EUREKA ACTUARIAL CONSULTING

SAFELIFE'S AUTONOMOUS VEHICLE INSURANCE POLICY

CASE STUDY CHALLENGE 2019

TOWSON UNIVERSITY

TYLER UNG TUNG2@STUDENTS.TOWSON.EDU
MARK CUNNINGHAM MCUNNI10@STUDENTS.TOWSON.EDU
MARK DIBASTIANI MDIBAS2@STUDENTS.TOWSON.EDU
YONG MA YMA3@STUDENTS.TOWSON.EDU
ZIXU WANG ZWANG5@STUDENTS.TOWSON.EDU

FACULTY ADVISOR
MIN DENG
MDENG@TOWSON.EDU

Table of Contents

I. Executive Summary

Eureka Actuarial Consulting (EAC) analyzed and forecasted the impact of Safelife introducing an autonomous vehicle (AV) policy. EAC concluded that AVs will be subject to the same types of risk as traditional vehicles, but at a reduced level of risk. EAC also reached out to the American Automobile Association (AAA) and conducted a phone interview with their Manager of Business Operations for Public and Government Affairs, Ana Veraart. We requested the aggregate results of their annual survey on driver opinion on autonomous vehicles, which is shown in Appendix A.1. From our research, EAC expects claim frequency for AVs to be 75% lower than traditional vehicles and claim severity for AVs to be larger for only the collision and comprehensive coverage types. In addition, EAC believes AVs will be subject to higher cybersecurity risk and legislative risk than traditional vehicles. By the end of 2030, we expect the pure premium to be as follows:

- Ĉ2,447,000,000 for fully traditional insurance.
- Ĉ919,000,000 for fully autonomous vehicle insurance.
- Between Ĉ1,950,000,000 and Ĉ2,294,000,000 for mixed insurance policies.

We recommend that Safelife should launch the AV policy in 2020. This would allow Safelife to benefit from a first-mover advantage over competitors and expected total pure premium will be significantly lower with more AV business.

II. Introduction

EAC was approached by Safelife to design an automobile insurance product for autonomous vehicles. Safelife currently reports that no other company in Carbia shows intentions to design an insurance policy for AVs, giving Safelife a first-mover advantage. Safelife's goal for the new policy is to have AVs account for 20-25% of their overall business by the year 2030.

Currently, all Safelife policies reflect the following coverages, which are required for all automobile owners according to Carbian law. Additionally, Safelife management reported that Carbia is developing legislature on autonomous vehicles similar to that of the United States.

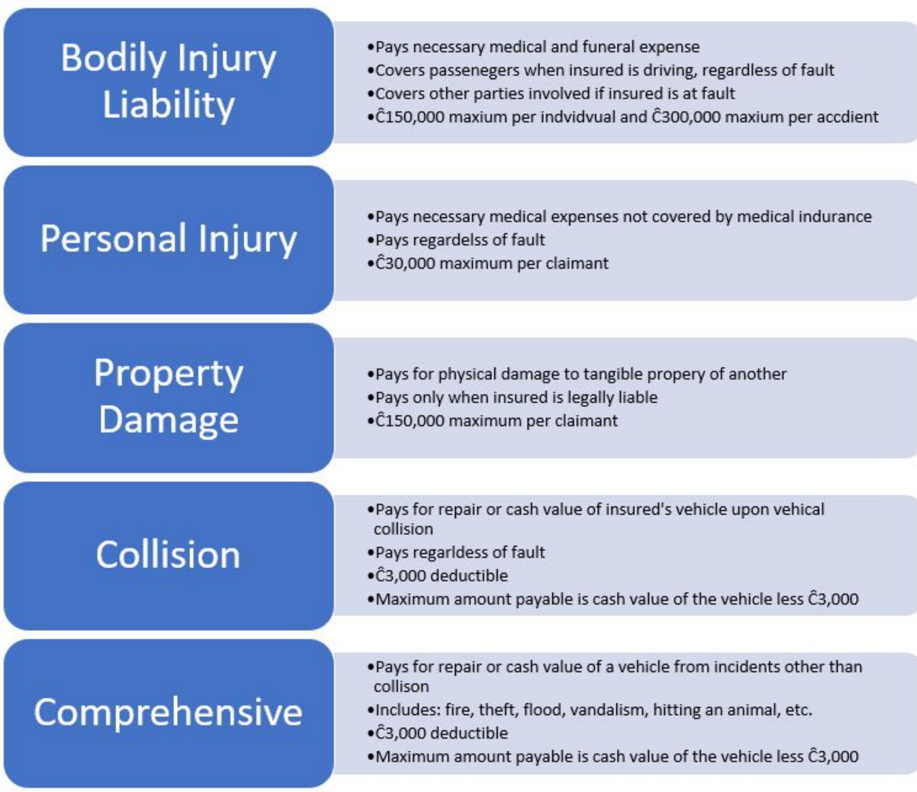

Figure 2.1: Summary of Insurance Policies of Carbia

Safelife also provided EAC with ten years of historical claims data. These data are sorted by four main categories in chronological order:

- Vehicle Size (Small, Medium, Large)
- Driver Age (Young, Middle, Senior)
- Driver Risk (Low, Average, High)
- Policy Type (Personal, Commercial)

Claim amounts are given in Carbs (Ĉ), the national currency of Carbia, and are net of deductibles and copayments.

Autonomous vehicles are vehicles whose functions are partially, or completely, controlled by automated systems. Whereas traditional vehicles are operated by the driver, autonomous vehicles are operated by computer software and a series of sensors. The Society of Automotive Engineers (SAE) published international standards for six levels of autonomy which measure the autonomy of a vehicle.

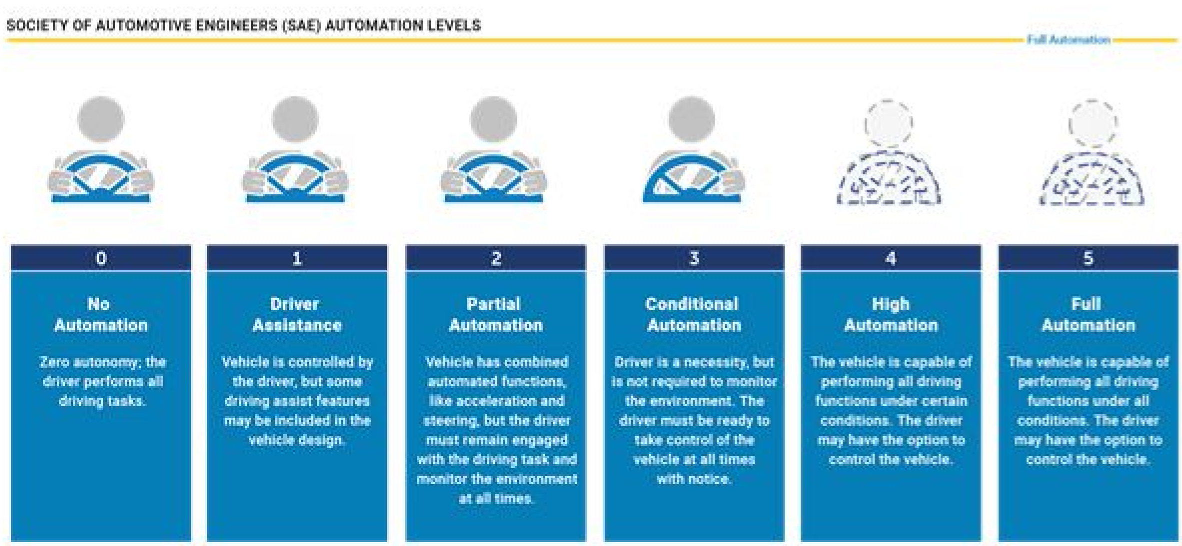

Figure 2.2 Levels of Automation Source: NHTSA, 2018

In today's market, autonomous vehicles are at Level-2. They have features such as automated braking, cruise control, collision warning, and automated parking. Level-4 AVs are currently in testing stages, with an industry trend of skipping Level-3 AVs.[3]

III. Preliminary Investigations and Literature Review

3.1 Policy Adoption

We believe that the target audience for Safelife should be the young to middle age consumers, as they are the most amenable to owning an autonomous vehicle. A survey conducted by the American Automobile Association (AAA) of 7,676 random drivers in the United States asks, "If a driverless car, bus, or shuttle were available in your location, would you be likely to ride in it, or not?"

	Base	Age				
		18 to 24	25 to 39	40 to 59	60 to 74	75 or older
Ride in Driverless Vehicle Yes/No						
Would ride in a driverless car, bus, or shuttle if it were available	**18%**	27%	29%	18%	14%	11%
Would not ride in a driverless car, bus, or shuttle if it were available	**77%**	69%	66%	76%	82%	84%
Not sure	**5%**	4%	5%	6%	4%	5%

Figure 3.1.1 Aggregate Survey Results Part 1 Source: Appendix A.1

An average of 77% of the respondents are averse to riding in an AV, with the younger population much more willing to do so[A.1]. These results show that while the general population is currently averse to riding in an autonomous vehicle, young drivers are more likely to adopt the use of an AV for public transportation services.

The survey also asks the question, "If you were to have access to a driverless vehicle, how would your habits using a vehicle change?"

	Base	Age: 18 to 24	25 to 39	40 to 59	60 to 74	75 or older
Change of Habits If Have Access to Driverless Vehicle						
Would probably use the driverless vehicle to transport me more than in my current vehicle	**9%**	19%	13%	9%	6%	5%
Would probably use the driverless vehicle to transport me less than in my current vehicle	**62%**	52%	57%	63%	66%	65%
Would probably use the driverless vehicle about the same amount as my current vehicle	**20%**	20%	27%	21%	19%	15%
Not sure	**8%**	9%	3%	7%	10%	15%

Figure 3.1.2 Aggregate Survey Results Part 2 Source: Appendix A.1

Only 9% of respondents would use an AV more frequently; 62% of respondents would use an AV less frequently[A.1]. Like the previous question, young drivers are much more likely to use an autonomous vehicle.

From these two questions, we can see that the younger generation is much more likely to adopt autonomous vehicles, even if there is considerable apprehension toward riding in an AV. These results also give us reason to believe that public transportation in an autonomous vehicle is preferable to personal ownership of an AV.

In order to secure first mover advantage in the market for autonomous vehicles, we recommend that Safelife launches its autonomous vehicle policy as early as 2020[6].

Stage	Decade	Vehicle Sales	Veh. Fleet	Veh. Travel
Available with large price premium	2020s	2-5%	1-2%	1-4%
Available with moderate price premium	2030s	20-40%	10-20%	10-30%
Available with minimal price premium	2040s	40-60%	20-40%	30-50%
Standard feature included on most new vehicles	2050s	80-100%	40-60%	50-80%
Saturation (everybody who wants it has it)	2060s	?	?	?
Required for all new and operating vehicles	???	100%	100%	100%

Autonomous vehicle implementation will probably take several decades.

Figure 3.1.3 Source: Litman, 2018, p. 19

This figure explains that autonomous vehicles will start as a small percentage of vehicles at launch, but will increase over time.

3.2 Policy Coverage

As we implement Level-4 and Level-5 AV into our policy, we assume that these AV will be safer than current vehicles, as more than 90% of accidents are caused by human error[5]. The effects of this on the policy coverage is summarized in the following chart.

Figure 3.2.1: Effect of Automation on Policy Coverage

Thus, the need for collision, bodily injury, personal injury, and property damage coverages will decrease across all risk classes for AV policy holders. However, comprehensive coverage would have no change in frequency and be expected to increase in severity initially. Since comprehensive coverage covers up to the full cost of the car less Ĉ3000, we expect it to be higher while the technology is still new and innovative. Estimates predict the saturation of AV’s will reduce this cost and consequently the impact of this change on AV policyholders within 30 to 40 years of launch[6]. In addition to the adjustments of old policies, we expect there to be a need for new technology related risks to be added to the policies. Examples of these risks include hacking, faulty software updates, and a fault in and or degrading of the sensors used in the AV’s[4][6].

3.3 Liability Assessment

Currently, in traditional automobile insurance, an insured is liable if they caused the accident. With the introduction of autonomous vehicles, an accident is no longer necessarily caused by the insured, but by the vehicle itself or its components. If the software within an autonomous vehicle fails and causes an accident, the software developer and/or vehicle manufacturer would be at fault and deemed liable for injuries and damages. The insured/driver of the autonomous vehicle can still be held liable if they do not perform routine maintenance.

It is likely that autonomous vehicles will have an accident log feature that will be able to pinpoint the cause of an accident. Since liability will be shifted away from the vehicle owner as autonomy increases, it is expected that the other parties will have a greater financial interest in autonomous vehicle insurance to protect themselves in the event they are held liable for an accident. The figure below demonstrates the transfer of liability from driver to manufacturer as the level of autonomy increases:

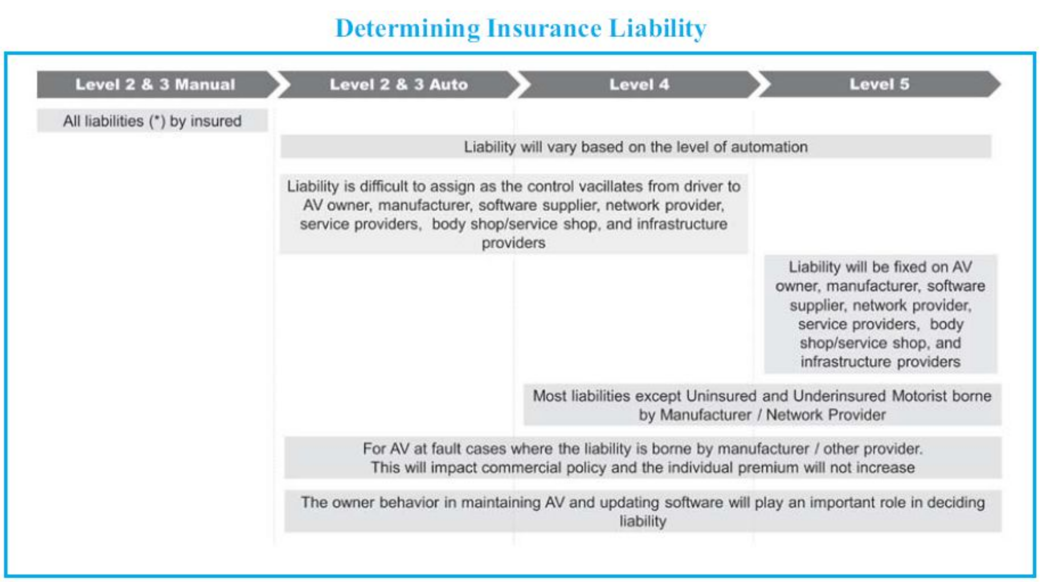

Figure 3.3.1: Determining Insurance Liability Source: Margan, 2018

3.4 Risk Identification

The introduction of autonomous vehicles in insurance policy brings about new risks that Safelife will need to consider for their insurance products. We used a risk categorization and definition tool (RCD) to demonstrate these risks:

Risk Category	Risk Subcategory	Definition of Risk Subcategory
Strategic	Strategy	Implemented strategy fails to meet expectations
Strategic	Governance	Restrictions set forth by changes in regulation delay development of autonomous vehicles
Operational	Technology	Use of autonomous systems are prone to cyber-attacks
Operational	Human Resource	Employees at Safelife may make errors in accuracy of claims
Operational	Disasters	Extreme weather may impact market timing of AVs
Operational	Infrastructure	Carbia may fail to adequately support AV technology for its cities
Financial	Market	Premiums for new vehicles may be too high; investors may find AVs to be unfavorable

Figure 3.4.1: RCD tool for Risks Associated with Autonomous Vehicles

Data security risk is new territory for the automated systems of AVs. Information may be transmitted wirelessly over Wi-fi or Bluetooth connections in an autonomous vehicle[1]. These channels are vulnerable to outside attacks from hackers, who may steal information such as diagnostics or vehicle registration. Because the potential amount of loss from a data breach could cover expenses beyond the value of the vehicle, we recommend that Safelife include cyber security coverage in their comprehensive insurance and limit that coverage to the value of the car.

3.5 Legislative Impact

In the United States, there are 33 states that introduced legislation about autonomous vehicles in 2017. The current legislation focuses on the testing of autonomous vehicles, vehicle registration, licensing, insurance, traffic regulations, and car ownership responsibilities and liabilities[2]. The legal definition of liability between drivers and autonomous systems are determined by regulations. Some areas require drivers and vehicle manufacturers to assume different responsibilities when accidents occur. However, vehicles and drivers are considered as a single entity in several jurisdictions, which means that a human fault or an automatic driving system failure will bear the same responsibility. Therefore, it is necessary to pay close attention to the changes in regulations and make timely adjustments to insurance policies.

IV. Model Construction and Data Analytics

"Generalized linear models (GLMs) are a means of modeling the relationship between a variable whose outcome we wish to predict and one or more explanatory variables."[5] We selected GLMs for classifying risks and rating our auto insurance policies.

4.1 Model Construction

Using the GLM, we forecasted exposure, claim frequency, and claim severity. The following models were built using two subsets of data from the claims data provided by Safelife in order to avoid overfitting the models. The train dataset was used to estimate model parameters and includes claims data from 2009 to 2015 inclusive. The test dataset was used to measure the accuracy of the models and includes claims data from 2016 to 2018 inclusive. Our objective with these two data sets was to use 70% of available data for model training and the remaining 30% of available data for model testing.

Model summaries with more detailed statistics and validation results can be found in Appendix A.2.

4.2 Exposure Projections

In order to successfully model pure premium, we first model car-year exposure. It will be later shown that both claim frequency and claim severity are dependent on quarterly exposure. The following is a GLM with an inverse gaussian family and log-link function:

$$Exposure = -87.634119 + 0.047925(Year) + \beta_{Qtr} + \beta_{VehicleSize} + \beta_{DriverAge} + \beta_{DriverRisk} + \beta_{Type}$$

$$\beta_{Qtr} = \begin{cases} 0, & Qtr = 1 \\ -0.004266, & Qtr = 2 \\ 0.030036, & Qtr = 3 \\ 0.030014, & Qtr = 4 \end{cases}$$

$$\beta_{VehicleSize} = \begin{cases} -0.016311, & VehicleSize = Small \\ 0.029462, & VehicleSize = Medium \\ 0, & VehicleSize = Lage \end{cases}$$

$$\beta_{DriverAge} = \begin{cases} -1.688967, & DriverAge = Young \\ 0, & DriverAge = Middle \\ -0.624749, & DriverAge = Senior \end{cases}$$

$$\beta_{DriverRisk} = \begin{cases} -0.459264, & DriverRisk = Low \\ 0, & DriverRisk = Medium \\ -0.106847, & DriverRisk = High \end{cases}$$

$$\beta_{Type} = \begin{cases} 1.557999, & Type = Personal \\ 0, & Type = Commercial \end{cases}$$

Figure 4.2.1: Model for Car-years Exposure

4.3 Claim Frequency Projections

It is important to note that claim frequency across the five insurance coverages is highly correlated.

Index	Bodily Injury	Property Damage	Comprehensive	Collision	Personal Injury
Bodily Injury	1	0.881799	0.739685	0.841122	0.754842
Property Damage	0.881799	1	0.815629	0.97146	0.829498
Comprehensive	0.739685	0.815629	1	0.769125	0.697999
Collision	0.841122	0.97146	0.769125	1	0.828441
Personal Injury	0.754842	0.829498	0.697999	0.828441	1

Figure 4.3.1: Correlation Matrix of claim frequencies using historical data

Property Damage claim frequency is observed to have the strongest correlation with all other coverage types. It is reasonable for correlations to be strong because an accident resulting in property damage can expectedly result in bodily injury, or collision damage. As a result of this observation, EAC modeled property damage claim frequency and then modeled the other coverages using property damage claim frequency as the dependent variable. Per the suggestion of CAS[5], claim frequency is modeled using a GLM with a negative binomial family and log-link function.

$$F_{PropertyDamage} = -14.425 + 0.006074(Year) + \beta_{Qtr} + \beta_{VehicleSize} + \beta_{DriverAge} + \beta_{DriverRisk} + \beta_{Type} + \log(Exposure)$$

$$\beta_{Qtr} = \begin{cases} 0, & Qtr = 1 \\ 0.016112, & Qtr = 2 \\ 0.020612, & Qtr = 3 \\ 0.042033, & Qtr = 4 \end{cases}$$

$$\beta_{VehicleSize} = \begin{cases} 0, & Large \\ 0.055843, & Medium \\ 0.128635, & Small \end{cases}$$

$$\beta_{DriverAge} = \begin{cases} 0.048175, & Young \\ 0, & Middle \\ 0.047267, & Senior \end{cases}$$

$$\beta_{Type} = \begin{cases} -0.125365, & Personal \\ 0, & Commerical \end{cases}$$

$$F_{BodilyInjury} = -1.16367 + 0.94233 * \log(F_{PropertyDamage})$$

$$F_{Comprehensive} = 0.57458 + 0.99267 * \log(F_{PropertyDamage})$$

$$F_{Collision} = 0.408419 + 1.008144 * \log(F_{PropertyDamage})$$

$$F_{PersonalInjury} = -1.06044 + 0.99458 * \log(F_{PropertyDamage})$$

$$\beta_{DriverRisk} = \begin{cases} -0.134883, & Low \\ 0, & Avgerage \\ 0.272413, & High \end{cases}$$

Figure 4.3.2 Model for Claim Frequency of Traditional Vehicles

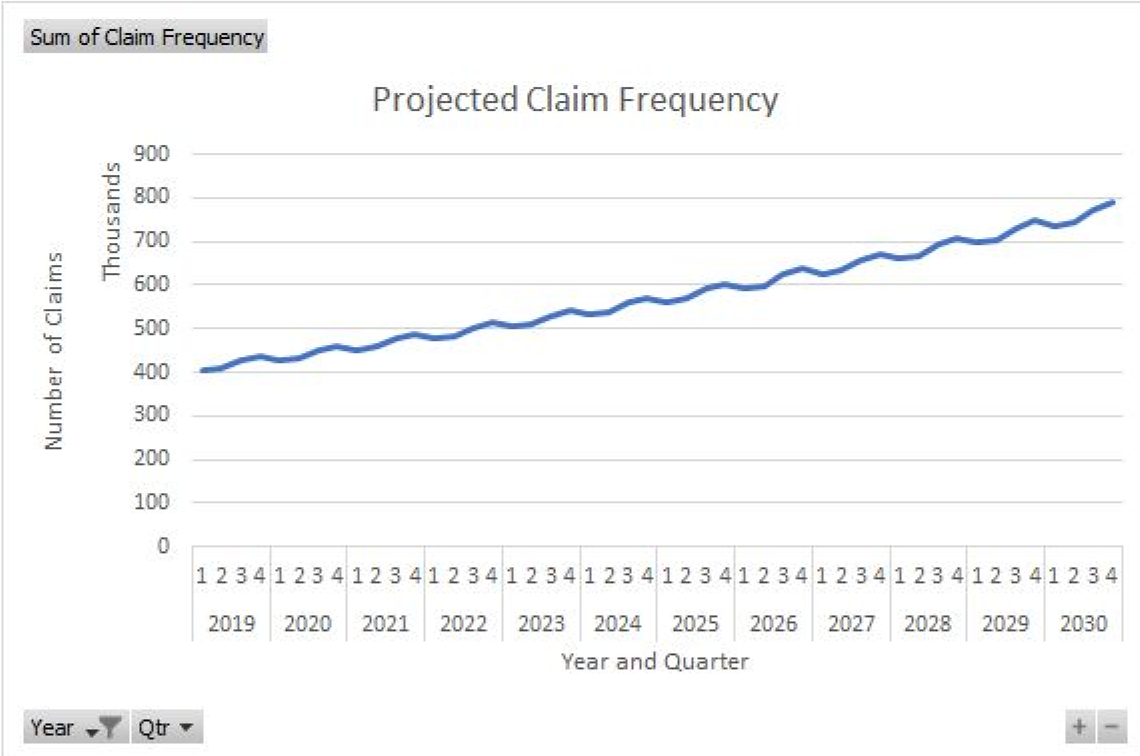

Figure 4.3.3: Claim Frequency Ten-year Forecast for Traditional Vehicles

Based on our model, we predict there will be about 790,000 claims for traditional vehicle policies during the fourth quarter of 2030.

4.4 Claim Severity Projections

Like with claim frequency, high correlations are observed between the aggregate claim severity across the five coverage types.

Index	BodilyInjury	PropertyDamage	Comprehensive	Collision	PersonalInjury
BodilyInjury	1	0.908415	0.644861	0.907095	0.736874
PropertyDama…	0.908415	1	0.721167	0.96169	0.733902
Comprehensive	0.644861	0.721167	1	0.692599	0.557944
Collision	0.907095	0.96169	0.692599	1	0.760098
PersonalInju…	0.736874	0.733902	0.557944	0.760098	1

Figure 4.4.1: Correlation Matrix of Claim Severity using Historical Data

Once again, Property Damage is observed to have the strongest correlations with the other coverage types. These strong, positive correlations are deemed reasonable because a large severity in one coverage is likely to result in a large severity in another.

Due to the strong, positive correlations, EAC modeled property damage severity and then used that model to model the severities of the remaining coverage types.

$$S_{PropertyDamage} = 27.975783 - 0.009852(Year) + \beta_{Qtr} + \beta_{VehicleSize} + \beta_{DriverAge} + \beta_{DriverRisk} + \beta_{Type} + 0.97325\log(num\_claims_{PropertyDamage})$$

$$\beta_{Qtr} = \begin{cases} 0, & Qtr = 1 \\ 0.044744, & Qtr = 2 \\ 0.021449, & Qtr = 3 \\ 0.016444, & Qtr = 4 \end{cases} \qquad \beta_{VehicleSize} = \begin{cases} 0, & Large \\ 0.09593, & Medium \\ -0.021563, & Small \end{cases}$$

$$\beta_{DriverAge} = \begin{cases} 0.07185, & Young \\ 0, & Middle \\ 0.022444, & Senior \end{cases} \qquad \beta_{DriverRisk} = \begin{cases} -0.06327, & Low \\ 0, & Avgerage \\ 0.104571, & High \end{cases}$$

$$\beta_{Type} = \begin{cases} -0.047589, & Personal \\ 0, & Commerical \end{cases}$$

$$S_{BodilyInjury} = 7.864404 + 0.207354 * \log(S_{PropertyDamage}) + 0.780798 * \log(num\_claims_{BodilyInjury})$$

$$S_{Comprehensive} = 6.81541 + 0.01798 * \log(S_{PropertyDamage}) + 1.00873 * \log(num\_claims_{Comprehensize})$$

$$S_{Collision} = 6.55573 + 0.20832 * \log(S_{PropertyDamage}) + 0.78539 * \log(num\_claims_{Collision})$$

$$S_{PersonalInjury} = 8.204885 + 0.060314 * \log(S_{PropertyDamage}) + 0.911836 * \log(num\_claims_{PersonalInjury})$$

Figure 4.4.2: Model for Claim Severity of Traditional Vehicles

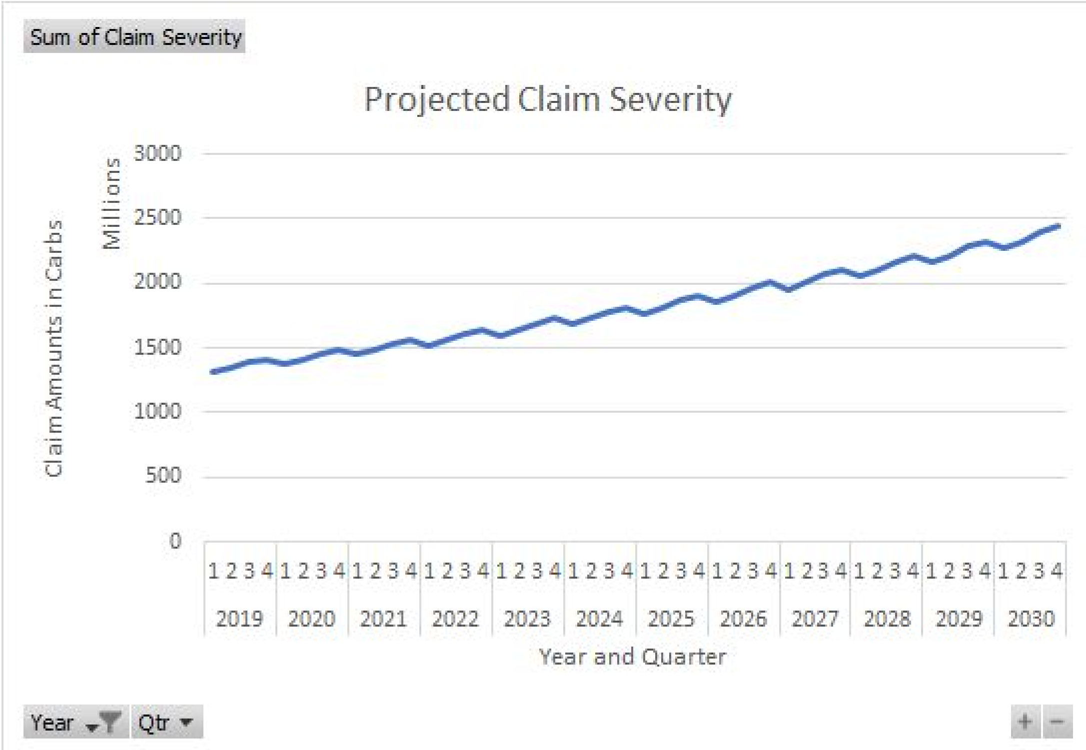

Figure 4.2.3: Claim Severity Ten-year Forecast for Traditional Vehicles

Based on our model, we predict the loss amounts will be about Ĉ2,447,000,000 for traditional vehicle policies during the fourth quarter of the year 2030.

4.5 Pure Premiums Forecasting Results

Since claim data for autonomous vehicles is not available, EAC introduced adjustment factors into both the claim frequency and claim severity models. As discussed above, we predict that the introduction of autonomous vehicles will reduce the number of claims by 90%. EAC has chosen a conservative claim frequency adjustment factor of 0.25, which represents a reduction in claim frequency of 75%. As for claim severity, EAC only expects comprehension and collision severities to be affected by the introduction of autonomous vehicles. This is because the collision and autonomous vehicles coverages have policy limits of the vehicle's value less Ĉ3,000. Autonomous vehicles are projected to be more expensive than traditional vehicles early on, so that would result in large claim severity. EAC has chosen a severity adjustment factor of 2.0. All other policy coverages have a policy limit independent of vehicle value, and EAC does not expect the severities of these coverages to be influenced by autonomous vehicles.

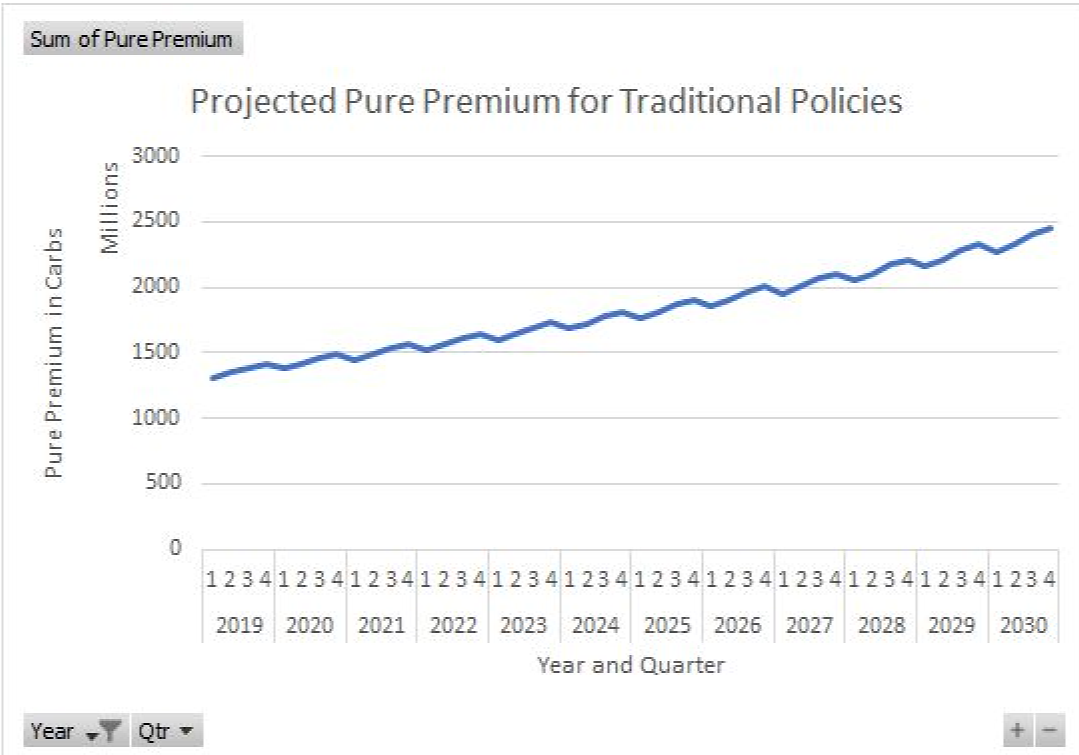

Figure 4.5.1 Pure Premium Projections for Traditional Vehicles

The increasing, linear trend in total pure premium is reasonable because Safelife will continue to acquire new business in the future. An increase in exposure will surely increase the total pure premium. We expect the pure premium to be about Ĉ2,447,000,000 for traditional vehicle policies during the fourth quarter of 2030.

The following chart shows the projected total pure premium in millions if Safelife includes only autonomous vehicles in its business.

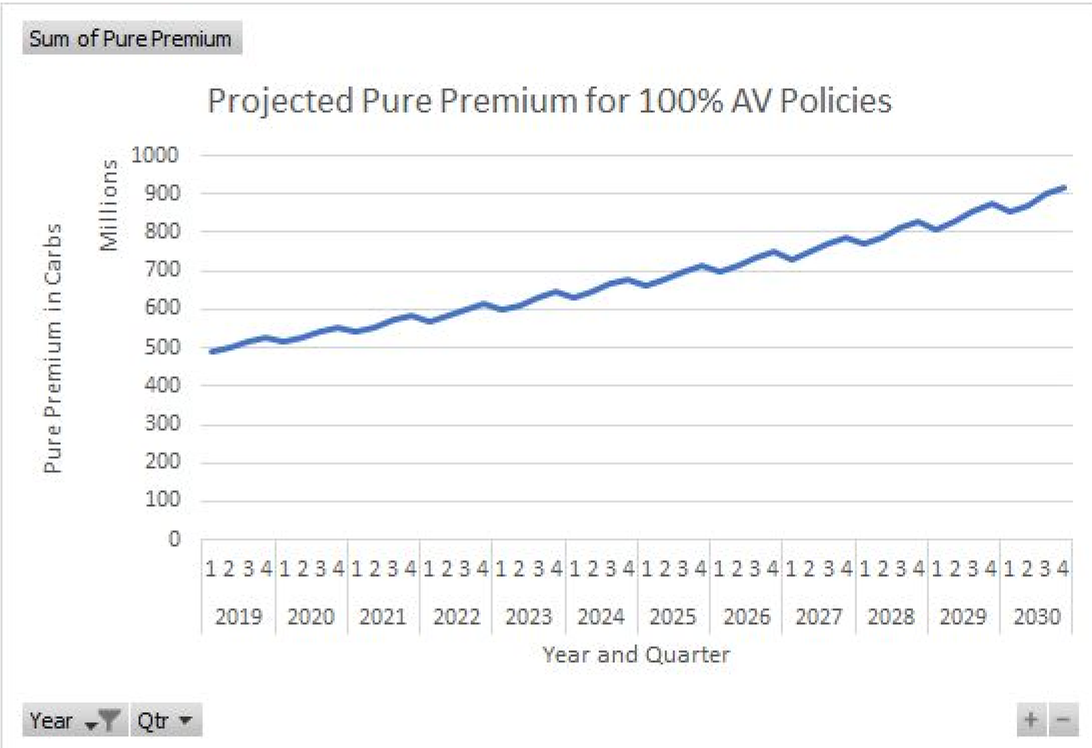

Figure 4.5.2 Pure Premium Projections for AV

Again, we see a positive, linear trend in total pure premium. However, total pure premium in this scenario is considerably less than the total pure premium in the previous scenario of only traditional vehicle business. The rate at which pure premium increases in relation to time is also notably smaller in this scenario. This is expected because while Safelife is continuously acquiring new business, and therefore increasing its exposure, autonomous vehicles are less likely to have accidents, thus reducing the increasing trend in total pure premium. We expect the pure premium to be about Ĉ919,000,000 for 100% autonomous vehicle composition during the fourth quarter of 2030.

4.6 Sensitivity Analysis on Business Composition

EAC performed the following sensitivity analysis, where the variable of interest is the percentage of overall business composed of autonomous vehicles.

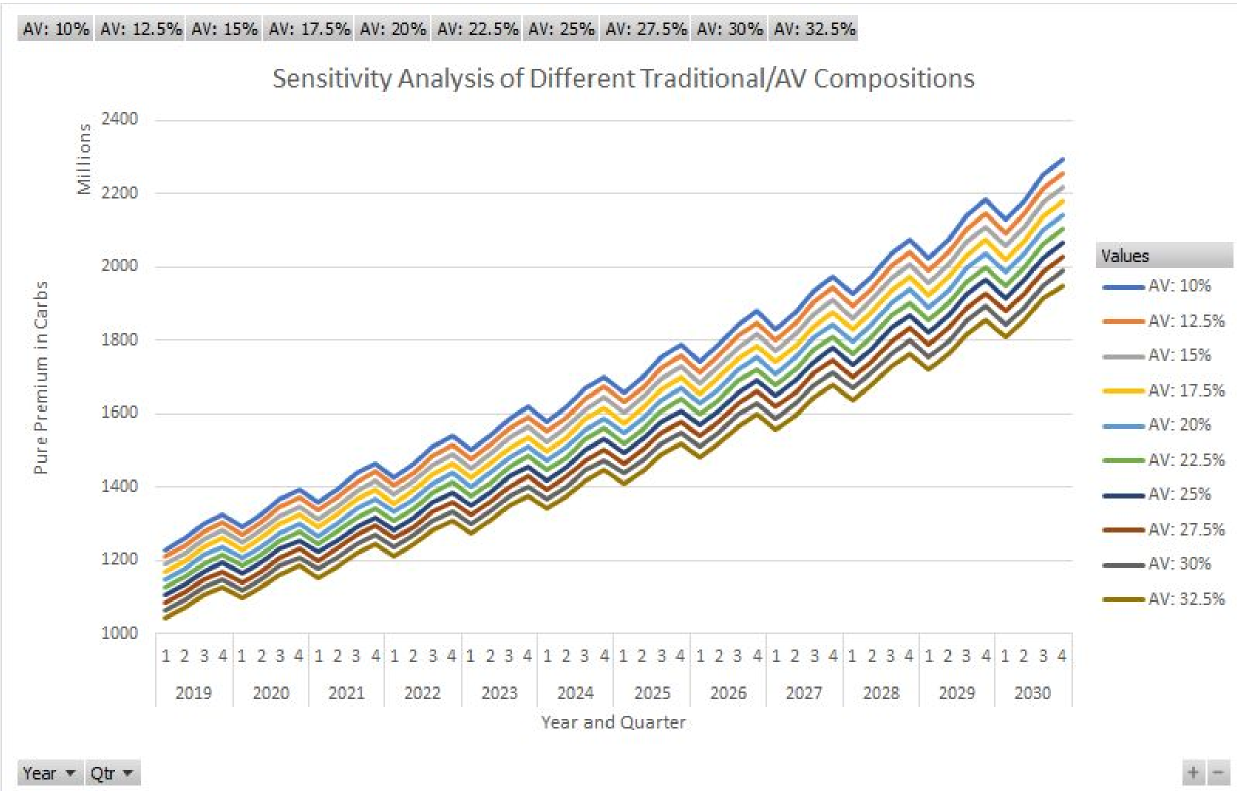

Figure 4.6.1 Pure Premium Projections for Various Compositions of Traditional and AV

Safelife's goal is to have approximately 20% to 25% of its overall business be autonomous vehicle policies by 2030. The chart above shows that the higher the percentage of autonomous vehicle business, the smaller the total pure premium. Thus, we expect the range of pure premiums to be between Ĉ1,950,000,000 and Ĉ2,294,000,000 by the fourth quarter of 2030.

V. Assumption and Data Limitations

- We assume that Level-0 to Level-3 AV are reflected in historical claims data.
- We assume that Level-4 and Level-5 AV will reduce the number of claims.
- We assume the claim frequency and claim severity of data are independent.

- We assume that the consumers' preference of the sizes of vehicles and age structure of population in Carbia will not change in the future.
- We assume the value of Carbs (Ĉ) is equivalent to the value of the U.S. dollar ($).
- We have limited information for the future estimated cost of AV technology.
- Unpredicted legislation can be a limiting factor for policy deployment.

VI. Conclusion and Recommendation

We reviewed the policy adoption, coverage, liability assessment, risk identification and legislative impact about autonomous vehicle insurance. Then, we calculated the pure premiums for fully traditional insurance Ĉ2,447,000,000, and fully autonomous vehicle insurance is Ĉ919,000,000. Finally, we forecasted the range of pure premiums through sensitivity analysis, which is between Ĉ1,950,000,000 and Ĉ2,294,000,000.

Based on the model we have generated and qualitative analysis from our literature review, we recommend that Safelife launch its autonomous vehicle policy by the year 2020. Safelife stands to benefit from the first-mover advantage in the market for autonomous vehicles and can reduce its pure premiums by moving to a partially autonomous vehicle model. EAC recommends Safelife should watch over developments in legislation regarding AVs and the potential risk of cybersecurity threats to AVs.

VII. References

1. Anderson, James M, et al. “Autonomous Vehicle Technology A Guide for Policymakers.” *Rand Corporation*, 2016, www.rand.org/pubs/research_reports/RR443-2.html.

2. “AUTONOMOUS VEHICLES | SELF-DRIVING VEHICLES ENACTED LEGISLATION.” *National Conference of State Legislatures*, 7 Nov. 2018. www.ncsl.org/research/transportation/autonomous-vehicles-self-driving-vehicles-enacted-legislation.aspx.

3. “Automated Vehicles for Safety.” *National Highway Traffic Safety Administration.* 2018, https://www.nhtsa.gov/technology-innovation/automated-vehicles-safety.

3. “Automated Vehicles Policy Fact Sheet Overview.” *US Department of Transportation*, United States Department of Transportation, 20 Sept. 2016, www.transportation.gov/AV-factsheet.

4. “Auto Insurance for Automated Vehicles: Preparing for the Future of Mobility.” *Insurance Bureau of Canada*, 2018, assets.ibc.ca/Documents/The-Future/Automated-Vehicle-Report.pdf.

5. Goldburd, Mark et al. “Generalized Linear Models for Insurance Rating.” *Casualty Actuary Society*, 2018, https://www.casact.org/pubs/monographs/papers/05-Goldburd-Khare-Tevet.pdf

6. Litman, Todd. “Autonomous Vehicle Implementation Predictions Implications for Transport Planning.” *Victoria Transport Policy Institute*, 26 Nov. 2018, www.vtpi.org/avip.pdf.

7. Margan, Srivathsan K. “Autonomous Vehicles and Insurance.” *BimaQuest: The Journal of Insurance & Management.* 2018;18(3):15

A. Appendix

A.1 AAA Survey Details

The survey was conducted by AAA on March 27-29th, 2018 across the AAA club territory in the following states: CT, DC, DE, KS, KY, MD, NJ, OH, OK, PA, SD, VA, and WV. 7,676 respondents were selected by a random selection of both landline phones and cellular phones. The survey questions were as follows:

Q1: Some newer cars have some of the same technology being used in autonomous vehicles. Of the following list of choices, which of these features do you use most often in your car, or do you not use any of these: lane departure warning, parking assist, adaptive cruise control, crash avoidance braking, or none of these?

Q2: If a driverless car, bus, or shuttle were available in your location, would you be likely to ride in it, or not?

Q3: From the following list of choices, what is your greatest concern about the introduction of autonomous vehicle technology: the reliability and safety of the technologo, mechanical breakdowns and cost to repair, data and cyber security, purchase price, or understanding how to use the technology?

Q4: If you were to have access to a driverless vehicle, how would your habits using a vehicle change: would you probably use the driverless vehicle to transport you more than in your current vehicle, transport you less than in your current vehicle, or about the same amount?

Q5: In order for an autonomous vehicle to operate, it needs to exchange data regularly with other vehicles and infrastructure. How concerned are you about the security of the data sent to and from autonomous vehicles: very concerned, somewhat concerned, not very concerned, or not at all concerned?

Q6: Who do you think should be responsible for liability while riding in a driverless vehicle: the car owner, the car manufacturer, the technology company, or the licensed driver?

Q7: Are you a member of AAA?

Q8: Do you have a valid US driver’s license?

Q9: If you are a woman, press 1. If a man, press 2.

Q10: If you are 18-24 years old, press 1. If 25-39, press 2. If 40-59, press 3. If 60-74, press 4. If 75 or older, press 5.

A.2 R Code and Summaries

Exposure:

```
Call:
glm(formula = Exposure ~ Year + Qtr.f + C(VehicleSize) + C(DriverAge) +
    C(DriverRisk) + C(Type), family = inverse.gaussian(link = log),
    data = Train_Data)

Deviance Residuals:
       Min         1Q      Median          3Q         Max
-0.0250107  -0.0034326  -0.0003346   0.0029164   0.0111020

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)         -87.634119   7.832399 -11.189  < 2e-16 ***
Year                  0.047925   0.003893  12.310  < 2e-16 ***
Qtr.f2               -0.004266   0.021786  -0.196    0.845
Qtr.f3                0.030036   0.021975   1.367    0.172
Qtr.f4                0.030014   0.021974   1.366    0.172
C(VehicleSize)Medium  0.029462   0.019119   1.541    0.124
C(VehicleSize)Small  -0.016311   0.018901  -0.863    0.388
C(DriverAge)Senior   -0.624749   0.027686 -22.566  < 2e-16 ***
C(DriverAge)Young    -1.688967   0.024320 -69.449  < 2e-16 ***
C(DriverRisk)High    -0.106847   0.020566  -5.195 2.33e-07 ***
C(DriverRisk)Low     -0.459264   0.019066 -24.088  < 2e-16 ***
C(Type)Personal       1.557999   0.020483  76.064  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for inverse.gaussian family taken to be 2.815602e-05)

    Null deviance: 0.355505  on 1511  degrees of freedom
Residual deviance: 0.058957  on 1500  degrees of freedom
AIC: 27761

Number of Fisher Scoring iterations: 10
```

Claim Frequency:

```
Call:
glm.nb(formula = num_PropertyDamage ~ Year + Qtr.f + C(VehicleSize) +
    C(DriverAge) + C(DriverRisk) + C(Type) + offset(log(Exposure)),
    data = Train_Data, link = log, init.theta = 59.41934195)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.93514  -0.69473  -0.00788   0.71203   2.44174

Coefficients:
                       Estimate Std. Error z value Pr(>|z|)
(Intercept)          -14.425028   3.587836  -4.021 5.81e-05 ***
Year                   0.006074   0.001783   3.406 0.000659 ***
Qtr.f2                 0.016112   0.010099   1.595 0.110617
Qtr.f3                 0.020612   0.010089   2.043 0.041056 *
Qtr.f4                 0.042033   0.010083   4.169 3.07e-05 ***
C(VehicleSize)Medium   0.055843   0.008744   6.387 1.69e-10 ***
C(VehicleSize)Small    0.128635   0.008754  14.694  < 2e-16 ***
C(DriverAge)Senior     0.047267   0.008529   5.542 2.99e-08 ***
C(DriverAge)Young      0.048175   0.008830   5.456 4.87e-08 ***
C(DriverRisk)High      0.272413   0.008622  31.597  < 2e-16 ***
C(DriverRisk)Low      -0.134883   0.008817 -15.299  < 2e-16 ***
C(Type)Personal       -0.125365   0.007160 -17.510  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(59.4193) family taken to be 1)

    Null deviance: 4395.0  on 1511  degrees of freedom
Residual deviance: 1500.8  on 1500  degrees of freedom
AIC: 17812

Number of Fisher Scoring iterations: 1


              Theta:  59.42
          Std. Err.:  2.43

 2 x log-likelihood:  -17785.58
```

```
Call:
glm.nb(formula = num_Collision ~ log(num_PropertyDamage), data = Train_Data,
    link = log, init.theta = 26.77159963)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.8513  -0.7174  -0.1505   0.4377   3.8765

Coefficients:
                        Estimate Std. Error z value Pr(>|z|)
(Intercept)             0.408419   0.031437   12.99   <2e-16 ***
log(num_PropertyDamage) 1.008144   0.004785  210.70   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for Negative Binomial(26.7716) family taken to be 1)

    Null deviance: 41602.3  on 1511  degrees of freedom
Residual deviance:  1523.5  on 1510  degrees of freedom
AIC: 20211

Number of Fisher Scoring iterations: 1


              Theta:  26.77
          Std. Err.:  1.01

 2 x log-likelihood:  -20205.17


Call:
glm.nb(formula = num_BodilyInjury ~ log(num_PropertyDamage),
    data = Train_Data, link = log, init.theta = 4.540082738)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.5982  -0.9266   0.2204   0.6031   1.5861

Coefficients:
                        Estimate Std. Error z value Pr(>|z|)
(Intercept)             -1.16367    0.07672  -15.17   <2e-16 ***
log(num_PropertyDamage)  0.94233    0.01167   80.75   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for Negative Binomial(4.5401) family taken to be 1)

    Null deviance: 7870.8  on 1511  degrees of freedom
Residual deviance: 1574.7  on 1510  degrees of freedom
AIC: 16677

Number of Fisher Scoring iterations: 1


              Theta:  4.540
          Std. Err.:  0.170
```

```
Call:
glm.nb(formula = num_Comprehensive ~ log(num_PropertyDamage), 
    data = Train_Data, link = log, init.theta = 4.096916231)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-2.7223  -0.7111  -0.1775   0.4129   3.3544  

Coefficients:
                        Estimate Std. Error z value Pr(>|z|)    
(Intercept)              0.57458    0.07713   7.449 9.38e-14 ***
log(num_PropertyDamage)  0.99267    0.01181  84.063  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(4.0969) family taken to be 1)

    Null deviance: 7721.0  on 1511  degrees of freedom
Residual deviance: 1571.2  on 1510  degrees of freedom
AIC: 22965

Number of Fisher Scoring iterations: 1


              Theta:  4.097 
          Std. Err.:  0.144 

 2 x log-likelihood:  -22958.549 
```

```
Call:
glm.nb(formula = num_PersonalInjury ~ log(num_PropertyDamage),
    data = Train_Data, link = log, init.theta = 4.201842606)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.4876  -0.7066  -0.0559   0.2888   4.0982

Coefficients:
                        Estimate Std. Error z value Pr(>|z|)
(Intercept)             -1.06044    0.07838  -13.53   <2e-16 ***
log(num_PropertyDamage)  0.99458    0.01195   83.22   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for Negative Binomial(4.2018) family taken to be 1)

    Null deviance: 7871.7  on 1511  degrees of freedom
Residual deviance: 1574.6  on 1510  degrees of freedom
AIC: 18071

Number of Fisher Scoring iterations: 1


              Theta:  4.202
          Std. Err.:  0.153

 2 x log-likelihood:  -18065.042
```

Severity Models:

```
Call:
glm(formula = PropertyDamage ~ Year + Qtr.f + C(VehicleSize) +
    C(DriverAge) + C(DriverRisk) + C(Type) + log(num_PropertyDamage),
    family = inverse.gaussian(link = log), data = Train_Data)

Deviance Residuals:
       Min          1Q      Median          3Q         Max
-6.438e-04  -7.310e-05  -3.630e-06   6.732e-05   3.971e-04

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)             27.975783   4.052035   6.904 7.44e-12 ***
Year                    -0.009852   0.002022  -4.873 1.22e-06 ***
Qtr.f2                   0.044744   0.010993   4.070 4.94e-05 ***
Qtr.f3                   0.021449   0.011019   1.947 0.051769 .
Qtr.f4                   0.016444   0.011119   1.479 0.139377
C(VehicleSize)Medium     0.095930   0.010076   9.521  < 2e-16 ***
C(VehicleSize)Small     -0.021563   0.009787  -2.203 0.027726 *
C(DriverAge)Senior       0.022444   0.016629   1.350 0.177328
C(DriverAge)Young        0.071850   0.019997   3.593 0.000337 ***
C(DriverRisk)High        0.104571   0.011549   9.055  < 2e-16 ***
C(DriverRisk)Low        -0.063270   0.011662  -5.426 6.73e-08 ***
C(Type)Personal          0.047589   0.017826   2.670 0.007675 **
log(num_PropertyDamage)  0.973250   0.010032  97.016  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for inverse.gaussian family taken to be 2.037733e-08)

    Null deviance: 8.9913e-04  on 1511  degrees of freedom
Residual deviance: 3.3655e-05  on 1499  degrees of freedom
AIC: 43493

Number of Fisher Scoring iterations: 5
```

```
Call:
glm(formula = BodilyInjury ~ log(PropertyDamage) + log(num_BodilyInjury),
    family = inverse.gaussian(link = log), data = Train_Data)

Deviance Residuals:
       Min          1Q      Median          3Q         Max
-1.107e-03  -1.372e-04  -2.901e-05   1.085e-04   1.094e-03

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)           7.864404   0.134745   58.37   <2e-16 ***
log(PropertyDamage)   0.207354   0.011863   17.48   <2e-16 ***
log(num_BodilyInjury) 0.780798   0.009022   86.54   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for inverse.gaussian family taken to be 5.69943e-08)

    Null deviance: 1.0266e-03  on 1511  degrees of freedom
Residual deviance: 8.8941e-05  on 1509  degrees of freedom
AIC: 45256
```

```
Call:
glm(formula = Comprehensive ~ log(PropertyDamage) + log(num_Comprehensive),
    family = inverse.gaussian(link = log), data = Train_Data)

Deviance Residuals:
       Min          1Q      Median          3Q         Max
-1.654e-03  -2.518e-04  -8.607e-05   1.289e-04   1.842e-03

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)             6.81541    0.14305  47.644   <2e-16 ***
log(PropertyDamage)     0.01798    0.01484   1.211    0.226
log(num_Comprehensive)  1.00873    0.01401  72.012   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for inverse.gaussian family taken to be 1.596013e-07)

    Null deviance: 0.00210731  on 1511  degrees of freedom
Residual deviance: 0.00022509  on 1509  degrees of freedom
AIC: 43523

Number of Fisher Scoring iterations: 5
```

```
Call:
glm(formula = Collision ~ log(PropertyDamage) + log(num_Collision),
    family = inverse.gaussian(link = log), data = Train_Data)

Deviance Residuals:
       Min          1Q      Median          3Q         Max
-4.012e-04  -5.257e-05   1.700e-07   4.164e-05   3.667e-04

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)          6.55573    0.10502   62.42   <2e-16 ***
log(PropertyDamage)  0.20832    0.01266   16.46   <2e-16 ***
log(num_Collision)   0.78539    0.01207   65.06   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for inverse.gaussian family taken to be 9.222602e-09)

    Null deviance: 5.9487e-04  on 1511  degrees of freedom
Residual deviance: 1.4823e-05  on 1509  degrees of freedom
AIC: 44270

Number of Fisher Scoring iterations: 4
```

```
Call:
glm(formula = PersonalInjury ~ log(PropertyDamage) + log(num_PersonalInjury),
    family = inverse.gaussian(link = log), data = Train_Data)

Deviance Residuals:
       Min          1Q      Median          3Q         Max
-1.384e-03  -3.374e-04  -1.465e-05   2.015e-04   1.348e-03

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)             8.204885   0.134045  61.210  < 2e-16 ***
log(PropertyDamage)     0.060314   0.011695   5.157 2.84e-07 ***
log(num_PersonalInjury) 0.911836   0.009354  97.481  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for inverse.gaussian family taken to be 1.650308e-07)

    Null deviance: 0.00254243  on 1511  degrees of freedom
Residual deviance: 0.00027176  on 1509  degrees of freedom
AIC: 43303

Number of Fisher Scoring iterations: 5
```