

Casualty Actuarial Society E-Forum, Spring 2018



The CAS *E-Forum*, Spring 2018

The Spring 2018 edition of the CAS *E-Forum* is a cooperative effort between the CAS *E-Forum* Committee and various CAS committees, task forces, working parties and special interest sections.

This *E-Forum* contains the report of the CAS Automated Vehicles Task Force and one independent research paper.

CAS *E-Forum*, Spring 2018

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CASUALTY ACTUARIAL SOCIETY

Automated Vehicles and the Insurance Industry

A Pathway to Safety: The Case for Collaboration

The CAS Automated Vehicles Task Force

CASUALTY ACTUARIAL SOCIETY

The Casualty Actuarial Society (CAS) is a leading international organization for credentialing and professional education. Founded in 1914, the CAS is the world's only actuarial organization focused exclusively on property and casualty risks and serves over 8,000 members worldwide. CAS members are experts in property and casualty insurance, reinsurance, finance, risk management, and enterprise risk management. Professionals educated by the CAS empower business and government to make well-informed strategic, financial and operational decisions.

THE CAS AUTOMATED VEHICLES TASK FORCE

Autonomous vehicles represent a revolution in the automobile industry, one that will affect not only vehicle safety, but our lives and society as well. The CAS Automated Vehicles Task Force (AVTF) was formed to research the impact on insurance and risk management of the implementation of this technology, as well as the legislative implications that will arise.

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PREFACE

Automated vehicles (AVs) have the potential to significantly change people's lives. While there are many specific questions and issues — for example, when AVs are likely to be rolled out, or become the predominate mode of travel — that are the subject of vigorous, even contentious debate with respect to AVs, the potential of AVs to change transportation and the way we live is basically undeniable.

Much of the thinking, research, and public pronouncements regarding AVs has occurred in silos, focusing on issues or technological advancements of most interest to a particular group, organization, or industry. Indeed, it is understandable that, for an innovation whose effects are potentially so deep and far-reaching, a wide variety of industries and organizations would have interest, both in the topic and in its outcome. But is working independently the most effective and efficient environment in which to bring such new technology safely to the public?

This document reflects the research, deliberations, and current thinking of the Automated Vehicles Task Force (AVTF) of the Casualty Actuarial Society (CAS). Our overarching theme and belief is that actuaries, and the insurance and risk management industries, have a critical role to play in responsibly and cost-effectively bringing new technologies such as this to market. We also believe that it is imperative for the various parties and stakeholders — manufacturers, technologists, policymakers, attorneys, risk managers, insurers, and actuaries — to cooperate during the development and rollout of AV technology, and address collaboratively issues such as defining and collecting appropriate data, considering potential liability systems for an AV world, and establishing appropriate performance benchmarks by which to evaluate AV technologies.

Why actuaries? Actuaries are skilled and experienced in identifying, quantifying, and managing risks. Only through a proper assessment of risk can certain critical decisions be responsibly made: e.g., when AV technology is ready for deployment, how risk should be priced and managed, and what is the optimal public policy approach to take toward resolving potential future liabilities associated with the technology.

Why multidisciplinary cooperation? Collaboration early in the developmental and testing phases will allow for identification and specification of consistent data formatting and collection processes. Clean, consistent data are essential for proper analytical evaluation, which is necessary in order to quantify the risks associated with AVs. In addition, many other critical decisions will need to be made, including a risk-minimizing AV rollout strategy, and an optimal liability system for an AV world. A multidisciplinary approach, across functions and industries, will help ensure that all perspectives are considered and included.

More generally, the CAS AVTF has taken a somewhat different approach to AV research than other organizations. Our motivation is action-oriented: we are focused on what should be done to ensure the technology is brought to market as safely and efficiently as possible. We are not concerned with predicting when the technology will arrive or what its societal impact will be. While interesting, such predictions will not make the technology safer or more affordable. Nor do they allow us to see what decisions or changes need to be made to accomplish these goals. While actuaries will not be the ultimate arbiters of these decisions, we can help ensure the right questions are being asked and the right data are being used and analyzed by the right people to answer these questions.

We have purposely restricted our studies to areas in which casualty actuaries have expertise: the implementation and evaluation of insurance pricing models, the quantification of liability costs, and the analysis of risks. It should not be inferred that we believe the selected topics are the ones most important to

the automated vehicle discussion — but they *are* important topics, and we believe that our involvement in them can benefit and expedite the entire process.

For the general reader, this report may appear, deliberately so, to be somewhat lengthy and detailed. This is because we have multiple audiences in mind. While we want our research and conclusions to be accessible to the general public, the report is consciously written to accommodate individuals interested in gaining a detailed understanding of the issues, with a view toward what can be done to improve the autonomous vehicle development and risk management process, as well as an understanding of why these steps are needed and how they will benefit the introduction of AVs. It is our hope and desire that this document represents an early stage of an ongoing dialogue, and that the details and assumptions described will allow future studies to build upon this work.

Furthermore, it is essential that the complexity and nuance involved in each of the issues addressed herein is fully appreciated. Many of the questions surrounding automated vehicles involve tradeoffs and uncertainties. Embracing the complexity and working to better understand the risks will ensure a purposeful, balanced decision-making process with respect to developing, introducing, and sustaining AVs.

Where there is risk and uncertainty, actuaries facilitate better decision-making. We hope that this report will help “contribute to the well-being of society as a whole,” as dictated by the Casualty Actuarial Society’s mission statement.

EXECUTIVE SUMMARY OF THE OVERALL REPORT

Introduction

The development, introduction, and rollout of automated vehicle technology depends upon the collection of relevant data and its analysis. The specification of collected data types and formats should be a cooperative effort amongst all parties to AVs — manufacturers, technologists, policymakers, attorneys, risk managers, insurers, and actuaries — in order to ensure that all perspectives and stakeholder needs are considered.

Casualty actuaries, properly engaged and utilized, can help automated vehicle technology reach market as safely and efficiently as possible. Where safety and efficiency diverge or come into conflict, casualty actuaries, skilled and experienced in assessing risks, can quantify and clarify the inherent tradeoffs involved.

There are three specific areas where casualty actuaries' involvement can aid the technology's development. These topics correspond to the three papers comprising this report.

Topic 1: Insurance Premiums

The pricing of insurance for automated vehicles depends upon collecting appropriate and adequate data, making a variety of assumptions, and possibly requiring the development of new actuarial techniques.

In the long-run, insurers will price automated vehicles appropriately. Basic insurance pricing practices require premiums to follow costs, so if AVs lead to lower losses, those will eventually lead to lower premiums. However, the long-run view tells us nothing about the actual insurance premium discount the technology will receive when first introduced. And the cost of risk in the marketplace is important to the disposition of the technology: overpricing the technology may make this potentially lifesaving advancement too expensive for some, while underpricing the technology forces the individuals in non-AVs (presumably less-safe vehicles) to subsidize the AV-insureds' premiums and shoulder a greater portion of the cost and driving risk. Accurate pricing of risks is necessary to avoid such cross-subsidies.

Using some traditional techniques, insurers' pricing models could take a long time to recognize improved performance that results from vehicle construction (such as improved safety resulting from AV technology). Based on the model we used and on certain assumptions which are meant to be illustrative, a vehicle that reduces losses by 50 percent will only receive an 8 percent discount after four years. If completely crashless, the discount will only be 15 percent. However, this is dependent on the technology's introduction, the number of vehicles with the technology, and the insurer's view of the risk. The more vehicles with the technology, the greater the discount will be. When varying these assumptions, a completely crashless car could earn up to a 78 percent discount after four years (see [Table 4](#)). Today, insurers are often unable to identify the technology's presence on vehicles; thus, they are unable to distinguish between vehicles with the technology and those without. This is an example of the need for cooperative and multidisciplinary data specification and collection: insurers and manufacturers need a more direct and transparent collaboration to ensure the technology is clearly identifiable in the insurers' datasets and its performance is explicitly quantified.

Topic 2: Liability System

To insure the risks associated with automated vehicles, policymakers may consider a shift from a negligence-based personal auto liability system, to a strict products liability setting — but such decisions should contemplate all potential system costs, not just claims costs.

The mechanisms by which automated vehicle liability will (or should) be evaluated, and responsibility assessed, are complex issues that necessarily involve tradeoffs. From an insurance and risk management standpoint, greater coverage for such liability is accompanied by greater costs. Adopting certain provisions for legal responsibility in the liability system might make it more difficult to achieve certain claim settlement goals. A detailed, transparent evaluation of the costs, benefits, and risks is necessary for the American public, through their democratically elected representatives, to ensure the optimal liability system is in place when automated vehicles are brought to market.

With the move toward automated vehicles, it is possible that the liability insurance mechanism will shift from personal automobile to products liability. Such a shift would bring with it greater coverage — but that greater coverage would be accompanied by higher frictional costs. Combining coverage and costs, the shift would double or perhaps even triple the average vehicle premium, with a smaller portion of each premium dollar going toward claimant compensation. Frequency would have to decrease by almost 75 percent for the vehicle premium to be unchanged. While other issues may be more important than the cost of coverage, they should be evaluated through a similar prism, with the end result being purposefully selected. The active participation of casualty actuaries (who facilitate better decision-making where there is risk and uncertainty) and the insurance industry (which specializes in compensating claimants fairly and efficiently) in the evaluation will support and enhance the analysis and the decision-making process.

Topic 3: Automated Vehicle Risks

AV risks need to be accurately and realistically measured and understood, and compared to appropriate benchmarks.

The safe introduction of automated vehicles requires a direct recognition of the risks that the technology will encounter. Identifying and addressing these risks requires detailed datasets and risk management expertise. After identifying and quantifying the risks and their correlations, the risk-minimizing introduction strategy requires the creation of a single, comprehensive approach that looks at the risk holistically and in total. Analyzing and addressing risks in a linear, silo-type fashion fails to recognize the reality of the situation, and therefore fails to accomplish its goal.

Once a rollout strategy is developed, the technology's performance must be understood. This requires the calculation of an accurate benchmark that the technology's experience can be compared against. Only casualty actuaries' predictive models, built off insurers' robust datasets, are granular, accurate, unbiased, responsive, and stable enough to effectively evaluate the technology's performance. For example, these models could be used to compare an automated vehicle's performance against groups of drivers based upon type of driver, geography, including or excluding certain kinds of drivers or accidents, etc. An accurate benchmark permits the performance to be better understood, thereby allowing safer vehicles to reach market quicker.

Conclusion

Casualty actuaries will not build the transformational AV technology — however, by pricing the technology accurately, we can provide a financial incentive to purchase technology that reduces losses and makes life more convenient and flexible. Casualty actuaries will not create the liability system that governs automated vehicle incidents, however, by quantifying the premiums and other costs involved in the different systems, we can illuminate and quantify the costs and benefits involved in the tradeoffs, thereby ensuring a transparent and unbiased decision-making process. Casualty actuaries will not bring the technology to market, however, by establishing a more granular, accurate, and responsive benchmark, we can place the technology's performance in more appropriate context and allow safer products to reach the market quicker. Through these small but important contributions, casualty actuaries can help ensure the technology is brought to market as quickly, efficiently, and safely as possible.

1: Automated Vehicles’ Impact on Personal Automobile Premiums — “What discount will I receive?”

EXECUTIVE SUMMARY OF TOPIC 1

Accurate pricing of products and services, including automated vehicle technology, benefits society. If AV risk is overpriced, resulting in consumers being overcharged for AV insurance, their cost is increased, making them less affordable. This unnecessarily slows the adoption of potentially lifesaving AV technology. Conversely, underpricing AV risk, and thus undercharging for AV insurance, reduces their cost, making AVs more attractive than their risks warrant, and forcing other non-AV insureds (with presumably less-safe vehicles) to be overcharged for insurance. In such a situation, the individuals with the least-safe vehicles are not only taking on a disproportionate share of risk, they are also shouldering a disproportionate share of the insurance costs. Such a circumstance is generally considered an undesirable cross-subsidy. Accurately pricing AVs when they are introduced allows consumers to make more informed decisions. To the extent the technology reduces insured losses, accurate pricing of risk and insurance provides a financial incentive for consumers to purchase vehicles with the technology.

The question “what premium discount will an insured receive for purchasing a vehicle with loss-reducing technology” requires an evaluation of the effectiveness of insurers’ pricing models. In this research, the CAS AVTF received unique access to an actual insurer’s pricing model and data. Access to this model has allowed the AVTF to differentiate its research and findings from other studies, which have simply evaluated the aggregate premium change. Focusing on aggregates leaves unanswered the question of what must be done to ensure the vehicles are priced appropriately.

Current auto insurance pricing models are created for today’s driving environment, where the individual is the largest determinant of accident costs. Our research demonstrates that, by using these current models in an emerging AV environment, there may be a significant lag between introducing safer technology and seeing the consequent impact reflected in auto insurance premiums. For example, based on one insurer’s pricing model, we found that, if the vehicle is categorized as a “new” model, with no comparable prior model year, then a vehicle that lowers loss costs by 50 percent will only receive an 8 percent premium discount after four years. Even a vehicle with no losses will still only receive a 15 percent premium discount after four years. On the other hand, if the technology is introduced on existing automobile models, the insurance pricing model will give its experience more weight, resulting in a larger premium discount. With this approach, the average premium discount after four years for a vehicle that reduces losses by 50 percent will be 21 percent; the maximum discount will be 38 percent (see [Table 4](#)).

These figures are examples, based upon several other illustrative assumptions. The actual discount the vehicle receives depends not only on the technology’s ability to reduce losses and on how the insurer categorizes the vehicle (new or existing car model), but also on the number of vehicles with the technology, and how the technology is rolled out. For example, the numerical results above assume manufacturers will introduce the technology as a standard automobile feature — although this is not reflective of today’s reality. Currently, it is very difficult, and sometimes impossible, for insurers to distinguish between vehicles with and without advanced technology. Unless this changes, improved performance will take even longer to be reflected in premium discounts. This is one reason that a multidisciplinary, collaborative effort to specify types and formats of data, and then to collect that data, is so important.

The best way for the technology to be priced accurately is for insurers, manufacturers, and others to develop a more direct, open, and collaborative relationship — starting with a multidisciplinary, cooperative effort to specify types and formats of data, and then to collect and analyze that data. Insurers need to better

understand the technology's performance — not to mention being able to identify whether or not advanced technology is present in the various cars that underlie the data — to quantify its impact.

In the long-run, the technology will be priced appropriately. Insurers have shown the ability to adapt to changes and trends in losses, and to develop more accurate models to meet the challenges they face. Collaboration between insurers and manufacturers will accelerate recognition of the evidence and promote pricing accuracy.

INTRODUCTION

In order for AV technology to be brought to market as safely and efficiently as possible, it is important that any reduction in insurance losses be reflected in the insurance premium. The greater the discount, the more affordable the product becomes and the quicker it will proliferate through the automobile population. Therefore, the correct question to ask is “what discount will be afforded a vehicle that reduces potential insurance losses?” This is a different question than “how will automated vehicles impact insurance premiums?” The second question can be answered by some very simple assumptions and calculations. However the first question requires access to pricing models that utilize proprietary data and complex statistical analysis. It should be no surprise then that the existing research has failed to answer the more pertinent question.

For this research, the CAS AVTF was granted access to the actual auto insurance pricing model of an insurer. While some of the data and statistics are necessarily hidden to protect this insurer, the results of our research and scenario testing are clear: based upon a pricing model like the one to which we were granted access, without more data and collaboration between interested parties, it will take a long time for improved vehicle performance to result in a significant insurance premium discount. For the interested reader’s benefit, we will first walk through the generics of insurance pricing to provide adequate context. Then, we will clearly define our assumptions, discuss the results, and recommend a pathway for improvement.

PART I: INSURANCE PRICING BASICS

Before diving into the analysis, we must first understand the basics of insurance pricing.

A. Cost Based vs. Market Pricing Approach

Personal auto insurance premiums are determined using a cost-based pricing approach. This means that your insurer estimates how much it expects to pay in claims for an insurance policy then adds its expenses and profit to it to calculate the final premium. In most states, insurers have to submit these numbers to, and sometimes gain approval from, state departments of insurance before they can finalize this price.

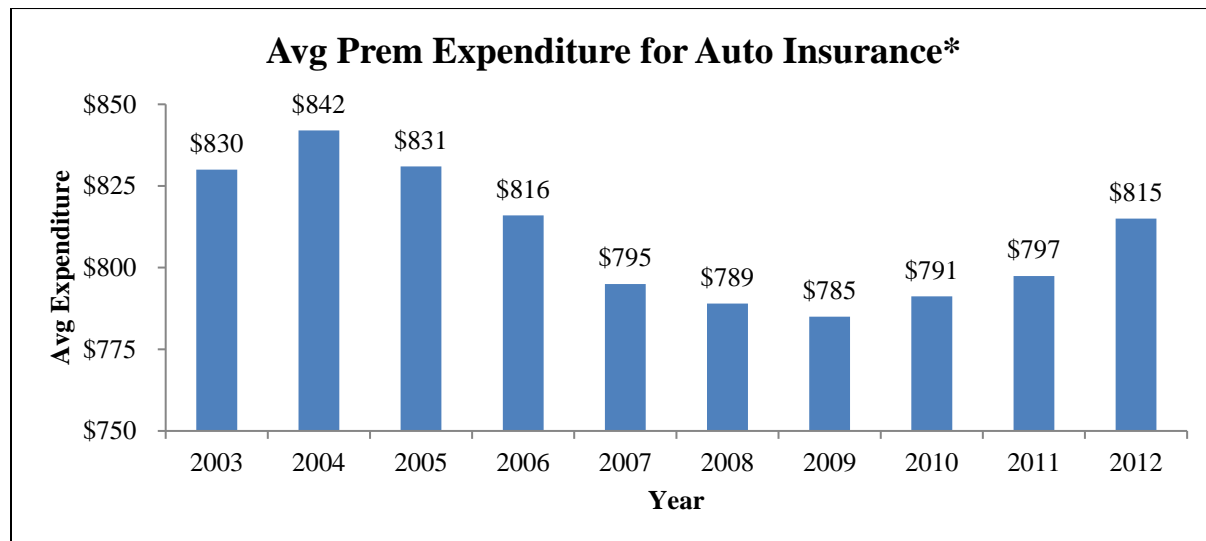
This approach differs from a market-based pricing approach where companies are allowed to charge whatever the market allows. In a cost-based system, a pair of shoes’ price would equal the cost of its inputs plus, in the case of insurance, a state approved profit margin. In a market-based system, shoes’ prices are determined by the buyers and cost however much they will pay.

If insurance losses decrease, so will premiums. This is what happened in the late 2000’s, as the average auto insurance premium decreased every year from 2005 to 2009. 2012’s average premium was lower than 2003’s average premium.¹ Assuming automated vehicles reduce insurance losses, what is important is not *if* premiums will change, but *how* and *when* premiums will change.

Note that an additional aspect of the cost-based pricing approach is that the premiums will only change if one or more of the cost components (losses, expenses, or profit load) change. Shifting the responsibility for paying these losses, say from the individual to the manufacturer, does not eliminate these costs.

¹ Source NAIC republished: <http://www.iii.org/table-archive/21247>

Table 1



*Source NAIC republished: <http://www.iii.org/table-archive/21247>

B. Law of Large Numbers

Unlike other products, insurers do not know how much their product will cost when they sell it. Consider a simple financial bond — i.e., a fixed-income security. Aside from the possibility that the issuer of the bond will default, the cash flows on a bond are fixed and predictable: the bondholder and the bond issuer know both the amount and timing of the cash flows to be received. Contrast that with auto insurance: not only are the amounts and timing of any losses uncertain at the beginning of the policy period — it is not even known *whether* there will be a loss.

The law of large numbers provides a way for insurers to come up with a stable, accurate prediction of the cost. The law states that the average result from a large number of trials will trend towards the expected value. Put simply, if insurers group a lot of similar risks together, that group’s actual costs will equal its expected costs. This allows insurers to use historical experience to predict future experience.

C. State-Based Pricing Approach

There is one final nuance to insurance pricing that may not be clear to the casual reader: insurance premiums are set at the state level. The very first step of each pricing analysis determines the state’s overall rate need. If the actuary projects a 0 percent rate need for the state, it means that the premium we expect to need is exactly the same we expect to collect. However, this doesn’t mean that every individual insured will be charged exactly the same rate. If the actuary finds that 50 percent of customers deserve a 5 percent increase, then the other half of customers will receive a 5 percent decrease to get back to the 0 percent overall change.

If loss-reducing technology is unidentified, then their lower loss potential will be shared by all the insureds in the state. Assuming the vehicles with the technology account for a small share of the state, the discount will be extremely small. Looking at the aggregate premium change, as other studies have done, tell us nothing about the premium change the individual will see. A more applicable impact analysis will calculate the discount the loss-reducing technology will receive. This will quantify the insurers’ pricing model deficiency (if any exists). It will also quantify the benefit (discount) that can be achieved by proactively addressing any deficiencies.

PART I CONCLUSION

The cost-based pricing nature of insurance guarantees that lower insurance costs will be followed by reduced premiums. What is uncertain is not if premiums will change but how and when the change will occur. How much cheaper or more expensive will AV insurance premiums be compared with their non-automated counterparts?

Accurately matching price to risk provides societal benefits. Overpricing automated vehicle technology risk and loss potential will make safer vehicles more expensive than they should be, putting them out of reach for many Americans and slowing their adoption. Conversely, underpricing AV risk will force the other drivers — in presumably less safe vehicles — to subsidize these vehicles' insurance premiums. The goal should be to price the vehicles and their risks as accurately as possible as quickly as possible.

PART II: VEHICLE PRICING MODEL BACKGROUND

Most insurers adjust insured's premiums for the cars they drive through the assignment of symbols to vehicles. A Honda Civic will (likely) have a lower symbol and insurance premium than a Bentley, reflecting its lower repair costs. So how responsive are these models to changes in vehicle technology that drives insurance losses? While these models are proprietary, the CAS's AVTF has partnered with one of the few companies that own such a model. Without direct access to such a model, the analysis would be effectively useless.

A. Model setup

For simplicity purposes, the model was run using countrywide liability (Bodily Injury/Property Damage — BI/PD) data. There is no reason to believe the results would vary significantly for individual states. It was also determined that the BI/PD results would be a reasonable proxy for the other coverages.

This does not represent an actuarial opinion that the technology will impact all coverages the same. Instead, it can only be read that if the technology reduces the coverage losses by the stated amount, the coverage specific premium will be impacted by the calculated discount.

B. Model formula

The model's basic formula is simplistic enough such that it can be shown. However, the true value lies in the underlying data that allows the insurer to come up with the most accurate pricing for each vehicle.

The vehicle's symbol is a function of the vehicle's actual experience, its prior model year's experience, and its body style (sports car, sedan, coupe, SUV, etc...). It is calculated as follows:

$$\begin{aligned} & \text{2016 Toyota Corolla vehicle symbol} \\ &= W_1 * (\text{Experience}_{2016 \text{ Toyota Corolla}}) + W_2 * (\text{Symbol}_{2015 \text{ Toyota Corolla}}) \\ &+ (1 - W_1 - W_2) * (\text{Body Style Factor}) \end{aligned}$$

W_i = Weight assigned to each factor

This has two important implications for interested stakeholders. First, the number of vehicles in the insurer's dataset matters a great deal. The more vehicles there are in the experience data the more weight will be given

to its actual experience (W_1). However, we also need to know how much weight should be given to last year's symbol (W_2). Second, how the insurer views the vehicle also matters a great deal. If the insurer believes the vehicle is so new that there is no prior model year to use in the formula, or if the vehicle is a drastic enough change where prior model years are not representative, its symbol will be driven by the Body Style Factor, a much broader category. Therefore, two separate scenarios were run to estimate how the technology might impact insurance premiums.

C. Insured loss reduction

Discussions surrounding automated vehicle impact have typically centered on its ability to decrease accident frequency. However, insurers care about the impact on *total* insurance losses, which are determined as shown:

$$\text{Insured Losses} = (\text{Number of Accidents}) * (\text{Cost of Accident}) = \text{Exposure} * \text{Frequency} * \text{Severity}$$

Reducing the frequency does not guarantee that total insured losses will also decrease, for the following possible reasons:

1. **Exposure Increase:** If drivers respond to the technology's introduction by driving more miles, then a reduction in frequency (number of accidents per mile) may be offset by an exposure increase (number of miles driven).
2. **Exposure Change:** If the technology's introduction increases driver distraction or deteriorates the driver's skill, then overall accident frequency may not change: the lower frequency while the technology is driver may be offset by a higher frequency while the individual is driving.
3. **Severity Increase:** More vehicle technology, and possibly more expensive technology, may increase the cost of repairs and offset the lower frequency.

In order to test the pricing model's effectiveness, we assume that the technology will reduce total insured losses by 25 percent, 50 percent, 75 percent and 100 percent. This is not an actuarial opinion on the technology's actual or expected effectiveness; these assumptions are provided and used for illustrative purposes.

PART III: PRICING MODEL RESULTS

A. Scenario 1 — New Vehicle

The introduction of such a transformative vehicle as one that can completely eliminate crashes (and insured losses) is likely to follow this path. Insurers will look at the vehicle as brand new vehicle and will rate it as such. This approach requires an assumed growth pattern to estimate the weights that will be used. Based on other new vehicles, we have assumed the insurer will have 2,500 vehicles in year one; 5,000 vehicles in year two; 7,500 vehicles in year three; and 10,000 vehicles in year four. These numbers appear to be reasonable, if slightly aggressive, based on vehicles counts for other new vehicles in the insurer's data set. The results are as follows:

Table 2

Vehicle Symbol Discount					
Year	Number of Vehicles	Insured Loss Reduction			
		25%	50%	75%	100%
1	2,500	0.5%	0.9%	1.3%	1.8%
2	5,000	1.4%	2.6%	3.9%	5.1%
3	7,500	2.8%	5.1%	7.4%	9.7%
4	10,000	4.4%	8.0%	11.6%	15.2%

When the technology is introduced, the vehicle will have the same symbol as its Body Style Factor. After one year of experience, the next model year will receive between a 0 percent and a 1.8 percent discount depending on how much the technology actually reduces insured losses. After four years, a vehicle that reduces insured losses by 50 percent will only be given an 8 percent discount. Four years with zero insured losses will lead to a 15.2 percent discount (based on the stated assumptions). At 10,000 exposures in Year 4, the credibility factor is still low enough that the majority of the automated vehicle’s symbol is based on the body style factor. Therefore, even a completely crashless vehicle will receive only a modest discount after four years of use.

B. Scenario 2 — Existing Vehicles

This approach uses actual vehicle counts. The assumption is that the exact same number of Honda Civics, Volvo XC 60’s, etc.... will be on the road as there are currently. This bypasses the exposure-growth period but may be less-accurate from a real-world-scenario standpoint. It has the benefit of showing how the results change in a somewhat steady-state environment. In this approach, since there are established exposures for most of the vehicles, the starting factor is the individual vehicle’s actual factor (which is a credibility-weighted mixture of vehicle and body style results). The average vehicle discount is shown below:

Table 3

Average Vehicle Symbol Discount					
Year	Number of Vehicles	Insured Loss Reduction			
		25%	50%	75%	100%
1	Actual	4.3%	7.4%	10.5%	13.6%
2	Actual	7.1%	13.7%	20.0%	26.3%
3	Actual	9.7%	18.2%	25.7%	35.4%
4	Actual	11.1%	21.0%	31.0%	41.2%

With the greater credibility, the impact of loss reduction is realized more quickly. Under this approach, after four years of zero losses, the average discount is 41.2 percent. This is because no vehicle is 100 percent credible (in fact, the maximum credibility is 78 percent for an individual vehicle), so there is always some amount — and in many cases a significant amount — of body style factor being incorporated.

There is also a large amount of variation in the answer when you use this method due to the wide range of credibility values for the individual vehicles: the more exposure data on a vehicle, the more credible its results, and the larger its potential discount. The maximum vehicle discount is shown below:

Table 4

Max Vehicle Symbol Discount					
Year	Number of Vehicles	Insured Loss Reduction			
		25%	50%	75%	100%
1	Actual	7.4%	15.0%	22.7%	30.6%
2	Actual	12.2%	24.7%	37.5%	50.5%
3	Actual	15.8%	31.9%	48.3%	65.6%
4	Actual	18.8%	38.0%	57.6%	77.6%

The difference between the tables is most easily explained through a thought experiment. Assume one 2016 Bentley is sold and does not get into an accident over the next year. How much should this experience reduce the premium for a 2017 Bentley purchased by someone else? The obvious answer is that it should have very little impact. This is what we see in Table 2, where the discount is very small.

Conversely, what if there are 400,000 Toyota Camrys sold in 2016 and none of these have an insured loss? As no vehicle is 100 percent credible, it doesn't mean that it is impossible for future Camrys to have a loss, but it does provide much more information than the Bentley. Therefore, the 2017 Camry will receive a much greater discount than the 2017 Bentley. The difference between Table 2 and Table 4 illustrates the impact that volume has on the calculation.

C. Complicating Factor

The prior analysis assumed that, when the loss-reducing technology was introduced on a vehicle, it was introduced as a standard feature. However, this is not reflective of reality. On many vehicles, advanced technology is optional, and its presence is not included in the VIN. When this is the case, insurers can have trouble distinguishing between the vehicles that have the technology and those that do not. The vehicles with the technology and those without the technology are grouped together in the insurer's data. This will mute the technology's observed impact. Assuming the insurer cannot identify the vehicles with and without the technology, then having every Honda Civic equipped with technology that reduces losses by 50 percent will be viewed as the same way as having half of Honda Civics equipped with technology that reduces losses by 100 percent. Therefore, the actual discount depends not only on the insurer's model, but also on the way the manufacturer introduces it (e.g., standard equipment vs. optional equipment, whether it's identifiable in the VIN, etc.).

PART III - CONCLUSION

Auto insurers have shown a willingness to invest in data and improve their models to develop the most accurate price possible for insuring the risk of potential losses. Many have implemented a multi-variate rating approach, expanded the number of variables in their data set, and developed coverage level vehicle rating factors. If automobile accident risk factors change, competitive pressures will force insurers to develop new models that more accurately match the premium to the risk.

However, the creation of these models will not be quick or easy. Current auto insurance pricing models are built off and built for the current driving environment, where the individual is the main cause of the accident. Therefore, it will take a long time for improved expected performance, driven by the vehicle, to result in a lower insurance premium. The length of time it takes will be impacted by technology's ability reduce costs,

the number vehicles with the technology, how the insurer views the data, and how the manufacturer introduces the technology.

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TOPIC 1
AUTO INSURANCE PRICING
RECOMMENDATION

The best way for these vehicles to be priced as accurately as possible and as quickly as possible is for manufacturers and casualty actuaries to develop a much more direct, open, and collaborative relationship.

The better and sooner auto insurers understand AV technology, the faster its impact on insurance premiums will work its way into and through auto insurance pricing. Insurers need to understand how the technology works, assess how individuals will use it, and ultimately estimate how it will impact insurance losses. This requires the insurer to figure out what data must be collected and how to interpret that data. This will necessitate insurers and manufacturers working more closely together and sharing data and experience. Engaging the insurance industry in any automated vehicles tests that are being conducted can help insurers progress more quickly along the learning curve and decrease the time it takes to accurately price the new technology.

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2: Automated Vehicle Liability — Compensating claimants fairly and efficiently

EXECUTIVE SUMMARY OF TOPIC 2

The fully self-driving car is unique in terms of its potential liability. No other common consumer product is as necessary, as utilized, and as dangerous as the automobile. This potential liability is demonstrated by statistics for the two most recent years for which final mileage and fatality figures are available. Americans drove over three trillion miles in 2015, or “approximately 337 round trips from Earth to Pluto.”² This volume of driving resulted in over 35,000 deaths.³ The year 2016 saw vehicle miles driven increase by 2 percent, with over 37,000 deaths.⁴

A shift to a driverless world will be unlike anything we’ve ever encountered. Neither airplanes, elevators, nor any other historical product introduction can serve as an effective guide for automated vehicles; the risk and scale are simply incomparable. What we do have, fortunately, is time. Unlike other transformational advancements, this is one we are able to (somewhat) foresee. Therefore, we should use this time to ensure the liability system surrounding the technology will be ready when the technology is.

Currently, auto liability is based primarily on a negligence system, and financial accountability in the event of a loss is ascribed to the responsible party. The purchase of a personal auto insurance policy is the typical manner in which an insured protects herself or himself from losses associated with owning and operating a vehicle. In a future AV world, some believe that a strict liability system, directed at (probably) the manufacturers of AVs, would be more appropriate and efficient, with possibly a type of products liability insurance as the standard method of protecting against liability.

The decision as to the best liability system in an AV world is an important one, with deep implications — and also several factors to consider up-front. Among other things, the ideal liability system will align responsibility and accountability, encourage manufacturers to invest in product improvement, compensate claimants fairly and efficiently, and minimize frictional costs.

Certainly a critical factor to consider and evaluate is the cost of providing liability insurance coverage in an AV environment. Conceptually, this cost is most easily quantified as the change in insurance premium resulting from the introduction of AVs. Actually quantifying the premium change is an extremely complex calculation, even with the aid of numerous simplifying assumptions, but we have attempted to do so. Assume the following: every vehicle is owned by the manufacturer; every vehicle is fully autonomous; manufacturers purchase first dollar liability coverage but self-insure physical damage claims; each vehicle has \$1 million of liability coverage; and accident frequency and severity is unchanged. Under these assumptions, we estimate that shifting liability from personal automobile insurance to products liability will increase the average vehicle premium (in 2011 dollars) from \$781 to \$1,578 — \$2,355. (The large prospective premium range demonstrates the uncertainty involved in such a simplistic analysis.) Based on these figures, accident frequency would have to decrease approximately 75 percent for a vehicle’s premium to be lower than today’s (in real dollars). Essentially, products liability is simply a more expensive type of insurance: it affords more coverage for each vehicle and that coverage costs more, with less of the premium dollar going towards claimants.

However, there are many other considerations that must be taken into account to create the optimal liability system. Pushing the costs to the manufacturers, rather than the individuals, more closely aligns accountability

² <https://www.fhwa.dot.gov/pressroom/fhwa1607.cfm>

³ <http://www.nhtsa.gov/About+NHTSA/Press+Releases/nhtsa-2015-traffic-deaths-up-07012016>

⁴ <https://www.nhtsa.gov/press-releases/usdot-releases-2016-fatal-traffic-crash-data>

and responsibility. Products liability's potentially unlimited liability affords the consumer greater coverage in the event the product does not work as intended. On the other hand, shifting claims settlement responsibility to the manufacturer decreases the chance of a fair and efficient settlement: accountability and responsibility become misaligned as manufacturers are not rewarded for fair and efficient claims handling. Neither manufacturers nor products liability insurers can match personal automobile insurers' claims handling capabilities. Personal auto insurers spend over \$20 billion a year on claims handling, which is ten times more than products liability insurers spend, twenty-times larger than NHTSA's total budget, and 150 times larger than NHTSA's "Vehicle Safety Research" budget.

Through a more collaborative and inquisitive approach, the strengths and weaknesses of different liability systems' ability to handle automated vehicles can be identified and quantified. Any deficiencies will have a better chance of being eliminated if we act soon. An effective and efficient liability system can encourage manufacturers to develop and produce a safer product while also affording the public more protection when adverse events occur.

2.1: Automated Vehicle Liability — From personal automobile to products liability: calculating the premium impact

INTRODUCTION

Any evaluation of liability necessarily involves an estimate of the costs involved. Currently, automated vehicle liability discussion has centered on auto liability versus products liability. Despite some apparent similarities, these coverages are extremely different. They are sold through different distribution and cost structures and have different coverage definitions, triggers, and amounts. These nuances' impact on premium can only be effectively quantified by casualty actuaries trained in both personal automobile and products liability pricing.

The goal of this study is not to predict what will happen or to estimate the impact on any individual policyholder, but rather to provide an understanding of the efficacy of the two liability systems as defined by the coverage they afford and the costs associated with that coverage. In the end, we can see how different the cost and coverage would be if products liability insurance rather than personal automobile insurance covered every vehicle.

PART I — ASSUMPTIONS

A. Data Sources

This analysis is focused on industry-wide results. Therefore, a single insurer's dataset would be an insufficient foundation from which to base our analysis. Therefore, we have opted to use the following industry sources:

- NAIC 2011/2012 Auto Insurance Database Report:⁵ This serves as the basis of the analysis. It provides earned exposures, earned premiums, incurred losses, and claim counts by coverage and state for the voluntary and involuntary market.
- Insurance Research Council:⁶ This is used to estimate the number of uninsured drivers in each state.
- S&P Global Market Intelligence: This was used to calculate the expense ratios for each state by expense type and coverage. It was also used to select appropriate profit targets.
- Rate Filings: Actual rate filings were used to select appropriate profit targets
- Proprietary industry data sources: Our analysis makes use of multiple, proprietary data sources. These sources will be noted and will be detailed to the extent possible.

B. Data Assumptions

The data sources, while robust, were not created with this analysis in mind. Therefore, a number of assumptions were made to allow the analysis to progress:

- Texas is excluded from the analysis. No good data source exists for the Texas private passenger auto insurance market. Rather than use inaccurate data, Texas is simply excluded from all of the numbers.
 - We assume excluding Texas will not bias the average vehicle premium calculation.
 - We will only measure the change in total insurance market relative to the benchmark; it will only be shown in percentage terms. For example, we can still conclude that the market will shrink by

⁵ http://www.naic.org/documents/prod_serv_statistical_aut_pb.pdf

⁶ <http://www.iii.org/fact-statistic/uninsured-motorists>

5 percent while excluding Texas, but we cannot conclude that the market shrink by \$500 million without having a Texas premium estimate.

- Only private passenger autos are included. Commercial automobiles and miscellaneous vehicles are excluded.
- Baseline: The 2011 private passenger insurance market, excluding Texas, is the being used as the baseline.

C. End State Assumptions

While the current personal automobile insurance market is well understood, it is much less clear what the automated vehicle market will look like. Clearly defining the end-state allows us to, piece-by-piece, replace personal automobile insurance coverage with products liability. This is not a prediction of what will happen. Nor is it a recommendation of what should happen. These simplifying assumptions merely allow for a more direct calculation of the premium change.

- The number of vehicles is unchanged.
- Every vehicle is owned by the manufacturer.
- Every vehicle is fully autonomous.
- Manufacturers purchase first dollar liability coverage but self-insure the physical damage. In other words, insurers will pay all liability claims and manufacturers will pay to fix their own vehicles.
- Severity: underlying accident severity is unchanged from today:
 - Physical damage coverage: Vehicle values are expected to be the same as they are today.
 - Liability coverage: Vehicles will carry \$1,000,000/\$1,000,000/\$1,000,000 liability limits. This means there will be \$1,000,000 of bodily injury coverage per accident and \$1,000,000 of property damage coverage for each accident.
- Claim Frequency: The end-state claim frequency is treated as an independent variable with five scenarios tested: no change (base), 10 percent reduction, 25 percent reduction, 50 percent reduction, 75 percent reduction, and 90 percent reduction.
- Other insurance coverage impacts: The impact on other insurance premiums, such as health insurance, are outside the scope of the analysis.
- “Premium” definition: we will use the term “premium” as the cost incurred to pay liability claims and physical damage repairs caused by automobile usage. This broader definition is used to better understand the true change in costs.

D. Scenarios

A singular point estimate of the premium change fails to connote the level of uncertainty involved in the analysis and outcome.

- Claim frequency: Five scenarios were run to estimate the impact changing frequency would have on premiums: No change (base), 25 percent decrease, 50 percent decrease, 75 percent decrease, and 90 percent decrease. These are not predictions of what will happen.

- Coverage: Generally, automobile insurance has bodily injury, property damage, medical coverage, uninsured/underinsured motorists coverage, comprehensive coverage, and collision coverage all split out. Many of these coverages have their own, coverage-specific limits. However, products liability would cover many of these coverages under its single liability limit. Two scenarios were calculated: adjusting the split sub-limits and rolling the sub-limits together into a single limit products liability limit.
- Tort vs. No-Fault: Auto liability claims settlement rules differ among states. In “no-fault” states, your insurer will pay your claim regardless of who is at fault. In “tort” states, the at-fault driver is responsible for the payments. We use state-specific increased limit factor adjustments to calculate the additional cost associated with higher liability limits. Therefore, we are explicitly considering the different liability systems’ impact on liability costs.
- Fixed vs. Variable Expenses: Actuarial pricing indications will split expenses into its fixed and variable components. Some expenses, like taxes and commissions, scale with premiums. Others, like salaries, are typically fixed and are not impacted by small premium changes. However, fixed expenses must change when there are large changes in the business: if a company grows by 50 percent it must hire more workers, and the salary growth will scale, somewhat, with the premium growth. Due to the uncertainty involved in such a dramatic shift in coverage, two scenarios were calculated: first, assuming expenses will be 100 percent variable and second, splitting the expenses into their fixed and variable components.

E. Industry Premium Impact

While the focus of the study is on the change in average vehicle cost, we also calculate the change in the insurance industry’s overall premium size. This calculation is aimed at providing additional context for the changes. The impacts are shown in blue, bold, and italicized font after the average vehicle premium change is shown. The industry impact numbers are only shown in percentage terms (due to Texas’ exclusion). The average vehicle premium change and industry premium change will not match. Do not try to tie the industry change to any number in the chart shown above it.

PART II — BASELINE INSURANCE PREMIUM CALCULATION

In order to calculate the premium will change, we first must begin by breaking down current automobile insurance premiums into their underlying components:

Premium = Expected Claim Payments + Expenses + Profit

- Expected Claim Payment = Exposure * Frequency * Severity
 - Exposure = Earned vehicle year
 - Frequency = Number of claims per vehicle year
 - Severity = Loss dollars per claim
- Expenses = Loss adjustment expenses + Acquisition expenses + General & other expenses + Taxes
 - Loss adjustment expenses = Defense Costs + Other adjustment expenses
 - Acquisition expenses = Commission + Other Acquisition expenses
 - Taxes = Taxes, licenses & fees

Defense Costs and Containment (DCC)

Defense costs merit special discussion before moving on. These costs are the amount the insurer spends on lawyers and other claim specific expenses. The costs typically fall outside the policy limits and are small for personal auto insurance. While this is often included with claim payments, it is important to split it out as the costs scale with the limit — the higher the limit, the higher the potential payment, and the greater incentive to incur DCC to manage costs. Therefore, we will keep these expenses split out. See Liability Appendix A for the detailed calculations underlying the benchmark calculation.

Market	% of Insureds	Allocation of Premium Dollar					
		Claim Payment	DCC*	Expenses	Profit	Total	Avg Prem
Voluntary	99.8%	60.3%	2.2%	34.4%	3.1%	100%	\$ 779.85
Residual ⁷	0.2%	62.3%	3.3%	34.4%	0.0%	100%	\$ 1,554.22
Combined	100.0%	60.3%	2.2%	34.4%	3.1%	100%	\$ 781.23

EXPECTED CLAIM PAYMENT

The expected claim payments, here on out referred to as the “expected loss,” can be further split into the likelihood the insured gets into an accident and the amount that will be paid if an accident occurs. These calculations were done separately by coverage and market and are shown in Liability Appendix A (pages 5-6).

Expected Loss Components by Market

Market	Frequency	Severity	Expected Loss
Voluntary	0.16	2,971	\$ 470.28
Residual	0.26	3,786	\$ 968.47
Combined	0.16	2,973	\$ 471.16

It is important to differentiate between the voluntary market and residual market risks. The residual market exists for those who cannot find coverage in the voluntary market. These risks often have much worse experience and select less coverage (lower limits and forgo physical damage coverage) than risks in the voluntary market.

Expected Loss Components by Coverage

Coverage	Frequency	Severity	Expected Loss
Bodily Injury	0.01	12,797	\$ 120.3
Property Damage	0.03	2,558	\$ 89.5
Combined Single Limit (BI/PD)	0.04	5,388	\$ 213.7
Personal Injury Protection	0.02	6,305	\$ 101.7
Medical Payments	0.01	2,751	\$ 21.3
Uninsured/Underinsured Motorists	0.00	9,608	\$ 41.1
Comprehensive	0.08	919	\$ 72.3
Collision	0.06	2,985	\$ 171.9
Total	0.16	2,973	\$ 471.2

The frequency, severity, and expected loss amounts and percentages vary by coverage. Some of these coverages are mutually exclusive; the total will not equal the sum of the pieces. Individuals will either choose BI/PD or Combined Single Limit coverage but not both. The same typically goes for Medical Payments coverage and Personal Injury Protection. The expected losses can also vary widely by state as the different state laws impact claim payments. Lastly, only approximately 76 percent of vehicles carry Comprehensive coverage and 72 percent carry Collision. The total is the weighted average across all vehicles, which considers the underlying distribution of risks and coverages.

Uninsured Motorists

Using the Insurance Research Council’s 2012 Uninsured Motorists report,⁸ 13.4 percent of private passenger automobiles are uninsured. We assumed their accident frequencies and severities mirror those in the residual market.

PART III — PREMIUM ADJUSTMENTS TO PRODUCTS LIABILITY COVERAGE

INTRODUCTION

Our goal is to calculate how the vehicle and industry premiums if:

- 100 percent of vehicles are self-driving and owned by the manufacturer
- Manufacturers purchase first dollar liability coverage but self-insure physical damage coverage

⁸ <http://www.iii.org/fact-statistic/uninsured-motorists> Table “ESTIMATED PERCENTAGE OF UNINSURED MOTORISTS BY STATE, 2012 (1)”

We’ve broken the calculation into seven steps to adjust the current market to this desired state. While the impact of each step is quantified, both as a change from the prior step and as a change from the benchmark, the relative size of impact should be used with caution. The order in which the adjustments are made will impact the size of the change.

1. Insured population adjustment: 100 percent vehicles receive full insurance coverage
2. Provide voluntary liability limit coverage to every vehicle
3. Pass physical damage coverage to manufacturer
4. Redefine claim coverage based on manufacturer ownership liability
5. Eliminate physical damage deductibles
6. Replace personal automobile expenses and profit provisions with commercial insurance assumptions
7. Increase limits to \$1 million

PREMIUM ADJUSTMENTS

Step 1 — Insured population⁹

If the manufacturers own and insure every vehicle, then there will be no uninsured vehicles. This will eliminate the need for uninsured motorists coverage¹⁰ and provide everyone full coverage (liability and physical damage). Currently uninsured motorists’ coverage and premium is assumed to match the residual markets’ at the state level. Differences in the countrywide results, shown below, reflect the different state residual market and uninsured market distributions.

Average Premium		
Market	Baseline	New
Voluntary	\$ 780	\$ 850
Residual	\$ 1,554	\$ 2,312
Uninsured	-	\$ 2,118
Total	\$ 781	\$ 1,022

Uninsured motorists’ frequency and severity was set equal to the residual markets’ frequency and severity in each state. The difference in average premium is a result of distributional differences: the uninsured population and residual market differ in size in each state.

Impact on Insurance Market Size: Adding the uninsured drivers to the insurance pool, adding full coverage to all vehicles, and removing UM/UIM coverage causes the total insurance market premium to increase 51 percent. As a reminder, the change in market size can only be measured on a percentage basis due to the exclusion of Texas from the underlying dataset.

⁹ Details can be found in Liability Appendix B

¹⁰ The need for underinsured motorist coverage won’t truly be eliminated until step 2, but UM/UIM premiums cannot be separated. Therefore, its elimination is being included in this step.

Step 2 — Voluntary market liability limits

Risks forced into the residual market typically buy lower limits, often purchasing the minimum required limits. This effectively caps the liability claim payment when that insured is at fault in an accident. However, if the manufacturer owns and operates the vehicle, then all vehicles will have the same coverage and limit. Therefore, the residual market (and recently added uninsured market) needs to have their observed severities adjusted to reflect their higher liability limits.

The cost of higher limits is quantified through the calculation and application of increased limit factors. These factors tell us how much more premium needs to be collected to provide the higher coverage limit.

The Bodily Injury and Property Damage increased limit factors (ILF's) are calculated from a proprietary industry data source. The factors were calculate separately for each state to account for the different liability systems. The factors were aggregated to a countrywide estimate using the NAIC state exposure distributions.

No adjustment was made to Comprehensive and Collision coverage.

This assumes the differences in repair costs between markets (voluntary, residual, uninsured) is immaterial.

Covg	Increased Limit Adjustment Factor
BI	1.70
PD	1.14
CSL_BI	1.05
CSL_PD	1.05
PIP	1.10
MP	1.10
Comp	1.00
Collision	1.00

Average Premium				
Market	Baseline	Step 1	Step 2	Chg from baseline
Voluntary	\$ 780	\$ 850	\$ 850	9%
Residual	\$ 1,554	\$ 2,312	\$ 2,755	77%
Uninsured	-	\$ 2,118	\$ 2,545	-
Total	\$ 781	\$ 1,022	\$ 1,080	38%

Impact on Insurance Market Size: Increasing the residual market and uninsured drivers' limits will increase the insurance market's total premium by 9 percent. It will be 60 percent larger than it is today. The premium observed premium increase for each vehicle and the overall market is due to an expansion of coverage: every vehicle in the market is now fully insured at the voluntary market's liability limits.

Step 3 — Manufacturers self-insure physical damage coverage

If the manufacturers own the vehicles, it seems reasonable that they will not purchase physical damage coverage from insurers. The companies are large enough to accept the financial risk and pay for the repairs themselves. The cost of the repairs will still be factored into the overall operational cost. However, the insurance industry’s expenses and profit loads for comprehensive and collision coverages will be eliminated (set to 0 percent).

Physical Damage Expense Ratio			Physical Damage Profit Target		
Vehicle Market	Baseline	Step 3	Vehicle Market	Baseline	Step 3
Voluntary	34.4%	0.0%	Voluntary	5.0%	0.0%
Residual	34.4%	0.0%	Residual	0.0%	0.0%
Uninsured	34.4%	0.0%	Uninsured	0.0%	0.0%

Shifting the responsibility for physical damage payments from the insurer to the manufacturer reduces the average premium 16.4 percent, from \$1,080 to \$902 per vehicle. Of the \$902, the insurer will only receive \$601. The other \$301 goes to the manufacturer to pay for repairs. The repair shops will continue to make their same profits, but the manufacturer will not make any money for accepting this risk.

Average Premium ¹¹					
Market	Baseline	Step 2	Step 3	Step Chg	Chg from baseline
Voluntary	\$ 780	\$ 850	\$ 692	-19%	-11%
Residual	\$ 1,554	\$ 2,755	\$ 2,462	-11%	58%
Uninsured	-	\$ 2,545	\$ 2,245	-12%	-
Total	\$ 781	\$ 1,080	\$ 902	-16%	+16%

Impact on Insurance Market Size: Shifting the physical damage losses to the manufacturer causes the size of the insurance market to decrease by 71 percent. It will now be 11 percent smaller than it is today. The difference between the +16 percent vehicle “premium” increase and the 11 percent market decline is the fact that the \$301 of the vehicle premium is going to the manufacturer, not the insurer.

¹¹ We will refer to the “premium” as the operational cost required for the liability plus physical damage payments. However, insurers will only be responsible for the liability piece.

Step 4- Claim coverage definition change

Shifting the ownership and liability from the individual to the manufacturer will cause some claim coverage definitions to change. If a driver, driving alone, hits an animal, the liability coverage is not triggered. The damage to the vehicle will be covered under the comprehensive coverage, subject to the insured’s deductible. The individual’s injuries will be covered under the medical coverage (medical payments or personal injury protection). If the injuries exceed the medical coverage limit, the insured’s health coverage will drop down and pay for its portion of the loss (subject to the health insurance coverage rules). In the new environment, the manufacturer will be held liable for all accidents regardless of their cause. Therefore, these accidents need to be added to the liability frequency.

Using a proprietary industry data source, we calculate that 4.1 percent of comprehensive claims are caused by animal hits. Applying this 4.1 percent to Comprehensive’s frequency of 9.06 claims per 100 vehicle years, we calculate 0.37 claims per 100 vehicles are caused by animal hits. These claims need to be added to the bodily injury frequency.¹² This increases bodily injury frequency from 1.29 claims per 100 vehicle years to 1.66 claims per 100 vehicle years. We decided to only increase the bodily injury frequency and not the bodily injury and property damage frequencies to err on the side of conservatism. Simply increasing property damage’s frequency and ignoring the impact the accidents would have on bodily injury lawsuits would understate the impact. Applying the frequency increase to both coverages would likely overstate the impact. Therefore, rather than judgmentally selecting a different frequency, we opted to only apply the frequency increase to bodily injury coverage.

Conversely, 0.3 percent of Comprehensive claims are “personal effects.” The manufacturer will not be liable for lost items, just as a taxi-cab’s liability policy does not cover passengers’ lost items.¹³ Therefore, these claims have to be removed. This reduces the Comprehensive frequency from 9.06 to 9.03 claims per 100 vehicle years.

Average Premium					
Market	Baseline	Step 3	Step 4	Step 4 Chg	Chg from baseline
Voluntary	\$ 780	\$ 692	\$ 766	11%	-2%
Residual	\$ 1,554	\$ 2,462	\$ 2,557	4%	65%
Uninsured	-	\$ 2,245	\$ 2,340	4%	-
Total	\$ 781	\$ 902	\$ 980	9%	25%

Impact on Insurance Market Size: Changing the claim coverage definition expands coverage on each automobile. The average liability premium increases from \$601 to \$679. The total insurance market grows by 11 percent and will be approximately the same size as today (+0 percent change from today).

¹² If the driver hits an animal with a non-immediate family member in the vehicle, liability coverage can be triggered. It was decided not to make an adjustment for these potential claims as it is expected the number of these claims is small and will be offset by tree-hit claims that are excluded from the adjustment.

¹³ Lost items can be covered under the passengers’ homeowners policy, but that impact is beyond the scope of this analysis

Step 5 — Elimination of physical damage deductible

Shifting vehicle ownership and physical damage payment responsibility to the manufacturer requires one last change: removing the physical damage deductible. Currently, the model assumes the individual is responsible for the deductible payments. With all the claims accurately grouped into their new coverage definitions, we can remove the deductibles so the manufacturer pays all the physical damage claim costs.

Eliminating the deductible will increase the number of claims and the amount of each claim. However, no data source allows us to accurately calculate how the frequency will change — insurers do not receive data about claims that are smaller than an insured’s deductible. Our proprietary industry data source allowed us to calculate the impact deductibles have on claim severity. The change in severity was calculated by adding the deductible to every claim to calculate the claim’s gross cost. Removing the deductible increases Comprehensive’s severity by a factor of 1.64 and Collision’s severity by a factor of 1.15.

Average Premium					
Market	Baseline	Step 4	Step 5	Step 5 Chg	Chg from baseline
Voluntary	\$ 780	\$ 766	\$ 837	9%	7%
Residual	\$ 1,554	\$ 2,557	\$ 2,732	7%	76%
Uninsured	-	\$ 2,340	\$ 2,515	8%	-
Total	\$ 781	\$ 980	\$ 1,065	9%	36%

Impact on Insurance Market Size: As the manufacturer, not the insurer, is responsible for paying physical damage losses, this adjustment does not change the insurance industry’s premium volume.

Steps 1 — 5 Summary

In the analysis’ current state, every private passenger auto is fully autonomous and owned by the manufacturer. The manufacturer buys a private passenger automobile insurance policy to cover its liability losses but pays for any vehicle damage itself. Each vehicle has the same bodily injury and property damage limits of, approximately, \$115K/\$250K/\$70K. If the vehicle gets into an accident, each claimant can only receive \$115,000 with each accident’s payment capped at \$250,000 for bodily injuries. Any property that is damaged in the accident is covered up to \$70,000. Medical Payment and Personal Injury Protection provide additional coverage. Medical Payments limits are typically around \$5,000 - \$10,000, while PIP varies widely by state.

The average vehicle premium has increased from \$781 to \$1,065, but the amount of coverage has also expanded dramatically. In this scenario, every vehicle has the same coverage and is charged the same premium. In today’s market, insured’s rates vary dramatically based on their expected losses. The individual impact will vary widely; the best risks will see a rate increase while the worst risks will see a decrease (automated vehicles assumed to have the average accident frequency and severity). The size of the insurance market is largely unchanged. While insurers are no longer responsible for physical damage claims, it now covers liability on 15 percent more vehicles.

Adjustments	# of Covered Vehicles ¹⁴	Avg Vehicle Prem			Chg in Insurance Mkt	
		Total	Paid to insurers	Paid to manufacturer	Incremental	Cumulative
Baseline	178,476,905	781	781	0	-	-
1. 100% Insured	206,636,973	1,022	1,022	0	51%	51%
2. Voluntary Limits	206,636,973	1,080	1,080	0	9%	60%
3. Self-insure Phys Dam	206,636,973	902	601	301	-71%	-11%
4. Claims Covg Definition	206,636,973	979	679	301	11%	0%
5. First dollar phys dam	206,636,973	1,065	679	386	0%	0%

Step 6 — Expenses and Profit¹⁵

Personal auto insurance and products liability insurance have very different cost structures. Shifting coverage also requires a consideration of the differences in these structures.

Products liability is sold through different distributions with higher associated acquisition expenses (expenses are shown per premium dollar). This is due, in part, to products liability’s bespoke nature. The coverages and pricing are determined through extension negotiations and are tailored specifically to that manufacturer. On the other hand, personal automobile coverages and prices are necessarily pre-determined as they must be approved by state departments of insurance. Therefore, customers get to pick and choose pre-priced features. In total, products liability policies have \$0.043 higher expenses for every premium dollar.

Expense Ratio	Personal Auto	Selected Products Liability
Commissions & Brokerage	8.8%	13.7%
<u>Other Acquisition</u>	<u>8.4%</u>	<u>6.4%</u>
Total Acquisition Expense	17.2%	20.2%
General Expenses	5.5%	7.5%
Adjusting and other expenses	9.5%	9.5%
<u>Taxes, licenses & fees</u>	<u>2.2%</u>	<u>1.6%</u>
Total Expenses	34.4%	38.7%

Products liability insurers also have different profit targets than personal auto insurers. Products liability is a much longer-tailed line of business, meaning insurers are able to hold onto each dollar of premium for longer and earn a higher investment return. However, this is typically more than offset by the underlying riskiness of the product. Insurers have to hold more capital per dollar of insurance for products liability than they do for personal auto insurance; therefore, they have to target a higher profit margin to achieve their desired return on risk adjusted capital. We have assumed that products liability insurers will target a 90 percent combined ratio, or a 10 percent profit margin. However, the exact target will be highly dependent on the specific nature of the product. The greater the uncertainty surrounding the product, the average settlement, and the rating agencies’ capital requirements, the higher the profit margin will be.

¹⁴ Excludes Texas

¹⁵ A detailed explanation of the expense differences and additional information on other commercial lines of business is discussed in Appendix D.

Average Premium					
Market	Baseline	Step 5	Step 6	Step 6 Chg	Chg from baseline
Total*	\$ 781	\$ 1,065	\$ 1,229	15%	57%

*All vehicles are expected to have the expected performance, and therefore, they will all be charged the same premium.

Impact on Insurance Market Size: Increasing the expenses and profit targets increases the insurance market by 24.2 percent, leading it to be 24.5 percent larger than it is today.

Step 7 — \$1 million limit

Currently, injured parties’ settlement is capped at relatively low limits (\$115K per person and \$250K per accident for bodily injury). In reality, manufacturers’ products liability risk is unlimited. Therefore, the liability cap should be removed to reflect the true cost of shifting liability to the manufacturer. Unfortunately, we do not have a good way to estimate the cost of such an unlimited cap. We have opted instead to increase the limits to \$1 million of bodily injury coverage and \$1 million of property damage coverage per accident. We will continue to use the personal automobile increased limit factors as they are the most closely tied to automobile accident severities. If automated vehicles accident severity differs from current severities, this adjustment will need to be updated.

Using the same methodology as before, an increased limit factor of 1.82 is required to increase the bodily injury limits to \$1,000,000/\$1,000,000 and 1.21 to increase the property damage limit to \$1,000,000.

Increasing the limit also increases the amount of money that will be spent on defense cost and containment. The insurer has a greater incentive to employ lawyers to defend its insured the greater the potential claim payment. This can be seen by looking at how much insurers currently spend defending claims for different liability coverages. For every dollar an insurer spends on personal automobile liability payments, it spends six cents on defense costs and containment. Conversely, it spends seventy-six cents on defense costs and containment for every dollar it spends on products liability claim payments.

We decided to use the Commercial Auto Liability factors to match the \$1 million liability cap. Removing the cap will increase the average accident severity and increase the defense cost and containment expenses.

Coverage	DCC Factor ¹⁶	DCC Factor		
		Coverage	Baseline ¹⁷	Selected
PPA Liability	1.06	BI	1.05	1.11
Commercial Auto Liability	1.11	PD	1.05	1.11
Products Liability	1.76	CSL_BI	1.06	1.11
Other Liab - Occurrence	1.24	CSL_PD	1.06	1.11
CMP - Liability	1.40	PIP	1.09	1.11
Medical Malpractice	1.47	MP	1.05	1.11
Workers Compensation	1.13	Comp	1.00	1.00
		Collision	1.00	1.00

¹⁶ Calculated from S&P Global Market Intelligence using 2012-2014.

¹⁷ Calculated from NAIC database using 2009-2011.

Step 7 — Liability Coverage Scenarios

As stated in the introduction, two different liability scenarios were tested: adjusting the underlying coverages (split coverage) and rolling the coverages together into a single, liability coverage. The split coverage approach is the simplest and most straightforward as we simply apply the new increased limit factors to the bodily injury and property damage premiums. Medical payment and personal injury protection payments are added on top.

Combining all the liability payments into a single coverage is more reflective of the future state, but it is also more difficult to do. We aim to replicate the Step 6 loss costs and then calculate the new single coverage premium.

Average Vehicle Liability Premium		
Liability	Step 6	Single Covg
Freq	7.31	7.51
<u>Severity</u>	<u>5,579</u>	<u>5,428</u>
E[L]	408	408
DCC	24	22
Expenses	326	325
Profit	84	84
Prem	842	839

While both options start with the same expected loss dollars, the increased limit factors are not applied to medical payment or personal injury protection coverages in Option 1 — Split Coverage. Option 2 — Single Coverage assumes that all of the current liability and medical payments claims have the same distribution, and therefore, it is appropriate to apply the same bodily injury increased limit factor to both.

Average Vehicle Liability Premium			
Liability	Step 6	Step 7 - Opt 1	Step 7 - Opt 2
Frequency	7.31	7.31	7.51
<u>Severity</u>	<u>5,579</u>	<u>8,885</u>	<u>12,083</u>
E[L]	408	649	908
DCC	24	73	101
Expenses	326	545	762
Profit	84	141	197
Liab Vehicle Prem	842	1,408	1,968

Adding physical damage losses to the liability losses produces the following average premiums:

Average Premium					Option 1		Option 2	
Market	Baseline	Step 6	Step 7 - Opt 1	Step 7 - Opt 2	Step 7 Chg	Chg from baseline	Step 7 Chg	Chg from baseline
Total	\$ 781	\$ 1,229	\$ 1,794	\$ 2,355	46 percent	92 percent	92 percent	201 percent

Impact on Insurance Market Size: Increasing the limits on each vehicle to \$1,000,000 for bodily injury and \$1,000,000 for property damage increases the average premium and total market premium. Under the Option 1 — Split Coverage, medical payment and personal injury protection coverages are capped at the current voluntary limit and the total insurance market will grow an additional 84 percent; it will be 108 percent larger than it is today.

Under Option 2 — Single Coverage, first party medical payments and personal injury protection coverages have no sublimit and the total insurance market will grow an additional 166 percent; it will be 191 percent larger than it is today

Step 1 — 7 Summary

With the same accident frequency and \$1 million limits, shifting the automobile accident coverage from personal automobile insurance to products liability will double to triple the average vehicle premium: from \$781 to \$1,794-\$2,355 (depending on the liability coverage assumption). Most of the change comes from dramatically expanding each vehicle’s coverage.

However, higher liability expenses and profit also contribute to the increase. Under our assumptions, approximately \$0.60 of every auto premium dollar is used to pay claimants. Even after removing the insurer’s expense and profit provisions on physical damage claims, a smaller portion of each premium dollar goes to claimant compensation in the new, products liability coverage environment. However, it should be noted that “target” profits are not the same as “achieved” profits. Not once in the past nine years has the personal automobile insurance market achieved the assumed target underwriting profits.¹⁸

Prem Dollar Dist	Current		
	Baseline	Option 1	Option 2
Expected Loss	60.3%	57.7%	55.0%
DCC	2.2%	4.0%	4.3%
Expenses	34.4%	30.4%	32.4%
Profit	3.1%	7.8%	8.4%
Total	100%	100%	100%

While it is obvious that the higher premium’s greatest driver is the higher losses — due to the expansion of coverage — the amount insurers will spend on lawyers to fight claims increases over 300 percent than in

¹⁸ See Liability Appendix E for details

today’s personal automobile insurance market. Higher limits increase the amount the insureds receive for each claim, but they also increase the insurers’ claim settlement expenses and target underwriting profit.

Average Vehicle Premium			
Avg Prem	Baseline	Step 7	
		Option 1	Option 2
Freq	15.8	23.5	23.7
Severity	<u>2,973</u>	<u>4,410</u>	<u>5,462</u>
Expected Loss	471	1,036	1,294
DCC	17	73	101
Expenses	268	545	762
Profit	24	141	197
Total	\$ 781	\$ 1,794	\$ 2,355

Step 8 — Frequency Reduction Scenarios

It is generally assumed that automated vehicles will reduce the number of accidents — safety being one of their key selling points. Therefore, assuming the same frequency in the long-run end-state may paint an inaccurate picture of the true expected costs. The end-state is re-calculated under five frequency reduction scenarios, shown below. We applied the frequency reduction factor similarly across all coverages: liability, medical payments, comprehensive, and collision. Comprehensive claims are the most likely to experience their own, unique claim frequency change pattern.¹⁹ The assumed patterns are for simplicity sake only and do not represent an actuarial opinion on the projected frequency change.

Baseline Avg Prem	\$ 781
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Average vehicle premium		
	Option 1	Option 2
Step 7	\$ 1,794	\$ 2,355
<i>Freq Reduction</i>		
10%	\$ 1,628	\$ 2,041
25%	\$ 1,378	\$ 1,722
50%	\$ 963	\$ 1,192
75%	\$ 547	\$ 662
90%	\$ 297	\$ 343

Cumulative change in insurance market premium		
	Option 1	Option 2
Step 7	108%	191%
<i>Freq Reduction</i>		
10%	87%	148%
25%	56%	107%
50%	4%	38%
75%	-48%	-31%
90%	-79%	-72%

¹⁹ Automated vehicle technology’s impact on hail damage, car theft, glass breakage, fires, and other comprehensive claims is unlikely to follow the same reduction pattern that automobile accidents experience.

Even with a 50 percent reduction in all claims, insureds will still be paying more per vehicle than they do today — in part because they will be receiving much more coverage. The insurance market’s total premium will also be greater than it is today. It isn’t until accidents are decreased by 75 percent that the average vehicle premium is less than it is today. This can conversely be interpreted as saying, if automated vehicles reduce frequency by 75 percent, each vehicle will be afforded with \$1 million liability coverage and first dollar physical damage coverage at a lower premium than the today’s countrywide average (in real dollars).

Step 9 — Fixed vs. Variable Expenses Scenarios

There is one last consideration that should be taken into account before wrapping up the premium impact discussion and that is the treatment of expenses. There is a minimum premium that insurers must charge to issue a policy, no matter how low the expected losses are. These minimum premiums set a floor on how low premiums can go. Therefore, impacts that cause the premium to approach this floor, such as dramatic frequency reductions, must explicitly address this consideration by splitting the expenses into their fixed and variable components.

Up until now, we have assumed that all expenses are variable — the expenses are proportional to premium. However, this is not a true reflection of reality. Some expenses, such as profit, commissions, and taxes, vary directly with premium: an additional dollar of premium increases these expenses by the same amount. Other expenses, such as the staff’s salary, do not scale with premium: an additional dollar of premium doesn’t change the amount the insurer spends on salaries. Each expense ratio is allocated to “fixed²⁰” and “variable” as follows:

Expense Ratio	% Fixed	% Variable
Commissions & Brokerage	0	100
Other Acquisition	50	50
General Expenses	100	0
Adjusting and other	100	0
Taxes, licenses & fees	0	100

The baseline fixed and variable expense ratios are 19.2 percent and 15.2 percent, respectively. This corresponds to a fixed expense per vehicle charge of \$150. This decreases to \$130 per vehicle by keeping the total fixed expense dollars unchanged but increasing the number of insured vehicles. Treating expenses in this manner lowers the starting premium but also sets a floor on how low the premiums can decrease. With expenses fixed at \$130 per vehicle, a 90 percent accident reduction only reduces the average vehicle premium by approximately 40 percent versus a 60 percent decrease if all expenses are variable.

²⁰ Note that even “fixed” expenses are not truly fixed. The staff’s salary that is assumed to be fixed will surely be cut if the insurer shrinks by 50 percent. Conversely, if the insurer grows by 50 percent, it will surely need more staff and will increase salaries. In this way, even “fixed” expenses are somewhat variable. Therefore, caution should be used when interpreting both expense treatments.

Average vehicle premium			Cumulative chg in insurance market prem		
Step 7	Option 1	Option 2	Step 7	Option 1	Option 2
w/o split	\$ 1,794	\$ 2,355	w/o split	108%	191%
Split expenses	\$ 1,578	\$ 1,980	Split expenses	77%	136%
<i>Freq Reduction</i>			<i>Freq Reduction</i>		
10%	\$ 1,451	\$ 1,747	10%	62%	106%
25%	\$ 1,262	\$ 1,508	25%	39%	76%
50%	\$ 945	\$ 1,110	50%	2%	26%
75%	\$ 629	\$ 711	75%	-36%	-23%
90%	\$ 439	\$ 472	90%	-58%	-53%

PART IV — CONCLUSION

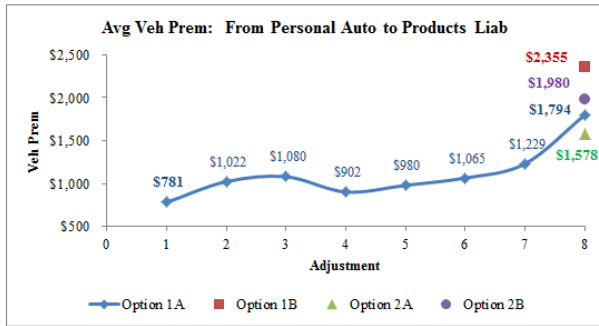
Insurance premiums offer one way to evaluate different liability systems’ efficacy. Even after our numerous simplifying (and unrealistic) assumptions, calculating the shift in liability system from personal automobile to products liability is a labor intensive calculation that requires a great deal of product and pricing expertise. Liability system evaluations that leave out the premium cost ignore a key aspect of the system’s effectiveness.

Beyond simply highlighting the complexities involved in such a calculation, the analysis illuminates and quantifies many of the nuances between the coverages. Under our assumptions, products liability affords greater coverage than personal automobile: covering the vehicles with higher liability limits and no physical damage deductibles. Certain claims, such as animal hits, will now be covered under these higher limits compared to today, where medical expenses beyond the low automobile policy limits are covered under the claimant’s health insurance policy. The expanded coverage is passed to the consumer through higher premiums.

Products liability is also a more expensive coverage. The complexity and uniqueness of the product is accompanied by higher distribution costs. Higher limits increase the claim settlement costs. Unlimited liability increases the amount of capital that must be held, and subsequently, the underwriting profit insurers must target. Even with the manufacturer providing physical damage coverage at cost (removing the insurer’s expenses and profit from these coverage premiums), the shift to products liability results in a lower percentage of each premium dollar going to claimant payments.

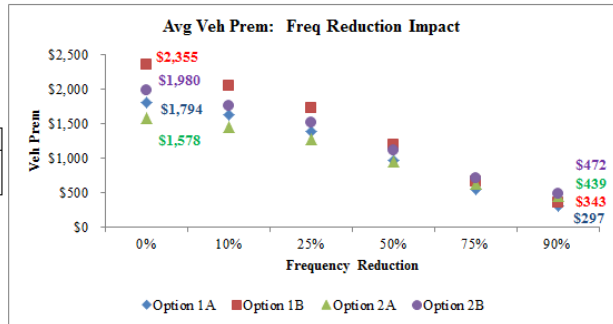
Lastly, the shift to products liability involves a great deal of uncertainty, not only over the product’s performance but also in premium cost. Therefore, the potential cost — as measured through insurance premium — is best viewed as a range rather than a simple point estimate.

Table 2



Options			
1	Split Coverage	A	100% Variable Expenses
2	Single Covg	B	Variable & Fixed Expense ratios split

Step	Adjustments
1.	Baseline
2.	Provide coverage to Uninsured @ Residual Mkt limits & rates
3.	Increase Residual Mkt liab limit to Voluntary Mkt limits
4.	Shift Physical Damage coverage to Manufacturers with 0% Expense & Profit
5.	Adjust claim coverage definitions
6.	Remove Phys Dam deductibles
7.	Adjust Expense & Profits to Commercial
8.	Increase Liab limits to \$1 million



2.2: Automated Vehicle Liability — Non-premium considerations

PART I - INTRODUCTION

The premium cost of the liability system is just one of many considerations that should be taken into account when weighing a potential system's efficacy. The ideal liability system will aim to balance many goals.

- It should align responsibility and accountability.
- It should encourage manufacturers to invest in product improvement.
- Claimants should be compensated fairly and efficiently.
- Keeping all else equal, the system that accomplishes these tasks at the lowest cost will be superior to another one.

While we will discuss a number of additional issues concerning the liability system, this is neither an exhaustive list of the issues nor is it a complete discussion of the identified issues. Instead, this is an addendum to the prior study aimed at placing the premium costs in proper context. Without such a discussion we worry that the reader may infer that we believe that the premium cost is the only piece worth considering.

PART II - PRODUCT: AUTOMATED VEHICLE LIABILITY COVERAGE

ACCOUNTABILITY AND RESPONSIBILITY

To the extent the product, and not the individual, causes the accident, it seems reasonable to assume the liability should rest with the manufacturer(s) of that product. A level five, fully automated vehicle that has no steering wheel or brake (no way for the driver to take over), seems to mandate the assignment of liability to the product and not the passenger. Therefore, products liability — despite its higher costs — more closely aligns accountability and responsibility than personal automobile insurance (in the level five automated vehicle, end-state scenario).

COVERAGE

Technically, manufacturers' products have no liability cap in that claimants can sue for any amount they want. Some states cap non-economic damages for some claim types. For example, "Michigan places a cap on noneconomic damages for product liability actions in an amount not to exceed \$280,000 unless the product's defect caused death or permanent loss of a vital bodily function. In such circumstances, the amount recoverable shall not exceed \$500,000. The \$500,000 cap will not apply if the defendant was grossly negligent."²¹

Without caps, manufacturers may decide not to offer the product if they feel the potential cost is too high. Higher caps, or unlimited caps, are also accompanied by higher frictional costs. For every \$1 that goes to a claimant, insurers only spend \$0.06 on defense cost and containment for personal auto liability claims versus spending \$0.11, \$0.40, and \$0.76 on defense cost and containment for commercial auto liability, commercial general liability, and products liability coverage. Conversely, capping losses shifts the risk from the

²¹ http://www.iadclaw.org/assets/1/19/Product_Liability_June_2014.pdf

manufacturer to the individual. This tradeoff is best left to the public and their democratically elected representatives.

PART III - CLAIMS HANDLING

Effective claims handling treatment reduces the cost of fraud. “The Insurance Research Council estimated that fraud and claim buildup added over \$5.6 billion of excess auto injury payments in the United States in 2012.”²² Fraud increases the auto insurance premiums for everyone else.

ACCOUNTABILITY AND RESPONSIBILITY

While it makes sense that the manufacturer of a product be held accountable for product defects, making that same manufacturer responsible for compensating claimant creates misaligned incentives. We should aim to align the customer’s purchase incentives with the seller’s incentives. Splitting out the product purchase decision, which product will give me the best value for my dollar, and the claim settlement purchase decision, which provider will settle my claim fairly and efficiently, increases the system’s transparency and empowers the customer.

EXPERTISE & INFRASTRUCTURE

In 2013, the personal automobile insurance industry spent approximately \$17 billion on claims handling personnel salaries (adjusting and other expenses). It spent an additional \$5 billion on claim specific expenses (defense cost and containment). NHTSA’s 2015 budget was \$830 million, less than 4 percent what the personal automobile insurance industry spends on claims adjusting expenses. Of the \$830 million, only \$130 million went towards Vehicle Safety Research.²³ Products liability insurance market spent almost 80 percent of its 1.75 billion claims handling expenses on defense cost and containment. Shifting the claims handling responsibility away from personal automobile insurers may be accompanied by a dramatic loss of claims handling expertise and infrastructure.

SETTLEMENT FAIRNESS

When an accident occurs, each party should have equal representation. In today’s environment, each party is represented by his/her insurance company. Each company has equal access to the accident facts. Thus, a negotiated agreement between equal parties with equal information can ensue. The outcome is less certain if the individual has to bring a claim against the manufacturer. The manufacturer, with more financial resources and access to its proprietary data, has much more leverage over the individual. Where the accident fault and the potential settlement is unknowable in advance, the system should provide all parties equal opportunity to a fair outcome.

²² <http://www.insurance-research.org/sites/default/files/downloads/IRC%20Fraud%20News%20Release.pdf>

²³ See Non-Premium Liability Considerations: Appendix F for detailed NHTSA budget.

PART IV - CONCLUSION

Beyond its simple legal definition, automated vehicle liability is a complex and nuanced issue. Restricting the analysis to an environment with 100 percent level five, manufacturer-owned vehicles greatly simplifies the issue. Even with such a simplifying assumption, the answers are unclear. If we are going to devise the optimal system to govern partial and fully automated vehicles — if such a system exists — our democratically elected representatives will need a clear view of the risks, costs, and benefits involved in each of the tradeoffs. Our representatives should aim at gathering the facts needed to evaluate these tradeoffs. Actuaries can help quantify some of these tradeoffs to facilitate better decision making.

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TOPIC 2
AUTOMATED VEHICLE LIABILITY
RECOMMENDATION

The American public should be the ultimate arbiters of automated vehicle liability. They must evaluate the costs and benefits involved in each of the many decisions: should we use an existing system or try to create a new one? How much coverage should be provided? What data should be reported? And so on. The answers to these, and other, questions should be made in a purposeful and transparent manner after an unbiased assessment of the issues.

The complexity and uncertainty of these issues calls for a more open collaboration between the American public (through their representatives), legal experts, manufacturers, and casualty actuaries. The first step in solving any complex problem is bringing the right people together. This will ensure the right questions are being asked, the appropriate data is gathered, and the subsequent analysis is accurate. The tradeoff decision is the public's choice, and theirs alone to make. However, the facts and understanding that is needed for these decisions to be made in an informed and unbiased fashion will rely on an open, transparent, and candid collaboration between the various stakeholders. Thus, the final decision, whatever it may be, will be sure to reflect the public's true desires.

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3: Automated Vehicle Risk

EXECUTIVE SUMMARY

The introduction of automated vehicles may eliminate some risks (e.g., certain types of behavioral driver errors) — but it may at the same time exacerbate other risks (e.g., hacking). Risks cannot be evaluated or managed in silos. They are intertwined: the elimination of one accident causation risk does not guarantee the accident will be prevented, or that other causes may not emerge in the absence of the original cause. To the extent that a goal of AV rollout is increased safety through overall accident reduction, we must develop a single, comprehensive AV introduction strategy that minimizes the risk in total. The creation of such a strategy requires access to detailed, quantifiable data on both the technology’s performance and general driving incidents. This data must be supplemented by risk management expertise to partially adjust for the uncertainty that exists from the risks that will only be observed through the actual introduction of AVs.

Even a basic study, such as the one performed here by the AVTF, can provide guidance on what must be done. First, more data is needed: more recent and granular accident causation data, in addition to the obvious need for technological performance data. Second, AV operation can be supported by non-technological solutions: for example, strategies can be used to increase non-AV drivers’ familiarity with AV technology and tendencies, thus decreasing the risk further. Third, the risks and subsequent safety benchmarks are location and circumstance dependent: snow, deer, infrastructure issues, and the behavior of other drivers are just a few of the risks that differ based on where the technology operates. One implication of this circumstance-dependent benchmark is that municipalities, especially familiar with their indigenous local conditions, may be able to take actions to reduce the technology’s operational risk.

In much AV discussion to-date, the evaluation of AV technology’s performance has been against one particular benchmark: the NHTSA’s police-reported, countywide data. However, this approach is decidedly insufficient. This dataset is biased, incomplete, and not granular enough for thorough and insightful performance analysis. Comparing the accident rate for a vehicle that only operates in Pittsburg or San Francisco to the countrywide average tells us little about the technology’s relative performance. Looking at the aggregate “average” accident rate, which includes accidents from drunk drivers, teen drivers, and elderly drivers, may also not be the benchmark we want. Instead, a more nuanced view, that allows the technology to be compared against a specific subset of drivers or placed in context, such as being able to compare the technology to the top 10 percent of drivers, allows for a more accurate understanding of the technology’s performance. With accident rates and circumstances always changing, comparing actual performance to historical performance may be inappropriate. The benchmark against which to measure performance must be responsive enough to consider these changes while also being stable enough to overcome the natural statistical noise in the data.

Casualty actuaries’ predictive models based on insurers’ robust automobile accident data provide the best avenue and starting point for calculating a benchmark that accurately illustrates the technology’s performance. Only through the use of this data and these models can the NHTSA be confident that self-driving cars meet its safety standard.²⁴

²⁴ <http://www.bloomberg.com/news/articles/2016-06-08/u-s-auto-regulator-says-self-driving-cars-must-be-twice-as-safe>

3.1: Automated Vehicle Risk — Risk minimization introduction strategy

INTRODUCTION

The arrival of an AV world has been the focus of much speculation, with many introduction and adoption timelines finding their way into publication. These predictions in turn generate discussion on the hurdles the technology faces and the risks entailed in its introduction. These discussions raise important issues that must be addressed. The CAS AVTF has aimed to support the discussion of automated vehicle risk through the creation of a more concrete framework in which these issues can be evaluated and understood.

To accomplish this task, we have undertaken a thought experiment: if we were charged with creating the risk minimizing introduction strategy for AVs, how would we go about it and what would that strategy look like? This thought experiment is meant to serve as an example for future analyses (which will be based on actual data emerging from the experience of developing and testing AVs). This work should not be taken as an actuarial opinion on what should be done or even be read as what actually minimizes automated vehicle risk. At this early date, there are simply too many uncertainties and assumptions around the technology's operation to overcome.

PART I — OBJECTIVE

Goal Definition

Our goal is to develop a risk management program for the introduction of a level five,²⁵ fully self-driving vehicle that minimizes the manufacturer's liability costs. If the liability system is designed properly, manufacturers will pay for product failures. Defining the problem in this manner provides two key benefits. First, it allows "risk" to be quantified through the calculation of a liability premium. Second, by looking at the issue from the manufacturer's viewpoint, we more accurately reflect the issue as it will be addressed in the real-world.

Goal Prioritization

Liability costs are a combination of the number of incidents and the cost of each incident and will be calculated as:

$$\sum_{i=1}^n (\text{Incident exposure})_i * (\text{Incident frequency})_i * (\text{Average incident severity})_i$$

Unfortunately, the CAS Automated Vehicles Task Force does not have access to the data needed to calculate a quantified risk assessment. Instead, we are forced to take a more generic approach leveraging the work done in the Liability Premium Calculation analysis. Products liability insurers spend \$0.60 - \$0.80 on defense costs for every \$1.00 they pay to claimants.²⁶ This means the mere act of being sued costs almost as the settlement payments. Therefore, manufacturers' risk minimization goals will be prioritized as follows:

²⁵ NHTSA has adopted the six-level automated vehicle definition (Levels 0 through 5) of the Society of Automotive Engineers (SAE): <http://www.nhtsa.gov/technology-innovation/automated-vehicles-safety>.

²⁶ Source S&P Global Market Intelligence – republished: <http://www.iij.org/fact-statistic/products-liability> table titled "Defense Costs And Cost Containment Expenses As A Percent Of Incurred Losses, 2012 – 2014."

The primary goal is to minimize the number of incidents — if nothing bad happens, there will be no lawsuit.²⁷ The secondary goal is to minimize the severity of any incident that does occur — if something bad does happen the goal is to minimize the pain. Our use of the term “incident” is intended to mirror the definition used in negligence lawsuits, in which the plaintiff must prove harm was incurred. This definition extends beyond simple bodily injury claims to property damage and other forms of harm²⁸.

PART II — DATA ACQUISITION

The strength of any analysis is constrained by the data on which it is based. In the real analysis, the technology’s test data and simulated data will be needed. This should be supplemented with additional driving data to place the technology’s operation in a broader context. Finally, judgment needs to be used to extrapolate future performance from test data. The goal of the data should be to identify and quantify risks that will prevent the technology’s successful operation (getting the individual from point A to point B safely).

Dataset 1 — Adjusted National Motor Vehicle Crash Causation Survey

NHTSA’s 2008 National Motor Vehicle Crash Causation Survey provides the most detail on automobile accident causation available to the Task Force. However, the data needs to be adjusted so that we can use it to identify risks to automated vehicles rather than to human drivers. Even after such an adjustment, a number of issues still reside within the data that future studies should look to overcome.

Dataset Deficiencies

- **Out-of-date:** It only includes accidents from 2005-2007. Today’s vehicle technology has improved significantly since then. More current data will provide more accurate insights into today’s driver-vehicle relationship and will therefore be more predictive of the future relationship.
- **Completeness:** It excludes a large number of accidents including, but not limited to: any accident that occurred from 12:00am — 5:59am, any accident that didn’t have an emergency medical service dispatched to the scene, and any accident without an available police report. Additionally, important variables, such as location, are not included in the dataset.
- **Focus:** It focuses on accident causation in today’s driving environment. Events that are handled easily by human drivers but can cause an automated vehicle to malfunction — like potholes or snow — are excluded from the dataset (these events do not result in an accident in today’s driving environment but might if the technology were at the helm).

Dataset 2 — Judgment

²⁷ Fraud can still occur, but it’s uncertain how the introduction strategy will be changed by these costs.

²⁸ The details and nuances of negligence and liability law are beyond the scope of this paper. While negligence lawsuits typically require a pecuniary loss, our definition is simply “something unintended or bad” occurred.

Even if testing data is obtained and used, it will need to be supplemented with unidentified risks. Judgmental risks need to be explicitly identified and prioritized if not quantified. The number of unknown and judgmental risks can be reduced through more direct testing of the product's use. However, we must be careful not to extrapolate too much from the test data as the risks may change as the technology progresses through the market.

Dataset 3 — Technological Performance

Actual data on the technology's capabilities is not available to the Task Force. Therefore, we have replaced the actual data with generic assumptions. Using assumptions allows us to demonstrate how to construct a risk minimization introduction strategy; however, replacing the most important piece of the analysis — the technology's performance — with predetermined performance assumptions negates the ability to use the conclusion as anything other than a thought experiment.

Assumptions

- The technology does not operate in inclement weather (rain, snow, etc.).²⁹
- The technology needs accurate, up-to-date maps of the surrounding environment.
- All other errors will be random.
 - The technology's error rate is lower than a human driver. The more the technology is in control, the fewer accidents there will be.

PART III — RISK IDENTIFICATION & QUANTIFICATION

Now that our data sources have been clearly defined, we can begin the process of identifying the risks and quantifying as much as we can.

Dataset 1 — Adjusted National Motor Vehicle Crash Causation Survey

We will use the adjusted NMVCCS to identify and quantify risks to automated vehicles' successful operation. Eight risks have been explicitly identified from the dataset. These risks fall into two generic groups: risks surrounding the technology's operation and driver usage, or behavioral, risks.

A. Technological Issues

A1 - Weather: Technology disabling inclement weather was present in 12.2 percent of accidents. We have assumed the technology will not work in inclement weather. Therefore, the driver would have still been in control and the accident would have occurred in the same fashion that it did. The NMVCCS doesn't have any

²⁹ Recent reports indicate that manufacturers may be able to overcome the weather problem.

Ford: <http://www.detroitnews.com/story/business/autos/detroit-auto-show/2016/01/11/ford-fusion-driverless-snow/78612944/>
Google: <http://static.googleusercontent.com/media/www.google.com/en//selfdrivingcar/files/reports/report-1215.pdf>

location identifying characteristics, so no further refinement was possible. However, in the real world, weather's impact varies by location.

A2 - Vehicle Condition: The NHTSA defined variable, "Vehicle Condition," was present in 11.6 percent of accidents. These include such errors as "tire/wheel deficiency" and "lighting deficiency." While the Vehicle Condition was only identified as the critical reason in 2.5 percent of the accidents, it indicates that the vehicles involved in accidents often have minor issues with them that may contribute to the accident. Non-technological vehicle deficiencies can increase the accident risk in automated vehicles. In other words, individuals don't always maintain their vehicles. If the technology's success rate requires the vehicle to be in mint condition, it may underperform the manufacturer's expectations.

A3 - Infrastructure: We are not able to identify or quantify the other environmental factors that might cause an automated vehicle to malfunction. Reports have indicated that potholes and unmapped roads can create problems for automated vehicle technology.³⁰ These issues are typically handled by today's drivers and thus, are not in the NMVCCS dataset as no accident results. The 0.4 percent of accidents that occurred with an inoperable traffic control device is to be interpreted as a placeholder: infrastructure errors might pose a risk to automated vehicles. The size and scope of the risks cannot be calculated without additional data. The exact data that is needed will depend on the vehicle's use.

B. Behavioral Issues

Manufacturers who want to minimize the number of incidents involving their technology need to be concerned not only with the technology's operation but also with its use. While seatbelts are available in every vehicle and are legally required to be worn in 49 states,³¹ one in seven adults refuse to buckle up. If the automated vehicle technology is ignored or used incorrectly and an accident occurs, the manufacturer may have to spend money to defend itself regardless of its fault.

B1 - Driver Disables: In 3.1 percent of accidents, drivers told the police officer they were 'racing,' 'fleeing,' 'in a hurry,' or 'always drove (aggressively).' It's unclear if these drivers would have used the technology or how these drivers would have used the technology.

B2 - Drugs: Alcohol, illegal drugs, or potentially drowsy medication were present in 11.0 percent of accidents.³² However, this number likely understates the drugs' actual presence in drivers as accidents from midnight to 5:59am are excluded from the study. Manufacturers cannot be certain how drivers under the influence will use their product. Furthermore, while automated vehicles may make driving under the influence safer — by shifting the driving responsibility from the impaired driver to the unimpaired vehicle — they may also make driving under the influence more prevalent. Hence, the net impact cannot be predicted.

B3 - Physical Impairment: 2.3 percent of accidents were caused by the driver having a heart attack or other physical impairment. Automated vehicles cannot prevent heart attacks, so the focus in these instances will be minimizing the severity.

³⁰ <http://www.technologyreview.com/news/530276/hidden-obstacles-for-googles-self-driving-cars/>

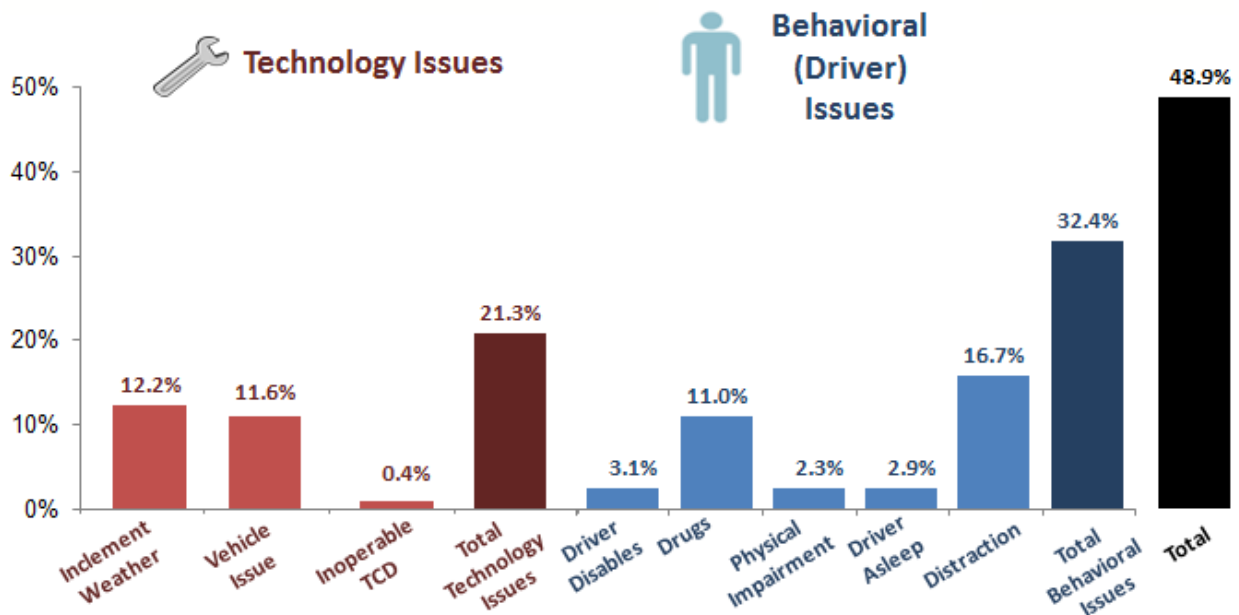
³¹ http://www.ghsa.org/html/stateinfo/laws/seatbelt_laws.html

³² Just including alcohol and illegal drugs reduces their presence to 9.4 percent

B4 - Sleeping: A sleeping driver was the cause of 2.9 percent of accidents. Again, this risk is likely understated as accidents occurring from midnight to 5:59am are excluded. If the technology’s safe operation requires a vigilant driver, these accidents would have likely still occurred.

B5 - Distraction: Driver distraction is the cause of 16.7 percent of accidents, with internal distraction being the main issue (9.9 percent). Despite being fully responsible for the vehicle, drivers are easily distracted. As they become less engaged in the driving function, distraction is likely to increase.

Table 3



At least one limiting variable, technological or behavioral, was present in 48.9 percent of accidents. Note, that the summation of the pieces does not equal the totals. This accounts for correlations between variables, ensuring that an accident with multiple causes is only counted once. This analysis tells us nothing about when the technology will actually fail. Instead, it allows us to identify future data that is needed, such as location specific weather information and infrastructure issues. It also highlights the importance of the driver’s relationship with the technology. Just because the technology is safe and available does not mean that it will be used or used correctly. Manufacturers fearing lawsuits for incidents occurring in their vehicle, regardless if the technology, individual, or both are at fault must have an introduction strategy that addresses this issue.

Dataset 2 — Judgement

Until automated vehicles are fully utilized by the public, no dataset exists that provides a comprehensive risk analysis. Even real-world testing and millions of miles of simulations will have gaps. Additionally, the risks will change as the technology evolves over time. Therefore, a comprehensive understanding of risk requires that any dataset be supplemented with a set of factors that need to be included in the analysis. Seven additional risks are identified, and incident severity causes, previously ignored, are discussed.

C1 - Driver Skill Deterioration: The more the technology is in control, the more out of practice individuals might become. Therefore, certain scenarios that individuals are able to handle today may result in an accident in the future. If the technology's ability increases at a faster rate than the driver's deteriorates, this may not pose much of a problem. However, manufacturers need to recognize the risk is dynamic. The situation needs constant monitoring as the risk minimization actions may change over time.

C2 - Pass-Off Risk: This is the risk that is created when the vehicle goes from technological control back to human control. This scenario could be triggered by the human choosing to take control or by the vehicle passing responsibility to the individual when it encounters a scenario it is unable to handle.

C3 - Other Driver Interaction: How other drivers, pedestrians, and bikers on the road react is also unknown. Drivers' reactions can change based on their age, driving experience, familiarity with the technology, their mood, or almost any other factor.

C4 - Animal Hits: While accidents involving animals are included in the NMVCCS, the dataset appears to be insufficient extrapolation. State Farm estimates that there are over 1.2 million deer-vehicle collisions annually;³³ however, the NMVCCS's extrapolated number of accidents involving animals is only 22,366 — or approximately 1.0 percent of all accidents. This could be due to NHTSA's requirement that a police report be filed to be included in the data, and claimants may be less inclined to call the police in a single vehicle animal hit. The risks animals pose to vehicles varies dramatically by location and time of year. It's also uncertain how the technology interacts with the animals. While it may be able to avoid some accidents, animals may be even more unpredictable than people. Residents in areas with significant animal populations will undoubtedly know someone who has had a deer run into the side of their car while driving. There's nothing that can be done in times like these.

C5 - Hacking: The introduction of more technology in the vehicle may increase the risk that vehicles will be hacked. In the future, the risk of hacking may increase regardless of the vehicle's automation.³⁴ At this point, we do not know what hacking's causes or risk factors may be. Operating in a city may increase the risk by exposing other drivers to the hacked vehicle. It may also decrease part of the risk by reducing the average speed and enabling emergency response teams to respond more quickly. More research will be required to properly evaluate the risk.

C6 - Random Errors: As stated in our assumptions, technological errors will still occur. However, their appearance will be random. Therefore, it is important that when an incident occurs, its severity minimized.

C7 - Unknown: It's important to include a placeholder for unknown events. It's impossible to predict everything that will happen. Therefore, we must accept the fact that there are things that we don't know and cannot predict.

C8 - Incident Severity Risks: There are a number of factors that determine how severe an incident will be. By breaking the drivers into their respective risk components, we can create a risk management structure that minimizes severity of unpreventable incidents.

- Speed: The number one determinant of accident severity is the vehicle's speed.

³³ <http://www.insurancejournal.com/news/national/2012/10/24/267786.htm>

³⁴ <http://www.wired.com/2015/07/hackers-remotely-kill-jeep-highway/>

- Pedestrians: The second biggest determinant of severity is if the accident involves a vehicle and an individual. Pedestrian-vehicle interactions are most likely to occur at cross-walks or in parking lots.
- Location: If an accident occurs, it is important that the passengers receive medical attention as quickly as possible. Where the accident occurs has a large impact on its potential severity.
- Vehicle design: Design choices can be made to minimize the impact to the vehicle's passengers and to the external parties.

PART IV — INTRODUCTION STRATEGY

With the risks identified and (somewhat) quantified, the risk management strategy can be created. The goal is to select the introduction strategy that minimizes the risks (costs) in total. The approach cannot be a piecemeal approach that addresses each risk in isolation. The following approach represents our attempt to do so. In reality, manufacturers will want to run scenarios that explicitly quantify the costs of different strategies and select the one that results in the lowest cost.³⁵

A. Approach to Vehicle Introduction

- Introduce the vehicle as a manufacturer-owned public transportation-service
- Do not allow humans to take over.
- Only allow the vehicle to operate in a small, pre-defined location.
 - The location should be in a major city where high speeds can be avoided.
 - The location should be in a favorable climate.
 - Hospitals should be easily accessible.
- If it is the first company to release its product in the area, it should conduct tests with a small number of vehicles in the specified area before introduction.
- It should introduce a fleet large enough to reach scale but not so large as to eliminate other public transportation options.

B. Vehicle Design

- The vehicle should include an emergency response call button.
- The vehicle design should be created to minimize the risk to pedestrians and passengers.
 - In-vehicle safety equipment should be included (e.g., airbags).

C. Operation Details

- The fleet should be shut down during inclement weather.
- The fleet should be serviced regularly — at the manufacturer's discretion.

³⁵ In actuality, they will select the strategy that results in the greatest profit which may differ. However, the greater the liability costs, the more the profitability decision will be driven by minimizing costs.

D. Caveat

A key assumption underpinning this introduction strategy is that the technology can operate without a human. If not, then a fully self-driving car (NHTSA and SAE Level 5) cannot be introduced. Instead, the technology will be introduced to support the driver while keeping the driver at the center of the equation. The risk minimization introduction strategy for this approach is not included.

PART V — INTRODUCTION EVALUATION

We will walk through how the approach laid out above is expected to minimize the risk. We also highlight flaws in the approach and lingering risks. Risk minimization is not the same as risk elimination. Having a sober, well-trained individual drive in good weather with low traffic may minimize automobile accident risk in today's environment, but it does not eliminate it. The same can be said when analyzing automated vehicles.

Goal 1: Minimize Incident Frequency

A. Removing the Driver

Removing the driver eliminates the greatest source of uncertainty. Now the technology's success or failure is completely dependent on its own abilities. It is much easier for the company to predict how its technology will react than how an individual will. This also eliminates the driver's learning curve and driver ability deterioration risks.

By owning the vehicles itself, the manufacturer can be assured that the vehicle maintenance is done correctly and in a timely manner. This more closely aligns incentives and decision making — when should the brakes or tires be replaced? The answer to the question is very different if the individual owns the vehicle and is held liable; if the manufacturer owns the vehicle and is held liable; and if the individual owns the vehicle but the manufacturer is held liable.

Removing the driver also eliminates the strongest risk mitigation tool: having the driver take over. Therefore, this strategy increases the technology's burden. (This caveat will continue to be mentioned to ensure the reader does not interpret any of our statements as opinions on the technology's actual performance.)

B. Restricting Location

Restricting the vehicle's operating location to a major city with lower speeds and a favorable climate greatly reduces the incident risk, incident severity, and manufacturer cost.

- This introduction strategy minimizes the vehicle's speed and the trip length (distance and time).
- Restricting its location minimizes the service cost — it's cheaper to service vehicles that are nearby than if they reside all over the country.

- Having a fleet of vehicles operate within a small area decreases the chance that unknown infrastructure changes will arise. When an issue does arise, the issue can be identified and fixed more quickly.
- Weather is very difficult to predict. Therefore, a risk avoidance strategy — selecting a city with a favorable climate — is the best way to minimize this risk. Limiting the fleet’s size will allow the company to shut down its vehicle when the weather calls for it without completely disrupting the city’s travel.
- Unknown risks are also minimized by limiting the operating radius. The more diverse the environment and drivers encountered, the more unknowns there are.

C. Testing and Implementation

Introducing a large number of vehicles in a small area, after tests are done with a smaller number of vehicles in the same area, decreases the risk other drivers pose. This approach increases the other drivers’ familiarity with the technology by slowly exposing them to the technology and keeping them engaged with the technology. However, restricting the technology to specific areas increases the “tourist risk:” a driver new to the area will have no experience driving around the technology. These drivers will now be surrounded by a large number of automated vehicles.

Operating in a city increases the risks to pedestrians. However, this can be reduced through the introduction of other risk mitigation structures: such as the creation of automated vehicle pick-up and drop-off zones in businesses’ parking lots to minimize the technology-pedestrian interaction. For these sorts of actions to be cost-benefit positive, scale is required. Therefore, introducing a large number of vehicles in a small area allows scale to be reached sooner and additional risk mitigation approaches to be implemented.

Goal 2: Minimize Incident Severity

D. Restricting Location to a City

Restricting the vehicle’s operation can help reduce incident severity along three dimensions:

D1. Speed - The average speed in cities is much lower than highway driving. Therefore, restricting the operating location to roads with lower speed limits — avoiding high speeds altogether — imposes a natural cap on vehicle speed. However, operating in a city dramatically increases the vehicle-pedestrian interaction risk. This risk will be discussed in more detail later.

D2. Hospital proximity - Operating close to a hospital further reduces the potential severity by decreasing the time it takes for emergency response teams to reach the accident scene.

D3. Physical impairment - Physical impairments, such as heart attacks, were responsible for 2.3 percent of accidents based on NHTSA’s NNVCCS. Automated vehicles won’t prevent a heart attack from occurring; however, we can try to minimize the severity when they occur. The deployment approach minimizes the severity of these incidents in three ways:

- Including an emergency response call button allows the passenger to alert the proper authority.
- Operating close to a hospital again makes it easier and quicker for the proper authorities to reach the injured party.

- Operating in a small area imposes a time-cap on each trip length. The injury is more likely to go unnoticed the longer the trip. Shortening the length of the trip decreases the length of time the injury goes unnoticed.

Remaining Risks

The introduction strategy aims to minimize the risk, but it will not eliminate it. The process leaves (at least) five risks to be aware of.

E1. Increased technological demands: As mentioned, removing the driver dramatically removes a key support function. Without the driver to act as a failsafe, 100 percent of the driving function falls on the technology.

E2. Vehicle-pedestrian interaction: Removing the driver from the vehicle and operating exclusively in a city reduces two key sources of risk (the driver and the environment), but it also increases the risk pedestrians face.

E3. Hacking: This risk hasn't been addressed. Removing the driver from the equation may actually increase this risk. The net impact will have to be estimated and benchmark goals must be established.

E4. Exposure change: Historically, making transportation easier (whether because it's cheaper, faster, or more comfortable) has led to an increase in use. However, future travel patterns are unknown. Changing travel patterns could change the risks the technology faces.

E5. Future risks: The risks the vehicles encounter will change over time. Other drivers and pedestrians may change their behavior — taking more risks. Less frequent active driving may decrease the driver's ability when they drive their own vehicle.

PART VI - IMPLICATIONS

Our analysis relies on outdated and incomplete data. However, the output from an accurate risk analysis will have important implications for other stakeholders. Using our analysis as an example, we discuss some of the implications that result from the conclusion.

This introduction approach indicates that the technology will not progress down the NHTSA levels of automation in a nice and orderly fashion. A new, city-based public transportation alternative will provide a great deal of value, but it won't negate the need for private vehicle ownership. Therefore, manufacturers will continue introducing technology that supports but does not replace the driver.

This indicates that multiple safety benchmarks will be required. The safety benchmark for a vehicle that removes the driver from the equation may differ from driver-centric benchmark. Without a driver, incidents per trip may be required in addition to incidents per mile.

Non-technological actions can reduce the technology's risk. The testing approach can be used to improve the technology's actual performance and reduce the risk other drivers pose to the vehicles.

Risks, and benchmarks, include a location-dependent aspect. In addition to learning the local driving norms, the technology will encounter different environmental risks depending on where it operates. A “safe” product in Austin, Texas may not be as safe if introduced in Milwaukee, Wisconsin. This further indicates that municipalities may be able to encourage the technology’s development. Knowing that a complete solution isn’t necessary for the technology to come to market, local officials may be able to take actions that create a safe haven for the technology.

PART VII — CONCLUSION

Individuals navigate a myriad of risks every time they get behind the wheel. Policies, such as driver licensing laws, vehicle safety requirements, and roadway design, have been created to minimize the risk. Similarly, automated vehicles will encounter numerous risks. These risks do not negate the potential of automated vehicles to increase safety and change lives and society. However, it is important not to dismiss these risks that AVs will indeed encounter. Instead, the risks should be clearly acknowledged, enumerated, quantified, and addressed in a concrete fashion.

First, we must gather the necessary data. Without data, no analysis can progress. The data should be specific to the technology’s use and allow for risks and correlations to be quantified. Quantifying the risks provides the necessary context for decisions to be made. For example, if automated vehicles — which will certainly be subject to hacking risk — will result in 1,000 hacking deaths, the technology may look unappealing from that “hacking risk silo” viewpoint. But if AVs also eliminate all other accidents, and thus reduce the number of automobile accident deaths by over 30,000, the increased hacking risk may be viewed as acceptable. It may not, but policymakers and society must ultimately make such decisions, and context is needed in order to properly evaluate the tradeoff.

Second, a singular, comprehensive strategy is required. Risks do not occur in a linear fashion, or in silos, and we must not try to address them that way. The introduction strategy must view risk as the interconnected continuum it is, and develop an approach to minimize the risk in aggregate. The optimal strategy will therefore be the one which produces the lowest overall cost of risk.

Third, the risk analysis should be used to as a guide and not a verdict. The results can help us identify what can be done to improve the product’s safety. The mere act of highlighting the risk can help reduce its impact.

Casualty actuaries’ risk management and automobile accident expertise can help these risks be more explicitly identified and quantified. We can also help create a more robust introduction strategy to bring the technology to market as safely and efficiently as possible.

3.2: Automated Vehicle Risk — Safety Benchmark

INTRODUCTION

Thus far, auto manufacturers and technology companies have, for the most part, been extremely cautious and safety-conscious in rolling out automated vehicle technology. Collectively, over a billion dollars has been invested, and the technology has undergone over a million miles of real-world tests plus countless more simulated miles. At some point, however, not offering the technology to the public will be more harmful than offering it, as the technology's absence will enable preventable accidents and deaths will continue to occur. A performance standard is therefore an essential piece of the equation that brings the technology to market safely and efficiently. Mark Rosekind, the Administrator of NHTSA, stated in 2016 that self-driving cars must start by being twice as safe.³⁶ However, without the active participation of personal auto insurers, AV performance cannot be effectively measured against even this simple goal. Only personal auto insurers' actuarial predictive models provide the necessary detail to compare accident rates by location and, more importantly, driver risk characteristic.³⁷

I - BENCHMARK CALCULATION

An accurate benchmark is necessary to understand the technology's safety. Auto insurers' actuarial predictive models represent the best way to calculate such a benchmark. The following items are the key components of an effective benchmark.

A — COMPLETE & UNBIASED

If we are going to prevent potentially life-saving technology from entering the market, or if we are going to allow an unmanned vehicle to transport individuals, we want to be as confident as possible in the safety measurement. The benchmark we compare the technology's performance against ought to use a complete set of accidents. However, according to NHTSA, only 55 percent of accidents are reported to the police.³⁸ Therefore, any benchmark based off NHTSA's police reported data will be incomplete and inaccurate.

The completeness issue may be overcome if the dataset is representative of the accident rate in its entirety. Unfortunately, using only police reported accidents biases the benchmark by ignoring specific accident types: both high frequency/low severity accidents and single vehicle, lower severity accidents are less likely to result in a police report. Forcing automated vehicles to report all incidents will cause their "accident rate" to exceed the benchmark, all things being equal, due to the biased benchmark. Actuarial models are built off a more complete and unbiased dataset as insureds have a financial incentive to report most accidents to their insurer.

B - GRANULARITY

Accident risk differs by four key characteristics: the individual, the vehicle, the driving environment, and the vehicle's use. NHTSA's 2008 Motor Vehicle Crash Causation Survey confirmed other studies' findings that

³⁶ <http://www.bloomberg.com/news/articles/2016-06-08/u-s-auto-regulator-says-self-driving-cars-must-be-twice-as-safe>

³⁷ For an interesting perspective, see <https://www.rand.org/blog/articles/2017/11/why-waiting-for-perfect-autonomous-vehicles-may-cost-lives.html>

³⁸ <http://www-nrd.nhtsa.dot.gov/pubs/812013.pdf>

humans are the main cause of automobile accidents.³⁹ The accident rate benchmark must first and foremost explicitly account for the individual behind the wheel. Do we want to include 16 year olds' experience in the benchmark? What about 90 year olds? The accident rate will further differ based on the driving environment: city frequency rates differ from rural; rush-hour frequencies differ from off-peak driving; inclement weather increases the accident risk. If the automated vehicle is tested in optimal weather, driving on highways during off-peak hours, and controlled by engineers with perfect driving records, we would naturally expect the accident rate to be lower than an "average" driver.

Only insurers' datasets include driving statistics at such a granular level. From this data, separate benchmarks can be calculated for city and rural driving, for drivers with prior accidents and without, and by business versus pleasure use.

C - CONTINUUM

Using a simple average accident rate benchmark has the advantage of being simple to calculate; however, it is inadequate for such an important decision. Accident rates are not uniformly distributed. Therefore, the "average" rate is not the same as the accident rate of the "average" driver. Having an accident rate that is half the average is not the same as having an accident rate equivalent to the best 25 percent of drivers.

The additional detail afforded by insurers' actuarial predictive models allows for a continuum of accident rates to be calculated. Therefore, automated vehicles' performance can be put in more proper context. The vehicles' accident rate can be compared against the top 5 percent, 10 percent, 25 percent, or 50 percent for the specified details: individuals, location, vehicles, and usage.

For example, only insurers' data and the actuarial models will allow for a statement such as: "automated vehicles' accident rate falls within the top 10 percent of Los Angeles drivers' accident rates."

II - BENCHMARK APPLICATION

Beyond the data and statistical expertise needed to calculate an accurate benchmark is the ability to deploy the benchmark in such a way to accurately measure the technology's actual performance. Three additional issues must be considered:

D - RESPONSIVENESS

Accident rates are always changing. Weather patterns, demographic changes, construction, and economic trends are just a few of the variables that can cause accident rates to vary from year-to-year. An effective benchmark must be responsive enough to account for these changes. Comparing automated vehicles' actual performance against a benchmark calculated from prior years' experience will exacerbate the issue. Therefore, the ideal benchmark will need to be updated continuously to provide the most accurate measurement. Insurers are constantly updating their models to reflect the most up-to-date data available. Additionally, insurers' models are forward facing: they try to predict next year's performance. Therefore, their actuarial

³⁹ <https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/811059>

predictive models are already being done in such a way as to produce the most up-to-date accident rate performance.

E — STABILITY

The goal for a more responsive benchmark needs to be balanced against the goal of having a stable benchmark. The more granular the measurement, the more susceptible it is to having statistical noise distort the results. Statistical noise is the natural variation that can occur in the data. We need to be careful not to extrapolate from the noise. The benchmark calculation and the performance measurement need to be created and calculated to produce a stable evaluation. Increasing the amount of data and utilizing different statistical variance minimization techniques allows actuarial models to produce more stable results. The models can also tell us once our measurement has become too granular to act as an effective and stable benchmark

F - INDEPENDENCE

A final, but important, distinction lies in who calculates the benchmark and tracks performance. A simple way to balance the previous issues is by making insurers responsible for calculating the benchmark and tracking the vehicles' performance. If an insurer predicts the vehicles will be safer than they truly are, it will pay out more claims than it expected. Conversely, if an insurer predicts the vehicles will be less safe than they truly are, other insurers will be able to compete for and steal the business at a profitable price. Insurers are then able to pass on the costs to the manufacturer through the premium they charge. Having manufacturers calculate the benchmark to which they will compare themselves creates a conflict of interest.

III — CAVEAT

The safety benchmark will further depend on how automated vehicles are used. Quantifying the technology's risk as accidents per mile driven may make sense if the technology tracks closely with today's driving. However, there are many reasons this may be an inadequate measure. If the driver is removed from the equation, then the technology's performance may be better measured by its incident per trip experience. As an extreme example, a technology that errors out every trip, may have a very low accident per mile rate while still not being considered "safe" by today's standard. Additionally, the use of accidents as the measurement may be deemed too extreme in the future. Instead, the number of incidents per mile may be more predictive of future performance — where an incident is defined a precursor to an accident, such as crossing the center line, making too wide of a turn, or having the technology disengage. Data of this nature is not readily available. Therefore, the data would have to be defined, then gathered and analyzed. All of this takes time. The earlier we start, the better chance the technology's performance will be appropriately quantified, thereby allowing it to come to market as safely and efficiently as possible.

IV - CONCLUSION

While automated vehicles hold the promise to transform the transportation system and save millions of lives around the world, their performance cannot be appropriately understood without the calculation of an

effective benchmark. Even goals as simple as NHTSA's, that automated vehicles be twice as safe as today's driven vehicles, require detailed data and complex statistical analyses. Casualty actuaries, effectively engaged, can help policymakers develop the benchmarks needed to understand the technology's performance. Manufacturers can have a more concrete target to hit and be better rewarded by surpassing a target more specific to their technology's use.

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TOPIC 3
AUTOMATED VEHICLE RISK
RECOMMENDATION

Automated vehicle risk is an extremely complex issue. The technological risks are intertwined with human and environmental factors largely outside the control of the engineers. An effective analysis will look neither to disqualify the technology nor to turn a blind eye to its inherent dangers. Instead, we must address the risks head on. Bringing manufacturers, casualty actuaries, and policymakers together will allow for the creation of a more accurate and robust risk management program. Insurers' data and automobile accident causation expertise can supplement manufacturers' automated vehicle tests. Insurers can also provide policymakers with an independent and unbiased evaluation of the technology's performance. Together, we can develop a robust introduction strategy to minimize the technology's risk and more appropriately quantify and compare the expected performance to today's driving environment.

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Appendices

Liability Insurance Premiums: Appendix A

- Calculating the Baseline -

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Step 1 — Adjusting NAIC Dataset

The “NAIC Auto Insurance Database Report: 2011/2012” includes state and coverage level data. Therefore, adjustments were made at the state and coverage level.

Step 1A — Remove adjusting and other expenses (AAO)

“Adjusting and other expense” is included in the loss dollars for all coverages in every state except California and Maryland⁴⁰. AAO is made up things like salaries for claims personnel and typically doesn’t vary by state. Therefore, a single AAO factor was selected for liability coverages and physical damage coverages. Based on S&P Global Market Intelligence, a liability AAO factor of 1.13 was selected and a physical damage AAO factor of 1.15 was selected.

<u>Private Passenger Auto Liability</u>	<u>2010</u>	<u>2011</u>	<u>2012</u>	<u>2013</u>	<u>Total</u>
Incd Loss	68,985,019	71,335,030	71,475,681	74,021,834	285,817,564
Incd DCC	3,964,878	3,972,365	4,433,924	4,622,986	16,994,153
Incd AAO	9,403,788	9,532,868	10,202,259	10,487,747	39,626,662
AAO Factor	1.13	1.13	1.13	1.13	1.13
<u>Private Passenger Auto Physical Damage</u>	<u>2010</u>	<u>2011</u>	<u>2012</u>	<u>2013</u>	<u>Total</u>
Incd Loss	37,978,150	41,984,676	42,944,513	43,318,804	166,226,143
Incd DCC	243,368	227,022	261,054	199,766	931,210
Incd AAO	6,027,089	6,084,011	6,424,617	6,663,251	25,198,968
AAO Factor	1.16	1.14	1.15	1.15	1.15

Source: S&P Global Market Intelligence IEE

$$\text{AAO Factor} = (\text{Incurred Loss} + \text{Incurred DCC} + \text{Incurred AAO}) / (\text{Incurred Loss} + \text{Incurred DCC})$$

⁴⁰ Texas’ loss dollars also excluded AAO, but as Texas data are completely removed from the analysis, no adjustment is required. It is being mentioned only for completeness sake.

Liability Insurance Premiums: Appendix A

- Calculating the Baseline -

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Step 1B — Remove defense cost and containment expenses (DCC)

“Defense cost and containment expense” is mostly made up of payments to lawyers to litigate claims. These costs vary more widely by state as each state’s legal environment and insurance rules impacts an insurer’s decision to settle or fight a claim in court. Using the state pages from S&P Global Market Intelligence, separate DCC factors are selected for each state and coverage group: PIP and Other PPA Liability (Physical Damage DCC = 1.0). The selected factor is the weighted average of 2010-2014: $DCC\ Factor = \frac{Paid\ Loss + Paid\ DCC}{Paid\ Loss}$

DCC Adj Factor			DCC Adj Factor		
State	Other PPA Liab	PIP	State	Other PPA Liab	PIP
AK	1.05	1.03	MT	1.05	1.03
AL	1.04	1.13	NC	1.02	1.09
AR	1.03	1.02	ND	1.03	1.03
AZ	1.04	1.07	NE	1.03	1.09
CA	1.06	1.19	NH	1.03	1.10
CO	1.05	1.14	NJ	1.10	1.13
CT	1.05	1.11	NM	1.04	1.07
DC	1.05	1.02	NV	1.07	1.09
DE	1.06	1.06	NY	1.08	1.15
FL	1.07	1.10	OH	1.05	1.07
GA	1.04	1.17	OK	1.04	1.06
HI	1.05	1.03	OR	1.05	1.06
IA	1.04	1.05	PA	1.06	1.03
ID	1.04	1.04	RI	1.04	1.15
IL	1.06	1.09	SC	1.03	1.05
IN	1.05	1.05	SD	1.04	1.06
KS	1.03	1.02	TN	1.05	1.06
KY	1.04	1.03	TX	1.04	1.02
LA	1.07	1.12	UT	1.04	1.03
MA	1.04	1.10	VA	1.04	1.06
MD	1.04	1.02	VT	1.03	1.08
ME	1.03	1.12	WA	1.06	1.05
MI	1.11	1.07	WI	1.05	1.07
MN	1.05	1.11	WV	1.06	1.02
MO	1.04	1.04	WY	1.04	1.32
MS	1.04	0.90			

Liability Insurance Premiums: Appendix A

- Calculating the Baseline -
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Step 1C — Adjust PIP and Med Pay state definitions

In speaking with the NAIC analyst who worked on the dataset, some PIP-only states had exposures and losses assigned to both Med Pay and PIP coverages. While updates will be made in future NAIC publications, an external adjustment was required for this analysis.

Step 2 — Segmenting premium into its components

We assume the 2011 earned premiums are priced adequately. Therefore, the average premium can be split into its expected losses, expenses, and profit. Since the expense ratios and profit targets are more stable, the expected losses were calculated as Average Premium * (1 — selected expense ratio — selected profit target).

Step 2A — Select expense ratio

The expense ratios, which come from S&P Global Market Intelligence, are selected on a countrywide basis to match the subsequent analysis. The expense ratios did not vary enough by coverage to vary the selections.

PPA Liab	Calculation	2010	2011	2012	2013	Total	Selected
AAO	<i>Incl AAO/EP</i>	9.4%	9.3%	9.6%	9.5%	9.5%	9.5%
Gen Exp	<i>GE/EP</i>	5.4%	5.6%	5.6%	5.7%	5.6%	5.5%
Comm & Brok	<i>Comm & Brok / WP</i>	8.9%	8.8%	8.7%	8.5%	8.7%	8.8%
Other Acq	<i>OA / WP</i>	8.1%	8.4%	8.5%	8.6%	8.4%	8.4%
Taxes	<i>TLF/WP</i>	2.3%	2.2%	2.2%	2.2%	2.2%	2.2%

PPA Phys Dam	Calculation	2010	2011	2012	2013	Total	Selected
AAO	<i>Incl AAO/EP</i>	9.2%	9.3%	9.7%	9.6%	9.5%	9.5%
Gen Exp	<i>GE/EP</i>	5.1%	5.3%	5.4%	5.6%	5.4%	5.5%
Comm & Brok	<i>Comm & Brok / WP</i>	8.9%	8.9%	8.8%	8.7%	8.8%	8.8%
Other Acq	<i>OA / WP</i>	8.1%	8.3%	8.5%	8.7%	8.4%	8.4%
Taxes	<i>TLF/WP</i>	2.2%	2.2%	2.2%	2.2%	2.2%	2.2%

PPA Total	Calculation	2010	2011	2012	2013	Total	Selected
AAO	<i>Incl AAO/EP</i>	9.3%	9.3%	9.6%	9.6%	9.5%	9.5%
Gen Exp	<i>GE/EP</i>	5.3%	5.5%	5.5%	5.7%	5.5%	5.5%
Comm & Brok	<i>Comm & Brok / WP</i>	8.9%	8.9%	8.8%	8.6%	8.8%	8.8%
Other Acq	<i>OA / WP</i>	8.1%	8.3%	8.5%	8.7%	8.4%	8.4%
Taxes	<i>TLF/WP</i>	2.2%	2.2%	2.2%	2.2%	2.2%	2.2%

Liability Insurance Premiums: Appendix A

- Calculating the Baseline -

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Step 2B — Split fixed versus variable expenses

In order to estimate the minimum premium, the expense selections were further segmented into fixed and variable expense. Actuarial judgment was used to allocate the expenses.

Expense	Expense Ratio	Fixed Expense %
AAO	9.5%	100%
General Expenses	5.5%	100%
Commission & Brokerage	8.8%	0%
Other Acquisition	8.4%	50%
Taxes, Licenses, Fees	2.2%	0%

Step 2C — Select profit target

Because we are conducting a pricing approach, a target profit ratio needs to be used instead of the actual achieved profit. This removes any pricing inadequacies or redundancies from the analysis. The selected profit targets differ by coverage and market and were selected largely based on judgment after reviewing a number of companies' indication filings across a myriad of states.

Insurers typically require a higher profit margin on physical damage coverage than liability coverage. This is because the liability claims have a longer tail, so the insurer can make a higher investment return on the liability premium than on the physical damage premium. We assume that insurers do not target any profit on residual market risks.

Coverage	Profit Target	
	Voluntary	Residual
Liability	2.0%	0.0%
Physical Damage	5.0%	0.0%

Liability Insurance Premiums: Appendix A

- Calculating the Baseline -

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Step 2D — Calculate expected losses

The expected loss and DCC ratio is calculated for each coverage as: 1 — expense ratio — profit target. The coverage expected losses are then calculated by multiplying the 2011 earned premium from the NAIC database by the ratio and dividing out the DCC.

Coverage	Voluntary				Residual			
	Expected Loss & DCC Ratio	Avg Prem	DCC Adj. Factor	E[L]	Expected Loss & ALAE Ratio	Avg Prem	DCC Adj. Factor	E[L]
BI	63.6%	199	1.05	119.9	65.6%	496	1.05	308.9
PD	63.6%	148	1.05	89.2	65.6%	428	1.05	267.0
CSL	63.6%	356	1.06	213.6	65.6%	1,137	1.06	703.0
PIP	63.6%	174	1.09	101.2	65.6%	381	1.09	228.9
MP	63.6%	35	1.05	21.3	65.6%	68	1.05	42.5
UM	63.6%	68	1.05	41.1	65.6%	39	1.05	24.4
Comp	60.6%	119	1.00	72.3	65.6%	238	1.00	156.2
Collision	60.6%	283	1.00	171.7	65.6%	775	1.00	508.8

Step 2E — Calculate frequency and severity

The expected losses are further segmented into its specific components: the probability a loss occurs (frequency) and the amount that will be paid if a loss occurs (the severity). A priori frequency and severity estimates are calculated using the NAIC adjusted dataset (which removes AAO and DCC from the loss results).

The 2011 experience was used for the voluntary market. This experience should be more reflective of the expected experience embedded in the 2011 rates. The experience was sufficiently stable. The 2009-2011 experience was used for the residual market. The experience was simply too variable to extrapolate from a single year.

Caveat: There is an issue with the NAIC claim counts. The counts are not reportedly consistently across all companies. Some companies report claimant counts while others report claim counts. This means that a single vehicle accident with two injured passengers will be reported as two claim counts by one company and one claim count by another. As this issue exists in other industry data sources, no adjustment could be made. Therefore, the selected final frequency was balanced to ensure that

$$\text{Expected loss} = \text{Expected frequency} \times \text{Expected severity}$$

Liability Insurance Premiums: Appendix A

- Calculating the Baseline -

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The combined single limit coverage is split into its bodily injury and property damage components on the loss side and rolled up and balanced at overall coverage level since only one premium is charged for both coverages.

Voluntary		A priori				Selected		
Loss Covg	Freq	Severity	E[L]	Target E[L]	Freq Adj Factor	Freq	Severity	E[L]
BI	1.01	12,820	129.35	119.9	0.93	0.94	12,820	119.9
PD	3.89	2,557	99.59	89.2	0.90	3.49	2,557	89.2
CSL_BI	0.76	17,124	130.82	213.6	0.97	0.74	17,124	127.5
CSL_PD	3.30	2,674	88.38		0.97	3.22	2,674	86.1
PIP	1.88	6,304	118.53	101.2	0.85	1.60	6,304	101.2
MP	0.85	2,751	23.36	21.3	0.91	0.77	2,751	21.3
UM_BI	0.15	21,478	32.70	41.1	1.16	0.18	21,478	37.8
UM_PD	0.22	1,292	2.80		1.16	0.25	1,292	3.2
Comp	9.54	919	87.70	72.3	0.82	7.86	919	72.3
Collision	5.83	2,985	173.90	171.7	0.99	5.75	2,985	171.7

Residual		A priori				Selected		
Loss Covg	Freq	Severity	E[L]	Target E[L]	Freq Adj Factor	Freq	Severity	E[L]
BI	4.57	9,098	415.52	308.9	0.74	3.39	9,098	308.9
PD	12.57	2,691	338.18	267.0	0.79	9.92	2,691	267.0
CSL_BI	1.74	23,163	402.34	702.9	1.12	1.95	23,163	452.3
CSL_PD	6.39	3,489	222.93		1.12	7.18	3,489	250.6
PIP	5.70	6,461	368.46	228.9	0.62	3.54	6,461	228.9
MP	2.48	2,210	54.78	42.5	0.78	1.92	2,210	42.5
UM_BI	0.84	5,005	42.23	24.4	0.57	0.48	5,005	24.0
UM_PD	0.03	2,360	0.74		0.57	0.02	2,360	0.4
Comp	18.77	936	175.58	156.2	0.89	16.70	936	156.2
Collision	18.20	3,178	578.46	508.8	0.88	16.01	3,178	508.8

Liability Insurance Premiums: Appendix B
 - Step 1: Insured Population Adjustment -
 Page 1 of 1

Current	% of market	% with Collision	% with Comprehensive	Updated	% of market	% with Collision	% with Comprehensive
Voluntary	86.5%	72.0%	76.4%	Voluntary	86.5%	100.0%	100.0%
Residual	0.2%	24.2%	28.4%	Residual	0.2%	100.0%	100.0%
Uninsured	13.4%	0.0%	0.0%	Uninsured	13.4%	100.0%	100.0%

Voluntary Market

Covg	Avg Vehicle Prem			Chg	Covg	# of Vehicles			Chg
	Baseline	New				Baseline	New		
BI	\$ 198.68	\$ 198.68	0.0%	BI	168,102,794	168,594,577	0.3%		
PD	\$ 147.57	\$ 147.57	0.0%	PD	168,594,577	168,594,577	0.0%		
CSL	\$ 356.38	\$ 356.38	0.0%	CSL	10,075,709	10,075,709	0.0%		
PIP	\$ 173.64	\$ 173.64	0.0%	PIP	65,802,486	84,876,070	29.0%		
MP	\$ 35.05	\$ 35.05	0.0%	MP	72,716,521	93,794,216	29.0%		
UM	\$ 68.03	\$ -	-100.0%	UM	158,462,800	0	-100.0%		
Comp	\$ 119.21	\$ 119.21	0.0%	Comp	136,459,637	178,670,286	30.9%		
Collision	\$ 283.22	\$ 283.22	0.0%	Collision	128,685,976	178,670,286	38.8%		
Total	\$ 779.85	\$ 850.13	9.0%	Total	178,670,286	178,670,286	0.0%		

Residual Market

Covg	Avg Prem			Chg	Covg	# of Vehicles			Chg
	Baseline	New				Baseline	New		
BI	\$ 496.11	\$ 496.11	0.0%	BI	296,509	316,194	6.6%		
PD	\$ 428.45	\$ 428.45	0.0%	PD	316,194	316,194	0.0%		
CSL	\$ 1,137.04	\$ 1,137.04	0.0%	CSL	1,893	1,893	0.0%		
PIP	\$ 380.89	\$ 380.89	0.0%	PIP	308,994	309,613	0.2%		
MP	\$ 67.90	\$ 67.90	0.0%	MP	1,932	8,474	338.6%		
UM	\$ 39.19	\$ -	-100.0%	UM	273,257	0	-100.0%		
Comp	\$ 238.00	\$ 238.00	0.0%	Comp	90,487	318,087	251.5%		
Collision	\$ 775.18	\$ 775.18	0.0%	Collision	76,865	318,087	313.8%		
Total	\$ 1,554.22	\$ 2,311.55	48.7%	Total	318,087	318,087	0.0%		

Liability Insurance Premiums: Appendix C
- Step 2: Residual Market Liability Limit Adjustment -
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Bodily Injury

A proprietary data source was used to calculate the state increased limit factors (ILF's) and the distribution of vehicles with each limit. The NAIC state exposure distribution was then used to aggregate the state ILF's to a countrywide estimate.

The residual market was assumed to select the minimum liability limits in each state. Using the proprietary state increased limit factors and NAIC exposures, the countrywide minimum increased limit factor was calculated to be 0.71. The countrywide average increased limit factor was calculated to be 1.21. Therefore, the ILF required to bring the residual market to the voluntary market's coverage is $1.21/0.71 = 1.70$. The average limits are approximately \$115K/\$250K. This is read as the vehicle has \$115,000 of liability coverage per claimant and \$250,000 per accident, which isn't a real limit offering. However, it gives a general sense of the amount of coverage the average voluntary market risk is carrying. The ILF required to bring the residual market to the voluntary market's coverage is therefore $1.21/0.71 = 1.70$.

Property Damage

The same process was used to calculate property damage's ILF. The minimum PD ILF is 0.94 and equates to a limit of approximately \$15,000 of coverage. The average property damage ILF is 1.07 and equates to a limit of approximately \$70,000 of coverage. The ILF required to bring the residual market and uninsured vehicles to the voluntary market's average is $1.07/0.94 = 1.14$.

Combined Single Limit

No data source could be found that would have allowed us to differentiate the minimum combined single limits and the voluntary average combined single limit. A factor of 1.05 was judgmentally selected. There are very few exposures in the residual market that have this coverage, so the selection — even if it's wrong — will not have a material impact on the conclusions.

Medical Coverage (Personal Injury Protection and Medical Payments)

A factor of 1.10 was judgmentally selected as no data source was identified that will enable a more explicit calculation to be done. If it was assumed that no adjustment was required — selecting an increased limit factor of 1.0 — the average premium would only change by \$3. So again, this selection does not have a material impact on the conclusions.

Physical Damage

No increased limit factor is applied. This implies that voluntary, residual, and uninsured vehicles are similar in value and deductible. Furthermore, it implies that fully self-driving vehicles will not cost more to repair than today's vehicles. As we are assuming the end-state (100 percent of vehicles are fully autonomous), the technology's costs may not be materially different than the today's costs. Even if they are higher, they are unlikely to be a material consideration of the liability structure surrounding automated vehicles.

Liability Insurance Premiums: Appendix D

- Step 6: Expenses -

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The cost structures for products liability and personal automobile are materially different. Using the industry’s annual statements (from S&P Global Market Intelligence), we can quantify the expense differences between the two products. The expenses are shown as a percent of premium to allow them to be comparable.

Distribution

Personal auto insurance and products liability are sold through very different mechanisms. Auto insurance is typically sold through a local agent or direct through the internet. Companies use public advertisements and commissions to encourage customers to choose their product. Products liability insurance has higher commissions and broker expenses. An agent placing products liability insurance is able to negotiate with the insurance company over both the price and the contract features. This allows companies to create their own insurance policy. Personal auto policies offer a number of pre-defined and pre-priced features.

Products liability insurance entails lower marketing costs, but this does not offset the higher commissions. In total, switching the liability from personal auto to products liability will increase the distribution cost per dollar of insurance from 17.2 percent to 20.2 percent. Commercial auto (20.6 percent), other liability — occurrence (19.4 percent), and CMP (Commercial Multiple Peril) — liability (24.1 percent) all have higher acquisition costs than personal auto insurance. Hence, the costs would be expected to increase regardless of the commercial line of business after which we model the new product.

Acquisition Expense	Personal Auto	Products Liability
Commissions & Brokerage	8.8%	13.7%
<u>Other Acquisition</u>	<u>8.4%</u>	<u>6.4%</u>
Total	17.2%	20.2%

General Expenses

Products liability also has higher “General Expenses” than personal auto insurance. This is mostly attributed to the fact that products liability has more personal touch points than personal auto insurance. The more an actual person needs to get involved, the greater the costs. Commercial auto (7.2 percent), other liability — occurrence (7.0 percent), and CMP — liability (7.1 percent) also have higher general expenses than personal auto insurance.

Expense	Personal Auto	Products Liability
General Expenses	5.5%	7.5%

Liability Insurance Premiums: Appendix D

- Step 6: Expenses -

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Taxes, Licenses and Fees

Products liability has lower taxes, licenses, and fees than personal auto insurance, as well as commercial auto (2.5 percent), other liability — occurrence (1.8 percent), and CMP — liability (2.2 percent).

Expense	Personal Auto	Products Liability
Taxes, Licenses, Fees	2.2%	1.6%

Adjusting and Other Expenses

The insurance company's claims handling costs, which cannot be assigned to a specific claim, are allocated in the Adjusting and other expense bucket. These expenses are mostly made up of the Claims department's salaries. These costs are similar for both products.

Expense	Personal Auto	Products Liability
AAO	9.5%	9.5%

Total

In total, products liability insurance spends \$0.387 of every premium dollar on these expenses while personal auto insurance spends \$0.344. For comparison, commercial auto insurance spends \$0.368; other liability — occurrence insurance spends \$0.338; and CMP — liability spends \$0.391.

Liability Insurance Premiums: Appendix E

- Step 7: Actual Underwriting Profit-

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Personal Automobile

While the gross combined ratio is going to provide a more apples-to-apples comparison to the analysis, a net combined ratio view provides similar insights. As shown, personal automobile only achieved the selected target combined ratio (96.9 percent) in two of the past eleven years (2005 and 2006). The assumption that \$0.60 of every premium dollar goes to claimants understates what actually has occurred over the past nine years.

Net Combined Ratio, 2005-2015



Loss Ratios Have Been Rising for A Decade. 2015 Return on Net Worth Is Likely Close to Zero or Negative.

SOURCE: National Association of Insurance Commissioners data, sourced from S&P Global Market Intelligence; Insurance Information Institute.

<http://www.iii.org/presentation/2015-2016-and-beyond-financial-results-from-an-actuarial-point-of-view-052416>, see slide 60

Non-Premium Liability Considerations: Appendix F
NHTSA BUDGET

EXHIBIT II-2
FY 2016 TOTAL BUDGETARY RESOURCES BY APPROPRIATION ACCOUNT
NATIONAL HIGHWAY TRAFFIC SAFETY ADMINISTRATION
Appropriation, Obligation Limitation, and Exempt Obligation

	(\$000)		
<u>ACCOUNT NAME</u>	<u>FY 2014 ACTUAL</u>	<u>FY 2015 ENACTED</u>	<u>FY 2016 REQUEST</u>
VEHICLE SAFETY RESEARCH (GF)	\$ 134,000	\$ 130,000	\$ -
Rulemaking	20,662	20,010	
Enforcement	18,845	18,980	
Research and Analysis	32,483	29,000	
Program Unallocated			
Administrative Expenses	62,010	62,010	
Administrative Expenses Unallocated			
VEHICLE SAFETY RESEARCH (TF)	\$ -	\$ -	\$ 179,000
Safety Performance (Rulemaking)			24,920
Safety Assurance (Enforcement)			40,756
Research and Analysis			40,190
Administrative Expenses			73,134
Administrative Expenses Unallocated			
HIGHWAY SAFETY RESEARCH AND DEVELOPMENT (TF)	\$ 123,500	\$ 138,500	\$ 152,000
Highway Safety Programs	46,659	48,859	62,659
Research and Analysis - NCSA	35,466	32,966	45,966
Program Unallocated		6,000	
Administrative Expenses	41,375	50,675	43,375
Administrative Expenses Unallocated			
TOTAL OPERATIONS AND RESEARCH	\$ 257,500	\$ 268,500	\$ 331,000
HIGHWAY TRAFFIC SAFETY GRANTS			
Section 402 Formula Grants	235,000	235,000	241,146
Section 2009 High Visibility Enforcement Program	29,000	29,000	29,000
Section 405 National Priority Safety Programs	272,000	272,000	278,705
Section 405 Occupant Protection Grants	43,520	43,520	44,592
Section 405 State Traffic Safety Information System Grants	39,440	39,440	40,412
Section 405 Impaired Driving Countermeasures Grants	142,800	142,800	146,320
Section 405 Distracted Driving Grants	23,120	23,120	23,690
Section 405 Motorcycle Safety Grants	4,080	4,080	4,181
Section 405 State Graduated Licensing Laws	13,600	13,600	13,935
Section 403h In- Vehicle Alcohol Detection Device Research	5,440	5,440	5,574
Administrative Expenses	25,500	25,500	28,149
Administrative Expenses Unallocated			
TOTAL HIGHWAY TRAFFIC SAFETY GRANTS (TF)	\$ 561,500	\$ 561,500	\$ 577,000
TOTAL	\$ 819,000	\$ 830,000	\$ 908,000

Note: Totals may not add due to rounding

Note: FY 2016 Target is only at the approximation level. The variance from 2015 is only at the appropriation

Note: FY 2016 Target based on OMB-MAX Levels for General Fund and Trust Fund Contract Authority

FY 2015 Request ties to OMB-MAX Levels for Obligation Limitation

Note: In FY 2015, the Administration proposed to move a number of General Fund programs into the Transportation Trust Fund. Vehicle Safety Research is funded from the Trust Fund in 2015 and re-based from the General Fund in 2014.

Source: "Budget Estimates Fiscal Year 2016: National Highway Traffic Safety Administration", page 18.

Practical LDF Interpolation for Well-Behaved IBNR

Ira Robbin, Ph.D.

Abstract

Actuaries have devised numerous methods for interpolating annual evaluation loss development factors (LDF) to arrive at quarterly evaluation factors. Not all of these work as well as might be hoped. Some introduce oscillations not found in the original factors. Many lead to IBNR projections that move erratically or have blips that are hard to explain. This paper advances the approach to interpolation by taking a whole curve perspective, defining properties of well-behaved interpolates, and focusing on attributes of the resulting IBNR projections. It demonstrates a set of simple practical techniques including a backfill algorithm to compute factors at immature ages.

Keywords Loss Development Patterns, Interpolation, Equilibrium, IBNR

1. INTRODUCTION

Many practicing property casualty reserving actuaries face a recurring challenge each quarter: how to update IBNR balances for a multitude of splits by line of business, distribution channel, market segment, and geographic division. Given the lack of time and resources, doing a complete granular analysis is simply not practical. Further many of the splits do not have sufficient data to support a credible full-triangle analysis when the data is evaluated by quarter.

How do actuaries meet this challenge? One popular solution is to take the year-ending IBNR balances and use loss development factors (LDF) at quarterly evaluations to estimate the run-off. The quarterly LDF are often derived by interpolating annual LDF. To obtain the annual evaluation LDF, actuaries tend to rely on a segment's own data if it is sufficiently credible. However, when the data for a cell is too volatile even after grouping it at annual evaluation points, it is a common and accepted practice to derive default annual evaluation factors based on triangles of loss data aggregated over similar lines and segments. Both aggregation and annual evaluation increase the stability of the factors. The resulting annual evaluation default LDF are sometimes further refined by cell based on a review of industry data, claims department statistics, and other information.¹ Once the annual evaluation

¹ For example default LDF for northwest region small commercial risk division general liability (GL) losses might be derived from loss triangles for the full general liability line of business and then reduced slightly based on the actuary's belief that risks in the small commercial division have losses that develop a bit more quickly than other GL business.

development factors for a particular segment are selected, the next step is to interpolate them by quarter.²

Though interpolation of LDF might seem a trivial task, there are many available techniques and they can produce a range of answers. Some are vulnerable to anomalies or require too many actuarial overrides. Others induce seasonality that does not exist or an apparent trend that later turns out to be illusory. Many don't work well at early ages because they fail to distinguish *development of exposure to loss* from *development of loss on exposures that have already occurred*. Others implicitly forecast blips in expected quarterly IBNR run-off. At this time, no particular interpolation approach has been universally accepted. Actuaries want a set of interpolation techniques that are simple to implement, yet robust and free from anomalies. This aim of this paper is to provide a framework for achieving that goal.

1.1 Three Properties of Well-Behaved Interpolates

The first specific objective this paper is to propose a non-exhaustive set of properties that well-behaved interpolation algorithms should satisfy. In this paper three will be proposed.

The first is that the method should not introduce extra oscillations. The term, *inherited monotonicity*, will be used to describe this:

- **Inherited Monotonicity:** The quarterly age-to-age (ATA) LDF interpolates do not oscillate more often than the original annual ATA LDF. For example, suppose the 24-36 ATA LDF was larger than the 36-48 ATA LDF. A violation of inherited monotonicity would exist if the 36-39 month interpolate was larger than the 33-36 month factor. See Table 1 for an example of such a violation.

²² Another option is to interpolate the default annual LDF for the aggregation and use those as default interpolates for each cell.

Practical LDF Interpolation for Well-Behaved IBNR

Table 1

Inherited Monotonicity Violation								
	Annual Evaluation Factors							
Age	24-36				36-48			
ATA LDF	1.500				1.300			
	Quarterly Interpolates				Quarterly Interpolates			
Age	24 - 27	27 - 30	30 - 33	33 - 36	36 - 39	39 - 42	42 - 45	45 - 48
ATA LDF	1.150	1.120	1.090	1.068	1.120	1.065	1.050	1.038

The second and third properties are defined by examining the resulting IBNR evolution on a hypothetical book of business produced by a growth model in equilibrium. In this growth model, it is assumed all accident years have the same actual ultimate losses and the same pattern of development: The second and third properties are *equilibrium IBNR stability* and *monotonicity of total runoff from all prior years*:

- Equilibrium IBNR Stability:** Once equilibrium is achieved, total IBNR stays level each quarter. Each quarter the growth of IBNR from the new accident year is exactly offset by the total of IBNR runoff from all prior accident years. Table 2 shows an example of a violation of Equilibrium IBNR stability normalized so the year-ending balance is \$1,000 and quarter ending “0” is the end of the first year in which equilibrium is attained.

Table 2

Equilibrium IBNR Stability Violation						
	Quarter ending IBNR balance					
Qtr	0	1	2	3	4	5
IBNR All Prior AY	1,000	800	625	450	300	225
IBNR Current AY	-	300	450	500	700	575
IBNR Total	1,000	1,100	1,075	950	1,000	800

- Monotonically Decreasing Total Prior Year IBNR Runoff:** In equilibrium, the

Practical LDF Interpolation for Well-Behaved IBNR

quarterly totals of IBNR runoff from all prior accident years form a monotonic decreasing sequence under the assumption the development pattern never goes negative (i.e. the LDF are never below unity). Table 3 has an example of this.

Table 3

Prior Year IBNR Runoff Monotonicity Violation						
	Quarter ending IBNR balance					
Qtr	0	1	2	3	4	5
Prior AY IBNR	\$1,000	\$700	\$600	\$450	\$300	\$225
Prior Year IBNR Runoff		\$300	\$100	\$150	\$150	\$75

It might be initially surprising to realize that an arbitrary interpolation scheme will not necessarily satisfy any of these properties. Many methods introduce oscillating LDF, non-level equilibrium IBNR and a bouncy ride for the prior year IBNR run-off pattern.

Some may object that equilibrium conditions are unrealistic and of not much relevance to real-world situations. However, it is more accurate to think of it in the converse. If an interpolation routine produces IBNR fluctuations in the ideal conditions of level-growth equilibrium, then who knows what mischief may ensue in actual scenarios. In real-world scenarios problems do not jump out as clearly as they do in equilibrium. Later in this paper, it will be proved that an accident year LDF pattern will satisfy equilibrium IBNR stability if it is generated from uniform exposure to loss, the usual assumption made for a non-seasonal accident year, and a fixed underlying claim development pattern.

1.2 Three Interpolation Tools

This paper will present several practical techniques for use in the interpolation process. The first, *tail-tapering*, is not strictly an interpolation tool but rather a procedure that quickly smooths out the tail of the initial set of annual evaluation factors. However, it is essential to taper the tail before attempting to interpolate and in that sense it is the first step of the interpolation process. Tail-tapering takes the user selected percent of ultimate value at the user-selected tapering onset age and then employs a straightforward routine to smoothly taper

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to ultimate at the user-selected selected ultimate age.³

The second is *normalized cross-year increment smoothing with monotonicity adjustment*. This starts by computing level quarterly increments separately for each year. Then simple arithmetic smoothing is applied over all quarters beyond month 12. The increments by year are then normalized so as to reproduce the original annual evaluation LDF. If the provisional results violate the inherited monotonicity property, averages against the initial level increments are performed for any year in need of correction. This stage produces interpolates that are relatively smooth and which inherit monotonicity. Other methods unknowingly court difficulty when they examine each year in isolation and pay no attention to the transition from one year to the next. The averaging across years is one very simple way (not necessarily the only or the best way) to address that neglect.

The third tool is the *stability backfill* technique. This is an algorithm for determining the factors at immature ages by requiring the resulting factors to produce IBNR values satisfying the Equilibrium IBNR Stability property.

The overall method with tail tapering, cross-year smoothing, and stability backfill will be identified by the acronym, SWIMON (**S**oothing **W**ith **I**ncrements - **M**onotonically **N**ormalized).

1.2.1 Tapering the Tail

It is best to first taper the tail of the annual evaluation LDF before performing quarterly interpolation. This assumes the initial tail goes all the way to ultimate. More sophisticated approaches are needed if this is not true and the tail factors must be extrapolated. Also it is assumed that the actuary has LDF deemed acceptable up to a certain age. They may be all-weighted year averages for example or averages ex Hi/Lo. The problem in this situation is that the tail factors may be quite erratic even if close to unity. There may be a few unity factors interspersed with occasional blips up and down that over the span of a few years might add up to point or two. Some actuaries would set the curve to unity and write-off this small amount. Others will try their hand at smoothing by eye. This tends to absorb an inordinate amount of actuarial effort, with students tapering by eye and managers and chief actuaries refining the numbers. For example, a student upon seeing annual LDF machine averages of

³³ See the Appendix for the definitions of increments, age-to-age-factors, tail decay rates and other representations of loss development.

1.008, 0.995, and 1.003, might propose a string of three factors equal to 1.002. The manager may refine that to 1.0025, 1.0020, and 1.00195. Others will try curve fitting that sometimes works well, but which is sometimes confounded by the oscillations in the tail and the need to remove outliers to arrive at a good fit. Even after fitting there may be a small tail out to infinity that the actuary would like to close out.

So how is it possible to extricate actuaries from this tedious and low value-added part of the process? The solution to be demonstrated in Chapter 2 is to taper the annual evaluation factors from a selected age onward to a selected ultimate age. The resulting tapered annual evaluation factors can then be grafted onto the body of the curve. Essentially the idea is to take the three key parameters that the actuary can readily select to define the tail and use those to construct a smooth tail. The tail-tapered curve can be interpolated by quarter as will be explained in the next section.⁴

1.2.2. Avoiding Middle Age Interpolation Disorders

Assuming relatively stable patterns of LDF in the middle and later stages of development, the problem is how to interpolate to a quarterly basis without inducing seasonal bias or producing erratic patterns going from one quarter to the next. For instance, a method might overstate the IBNR takedown for the first quarter of each prior accident year so the company more often than not sees what looks like beneficial prior year development in the first quarter of each year. Note that the IBNR runoff in a quarter is the expected development. If the IBNR runoff is overstated, then actual development will tend to come in low relative to this false benchmark. The company may conclude results are better than they truly are. By the time this gets corrected in the remaining quarters the biased figures may have led to incorrect business decisions. Another problem is that some interpolation routines yield answers prone to jumps at year-end. These routines usually generate quarterly expected development that proceeds nicely from quarter to quarter during the year and all seems fine. However, the pattern then might break sharply for the first quarter of the subsequent year (quarter 5 from the starting quarter). This can only be explained if the annual factors increase instead of decrease from one year to the next. Otherwise this would be a manifestation of a failure of

⁴ Preliminary tail-tapering is often useful even if one is not doing quarterly interpolation. It may improve the performance of curve-fitting routines being used to smooth out factors at earlier ages. Even the step of setting factors to unity beyond a selected ultimate age is beneficial since some machine-generated averages that appear to be unity on a display are not. These can lead to small sums that make their appearance in unexpected places.

inherited monotonicity. The overall point is that faulty interpolation routines lead to blips in IBNR evolution that are difficult to explain.

The increment smoothing, normalization, and monotonicity adjustment procedure is designed to address these potential problems. It is presented in more detail in Chapter 3.

1.2.3. Exposure Growth Problems in Early Age Interpolation

Finally there is the question of what to do about the start-up period. Many methods fail to extend reasonably to early ages simply because they fail to account for the increasing exposure separately from the development of losses already incurred. The general solution as explained by Robbin [3] and Robbin and Homer [4] is to explicitly account for the dependence of loss development patterns on underlying exposure period development. Those papers describe fitting different parametric forms against data. In this paper a simpler backfill technique will be used in which the early age factors are determined so that the IBNR stays fixed each quarter in a level growth model. The approach will be demonstrated in Chapter 4. In Chapter 5, it will be shown that an accident year LDF pattern generated via the Robbin formula under reasonable uniformity assumptions will produce IBNR that automatically satisfies the backfill formula.

1.3 Existing Literature

Recent works by Boor [2] and by Bloom [1] provide useful quick methods (“hacks”) for interpolating LDF. Bloom’s paper shows interpolates of 12, 24, 36 ... month factors at ages 15, 27, 39, ..., computed with a variety of methods including Linear, Inverse Power Curve (IVP), IVP decay, Exponential, and Exponential Decay. Her paper also has methods for extrapolating to immature ages.

Boor fits a Weibull curve form to the implicit IBNR percentages derived from the original annual evaluation factors. He then uses the Weibull curve shape to arrive at monthly interpolates between the annual factors. He extends to early ages and makes monthly exposure adjustments to convert the scaled Weibull factors to be on an accident year basis.

This paper is intended to advance actuarial interpolation tools and concepts beyond what is found in these works and other existing literature. It promotes a new “whole-curve” perspective on interpolation and highlights the need to define properties of behavior for interpolates. It also adds to the literature by stressing the importance of evaluating the qualities of interpolates by examining the resulting evolution of IBNR. The three techniques

demonstrated in this paper are offered as useful if basic additions to the actuarial toolbox of practical methods.

To be clear, many actuaries do produce IBNR projections as a standard component of reserve analysis. However, documentation of this important part of the process does not appear to have previously found its way into the literature or at least not in the standard articles on interpolation of LDF.

1.4 Comparison Example

To clarify the distinction between different methods and the properties of their resulting interpolates, methods from the Bloom paper, the Boor paper, and this paper will be used to interpolate the sample annual factors from the Bloom paper. This will be done in Chapter 6.

First the IVP method in the Bloom paper will be extended to show interpolates at all intermediate quarters beyond age 12 months.(e.g. for ages 18 and 21, not just age 15). Then the “Method of 12” described in that paper will be used to fill in the early quarters.⁵ Boor’s Weibull fitting and splicing method will be applied to the same set of factors and summarized by quarter.⁶ The three alternative sets of interpolated LDF will then be compared.

1.5 Expected Quarterly Development and Projected IBNR Run-off

A fundamental message of this paper is that the actuary should review predicted amounts of expected quarterly development by accident year over at least five projected calendar quarters. Dubious patterns of expected development indicate a poorly performing interpolation method. The actuary should be able to explain any strange blips or else go back and derive new interpolates.

The schedule of expected quarterly IBNR and IBNR run-off based on the SWIMON interpolates will be computed starting with an arbitrary hypothetical set of year-end balances. This will be done in Chapter 7. It should be noted that many reserving actuaries already produce IBNR runoff projections and study them carefully for anomalies.

1.6 Equilibrium Run-off Comparison

Equilibrium IBNR projections by quarter will be computed for the SWIMON, IVF/12, and Spliced Weibull IBNR interpolates in Chapter 8. Some may initially feel this has little

⁵ Bloom presented many methods and did not recommend these over any others.

⁶ Boor shows interpolates on a monthly basis.

relevance since there are few stable equilibrium scenarios in the real world. The author's perspective is that any equilibrium oscillations need to be subtracted out of real world indications. A scale that is not calibrated properly will yield incorrect results. In effect, the equilibrium analysis can indicate if a set of interpolates is appropriately balanced.

1.7 Conclusion

It is hoped the practical techniques presented in this paper will achieve acceptance as useful additions to the actuarial toolbox. The tail-tapering technique could be employed in deriving LDF patterns outside of an interpolation context. Also, there is nothing to prevent the actuary from applying the interpolation methods in this paper to interpolate Paid LDF and then project estimated Unpaid Losses instead of IBNR.

While the comparison of methods was necessary to clarify distinctions between different algorithms, the fundamental message of this paper is not that one method did or did not work better than others on a specific example. It is that actuaries should analyze the behavior and characteristics of the interpolated LDF and the resulting IBNR evolution. Indeed, many already do and in that sense this paper can be viewed as an initial attempt to codify and extend existing practice. Whether actuaries accept or reject those particular interpolation techniques, a major objective of the author will have been achieved if it fosters a greater awareness of the importance of examining the behavior of the whole curve of LDF interpolates and the resulting quarterly IBNR run-off projections.

2. TAIL TAPERING AND TRUNCATION

Given that an initial percent of ultimate selection, $PCT_0(t_1)$, has been made for month t_1 , which is divisible by 12, and a subsequent decay rate of unreported loss, q , has been selected, the infinitely extrapolated annual evaluation percent of ultimate series $PCT^*(t)$ for $t > t_1$ is generated inductively via:

$$PCT^*(t_1) = PCT_0(t_1) \tag{2.1}$$

$$PCT^*(t_1 + k \cdot 12) = PCT^*(t_1 + (k - 1) \cdot 12) + q \cdot Q^*(t_1 + (k - 1) \cdot 12)$$

where $Q = 1 - PCT$ and k is a positive integer

For example, if PCT_0 is 90% at 120 months and q is 40%, then PCT^* is 94% at 132 and

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96.4% at age 144.

Now suppose the actuary selects an age, t_F , at which it is desired the development pattern will reach ultimate. Set the multiplier, M , via:

$$M = \frac{1 - PCT^*(t_I)}{PCT^*(t_F) - PCT^*(t_I)} \quad (2.2)$$

Then set annual increments, INC , between t_I and t_F , via

$$INC^*(t_I + k \cdot 12) = PCT^*(t_I + k \cdot 12) - PCT^*(t_I + (k - 1) \cdot 12) \quad (2.3)$$

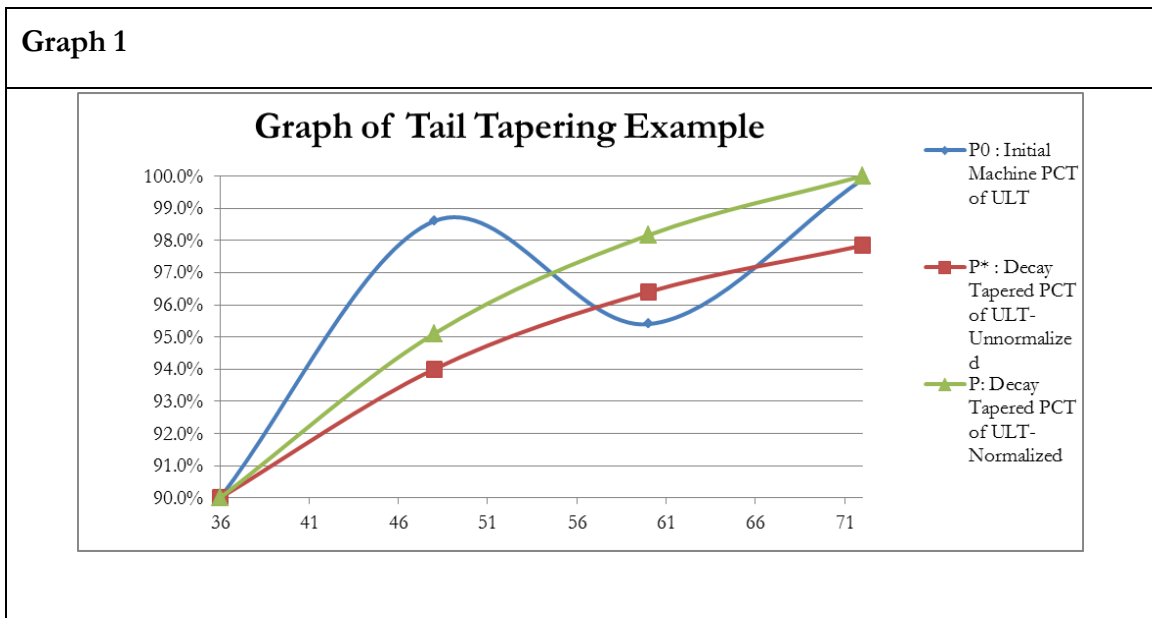
$$INC(t_I + k \cdot 12) = M \cdot INC^*(t_I + k \cdot 12)$$

The actuary should set initial and final ages and the value of q so that the increments appear reasonable. An example is shown in Table 4.

Table 4 Tail-tapering Example				
		Age	Pct Ult	
	Initial	36	90%	
	Ultimate	72	100%	
	Decay Rate	40.0%		
	Multiplier	1.276		
Age (Months)	36	48	60	72
P0 : Initial Machine PCT of ULT	90.0%	98.6%	95.4%	99.9%
P* : Decay Tapered PCT of ULT- Unnormalized	90.0%	94.0%	96.4%	97.8%
P: Decay Tapered PCT of ULT- Normalized	90.0%	95.1%	98.2%	100.0%

The initial machine generated percentages of ultimate, the un-normalized, and final normalized tail-tapered curves are shown in Graph 1.

Graph 1



3. CROSS-YEAR QUARTERLY SMOOTHING, NORMALIZATION, AND MONOTONICITY FIXING

The next step in the SWIMON procedure is to obtain annual increments of development. This is done by taking differences between the percent of ultimate values. After that preparatory step, each annual increment is divided equally to get initial increments by quarter. For example if the percent of ultimate goes from 80.0% to 90.0% over months 48 to 60, then the increment for year five is 10.0% and the initial set of quarterly increments for year five is 2.5% for each quarter.

The next step is to smooth these across all quarters starting with quarter five out to ultimate. In the example shown in Exhibit 1B, three point smoothing is done twice. The initial annual evaluation LDF are taken from the example in Bloom's paper. The smoothed increments are then renormalized to preserve the annual totals.

Though the initial level increments will satisfy the inherited monotonicity property, the same cannot be guaranteed after they are smoothed and normalized. So the resulting increments are examined and if any violation is found, it can be removed by averaging the increments for the year in which the violation occurs with the initial level increments for that year. This is also shown in Exhibit 1B. Overall, this procedure tempers the jump from one

year to the next and leads to quarterly increments that evolve more reasonably than the initial flat values, but which still balance to the desired annual totals.

4. IMMATURE AGE IBNR EQUILIBRIUM STABILITY BACKFILL

To extrapolate back to quarters over the first year, the SWIMON approach is to backfill so as to achieve level IBNR each quarter in the equilibrium growth phase on a level book of business. The key idea is the IBNR added from the new accident year must offset the sum of IBNR run-off for all prior accident years.

The mathematical construction is begun with some general definitions. Let $IBNR\%(t)$ be the IBNR percentage for the t^{th} month of development of an accident year as a percent of ultimate loss and let $IBNRQ(w,k)$ be the IBNR percentage for the w^{th} prior accident year as of the k^{th} calendar quarter after the end of year $y-1$. Here k runs from 1 to 4. For example $IBNRQ(2,3)$ is the IBNR percentage as of the end of the third quarter for the second prior accident year. Let $w=0$ correspond to the current accident year. It follows that:

IBNR Definitions (4.1)

$$IBNRQ(0, k) = \frac{k}{4} - PCT(3k) \qquad \text{for } w = 0$$

$$IBNRQ(w, k) = IBNR\%(12w + 3k) = 1 - PCT(12w + 3k)$$

for $w = 1, 2, \dots$

When $w=0$, the “ $k/4$ ” term is needed because it is the percent of ultimate exposure incurred as of the k^{th} quarter under the usual uniformity assumptions for an accident year. For example, if $k=3$, and the percent of ultimate as of the end of the third quarter is 40%, then the $IBNR\%$ for the third quarter of the current accident year is $75\% - 40\% = 35\%$. The “ $k/4$ ” term gets replaced by unity when $w = 1, 2, \dots$. For example, the IBNR for the second prior accident year as of the third quarter after year-end is the IBNR percentage at month 33 which is 100% minus the percent of ultimate at month 33.

The quarterly IBNR run-off for the w^{th} prior AY as of the k^{th} subsequent quarter is defined as the difference in IBNR for the $k-1^{\text{st}}$ and k^{th} quarters and denoted as $R(IBNRQ)(w,k)$:

IBNR Run-off (4.2)

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$$\begin{aligned} R(\text{IBNRQ})(w, k) &= -\Delta\text{IBNRQ}(w, k) = \text{IBNRQ}(w, k - 1) - \text{IBNRQ}(w, k) \\ &= \text{IBNR}\% (12 * w + 3(k - 1)) - \text{IBNR}\% (12w + 3k) \end{aligned}$$

For example the third quarter IBNR Runoff percentage for the second prior accident year is the difference between the IBNR percentage at 30 ($2*12+3*2$) months and 33 ($2*12 + 3*3$) months.

The next part of the exposition is to determine formulas for IBNR in equilibrium under uniform growth assumptions. The equilibrium and level growth assumptions mean that ultimate losses are the same for all accident years and that IBNR totals can be obtained by summing the appropriate percentages. Thus, to attain stability in equilibrium, the increase in IBNR for the current accident year must equal the total runoff for the prior years:

$$\begin{aligned} \Delta\text{IBNRQ}(0, k) = R(\text{IBNRQ})(\text{All Prior AY}, k) &= \sum_{w=1} R(\text{IBNRQ})(w, k) \\ &\text{for } k = 1, 2, 3, 4 \end{aligned} \tag{4.3}$$

Recall $w=0$ is used here to stand for the current accident year.

Knowing the change in IBNR is enough to solve for the incremental percent of ultimate, INCQ, for the current accident year. Let ETD(k) be the percentage of ultimate loss exposure earned to date as of the kth quarter. For an accident year, the ETD function is 25%, 50%, 75%, and 100% for the first four quarters and 100% thereafter. Then for $k= 1, 2, 3, 4$, it follows that:

$$\text{INCQ}(k) = \text{PCT}(3k) - \text{PCT}(3(k - 1)) = \Delta\text{ETD} - \Delta\text{IBNR}(0, k) \tag{4.4}$$

For example, if total prior year IBNR runoff for the second quarter is 14.0%, then the incremental increase in percent of ultimate in the second quarter is 11.0% (25%-14%).

This method is shown in Exhibit 1C again using the example from Bloom's paper and the mature year interpolates derived in Exhibit 1B. The quarterly interpolated LDF are then grafted together to make one curve from age 3 months on to ultimate. This is shown in Exhibit 1A

As will be proved in the next section, under level growth model assumptions, the IBNR for immature periods of a uniform accident year must grow enough to offset the run-off for all prior years.

5. EQUILIBRIUM IBNR STABILITY

Many readers accept the concept of equilibrium IBNR stability because it is intuitively appealing. Others might not be entirely convinced and perhaps wonder if some non-seasonal development pattern might nonetheless give rise to IBNR oscillations in equilibrium. In this section it will be shown that under the usual uniformity assumptions and other reasonable assumptions, the IBNR must be stable in equilibrium under level growth.

To set the groundwork, it is necessary to quickly summarize the general loss development pattern representation theory of Robbin and Homer [3] and an additional accident year result from Robbin [2]. Under slightly revised notation, let T be the underlying claim settlement lag random variable defined as the time elapsed from when a claim occurs until it settles. Let A be a loss exposure bucketing random variable defined as the lag from the start of an exposure period until a loss occurs. For an accident year under the usual assumptions, A is uniform on $[0, 1]$. The percent of ultimate for the underlying development variable T and the exposure bucketing variable A is given by the convolution integral:

$$\text{Robbin-Homer Convolution Formula for Percent of Ultimate} \quad (5.1)$$

$$PCT_{T|A}(t) = F_{A+T}(t) = \int_0^t ds f_A(s) * F_T(t - s)$$

The integral representation assumes the random variables A and T are independent. Independence can be asserted based on the general grounds that the manner in which loss exposures are bucketed for purposes of accounting and reporting should not have any impact on how the claims are settled.

For an accident year, Equation 5.1 can be expressed using formulas that include the limited expected value of T , denoted here as LEV :

$$\text{Robbin Accident Year Percent of Ultimate Formula Based on LEVs} \quad (5.2)$$

$$PCT_{T|A}(t) = \begin{cases} t - LEV(t) & \text{for } t < 1 \\ 1 - (LEV(t) - LEV(t - 1)) & \text{for } t > 1 \end{cases}$$

The proof is in Robbin [2]. Equation 5.2 provides a convenient way to generate accident year loss development curves given a parametric non-negative random variable such as a Pareto or exponential that has a tractable limited expected value formula.

The new result in this paper is that Equation 5.2 implies IBNR stability in equilibrium.

AY Equilibrium IBNR Stability (5.3)

Let an AY development pattern, $PCT^(t)$, be given.*

*If there exists a non
– negative random lag variable, T , with finite mean
such that
 $PCT^*(t) = PCT_{T|A}(t)$,*

*then IBNR is constant in equilibrium in a
growth model with level growth.*

Proof: The change in IBNR for quarter k is given using 4.2 as

$$\Delta IBNRQ(k) = \sum_{w=0} \Delta IBNRQ(w, k) \quad (5.4)$$

Expanding each of the change in IBNR terms for an accident year, A , with a fixed development distribution T in terms of the PCTs of ultimate and then substituting in 5.2, one finds for $w=0$:

$$\begin{aligned} \Delta IBNRQ_{T|A}(0, k) &= \frac{1}{4} - \{PCT_{T|A}(3k) - PCT_{T|A}(3(k-1))\} \\ &= \frac{1}{4} - \left\{ \frac{3k}{4} - E(3k) - \left(\frac{3(k-1)}{4} - E(3(k-1)) \right) \right\} \\ &= \{E(3k) - E(3(k-1))\} \end{aligned} \quad (5.5)$$

For $w=1, 2, \dots$

$$\begin{aligned} \Delta IBNRQ_{T|A}(w, k) = & \hspace{15em} (5.6) \\ 1 - PCT_{T|A}(12w + 3k) - \{1 - PCT_{T|A}(12w + 3(k - 1))\} \\ & = E(12(w - 1) + 3k) - E(12w + 3k) \\ & - \{E(12(w - 1) + 3(k - 1)) - E(12w + 3(k - 1))\} \end{aligned}$$

Plugging 5.5 and 5.6 back into 5.4, one finds that each new term in the sum offsets the residual of previous term and leaves a residual that is offset by the next term.

For example with $k=2$, one has after 4 terms:

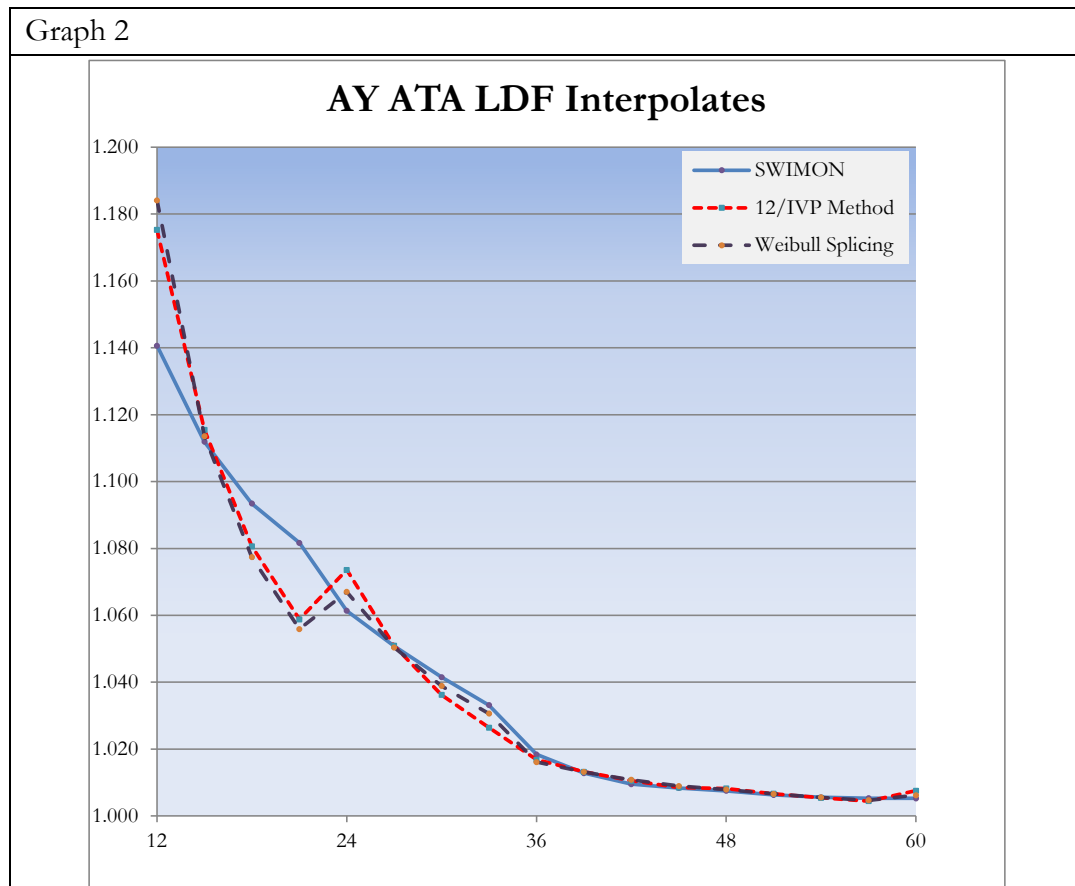
$$\begin{aligned} \Delta IBNRQ(2) = & \hspace{15em} (5.7) \\ & E(6) - E(3) \\ & + E(18) - E(6) - \{E(15) - E(3)\} \\ & + E(30) - E(18) - \{E(27) - E(15)\} \\ & E(42) - E(30) - \{E(39) - E(27)\} \\ & = E(42) - E(39) \end{aligned}$$

Assuming T has a finite mean, the difference in the limited expected values must go to zero. It follows the $\Delta IBNRQ(k)=0$. Therefore total IBNR does not change by quarter in equilibrium for an accident year pattern generated by A given T .

So the entire suite of AY development curves that can be generated by Equation 5.2 are curves that will satisfy equilibrium IBNR stability.

6. COMPARISON OF LDF FOR DIFFERENT METHODS

In this chapter, different interpolation methods are compared on the specific set of annual factors in the Bloom paper [1]. Interpolations from the SWIMON procedure are derived and compared with those derived from the IVP Method and Method of 12 as shown in Bloom [1] and the fitted Weibull Spliced IBNR model presented by Boor[2]. The derivation and results are shown in Exhibits 2 and 3 respectively. Readers with questions about those methods should refer back to the Bloom and Boor papers. The resulting sets of ATA and ATU LDF are compared in Exhibit 4A and the corresponding percent of ultimate and incremental curves are shown in Exhibit 4B. Graph 2 shows the ATA LDF.



Since the original annual LDF are monotonically decreasing, the bounce in the 12/IVP and Weibull spliced curves indicate a violation of the inherited monotonicity property.

7. QUARTERLY INTERPOLATED LDF AND INDICATED IBNR

Any set of quarterly interpolated LDF can be used to project IBNR Runoff by quarter for each prior accident year. Starting with the year-end prior accident year IBNR balances at the end of the prior calendar year as given, this chapter will show how the LDF can be used to compute IBNR run-off percentages or equivalent IBNR decay factors.

7.1 IBNR Runoff by Accident Year

Let $INCQ(w,k)$ be the percentage increment of development during the k th quarter after year end for the w th prior AY. Let $PCT(t)$ be the interpolated percent of ultimate pattern derived from the interpolated LDF, where t is expressed in months. Then the increments are

given as:

$$INCQ(w, k) = PCT(12w + 3k) - PCT(12w + 3(k - 1)) \quad (7.1)$$

The resulting IBNR run-off percentages, $RUNQ(w, k)$, as factors against their respective year-end balances are given as:

$$RUNQ(w, k) = \frac{INCQ(w, k)}{1 - PCT(12y)} \quad (7.2)$$

The runoff can also be expressed as a series of decay ratios applied against the each prior IBNR balance.

$$DRQ(w, k) = 1 - \frac{INCQ(w, k)}{IBNRQ(w, k - 1)} \quad (7.3)$$

For example, if IBNR for the second prior accident year was 48% of ultimate as of year-end and 40% of ultimate for the as of the end of the second quarter of the current calendar year and the increment during the third quarter was 4.0%, then the Run-off percentage would 8.25% ($=4/48$) and the Decay Ratio for the third quarter would be 90% ($=1-4/40$).

Exhibit 5 shows IBNR Runoff tables that result from applying the SWIMON interpolates of the Bloom annual LDF to a set of sample year-ending IBNR balances. These balances are not derived from any equilibrium condition, but are instead meant to typify a real-world situation. Nonetheless, using the SWIMON interpolates, the resulting IBNR Runoff schedule evolves in a reasonable fashion.

8. EQUILIBRIUM IBNR COMPARISON

In this section Equilibrium IBNR percentages by quarter are computed under the assumption of level growth and based on the three different methods of interpolation applied to the annual factors from Bloom's example. Formulas from Chapters 4 and 5 are used and all values are expressed as percentages of ultimate loss for an accident year. Results are shown in Exhibit 6 for the SWIMON method, in Exhibit 7 for the 12/IVP procedure, and in Exhibit 8 for the Weibull Splices approach. The "B" sections of these exhibits show the computation of the change in IBNR by quarter based on the interpolated factors. The "A" sections show

the change in IBNR by accident year and quarter for five subsequent quarters. The “A” sections have prior year and current year totals and the grand totals for each quarter. A summary comparison is provided in Exhibit 9.

Exhibit 9 shows that the SWIMON method is the only one to satisfy Equilibrium IBNR stability. It also shows that the SWIMON and the Weibull Splicing methods satisfy the monotonic decreasing total prior year IBNR runoff property.

9.CONCLUSION

This paper has made the initial effort in defining some basic properties that are desirable in an LDF interpolation routine. It has gone beyond the purely mathematical aspects of general interpolation to focus on the particular qualities of LDF interpolation. It has documented the widespread actuarial practice of producing quarterly IBNR run-off schedules and highlighted the importance of examining the IBNR run-off projections out to five quarters at least.

It has demonstrated one set of simple tools for interpolating LDF. The tail-tapering is useful in its own right. The cross-year averaging of increments of development with annual normalization and monotonicity adjustment combines a series of mathematically basic steps to produce a robust result. The strategy of cross-year smoothing, of not looking at each year in isolation, is an advance over splicing. Even though the back-filling for level equilibrium IBNR is computationally straightforward, it has a stronger conceptual foundation than various numerical extension routines and it eliminates unintended, algorithmic-induced seasonality.

In conclusion, it has been argued in this paper that LDF interpolation should be done on a whole curve basis with focus on the behavior of the resulting IBNR projections. Other approaches that examine years in isolation or ignore IBNR evolution are effectively missing one of the key reasons why actuaries interpolate LDF in the first place. This paper was written to address the challenge faced by reserving actuaries in updating and projecting IBNR each quarter. Such a practical focus has led to a better understanding of the conceptual attributes of desirable interpolation routines. It is hoped others will advance this line of thinking further perhaps by proposing more sophisticated sets of properties interpolates should satisfy or by developing more sophisticated set of tools to produce even better-behaved interpolations.

Appendix A – Different Representations of Loss Development

One of the practical observations offered in this paper is that there is useful flexibility to be gained in keeping on hand several equivalent ways to describe loss development. The actuary can then adopt whatever perspective is most convenient for solving a particular problem. The different representations are:

- age-to-age factors
- age-to-ultimate factors
- percent of ultimate values
- incremental percentages = IBNR takedown schedules
- IBNR and tail decay rates

For $t = 1, 2, 3, \dots$, let $X(t)$ be the incremental amount of loss development in the t^{th} period for one particular exposure period and let $S(t)$ be the cumulative development so that:

$$S(t) = X(1) + X(2) + \dots + X(t)$$

Define the Age-to-Age factor:

$$ATA(t) = S(t+1)/S(t).$$

Let $X(t) = B \cdot INC(t)$ and $S(t) = B \cdot PCT(t)$ where

$$INC(t) = PCT(t) - PCT(t-1).$$

Also define the Age-to-Ultimate factor

$$ATU(t) = 1/PCT(t).$$

In this construction, B is the ultimate loss, PCT is the percent of ultimate, and INC is the increment of development. Note that B, S, X, PCT, INC, ATA , and ATU are all random variables.

Define random variables, $Q(1), Q(2), \dots, Q(t)$, where $0 < Q(t) < 1$, via:

$$Q(1) = PCT(1) \tag{Eq(1)}$$

$$Q(t + 1) = \frac{INC(t + 1)}{1 - PCT(t)}$$

Practical LDF Interpolation for Well-Behaved IBNR

The Q random variables are called the tail decay rate random variables. $Q(t)$ is called the decay rate and is interpreted as the fraction of the loss development tail remaining after time, $t-1$, that will be reported during the t^{th} period. If one has a set of decay rate variables, the process can be run in reverse to generate a percent of ultimate pattern.

Eq (2)

$$PCT(t) = 1 - \prod_{s=1}^t (1 - Q(s)) \quad (2.1)$$

$$INC(t) = Q(t) \cdot \prod_{s=1}^{t-1} (1 - Q(s)) \quad (2.2)$$

For example, if $Q(1)$ is 20% and $Q(2)$ is 10%, then $PCT(2) = 1 - (.8)(.9) = 28\%$ and $INC(2) = .10 * (1 - .8) = 8\%$.

EXHIBITS

Glossary of Exhibits

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	1A Full curve
	1B Smoothing Increments for Mature AY
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Practical LDF Interpolation for Well-Behaved IBNR

Exhibit 1A										
Quarterly LDF Interpolation SWIMON										
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Age	Interval	AY ATA LDF	AY ATU LDF	AY PCT ULT	AY Incrē by Yr	AY Incrē Interp by Q	AY PCT ULT	AY ATA LDF	AY ATU LDF	ITD ATU LDF
						Running sum of (7) From Ex 1C	Ratios of consec rows of (8)		1/(9)	ITD Expos as % of AY*(10)
0				0.00%						
3	0 - 3					9.38%	9.38%	2.268	10.661	2.665
6	3 - 6					11.90%	21.28%	1.648	4.700	2.350
9	6 - 9					13.79%	35.06%	1.429	2.852	2.139
12	9 - 12	1.500	1.996	50.11%	50.11%	15.04%	50.11%	1.156	1.996	1.996
15	12 - 15					7.83%	57.94%	1.113	1.726	1.726
18	15 - 18					6.52%	64.46%	1.087	1.551	1.551
21	18 - 21					5.61%	70.07%	1.073	1.427	1.427
24	21 - 24	1.200	1.331	75.16%	25.05%	5.09%	75.16%	1.061	1.331	1.331
27	24 - 27					4.61%	79.77%	1.051	1.254	1.254
30	27 - 30					4.05%	83.82%	1.041	1.193	1.193
33	30 - 33					3.48%	87.30%	1.033	1.145	1.145
36	33 - 36	1.050	1.109	90.19%	15.03%	2.89%	90.19%	1.018	1.109	1.109
39	36 - 39					1.66%	91.85%	1.013	1.089	1.089
42	39 - 42					1.18%	93.03%	1.010	1.075	1.075
45	42 - 45					0.89%	93.91%	1.008	1.065	1.065
48	45 - 48	1.025	1.056	94.70%	4.51%	0.79%	94.70%	1.008	1.056	1.056
51	48 - 51					0.71%	95.41%	1.006	1.048	1.048
54	51 - 54					0.60%	96.02%	1.006	1.041	1.041
57	54 - 57					0.54%	96.55%	1.005	1.036	1.036
60	57 - 60	1.020	1.030	97.07%	2.37%	0.51%	97.07%	1.005	1.030	1.030
63	60 - 63					0.51%	97.58%	1.005	1.025	1.025
66	63 - 66					0.50%	98.08%	1.005	1.020	1.020
69	66 - 69					0.48%	98.56%	1.005	1.015	1.015
72	69 - 72	1.010	1.010	99.01%	1.94%	0.45%	99.01%	1.003	1.010	1.010
75	72 - 75					0.30%	99.31%	1.002	1.007	1.007
78	75 - 78					0.25%	99.55%	1.002	1.004	1.004
81	78 - 81					0.22%	99.78%	1.002	1.002	1.002
84	81 - 84	1.000	1.000	100.00%	0.99%	0.22%	100.00%	1.000	1.000	1.000

Practical LDF Interpolation for Well-Behaved IBNR

Exhibit 1B

**Quarterly LDF Interpolation
Normalized Cross-Year Smoothing of AY Increments
Fixed to Inherit Monotonicity**

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Age	Interval	AY ATA LDF	AY ATU LDF	AY PCT ULT	AY Increm by Yr	Initial AY Increm by Qtr	AY Increm Smooth 1	AY Increm Smooth 2	Norm AY Increm	Mono Fixed Norm AY Increm
						<i>By year, (6)/4</i>	<i>3-pt smooth of (7)</i>	<i>3-pt smooth of (8)</i>	<i>Normalized by year to match (10) and (7)</i>	<i>(10) or Average (10) and (7)</i>
0				0.00%						
3	0 - 3					12.53%				
6	3 - 6					12.53%				
9	6 - 9					12.53%	12.53%			
12	9 - 12	1.500	1.996	50.11%	50.11%	12.53%	10.44%	10.44%		
15	12 - 15					6.26%	8.35%	8.35%	7.83%	7.05%
18	15 - 18					6.26%	6.26%	6.96%	6.52%	6.39%
21	18 - 21					6.26%	6.26%	5.98%	5.61%	5.94%
24	21 - 24	1.200	1.331	75.16%	25.05%	6.26%	5.43%	5.43%	5.09%	5.68%
27	24 - 27					3.76%	4.59%	4.59%	4.61%	4.61%
30	27 - 30					3.76%	3.76%	4.04%	4.05%	4.05%
33	30 - 33					3.76%	3.76%	3.47%	3.48%	3.48%
36	33 - 36	1.050	1.109	90.19%	15.03%	3.76%	2.88%	2.88%	2.89%	2.89%
39	36 - 39					1.13%	2.00%	2.00%	1.66%	1.66%
42	39 - 42					1.13%	1.13%	1.42%	1.18%	1.18%
45	42 - 45					1.13%	1.13%	1.07%	0.89%	0.89%
48	45 - 48	1.025	1.056	94.70%	4.51%	1.13%	0.95%	0.95%	0.79%	0.79%
51	48 - 51					0.59%	0.77%	0.77%	0.71%	0.71%
54	51 - 54					0.59%	0.59%	0.65%	0.60%	0.60%
57	54 - 57					0.59%	0.59%	0.58%	0.54%	0.54%
60	57 - 60	1.020	1.030	97.07%	2.37%	0.59%	0.56%	0.56%	0.51%	0.51%
63	60 - 63					0.49%	0.52%	0.52%	0.54%	0.51%
66	63 - 66					0.49%	0.49%	0.50%	0.51%	0.50%
69	66 - 69					0.49%	0.49%	0.46%	0.47%	0.48%
72	69 - 72	1.010	1.010	99.01%	1.94%	0.49%	0.41%	0.41%	0.42%	0.45%
75	72 - 75					0.25%	0.33%	0.33%	0.30%	0.30%
78	75 - 78					0.25%	0.25%	0.27%	0.25%	0.25%
81	78 - 81					0.25%	0.25%	0.25%	0.22%	0.22%
84	81 - 84	1.000	1.000	100.00%	0.99%	0.25%	0.25%	0.25%	0.22%	0.22%

Practical LDF Interpolation for Well-Behaved IBNR

Exhibit 1C									
Quarterly LDF Interpolation Backfill for Equilibrium IBNR Stability									
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Age	Interval	AY Interp Qtrly Increm after 12 mos	Change in IBNR	Cal Q in Year y	Prior AY Total Change in Equil IBNR	AY Loss Exposure ITD	Change in Exposure	Change in Equil IBNR	AY Increm
			-(3)			$\frac{\min((1),12)}{12}$	$\frac{\text{Diff of consec rows of (7)}}{7}$	-(6)	(8)-(9)
0						0.00%			
3	0 - 3			1	-15.62%	25.00%	25.00%	15.62%	9.38%
6	3 - 6			2	-13.10%	50.00%	25.00%	13.10%	11.90%
9	6 - 9			3	-11.21%	75.00%	25.00%	11.21%	13.79%
12	9 - 12			4	-9.96%	100.00%	25.00%	9.96%	15.04%
15	12 - 15	7.83%	-7.83%			100.00%	0.00%	-7.83%	7.83%
18	15 - 18	6.52%	-6.52%			100.00%	0.00%	-6.52%	6.52%
21	18 - 21	5.61%	-5.61%			100.00%	0.00%	-5.61%	5.61%
24	21 - 24	5.09%	-5.09%			100.00%	0.00%	-5.09%	5.09%
27	24 - 27	4.61%	-4.61%			100.00%	0.00%	-4.61%	4.61%
30	27 - 30	4.05%	-4.05%			100.00%	0.00%	-4.05%	4.05%
33	30 - 33	3.48%	-3.48%			100.00%	0.00%	-3.48%	3.48%
36	33 - 36	2.89%	-2.89%			100.00%	0.00%	-2.89%	2.89%
39	36 - 39	1.66%	-1.66%			100.00%	0.00%	-1.66%	1.66%
42	39 - 42	1.18%	-1.18%			100.00%	0.00%	-1.18%	1.18%
45	42 - 45	0.89%	-0.89%			100.00%	0.00%	-0.89%	0.89%
48	45 - 48	0.79%	-0.79%			100.00%	0.00%	-0.79%	0.79%
51	48 - 51	0.71%	-0.71%			100.00%	0.00%	-0.71%	0.71%
54	51 - 54	0.60%	-0.60%			100.00%	0.00%	-0.60%	0.60%
57	54 - 57	0.54%	-0.54%			100.00%	0.00%	-0.54%	0.54%
60	57 - 60	0.51%	-0.51%			100.00%	0.00%	-0.51%	0.51%
63	60 - 63	0.51%	-0.51%			100.00%	0.00%	-0.51%	0.51%
66	63 - 66	0.50%	-0.50%			100.00%	0.00%	-0.50%	0.50%
69	66 - 69	0.48%	-0.48%			100.00%	0.00%	-0.48%	0.48%
72	69 - 72	0.45%	-0.45%			100.00%	0.00%	-0.45%	0.45%
75	72 - 75	0.30%	-0.30%			100.00%	0.00%	-0.30%	0.30%
78	75 - 78	0.25%	-0.25%			100.00%	0.00%	-0.25%	0.25%
81	78 - 81	0.22%	-0.22%			100.00%	0.00%	-0.22%	0.22%
84	81 - 84	0.22%	-0.22%			100.00%	0.00%	-0.22%	0.22%

Practical LDF Interpolation for Well-Behaved IBNR

Exhibit 2

**Quarterly LDF Interpolation
IVP and Method of 12**

Early Age Plus 12 Method
Mature Age IVP Decay for each year
 $\ln(ATU-1) = \ln(a) + b \cdot \ln(1/T)$

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Age	AY ATA LDF	AY ATU LDF	AY PCT ULT	Exposure (ETD) as % of AY ULT	Interval			AY ATU LDF	AY PCT ULT	AY ATA LDF
			1/(4)							
0			0.00%	0.00%	0 - 3	Plus 12 Method			0.00%	
3				25.00%	3 - 6	$\frac{\{[ATU^{12}]^{(12+t)}\}}{ETD}$	13.404	7.46%	2.377	
6				50.00%	6 - 9		5.639	17.73%	1.783	
9				75.00%	9 - 12		3.163	31.62%	1.585	
12	1.500	1.996	50.11%	100.00%	12 - 15		1.996	50.11%	1.175	
15				100.00%	15 - 18	a	51.9	1.698	58.89%	1.115
18				100.00%	18 - 21	b	1.6	1.522	65.69%	1.081
21				100.00%	21 - 24			1.409	70.99%	1.059
24	1.200	1.331	75.16%	100.00%	24 - 27			1.331	75.16%	1.074
27				100.00%	27 - 30	a	2008.5	1.239	80.69%	1.051
30				100.00%	30 - 33	b	2.7	1.179	84.80%	1.036
33				100.00%	33 - 36			1.138	87.87%	1.026
36	1.050	1.109	90.19%	100.00%	36 - 39			1.109	90.19%	1.017
39				100.00%	39 - 42	a	428.0	1.090	91.71%	1.013
42				100.00%	42 - 45	b	2.3	1.076	92.92%	1.011
45				100.00%	45 - 48			1.065	93.90%	1.009
48	1.025	1.056	94.70%	100.00%	48 - 51			1.056	94.70%	1.008
51				100.00%	51 - 54	a	2479.2	1.047	95.48%	1.007
54				100.00%	54 - 57	b	2.8	1.040	96.12%	1.005
57				100.00%	57 - 60			1.035	96.64%	1.004
60	1.020	1.030	97.07%	100.00%	60 - 63			1.030	97.07%	1.008
63				100.00%	63 - 66	a	1.8E+09	1.022	97.80%	1.005
66				100.00%	66 - 69	b	6.1	1.017	98.33%	1.004
69				100.00%	69 - 72			1.013	98.72%	1.003
72	1.010	1.010	99.01%	100.00%	72 - 75	Linear ATU		1.010	99.01%	1.002
75				100.00%	75 - 78	a	#####	1.008	99.26%	1.002
78				100.00%	78 - 81	b	134.4	1.005	99.50%	1.002
81				100.00%	81 - 84			1.003	99.75%	1.003
84	1.000	1.000	#####	100.00%	84 -			1.000	100.00%	1.000

Practical LDF Interpolation for Well-Behaved IBNR

Exhibit 3

Quarterly LDF Interpolation
Weibull Splicing

Weibull Fit age 12-60	a	(1.7469)
IBNR= exp(-c*T^b)	b	0.7517
T = Avg Maturity	C= exp(a)	0.1743

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Age	Avg Loss Maturity	AY ATA LDF	AY ATU LDF	IBNR	ln(-ln(5))	ln(2)	Weibull Fit IBNR Curve	Weibull IBNR Interp	PCT ULT for Maturity	ATU LDF for Maturity	AY ATU LDF	AY ATA LDF
				1-1/(4)	ln(-ln(5))	ln(2)	Scale (8)	by year to bit (5)	1-(9)	1/(10)	(11)*min (1,12/(1))	(12)/(12) next row
0	0.0			100.0%			100.0%	100.0%	0.0%			
3	1.5						78.9%	78.4%	21.6%	4.629	#####	3.119
6	3.0						67.2%	66.3%	33.7%	2.968	5.937	1.906
9	4.5						58.3%	57.2%	42.8%	2.336	3.115	1.561
12	6.0	1.500	1.996	49.89%	(0.363)	1.792	51.2%	49.9%	50.1%	1.996	1.996	1.184
15	9.0						40.3%	40.7%	59.3%	1.685	1.685	1.114
18	12.0						32.4%	33.9%	66.1%	1.514	1.514	1.077
21	15.0						26.3%	28.8%	71.2%	1.405	1.405	1.056
24	18.0	1.200	1.331	24.84%	0.331	2.890	21.6%	24.8%	75.2%	1.331	1.331	1.067
27	21.0						17.9%	19.8%	80.2%	1.247	1.247	1.050
30	24.0						15.0%	15.8%	84.2%	1.187	1.187	1.039
33	27.0						12.5%	12.5%	87.5%	1.143	1.143	1.031
36	30.0	1.050	1.109	9.81%	0.842	3.401	10.6%	9.8%	90.2%	1.109	1.109	1.016
39	33.0						8.9%	8.4%	91.6%	1.091	1.091	1.013
42	36.0						7.6%	7.1%	92.9%	1.077	1.077	1.011
45	39.0						6.5%	6.1%	93.9%	1.065	1.065	1.009
48	42.0	1.025	1.056	5.30%	1.078	3.738	5.5%	5.3%	94.7%	1.056	1.056	1.008
51	45.0						4.7%	4.6%	95.4%	1.048	1.048	1.007
54	48.0						4.1%	3.9%	96.1%	1.041	1.041	1.006
57	51.0						3.5%	3.4%	96.6%	1.035	1.035	1.005
60	54.0	1.020	1.030	2.93%	1.261	3.989	3.0%	2.9%	97.1%	1.030	1.030	1.006
63	57.0						2.6%	2.3%	97.7%	1.024	1.024	1.005
66	60.0						2.3%	1.8%	98.2%	1.018	1.018	1.005
69	63.0						2.0%	1.4%	98.6%	1.014	1.014	1.004
72	66.0	1.010	1.010	0.99%	1.529	4.190	1.7%	1.0%	99.0%	1.010	1.010	1.003
75	69.0						1.5%	0.7%	99.3%	1.007	1.007	1.003
78	72.0						1.3%	0.4%	99.6%	1.004	1.004	1.002
81	75.0						1.1%	0.2%	99.8%	1.002	1.002	1.002
84	78.0	1.000	1.000	0.00%			1.0%	0.0%	100.0%	1.000	1.000	1.000

Practical LDF Interpolation for Well-Behaved IBNR

Exhibit 4A

**Interpolation Methods Comparison
ATU and ATA**

Age	Interval	Original ATU LDF	AY ATU LDF			AY ATA LDF		
			SWIM	12-12 and IVF Method	Weibull Splicing	SWIM	12-12 and IVF Method	Weibull Splicing
0								
3	0 - 3		10.661	13.404	18.518	2.268	2.377	3.119
6	3 - 6		4.700	5.639	5.937	1.648	1.783	1.906
9	6 - 9		2.852	3.163	3.115	1.429	1.585	1.561
12	9 - 12	1.996	1.996	1.996	1.996	1.156	1.175	1.184
15	12 - 15		1.726	1.698	1.685	1.113	1.115	1.114
18	15 - 18		1.551	1.522	1.514	1.087	1.081	1.077
21	18 - 21		1.427	1.409	1.405	1.073	1.059	1.056
24	21 - 24	1.331	1.331	1.331	1.331	1.061	1.074	1.067
27	24 - 27		1.254	1.239	1.247	1.051	1.051	1.050
30	27 - 30		1.193	1.179	1.187	1.041	1.036	1.039
33	30 - 33		1.145	1.138	1.143	1.033	1.026	1.031
36	33 - 36	1.109	1.109	1.109	1.109	1.018	1.017	1.016
39	36 - 39		1.089	1.090	1.091	1.013	1.013	1.013
42	39 - 42		1.075	1.076	1.077	1.010	1.011	1.011
45	42 - 45		1.065	1.065	1.065	1.008	1.009	1.009
48	45 - 48	1.056	1.056	1.056	1.056	1.008	1.008	1.008
51	48 - 51		1.048	1.047	1.048	1.006	1.007	1.007
54	51 - 54		1.041	1.040	1.041	1.006	1.005	1.006
57	54 - 57		1.036	1.035	1.035	1.005	1.004	1.005
60	57 - 60	1.030	1.030	1.030	1.030	1.005	1.008	1.006
63	60 - 63		1.025	1.022	1.024	1.005	1.005	1.005
66	63 - 66		1.020	1.017	1.018	1.005	1.004	1.005
69	66 - 69		1.015	1.013	1.014	1.005	1.003	1.004
72	69 - 72	1.010	1.010	1.010	1.010	1.003	1.002	1.003
75	72 - 75		1.007	1.008	1.007	1.002	1.002	1.003
78	75 - 78		1.004	1.005	1.004	1.002	1.002	1.002
81	78 - 81		1.002	1.003	1.002	1.002	1.003	1.002
84	81 - 84	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Practical LDF Interpolation for Well-Behaved IBNR

Exhibit 4B

**Interpolation Methods Comparison
PCT ULT and Increments**

Age	Interval	Original AY PCT ULT	AY PCT ULT			AY Increments		
			SWIM	12-12 and IVF Method	Weibull Splicing	SWIM	12-12 and IVF Method	Weibull Splicing
0								
3	0 - 3		9.4%	7.5%	5.4%	9.4%	7.5%	5.4%
6	3 - 6		21.3%	17.7%	16.8%	11.9%	10.3%	11.4%
9	6 - 9		35.1%	31.6%	32.1%	13.8%	13.9%	15.3%
12	9 - 12	50.1%	50.1%	50.1%	50.1%	15.0%	18.5%	18.0%
15	12 - 15		57.9%	58.9%	59.3%	7.8%	8.8%	9.2%
18	15 - 18		64.5%	65.7%	66.1%	6.5%	6.8%	6.7%
21	18 - 21		70.1%	71.0%	71.2%	5.6%	5.3%	5.1%
24	21 - 24	75.2%	75.2%	75.2%	75.2%	5.1%	4.2%	4.0%
27	24 - 27		79.8%	80.7%	80.2%	4.6%	5.5%	5.0%
30	27 - 30		83.8%	84.8%	84.2%	4.1%	4.1%	4.0%
33	30 - 33		87.3%	87.9%	87.5%	3.5%	3.1%	3.3%
36	33 - 36	90.2%	90.2%	90.2%	90.2%	2.9%	2.3%	2.7%
39	36 - 39		91.9%	91.7%	91.6%	1.7%	1.5%	1.5%
42	39 - 42		93.0%	92.9%	92.9%	1.2%	1.2%	1.2%
45	42 - 45		93.9%	93.9%	93.9%	0.9%	1.0%	1.0%
48	45 - 48	94.7%	94.7%	94.7%	94.7%	0.8%	0.8%	0.8%
51	48 - 51		95.4%	95.5%	95.4%	0.7%	0.8%	0.7%
54	51 - 54		96.0%	96.1%	96.1%	0.6%	0.6%	0.6%
57	54 - 57		96.6%	96.6%	96.6%	0.5%	0.5%	0.5%
60	57 - 60	97.1%	97.1%	97.1%	97.1%	0.5%	0.4%	0.5%
63	60 - 63		97.6%	97.8%	97.7%	0.5%	0.7%	0.6%
66	63 - 66		98.1%	98.3%	98.2%	0.5%	0.5%	0.5%
69	66 - 69		98.6%	98.7%	98.6%	0.5%	0.4%	0.4%
72	69 - 72	99.0%	99.0%	99.0%	99.0%	0.5%	0.3%	0.4%
75	72 - 75		99.3%	99.3%	99.3%	0.3%	0.2%	0.3%
78	75 - 78		99.6%	99.5%	99.6%	0.2%	0.2%	0.3%
81	78 - 81		99.8%	99.8%	99.8%	0.2%	0.2%	0.2%
84	81 - 84	100.0%	100.0%	100.0%	100.0%	0.2%	0.2%	0.2%

Practical LDF Interpolation for Well-Behaved IBNR

Exhibit 5A

AY IBNR Run-off by Q
LDF Interpolation: SWIMON

AY	Year end IBNR	Q1	Q2	Q3	Q4	Q5
y						
y-1	800	674	570	480	398	324
y-2	610	497	397	312	241	200
y-3	320	266	227	199	173	150
y-4	500	433	376	325	277	228
y-5	80	66	52	39	27	19
y-6	10	7	5	2	-	-
Total Prior AY	2,320	1,943	1,627	1,357	1,116	921
IBNR Run-off						
AY		Q1	Q2	Q3	Q4	Q5
y						
y-1		126	105	90	82	74
y-2		113	99	85	71	41
y-3		54	38	29	26	23
y-4		67	57	51	49	48
y-5		14	14	13	12	8
y-6		3	3	2	2	-
Total Prior AY		377	315	270	241	194

Practical LDF Interpolation for Well-Behaved IBNR

Exhibit 5B

IBNR Runoff Calculations
LDF Interpolation: SWIMON

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Age	Interval	Interp ATA LDF	ATU LDF	AY PCT ULT	Tail of ULT Loss	Increment	IBNR Runoff Factor	Exposure to Date (ETD)%	ETD IBNR%	Change in IBNR (%) AY ULT
		<i>Running back product of (3)</i>			<i>1/(4)</i>	<i>1-(5)</i>	<i>Row Diffs of (6)</i>	<i>(7)/(6)</i>	<i>AY Uniform Expos (9)-(5)</i>	
0				0.00%	100.00%			0.00%		
3	0 - 3	2.268	10.661	9.38%	90.62%	9.38%		25.00%	15.62%	15.62%
6	3 - 6	1.648	4.700	21.28%	78.72%	11.90%		50.00%	28.72%	13.10%
9	6 - 9	1.429	2.852	35.06%	64.94%	13.79%		75.00%	39.94%	11.21%
12	9 - 12	1.156	1.996	50.11%	49.89%	15.04%		100.00%	49.89%	9.96%
15	12 - 15	1.113	1.726	57.94%	42.06%	7.83%	15.69%	100.00%	42.06%	-7.83%
18	15 - 18	1.087	1.551	64.46%	35.54%	6.52%	15.51%	100.00%	35.54%	-6.52%
21	18 - 21	1.073	1.427	70.07%	29.93%	5.61%	15.79%	100.00%	29.93%	-5.61%
24	21 - 24	1.061	1.331	75.16%	24.84%	5.09%	17.00%	100.00%	24.84%	-5.09%
27	24 - 27	1.051	1.254	79.77%	20.23%	4.61%	18.56%	100.00%	20.23%	-4.61%
30	27 - 30	1.041	1.193	83.82%	16.18%	4.05%	20.03%	100.00%	16.18%	-4.05%
33	30 - 33	1.033	1.145	87.30%	12.70%	3.48%	21.50%	100.00%	12.70%	-3.48%
36	33 - 36	1.018	1.109	90.19%	9.81%	2.89%	22.77%	100.00%	9.81%	-2.89%
39	36 - 39	1.013	1.089	91.85%	8.15%	1.66%	16.94%	100.00%	8.15%	-1.66%
42	39 - 42	1.010	1.075	93.03%	6.97%	1.18%	14.44%	100.00%	6.97%	-1.18%
45	42 - 45	1.008	1.065	93.91%	6.09%	0.89%	12.70%	100.00%	6.09%	-0.89%
48	45 - 48	1.008	1.056	94.70%	5.30%	0.79%	12.92%	100.00%	5.30%	-0.79%
51	48 - 51	1.006	1.048	95.41%	4.59%	0.71%	13.45%	100.00%	4.59%	-0.71%
54	51 - 54	1.006	1.041	96.02%	3.98%	0.60%	13.15%	100.00%	3.98%	-0.60%
57	54 - 57	1.005	1.036	96.55%	3.45%	0.54%	13.48%	100.00%	3.45%	-0.54%
60	57 - 60	1.005	1.030	97.07%	2.93%	0.51%	14.94%	100.00%	2.93%	-0.51%
63	60 - 63	1.005	1.025	97.58%	2.42%	0.51%	17.44%	100.00%	2.42%	-0.51%
66	63 - 66	1.005	1.020	98.08%	1.92%	0.50%	20.62%	100.00%	1.92%	-0.50%
69	66 - 69	1.005	1.015	98.56%	1.44%	0.48%	24.94%	100.00%	1.44%	-0.48%
72	69 - 72	1.003	1.010	99.01%	0.99%	0.45%	31.34%	100.00%	0.99%	-0.45%
75	72 - 75	1.002	1.007	99.31%	0.69%	0.30%	29.82%	100.00%	0.69%	-0.30%
78	75 - 78	1.002	1.004	99.55%	0.45%	0.25%	35.62%	100.00%	0.45%	-0.25%
81	78 - 81	1.002	1.002	99.78%	0.22%	0.22%	50.00%	100.00%	0.22%	-0.22%
84	81 - 84	1.000	1.000	100.00%	0.00%	0.22%	100.00%	100.00%	0.00%	-0.22%

Practical LDF Interpolation for Well-Behaved IBNR

Exhibit 6A

IBNR Change Projection in Equilibrium Assuming Level Growth
Interpolation: SWIMON

Change in IBNR Projected by Q					
AY	Q1	Q2	Q3	Q4	Q5
y	15.62%	13.10%	11.21%	9.96%	-7.83%
y-1	-7.83%	-6.52%	-5.61%	-5.09%	-4.61%
y-2	-4.61%	-4.05%	-3.48%	-2.89%	-1.66%
y-3	-1.66%	-1.18%	-0.89%	-0.79%	-0.71%
y-4	-0.71%	-0.60%	-0.54%	-0.51%	-0.51%
y-5	-0.51%	-0.50%	-0.48%	-0.45%	-0.30%
y-6	-0.30%	-0.25%	-0.22%	-0.22%	
AY y	15.62%	13.10%	11.21%	9.96%	-7.83%
All Prior	-15.62%	-13.10%	-11.21%	-9.96%	-7.79%
Total	0.00%	0.00%	0.00%	0.00%	-15.62%

Practical LDF Interpolation for Well-Behaved IBNR

Exhibit 6B

Calculation of IBNR Change Assuming Level Equilibrium
Interpolation: SWIMON

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Age	Interval	Interp ATA LDF	ATU LDF	AY PCT ULT	Tail of AY ULT Loss	Expos to Date (ETD) Increm	Change in %	Tail of Loss ETD as % of AY Ult	Change in IBNR	
		<i>Running back product of</i>		<i>1/(4)</i>	<i>1-(5)</i>	<i>Row Diffs of (6)</i>	<i>min(12,(1))/12</i>	<i>Row Diffs of (8)</i>	<i>(8)-(5)</i>	<i>(9)-(7)</i>
			(3)							
0				0.00%	100.00%		0.00%			
3	0 - 3	2.268	10.661	9.38%	90.62%	9.38%	25.00%	25.00%	15.62%	15.62%
6	3 - 6	1.648	4.700	21.28%	78.72%	11.90%	50.00%	25.00%	28.72%	13.10%
9	6 - 9	1.429	2.852	35.06%	64.94%	13.79%	75.00%	25.00%	39.94%	11.21%
12	9 - 12	1.156	1.996	50.11%	49.89%	15.04%	100.00%	25.00%	49.89%	9.96%
15	12 - 15	1.113	1.726	57.94%	42.06%	7.83%	100.00%	0.00%	42.06%	-7.83%
18	15 - 18	1.087	1.551	64.46%	35.54%	6.52%	100.00%	0.00%	35.54%	-6.52%
21	18 - 21	1.073	1.427	70.07%	29.93%	5.61%	100.00%	0.00%	29.93%	-5.61%
24	21 - 24	1.061	1.331	75.16%	24.84%	5.09%	100.00%	0.00%	24.84%	-5.09%
27	24 - 27	1.051	1.254	79.77%	20.23%	4.61%	100.00%	0.00%	20.23%	-4.61%
30	27 - 30	1.041	1.193	83.82%	16.18%	4.05%	100.00%	0.00%	16.18%	-4.05%
33	30 - 33	1.033	1.145	87.30%	12.70%	3.48%	100.00%	0.00%	12.70%	-3.48%
36	33 - 36	1.018	1.109	90.19%	9.81%	2.89%	100.00%	0.00%	9.81%	-2.89%
39	36 - 39	1.013	1.089	91.85%	8.15%	1.66%	100.00%	0.00%	8.15%	-1.66%
42	39 - 42	1.010	1.075	93.03%	6.97%	1.18%	100.00%	0.00%	6.97%	-1.18%
45	42 - 45	1.008	1.065	93.91%	6.09%	0.89%	100.00%	0.00%	6.09%	-0.89%
48	45 - 48	1.008	1.056	94.70%	5.30%	0.79%	100.00%	0.00%	5.30%	-0.79%
51	48 - 51	1.006	1.048	95.41%	4.59%	0.71%	100.00%	0.00%	4.59%	-0.71%
54	51 - 54	1.006	1.041	96.02%	3.98%	0.60%	100.00%	0.00%	3.98%	-0.60%
57	54 - 57	1.005	1.036	96.55%	3.45%	0.54%	100.00%	0.00%	3.45%	-0.54%
60	57 - 60	1.005	1.030	97.07%	2.93%	0.51%	100.00%	0.00%	2.93%	-0.51%
63	60 - 63	1.005	1.025	97.58%	2.42%	0.51%	100.00%	0.00%	2.42%	-0.51%
66	63 - 66	1.005	1.020	98.08%	1.92%	0.50%	100.00%	0.00%	1.92%	-0.50%
69	66 - 69	1.005	1.015	98.56%	1.44%	0.48%	100.00%	0.00%	1.44%	-0.48%
72	69 - 72	1.003	1.010	99.01%	0.99%	0.45%	100.00%	0.00%	0.99%	-0.45%
75	72 - 75	1.002	1.007	99.31%	0.69%	0.30%	100.00%	0.00%	0.69%	-0.30%
78	75 - 78	1.002	1.004	99.55%	0.45%	0.25%	100.00%	0.00%	0.45%	-0.25%
81	78 - 81	1.002	1.002	99.78%	0.22%	0.22%	100.00%	0.00%	0.22%	-0.22%
84	81 - 84	1.000	1.000	100.00%	0.00%	0.22%	100.00%	0.00%	0.00%	-0.22%

Practical LDF Interpolation for Well-Behaved IBNR

Exhibit 7A

**IBNR Change Projection in Equilibrium Assuming Level Growth
Interpolation: 12/IVP**

Change in IBNR Projected by Q					
AY	Q1	Q2	Q3	Q4	Q5
y	17.54%	14.73%	11.12%	6.51%	-8.78%
y-1	-8.78%	-6.80%	-5.30%	-4.17%	-5.53%
y-2	-5.53%	-4.11%	-3.07%	-2.32%	-1.52%
y-3	-1.52%	-1.21%	-0.98%	-0.80%	-0.78%
y-4	-0.78%	-0.63%	-0.52%	-0.43%	-0.73%
y-5	-0.73%	-0.53%	-0.39%	-0.29%	-0.25%
y-6	-0.25%	-0.25%	-0.25%	-0.25%	
AY y	17.54%	14.73%	11.12%	6.51%	-8.78%
All Prior	-17.59%	-13.53%	-10.51%	-8.26%	-8.81%
Total	-0.05%	1.19%	0.61%	-1.75%	-17.59%

Practical LDF Interpolation for Well-Behaved IBNR

Exhibit 7B										
Calculation of IBNR Change Assuming Level Equilibrium										
Interpolation: 12/IVP										
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Age	Interval	Interp ATA LDF	ATU LDF	AY PCT ULT	Tail of AY ULT Loss	Expos to Date (ETD) as % of AY ULT	Change in ETD	Tail of Loss ETD as % of AY Ult	Change in IBNR	
		<i>Running back product of</i>		<i>1/ (4)</i>	<i>1-(5)</i>	<i>Row Diff's of (6)</i>	<i>min(12,(1))/ 12</i>	<i>Row Diff's of (8)</i>	<i>(8)-(5)</i>	<i>(9)-(7)</i>
0				0.00%	100.00%		0.00%			
3	0 - 3	2.377	13.404	7.46%	92.54%	7.46%	25.00%	25.00%	17.54%	17.54%
6	3 - 6	1.783	5.639	17.73%	82.27%	10.27%	50.00%	25.00%	32.27%	14.73%
9	6 - 9	1.585	3.163	31.62%	68.38%	13.88%	75.00%	25.00%	43.38%	11.12%
12	9 - 12	1.175	1.996	50.11%	49.89%	18.49%	100.00%	25.00%	49.89%	6.51%
15	12 - 15	1.115	1.698	58.89%	41.11%	8.78%	100.00%	0.00%	41.11%	-8.78%
18	15 - 18	1.081	1.522	65.69%	34.31%	6.80%	100.00%	0.00%	34.31%	-6.80%
21	18 - 21	1.059	1.409	70.99%	29.01%	5.30%	100.00%	0.00%	29.01%	-5.30%
24	21 - 24	1.074	1.331	75.16%	24.84%	4.17%	100.00%	0.00%	24.84%	-4.17%
27	24 - 27	1.051	1.239	80.69%	19.31%	5.53%	100.00%	0.00%	19.31%	-5.53%
30	27 - 30	1.036	1.179	84.80%	15.20%	4.11%	100.00%	0.00%	15.20%	-4.11%
33	30 - 33	1.026	1.138	87.87%	12.13%	3.07%	100.00%	0.00%	12.13%	-3.07%
36	33 - 36	1.017	1.109	90.19%	9.81%	2.32%	100.00%	0.00%	9.81%	-2.32%
39	36 - 39	1.013	1.090	91.71%	8.29%	1.52%	100.00%	0.00%	8.29%	-1.52%
42	39 - 42	1.011	1.076	92.92%	7.08%	1.21%	100.00%	0.00%	7.08%	-1.21%
45	42 - 45	1.009	1.065	93.90%	6.10%	0.98%	100.00%	0.00%	6.10%	-0.98%
48	45 - 48	1.008	1.056	94.70%	5.30%	0.80%	100.00%	0.00%	5.30%	-0.80%
51	48 - 51	1.007	1.047	95.48%	4.52%	0.78%	100.00%	0.00%	4.52%	-0.78%
54	51 - 54	1.005	1.040	96.12%	3.88%	0.63%	100.00%	0.00%	3.88%	-0.63%
57	54 - 57	1.004	1.035	96.64%	3.36%	0.52%	100.00%	0.00%	3.36%	-0.52%
60	57 - 60	1.008	1.030	97.07%	2.93%	0.43%	100.00%	0.00%	2.93%	-0.43%
63	60 - 63	1.005	1.022	97.80%	2.20%	0.73%	100.00%	0.00%	2.20%	-0.73%
66	63 - 66	1.004	1.017	98.33%	1.67%	0.53%	100.00%	0.00%	1.67%	-0.53%
69	66 - 69	1.003	1.013	98.72%	1.28%	0.39%	100.00%	0.00%	1.28%	-0.39%
72	69 - 72	1.002	1.010	99.01%	0.99%	0.29%	100.00%	0.00%	0.99%	-0.29%
75	72 - 75	1.002	1.008	99.26%	0.74%	0.25%	100.00%	0.00%	0.74%	-0.25%
78	75 - 78	1.002	1.005	99.50%	0.50%	0.25%	100.00%	0.00%	0.50%	-0.25%
81	78 - 81	1.003	1.003	99.75%	0.25%	0.25%	100.00%	0.00%	0.25%	-0.25%
84	81 - 84	1.000	1.000	100.00%	0.00%	0.25%	100.00%	0.00%	0.00%	-0.25%

Practical LDF Interpolation for Well-Behaved IBNR

Exhibit 8A

IBNR Change Projection in Equilibrium Assuming Level Growth
Interpolation: Weibull Splice

Change in IBNR Projected by Q					
AY	Q1	Q2	Q3	Q4	Q5
y	19.60%	13.56%	9.74%	6.99%	-9.22%
y-1	-9.22%	-6.74%	-5.11%	-3.98%	-5.04%
y-2	-5.04%	-4.04%	-3.28%	-2.68%	-1.46%
y-3	-1.46%	-1.21%	-1.01%	-0.84%	-0.75%
y-4	-0.75%	-0.63%	-0.53%	-0.45%	-0.60%
y-5	-0.60%	-0.52%	-0.44%	-0.38%	-0.30%
y-6	-0.30%	-0.26%	-0.23%	-0.20%	
AY y	19.60%	13.56%	9.74%	6.99%	-9.22%
All Prior	-17.37%	-13.39%	-10.60%	-8.53%	-8.15%
Total	2.23%	0.16%	-0.85%	-1.53%	-17.37%

Practical LDF Interpolation for Well-Behaved IBNR

Exhibit 8B										
Calculation of IBNR Change Assuming Level Equilibrium Interpolation: Weibull Splice										
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Age	Interval	Interp ATA LDF	ATU LDF	AY PCT ULT	Tail of AY ULT Loss	Increm	Expos to Date (ETD) as % of AY ULT	Change in ETD	Tail of Loss ETD as % of AY Ult	Change in IBNR
		<i>Running back product of</i>		<i>1/ (4)</i>	<i>1-(5)</i>	<i>Row Diff's of (6)</i>	<i>min(12,(1))/ 12</i>	<i>Row Diff's of (8)</i>	<i>(8)-(5)</i>	<i>(9)-(7)</i>
0				0.00%	100.00%		0.00%			
3	0 - 3	3.119	18.518	5.40%	94.60%	5.40%	25.00%	25.00%	19.60%	19.60%
6	3 - 6	1.906	5.937	16.84%	83.16%	11.44%	50.00%	25.00%	33.16%	13.56%
9	6 - 9	1.561	3.115	32.10%	67.90%	15.26%	75.00%	25.00%	42.90%	9.74%
12	9 - 12	1.184	1.996	50.11%	49.89%	18.01%	100.00%	25.00%	49.89%	6.99%
15	12 - 15	1.114	1.685	59.33%	40.67%	9.22%	100.00%	0.00%	40.67%	-9.22%
18	15 - 18	1.077	1.514	66.07%	33.93%	6.74%	100.00%	0.00%	33.93%	-6.74%
21	18 - 21	1.056	1.405	71.18%	28.82%	5.11%	100.00%	0.00%	28.82%	-5.11%
24	21 - 24	1.067	1.331	75.16%	24.84%	3.98%	100.00%	0.00%	24.84%	-3.98%
27	24 - 27	1.050	1.247	80.20%	19.80%	5.04%	100.00%	0.00%	19.80%	-5.04%
30	27 - 30	1.039	1.187	84.24%	15.76%	4.04%	100.00%	0.00%	15.76%	-4.04%
33	30 - 33	1.031	1.143	87.51%	12.49%	3.28%	100.00%	0.00%	12.49%	-3.28%
36	33 - 36	1.016	1.109	90.19%	9.81%	2.68%	100.00%	0.00%	9.81%	-2.68%
39	36 - 39	1.013	1.091	91.65%	8.35%	1.46%	100.00%	0.00%	8.35%	-1.46%
42	39 - 42	1.011	1.077	92.85%	7.15%	1.21%	100.00%	0.00%	7.15%	-1.21%
45	42 - 45	1.009	1.065	93.86%	6.14%	1.01%	100.00%	0.00%	6.14%	-1.01%
48	45 - 48	1.008	1.056	94.70%	5.30%	0.84%	100.00%	0.00%	5.30%	-0.84%
51	48 - 51	1.007	1.048	95.45%	4.55%	0.75%	100.00%	0.00%	4.55%	-0.75%
54	51 - 54	1.006	1.041	96.08%	3.92%	0.63%	100.00%	0.00%	3.92%	-0.63%
57	54 - 57	1.005	1.035	96.61%	3.39%	0.53%	100.00%	0.00%	3.39%	-0.53%
60	57 - 60	1.006	1.030	97.07%	2.93%	0.45%	100.00%	0.00%	2.93%	-0.45%
63	60 - 63	1.005	1.024	97.67%	2.33%	0.60%	100.00%	0.00%	2.33%	-0.60%
66	63 - 66	1.005	1.018	98.19%	1.81%	0.52%	100.00%	0.00%	1.81%	-0.52%
69	66 - 69	1.004	1.014	98.63%	1.37%	0.44%	100.00%	0.00%	1.37%	-0.44%
72	69 - 72	1.003	1.010	99.01%	0.99%	0.38%	100.00%	0.00%	0.99%	-0.38%
75	72 - 75	1.003	1.007	99.31%	0.69%	0.30%	100.00%	0.00%	0.69%	-0.30%
78	75 - 78	1.002	1.004	99.58%	0.42%	0.26%	100.00%	0.00%	0.42%	-0.26%
81	78 - 81	1.002	1.002	99.80%	0.20%	0.23%	100.00%	0.00%	0.20%	-0.23%
84	81 - 84	1.000	1.000	100.00%	0.00%	0.20%	100.00%	0.00%	0.00%	-0.20%

Practical LDF Interpolation for Well-Behaved IBNR

Exhibit 9

**IBNR Change Projection in Equilibrium Assuming Level Growth
Comparison of Interpolation Methods**

Change in IBNR Projected by Q									
Qtr	SWIMON			12/IVP			Weibull Spliced		
	All Prior			All Prior			All Prior		
	AY y	AY	Total	AY y	AY	Total	AY y	AY	Total
Q1	15.62%	-15.62%	0.00%	17.54%	-17.59%	-0.05%	19.60%	-17.37%	2.23%
Q2	13.10%	-13.10%	0.00%	14.73%	-13.53%	1.19%	13.56%	-13.39%	0.16%
Q3	11.21%	-11.21%	0.00%	11.12%	-10.51%	0.61%	9.74%	-10.60%	-0.85%
Q4	9.96%	-9.96%	0.00%	6.51%	-8.26%	-1.75%	6.99%	-8.53%	-1.53%
Q5	-7.83%	-7.79%	-15.62%	-8.78%	-8.81%	-17.59%	-9.22%	-8.15%	-17.37%

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Abbreviations and Notations

ATA, Age-to-Age
ATU, Age-to-Ultimate

LDF, Loss Development Factor
PCT ULT, Percent of Ultimate

Biography of the Author

Ira Robbin is currently Assistant Vice-President in Economic Capital Modeling at TransRe in New York City. Ira received a Bachelor's Degree in Math from Michigan State University and a PhD in Math from Rutgers University. He has served in a variety of research, actuarial pricing, reserving, and corporate roles over his career at companies including the Insurance Company of North America (INA), CIGNA Property and Casualty, ACE, Partner RE, Endurance, and AIG. While developing new techniques and theories, he has headed large risk property and casualty pricing units, developed pricing algorithms, produced price monitors, conducted reserve reviews, priced treaties, allocated capital, and computed ROE. He has written several Proceedings, Forum, and Study Note papers on a range of subjects, taught exam preparation classes and made numerous presentations at actuarial meetings.

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