



Golden Retriever

Insurance Company

Golden Price Model v2.0

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Introduction

Big Dogs Insurance Group is pleased to open a new charter, Golden Retriever Insurance Company, for new business in your state. The new charter will utilize a new rating algorithm based on our latest model, the Golden Price Model v2.0. This model leverages our latest internal data and expands our segmentation power by also incorporating external data. Our external data comes from Reputable Consumer Database, a third-party data vendor with data on the purchasing habits for roughly 70% of Americans. This additional segmentation power will allow us to differentiate our product from competitors and avoid adverse selection. All available variables from Reputable Consumer Database were analyzed in a preliminary model, but only the variables with the low p-values were kept in our final pricing model. The Golden Price Model v2.0 will not be applied to renewal business in our existing charters in order to limit price disruptions to existing business.

Certification

I, Dug Waffles Kloese, am an insurance expert. I have over 3 years of experience working closely with a credentialed P&C Actuary. I am responsible for the contents of this document. This is a confidential document for use in supporting rate models filed with departments of insurance companies. This document is assembled to disclose the methods, assumptions, data, and decisions used to derive the indicated rating factors for our latest rating plan. The model adheres to the principles of ASOP 12, 23, 41, and 56.



Dug Waffles Kloese

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Data

All claims data and current policy characteristics come from our internal data center. Big Dogs Insurance Group operates in the following states: Iowa, Illinois, Missouri, Ohio, and Wisconsin. The modeling dataset includes accident years 2022-2024 with losses as of June 2025. Earned Exposures were measured in terms of earned car years. The modeling dataset was split into two separate datasets: training and test dataset. 80% of the data was used for training and 20% was reserved for the test dataset. The following table summarizes the data volume by year in our datasets:

Dataset	Year	Exposures	Claim Count	Losses
Train	2022	209,627	8,366	91,790,993
Train	2023	245,197	9,737	110,192,174
Train	2024	245,176	10,326	120,358,806
	Sub-total	700,000	28,429	322,341,972
Test	2022	89,896	3,552	38,722,579
Test	2023	105,361	4,190	46,352,102
Test	2024	104,743	4,431	53,379,998
	Sub-total	300,000	12,173	138,454,680

The following table summarizes data volume by state in our datasets:

State	Exposures	Claim Count	Losses
Illinois	299,844	12,487	145,784,576
Iowa	299,657	11,731	127,935,867
Missouri	200,524	8,596	103,228,746
Ohio	99,752	3,887	41,537,028
Wisconsin	100,223	3,901	42,310,436
	1,000,000	40,602	460,796,652

100 sample modeling data records is included in this filing as Exhibit 4.

A data dictionary for the variables in the Golden Price Model v2.0 is included in Exhibit 1.

The following columns are included in the data dictionary:

- Variable Name: A plain text name that describes the variable.
- Modeled Name: The exact name used in the code to run the model.
- Source: Either “Internal” or “Reputable Consumer Data”
- Description: The description of the variable.
- Variable Treatment: Whether the variable is a control, offset, target, or predictor variable.
- Data Type: Either numeric or categorical.

- Rational Explanation: A plausible explanation for how a differing value in the predictor variable would indicate a difference in insurance risk.
- Possible Values: Empirical range is given for numeric variables. Possible categories is given for categorical variables.

The dataset was explored using a correlation matrix to assess the risk of collinearity. For the purposes of the correlation matrix, the categorical variables were first one-hot encoded. The categorical variables were not one-hot encoded when later building the pricing GLM. The correlation metric analyzed was the Pearson correlation. The correlation matrix appears in Exhibit 1. Correlation metrics between most variables were < 0.1 .

Correlations were strong between variable levels of the same categorical variable. Furthermore, correlations were strong between the “Missing” data level of the variables from Reputable Consumer Database. When an individual could not be found in the Reputable Consumer Database, all of the Credible Consumer Database variables were encoded as “Missing”.

Generalized Variance Inflation Factors (GVIFs) were also explored. GVIFs could not be calculated for the Reputable Consumer Database variables since there was an aliasing issue. A model excluding the variables with aliasing was built to calculate GVIFs for the other variables. The results are incorporated into this report as Exhibit 2. Most variables had a GVIF < 2.0 , with the exception of the Driver Age variables. A polynomial fit was achieved by including (Driver Age), (Driver Age)², and (Driver Age)³ as terms in the model. As a result, these variables have high GVIF, as (Driver Age)² and (Driver Age)³ are directly derived from (Driver Age).

Model

The pricing plan is based on a General Linearized Model (GLM). The target variable is combined coverage pure premium. Pure premium is defined as incurred losses divided by earned car years. The GLM assumes that the error distribution follows a Gamma distribution. The Gamma distribution is useful because it is a blend of Poisson and Tweedie distributions. The Gamma distribution is also especially useful in the pure premium context because it can accommodate a target variable where many records have a value of 0. We selected a p power parameter value equal to 1.5 for the Gamma distribution. An identity link function was chosen as it was desirable to derive multiplicative indicated rating factors. Deviance residuals are provided in Exhibit 7 to demonstrate that the modeling assumptions are reasonable.

State and Year were included as control variables in the model. Coverage Package level was included as an offset to account for varying coverage levels. The coverage package levels are grouped into minimum, medium, and maximum coverage. Golden Retriever Insurance Company only operates in Medical Payments states and therefore did not make any adjustments for PIP coverage differences across states. All variables with the exception of state, year, and coverage package level were modeled as predictor variables and later used in the proposed rating factors.

Beta coefficients, standard errors, and p-values are included in this report in Exhibit 5. F nested model tests and an AIC analysis were done to assess the predictiveness of each variable. AIC was calculated for the full model and each subset model excluding one variable at a time. The F nested model tests and AIC analysis are included in this report as Exhibit 6.

Validation

Model fit by variable was checked by assembling actual vs. expected plots by variable. Model predictions were appended to the training set based on the final GLM. This allowed us to compare actual pure premiums to predicted pure premiums. These plots are shown in Exhibit 8. The gold lines (for numeric variables) and gold points (for categorical variables) represent the predicted pure premiums. The red points represent the actual pure premiums. The predicted pure premiums follow the general pattern of the actual pure premiums. Exhibit 8 also includes bar charts showing data volume by variable level for reference.

Overall fit was checked by reviewing decile plots. The decile plots are included in Exhibit 9. The records were sorted by predicted premium and then bucketed into deciles of equal volume. The actual and predicted premium were calculated for each decile and plotted together. The decile plots demonstrate lift, monotonicity, and predictive accuracy. Separate decile plots were created for both training data and test data. The plots are also very consistent further demonstrating the model generalizing well to unseen data.

Segmentation power was checked by reviewing Lorenz curves. The Lorenz curves are included in Exhibit 9. Lorenz curves showing a significantly large area between the model's curve and the reference line demonstrate segmentation power, the ability to distinguish between low risk and high risk. Separate Lorenz curves were created for both training and test data. The plots are very consistent, further demonstrating the model generalizing well to unseen data. The Gini coefficients for the training and test Lorenz curves are 0.2887 and 0.2890 respectively.

Implementation

Indicated factors were derived from the GLM's coefficients. Proposed factors were based on these indicated factors and other business considerations. A complete set of indicated vs. selected factors is provided in Exhibit 10. There were only a handful of variables with deviations between indicated and selected, as summarized below:

- Primary Insured Driver Age – The selections were tempered to minimize rate disruptions as insureds age.
- Insurance Score Tier – Selections were made based on current underwriting appetite.
- Prior Claim Count – Selections were made based on market considerations.
- Marital Status – Selections were made such that “Widowed” receives the same factor as “Married” and “Separated” receives the same factor as “Single”.
- Recent Fender Purchase – Actuarial judgement was applied to vary the discount based on the type of fender purchased.
- CAS Seminar – The proposed factor for the “Missing” level is set equal to the same rating factor for “No”.
- Cold Play Tickets – The proposed factor for the “Missing” level is set equal to the same rating factor for “Yes”.

The base rate was set to \$500. The coverage package level factors were set equal to the factors previously approved for our existing charters. The proposed rating algorithm is expected to result in premiums that are on average 10% below our existing charters. Sample rating examples are included in Exhibit 11.

Exhibit 1: Data Dictionary

Variable Name	Modeled Name	Source	Description	Variable Treatment	Data Type
State	State	Internal	The policy state	Control	Categorical
Year	Year	Internal	The year corresponding to the calendar year for the earned exposure and the accident year	Control	Categorical
Coverage Package Level	Coverage	Internal	Each package has specified limits and deductibles. The minimum package includes the lowest liability limits offered and the highest deductibles offered. The maximum package includes the highest liability limits and the lowest deductibles offered.	Offset	Categorical
Primary Insured Driver Age	Driver_Age	Internal	The age of the primary driver for the specified vehicle	Modeled	Numeric
Number of Drivers	Number_Drivers	Internal	The number of licensed drivers on the auto insurance policy	Modeled	Numeric
Number of Cars	Number_Cars	Internal	The number of insured vehicles on the auto insurance policy	Modeled	Numeric
Insurance Score Tier	Insurance_Score	Internal	Our policies were scored based on previously approved scoring model. Policies were then bucketed into deciles, each containing about 10% of exposures. Decile number is included as the insurance score tier.	Modeled	Numeric
Telematics Score Tier	Telematics_Score	Internal	Our policies were scored based on our previously approved telematics scoring model. Policies were then bucketed into deciles, each containing about 10% of exposures. Decile number is included as the telematics score tier.	Modeled	Numeric
Vehicle Model Year	Model_Year	Internal	The model year of the insured vehicle	Modeled	Numeric
Prior Claim Count	Prior_Claims	Internal	The count of at-fault claims where the sum of Bodily Injury, Property Damage, and Collision losses exceed \$1,000.	Modeled	Numeric
Primary Insured Marital Status	Marital_Status	Internal	The marital status of the primary driver for the specified vehicle	Modeled	Categorical
Vehicle Usage	Vehicle_Use	Internal	The way the vehicle is currently being used by the household, as reported by the insured.	Modeled	Categorical
Vehicle Type	Vehicle_Type	Internal	The type of vehicle based on size and expected use.	Modeled	Categorical
Recent Fender Purchase	New_Fender	Reputable Consumer Database	The primary insured has purchased a Fender electric, acoustic, or bass guitar within the 3 years prior the policy term effective date.	Modeled	Categorical
Recent CAS Seminar Purchase	CAS_Seminar	Reputable Consumer Database	The primary insured has purchased access to a Casualty Actuarial Society within the 3 years prior the policy term effective date.	Modeled	Categorical
Recent Cold Play Tickets Purchase	Cold_Play_Tickets	Reputable Consumer Database	The primary insured has purchased tickets to a Cold Play concert within the 3 years prior the policy term effective date.	Modeled	Categorical
Combined Coverage Incurred Pure Premium	amount	Internal	The sum of the incurred losses from all coverages over the entire car year. Each record in the dataset represents exactly one earned car year.	Target	Numeric

Variable Name	Modeled Name	Rational Explanation	Possible Values
State	State	Vehicle repair costs vary by state	Iowa; Illinois; Missouri; Ohio; Wisconsin
Year	Year	Vehicle repair costs have been rising leading to differences in cost by year	Year_2022; Year_2023; Year_2024
Coverage Package Level	Coverage	The level of coverage selected impacts frequency and severity of losses.	Minimum; Medium; Maximum
Primary Insured Driver Age	Driver_Age	Younger drivers have less experience which results in riskier driving. Older drivers also have reduced reaction times as they age.	16 - 75
Number of Drivers	Number_Drivers	Vehicles in a household with more drivers are driven more often, which increases claims per earned year.	1 - 4
Number of Cars	Number_Cars	Vehicles in a household with more vehicles have lower mileage per vehicle, lowering the claims per earned car year.	1 - 4
Insurance Score Tier	Insurance_Score	Insurance_Score have a very low p-value, demonstrating predictiveness.	1 - 10
Telematics Score Tier	Telematics_Score	The telematics model measures driving behavior, including risky driving behaviors like hard braking events.	1 - 10
Vehicle Model Year	Model_Year	Newer vehicles have higher repair costs due to the additional technology in modern vehicles.	2000 - 2025
Prior Claim Count	Prior_Claims	Drivers who have previously caused an at-fault accident often have worse than average driving behaviours which will likely result in additional future claims.	0 - 5
Primary Insured Marital Status	Marital_Status	Married individuals tend to be more risk averse which leads to less claims per exposure year.	Single; Married; Widowed; Separated
Vehicle Usage	Vehicle_Use	The amount a vehicle is used influences how often it is exposed to a risk of an insurance claim.	Pleasure_Use; Drive_To_Work; Retired; In_Storage
Vehicle Type	Vehicle_Type	Different vehicle types have different average horsepower, average size, and average number of passengers. These elements can impact claim severity.	Private_Passenger; SUV; Van; Pickup; Other
Recent Fender Purchase	New_Fender	People who play Fender guitars have good taste and avoid distasteful activities such as car accidents.	Yes; No; Missing
Recent CAS Seminar Purchase	CAS_Seminar	People who attend CAS Seminars are more risk conscious and drive more conservatively.	Yes; No; Missing
Recent Cold Play Tickets Purchase	Cold_Play_Tickets	People who purchase Cold Play tickets often make poor decisions. Poor decision makers get in car accidents more frequently.	Yes; No; Missing
Combined Coverage Incurred Pure Premium	amount		0 - 252,088

Exhibit 2: Correlation Matrix

Variable	Driver_Age	Number_Drivers	Number_Cars	Insurance_Score	Telematics_Score	Model_Year	Prior_Claims	Marital_Status_Married	Marital_Status_Single	Marital_Status_Seperated	Marital_Status_Widowed	Vehicle_Use_Drive_To_Work	Vehicle_Use_Pleasure_Use	Vehicle_Use_In_Storage	Vehicle_Use_Retired
Driver_Age	1.000	(0.000)	(0.004)	(0.001)	(0.000)	(0.001)	0.000	0.002	(0.001)	(0.000)	(0.001)	0.001	0.003	(0.001)	(0.003)
Number_Drivers	(0.000)	1.000	(0.000)	0.002	(0.001)	0.000	(0.001)	(0.001)	0.001	0.001	0.000	(0.000)	0.001	(0.001)	(0.000)
Number_Cars	(0.004)	(0.000)	1.000	0.000	0.001	(0.001)	0.000	0.001	(0.001)	(0.001)	0.001	0.001	(0.001)	(0.001)	(0.000)
Insurance_Score	(0.001)	0.002	0.000	1.000	(0.002)	(0.003)	(0.001)	(0.000)	0.000	(0.001)	0.001	0.002	(0.001)	0.001	(0.002)
Telematics_Score	(0.000)	(0.001)	0.001	(0.002)	1.000	(0.000)	0.000	(0.001)	0.001	(0.002)	0.000	0.000	(0.001)	0.001	0.000
Model_Year	(0.001)	0.000	(0.001)	(0.003)	(0.000)	1.000	0.002	0.003	(0.003)	(0.002)	0.000	(0.001)	0.000	0.001	0.001
Prior_Claims	0.000	(0.001)	0.000	(0.001)	0.000	0.002	1.000	0.000	(0.001)	0.001	0.001	0.000	(0.001)	(0.001)	0.000
Marital_Status_Married	0.002	(0.001)	0.001	(0.000)	(0.001)	0.003	0.000	1.000	(0.903)	(0.111)	(0.224)	(0.003)	0.001	(0.001)	0.003
Marital_Status_Single	(0.001)	0.001	(0.001)	0.000	0.001	(0.003)	(0.001)	(0.903)	1.000	(0.082)	(0.167)	0.003	(0.001)	0.002	(0.003)
Marital_Status_Seperated	(0.000)	0.001	(0.001)	(0.001)	(0.002)	(0.002)	0.001	(0.111)	(0.082)	1.000	(0.020)	(0.000)	(0.001)	(0.001)	0.001
Marital_Status_Widowed	(0.001)	0.000	0.001	0.001	0.000	0.000	0.001	(0.224)	(0.167)	(0.020)	1.000	0.000	(0.000)	(0.000)	0.000
Vehicle_Use_Drive_To_Work	0.001	(0.000)	0.001	0.002	0.000	(0.001)	0.000	(0.003)	0.003	(0.000)	0.000	1.000	(0.594)	(0.123)	(0.612)
Vehicle_Use_Pleasure_Use	0.003	0.001	(0.001)	(0.001)	(0.001)	0.000	(0.001)	0.001	(0.001)	(0.001)	(0.000)	(0.594)	1.000	(0.049)	(0.241)
Vehicle_Use_In_Storage	(0.001)	(0.001)	(0.001)	0.001	0.001	0.001	(0.001)	(0.001)	0.002	(0.001)	(0.000)	(0.123)	(0.049)	1.000	(0.050)
Vehicle_Use_Retired	(0.003)	(0.000)	(0.000)	(0.002)	0.000	0.001	0.000	0.003	(0.003)	0.001	0.000	(0.612)	(0.241)	(0.050)	1.000
Vehicle_Type_Private_Passenger	(0.000)	0.001	(0.000)	0.001	(0.001)	0.000	(0.000)	(0.002)	0.003	(0.001)	(0.001)	0.002	(0.003)	0.001	(0.000)
Vehicle_Type_SUV	(0.000)	(0.001)	0.000	0.000	(0.001)	(0.000)	0.000	0.002	(0.003)	0.000	0.001	0.001	0.001	(0.001)	(0.002)
Vehicle_Type_Van	0.001	(0.001)	(0.000)	0.001	0.001	0.002	(0.001)	0.001	(0.001)	(0.000)	(0.001)	(0.001)	0.001	0.001	(0.000)
Vehicle_Type_Pickup	0.000	0.000	0.001	(0.001)	(0.000)	0.000	0.000	(0.001)	0.001	0.000	(0.001)	0.001	(0.001)	(0.001)	0.000
Vehicle_Type_Other	(0.000)	0.000	(0.000)	(0.000)	0.001	(0.001)	0.000	0.001	(0.002)	0.001	0.001	(0.003)	0.003	(0.000)	0.002
New_Fender_No	0.000	0.002	(0.000)	0.001	0.000	(0.002)	0.001	0.000	0.000	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	0.001
New_Fender_Yes	0.001	0.000	0.002	(0.001)	0.002	0.002	0.001	0.000	0.001	0.000	(0.003)	(0.001)	0.002	0.000	(0.000)
New_Fender_Missing	(0.000)	(0.002)	(0.001)	(0.000)	(0.001)	0.001	(0.001)	(0.000)	(0.000)	0.001	0.002	0.001	(0.000)	0.001	(0.001)
CAS_Seminar_No	0.000	0.002	0.001	(0.000)	0.001	(0.001)	0.001	0.000	0.001	(0.001)	(0.001)	(0.001)	0.000	(0.000)	0.001
CAS_Seminar_Yes	0.001	(0.001)	(0.000)	0.001	0.001	(0.001)	0.000	0.001	(0.001)	0.000	(0.001)	0.001	(0.000)	(0.002)	(0.000)
CAS_Seminar_Missing	(0.000)	(0.002)	(0.001)	(0.000)	(0.001)	0.001	(0.001)	(0.000)	(0.000)	0.001	0.002	0.001	(0.000)	0.001	(0.001)
Cold_Play_Tickets_No	(0.000)	0.003	0.000	0.000	0.001	(0.001)	0.002	(0.000)	0.001	(0.001)	(0.002)	(0.001)	0.000	(0.001)	0.001
Cold_Play_Tickets_Yes	0.001	(0.002)	0.001	0.001	0.001	(0.001)	(0.001)	0.002	(0.002)	(0.001)	0.000	0.000	(0.001)	(0.001)	0.000
Cold_Play_Tickets_Missing	(0.000)	(0.002)	(0.001)	(0.000)	(0.001)	0.001	(0.001)	(0.000)	(0.000)	0.001	0.002	0.001	(0.000)	0.001	(0.001)

Variable	Vehicle_Type_Private_Passenger	Vehicle_Type_SUV	Vehicle_Type_Van	Vehicle_Type_Pickup	Vehicle_Type_Other	New_Fender_No	New_Fender_Yes	New_Fender_Missing	CAS_Seminar_No	CAS_Seminar_Yes	CAS_Seminar_Missing	Cold_Play_Tickets_No	Cold_Play_Tickets_Yes	Cold_Play_Tickets_Missing
Driver_Age	(0.000)	(0.000)	0.001	0.000	(0.000)	0.000	0.001	(0.000)	0.000	0.001	(0.000)	(0.000)	0.001	(0.000)
Number_Drivers	0.001	(0.001)	(0.001)	0.000	0.000	0.002	0.000	(0.002)	0.002	(0.001)	(0.002)	0.003	(0.002)	(0.002)
Number_Cars	(0.000)	0.000	(0.000)	0.001	(0.000)	(0.000)	0.002	(0.001)	0.001	(0.000)	(0.001)	0.000	0.001	(0.001)
Insurance_Score	0.001	0.000	0.001	(0.001)	(0.000)	0.001	(0.001)	(0.000)	(0.000)	0.001	(0.000)	0.000	0.001	(0.000)
Telematics_Score	(0.001)	(0.001)	0.001	(0.000)	0.001	0.000	0.002	(0.001)	0.001	0.001	(0.001)	0.001	0.001	(0.001)
Model_Year	0.000	(0.000)	0.002	0.000	(0.001)	(0.002)	0.002	0.001	(0.001)	(0.001)	0.001	(0.001)	(0.001)	0.001
Prior_Claims	(0.000)	0.000	(0.001)	0.000	0.000	0.001	0.001	(0.001)	0.001	0.000	(0.001)	0.002	(0.001)	(0.001)
Marital_Status_Married	(0.002)	0.002	0.001	(0.001)	0.001	0.000	0.000	(0.000)	0.000	0.001	(0.000)	(0.000)	0.002	(0.000)
Marital_Status_Single	0.003	(0.003)	(0.001)	0.001	(0.002)	0.000	0.001	(0.000)	0.001	(0.001)	(0.000)	0.001	(0.002)	(0.000)
Marital_Status_Seperated	(0.001)	0.000	(0.000)	0.000	0.001	(0.001)	0.000	0.001	(0.001)	0.000	0.001	(0.001)	(0.001)	0.001
Marital_Status_Widowed	(0.001)	0.001	(0.001)	(0.001)	0.001	(0.000)	(0.003)	0.002	(0.001)	(0.001)	0.002	(0.002)	0.000	0.002
Vehicle_Use_Drive_To_Work	0.002	0.001	(0.001)	0.001	(0.003)	(0.000)	(0.001)	0.001	(0.001)	0.001	0.001	(0.001)	0.000	0.001
Vehicle_Use_Pleasure_Use	(0.003)	0.001	0.001	(0.001)	0.003	(0.000)	0.002	(0.000)	0.000	(0.000)	(0.000)	0.000	(0.001)	(0.000)
Vehicle_Use_In_Storage	0.001	(0.001)	0.001	(0.001)	(0.000)	(0.001)	0.000	0.001	(0.000)	(0.002)	0.001	(0.001)	(0.001)	0.001
Vehicle_Use_Retired	(0.000)	(0.002)	(0.000)	0.000	0.002	0.001	(0.000)	(0.001)	0.001	(0.000)	(0.001)	0.001	0.000	(0.001)
Vehicle_Type_Private_Passenger	1.000	(0.419)	(0.230)	(0.333)	(0.500)	0.003	(0.002)	(0.002)	0.002	0.001	(0.002)	0.003	(0.002)	(0.002)
Vehicle_Type_SUV	(0.419)	1.000	(0.097)	(0.140)	(0.210)	0.000	0.000	(0.000)	0.000	0.000	(0.000)	(0.000)	0.002	(0.000)
Vehicle_Type_Van	(0.230)	(0.097)	1.000	(0.077)	(0.115)	(0.004)	0.000	0.004	(0.005)	0.003	0.004	(0.003)	(0.001)	0.004
Vehicle_Type_Pickup	(0.333)	(0.140)	(0.077)	1.000	(0.167)	(0.002)	0.002	0.001	(0.001)	(0.002)	0.001	(0.002)	0.001	0.001
Vehicle_Type_Other	(0.500)	(0.210)	(0.115)	(0.167)	1.000	(0.000)	0.001	0.000	0.000	(0.001)	0.000	(0.001)	0.001	0.000
New_Fender_No	0.003	0.000	(0.004)	(0.002)	(0.000)	1.000	(0.268)	(0.922)	0.851	0.115	(0.922)	0.852	0.114	(0.922)
New_Fender_Yes	(0.002)	0.000	0.000	0.002	0.001	(0.268)	1.000	(0.125)	0.115	0.015	(0.125)	0.115	0.016	(0.125)
New_Fender_Missing	(0.002)	(0.000)	0.004	0.001	0.000	(0.922)	(0.125)	1.000	(0.923)	(0.124)	1.000	(0.923)	(0.124)	1.000
CAS_Seminar_No	0.002	0.000	(0.005)	(0.001)	0.000	0.851	0.115	(0.923)	1.000	(0.267)	(0.923)	0.852	0.115	(0.923)
CAS_Seminar_Yes	0.001	0.000	0.003	(0.002)	(0.001)	0.115	0.015	(0.124)	(0.267)	1.000	(0.124)	0.114	0.015	(0.124)
CAS_Seminar_Missing	(0.002)	(0.000)	0.004	0.001	0.000	(0.922)	(0.125)	1.000	(0.923)	(0.124)	1.000	(0.923)	(0.124)	1.000
Cold_Play_Tickets_No	0.003	(0.000)	(0.003)	(0.002)	(0.001)	0.852	0.115	(0.923)	0.852	0.114	(0.923)	1.000	(0.267)	(0.923)
Cold_Play_Tickets_Yes	(0.002)	0.002	(0.001)	0.001	0.001	0.114	0.016	(0.124)	0.115	0.015	(0.124)	(0.267)	1.000	(0.124)
Cold_Play_Tickets_Missing	(0.002)	(0.000)	0.004	0.001	0.000	(0.922)	(0.125)	1.000	(0.923)	(0.124)	1.000	(0.923)	(0.124)	1.000

Exhibit 3: Generalized Variance Inflation Factors (GVIFs)

Variable	GVIF	Df	GVIF ^{(1/(2*Df))}
State	1.00	4	1.00
Year	1.00	2	1.00
Driver_Age	587.35	1	24.24
Driver_Age_2	2580.34	1	50.80
Driver_Age_3	761.44	1	27.59
Number_Drivers	1.00	1	1.00
Number_Cars	1.00	1	1.00
Insurance_Score	1.00	1	1.00
Telematics_Score	1.00	1	1.00
Model_Year	1.00	1	1.00
Prior_Claims	1.00	1	1.00
Marital_Status	1.00	3	1.00
Vehicle_Use	1.00	3	1.00
Vehicle_Type	1.00	4	1.00

*GVIF is high for the Driver_Age variables because Driver_Age_2 = (Driver_Age)² and Driver_Age_3 = (Driver_Age)³.

**Variables from Reputable Consumer Database were excluded from this analysis because there is an aliasing issue with “Missing” data.

Exhibit 4: Sample Modeling Data

Record	State	Year	Driver Age	Number Drivers	Number Cars	Insurance Score	Telematics Score	Model Year	Prior Claims	Marital Status	Vehicle Use	Vehicle Type	New Fender	CAS Seminar	Cold Play Tickets	amount
1	Illinois	Year 2022	72	2	3	8	2	2002	0	Married	Drive To Work	Pickup	No	No	No	0
2	Missouri	Year 2022	42	1	1	9	3	2023	0	Single	Drive To Work	Pickup	No	No	No	0
3	Iowa	Year 2022	27	1	1	3	6	2016	0	Single	Pleasure Use	Private Passenger	No	No	No	0
4	Wisconsin	Year 2023	26	1	2	7	1	2005	1	Married	Drive To Work	SUV	No	No	No	0
5	Wisconsin	Year 2024	45	2	3	4	10	2015	0	Single	Drive To Work	Private Passenger	No	No	No	0
6	Iowa	Year 2024	53	2	3	6	7	2021	1	Married	Drive To Work	Private Passenger	No	No	No	0
7	Illinois	Year 2024	42	1	2	3	8	2019	0	Married	Drive To Work	Private Passenger	Missing	Missing	Missing	0
8	Wisconsin	Year 2022	38	2	1	10	5	2007	0	Married	Drive To Work	Pickup	Missing	Missing	Missing	0
9	Iowa	Year 2022	45	2	3	5	8	2017	0	Single	Retired	SUV	No	No	No	0
10	Illinois	Year 2024	29	2	2	9	9	2020	2	Single	Pleasure Use	SUV	No	No	No	0
11	Missouri	Year 2023	51	2	2	6	10	2021	0	Married	Drive To Work	Private Passenger	No	No	No	0
12	Iowa	Year 2022	51	2	2	3	4	2023	0	Single	Drive To Work	Other	No	No	No	0
13	Illinois	Year 2024	48	1	2	7	6	2025	0	Married	Retired	Private Passenger	No	No	No	0
14	Illinois	Year 2023	59	1	2	3	4	2025	0	Widowed	Drive To Work	Private Passenger	No	No	No	0
15	Iowa	Year 2023	37	1	3	8	6	2021	0	Separated	Drive To Work	SUV	No	No	No	0
16	Iowa	Year 2024	34	2	2	1	5	2021	0	Single	Drive To Work	SUV	No	No	No	0
17	Wisconsin	Year 2024	49	2	1	1	4	2022	0	Single	Pleasure Use	Private Passenger	Missing	Missing	Missing	0
18	Iowa	Year 2022	51	2	2	1	2	2022	0	Widowed	Retired	Private Passenger	No	No	No	0
19	Iowa	Year 2024	72	2	3	1	5	2021	0	Single	Drive To Work	Private Passenger	No	Yes	No	0
20	Missouri	Year 2024	43	2	2	1	10	2018	0	Single	Drive To Work	Other	No	No	No	5118.239778
21	Illinois	Year 2022	73	2	1	10	8	2011	0	Single	Drive To Work	SUV	Missing	Missing	Missing	0
22	Ohio	Year 2024	69	2	2	7	3	2000	0	Married	Retired	Other	No	No	No	0
23	Missouri	Year 2024	22	2	1	6	3	2014	0	Widowed	Drive To Work	Other	No	No	No	0
24	Iowa	Year 2023	47	2	1	2	2	2022	0	Married	Pleasure Use	Private Passenger	No	No	No	1480.951826
25	Iowa	Year 2022	49	2	2	5	6	2017	0	Single	Retired	Private Passenger	No	No	No	0
26	Iowa	Year 2023	54	2	3	10	5	2007	0	Married	Drive To Work	Private Passenger	No	Yes	No	0
27	Missouri	Year 2023	23	1	1	8	1	2019	1	Single	Retired	Private Passenger	Missing	Missing	Missing	0
28	Missouri	Year 2022	55	2	3	4	7	2009	0	Single	Retired	SUV	Missing	Missing	Missing	0
29	Iowa	Year 2022	21	1	1	2	10	2018	5	Single	Drive To Work	Private Passenger	Missing	Missing	Missing	0
30	Illinois	Year 2023	35	2	1	10	4	2023	0	Single	Retired	SUV	Missing	Missing	Missing	0
31	Ohio	Year 2024	47	2	1	4	4	2020	0	Married	Drive To Work	Private Passenger	Missing	Missing	Missing	0
32	Iowa	Year 2023	65	1	1	5	8	2011	0	Married	Retired	Private Passenger	No	No	No	0
33	Iowa	Year 2022	42	2	2	1	8	2016	0	Married	Retired	Pickup	No	No	No	0
34	Missouri	Year 2024	49	2	2	4	2	2017	0	Single	Pleasure Use	SUV	No	No	No	0
35	Ohio	Year 2023	42	1	2	8	1	2019	0	Married	Retired	SUV	Missing	Missing	Missing	1273.890792
36	Illinois	Year 2022	41	3	2	9	7	2017	0	Single	Retired	Private Passenger	No	No	No	0
37	Iowa	Year 2024	23	2	1	7	3	2017	1	Single	Retired	Other	Missing	Missing	Missing	0
38	Illinois	Year 2024	36	1	3	2	5	2021	0	Single	Retired	SUV	Missing	Missing	Missing	0
39	Iowa	Year 2022	40	2	2	8	10	2020	0	Single	Drive To Work	SUV	No	No	No	0
40	Iowa	Year 2022	44	2	2	7	3	2011	0	Single	Drive To Work	Private Passenger	Missing	Missing	Missing	0
41	Iowa	Year 2024	39	2	2	7	4	2005	2	Married	Pleasure Use	SUV	Missing	Missing	Missing	0
42	Iowa	Year 2024	30	2	1	10	10	2010	2	Married	Retired	SUV	No	No	No	0
43	Iowa	Year 2022	59	2	1	2	5	2018	1	Married	Pleasure Use	Other	No	No	No	0
44	Ohio	Year 2023	59	1	1	8	7	2021	0	Married	Drive To Work	Private Passenger	No	No	No	0
45	Iowa	Year 2022	30	1	1	4	3	2018	4	Single	Pleasure Use	SUV	No	No	No	0
46	Wisconsin	Year 2023	36	2	2	3	9	2017	0	Married	Drive To Work	Other	No	No	No	0
47	Ohio	Year 2024	35	1	1	5	1	2024	0	Single	Drive To Work	Private Passenger	Missing	Missing	Missing	0
48	Iowa	Year 2023	27	1	2	9	1	2021	0	Married	Drive To Work	SUV	No	No	No	0
49	Iowa	Year 2022	46	2	2	2	4	2019	0	Married	Drive To Work	SUV	Missing	Missing	Missing	0
50	Ohio	Year 2022	71	2	1	9	9	2007	0	Single	Drive To Work	Private Passenger	No	No	No	8360.222344

Record	State	Year	Driver Age	Number Drivers	Number Cars	Insurance Score	Telematics Score	Model Year	Prior Claims	Marital Status	Vehicle Use	Vehicle Type	New Fender	CAS Seminar	Cold Play Tickets	amount
51	Illinois	Year 2022	36	1	2	7	1	2007	2	Single	Drive_To_Work	Other	No	No	No	0
52	Iowa	Year 2022	44	2	3	10	3	2004	0	Single	Drive_To_Work	Private Passenger	Missing	Missing	Missing	0
53	Iowa	Year 2022	33	2	2	5	8	2017	0	Married	Drive_To_Work	Pickup	No	No	No	0
54	Iowa	Year 2022	26	2	1	9	1	2023	5	Single	Drive_To_Work	Other	No	No	No	0
55	Iowa	Year 2022	29	2	1	9	5	2018	0	Single	Drive_To_Work	SUV	No	No	No	0
56	Illinois	Year 2023	23	1	2	5	3	2003	0	Single	Pleasure_Use	Private Passenger	Yes	No	No	0
57	Illinois	Year 2023	55	1	2	10	8	2023	0	Married	Drive_To_Work	Private Passenger	Missing	Missing	Missing	0
58	Missouri	Year 2024	32	1	4	7	8	2003	0	Married	Drive_To_Work	Private Passenger	No	No	No	0
59	Iowa	Year 2022	55	2	2	3	3	2015	0	Married	Drive_To_Work	Other	No	No	No	0
60	Iowa	Year 2022	46	1	2	8	1	2021	0	Single	Pleasure_Use	Private Passenger	Missing	Missing	Missing	0
61	Ohio	Year 2024	44	1	1	6	10	2020	0	Married	Pleasure_Use	SUV	No	No	No	0
62	Wisconsin	Year 2024	36	1	2	1	6	2001	2	Widowed	Retired	Other	No	No	No	0
63	Iowa	Year 2023	58	2	2	5	4	2017	0	Married	Drive_To_Work	Pickup	No	No	No	0
64	Missouri	Year 2023	37	2	2	8	6	2017	2	Single	Drive_To_Work	Private Passenger	Missing	Missing	Missing	0
65	Missouri	Year 2024	42	1	2	7	7	2007	1	Single	Drive_To_Work	Private Passenger	No	No	No	0
66	Iowa	Year 2023	27	2	3	4	2	2020	0	Married	Drive_To_Work	Pickup	No	No	No	324.6790404
67	Illinois	Year 2024	29	1	2	9	6	2019	0	Single	Drive_To_Work	Private Passenger	No	No	No	0
68	Ohio	Year 2022	32	2	2	3	6	2020	0	Single	Drive_To_Work	Other	No	No	No	0
69	Missouri	Year 2023	41	3	3	1	9	2002	1	Married	Pleasure_Use	Private Passenger	No	No	No	0
70	Iowa	Year 2022	65	2	2	8	8	2019	0	Single	Drive_To_Work	Pickup	No	No	No	0
71	Iowa	Year 2022	29	2	3	8	2	2022	0	Single	Retired	SUV	No	No	No	0
72	Ohio	Year 2023	48	1	2	5	2	2020	0	Single	Drive_To_Work	Private Passenger	No	No	No	0
73	Illinois	Year 2023	35	1	2	10	9	2019	0	Separated	Pleasure_Use	Other	No	No	No	0
74	Missouri	Year 2023	48	2	1	10	7	2023	0	Married	Drive_To_Work	Private Passenger	No	No	No	0
75	Illinois	Year 2023	40	1	2	7	5	2017	0	Single	Pleasure_Use	Private Passenger	No	No	No	0
76	Illinois	Year 2024	44	1	2	2	1	2018	0	Single	Retired	Private Passenger	No	No	No	0
77	Illinois	Year 2024	45	1	1	4	8	2010	2	Married	Pleasure_Use	Pickup	Yes	No	No	0
78	Wisconsin	Year 2022	27	2	1	7	8	2018	2	Single	Drive_To_Work	SUV	No	No	No	0
79	Ohio	Year 2022	46	2	2	5	1	2003	0	Married	Drive_To_Work	Private Passenger	No	No	No	0
80	Ohio	Year 2023	39	1	2	2	7	2020	0	Married	Pleasure_Use	Pickup	No	No	No	0
81	Iowa	Year 2023	28	2	2	10	1	2018	0	Married	Retired	Other	No	No	No	0
82	Wisconsin	Year 2023	52	2	1	4	1	2020	0	Married	Pleasure_Use	Other	No	No	No	0
83	Illinois	Year 2024	39	3	2	4	3	2019	0	Single	Pleasure_Use	Private Passenger	No	No	No	0
84	Wisconsin	Year 2024	58	2	1	2	2	2009	0	Married	Retired	SUV	No	No	No	0
85	Illinois	Year 2022	38	1	2	9	6	2016	0	Single	Drive_To_Work	Private Passenger	No	No	No	0
86	Missouri	Year 2024	32	2	4	10	5	2019	0	Married	Pleasure_Use	Private Passenger	Yes	No	No	0
87	Iowa	Year 2023	48	2	1	9	9	2013	1	Single	Retired	SUV	No	No	No	0
88	Wisconsin	Year 2022	37	1	2	1	6	2024	0	Single	Pleasure_Use	SUV	No	No	No	0
89	Ohio	Year 2024	16	2	3	7	10	2022	1	Single	Drive_To_Work	Other	No	No	No	0
90	Iowa	Year 2024	44	2	1	9	6	2019	0	Married	Pleasure_Use	SUV	No	No	Yes	1215.970738
91	Wisconsin	Year 2024	54	2	3	8	4	2008	0	Married	Drive_To_Work	SUV	No	No	No	0
92	Ohio	Year 2023	42	2	1	2	7	2002	2	Married	Drive_To_Work	Other	No	No	No	0
93	Missouri	Year 2024	28	4	1	5	7	2020	0	Married	Drive_To_Work	Pickup	No	No	No	0
94	Iowa	Year 2024	24	1	1	6	1	2021	0	Married	Drive_To_Work	Private Passenger	No	No	No	0
95	Missouri	Year 2024	27	2	2	6	6	2016	0	Married	Drive_To_Work	Pickup	No	No	No	15897.47926
96	Illinois	Year 2022	49	1	1	8	2	2018	0	Widowed	Drive_To_Work	Pickup	No	No	No	0
97	Iowa	Year 2022	56	2	2	8	6	2020	0	Married	Drive_To_Work	Private Passenger	No	No	No	11852.37153
98	Illinois	Year 2024	17	1	3	7	5	2020	0	Single	Retired	Private Passenger	No	No	No	0
99	Iowa	Year 2022	44	2	2	5	1	2018	0	Single	Drive_To_Work	SUV	Missing	Missing	Missing	0
100	Missouri	Year 2024	50	2	1	6	8	2006	0	Married	Retired	SUV	No	No	No	0

Exhibit 5: Beta Coefficients and P-Values

Variables	coefficients	std_errors	p_values
(Intercept)	-12.713	2.647	0.000
Statelowa	-0.117	0.021	0.000
StateMissouri	0.037	0.023	0.110
StateOhio	-0.145	0.031	0.000
StateWisconsin	-0.142	0.030	0.000
YearYear_2023	0.025	0.021	0.228
YearYear_2024	0.128	0.021	0.000
Driver_Age	-0.154	0.014	0.000
Driver_Age_2	0.003	0.000	0.000
Driver_Age_3	0.000	0.000	0.000
Number_Drivers	0.306	0.012	0.000
Number_Cars	-0.150	0.011	0.000
Insurance_Score	0.067	0.003	0.000
Telematics_Score	0.109	0.003	0.000
Model_Year	0.010	0.001	0.000
Prior_Claims	0.122	0.008	0.000
Marital_StatusSingle	0.080	0.017	0.000
Marital_StatusSeperated	0.037	0.084	0.657
Marital_StatusWidowed	-0.055	0.044	0.206
Vehicle_UsePleasure_Use	-0.212	0.022	0.000
Vehicle_UseIn_Storage	-2.368	0.145	0.000
Vehicle_UseRetired	-0.332	0.022	0.000
Vehicle_TypeSUV	0.110	0.024	0.000
Vehicle_TypeVan	0.231	0.037	0.000
Vehicle_TypePickup	0.125	0.028	0.000
Vehicle_TypeOther	0.067	0.022	0.002
New_FenderYes	-0.089	0.046	0.053
New_FenderMissing	0.000	0.018	0.997
CAS_SeminarYes	-0.118	0.047	0.012
CAS_SeminarMissing	NA	NA	NA
Cold_Play_TicketsYes	0.119	0.044	0.007
Cold_Play_TicketsMissing	NA	NA	NA

Exhibit 6: F Nested Model Tests and AIC

	Deviance	Parameters	Dispersion	Records	AIC	
Full Model	94,798,414	25	987	700,000	1,281,617	
Variable Removed	Deviance	Parameters	F Statistic	P-value	AIC	AIC Difference
Driver_Age	95,035,580	3	80	0.000	1,281,732	115
Number_Cars	94,971,789	1	176	0.000	1,281,704	86
Number_Drivers	95,459,334	1	670	0.000	1,281,952	334
Insurance_Score	95,338,085	1	547	0.000	1,281,890	273
Telematics_Score	96,172,457	1	1,392	0.000	1,282,313	696
Model_Year	94,852,933	1	55	0.000	1,281,643	26
Prior_Claims	95,042,206	1	247	0.000	1,281,740	122
Marital_Status	94,824,493	3	9	0.000	1,281,625	7
Vehicle_Use	95,331,683	3	180	0.000	1,281,883	266
Vehicle_Type	94,858,936	4	15	0.000	1,281,640	23
New_Fender	94,802,096	2	2	0.155	1,281,617	(0)
CAS_Seminar	94,804,696	2	3	0.041	1,281,619	1
Cold_Play_Tickets	94,805,595	2	4	0.026	1,281,619	2

Exhibit 7: Deviance Residual Plot

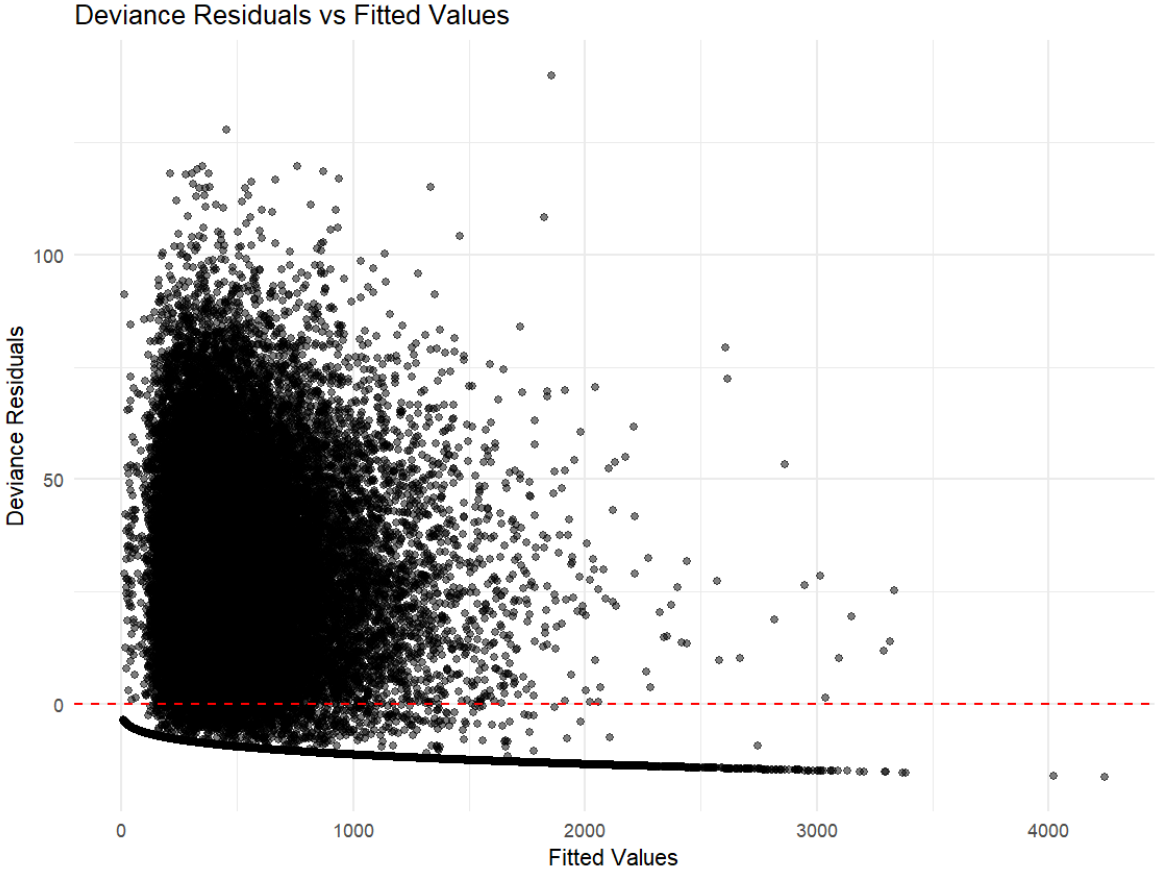
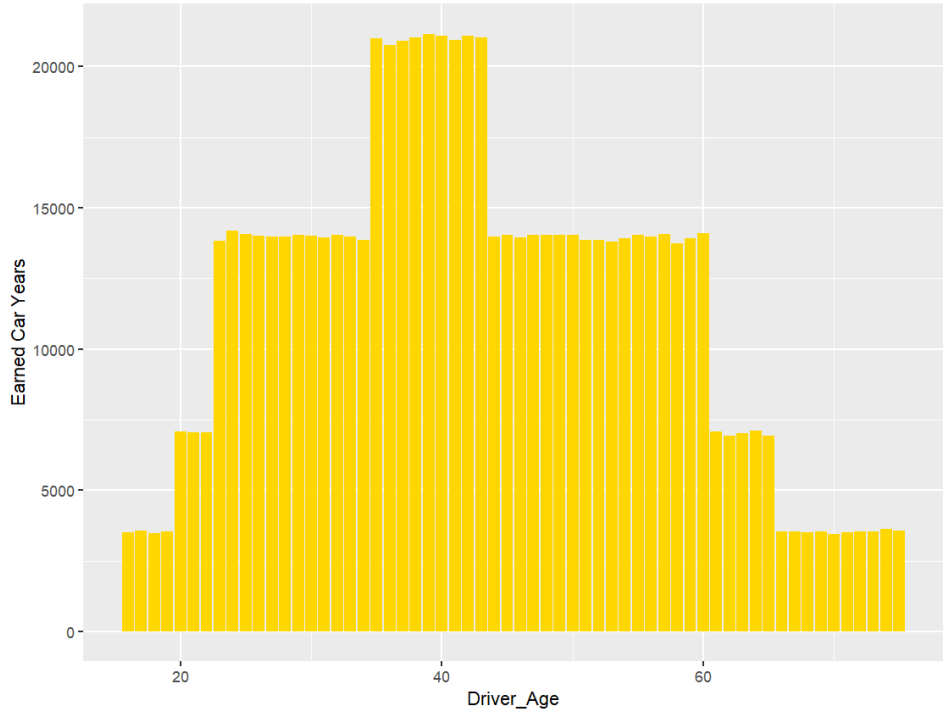
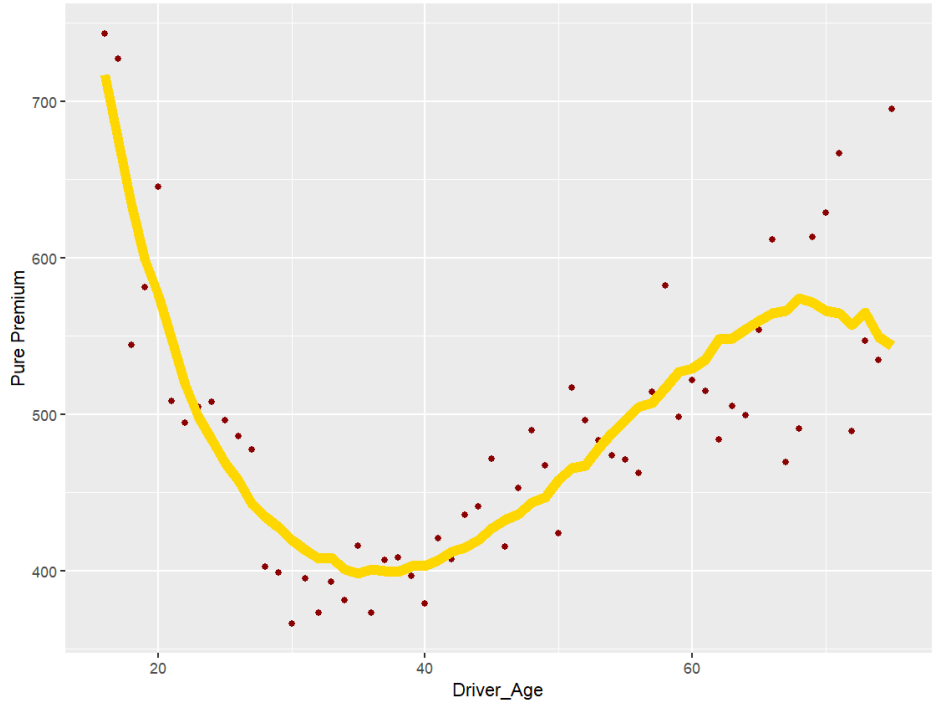
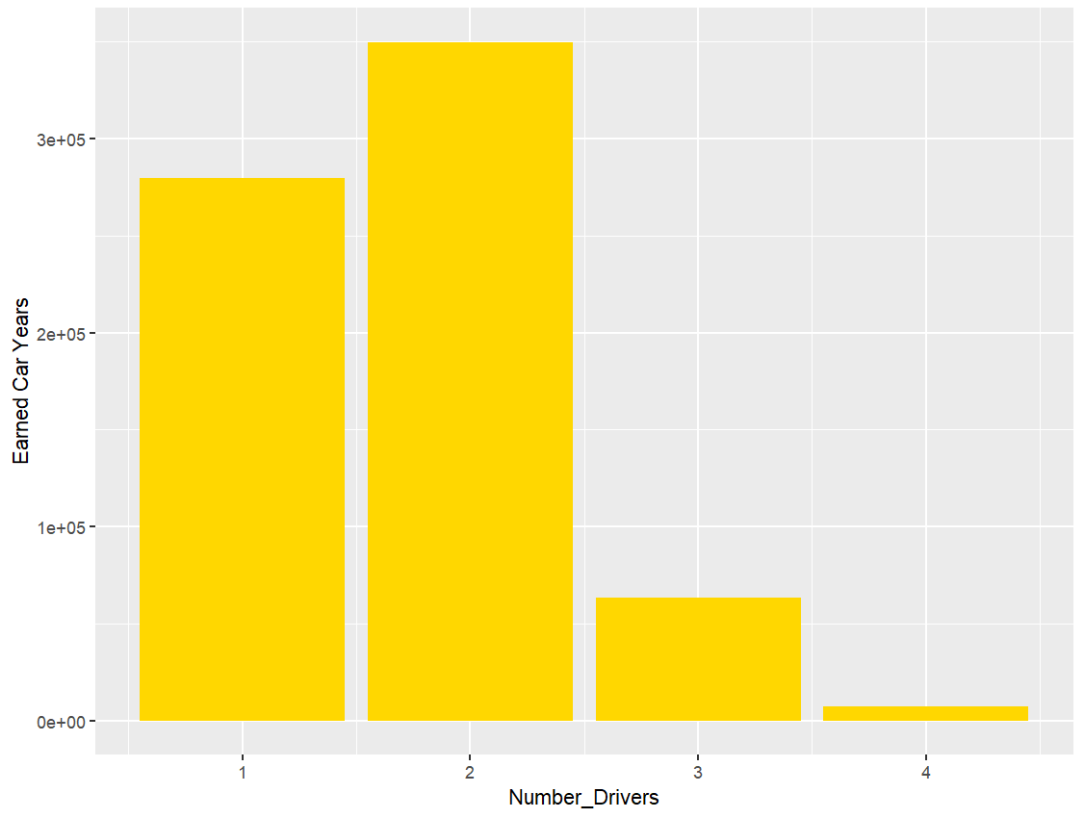
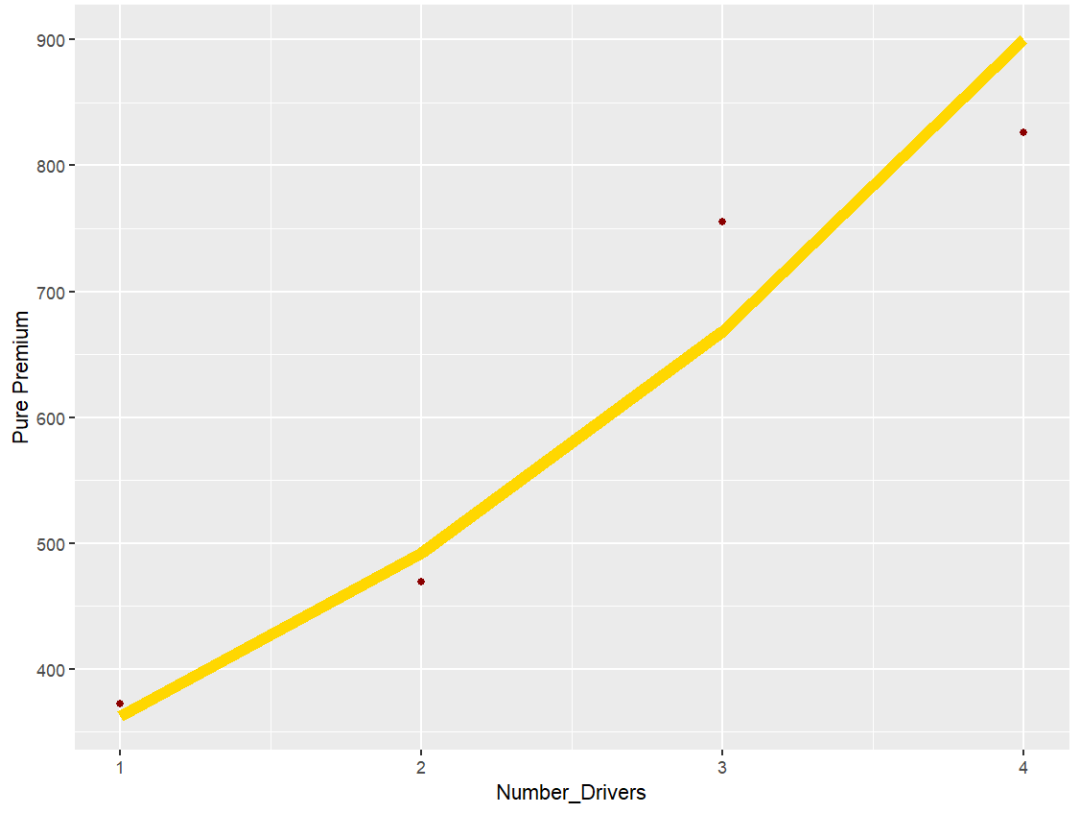
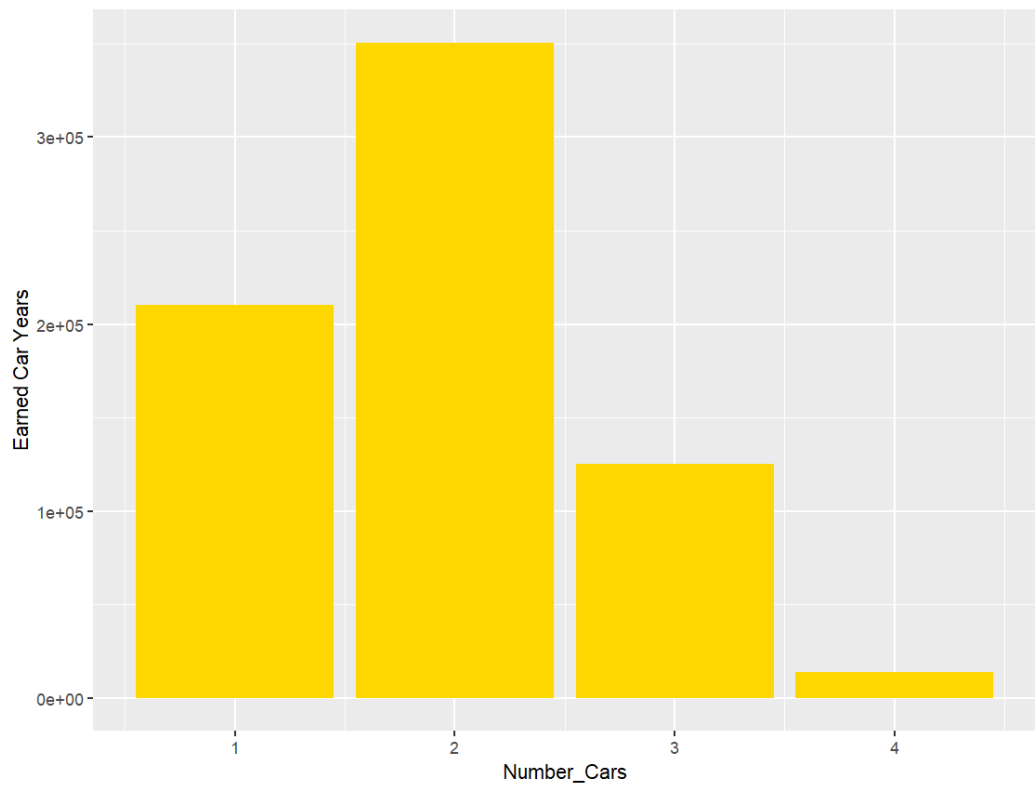
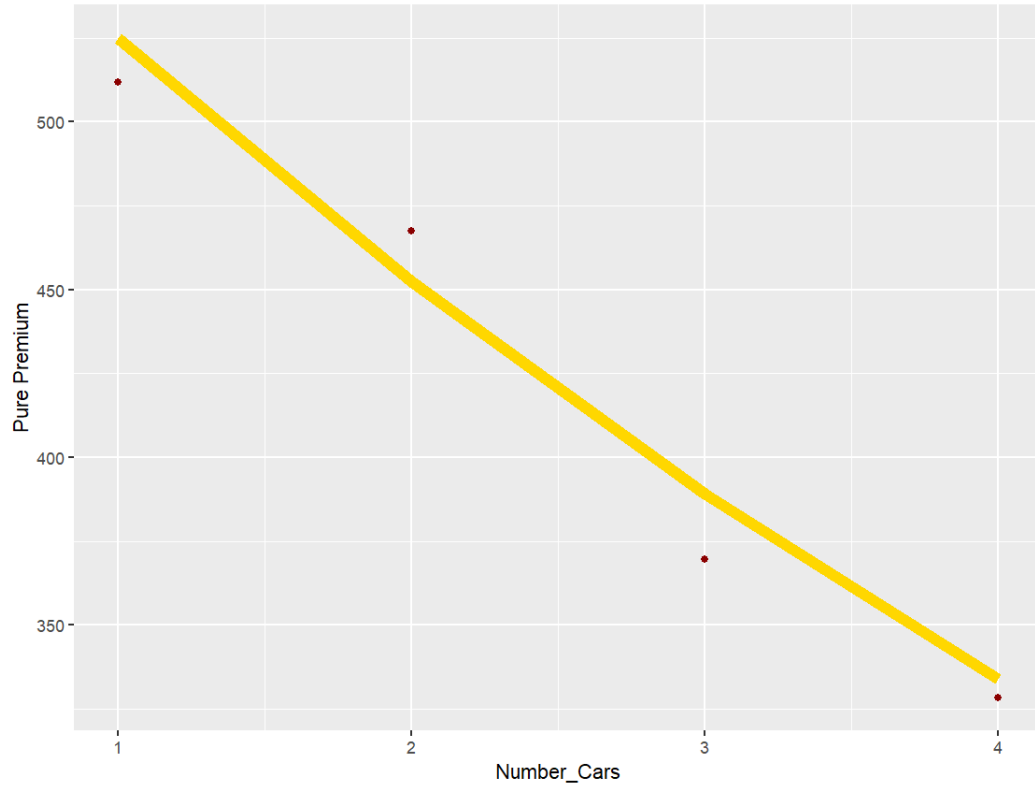
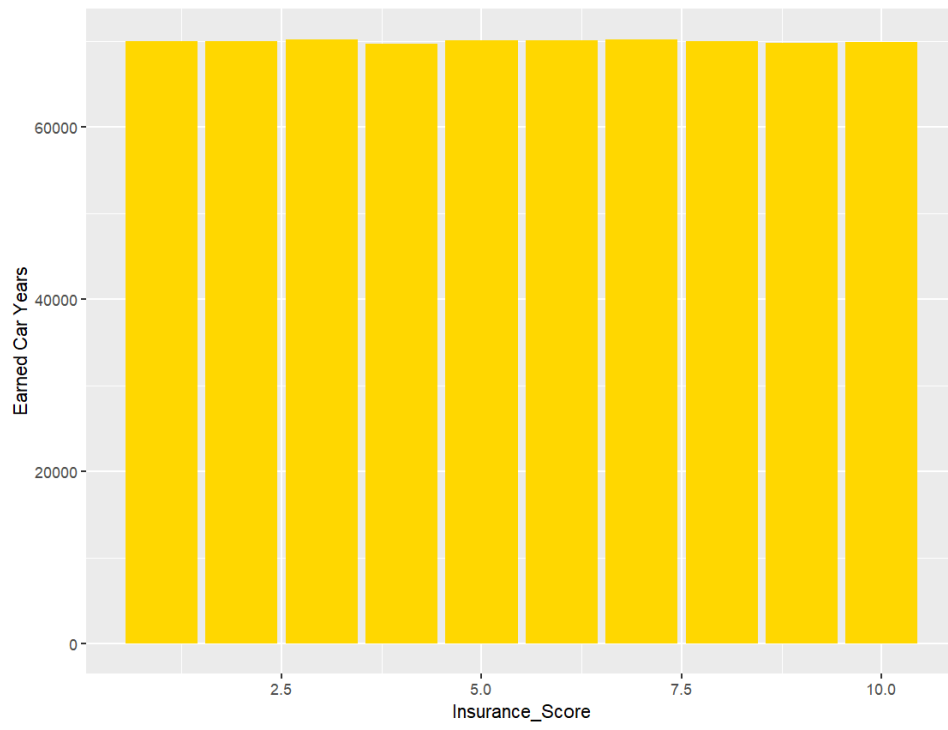
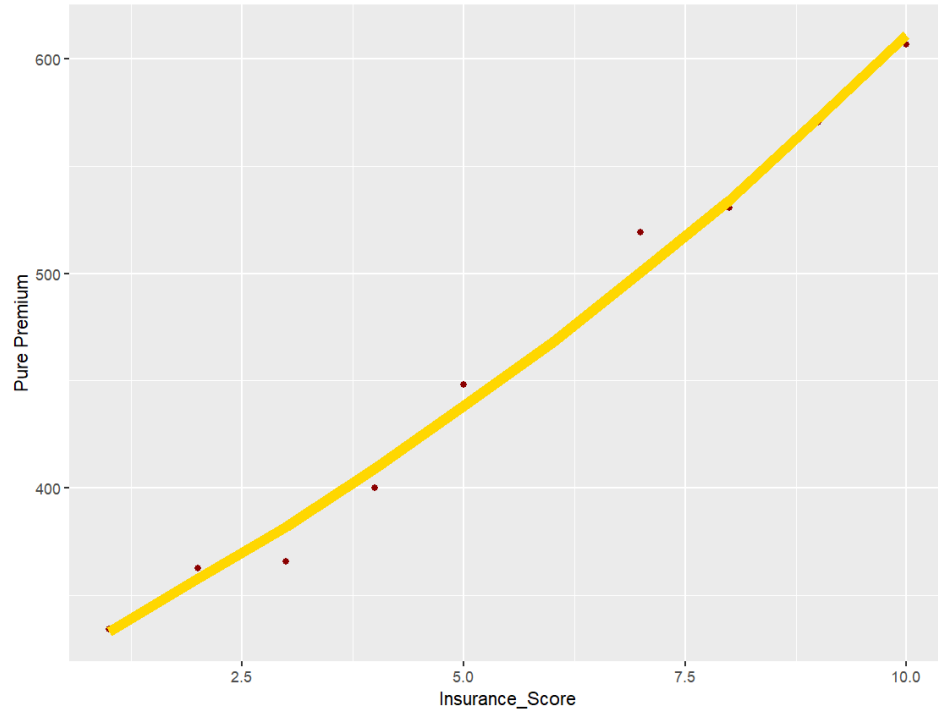


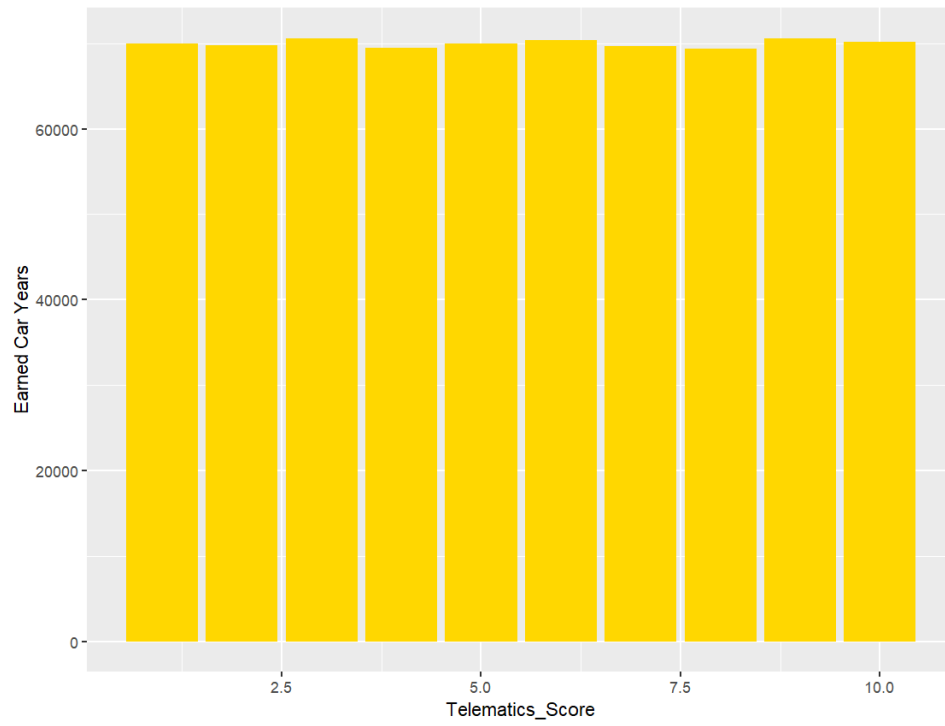
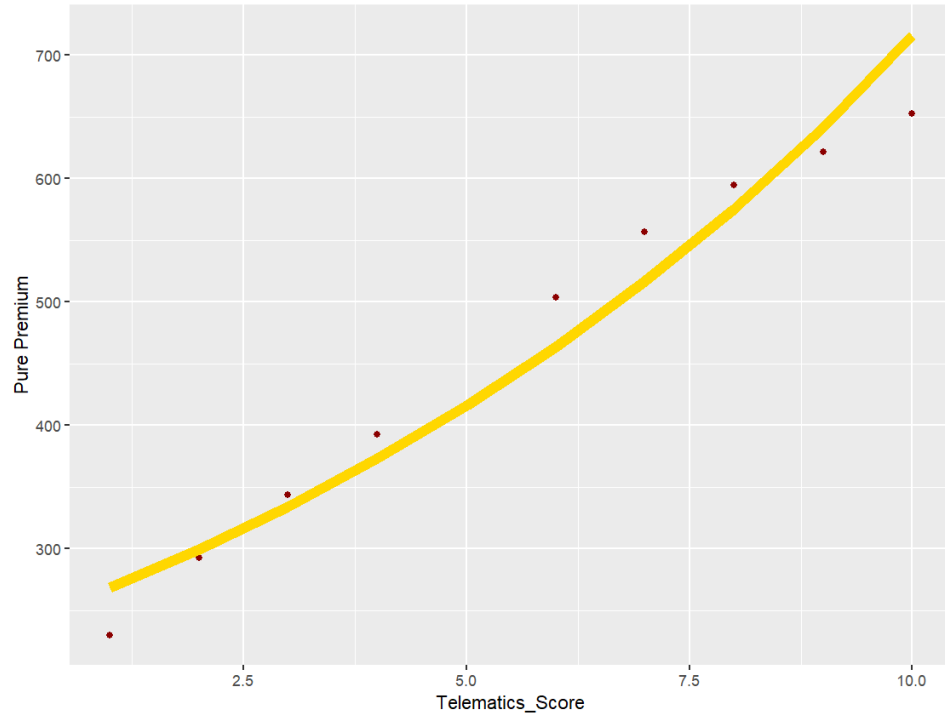
Exhibit 8: Actual vs. Expected by Variable

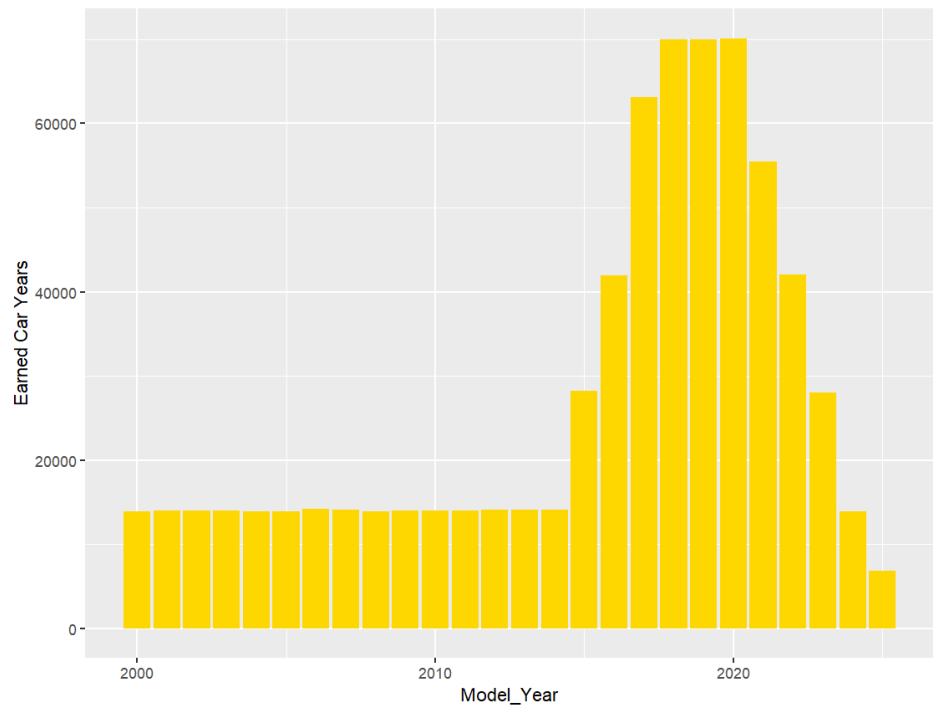
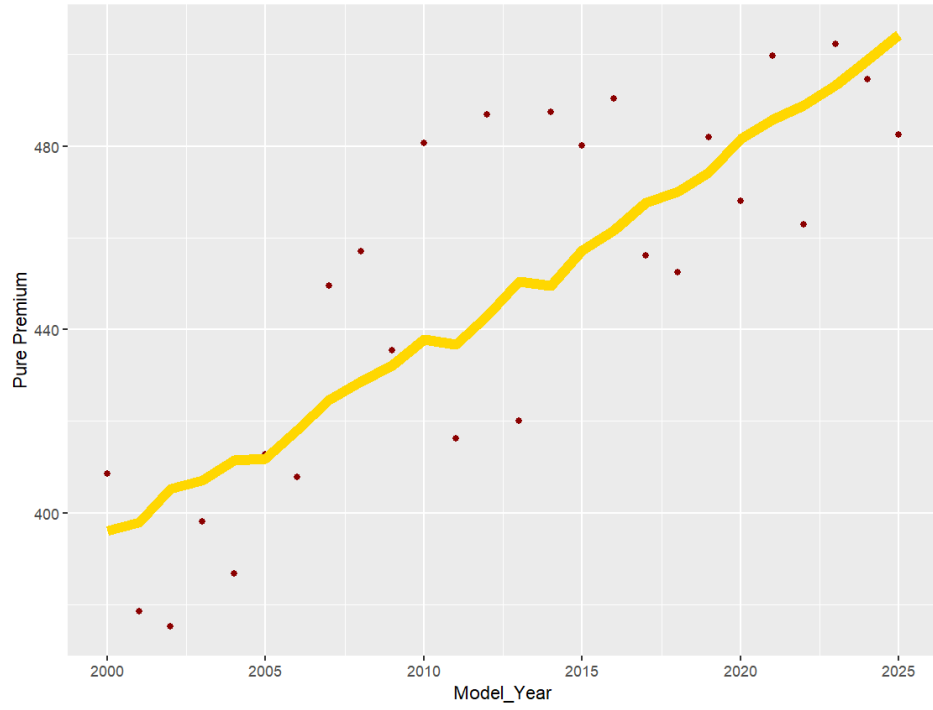


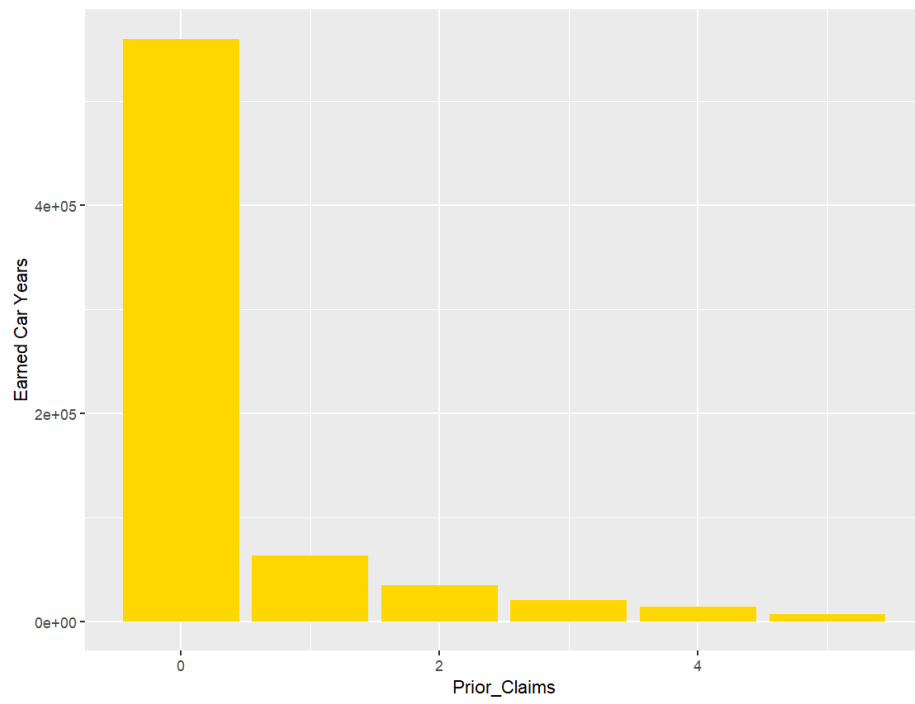
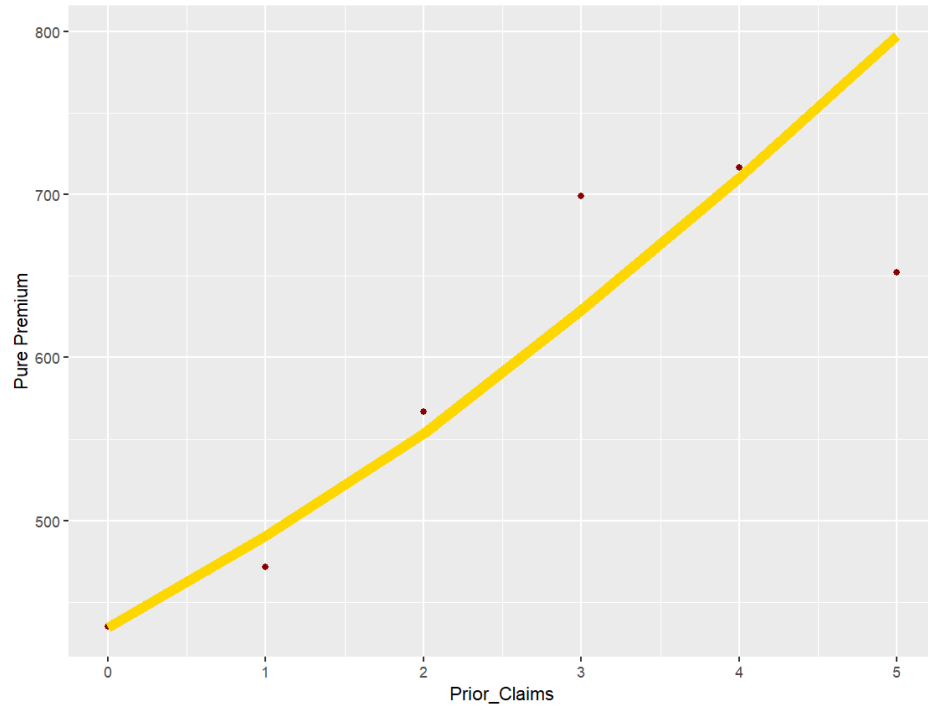


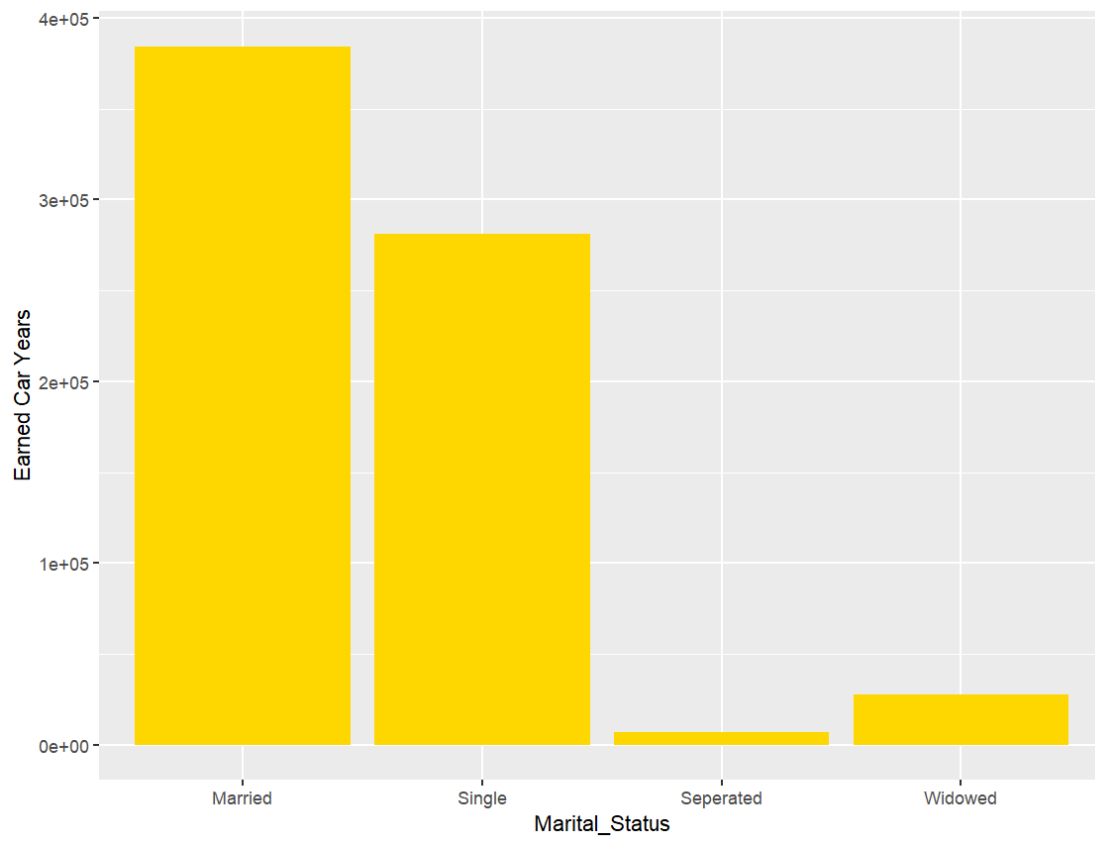
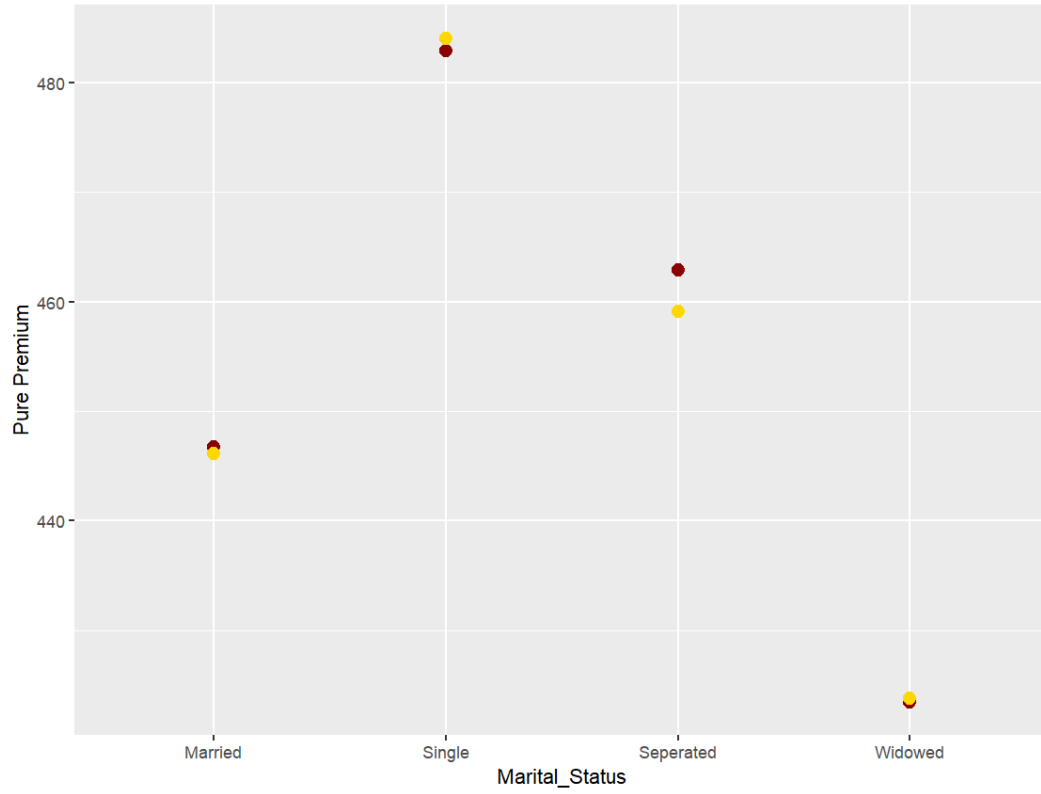


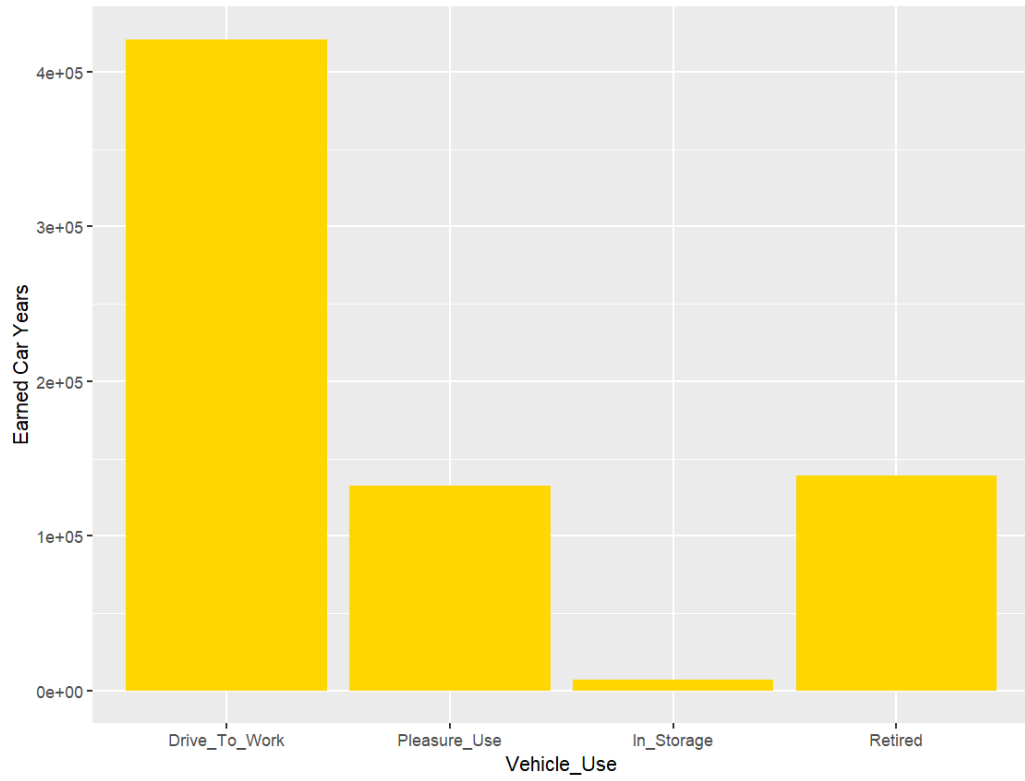
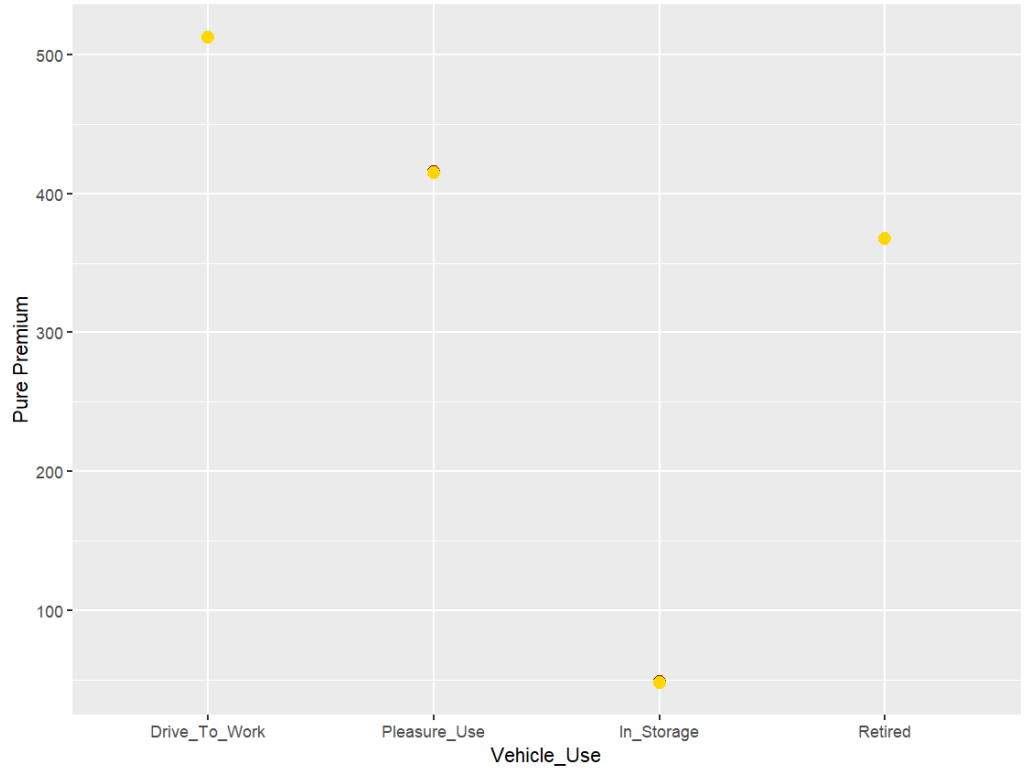


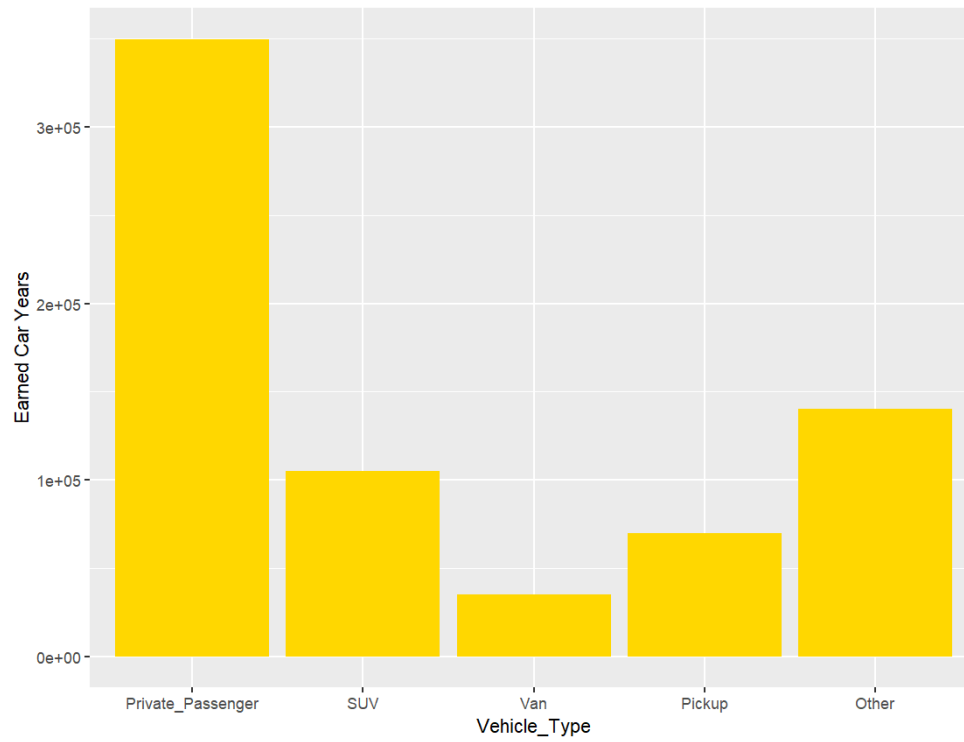
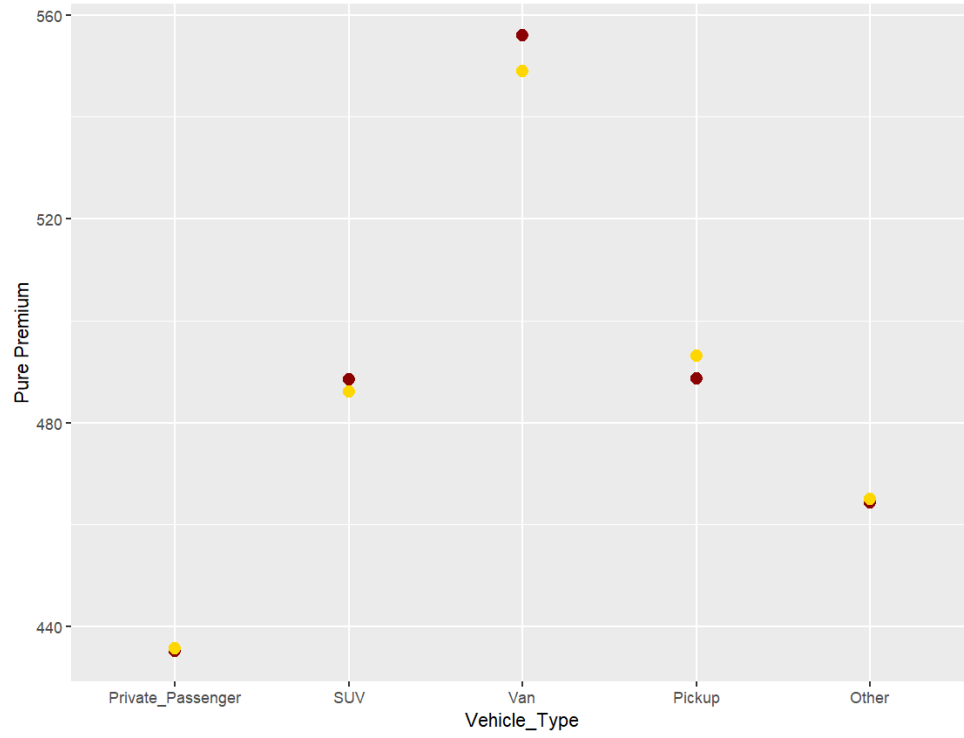


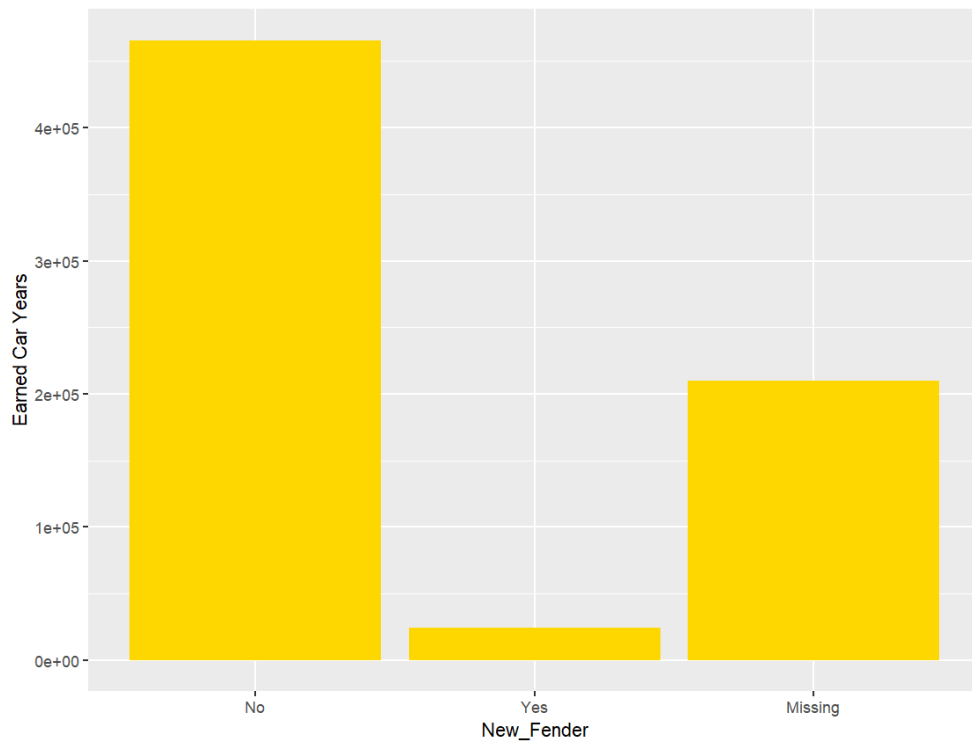
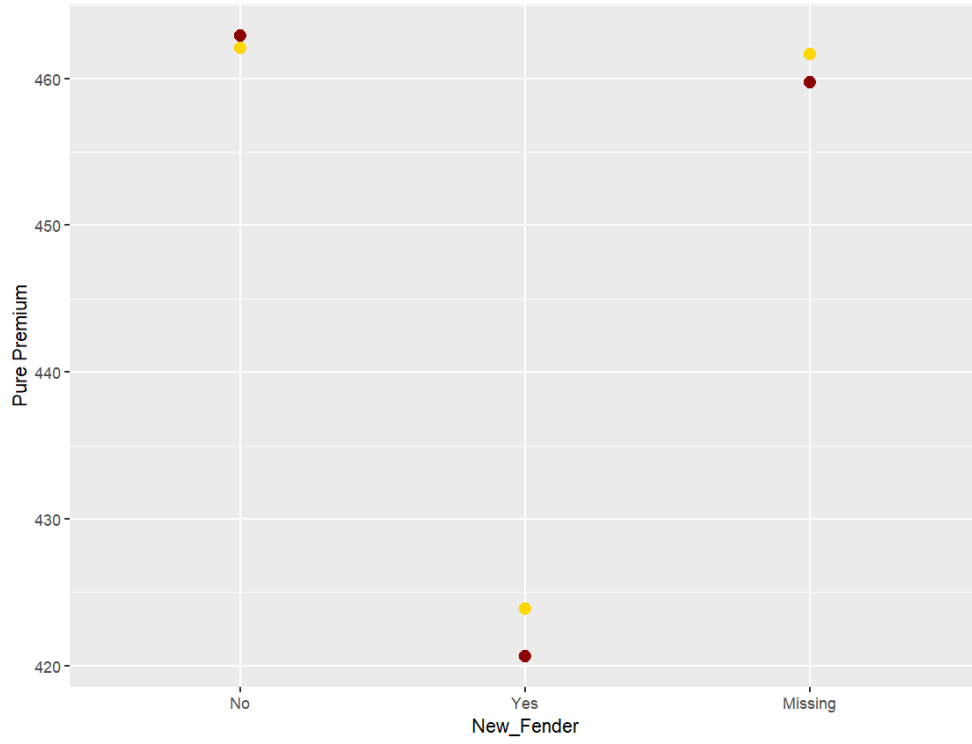


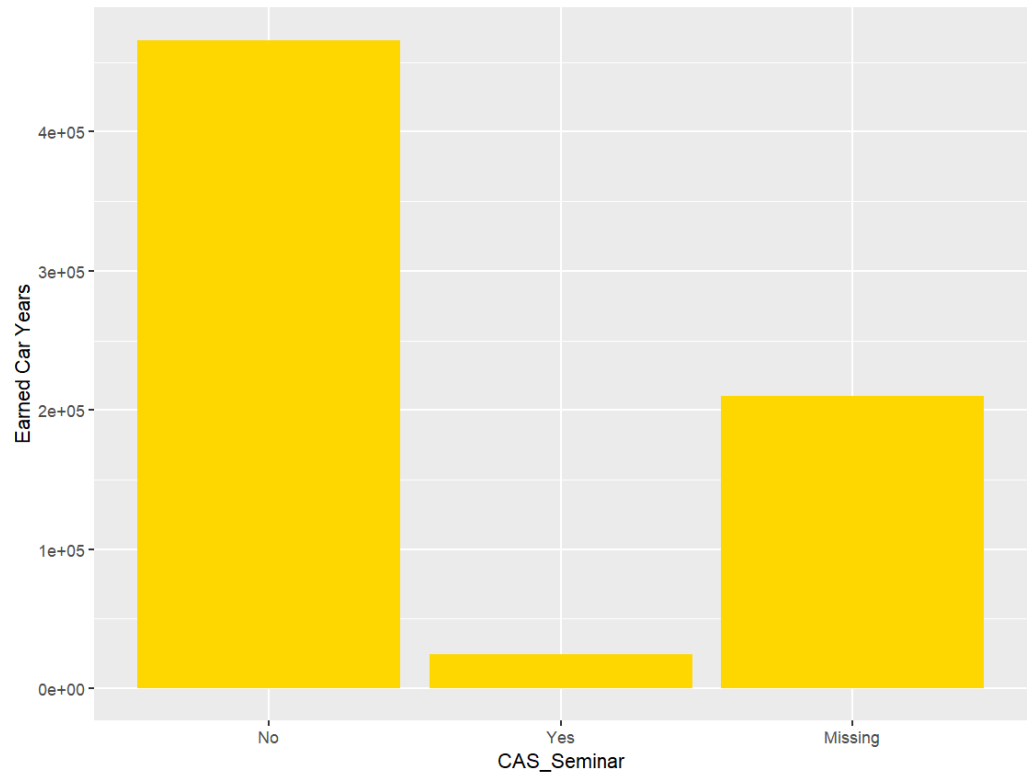
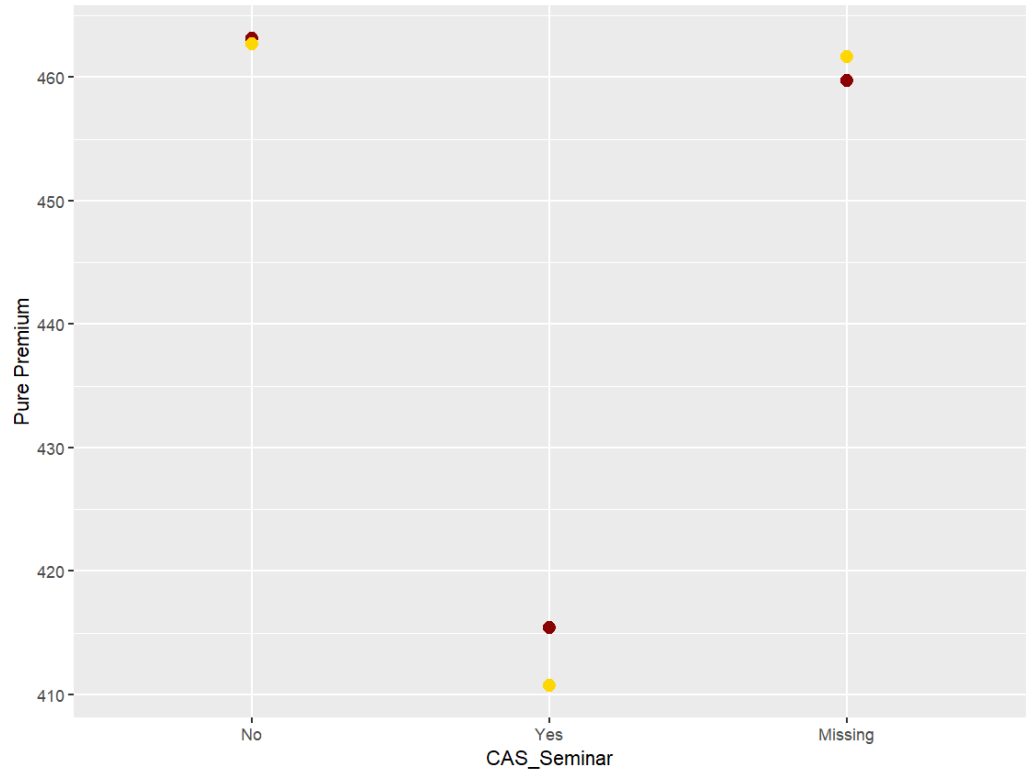












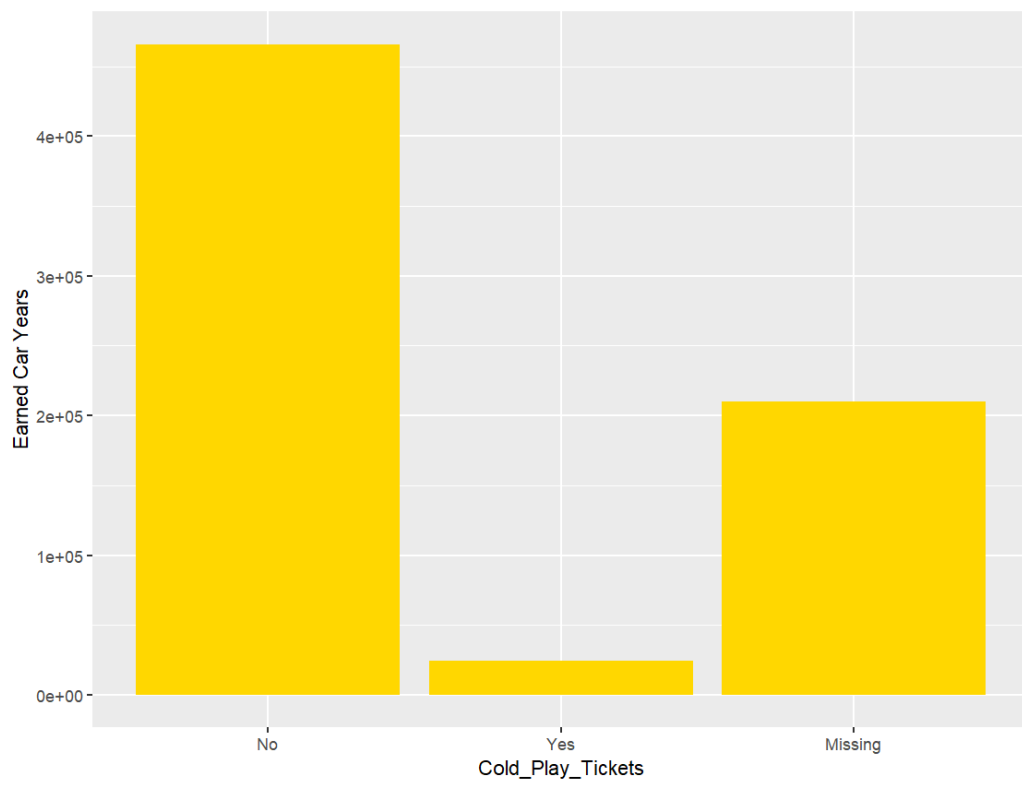
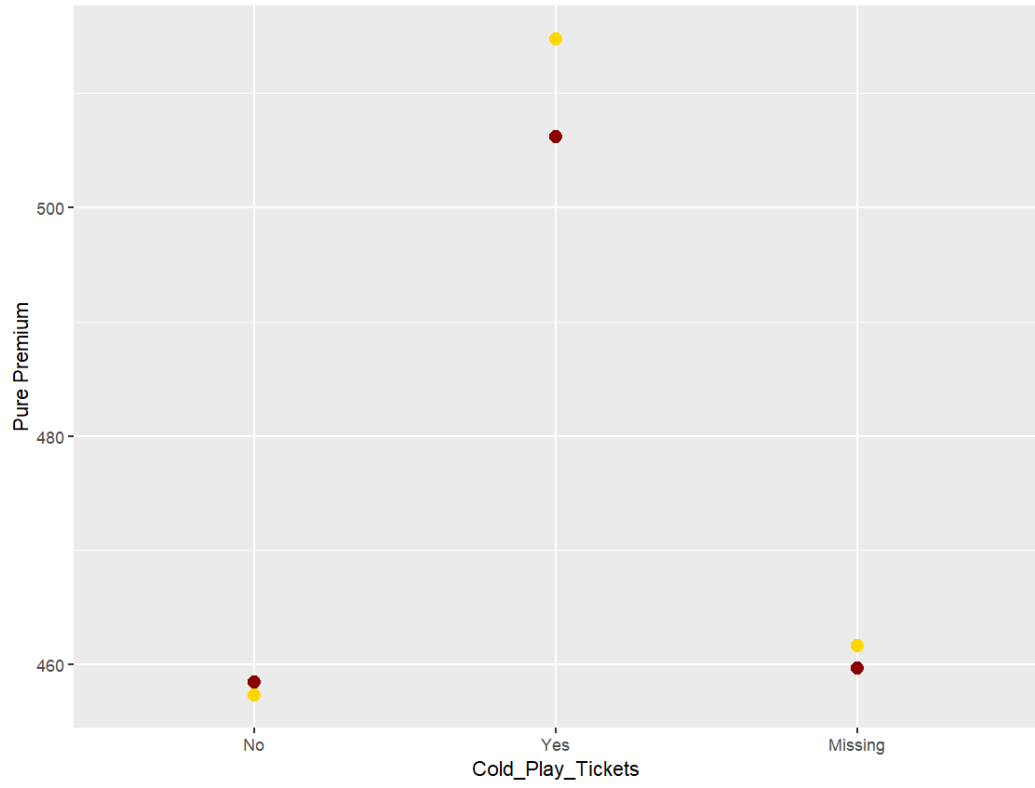
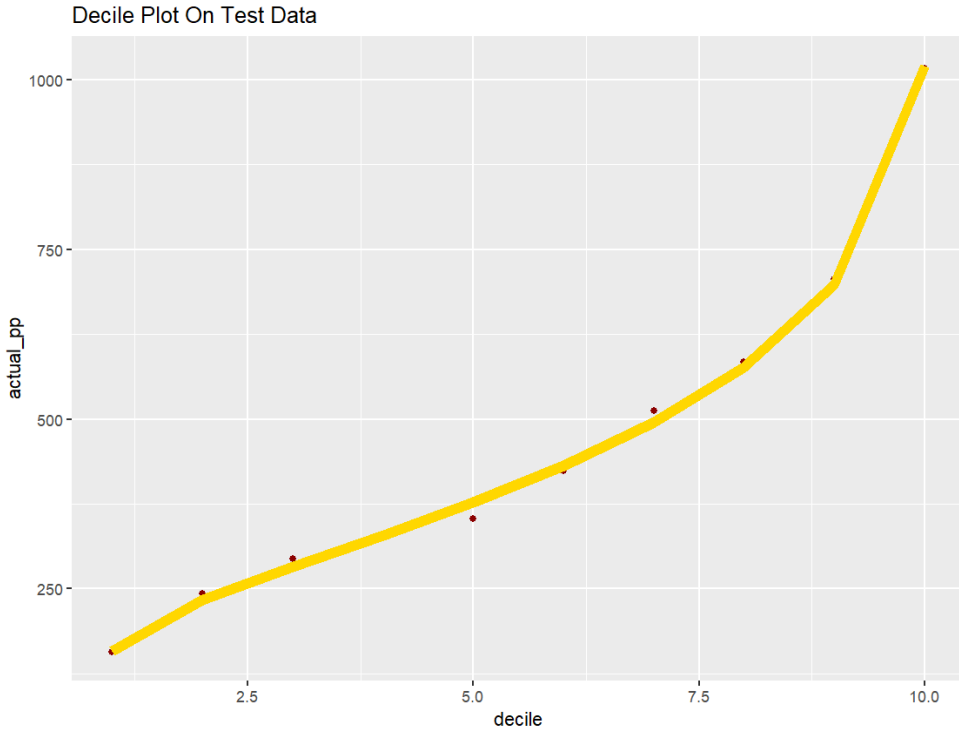
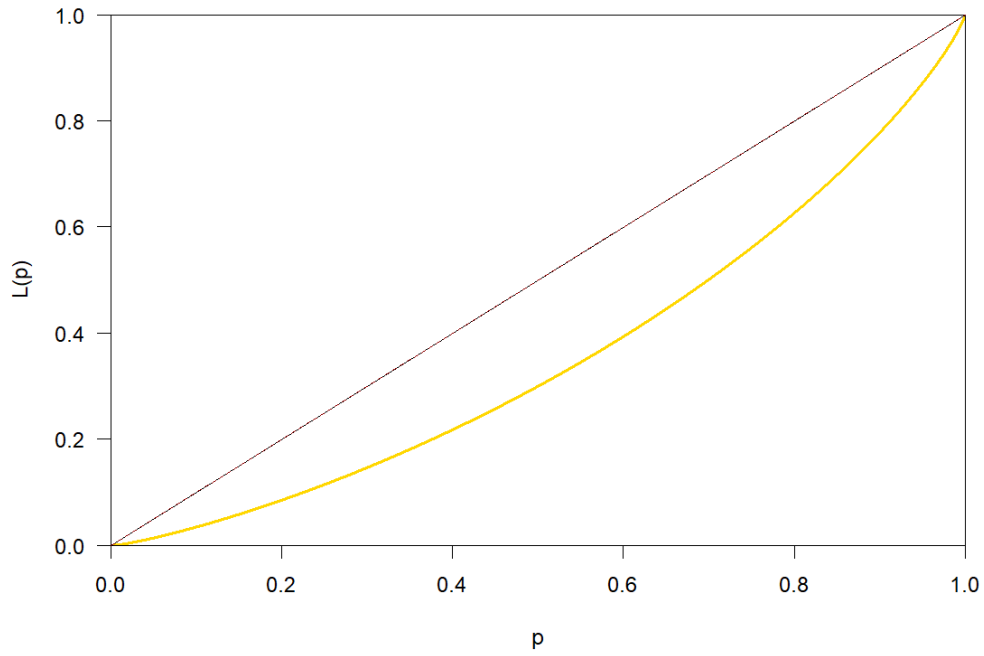


Exhibit 9: Validation Plots

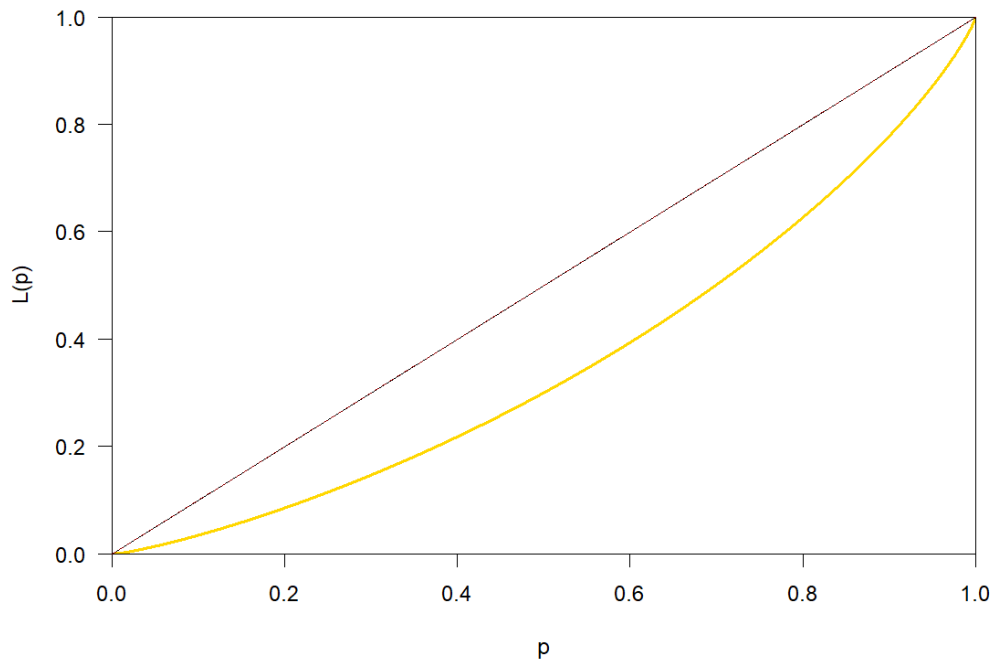


Lorenz Curve on Training Data



Gini on Train Data = 0.2887

Lorenz Curve on Test Data



Gini on Test Data = 0.2890

Exhibit 10: Indicated vs. Proposed Factors

Indicated vs. Proposed Factors				
Driver Age				
Driver Age	Current	Indicated	Proposed	(Proposed / Indicated) - 1
16	NA	1.703	1.500	-11.9%
17	NA	1.598	1.450	-9.3%
18	NA	1.506	1.400	-7.1%
19	NA	1.426	1.350	-5.3%
20	NA	1.355	1.300	-4.1%
21	NA	1.293	1.250	-3.4%
22	NA	1.239	1.200	-3.2%
23	NA	1.192	1.192	0.0%
24	NA	1.151	1.151	0.0%
25	NA	1.115	1.115	0.0%
26	NA	1.084	1.084	0.0%
27	NA	1.057	1.057	0.0%
28	NA	1.035	1.035	0.0%
29	NA	1.016	1.016	0.0%
30	NA	1.000	1.000	0.0%
31	NA	0.987	0.987	0.0%
32	NA	0.978	0.978	0.0%
33	NA	0.970	0.970	0.0%
34	NA	0.966	0.966	0.0%
35	NA	0.963	0.963	0.0%
36	NA	0.963	0.963	0.0%
37	NA	0.965	0.965	0.0%
38	NA	0.969	0.969	0.0%
39	NA	0.975	0.975	0.0%
40	NA	0.982	0.982	0.0%
41	NA	0.991	0.991	0.0%
42	NA	1.002	1.002	0.0%
43	NA	1.015	1.015	0.0%
44	NA	1.028	1.028	0.0%
45	NA	1.044	1.044	0.0%
46	NA	1.060	1.060	0.0%
47	NA	1.078	1.078	0.0%
48	NA	1.097	1.097	0.0%
49	NA	1.118	1.100	-1.6%
50	NA	1.139	1.105	-3.0%
51	NA	1.161	1.110	-4.4%
52	NA	1.184	1.115	-5.8%
53	NA	1.208	1.120	-7.3%
54	NA	1.232	1.125	-8.7%
55	NA	1.257	1.130	-10.1%
56	NA	1.282	1.135	-11.5%
57	NA	1.307	1.140	-12.8%
58	NA	1.333	1.145	-14.1%
59	NA	1.358	1.150	-15.3%
60	NA	1.383	1.155	-16.5%
61	NA	1.407	1.160	-17.5%
62	NA	1.430	1.165	-18.5%
63	NA	1.452	1.170	-19.4%
64	NA	1.473	1.175	-20.3%
65	NA	1.493	1.180	-21.0%
66	NA	1.511	1.185	-21.6%
67	NA	1.526	1.190	-22.0%
68	NA	1.540	1.195	-22.4%
69	NA	1.551	1.200	-22.6%
70	NA	1.559	1.205	-22.7%
71	NA	1.564	1.210	-22.6%
72	NA	1.566	1.215	-22.4%
73	NA	1.565	1.220	-22.0%
74	NA	1.560	1.225	-21.5%
75	NA	1.551	1.230	-20.7%

**Indicated vs. Proposed Factors
Coverage Package Level**

Level	Current	Indicated*	Proposed	(Proposed / Indicated) - 1
Minimum	NA	0.900	0.900	0.0%
Medium	NA	1.000	1.000	0.0%
Maximum	NA	1.200	1.200	0.0%

*Indicated Coverage Package Level come from separate Loss Elimination Ratio studies
Coverage Package Level was included in the GLM as offsets.

**Indicated vs. Proposed Factors
Number of Drivers**

# of Drivers	Current	Indicated	Proposed	(Proposed / Indicated) - 1
1	NA	0.737	0.737	0.1%
2	NA	1.000	1.000	0.0%
3	NA	1.358	1.358	0.0%
4+	NA	1.844	1.844	0.0%

**Indicated vs. Proposed Factors
Number of Cars**

# of Cars	Current	Indicated	Proposed	(Proposed / Indicated) - 1
1	NA	1.162	1.162	0.0%
2	NA	1.000	1.000	0.0%
3	NA	0.861	0.861	0.0%
4	NA	0.741	0.741	0.0%

**Indicated vs. Proposed Factors
Insurance Score Tier**

Insurance Score Tier	Current	Indicated	Proposed	(Proposed / Indicated) - 1
1	NA	0.545	0.545	0.0%
2	NA	0.583	0.583	0.0%
3	NA	0.624	0.624	0.0%
4	NA	0.667	0.667	0.0%
5	NA	0.714	0.714	0.0%
6	NA	0.764	0.764	0.1%
7	NA	0.817	1.000	22.4%
8	NA	0.874	2.000	128.9%
9	NA	0.935	3.000	220.9%
10	NA	1.000	4.000	300.0%

Indicated vs. Proposed Factors				
Telematics Score Tier				
Telematics Score Tier	Current	Indicated	Proposed	(Proposed / Indicated) - 1
1	NA	0.579	0.579	0.0%
2	NA	0.646	0.646	0.0%
3	NA	0.721	0.721	0.1%
4	NA	0.804	0.804	0.0%
5	NA	0.897	0.897	0.1%
6	NA	1.000	1.000	0.0%
7	NA	1.115	1.115	0.0%
8	NA	1.244	1.244	0.0%
9	NA	1.388	1.388	0.0%
10	NA	1.548	1.548	0.0%

Indicated vs. Proposed Factors				
Model Year				
Telematics Score Tier	Current	Indicated	Proposed	(Proposed / Indicated) - 1
2000	NA	0.907	0.907	0.0%
2001	NA	0.916	0.916	0.0%
2002	NA	0.925	0.925	0.0%
2003	NA	0.934	0.934	0.0%
2004	NA	0.943	0.943	0.0%
2005	NA	0.952	0.952	0.0%
2006	NA	0.962	0.962	0.0%
2007	NA	0.971	0.971	0.0%
2008	NA	0.981	0.981	0.0%
2009	NA	0.990	0.990	0.0%
2010	NA	1.000	1.000	0.0%
2011	NA	1.010	1.010	0.0%
2012	NA	1.020	1.020	0.0%
2013	NA	1.030	1.030	0.0%
2014	NA	1.040	1.040	0.0%
2015	NA	1.050	1.050	0.0%
2016	NA	1.060	1.060	0.0%
2017	NA	1.071	1.071	0.0%
2018	NA	1.081	1.081	0.0%
2019	NA	1.092	1.092	0.0%
2020	NA	1.103	1.103	0.0%
2021	NA	1.113	1.113	0.0%
2022	NA	1.124	1.124	0.0%
2023	NA	1.135	1.135	0.0%
2024	NA	1.146	1.146	0.0%
2025	NA	1.158	1.158	0.0%

Indicated vs. Proposed Factors				
Prior Claims				
Prior Claims	Current	Indicated	Proposed	(Proposed / Indicated) - 1
0	NA	1.000	1.000	0.0%
1	NA	1.130	1.130	0.0%
2	NA	1.277	1.277	0.0%
3	NA	1.443	1.443	0.0%
4	NA	1.631	1.631	0.0%
5+	NA	1.843	1.843	0.0%

Indicated vs. Proposed Factors				
Marital Status				
Marital Status	Current	Indicated	Proposed	(Proposed / Indicated) - 1
Married	NA	0.923	0.950	2.9%
Single	NA	1.000	1.000	0.0%
Widowed	NA	0.873	0.950	8.8%
Seperated	NA	0.958	1.000	4.4%

Indicated vs. Proposed Factors				
Vehicle Use				
Vehicle Use	Current	Indicated	Proposed	(Proposed / Indicated) - 1
Pleasure_Use	NA	0.809	0.809	0.0%
Drive_To_Work	NA	1.000	1.000	0.0%
Retired	NA	0.717	0.717	0.0%
In_Storage	NA	0.094	0.094	0.3%

Indicated vs. Proposed Factors				
Vehicle Type				
Vehicle Type	Current	Indicated	Proposed	(Proposed / Indicated) - 1
Private_Passenger	NA	1.000	1.000	0.0%
SUV	NA	1.116	1.116	0.0%
Van	NA	1.260	1.260	0.0%
Pickup	NA	1.134	1.134	0.0%
Other	NA	1.069	1.069	0.0%

Indicated vs. Proposed Factors				
New Fender				
New Fender	Current	Indicated	Proposed	(Proposed / Indicated) - 1
No	NA	1.000	1.000	0.0%
Yes - Squire	NA	0.915	0.980	7.1%
Yes - Other	NA	0.915	0.950	3.9%
Yes - American Series	NA	0.915	0.900	-1.6%
Missing	NA	1.000	1.000	0.0%

Indicated vs. Proposed Factors				
CAS Seminar				
CAS Seminar	Current	Indicated	Proposed	(Proposed / Indicated) - 1
No	NA	1.000	1.000	0.0%
Yes	NA	0.889	0.889	0.0%
Missing	NA	NA	1.000	NA

*There is no indicated factor for "Missing" because the variable level is aliased with "Missing" for "New Fender"

Indicated vs. Proposed Factors				
Cold Play Tickets				
Cold Play Tickets	Current	Indicated*	Proposed	(Proposed / Indicated) - 1
No	NA	1.000	1.000	0.0%
Yes	NA	1.127	1.127	0.0%
Missing	NA	NA	1.127	NA

*There is no indicated factor for "Missing" because the variable level is aliased with "Missing" for "New Fender"

Exhibit 11: Rating Examples

Example #	1		2		3		4	
Base Rate		\$ 500.00		\$ 500.00		\$ 500.00		\$ 500.00
	Attribute	Factor	Attribute	Factor	Attribute	Factor	Attribute	Factor
Coverage Package Level	Minimum	0.900	Minimum	0.900	Medium	1.000	Medium	1.000
Driver Age	16	1.500	21	1.250	65	1.180	34	0.966
Number of Drivers	1	0.737	1	0.737	2	1.000	3	1.358
Number of Cars	1	1.162	1	1.162	2	1.000	4	0.741
Insurance Score Tier	5	0.714	6	0.764	1	0.545	3	0.624
Telematics Score Tier	1	0.579	3	0.721	2	0.646	4	0.804
Model Year	2021	1.113	2025	1.158	2010	1.000	2012	1.020
Prior Claims	0	1.000	0	1.000	0	1.000	0	1.000
Marital Status	Single	1.000	Single	1.000	Widowed	0.950	Married	0.950
Vehicle Use	Drive_To_Work	1.000	Drive_To_Work	1.000	Retired	0.717	Drive_To_Work	1.000
Vehicle Type	Private_Passenger	1.000	Private_Passenger	1.000	Private_Passenger	1.000	Van	1.260
New Fender	No	1.000	No	1.000	Missing	1.000	No	1.000
CAS Seminar	No	1.000	No	1.000	Missing	1.000	No	1.000
Cold Play Tickets	No	1.000	No	1.000	Missing	1.127	No	1.000
Premium		\$ 265.98		\$ 307.28		\$ 159.46		\$ 297.71

Example #	5		6		7		8	
Base Rate		\$ 500.00		\$ 500.00		\$ 500.00		\$ 500.00
	Attribute	Factor	Attribute	Factor	Attribute	Factor	Attribute	Factor
Coverage Package Level	Medium	1.000	Minimum	0.900	Maximum	1.200	Maximum	1.200
Driver Age	45	1.044	19	1.350	27	1.057	37	0.965
Number of Drivers	3	1.358	1	0.737	2	1.000	3	1.358
Number of Cars	3	0.861	2	1.000	1	1.162	3	0.861
Insurance Score Tier	2	0.583	6	0.764	3	0.624	5	0.714
Telematics Score Tier	7	1.115	2	0.646	8	1.244	5	0.897
Model Year	2013	1.030	2007	0.971	2009	0.990	2016	1.060
Prior Claims	1	1.130	0	1.000	0	1.000	2	1.277
Marital Status	Married	0.950	Single	1.000	Single	1.000	Married	0.950
Vehicle Use	Pleasure_Use	0.809	Drive_To_Work	1.000	Drive_To_Work	1.000	Drive_To_Work	1.000
Vehicle Type	Van	1.260	Private_Passenger	1.000	Private_Passenger	1.000	Van	1.260
New Fender	Missing	1.000	No	1.000	No	1.000	Missing	1.000
CAS Seminar	Missing	1.000	No	1.000	No	1.000	Missing	1.000
Cold Play Tickets	Missing	1.127	No	1.000	Yes	1.127	Missing	1.127
Premium		\$ 503.96		\$ 214.56		\$ 638.26		\$ 791.75

Example #	9		10	
Base Rate		\$ 500.00		\$ 500.00
	Attribute	Factor	Attribute	Factor
Coverage Package Level	Maximum	1.200	Maximum	1.200
Driver Age	48	1.097	54	1.125
Number of Drivers	2	1.000	2	1.000
Number of Cars	2	1.000	2	1.000
Insurance Score Tier	7	1.000	9	3.000
Telematics Score Tier	9	1.388	10	1.548
Model Year	2020	1.103	2024	1.146
Prior Claims	0	1.000	0	1.000
Marital Status	Married	0.950	Married	0.950
Vehicle Use	Drive_To_Work	1.000	Pleasure_Use	0.809
Vehicle Type	Private_Passenger	1.000	Private_Passenger	1.000
New Fender	No	1.000	Yes - American Series	0.900
CAS Seminar	No	1.000	Yes	0.889
Cold Play Tickets	No	1.000	No	1.000
Premium		\$ 957.30		\$ 2,209.01