Social Inflation: A Survey

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Abstract

This project sought to analyze the phenomenon known as Social Inflation, taking a closer look at its definition and what factors affect it. Our team assessed the impact that Social Inflation may be having on the insurance industry through the use of models from the CAS monograph "Stochastic Loss Reserving Using Bayesian MCMC Models." Utilizing the Correlated Chain Ladder model, our group was able to find a possible indication that Social Inflation has historically impacted the insurance industry. While we were unable to access more recent data, our team feels that the evidence of under-estimations for claim payouts were substantial enough to support this view. We have concluded that Social Inflation has negatively impacted the insurance industry, at least to some degree.

Acknowledgements

Our team would like to acknowledge the individuals who helped to make this project possible. We thank Professor Barry Posterro and Professor Jon Abraham for advising this project and for their knowledge, guidance, and support. We also would like to thank Travelers' Don Mahoney and Megan Fesser for being interviewed on their knowledge of Social Inflation.

Executive Summary

The purpose of this paper is to provide a definition and analysis of Social Inflation and its causes, as well as to identify and utilize a model for recognizing its impact on the insurance industry, specifically the sufficiency of insurance companies' reserves.

The term Social Inflation has been around with some variation in the definition since the 1970s, so we consolidated these variations and defined Social Inflation as: *the phenomenon of rising claim costs, over and above economic inflation, due to societal changes and shifting juror perspective to side with the plaintiff.* Some of the most commonly discussed causes of Social Inflation are:

- How juries view corporations
- Attorney practices and strategies (i.e. Attorneys using methods to incentivize people to file lawsuits)
- Emotional juries
- The legal environment (i.e. States extending the statutes of limitations)
- The normalization of large sums of money in the media

One possible way to see the impact of Social Inflation in the insurance industry is through Loss Development Factors (LDFs), and in this paper we look at the trend of LDFs in the Commercial Auto Industry, which, with fluctuations, have been steadily increasing since 2004. However, other influences could impact the LDFs, so it is important in future research to find more evidence. Another example of the impact of Social Inflation is Nuclear Verdicts, which are extremely large jury awards that exceed what the expected and "reasonable" payout would have been. Since these verdicts are large and unexpected, a company would be more likely to be unprepared or have insufficient reserves to make these payouts. This could lead them to resort to methods such as raising premiums to compensate for these Nuclear Verdicts. Social Inflation has a negative impact on the insurance industry due to a variety of factors, such as:

- Costing companies more money
- Providing for the challenging task of accounting for Social Inflation
- Making for hesitant investors

Social Inflation has been described by some as a hoax or a catch-all term for problems that insurance companies face. One study states that insurance rates have risen and fallen with the economic cycle of the insurance industry, and that the insurance industry is doing well and signaling for a raise in prices.

We used The Casualty Actuarial Society (CAS) monograph "Stochastic Loss Reserving Using Bayesian MCMC Models" by Glenn Meyers to identify models for our purposes. Meyers introduces a way to test the predictive power of methodologies. He discusses how the evolution of technology allows these MCMC models to be more practical to use, and he validates and tests these models using a large number of insurers in the CAS Loss Reserve Database. For our purposes, we used the data used by Meyers, which is from The National Association of Insurance Commissioners (NAIC) database and was made available on the CAS website. This data is Schedule P, which displays historical triangles of net paid losses, net incurred losses, and net premiums (Meyers, 2015). Schedule P shows the development observed over ten years and contributes to estimating future development (Feldblum, 2002). Triangles from 1997 were squared and quality assurance was performed. The monograph tested models on a set of 200 insurer loss triangles from four lines of insurance from Schedule P, "50 from each of Commercial Auto, Personal Auto, Workers' Compensation and Other Liability" (Meyers, 2015).

The model from the monograph we identified to use for our purposes was the Correlated Chain Ladder (CCL) model. To implement the model we used the same steps as Meyers in the monograph and used the R scripts available in a provided excel sheet. Using this model, we analyzed Commercial Auto, Personal Auto, Workers' Compensation, and Other Liability. In Commercial Auto, we found that 8 out of the 23 observed companies appear to have lower estimated reserves than the actual outcome needed to pay out. Many were only under-reserved by very small percentages, though even small percentages can be detrimental as these losses can be thousands of dollars, if not more, depending on the company size. In Personal Auto, we found that 4 out of the 12 observed companies had higher outcomes than expected. This number is in line with what we observed in our main focus, Commercial Auto, showing that there is potential for under-reserving in these other lines of business. In Workers' Compensation, we see that 6 out of the 12 observed companies show higher outcomes than estimated reserves. In Other Liability only 2 out of the 12 observed companies were seen to have estimated less than their actual claims outcome.

We believe that Social Inflation exists and has impacts on the insurance industry, including a pattern of reserve underestimation. We cannot say this with complete certainty, but due to causes such as jury attitudes and legal trends, as well as our observed findings using the CCL method, it is our belief that Social Inflation holds some responsibility for those outcomes.

Table of Contents

Table of Figures

Table of Tables

1.0 Introduction

The focus of this project was to research and observe the phenomenon known as "Social Inflation" and attempt to define the concept. Since its conception, Social Inflation has lacked a clear definition, so through this project we aimed to not only define it, but to see if there was any mathematical basis to its existence. Despite not having a single definition, many sources agree on the general idea of Social Inflation, as well as some of the factors that may be contributing to its existence. Overall, Social Inflation has been tied to shifts in how society views corporations as well as money. Many people believe that large businesses have a moral obligation to their customers, oftentimes with people viewing them as "evil" or "greedy". There is also the notion that large insurance companies possess copious amounts of funds and so it is seen as a non-issue when they are then required to pay out large and unexpected funds of money. While many people see this change as an issue that is bringing about Social Inflation, there are those who also believe it is a 'catch-all' problem created by insurance companies to explain rising claim costs over time.

Our goal was to establish the different points of views on Social Inflation, as well as try to assess if there is any quantitative proof of its existence. To accomplish this, our team researched a Casualty Actuarial Society (CAS) monograph paper titled, "Stochastic Loss Reserving Using Bayesian MCMC Models", which was used to help develop the methodology of this paper. Using one of the models laid out in the monograph, called the Correlated Chain Ladder (CCL) model, our team investigated and analyzed Schedule P data from the The National Association of Insurance Commissioners (NAIC) database. Utilizing the R scripts and code laid out by the author of the CAS monograph, Glenn Meyers, our team was able to analyze numerous lines of business data from different U.S. property casualty insurers.

While the data used only covers claims that occurred in accident years 1988-1997, the methods used in this paper can be replicated on data from more recent years and can then be used to assess if there is any suggestion that Social Inflation may contribute to rising claims costs for insurance companies. This project can provide the framework for future actuaries and others who are looking to research and analyze Social Inflation and its potential impact on the insurance industry.

2.0 Background

In this chapter, we will provide important background information on **Social Inflation** and what it means in terms of the insurance industry. We will further explain what the main and prevalent causes of Social Inflation are and how litigation trends are affecting Social Inflation and the associated rise in claim costs over economic inflation.

2.1 What is Social Inflation?

Social Inflation is a concept that has existed since the 1970s when Warren Buffet used it to explain the change in the scope of what is covered by insurance policies by both society and juries. In more recent years, the term has gained media popularity, being discussed by many companies in their recent earnings calls as a cause for concern. What makes the concept of Social Inflation particularly illusive is that it has no concrete definition, but has general overarching themes that can help to create a picture of what Social Inflation really is. For the purposes of this project we developed the following definition:

Social Inflation is the phenomenon of rising claim costs, over and above economic inflation, due to societal changes and shifting juror perspective to side with the plaintiff.

There are many different factors that appear to play a key role in both defining and understanding the concept of Social Inflation, those being (Bergen, 2020):

- Litigation changes
- Different attorney practices and strategies
- Emotional juries
- The general legal environment
- How juries and society view corporations and money

Throughout the chapter, these different drivers of Social Inflation will be discussed and observed to understand their role in the rise of claim costs in the insurance industry.

2.1.1 What causes Social Inflation?

Litigation is closely linked with Social Inflation. Third-party litigation funding specifically has become a prevalent topic in the Social Inflation discussion. This funding provides financing for legal expenses associated with an individual, usually an investor, who provides money to an attorney for a stake in the settlement of a lawsuit. This term also goes by many names such as legal funding, legal financing, alternative litigation funding, and others. This global industry is near a value of $17 billion, which is expected to rise to about $30 billion by 2028. Litigation funding allows for a lengthier litigation process in general, which can result in more expensive insurance coverage (*Social inflation,* 2022).

In the last few years, there has been an increase in general public awareness on the goings-on of different corporations, and many people assert that these companies are ‘evil’ and ‘greedy’, only caring about profits and not their customers. Many individuals do not trust large corporations, which has led to a shift in jury perspectives towards these organizations. It is also theorized that social media is a cause of increased expectations of companies to exhibit ethical behavior. Social media has provided a new fast-acting and far-reaching platform for social justice movements which exacerbates frustration towards corporations (Lemay et al., 2021).

Another theory is that social media and traditional media have changed perceptions of money, therefore impacting Social Inflation. As people hear about large sums of money more frequently in the form of movie budgets, celebrity incomes, house prices, and more, equally large numbers are no longer shocking (Lemay et al., 2021). From 2014 to 2018 U.S. verdicts have nearly doubled in dollar amounts, with a small number of verdicts in excess of $1 billion (Bergen, 2020). Nuclear Verdicts is a term representing large dollar verdicts that can have adverse effects on the solvency of the insurance provider paying out these verdicts. To put it simply, when insurance companies are forced to pay out these amounts of money, most times not taken into account for their reserves, companies are forced to raise insurance premiums for all their customers to maintain profit. While the plaintiff is able to receive the large payout, the company, its customers, and shareholders are negatively impacted by these litigation changes.

Attorney practices and strategies are another driver in the Social Inflation phenomena. As explained in McConkey's Insurance and Benefits webpage on Social Inflation, attorneys utilize advertisements to incentivize people to file a lawsuit against their insurance provider to gain a higher payout then they would have through the insurance company. Many attorneys also use litigation funding, which means that plaintiffs do not need to settle for a lesser amount since they will then have the funds to support them through the litigation process, incentivizing them to pursue the lawsuit (Bergen, 2020). These tactics can contribute to the number of claims taken to court and similarly the actual verdict size of these cases.

Emotional juries tie closely to how juries view corporations but also attorney strategies and tactics. Tod Bergen of McConkey claims that attorneys have created psychological ways to put jurors in the plaintiff's position, giving the attorney an emotional edge over the insurance company. This advantage is very achievable, as the jurors can much more easily imagine themselves in the position of the individual than in the position of an insurance company. He claims that this allows jurors to focus more on what the company could have done to prevent the loss as opposed to if there was any wrongdoing on the defendant's part.

The legal environment has also been seen as another driver contributing to Social Inflation. A number of different states have enacted laws that eliminate or extend the time in which a plaintiff can file a lawsuit, meaning they extend the statute of limitation, which is the deadline for filing a lawsuit (Bergen, 2020).

There are many other drivers or factors that appear to contribute to Social Inflation and the rise in claims costs, but these stand out as the key drivers. It is clear that these drivers and Social Inflation as a whole is something insurance companies should be wary of, and try to take into account in their reserving and pricing processes.

2.2 Social Inflation's Quantitative Impact on Insurance

Despite how many people in the insurance industry point toward Social Inflation as a driving force in increased claim costs, it is difficult to find concrete and quantitative information to back up this argument. For this research, we will look at Commercial Auto Insurance Loss Development Factors (LDFs).

Chart 4. Net case incurred loss and DCC CYR 12–60 loss development factors—commercial auto liability

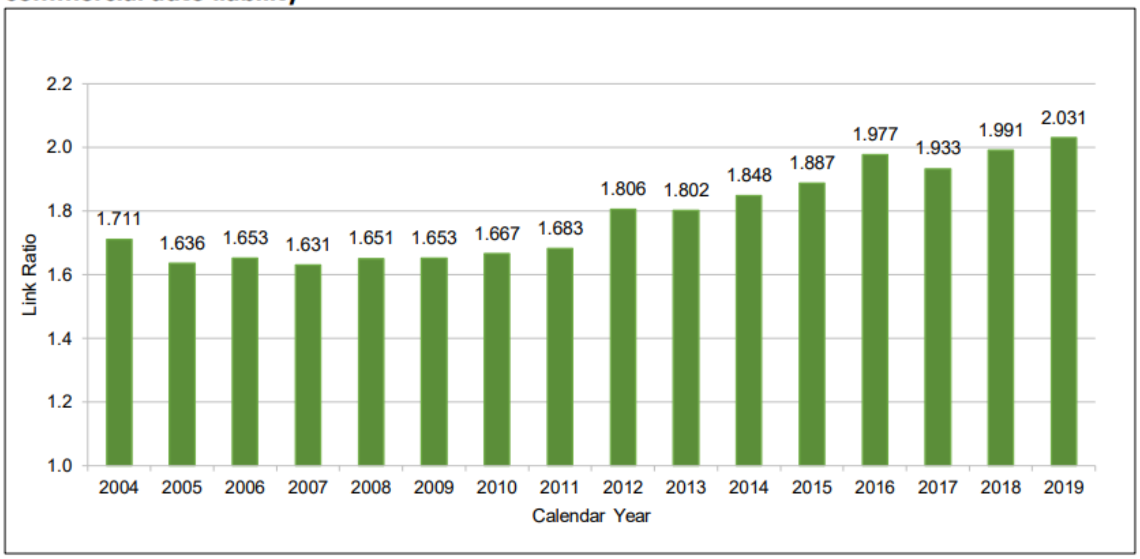

Figure 1: Net Case Incurred Loss Commercial Auto Liability

In Figure 1 (Lynch, 2022), we can see that loss development factors for Commercial Auto have been overall steadily increasing since 2004, with some slight fluctuations. LDF's are used to determine the actual payout by multiplying the initial claim estimate by this factor to create a more accurate representation of the final payout. When LDF's are increasing, that means that claims that would have had lower payouts in the past, are expected to cost the company much more now. For example, in 2010, a claim of $1,000 would actually be expected to reach $1,667 by the time of the final payout, whereas that same claim in 2019 would result in an expected payout of $2,031. This means that in 2019, insurers were expecting on average to need to pay out double the amount of the claim. While this is an indicator that more losses are expected, it does not show a direct correlation to Social Inflation. It is important to remember that many factors could impact the LDFs, and more evidence will be required to prove that Social Inflation has anything to do with it in future research.

2.2.1 Nuclear Verdicts and Rise in Claims Costs

Most quantitative proof of Social Inflation can be found in looking at the changes in Nuclear Verdicts and the rise in claims costs over time. How much of these changes can truly be attributed to the Social Inflation phenomenon? To get a holistic view of one industry as an example, we will continue to look at Commercial Auto Insurance.

Nuclear Verdicts refer to an extremely large jury award that exceeds what the expected and "reasonable" award would have been. Many Nuclear Verdicts, especially those widely portrayed in the media, can be thousands to millions of dollars more than what an insurance company was expecting to pay. This means that even if an insurance company has been reserving and preparing for expected losses due to these trials, they will not be prepared for the additional unexpected losses. In Figure 2 (Insurance Information, 2022) it can be seen that from 2010 to 2019, there was a $20 billion increase in expected losses compared to actual payouts. Since the company was not prepared to take on such large risks, that money needs to be accounted for in other ways. Often, it is accounted for by raising customers' premiums.

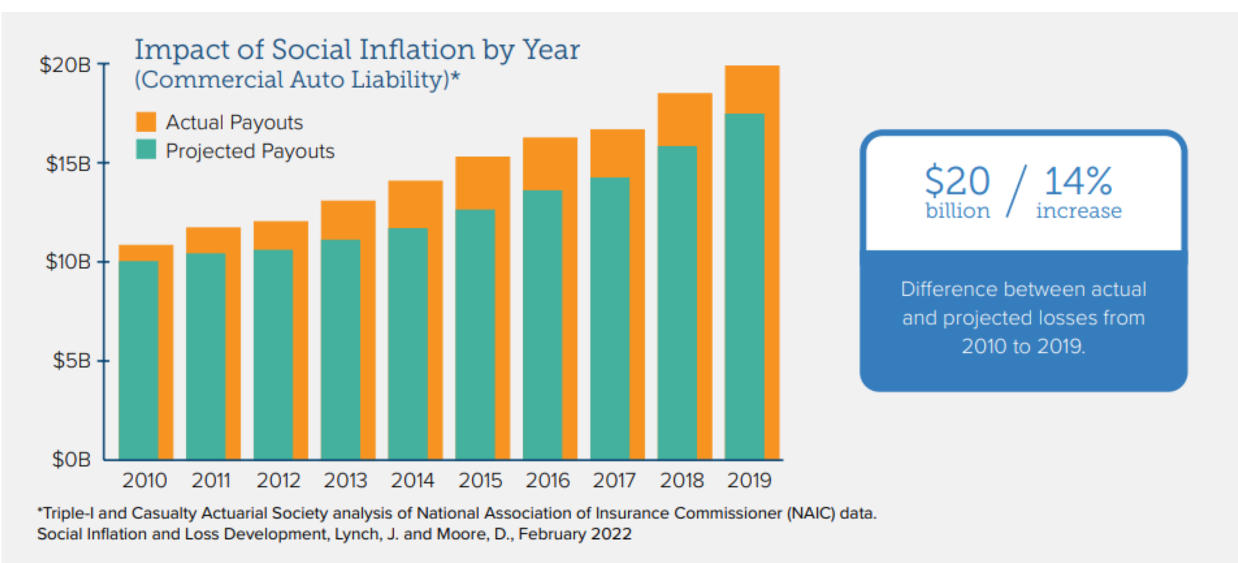

Figure 2: Impact of Social Inflation by Year

Furthermore, a study from 2020 reported that from 2010 to 2018, the size of jury awards increased by 33%, which only further shows that these Nuclear Verdicts are causing larger losses year after year (Insurance Information, 2022). With losses increasing, the premium needs to increase as well, hence the 5.9% premium increase in Q1 2022, which marks the 29th consecutive quarter of premium increases. This suggests that for the past seven years, the cost of the coverage for Commercial Auto Insurance has continuously increased, matching the constant rise in loss development over that same time frame.

2.3 The Debate on Social Inflation

The causes and impacts of Social Inflation are widely varied and debated. Social Inflation negatively impacts the insurance industry and the insurance market in a variety of ways. There are also arguments that these impacts are not entirely accurate and that Social Inflation is an insurance industry hoax.

2.3.1 Impacting The Insurance Industry Negatively

Social Inflation has negative impacts on the insurance industry, costing companies more money, providing for the challenging task of accounting for Social Inflation, and making for hesitant investors.

Increased claims make for more costs. One example of this can be observed in the Commercial Auto insurance line of business. As explained by Bethan Moorcraft (2020), this market has been in trouble due to several wrong place at the wrong time scenarios. Trucking firms have seen large verdicts, sometimes as high as $100 million, which burns through Primary Liability coverage and gets into the Umbrella and Excess Liability layers. Social Inflation makes it more challenging to account for this change and make estimations. It makes estimating using historical data difficult, and since casualty business has a long tail to it (has a long settlement period), present claims have to be dealt with at the same time as claims that have been developing for longer (Moorcraft, 2020). Another impact is the uncertainty of investors. Social inflation is often discussed during challenging times for the insurance industry, which can make investors anxious. As of December 2019, property and casualty and multi line insurers in the S&P 500 were down 3%, performing the worst in the financial sector since the start of October 2019 (Demos, 2019).

2.3.2 Social Inflation is a Hoax

A theory about Social Inflation is that it is a hoax perpetuated by the insurance industry for insurers' own purposes. In a 2020 study by the Consumer Federation of America (CFA), it is argued that while the insurance industry claims to be suffering, it is instead doing well, as seen by record levels of insurers' surplus. They state that insurance rates have risen and fallen with the economic cycle of the insurance industry, and the industry has been in a state of decreasing rates since approximately 2006. In an attempt to end it, the insurance industry is signaling for a raise in prices (Hunter et al., 2020).

The study continues to take an opposing position and claims that Social Inflation is in fact opposed by litigation trends, jury verdict trends, insurance claims data, and more. They state that the insurance industry blames Social Inflation for its own manipulation and raising of claim reserves. This would be done to make rate increases seem reasonable and lower tax liabilities, and that reserves are later released to profits (Hunter et al., 2020).

While premiums and reserves go up and down, the study claims that this is not an indicator of paid claims trends, and Commercial Insurance payouts have not spiked, but they have followed inflation and population growth. In fact, they claim losses have decreased in Commercial Multi-Peril, Commercial Auto Liability, and Medical Malpractice. Examples given of this are that doctors paid rising high premiums even though paid claims dropped during the last cycle period of increasing rates, "insurers were overstating 'Other Liability' losses by about $7.3 billion or 30%" (Hunter et al., 2020), and high premiums in Commercial Auto were not matched by paid or incurred claims. A trend shown in this study is that the insurance industry is reserving and increasing rates excessively (Hunter et al., 2020).

2.4 Interviews with Travelers Insurance

Throughout the course of our background research, our team had the opportunity to interview and speak with two Travelers Insurance employees, who were generous enough to speak with us about their knowledge of Social Inflation. The following section will highlight the two interview sessions with Don Mahoney and Megan Fesser.

Don Mahoney is the current Vice President of Business Insurance Products, General Liability, Umbrella, Professional, and Compliance at Travelers Insurance. During our interview with Don, we asked a series of questions pertaining to how he would define Social Inflation, and what were the biggest factors he believed were contributing to higher claims costs. The way he defined Social Inflation was as the increase in claim severity that cannot be explained by traditional external inflation indices. In terms of contributing factors to Social Inflation, Don mentions the term Nuclear Verdicts and the idea that these large payouts can have a trickle-down effect on all other claims. He concludes that there is a change in how people value claims and money and what is ‘the right thing to do,’ noting that there is a lot of anti-corporation sentiment, and people believe that these large corporations can handle making such large payouts.

Megan Fesser is an Assistant Vice President of Business Insurance Underwriting Casualty at Travelers Insurance. During this interview, our team wanted to gain another perspective on how she would define Social Inflation. Megan explained how she defines it as the increase in what is paid on average for the same set of injuries. She gave us a great example of an individual slipping and falling in a grocery store. In this scenario the injured individual can do a few things; they can leave the store, bringing no attention to their injury, they can settle for some form of store credit, or in extreme cases, sue the grocery store and go to trial. Megan believes that Social Inflation would be that every group of this population is growing in size, except for those that would simply choose to leave the store. Similarly to Don, she expressed how today, many people believe companies have a higher obligation to ensure the safety of their premises, products, and all other factors of their business.

3.0 Methodology

In the following chapter we will lay out the methodology to be used and analyzed in later chapters. We will begin by detailing the objectives we have for our methodology and what we are seeking to achieve through our research. Then we will give an overview of one of the key documents which we are developing much of our methodology from. We will then conclude the chapter by explaining where and how we will be obtaining the data that will be utilized in Chapter 4.0 Findings, as well as some of the limitations we ran into during the research process.

3.1 Objectives

Our project dives deeper into the issue of Social Inflation and analyzes how its growth has impacted the insurance industry. We will analyze this impact by answering the following questions:

1. How much causation can we find between Social Inflation and the rise in insurance claims?
2. How are insurance companies accounting for the changes caused by Social Inflation?
3. What can we expect to happen if companies do not make the necessary shifts to account for these impacts?

3.2 Meyers' Monograph

Our research stems from the Casualty Actuarial Society's publication titled "Stochastic Loss Reserving Using Bayesian MCMC Models" by Glenn Meyers. This paper was the first in a series of a new CAS monograph Series in 2015. Meyers introduces a way to test the predictive power of two loss-reserving methodologies, the Mack and Bootstrap Over-dispersed Poisson (ODP) models.

Through the monograph, he first shows that the most common model used to determine incurred losses, the Mack Model, can understate the range of possible outcomes. To attempt to improve the predictive power of these models, he applied Bayesian Markov Chain Monte-Carlo models (Bayesian MCMC). He additionally shows how the range of expected outcomes is overstated for paid losses using the Mack and Bootstrap ODP models.

The data used to test his hypothesis were taken from the CAS database of loss development triangles. For our own research and methodology, we look to use the same data set. This will be discussed further in Section 3.3 Data.

3.2.1 Summary of Meyers' Monograph

Meyers discusses how the evolution of technology, specifically in regards to computer processing power, now allows these MCMC models to be more practical to use to determine the distribution of outcomes. He validates and tests different models using a large number of insurers in the CAS Loss Reserve Database. One idea that is discussed in this monograph is that of "Black Swan" events, which are unpredictable and highly unlikely events that if they were to occur could be disastrous. Meyers specifically notes that should the insurance loss environment not be dominated by these "Black Swan'' events, that there should be a way to systematically search for models and data to validate them.

Meyers writes that his work seeks not to comment on any insurers themselves, but to test the accuracy of specific models on their predictions. He even notes that if created models yield any shortcomings, the MCMC models can be applied to overcome this.

When dealing with incurred loss data, Meyers explains that the variability predicted by the Mack model is understated because it assumes that the losses from different accident years are independent. In its place, Meyers suggests the Correlated Chain Ladder (CCL) model as a good alternative since it allows for a particular form of dependency between accident years. He also found that the CCL model predicts the distribution of outcomes correctly within a specified confidence level.

For paid data, Meyers found that the Bootstrap ODP, Mack, and the CCL models tend to give estimates of the distribution where there is more in the tail than expected, which suggests that there is a change in the loss environment that is not being captured in these models.

While observing the “Other Liability” line of insurance, Meyers notes that both the Mack and Bootstrap ODP models were able to validate better than any of the newer models that were presented in the monograph. He concludes that this means more studies need to be done, particularly repeated for other annual year statements to evaluate if his conclusions still hold true.

Meyers concludes the monograph by discussing the efforts he made to make sure the data utilized through the paper and any software he uses are both publicly available for free. More details on the data selection process and what was done with the data in this monograph will be discussed in the following sections.

3.3 Data

In the following section we explain what data was used in Meyers’ monograph and how it can be utilized generally. We also explain how this data was prepared and where it can be found.

3.3.1 Data Used In Meyers' Monograph

The National Association of Insurance Commissioners (NAIC) Schedule P data has claim information for property-casualty insurers that write business in the United States (Feldblum, 2002). The data in Schedule P displays historical triangles of net paid losses, net incurred losses, and net premiums (Meyers, 2015). Schedule P shows the development observed over ten years and contributes to estimating future development (Feldblum, 2002). Below is an example of a hypothetical loss development triangle and how to square it. First, we take the original triangle and make the claims cumulative.

	Development Year						
Accident Year	**1**	**2**	**3**	**4**	**5**	**6**	**7**
2002	9,500	50,500	50,000	27,500	9,500	5,000	3,000
2003	13,000	44,000	53,000	33,500	11,500	5,000	
2004	14,000	47,000	56,000	29,500	15,000		
2005	15,000	52,000	48,000	35,000			
2006	13,000	60,000	64,000				
2007	16,000	47,000					
2008	17,000						

	Development Year						
Accident Year	**1**	**2**	**3**	**4**	**5**	**6**	**7**
2002	9,500	60,000	110,000	137,500	147,000	152,000	155,000
2003	13,000	57,000	110,000	143,500	155,000	160,000	
2004	14,000	61,000	117,000	146,500	161,500		
2005	15,000	67,000	115,000	150,000			
2006	13,000	73,000	137,000				
2007	16,000	63,000					
2008	17,000						

Figure 3: Example Triangle and Cumulative Claims

Next, we find the development factors that take the claims to the next development year (DY) by dividing the sum of the claims in a DY by the sum of the claims in the previous DY (Example: dev factor Year 1-2 = sum(DY2 2002-2007)/sum(DY1 2002-2007)).

	Year 1-2	**Year 2-3**	**Year 3-4**	**Year 4-5**	**Year 5-6**	**Year 6-7**
dev factors	4.7329193	1.8522013	1.27765487	1.08421053	1.03311258	1.01973684

Figure 4: Development Factors

Next, we complete the triangle by multiplying the claims by the relevant development factor to get the claims in the next DY (Example: 17,000 x dev factor Year 1-2 = 80,460).

	Development Year						
Accident Year	**1**	**2**	**3**	**4**	**5**	**6**	**7**
2002	9,500	60,000	110,000	137,500	147,000	152,000	155,000
2003	13,000	57,000	110,000	143,500	155,000	160,000	163,158
2004	14,000	61,000	117,000	146,500	161,500	166,848	170,141
2005	15,000	67,000	115,000	150,000	162,632	168,017	171,333
2006	13,000	73,000	137,000	175,039	189,779	196,063	199,933
2007	16,000	63,000	116,689	149,088	161,643	166,995	170,291
2008	17,000	80,460	149,027	190,406	206,440	213,276	217,485

Figure 5: Completed Triangle

We can also find the outstanding claims by taking the claims from DY7 and subtracting the last given (unhighlighted) claims data (Example: 163,158-160,000=3,158).

Accident Year	Outstanding Claims
2002	0
2003	3,158
2004	8,641
2005	21,333
2006	62,933
2007	107,291
2008	200,485
Total	**403,840**

Figure 6: Outstanding Claims

Below is an example of how to use the CCL model on the same triangle.

	Development Year						
Accident Year	1	2	3	4	5	6	7
2002	9,500	50,500	50,000	27,500	9,500	5,000	3,000
2003	13,000	44,000	53,000	33,500	11,500	5,000	
2004	14,000	47,000	56,000	29,500	15,000		
2005	15,000	52,000	48,000	35,000			
2006	13,000	60,000	64,000				
2007	16,000	47,000					
2008	17,000						

Figure 7: Example Triangle for CCL

First we choose link ratios by dividing the sum of the claims in a DY by the sum of the claims in the previous development year (DY).

(Example: link ratio Year 1-2 = sum(DY2 2002-2007)/sum(DY1 2002-2007))

	Year 1-2	Year 2-3	Year 3-4	Year 4-5	Year 5-6	Year 6-7
Chosen Link	3.73292	1.06903	0.60628	0.39779	0.47619	0.60000

Figure 8: Link Ratios

Next, we find the last accident year (AY) Errors, which is calculated by:

cell(w-1,d)-cell(w-1,d-1)*link ratio (Ex: 50,500-9,500*3.73 = 15,037).

	Development Year						
Accident Year	1	2	3	4	5	6	7
2002		15,037	-3,986	-2,814	-1,439	476	0
2003		-4,528	5,963	1,367	-1,826	-476	
2004		-5,261	5,755	-4,452	3,265		
2005		-3,994	-7,590	5,899			
2006		11,472	-142				
2007		-12,727					

Figure 9: Last AY Errors

Next, we find the estimated values, which is calculated by:

cell(w,d-1)*link ratio + last AY error (Ex: 44,000*1.069+15037.27 = 62,075).

Development Year							
Accident Year	**1**	**2**	**3**	**4**	**5**	**6**	**7**
2002							
2003			62,075	28,147	10,512	4,037	3,476
2004			45,717	39,914	13,102	5,317	
2005			50,329	34,857	9,471		
2006			60,148	31,212			
2007			61,717				

Figure 10: Estimated Values

For our purposes, we used the data used in the second edition of Meyers' monograph, which is from the NAIC database and was made available on the Casualty Actuarial Society (CAS) website (Meyers & Shi). This dataset is a set of loss triangles prepared from "Schedule P – Analysis of Losses and Loss Expenses" (Meyers & Shi). The six lines of business in this database are (Meyers & Shi):

1. Private Passenger Auto Liability/Medical
2. Commercial Auto/Truck Liability/Medical
3. Workers' Compensation
4. Medical Malpractice
5. Other Liability
6. Product Liability

The variables included for each line were pulled from four parts of Schedule P and are (Meyers & Shi):

1. Earned premium and some summary loss data
2. Incurred net loss triangles
3. Paid net loss triangles
4. Bulk and IBNR reserves on net losses and cost containment expenses

3.3.2 Preparation of Data Used

In the data preparation for Meyers' monograph, there is a focus on single entities (insurer groups or true single insurers). This is due to the fact that the triangles consist of losses net of reinsurance and between companies within a group there are often mutual reinsurance arrangements. The data used was triangle data taken from 1997 Schedule P, with each triangle containing "claims of 10 accident years (1988-1997) and 10 development lags" (Meyers & Shi). The triangles were squared from the year 1997 "with outcomes from Schedule P of subsequent years" (Meyers & Shi) (As in the data from the accident year 1989 was pulled from Schedule P year 1998 and so on). Additionally, preliminary quality analysis was performed on the dataset. This analysis ensured the data was complete and available for all relevant years, the claims match those of subsequent years, and written net premiums are not zero. As the quality analysis was not the focus of our project, we relied on the analysis done here. After this preparation, the final dataset contained run-off triangles of six lines of business from the accident years 1988-1997 with 10 years of development. The dataset includes upper and lower triangles in order for the data to be useful in developing and testing a model (Meyers & Shi).

The monograph tested models on a set of 200 insurer loss triangles from four lines of insurance from Schedule P, "50 from each of Commercial Auto, Personal Auto, Workers' Compensation and Other Liability" (Meyers, 2015), leaving out Products Liability and Medical Malpractice due to insufficient amounts of insurers. The criteria for the selection of these triangles were intended to control the changes in the net premium and the ratio of net to direct premium from year to year. Schedule P can hint at these possible changes in insurer operations, but the models in the monograph assume there have not been any substantial changes. (Meyers, 2015).

3.4 Limitations

While we are very happy with the models we were able to work with, we also acknowledge that there is room for this work to expand and be analyzed even further. Here, we highlight some of the limitations we faced and where this could progress were someone without those limitations to continue this work.

3.4.1 Issues we faced

Throughout our project, the team ran into a variety of issues that caused us to shift our course. One of the first issues that we had to face was the time constraints of our project. Social Inflation is a broad and complex topic, and we had a finite amount of time, which worked against us. We began researching Social Inflation, a concept that has existed for many years. Once we had defined what Social Inflation meant for our purposes, we had to narrow our scope to fit within our allotted time, and we acknowledge that with more time this project could have grown in a variety of directions.

Another factor working against us was the data available to us. During our search for viable data, we came across multiple options that could have better suited our purposes, however, they were too far out of our budget and could not be used. We ideally wanted to find data that was more recent and could encapsulate the Social Inflation impacts over the course of the past 20 years or so, but ultimately found that that data was not readily available at a price we could afford. Were we to have access to these different data sets we believe we would have been able to get a better idea of how Social Inflation may require shifts in the insurance industry.

3.4.2 Expanding our Project

Our team's hope for this project is that one could take what we have created and, without the limitations previously discussed, expand this idea into a broader scope in order to fully understand the complexity of the issue. The first recommendation to do so would be to gain access to the more recent data and work through the models we discuss in this paper using the more relevant data sets. More so, when running through the models, we only analyzed a few of our select data triangles, so one may venture to, with more time, complete the calculations for far more than what our project touches upon.

With regards to the models, we used them as they were outlined in the original monograph. An idea that, had we come across it earlier on in the project, we could have pursued is to tweak the models to suit a variety of needs. As concluded in the monograph, “The models proposed in this monograph are offered as demonstrated improvements over current models. I expect to see further improvements over time. The Bayesian MCMC methodology offers a flexible framework with which one can make these improvements” (Meyers, 2015). While this is not something that our group is pursuing, we imagine more developed models could give more efficient and effective results.

Finally, one avenue that our team has heavily considered pursuing, and would be excited to see the outcomes of, is partnering with an insurance company. Not only would this likely lower limitations such as finances and data access, but this would also allow a better view of the impacts. While we did meet with Travelers Insurance to discuss the general topic of Social Inflation and its effects on the insurance industry, we feel there is a lot to gain from working directly with a company towards a common goal. Working with a company could open up the idea of mitigation strategies and lead this project into a larger scale that could be used to ensure that insurance companies were in a good position to handle the changes brought by Social Inflation.

3.4.3 Our Project's Importance

Despite the issues that we faced, and the avenues we did not pursue, our team feels confident in the idea that this project has opened the door for future discussion. While Social Inflation is by no means a new topic in the insurance world, it is one that seems to often get lost in translation. While we frequently found that differentiating between the impacts caused by Social Inflation and those caused by other outside factors has been a struggle, there is much that could be learned from achieving that differentiation. The debate on whether or not this idea truly causes a tangible impact is still ongoing, and our goal in this project was not to resolve that debate, but to add to the argument that this phenomenon is not something to be ignored.

4.0 Findings

In the following chapter, we will elaborate on the findings made by utilizing the models explained in the previous chapter, 3.0 Methodology. The chapter will begin with an outline of the used model, the Correlated Chain Ladder (CCL) model. We will then give a thorough example of the model in use on auto insurance data. We will then analyze what the results of our findings mean within this chapter and in greater detail in the final chapter, 5.0 Conclusions.

4.1 Correlated Chain Ladder Model

Before diving into the details of utilizing the model, it is important to understand its structure and purpose. The parameters listed out by Meyers for the CCL Model are as follows:

Let:

1. Each α_w ~ normal (log (*Premium*$_w$) + *logelr,* $\sqrt{10}$) where the parameter *logelr ~ uniform (-1, 0.5).*

2. $\mu_{1,d} = \alpha_1 + \beta_d$.

3. $\mu_{w,d} = \alpha_w + \beta_d + \rho \bullet (\log (C_{w-1,d}) - \mu_{w-1,d})$ for $w > 1$

4. $C_{w,d}$ has a lognormal distribution with log mean $\mu_{w,d}$ and log standard deviation σ_d subject to the constraint that $\sigma 1 > \sigma 2 > . . . > \sigma 10$.

Symbols used in this model:

1. **$C_{w,d}$:** Known for the "triangle" of data specified by $w + d \leq K + 1$, $C_{w,d}$ denotes the accumulated loss amount, either incurred or paid, for accident year, **w,** and development lag, **d**, for $1 \leq w \leq K$ and $1 \leq d \leq K$
2. **σ_d :** The log standard deviation, subject to the constraint $\sigma1 > \sigma2 > \ldots > \sigma10$
3. **α_w :** The group-level means or intercepts in the model, where each α_w corresponds to a particular group
4. **ρ :** The correlation coefficient
5. **β_d :** The regression coefficients or slopes in the model, where each β_d corresponds to a particular covariate
6. **$\mu_{w,d}$:** The log mean

4.2 Implementing the Correlated Chain Ladder Model

To mimic the process utilized by Glenn Meyers in his monograph, we followed the steps listed in the provided excel file, which contains the R scripts for all of his models as well as all of the produced outputs. A more in-depth walkthrough of our process to access and produce data results can be found in Appendix B.

The following image is a table produced by the R script for group code 9466, which is the group code for Lumber Insurance Services. The columns we are focusing on for our purposes are the CCL Estimate and the outcome. Essentially, the CCL total estimate is the amount that the company would expect to reserve based on the claims from their data from accident years 1988 to 1997 and the outcome is the total amount of actual payouts. In this case, we can see that the expected total is roughly 9.289% lower than the actual, showing that there is some likelihood that this company is actually under-reserving.

	W	Premium	CCL.Estimate	CCL.S.E.	CCL.CV	Outcome	CCL.Pct
1	1	4926	2881	0	0.0000	2881	NA
2	2	4534	3157	279	0.0884	3156	NA
3	3	4800	2356	210	0.0891	2364	NA
4	4	5511	2429	222	0.0914	2379	NA
5	5	7352	5206	477	0.0916	5199	NA
6	6	9775	8404	800	0.0952	8469	NA
7	7	12698	9829	982	0.0999	10026	NA
8	8	19226	14819	1676	0.1131	15814	NA
9	9	28256	21905	3103	0.1417	25369	NA
10	10	26155	19006	5486	0.2886	23550	NA
11	Total	123233	89991	7305	0.0812	99207	90.29

Figure 11: R Code Output

Using that same understanding, we created tables that highlight the estimated over and under-reserving of different insurance companies in the Commercial Auto, Personal Auto, Workers' Compensation, and Other Liability lines of insurance.

4.3 Results

The following subsections will contain the results for each of the different lines of business we analyzed through the CCL Model.

4.3.1 Commercial Auto Results

Group Code	CCL Estimate	Outcome	Outcome - CCL Estimate	Percent over or under Estimate
14257	6812	6871	59	0.87%
10308	5560	5429	-131	-2.36%
14044	5586	5403	-183	-3.28%
19020	15642	16976	1334	8.53%
15024	3436	2671	-765	-22.26%
18163	33347	32347	-1000	-3.00%
19780	1193	1170	-23	-1.93%
13889	2097	2100	3	0.14%
11118	30103	31665	1562	5.19%
9466	89991	99207	9216	10.24%
14974	37799	38445	646	1.71%
14508	10772	11807	1035	9.61%
15199	2077	2033	-44	-2.12%
14311	7957	7877	-80	-1.01%
11037	21746	21333	-413	-1.90%
8672	146672	140795	-5877	-4.01%
13439	3850	3667	-183	-4.75%
13528	20711	19930	-781	-3.77%
13641	8382	8591	209	2.49%
14176	25089	21775	-3314	-13.21%
14320	4304	1830	-2474	-57.48%
18767	84576	79694	-4882	-5.77%
18791	11131	11084	-47	-0.42%

Table 1: Commercial Auto Results

As shown in this table, 8 of the 23 of the companies appear to have lower estimated reserves than the actual outcome needed to pay out. When looking at these companies that we concluded could be under-reserved, we wanted to dig a little deeper to see what else we could infer. After researching the size of these companies that were under-reserved, we found that all but 1 had 500 or fewer employees, which are relatively small insurance companies. This could certainly play a role in the possible under-reserving, but it is also important to note that smaller companies may have less room to be losing money, so under-reserving of any kind could be more detrimental the smaller the size of the company. The smallest company in this group, code 19020, actually saw one of the highest percentages of under-reserving.

When observing the companies that are under-reserved, many were only under-reserved by very small percentages. While that may not seem like a large issue, even percentages as small as 0.1429%, seen from group code 13889, can be detrimental as these losses can be thousands of dollars, if not more, depending on the company size. Additionally, it isn't ideal for those that are over-reserved to have a very high percentage, like that of 28.64% seen from company code 15024, because while this does mean that they are able to afford their payouts with ease, they will likely have much higher premium costs than necessary, which can cause problems for their customers. Not to mention that the extra reserved money could have been better allocated or reinvested to help support the company's operations.

4.3.2 Personal Auto Results

Group Code	CCL Estimate	Outcome	Outcome - Estimate	Percent Under/Over Estimate
353	128640	125477	-3163	-2.46%
13587	6501	6344	-157	-2.42%
13889	116546	113934	-2612	-2.24%
1767	92171190	91532402	-638788	-0.69%
6807	11922	11771	-151	-1.27%
5185	261859	260501	-1358	-0.52%
14443	94564	96582	2018	2.13%
16373	9761	9780	19	0.19%
15024	119502	118706	-796	-0.67%
16799	35046	32851	-2195	-6.26%
18791	90681	93075	2394	2.64%
18163	128932	130352	1420	1.10%

Table 2: Personal Auto Results

In the line of insurance for Personal Auto we see 4 out of the 12 observed companies with higher outcomes than expected. This number is in line with what we observed in the Commercial Auto line, showing that while our main focus was Commercial Auto, we see this potential for under-reserving in these other lines of business as well. If anything, we had expected to see a smaller percentage of the observed companies with these results, so producing similar results causes us to think that this issue may be more spread across the lines of business than originally anticipated.

4.3.3 Workers' Compensation Results

Group Code	CCL Estimate	Outcome	Outcome - CCL Estimate	Percent over or under Estimate
14257	12893	13280	387	3.00%
9466	154254	164276	10022	6.50%
14974	30321	31222	901	2.97%
14508	58016	56590	-1426	-2.46%
15199	1451	1349	-102	-7.03%
8672	77539	80320	2781	3.59%
13439	6462	5701	-761	-11.78%
13528	27416	26562	-854	-3.11%
14176	127687	109695	-17992	-14.09%
14320	10600	11550	950	8.96%
18767	186382	180944	-5438	-2.92%
18791	1914	2107	193	10.08%

Table 3: Workers' Compensation Results

When looking at the 12 observed companies for Workers' Compensation, we see that 6 of them show higher outcomes than estimated reserves. Acknowledging that looking at a smaller pool of companies can result in a larger percentage of those with higher outcomes, we wanted to survey a smaller set of randomly selected companies from the list Meyers provides, especially for the lines of business apart from Commercial Auto, as that was our main line of focus.

4.3.4 Other Liability Results

Group Code	CCL Estimate	Outcome	Outcome - CCL Estimate	Percent over or under estimate
18791	1322	358	-964	-72.92%
14257	53121	31670	-21451	-40.38%
10308	1695	745	-950	-56.05%
13994	2671	2129	-542	-20.29%
15148	389	349	-40	-10.28%
1767	2488817	2207154	-281663	-11.32%
2135	86081	92770	6689	7.77%
2003	317661	277202	-40459	-12.74%
671	8499	6071	-2428	-28.57%
715	67175	65381	-1794	-2.67%
5320	6606	6671	65	0.98%
14885	554	505	-49	-8.84%

Table 4: Other Liability Results

Out of the 12 observed companies in this line of insurance, only 2 were seen to have estimated less than their actual claims outcome. This number does not aline as consistently with the numbers we saw in the previous lines of business we observed, however, this could largely be due to the fact that the companies we chose from the list provided were randomly selected, and had we chosen different ones or observed a larger set of companies we could potentially have seen this number increase. Nevertheless, it is also possible that some lines of business such as Other Liability are not affected as drastically by these social shifts.

5.0 Conclusion

Throughout this project, our team has reviewed the arguments on both sides pertaining to the existence of Social inflation, done our own research, conducted interviews, and reviewed company data. We know that we cannot definitively state that Social Inflation exists, however, based on the research we conducted, it is our belief that it does. It still may be true that it is used as a catch all term that companies can blame any of these discrepancies in estimations on, but due to the shifts we researched in public perceptions of companies, we argue that this is not always the case. In today's world, the idea of large corporations being viewed negatively is not a surprising one, as the media remains one of today's largest sources of information. With that being said, the way things are portrayed throughout the media can get muddled and can create and spread strong negative feelings about things such as insurance companies.

Additionally, while we cannot say with certainty that the under estimation of reserves is fully, or even partially, due to Social Inflation, we can see that it happens in many companies for one reason or another. After the work we conducted, it is our claim that Social Inflation holds some responsibility for these higher than expected outcomes. However, even if one does not believe that, it is clear that something needs to be reevaluated to adjust companies estimations to more accurately represent what will be seen for claims. This can be a difficult line to walk as overestimating your reserves is also not an ideal situation, so finding that balance can be very challenging. However, we urge those in the insurance world not to ignore these issues and continue to underestimate, as this could be far more detrimental. Not only can we see that there are already issues with under-estimating reserves, our team feels strongly that the social shifts will continue, and with that we may see claims continue to rise and witness more frequent Nuclear Verdicts that will only cause this problem to grow further.

It is important to acknowledge that this data is not as recent as we would have liked to review, but it is our assumption that these problems have not gone away, and had we looked at more recent data we may have seen very similar results. While there are various areas in which this project could be expanded on, we are confident in stating that the phenomenon of Social Inflation certainly deserves a place in the conversations in the insurance industry.

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Appendix A: Glossary of Terms

Case Reserve: The estimated amount of money that still needs to be paid to settle a claim (Werner et al., 2016).

Loss/Claims

> **Incurred/Reported:** The sum of paid loss and the current case reserve for the claim (Werner et al., 2016).
>
> **Paid:** Amounts paid to those who have made claims (Werner et al., 2016).
>
> **Incurred But Not Reported (IBNR):** Claims that have occurred but have not yet been reported to the insurer. This can also include more development on open claims or closed claims that will later be open (Huenefeldt and Rosenblum).

Loss Development Factors (LDFs): Factors used to develop losses, meaning to represent the change in loss between different ages (Huenefeldt and Rosenblum, 2022).

Loss Development Triangles: An organization of loss development data by year and age used to track and estimate claim development (Huenefeldt and Rosenblum, 2022).

Squaring a triangle: Filling in a loss development triangle with estimates using a chosen method.

Appendix B: Detailed Code Walkthrough

The R script used to create our results was submitted along side this paper and the following gives an in depth walkthrough of accessing and utilizing it.

The steps for downloading the necessary software, as written by Meyers, to complete the process are as follows:

1. Install R - http://www.r-project.org/
2. Install JAGS - http://mcmc-jags.sourceforge.net/
3. Install Rstudio - http://www.rstudio.com/
4. Open Rstudio
5. Copy the desired R scripts from this workbook into a new R Script in Rstudio
6. Download the Casualty Actuarial Society Loss Reserve Database into your working directory - http://www.casact.org/publications-research/research/research-resources/loss-reserving-data-pulled-naic-schedule-p
7. Install "ChainLadder," "actuar," "runjags," and "coda" R packages
8. Set the working directory in the R Script
9. Change other user inputs "insurer.data", "losstype", "grpcode" and "outfile" as needed
10. Run the R script by clicking on the "source" button in Rstudio

After we followed the above steps, we attempted to run the code to see if we ran into any errors that would need to be fixed. After analyzing the errors we did receive, we made small adjustments to the user input sections of the code as well as adding in the abs() function before taking the square root of the sigd2. This was a change we made because not only should the standard deviations never be negative, but to avoid taking the square root of a negative which would result in non-existent outputs. Once the code was running properly we were able to begin working on pulling the data into the R script and running the CCL model through R-Studio. Below is an outline of the process we went through using Commercial Auto data. This will act as an example of the process to allow for better understanding and replication.

Before we could pull the data, we needed to establish a working directory so that R-Studio knew where the data was coming from. To do so we completed the following steps:

1. Downloading, in this case, the Commercial Auto loss reserving data Excel file from the Casualty Actuarial Society's website, which contained data pulled from the NAIC schedule P. That data as well as the data for the other lines of insurance can be found here: https://www.casact.org/
2. Next, we created a file on our computer under "Documents" and labeled this new folder "R directory" and made sure all the data we needed from step 1 was moved to this folder.
3. Going back into R-Studio, to set up the directory we clicked on "Session" in the toolbar and toggled down to "Set Working Directory." From there we selected "Choose Directory" which allowed us to set the directory as the file on our computer that we created.

Now that this was set, R-Studio was able to find the data we had downloaded and we were able to start specifying which pieces of that data we needed. This portion of the process is where we utilized the user inputs as follows:

1. When looking at all of the different lines of insurance, it is important that you specify which line you are looking to examine. This is done by removing the # (which comments out code) from the data you wish to access. For example, when looking at the Commercial Auto data, that section of the code should look like this:

```
insurer.data="comauto_pos (3).csv"
#insurer.data="ppauto_pos.csv"
#insurer.data="wkcomp_pos.csv"
#insurer.data="othliab_pos.csv"
#insurer.data="prodliab_pos.csv"
#insurer.data="medmal_pos.csv"
```

It is also important to note that the name of the CSV file referenced needs to exactly match the name of the data file as it exists in the working directory folder previously created (i.e adding the (3) in the file name since that is how it was named in the file we created).

2. Next, we need to specify which specific insurer we want to look at. To do so we can change the “grpcode” input. This line is asking for a string of numbers that represents an insurer in the data triangles. Which specific insurers you choose to examine can vary, but for our purposes, we chose to follow the guidelines set by Meyers in his second edition monograph. For the purpose of this example, we used the group code 9466, which is the group code for .
3. The final user input we updated from the base code was the output file. This is another Excel file that is created within the working directory which is where certain outputs will

be printed. In our code, that line is as follows: outfile="CCL Model Outputs.csv," again noting that the names must match.

From this point, all that is left is to run the code and get the desired output. When running the code it is important to note that when running it you must use the "Source" button and not the "Run" button. This is because you want the code to pull data from the working directory you created. When using simply the "Run" button, the desired outputs will not be produced.