Optimizing Loan Approvals and Revenue: A Data-Driven Approach to Lender Matching

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Overview:

1) **Analyzing variables related to loan approval**
    - Exploratory EDA into approval rates
2) **Understanding lender-specific approval rates**
    - Exploratory EDA into approval rates based on the lender
3) **Identifying strategies to match customers with lenders for maximum bounty**
    - Developing a model to predict which lender a customer should apply to

Background

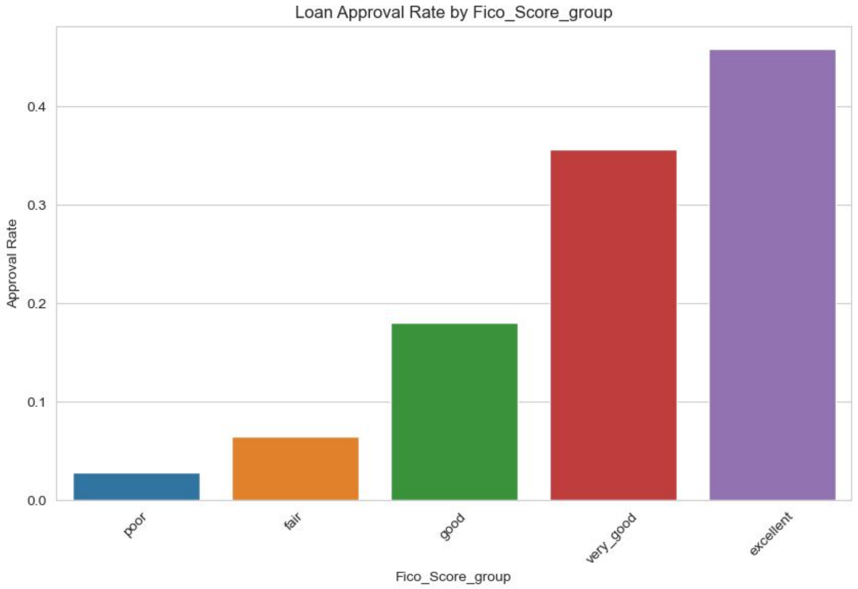
- **Context:** Bankrate, a leader in financial guidance, specializes in matching consumers with optimal personal loan options
- **Challenge:** Match customers with one of three lending partners (A, B, and C) to maximize loan approval rates and revenue
- **Objective:** Enhance matching strategy to increase revenue per application and improve customer satisfaction

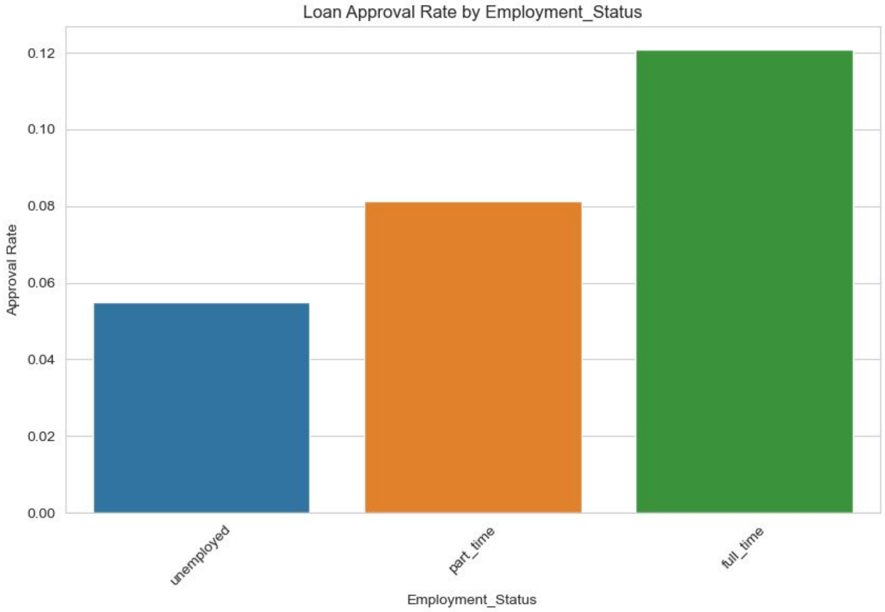
Understanding Approval Rates

Customer who are approved for loans tend to have higher credit scores and greater gross income

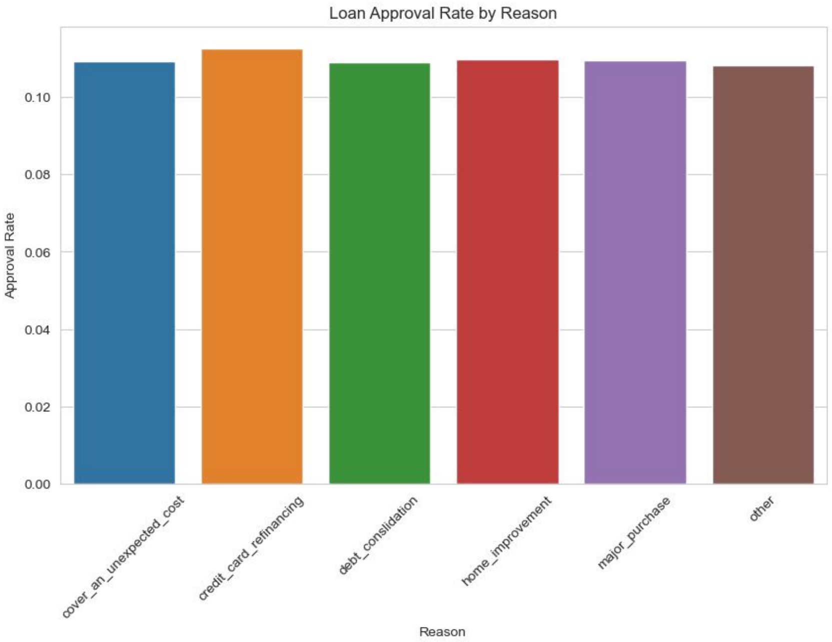
Approved	No	Yes
Loan Amount	$45,638.42	$41,957.00
FICO Score	621	697
Monthly Gross Income	$5,698.00	$7,282.38
Monthly Housing Payment	$1,655.73	$1,600.76
Bankrupt/Foreclose Rate	2.4%	0.7%

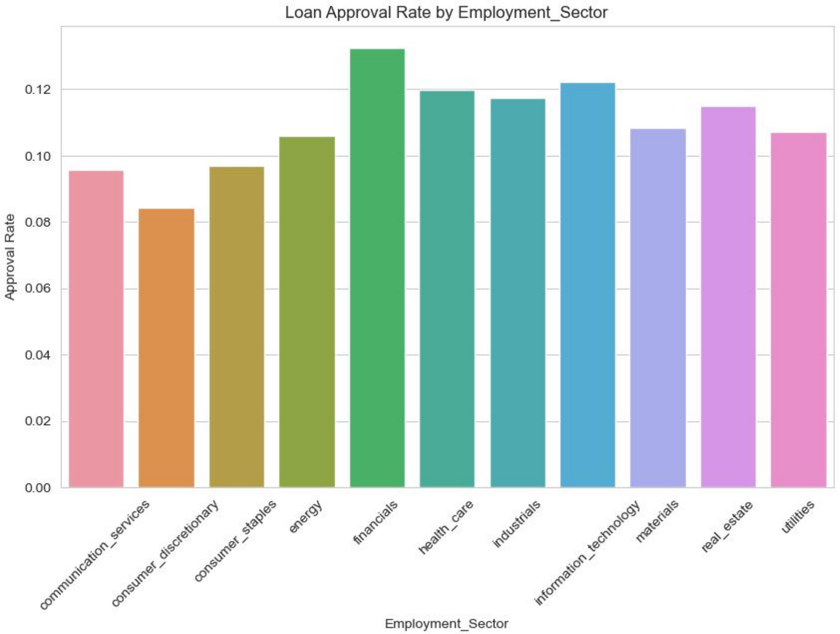
Customers with higher credit scores and customers that are employed have chance to be approved





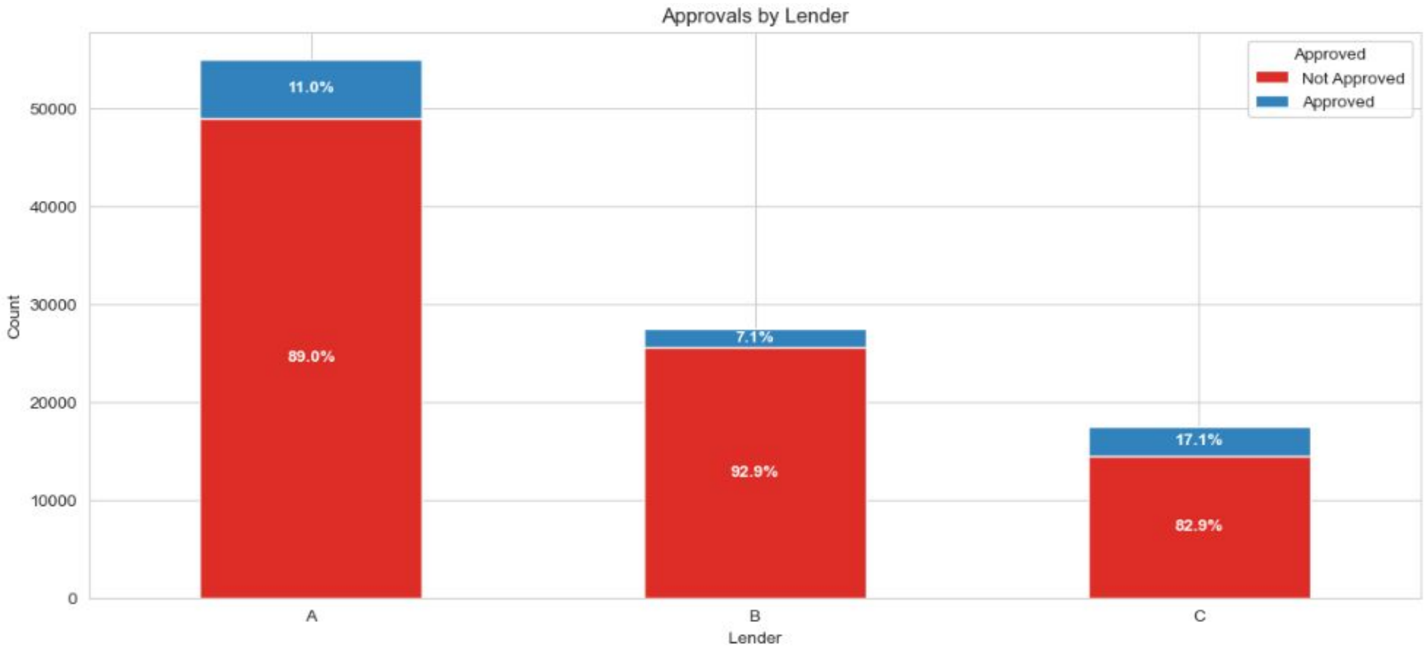
Reasonings and employment sector did not show any significant differences for loan approval rates



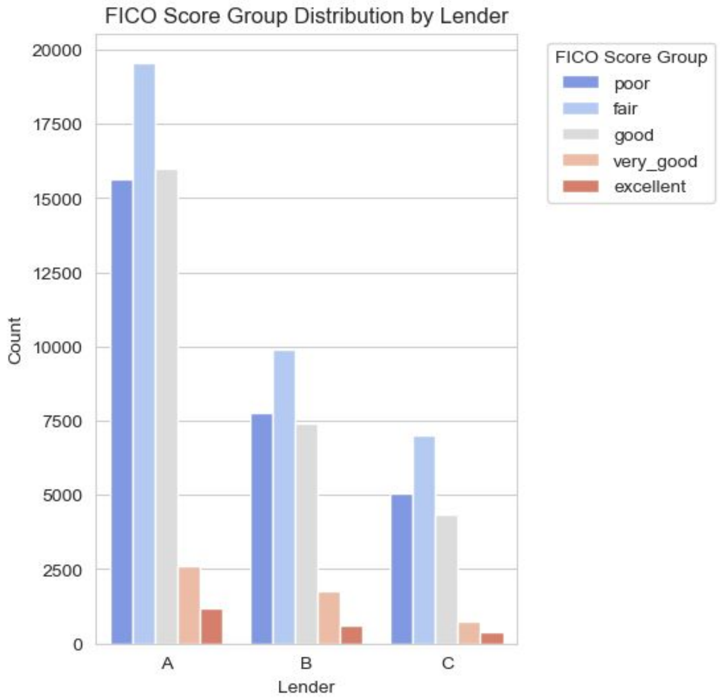


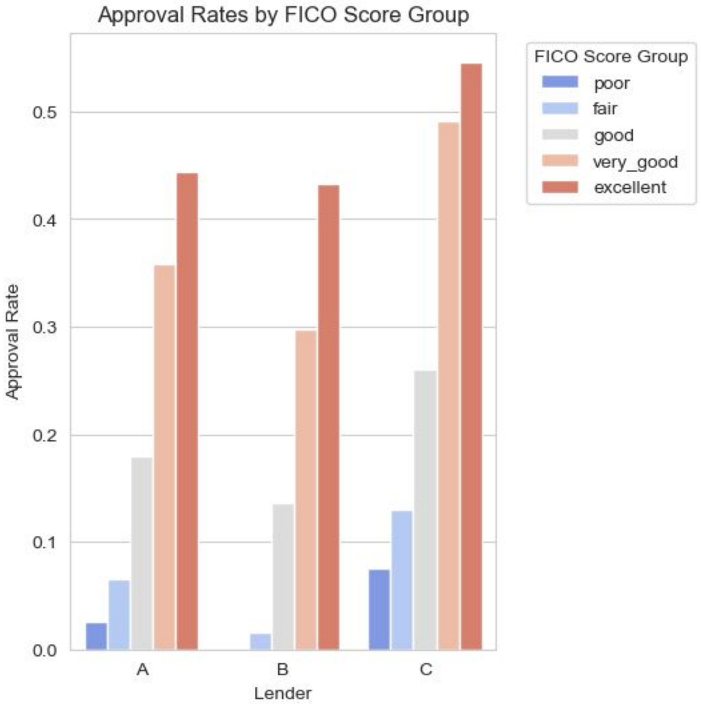
Understanding Lenders

Most customers have been applying to lender A, whereas lender C has the highest rate of approvals

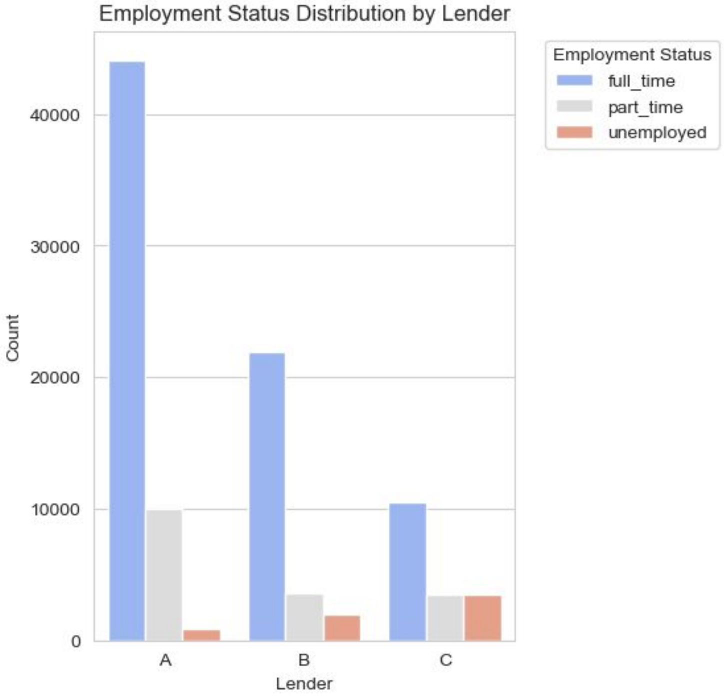


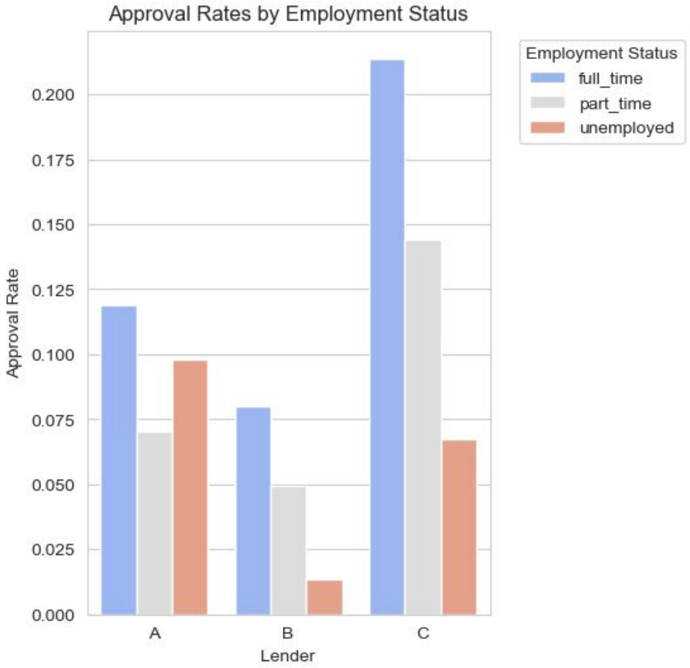
A majority of the people with low credit scores are applying to lender A and B instead of C



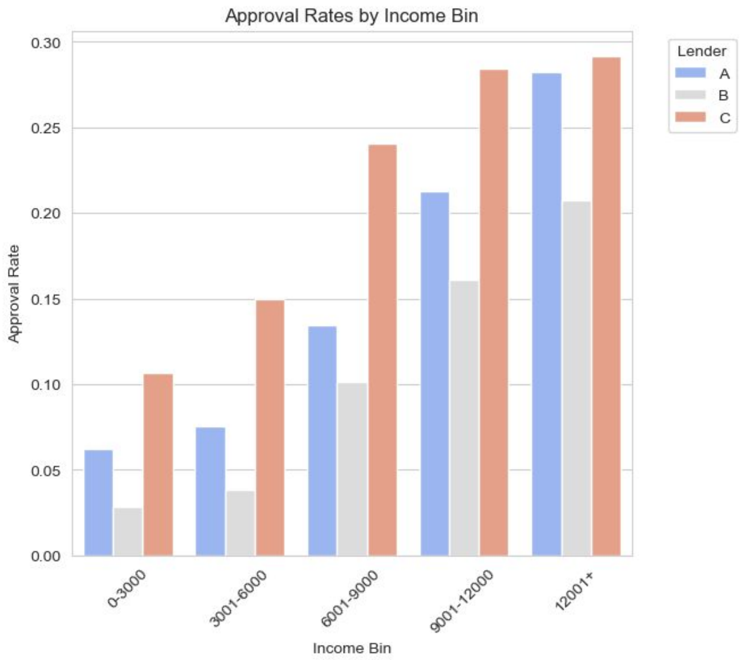


Lender C is the most lenient whereas lender B is stricter based on customer's employment status





Lenders show a consistent pattern on who they approve when it comes to income brackets



Predicting Lenders from Customer Information

Significant variables from Chi-square and ANOVA tests when grouping by lenders

Variable	Chi-squared Value	p-value
Fico_Score_group	312.741997	7.972857e-63
Employment_Status	8172.50945	0.00000e+00
Employment_Sector	17.116521	6.453950e-01
Reason	6.903158	7.345547e-01
Every_Bankrupt_or_Foreclose	506.329948	1.126805e-110

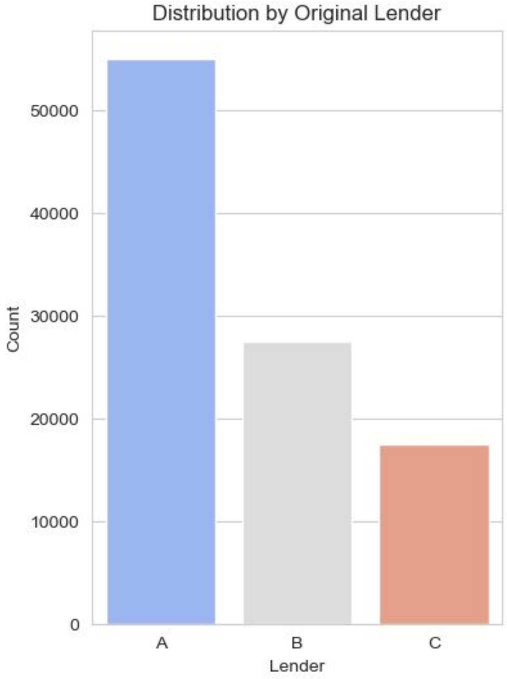
Variable	F-statistic	p-value
Monthly_Gross_Income	406.568950	1.391180e-18
Loan_Amount	0.054356	9.470948e-01
Monthly_Housing_Payment	1456.393213	0.00000e+00
FICO_score	20.009297	2.050270e-09
Money_Interaction	485.073276	2.242331e-21

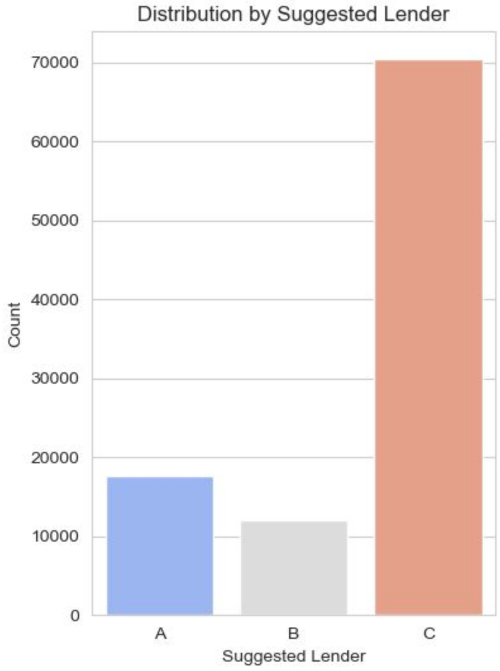
** Money_Interaction = Monthly_Gross_Income x Loan_Amount x Monthly_Housing_Payment*

Constructed a model for each lender to predict the probability a customer gets approved by each on test data

	Lender A	Lender B	Lender C
Accuracy	88.89%	92.52%	83.95%
AUC-ROC	0.754	0.866	0.739

Model predicts that most customers should apply with lender C rather than A to maximize bounty returns





Customer trends with new suggested lenders

Suggested Lender	Loan Amount (mean)	FICO Score (mean)	Monthly Gross Income (mean)	Monthly Housing Payment (mean)	Bankrupt/ Foreclose Rate (mean)	Reason (mode)	Employment Status (mode)	Employment Sector (mode
A	$44,763	655	$7,000	$2,018	3.67%	credit_card_refinancing	full_time	information_technology
B	$45,472	759	$8,209	$1,560	0.06%	debt_conslidation	full_time	information_technology
C	$45,312	601	$5,192	$1,573	2.26%	debt_conslidation	full_time	information_technology

Sample output with old and new suggested lenders

ID	Reason	FICO Score	Employment Status	Monthly Gross Income	Monthly Housing Payment	Bankrupt/Foreclosure?	Original Lender	Approved	Suggested Lender
…5a35	cover_an_unexpected_cost	669	full_time	5024	927	0	B	0	C
…cb1f	other	565	full_time	8061	658	0	C	0	C
…dadd	other	691	full_time	5103	1289	0	A	1	C
…83eb	major_purchase	537	full_time	5367	2731	0	B	0	C
…a788	other	724	full_time	5800	1460	0	A	0	B

Sample output with probabilities and expected values for new suggested lenders

ID	Original Lender	Approved	Suggested Lender	P(A)	P(B)	P(C)	Expected Value A	Expected Value B	Expected Value C
…5a35	B	0	C	10.9%	7.1%	29.4%	$27	$25	$44
…cb1f	C	0	C	5.1%	1.0%	12.7%	$13	$4	$19
…dadd	A	1	C	14.4%	8.4%	27.3%	$36	$30	$41
…83eb	B	0	C	2.8%	0.4%	6.7%	$7	$1	$10
…a788	A	0	B	20.4%	14.9%	33.0%	$51	$52	$50

Potential Incremental Revenue

Suggested Lender	Lost Revenue (Sum)	Lost Revenue (Avg)
A	$114,634	$6
B	$304,701	$25
C	$516,348	$7
Total	$935,683	$9

Real Time Considerations

- Technological infrastructure should be able to quickly process the data especially as user numbers grow
- Compliance with data privacy regulations since working with sensitive customer data
- Continuously monitor the system's performance and regularly test model to make sure it is the most optimal

Appendix

Linear Model to Predict Revenue

Logistic Regression Models to predict the probability of getting approved for their respective lender

Model A Coefficients:

	Coefficient
FICO_score	0.975605
Monthly_Gross_Income	0.236956
Monthly_Housing_Payment	-0.003865
Employment_Status_part_time	-0.215634
Employment_Status_unemployed	0.269352
Reason_credit_card_refinancing	0.080156
Reason_debt_conslidation	-0.041216
Reason_home_improvement	0.015602
Reason_major_purchase	-0.014626
Reason_other	0.074695
Ever_Bankrupt_or_Foreclose_1	-1.303941
Intercept	-2.473902

Model B Coefficients:

	Coefficient
FICO_score	1.743350
Monthly_Gross_Income	0.143109
Monthly_Housing_Payment	-0.156599
Employment_Status_part_time	-0.568005
Employment_Status_unemployed	-1.760496
Reason_credit_card_refinancing	0.034552
Reason_debt_conslidation	0.032915
Reason_home_improvement	-0.055903
Reason_major_purchase	-0.009849
Reason_other	-0.158099
Ever_Bankrupt_or_Foreclose_1	-1.981312
Intercept	-3.490824

Logistic Regression Models cont…

Model C Coefficients:

	Coefficient
FICO_score	0.824254
Monthly_Gross_Income	0.045147
Monthly_Housing_Payment	-0.173811
Employment_Status_part_time	-0.519309
Employment_Status_unemployed	-1.297491
Reason_credit_card_refinancing	-0.124124
Reason_debt_conslidation	-0.010395
Reason_home_improvement	-0.086545
Reason_major_purchase	-0.032936
Reason_other	-0.208831
Ever_Bankrupt_or_Foreclose_1	-0.668067
Intercept	-1.430821