

# Homework 4

*Group 1*

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# 1 Introduction

Consumers who own a car are often required to purchase car insurance to protect themselves from serious financial repercussions of being involved in a car accident. Insurance Providers must determine the risk of offering insurance coverage to a new customer through accurate statistical models that evaluate the consumers propensity for accidents. Since Insurance Providers are motivated by collecting the maximum amount of revenue from consumers while returning the lowest amount in accident claims, statistical modeling provides Insurance Providers with insight into the consumers behavior and the most appropriate pricing schemes<sup>1</sup>.

## 2 Statement of the Problem

The purpose of this report is to develop statistical models to make inference into the likelihood of a customer being involved in a car accident and the cost associated of a customer being involved in a car accident.

## 3 Data Exploration

### 3.1 Variables Explained

The variables provided in the Insurance Training Data Set are explained below:

Variable Code	Definition
INDEX	Identification Variable (do not use)
TARGET_FLAG	Was Car in a crash? 1=YES 0=NO
TARGET_AMT	If car was in a crash, what was the cost
AGE	Age of Driver
BLUEBOOK	Value of Vehicle
CAR_AGE	Vehicle Age
CAR_TYPE	Type of Car
CAR_USE	Vehicle Use
CLM_FREQ	# Claims (Past 5 Years)
EDUCATION	Max Education Level
HOMEKIDS	# Children at Home
HOME_VAL	Home Value
INCOME	Income
KIDSDRIV	# Driving Children
MSTATUS	Marital Status
MVR_PTS	Motor Vehicle Record Points
OLDCLAIM	Total Claims (Past 5 Years)
PARENT1	Single Parent
RED_CAR	A Red Car
REVOKE	License Revoked (Past 7 Years)
SEX	Gender
TIF	Time in Force
TRAVTIME	Distance to Work
URBANICITY	Home/Work Area
YOJ	Years on Job

<sup>1</sup>"Insider Information: How Insurance Companies Measure Risk - Insurance Companies.com." Insurance Companiescom. N.p., n.d. Web. 06 Nov. 2016.

### 3.1.1 Nominal Variables

We first look at our nominal variables and their applicable proportions. Interestingly, we see that in this data set only a quarter of the customer records indicate an accident occurred. Also, the majority of consumers in this data set have no kids at home, are married, more than a high school education but less than a PhD, use their car for private purposes, typically own a SUV or minivan, and also live in an urban environment. This provides an interesting insight to the type of customer this data set represents and should be considered when further interpreting our statistical model. Additionally, we should be mindful of any selection biases in this data set as consumers with extremely risky histories are likely to have not been extended insurance coverage.

Table 2: Table of nominal variables

Variable	Levels	n	%	$\sum\%$
TARGET_FLAG	0	6008	73.6	73.6
	1	2153	26.4	100.0
	all	8161	100.0	
KIDSDRV	0	7180	88.0	88.0
	1	636	7.8	95.8
	2	279	3.4	99.2
	3	62	0.8	100.0
	4	4	0.0	100.0
	all	8161	100.0	
HOMEKIDS	0	5289	64.8	64.8
	1	902	11.1	75.9
	2	1118	13.7	89.6
	3	674	8.3	97.8
	4	164	2.0	99.8
	5	14	0.2	100.0
	all	8161	100.0	
PARENT1	No	7084	86.8	86.8
	Yes	1077	13.2	100.0
	all	8161	100.0	
MSTATUS	No	3267	40.0	40.0
	Yes	4894	60.0	100.0
	all	8161	100.0	
SEX	F	4375	53.6	53.6
	M	3786	46.4	100.0
	all	8161	100.0	
EDUCATION	Less Than High School	1203	14.7	14.7
	High School	2330	28.6	43.3
	Bachelors	2242	27.5	70.8
	Masters	1658	20.3	91.1
	PhD	728	8.9	100.0
	all	8161	100.0	
JOB		526	6.4	6.4
	Blue Collar	1825	22.4	28.8
	Clerical	1271	15.6	44.4
	Doctor	246	3.0	47.4
	Home Maker	641	7.8	55.2
	Lawyer	835	10.2	65.5
	Manager	988	12.1	77.6
	Professional	1117	13.7	91.3
	Student	712	8.7	100.0
	all	8161	100.0	
CAR_USE	Commercial	3029	37.1	37.1
	Private	5132	62.9	100.0
	all	8161	100.0	
CAR_TYPE	Minivan	2145	26.3	26.3
	Panel Truck	676	8.3	34.6
	Pickup	1389	17.0	51.6
	Sports Car	907	11.1	62.7
	SUV	2294	28.1	90.8

Table 2: Table of nominal variables

Variable	Levels	n	%	$\sum\%$
	Van	750	9.2	100.0
	all	8161	100.0	
RED_CAR	no	5783	70.9	70.9
	yes	2378	29.1	100.0
	all	8161	100.0	
CLM_FREQ	0	5009	61.4	61.4
	1	997	12.2	73.6
	2	1171	14.3	88.0
	3	776	9.5	97.5
	4	190	2.3	99.8
	5	18	0.2	100.0
	all	8161	100.0	
REVOKE	No	7161	87.8	87.8
	Yes	1000	12.2	100.0
	all	8161	100.0	
URBANITY	Highly Rural/ Rural	1669	20.4	20.4
	Highly Urban/ Urban	6492	79.5	100.0
	all	8161	100.0	

### 3.1.2 Continuous and Discrete Variables

We can see that in our continuous and discrete variables there is some additional variability. The median claim amount (TARGET\_AMT) is 0 which would coincide with only a quarter for records indicating an accident. However, the spread is large since the average payout is only \$1,504.30 but the maximum payout was \$107,586.10. Surprisingly, the median AGE is 45 and the average AGE is 44.8 years, while we expected a lower average it could be due to simple selection bias in the data set source or the aging US population bringing this average higher <sup>2</sup>. We also noticed that an INCOME of \$0.00 seems unwise because it is unclear how the individual would be able to cover their premium costs without parental support. Finally, we should note that the data set has as CAR\_AGE of -3, which is impossible and will need to be removed.

There are many missing values for this portion of our data set, we have over 400 values missing for years on the job, income, home value, and car age. Due to these missing values we will need to impute to complete our statistical model.

Variable	n	Min	q <sub>1</sub>	$\tilde{x}$	$\bar{x}$	q <sub>3</sub>	Max	s	IQR	#NA
TARGET_AMT	8161	0	0	0	1504.3	1036	107586.1	4704.0	1036	0
TIF	8161	1	1	4	5.4	7	25.0	4.1	6	0
AGE	8155	16	39	45	44.8	51	81.0	8.6	12	6
YOJ	7707	0	9	11	10.5	13	23.0	4.1	4	454
INCOME	7716	0	28097	54028	61898.1	85986	367030.0	47572.7	57889	445
HOME_VAL	7697	0	0	161160	154867.3	238724	885282.0	129123.8	238724	464
TRAVTIME	8161	5	22	33	33.5	44	142.0	15.9	22	0
BLUEBOOK	8161	1500	9280	14440	15709.9	20850	69740.0	8419.7	11570	0
OLDCLAIM	8161	0	0	0	4037.1	4636	57037.0	8777.1	4636	0
MVR_PTS	8161	0	0	1	1.7	3	13.0	2.1	3	0
CAR_AGE	7651	-3	1	8	8.3	12	28.0	5.7	11	510

Table 3:

<sup>2</sup>Ortman, Jennifer M., Victoria A. Velkoff, and Howard Hogan. "An aging nation: the older population in the United States." Washington, DC: US Census Bureau (2014): 25-1140.

## 3.2 Imputing Missing Values

In order to address the missing values in our variables we used a non-parametric imputation method (Random Forest) using the `missForest` package. The function is particularly useful in that it can handle any type of input data and it will make as few assumptions about the structure of the data as possible.<sup>3</sup>

**Table 2 : Imputed Descriptive Statistics  
25 Variables 8161 Observations**

<b>TARGET_FLAG</b>													
n	missing	distinct	Info	Sum	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
8161	0	2	0.583	2153	0.3	0.4							
<b>TARGET_AMT</b>													
n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95	
8161	0	1949	0.601	1504	2574	0	0	0	0	1036	4904	6452	
lowest :	0.00000	30.27728	58.53106	95.56732	108.74150								
highest:	73783.46592	77907.43028	78874.19056	85523.65335	107586.13616								
<b>KIDSDRV</b>													
n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95	
8161	0	5	0.318	0.2	0.3								
lowest : 0 1 2 3 4, highest: 0 1 2 3 4													
0 (7180, 0.880), 1 (636, 0.078), 2 (279, 0.034), 3 (62, 0.008), 4 (4, 0.000)													
<b>AGE</b>													
n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95	
8161	0	66	0.999	45	10	0.05	0.30	0.33	0.39	0.45	0.51	0.56	
lowest : 16 17 18 19 20, highest: 72 73 76 80 81													
<b>HOMEKIDS</b>													
n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95	
8161	0	6	0.723	0.7	1								
lowest : 0 1 2 3 4, highest: 1 2 3 4 5													
0 (5289, 0.648), 1 (902, 0.111), 2 (1118, 0.137), 3 (674, 0.083), 4 (164, 0.020), 5 (14, 0.002)													
<b>YOJ</b>													
n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95	
8161	0	446	0.991	10	4	0.05	0.5	0.9	1.1	1.3	1.4	1.5	
lowest : 0.00 0.15 0.20 0.26 0.27, highest: 16.00 17.00 18.00 19.00 23.00													
<b>INCOME</b>													
n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95	
8161	0	7057	1	61569	50845	0e+00	5e+03	3e+04	5e+04	9e+04	1e+05	2e+05	
lowest : 0.00 5.00 7.00 18.00 26.33													
highest: 306277.00 309628.00 320127.00 332339.00 367030.00													
<b>PARENT1</b>													
n	missing	distinct	.05	.10	.25	.50	.75	.90	.95				
8161	0	2											
No (7084, 0.868), Yes (1077, 0.132)													
<b>HOME_VAL</b>													
n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95	
8161	0	5570	0.978	2e+05	1e+05	0e+00	0e+00	0e+00	2e+05	2e+05	3e+05	4e+05	
lowest : 0.000 4176.960 8196.080 8263.335 9438.009													
highest: 657804.000 682634.000 738153.000 750455.000 885282.000													

<sup>3</sup>Stekhoven, Daniel J., and Peter Bühlmann. "MissForest-non-parametric missing value imputation for mixed-type data." Bioinformatics 28.1 (2012): 112-118.

---

**MSTATUS**

n	missing	distinct
8161	0	2

No (3267, 0.4), Yes (4894, 0.6)

---

**SEX**

n	missing	distinct
8161	0	2

F (4375, 0.536), M (3786, 0.464)

---

**EDUCATION**

n	missing	distinct
8161	0	5

lowest : Bachelors	High School	Less Than High School	Masters	PhD
highest: Bachelors	High School	Less Than High School	Masters	PhD

Bachelors (2242, 0.275), High School (2330, 0.286), Less Than High School (1203, 0.147),  
Masters (1658, 0.203), PhD (728, 0.089)

---

**JOB**

n	missing	distinct
8161	0	8

lowest : Blue Collar	Clerical	Doctor	Home Maker	Lawyer
highest: Home Maker	Lawyer	Manager	Professional	Student

Value	Blue Collar	Clerical	Doctor	Home Maker	Lawyer	Manager
Frequency	1830	1273	254	643	865	1412
Proportion	0.224	0.156	0.031	0.079	0.106	0.173

Value	Professional	Student
Frequency	1172	712
Proportion	0.144	0.087

---

**TRAVTIME**

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
8161	0	97	1	33	18	7	13	22	33	44	54	60

lowest : 5 6 7 8 9, highest: 103 113 124 134 142

---

**CAR\_USE**

n	missing	distinct
8161	0	2

Commercial (3029, 0.371), Private (5132, 0.629)

---

**BLUEBOOK**

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
8161	0	2789	1	15710	9354	4900	6000	9280	14440	20850	27460	31110

lowest : 1500 1520 1530 1540 1590, highest: 57970 61050 62240 65970 69740

---

**TIF**

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
8161	0	23	0.961	5	5	1	1	1	4	7	11	13

lowest : 1 2 3 4 5, highest: 19 20 21 22 25

---

**CAR\_TYPE**

n	missing	distinct
8161	0	6

lowest : Minivan	Panel Truck	Pickup	Sports Car	SUV
highest: Panel Truck	Pickup	Sports Car	SUV	Van

Minivan (2145, 0.263), Panel Truck (676, 0.083), Pickup (1389, 0.170), Sports Car (907, 0.111), SUV (2294, 0.281), Van (750, 0.092)

---

**RED\_CAR**

n	missing	distinct
8161	0	2

no (5783, 0.709), yes (2378, 0.291)

---

#### OLDCLAIM

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
8161	0	2857	0.769	4037	6563	0	0	0	0	4636	9583	27090

lowest : 0 502 506 518 519, highest: 52507 53477 53568 53986 57037

---

#### CLM\_FREQ

n	missing	distinct	Info	Mean	Gmd
8161	0	6	0.763	0.8	1

lowest : 0 1 2 3 4, highest: 1 2 3 4 5

0 (5009, 0.614), 1 (997, 0.122), 2 (1171, 0.143), 3 (776, 0.095), 4 (190, 0.023), 5 (18, 0.002)

---

#### REVOKE

n	missing	distinct
8161	0	2

No (7161, 0.877), Yes (1000, 0.123)

---

#### MVR\_PTS

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
8161	0	13	0.9	2	2	0	0	0	1	3	5	6

lowest : 0 1 2 3 4, highest: 8 9 10 11 13

Value	0	1	2	3	4	5	6	7	8	9	10	11	13
Frequency	3712	1157	948	758	599	399	266	167	84	45	13	11	2
Proportion	0.455	0.142	0.116	0.093	0.073	0.049	0.033	0.020	0.010	0.006	0.002	0.001	0.000

---

#### CAR\_AGE

n	missing	distinct	Info	Mean	Gmd	.05	.10	.25	.50	.75	.90	.95
8161	0	507	0.985	8	6	1	1	4	8	12	16	18

lowest : 0.000 1.000 2.000 2.035 2.890, highest: 24.000 25.000 26.000 27.000 28.000

---

#### URBANICITY

n	missing	distinct
8161	0	2

Highly Rural/ Rural (1669, 0.205), Highly Urban/ Urban (6492, 0.795)

---

### 3.3 Exploration of Variables

## 4 Data Transformation

### 4.1 Outliers Treatment

We chose winsorizing as the method to address outliers. Instead of trimming values, winsorizing uses the interquartile range to replace values that are above or below the interquartile range multiplied by a factor. Those values above or below the range multiplied by the factor are then replaced with max and min value of the interquartile range. Using the factor 2.2 for winsorizing outliers is a method developed by Hoaglin and Iglewicz and published Journal of American Statistical Association in 1987<sup>4</sup>.

The below table is the summary results of the winsorizing of the data.

<sup>4</sup>Hoaglin, D. C., and Iglewicz, B. (1987), Fine tuning some resistant rules for outlier labeling, Journal of American Statistical Association, 82, 1147-1149.

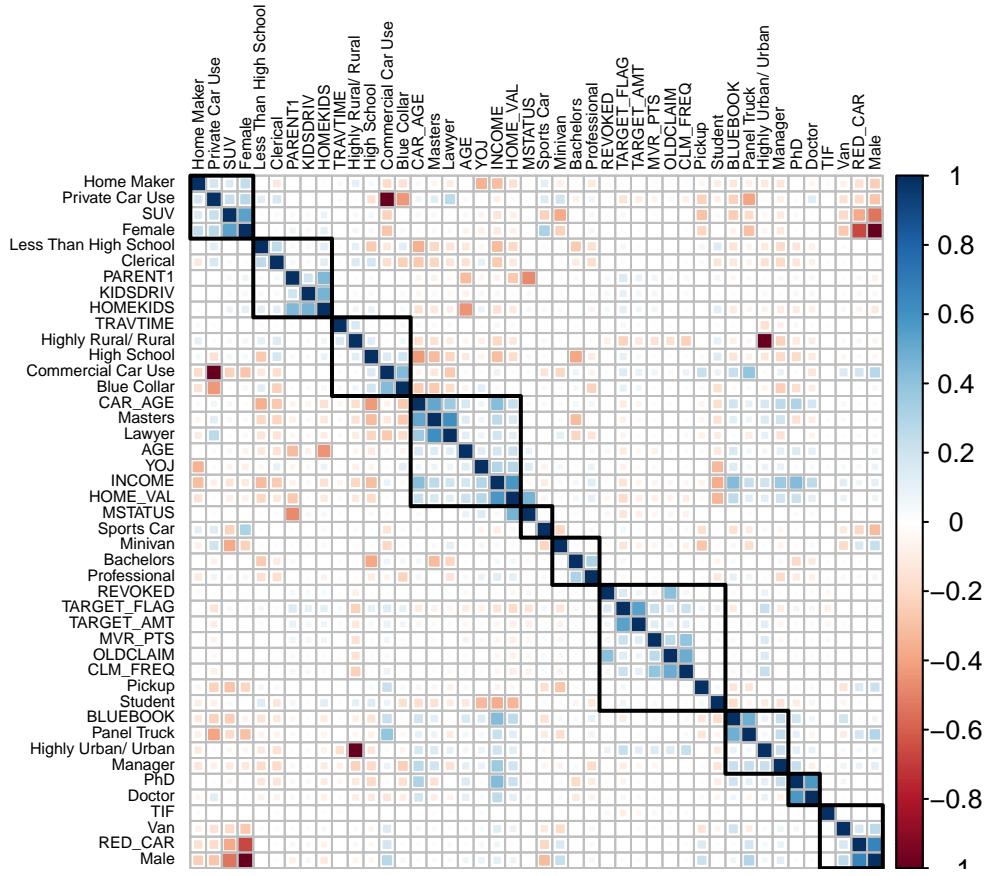


Figure 1: Correlation Plot of Training Data Set

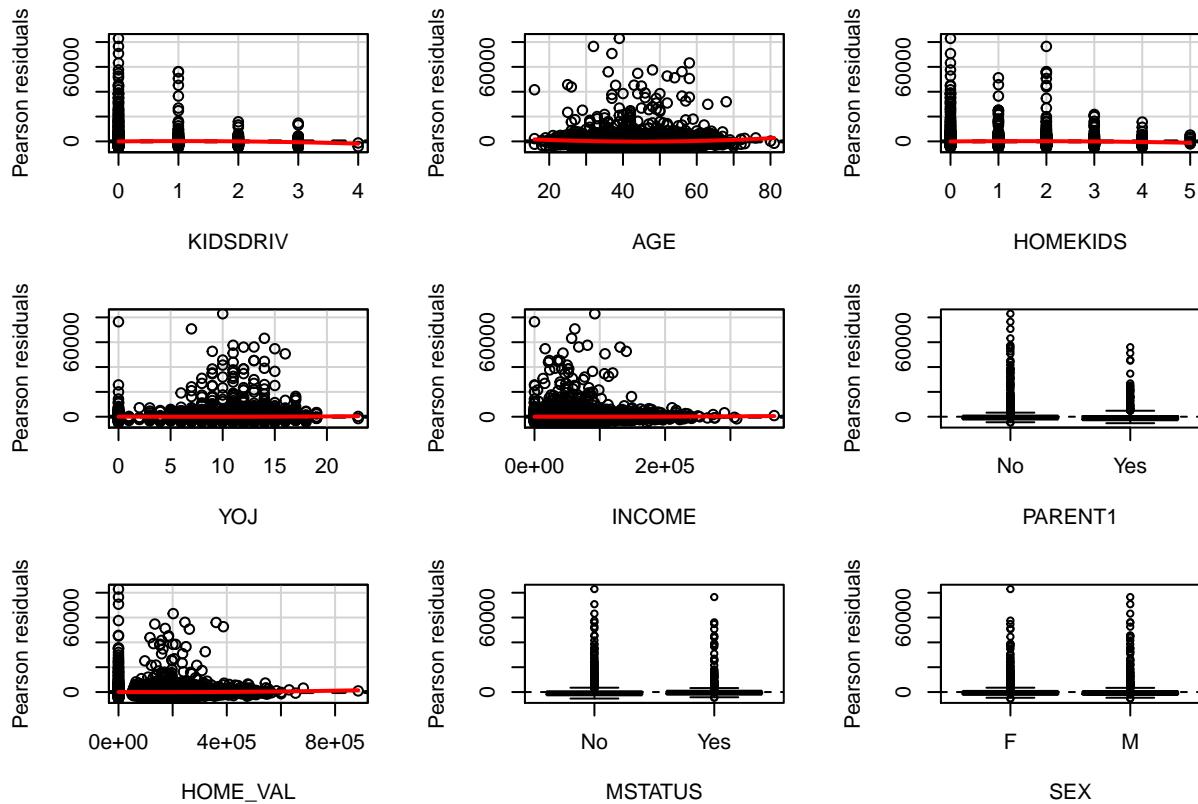
Table 4:

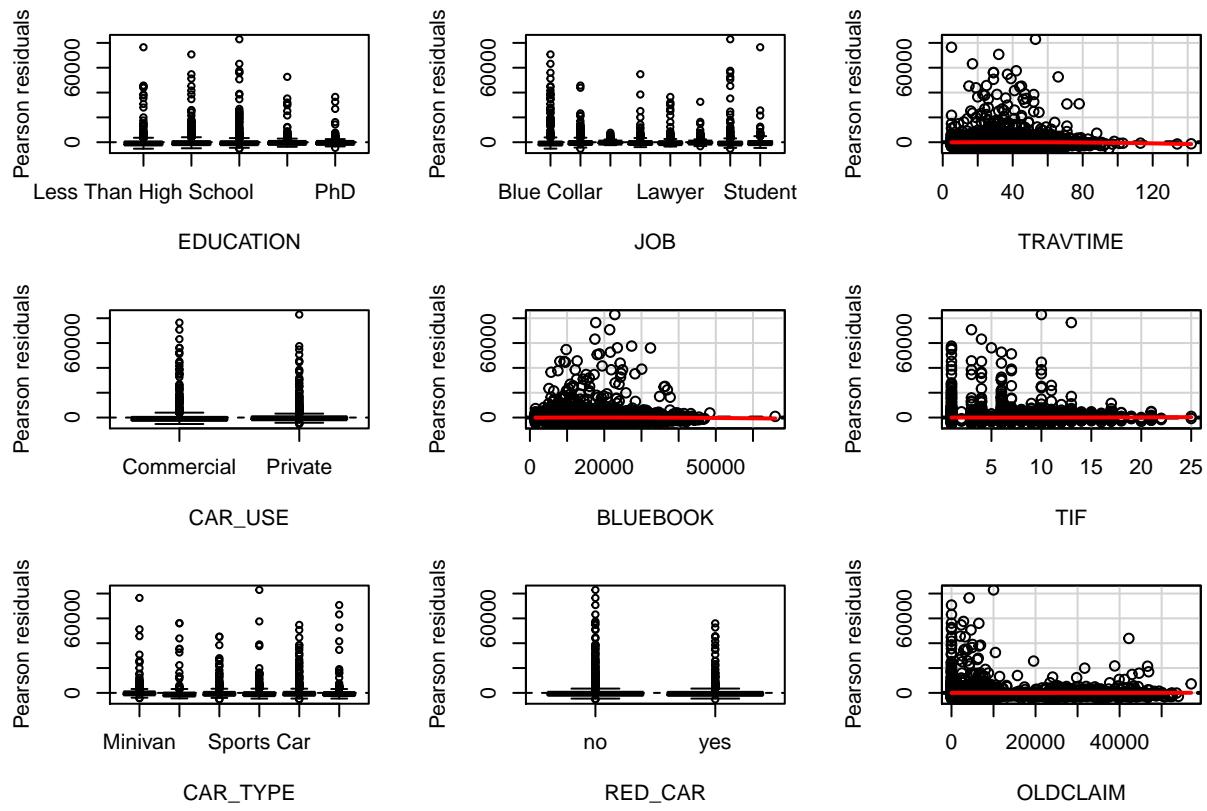
Statistic	N	Mean	St. Dev.	Min	Max
INCOME	8,161	61,225.430	45,828.110	0.000	210,660.000
HOME_VAL	8,161	154,982.200	127,401.100	0.000	750,455.000
OLDCLAIM	8,161	2,757.246	4,469.462	0	14,738
BLUEBOOK	8,161	15,696.740	8,359.971	1,500	46,250
TARGET_FLAG	8,161	0.264	0.441	0	1
TARGET_AMT	8,161	1,504.325	4,704.027	0.000	107,586.100
KIDSDRV	8,161	0.171	0.512	0	4
AGE	8,161	44.782	8.630	16.000	81.000
HOMEKIDS	8,161	0.721	1.116	0	5
YOJ	8,161	10.498	4.037	0.000	23.000
TRAVTIME	8,161	33.486	15.908	5	142
TIF	8,161	5.351	4.147	1	25
CLM_FREQ	8,161	0.799	1.158	0	5
MVR PTS	8,161	1.696	2.147	0	13
CAR_AGE	8,161	8.350	5.602	0.000	28.000

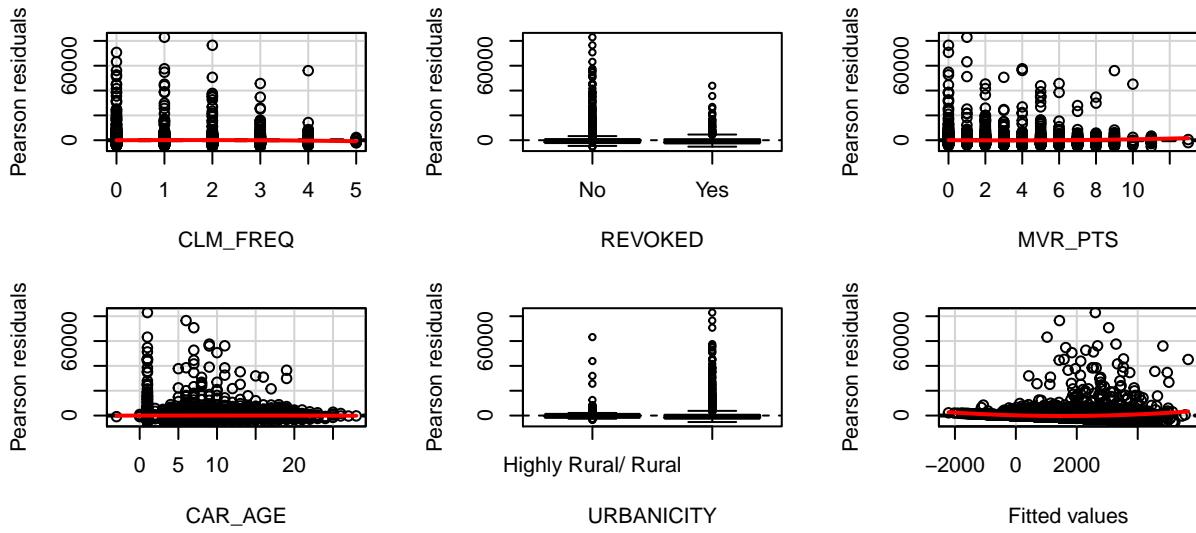
## 4.2 BoxCox Transformations

The Box-Cox transformations were done only on three of the input variables - income, house value, and the total number of claims during the past 5 years. These transformations were done based on the residual plots. In the residual plots, these three variables showed a great deal of non-constant variance because the plots were funnel-shaped.

```
## Non-constant Variance Score Test
## Variance formula: ~ KIDSDRV + AGE + HOMEKIDS + YOJ + INCOME + PARENT1 + HOME_VAL + MSTATUS + SEX + I
## Chisquare = 5720.739      Df = 36      p = 0
```







```
##           Test stat Pr(>|t|) 
## KIDSDRIV      -1.733   0.083 
## AGE            4.364   0.000 
## HOMEKIDS     -2.420   0.016 
## YOJ             1.003   0.316 
## INCOME          0.513   0.608 
## PARENT1         NA      NA    
## HOME_VAL        1.483   0.138 
## MSTATUS          NA      NA    
## SEX              NA      NA    
## EDUCATION        NA      NA    
## JOB              NA      NA    
## TRAVTIME       -1.033   0.302 
## CAR_USE          NA      NA    
## BLUEBOOK        -0.618   0.536 
## TIF              0.467   0.640 
## CAR_TYPE         NA      NA    
## RED_CAR          NA      NA    
## OLDCLAIM        0.171   0.864 
## CLM_FREQ        -1.784   0.074 
## REVOKED          NA      NA    
## MVR PTS         1.987   0.047 
## CAR AGE          -0.277  0.782 
## URBANICITY        NA      NA    
## Tukey test       8.214   0.000
```

Using the `BoxCox.lambda` function from the `forecast` package we are able to determine our necessary

transformations to our independent variables.

$\lambda$	Variables
0.268842617694589	INCOME
0.505233636014921	HOME_VAL
0.456635555660553	TRAVTIME

Utilizing the below table of common transformations based on the lambda value of the BoxCox we further transform our independent variables.

Common Box-Cox Transformations<sup>5</sup> <sup>6</sup>

$\lambda$	$Y'$
-2	$Y^{-2} = \frac{1}{Y^2}$
-1	$Y^{-1} = \frac{1}{Y^1}$
-0.5	$Y^{-0.5} = \frac{1}{\sqrt{(Y)}}$
0	$\log(Y)$
.25	$\sqrt[4]{Y}$
0.5	$Y^{0.5} = \sqrt{(Y)}$
1	$Y^1 = Y$
2	$Y^2$

Lambda values were truncated to the nearest tenth that match a common transformation as per the below table.

variable	variable transformation
INCOME	$\sqrt[4]{INCOME}$
HOME VAL	$\sqrt{(HOME VAL)}$
TRAVTIME	$\sqrt{TRAVTIME}$

<sup>5</sup>By Understanding Both the Concept of Transformation and the Box-Cox Method, Practitioners Will Be Better Prepared to Work with Non-normal Data.. . “Making Data Normal Using Box-Cox Power Transformation.” ISixSigma. N.p., n.d. Web. 29 Oct. 2016.

<sup>6</sup>Osborne, Jason W. “Improving your data transformations: Applying the Box-Cox transformation.” Practical Assessment, Research & Evaluation 15.12 (2010): 1-9.

## 5 Models Built

### 5.1 Logistic Model 1 - Backwards Selection Method

In the backward step selection model The resulting AIC was .

Table 6:

	fullModel
Constant	0.113*** (0.037)
KIDSDRV	0.065*** (0.009)
I(INCOME^(1/4))	-0.008*** (0.002)
PARENT1Yes	0.085*** (0.015)
I(sqrt(HOME_VAL))	-0.0001*** (0.00003)
MSTATUSYes	-0.059*** (0.012)
EDUCATIONHigh School	0.062*** (0.013)
EDUCATIONLess Than High School	0.054*** (0.016)
EDUCATIONMasters	0.024 (0.017)
EDUCATIONPhD	0.041* (0.022)
JOBClerical	0.012 (0.016)
JOBDoctor	-0.134*** (0.036)
JOBHome Maker	-0.053** (0.025)
JOBLawyer	-0.051* (0.026)
JOBManager	-0.136*** (0.019)
JOBProfessional	-0.028 (0.018)
JOBStudent	-0.069*** (0.023)
I(sqrt(TRAVTIME))	0.023*** (0.003)
CAR_USEPrivate	-0.126*** (0.014)
BLUEBOOK	-0.00000*** (0.00000)
TIF	-0.008*** (0.001)
CAR_TYPEPanel Truck	0.069*** (0.022)
CAR_TYPEPickup	0.073*** (0.015)
CAR_TYPESports Car	0.133*** (0.016)
CAR_TYPESUV	0.096*** (0.012)
CAR_TYPEVan	0.081*** (0.018)
OLDCLAIM	-0.00000** (0.00000)
CLM_FREQ	0.031*** (0.005)
REVOKEDYes	0.139*** (0.014)
MVR PTS	0.021*** (0.002)
URBANITYHighly Urban/ Urban	0.299*** (0.012)
N	8,161
Log Likelihood	-3,820.565
Akaike Inf. Crit.	7,703.130

Notes:

\*\*\*Significant at the 1 percent level.

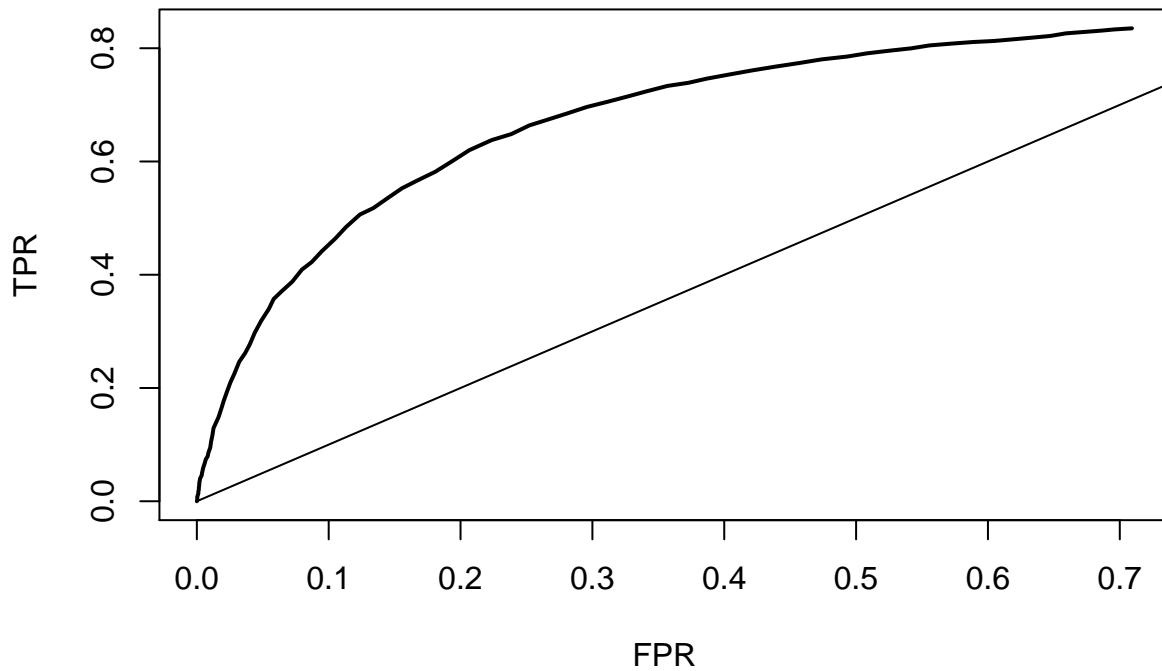
\*\*Significant at the 5 percent level.

\*Significant at the 10 percent level.

#### 5.1.1 Model Metrics for Backwards Selection

We first use an established threshold of .50 to determine our best possible threshold.

## Model Metrics for Backwards Selection



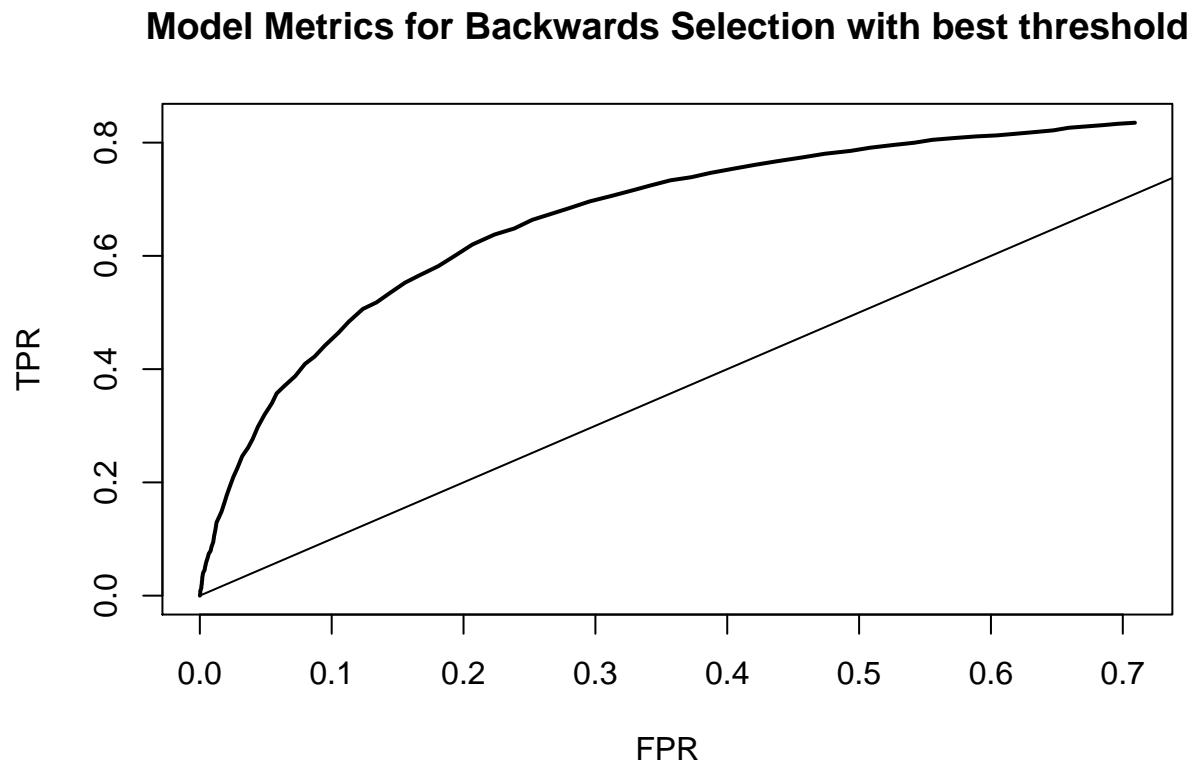
Act-Pos Act-Neg Pred-Pos 687 1466 Pred-Neg 294 5714

Model Metrics for Backwards Selection	
accuracy	0.784
classif.error	0.216
precision	0.700
sensitivity	0.319
specificity	0.951
f1score	0.438
auc	0.469
best.threshold	0.320
aic	7703.130
CVError	NA

Our previous results indicate that .320 would be the best threshold for this model so we re-run our metrics using this threshold.

### 5.1.1.1 Model Metrics for Backwards Selection with best threshold

Model Metrics using best threshold of .320.



Act-Pos Act-Neg Pred-Pos 1373 780 Pred-Neg 1343 4665

Model Metrics for Backwards Selection with best threshold	
accuracy	0.740
classif.error	0.260
precision	0.506
sensitivity	0.638
specificity	0.776
f1score	0.564
auc	0.469
best.threshold	0.320
aic	7703.130
CVError	NA

### 5.1.2 Multicollinearity for Backwards Selection

rn	GVIF	Df	GVIF^(1/(2*Df))
KIDSDRV	1.077269	1	1.037916
I(INCOME^(1/4))	3.303477	1	1.817547
PARENT1	1.411040	1	1.187872
I(sqrt(HOME_VAL))	2.093420	1	1.446866
MSTATUS	2.012248	1	1.418537
EDUCATION	6.363135	4	1.260256
JOB	25.141215	7	1.259005
TRAVTIME	1.037090	1	1.018376
CAR_USE	2.409461	1	1.552244
BLUEBOOK	1.671917	1	1.293026
TIF	1.007017	1	1.003502
CAR_TYPE	2.483562	5	1.095236
CLM_FREQ	1.262974	1	1.123821
REVOKE	1.020286	1	1.010092
MVR_PTS	1.213958	1	1.101798
URBANICITY	1.250699	1	1.118347

## 5.2 Logistic Model 2 - Forwards Selection Method

Table 10:

	fullModel
Constant	0.123** (0.048)
KIDSDRV	0.062*** (0.010)
AGE	-0.0004 (0.001)
HOMEKIDS	0.004 (0.006)
YOJ	0.001 (0.002)
I(INCOME^(1/4))	-0.009*** (0.002)
PARENT1Yes	0.075*** (0.017)
I(sqrt(HOME_VAL))	-0.0001*** (0.00003)
MSTATUSYes	-0.063*** (0.013)
SEXM	0.014 (0.016)
EDUCATIONHigh School	0.059*** (0.014)
EDUCATIONLess Than High School	0.049*** (0.018)
EDUCATIONMasters	0.028 (0.018)
EDUCATIONPhD	0.046** (0.023)
JOBClerical	0.010 (0.016)
JOBDoctor	-0.132*** (0.037)
JOBHome Maker	-0.051** (0.025)
JOBLawyer	-0.049* (0.026)
JOBManager	-0.134*** (0.019)
JOBProfessional	-0.027 (0.018)
JOBStudent	-0.070*** (0.023)
I(sqrt(TRAVTIME))	0.023*** (0.003)
CAR_USEPrivate	-0.126*** (0.014)
BLUEBOOK	-0.00000*** (0.00000)
TIF	-0.008*** (0.001)
CAR_TYPEPanel Truck	0.063*** (0.024)
CAR_TYPEPickup	0.074*** (0.015)
CAR_TYPESports Car	0.141*** (0.019)
CAR_TYPESUV	0.104*** (0.015)
CAR_TYPEVan	0.077*** (0.018)
RED_CARyes	-0.005 (0.013)
OLDCLAIM	-0.00000** (0.00000)
CLM_FREQ	0.031*** (0.005)
REVOKEYes	0.138*** (0.014)
MVR PTS	0.021*** (0.002)
CAR_AGE	-0.001 (0.001)
URBANITYHighly Urban/ Urban	0.299*** (0.012)
N	8,161
Log Likelihood	-3,819.035
Akaike Inf. Crit.	7,712.070

Notes:

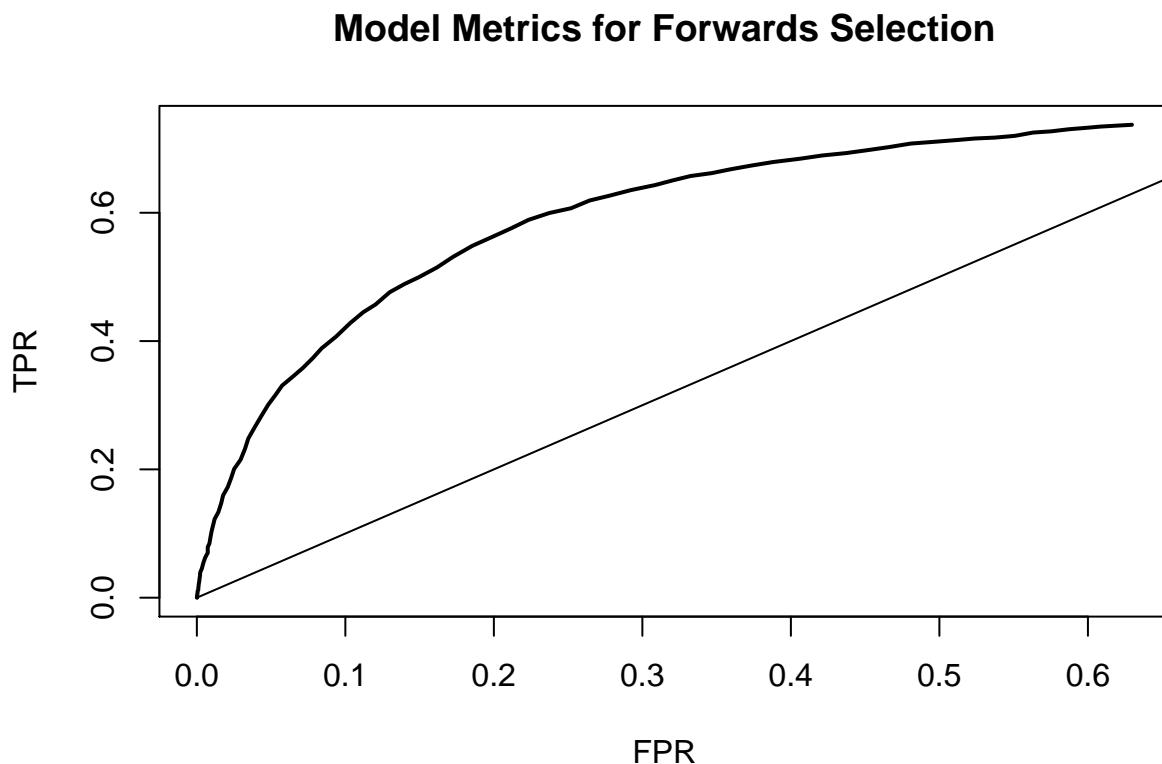
\*\*\*Significant at the 1 percent level.

\*\*Significant at the 5 percent level.

\*Significant at the 10 percent level.

### 5.2.1 Model Metrics for Forwards Selection

We first use an established threshold of .50 to determine our best possible threshold.



	Act-Pos	Act-Neg
Pred-Pos	614	1539
Pred-Neg	264	5744

Model Metrics for Forwards Selection	
accuracy	0.779
classif.error	0.221
precision	0.699
sensitivity	0.285
specificity	0.956
f1score	0.405
auc	0.368
best.threshold	0.300
aic	7712.070
CVError	NA

### 5.2.2 Multicollinearity for Forwards Selection

Here in our forward selection model we find that no variable exceeds our pre-established threshold of 5 for multicollinearity.

rn	GVIF	Df	GVIF^(1/(2*Df))
KIDSDRIV	1.325344	1	1.151236
AGE	1.487782	1	1.219747
HOMEKIDS	2.136050	1	1.461523
YOJ	2.043591	1	1.429542
I(INCOME^(1/4))	4.626874	1	2.151017
PARENT1	1.844294	1	1.358048
I(sqrt(HOME_VAL))	2.115696	1	1.454543
MSTATUS	2.204211	1	1.484659
SEX	3.324170	1	1.823231
EDUCATION	8.969420	4	1.315514
JOB	26.685061	7	1.264376
I(sqrt(TRAVTIME))	1.033912	1	1.016814
CAR_USE	2.409933	1	1.552396
BLUEBOOK	2.065326	1	1.437124
TIF	1.007641	1	1.003813
CAR_TYPE	5.489500	5	1.185641
RED_CAR	1.814257	1	1.346944
OLDCLAIM	2.193395	1	1.481011
CLM_FREQ	2.076612	1	1.441045
REVOKE	1.200779	1	1.095800
MVR_PTS	1.239981	1	1.113544
CAR_AGE	2.166209	1	1.471805
URBANICITY	1.248323	1	1.117284

## 5.3 Logistic Model 3 - Subset Selection Method

### 5.3.1 Subset Variable Selection

Using the `leaps` package and the `regsubsets` function we are able to subset our independent variables by looking at the best model for each predictor.

	1(1)	2(1)	3(1)	4(1)	5(1)	6(1)	7(1)	8(1)
KIDSDRV							*	
AGE								
HOMEKIDS								
YOJ								
I(INCOME^(1/4))					*	*	*	*
PARENT1Yes					*	*	*	
I(sqrt(HOME_VAL))	*	*	*					
MSTATUSYes							*	
SEXM								
EDUCATIONHigh School								
EDUCATIONLess Than High School								
EDUCATIONMasters								
EDUCATIONPhD								
JOBClerical								
JOBDoctor								
JOBHome Maker								
JOBLawyer								
JOBManager							*	*
JOBProfessional								
JOBStudent								
I(sqrt(TRAVTIME))								
CAR_USEPrivate					*	*	*	*
BLUEBOOK								
TIF								
CAR_TYPEPanel Truck								
CAR_TYPEPickup								
CAR_TYPESports Car								
CAR_TYPESUV								
CAR_TYPEVan								
RED_CARYes								
OLDCLAIM								
CLM_FREQ								
REVOKEDEYes						*	*	*
MVR PTS	*	*	*	*	*	*	*	*
CAR_AGE								
URBANICITYHighly Urban/ Urban	*	*	*	*	*	*	*	*

### 5.3.2 Subset Model

The variables as indicated in column 8 of the previous table will be further implement into our subset selection model in the following table. We don't see as strong of a relationship in our independent variables to the dependent variable in this model as our previous model. For example, the coefficient for tax was as high as 106 in the forward selection model but it is -5 in this model. However, our intercept in this model is larger than any other model.

Table 15:

	TARGET_FLAG
Constant	-1.135*** (0.185)
KIDSDRV	0.469*** (0.052)
I(INCOME^(1/4))	-0.085*** (0.010)
MSTATUSYes	-0.748*** (0.057)
JOBClerical	0.148 (0.099)
JOBDoctor	-0.972*** (0.218)
JOBHome Maker	-0.422*** (0.156)
JOBLawyer	-0.467*** (0.121)
JOBManager	-0.955*** (0.096)
JOBProfessional	-0.398*** (0.099)
JOBStudent	-0.343** (0.144)
CAR_USEPrivate	-0.725*** (0.070)
REVOKEDYes	0.753*** (0.078)
MVR PTS	0.151*** (0.012)
URBANICITYHighly Urban/ Urban	2.283*** (0.109)
N	8,161
Log Likelihood	-3,839.185
Akaike Inf. Crit.	7,708.369

Notes:

\*\*\* Significant at the 1 percent level.

\*\* Significant at the 5 percent level.

\* Significant at the 10 percent level.

### 5.3.3 Model Metrics for Subset Selection

We first use an established threshold of .50 to determine our best possible threshold.

### 5.3.4 Multicollinearity for Subset Selection

Here in our subset selection model we find that no variable exceeds our pre-established threshold of 5 for multicollinearity.

rn	GVIF	Df	GVIF^(1/(2*Df))
KIDSDRV	1.022204	1	1.011041
I(INCOME^(1/4))	3.012788	1	1.735739
MSTATUS	1.026972	1	1.013396
JOB	4.435051	7	1.112262
CAR_USE	1.491887	1	1.221428
REVOKE	1.004182	1	1.002089
MVR PTS	1.011248	1	1.005608
URBANITY	1.084428	1	1.041359