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

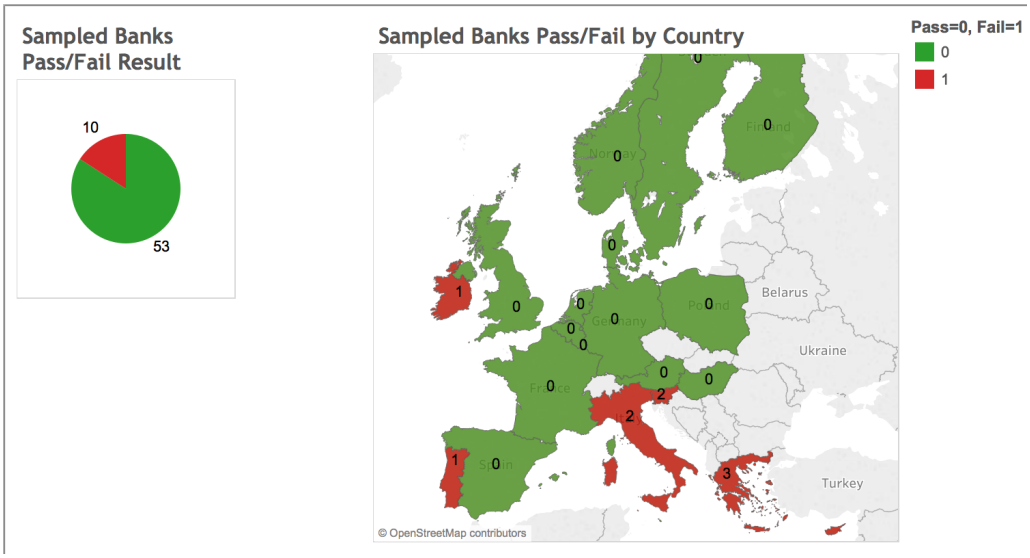

Figure 5: Breakdown of the sample by Jurisdiction and Outcome

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

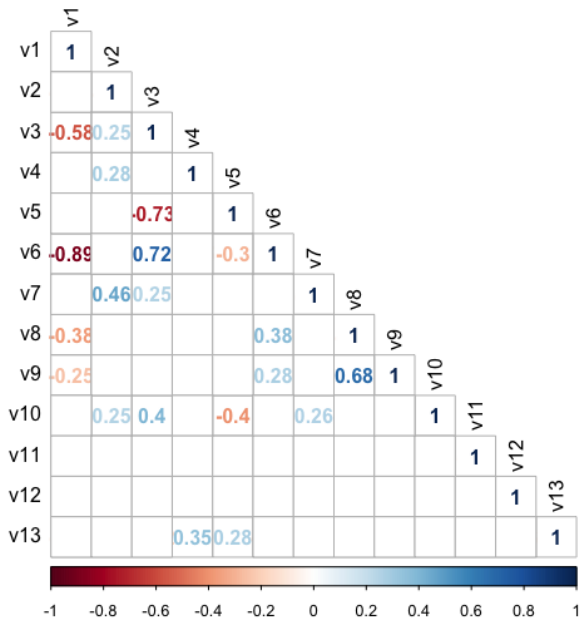

Figure 6: Statistically significant correlation matrix, sig. level p<0.05

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

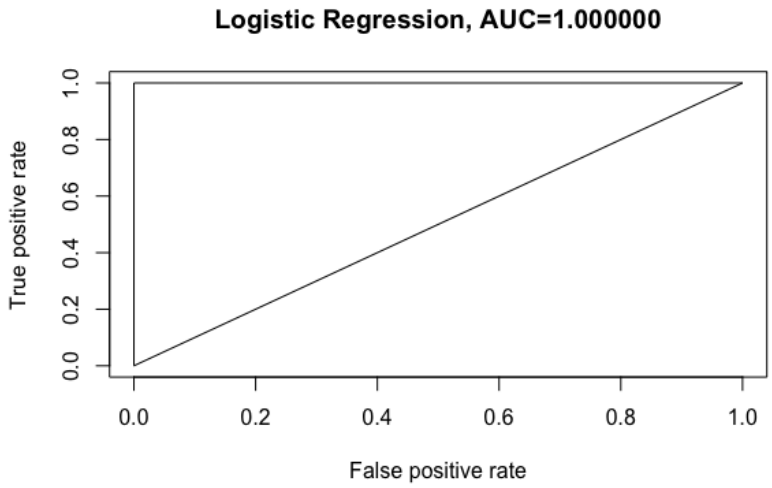

Figure 7: ROC curve for logistic regression

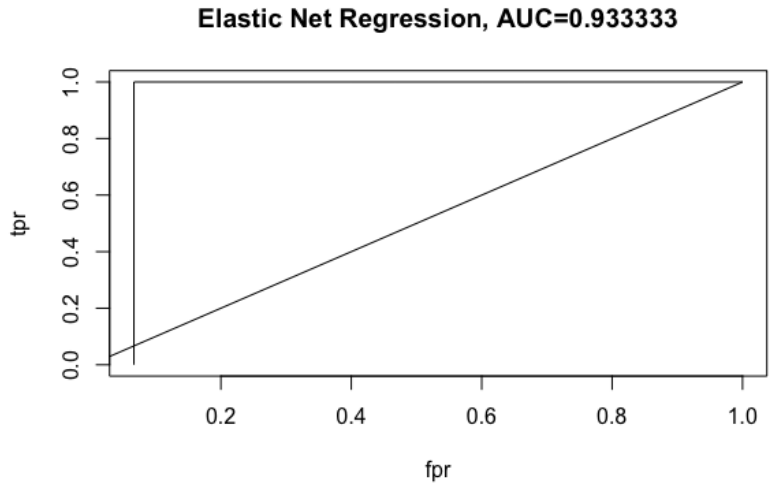

Figure 8: ROC curve for elastic net regression.

M Major contributing behaviours of banks to stress test results

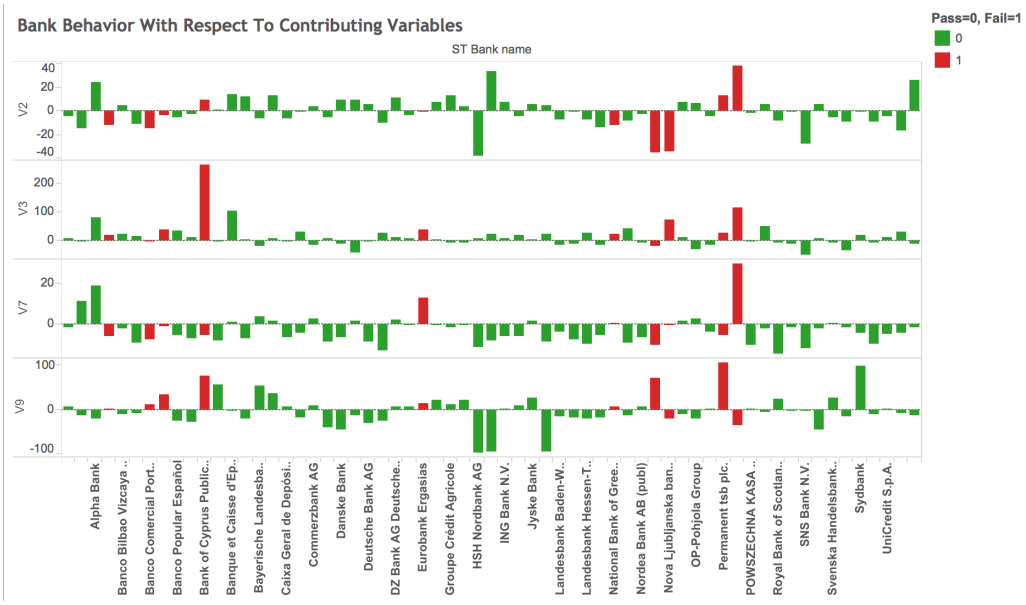

Figure 9: Major contributing behaviours of banks to stress test results

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