Report Project 3 – AI for Finance

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Goal

The primary objective of this project is to evaluate the performance of various AI models in predicting bank failures, with a focus on determining the key variables that possess leading information about systematic bank failures and identifying the most suitable forecast horizon.

To achieve this goal, the first step involves identifying the essential variables that have leading information about systematic bank failures. These variables will form the foundation of our predictive models, enabling them to accurately capture the factors contributing to the Systematic Bank Failure Index. Then, a range of AI models will be implemented to predict bank failures and assess their relative performance.

Data

```
Input dataset
 --> Start date: 1984-01-01
 --> End date: 2020-12-31
Dataset
```

obs	F/A_BANKS	FED	GDP	SP500STD	LDGDP	DELTAFED	XMRET	EBP	TERMSPREAD	DELTANIM	ROE	LLRR	PLL	ALL
1984Q2	0.001379691	11.06	7617.547	3.060281977	0.017130361	1.15	-3.85652	-0.137981731	3.335238095	3.87	10.57	1.18	-5.6	3.1
1984Q3	0.001310706	11.3	7690.985	3.070506517	0.009594462	0.24	2.78496	-0.027157524	2.522857143	3.91	11.11	1.2	45.2	7.4
1984Q4	0.001379691	8.38	7754.117	3.207636811	0.008175064	-2.92	2.72449	-0.124229303	2.95284153	3.95	10.56	1.24	-38.2	4.2
1985Q1	0.001942152	8.58	7829.26	3.955003816	0.009644069	0.2	8.15211	-0.096689749	3.405333333	3.97	12.31	1.29	44.7	7.3
1985Q2	0.002011514	7.53	7898.194	3.405234467	0.008766129	-1.05	4.51245	-0.131578425	3.331269841	4.04	12.05	1.35	0.0	5.1
2019Q4	0.0	1.55	19202.31	9.920249741	0.004680008	-0.49	3.58165	-0.241928387	0.20811828	3.31	11.38	1.15	253.0	59.5
2020Q1	0.000228571	0.65	18951.992	10.87337531	-0.01312154	-0.9	-1.2823	0.26688451	0.282096774	3.06	3.22	1.76	18.0	24.8
2020Q2	0.000228571	0.08	17258.205	12.1878153	-0.093621362	-0.57	-4.3565	0.368691016	0.545396825	2.89	3.21	2.19	-76.8	0.4
2020Q3	0.000228571	0.09	18560.774	11.58727628	0.072762747	0.01	14.42143	-0.148727808	0.5378125	2.88	5.31	2.22	-77.7	0.0
2020Q4	0.000228571	0.09	18767.778	12.9105337	0.011091034	0.0	8.96339	-0.391731046	0.772150538	2.82	6.88	2.18	-551.1	0.0

The given dataset comprises several dependent variables that are used for analyzing the stability of the banking sector. I have mapped each variable to a corresponding short notation for easier reference. Below is a brief description of each variable along with its respective notation:

- **INDEX (obs)**: This column represents the observation or time period, formatted as year and quarter (e.g., 1984Q1).
- **F/A_BANKS (Failed_to_Active_banks)**: This variable shows the ratio of the number of failed banks to the number of active banks.
- **FED (fed)**: This variable represents the Federal Reserve's discount rate, the interest rate at which banks can borrow money from the Federal Reserve.
- **GDP (gdp)**: This variable denotes the Gross Domestic Product (GDP), the total value of all goods and services produced within a country's borders in a specific time period.
- **SP500STD (sp500_dev)**: This variable represents the deviation of the S&P 500 index, a stock market index that measures the performance of 500 large companies listed on US stock exchanges.
- **LDGDP (ld_gdp)**: This variable is the log difference of real GDP..
- **DELTAFED (d_fedFunds_rate)**: This variable represents the change in the Federal Funds rate, the interest rate at which banks lend and borrow funds from each other.
- **XMRET (XMRET)**: This variable represents the excess market return, which is the difference between the return on the S&P 500 index and the risk-free rate of return.
- **EBP (EBP)**: This variable shows the corporate bond credit spreads
- **TERMSPREAD (TERM_SPREAD)**: This variable represents the difference between the yields of long-term and short-term Treasury securities.
- **DELTANIM (Net Interest Margin for all Commercial Banks)**: This variable shows the net interest income of all commercial banks as a percentage of their interest-earning assets.
- **ROE (Return on Equity)**: This variable represents the return on equity for all U.S. banks.

- **LLRR (Loan Loss Reserve to Total Loans for all U.S. Banks; Percent)**: This variable represents the ratio of loan loss reserves to total loans held by all U.S. banks, expressed as a percentage.
- **PLL (Provision for Loan and Lease Losses; Percent Change)**: This variable represents the percentage change in the amount of money set aside by banks to cover loan and lease losses.
- **ALL (Allowance for Loan and Lease Losses; Percent Change, Quarterly)**: This variable represents the percentage change in the amount of money set aside by banks to cover potential losses on loans and leases.

Some combination of these variables will be utilized to train the AI models for predicting the Systematic Bank Failure Index.

Data Preparation

Frequency distribution

In this section, the frequency distribution of the systematic failure ratio (F/A_BANKS) is analyzed to better understand its distribution and characteristics. Based on the chosen number of quantiles and the dataset provided, the mean, standard deviation, and quantiles for the F/A_BANKS variable are the following

```
Systematic failure frequency distribution (F/A_BANKS)
Quantiles --> 3

 Mean --> 0.12445672653061225
 Standard Deviation --> 0.1496295072830503

Frequency Distribution
+---------------+-----------+-----------+--------------------+----------------------+
|               | Midpoint  | Frequency | Relative Frequency  | Cumulative Frequency |
+---------------+-----------+-----------+--------------------+----------------------+
|  0.0-0.1739   | 0.0869254 |   103.0   | 0.7006802721088435  |  0.7006802721088435  |
| 0.1739-0.3477 | 0.2607762 |   28.0    | 0.19047619047619047 |  0.891156462585034   |
|  0.3477-1.0   | 0.434627  |   16.0    | 0.10884353741496598 |         1.0          |
+---------------+-----------+-----------+--------------------+----------------------+
```

The results indicate that 70.07% of the observations fall within the first interval (0.0-0.1739), which suggests that in most periods, the ratio of failed banks to active banks is relatively low. This could be interpreted as a sign of a generally stable banking sector in those periods. The remaining 29.93% of the observations are distributed between the second and third intervals, indicating that there are periods with a higher ratio of failed banks, which may signal a more turbulent banking environment.

Based on the frequency distribution, separate datasets with a binary F/A_BANKS variable are prepared. For example, with three thresholds, three datasets are created, each having F/A_BANKS = 1 if the original F/A_BANKS value falls within the corresponding threshold.

Multicollinearity analysis

To analyze multicollinearity among the independent variables, both the correlation matrix and the Variance Inflation Factor (VIF) are calculated. The correlation matrix shows the linear relationship between pairs of variables, while the VIF measures the degree to which the variance of the estimated regression coefficients is increased due to multicollinearity.

The following metrics were used:

1. **Single predictor correlation with F/A_BANKS**: This measures the correlation of each individual predictor with the dependent variable, F/A_BANKS.

Single predictor correlation with F/A_BANKS

	('ALL',)	('LDGDP',)	('DELTAFED',)	('PLL',)	('XMRET',)	('DELTANIM',)	('EBP',)	('TERMSPREAD',)	('ROE',)	('LLRR',)
Correlation	0.0044	0.0187	0.022	0.0364	0.0531	0.1986	0.2214	0.3625	0.5128	0.7504

2. **VIF**: A measure of the multicollinearity of the predictors in a regression model. A VIF value greater than 5-10 may indicate high multicollinearity.
3. **Correlation** (for a combination): calculated as the average of the correlation matrix given by the predictors in each combination.
4. **Score**: A combined metric incorporating correlation and VIF, calculated as (Correlation * Correlation_weight) + (VIF * VIF_weight). The weight to give to correlation and VIF can be adjusted dynamically, the default value is 1 for both of them.

Top 20 Predictor Combination Ranking for Score(= Correlation * Correlation_weight) + (VIF * VIF_weight)

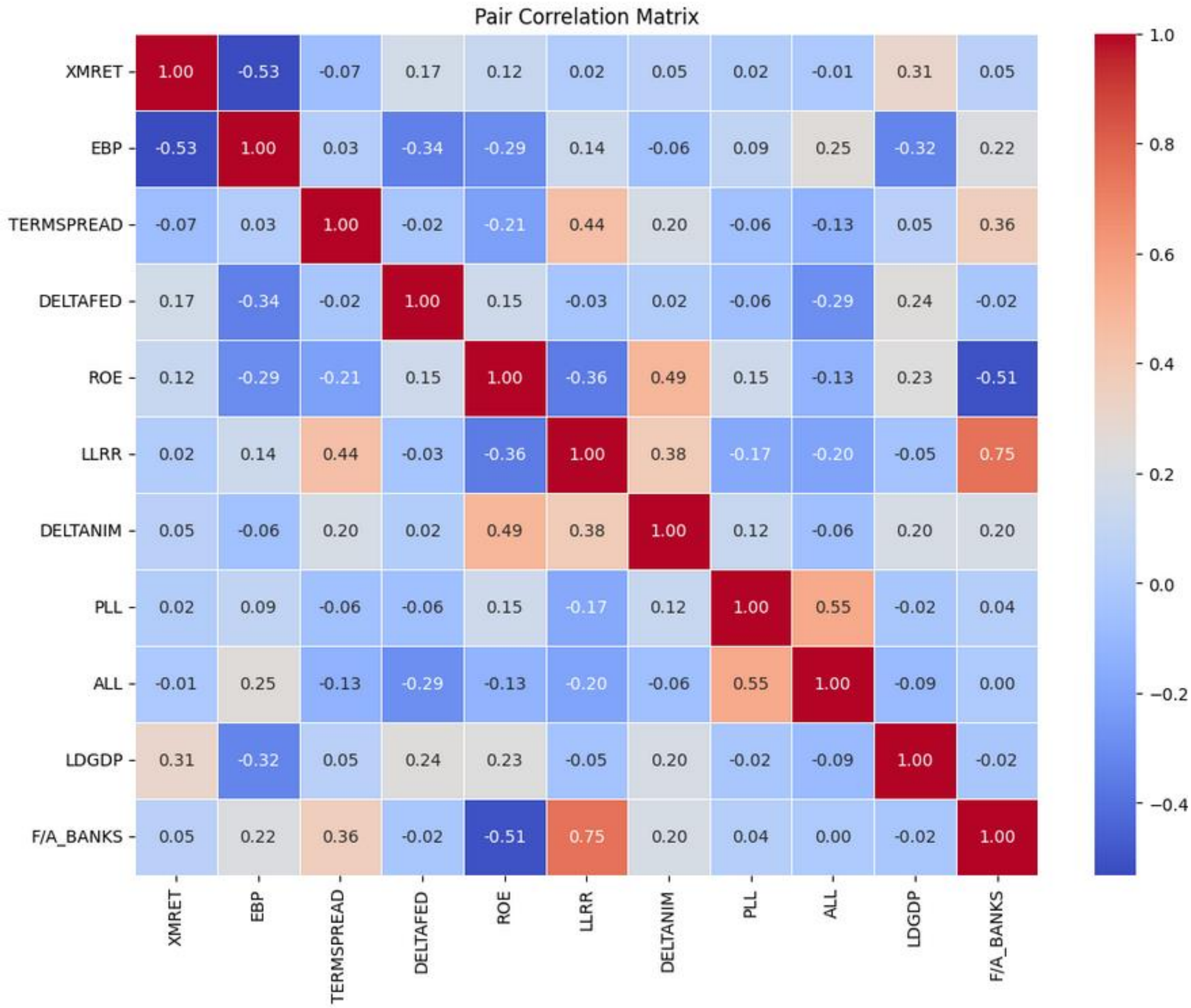
Combination	Len	Correlation	VIF	Score
('ALL', 'XMRET')	2.0	-0.009020549985640206	1.0059	1.0149205499856402
('LDGDP', 'PLL')	2.0	-0.017027360518554895	1.0	1.017027360518555
('PLL', 'XMRET')	2.0	0.023552571094607542	1.0013	1.0248525710946077
('EBP', 'PLL', 'ROE')	3.0	-0.019052527693685966	1.0109	1.0299525276936858
('DELTAFED', 'TERMSPREAD')	2.0	-0.01832384186935046	1.0133	1.0316238418693506
('EBP', 'PLL', 'TERMSPREAD')	3.0	0.018999459731443655	1.0169	1.0358994597314435
('DELTAFED', 'DELTANIM')	2.0	0.021876137031295047	1.0144	1.036276137031295
('DELTAFED', 'DELTANIM', 'PLL')	3.0	0.027158630375304943	1.0136	1.040758630375305
('EBP', 'LLRR', 'PLL')	3.0	0.017443030467268084	1.0262	1.0436430304672681
('EBP', 'TERMSPREAD')	2.0	0.026695828343597225	1.0171	1.043795828343597
('DELTAFED', 'LLRR')	2.0	-0.03358351771455686	1.0164	1.049983517714557
('PLL', 'TERMSPREAD')	2.0	-0.055150550045045384	1.0	1.0551505500450453
('DELTAFED', 'PLL', 'TERMSPREAD')	3.0	-0.04486535565606609	1.0117	1.0565653556560661
('DELTAFED', 'PLL', 'XMRET')	3.0	0.043781064384254866	1.0131	1.0568810643842548
('DELTAFED', 'PLL')	2.0	-0.061121675053802435	1.0043	1.0654216750538024
('DELTAFED', 'PLL', 'TERMSPREAD', 'XMRET')	4.0	-0.0024922210284891327	1.0639	1.0663922210284893
('DELTANIM', 'EBP', 'PLL')	3.0	0.04948889156923878	1.0173	1.066788891569239
('DELTANIM', 'EBP')	2.0	-0.057707855336484995	1.0165	1.0742078553364849
('DELTAFED', 'LDGDP', 'PLL')	3.0	0.05553631921401498	1.0194	1.0749363192140151
('PLL', 'TERMSPREAD', 'XMRET')	3.0	-0.034806702119913796	1.0523	1.087106702119914

Requested Scores

Combination	Len	Correlation	VIF	Score
('LLRR', 'ROE', 'TERMSPREAD')	3.0	-0.04281717366409108	5.3147	5.357517173664092

The predictor combinations were ranked according to their scores, wherein lower scores indicate less multicollinearity and possibly a more significant combination of predictors.

In addition, a pair correlation heatmap was created to visualize the relationships between variables. This heatmap shows the strength of the linear relationships between pairs of variables using color-coded values, with lighter colors indicating stronger positive correlations and darker colors indicating stronger negative correlations.



The pair correlation heatmap reveals the strength and direction of the relationships between the variables. Based on the heatmap, it may be possible to identify pairs of variables with high correlations, indicating that they may contain similar information and one of them could be dropped to reduce multicollinearity. For instance, if two variables have a high positive correlation, they could be providing similar information in the model, making one of them redundant. In contrast, variables with low correlations can be retained in the model, as they provide unique information and contribute to the model's predictive ability.

In conclusion, multicollinearity analysis can help in identifying which variables to include or exclude from the model to improve its performance and reduce potential issues arising from multicollinearity. Accordingly, to the results, I choose the top 20 variables combination as input for the models.

Analysis

Several AI and statistical models are employed to predict systematic bank failure. Here is a brief description of each model and the parameters used:

- Probit Model: A binary classification model that uses the cumulative distribution function of the standard normal distribution to model the probability of the dependent variable being 1.
- Logit Model: A binary classification model that uses the logistic function to model the probability of the dependent variable being 1.
- PNN (Perceptron Neural Network): A single-layer neural network with an identity activation function and the LBFGS solver for optimization.
- MLP (Multilayer Perceptron): A feedforward neural network with one hidden layer of 10 nodes and a ReLU activation function. The MLP is trained using the Adam optimizer.
- Random Forest: An ensemble learning method that constructs a multitude of decision trees at training time and outputs the class that is the mode of the classes of the individual trees.
- SVM (Support Vector Machine): A binary classification model that aims to find the best separating hyperplane between two classes. The data is first standardized using a StandardScaler, and then an SVM with a probability output is trained.
- Tree Ensemble (Gradient Boosting Classifier): An ensemble learning model that combines the predictions of multiple decision trees through a process called boosting. Gradient Boosting is a popular method for improving the performance of decision trees by focusing on areas where the model performs poorly.

For each of these models, various lags and thresholds are used to predict financial distress, allowing for a comprehensive comparison of their performance in different scenarios. This will help identify the best model or combination of models for predicting financial distress based on the given data.

The performance is evaluated using the Area Under the Receiver Operating Characteristic (AUROC) curve. The AUROC measures the ability of the model to discriminate between the two classes (financial distress vs. no financial distress). A higher AUROC value indicates better classification performance. Additionally, the R-squared value is reported for some models to provide an indication of the proportion of the variance in the dependent variable that is predictable from the independent variables.

Model performance

The table below presents the results of the training and evaluation of the models. The key column shows the combination of independent variables used, along with the threshold given by the frequency distribution of failed-to-active banks and the lag of the independent variables.

For some models, R-Squared is set manually to zero due to the specific algorithm used or the nature of the variables used.

Here are the top 30 models' performance, ordered by Auroc and R-squared. The columns 'Prd.Correlation' and 'Prd.VIF' are referred to the tuple inside each value of column 'Key'.

	Key	Model	Auroc	R-Squared	Prd.Correlation	Prd.VIF
0	(('LLRR', 'ROE', 'TERMSPREAD'), '0.0-17.3851', 1)	Random Forest	0.964286	0.000000	-0.042817	5.314700
1	(('LLRR', 'ROE', 'TERMSPREAD'), '17.3851-34.7702', 4)	Tree Ensemble	0.947832	0.000000	-0.042817	5.314700
2	(('LLRR', 'ROE', 'TERMSPREAD'), '17.3851-34.7702', 2)	Tree Ensemble	0.944444	0.000000	-0.042817	5.314700
3	(('LLRR', 'ROE', 'TERMSPREAD'), '17.3851-34.7702', 4)	Random Forest	0.935637	0.000000	-0.042817	5.314700
4	(('LLRR', 'ROE', 'TERMSPREAD'), '17.3851-34.7702', 3)	Random Forest	0.892857	0.000000	-0.042817	5.314700
5	(('EBP', 'LLRR', 'PLL'), '0.0-17.3851', 2)	Probit	0.889632	0.289622	0.017443	1.026200
6	(('EBP', 'PLL', 'ROE'), '0.0-17.3851', 4)	MLP	0.884615	0.337686	-0.019053	1.010900
7	(('LLRR', 'ROE', 'TERMSPREAD'), '17.3851-34.7702', 3)	Tree Ensemble	0.881746	0.000000	-0.042817	5.314700
8	(('EBP', 'LLRR', 'PLL'), '0.0-17.3851', 2)	Logit	0.881271	0.296306	0.017443	1.026200
9	(('EBP', 'LLRR', 'PLL'), '0.0-17.3851', 2)	PNN	0.881271	0.252906	0.017443	1.026200
10	(('LLRR', 'ROE', 'TERMSPREAD'), '0.0-17.3851', 1)	Tree Ensemble	0.876050	0.000000	-0.042817	5.314700
11	(('EBP', 'LLRR', 'PLL'), '0.0-17.3851', 2)	Random Forest	0.874582	0.000000	0.017443	1.026200
12	(('EBP', 'LLRR', 'PLL'), '0.0-17.3851', 2)	SVM	0.874582	0.000000	0.017443	1.026200
13	(('DELTAFED', 'LLRR'), '0.0-17.3851', 4)	MLP	0.872340	0.267558	-0.033584	1.016400
14	(('LLRR', 'ROE', 'TERMSPREAD'), '17.3851-34.7702', 4)	MLP	0.869919	0.357569	-0.042817	5.314700
15	(('LLRR', 'ROE', 'TERMSPREAD'), '0.0-17.3851', 1)	MLP	0.869748	0.388884	-0.042817	5.314700
16	(('LLRR', 'ROE', 'TERMSPREAD'), '17.3851-34.7702', 3)	MLP	0.868254	0.367022	-0.042817	5.314700
17	(('EBP', 'TERMSPREAD'), '17.3851-34.7702', 4)	MLP	0.863144	0.308013	0.026696	1.017100
18	(('LLRR', 'ROE', 'TERMSPREAD'), '0.0-17.3851', 1)	PNN	0.861345	0.402120	-0.042817	5.314700
19	(('LLRR', 'ROE', 'TERMSPREAD'), '0.0-17.3851', 1)	Logit	0.861345	0.355698	-0.042817	5.314700
20	(('EBP', 'LLRR', 'PLL'), '0.0-17.3851', 2)	Tree Ensemble	0.857860	0.000000	0.017443	1.026200
21	(('DELTAFED', 'LLRR'), '0.0-17.3851', 2)	Probit	0.856187	0.220559	-0.033584	1.016400
22	(('EBP', 'PLL', 'ROE'), '0.0-17.3851', 2)	MLP	0.856061	0.317626	-0.019053	1.010900
23	(('DELTAFED', 'LLRR'), '0.0-17.3851', 2)	PNN	0.854515	0.307616	-0.033584	1.016400
24	(('DELTAFED', 'LLRR'), '0.0-17.3851', 2)	Logit	0.854515	0.227635	-0.033584	1.016400
25	(('LLRR', 'ROE', 'TERMSPREAD'), '0.0-17.3851', 1)	Probit	0.854342	0.359391	-0.042817	5.314700
26	(('EBP', 'PLL', 'ROE'), '0.0-17.3851', 3)	PNN	0.846053	0.322287	-0.019053	1.010900
27	(('EBP', 'PLL', 'ROE'), '0.0-17.3851', 3)	Logit	0.846053	0.235964	-0.019053	1.010900
28	(('DELTANIM', 'EBP'), '17.3851-34.7702', 4)	MLP	0.845455	0.207576	-0.057708	1.016500
29	(('EBP', 'PLL', 'ROE'), '0.0-17.3851', 3)	Probit	0.844737	0.242135	-0.019053	1.010900
30	(('EBP', 'PLL', 'ROE'), '0.0-17.3851', 3)	Random Forest	0.843421	0.000000	-0.019053	1.010900
31	(('DELTAFED', 'LLRR'), '0.0-17.3851', 1)	MLP	0.842105	0.391371	-0.033584	1.016400

The Random Forest model (Row 0) has the highest AUROC value (0.964286) among all the models. This indicates that it performed the best in terms of distinguishing between failed and active banks. However, it is important to note that the R-squared value for this model is set to 0, which indicates that it has not been assessed in terms of the proportion of variance in the dependent variable explained by the independent variables.

The correlation values are generally low or negative, suggesting that there isn't a strong linear relationship between the variables of the combinations used. The VIF values for models using the combination of independent variables ('LLRR', 'ROE', 'TERMSPREAD') are consistently higher than those using other combinations. High VIF values indicate potential multicollinearity issues, which can affect the stability and interpretability of the models. In contrast, models using the combination ('EBP', 'LLRR', 'PLL') have lower VIF values, indicating less multicollinearity.

There were noticeable differences in the performance of the models when comparing AUROC, R-Squared, and other metrics. The models' performance varied significantly across the range intervals and combinations of independent variables. This suggests that certain model specifications may be more suited to specific data subsets or relationships among variables.

The combination of rows 0, 5, 6, and 26 represents the top-scoring models for each of the lags in the threshold range 0.0-17.3851. These models provide the best predictive performance across different time lags, allowing for more accurate forecasting in this specific threshold range.

For each lag, the best prediction models and the most significant variable(s) contributing to each model, based on p-values are the following.

- **Lag 1**:

  Random Forest, with an Auroc score of 0.964286 that indicates strong classification performance. It relies heavily on LLRR, ROE, and TERMSPREAD, which have very low p-values (0.000010, 0.000010, and 0.000303 respectively), indicating strong statistical significance. These variables, with very low p-values, suggest that past values of the long-term liquidity risk ratio (LLRR), return on equity (ROE), and term spread are important predictors for the systematic bank failure rate.

- **Lag 2**:

  Probit, with an Auroc score of 0.889632 and an R-Squared value of 0.289622, signifying good classification ability and a moderate linear relationship between predicted and observed values. The Probit model's primary contributing variable is LLRR, with a p-value of 0.000002, denoting a highly significant relationship with the outcome.

- **Lag 3**:

  Logit, with an Auroc score of 0.846053 and an R-Squared value of 0.235964, showing good classification performance and a weak linear relationship between predicted and observed values. The Logit model's key variable is ROE, with a p-value of 0.000417, signifying a strong statistical association with the outcome.

- **Lag 4**:

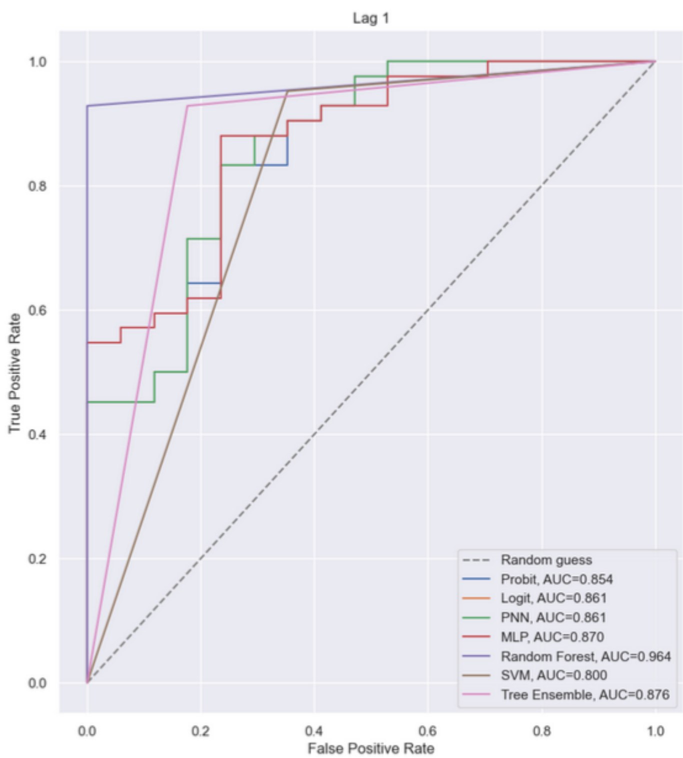
MLP, with an Auroc score of 0.884615 and an R-Squared value of 0.337686, suggests good classification ability and a moderately strong linear relationship between predicted and observed values. The MLP model's most influential variable is ROE, with a p-value of 0.000000, highlighting an extremely significant relationship with the outcome.

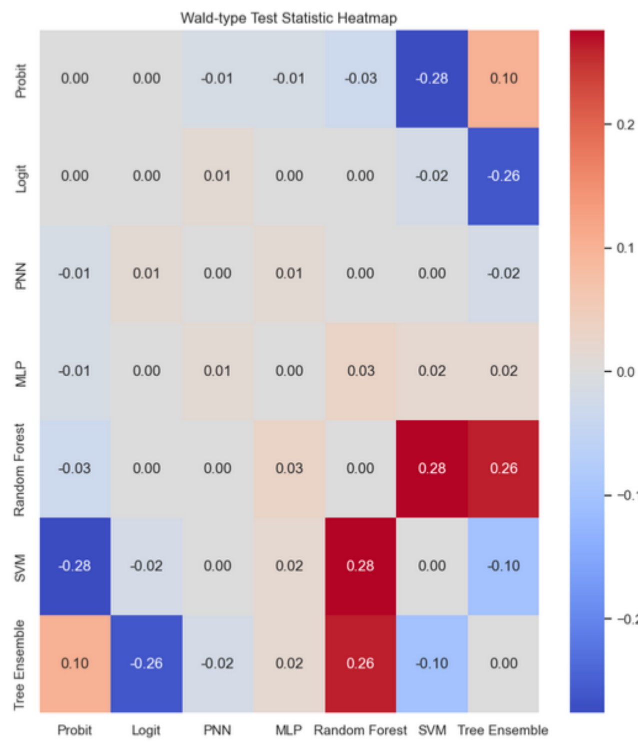
- Row 0

------------------------------------ Threshold 0.0-17.3851 - Lag 1 ------------------------------------

Auroc Score

	Threshold	Lag	Model	Auroc	R-Squared	LLRR_lag1_pvalue	ROE_lag1_pvalue	TERMSPREAD_lag1_pvalue	Auroc_Gains	R-Squared_Gains	LLRR_lag1_pvalue_Gains	ROE_lag1_pvalue_Gains	TERMSPREAD_lag1_pvalue_Gains
28	0.0-17.3851	1	Probit	0.854342	0.359391	0.000521	0.032244	0.210202	-0.109944	-0.042729	-0.000508	-0.009434	-0.095557
29	0.0-17.3851	1	Logit	0.861345	0.355698	0.001029	0.041678	0.305759	-0.102941	-0.046422	.	.	.
30	0.0-17.3851	1	PNN	0.861345	0.402120	0.000000	0.000010	0.000303	-0.102941	.	-0.001029	-0.041668	-0.305456
31	0.0-17.3851	1	MLP	0.869748	0.388884	0.000000	0.000010	0.000303	-0.094538	-0.013236	-0.001029	-0.041668	-0.305456
32	0.0-17.3851	1	Random Forest	0.964286	0.000000	0.000000	0.000010	0.000303	.	-0.402120	-0.001029	-0.041668	-0.305456
33	0.0-17.3851	1	SVM	0.799720	0.000000	0.000000	0.000010	0.000303	-0.164566	-0.402120	-0.001029	-0.041668	-0.305456
34	0.0-17.3851	1	Tree Ensemble	0.876050	0.000000	0.000000	0.000010	0.000303	-0.088235	-0.402120	-0.001029	-0.041668	-0.305456



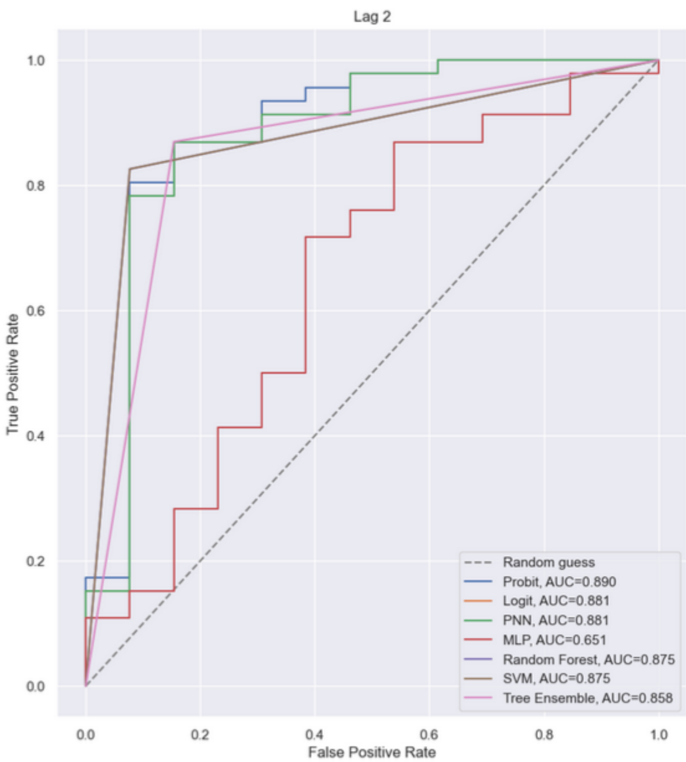


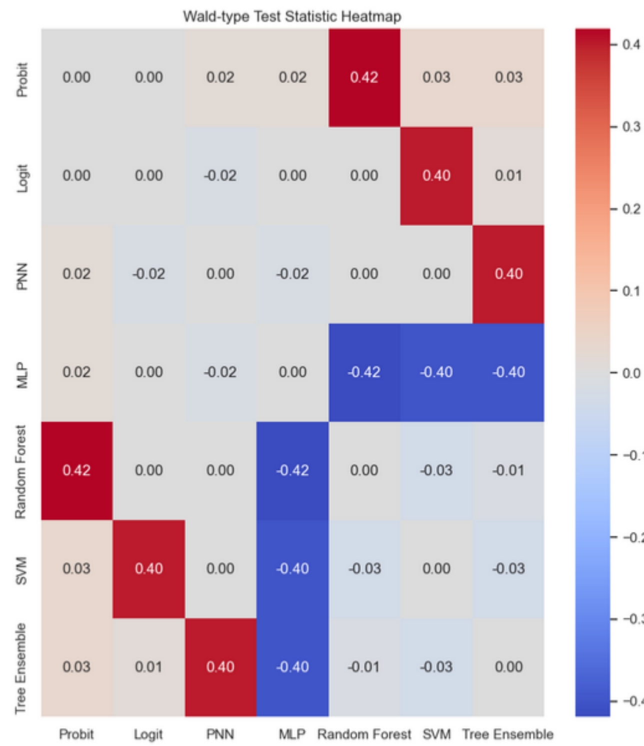
- Row 5

------------------------------------- Threshold 0.0-17.3851 - Lag 2 -------------------------------------

Auroc Score

	Threshold	Lag	Model	Auroc	R-Squared	EBP_lag2_pvalue	LLRR_lag2_pvalue	PLL_lag2_pvalue	Auroc_Gains	R-Squared_Gains	EBP_lag2_pvalue_Gains	LLRR_lag2_pvalue_Gains	PLL_lag2_pvalue_Gains
35	0.0-17.3851	2	Probit	0.889632	0.289622	0.158269	0.000002	0.115819	.	-0.006685	.	-0.000006	-0.113163
36	0.0-17.3851	2	Logit	0.881271	0.296306	0.148515	0.000008	0.130395	-0.008361	.	-0.009753	.	-0.098587
37	0.0-17.3851	2	PNN	0.881271	0.252906	0.083496	0.000000	0.228982	-0.008361	-0.043400	-0.074772	-0.000008	.
38	0.0-17.3851	2	MLP	0.650502	-0.174812	0.083496	0.000000	0.228982	-0.239130	-0.471118	-0.074772	-0.000008	.
39	0.0-17.3851	2	Random Forest	0.874582	0.000000	0.083496	0.000000	0.228982	-0.015050	-0.296306	-0.074772	-0.000008	.
40	0.0-17.3851	2	SVM	0.874582	0.000000	0.083496	0.000000	0.228982	-0.015050	-0.296306	-0.074772	-0.000008	.
41	0.0-17.3851	2	Tree Ensemble	0.857860	0.000000	0.083496	0.000000	0.228982	-0.031773	-0.296306	-0.074772	-0.000008	.

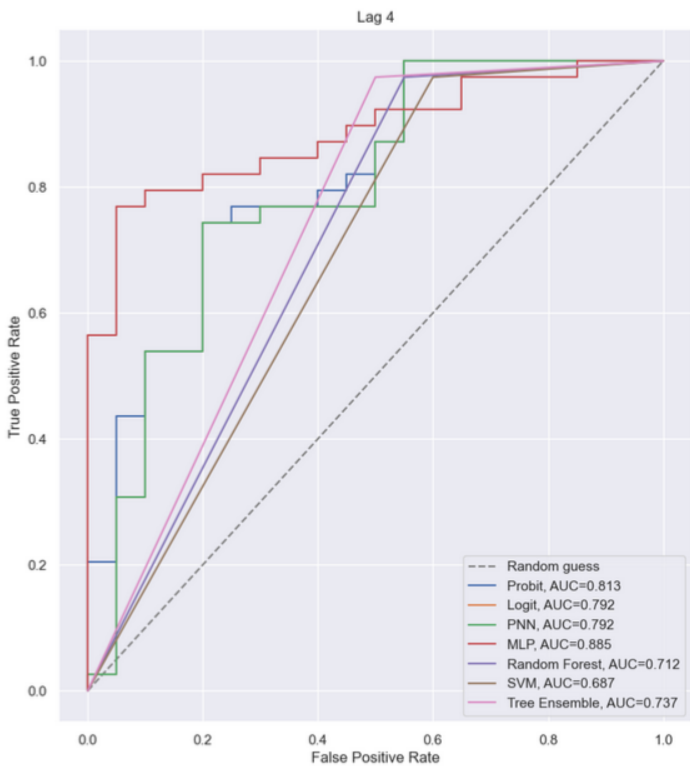


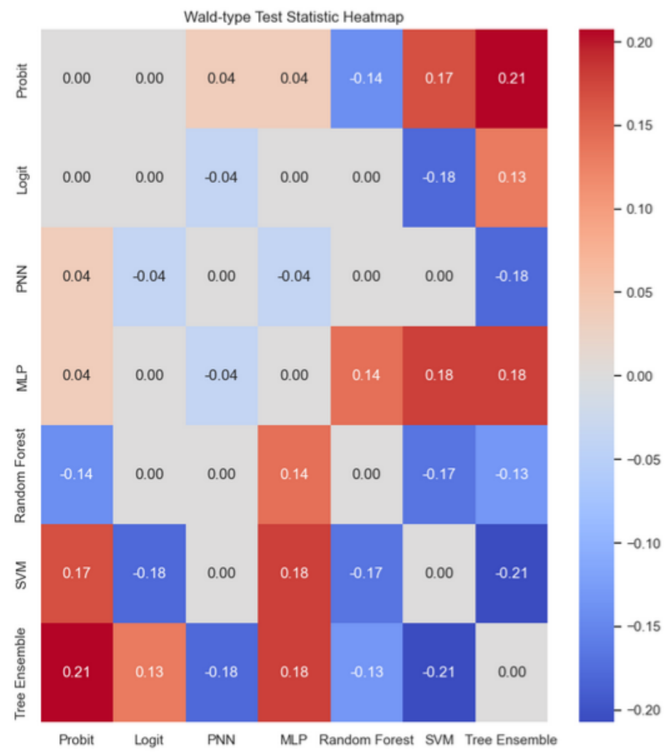


- Row 6

```
------------------------------------ Threshold 0.0-17.3851 - Lag 4 ------------------------------------
Auroc Score
```

	Threshold	Lag	Model	Auroc	R-Squared	EBP_lag4_pvalue	PLL_lag4_pvalue	ROE_lag4_pvalue	Auroc_Gains	R-Squared_Gains	EBP_lag4_pvalue_Gains	PLL_lag4_pvalue_Gains	ROE_lag4_pvalue_Gains
49	0.0-17.3851	4	Probit	0.812821	0.289058	0.169102	0.586142	0.000119	-0.071795	-0.048628	-0.005297	.	-0.000127
50	0.0-17.3851	4	Logit	0.792308	0.284613	0.174398	0.548021	0.000245	-0.092308	-0.053073	.	-0.038120	.
51	0.0-17.3851	4	PNN	0.792308	0.264234	0.031503	0.124289	0.000000	-0.092308	-0.073452	-0.142895	-0.461852	-0.000245
52	0.0-17.3851	4	MLP	0.884615	0.337686	0.031503	0.124289	0.000000	.	.	-0.142895	-0.461852	-0.000245
53	0.0-17.3851	4	Random Forest	0.712179	0.000000	0.031503	0.124289	0.000000	-0.172436	-0.337686	-0.142895	-0.461852	-0.000245
54	0.0-17.3851	4	SVM	0.687179	0.000000	0.031503	0.124289	0.000000	-0.197436	-0.337686	-0.142895	-0.461852	-0.000245
55	0.0-17.3851	4	Tree Ensemble	0.737179	0.000000	0.031503	0.124289	0.000000	-0.147436	-0.337686	-0.142895	-0.461852	-0.000245



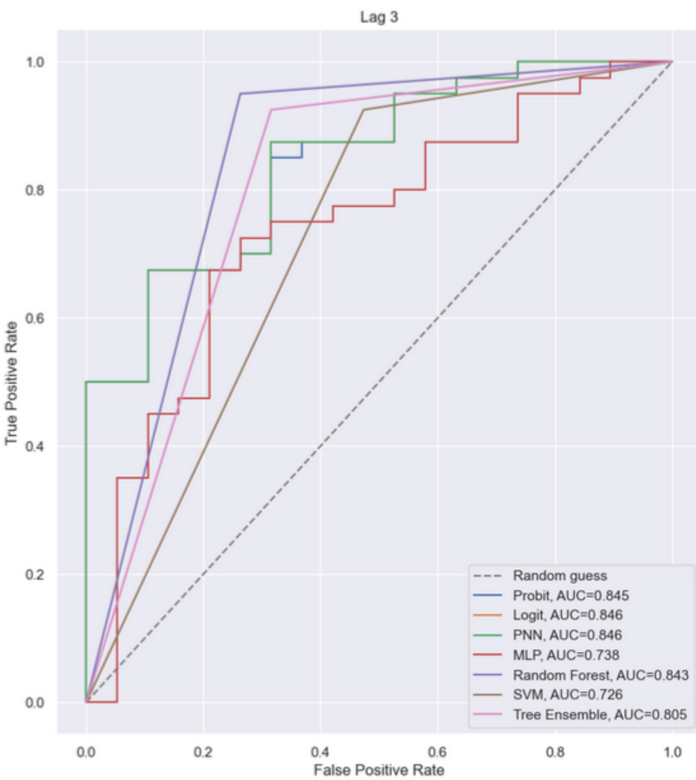


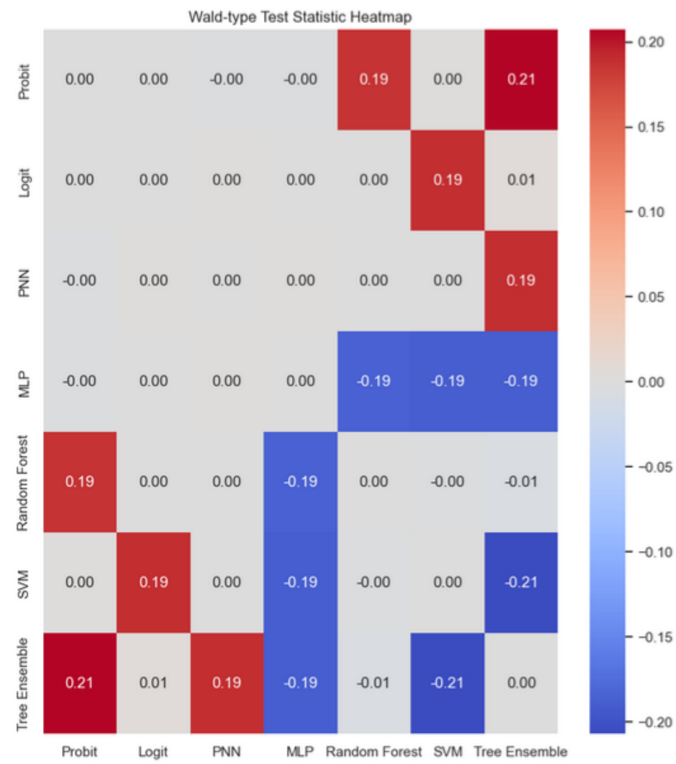
- Row 26

------------------------------------ Threshold 0.0-17.3851 - Lag 3 ------------------------------------

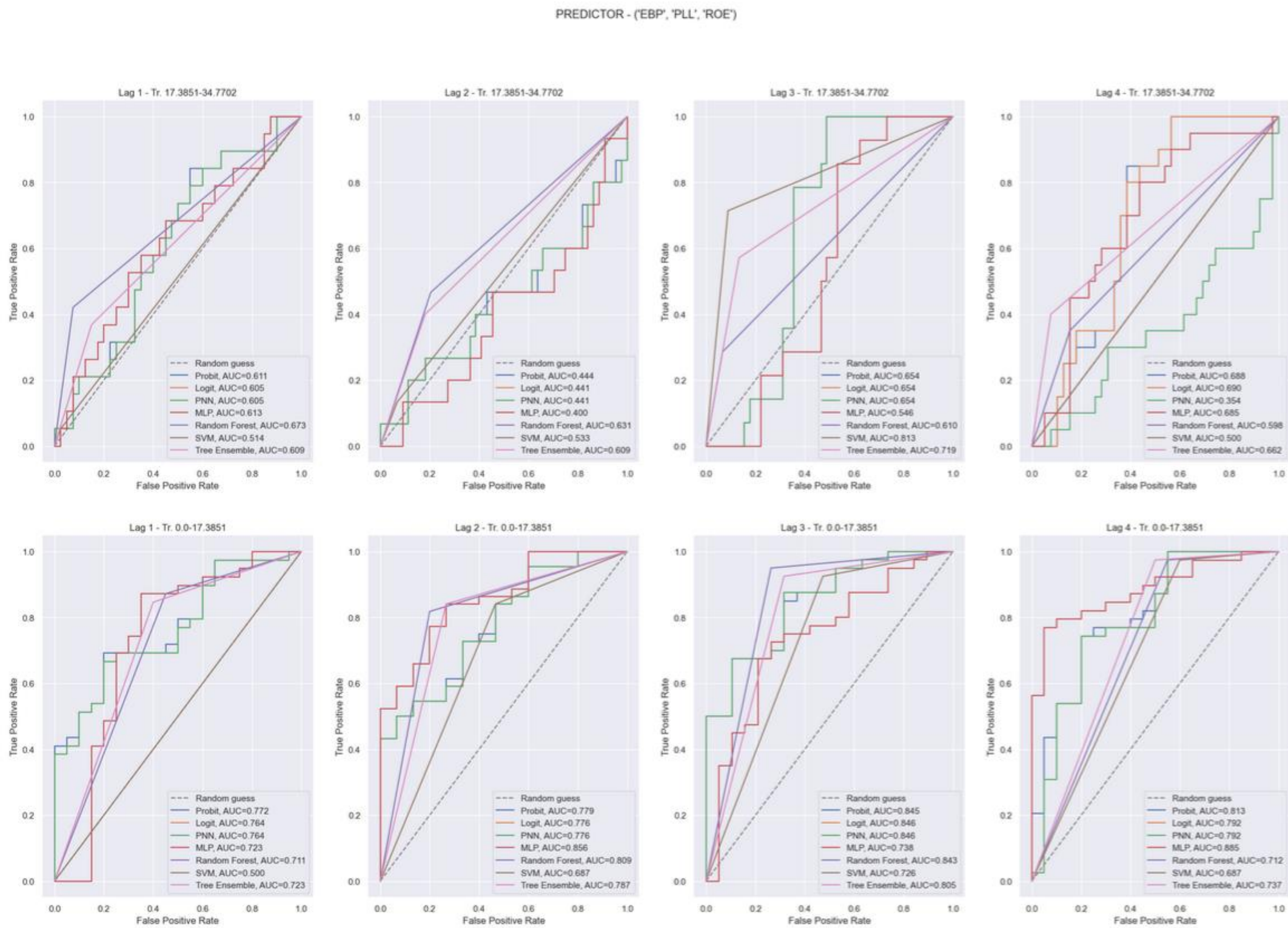
Auroc Score

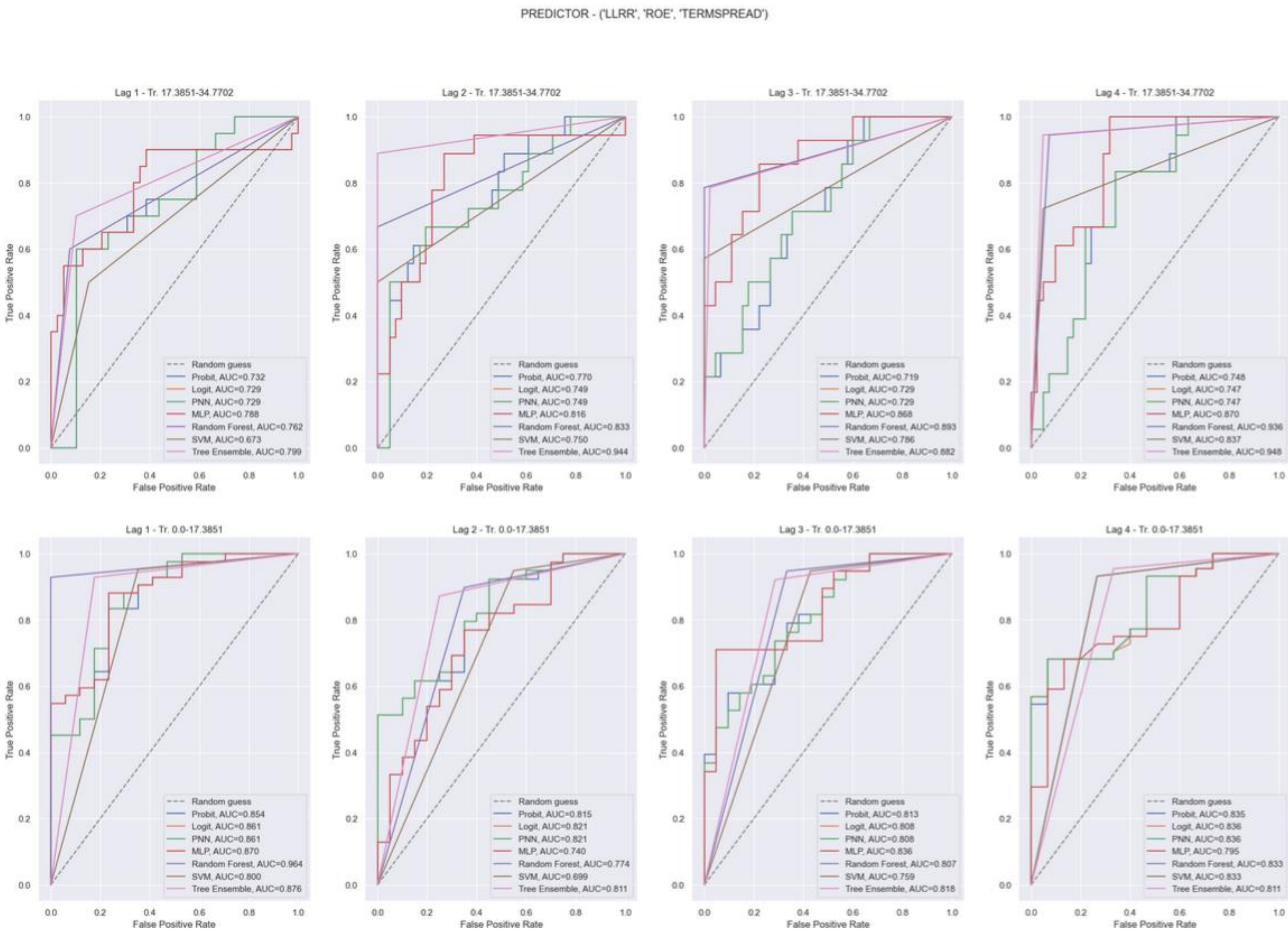
	Threshold	Lag	Model	Auroc	R-Squared	EBP_lag3_pvalue	PLL_lag3_pvalue	ROE_lag3_pvalue	Auroc_Gains	R-Squared_Gains	EBP_lag3_pvalue_Gains	PLL_lag3_pvalue_Gains	ROE_lag3_pvalue_Gains
42	0.0-17.3851	3	Probit	0.844737	0.242135	0.135312	0.317135	0.000243	-0.001316	-0.080152	.	-0.003551	-0.000174
43	0.0-17.3851	3	Logit	0.846053	0.235964	0.131132	0.320687	0.000417	.	-0.086323	-0.004179	.	.
44	0.0-17.3851	3	PNN	0.846053	0.322287	0.003923	0.256158	0.000002	.	.	-0.131389	-0.064529	-0.000415
45	0.0-17.3851	3	MLP	0.738158	0.141533	0.003923	0.256158	0.000002	-0.107895	-0.180755	-0.131389	-0.064529	-0.000415
46	0.0-17.3851	3	Random Forest	0.843421	0.000000	0.003923	0.256158	0.000002	-0.002632	-0.322287	-0.131389	-0.064529	-0.000415
47	0.0-17.3851	3	SVM	0.725658	0.000000	0.003923	0.256158	0.000002	-0.120395	-0.322287	-0.131389	-0.064529	-0.000415
48	0.0-17.3851	3	Tree Ensemble	0.804605	0.000000	0.003923	0.256158	0.000002	-0.041447	-0.322287	-0.131389	-0.064529	-0.000415





Plots


PREDICTOR - ('EBP', 'PLL', 'ROE')
Lag 1 - Tr. 17.3851-34.7702
True Positive Rate
False Positive Rate
Random guess
Probit, AUC=0.611
Logit, AUC=0.605
PNN, AUC=0.605
MLP, AUC=0.613
Random Forest, AUC=0.673
SVM, AUC=0.514
Tree Ensemble, AUC=0.609
Lag 2 - Tr. 17.3851-34.7702
True Positive Rate
False Positive Rate
Random guess
Probit, AUC=0.444
Logit, AUC=0.441
PNN, AUC=0.441
MLP, AUC=0.400
Random Forest, AUC=0.631
SVM, AUC=0.533
Tree Ensemble, AUC=0.609
Lag 3 - Tr. 17.3851-34.7702
True Positive Rate
False Positive Rate
Random guess
Probit, AUC=0.654
Logit, AUC=0.654
PNN, AUC=0.654
MLP, AUC=0.546
Random Forest, AUC=0.610
SVM, AUC=0.813
Tree Ensemble, AUC=0.719
Lag 4 - Tr. 17.3851-34.7702
True Positive Rate
False Positive Rate
Random guess
Probit, AUC=0.688
Logit, AUC=0.690
PNN, AUC=0.354
MLP, AUC=0.685
Random Forest, AUC=0.598
SVM, AUC=0.500
Tree Ensemble, AUC=0.662
Lag 1 - Tr. 0.0-17.3851
True Positive Rate
False Positive Rate
Random guess
Probit, AUC=0.772
Logit, AUC=0.764
PNN, AUC=0.764
MLP, AUC=0.723
Random Forest, AUC=0.711
SVM, AUC=0.500
Tree Ensemble, AUC=0.723
Lag 2 - Tr. 0.0-17.3851
True Positive Rate
False Positive Rate
Random guess
Probit, AUC=0.779
Logit, AUC=0.776
PNN, AUC=0.776
MLP, AUC=0.856
Random Forest, AUC=0.809
SVM, AUC=0.687
Tree Ensemble, AUC=0.787
Lag 3 - Tr. 0.0-17.3851
True Positive Rate
False Positive Rate
Random guess
Probit, AUC=0.845
Logit, AUC=0.846
PNN, AUC=0.846
MLP, AUC=0.738
Random Forest, AUC=0.843
SVM, AUC=0.726
Tree Ensemble, AUC=0.805
Lag 4 - Tr. 0.0-17.3851
True Positive Rate
False Positive Rate
Random guess
Probit, AUC=0.813
Logit, AUC=0.792
PNN, AUC=0.792
MLP, AUC=0.885
Random Forest, AUC=0.712
SVM, AUC=0.687
Tree Ensemble, AUC=0.737


PREDICTOR - ('LLRR', 'ROE', 'TERMSPREAD')
Lag 1 - Tr. 17.3851-34.7702
Random guess
Probit, AUC=0.732
Logit, AUC=0.729
PNN, AUC=0.729
MLP, AUC=0.788
Random Forest, AUC=0.762
SVM, AUC=0.673
Tree Ensemble, AUC=0.799
Lag 2 - Tr. 17.3851-34.7702
Random guess
Probit, AUC=0.770
Logit, AUC=0.749
PNN, AUC=0.749
MLP, AUC=0.816
Random Forest, AUC=0.833
SVM, AUC=0.750
Tree Ensemble, AUC=0.944
Lag 3 - Tr. 17.3851-34.7702
Random guess
Probit, AUC=0.719
Logit, AUC=0.729
PNN, AUC=0.729
MLP, AUC=0.868
Random Forest, AUC=0.893
SVM, AUC=0.786
Tree Ensemble, AUC=0.882
Lag 4 - Tr. 17.3851-34.7702
Random guess
Probit, AUC=0.748
Logit, AUC=0.747
PNN, AUC=0.747
MLP, AUC=0.870
Random Forest, AUC=0.936
SVM, AUC=0.837
Tree Ensemble, AUC=0.948
Lag 1 - Tr. 0.0-17.3851
Random guess
Probit, AUC=0.854
Logit, AUC=0.861
PNN, AUC=0.861
MLP, AUC=0.870
Random Forest, AUC=0.964
SVM, AUC=0.800
Tree Ensemble, AUC=0.876
Lag 2 - Tr. 0.0-17.3851
Random guess
Probit, AUC=0.815
Logit, AUC=0.821
PNN, AUC=0.821
MLP, AUC=0.740
Random Forest, AUC=0.774
SVM, AUC=0.699
Tree Ensemble, AUC=0.811
Lag 3 - Tr. 0.0-17.3851
Random guess
Probit, AUC=0.813
Logit, AUC=0.808
PNN, AUC=0.808
MLP, AUC=0.836
Random Forest, AUC=0.807
SVM, AUC=0.759
Tree Ensemble, AUC=0.818
Lag 4 - Tr. 0.0-17.3851
Random guess
Probit, AUC=0.835
Logit, AUC=0.836
PNN, AUC=0.836
MLP, AUC=0.795
Random Forest, AUC=0.833
SVM, AUC=0.833
Tree Ensemble, AUC=0.811
True Positive Rate
False Positive Rate

PREDICTOR - ('EBP', 'LLRR', 'PLL')