held within the banking Book (v12): This would be achieved mainly through disposal of securitization exposures within the banks balance sheet.

Raising the level of non-common equity capital (v14): Apart from raising common equity capital, banks opt to raise additional eligible capital in the form of either preference shares or corporate debt which give more security to investors because of higher preference over normal investors in worst case scenario of bankruptcy. In return of preferential status and security, investors invest in banks which raises non-common equity capital of the bank resulting in improved capital ratio.

Intercept: As intercept is large, it can be said that in presence of contributing behavioral changes in banks, starting position of the financial indicators is also equally important while making any financial decisions.

There are few known limitations of this study 1. Due to availability of data of only 63 banks which participated in 2013 transparency exercise, sample may not be completely random sample. 2. Due to small sample size, holdout validation is used which may cause variance. 3. H2O elastic net regression api does not support reporting of statistical confidence.

6 Conclusion and Future Work

Based on the results above, it can be concluded that, as there are at least four statistically significant behavioral change indicators that contribute towards the results of the supervisory stress test, we do not reject the null hypothesis, H0. It means, among the proposed financial behavioral change indicators, there are four statistically significant financial behavioral change indicators which contributes to the results of regulatory stress testing conducted in EU in 2014. The result points toward: (i) the potential incentive for supervisory bodies to focus on setting supervisory strategies that would drive banks to adopt the behavioral changes that are strong contributors to banks passing the stress testing as a way of improving the resilience of the individual banks and the overall financial sector to financial or economic shocks, and (ii) the need for more scrutiny on banks with the aim of identifying instances of Risk Weighted Assets (RWA) optimization which would result in the outcome of the stress testing exercise that are not fully reflective of the underlying risk.

Further this study can be extended to (i) analysis based on more granular data including those that were not available for this review as the analysis was based purely on publicly available data, (ii) comparison of behavioral changes across jurisdiction including comparison of the outcome for the EU banks versus US banks, (iii) supplementing the analysis through a questionnaire to be filled by the individual banks with the aim of further understanding the identified behavioral changes and (iv) implementation of centralized banking behavior change monitoring system which updates itself regularly with public/transparency data to help regulatory bodies to keep an eye on overall financial system for more resilient Tomorrow.

Acknowledgements

I would like to thank Prof. Oisin Creaner and Prof. Vikas Sahni for academic guidance and Ms. Ellen Burke and Mr. Henry Francis King for industrial guidance during the project. Also, I would like to thank domain experts Mr. Leonard Chumo from Central Bank of Ireland and Prof. Joe Naughton for providing me needed domain information and expert opinions throughout this project. I offer my gratitude to all of them by saying "Guru Brahma Guru Vishnu Guru Devo Maheshwara. Guru Sakshath Parambrahma Tasmai Shri Gurave Namaha."

References

Allison, P. D. (2008). Convergence failures in logistic regression, *SAS Global Forum*, Vol. 360, pp. 1–11.

Azevedo, A. I. R. L. and Santos, M. F. (2008). Kdd, semma and crisp-dm: a parallel overview., *ISCAP - Informtica - Comunicaes em eventos cientficos* pp. 182–185.
URL: *http://recipp.ipp.pt/bitstream/10400.22/136/1/KDD-CRISP-SEMMA.pdf*

Chao-Ying, J., Kuk, L. L. and Ingersoll, G. M. (2002). An introduction to logistic regression analysis and reporting, *The Journal of Educational Research* **96**(1): 3–14.
URL: *https://ezproxy.ncirl.ie/login?url=http://search.proquest.com/docview/204193914?accountid=103381*

Cihak, M. (2007). Introduction to applied stress testing, *IMF Working Paper* **07**(59).
URL: *https://www.imf.org/external/pubs/ft/wp/2007/wp0759.pdf*

Dutta, A., Bandopadhyay, G. and Sengupta, S. (2012). Prediction of stock performance in the indian stock market using logistic regression, *International Journal of Business and Information* **7**(1): 105–136.
URL: *https://ezproxy.ncirl.ie/login?url=http://search.proquest.com/docview/1069238195?accountid=103381*

Frawley, W. J., Piatetsky-Shapiro, G. and Matheus, C. J. (1992). Knowledge discovery in databases: An overview, *Al Magazine* **13**(3): 57–70.
URL: *http://aaaipress.org/ojs/index.php/aimagazine/article/viewFile/1011/929*

Glasserman, P. and Tangirala, G. (2015). Are the federal reserves stress test results predictable?, *Office of Financial Research Working Paper Series* **15**(02).
URL: *https://financialresearch.gov/working-papers/files/OFRwp-2015-02-Are-the-Federal-Reserves-Stress-Test-Results-Predictable.pdf*

Hui, Z. and Hastie, T. (2005). Regularization and variable selection via the elastic net., *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* **67**(2): 301 – 320.

Keane, M. P. and Wolpin, K. I. (2007). Exploring the usefulness of a nonrandom holdout sample for model validation: Welfare effects on female behavior*, *International Economic Review* **48**(4): 1351–1378.
URL: *http://dx.doi.org/10.1111/j.1468-2354.2007.00465.x*

Kwak, W., Cheng, X., Ni, J., Shi, Y., Gong, G. and Yan, N. (2014). Bankruptcy prediction for chinese firms: Comparing data mining tools with logit analysis, *Journal of Modern Accounting and Auditing* **10**(10).

Landset, S., Khoshgoftaar, T. M., Richter, A. N. and Hasanin, T. (2015). A survey of open source tools for machine learning with big data in the hadoop ecosystem, *Journal of Big Data* **2**(1): 1–36.
URL: *http://dx.doi.org/10.1186/s40537-015-0032-1*

Marcelo, A., Rodrguez, A. and Trucharte, C. (2008). Stress tests and their contribution to financial stability, *Journal of Banking Regulation* **9**(2): 65–81.

Matloff, N. (2011). *The Art of R Programming: A Tour of Statistical Software Design*, 1st edn, No Starch Press, San Francisco, CA, USA.

Neretina, E., Sahin, C. and de Haan, J. (2015). Banking stress test effects on returns and risks, *DNB Working Paper* (419).
URL: *http://www.dnb.nl/binaries/Working%20Paper%20419_tcm46-306356.pdf*

Olson, D. L., Delen, D. and Meng, Y. (2012). Comparative analysis of data mining methods for bankruptcy prediction, *Decision Support Systems* **52**(2): 464 – 473.
URL: *http://www.sciencedirect.com/science/article/pii/S0167923611001709*

Pallant, J. (2007). *SPSS Survival Manual: A Step by Step Guide to Data Analysis Using SPSS for Windows Version 15*, 3rd edn, Open University Press, Milton Keynes, UK, USA.

Pore, P. (2016). Key indicators of behavioural changes in banks contributing to results of regulatory stress testing, *Research In Computing Module* pp. 1–15.

Salehi, M., Shiri, M. M. and Pasikhani, M. B. (2016). Predicting corporate financial distress using data mining techniques: An application in tehran stock exchange, *International Journal of Law and Management* **58**(2): 216–230.
URL: *http://dx.doi.org/10.1108/IJLMA-06-2015-0028*

Worrell, D. (2008). Stressing to breaking point: Interpreting stress test results, *IMF Working Paper* **8**(148).
URL: *https://www.imf.org/external/pubs/ft/wp/2008/wp08148.pdf*

Zaghdoudi, T. (2013). Bank failure prediction with logistic regression, *International Journal of Economics and Financial Issues* **3**(2): 537–543.
URL: *https://ezproxy.ncirl.ie/login?url=http://search.proquest.com/docview/1348551775?accountid=103381*

A EU Banks In Stratified Sample

	Bank Name	Country	Result
1	ABN AMRO Bank N.V.	Netherlands	Pass
2	Allied Irish Banks plc	Ireland	Pass
3	Alpha Bank	Greece	Pass
4	Banca Monte dei Paschi di Siena S.p.A.	Italy	Fail
5	Banco Bilbao Vizcaya Argentaria	Spain	Pass
6	Banco BPI	Portugal	Pass
7	Banco Comercial Portugus	Portugal	Fail
8	Banco Popolare - SocietC Cooperativa	Italy	Fail
9	Banco Popular EspaC1ol	Spain	Pass
10	Banco Santander	Spain	Pass
11	Bank of Cyprus Public Company Ltd	Cyprus	Fail
12	Bank of Valletta plc	Malta	Pass
13	Banque et Caisse d'Epargne de l'Etat	Luxembourg	Pass
14	Barclays plc	UK	Pass
15	Bayerische Landesbank	Germany	Pass
16	BNP Paribas	France	Pass
17	Caixa Geral de DepC3sitos	Portugal	Pass
18	Caja de Ahorros y Pensiones de Barcelona	Spain	Pass
19	Coperatieve Centrale Raiffeisen-Boerenleenbank B.A.	Netherlands	Pass
20	Commerzbank AG	Germany	Pass
21	Danske Bank	Denmark	Pass
22	DekaBank Deutsche Girozentrale	Germany	Pass
23	Deutsche Bank AG	Germany	Pass
24	DNB Bank Group	Norway	Pass
25	DZ Bank AG Deutsche Zentral-Genossenschaftsbank	Germany	Pass
26	Erste Group Bank AG	Austria	Pass
27	Eurobank Ergasias	Greece	Fail
28	Groupe BPCE	France	Pass
29	Groupe Crdit Agricole	France	Pass
30	HSBC Holdings plc	UK	Pass
31	HSH Nordbank AG	Germany	Pass
32	Hypo Real Estate Holding AG	Germany	Pass
33	ING Bank N.V.	Netherlands	Pass

Table 2: EU Banks In Stratified Sample

	Bank Name	Country	Result
34	Intesa Sanpaolo S.p.A.	Italy	Pass
35	Jyske Bank	Denmark	Pass
36	KBC Group NV	Belgium	Pass
37	Landesbank Baden-Wrttemberg	Germany	Pass
38	Landesbank Berlin Holding AG	Germany	Pass
39	Landesbank Hessen-Thringen Girozentrale	Germany	Pass
40	Lloyds Banking Group plc	UK	Pass
41	National Bank of Greece	Greece	Fail
42	Norddeutsche Landesbank-Girozentrale	Germany	Pass
43	Nordea Bank AB (publ)	Sweden	Pass
44	Nova Kreditna Banka Maribor d.d.	Slovenia	Fail
45	Nova Ljubljanska banka d. d.	Slovenia	Fail
46	Nykredit	Denmark	Pass
47	OP-Pohjola Group	Finland	Pass
48	OTP Bank Ltd	Hungary	Pass
49	Permanent tsb plc.	Ireland	Fail
50	Piraeus Bank	Greece	Fail
51	POWSZECHNA KASA OSZCZEDNOSCI BANK	Poland	Pass
52	Raiffeisen Zentralbank Csterreich AG	Austria	Pass
53	Royal Bank of Scotland Group plc	UK	Pass
54	Skandinaviska Enskilda Banken AB (publ) (SEB)	Sweden	Pass
55	SNS Bank N.V.	Netherlands	Pass
56	Socit Gnrale	France	Pass
57	Svenska Handelsbanken AB (publ)	Sweden	Pass
58	Swedbank AB (publ)	Sweden	Pass
59	Sydbank	Denmark	Pass
60	The Governor and Company of the Bank of Ireland	Ireland	Pass
61	UniCredit S.p.A.	Italy	Pass
62	Unione Di Banche Italiane SocietC Cooperativa Per Azioni	Italy	Pass
63	WGZ Bank AG Westdeutsche Genossenschafts-Zentralbank	Germany	Pass

Table 3: EU Banks In Stratified Sample

B Sample Breakdown By Jurisdiction And Outcome

Jurisdiction	Total Banks Failed	Total Banks Passed	Total Banks In Sample
Austria	-	2	2
Belgium	-	1	1
Cyprus	1	-	1
Denmark	-	4	4
Finland	-	1	1
France	-	4	4
Germany	-	12	12
Greece	3	1	4
Hungary	-	1	1
Ireland	1	2	3
Italy	2	3	5
Luxembourg	-	1	1
Malta	-	1	1
Netherlands	-	4	4
Norway	-	1	1
Poland	-	1	1
Portugal	1	2	3
Slovenia	2	-	2
Spain	-	4	4
Sweden	-	4	4
UK	-	4	4
Total	10	53	63

Table 4: Breakdown of the sample by Jurisdiction and Outcome

C Total Population And Selected Sample Breakdown By Pass/Fail

	Passed Cases	Failed Cases	Total Cases	% of Failed Cases
Total Population	99	24	123	20%
Selected Sample	53	10	63	16%
Sample (%)	54%	42%	51%	

Table 5: Total Population And Selected Sample Breakdown By Pass/Fail

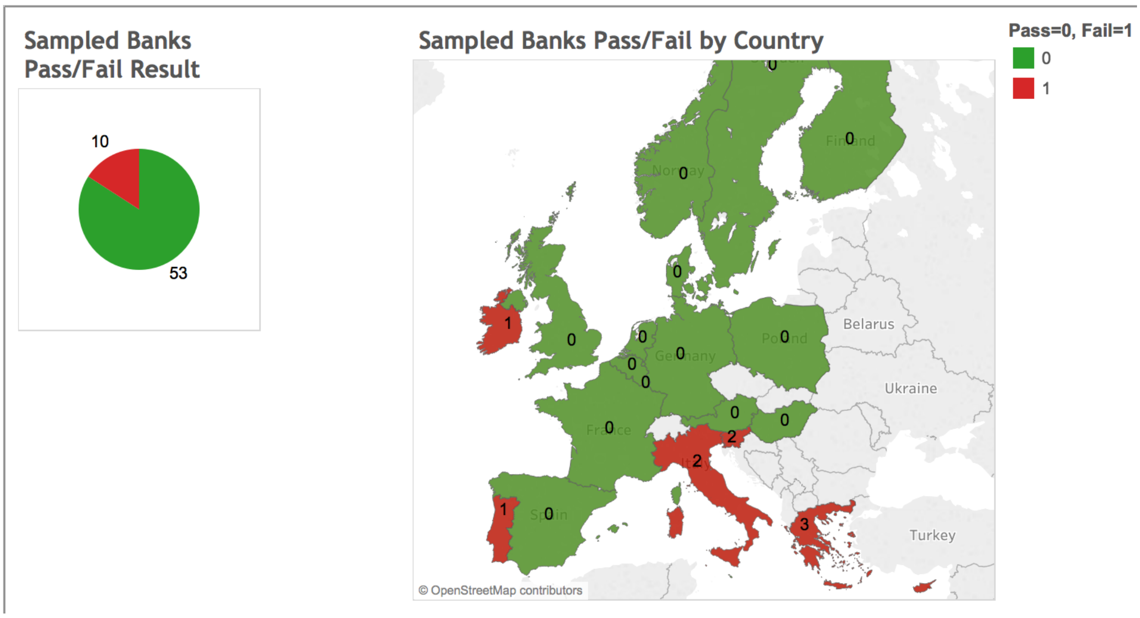


Figure 5: Breakdown of the sample by Jurisdiction and Outcome

D Proposed Indicators Of Banking Behavioural Change

Variable name: v1
Behavioral property: Raising of new common equity capital
Details: Year-on-year change in common equity
Comments: The general expectation is that banks with weak capita position will proactively raise new capital in anticipation of the supervisory stress test. The aim here being to ensure that it meets the set minimum capital threshold under the base and stress scenarios. We therefore expect banks that raise capital in the year leading to the supervisory stress test to have a much higher likelihood of passing the stress test that those that did not raise any additional new common equity.

Variable name: v2
Behavioral property: Change in the risk profile of the bank
Details: Year-on-year change in RWAs
Comments: The other option for banks to improve their solvency position in anticipation of the supervisory stress testing is to reduce the total Risk Weighted Assets (RWAs) of their exposures resulting in increase in the reported capital buffer.

Variable name: v3
Behavioral property: Deleveraging of the non-performing portfolio
Details:Year-on-year change in the level of exposure at default (non-performing)
Comments: The general expectation is that as part of initiative to improve their risk profile banks which are of the view that they are likely to fail the stress testing exercise would implement specific portfolio or balance sheet de-leveraging strategies. This could involve disposal of distressed exposures or assets.

Variable name: v4
Behavioral property: Reduction in the risk profile and/or exposure to securitization
Details: Year-on-year change in RWAs Securitization and re-securitizations
Comments: Our general expectation, is that banks with thin capital margin and holding securitization within their balance sheet would have significant incentives to reduce the holdings of securitization exposures to free up additional capital in anticipation of upcoming supervisory stress testing.

Variable name: v5
Behavioral property: Change in the structure and risk profile of the credit portfolio
Details: Year-on-year change in the average risk weight (RWA t/EAD t)
Comments: To improve the solvency ratio and the potential impact of the supervisory prescribed stress test shock, we would expect banks at risk of failing the supervisory stress test to implement strategies aimed at reducing their portfolio level risk weighted assets.

Variable name: v6
Behavioral property: Reduction in the overall level of trading activities
Details: Year-on-year changes in the market RWA
Comments: The general expectation is that banks at risk of failing the stress test would opt to carry out less trading activities leading up to the time of the supervisory stress

testing. The indicator of this behavioral change would be a reduction in the RWAs being held for market risk.

Variable name: v7
Behavioral property: Overall deleveraging
Details: Year-on-year changes in total exposures
Comments: The general expectation is that banks with thin capital margin prior to the stress test cut-off date would implement deleveraging strategies aimed in reducing the overall RWAs.

Variable name: v8
Behavioral property: Flight to quality
Details:
Difference in the total exposure to sovereign
Comments: One way the banks could reduce RWAs and improve their solvency position in anticipation of the stress testing exercise would be to shift the portfolio from high credit risk asses to high quality assets and particularly to exposures with sovereign entities and central banks.

Variable name: v9
Behavioral property: Changes in Pillar 1 treatment of exposures to sovereign
Details: Changes in the proportion of the sovereign under the Standardized Approach (SA)
Comments: The expectation is that banks at risk of failing the supervisory stress testing exercise will adopt specific strategies aimed at increasing the sovereign exposures under the standardized approach or at reducing the sovereign exposures under the internal rating based approaches so as to take advantage of the regulatory provisions which allows banks to assign risk weigh of zero to member state sovereign under the standardized approach.

Variable name: v10
Behavioral property: Change in overall balance sheet management resulting in changes in the provision level
Details: % change in Value adjustments and provisions
Comments: The expectation is that banks at risk of failing the supervisory stress testing exercise will implement debt restructuring arrangement with their defaulted customer with the objective of minimizing the overall losses and consequently reducing the expected level of loan loss provisions to be held. This behavioral change should be reflected in the reduction in the level of provisions for exposures in default.

Variable name: v11
Behavioral property: Changes in securitization held within the banking Book
Details: Year-on-year change in the level of Securitization
Comments: The expectation is that banks at risk of failing the supervisory stress test would implement strategies aimed at reducing the level of securitisation assets held within their banking book.

Variable name: v12
Behavioral property: Changes in securitization held within the trading portfolio
Details: Year-on-year change in the level of Securitization within the trading book
Comments: Similar to the above, we expect banks at risk of failing the supervisory stress test to implement strategies that would result in the reduction of the securitization within their trading portfolio.

Variable name: v13
Behavioral property: Raising of non-common equity capital
Details: Tier 1 Capital (Total original own funds for general solvency purposes) - Common equity
Comments: Apart from raising common equity capital, banks at risk of failing the stress test are expected to , in some instance, opt to raise additional eligible capital in from of either preference shares or corporate debt in addition to raising of capital through common equity (or rather than through common equity).

E Data Source, File Names And Description

2014 EU-wide stress test results data source
URL: http://www.eba.europa.eu/risk-analysis-and-data/eu-wide-stress-testing/2014/results

Local File name: <Project Dir>/data/2013/Data dictionary.xlsx
Description: This file contains description of all fields and filter criteria used in Credit_risk.csv file and Other_templates.csv file.

Local File name: <Project Dir>/data/2013/Metadata.xlsx
Description: This file contains meta-data about the fields used.

Local File name: <Project Dir>/data/2013/Credit_risk.csv
Description: This file contains all financial indicators of category Credit Risk, of 123 banks, published as part of 2014 EU Stress Test results.

Local File name: <Project Dir>/data/2013/Other_templates_v2.csv
Description: This file contains all other financial indicators of categories other than Credit Risk, of 123 banks, published as part of 2014 EU Stress Test results.

2013 EU-wide transparency exercise data source
URL: http://www.eba.europa.eu/risk-analysis-and-data/eu-wide-transparency-exercise/2013

Local File name: <Project Dir>/data/2012/Data_dictionary.xls
Description: This file contains description of all fields and filter criteria used in EBA_DISCLOSURE_EXERCISE_2013.csv file. It also contains meta-data about the fields used.

Local File name: <Project Dir>/data/2012/EBA_DISCLOSURE_EXERCISE_2013.csv
Description: This file contains all financial indicators of 63 banks collected during 2013 transparency exercise.

2014 and 2013 data mapping file
Local File name: <Project Dir>/data/BankNamesMapping.csv
Description: This file contains mapping of bank names, LEI code, country code from 2014 stress test results and bank names, bank code, and country code from 2013 transparency exercise.

F Transparency Exercise 2013 and Stress Test 2014 data field mapping

	2013 Field Id	2014 Field Id	Details
v1	100300	993402	
v2	100900	993107	
v3	400000	992902	filter by status 2, exposure 0 for both
v4	200101	993102	
v5	v2/v3	v2/v3	
v6	200300	993104	
v7	400000	992902	filter by status 1+2, exposure 0 filter for both
v8	400000	992902	filter by exposure 1, portfolio 1+3+4
v9	400000	992902	filter by exposure 1 and portfolio 1, portfolio 1+3+4
v10	401100	992904	filter by exposure 0, status 1+2, portfolio 1+3+4
v11	700100	993201	
v12	700200+700300	993202+993203	
v13	100800-100300	993432-993402	

Table 6: Transparency Exercise 2013 and Stress Test 2014 data field mapping

G Correlation matrix

Table 7 is a correlation matrix of all predictor variables considered in this analysis. The cells in red color indicates presence of potential multicollinearity problem.

	v1	v2	v3	v4	v5	v6	v7	v8	v9	v10	v11	v12
v1	1											
v2	-0.04	1										
v3	-0.58	0.25	1									
v4	0.05	0.28	0.12	1								
v5	0.25	0.22	-0.73	0.01	1							
v6	-0.89	0.1	0.72	-0.05	-0.3	1						
v7	0.22	0.46	0.25	-0.03	-0.03	-0.03	1					
v8	-0.38	-0.2	0.19	-0.11	-0.2	0.38	-0.04	1				
v9	-0.25	-0.04	0.12	-0.09	-0.06	0.28	0.05	0.68	1			
v10	0.04	0.25	0.4	0.12	-0.4	0.1	0.26	0.02	0.08	1		
v11	0.05	-0.1	0.03	0.1	-0.09	0.01	-0.08	0.08	0.07	-0.03	1	
v12	0.01	-0.05	0.03	-0.11	-0.07	0.01	-0.07	-0.03	0.00	0.17	0.03	1
v13	-0.04	0.24	-0.22	0.35	0.28	-0.15	-0.21	-0.01	-0.05	-0.05	-0.16	-0.06

Table 7: Correlation matrix

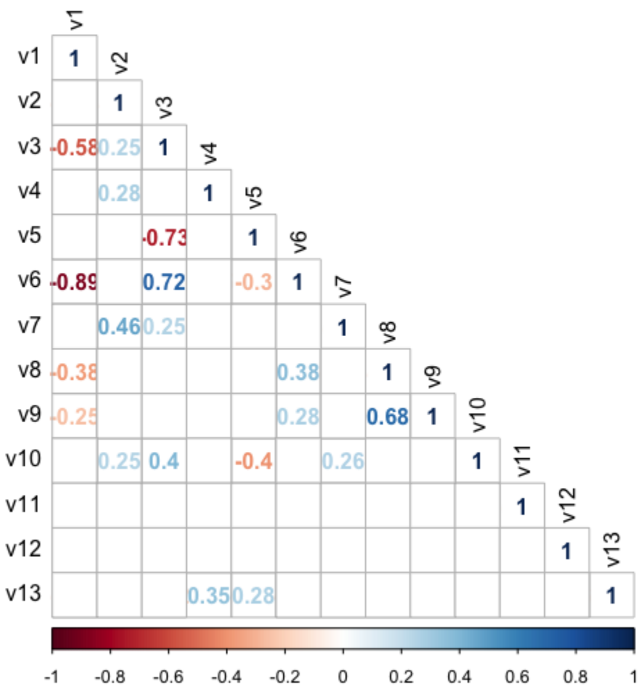


Figure 6: Statistically significant correlation matrix, sig. level p<0.05

H Logistic regression output after removing problematic pre-dictors

Listing 1: R output

```
Call:
glm(formula = t_pass_overall ~ v1 + v2 + v3 + v4 + v6 + v7 +
    v8 + v9 + v10 + v12, family = binomial((link = "logit")),
    data = df_train, maxit = 100)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-1.58137  -0.23674  -0.04257  -0.00247   2.09600

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -5.806008   2.971641  -1.954   0.0507 .
v1           0.040483   0.038184   1.060   0.2890
v2          -0.281605   0.149944  -1.878   0.0604 .
v3           0.114193   0.065758   1.737   0.0825 .
v4          -0.007266   0.006758  -1.075   0.2823
v6           0.001062   0.007172   0.148   0.8823
v7           0.180057   0.116466   1.546   0.1221
v8          -0.062030   0.039382  -1.575   0.1152
v9           0.097915   0.047519   2.061   0.0393 *
v10         -0.009908   0.024240  -0.409   0.6827
v12          0.002189   0.004414   0.496   0.6200
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 42.507  on 45  degrees of freedom
Residual deviance: 15.681  on 35  degrees of freedom
AIC: 37.681

Number of Fisher Scoring iterations: 8
```

I Stepwise regression output

Listing 2: R output

```
> step(glm.fit.null, scope=list(lower=glm.fit.null,
    upper=glm.fit.full), direction="forward")
Start:  AIC=44.51
t_pass_overall ~ 1

        Df Deviance    AIC
+ v3     1   35.587 39.587
+ v9     1   35.951 39.951
+ v8     1   38.401 42.401
+ v6     1   39.282 43.282
+ v7     1   39.285 43.285
+ v10    1   39.704 43.704
<none>       42.507 44.507
+ v1     1   41.023 45.023
+ v4     1   41.890 45.890
+ v2     1   42.498 46.498
+ v12    1   42.506 46.506

Step:  AIC=39.59
t_pass_overall ~ v3

        Df Deviance    AIC
+ v9     1   30.177 36.177
+ v8     1   32.802 38.802
+ v2     1   33.435 39.435
<none>       35.587 39.587
+ v4     1   33.870 39.870
+ v7     1   34.511 40.511
+ v1     1   34.850 40.850
+ v10    1   35.143 41.143
+ v6     1   35.584 41.584
+ v12    1   35.586 41.586
```

Listing 3: R output

```
Step:  AIC=36.18
t_pass_overall ~ v3 + v9

       Df Deviance    AIC
+ v2    1   26.893 34.893
<none>      30.177 36.177
+ v1    1   28.392 36.392
+ v4    1   28.415 36.415
+ v7    1   28.868 36.868
+ v10   1   29.513 37.513
+ v6    1   30.009 38.009
+ v8    1   30.162 38.162
+ v12   1   30.162 38.162

Step:  AIC=34.89
t_pass_overall ~ v3 + v9 + v2

       Df Deviance    AIC
+ v7    1   20.595 30.595
+ v4    1   24.332 34.332
+ v1    1   24.640 34.640
<none>      26.893 34.893
+ v8    1   25.713 35.713
+ v10   1   26.420 36.420
+ v6    1   26.422 36.423
+ v12   1   26.890 36.890

Step:  AIC=30.6
t_pass_overall ~ v3 + v9 + v2 + v7

       Df Deviance    AIC
+ v8    1   18.070 30.071
<none>      20.595 30.595
+ v4    1   19.982 31.982
+ v1    1   20.123 32.123
+ v10   1   20.348 32.348
+ v12   1   20.446 32.446
+ v6    1   20.595 32.595
```

Listing 4: R output

```
Step:   AIC=30.07
t_pass_overall ~ v3 + v9 + v2 + v7 + v8

       Df Deviance    AIC
<none>      18.070 30.071
+ v1    1   17.402 31.402
+ v4    1   17.419 31.419
+ v10   1   17.933 31.933
+ v12   1   17.959 31.960
+ v6    1   18.064 32.065

Call:  glm(formula = t_pass_overall ~ v3 + v9 + v2 + v7 + v8,
    family = binomial((link = "logit")),
    data = df_train, maxit = 100)

Coefficients:
(Intercept)           v3           v9           v2
v7          v8
   -3.92293      0.06418      0.07279     -0.23716
0.24825     -0.05009

Degrees of Freedom: 45 Total (i.e. Null);  40 Residual
Null Deviance:      42.51
Residual Deviance: 18.07        AIC: 30.07
```

J Logistic regression output

Listing 5: R output

```
Call:
glm(formula = t_pass_overall ~ v2 + v3 + v7 + v8 + v9,
    family = binomial((link = "logit")),
    data = df_train, maxit = 100)

Deviance Residuals:
     Min         1Q     Median         3Q        Max
-1.55065   -0.24605   -0.11639   -0.01591    2.14571

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -3.92293    1.48246  -2.646  0.00814 **
v2          -0.23716    0.09835  -2.411  0.01589 *
v3           0.06418    0.03099   2.071  0.03839 *
v7           0.24825    0.10569   2.349  0.01883 *
v8          -0.05009    0.03531  -1.419  0.15604
v9           0.07279    0.02994   2.431  0.01506 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 42.507  on 45  degrees of freedom
Residual deviance: 18.071  on 40  degrees of freedom
AIC: 30.071

Number of Fisher Scoring iterations: 7
```

Listing 6: R output

```
> pR2(tmodel)
          llh       llhNull            G2      McFadden
r2ML           r2CU
  -9.0352563  -21.2536978   24.4368830    0.5748854    0.4121224
0.6833388
#-----------------------------------------------------------------------

> anova(tmodel, test="Chisq")
Analysis of Deviance Table

Model: binomial, link: logit

Response: t_pass_overall

Terms added sequentially (first to last)


     Df Deviance Resid. Df Resid. Dev Pr(>Chi)
NULL                    45     42.507
v2    1   0.0094        44     42.498 0.922862
v3    1   9.0627        43     33.435 0.002609 **
v7    1   5.0079        42     28.427 0.025232 *
v8    1   1.4303        41     26.997 0.231714
v9    1   8.9266        40     18.071 0.002810 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#-----------------------------------------------------------------------

> hoslem.test(df_train$t_pass_overall, fitted(tmodel), g=10)

        Hosmer and Lemeshow goodness of fit (GOF) test

data:  df_train$t_pass_overall, fitted(tmodel)
X-squared = 3.1212, df = 8, p-value = 0.9265
#-----------------------------------------------------------------------

    FALSE TRUE
  0    15    0
  1     1    1
```

K Elastic net regression output

Listing 7: R output

```
> h2o.glm.tfit = h2o.glm(y = "t_pass_overall",
+ x = c("v1","v2","v3","v4","v5","v6","v7","v8","v9",
+ "v10","v11","v12","v13"),
+ training_frame = h2odf.train, family = "binomial",
+ nfolds = 0, seed = SEED_VALUE, link = "logit")
|=====================================================================| 100%
> print(h2o.glm.tfit)
Model Details:
==============
H2OBinomialModel: glm
Model ID:   GLM_model_R_1471654396257_13
GLM Model: summary
    family   link
    1        binomial
    regularization
    logit  Elastic Net (alpha = 0.5, lambda = 0.03205 )
    number_of_predictors_total
    13
    number_of_active_predictors  number_of_iterations
training_frame
    8                            7                             df_train
```

Listing 8: R output

```
Coefficients: glm coefficients
      names coefficients standardized_coefficients
1  Intercept    -3.227831                 -2.519552
2         v1     0.000000                  0.000000
3         v2    -0.005077                 -0.069571
4         v3     0.000694                  0.033972
5         v4     0.000000                  0.000000
6         v5    -0.032265                 -0.853458
7         v6     0.000000                  0.000000
8         v7     0.075186                  0.519851
9         v8     0.000000                  0.000000
10        v9     0.025184                  0.970304
11       v10     0.005327                  0.227685
12       v11     0.006281                  0.553140
13       v12     0.000000                  0.000000
14       v13    -0.014592                 -0.637787

H2OBinomialMetrics: glm
** Reported on training data. **

MSE:  0.05244892
R^2:  0.6349279
LogLoss:  0.1857637
Mean Per-Class Error:  0.07565789
AUC:  0.9769737
Gini:  0.9539474
Null Deviance:  42.5074
Residual Deviance:  17.09026
AIC:  35.09026
```

Listing 9: R output

```
Confusion Matrix for F1-optimal threshold:
        0 1    Error    Rate
0      37 1 0.026316  =1/38
1       1 7 0.125000   =1/8
Totals 38 8 0.043478  =2/46

Maximum Metrics: Maximum metrics at their respective thresholds
                        metric threshold    value idx
1                       max f1  0.353904 0.875000   7
2                       max f2  0.243679 0.888889  12
3                 max f0point5  0.562923 0.892857   4
4                 max accuracy  0.353904 0.956522   7
5                max precision  0.914585 1.000000   0
6                   max recall  0.243679 1.000000  12
7              max specificity  0.914585 1.000000   0
8             max absolute_MCC  0.353904 0.848684   7
9   max min_per_class_accuracy  0.353904 0.875000   7
10 max mean_per_class_accuracy  0.243679 0.934211  12

Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)`
    or `h2o.gainsLift(<model>, valid=<T/F>, xval=<T/F>)`

#-----------------------------------------------------------------

> h2o.confusionMatrix(tperf)
Confusion Matrix for max f1 @ threshold = 0.609399425584606:
        0 1    Error    Rate
0      14 1 0.066667  =1/15
1       0 2 0.000000   =0/2
Totals 14 3 0.058824  =1/17
```

L ROC curve comparison

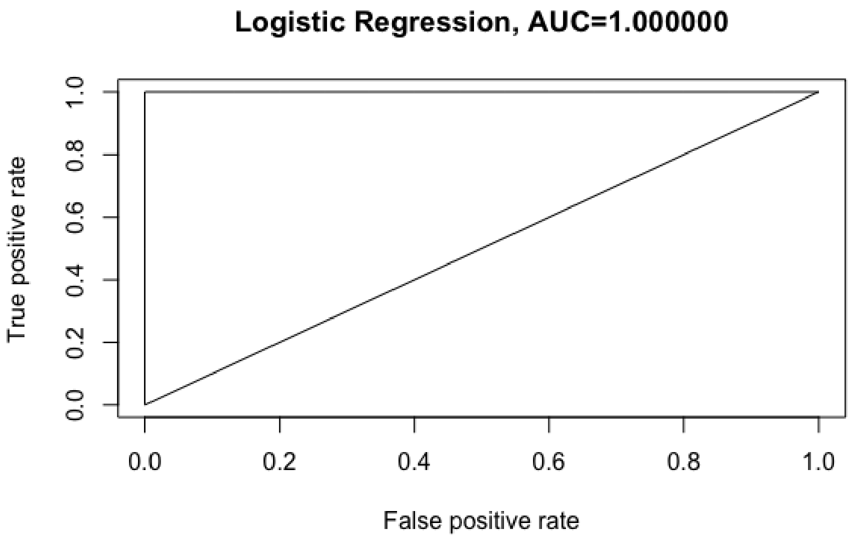


Figure 7: ROC curve for logistic regression

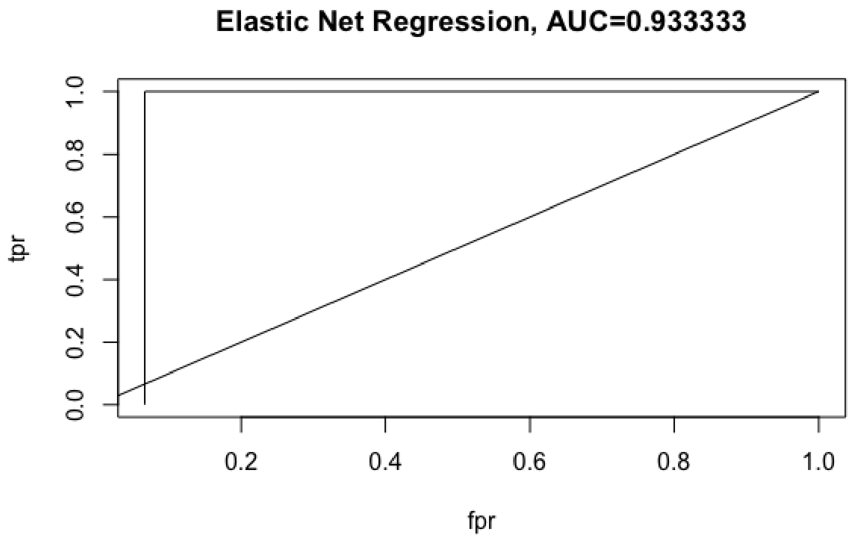


Figure 8: ROC curve for elastic net regression.

M Major contributing behaviours of banks to stress test results

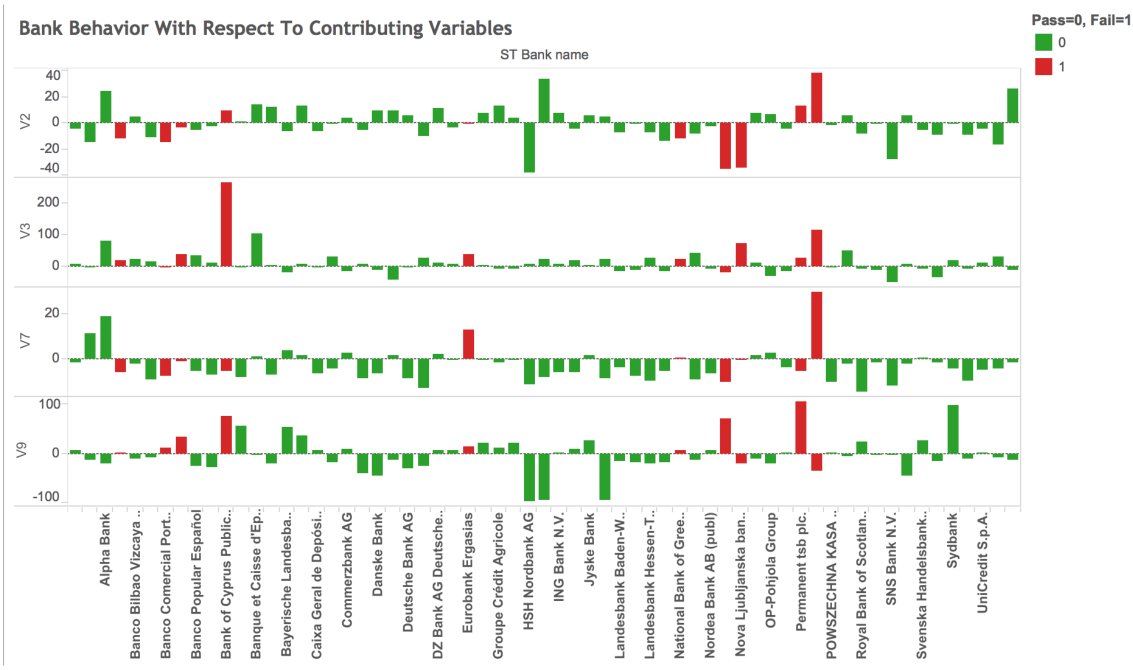


Figure 9: Major contributing behaviours of banks to stress test results

N Environment set up

Prerequisite: Following tools and softwares are prerequisites for this project.
1. Operating system: Windows/Linux/Mac
2. Analytics tools: R version 3.3.1
3. Integrated development environment (IDE): R Studio version 0.99.903
4. Third party api: H2O version 3.8.1.3 and other R packages listed in code.
5. Visualization tools: Tableau Desktop - Version 9.3.5

Project environment set up:
Step 1: Extract the x15006298.zip file to $HOME directory.
Step 2: Check following files are extracted successfully.

$HOME\MSCDA\
$HOME\MSCDA\DESCRIPTION
$HOME\MSCDA\NAMESPACE
$HOME\MSCDA\MSCDA.Rproj
$HOME\MSCDA\data
$HOME\MSCDA\output
$HOME\MSCDA\man
$HOME\MSCDA\MSCDA.twb
$HOME\MSCDA\R\
$HOME\MSCDA\R\common.R
$HOME\MSCDA\R\init.R
$HOME\MSCDA\R\constant.R
$HOME\MSCDA\R\main.R
$HOME\MSCDA\R\transparency_ex.R
$HOME\MSCDA\R\credit_risk.R
$HOME\MSCDA\R\model.R
$HOME\MSCDA\R\etl.R
$HOME\MSCDA\R\other_template.R
$HOME\MSCDA\data\BankNamesMapping$HOME
$HOME\MSCDA\data\2012
$HOME\MSCDA\data\2012 \Data_dictionary.xls
$HOME\MSCDA\data\2012 \EBA_DISCLOSURE_EXERCISE_2013$HOME
$HOME\MSCDA\data\2013
$HOME\MSCDA\data\2013 \CSV guide.pdf
$HOME\MSCDA\data\2013 \Data dictionary.xlsx
$HOME\MSCDA\data\2013 Other_templates_v2$HOME
$HOME\MSCDA\data\2013 Credit_risk$HOME
$HOME\MSCDA\data\2013 Metadata.xlsx

Step 3: Open R Studio
Step 4: Go to File menu -> Open Project
Step 5: Select MSCDA.Rproj file from $HOME\MSCDA directory
Step 6: Finish.

O Application execution procedure

Step 1: Verify all required packages from $HOME\MSCDA\R\init.R file.
Step 2: Install all required packages before running the application.
Step 3: Open main.R file from $HOME\MSCDA\R directory
Step 4: Go to Code menu -> Run Region -> Run All
Step 5: Wait till the end of execution.
Step 6: Open Tableau Desktop software
Step 7: Go to File menu -> Open
Step 8: Select MSCDA.twb file from $HOME\MSCDA directory
Step 8: Open Story Board - Story 1
Step 9: Click Presentation Mode
Step 10: Analyse the graphs from business perspective.
Step 11: Finish