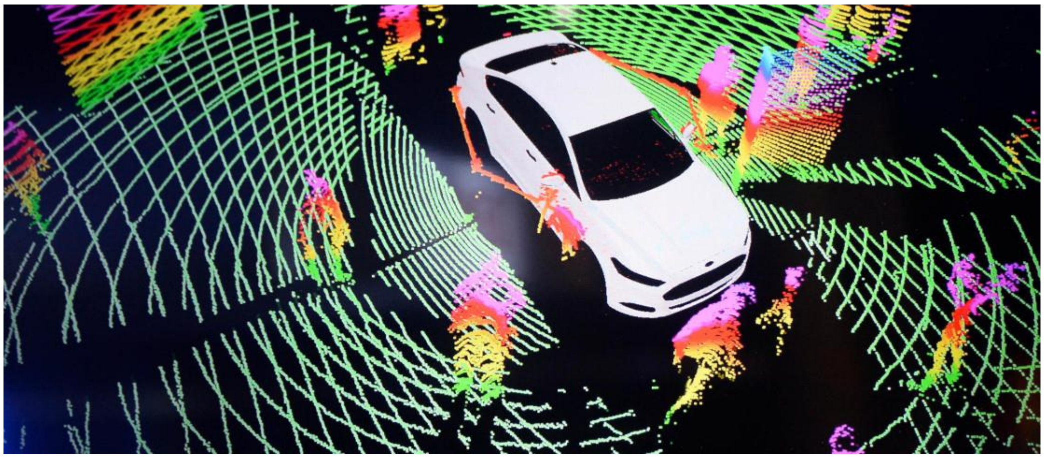
SAFELIFE'S NEW AUTONOMOUS

POLICY PROPOSAL



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3/22/19 Drake University A Team Actuarial Solutions

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Safelife's New Autonomous Policy Proposal

DRAKE UNIVERSITY A TEAM ACTUARIAL SOLUTIONS

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1. EXECUTIVE SUMMARY

This report analyzes the insurability of autonomous vehicles (AVs) and explores how Safelife can introduce a new insurance product for these vehicles that effectively considers their unique exposure as well as their potential socioeconomic impact on Carbia. This report provides a comprehensive proposal for a new insurance policy specifically oriented toward autonomous vehicles, complete with long-term forecasts and other necessary considerations.

In the next decade, the introduction and growth of AVs will not only have a revolutionary impact on the Carbian economy, but will also completely change the universal approach to auto insurance. This report seeks to identify all of these changes and, more importantly, how Safelife can design a policy that best addresses these impacts.

Analysis based on both Safelife's internal data and outside research demonstrates that AVs are a highly insurable risk. This report provides what we believe to be the most accurate solution for a new policy tailored to these vehicles given the data limitations and uncertainties. Since several assumptions and complex estimates were required to mitigate these uncertainties, extensive justification, supporting calculations, and alternative considerations have been provided in the appendices as well as in the attached Excel workbooks; however, the main report will focus on the conclusions, limitations, and their impacts on Safelife.

2. METHODOLOGIES

Below, Table 1 gives a high-level overview of the methodologies used in our analyses and calculations. Each is discussed in depth in the appendices; a discussion of our assumptions can be found in Section 8.

Table 1: Methodologies			
Methodology	**Application**	**Further Support**	**Justification**
ARIMA Modeling	Safelife Pure Premium Trend Projections	Appendix A	Widely accepted method for evaluating trends in time series data
Ordinary Linear Regression	Supporting Calculations	Appendix E	Used when data was too limited to lend itself to ARIMA modeling (See Appendix E for further justification)
Competitive Analysis	Rate Benchmarking and Competitor Profiling	Appendix B	It is important to evaluate the competitive environment for AV insurance to ensure that Safelife can create a sustainable competitive advantage
General Research	Development of Numerical Estimates & Assumptions	Works Cited & Appendices	Safelife's data sufficiently depicted the risk of traditional vehicles, but not autonomous vehicles; therefore, we felt it appropriate to seek outside data to supplement Safelife's data
Sensitivity Analysis	Evaluation of Management's Goal	Appendix G	Requested by Safelife Management

Table 1: Methodologies

3. AUTONOMOUS POLICY OVERVIEW

Before an adequate insurance policy for AVs can be created, we must define what constitutes an AV. While there has been extensive discussion on this topic, the most widely accepted framework for defining AVs comes from SAE International's Levels of Driving Automation (Figure 1).

Figure 1: Levels of Automation

Automation Level	Degree of Driver Intervention	Example Features	Feature Scope
0	Constant supervision	Emergency braking Lane departure warning	Warnings Brief assistance
1		Adaptive cruise control Lane centering (Only level 2 has both)	Steering and brake support
2			
3	Occasional supervision	Traffic jam chauffeur	Complete automation in some conditions
4	No supervision	No need for pedals or steering wheel (Level 5 can drive in any conditions)	
5			Automation in all conditions

Figure 1: Levels of Driving Automation
Source: "SAE International Releases Updated Visual Chart for Its 'Levels of Driving Automation' Standard for Self-Driving Vehicles", 2018

For our analysis, we have condensed these levels into three groups: Fully-Autonomous Vehicles, Semi-Autonomous Vehicles, and Traditional Vehicles. Table 2 includes all definitions relevant to this new policy proposal as well as abbreviations that will be used throughout this report.

Table 2: Definitions & Abbreviations		
Term	**Abbreviation**	**Definition**
Fully Autonomous Vehicle	FAV	A car that does not require human operation to drive (i. e. must be at least level 4)
Semi-Autonomous Vehicle	SAV	A car that can operate autonomously but may require manual takeover (i. e. only level 3 cars)
Traditional Vehicle	TV	Any car without driverless capabilities (i. e. any car below level 3)
Commercial Autonomous Vehicle	CAV	A commercially-owned FAV
Personal Autonomous Vehicle	PAV	A personally-owned FAV
Traditional Line	TL	The formal name we will use for Safelife's old policy for traditional vehicles
Autonomous Line	AL	The formal name we will use for Safelife's new policy for autonomous vehicles
Cybersecurity Coverage	CYB	An insurance endorsement which provides coverage for cybersecurity related damages

Table 2: Definitions & Abbreviations

We recommend a two-fold approach to writing AVs to Safelife:

1. **Design a new policy exclusively for FAVs, to be launched in 2022**
2. **Begin to write SAVs onto our current policy with a small discount immediately**

We believe that only FAVs warrant a new policy because SAVs still include the propensity for human error since manual takeover is still required. However, we believe that SAVs should still be written through the old policy—with a discount—in order to be consistent with Safelife's primary competitors. Table 3 illustrates the policy characteristics for both the Traditional Line policy and the Autonomous Line policy.

Table 3: Policy Characteristics		
Line	**Traditional Line**	**Autonomous Line**
Eligibility	Any Car Without Fully Autonomous Capabilities	Level 4 and Level 5 Autonomous Vehicles
Coverages	BI, PI, PD, COL, COMP	BI, PI, PD, COL, COMP, CYB
Features	SAV Discount Endorsement	Personal Cyber Endorsement, Commercial Cyber Endorsement

Table 3: Policy Characteristics

Section 3.1 New Risks

While our research indicates that the inherent risk of AVs is monumentally smaller than the risk of insuring traditional vehicles, there are several new risks to consider with the inception of autonomous vehicles (Table 4).

Table 4: New Risks			
New Risk	**Description**	**Impact**	**Recommendation**
Hardware/Software Failures	Vehicle failure attributed to random and unpredictable failure in the car's technology	Creates a new source of risk: *First and third party technological error*	Write an exclusion for hardware/software failure in the coverage terms for the old policy. Add damages/liability resulting from hardware/software failure as coverage terms to new policy.
Increased Risk-Taking Behavior	The tendency for humans to over-trust technology and engage in riskier behavior as a result	Severity of medical payments may see slight increases	Ensure that coverage terms for personal injury in the new policy require drivers to adhere to all legally required safety standards in order for coverage to apply, even if the insured is not driving.
Platooning	Vehicles operating close together at high speeds on dedicated lanes	Platooning accidents will have high severity	Collect data on cities implementing platooning lanes as well as data on insured vehicles involved in platooning on the new policy. Develop modifications based on data collected.
Increased Vehicle Miles Traveled	The inception of AVs will likely increase total VMT due to the commercial opportunities	Increased VMT results in more time that cars are exposed to risk	Collect highly granular geographic data which can be used to assess which locations in Carbia carry the most risk.
Object Detection Issues	AV software experiencing difficulty detecting objects, such as pedestrians	Liability claims involving these issues will be very severe, but also very infrequent	Write an exclusion for hardware/software failure in the coverage terms for the old policy. Add damages/liability resulting from hardware/software failure as coverage terms to new policy.
Cybersecurity	Connected cars means that automobiles can be hacked	This will be a growing concern for consumers as cars become more connected	Add a new optional coverage for cybersecurity. Offer both a personal and a commercial version of the endorsement.

Source: Litman, 2019

One of the most significant new concerns is the cybersecurity risk that comes with the emergence of autonomous vehicles (Teows, 2016). We propose that the Autonomous Line includes different cybersecurity endorsements for personal versus commercial policies since this risk differs greatly between these lines. We have chosen to use competitive analysis to develop rates for these coverages (summarized in Table 5).

Table 5: Cyber Endorsement Competitive Analysis Summary		
Information	**Personal Cyber Endorsement**	**Commercial Cyber Endorsement**
Company Benchmarked	Main Street America Protection Insurance Company	GuideOne Insurance Company
Insurance Line Benchmarked	Personal Homeowners	Businessowners
Benchmarked Rate	$50.00	$137.37
Selected Charge	Ĉ94.34	Ĉ164.85

Sourced from Main Street America Protection Public Filing NGMC-131652718 and GuideOne Mutual Public Filing GDEA-131791204

Please see Appendix B for a complete derivation of these coverages, their terms, and their rates. Table 6 summarizes our final proposal for these endorsements, which we will refer to in later analyses.

Table 6: Full Cybersecurity Endorsement Proposal		
Endorsement	**Personal Cyber Endorsement**	**Commercial Cyber Endorsement**
Source	Main Street America Protection filing NGMC-131652718	GuideOne Mutual filing GDEA-131791204
Proposed Coverage Terms	Up to Ĉ90,000 of coverage for cyber attacks, cyber extortion, fraud, data breach, and cyberbullying with respect to connected and autonomous vehicular technology subject to a deductible of Ĉ3,000	Up to Ĉ300,000 of coverage for Computer Attacks, Data Compromise Response Expenses, Data Compromise Liability, and Network Security Liability. In addition, up to Ĉ1,500,000 in Identity Recovery coverage as well as up to Ĉ60,000 for Cyber Extortion losses
Eligibility	Fully autonomous personal vehicles only	Fully autonomous commercial vehicles only
Optional or Mandatory	Optional, with an expected 30% of PHs choosing this option	Mandatory
Pure Premium Per Exposure	Ĉ94.3396	Ĉ164.8477

Section 3.2: Liability

One of the biggest concerns surrounding AVs is who will be liable for an accident caused by a driverless car. We have identified several different potential sources of liability in Figure 2 below:

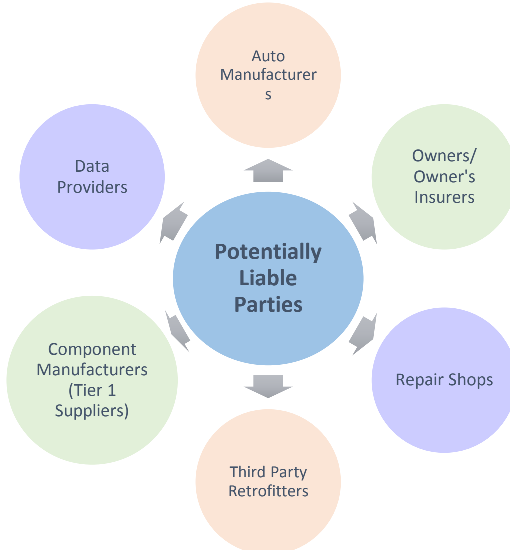


Figure 2: Sources Of Liability
Source: Falvey, Foggan, & Panagakos, 2018

Numerous governments, including Japan, Germany, the United Kingdom, China, and select US States, have all either passed or are currently forming regulations that place the owner/owner's insurance company primarily liable for damages in an accident caused by an autonomous vehicle, though AV manufacturers retain limited liability for cases of system flaws (Miles, 2018; Sanitt, Evans, Daddar, & Hidaka, 2017; "Japan to place accident liability on self-driving car owners"; Mallesons, 2017).

In addition, we have also seen insurance companies making the assumption that vehicle owners of autonomous vehicles are still liable for everything that a traditional vehicle is liable for (Appendix B). Therefore, for the purpose of this analysis, we have assumed liability regulations in Carbia will form in a similar manner: the owner of an AV, and his or her insurers, will remain the primarily liable parties in the case of an accident, excluding cases of system flaws, in which the manufacturer assumes liability.

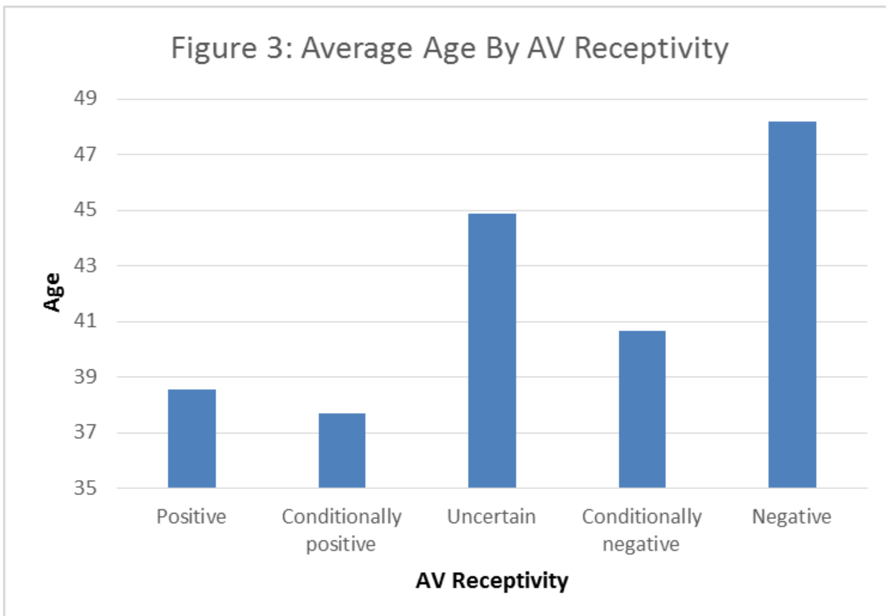
These types of regulations are very complex and dynamic; due to their uncertain nature, it will be crucial for Safelife to stay informed on Carbia's regulatory decisions and adjust their pricing plans accordingly. Therefore, we have included an extended analysis of the assignment of liability in Appendix F.

4: POLICY IMPLEMENTATION STRATEGY

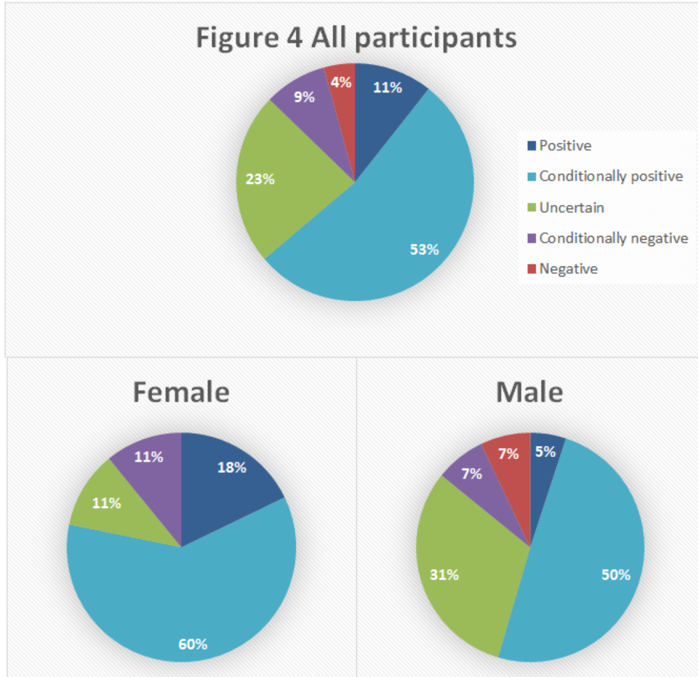
This section will provide Safelife with an overview of what we believe to be the most important strategies for implementation for this new insurance product.

Section 4.1: Demographics and Target Audiences

Surveys have shown that the most likely demographics to adopt autonomous vehicles are young people and males (Figures 3 & 4):

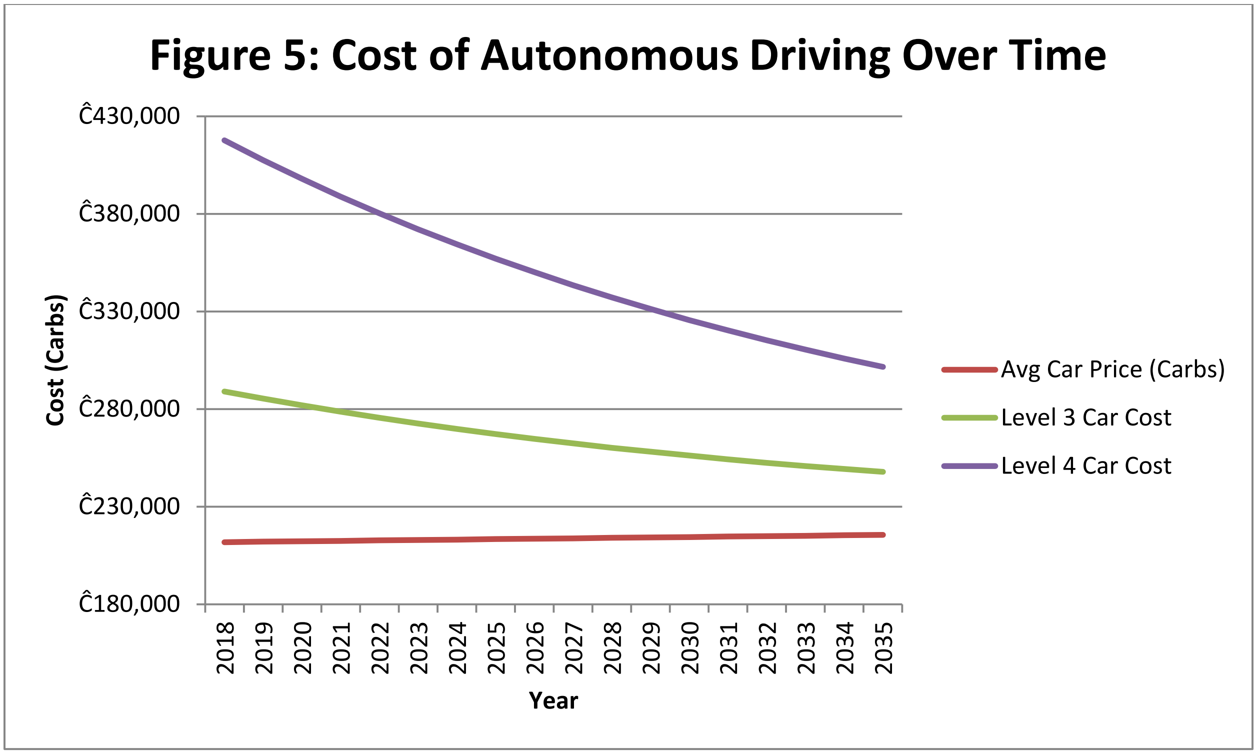


Source: Hulse, Xie, & Galea 2018



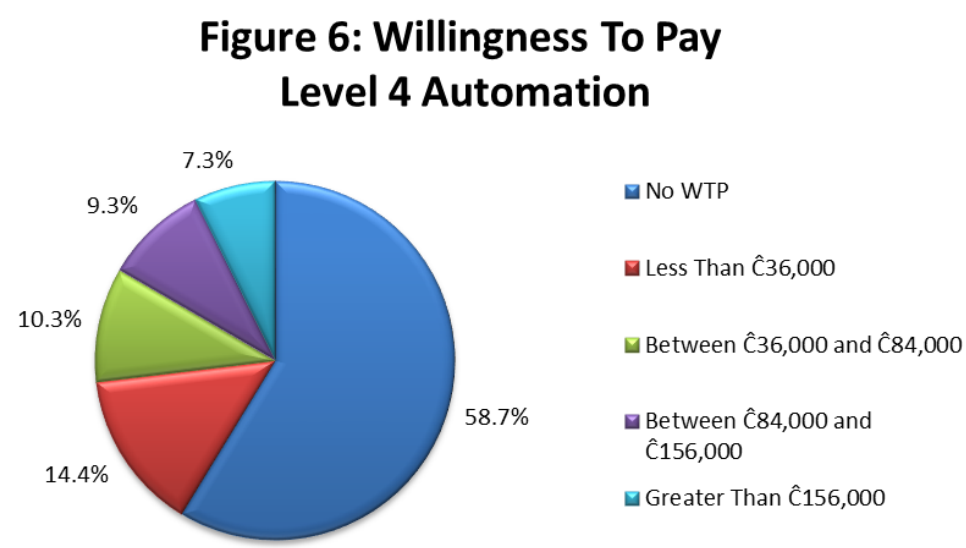
Source: Hulse, Xie, & Galea, 2018

However, under the assumption that a person is not operating an autonomous vehicle at any time, we do not believe these characteristics have any impact on the inherent risk that an autonomous vehicle carries other than a slight increase in risk-taking behavior (Litman, 2019). Furthermore, since autonomous vehicles are projected to be very costly (Figure 5), personal sales are anticipated to be a much smaller market than the commercial sector.



Source: Appendix E

This is likely to limit the size of the personal market initially, as many are not willing to pay these prices for autonomy (Figure 6):



Source: Bansal, 2017

Rather, AVs provide a much more unique opportunity for businesses. Despite their large initial purchase prices, these vehicles create the potential for significant large-scale savings on top of other lucrative opportunities (Figure 7):

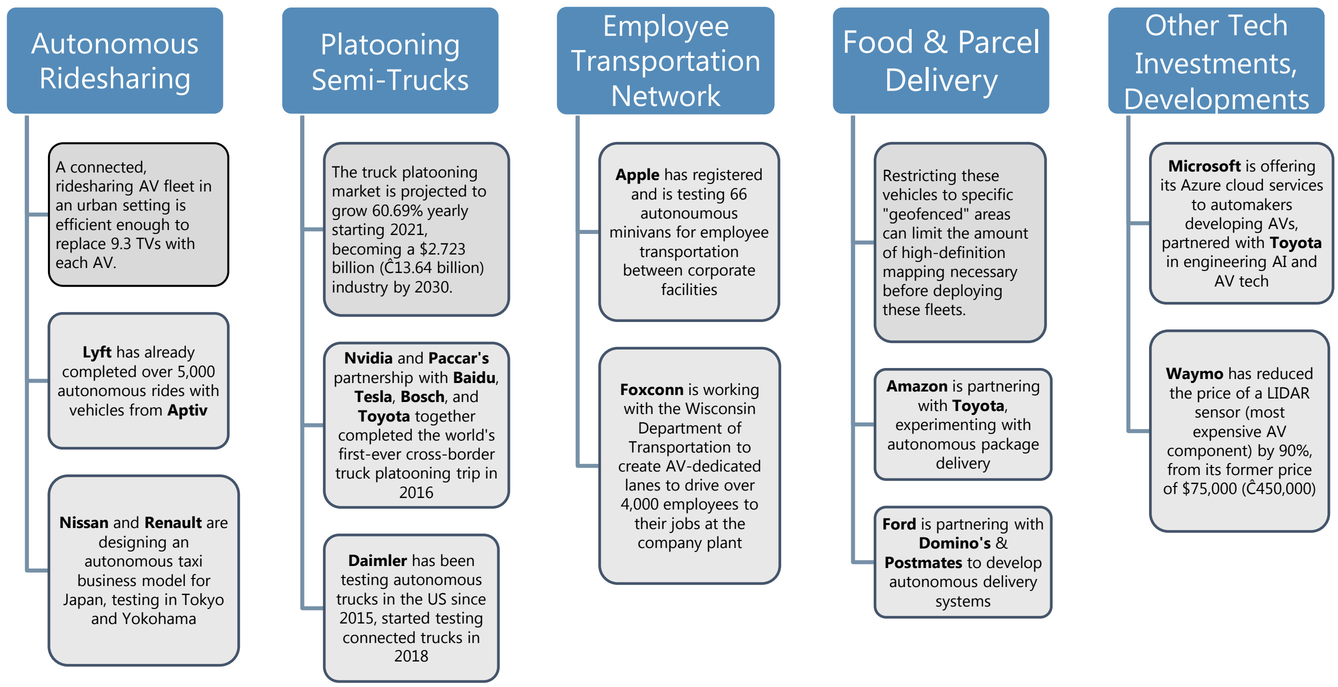


Figure 7: Commercial AV Opportunities/Advantages
Sources: Fagnant, Kockelman, & Bansal, 2015; Amedeo, 2017; Trego, 2018; Somerville, 2018; Autotech, 2018

Due to these reasons, as well as the results of our projections, we believe commercial entities will be the primary users of autonomous vehicles. For Safelife, as the largest auto insurer in Carbia, these developments present a unique and extremely advantageous opportunity, as many commercial companies are eager to take advantage of these benefits. By establishing relationships with these commercial entities early, Safelife can identify concerns specific to each potential client, work to address these concerns, and develop specialized contracts uniquely suited to the size and location needs of each fleet. As a result, other companies will struggle to cater to these fleets in the future as Safelife will have the best policy tailored towards these risks.

Based on this research, we have developed a chronological list of marketing recommendations for Safelife (Figure 8):

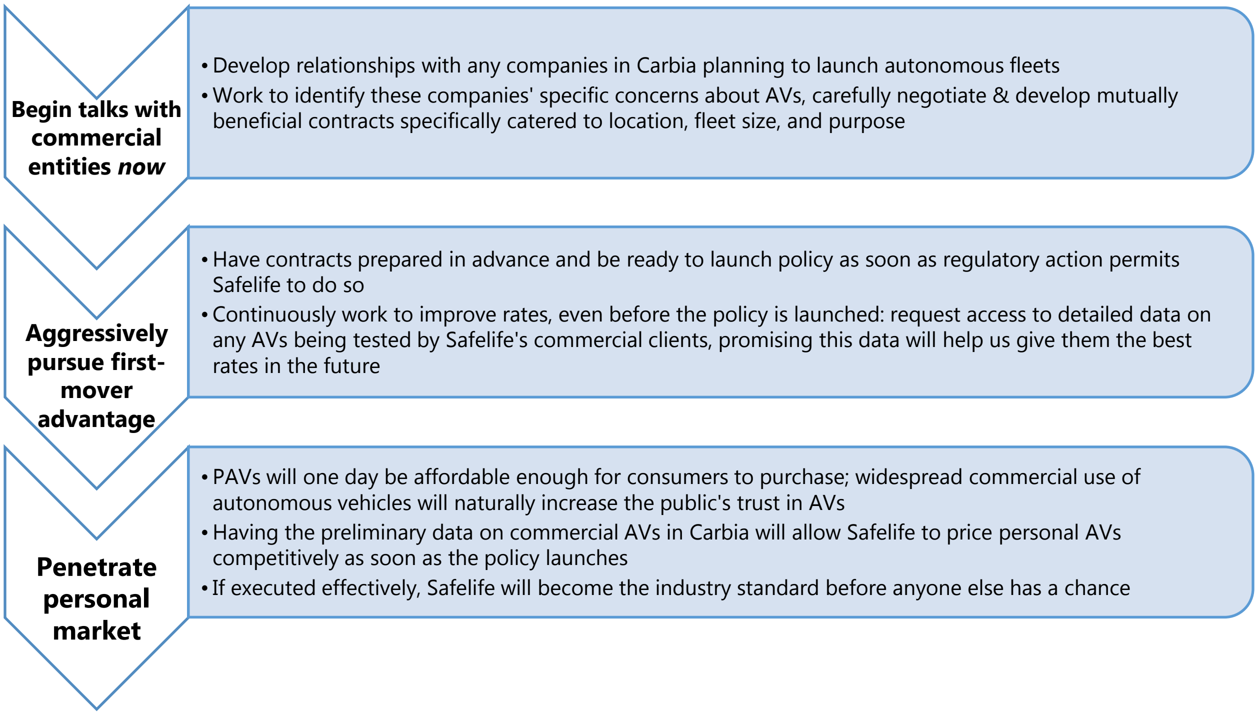


Figure 8: Safelife Marketing Recommendations

Section 4.2: Regulatory Outlook

As discussed in Section 3.2, future legislature related to fault and liability will be the most crucial regulations to monitor when designing rating plans for AVs. However, there are numerous additional regulations to consider. Figure 9 summarizes potential areas for AV legislation as well as entities who have adopted each type of legislation.

Figure 9

Truck Platooning	Insurance Requirements	Liability of Repair Shops	Cyber Security	Manufacturer Liability
• Decreases the required trailing distances between trucks when they are equiped with AV technologies • Regulations passed in USA, Spain, & UK	• Specifies additional insurance requirements for AVs • Regulations passed in USA & UK	• Limits the liability of repair shops that repair AVs • Regulations passed in USA	• Addresses need for increasing cybersecruity regulations to protect owners of AVs from hackers • Regulations passed in USA, UK, & Singapore	• Regulations passed to protect manufacturers of AVs from products liability lawsuits • Regulations passed in USA, UK, & Germany

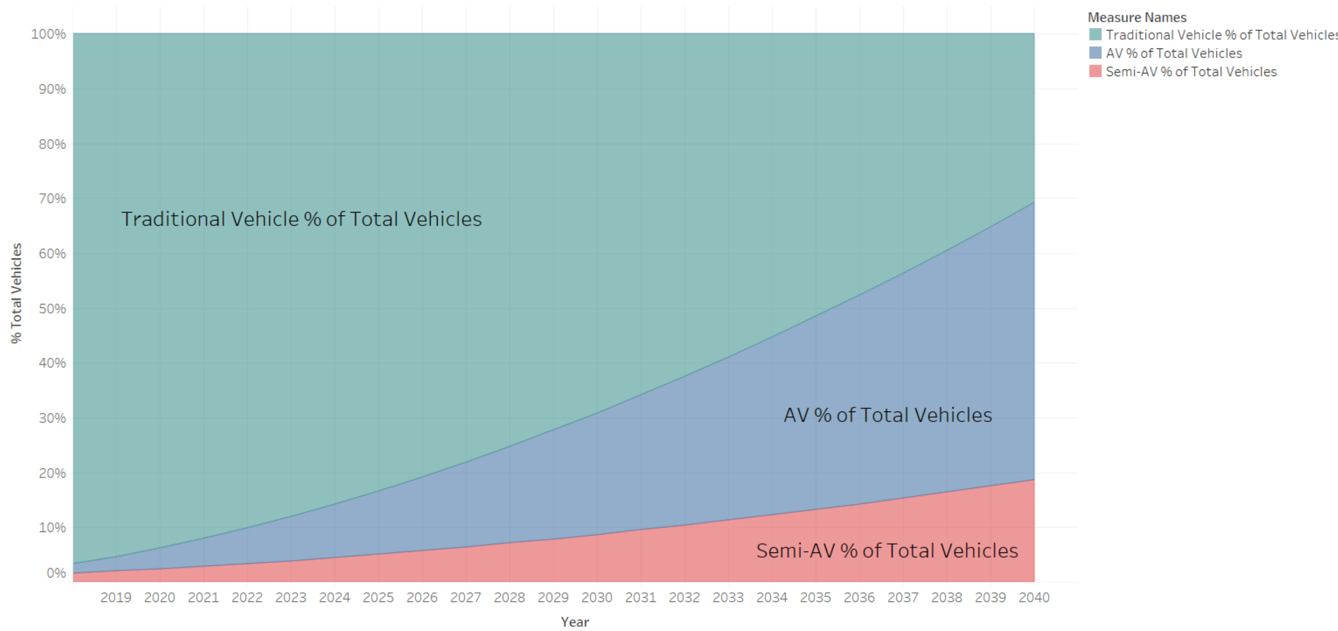
Source: Falvey, Foggan, & Panagakos, 2018

Since all of these regulations could potentially impact Safelife, it is crucial that the company stays up-to-date on all new AV regulations in Carbia. Some of the most potentially influential include laws related to truck platooning, as changes in trailing distance regulations may impact claim severity. Additionally, any additions/changes in insurance requirements in Carbia, or specific laws regarding cybersecurity provisions for AVs, would need to be reflected in Safelife's premiums. However, if Safelife follows this proposal and includes cybersecurity coverage in the new policy, we believe that Safelife will be well-equipped for these types of regulatory changes in the future.

Section 4.3: Adoption Timeline

There is a very promising adoption curve for autonomous vehicles in the next decade. The adoption timeline for Safelife was developed by averaging the results of five different credible empirical projections of the AV adoption timeline (Figure 10). Appendix C explains how these adoption timelines were developed in detail.

Figure 10: AV & SAV Adoption Curves

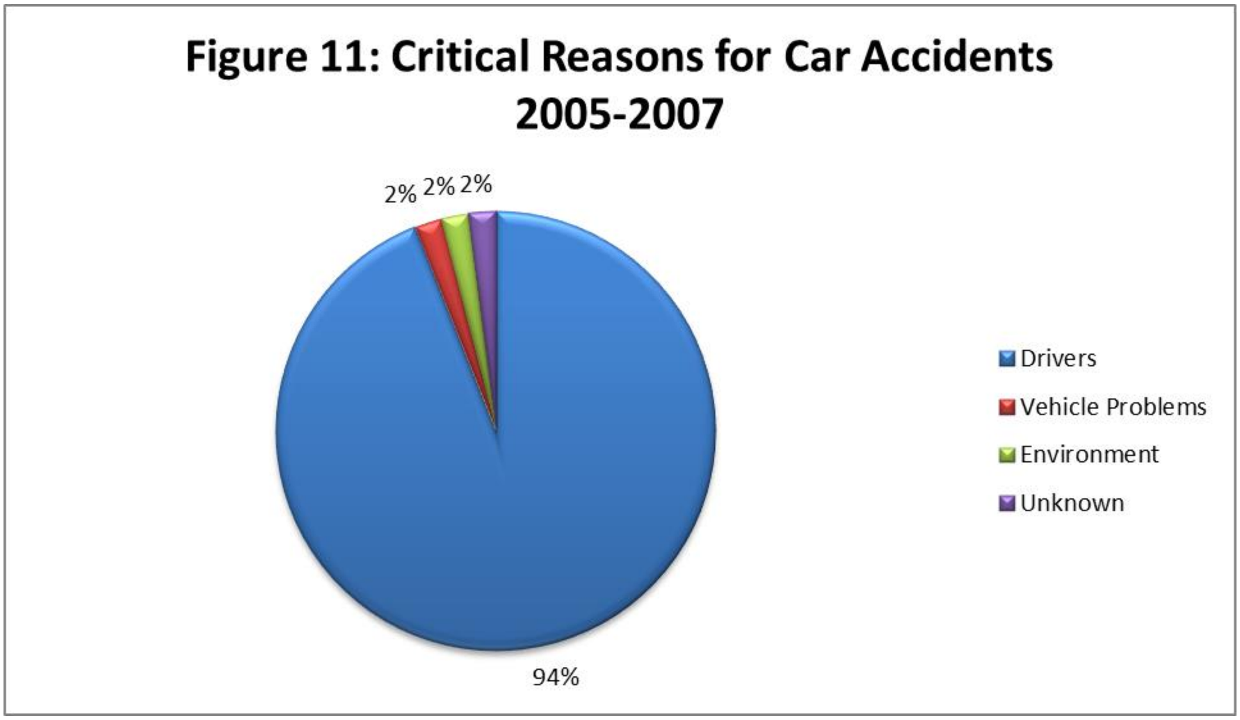


Source: Appendix C

It is important to acknowledge that the adoption timeline for autonomous vehicles is subject to many unknowns and uncertainties. In addition, technology was the most volatile sector of the market in 2018 (Buchbinder, Casey, & O'Neal, 2018), which indicates that the global AV market could also experience volatility like this in the near future. Therefore, we recommend that Safelife pay close attention to this market and continually update forecasts.

5. PURE PREMIUM PROJECTIONS

The pure premiums for FAVs will be vastly different from the pure premiums for TVs as human error accounts for the majority of the risk involved in driving (Figure 11):



Source: Singh, 2015

By taking human error out of the equation, nearly all of the risk inherent to AVs will come from technological and environmental factors, which carry significantly less uncertainty than human behavior (The CAS Automated Vehicles Task Force, 2018).

Section 5.1: Impact on Claim Frequency/Severity

To develop loss cost projections, we first considered, at a high level, how FAVs will change the frequency and severity of claims by individual coverage, as compared to traditional vehicles (Table 7):

Table 7: AV Frequency/Severity Impacts				
Coverage	**Claim Frequency**		**Claim Severity**	
Bodily Injury Liability	*Modest Decrease*	↘	*No Change Initially*	→
Personal Injury	*Modest Decrease*	↘	*No Change Initially*	→
Property Damage	*Strong Decrease*	↓	*No Change*	→
Collision	*Modest Decrease*	↘	*Modest Increase*	↗
Comprehensive	*No Change*	→	*Modest Increase*	↗
Primary Consideration	**Autonomous technology will heavily reduce claim frequency without the propensity for human error**		**Autonomous technology is pricey and difficult to replace, which results in greater severity**	

Source: Appendix D

In order to quantify these estimates, we began with the 10 years of history provided by Safelife. We utilized ARIMA modeling techniques to extract the trend from the aggregate pure premiums and developed a baseline forecast of Safelife's pure premium per exposure (Appendix A). However, while this data accurately depicted the risk of traditional vehicles, we felt that there should be adjustments to this baseline forecast to account for the impact on risk from FAVs.

In order to determine how to adjust the baseline forecasts, we first categorized the major sources of risk, determined what coverages would be impacted, and developed numerical proxies to quantify the impact on individual coverages (Figure 12):

Figure 12: Preliminary Analysis of New Sources of Risk							
Risks Added	**BI**	**PI**	**PD**	**COL**	**COMP**	**CYB**	**Numerical Proxy**
Third-Party Human Error	x	x		x			Estimate for Human Error Multiplied by Proportion of TVs
First-Party Technological Issues	x	x	x	x			2018 Disengagement Rate
Third-Party Technological Issues	x	x		x			2018 Disengagement Rate
External Factors Unrelated to Driving					x		Relative Cost of Adding Autonomy to a Car
Cyber Attacks and Data Compromise			x	x	x	x	Competitor Benchmarking

Source: Appendix D

We elected to develop adjustment factors that would vary based on how our numerical proxies varied with time. Table 8 summarizes the steps and research involved in developing the adjustment factors for each individual coverage, while Table 9 displays the final (simplified) adjustment factor formulas.

Table 8: Steps In Developing AV Pure Premium Adjustment Factors							
Steps	BI	PI	PD	COL	COMP	Source	Justification
Step 1: Base Discount Factor	0.78275	0.8075	0.756	0.791875	0.88875	Competitive Analysis (See Appendix B)	This puts our pure premiums in-line with our competitors
Step 2: Additional Discount for Removing First-Party Human Error	-0.324	-0.324	-0.324	-0.324	0	The CAS Automated Vehicles Task Force, 2018	This adjustment is to remove the frequency from first-party human error
Step 3: Add Back Third-Party Human Error	0.324*T	0.324*T	0	0.324*T	0	The CAS Automated Vehicles Task Force, 2018; Adoption Curve Analysis	We must add back the third-party risk (proportional to total proportion of traditional cars) that was removed in Step 2 from subtracting total human error
Step 4: Additional Discount for Third-Party SAVs	(1 - SAV Discount Factor)*S	(1 - SAV Discount Factor)*S	0	(1 - SAV Discount Factor)*S	0	Competitive Analysis & Adoption Curve Analysis	Step 3 and Step 4 do not apply to PD and COMP since there is never a third-party in these claims (see assumptions)
Step 5: Adjust for value of car	1	1	1	Steps 1-4 * ACVR	Steps 1-4 * ACVR	Bansal, 2017; Cost of Autonomy Analysis	This should only apply to coverages involving damage to the insured's car

Symbols	Definition
T	Total Autonomous Vehicles in Carbia / Total Vehicles in Carbia
S	Total Semi-Autonomous Vehicles in Carbia / Total Vehicles in Carbia
ACVR	Autonomous Car Value Rate: An estimate for how much cost autonomy adds to a car
SAV Discount Factor	Obtained from competitive analysis (See Appendix B)

Source: Appendix G

Table 9: Indicated/Selected Adjustment Factor Formulas		
Coverage	Indicated Adjustment Factor	Selected Adjustment Factor
BI	0.45875 + 0.324*T - 0.14687*S	Indicated Formula
PI	0.4835 + 0.324*T - 0.16867*S	Indicated Formula
PD	0.432	0.213
COL	ACVR*(0.467875 + 0.324*T - 0.14575*S)	Indicated Formula
COMP	ACVR*(0.88875)	Indicated Formula
Justification	Result of all five steps	We selected the CAS' estimate for proportion of accidents caused by technological error as a proxy for PD instead of the indicated charge

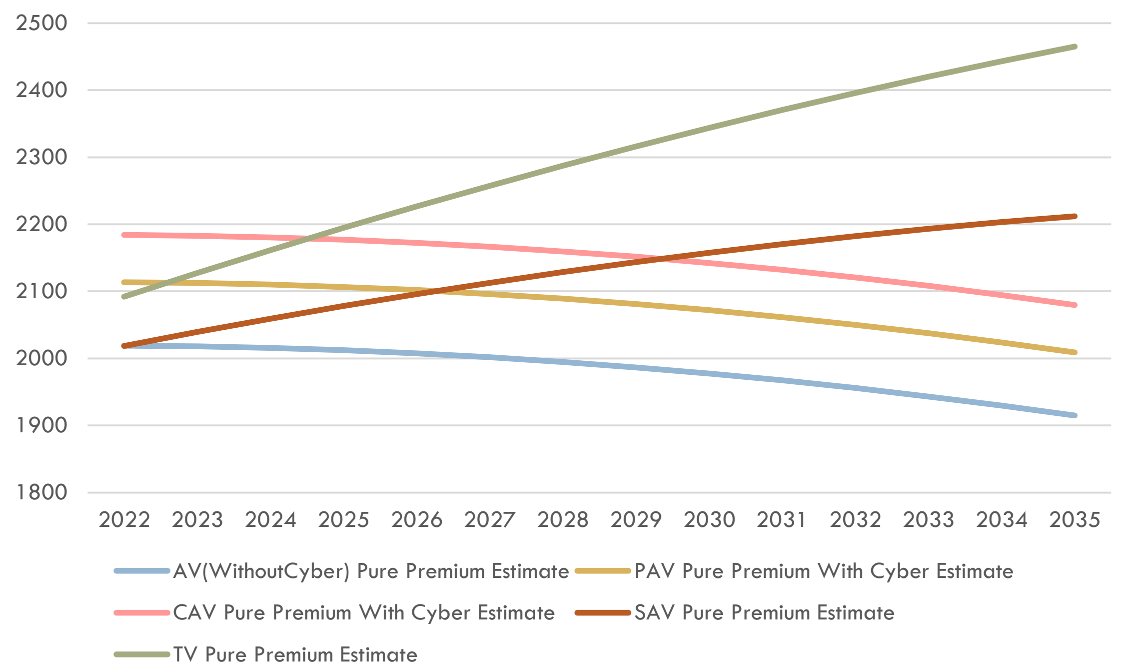
Symbols	Definition
T	Total Non-Autonomous Vehicles in Carbia / Total Vehicles in Carbia
S	Total Semi-Autonomous Vehicles in Carbia / Total Vehicles in Carbia
ACVR	Autonomous Car Value Rate: An estimate for how much cost autonomy adds to a car at any given time T
SAV Discount Factor	Obtained from competitive analysis (See Appendix B)

Source: Appendix G

We also developed similar adjustment factors for SAVs and TVs because we believe that their overall risk will also decrease as more cars on the road become autonomous, thereby reducing overall third-party risk. Please see Appendix D for a thorough development of these adjustment factors.

Initially, we predict a small net increase in pure premium per exposure for PAVs and a larger net increase for CAVs, but our estimates show that both commercial and personal will have pure premiums below that of traditional vehicles by 2025 (Figure 13 and Table 10).

Figure 13: Pure Premium Per Exposure Over Time



Source: Appendix G

Table 10: Pure Premiums Per Exposure (10 Year Projection)

Year	PAV Standard Pure Premium Estimate	PAV Pure Premium With Cyber Estimate	CAV Pure Premium Estimate	SAV Pure Premium Estimate	TV Pure Premium Estimate
2022	Ĉ2,019.21	Ĉ2,113.55	Ĉ2,184.06	Ĉ2,018.69	Ĉ2,092.19
2023	**Ĉ2,018.08**	**Ĉ2,112.42**	**Ĉ2,182.93**	**Ĉ2,039.45**	**Ĉ2,127.32**
2024	Ĉ2,015.74	Ĉ2,110.08	Ĉ2,180.58	Ĉ2,059.23	Ĉ2,161.44
2025	**Ĉ2,012.21**	**Ĉ2,106.55**	**Ĉ2,177.06**	**Ĉ2,078.04**	**Ĉ2,194.52**
2026	Ĉ2,007.52	Ĉ2,101.86	Ĉ2,172.37	Ĉ2,095.88	Ĉ2,226.55
2027	Ĉ2,001.70	Ĉ2,096.04	Ĉ2,166.55	Ĉ2,112.76	Ĉ2,257.52
2028	Ĉ1,994.76	Ĉ2,089.10	Ĉ2,159.60	Ĉ2,128.67	Ĉ2,287.40
2029	Ĉ1,986.70	Ĉ2,081.04	Ĉ2,151.55	Ĉ2,143.59	Ĉ2,316.18
2030	Ĉ1,977.52	Ĉ2,071.86	Ĉ2,142.37	Ĉ2,157.54	Ĉ2,343.85
2031	Ĉ1,967.23	Ĉ2,061.57	Ĉ2,132.08	Ĉ2,170.49	Ĉ2,370.38

Year that PAV with Cyber Falls Below TV

Year that CAV Falls Below TV

Source: Appendix G

Until true accident frequency and severity data on AVs is available, any estimate of their loss costs will naturally be a rough approximation. With this in mind, we intentionally selected justifiably conservative estimates when predicting the reduction in claim frequency, to protect Safelife from potential large deviations from these projections.

Section 5.2: Timing of Market Entrance

Naturally, timing of market entrance will majorly impact Safelife's loss cost estimates, due not only to market share impacts, but also to many time-sensitive factors.

We recommend that Safelife launches this policy in 2022. This will guarantee Safelife's position as a first-mover and that Safelife's Autonomous Line follows an adaptive new entry strategy, which involves creating a highly differentiated product that captures customer value by incorporating modern marketing trends (Dess, Lumpkin, Eisner, McNamara, 2014). Figure 14 summarizes the implications of various possible launch dates.

Figure 14: Impact of Different Launch Dates

Recommended Launch Year

Market Position	First Mover		Second Mover	
Year	**2020**	**2022**	**2024**	**2026**
Carbia PAVs	–	48,312	132,103	230,115
Carbia CAVs	255,742	399,725	551,876	731,867
Safelife AV Market Share	65.05%	65.05%	34.00%	34.00%
PAVs Written First Year	–	**32,279**	**46,439**	**81,483**
CAVs Written First Year	**166,355**	**267,096**	**194,092**	**259,100**
Total AVs	**166,355**	**299,375**	**240,531**	**340,583**
Market Position	**Third Mover**		**Fourth Mover**	
Year	**2028**	**2030**	**2032**	**2034**
Carbia PAVs	346,298	481,735	636,973	812,414
Carbia CAVs	934,901	1,159,474	1,404,890	1,670,778
Safelife AV Market Share	19.00%	19.00%	10.00%	10.00%
PAVs Written First Year	**68,951**	**96,507**	**67,556**	**86,661**
CAVs Written First Year	**186,146**	**232,292**	**149,017**	**178,229**
Total AVs	**255,097**	**328,799**	**216,573**	**264,890**

34% is very optimistic, as many other insurers will have established policies by this time

Sources: Appendices; Cha & Yu, 2014

We also must acknowledge that it is difficult to estimate what the best time to launch a new insurance policy is and that we were limited to analyzing small data sets in order to develop these conclusions (Appendix E). ***We recommend that Safelife begin establishing relationships with commercial entities as soon as possible in order to ensure that a first-mover market share is attainable.***

6. 10-YEAR PROJECTIONS

We have provided Safelife with 10-year pure premium projections for this new policy, as well as the old policy, beginning in 2022. Table 10 summarizes the total pure premium for the first 10 years broken out by type of vehicle insured. Table 11 shows the combined pure premium as well as the per exposure pure premium.

Table 10: 10-Year Pure Premium Projections By Car Type

Year	TV Total Pure Premium	SAV Total Pure Premium	PAV Total Pure Premium	CAV Total Pure Premium	Traditional Policy Total Pure Premium	Autonomous Policy Total Pure Premium
2022	Ĉ4,551,857,557	Ĉ169,535,366	Ĉ66,091,619	Ĉ583,352,938	Ĉ4,721,392,922	Ĉ649,444,557
2023	Ĉ4,577,741,442	Ĉ200,512,465	Ĉ119,525,196	Ĉ675,337,367	Ĉ4,778,253,908	Ĉ794,862,563
2024	Ĉ4,588,405,387	Ĉ234,695,092	Ĉ173,694,126	Ĉ774,462,501	Ĉ4,823,100,479	Ĉ948,156,627
2025	Ĉ4,583,308,269	Ĉ272,086,687	Ĉ230,363,354	Ĉ877,627,731	Ĉ4,855,394,955	Ĉ1,107,991,086
2026	Ĉ4,561,968,744	Ĉ312,890,256	Ĉ289,728,193	Ĉ983,064,375	Ĉ4,874,859,000	Ĉ1,272,792,568
2027	Ĉ4,523,909,137	Ĉ357,098,975	Ĉ351,407,627	Ĉ1,089,706,603	Ĉ4,881,008,112	Ĉ1,441,114,230
2028	Ĉ4,468,663,680	Ĉ404,847,494	Ĉ415,174,180	Ĉ1,196,485,837	Ĉ4,873,511,174	Ĉ1,611,660,018
2029	Ĉ4,395,805,377	Ĉ456,278,813	Ĉ480,676,653	Ĉ1,302,538,301	Ĉ4,852,084,191	Ĉ1,783,214,954
2030	Ĉ4,304,812,354	Ĉ511,354,437	Ĉ547,289,594	Ĉ1,406,991,917	Ĉ4,816,166,791	Ĉ1,954,281,511
2031	Ĉ4,195,336,665	Ĉ570,196,667	Ĉ614,630,509	Ĉ1,509,079,827	Ĉ4,765,533,333	Ĉ2,123,710,336

Appendix G

Table 11: 10-Year Total Pure Premium Projections					
Year	Safelife Total Exposure	Traditional Policy Total Pure Premium	Autonomous Policy Total Pure Premium	Total Pure Premium	Pure Premium Per Exposure
2022	2,559,000	Ĉ4,721,392,922	Ĉ649,444,557	**Ĉ5,370,837,479**	**Ĉ2,098.80**
2023	2,617,974	Ĉ4,778,253,908	Ĉ794,862,563	**Ĉ5,573,116,471**	**Ĉ2,128.79**
2024	2,676,956	Ĉ4,823,100,479	Ĉ948,156,627	**Ĉ5,771,257,106**	**Ĉ2,155.90**
2025	2,735,479	Ĉ4,855,394,955	Ĉ1,107,991,086	**Ĉ5,963,386,041**	**Ĉ2,180.02**
2026	2,793,032	Ĉ4,874,859,000	Ĉ1,272,792,568	**Ĉ6,147,651,568**	**Ĉ2,201.07**
2027	2,849,028	Ĉ4,881,008,112	Ĉ1,441,114,230	**Ĉ6,322,122,341**	**Ĉ2,219.05**
2028	2,903,035	Ĉ4,873,511,174	Ĉ1,611,660,018	**Ĉ6,485,171,192**	**Ĉ2,233.93**
2029	2,954,667	Ĉ4,852,084,191	Ĉ1,783,214,954	**Ĉ6,635,299,145**	**Ĉ2,245.70**
2030	3,003,241	Ĉ4,816,166,791	Ĉ1,954,281,511	**Ĉ6,770,448,302**	**Ĉ2,254.38**
2031	3,048,401	Ĉ4,765,533,333	Ĉ2,123,710,336	**Ĉ6,889,243,669**	**Ĉ2,259.95**

Source: Appendix G

Table 12: 10-Year Total Pure Premium Projections (Baseline)					
Year	Safelife Total Exposure	Traditional Vehicle Pure Premium	Semi-AV Vehicle Pure Premium	Total Pure Premium	Pure Premium Per Exposure
2022	2,257,225	Ĉ4,551,857,557	Ĉ170,687,179	**Ĉ4,722,544,735**	**Ĉ2,092.19**
2023	2,247,385	Ĉ4,577,741,442	Ĉ203,176,543	**Ĉ4,780,917,985**	**Ĉ2,127.32**
2024	2,233,561	Ĉ4,588,405,387	Ĉ239,306,163	**Ĉ4,827,711,549**	**Ĉ2,161.44**
2025	2,215,717	Ĉ4,583,308,269	Ĉ279,127,618	**Ĉ4,862,435,886**	**Ĉ2,194.52**
2026	2,193,921	Ĉ4,561,968,744	Ĉ322,900,600	**Ĉ4,884,869,344**	**Ĉ2,226.55**
2027	2,168,122	Ĉ4,523,909,137	Ĉ370,661,600	**Ĉ4,894,570,737**	**Ĉ2,257.52**
2028	2,138,350	Ĉ4,468,663,680	Ĉ422,607,074	**Ĉ4,891,270,755**	**Ĉ2,287.40**
2029	2,104,641	Ĉ4,395,805,377	Ĉ478,931,353	**Ĉ4,874,736,730**	**Ĉ2,316.18**
2030	2,066,875	Ĉ4,304,812,354	Ĉ539,642,043	**Ĉ4,844,454,397**	**Ĉ2,343.85**
2031	2,025,095	Ĉ4,195,336,665	Ĉ604,917,420	**Ĉ4,800,254,085**	**Ĉ2,370.38**

Source: Appendix G

Although total pure premium is significantly lower in the baseline projection, if we look at the pure premium on a per exposure basis, we see that Safelife is obtaining significantly more business while incurring significantly lower losses in the projection with the new policy.

7. SENSITIVITY ANALYSIS FOR 2030

Safelife's goal for this new policy is for approximately 20-25% of Safelife's business to be in the Autonomous Line by 2030. Our timeline and market share projections have indicated that this is a realistic goal *if Safelife effectively establishes itself as a first-mover*. In order to provide a proper sensitivity analysis, many assumptions were made to compensate for the data limitations. Table 13 provides these assumptions, while Table 14 provides the sensitivity analysis below.

Table 13: Sensitivity Analysis Assumptions	
Safelife Total Exposure	3,003,241
Traditional Line	
SAV %	11.429%
TV % (1 - SAV %)	88.571%
Autonomous Line	
Commercial %	70.648%
Personal % (1 - Commercial %)	29.353%
Pure Premium	***Base Estimate***
PAV (No CYB) Pure Premium	Ĉ1,977.52
PAV (With CYB) Pure Premium	Ĉ2,071.86
CAV (With CYB) Pure Premium	Ĉ2,142.37
SAV Pure Premium	Ĉ2,157.54
TV Pure Premium	Ĉ2,343.85
Other	
% PAV with CYB Attached	30%

Source: Appendix G

Table 14: 2030 Safelife Sensitivity Analysis						
Autonomous Line %	20%	21%	22%	23%	24%	25%
Traditional Line						
Exposure						
SAV Exposure	274,600	271,167	267,735	264,302	260,870	257,437
TV Exposure	2,127,993	2,101,393	2,074,793	2,048,194	2,021,593	1,994,994
Total Exposure	2,402,593	2,372,560	2,342,528	2,312,496	2,282,463	2,252,431
Pure Premium						
SAV Pure Premium	Ĉ592,460,711.99	Ĉ585,053,874.32	Ĉ577,649,194.19	Ĉ570,242,356.52	Ĉ562,837,676.39	Ĉ555,430,838.72
TV Pure Premium	Ĉ4,591,231,783.99	Ĉ4,533,841,197.91	Ĉ4,476,450,611.83	Ĉ4,419,062,183.28	Ĉ4,361,669,439.66	Ĉ4,304,281,011.11
Total TL Pure Premium	Ĉ5,183,692,495.98	Ĉ5,118,895,072.23	Ĉ5,054,099,806.01	Ĉ4,989,304,539.80	Ĉ4,924,507,116.04	Ĉ4,859,711,849.83
Autonomous Line						
Exposure						
CAV Exposure	424,343	445,560	466,777	487,994	509,212	530,428
PAV Exposure	176,305	185,121	193,936	202,751	211,566	220,382
Total Exposure	600,648	630,681	660,713	690,745	720,778	750,810
Pure Premium						
CAV Pure Premium	Ĉ909,100,443.96	Ĉ954,555,144.81	Ĉ1,000,009,845.65	Ĉ1,045,464,546.49	Ĉ1,090,921,389.71	Ĉ1,136,373,948.18
PAV Pure Premium	Ĉ353,637,133.46	Ĉ371,320,494.51	Ĉ389,001,849.72	Ĉ406,683,204.94	Ĉ424,364,560.16	Ĉ442,047,921.20
Total AL Pure Premium	Ĉ1,262,737,577.43	Ĉ1,325,875,639.31	Ĉ1,389,011,695.37	Ĉ1,452,147,751.43	Ĉ1,515,285,949.86	Ĉ1,578,421,869.37
All Lines						
Total Exposure	3,003,241	3,003,241	3,003,241	3,003,241	3,003,241	3,003,241
Total Pure Premium	Ĉ6,446,430,073.41	Ĉ6,444,770,711.54	Ĉ6,443,111,501.38	Ĉ6,441,452,291.23	Ĉ6,439,793,065.90	Ĉ6,438,133,719.20
Total Pure Premium Per Exposure	Ĉ2,146.49	Ĉ2,145.94	Ĉ2,145.39	Ĉ2,144.83	Ĉ2,144.28	Ĉ2,143.73
Incremental Impact		-0.0257%	-0.0257%	-0.0258%	-0.0258%	-0.0258%

Source: Appendix G

It is clear that increasing the portion of business in the Autonomous Line decreases pure premium per exposure. Autonomous vehicles are undoubtedly much safer to insure. ***Therefore, we recommend that Safelife alter their goal so that 30% of their business is in the Autonomous Line by 2030***. Our 10-year projections have indicated that it is quite feasible, and our sensitivity analysis shows that overall risk decreases as more of Safelife's business becomes autonomous.

In addition, we have developed other smaller recommendations that Safelife can pursue to further decrease pure premiums with autonomous business. Looking at the breakdown of pure premium in 2030 (Table 15), we can identify some clear areas for improvement.

Table 15: 2030 Pure Premium (Per Exposure) Breakdown								
Car Type	PI Pure Premium	BI Pure Premium	PD Pure Premium	COL Pure Premium	COMP Pure Premium	CYB Pure Premium	Total Pure Premium (No CYB)	Total Pure Premium (With CYB)
PAV	323.4099068	255.9566294	102.91095	831.0120197	464.2344969	94.33962264	1977.524003	2071.863625
CAV	323.4099068	255.9566294	102.91095	831.0120197	464.2344969	164.84772	NA	2142.371723
SAV	275.1361813	370.936131	406.4902	740.2052837	364.1391741	NA	2157.54083	NA
TV	337.4337881	441.8155411	483.15	737.4931322	343.9621	NA	2343.854561	NA

Source: Appendix D, Appendix G

As a result, we have tailored our additional recommendations around Collision and Comprehensive. Table 16 summarizes our recommendations based on the observations depicted above.

Table 16: Recommendations From Sensitivity Analysis		
Recommendation	**Benefits**	**Costs**
Safelife should implement pure premiums based on location rather than other rating variables	• This will help to identify which locations have the most collision and comprehensive risk as well as the areas with the most human-operated vehicles • Other insurers will not have possessed an autonomous line for long enough to create geographic pure premiums	• Changing base rates of a rating plan is a lengthy and difficult process that may require months of work
Safelife should offer insureds a discount for taking a network security training course provided by Safelife for free	• Studies have shown that security awareness training can mitigate large losses from data breaches (Brodie, 2009) • Relatively low-cost investment for Safelife to establish	• Safelife will have to routinely update the course to account for emerging cybersecurity risks
Safelife should offer insureds a discount for having a locked garage or other storage unit for inactive vehicles	• Encourages insureds to keep their valuable autonomous cars in safer, more protected places in order to mitigate comprehensive claims • Both commercial and personal insureds will likely be willing to take this small measure for a sizable insurance discount	• It could be challenging to verify that insureds are actually storing the cars in their garages
Consider including a factor in the AV rating plan which discounts/surcharges based on annual average Vehicle Miles Traveled	• In the future, we expect that VMT will eventually become a better exposure base for auto insurance than car years of exposure since it captures how frequently the vehicle is actually exposed to perils • It would be relatively easy to track this continually with connected cars for renewal business and commercial entities likely will already be tracking this number	• Annual VMT would likely have to be approximated for new business if this was not information their prior carrier or agent tracked

8. DATA LIMITATIONS & ASSUMPTIONS

While the data provided by Safelife was sufficient to evaluate the risk of traditional vehicles, it did not capture the risk of autonomous vehicles. In addition, several assumptions were required to account for unknowns and uncertainties that we did not have conclusive data for. Table 17 details all of the general data limitations, corresponding assumptions, and relevant justification below.

Table 17: Data Limitations and Corresponding Assumptions

Data Limitation	Corresponding Assumption	Justification
No information on Carb exchange rates	**Exchange Rate = Ĉ6/$1**	We compared a common deductible in US dollars of $500 ("How Do I Set My Auto Insurance Deductible?", 2018) to the mandatory Carbian deductible of Ĉ3000 to develop this rate
We cannot predict the true behavior of those who own Level 4 and Level 5 vehicles in the future	**We assume that owners of Level 4/5 vehicles will not engage in manual driving if their insurance policy includes this as a provision**	We are recommending that Safelife primarily targets commercial entities. We believe commercial entities will be perfectly willing to accept this provision for the advantages they gain with this autonomous policy
It is not specified if Carbia is a no-fault state, a tort state, or some type of hybrid	**We assume Carbia is a hybrid in the sense that vehicle owners (and thus the insurers who cover them) are liable for all vehicle payments unless liabilty can clearly be assigned to a third-party driver**	Carbia's mandatory coverage language specifies "regardless of fault," but still requires liabilty coverage
Data to calculate AV adoption curves was not included in the provided data	**We assume that the projections we used accurately depict the adoption of autonomous vehicles**	We took the weighted average of five different projections that were based on credible data in order to develop accurate and conservative adoption curves
Carbia market data, vehicle data, and other data outside of Safelife was not provided	**We assume proportions of data from the US analyzed are representative of proportions in Carbia**	We are told that Carbia is a developed nation that has similar laws and regulations to the majority of states in the United States, so we believe other data from the US is also representative of Carbia
We are not told about the specifics of Carbia's legal environment	**We assume that no drivers commit hit-and-runs and that insurance fraud is negligibly rare in Carbia**	We are told that laws are enforced very strictly in Carbia
There is no data about how a recession or other major economic event would impact this market in the future given how miniscule the market is at this time	**Our analysis assumes a stable economy for the scope of our projections**	Safelife's data appears to indicate a relatively stable economy historically

9. CONCLUSION

We recommend that Safelife implements an Autonomous Line policy by 2022 with all of the specified characteristics in order to become a first-mover in this emerging market and establish itself as a reputable insurer of autonomous vehicles. Our analysis has shown that these vehicles are not only a highly insurable risk, but that Safelife has the means to establish a first-mover advantage that other competitors will never be able to keep up with.

APPENDICES

Appendix A – ARIMA Time-Series Regression & Forecasting

To develop pure premium projections for our traditional line, we utilized ARIMA forecasting with Safelife's 2009-2018 claims data, forecasting average severity per car year of exposure over time. We developed five separate models, one per coverage. This appendix will detail the process of selecting these models.

Section A-1: Quarterly vs. Annual Modeling

We first examined our time series. The first step to projecting pure premium was to determine how to aggregate the 10 years of claim/loss data provided by Safelife. Ultimately, we wish to forecast the average pure premium per exposure for each coverage individually, over the next ten years. While quarterly data for Safelife is available, we chose to examine whether or not annual data would produce more accurate results over the course of the 10 years for the projections.

We developed and compared two time series for each coverage: each is calculated as total losses for a time period, divided by car years of exposure in that period, on a quarterly and on a yearly basis. We then compare their plots in Figure A-1:

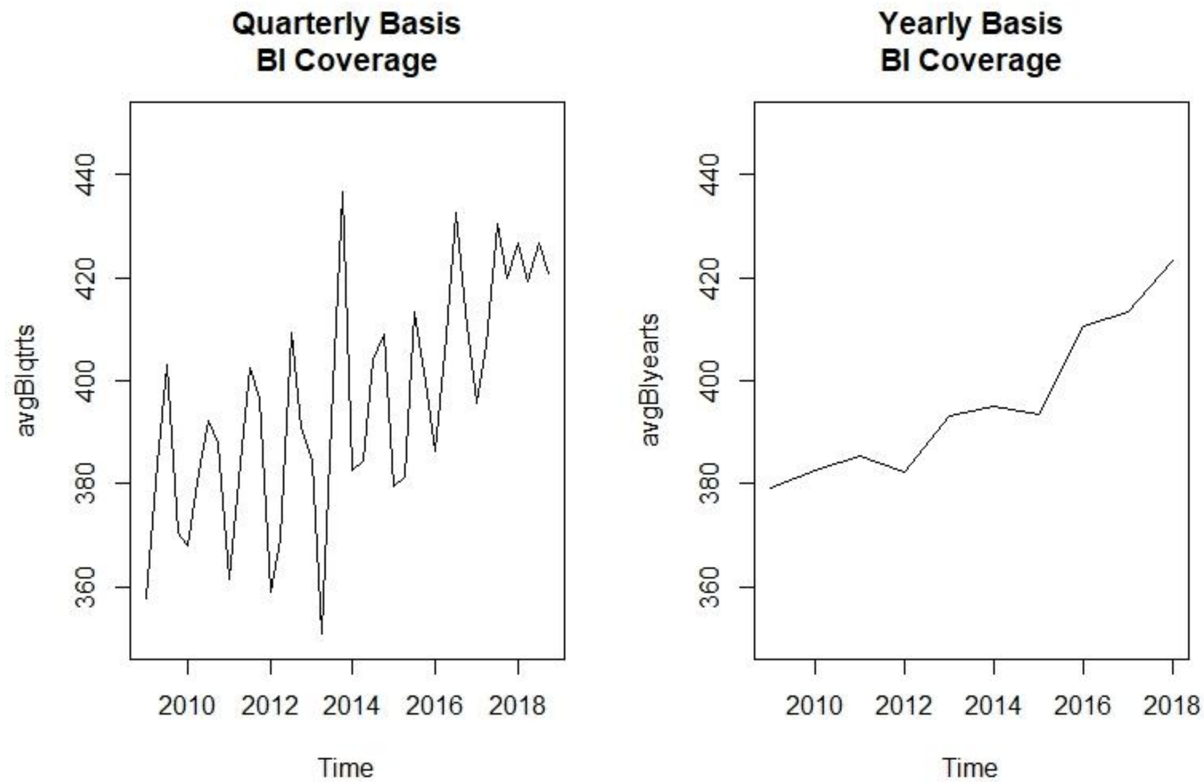


Figure A-1: Pure Premium Quarterly Vs. Yearly Projections (Bodily Injury Liability)

As shown above, there is significant quarterly variation for bodily injury pure premium, which flattens into a much more stable trend when aggregated on a yearly basis. Other coverages produced very similar results (Figure A-2).

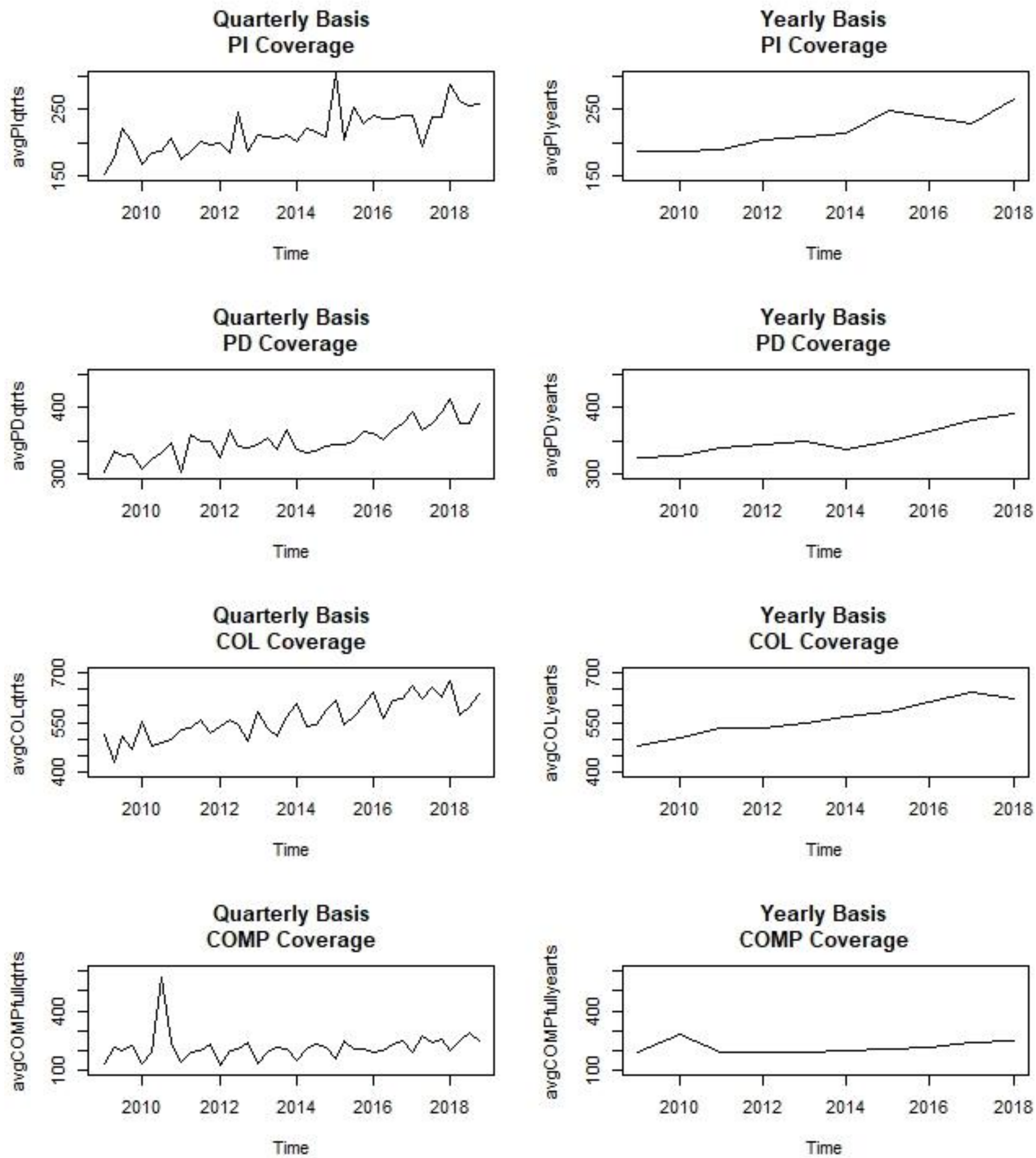


Figure A-2: Pure Premium Quarterly Vs. Yearly Projections (All Coverages)

Once the data is aggregated on a yearly level, a much more stable, gradual positive trend can be observed in each plot. To account for the large outlier in 2010, we decide to model comprehensive coverage using only the last eight years. We further compare these time series, by plotting their autocorrelation functions side-by-side (Figure A-3).

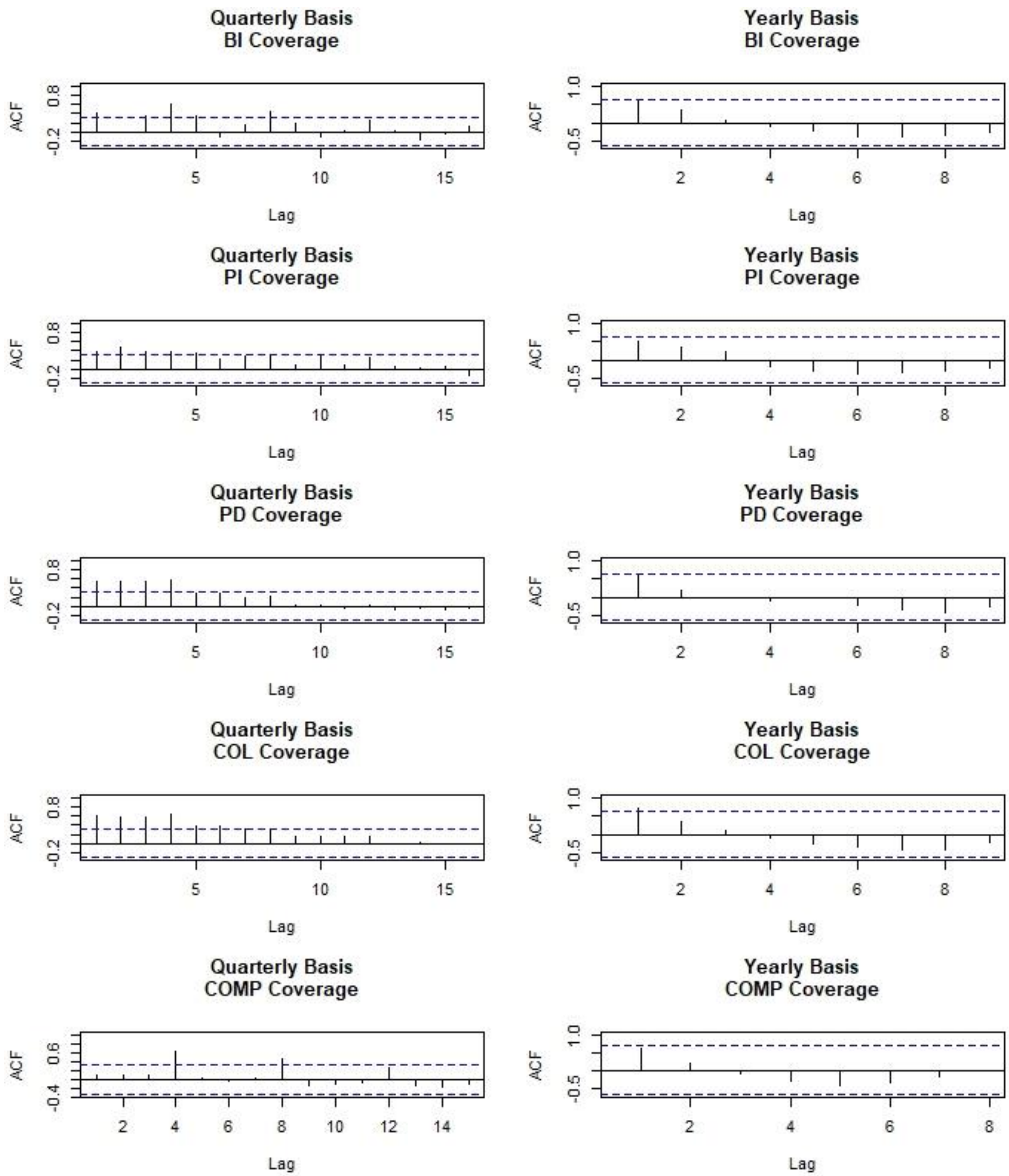


Figure A-3: Autocorrelation Functions

Each quarterly time series displays numerous spikes above the significant level, indicating that significant differencing must be done to obtain a stationary dataset that can be modeled. The yearly time series, on the other hand, displays much less significant spikes. Each coverage exhibits the largest autocorrelation at lag 1, but this spike is under the significant level for every coverage besides collision. Given the existing outside data limitations, as well as the complications that would arise in differencing the quarterly data, we decide to apply ARIMA models to the aggregated yearly data.

Section A-2: Annual ARIMA Model Summary

Using an automatic ARIMA modeling method, we fit a model to each coverage. Every time series was identified as a (0,1,0) ARIMA process with drift; each is summarized in Table A-1 below.

Table A-1: Model Summary By Coverage

Coverage	AIC	BIC	Standard Error	Drift
BI	61.95	62.35	2.02	4.93
PI	79.75	80.14	5.42	8.6
PD	69.17	69.56	3.01	7.56
COL	79.44	79.83	5.33	15.41
COMP	53.51	53.4	3.14	7.9

Given the low standard errors for each of the coverages, we decided to move forward with these models.

Section A-3: Consideration of Risk Classes

When considering the data on a more granular level, there are four ways to classify each policy. Examining each of these trends broadly, an overwhelming consistency in trends, yet a difference in means is observed across all groups, for all coverages. Bodily Injury coverage is shown below as an example (Figure A-4).

Figure A-4: Risk Class Comparisons

Given the overwhelming consistency of the trends shown above, we decide to continue modeling an aggregated version of the entire dataset on a yearly level, to capture as much exposure as possible in our time series (Section A-4). From there, we derive factors for each risk class based on the differences in means between these risk classes (Section A-5).

Section A-4: Ten Year Aggregate Pure Premium Forecasts

We then applied ARIMA Forecasting to each model, forecasting forward 14 periods, through 2032. The forecasts, along with 80% and 95% confidence intervals, are provided below in Figure A-5, Figure A-6, and summarized numerically in Table A-2.

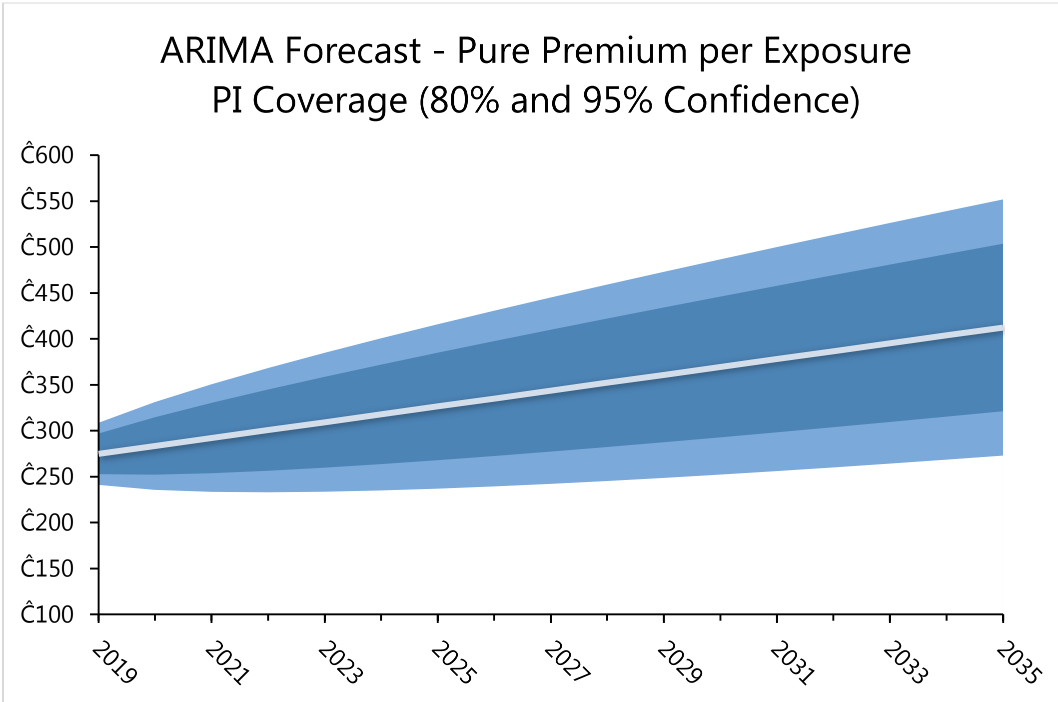


Figure A-5

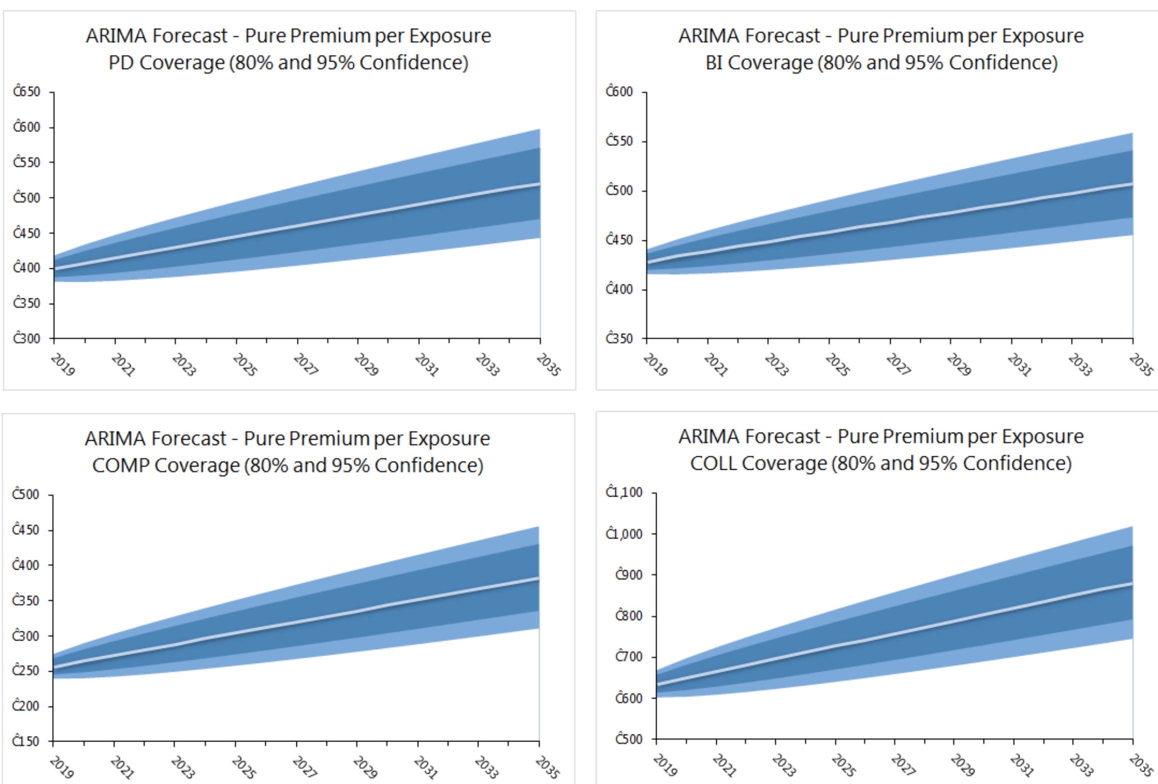


Figure A-6

Table A-2: Traditional Vehicle Base Pure Premium Projections through 2035						
Year	PI Estimate	BI Estimate	PD Estimate	COL Estimate	COMP Estimate	Total
2019	Ĉ274.78	Ĉ428.34	Ĉ399.97	Ĉ636.03	Ĉ257.11	**Ĉ1,996.23**
2020	Ĉ283.37	Ĉ433.27	Ĉ407.53	Ĉ651.44	Ĉ265.01	**Ĉ2,040.63**
2021	Ĉ291.97	Ĉ438.21	Ĉ415.10	Ĉ666.84	Ĉ272.91	**Ĉ2,085.02**
2022	Ĉ300.57	Ĉ443.14	Ĉ422.66	Ĉ682.25	Ĉ280.80	**Ĉ2,129.42**
2023	Ĉ309.17	Ĉ448.07	Ĉ430.22	Ĉ697.66	Ĉ288.70	**Ĉ2,173.81**
2024	Ĉ317.77	Ĉ453.01	Ĉ437.78	Ĉ713.06	Ĉ296.59	**Ĉ2,218.21**
2025	Ĉ326.36	Ĉ457.94	Ĉ445.34	Ĉ728.47	Ĉ304.49	**Ĉ2,262.60**
2026	Ĉ334.96	Ĉ462.88	Ĉ452.90	Ĉ743.88	Ĉ312.38	**Ĉ2,307.00**
2027	Ĉ343.56	Ĉ467.81	Ĉ460.47	Ĉ759.28	Ĉ320.28	**Ĉ2,351.39**
2028	Ĉ352.16	Ĉ472.74	Ĉ468.03	Ĉ774.69	Ĉ328.17	**Ĉ2,395.79**
2029	Ĉ360.76	Ĉ477.68	Ĉ475.59	Ĉ790.10	Ĉ336.07	**Ĉ2,440.19**
2030	Ĉ369.35	Ĉ482.61	Ĉ483.15	Ĉ805.50	Ĉ343.96	**Ĉ2,484.58**
2031	Ĉ377.95	Ĉ487.54	Ĉ490.71	Ĉ820.91	Ĉ351.86	**Ĉ2,528.98**
2032	Ĉ386.55	Ĉ492.48	Ĉ498.27	Ĉ836.32	Ĉ359.75	**Ĉ2,573.37**

Section A-5: Development of Risk Class Factors

Although it is clear that there is no significant difference in trend between different risk classes, if we simply look at the pure premium by risk class, we can still see that there is a clear, consistent difference in average premiums by risk class, as shown in the previous section. While our base model produced an accurate projection of aggregate pure premiums over time based on our assumptions, we realize that in order to remain competitive and not subject to adverse selection, Safelife must still charge an appropriate granular rate for individual risks. Therefore, in order to address this issue, we decided to calculate rating factors for each risk class that would appropriately adjust the aggregate pure premium from the model output to be consistent with that risk class' average pure premium.

All calculations expressed in this section can be found in the attached Excel file "A Team – Safelife Traditional Factor Development."

We began by individually analyzing each risk characteristic and comparing the pure premium for just the specific characteristic with the overall aggregate pure premium. We used the following formula to calculate the difference between the individual pure premium and the aggregate pure premium (shown once as a general formula and again using the Small Vehicle Size as an example):

General Formula: $\frac{\textit{Individual Characteristic Average Pure Premium}}{\textit{Aggregate Average Pure Premium}}$

Example Formula (Small Vehicle Class): $\frac{\textit{Small Vehicle Average Pure Premium}}{\textit{Aggregate Average Pure Premium}}$

We ran this calculation across each individual year as well as across the entire 10-year range. We also ran this calculation for each individual risk characteristics. We selected the straight average of the ratio across the 10 years as our final factor for each individual risk class.

The results of this analysis are shown in Table A-3.

Table A-3: Traditional Policy Factors by Risk Class

	Personal					Commercial				
Risk Class	BI	PI	PD	COL	COMP	BI	PI	PD	COL	COMP
SML	0.4707	0.3290	0.7138	0.6748	0.9433	0.5120	0.3874	0.7926	0.7567	1.0701
LSL	0.7397	0.6044	0.6691	0.6569	1.2249	0.8046	0.7115	0.7430	0.7367	1.3896
MYA	1.2743	1.1737	1.1130	1.0778	0.7174	1.3861	1.3818	1.2358	1.2087	0.8139
SMA	0.6996	0.8832	0.8842	0.9829	0.7122	0.7610	1.0398	0.9818	1.1023	0.8080
MSL	0.7344	0.4340	0.8032	0.7122	1.3740	0.7989	0.5109	0.8919	0.7986	1.5588
LYL	0.8634	0.6089	0.7485	0.6825	0.8470	0.9392	0.7169	0.8311	0.7654	0.9609
LSA	1.0994	1.6224	0.8289	0.9569	0.9248	1.1959	1.9100	0.9203	1.0731	1.0492
LMA	0.8405	1.6423	0.7327	0.8591	0.7164	0.9143	1.9335	0.8136	0.9634	0.8127
SYL	0.7187	0.3275	0.9033	0.7809	0.8421	0.7818	0.3855	1.0030	0.8757	0.9554
MYL	0.8573	0.4372	0.8985	0.7399	0.9502	0.9326	0.5148	0.9976	0.8297	1.0780
MYH	1.9116	1.0156	1.6759	1.4231	0.9624	2.0793	1.1957	1.8609	1.5959	1.0918
LML	0.5655	0.6118	0.5915	0.5898	0.9488	0.6151	0.7203	0.6568	0.6614	1.0764
MSA	1.0917	1.1650	0.9950	1.0374	1.0375	1.1875	1.3715	1.1048	1.1634	1.1770
LYA	1.2834	1.6346	0.9271	0.9942	0.6395	1.3960	1.9244	1.0295	1.1149	0.7255
MMA	0.8346	1.1793	0.8796	0.9313	0.8036	0.9079	1.3883	0.9766	1.0444	0.9117
LYH	1.9251	1.4145	1.3961	1.3127	0.8579	2.0941	1.6652	1.5502	1.4721	0.9733
SSA	0.9151	0.8725	1.0003	1.0948	0.9195	0.9954	1.0272	1.1107	1.2278	1.0431
MML	0.5615	0.4393	0.7100	0.6394	1.0643	0.6108	0.5172	0.7884	0.7170	1.2075
LMH	1.2609	1.4211	1.1033	1.1343	0.9610	1.3715	1.6731	1.2250	1.2721	1.0902
SSL	0.6157	0.3250	0.8075	0.7516	1.2178	0.6697	0.3827	0.8966	0.8429	1.3815
SSH	1.3727	0.7550	1.5062	1.4456	1.2334	1.4932	0.8888	1.6725	1.6211	1.3993
MMH	1.2520	1.0204	1.3244	1.2297	1.0780	1.3619	1.2013	1.4706	1.3790	1.2230
SYA	1.0682	0.8791	1.1189	1.1375	0.6358	1.1620	1.0349	1.2424	1.2756	0.7214
LSH	1.6492	1.4039	1.2481	1.2635	1.2406	1.7939	1.6528	1.3858	1.4169	1.4074
SYH	1.6024	0.7607	1.6848	1.5019	0.8530	1.7430	0.8955	1.8708	1.6843	0.9677
MSH	1.6376	1.0081	1.4982	1.3697	1.3917	1.7813	1.1868	1.6636	1.5360	1.5789
SMH	1.0495	0.7643	1.3314	1.2978	0.9554	1.1416	0.8997	1.4784	1.4554	1.0839

Source: Appendix G

Appendix B – Competitive Analysis

Competitive analysis - defined as the benchmarking of competitors rates as can be reasonably obtained from publicly available rate filings - is a common practice for insurers launching a new insurance product for which they do not have data to properly assess (Wener, Modlin, 2016). In the United States, all Property and Casualty insurance filings are open to the public when they are filed with a state's Department of Insurance (DOI). While some states allow confidentiality requests, others do not; as a result, numerous public rate filing databases exist.

For our project, we chose to use ratefilings.com through S&P Global Market Intelligence. However, many state DOIs also host databases with rate filings on their department websites, which can be accessed without making an account.

In order for this competitive analysis to be applicable to this analysis, we had to make the following assumptions:

- The insurance market in the United States is representative of the insurance market in Carbia
- All competitors who filed rates in the United States are have assumed to have filed the same rates with Carbia's DOI
- Carbia's DOI allows filings outside of Carbia to be referenced or benchmarked
- All approved rates in insurance rate filings are assumed to accurately depict the pure premium of each risk being insured

In addition to profiling the current market trends in the automobile insurance industry, we used competitive analysis to benchmark autonomous vehicle rates as well as cybersecurity coverage rates in order to develop some of the projected pure premiums for Safelife's new policy. In the end, we conducted both a qualitative analysis and a quantitative analysis. Table B-1 contains furnished referential information related to all public filings used in this report for the qualitative analysis, while Table B-2 shows the same information for the quantitative analysis.

Table B-1: Competitive Analysis (Qualitative) Referential Information					
Company	**Group**	**State**	**Type of Insurance**	**SERFF Tracking #**	**Page or Section Benchmarked**
United Service Protection Corporation	United Service Protection	Nebraska	Vehicle Service Contract	ASPX-131669469	Delcarations Page
MIC Property and Casualty Insurance Corporation	ALLY Insurance Holdings	California	Contractual Liability	GMAX-131346091	Trending (Page 144)
Peerless Indemnity Insurance Company	Liberty Mutual	Illinois	Personal Auto	LBPM-131349334	Page 27
Economy Fire & Casualty Company	Metropolitan Group	Illinois	Umbrella	METX-131395764	DOI Objection Responses
Metropolitan Direct Property and Casualty Insurance Company	Metropolitan Group	New Jersey	Umbrella	METX-131275980	Insurance Agreement
Dealers Alliance Corporation	Dealers Alliance Corporation	Alabama	Vehicle Service Contract	DACO-131779179	Terms & Conditions
State Farm Fire & Casualty Company	State Farm Insurance	Illinois	Personal Auto	SFMA-131789218	Auto Cost Containment

Table B-2: Competitive Analysis (Quantitative) Referential Information						
Purpose	**Company**	**Group**	**State**	**Type of Insurance**	**SERFF Tracking #**	**Page or Section Benchmarked**
Benchmarking Commercial Cyber	GuideOne Mutual Insurance Company	GuideOne Insurance	Utah	Businessowners	GDEA-131791204	Cyber Suite Coverage
Benchmarking Personal Cyber Rates	Main Street America Protection Insurance	Main Street America Group	Virginia	Personal Homeowners	NGMC-131652718	VA-HO-R-69
Benchmarking LCM	Austin Mutual Insurance Company	Main Street America Group	Utah	Personal Homeowners	AUST-131724890	Loss Cost Multiplier Forms Page 2
Benchmarking AV Rates	Amica Mutual Insurance Company	Amica Mutual	Kansas	Personal Auto	AMMA-131731631	Page 138
Benchmarking AV Rates	Liberty Mutual General Insurance Company	Liberty Mutual	Louisiana	Personal Auto	LBPM-131273090	Page 45
Benchmarking AV Rates	GoAuto Insurance Company	GoAuto Insurance Company	Louisiana	Personal Auto	PERR-131414992	Page 35
Benchmarking AV Rates	Acuity, A Mutual Insurance Company	Acuity, A Mutual Insurance	Nevada	Personal Auto	ACUT-131342963	Level By Coverage

All of the calculations developed in this section are shown in the attached workbook "A Team – Competitive Analysis Summary." In addition, we have included screenshots of the rating or the verbiage we benchmarked or analyzed from each company filing in this Excel file.

Section B-1: Qualitative Competitive Analysis

We conducted a qualitative competitive analysis in order to see how other insurers are treating autonomous technology. This exercise was important to confirm that Safelife is in a position to become a first-mover by launching an Autonomous Line. In addition, we used this analysis to develop some assumptions about liability and claims handling.

First of all, we were able to confirm Safelife would gain a first-mover advantage by launching an Autonomous Line. We have observed many different ways in which insurers are treating autonomous vehicles. Table B-3 summarizes our observations along with examples:

Table B-3: Qualitative Competitive Analysis Observations		
Observation	**Implication**	**Examples**
Some insurers are currently excluding damages to autonomous technology	*There is an untapped insured market for Safelife*	United Service Protection Corporation, Dealers Alliance Corporation
No insurers are currently writing an exclusively autonomous line of business	*Safelife can gain a first-mover advantage by creating an autonomous line*	All companies in the analysis
Some insurers are currently writing FAVs in personal auto lines	*We believe many insurers will not treat these vehicles differently until they take up a significant chunk of total vehicle miles traveled*	Amica, Liberty Mutual, Acuity A, GoAuto, Metropolitan Group
Insurers who write autonomous vehicles typically give discounts for autonomous technology	*Autonomous technology clearly mitigates at least some degree of risk*	Amica, Liberty Mutual, Acuity A, GoAuto
Insurers do not currently treat liability differently for autonomous vehicles	*We expect to see this as the case until new legislation requires the liability to be treated differently*	ALLY Insurance Holdings
Some insurers are comitting to researching this industry	*We expect other insurers to start writing autonomous lines by late 2022 or early 2023*	State Farm

Section B-2: Quantitative Analysis – Pure Premium Adjustment Basis

Our primary application of the quantitative competitive analysis was comparing competitor rates in order to develop a basis for the adjustment factors (Step 1 of Table 9). While no insurance company has an autonomous line, a small handful of companies offer discounts for autonomous technology. However, most of these discounts are not as large as we believe they should be, simply because these companies do not have enough credible autonomous vehicle data to determine the true reduction in risk. Therefore, we used outside research to supplement the results of the competitive analysis. However, we believe the competitive analysis is a good basis since it guarantees that Safelife will be more competitive than the current market with this new policy.

We benchmarked a basis for these adjustment factors separately for both AVs and SAVs. In addition, we conducted separate benchmarking for each different coverage currently offered in Carbia.

We developed the basis for our adjustment factors by taking the average of the factors being applied to autonomous vehicles by four different competitors. In addition to using these four competitors, we also used results of a study which focused on assessing the reduction in claim frequency from adding autonomous technology to a car ("Crash avoidance features reduce crashes, insurance claims study shows; autonomous braking and adaptive headlights yield biggest benefits", 2012). By taking the average of the competitors' rates as well as the indications from this study, we developed the bases for each coverage separately for both FAVs and SAVs. The individual competitor factors, as well as the development of the final average, are contained in Tables B-4 (FAVs) and B-5 (SAVs) below:

Table B-4: Adjustment Factor Basis Calculation (Fully Autonomous)

Competitor/Source	Original or Adjusted	BI Factor	PI Factor	PD Factor	COL Factor	COMP Factor	Adjustment From Original Rates
Acuity, A	Adjusted	0.725	0.55	0.6	0.615	0.605	Removed granularity by averaging Autonomous Level Discount Factors
GoAuto	Original	0.75	1	0.75	0.75	0.95	No Adjustment
Liberty Mutual	Adjusted	0.9	1	0.9	0.9	1	Removed granularity by averaging the factors
IIHS Claim Frequency Study	Original	0.756	0.68	0.774	0.9025	1	No adjustment
Average/Basis		0.7828	0.8075	0.756	0.7919	0.8888	Straight Average

Source: Appendix G; "Crash Avoidance Features Reduce Crashes, Insurance Claims Study Shows; Autonomous Braking and Adaptive Headlights Yield Biggest Benefits", 2012

Table B-5: Adjustment Factor Basis Calculation (Semi-Autonomous)							
Competitor/Source	Original or Adjusted	BI Factor	PI Factor	PD Factor	COL Factor	COMP Factor	Adjustment From Original Rates
Acuity, A	Adjusted	0.6167	0.5167	0.5667	0.56	0.5233	Removed granularity by averaging Autonomous Level Discount Factors
GoAuto	Original	0.9	1	0.9	0.9	0.95	No Adjustment
Liberty Mutual	Adjusted	0.925	1	0.925	0.925	1	Removed granularity by averaging the factors
Amica	Original	0.96	0.96	0.96	0.96	0.96	No Adjustment
IIHS Claim Frequency Study	Original	0.864	0.68	0.855	0.9263	1	No adjustment
Average/Basis		0.8531	0.8313	0.8413	0.8543	0.8867	Straight Average

Source: Appendix G; "Crash Avoidance Features Reduce Crashes, Insurance Claims Study Shows; Autonomous Braking and Adaptive Headlights Yield Biggest Benefits" 2012

Subsequently, we used these numbers in Step 1 of our calculations of the Pure Premium Adjustment Factors. It is assumed that the basis for traditional vehicles is 1.00, so no competitive analysis was conducted for these vehicles.

Section B-3: Quantitative Analysis – Cybersecurity Pure Premiums

In addition to benchmarking competitor rates for the Pure Premium Adjustment Factors, we also utilized competitive analysis to directly develop pure premiums for both of the newly proposed cybersecurity endorsements.

For the personal cybersecurity endorsement, we benchmarked the coverage terms and rating from the personal homeowners program of Main Street America Protection Insurance company (public filing NGMC-131652718). They filed a $50 USD charge for their Home Cyber Protection Coverage. In addition to basing the terms of our endorsement off of their terms, we applied some modifications to convert this number to a pure premium in Carbs. First of all, we are required to modify this charge since it is assumed to include expenses, not just pure premium. In order to get from this charge to a pure premium, we must divide this charge by the company's Loss Cost Multiplier, which is a factor that is applied to pure premiums in order to load a company's expenses into the calculation. We found Main Street America Group's LCM at 3.18 from a different filing (public filing AUST-131724890). After dividing the $50 charge by the LCM, we multiplied the result by our currency exchange rate assumption of Ĉ6/$1 to obtain our final charge for the personal cybersecurity endorsement. Table B-6 summarizes the steps involved in this calculation.

Table B-6: Personal Cyber Endorsement Rate Development		
Step	**Source or Formula**	**Calculation**
Step 1: Benchmark Competitor Charge	NGMC-131652718	$50.00
Step 2: Benchmark Competitor LCM	AUST-131724890	3.18
Step 3: Remove Expenses from Competitor	Step 1 / Step 2	$15.72
Step 4: Apply Ĉ/$ Exchange Rate to Step 3	6 * Step 3	Ĉ94.34
Final Selected Charge per Exposure	**Result of Step 4**	**Ĉ94.34**

Source: Appendix G

We chose to turn to a different public filing for the commercial cybersecurity endorsement. We believe that the nature of confidential information susceptible to cyber-attacks holds a lot more risk for a business, which typically stores sensitive customer and company information, than it does for an individual person. For this reason, we elected to benchmark our commercial cybersecurity endorsement from the businessowners program of GuideOne Mutual Insurance (public filing GDEA-131791204). GuideOne filed a cyber suite coverage with numerous coverage terms and sublimits for each of the covered perils. In addition, this company provided an explanatory memorandum which directly provided pure premiums for each peril in this coverage, meaning no adjustments to remove expenses were required.

We assumed that Safelife's endorsement would only use the lowest sublimit from each peril under this coverage. We directly summed the individual pure premiums from each peril to obtain the total pure premium for this endorsement. In addition, GuideOne's policy allows for a business to insure up to 5 buildings and locations. Therefore, we feel appropriate to only apply this charge to every 5 car years exposure as opposed to 1. In order to obtain a charge per car year of exposure, we divided the sum of the pure premiums by 5. Table B-7 summarizes the calculation of pure premium for each component of this endorsement, while Table B-8 illustrates the development of our final pure premium for this endorsement.

Table B-7: Cyber Suite Coverage Pure Premium				
Cyber Coverage Component	**Limit**	**Frequency**	**Severity**	**Pure Premium**
Data Compromise Response Expenses	$50,000	0.001853	$16,700	$30.95
Computer Attack	$50,000	0.003	$14,900	$44.70
Cyber Extortion	$10,000	0.003	$7,400	$22.20
Identity Recovery	$250,000	0.07	$18	$1.26
Data Compromise Liability	$50,000	0.000556	$27,000	$15.01
Network Security Liability	$50,000	0.00171	$13,600	$23.26

Source: Appendix G

Table B-8: Personal Cyber Endorsement Rate Development		
Step	**Source or Formula**	**Calculation**
Step 1: Benchmark Data Compromise Expenses Pure	GDEA-131791204	$30.95
Step 2: Benchmark Cyber Extortion Pure Premium	GDEA-131791204	$22.20
Step 3: Benchmark Computer Attack Pure Premium	GDEA-131791204	$44.70
Step 4: Benchmark Identity Recovery Pure Premium	GDEA-131791204	$1.26
Step 5: Benchmark Data Compromise Liability Pure	GDEA-131791204	$15.01
Step 6: Benchmark Network Security Liability Pure	GDEA-131791204	$23.26
Step 7: Sum together individual pure premiums	Sum(Step 1, ..., Step 6)	$137.37
Step 8: Divide by 5 to obtain the pure premium per	Step 7 / 5	$27.47
Step 9: Apply Ĉ/$ Exchange Rate to Step 8	6 * Step 8	Ĉ164.85
Final Selected Charge per Exposure	**Result of Step 9**	**Ĉ164.85**

Source: Appendix G

Appendix C – Adoption Curve Estimation

There is a lot of speculation floating around from executives and other influencers, primarily within the industry, about when we will or will not see autonomous cars on every street. However, these speculations are often exaggerated as a marketing tactic and are not necessarily backed up by credible projections. Therefore, we felt it appropriate to gather several different adoption curves—all based on credible data—and take the average of these curves in order to develop the final curve for our analysis.

All calculations illustrated in this section are provided in the attached Excel workbook titled "A Team – Adoption Curve Analysis." We encourage Safelife to browse through these calculations for more detail.

Section C-1: Adoption Curve Scenario Analysis (Fully Autonomous)

Ultimately, we gathered five unique adoption scenarios across two different sources in order to conduct this analysis. Table C-1 summarizes these five scenarios, while Table C-2 shows the results of averaging these scenarios.

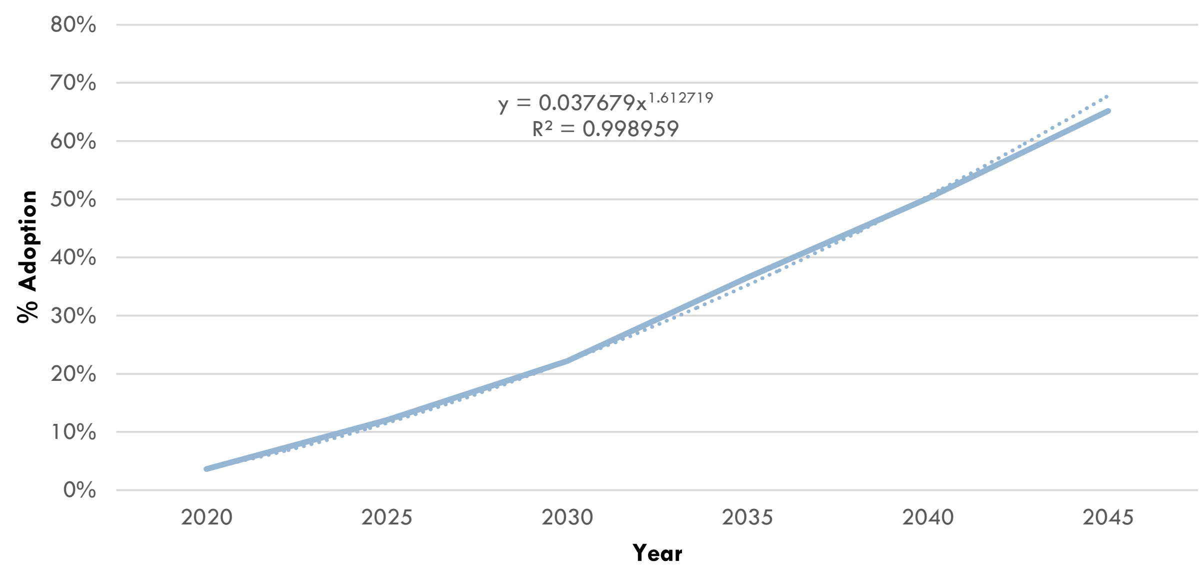
Table C-1: Adoption Curve Scenarios		
Scenarios	**Source**	**Description**
Scenario 1	Bansal, 2017	This scenario assumes that the price of autonomous technology drops by 5% while the willingness to pay for autonomous technology increases by 5%
Scenario 2	Bansal, 2017	This scenario assumes that the price of autonomous technology drops by 10% while the willingness to pay for autonomous technology increases by 5%
Scenario 3	Bansal, 2017	This scenario assumes that the price of autonomous technology drops by 5% while the willingness to pay for autonomous technology increases by 10%
Scenario 4	Bansal, 2017	This scenario assumes that the price of autonomous technology drops by 10% while the willingness to pay for autonomous technology increases by 10%
Scenario 5	Collie, Rose, Choraria, & Wegsheider, 2017	This scenario is based on an adoption model built by BCG based on granular, time-series data as well as real client data

	Table C-2: Adoption Curve Scenario Development							
	Scenario	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
FAV	Scenario 1	0.000	0.033	0.108	0.190	0.272	0.359	0.432
	Scenario 2	0.000	0.047	0.151	0.272	0.383	0.457	0.707
	Scenario 3	0.000	0.047	0.138	0.255	0.364	0.443	0.597
	Scenario 4	0.000	0.055	0.194	0.338	0.442	0.747	0.872
	Scenario 5	0.000	0.000	0.011	0.054	0.000	0.000	0.000
	Average	**0.000**	**0.036**	**0.120**	**0.222**	**0.365**	**0.502**	**0.652**
SAV	Scenario 1	0.000	0.023	0.053	0.081	0.085	0.083	0.082
	Scenario 2	0.000	0.021	0.061	0.084	0.085	0.286	0.163
	Scenario 3	0.000	0.025	0.059	0.083	0.082	0.265	0.255
	Scenario 4	0.000	0.035	0.060	0.077	0.277	0.116	0.029
	Average	**0.000**	**0.026**	**0.058**	**0.081**	**0.132**	**0.188**	**0.132**

Source: Appendix G

While ARIMA time series forecasting was appropriate for analyzing Safelife's data, we did not believe that these adoption curve projections lent themselves to the same type of analysis due to having very few data points. As you can see, four of the five scenarios provided data in five-year increments. As a result, we simply fit a line to the average of the five projections to develop an equation for the percent of vehicles on the road with autonomous capabilities. We used this equation to calculate the projected numbers between the five-year increments. Figure C-1 graphically illustrates this adoption curve and provides the regression equation used to develop our adoption curve.

Figure C-1: FAV Adoption Curve Regression Equation



Source: Appendix G

Note: Because Excel provided us with an equation based on five-year increments, we must make an adjustment in order to obtain an equation for one-year increments. This adjustment is found by multiplying 3.7679 by $\left(\frac{1}{5}\right)^{1.612719}$ in order to obtain a new coefficient of 0.002811.

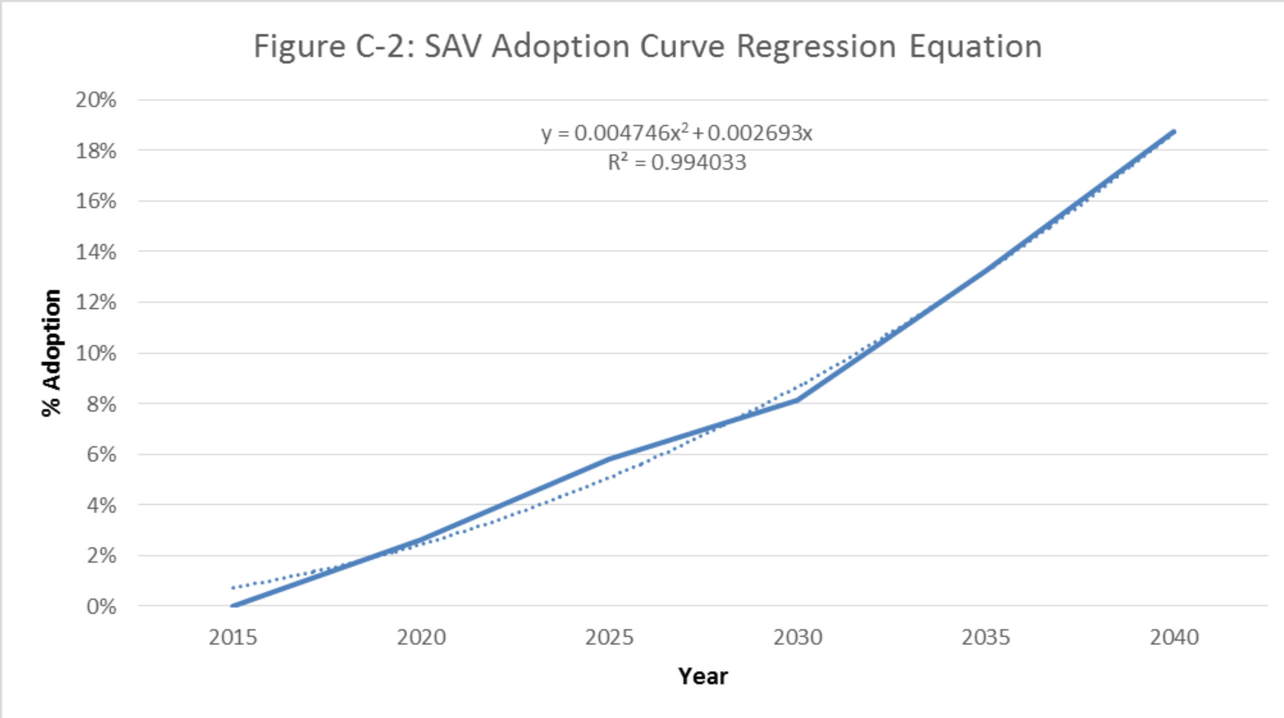
As you can see, the regression equation we have built fits the data obtained from averaging these scenarios extremely well. Although R-Squared normally is not a valid method of evaluating time series, we believe this methodology is sufficient since we are only using it to interpolate values for the years between the five-year increments in the original scenarios. Table C-3 shows the numerical results of this equation.

Table C-3: FAV Adoption Curve Projections			
Year	FAV%	Year	FAV%
2016	0.2811%	2026	13.4377%
2017	0.8597%	2027	15.4620%
2018	1.6532%	2028	17.5925%
2019	2.6291%	2029	19.8258%
2020	3.7679%	2030	22.1591%
2021	5.0559%	2031	24.5898%
2022	6.4828%	2032	27.1153%
2023	8.0405%	2033	29.7336%
2024	9.7225%	2034	32.4426%
2025	11.5231%	2035	35.2404%

Source: Appendix G

Section C-2: Adoption Curve Scenario Analysis (Semi-Autonomous)

We have also conducted a similar analysis to project the number of Semi-Autonomous vehicles. However, the fifth scenario only projected fully autonomous vehicles. Therefore, our analysis only included the first four scenarios for Semi-Autonomous Vehicles. The average of the scenarios is shown in table C-2 above, while the results of this are summarized in Figure C-2 and Table C-4 below.



Source: Appendix G

Table C-4: SAV Adoption Curve Projections			
Year	**SAV%**	**Year**	**SAV%**
2016	1.0066%	2026	5.7217%
2017	1.3072%	2027	6.4020%
2018	1.6459%	2028	7.1203%
2019	2.0224%	2029	7.8766%
2020	2.4370%	2030	8.6708%
2021	2.8895%	2031	9.5030%
2022	3.3800%	2032	10.3732%
2023	3.9085%	2033	11.2813%
2024	4.4749%	2034	12.2274%
2025	5.0793%	2035	13.2115%

Source: Appendix G

Section C-3: Personal/Commercial Adoption Differences

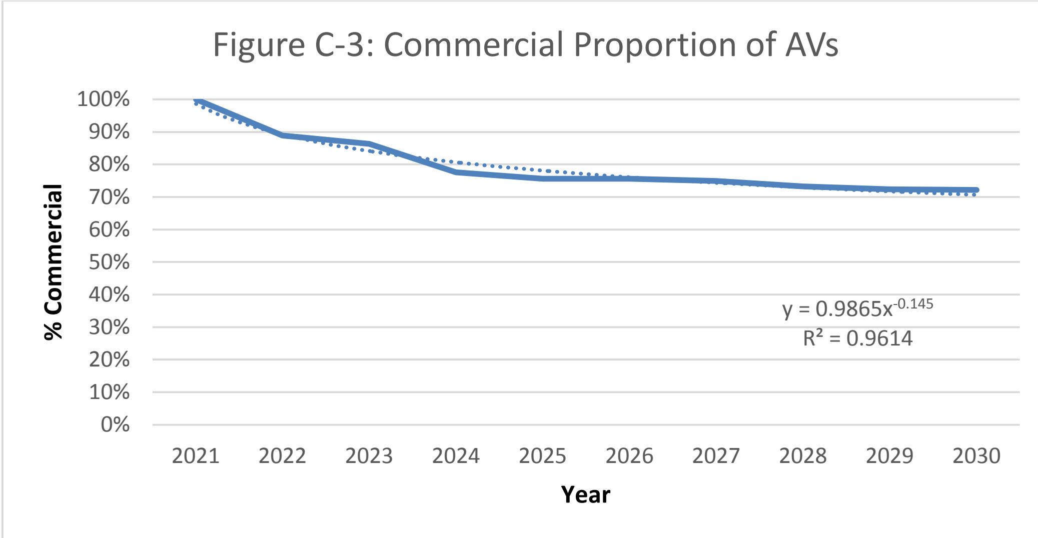
Only Scenario 5 (from the Boston Consulting Group) distinguished between Personal AVs and Commercial AVs. However, we believe their analysis of the split between commercial versus personal is still credible. Therefore, we maintained the proportions of personal to commercial that were indicated by scenario five.

We plotted the proportion of FAVs that were commercially owned as indicated by the Boston Consulting Group and subsequently fit a line to these points in order to obtain a regression equation. Again, this is not necessarily the best methodology for evaluating time series, but we do not believe the data is sufficient for ARIMA modeling. Table C-5 shows the proportions we used to create this equation, and Figure C-3 shows the fitted line and the regression equation. Also, please note that these percentages represent the percentage of total autonomous vehicles, so they do not consider traditional vehicles.

Table C-5: Personal Versus Commercial Autonomous Vehicle Proportions

Year	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
Personal %	0.00%	0.00%	11.11%	13.64%	22.41%	24.37%	24.38%	25.09%	26.76%	27.59%	27.86%
Commercial %	100.00%	100.00%	88.89%	86.36%	77.59%	75.63%	75.62%	74.91%	73.24%	72.41%	72.14%

Source: Appendix G



Source: Appendix G

We chose to build a regression equation for the commercial proportion of total autonomous vehicles because the line exhibits a very strong fit as exhibited by the high R-Squared. Once we obtain the commercial proportion using this equation for any given year, we subtract this number from 1 in order to calculate the personal proportion. We have displayed the results of this equation for both personal and commercial through 2034 in table C-6 below.

Table C-6: Projected Personal Versus Commercial % of Total FAVs

Year	2020	2022	2024	2026	2028	2030	2032	2034
Projected Personal %	0.00%	10.78%	19.31%	23.92%	27.03%	29.35%	31.20%	32.72%
Projected Commercial %	100.00%	89.22%	80.69%	76.08%	72.97%	70.65%	68.80%	67.28%

Source: Appendix G

Appendix D – Pure Premium Adjustment Factors

This section will provide more detail about the Pure Premium Adjustment Equations shown in the report. These adjustment equations were applied to the base projections that our ARIMA modeling analysis forecasted.

These adjustment factors are also developed in the Excel workbook "A Team – Pure Premium Development Workbook." We encourage Safelife to browse through this workbook to explore how these calculations are processed in action.

Section D-1: Fully-Autonomous Adjustment Factors

This section will cover the fully autonomous vehicle pure premium adjustment factors that were developed in Section 4 of the report. We have recreated Tables 9 and 10 below as tables D-1 and D-2.

Table D-1: Steps In Developing AV Pure Premium Adjustment Factors

Steps	BI	PI	PD	COL	COMP	Source	Justification
Step 1: Base Discount Factor	0.78275	0.8075	0.756	0.791875	0.88875	Competitive Analysis (See Appendix B)	This puts our pure premiums in-line with our competitors
Step 2: Additional Discount for Removing First-Party Human Error	-0.324	-0.324	-0.324	-0.324	0	The CAS Automated Vehicles Task Force, 2018	This adjustment is to remove the frequency from first-party human error
Step 3: Add Back Third-Party Human Error	0.324*T	0.324*T	0	0.324*T	0	The CAS Automated Vehicles Task Force, 2018; Adoption Curve Analysis	We must add back the third-party risk (proportional to total proportion of traditional cars) that was removed in Step 2 from subtracting total human error
Step 4: Additional Discount for Third-Party SAVs	(1 - SAV Discount Factor)*S	(1 - SAV Discount Factor)*S	0	(1 - SAV Discount Factor)*S	0	Competitive Analysis & Adoption Curve Analysis	Step 3 and Step 4 do not apply to PD and COMP since there is never a third-party in these claims (see assumptions)
Step 5: Adjust for value of car	1	1	1	Steps 1-4 * ACVR	Steps 1-4 * ACVR	Bansal, 2017; Cost of Autonomy Analysis	This should only apply to coverages involving damage to the insured's car

Symbols	Definition
T	Total Autonomous Vehicles in Carbia / Total Vehicles in Carbia
S	Total Semi-Autonomous Vehicles in Carbia / Total Vehicles in Carbia
ACVR	Autonomous Car Value Rate: An estimate for how much cost autonomy adds to a car
SAV Discount Factor	Obtained from competitive analysis (See Appendix B)

Table D-2: Indicated/Selected Adjustment Factor Formulas		
Coverage	**Indicated Adjustment Factor**	**Selected Adjustment Factor**
BI	0.45875 + 0.324*T - 0.14687*S	Indicated Formula
PI	0.4835 + 0.324*T - 0.16867*S	Indicated Formula
PD	0.432	0.213
COL	ACVR*(0.467875 + 0.324*T - 0.14575*S)	Indicated Formula
COMP	ACVR*(0.88875)	Indicated Formula
Justification	Result of all five steps	We selected the CAS' estimate for proportion of accidents caused by technological error as a proxy for PD instead of the indicated charge

Symbols	Definition
T	Total Non-Autonomous Vehicles in Carbia / Total Vehicles in Carbia
S	Total Semi-Autonomous Vehicles in Carbia / Total Vehicles in Carbia
ACVR	Autonomous Car Value Rate: An estimate for how much cost autonomy adds to a car at any given time T
SAV Discount Factor	Obtained from competitive analysis (See Appendix B)

These steps were applied separately by coverage; however, not every step is applied to each coverage. Some of these steps are applied to account for third-party risk or to account for the value of the car itself; however, not every coverage includes third-party risk or involves damage to the vehicle. Therefore, we must look at the purpose of each step in order to determine which coverages it should apply to. Table D-3 summarizes the purpose of each step:

Table D-3: Adjustment Factor Calculation Steps			
Step	**Description**	**Purpose**	**Applicable Coverages**
1	Base Discount Factor from Comp Analysis	Set the basis of the adjustment factors to be in-line with competitors	All
2	Additional Discount for Removing First-Party Human Error	Discount for the amount of risk removed from having no first-party human error	BI, PI, PD, COL
3	Add Back Third-Party Human Error	Since ALL human error was removed in step 2, we must add back some of that in step 3, but only enough to account for third-party drivers	BI, PI, COL
4	Additional Discount for Third-Party SAVs	Accounts for the reduction of third-party risk from having more SAVs on the road	BI, PI, COL
5	Adjust for Value of Car	Accounts for higher severity that comes with autonomous technology	COL, COMP

Several different numbers went into these steps. Table D-4 summarizes all the numerical estimates and inputs for these calculations.

Table D-4: Numeric Inputs for Pure Premium Adjustment Factors				
Numerical Estimate	**Purpose**	**Source**	**Fixed or Variable**	**Derivation**
Basis for Adjustments	Puts Safeline's base adjustment in-line with competition	Competitive Analysis	Fixed	Appendix B
% Claims/Accidents Caused By Human Error	Proxy for automobile risk that comes from human error	Casualty Actuary Society	Fixed	NA
Compliment of SAV Discount Factor	Proxy for third-party risk reduced by semi-autonomous technology	Competitive Analysis	Fixed	Appendix B
Proportion of FAVs, SAVs, and TVs	Applying discounts/surcharges relative to car proportions	Adoption Curve Analysis	Variable	Appendix C
Average Car Value Factor	Applies a factor to autonomous and semi-autonomous vehicles based on how much value autonomous technology adds to the car	AV Car Value Analysis	Variable	Appendix G

The adjustment factor by year (for the range of our projections) is shown in Table D-5.

Table D-5: AV Adjustment Factor by Year					
Year	**AV BI Factor**	**AV PI Factor**	**AV PD Factor**	**AV COL Factor**	**AV COMP Factor**
2022	0.7458	0.7698	0.213	1.3165	1.5882
2023	0.7383	0.7622	0.213	1.2711	1.5524
2024	0.7302	0.7540	0.213	1.2268	1.5183
2025	0.7215	0.7451	0.213	1.1835	1.4861
2026	0.7123	0.7358	0.213	1.1411	1.4554
2027	0.7025	0.7259	0.213	1.0997	1.4264
2028	0.6922	0.7154	0.213	1.0592	1.3988
2029	0.6814	0.7045	0.213	1.0196	1.3726
2030	0.6701	0.6930	0.213	0.9808	1.3478
2031	0.6583	0.6810	0.213	0.9427	1.3243

Source: Appendix G

Note: We used the indicated factors for every coverage except Property Damage. Since this coverage only carries first-party risk, we felt that the discount for this coverage should be larger than what our formula indicated. We selected 0.213 because this is the number the Casualty Actuary Society calculated for accidents/claims attributed to technological/environmental issues.

Section D-2: Semi-Autonomous Adjustment Factors

The steps used in calculating the adjustment factors for semi-autonomous vehicles are almost exactly the same as the steps for the autonomous factors with a few slight adjustments. Since these vehicles are not the focus of the report, we have briefly summarized the differences in Table D-6 below.

Table D-6: Adjustment Factor Calculation Steps

Step	FAV Step Description	SAV Step Description	SAV Difference
1	Base FAV Discount Factor from Comp Analysis	Base SAV Discount Factor from Comp Analysis	The base adjustment factors are different for FAVs and SAVs
2	Additional Discount for Removing First-Party Human Error	Additional Discount for Reduction in Human Error from Third-Party Fully-Autonomous Vehicles	No discount is given for first-party risk since manual intervention is still necessary
3	Add Back Third-Party Human Error	None	Step 3 does not apply since human error was not subtracted for SAVs
4	Additional Discount for Third-Party SAVs	Additional Discount for Third-Party SAVs	No difference
5	Adjust for Value of Car	Adjust for Value of Car	Factor is different for SAVs because autonomous technology price varies with level of autonomy

The resulting equations, as well as the results over the 10-year projection range, have been provided in Tables D-7 and D-8, respectively, below.

Table D-7: SAV Pure Premium Adjustment Factors	
Coverage	**Indicated Adjustment Factor**
BI	0.853133 - 0.324*F - 0.14687*S
PI	0.831333 - 0.324*F - 0.16867*S
PD	0.841333
COL	ACVR*(0.85425 - 0.324*F - 0.14575*S)
COMP	ACVR*(0.88667)

Symbols	Definition
F	Total Fully-Autonomous Vehicles in Carbia / Total Vehicles in Carbia
S	Total Semi-Autonomous Vehicles in Carbia / Total Vehicles in Carbia
ACVR	Autonomous Car Value Rate: An estimate for how much cost autonomy adds to a car at any given time T
SAV Discount Factor	Obtained from competitive analysis (See Appendix B)

Table D-8: SAV Adjustment Factor by Year

Year	SAV BI Factor	SAV PI Factor	SAV PD Factor	SAV COL Factor	SAV COMP Factor
2022	0.8272	0.8046	0.8413	1.0728	1.1484
2023	0.8213	0.7987	0.8413	1.0528	1.1349
2024	0.8151	0.7923	0.8413	1.0331	1.1222
2025	0.8083	0.7854	0.8413	1.0135	1.1101
2026	0.8012	0.7781	0.8413	0.9942	1.0987
2027	0.7936	0.7704	0.8413	0.9751	1.0878
2028	0.7857	0.7623	0.8413	0.9562	1.0775
2029	0.7773	0.7538	0.8413	0.9375	1.0677
2030	0.7686	0.7449	0.8413	0.9189	1.0584
2031	0.7595	0.7356	0.8413	0.9005	1.0496

Source: Appendix G

Section D-3: Non-Autonomous Adjustment Factors

There are less extensive adjustments made to the pure premiums for non-autonomous vehicles. We gave other types of cars a discount for the proportion of autonomous cars that were on the road in any given year, so naturally, we must apply that same discount to non-autonomous vehicles since their third-party risk is also reduced. Other than discounting for FAVs and SAVs on the road in any given year, no other adjustments should be made.

The formulas for these adjustment factors and the results of these formulas are shown below in Tables D-9 and D-10, respectively.

Table D-9: Non-Autonomous Pure Premium Adjustment Factors					
	BI	PI	PD	COL	COMP
Indicated Adjustment Factor	1 - 0.324*F - 0.14687*S	1 - 0.324*F - 0.16867*S	1	1 - 0.324*F - 0.14575*S	1

Symbols	Definition
F	Total Fully-Autonomous Vehicles in Carbia / Total Vehicles in Carbia
S	Total Semi-Autonomous Vehicles in Carbia / Total Vehicles in Carbia

Table D-10: TV Adjustment Factor by Year					
Year	TV BI Factor	TV PI Factor	TV PD Factor	TV COL Factor	TV COMP Factor
2022	0.9740	0.9733	1.0000	0.9741	1.0000
2023	0.9682	0.9674	1.0000	0.9683	1.0000
2024	0.9619	0.9610	1.0000	0.9620	1.0000
2025	0.9552	0.9541	1.0000	0.9553	1.0000
2026	0.9481	0.9468	1.0000	0.9481	1.0000
2027	0.9405	0.9391	1.0000	0.9406	1.0000
2028	0.9325	0.9310	1.0000	0.9326	1.0000
2029	0.9242	0.9225	1.0000	0.9243	1.0000
2030	0.9155	0.9136	1.0000	0.9156	1.0000
2031	0.9064	0.9043	1.0000	0.9065	1.0000

Source: Appendix G

Appendix E: Miscellaneous Supporting Calculations

In addition to the supporting calculations shown in previous exhibits, other calculations and analyses were conducted which served to develop an input or other variable found in our final analyses. This section will detail the following supporting calculations:

- Supporting Analysis 1: Safelife's Autonomous Line Market Share
- Supporting Analysis 2: Total Cars in Carbia Over Time
- Supporting Analysis 3: Cost of Autonomous Technology Over Time

All supporting calculations are provided in the attached Excel file "A Team – Miscellaneous Supporting Calculations."

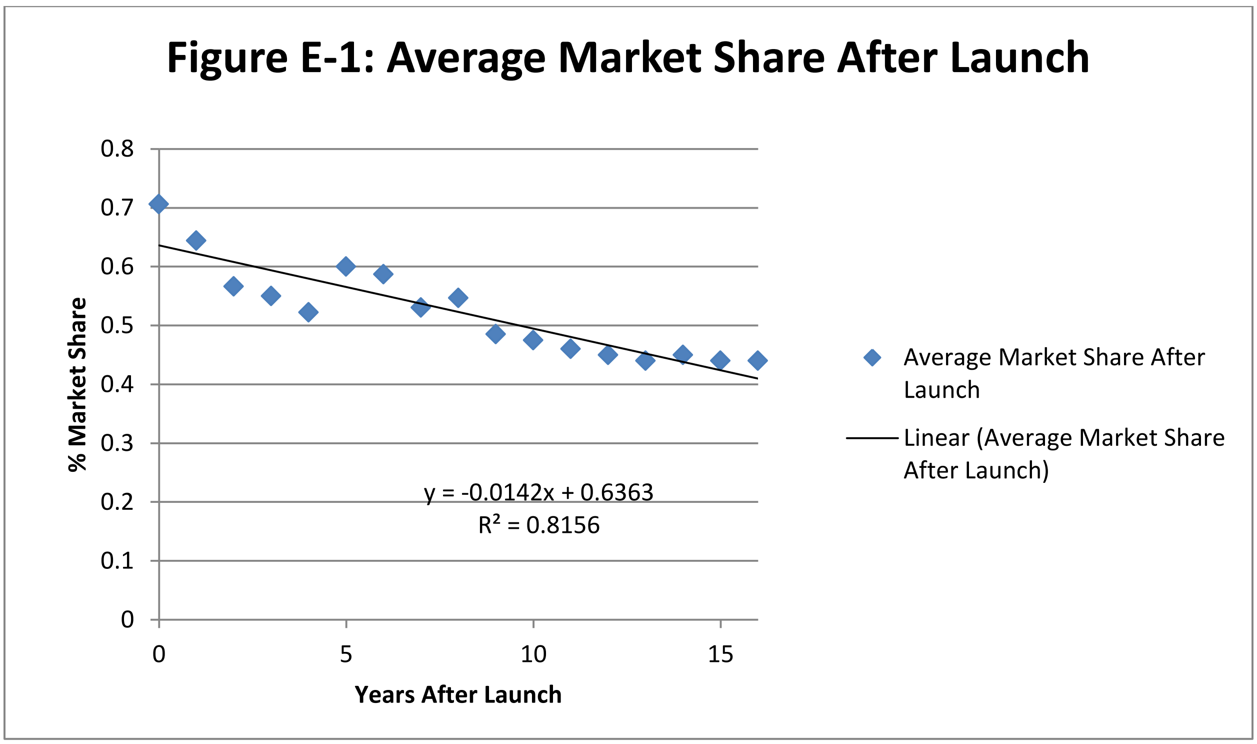
Section E-1: Safelife's Autonomous Vehicle Market Share

Under the assumption that Safelife will obtain a first-mover market share if it launches this policy by 2022, we turned to a general study about first-mover market shares in order to estimate Safelife's market share for autonomous vehicles. We chose a study that provided T-Mobile's market share data by year in several different European countries from the years they launched in each country (Whalley & Curwen, 2012). While not every launch represents a first-mover advantage, we selected patterns that represented a first-mover advantage by choosing patterns that began above 40% and exhibit a relatively decreasing trend. We then took an average of the market share from every *t* years from launch. The results of this are shown in Table E-1.

Table E-1: T-Mobile Market Share By Country Average By Year After Launch													
Years After Launch	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Hungary	100%	80%	73%	64%	63%	60%	58%	53%	51%	51%	48%	46%	45%
Macedonia	100%	100%	86%	76%	69%	67%	62%	58%	66%	NA	NA	NA	NA
Croatia	62%	55%	51%	53%	51%	53%	56%	48%	47%	46%	47%	NA	NA
Montenegro	47%	42%	33%	41%	37%	NA	NA	NA	NA	NA	NA	NA	NA
Slovakia	44%	45%	40%	41%	41%	NA	NA	NA	NA	NA	NA	NA	NA
Average Market Share After	70.6%	64.4%	56.6%	55.0%	52.2%	60.0%	58.7%	53.0%	54.7%	48.5%	47.5%	46.0%	45.0%

Source: Appendix G

We fit a linear regression line to these averages in order to smooth them, as there was an awkward and unrealistic jump in the averages between the fourth and fifth years. Fitting a linear regression line to this data created a more realistic decreasing pattern. Figure E-1 illustrates the data, the regression line, and the regression equation as well as the corresponding R-Squared value.



Source: Appendix G

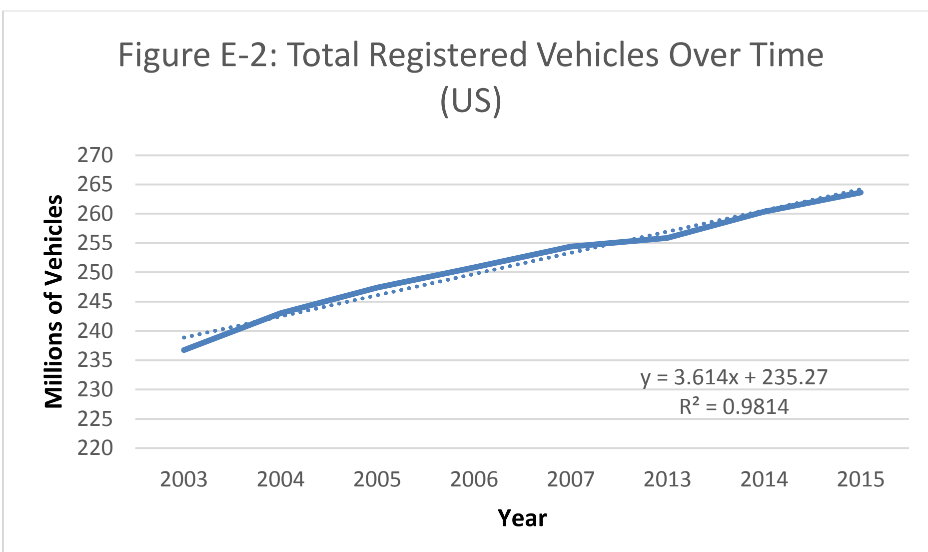
We acknowledge that linear regression is not the best method for analyzing time-series data; however, we believe it is justified since we are merely using it to smooth the indicated averages.

We also acknowledge that the data underlying this analysis is limited due to the small sample size. In addition, we must also make an assumption that the market share data for T-Mobile is representative of what Safelife's market share would be for launching an autonomous insurance policy. Therefore, we recommend taking the strategic marketing actions recommended in Section 4 of the report in order to guarantee that this market share is attainable.

Section E-2: Projection of Total Cars in Carbia Over Time

Another analysis that was necessary for projecting Safelife's total pure premium was determining the total amount of cars in Carbia over time. We decided to assume that the number of cars in Carbia would grow at the same rate as that of the United States.

We used a report from the NHTSA to assemble a dataset containing the total number of registered highway vehicles in the U.S. over time (Sprung et al., 2017). We then fit a linear regression line to this data over time. The results of this regression are shown in figure E-2 below.



Source: Appendix G

We omitted the years 2008-2012 from this analysis as the global recession clearly impacted this number across those years. The fit of this line was also much stronger after omitting these years.

Therefore, we project that the number of cars in the US will increase by about 3.614 million cars each year. Starting from 2015, where we know the total number of registered vehicles, we carried this projection forward through 2035. We then examined the year-to-year rate of change from this projection. We then applied the same rate of change to Carbia for each year starting from the year 2018. We found the total Carbia cars in 2018 by taking Safelife's exposure in 2018 (2,292,932 car years of exposure) and divided it by Safelife's market share (34%) in order to estimate Carbia's total cars at 6,743,918 cars. The results of applying the rate of vehicle number increase to this number are shown in table E-2 below:

Table E-2: Total Carbia Cars Projection			
Year	Total US Cars	Rate of Increase	Total Carbia Cars
2018	274,452,219	1.334%	6,743,918
2019	278,066,219	1.317%	6,832,722
2020	281,680,219	1.300%	6,921,526
2021	285,294,219	1.283%	7,010,331
2022	288,908,219	1.267%	7,099,135
2023	292,522,219	1.251%	7,187,939
2024	296,136,219	1.235%	7,276,743
2025	299,750,219	1.220%	7,365,548
2026	303,364,219	1.206%	7,454,352
2027	306,978,219	1.191%	7,543,156
2028	310,592,219	1.177%	7,631,960
2029	314,206,219	1.164%	7,720,765
2030	317,820,219	1.150%	7,809,569
2031	321,434,219	1.137%	7,898,373
2032	325,048,219	1.124%	7,987,177
2033	328,662,219	1.112%	8,075,982
2034	332,276,219	1.100%	8,164,786
2035	335,890,219	1.088%	8,253,590

Source: Appendix G

Section E-3: Cost of Autonomy Analysis

Another analysis required for this project was determining how much value autonomous technology adds to a car on average. We believe this will be directly tied to the severity of car accidents with AVs in the future, so this was an important analysis for our project.

We found a study that provided the cost of Level 3 and Level 4 autonomous technology as of 2015 and how this cost is expected to decrease over time (Bansal, 2017).

We found the average car price in USD for February 2018 to be about $35,300 ("Average New-Car Prices Jump 2 Percent for March 2018 on SUV Sales Strength, According to Kelley Blue Book", 2018). In addition, we also found that the average annual car price inflation from 2000 to 2018 to be about 0.1017% ("Historical Price Inflation for Cars", n.d.). We used this to project the average car price through 2035. In order to determine how much cost autonomous technology adds to a car, we used the following formula:

$$\frac{Avg.\,Car\ Price + Estimated\ Cost\ of\ Autonomy}{Avg.\,Car\ Price}$$

We conducted this calculation separately for Level 3 and Level 4 technology. We assumed that the price of Level 4 technology is representative of the price of all autonomous vehicles while we assumed that the price of Level 3 technology is representative of the price for all SAVs.

We applied the factors directly from the above formula to the FAV and SAV adjustment factors for only Collision and Comprehensive. We believe these factors are only relevant to these two coverages since other coverages are oriented around damage to people or property other than the vehicle.

The cost of autonomy data, as well as the development of these factors, is found in Table E-3 below:

Table E-3: Cost of Autonomy Analysis							
Year	Avg Car Price	Level 3 Autonomy Cost	Level 4 Autonomy Cost	Level 3 Car cost	Level 4 Car Cost	L3 Addl Cost Factor	L4 Addl Cost Factor
2018	$ 35,300	$ 12,861	$ 34,295	$ 48,161	$ 69,595	1.36432	1.97153
2019	$ 35,336	$ 12,218	$ 32,580	$ 47,553	$ 67,916	1.34576	1.92202
2020	$ 35,372	$ 11,607	$ 30,951	$ 46,979	$ 66,323	1.32813	1.87503
2021	$ 35,408	$ 11,026	$ 29,404	$ 46,434	$ 64,811	1.31141	1.83043
2022	$ 35,444	$ 10,475	$ 27,933	$ 45,919	$ 63,377	1.29554	1.78811
2023	$ 35,480	$ 9,951	$ 26,537	$ 45,431	$ 62,017	1.28048	1.74794
2024	$ 35,516	$ 9,454	$ 25,210	$ 44,970	$ 60,726	1.26618	1.70982
2025	$ 35,552	$ 8,981	$ 23,949	$ 44,533	$ 59,501	1.25262	1.67365
2026	$ 35,588	$ 8,532	$ 22,752	$ 44,120	$ 58,340	1.23974	1.63931
2027	$ 35,624	$ 8,105	$ 21,614	$ 43,730	$ 57,239	1.22752	1.60673
2028	$ 35,661	$ 7,700	$ 20,534	$ 43,361	$ 56,194	1.21593	1.57581
2029	$ 35,697	$ 7,315	$ 19,507	$ 43,012	$ 55,204	1.20492	1.54646
2030	$ 35,733	$ 6,949	$ 18,532	$ 42,682	$ 54,265	1.19448	1.51861
2031	$ 35,769	$ 6,602	$ 17,605	$ 42,371	$ 53,374	1.18457	1.49218
2032	$ 35,806	$ 6,272	$ 16,725	$ 42,078	$ 52,531	1.17516	1.46710
2033	$ 35,842	$ 5,958	$ 15,889	$ 41,800	$ 51,731	1.16623	1.44329
2034	$ 35,879	$ 5,660	$ 15,094	$ 41,539	$ 50,973	1.15776	1.42070
2035	$ 35,915	$ 5,377	$ 14,339	$ 41,292	$ 50,255	1.14972	1.39926

Source: Appendix G

Appendix F – Extended Liability Discussion

Our calculations rely on the assumption that liability will fall primarily on owners/owner's insurers. Instead, some maintain that products liability law will cause manufacturers to retain full liability for their vehicles. This outcome has two major assumptions: (1) Manufacturers own ALL vehicles; (2) Every vehicle is fully autonomous (The CAS Automated Vehicles Task Force, 2018). The CAS Automated Vehicles Task Force believes this shift to products liability could cause the average vehicle premium to increase two to three times. For premiums to remain level, the accident frequency would need to decrease by an estimated 75% (The CAS Automated Vehicles Task Force, 2018). However, a shift to products liability may have less impact on premiums if manufacturers accept liability if their self-driving vehicles cause a collision. In the United States, Volvo, Google, Mercedes-Benz, and Audi have stated they will accept this full liability (Branman, 2015 & "Audi confirms acceptance of liability in self-driving car accidents", 2017). We believe that this type of legislation is outside the scope of our projections and likely won't reach Carbia within the ten years of our projection. However, the possibility of this legislation should be kept in mind for long-term planning.

Appendix G – Attached Excel Files

Table G-1 provides an overview of the Excel workbooks included with this report.

Table G-1: Attached Excel Files		
Excel File Name	**Scope**	**Description**
A Team - Adoption Curve Analysis	Appendix C	Provides the analysis utilized to develop the adoption curves shown in the report
A Team - Competitive Analysis Summary	Appendix B	Provides the calculations derived from competitive analysis AND samples of competitor filings which we referenced
A Team - Miscellaneous Supporting Calculations	Appendix E	Includes the three supporting analyses discussed in Appendix E
A Team - Pure Premium Development Workbook	Appendix D, Sections 5-6	Includes all calculations relevant to developing the final premium on both a per exposure basis and an aggregate basis
A Team - Safelife 2030 Sensitivity Analysis	Section 7	Provides both a static and a flexible version of the 2030 sensitivity analysis
A Team - Safelife Traditional Factor Development	Appendix A	Includes the development of all Risk Class factors as discussed in Appendix A.
A Team - Data for R Code	Appendix A	Includes the data we used in R with exact data names so that ARIMA models can be recreated

Appendix H – R-Code

```
# Setting up quarterly variables
claimdataqtr = read.csv("CarbiaClaims_Quarterly.csv")
claimdataqtr1 = subset(claimdataqtr, Year>=2011)

avgBIqtr = claimdataqtr$sBI/claimdataqtr$Exposure
avgPIqtr = claimdataqtr$sPI/claimdataqtr$Exposure
avgPDqtr = claimdataqtr$sPD/claimdataqtr$Exposure
avgCOLqtr = claimdataqtr$sCOL/claimdataqtr$Exposure
avgCOMPqtrfull = claimdataqtr$sCOMP/claimdataqtr$Exposure
avgCOMPqtr = claimdataqtr1$sCOMP/claimdataqtr1$Exposure

# Setting up yearly variables
claimdatayear = read.csv("CarbiaClaims_Yearly.csv")
claimdatayear1 = subset(claimdatayear, Year>=2011)
avgBIyear = claimdatayear$sBI/claimdatayear$Exposure
avgPIyear = claimdatayear$sPI/claimdatayear$Exposure
avgPDyear = claimdatayear$sPD/claimdatayear$Exposure
avgCOLyear = claimdatayear$sCOL/claimdatayear$Exposure
avgCOMPyearfull = claimdatayear$sCOMP/claimdatayear$Exposure
avgCOMPyear = claimdatayear1$sCOMP/claimdatayear1$Exposure

# Quarterly Aggregate Model setup
avgBIqtrts = ts(avgBIqtr,start=c(2009,1),end=c(2018,4), frequency=4)
avgPIqtrts = ts(avgPIqtr,start=c(2009,1),end=c(2018,4), frequency=4)
avgPDqtrts = ts(avgPDqtr,start=c(2009,1),end=c(2018,4), frequency=4)
avgCOLqtrts = ts(avgCOLqtr,start=c(2009,1),end=c(2018,4), frequency=4)
avgCOMPfullqtrts = ts(avgCOMPqtrfull,start=c(2009,1),end=c(2018,4), frequency=4)
avgCOMPqtrts = ts(avgCOMPqtr,start=c(2011,1),end=c(2018,4), frequency=4)

acfavgBIqtr = Acf(avgBIqtr)
acfavgPIqtr = Acf(avgPIqtr)
acfavgPDqtr = Acf(avgPDqtr)
acfavgCOLqtr = Acf(avgCOLqtr)
acfavgCOMPqtr = Acf(avgCOMPqtr)

autoArimaavgBIqtr = auto.arima(avgBIqtrts, ic = "aic")
autoArimaavgPIqtr = auto.arima(avgPIqtrts, ic = "aic")
autoArimaavgPDqtr = auto.arima(avgPDqtrts, ic = "aic")
autoArimaavgCOLqtr = auto.arima(avgCOLqtrts, ic = "aic")
autoArimaavgCOMPqtr = auto.arima(avgCOMPqtrts, ic = "aic")

# Yearly Aggregate Model Setup
avgBIyearts = ts(avgBIyear,start=c(2009),end=c(2018), frequency=1)
avgPIyearts = ts(avgPIyear,start=c(2009),end=c(2018), frequency=1)
avgPDyearts = ts(avgPDyear,start=c(2009),end=c(2018), frequency=1)
```

```
avgCOLyearts = ts(avgCOLyear,start=c(2009),end=c(2018), frequency=1)
avgCOMPfullyearts = ts(avgCOMPyearfull,start=c(2009),end=c(2018), frequency=1)
avgCOMPyearts = ts(avgCOMPyear,start=c(2011),end=c(2018), frequency=1)

acfavgBIyear = Acf(avgBIyear)
acfavgPIyear = Acf(avgPIyear)
acfavgPDyear = Acf(avgPDyear)
acfavgCOLyear = Acf(avgCOLyear)
acfavgCOMPyear = Acf(avgCOMPyear)

autoArimaavgBIyear = auto.arima(avgBIyearts, ic = "aic")
autoArimaavgPIyear = auto.arima(avgPIyearts, ic = "aic")
autoArimaavgPDyear = auto.arima(avgPDyearts, ic = "aic")
autoArimaavgCOLyear = auto.arima(avgCOLyearts, ic = "aic")
autoArimaavgCOMPyear = auto.arima(avgCOMPyearts, ic = "aic")

par(mfrow=c(1,2))
# Plotting time series side-by-side
plot(avgBIqtrts, main="Quarterly Basis\nBI Coverage", ylim=c(350,450))
plot(avgBIyearts, main="Yearly Basis\nBI Coverage", ylim=c(350,450))

par(mfrow=c(4,2))

plot(avgPIqtrts, main="Quarterly Basis\nPI Coverage", ylim=c(150,300))
plot(avgPIyearts, main="Yearly Basis\nPI Coverage", ylim=c(150,300))

plot(avgPDqtrts, main="Quarterly Basis\nPD Coverage", ylim=c(300,450))
plot(avgPDyearts, main="Yearly Basis\nPD Coverage", ylim=c(300,450))

plot(avgCOLqtrts, main="Quarterly Basis\nCOL Coverage", ylim = c(400,700))
plot(avgCOLyearts, main="Yearly Basis\nCOL Coverage", ylim = c(400,700))

plot(avgCOMPfullqtrts, main="Quarterly Basis\nCOMP Coverage", ylim = c(100,600))
plot(avgCOMPfullyearts, main="Yearly Basis\nCOMP Coverage", ylim = c(100,600))

# Plotting autocorrelations
par(mfrow=c(5,2))

plot(acfavgBIqtr, main="Quarterly Basis\nBI Coverage", xlim=c(1,16))
plot(acfavgBIyear, main="Yearly Basis\nBI Coverage", xlim=c(0.5,9))

plot(acfavgPIqtr, main="Quarterly Basis\nPI Coverage", xlim=c(1,16))
plot(acfavgPIyear, main="Yearly Basis\nPI Coverage", xlim=c(0.5,9))

plot(acfavgPDqtr, main="Quarterly Basis\nPD Coverage", xlim=c(1,16))
plot(acfavgPDyear, main="Yearly Basis\nPD Coverage", xlim=c(0.5,9))
```

```r
plot(acfavgCOLqtr, main="Quarterly Basis\nCOL Coverage", xlim=c(1,16))
plot(acfavgCOLyear, main="Yearly Basis\nCOL Coverage", xlim=c(0.5,9))

plot(acfavgCOMPqtr, main="Quarterly Basis\nCOMP Coverage", xlim=c(1,15))
plot(acfavgCOMPyear, main="Yearly Basis\nCOMP Coverage", xlim=c(0.5,8))

# Summary of each forecast
summary(autoArimaavgBIyear)
summary(autoArimaavgPIyear)
summary(autoArimaavgPDyear)
summary(autoArimaavgCOLyear)
summary(autoArimaavgCOMPyear)

# Yearly forecasts thru 2032
avgBIyearforecast = forecast(autoArimaavgBIyear, h=12)
avgPIyearforecast = forecast(autoArimaavgPIyear, h=12)
avgPDyearforecast = forecast(autoArimaavgPDyear, h=12)
avgCOLyearforecast = forecast(autoArimaavgCOLyear, h=12)
avgCOMPyearforecast = forecast(autoArimaavgCOMPyear, h=12)
```

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