



# WPI

Major Qualifying Project

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# Reserving Trends in the Health Insurance Industry

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Date: December 11, 2020

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## Abstract

This paper evaluates reserving trends in the health insurance industry. Our analysis used 2016 to 2019 data from Annual Health Statements and includes 1,749 distinct health companies and subsidiaries in Medical, Medicare, Medicaid, and the Total of lines of business. We created and examined various distributions that describe the accuracy and conservativeness of the industry. Also, we analyzed how past reserving trends relate to future trends and identified various attributes that are correlated with reserve estimates. Lastly, using our analysis and 2016 to 2018 data, we created a model to forecast future reserve adequacy. We tested the model by predicting 2019 reserve accuracy and comparing it to the actual 2019 data.

## Acknowledgements

### **Our Advisors**

We would like to thank our advisors, Professor Barry Posterro and Professor Jon Abraham for their guidance, feedback, and expertise throughout our project.

### **Milliman**

We would like to extend our gratitude towards Dave Liner for conceptualizing our project and helping with project logistics. We would also like to thank Kevin Pierce for taking the time to provide any data we required and for meeting with us on a regular basis to provide important insight and direction into the work we were doing.

## 1.0 Introduction

Health insurers make promises to policyholders to pay for future health costs in exchange for a monthly premium. In order to pay off these liabilities, they must hold cash aside for the sole purpose of paying claims, as opposed to investing back into the company or the market. The money that insurance companies set aside to pay claims is known as a reserve. The claims department is responsible for setting reserves for each individual claim, actuaries are responsible for forecasting the reserves, and the CFO makes the final decision about setting the reserve.

When insurers predict and set reserves, they must consider two different types of uncertainty. Incurred but not reported (IBNR) are the costs that have already happened but have not been reported to the insurance company yet. Incurred but not enough reported (IBNER) are claims the insurer already knows about but has yet to pay in full. Health insurance operates on a fast timeline compared to other insurances, so most claims are fully paid within a few months, as opposed to the years it can sometimes take property and casualty or other insurers to fully pay out their claims.

A reserve is considered “conservative” when the estimated amount exceeds the ultimate claims. An “aggressive” reserve is lower than the ultimate claims. Our project sponsor Milliman would like to gauge how accurate and how conservative the health insurance industry is with their reserving estimates. Additionally, they would like us to identify factors that are correlated with future reserve estimates to help Milliman forecast how accurate and conservative their current and future clients’ reserve estimates may be in the future. Milliman can also use our report to identify potential clients who are currently reserving extremely aggressively or conservatively.

## 2.0 Background

### 2.1 Regulation Around Reserves

In order to ensure that insurance companies can adequately pay their policyholders, each state has insurance regulators. State regulators not only ensure insurers have adequate solvency, but they also ensure that insurers are not maneuvering around insurance laws with their reserve practices. Reserves should be slightly conservative, so health insurers can pay their policyholders in the event that claims were higher than expected. Reserves also play a role in how health insurers declare profit, and therefore affect the amount of federal income taxes paid.

Actuaries estimate the losses and then provide a suggestion for the reserve size. The CFO then takes the suggestion into consideration. However, ultimately the CFO sets the reserve. If the final reserve greatly differs from than the actuary's suggestion, an actuary at the company must submit a report to state regulators explaining why they do not think the reserve number is correct. The actuaries in these roles are extremely difficult to fire to ensure that they can give their honest actuarial opinion to the state.

State regulators also want to ensure that health insurers are prepared for a year with unprecedentedly high claims. They require insurance companies to hold capital outside of their reserves. This requirement is known as risk based capital (RBC). Reserves are a large factor in calculating RBC levels, and a larger reserve estimate equates to more required capital. Insurers that fail to hold enough capital are subject to extra regulatory scrutiny, and in extreme cases, regulators can take over the insurance company until the capital levels are satisfactory. These rules apply when the insurer holds less capital than 200% of the calculated RBC amount. Insurers with an RBC ratio over 200% do not face any additional regulations. An overview of the regulations is provided in Table 1.

Table 1: Risk Based Capital Regulations (Odmirok, 282)

Action Level	Adjusted Capital as a % of ACL Benchmark	Action by State Department	Action by Company
Mandatory control level	Below 70%	Insurance commissioner will take over or liquidate the company	None initially
Authorized control	70-100%	Insurance commissioner is authorized to take over the company	None initially
Regulatory action	100-150%	Commissioner can take discretionary regulatory action, like restricting new business.	Must submit a plan of action
Company action	150-200%	None Initially	Must submit a plan of action
-	Over 200%	None	None

## 2.2 Consequences of Overly Aggressive and Overly Conservative Reserves

Companies with overly aggressive reserves risk not being able to pay their claims or they face additional scrutiny and regulation from the state. Health insurers want to avoid state regulators taking over operations, because regulators do not care about the company's profit, and instead, only care that the company can pay their claims.

On the other hand, companies that reserve too conservatively are missing out on profitable opportunities. Reserves cannot be invested back into the company, whereas other capital can. The median return on equity from the insurers we analyzed was 9%. A company with this return on equity that was too conservative in their reserving estimates by \$1 million, would effectively miss out on \$90,000 of profit.



## 3.0 Methodology

Our goal of this project was to evaluate the reserving patterns in the health insurance industry and identify factors to help predict an individual subsidiary's reserve adequacy in the future. This section will discuss the methods we utilized. We applied the same steps to the Medicaid, Medicare, Medical, and Total lines of business.

### 3.1 Data

The data we worked with is based on information found in the Health Annual Statement. Each insurer is required to submit this report to their respective state. We relied on summarized data from Milliman, for 1749 subsidiaries from 2016 to 2019. These subsidiaries are the individual entities insurers file their statement under. We used the data fields in the reports for our analysis (Table 2).

Table 2: Fields Pulled from Annual Health Statements

Data Field	Location in Health Annual Statement
Claims Incurred in Prior Years ( <i>Claims Paid and Unpaid</i> )	Underwriting and Investment, section 2b
Estimated Reserve and Claim Liability December 31 of Prior Years ( <i>Estimated Reserves</i> )	Underwriting and Investment, section 2b
Total Adjusted Capital	Five-Year Historical Data
Authorized Control Levels	Five-Year Historical Data
Net Income	Five-Year Historical Data
Revenue	Five-Year Historical Data
Stock Ticker	Five-Year Historical Data

We worked with data on the subsidiary level, as opposed to the parent organization level and only used subsidiaries that fit certain criteria. For all our analysis, we removed subsidiaries with negative actual reserves or negative reserve estimates. These values oftentimes resulted in

extremely aggressive-looking reserving outliers and are not necessarily indicative of the reserving trends as a whole. We also removed \$0 and NA value reserves for similar reasons. Additionally, in our Risk Based Capital Analysis, we excluded subsidiaries holding capital over 10,000% of their authorized control level and also negative RBC amounts, to prevent huge outliers.

In order to keep track of the subsidiaries we included for each line of business, we checked each of the 1749 unique subsidiaries for each criterion and created a list of subsidiaries that fit all the criteria to include. We also created a list of excluded subsidiaries.

### 3.2 Difference between Claims Paid and Unpaid and Estimated Reserve

Our analysis focused on reserve estimate inaccuracy. We calculated the inaccuracy for each subsidiary using the following actual to expected equations (“Claims Paid and Unpaid” are the “actual” reserves):

*Equation 1: Reserve Inaccuracy Equations*

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$$\text{By percent} = \frac{(\text{Estimated Reserve } \$ - \text{Claims Paid and Unpaid } \$)}{\text{Claims Paid and Unpaid } \$}$$

$$\text{By Dollar} = \text{Estimated Reserve } \$ - \text{Claims Paid and Unpaid } \$$$

---

Using these two equations, a negative value indicates that the estimate was aggressive whereas a positive value indicates that the estimate was conservative. Therefore, 0% indicates that the estimated reserve covered the claims exactly; however, no reserve estimate is exact.

Throughout our analysis, we also examined the data through two lenses. First, we analyzed data by number of subsidiaries. This allowed us to observe how likely a subsidiary is to have a certain characteristic, such as a conservative reserve estimate. Additionally, we looked at

the data weighed by actual reserve dollars; we could gain insight on the industry as a whole without small reserve estimates holding too much weight compared to large reserve estimates.

### 3.3 Creating Distributions

In order to get a full perspective on the industry’s reserving estimate habits, we created three different types of empirical distributions. We applied each distribution to each year of analysis; we also created a distribution with all the 2016 to 2019 data. The first distribution showcased reserve inaccuracy by percent across the industry. We created 22 different groupings based on accuracy and conservativeness, and we counted the number of subsidiaries in each grouping. We did not have any data in the >100% aggressive bracket, as that would indicate that either the reserve estimate was negative or the claims paid and unpaid was negative, data we excluded.

Table 3: Distribution by Percent Groupings- 22 Groupings

Too Aggressive	Too Conservative
< -100%	0 to 10%
-100 to -90%	10 to 20%
-90 to -80%	20 to 30%
-80 to -70%	30 to 40%
-70 to -60%	40 to 50%
-60 to -50%	50 to 60%
-50 to -40%	60 to 70%
-40 to -30%	70 to 80%
-30 to -20%	80 to 90%
-20 to -10%	90 to 100%
-10 to 0%	> 100%

Using these same groupings, we also created a distribution weighted by claims dollars. We calculated each subsidiary’s percentage of the line of business’ total claims using Equation 2.

$$= \frac{\text{Subsidiary's Claims Paid and Unpaid \$}}{\text{Line of Business' Total Claims Paid and Unpaid \$}}$$

We added the subsidiaries' weighted percentages by grouping to calculate the percentage of total claims in each reserve inaccuracy grouping.

Our third distribution displayed the reserve inaccuracy by dollars. We created 26 groupings by \$2.5 million increments and counted the number of subsidiaries in each dollar grouping.

Table 4: Distribution by Dollar Groupings- 26 Groupings

Too Aggressive (\$ millions)	Too Conservative (\$ millions)
< - 30	0 to 2.5
-30 to -27.5	2.5 to 5
-27.5 to -25	5 to 7.5
-25 to -22.5	7.5 to 10
-22.5 to -20	10 to 12.5
-20 to -17.5	12.5 to 15
-17.5 to -15	15 to 17.5
-15 to -12.5	17.5 to 20
-12.5 to -10	20 to 22.5
-10 to -7.5	22.5 to 25
-7.5 to -5	25 to 27.5
-5 to -2.5	27.5 to 30
-2.5 to 0	> 30

Additionally, we calculated the standard deviation of each distribution.

### 3.4 Future Reserve Adequacy Based on Past Reserving Patterns

Our goal of the transition analysis was to find trends in how subsidiaries reserve over time based on how they reserved in the past. We evaluated how past reserve accuracy and conservativeness correlated to future reserve accuracy and conservativeness. Also, we considered

how past reserve estimate variance and volatility correlated to different likelihoods for future reserve volatility.

### 3.4.1 Likelihood of Being in a Reserve Inaccuracy Range

To begin our transition analysis, we split the reserve accuracy percentages into 6 groupings (Table 5) and assigned each subsidiary a grouping for each year it had data.

*Table 5: Accuracy and Conservativeness Groupings*

<b>Reserve Accuracy percentage</b>	<b>Accuracy and Conservativeness Grouping</b>
Less than -50%	-3, extremely aggressive
-50% to -15%	-2, moderately aggressive
-15%-0%	-1, slightly aggressive
0%-15%	1, slightly conservative
15%-50%	2, moderately conservative
50%-100%	3, extremely conservative

We compared subsidiaries' groupings in 2016 versus 2017, 2017 versus 2018 and 2018 versus 2019. Using this data, we calculated the probabilities of a subsidiary, given their grouping one year, falling into one of the six groupings the next year. We presented the aggregate of 2016 to 2019 data in transition matrices. Table 6 illustrates the basic concept of our transition matrices. In this fabricated matrix, we show a likelihood of previously conservative and previously aggressive reserving subsidiaries (rows) reserving aggressively or conservatively the next year (columns). If these numbers were our real data, we would conclude that 90% of previously conservative reserves remained conservative and 10% became aggressive.

Table 6: Example Transition Matrix

		Next Year's Groupings	
		Conservative	Aggressive
Analysis Year's Grouping	Conservative	90%	10%
	Aggressive	60%	40%

We created two transition matrices per line of business. One matrix calculated the probabilities for each grouping by counting subsidiaries and the other by summing claims. In our results chapter, we presented the information in the transition matrices as bubble graphs. The size of the bubble correlated to percent associated with each grouping. In addition to the transition matrices, we also made transition distributions. Using methodology similar to our distribution by percent, we made 12 distributions for each line of business, six counting subsidiaries for each of the transition groupings and the other six summing claims. Like the matrices, the distributions aggregate 2016 to 2019 data.

We also tracked how subsidiaries in 2016 reserved over the next 3 years. First, we split the subsidiaries by their 2016 reserve groupings. Next, we counted how many subsidiaries in each 2016 reserve grouping were conservative 0/3, 1/3, 2/3, and 3/3 of the next 3 years. Afterwards, we defined “accurate” as within a 15% margin of error, and “inaccurate” as greater than 50% inaccurate. We conducted a similar analysis focusing on how many subsidiaries were “accurate” and “inaccurate” for 0/3, 1/3, 2/3, and 3/3 years. We repeated both 3-year analyses summing claims instead of counting subsidiaries.

### 3.4.2 Likelihood of Changing Reserve Grouping

We also evaluated whether subsidiaries switching from conservative to aggressive reserving from year to year indicates that they would be more likely to switch in the future. We split the subsidiaries into groupings based on whether they had switched conservativeness 0, 1 or

2 times from 2016 to 2018. Next, we calculated the probability of each group switching conservativeness in 2019 given the number of times they switched from 2016 to 2018. We repeated this analysis, focusing on accuracy instead of conservativeness (“accuracy” defined as within a 15% margin of error and “inaccuracy” defined as over 15% inaccurate). Finally, we performed this analysis given the number of times a subsidiary switched both accuracy and conservativeness.

### 3.4.3 Variance of Reserve Inaccuracy

Lastly, we evaluated whether the relative variance of each subsidiary was related with their reserving tendencies. To start, we calculated the standard deviation of the percent inaccuracy of each transition grouping (-3, -2, -1, 1, 2 and 3) from 2016 to 2018 and the standard deviation of percent inaccuracy of each subsidiary from 2016 to 2018. We used these two standard deviations to create a ratio using the following equation:

*Equation 3: Standard Deviation Ratio*

---

$$= \frac{\text{(Subsidiary's Standard Deviation)}}{\text{(Subsidiary's 2018 Grouping's Standard Deviation)}}$$

---

Next, we split the subsidiaries into nine groups based on their standard deviation ratios from 0 to 3.5 in increments of 0.5, with an additional grouping for standard deviations greater than 3.5. For each grouping, we calculated the probability that aggressive reserves would remain in the same transition group in 2019 that they were in for 2018 and the probability that conservative reserves would remain in the same transition group in 2019. Additionally, we calculated the probability that 2018 aggressive reserves in each standard deviation grouping

would remain aggressive in 2019 and the probability that 2018 conservative reserves in each stand deviation grouping would remain conservative in 2019.

### 3.5 Analysis by Attribute

In addition to analyzing reserves over time, we also observed connects between different attributes and reserve estimate inaccuracy and conservativeness to help forecast reserve estimates in the future. We identified 4 key attributes: RBC, reserve size, revenue, and whether a subsidiary's parent organization was a public or private company. For each attribute we calculated its distribution by both counting the number of subsidiaries and summing claims dollars. Then, we identified relationships between the attribute and the reserve estimates.

#### 3.5.1 Risk Based Capital

Our initial RBC analysis grouped data according to RBC regulations (refer to Table 1). We calculated the percent of subsidiaries in each grouping by count of subsidiaries and sum of claims. Afterwards, we calculated the probability that a subsidiary would reserve conservatively for each RBC grouping. We also compared RBC ratio to reserve accuracy percentage by plotting every subsidiary.

#### 3.5.2 Reserve Size

We found the 10<sup>th</sup> percentiles for the reserve sizes per line of business and grouped subsidiaries by reserve dollars in increments of 10<sup>th</sup> percentile. Next, we found the average aggressive reserve inaccuracy and the average conservative reserve accuracy percentages for each grouping.



### 3.5.3 Revenue

Additionally, we examined the correlation between reserve estimates and revenue. We approached this analysis in two directions. Firstly, we analyzed how revenue and reserve estimates the same year are correlated. Next, we analyzed how reserve estimates relate to prior year revenue. Like our reserve size analysis, we found the 10<sup>th</sup> percentiles for the revenues per line of business. We grouped subsidiaries by revenue dollars in increments of 10<sup>th</sup> percentile. For each grouping, we calculated the average percent inaccuracy with regards to aggressiveness and conservativeness and the average reserve accuracy percentage regardless of conservativeness or aggressiveness. We also calculated the percent of conservative subsidiaries and the percent of conservative estimated reserve dollars for each grouping.

### 3.5.4 Subsidiary Type: Private or Public

We separated the subsidiaries into public and private and repeated the three types of distribution calculations as detailed in Section 3.3. Additionally, we calculated the percent of private companies and the percent of public companies that reserved conservatively, aggressively, accurately, and inaccurately.

## 4.0 Results

In this section, we will discuss our major findings from our analysis. The first finding was that the industry, as a whole, estimates too conservatively. Also, we discovered that the majority of the subsidiaries that reserved extremely conservatively in the past continued to do so year after year. Lastly, we summarize reserving trends based on reserve and revenue size, RBC ratio, and whether the subsidiary is public or private.

### 4.1 The Industry is Too Conservative

The industry should have a slight bias towards conservative reserving since insurers need to account for greater than expected IBNR and IBNER claims by adding a small margin to their estimate. We expected the industry to have a 2:1 conservative to aggressive ratio, and ideally most reserves would be within a 5 to 15% **margin of error (MoE)**. **However, the industry was considerably more conservative.** To estimate the consequences of overly conservative reserving habits, we multiplied each subsidiary's return on equity by their dollar inaccuracy. The industry potentially could have earned an additional \$6.61 billion, from 2016 to 2019, in returns if money in overly conservative reserves was invested elsewhere. Not only did the industry miss out on billions of dollars, but the money the industry lost out on increased each year from 2016 to 2019 (Appendix A). From 2016 to 2019, Medical, Medicare and **the aggregate of all reserves, Total**, were too conservative by over 20%. Only Medicaid reserved within a 15% MoE (Table 7).

Table 7: Industry Reserving Aggregated 2016 to 2019

Line of Business	Inaccurate	Total Claims Paid and Unpaid	Number of Subsidiaries	Average Claims Dollars per Subsidiary
<b>Medical</b>	25%	\$66 Billion	442	\$148 Million
<b>Medicare</b>	36%	\$49 Billion	425	\$114 Million
<b>Medicaid</b>	14%	\$58 Billion	237	\$244 Million
<b>Total</b>	23%	\$191 Billion	874	\$219 Million

Medicare was significantly less accurate than the Total reserves, and Medicaid was significantly more accurate than the Total reserves. Overall, from the 2016 to 2019, 86% of subsidiaries reserved conservatively and 14% of subsidiaries reserved aggressively. While the industry’s total claims paid and unpaid dollars increased each year, conservative reserving remained consistent (Appendix B). Figure 1 shows the Total distribution in 2019 of the reserve estimate percent accuracy (calculated with equation 1) for conservative (blue) and aggressive (red) subsidiaries.

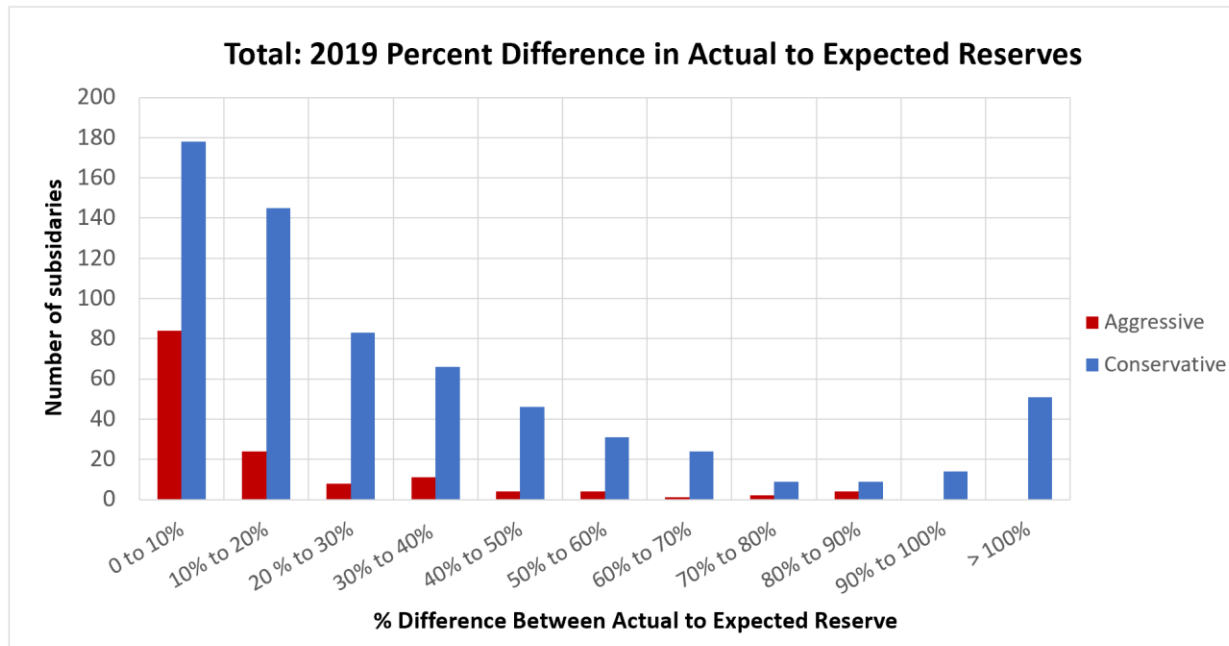


Figure 1: 2019 Reserves Distribution by Percent Difference

The Medicare and Medical lines of business followed an accuracy percentage distribution similar to the Total. The mode of the Total distribution is the 0 to 10% too conservative range.

However, the mean was 65% too conservative. **This is due to a significant portion, about 50, of the subsidiaries reserving over 100% too conservatively.** On the other hand, 60% of the aggressive reserves fell within a 10% MoE. This is expected; extremely aggressive reserves should be rare, as state regulators want to see slightly conservative reserves. In 2019, the standard deviation of accuracy percentage was 338.25%. This large variation is due to the extremely conservative outliers, some of which were over 1,000% too conservative. **In summary, aggressive reserves are typically only slightly aggressive, whereas conservative reserves tend to have more variation.**

Next, we examined the inaccuracy distribution by dollars. This distribution helped to identify subsidiaries with a large reserve and a high dollar inaccuracy, but a low reserve accuracy percentage (Figure 2).

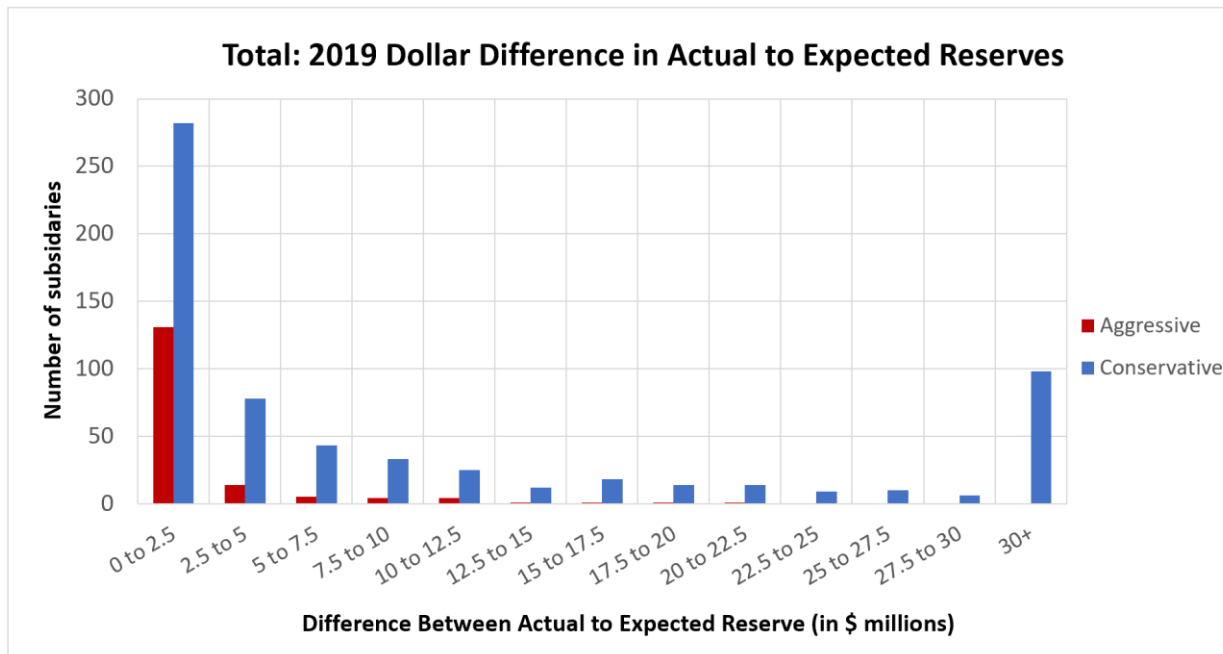


Figure 2: 2019 Dollar Difference Distribution

The majority of the subsidiaries, both conservative and aggressive, were accurate in reserving within a \$2.5 million MoE. Notably, very few subsidiaries were aggressive by over

\$2.5 million. **However, in 2019, over 100 subsidiaries reserved too conservatively by over \$30 million each.** These subsidiaries contributed significantly to the industry's overall conservative tendencies.

We investigated the 150 subsidiaries from 2016 to 2019 with reserves over \$30 million too conservative. Over 60 of these subsidiaries were consistently too conservative by over \$30 million. **Their parent organizations seemed to have overarching conservative reserving philosophies.** For example, the mutual company, Health Care Service Corporation, was too conservative by over \$1.6 billion from 2016 to 2018 and \$423 million too conservative in 2019. Many subsidiaries under parent organizations like Humana and Blue Cross Blue Shield were overly conservative by over \$30 million for multiple years. We hypothesized that mutual companies may have a pattern of conservative reserving since their main objective is paying all claims as opposed to maximizing their profits. Companies with more conservative reserves are more likely to be able to pay their claims, however the additional solvency benefit of being extremely conservative as opposed to moderately conservative is minimal compared to the amount of money the companies miss out on.

We also considered the number of small reserves that had extremely conservative percentages, thus overexaggerating the outliers. We found the reserve *dollars* in weighted distribution were about half as likely to fall into the over 100% too conservative grouping than *subsidiaries* in the unweighted distribution. However, as previously mentioned, a subsidiary being \$30 million dollars too conservative does not necessarily translate into a high accuracy percentage if the claims are large. **The differences between the unweighted and weighted distributions highlight that subsidiaries with large claims amounts to estimate are most likely to reserve conservatively** (Figure 3).

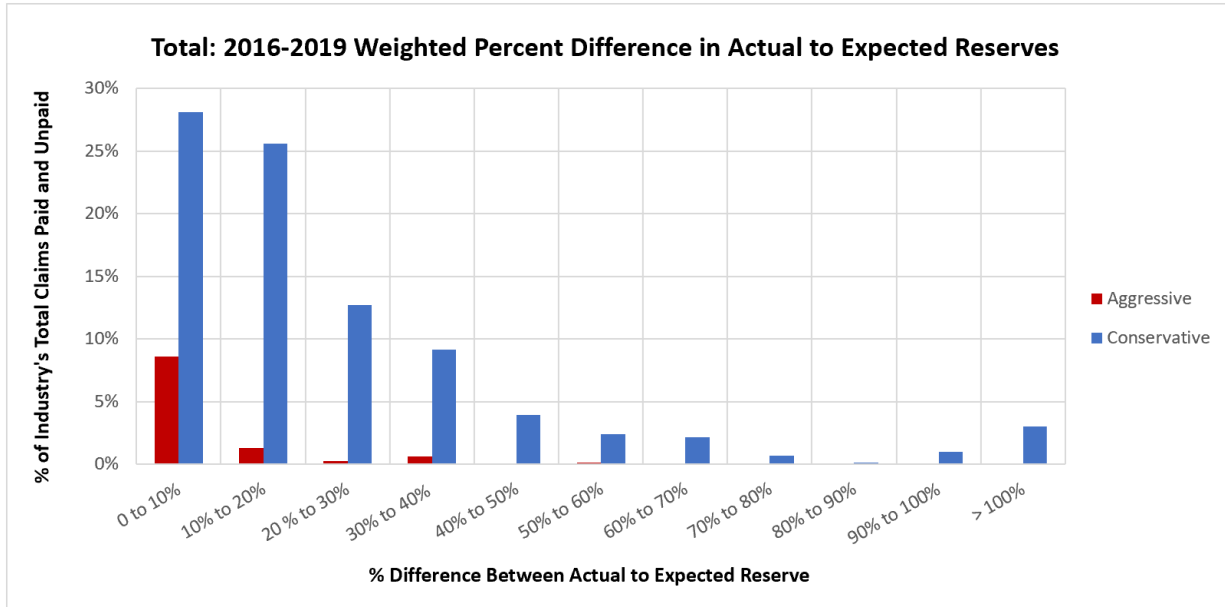


Figure 3: Total Weighted Distribution

The ratio of conservative to aggressive was 5:1 for the unweighted distribution, whereas the weighted distribution had an 8:1 ratio. The weighted distribution also had greater accuracy in reserving and less variation with subsidiaries' estimates. In 2019, the average inaccuracy was 20% and the standard deviation of the weighted accuracy percentage was 10%. The significantly lower standard deviation in the weighted distribution illustrates that small reserves were responsible for a lot of the excessively conservative estimates.

We also examined how individual lines of business contributed to the overall overly conservative reserve estimate trend. The unweighted and weighted distributions by line of business are provided in Appendices C and D. The individual lines of businesses often displayed similar trends, which was reflected in Total, the aggregate of the lines of businesses. However, Medicare was significantly more inaccurate, and Medicaid was significantly more accurate. Additionally, Medicare's weighted distribution (Figure 4) looked vastly different than any other line of business.

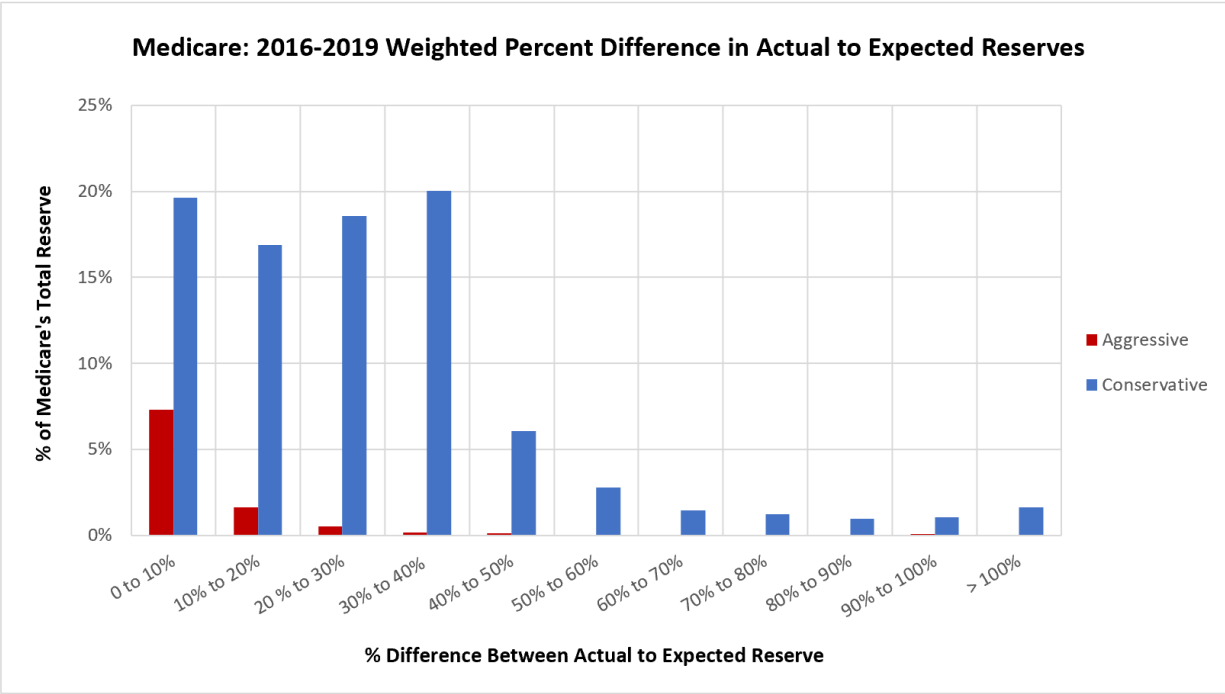


Figure 4: Medicare 2016 to 2019 Weighted Distribution

**Medicare was the most inaccurate and most conservative line of business we analyzed.** Over 90% of the 2016 to 2019 aggregated Medicare reserves were conservative. Unlike other lines of business with modes in the 0 to 20% range, the mode of the weighted Medicare reserve inaccuracy was the 30 to 40% too conservative range. The majority of the dollars were spread among the 0 to 40% too conservative ranges. Overall, the high amount moderately conservative Medicare dollars make Medicare the least accurate and most conservative line of business.

Even though the Medicaid weighted distribution bore resemblance to the Total weighted distribution, **Medicaid was notably more accurate in aggregate.** In an ideal distribution, the majority of the subsidiaries would reserve in the 0 to 20% conservative range and about a third of subsidiaries would reserve in the 0 to 10% aggressive range. The Medicaid weighted distribution (Figure 5), out of all lines of businesses, most closely resembled this ideal.

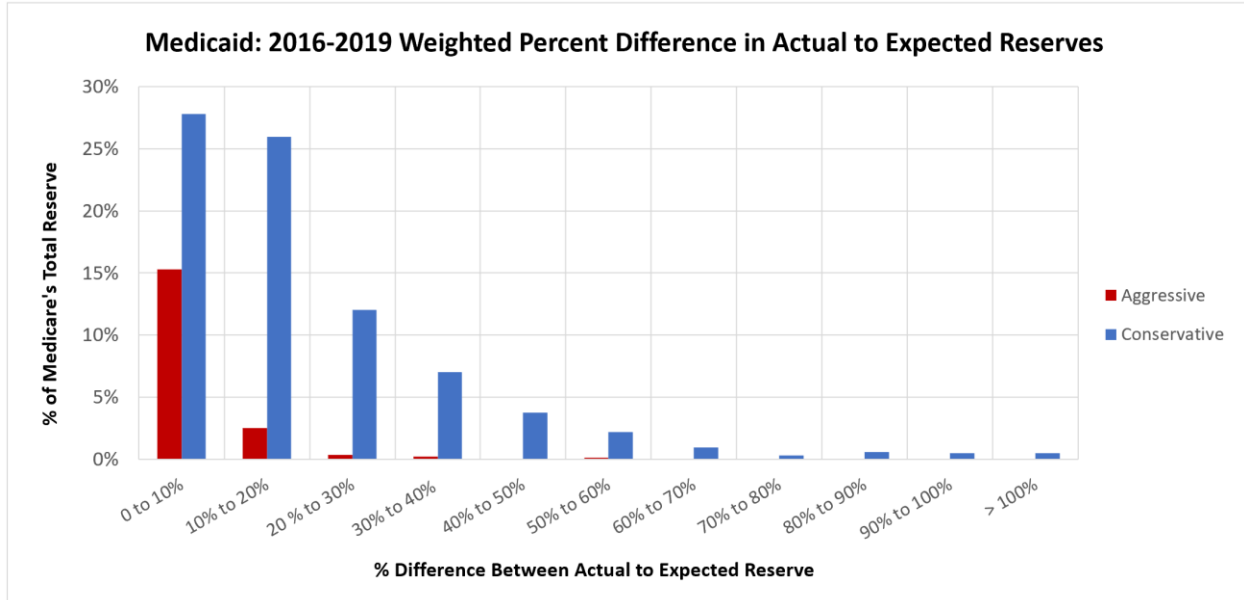


Figure 5: Medicaid 2016 to 2019 Weighted Distribution

The main difference between the Medicaid distribution and the Total distribution lied in the extremely conservative reserving. Whereas the Total distribution had a small but consequential percentage of claims paid and unpaid dollars lying in the greater than 50% too conservative categories, Medicaid had a marginal amount of dollars in these buckets. Even Medicaid’s unweighted distribution had far less outliers. In fact, Medicaid *subsidiaries* were two times less likely to be more than 100% too conservative (Figure 6).



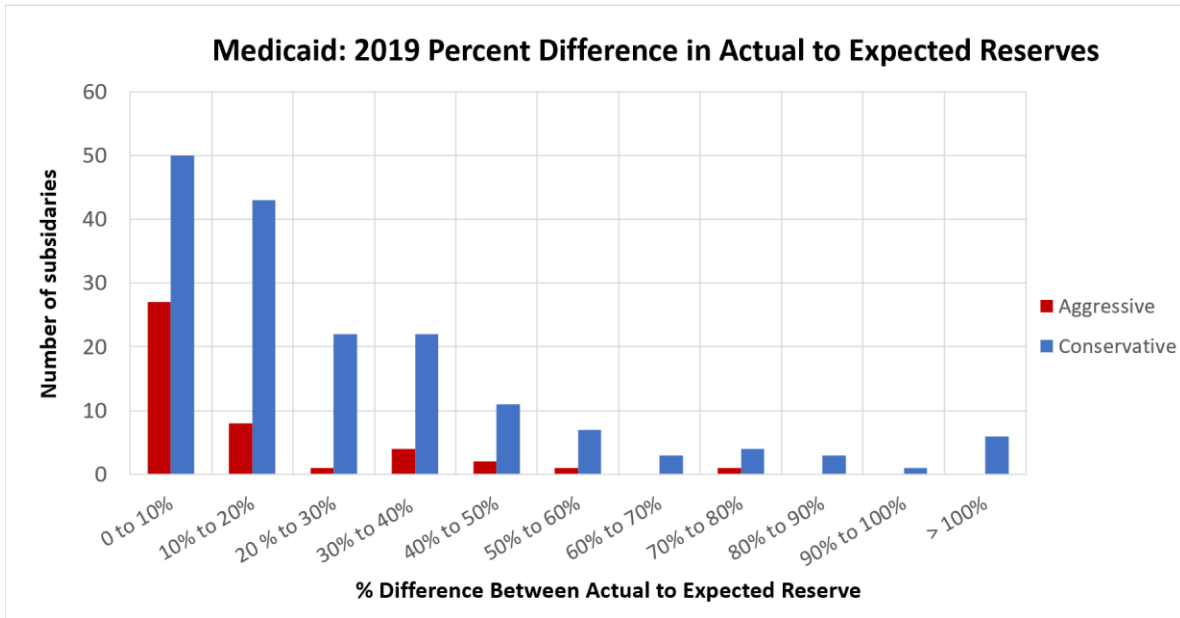


Figure 6: Medicaid 2019 Unweighted Distribution

One explanation for Medicaid’s superior accuracy may be a difference in payment methods compared to the other lines of businesses. Medicaid oftentimes pays by capitation, where the insurers and providers agree to pay a set amount per patient. On the other hand, the other lines of business are more likely to use fee for service, where insurers pay providers according to the services they perform. Thus, there is less variability in the Medicare claims, making them easier to predict.

#### 4.2 Subsidiaries Oftentimes Fail to Self-Correct Extremely Conservative Reserves

Our initial analysis revealed the industry’s tendency to conservatively reserve and showed an abundance of extremely conservative estimates. We examined how past year’s reserves are correlated with the next year’s estimate (Appendix E). **Overall, the health insurers tended to reserve similarly year-by-year.** We tracked conservativeness and accuracy year-to-year and over three years and identified self-adjustment trends. **The extremely conservative**

reserves oftentimes remained extremely conservative, but slightly aggressive oftentimes switched conservativeness while maintaining accuracy.

#### 4.2.1 Transition Analysis by Grouping

For each line of business, we performed two transitions analyses one based on the number of *subsidiaries* and the other based on the *dollars* of claims paid and unpaid. In Total, similar to our distribution analysis, the *dollar* analysis was less aggressive the next year compared to the *subsidiary* analysis. Our full transition matrices can be found in Appendices F and G. Figure 7 illustrates the probabilities associated with a subsidiary in a grouping one year (rows) transitioning to each of the groupings next year (columns) based on *dollar* data (the groupings are explained in Table 4). In Figure 7, larger circles indicate a larger dollar amount and smaller circles indicate a smaller dollar amount.

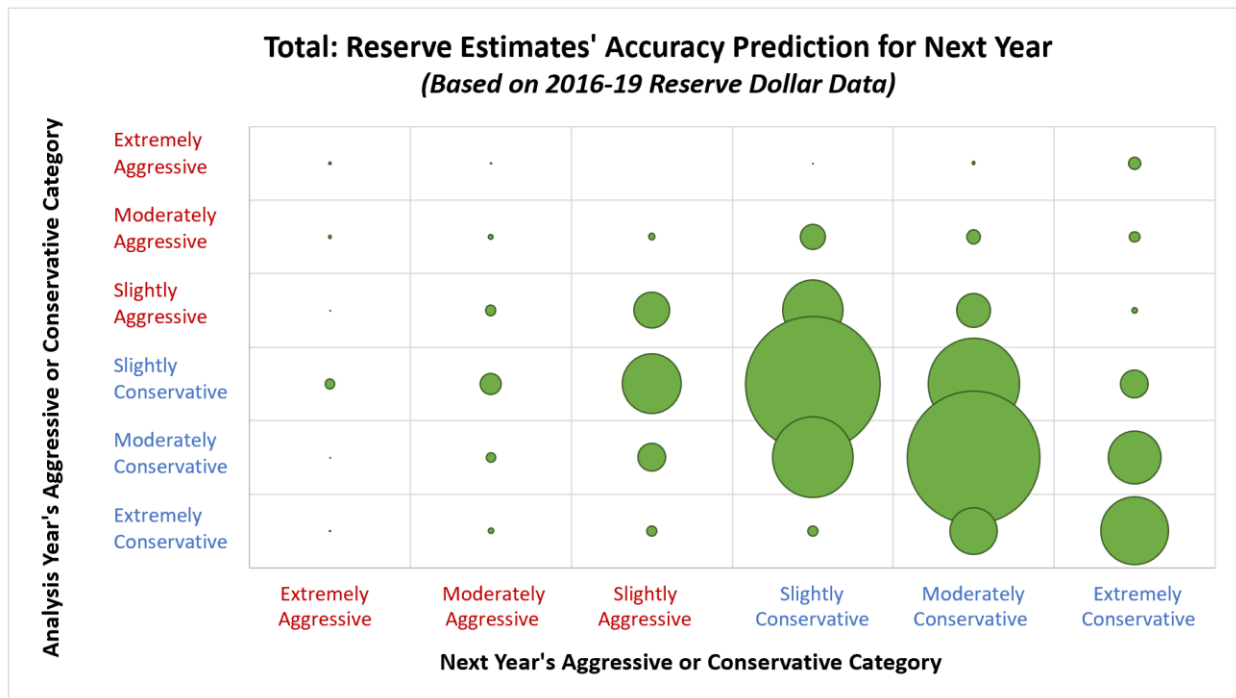


Figure 7: Total Reserve Accuracy as a Prediction for Future Years

Diagonal patterns from top-left to bottom-right show a tendency to reserve similarly year-by-year. A diagonal in the opposite direction would show a tendency of companies to change how they reserve year-by-year, and a random pattern would show no relationship between the past and future reserve estimates. **Figure 7 shows that conservative reserves tended to follow the same patterns year-by-year.** All three conservative reserve groupings had a 60% likelihood of being in the same grouping next year. Additionally, extremely conservative reserve *dollars* were only 2% likely to be aggressive the next year. Alternatively, extremely conservative *subsidiaries* were 11% likely to be aggressive the next year. Thus, while most extremely conservative reserves tend to remain extremely conservative, the extremely conservative reserves that self-adjusted were typically the smaller reserves. **Conversely, aggressive reserves leaned towards being slightly conservative the following year.** Aggressive reserves had around a 2:1 conservative to aggressive ratio the next year. Aggressive reserves were also extremely accurate compared to conservative reserves. 67% of moderately aggressive reserve *dollars* and 80% of slightly aggressive *dollars* were within a 15% MoE the next year.

**The individual lines of business also showed similar trends.** However, there were some key differences. As seen in Figure 8, extremely conservative Medicaid *dollars* (row 6) were more likely to be moderately conservative (column 5) the next year than stay in the same grouping (column 6).

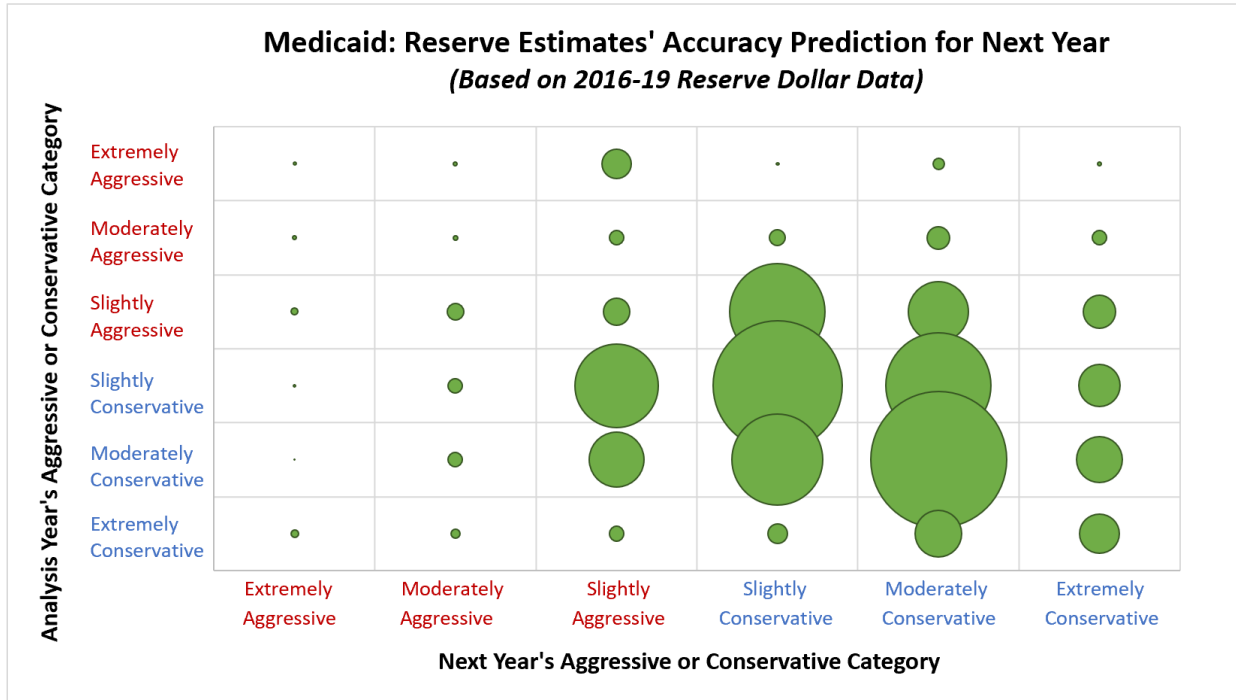


Figure 8: Medicaid Reserve Accuracy as a Prediction for Future Years

**Medicaid was the most effective out of any line of business at adjusting extremely conservative reserves.** The majority of these reserves changed grouping the next year. Only 35% of extremely conservative Medicaid reserves remained extremely conservative the next year, compared with 65% of the Total extremely conservative. Also, conservative Medicaid reserve estimates were almost twice as likely to be aggressive the next year as Total reserve estimates.

One of the largest differences between Medicare and other lines of business was in the distribution of slightly conservative reserve estimates. Like subsidiaries in other lines of business, Medicare *subsidiaries* tended to remain in the same conservative grouping the next year. However, slightly conservative Medicare reserve *dollars* were more likely to be moderately conservative the next year than to be slightly conservative (Figure 9).

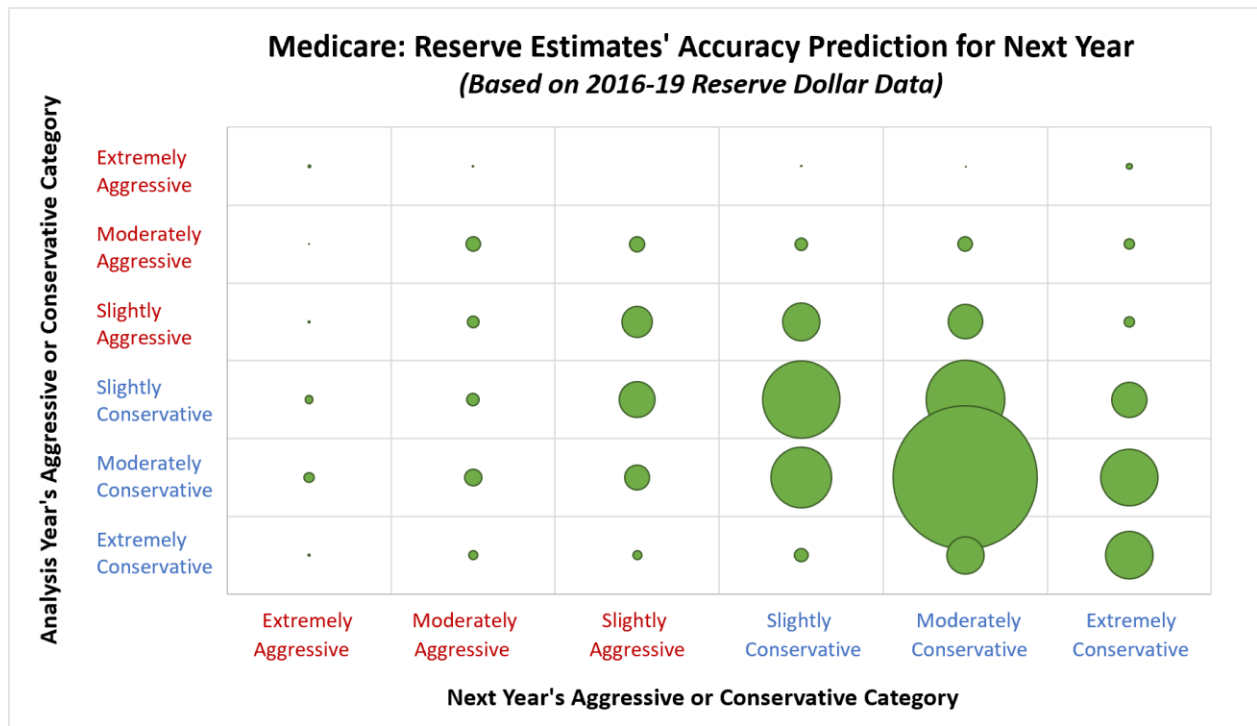


Figure 9: Medicare Reserve Accuracy as a Prediction for Future Years

Similarly, slightly aggressive Medicare *dollars* were almost as likely to be moderately conservative as slightly conservative. **Large Medicare reserves within a 15% MoE the prior year, were likely to be over 15% too conservative the next year.** Thus, Medicare reserve estimates across the board were less accurate the next year than reserve estimates in other lines of business.

#### 4.2.2 Distributions by Transition Grouping

We examined each transition grouping's unweighted and weighted reserve inaccuracy distributions for the next year. The 2016 to 2019 aggregate graphs by line of business are found in Appendices H and I. The distributions for extremely conservative and slightly aggressive were insightful in terms of self-correction. Extremely conservative needed to improve accuracy and slightly aggressive needed to become more conservative. **Most of the extremely conservative reserves not only remained extremely conservative but were also over 100% inaccurate.**

Figure 10 shows the weighted and unweighted distributions of reserve estimates that were extremely conservative the previous year.

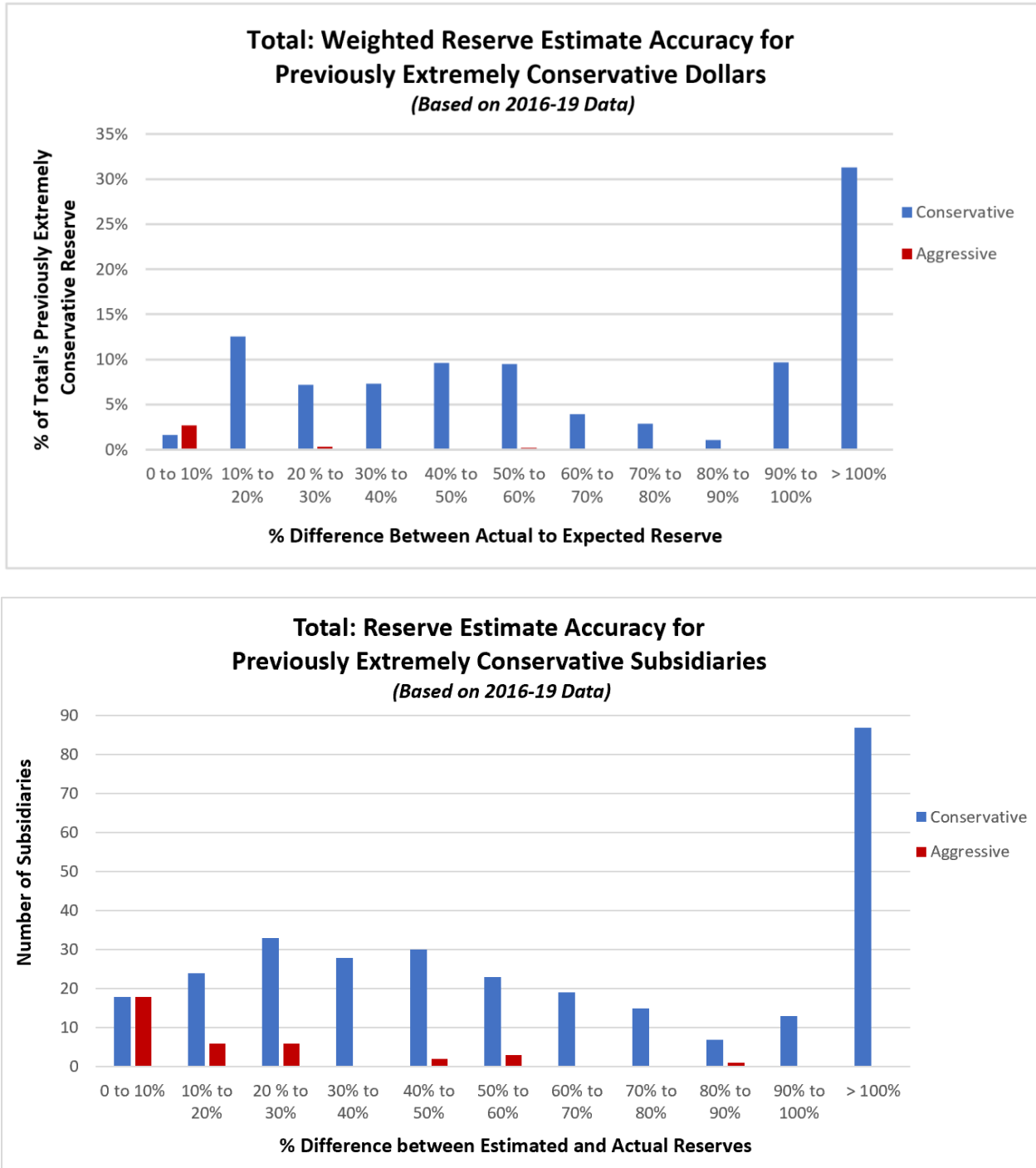


Figure 10: Total Extremely Conservative Weighted (Top) and Unweighted (Bottom) Reserve Distribution

Less than 5% of the extremely conservative reserve *dollars* were within a 10% MoE the next year. On the other hand, almost a third of the *dollars* were over 100% inaccurate the next year. Comparatively, *subsidiaries* that reserved extremely conservatively were 11% likely to be within a 10% MoE and 26% likely to be over 100% inaccurate the next year. This analysis once again illustrates how subsidiaries with smaller reserves self-corrected more when their estimate was off.

**The Medicare and Medical extremely conservative distributions were similar to the Total extremely conservative distribution.** Only 11% of extremely conservative Medicare reserve dollars and 6% of Medical reserve *dollars* were within a 10% MoE the next year. Furthermore, 52% of extremely conservative Medicare *dollars* and 57% of Medical *dollars* were extremely conservative the next year. For both Medicare and Medical, 37% of these extremely conservative estimates were too conservative by over 100%.

We examined the previously slightly aggressive grouping as well to compare levels of self-correction. Figure 11 shows the weighted and unweighted distribution of estimates that were slightly aggressive the year before.

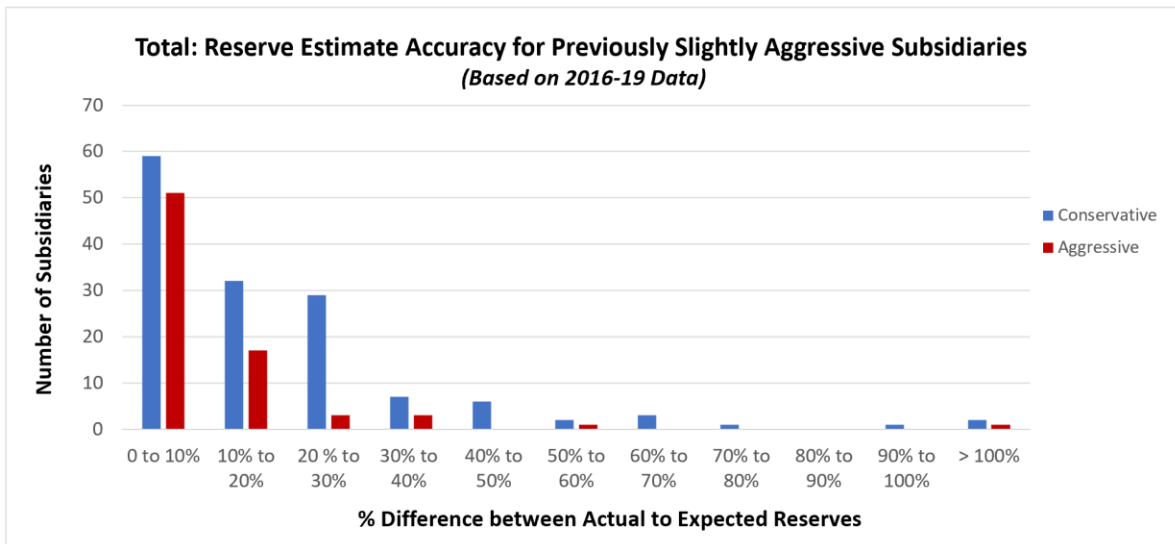
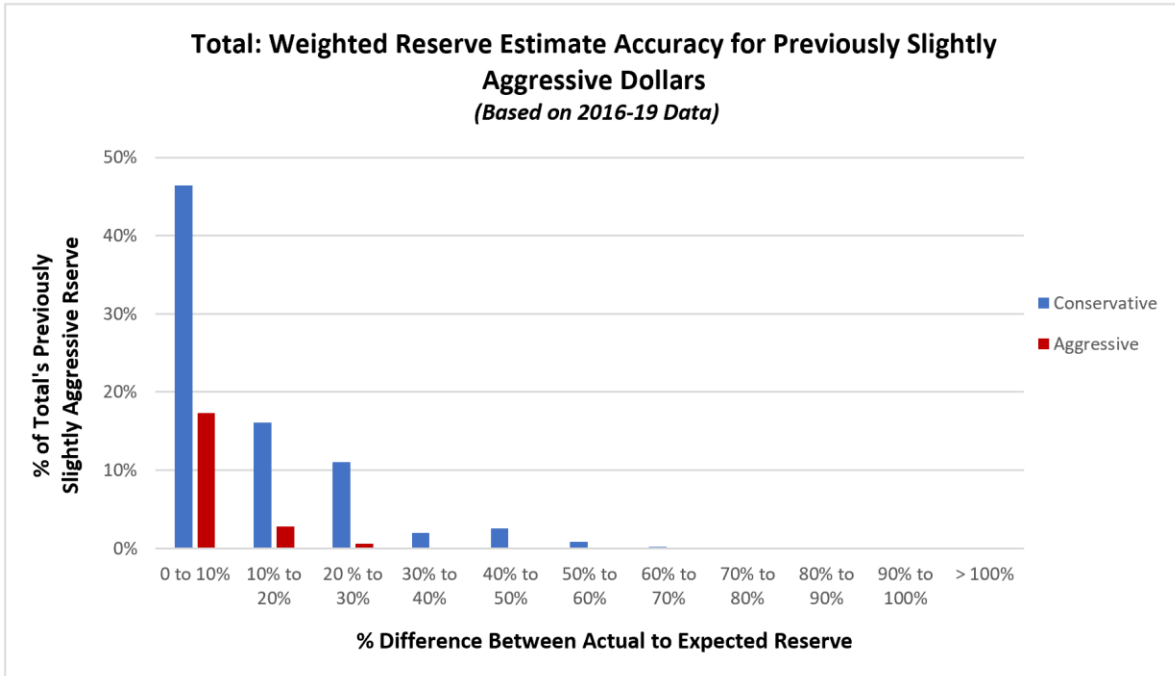


Figure 11: Total Slightly Aggressive Weighted (Top) and Unweighted (Bottom) Reserve Distribution

The slightly aggressive *subsidiaries* that were within a 10% MoE the following year had almost a 1:1 conservative to aggressive ratio. However, in terms of *dollars* the ratio was closer to 2:1. **Therefore, the large previously slightly aggressive reserves oftentimes reserved 0 to 10% too conservative the next year.** Also, the extremely conservative estimates were comparatively more accurate in the slightly aggressive distribution than in the extremely



conservative distribution. Only 4% of the *dollars* became extremely conservative. In contrast, 53% of the *dollars* in the previously extremely conservative distribution were too conservative by over 100%. Whereas 92% of the previously slightly aggressive reserve *dollars* and 86% of *subsidiaries* were within a 30% MoE the next year.

**Unlike the other lines of business, Medicaid had more variation and self adjustment.** This was true for both the weighted and unweighted distributions (Figure 12).

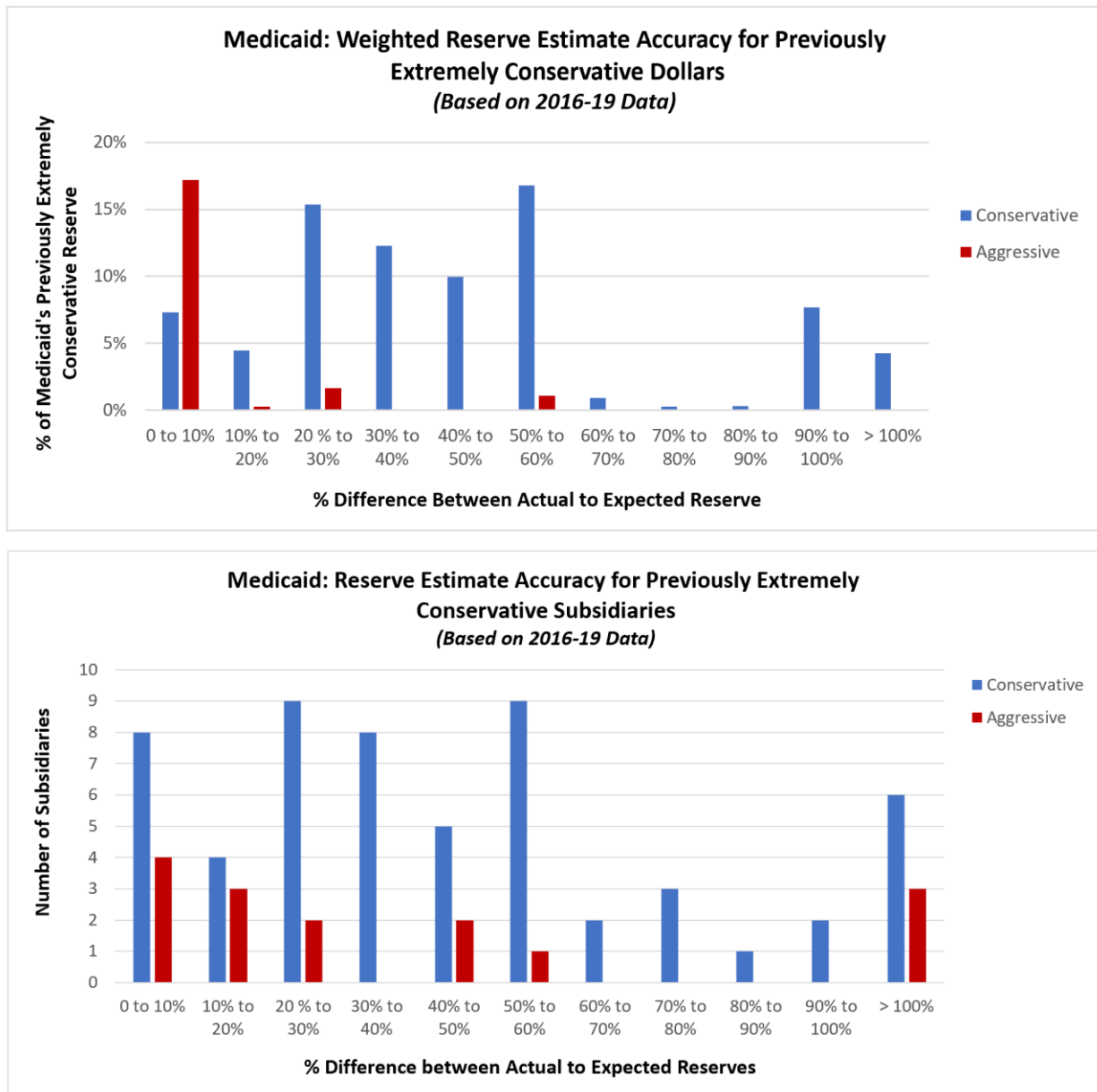


Figure 12: Medicaid Extremely Conservative Weighted (Top) and Unweighted (Bottom) Reserve Distribution

A quarter of extremely conservative Medicaid reserve *dollars* were within 10% accuracy the next year and 69% of Medicaid *dollars* were less than 50% too conservative the next year. Also, only 14% of the *dollars* in the previously extremely conservative distribution were inaccurate by greater than 100%.

#### 4.2.3 Tracking 2016 Reserve Estimates through 2019

We also observed that subsidiaries often followed the same reserving patterns over three years (Appendices J and K). We presumed that this pattern would continue year after year. Total and Medical had similar trends for 2016 data being conservative, within a 15% MoE and inaccurate in the following three years. Overall, aggressive reserve estimates were more likely to be aggressive and accurate the next year than conservative estimates. Slightly aggressive and slightly conservative reserve estimates had the most accurate distributions. Extremely conservative reserve estimates, with the exception of the Medicaid line of business, oftentimes were extremely conservative the next year. 97% of extremely conservative *dollars* in 2016 were conservative the next three years (Table 8). On the other hand, only 70% of extremely conservative *subsidiaries* were conservative the next three years. **Again, subsidiaries with small extremely conservative reserves were significantly more likely to adjust their estimates.**

Table 8: Total Percentage of Claims Dollars Conservative 0,1,2 and 3 Times, from 2016 to 2019 by 2016 Reserve Grouping

2016 Grouping	0 Conservative Estimates	1 Conservative Estimate	2 Conservative Estimates	3 Conservative Estimates
Extremely Aggressive	0%	25%	75%	0%
Moderately Aggressive	16%	9%	12%	63%
Slightly Aggressive	6%	15%	27%	52%
Slightly Conservative	0%	5%	26%	69%
Moderately Conservative	0%	1%	12%	86%
Extremely Conservative	0%	1%	3%	<b>97%</b>

Table 9 shows the percentage of *dollars* within a 15% MoE (top) and more than 50% inaccurate (bottom) for 0/3, 1/3, 2/3 and 3/3 years from 2017 to 2019 based on 2016 reserve groupings.

Table 9: Total Percentage of Claims Dollars Accurate (top) and Inaccurate (bottom) 0,1,2 and 3 Times, from 2016 to 2019 by 2016 Reserve Grouping

2016 Grouping	0 Accurate Estimates	1 Accurate Estimate	2 Accurate Estimates	3 Accurate Estimates
Slightly Aggressive	6%	17%	31%	45%
Slightly Conservative	16%	20%	21%	43%
Moderately Aggressive	43%	9%	16%	31%
Moderately Conservative	48%	29%	14%	10%
Extremely Aggressive	0%	100%	0%	0%
Extremely Conservative	<b>89%</b>	9%	2%	0%
2016 Grouping	0 Inaccurate Estimates	1 Inaccurate Estimate	2 Inaccurate Estimates	3 Inaccurate Estimates
Slightly Aggressive	<b>97%</b>	3%	0%	0%
Slightly Conservative	86%	4%	9%	1%
Moderately Aggressive	48%	45%	7%	0%
Moderately Conservative	75%	16%	8%	1%
Extremely Aggressive	0%	75%	25%	0%
Extremely Conservative	21%	4%	32%	<b>43%</b>

While *dollars* in other 2016 accuracy groupings were likely to be accurate at least once in the next three years, 89% of 2016 extremely conservative *dollars* were never within a 15% MoE from 2017 to 2019. Additionally, 43% of extremely conservative *dollars* were inaccurate by over 50% all three of the next three years. In every other grouping, there was at most a 1% chance of being over 50% inaccurate for all years from 2017 to 2019. This trend was consistent across all three lines of businesses we analyzed. The reserves within a 15% MoE in 2016 were the most likely to be accurate all years. Both the moderately conservative and aggressive groupings were about 45% likely never to be accurate from 2017 to 2019. However, 31% of moderately aggressive reserves were accurate all years, compared to 10% of moderately conservative

reserves. **The three-year analysis illustrates that aggressive reserves are more likely to be accurate, and conservative reserves, outside the 15% MoE, are less likely to self-correct.**

Medicare notably differs from Total in its year-by-year distributions, especially for moderately and extremely conservative 2016 estimates (Table 10).

Table 10: Medicare Percentage of Dollars (top) and Subsidiaries (Bottom) in 2016 Groups 2 and 3 that were Conservative 0,1,2, and 3 Times From 2017 to 2019

Medicare By Dollars of Claims Paid and Unpaid				
2016 Grouping	0 Conservative Estimates	1 Conservative Estimate	2 Conservative Estimates	3 Conservative Estimates
Moderately Conservative	0%	1%	8%	<b>91%</b>
Extremely Conservative	0%	2%	14%	<b>84%</b>
Medicare By Number of Subsidiaries				
2016 Grouping	0 Conservative Estimates	1 Conservative Estimate	2 Conservative Estimates	3 Conservative Estimates
Moderately Conservative	0%	8%	18%	<b>74%</b>
Extremely Conservative	0%	12%	14%	<b>74%</b>

Medicare’s 2016 moderately conservative *dollars* were more likely to remain conservative for the next three years than its extremely conservative *dollars*. *Dollars* in the 2016 moderately conservative and extremely conservative groupings had a 91% and 84% chance of remaining conservative for each of the next three years. However, *Subsidiaries* with moderately conservative and extremely conservative 2016 reserve estimates both had a 74% chance of remaining conservative through 2019. **Thus, larger subsidiaries with reserves that were not in a 15% MoE reserved more conservatively than the subsidiaries with smaller reserves in the same grouping.** Furthermore, 2016 moderately conservative subsidiaries with larger reserves were even more likely to estimate conservatively than 2016 extremely conservative subsidiaries with large reserves. Medicare’s 2016 moderately conservative *dollars* were also less accurate than Medicare’s 2016 extremely conservative *dollars* through 2019 (Table 11).

Table 11: Medicare Percentage of Dollars in 2016 Groups 2 and 3 that were Accurate (Top) and Inaccurate (Bottom) 0,1,2, and 3 Times from 2017-2019

2016 Grouping	0 Accurate Estimates	1 Accurate Estimate	2 Accurate Estimates	3 Accurate Estimates
Moderately Conservative	80%	10%	9%	2%
Extremely Conservative	68%	29%	1%	2%
2016 Grouping	0 Inaccurate Estimates	1 Inaccurate Estimate	2 Inaccurate Estimates	3 Inaccurate Estimates
Moderately Conservative	74%	14%	12%	0%
Extremely Conservative	30%	12%	15%	43%

Medicare’s 2016 moderately conservative *dollars* were 80% likely to never be within a 15% MoE from 2017 to 2019 versus a 68% likelihood for its extremely conservative *dollars*. 30% of the 2016 extremely conservative Medicare *dollars* were never over 50% inaccurate for the next three years, indicating that 30% of the extremely reserves became more accurate. The likelihood for this improvement is much lower for Medicaid (14%) and Medical (9%).

Medicaid also had its own unique three-year trends. Only 0.25% of all Medicaid *dollars* were aggressive all three years from 2017 to 2019. In addition, Table 12 shows that Medicaid reserves were less inaccurate compared to the other lines of businesses.

Table 12: Medicaid Percentage of Dollars in 2016 were Accurate 0 Times (Left) and Inaccurate 3 Times (Right) from 2017-2019

2016 Grouping	0 Accurate Estimates	3 Inaccurate Estimates
Extremely Aggressive	13%	1%
Moderately Aggressive	18%	0%
Slightly Aggressive	13%	0%
Slightly Conservative	32%	0%
Moderately Conservative	2%	2%
Extremely Conservative	48%	20%

Extremely conservative Medicaid *dollars* in 2016 only had a 20% likelihood of being inaccurate all three years from 2017 to 2019, compared to 43% of Medicare *dollars* and 43% of Total *dollars*. Likewise, across all 2016 groupings Medicaid *dollars* were less likely to never be

accurate from 2017 to 2019 than the other lines of businesses. 2016 extremely conservative Medicaid *dollars* were 48% likely to not be accurate at all within the next 3 years, compared to 68% of Medicare *dollars* and 89% of Total *dollars*. **Once again, this analysis illustrates not only how Medicaid reserves tend to be more accurate than reserves in any other line of business, but also how Medicaid's extremely conservative subsidiaries are more likely to correct themselves after an inaccurate year.**

In general, the three-year analysis reaffirmed the idea that extremely conservative subsidiaries tended to remain extremely conservative. In fact, 43% of 2016 extremely conservative *dollars* remained extremely conservative from 2017 to 2019, and 71% of extremely conservative *dollars* reserved extremely conservatively at least twice from 2017 to 2019.

### 4.3 Attributes with Correlation to Reserve Estimation

The differences between a distribution calculated using *dollars* and *subsidiaries* proved reserve size affects inaccuracy. Therefore, we looked at the range of reserve sizes for each line of business and examined the associated reserve accuracy percentage. **Most of the extremely conservative estimates were reserves smaller than \$1 million.** We also hypothesized that capital and the subsidiary's financial goals affect reserving. We measured this using revenue and RBC. **Prior year revenue and RBC were positively correlated with both reserve conservativeness and accuracy.** Finally, we analyzed the difference between privately and publicly owned subsidiaries' reserving. **Public subsidiaries had larger reserves but were less accurate than private.**

#### 4.3.1 Reserve Size

The reserve size played a huge role into why the weighted distributions (Figures 3, 4, 5, 6) were more accurate than the unweighted distributions. **Subsidiaries estimating large**

reserves were generally more accurate and more conservative than subsidiaries estimating small reserves (Appendix L). Figure 13 compares the size of the reserve with its accuracy. The reserve ranges are determined by every 10<sup>th</sup> percentiles of the Total reserve. The 90<sup>th</sup> to 100<sup>th</sup> percentile is separated into two ranges (\$180 million to \$1 billion and above \$1 billion).

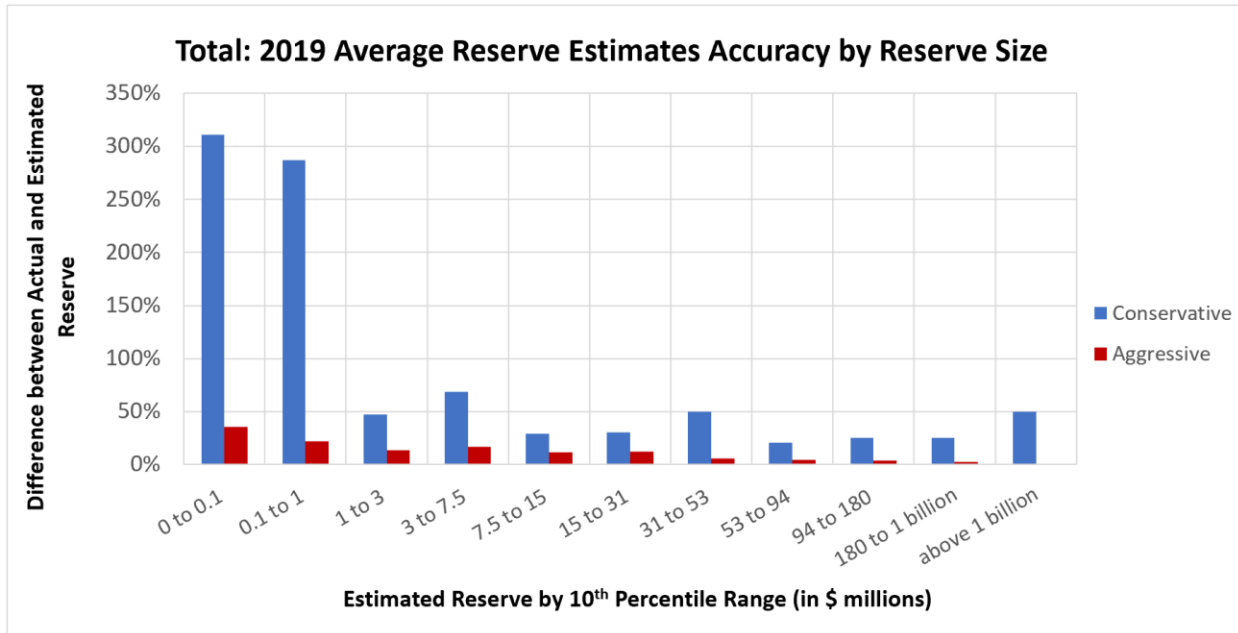


Figure 13: Total Reserve Accuracy versus Size

Unsurprisingly, reserves that were smaller than \$1 million tended to be extremely conservative. Insurance companies may not want to devote a lot of their resources towards reserving accurately if the reserve is small, and instead they may purposefully make the reserve overly conservative to avoid any regulatory scrutiny. Surprisingly, reserves over \$1 billion tended to be more overly conservative than other large reserves. Less than 20% of subsidiaries with reserve sizes above the 40<sup>th</sup> percentile (\$7.5 million) reserved aggressively and less than 10% of subsidiaries with reserve sizes above the 80<sup>th</sup> percentile (\$94 million) reserved aggressively. The three subsidiaries with reserve sizes over \$1 billion reserved conservatively all four years from 2016 to 2019. This trend was consistent across all lines of business. The relationship between reserve size and accuracy may be another reason why Medicaid reserve

estimates are more accurate. The average reserve size per Medicaid subsidiary from 2016 to 2019 was almost twice as large as any other line of business (Table 7).

#### 4.3.2 Revenue

**Subsidiaries with higher revenues in the prior year were more accurate in reserving the next year (Appendices M and N).** Similar to our reserve size analysis, the data up to the 20<sup>th</sup> percentile of revenue size was very inaccurate and everything else was more accurate. Unlike our reserve size analysis, there was a notable difference in the accuracy of subsidiaries in the 20<sup>th</sup> to 40<sup>th</sup> percentiles of revenue and subsidiaries over the 40<sup>th</sup> percentile (Figure 14).

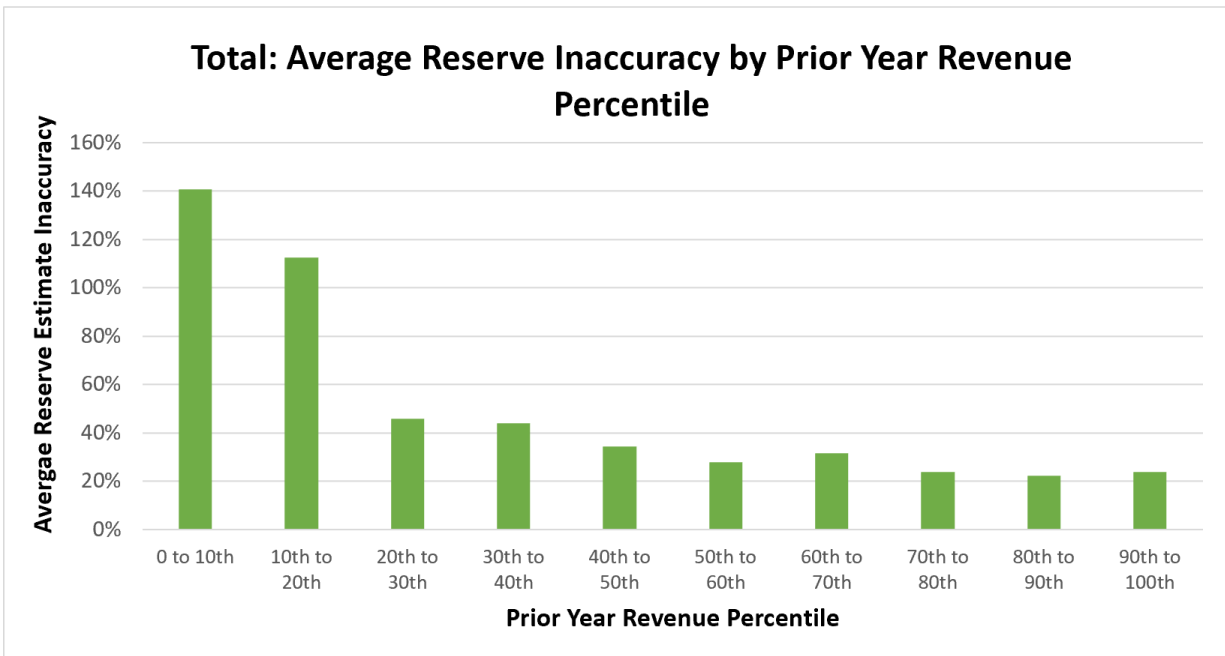


Figure 14: Average Reserve Inaccuracy by Prior Year Revenue Percentile

Perhaps a big factor in reserve accuracy is devoting resources to reserve estimations. Companies with higher revenues can afford to have higher expenses pertaining to reserve estimation and still make a profit. However, another less consequential explanation is that subsidiaries with high revenues could potentially have larger reserve sizes where a large dollar inaccuracy does not necessarily translate to a large percentage inaccuracy.



**Prior year revenue was also positively correlated with reserve conservativeness (Appendix O).** The 10<sup>th</sup> percentile of revenue from 2016 to 2019 was \$0. *Subsidiaries* with negative revenue in the prior year, which was the 0 to 10<sup>th</sup> percentile on Figure 15, were 90% likely to reserve aggressively the next year. On the other hand, *subsidiaries* with revenue over the 60<sup>th</sup> percentile in the prior year were conservative about 90% of the time.

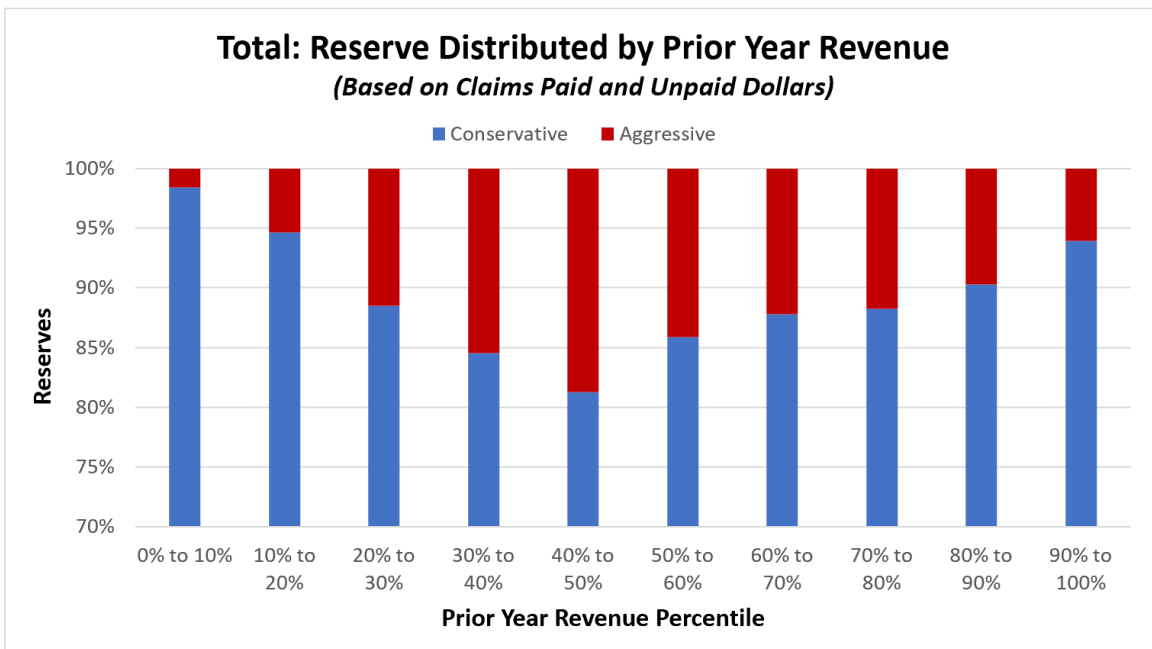
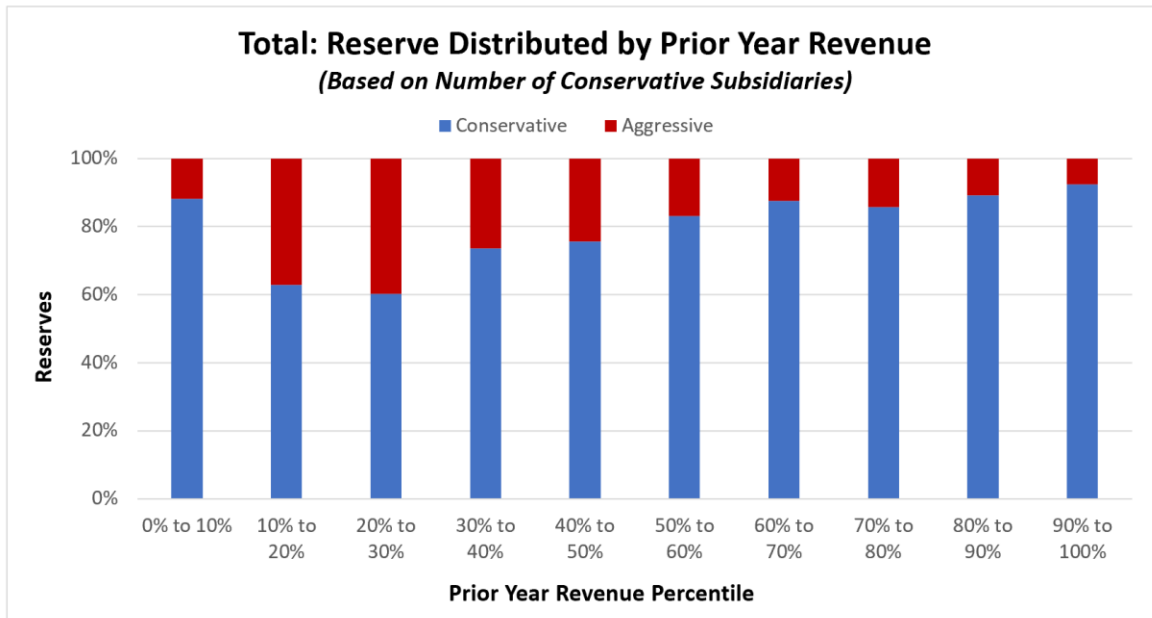


Figure 15: Percentage of Conservative Subsidiaries (Top) and Claims Paid and Unpaid Dollars (Bottom) by Revenue Size

The percentage of conservative *subsidiaries* and the percentage of conservative *dollars* was very similar for subsidiaries in the higher revenue percentiles. However, within the 10<sup>th</sup> to 40<sup>th</sup> revenue percentiles, the percentage of aggressive *subsidiaries* is much higher than the percentage of aggressive *dollars*. Therefore, a lot of the aggressive estimates in those percentiles were from smaller reserves.

### 4.3.3 Risk Based Capital

In our revenue analysis, we found that subsidiaries that severely struggled the year before tended to reserve aggressively. We saw a similar trend in our RBC analysis. **Subsidiaries that had RBC percentages below 200%, meaning they were not holding enough capital, were significantly more likely to reserve aggressively** (Table 11). We also identified a similar trend within each line of business (Table 12).

Table 11: RBC Percentage and Conservativeness 2016 to 2019

RBC %	Percent of Subsidiaries that Reserved Conservatively	Number of Subsidiaries
<b>Less Than 200%</b>	64%	59
<b>Greater than 200%</b>	84%	2775

Table 12: RBC Percentage and Conservativeness 2016 to 2019 by Line of Business

Line of Business and RBC Percentage	Percent of Subsidiaries that Reserved Conservatively	Number of Subsidiaries
<b>Medical &lt; 200%</b>	62%	26
<b>Medical &gt; 200%</b>	82%	1524
<b>Medicare &lt; 200%</b>	69%	39
<b>Medicare &gt; 200%</b>	81%	1264
<b>Medicaid &lt; 200%</b>	73%	26
<b>Medicaid &gt; 200%</b>	83%	751

In general, the more a company struggled to hold the appropriate amount of capital, the more likely they were to reserve aggressively. There was even a difference between subsidiaries

that were comfortably out of the range of regulatory scrutiny and subsidiaries that were closer, but still outside the range of regulatory scrutiny (Table 13).

Table 13: Total RBC Percentage and Conservativeness by RBC Regulation Grouping 2016 to 2019

RBC %	Percent of Subsidiaries that Reserved Conservatively	Number of Subsidiaries
0-70%	57%	7
70-100%	60%	5
100-150%	65%	17
150-200%	67%	30
200-400%	81%	778
400%+	85%	1997

The likelihood of a subsidiary being conservative increased each RBC regulation grouping. We also investigated the correlation between subsidiaries RBC ratios and reserve accuracy percentages (Figure 16).

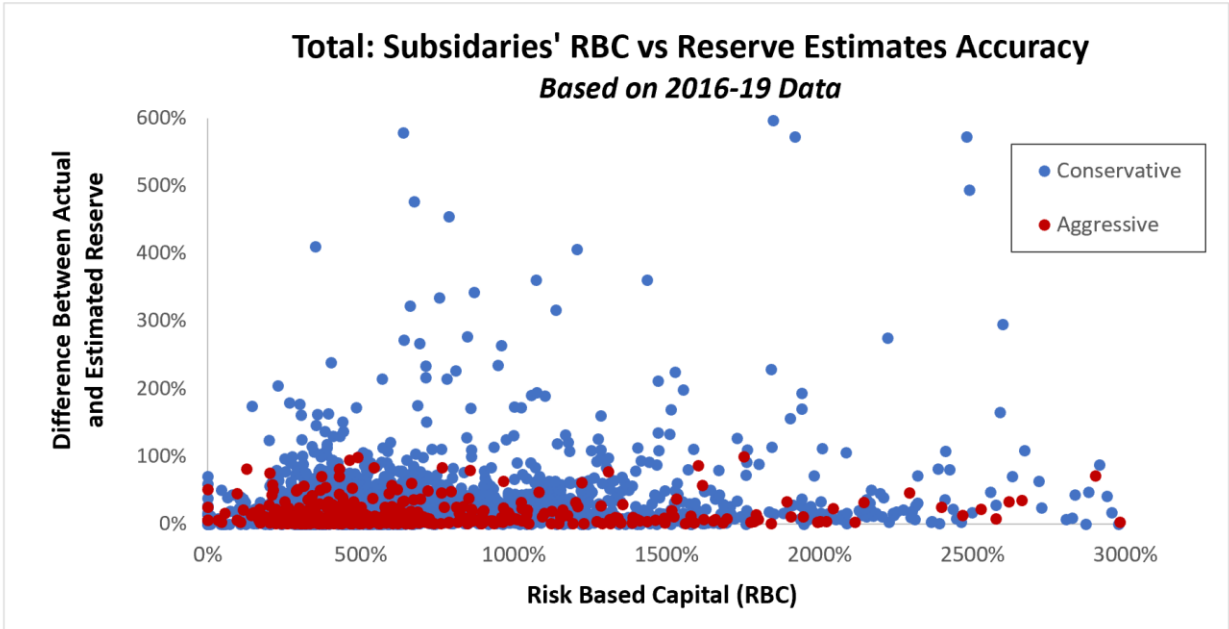


Figure 16: Total Comparison Between RBC ratio and Reserve Accuracy percentages

In general, reserve accuracy percentages were smaller in subsidiaries with higher RBC ratios, but there were a lot of outliers, especially with subsidiaries with RBC ratios above 400%. Perhaps some of these outliers are from smaller subsidiaries that do not need to hold a ton of

capital to have a high RBC%, but have smaller claims amounts to estimate. Additionally, while companies that struggled to hold enough capital were more likely to be aggressive, RBC % had little correlation with the magnitude of aggressiveness. **Aggressive reserves were more likely to be moderately and extremely aggressive when the RBC % was higher.** One explanation could be that regulators are potentially more critical of aggressive reserving estimates when the subsidiary is struggling to hold enough capital, and an extremely aggressive estimate would increase the likelihood of regulators taking over the company.

4.3.4 Private versus Public Companies

About one third of the subsidiaries from 2016 to 2019 were public subsidiaries two thirds were private. Public companies generally had larger reserve sizes.

Table 14: Overview of Public and Private Subsidiaries

Type of Company	Number of Subsidiaries	Total Claims Paid and Unpaid 2016 to 2019
Public	317	\$90,181,047.90
Private	557	\$100,475,863.41

As we suspected when we formed our initial distributions, public and private companies had different conservative reserving habits. **Despite the larger reserve sizes, public companies in general were less accurate.** 26% of public versus 36% of private reserved within a 10% MoE (Figures 17 and 18).

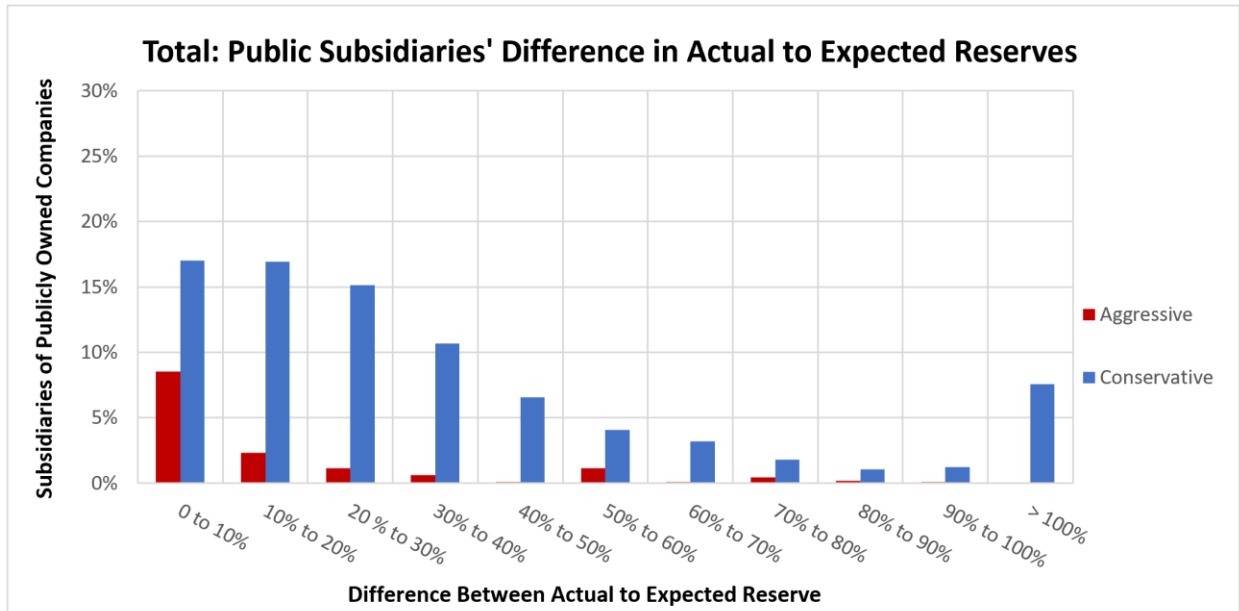


Figure 17: Distribution of Total Public Subsidiaries by Accuracy Percentage 2016 to 2019

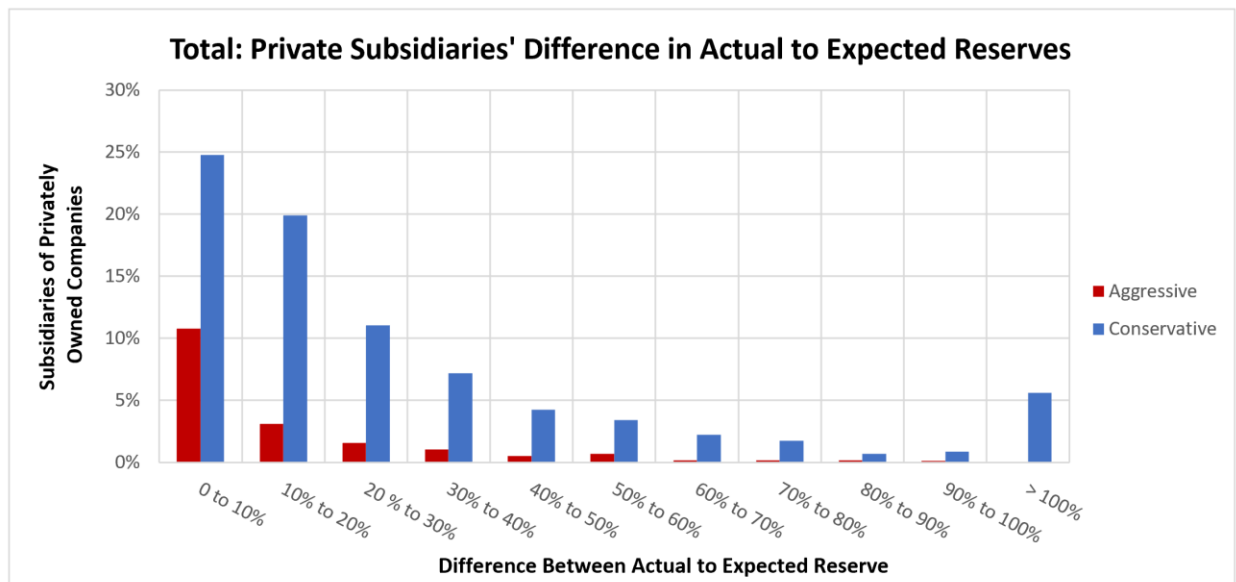


Figure 18: Distribution of Total Private Subsidiaries by Accuracy Percentage 2016 to 2019

Private companies were most likely to be 0 to 20% too conservative. Additionally, the number of subsidiaries in each grouping decreased with each additional 10% of reserve estimate inaccuracy. There were still outliers over 100% too conservative reserving but to a much lesser extent than with public subsidiaries. Private subsidiaries were 25% less likely than public subsidiaries to reserve more than 100% too conservatively. **Private subsidiaries also had a**

**slightly greater likelihood of reserving aggressively.** 18% of private subsidiaries reserved aggressively, compared to 14% of public subsidiaries. Conversely, there was a relatively even spread of public subsidiaries reserving too conservatively from 0 to 30%. Public subsidiaries' distribution from 40% to 100% inaccuracy was largely similar to the same range in the private distribution. Additionally, public subsidiaries were about twice as likely to reserve over \$30 million too conservatively than private. Thus, publicly owned subsidiaries had more outliers by both percent and dollar inaccuracy (Figures 19 and 20).

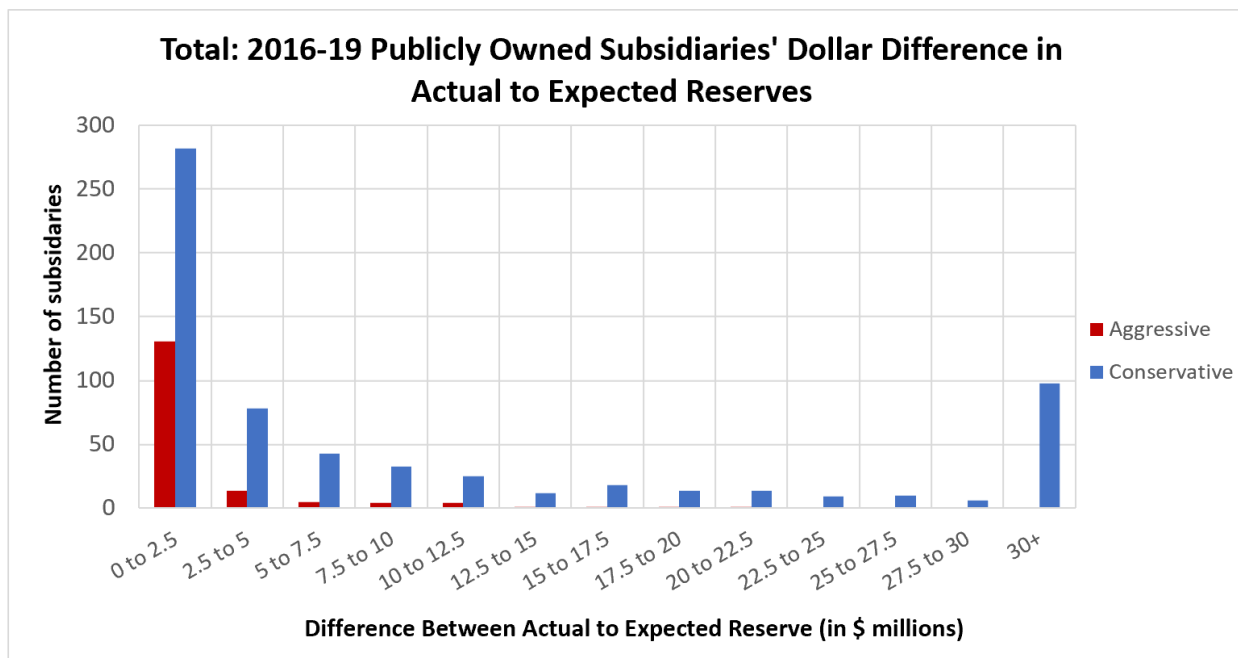


Figure 19: Distribution of Total Public Subsidiaries by Dollar Accuracy 2016 to 2019

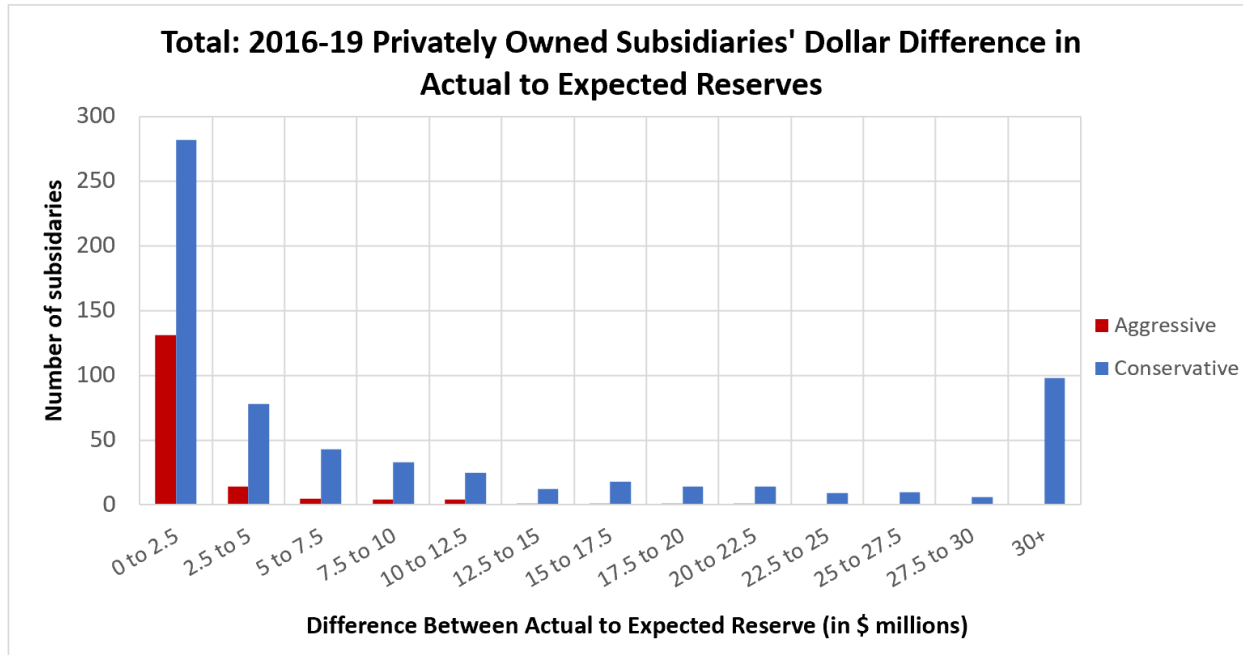


Figure 20: Distribution of Total Private Subsidiaries by Dollar Accuracy 2016 to 2019

**Private subsidiaries were more accurate in dollar amounts by almost every measure.**

Public subsidiaries were also slightly more likely to have a reserve estimate in any bucket between \$10 million and \$30 million. Private subsidiaries, on the other hand, were 22% more likely than public subsidiaries to reserve within a \$2.5 million MoE. There was still a notable difference in the accuracy of public subsidiaries versus the accuracy of private subsidiaries in the weighted distributions (Figures 21 and 22).

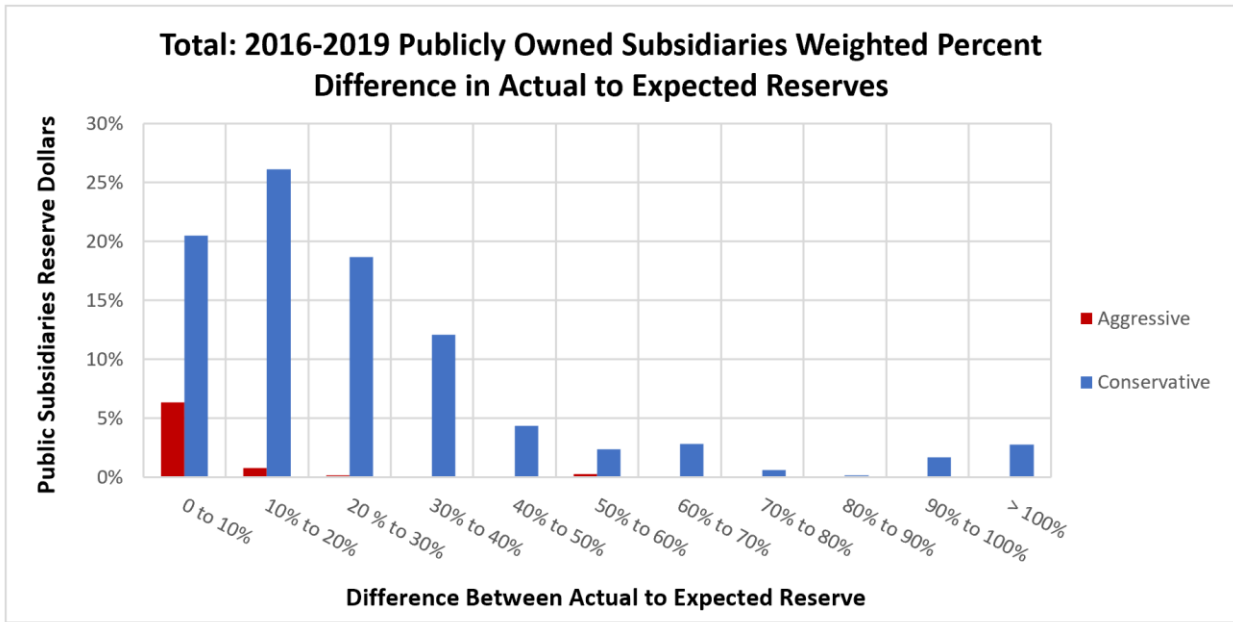


Figure 21: Weighted Distribution of Total Public Subsidiaries by Percent Inaccuracy 2016 to 2019

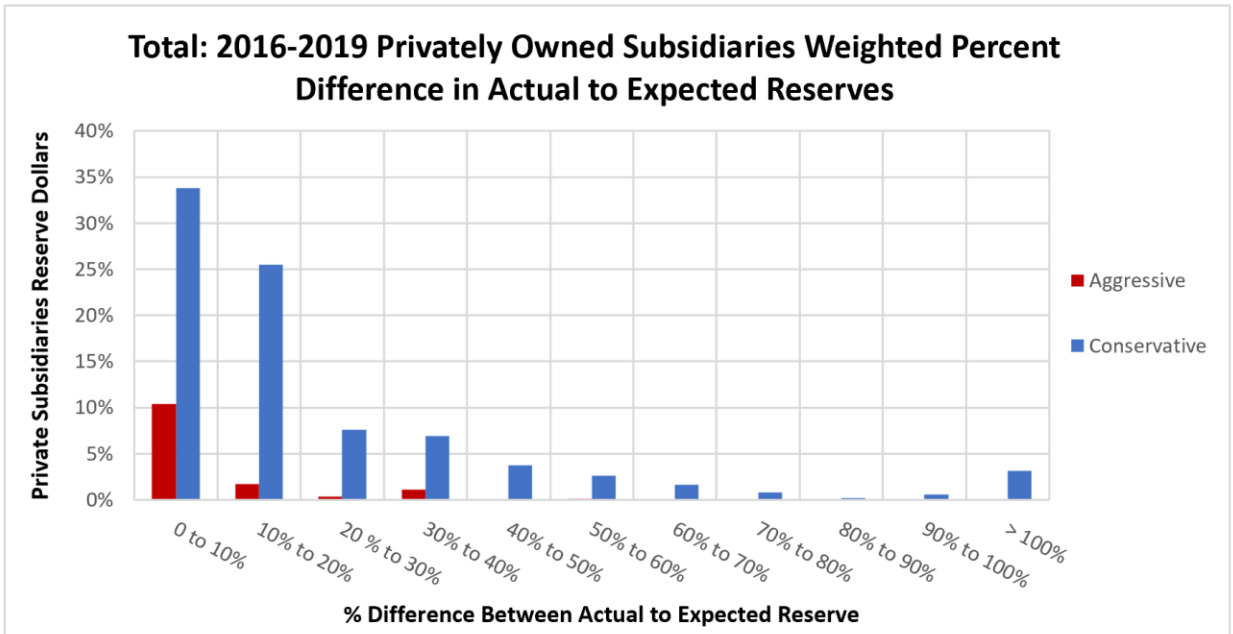


Figure 22: Weighted Distribution of Total Private Subsidiaries by Percent Inaccuracy 2016 to 2019

In the weighted distribution, public and private companies' reserves were almost equally likely to be extremely conservative. **Therefore, majority of the weighted accuracy differences lies in the 0 to 40% too conservative range of the data.** The mode of the public distribution, with over a quarter of the total claim dollars, was in the 10 to 20% too conservative grouping.



Reserves of public companies were almost twice as likely to reside in the 20 to 40% too conservative range as reserves of private companies. The mode of the private distribution however, with over a third of the total claim dollars, was in the 0 to 10% too conservative grouping. 45% of private *subsidiaries* were 0 to 20% too conservative versus 59%, of private *dollars*. This difference highlights that private subsidiaries with larger reserves are more accurate.

## 5.0 Prediction Model

We built a model to forecast how subsidiaries will reserve in the future. The model utilizes past reserving trends and various attributes, like RBC ratio, that were correlated with reserving patterns. Hence, it was akin to a benchmark for the health insurance reserves. The model produced an estimated reserve grouping, accuracy percentage and range for each subsidiary.

### 5.1 How the Prediction Model Works

#### 5.1.1 Attributes Included

We utilized 2016 to 2018 data as inputs to predict 2019 reserve estimates, and we compared our model's estimates with the actual 2019 values to evaluate the model's performance. Our model includes a drop-down list of company codes so that the user can view the prediction of any subsidiary. We incorporated the following data: reserve size, RBC ratio, company type (private or public), claims paid and unpaid size, and 2016, 2017, and 2018 reserve accuracy percentages. Our model uses the same groupings we used in our analysis with one exception. We made a significant change with the accuracy and conservativeness groupings. Instead of splitting aggressive reserves into 3 groupings, we split them into 2: we defined aggressive reserves within 10% accuracy as "slightly aggressive" and any other aggressive reserve as "extremely aggressive". The model calculates the subsidiary's groupings for each category, as described in Table 15, using the inputs.

Table 15: Prediction Model Categories and How to Calculate the Groupings

Category	Data Range	How value is calculated
Number of times subsidiary switched accuracy from 2016 to 2018	0, 1, 2	Counts how many times subsidiary switches from within a 15% margin of error to outside a 15% margin of error or vice versa from 2016-2018
Number of times subsidiary switched conservativeness from 2016 to 2018	0, 1, 2	Counts how many times subsidiary switches from conservative to aggressive or vice versa from 2016-2018
2018 Accuracy and conservativeness grouping	-2, -1, 1, 2, 3	Assigns 2018 groupings based on criterion explained in the paragraph above
Reserve size bracket	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11	Assigns groupings based on which reserve size percentile the subsidiary falls under (1 is the smallest, 11 is the largest)
Standard deviation ratio	A positive number	Empirical standard deviation of subsidiary's accuracy percentage from 2016 to 2018 / standard deviation for its 2018 accuracy and conservativeness grouping
Standard deviation group	1, 2, 3, 4, 5, 6, 7, 8	Assigns groupings based on standard deviation ratio used in analysis (1 is the smallest, 8 is the largest)
Extremely conservative group	1, 2, 3	Identifies if the reserve has remained extremely conservative the past 3 years, the past 2 years, or only the latest year.
Extremely Aggressive Group	1,0	Identifies if 2018 reserve estimate was more than 50% too aggressive (1) or not (0)

### 5.1.2 Process of Predicting Reserve Accuracy Grouping

An example of this process is provided in Appendix R. We predicted the grouping based on the most likely grouping in a transition matrix we customized for each subsidiary. We started with the transition matrix calculated by number of subsidiaries (refer to Section 3.4) and used only the row associated with the subsidiary's 2018 grouping (Table 16).

Table 16: Sample of Grouping Probability Distribution

Reserve Inaccuracy Grouping	-2 (Extremely Aggressive)	-1 (Slightly Aggressive)	1 (Slightly Conservative)	2 (Moderately Conservative)	3 (Extremely Conservative)
Subsidiary's 2018 Grouping	X <sub>1</sub> %	X <sub>2</sub> %	X <sub>3</sub> %	X <sub>4</sub> %	X <sub>5</sub> %

Using the categories in Table 15, we adjusted the original transition matrix's probabilities based on the subsidiaries past reserve trends and attributes. Our nine scale factors were: switchers conservativeness, switchers accuracy, RBC ratio, reserve size conservativeness, reserve size accuracy, variance accuracy and conservativeness, extremely conservative three-year trend, public versus private conservativeness, and public versus private accuracy. We included these attributes using the following method:

- 1. We decide what factors to include in the prediction:** For each factor, we included an indicator that determined whether the model would incorporate the factor into its calculations. Some of these factors, like our extremely conservative three-year trend and the extremely aggressive adjustment, only applied to certain subsidiaries, so the inclusion factor was formulaic. Others we could manually decide based on how the model performed.
- 2. We calculated scale factors using the following equation:**

*Equation 4: Model Scale Factor Equation*

---

$$= (\text{Likelihood given subsidiary's grouping}) / (\text{Total likelihood})$$

---

For example, in our reserve size factors calculations, if a subsidiary was in group 2, to calculate the conservative scale factor, we would divide the probability of a subsidiary with a group 2 reserve size reserving conservatively by the probability of *any* subsidiary reserving conservatively.

- 3. We multiplied the appropriate groupings by the scale factors:** We applied conservative and aggressive scale factors to conservative and aggressive groupings, accuracy factors to the -1 and 1 grouping, and inaccuracy factors to 2, -2, and 3

groupings. Additionally, we calculated certain factors based on probabilities of a subsidiary *switching* conservativeness or accuracy. If a subsidiary was conservative in 2018, we applied conservativeness switch factors to aggressive groupings and if a subsidiary was aggressive, we applied the switch factor to conservative groupings. Likewise, if a subsidiary was “accurate” (within a 15% margin of error), we applied accuracy switch factors to groupings 2, -2, and 3. If a subsidiary was not accurate, we applied the switch factor to the -1 and 1.

- 4. After applying the last model factor, we rescaled the probabilities to add up to 100%:** We calculated the sum of the percentages in the matrix. Next, we divided each grouping’s probability with the total sum of percentages.

These four steps produced Table 16 with probabilities customized to a subsidiary’s past reserving habits and attributes. This was the intermediate output of the model, which was the one of the two inputs for the three final outputs. The other input was the subsidiary’s prior year grouping; for our project the prior year was 2018.

### 5.1.3 Calculating Point Estimates and Ranges

First, we calculated point percentages to represent each of the five groupings. The point percentages functioned as weights for each grouping in the point estimate calculation. The five percentage points we used changed depending on the grouping with the highest probability in the intermediate output table. To calculate the percentage points used for each intermediate estimated grouping we used the following methodology:

1. We chose arbitrary cutoffs for the maximum percent inaccuracies (-125% and 125%)
2. We calculated the range of each 2019 grouping using Equation 5.

*Equation 5: 2019 Grouping Percentage Range*

---

$$= (\text{Maximum percentage in grouping}) - (\text{Minimum percentage in grouping})$$

---

3. We calculated the range between each grouping so that the percentage points would be evenly spaced within the range using the following equation:

*Equation 6: Spacing Between Percentage Points*

---

$$= (\text{Calculated Range in Step 1}) / 5$$

---

4. We assigned the minimum of the range to the -2 grouping and added the value from Step 2 to each percentage point grouping on the left to finish with the above percentage points.

We used this methodology to account for the fact that more conservative 2018 estimates tended to be more conservative within each range and more aggressive 2018 estimates tended to be more aggressive within each range.

We multiplied the probabilities for each grouping found from the intermediate output with the percentages points then summed the products (Equation 7).

*Equation 7: Point Estimate Calculated Using the Five Groupings*

$$= \sum_{1}^{5} (\text{Predicted Probability of Grouping } X) * (\text{Built in Percentage for Grouping } X)$$

Additionally, we found that a lot of our aggressive subsidiary estimates were too aggressive, so we divided our aggressive estimates by an arbitrary factor, 3.5, to make them less extreme.

We have included a sample calculation below (Equation 8). Note that arbitrary subsidiary XYZ’s 2018 grouping is 2, so the calculation includes the percentages from the group 2 column in Table 17.

Table 17: Data for Point Calculations

		2018 Grouping				
2019 Grouping		-2	-1	1	2	3
-2		-125%	-102%	-79%	-56%	-33%
-1		-10%	-8%	-6%	-4%	-2%
1		0%	3%	6%	9%	12%
2		15%	22%	29%	36%	43%
3		50%	65%	80%	95%	110%
Subsidiary XYZ Final Probabilities		-2	-1	1	2	3
2		5%	4%	19%	46%	26%

Equation 8: Point Percentage Calculation Example

---


$$\begin{aligned}
 &= (5\% * (-56\%)) + (4\% * (-4\%)) + (19\% * 9\%) + (46\% * 36\%) + (26\% * 95\%) \\
 &= 41\% \text{ (This number is conservative, so we do not divide by 3.5).}
 \end{aligned}$$


---

The estimate grouping was determined based on the point estimate. The model uses the same logic as it does to assign the subsidiary’s prior year grouping. We calculated the point range by adding and subtracting the median percent error from the model’s 2019 check associated with the subsidiary’s predicted grouping (Table 18).

Table 18: Median Error of 2019 Groupings’ Point Estimates and Defined Ranges for Each Grouping

Grouping	-2	-1	1	2	3
Median Error for 2019 Point Estimate	26%	9%	8%	17%	21%
Lower Bound of Grouping	-99%	-10%	0%	15%	50%
Upper Bound of Grouping	-10%	0%	15%	50%	200%
<i>Note: 200% was arbitrarily selected as the upper bound for the extremely conservative grouping, which had several outliers.</i>					

In the case of the lower or upper bound, or both bounds (Table 18), of the point range was much larger than the respective bound of the estimated grouping. Therefore, we added a condition for the point range calculations: if the predicted lower bound was over 10% less than the lower bound of the estimated grouping then the predicted lower bound the model uses the estimated grouping's lower bound instead. The same logic was applied for the upper bound except the condition was over 10% greater than the upper bound of the estimated grouping.

## 5.2 Validating and Improving the Model

In order to gauge how the model performed, we implemented several checks for each subsidiary:

1. Does the model accurately predict the subsidiary's 2019 accuracy and conservativeness grouping?
2. If the model does not predict the grouping, is the estimated within one grouping? For example, if a subsidiary's actual 2019 grouping was 2, did the model predict 1 or 3?
3. Does the model correctly predict whether the reserve is conservative or aggressive?
4. Is the predicted percent within a 5% margin of error?
5. What is the difference between the model estimate and the 2019 actual data? (We calculated this check by subtracting the actual 2019 data from the model estimate).

Next, we implemented a VBA macro to print the Company Code, 2018 and 2019 actual reserve groupings and the five checks' results for each subsidiary. After we ran the macro, we summarized the checks into a table. The table aggregated the subsidiaries by 2018 grouping and 2019 grouping so we could pinpoint weaknesses. The first five items were the percentage of subsidiaries that pass the associated check. The median error and mean error were the mean and median of the percent error data in check 5.



### 5.3 Strengths and Weaknesses of the Model

The model generated three predictions: reserve inaccuracy grouping, percentage, and range. We only ran the checks on subsidiaries that had data from 2016 to 2019. We aggregated the results to examine the accuracy in predicting inaccuracy groupings and percentages; we did not check the predicted range since we calculated it using grouping and percentage. Table 19 shows the model’s accuracy in terms of the subsidiary’s 2018 grouping, which was the base of the predictions. The first three rows assessed the predicted grouping. The last two rows assessed the predicted accuracy percentage.

*Table 19: Model Accuracy in Terms of 2018 Grouping*

2018 Grouping	-2	-1	1	2	3
Number of Subsidiaries	36	61	219	243	107
Predicts Exact Grouping	19%	38%	35%	47%	49%
Accurate Within 1 Grouping	53%	89%	87%	88%	82%
Predicts Conservativeness/Aggressiveness	61%	67%	78%	89%	91%
Point Estimate Within 5% Margin of Error	6%	21%	29%	13%	5%
Point Estimate was too Conservative	61%	74%	62%	74%	65%

The model was most effective at estimating extremely conservative subsidiaries’ future grouping (49% accuracy). Thus, the extremely conservative three-year trend factor was useful in predicting 2018 extremely conservative reserves. Even though the majority of predictions were not the correct grouping, a significant percentage of our predictions was accurate within one grouping. Therefore, the model struggled mainly to distinguish between similar groupings, especially when the subsidiary’s 2018 grouping was aggressive or marginally inaccurate. In fact, the model oftentimes predicted too aggressively with 2018 slightly conservative subsidiaries. On the other hand, the model’s point estimates were most accurate with the two slightly inaccurate groupings. **The model was the most effective at determining a subsidiary's future conservativeness or aggressiveness when the subsidiary was slightly or moderately conservative the previous year** (Table 19).

Table 20: Model Accuracy in Terms of Actual 2019 Grouping

2019 Grouping	-2	-1	1	2	3
Number of Subsidiaries	45	69	222	224	106
Predicts Exact Grouping	9%	4%	27%	69%	49%
Accurate Within 1 Grouping	20%	45%	95%	98%	89%
Predicts Conservativeness/Aggressiveness	20%	4%	96%	98%	96%
Point Estimate Within 5% Margin of Error	2%	6%	23%	24%	5%
Point Estimate was too Conservative	100%	99%	89%	56%	15%

The model was most inaccurate predicting the correct grouping for 2019 aggressive subsidiaries. However, 65% of slightly aggressive subsidiaries were predicted to be within one grouping and 97% of the point estimates were too conservative. Thus, the model oftentimes had difficulties distinguishing which accurate reserves were aggressive and which were conservative. Additionally, the point estimates for the 2019 extremely aggressive subsidiaries were often far too conservative, illustrating our current lack of factors to distinguish extremely aggressive reserves. **In general, the model had a conservative bias.** It was best at predicting 2019 slight and moderately conservative subsidiaries within one grouping.

While the model did not produce extremely accurate point estimates and groupings, **it was especially effective in determining subsidiaries at risk of being too conservative.** The model was over 90% accurate in predicting that a subsidiary reserved conservatively in 2019 but could only estimate the accurate grouping for about half of those subsidiaries. The model's accurate 2019 predictions highlight subsidiaries that closely followed the industry standard for reserving in 2019. The 49% accuracy rate in predicting grouping 3 likely signifies that many subsidiaries were considerably more conservative than they needed to be given the industry's benchmarks. **Therefore, the model would be a good resource for subsidiaries that consistently reserve moderately and extremely conservatively because the actuaries could check if their reserving habits are an outlier in the industry.**

## 6.0 Limitations and Future Considerations

The passage of the Affordable Care Act in 2014 transformed the landscape of how health insurance operates in the United States, and therefore changed how companies reserve. Therefore, despite health insurers submitting annual statements for decades, we were limited in the amount of data we could analyze. We saw the lack of data materialize in a few ways. Firstly, because most subsidiaries reserve conservatively, we did not have a lot of data on the trends of aggressive reserves, especially when we divided aggressive reserve estimates into accuracy subgroupings. When we built our model, the lack of aggressive reserving data made it difficult to predict both how aggressive subsidiaries would behave and what 2018 subsidiaries would reserve aggressively in 2019. Additionally, we lacked data on subsidiaries with low RBC percentages because the majority of subsidiaries hold adequate amounts of capital. This especially impacted our ability to make RBC conclusions by line of business. Lastly, the smaller lines of business, Medicare, and Medicaid, had more outliers due to their smaller data set. We would most likely find a lot of new meaning in this analysis if we performed it in a decade, on 15 years of data, and expanded our analysis towards smaller lines of business, such as vision and dental.

We spent a lot of time deliberating the factors and methods we used in our model. The model was oftentimes accurate within one grouping, but the lack of data made it difficult to accurately predict the exact group. While we could adjust various factors in the model to try to achieve greater accuracy, we worried about biasing the model towards the 2019 data trends only for it to be less accurate in predicting future years. Additionally, many model adjustments that improved one area of the model had a negative impact in a different area. For example, our extremely conservative three-year factor helped to distinguish a lot of extremely conservative

trends, but it also gave the model a more conservative bias. With more data the model would have an easier time predicting subsidiaries that tend to reserve differently from the industry as a whole.

Also, we hypothesized that many companies have consistent underlying reserving philosophies that significantly color how they reserve, but we do not have a lot of analysis on why certain companies tend to have certain philosophies. One factor that was particularly affective in distinguishing company's reserving philosophies was whether they were public or private. When we performed public versus private subsidiary analysis, we discovered a lot of differences in how private and public subsidiaries reserve. Researchers could reperform our year-to-year and attribute analysis, separating private subsidiaries and public subsidiaries to learn more about reserving philosophies. Future research should also focus on identifying more factors which are correlated to the overarching reserving philosophies. It may be useful analyze data on a parent organizational level to determine what parent organizations have what reserving philosophies and why.

Another area of contention was how to define “extremely”, “moderately”, and “slightly” inaccurate. We had to design our groupings to ensure each grouping had enough data, as opposed to designing groupings solely by how the trends operated. For example, aggressive reserves over 50% inaccurate had different trends than those over 10% inaccurate, but we did not have enough data to feel comfortable with a third aggressive grouping in the model. Additionally, while our groupings provided a lot of useful insight, they oftentimes failed to detect large claims paid and unpaid amounts with large dollar inaccuracies. A lot of subsidiaries that were over \$30 million dollars too conservative in their estimates fell into the “moderately conservative” or even “slightly conservative” groupings when realistically, they should be considered “extremely

conservative”. Future analysis of the reserves could define these accuracy groupings differently for small and large claims paid and unpaid or perform separate analysis for small and large claims paid and unpaid.

Another consideration is our methodology in analyzing reserves with regard to revenue, net income, and return on equity. Our analysis focused on how subsidiaries compared to the industry. However, we did not find any meaningful trends between net income and reserve estimates or return on equity and reserve estimates. Perhaps they are genuinely unrelated. Perhaps the trend is not in how subsidiaries performed compared to the industry, but how they performed compared to themselves. Future researchers could analyze the reserve estimates of subsidiaries, based on how their return on equity or net income compared with their own return on equity or net income in the past.

Lastly, we only applied our prediction model to the total of all lines of business, but we could theoretically apply the same model to other lines of business. However, as mentioned previously, there is not as much data in the other lines of business, so the model would most likely be less accurate.

## 7.0 Appendices

### Appendix A: Opportunity Cost of Foregone Returns (or Interest) on Excess (Beyond Requirement) Sums in Reserves

This appendix estimates the amount of money the health insurance industry as a whole missed out on yearly due to their overly conservative reserving habits

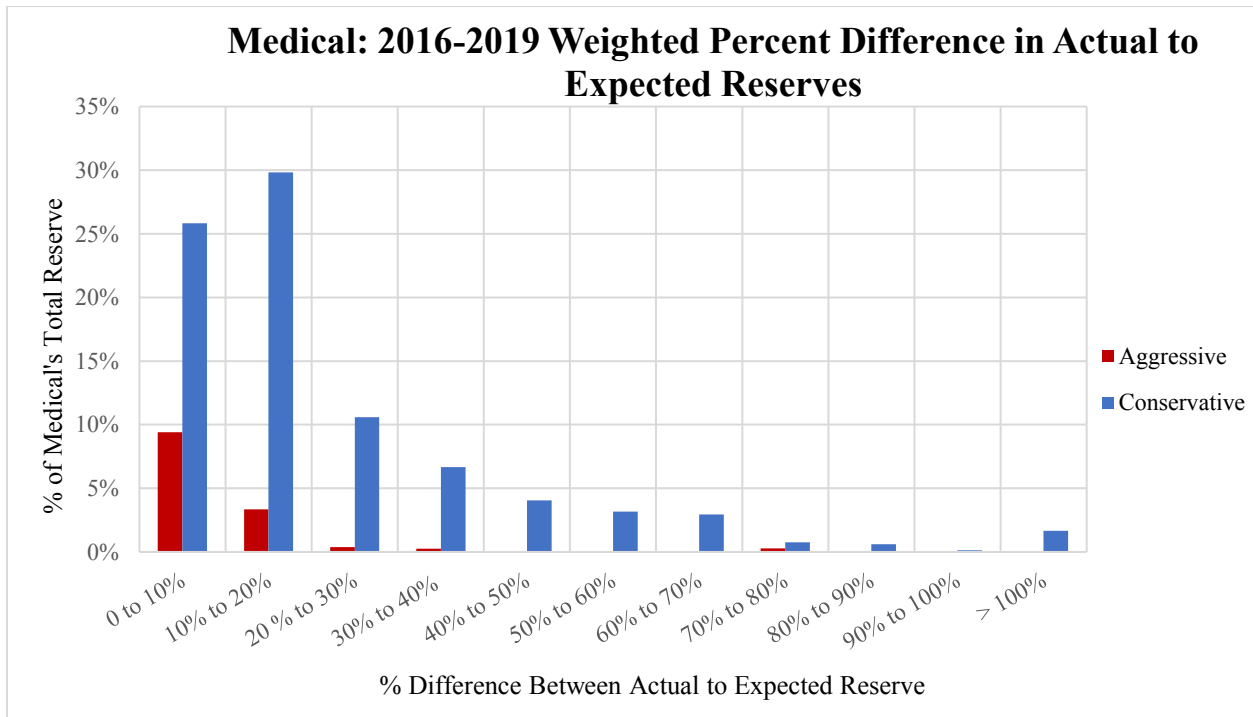
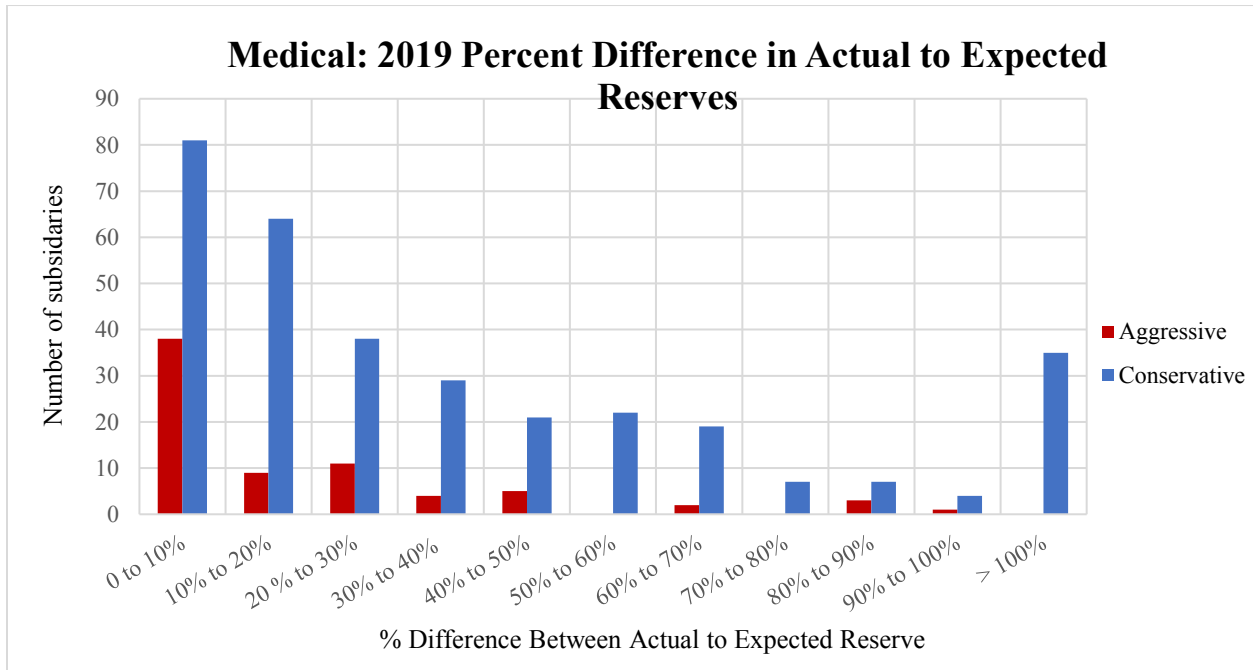
Year	Money Lost
<b>2016</b>	\$734 Million
<b>2017</b>	\$1.51 Billion
<b>2018</b>	\$2.27 Billion
<b>2019</b>	\$2.30 Billion
<b>Total</b>	6.61 Billion

Appendix B: Total Reserving Trends by Years

<b>Year</b>	<b>Total Claims Paid and Unpaid</b>	<b>Total Reserve Estimate</b>	<b>Percent Off</b>
<b>2016</b>	\$45.098 Billion	\$54.484 Billion	20.8%
<b>2017</b>	\$46.848 Billion	\$58.431 Billion	24.7%
<b>2018</b>	\$48.104 Billion	\$60.182 Billion	25.1%
<b>2019</b>	\$51.260 Billion	\$62.475 Billion	21.9%

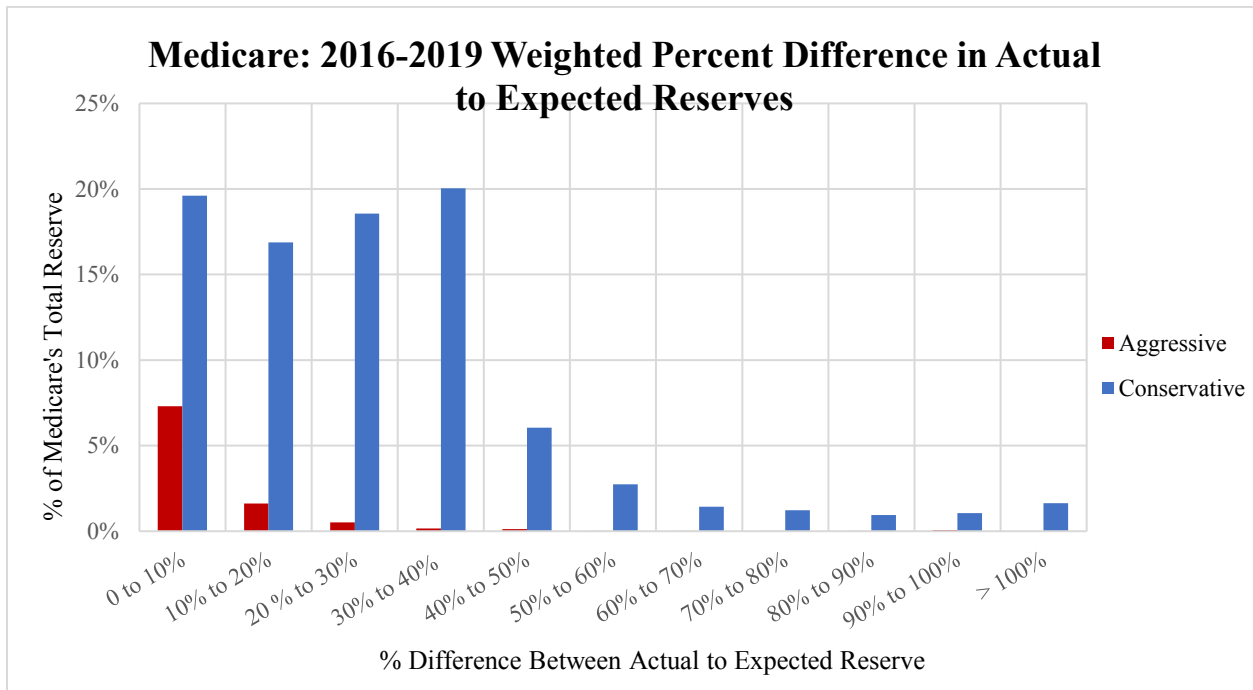
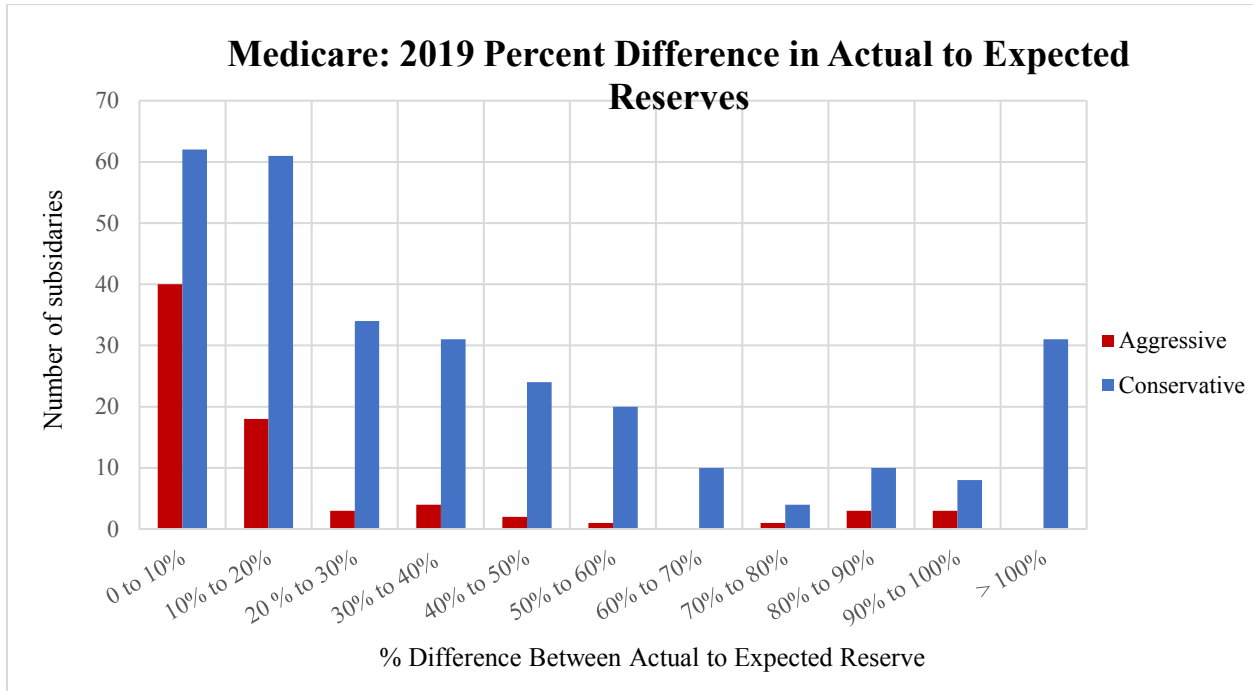
## Appendix C: Unweighted and Weighted Distributions by Percent

### Appendix C.1: Medical Unweighted and Weighted Distributions by Percent

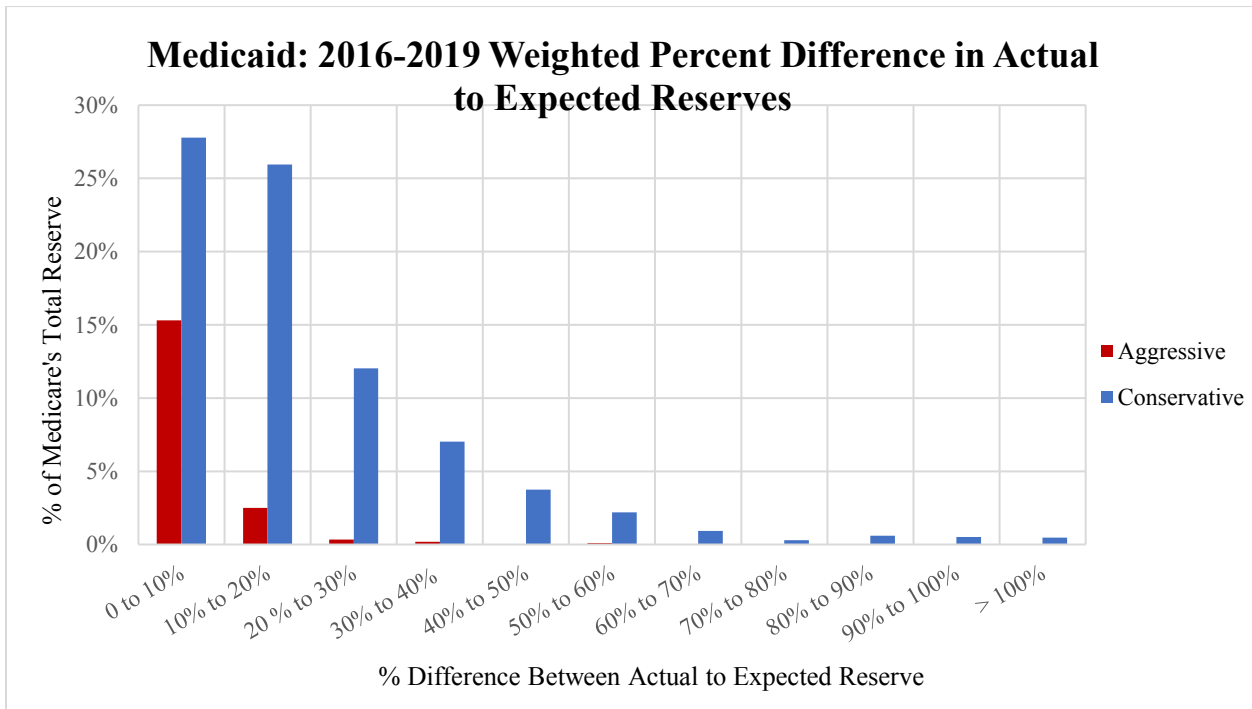
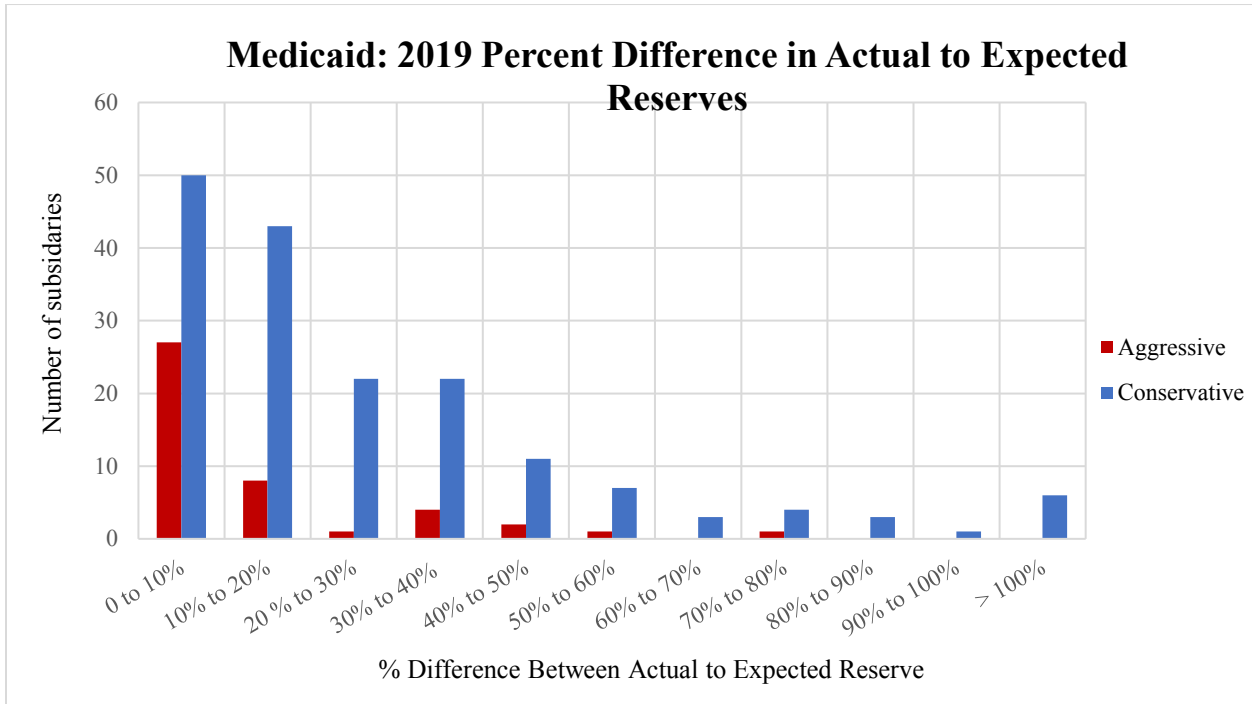




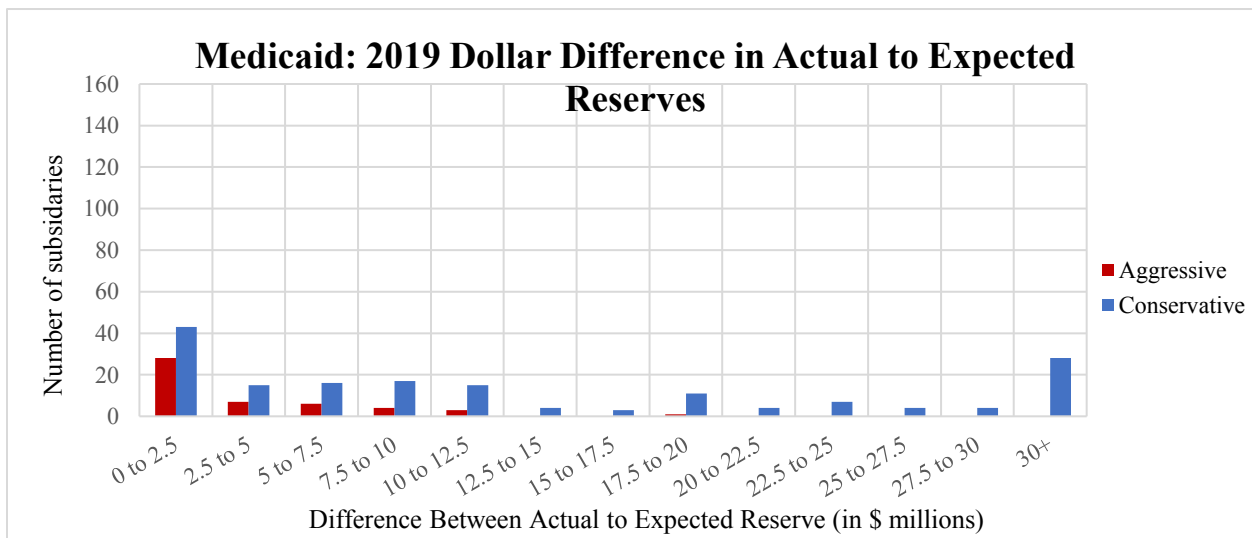
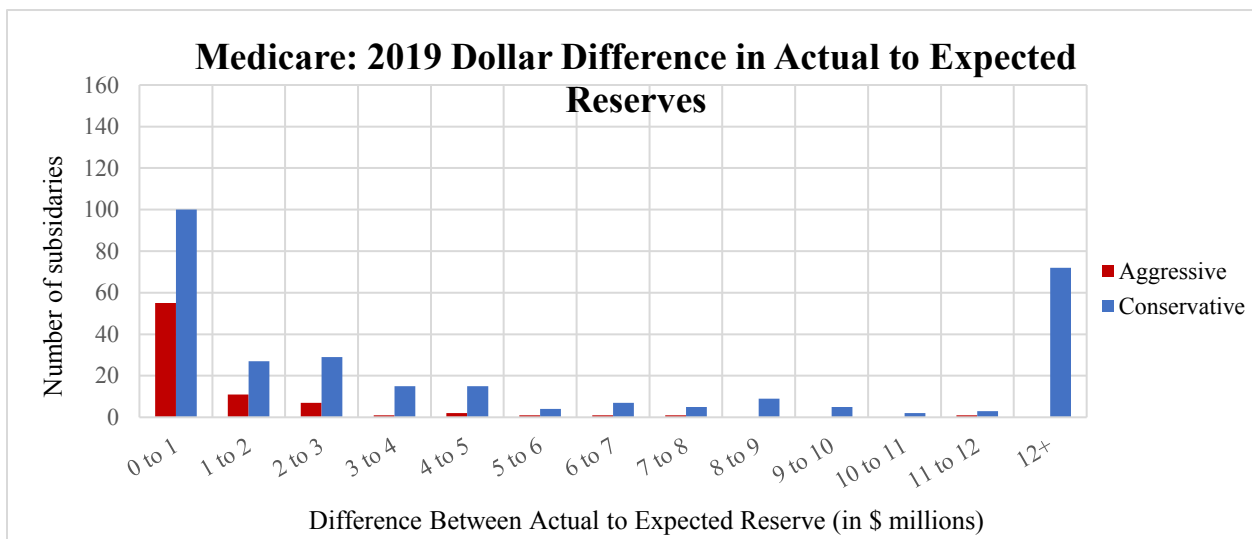
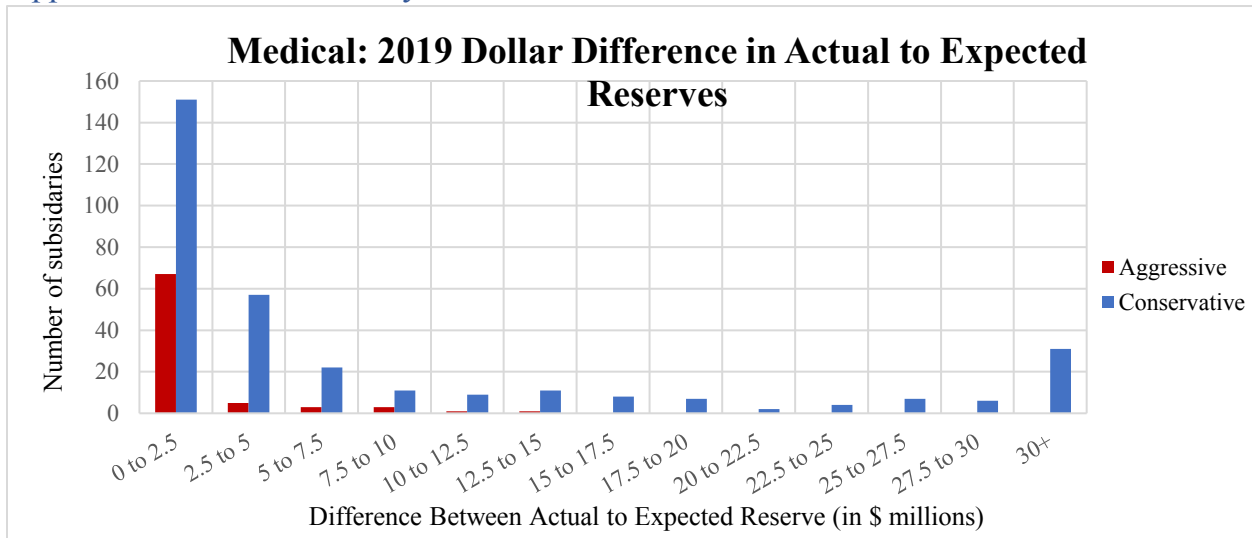
Appendix C.2: Medicare Unweighted and Weighted Distributions by Percent



Appendix C.3: Medicaid Unweighted and Weighted Distributions by Percent

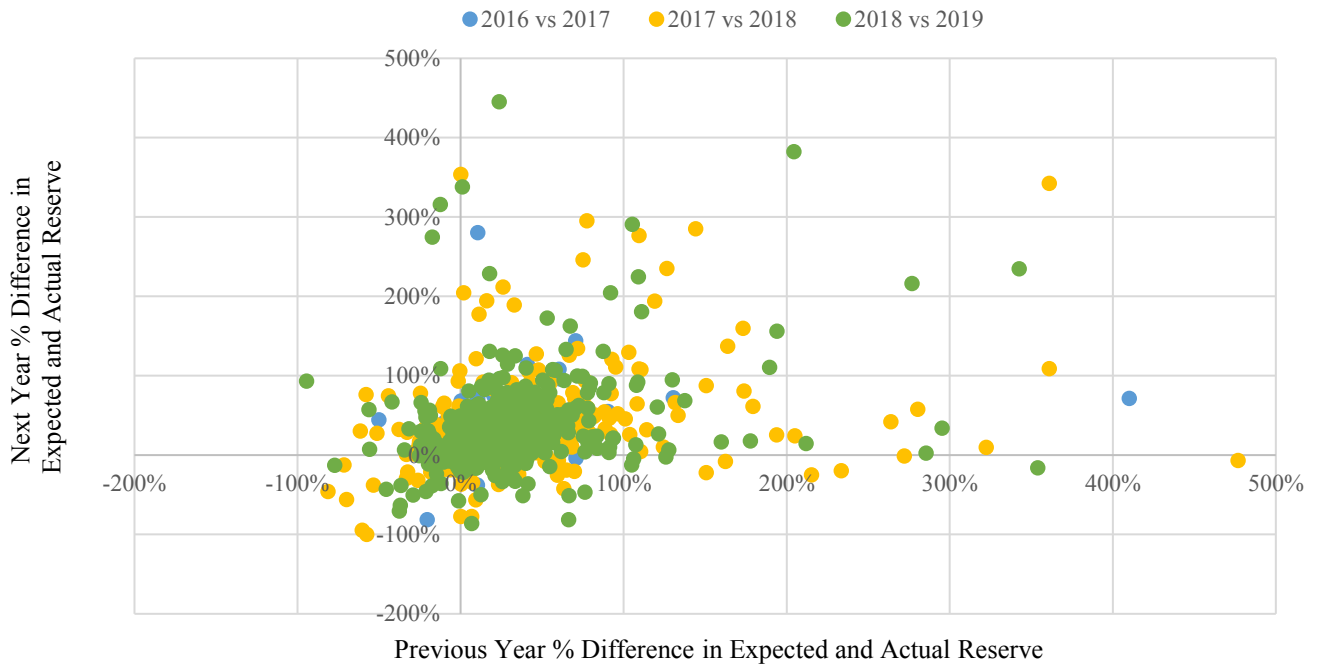


Appendix D: Distributions by Dollar

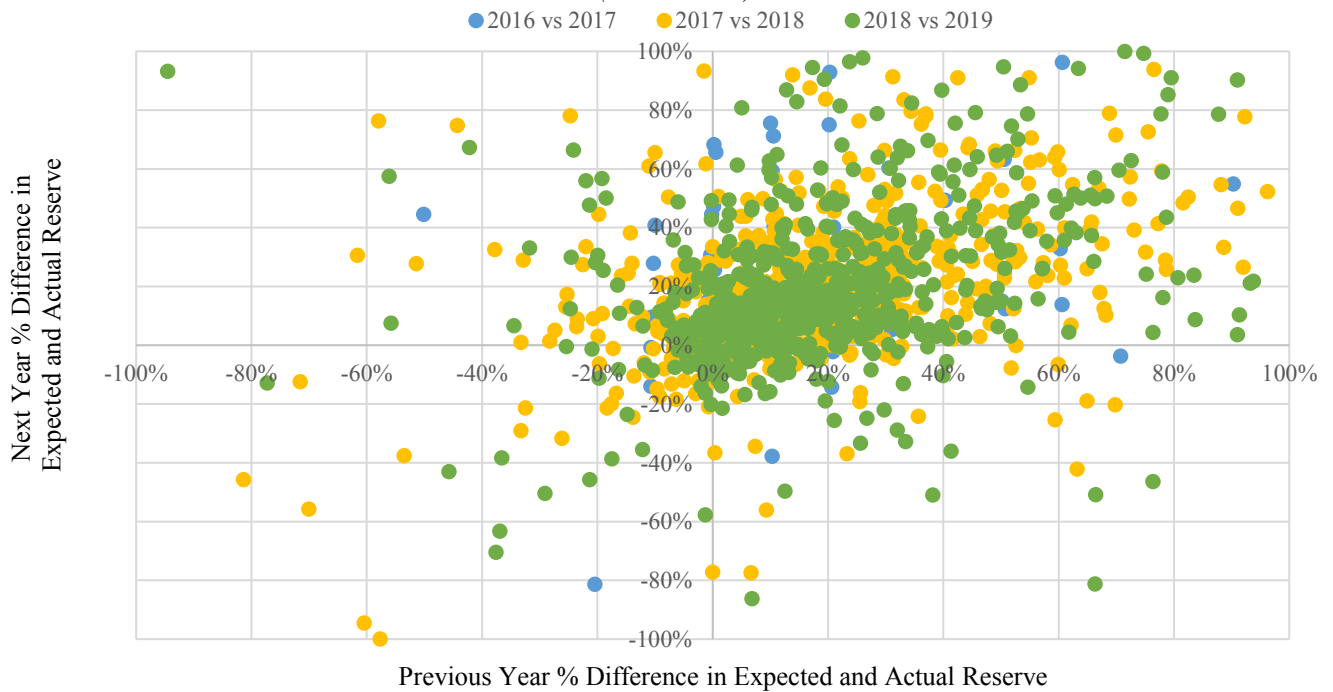


## Appendix E: Transition Scatterplots

### Total: Subsidiaries' Reserving Habits in the Prior Year vs the Next Year



### Total: Subsidiaries' Reserving Habits in the Prior Year vs the Next Year (Zoomed In)



## Appendix F: Transition Matrices by Count of Subsidiaries

Appendix F.1: Total Transition Matrix by Count of Subsidiaries

Groupings	-3	-2	-1	Total Aggressive	1	2	3	Total Conservative
-3	32%	9%	14%	<b>55%</b>	14%	14%	18%	<b>45%</b>
-2	7%	17%	10%	<b>34%</b>	22%	28%	17%	<b>66%</b>
-1	1%	6%	28%	<b>35%</b>	36%	24%	5%	<b>65%</b>
1	1%	2%	15%	<b>17%</b>	47%	28%	7%	<b>83%</b>
2	0%	3%	5%	<b>8%</b>	27%	49%	16%	<b>92%</b>
3	1%	3%	6%	<b>10%</b>	10%	30%	50%	<b>90%</b>

Appendix F.2: Medical Transition Matrix by Count of Subsidiaries

Groupings	-3	-2	-1	Total Aggressive	1	2	3	Total Conservative
-3	9%	0%	9%	<b>18%</b>	0%	18%	64%	<b>82%</b>
-2	6%	19%	7%	<b>31%</b>	26%	20%	22%	<b>69%</b>
-1	1%	4%	21%	<b>26%</b>	32%	35%	8%	<b>74%</b>
1	1%	3%	16%	<b>20%</b>	43%	29%	8%	<b>80%</b>
2	1%	5%	7%	<b>13%</b>	24%	39%	24%	<b>87%</b>
3	3%	5%	6%	<b>14%</b>	10%	30%	46%	<b>86%</b>

Appendix F.3: Medicare Transition Matrix by Count of Subsidiaries

Groupings	-3	-2	-1	Total Aggressive	1	2	3	Total Conservative
-3	54%	8%	0%	<b>62%</b>	15%	8%	15%	<b>38%</b>
-2	2%	16%	22%	<b>40%</b>	14%	32%	14%	<b>60%</b>
-1	2%	7%	26%	<b>35%</b>	29%	27%	9%	<b>65%</b>
1	2%	3%	17%	<b>22%</b>	36%	31%	11%	<b>78%</b>
2	1%	3%	6%	<b>9%</b>	20%	51%	20%	<b>91%</b>
3	2%	5%	8%	<b>15%</b>	14%	27%	45%	<b>85%</b>

Appendix F.4: Medicaid Transition Matrix by Count of Subsidiaries

Groupings	-3	-2	-1	Total Aggressive	1	2	3	Total Conservative
-3	14%	14%	21%	<b>50%</b>	14%	14%	21%	<b>50%</b>
-2	5%	10%	19%	<b>33%</b>	5%	33%	29%	<b>67%</b>
-1	1%	6%	10%	<b>17%</b>	41%	32%	10%	<b>83%</b>
1	1%	2%	19%	<b>21%</b>	39%	33%	7%	<b>79%</b>
2	0%	2%	9%	<b>11%</b>	29%	47%	12%	<b>89%</b>
3	6%	7%	8%	<b>21%</b>	13%	35%	32%	<b>79%</b>

## Appendix G: Transition Matrices by Sum of Reserve Dollars

Appendix G.1: Total Transition Matrix by Sum of Reserve Dollars

Groupings	-3	-2	-1	Total Aggressive	1	2	3	Total Conservative
-3	3%	1%	0%	4%	0%	6%	89%	96%
-2	1%	2%	4%	8%	63%	19%	11%	92%
-1	0%	2%	21%	22%	59%	18%	0%	78%
1	0%	1%	11%	13%	58%	27%	2%	87%
2	0%	0%	3%	3%	23%	63%	10%	97%
3	0%	0%	1%	2%	1%	31%	65%	98%

Appendix G.2: Medical Transition Matrix by Sum of Reserve Dollars

Groupings	-3	-2	-1	Total Aggressive	1	2	3	Total Conservative
-3	1%	0%	1%	2%	0%	6%	92%	98%
-2	3%	13%	7%	22%	41%	24%	13%	78%
-1	0%	0%	22%	23%	43%	33%	1%	77%
1	1%	0%	11%	12%	60%	22%	5%	88%
2	0%	2%	7%	9%	26%	50%	15%	91%
3	0%	1%	2%	3%	5%	35%	57%	97%

Appendix G.3: Medicare Transition Matrix by Sum of Reserve Dollars

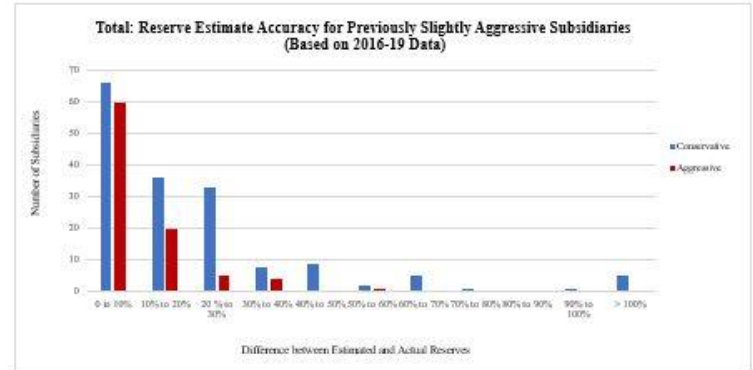
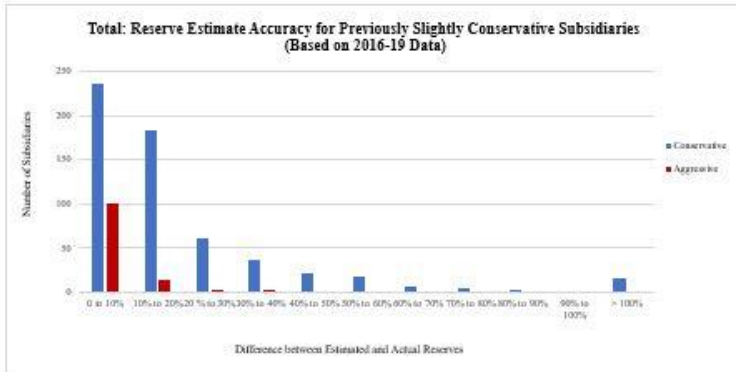
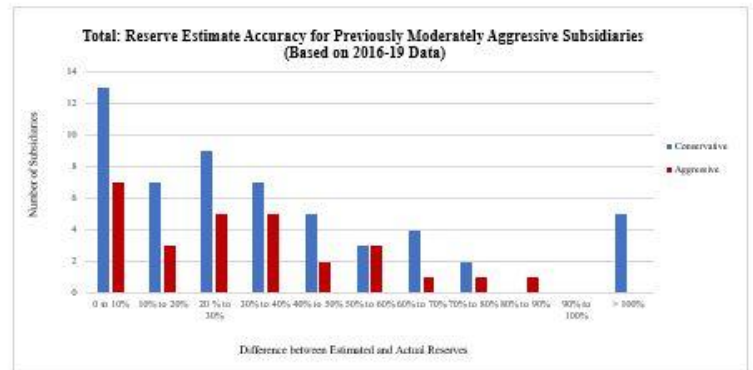
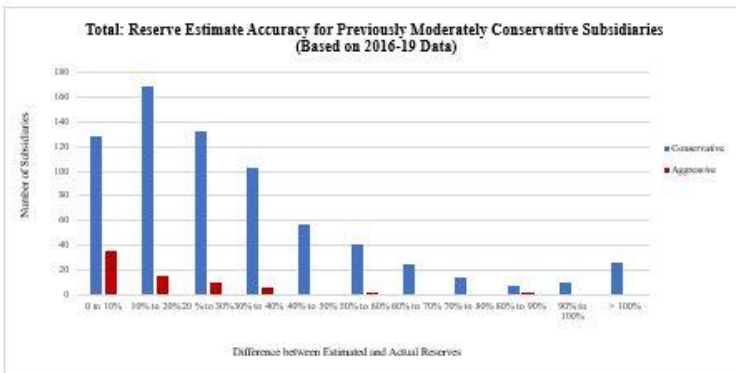
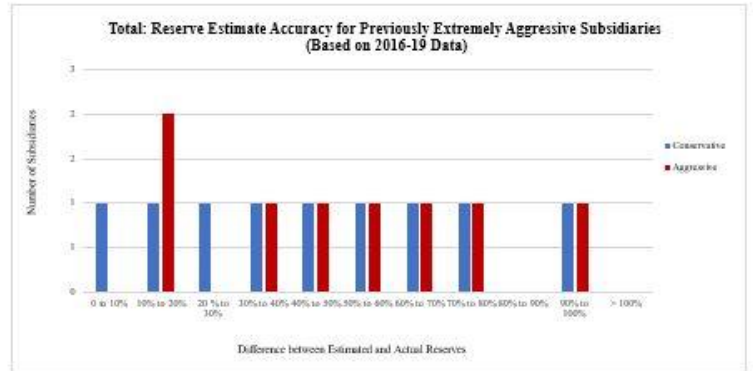
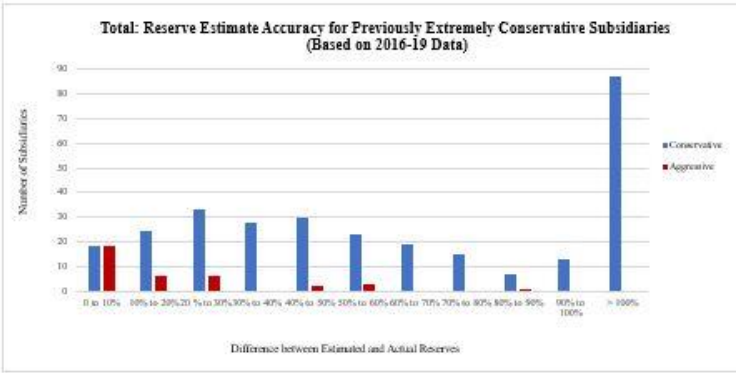
Groupings	-3	-2	-1	Total Aggressive	1	2	3	Total Conservative
-3	17%	4%	0%	21%	1%	0%	78%	79%
-2	0%	24%	26%	50%	16%	22%	11%	50%
-1	0%	4%	25%	29%	37%	31%	3%	71%
1	0%	1%	9%	10%	40%	42%	8%	90%
2	0%	1%	2%	3%	13%	73%	11%	97%
3	0%	2%	2%	4%	4%	35%	57%	96%

Appendix G.4: Medicaid Transition Matrix by Sum of Reserve Dollars

Groupings	-3	-2	-1	Total Aggressive	1	2	3	Total Conservative
-3	1%	1%	83%	86%	1%	12%	1%	14%
-2	1%	2%	16%	19%	21%	42%	18%	81%
-1	0%	2%	5%	7%	62%	25%	7%	93%
1	0%	1%	19%	20%	46%	30%	5%	80%
2	0%	1%	9%	10%	26%	58%	7%	90%
3	1%	2%	5%	8%	9%	48%	35%	92%

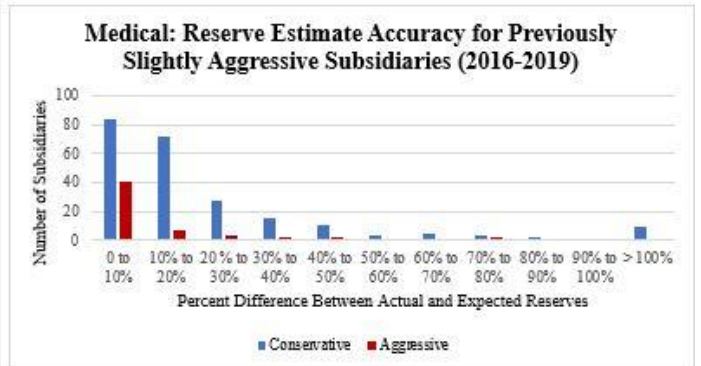
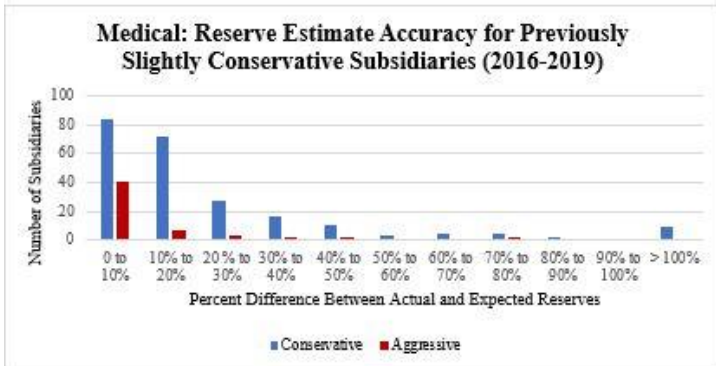
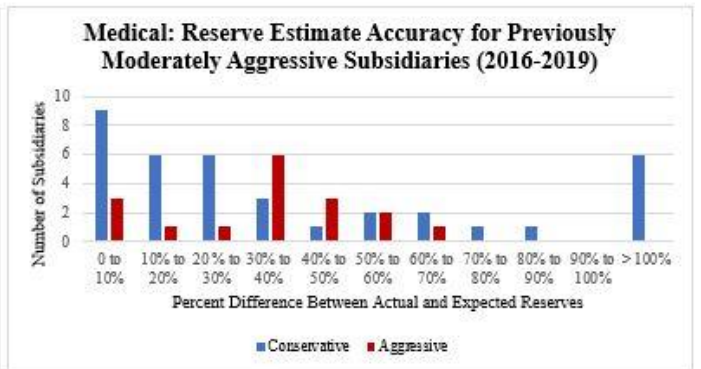
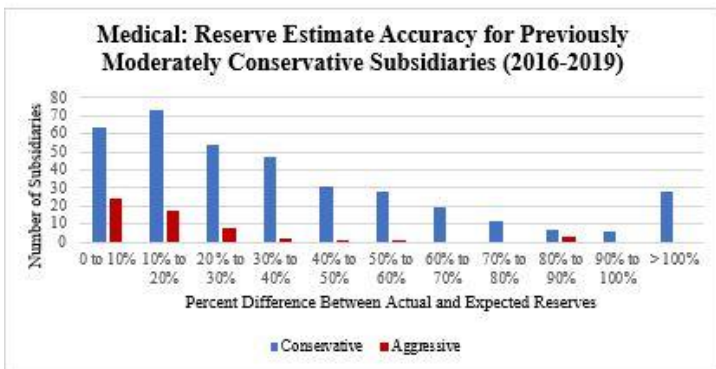
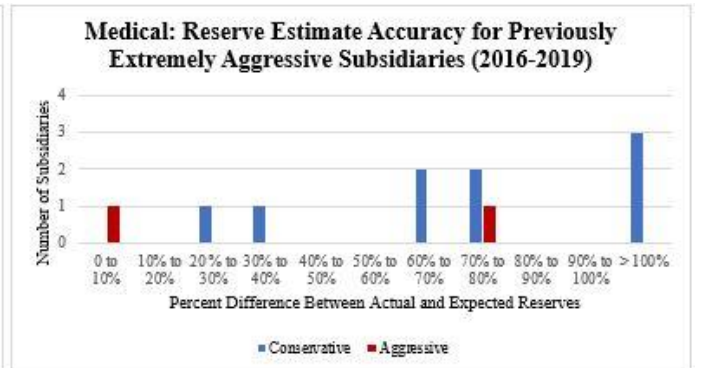
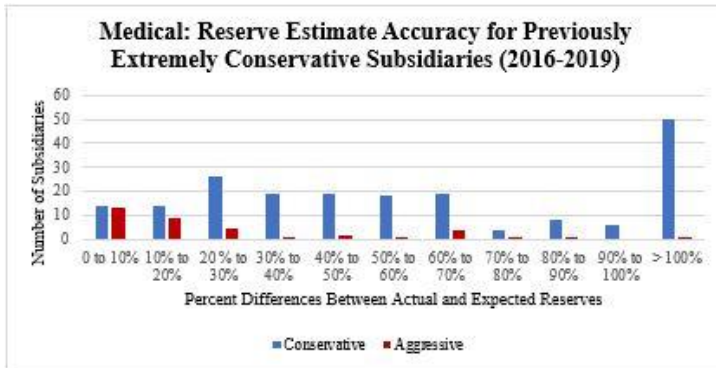
# Appendix H: Unweighted Transition Distributions

## Appendix H.1: Total Unweighted Transition Distributions



Total Transition Unweighted Distributions: Extremely Conservative (top left), Extremely Aggressive (top right), Moderately Conservative (middle left), Moderately Aggressive (middle left), Slight Conservative (bottom left), and Slightly Aggressive (bottom right)

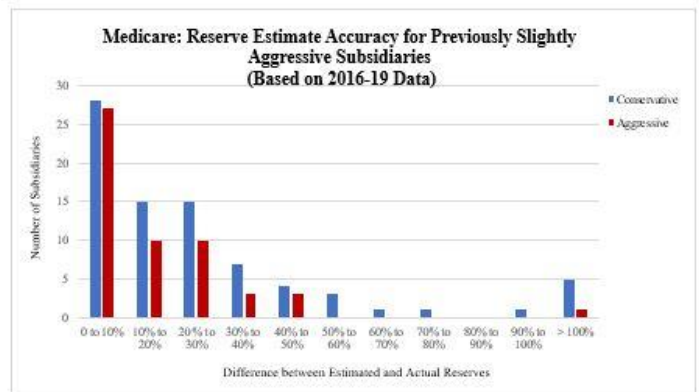
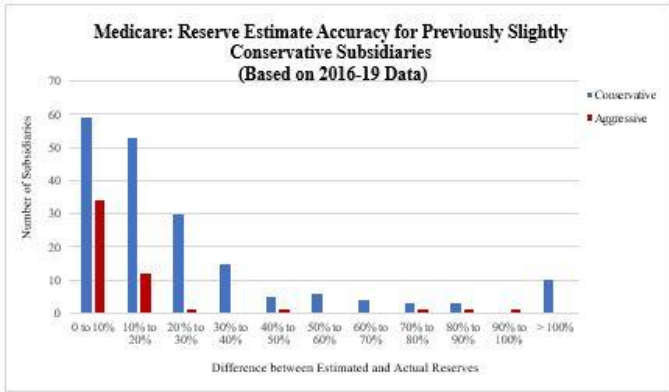
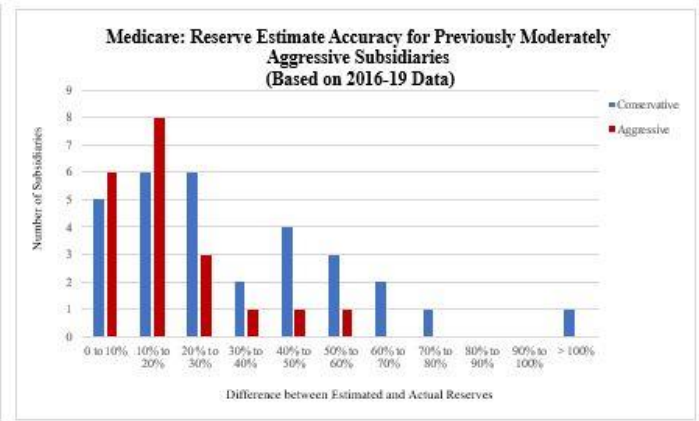
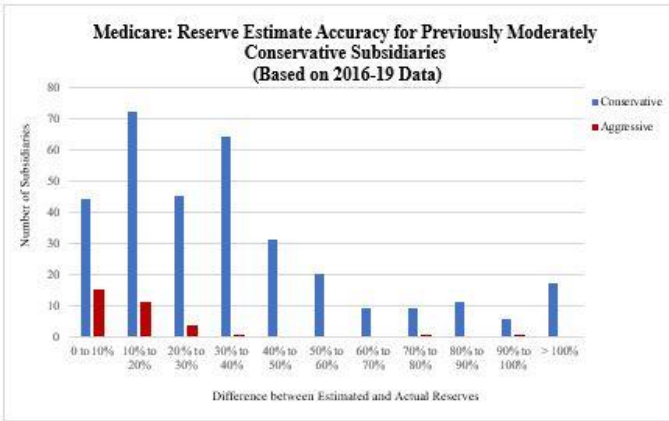
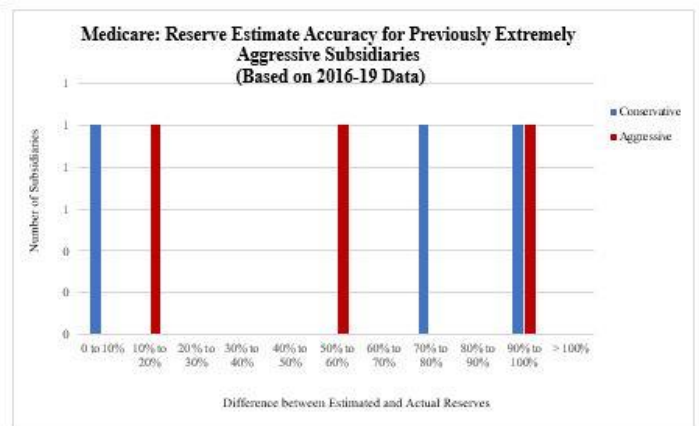
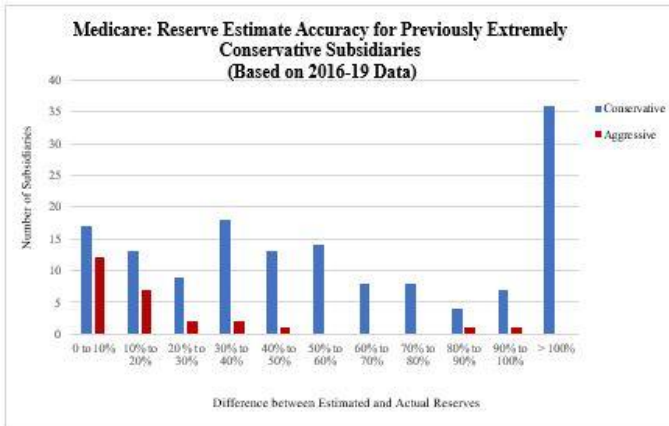
Appendix H.2: Medical Unweighted Transition Distributions



Medical Transition Unweighted Distributions: Extremely Conservative (top left), Extremely Aggressive (top right), Moderately Conservative (middle left), Moderately Aggressive (middle left), Slight Conservative (bottom left), and Slightly Aggressive (bottom right)

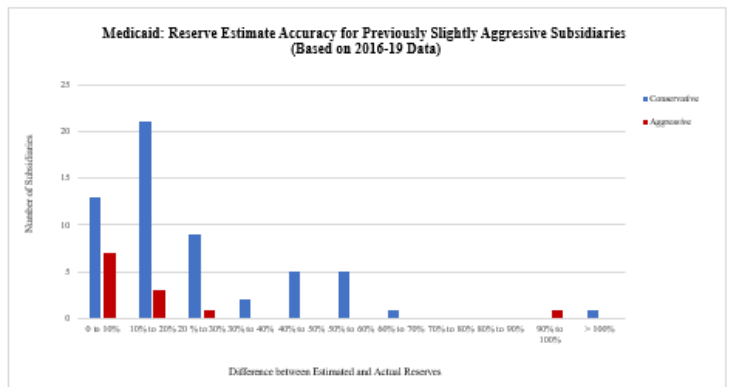
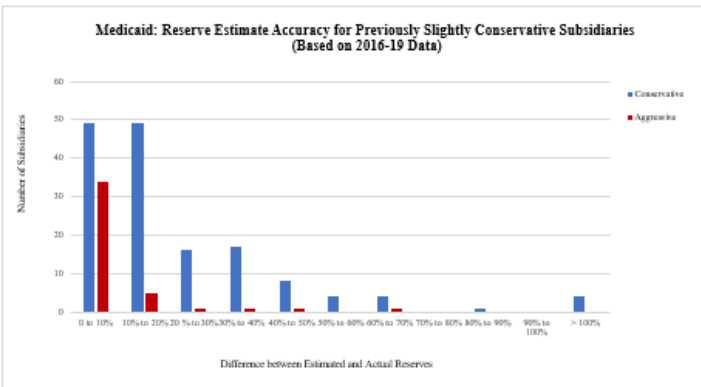
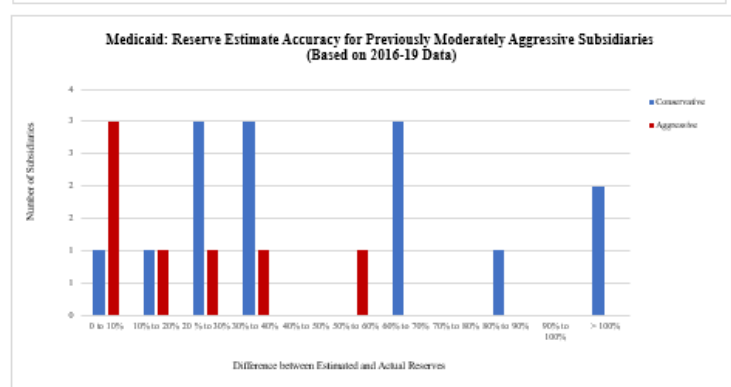
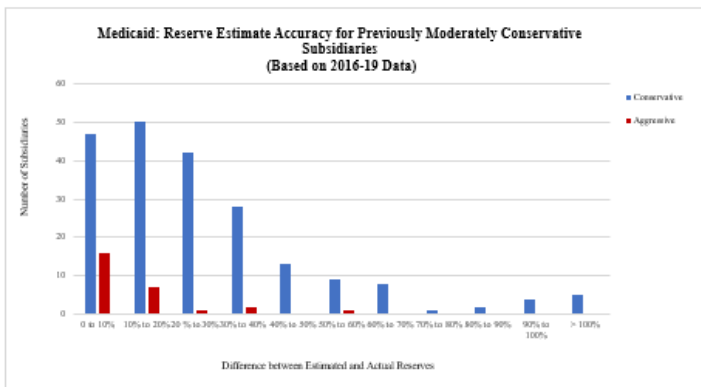
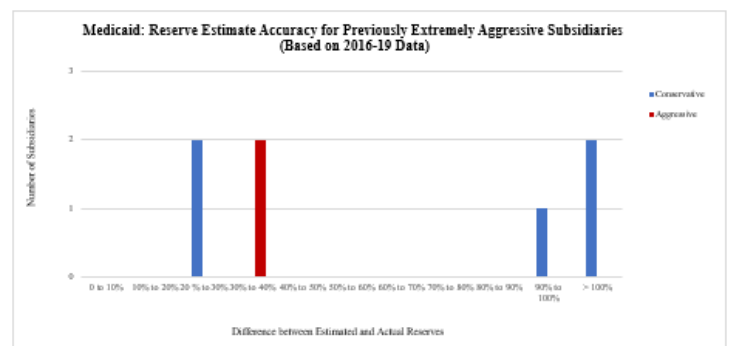
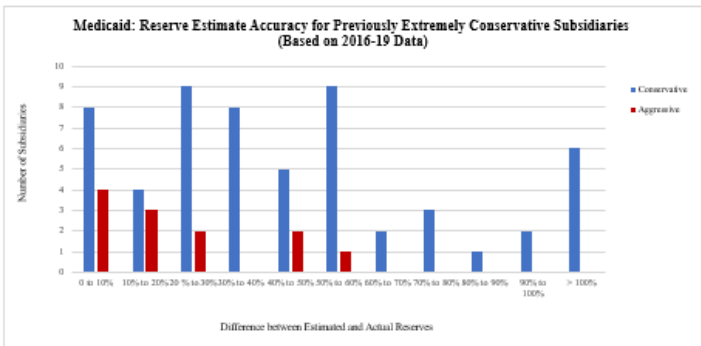


Appendix H.3: Medicare Unweighted Transition Distributions



Medicare Transition Unweighted Distributions: Extremely Conservative (top left), Extremely Aggressive (top right), Moderately Conservative (middle left), Moderately Aggressive (middle left), Slight Conservative (bottom left), and Slightly Aggressive (bottom right)

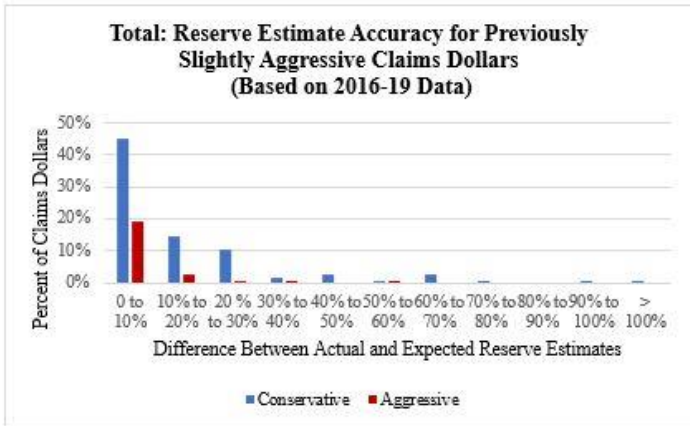
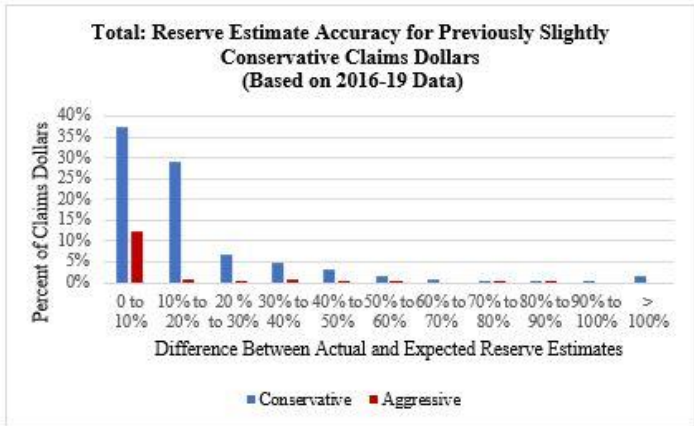
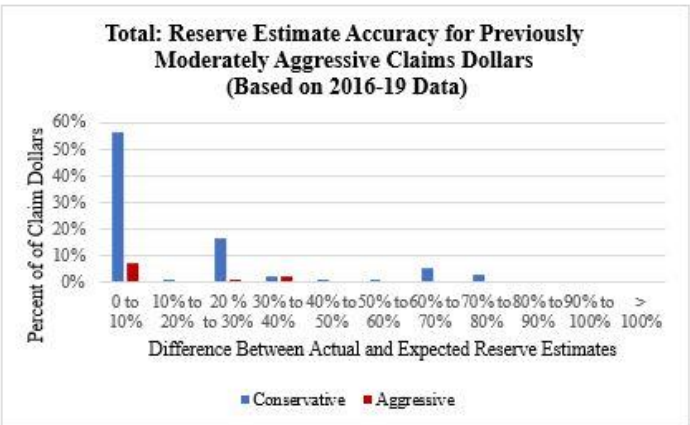
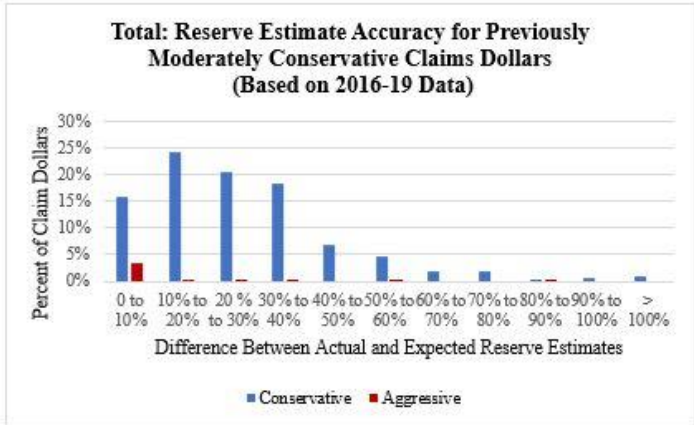
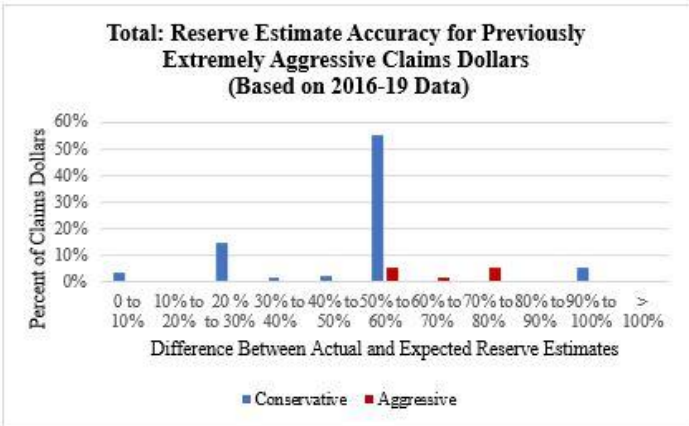
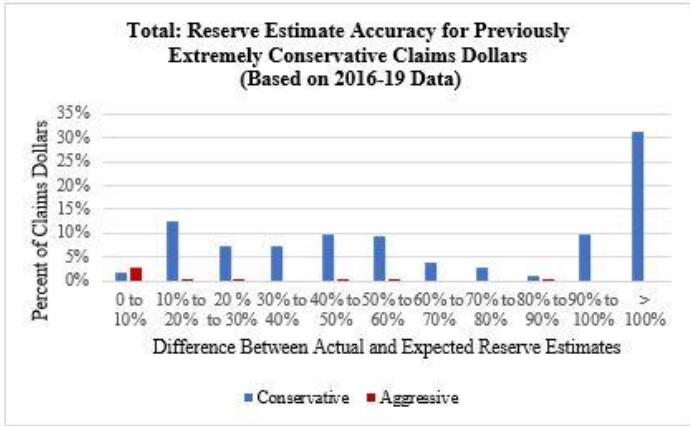
## Appendix H.4: Medicaid Unweighted Transition Distributions



*Medicaid Transition Unweighted Distributions: Extremely Conservative (top left), Extremely Aggressive (top right), Moderately Conservative (middle left), Moderately Aggressive (middle left), Slight Conservative (bottom left), and Slightly Aggressive (bottom right)*

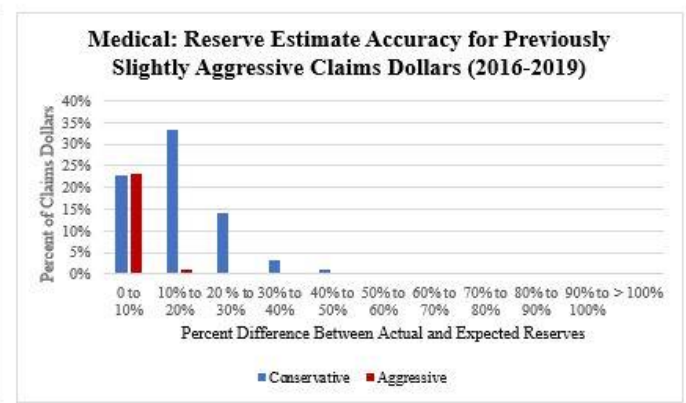
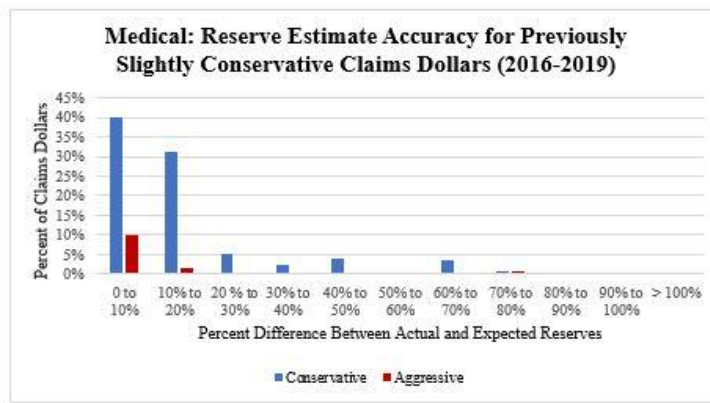
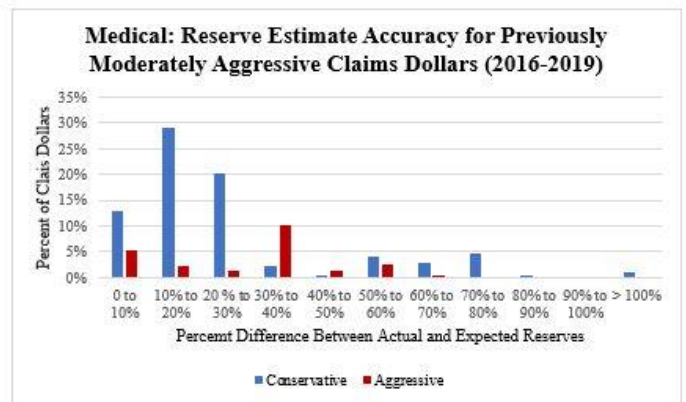
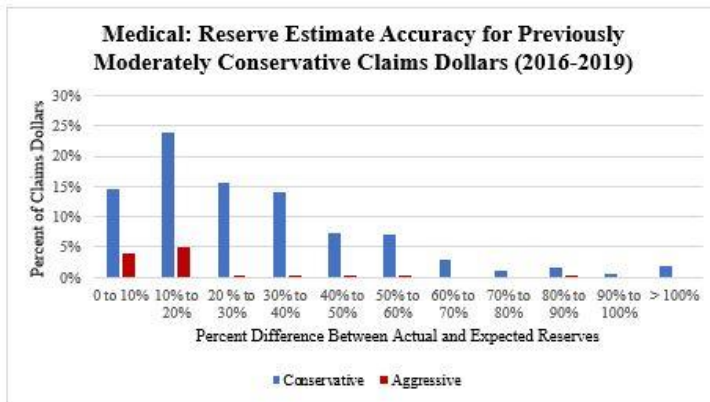
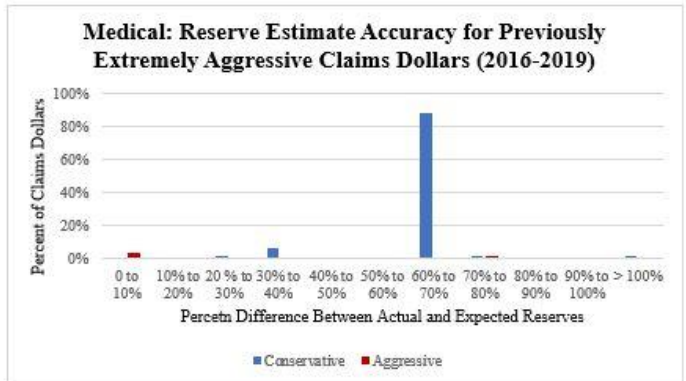
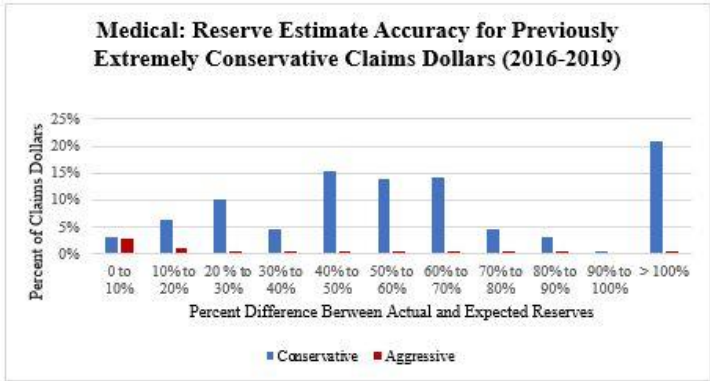
# Appendix I. Weighted Transition Distributions

## Appendix I.1: Total Weighted Transition Distributions



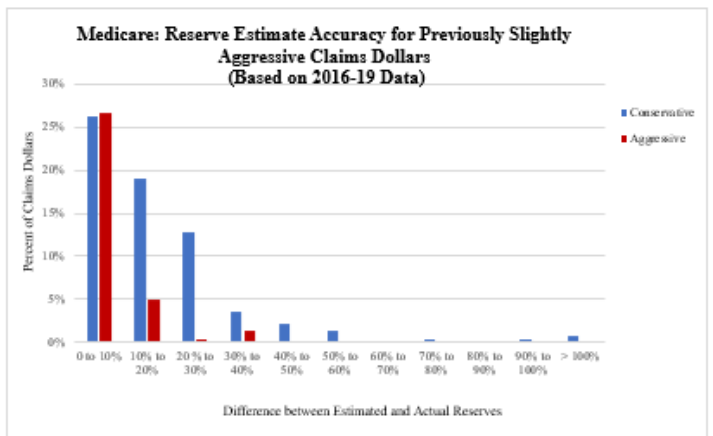
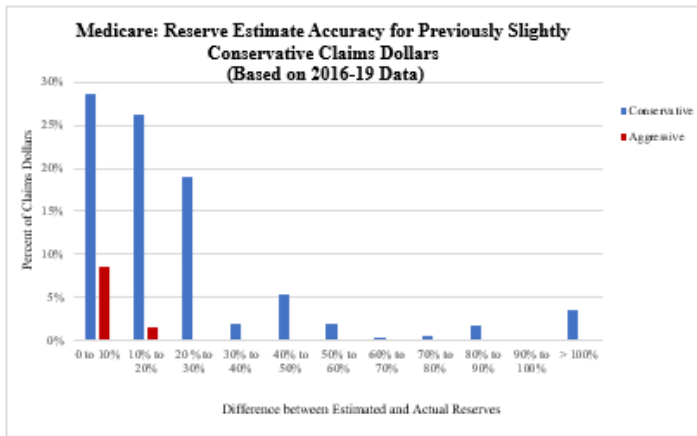
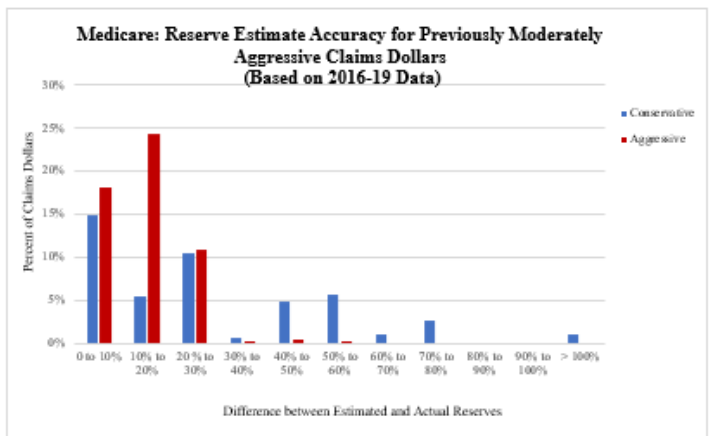
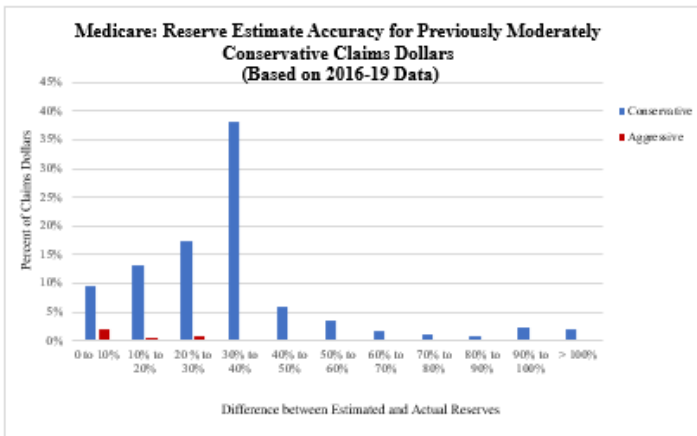
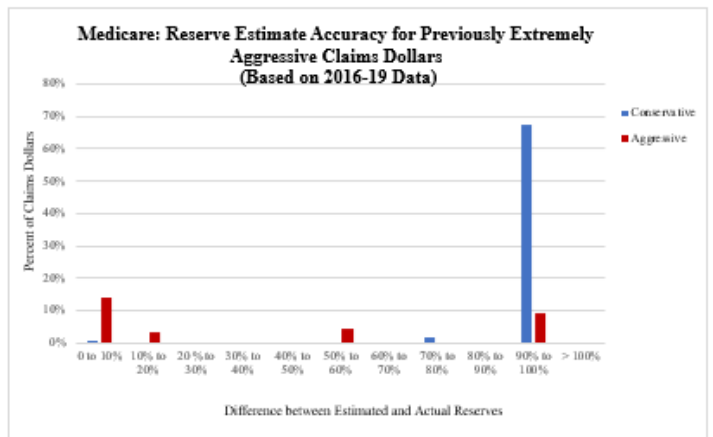
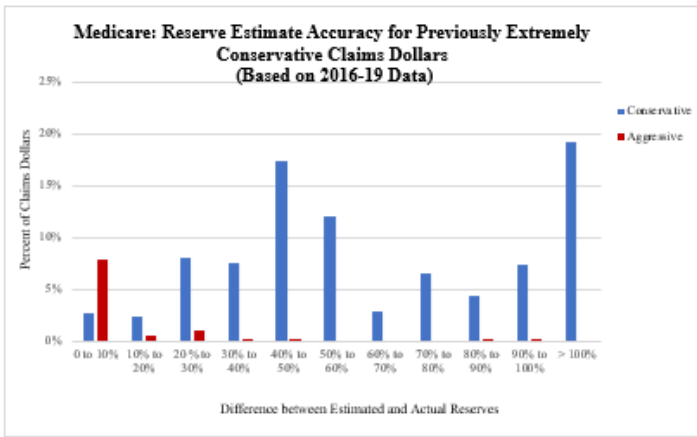
Total Transition Weighted Distributions: Extremely Conservative (top left), Extremely Aggressive (top right), Moderately Conservative (middle left), Moderately Aggressive (middle right), Slight Conservative (bottom left), and Slightly Aggressive (bottom right)

Appendix I.2: Medical Weighted Transition Distributions



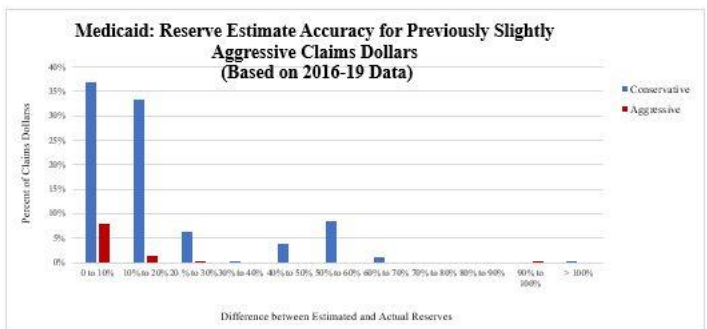
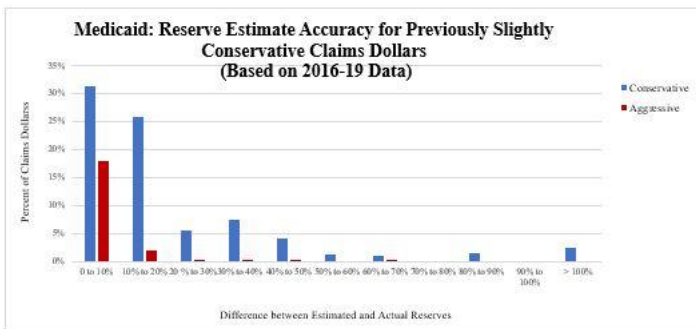
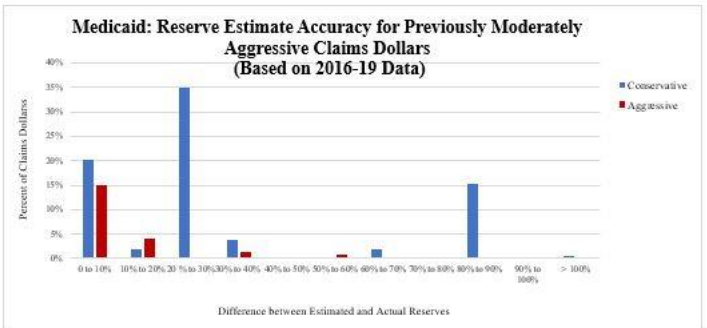
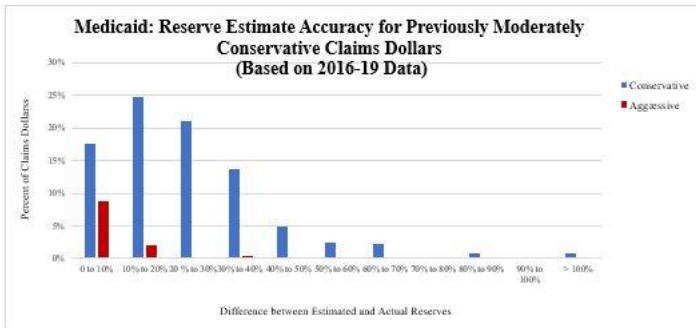
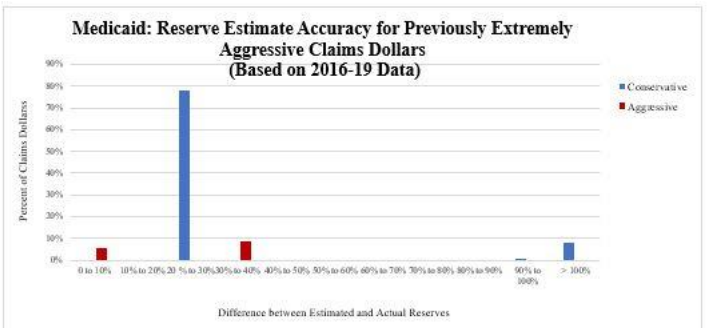
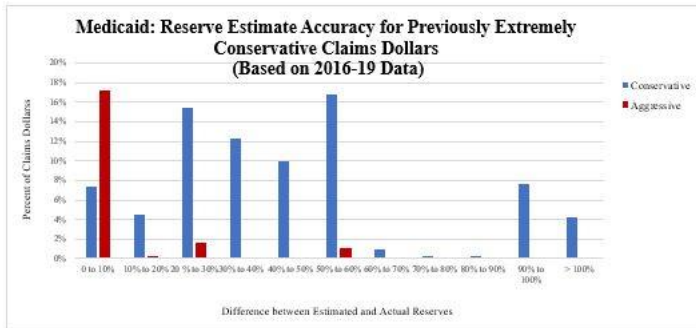
Medical Transition Weighted Distributions: Extremely Conservative (top left), Extremely Aggressive (top right), Moderately Conservative (middle left), Moderately Aggressive (middle right), Slight Conservative (bottom left), and Slightly Aggressive (bottom right)

Appendix I.3: Medicare Weighted Transition Distributions



Medicare Transition Weighted Distributions: Extremely Conservative (top left), Extremely Aggressive (top right), Moderately Conservative (middle left), Moderately Aggressive (middle left), Slight Conservative (bottom left), and Slightly Aggressive (bottom right)

## Appendix I.4: Medicaid Weighted Transition Distributions



*Medicaid Transition Weighted Distributions: Extremely Conservative (top left), Extremely Aggressive (top right), Moderately Conservative (middle left), Moderately Aggressive (middle right), Slight Conservative (bottom left), and Slightly Aggressive (bottom right)*

## Appendix J. Three-Year Transition Analysis by Number of Subsidiaries

Appendix J.1: Total Three-Year Transition Analysis by Number of Subsidiaries

2016 Transition Grouping	0 Conservative Estimates	1 Conservative Estimate	2 Conservative Estimates	3 Conservative Estimates
-3	0%	25%	75%	0%
-2	10%	5%	29%	57%
-1	8%	14%	27%	51%
1	2%	7%	27%	64%
2	1%	6%	15%	77%
3	1%	9%	20%	70%

2016 Transition Grouping	0 Accurate Estimates	1 Accurate Estimate	2 Accurate Estimates	3 Accurate Estimates
-3	25%	50%	25%	0%
-2	33%	52%	14%	0%
-1	83%	13%	4%	0%
1	85%	7%	5%	2%
2	65%	22%	10%	3%
3	25%	22%	28%	25%

2016 Transition Grouping	0 Inaccurate Estimates	1 Inaccurate Estimate	2 Inaccurate Estimates	3 Inaccurate Estimates
-3	25%	50%	25%	0%
-2	33%	52%	14%	0%
-1	83%	13%	4%	0%
1	85%	7%	5%	2%
2	65%	22%	10%	3%
3	25%	22%	28%	25%

*Total Three-Year Transition Analysis. These tables calculate the percentage of subsidiaries by 2016 transition grouping that were conservative (top), accurate within a 15% margin (middle) and inaccurate more than 50% (bottom) 0,1,2, and 3 times out from 2017-2019*

Appendix J.2: Medical Three-Year Transition Analysis by Number of Subsidiaries

2016 Transition Grouping	0 Conservative Estimates	1 Conservative Estimate	2 Conservative Estimates	3 Conservative Estimates
-3	0%	0%	40%	60%
-2	8%	15%	46%	31%
-1	4%	22%	26%	48%
1	2%	8%	25%	65%
2	0%	8%	22%	70%
3	0%	4%	31%	65%

2016 Transition Grouping	0 Accurate Estimates	1 Accurate Estimate	2 Accurate Estimates	3 Accurate Estimates
-3	60%	40%	0%	0%
-2	23%	23%	38%	15%
-1	24%	28%	32%	16%
1	16%	25%	33%	26%
2	43%	28%	19%	10%
3	61%	29%	6%	4%

2016 Transition Grouping	0 Inaccurate Estimates	1 Inaccurate Estimate	2 Inaccurate Estimates	3 Inaccurate Estimates
-3	0%	60%	20%	20%
-2	69%	15%	15%	0%
-1	78%	20%	2%	0%
1	78%	14%	7%	1%
2	52%	27%	13%	8%
3	20%	29%	39%	12%

*Medical Three-Year Transition Analysis. These tables calculate the percentage of subsidiaries by 2016 transition grouping that were conservative (top), accurate within a 15% margin (middle) and inaccurate more than 50% (bottom) 0,1,2, and 3 times out from 2017-2019*



Appendix J.3: Medicare Three-Year Transition Analysis by Number of Subsidiaries

2016 Transition Grouping	0 Conservative Estimates	1 Conservative Estimate	2 Conservative Estimates	3 Conservative Estimates
-3	0%	0%	0%	100%
-2	17%	8%	42%	33%
-1	13%	15%	31%	41%
1	1%	8%	27%	64%
2	0%	8%	18%	74%
3	0%	12%	14%	74%

2016 Transition Grouping	0 Accurate Estimates	1 Accurate Estimate	2 Accurate Estimates	3 Accurate Estimates
-3	0%	100%	0%	0%
-2	25%	42%	33%	0%
-1	27%	33%	25%	16%
1	27%	33%	25%	16%
2	54%	25%	14%	7%
3	42%	37%	9%	12%

2016 Transition Grouping	0 Inaccurate Estimates	1 Inaccurate Estimate	2 Inaccurate Estimates	3 Inaccurate Estimates
-3	100%	0%	0%	0%
-2	58%	17%	25%	0%
-1	69%	16%	12%	4%
1	69%	16%	12%	4%
2	59%	24%	16%	1%
3	47%	16%	16%	21%

*Medicare Three-Year Transition Analysis. These tables calculate the percentage of subsidiaries by 2016 transition grouping that were conservative (top), accurate within a 15% margin (middle) and inaccurate more than 50% (bottom) 0,1,2, and 3 times out from 2017-2019*

Appendix J.4: Medicaid Three-Year Transition Analysis by Number of Subsidiaries

2016 Transition Grouping	0 Conservative Estimates	1 Conservative Estimate	2 Conservative Estimates	3 Conservative Estimates
-3	0%	33%	33%	33%
-2	0%	43%	29%	29%
-1	0%	6%	28%	67%
1	1%	7%	44%	47%
2	1%	8%	13%	77%
3	0%	0%	25%	75%

2016 Transition Grouping	0 Accurate Estimates	1 Accurate Estimate	2 Accurate Estimates	3 Accurate Estimates
-3	33%	33%	33%	0%
-2	29%	57%	14%	0%
-1	18%	28%	25%	29%
1	18%	28%	25%	29%
2	32%	36%	21%	11%
3	50%	38%	13%	0%

2016 Transition Grouping	0 Inaccurate Estimates	1 Inaccurate Estimate	2 Inaccurate Estimates	3 Inaccurate Estimates
-3	33%	33%	0%	33%
-2	43%	29%	29%	0%
-1	79%	13%	7%	1%
1	79%	13%	7%	1%
2	65%	24%	8%	3%
3	38%	25%	13%	25%

*Medicare Three-Year Transition Analysis. These tables calculate the percentage of subsidiaries by 2016 transition grouping that were conservative (top), accurate within a 15% margin (middle) and inaccurate more than 50% (bottom) 0,1,2, and 3 times out from 2017-2019*

## Appendix K: Three-Year Transition Analysis by Sum of Claims Dollars

### Appendix K.1: Total Three-Year Transition Analysis by Sum of Claims Dollars

2016 Transition Grouping	0 Conservative Estimates	1 Conservative Estimate	2 Conservative Estimates	3 Conservative Estimates
-3	0%	25%	75%	0%
-2	16%	9%	12%	63%
-1	6%	15%	27%	52%
1	0%	5%	26%	69%
2	0%	1%	12%	86%
3	0%	1%	3%	97%

2016 Transition Grouping	0 Accurate Estimates	1 Accurate Estimate	2 Accurate Estimates	3 Accurate Estimates
-3	0%	100%	0%	0%
-2	43%	9%	16%	31%
-1	16%	20%	21%	43%
1	16%	20%	21%	43%
2	48%	29%	14%	10%
3	89%	9%	2%	0%

2016 Transition Grouping	0 Inaccurate Estimates	1 Inaccurate Estimate	2 Inaccurate Estimates	3 Inaccurate Estimates
-3	0%	75%	25%	0%
-2	48%	45%	7%	0%
-1	86%	4%	9%	1%
1	86%	4%	9%	1%
2	75%	16%	8%	1%
3	21%	4%	32%	43%

*Total Three-Year Transition Analysis. These tables calculate the percentage of claims dollars by 2016 transition grouping that were conservative (top), accurate within a 15% margin (middle) and inaccurate more than 50% (bottom) 0,1,2, and 3 times out from 2017-2019*

Appendix K.2: Medical Three-Year Transition Analysis by Sum of Claims Dollars

2016 Transition Grouping	0 Conservative Estimates	1 Conservative Estimate	2 Conservative Estimates	3 Conservative Estimates
-3	0%	0%	23%	77%
-2	6%	16%	55%	23%
-1	5%	27%	23%	45%
1	0%	5%	17%	77%
2	0%	5%	16%	79%
3	0%	1%	6%	92%

2016 Transition Grouping	0 Accurate Estimates	1 Accurate Estimate	2 Accurate Estimates	3 Accurate Estimates
-3	58%	42%	0%	0%
-2	9%	36%	40%	15%
-1	8%	24%	25%	43%
1	8%	24%	25%	43%
2	43%	26%	13%	18%
3	89%	3%	3%	4%

2016 Transition Grouping	0 Inaccurate Estimates	1 Inaccurate Estimate	2 Inaccurate Estimates	3 Inaccurate Estimates
-3	0%	73%	25%	3%
-2	74%	25%	0%	0%
-1	88%	8%	2%	1%
1	88%	8%	2%	1%
2	63%	19%	10%	8%
3	9%	32%	32%	28%

*Medical Three-Year Transition Analysis. These tables calculate the percentage of claims dollars by 2016 transition grouping that were conservative (top), accurate within a 15% margin (middle) and inaccurate more than 50% (bottom) 0,1,2, and 3 times out from 2017-2019*

Appendix K.3: Medicare Three-Year Transition Analysis by Sum of Claims Dollars

2016 Transition Grouping	0 Conservative Estimates	1 Conservative Estimate	2 Conservative Estimates	3 Conservative Estimates
-3	0%	0%	0%	100%
-2	39%	1%	27%	33%
-1	5%	14%	31%	51%
1	1%	3%	18%	78%
2	0%	1%	8%	91%
3	0%	2%	14%	84%

2016 Transition Grouping	0 Accurate Estimates	1 Accurate Estimate	2 Accurate Estimates	3 Accurate Estimates
-3	0%	100%	0%	0%
-2	21%	74%	5%	0%
-1	37%	15%	37%	11%
1	37%	15%	37%	11%
2	80%	10%	9%	2%
3	68%	29%	1%	2%

2016 Transition Grouping	0 Inaccurate Estimates	1 Inaccurate Estimate	2 Inaccurate Estimates	3 Inaccurate Estimates
-3	100%	0%	0%	0%
-2	78%	3%	20%	0%
-1	70%	13%	15%	2%
1	70%	13%	15%	2%
2	74%	14%	12%	0%
3	30%	12%	15%	43%

*Medicare Three-Year Transition Analysis. These tables calculate the percentage of claims dollars by 2016 transition grouping that were conservative (top), accurate within a 15% margin (middle) and inaccurate more than 50% (bottom) 0,1,2, and 3 times out from 2017-2019*

Appendix K.4: Medicaid Three-Year Transition Analysis by Sum of Claims Dollars

2016 Transition Grouping	0 Conservative Estimates	1 Conservative Estimate	2 Conservative Estimates	3 Conservative Estimates
-3	0%	2%	94%	4%
-2	0%	6%	22%	73%
-1	0%	2%	48%	50%
1	0%	2%	50%	48%
2	0%	4%	15%	80%
3	0%	0%	7%	93%

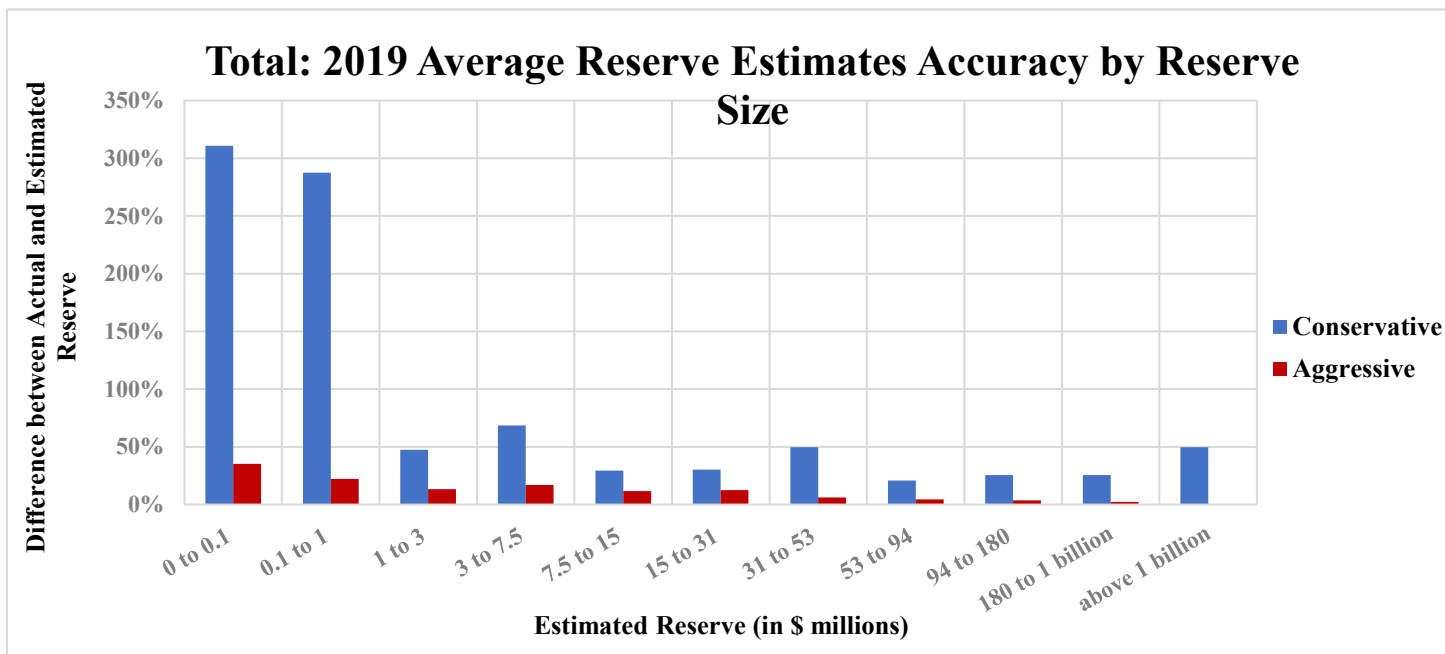
2016 Transition Grouping	0 Accurate Estimates	1 Accurate Estimate	2 Accurate Estimates	3 Accurate Estimates
-3	2%	94%	4%	0%
-2	13%	87%	0%	0%
-1	18%	23%	24%	35%
1	18%	23%	24%	35%
2	32%	37%	17%	14%
3	48%	51%	1%	0%

2016 Transition Grouping	0 Inaccurate Estimates	1 Inaccurate Estimate	2 Inaccurate Estimates	3 Inaccurate Estimates
-3	4%	94%	0%	2%
-2	73%	14%	13%	0%
-1	80%	9%	11%	0%
1	80%	9%	11%	0%
2	81%	16%	2%	0%
3	14%	28%	37%	20%

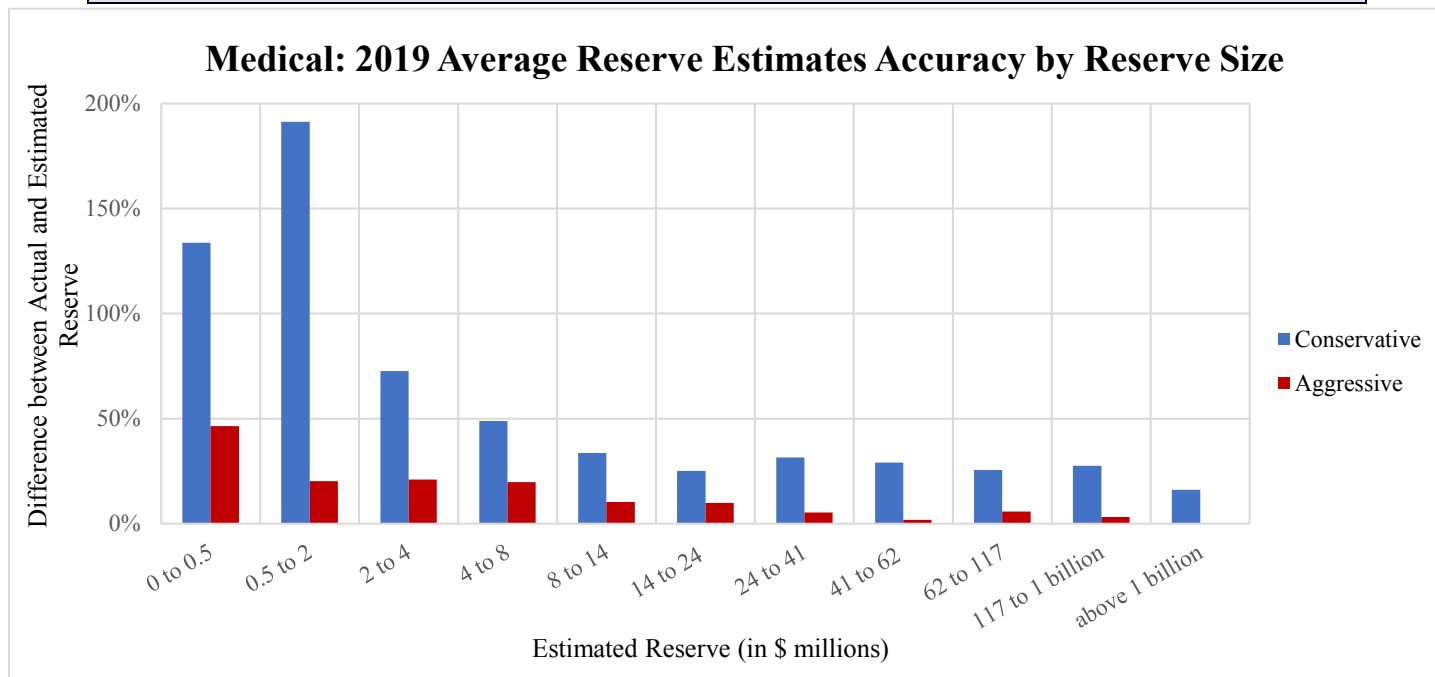
*Medicaid Three-Year Transition Analysis. These tables calculate the percentage of claims dollars by 2016 transition grouping that were conservative (top), accurate within a 15% margin (middle) and inaccurate more than 50% (bottom) 0,1,2, and 3 times out from 2017-2019*

## Appendix L: Reserve Size versus Reserve Accuracy and Conservativeness

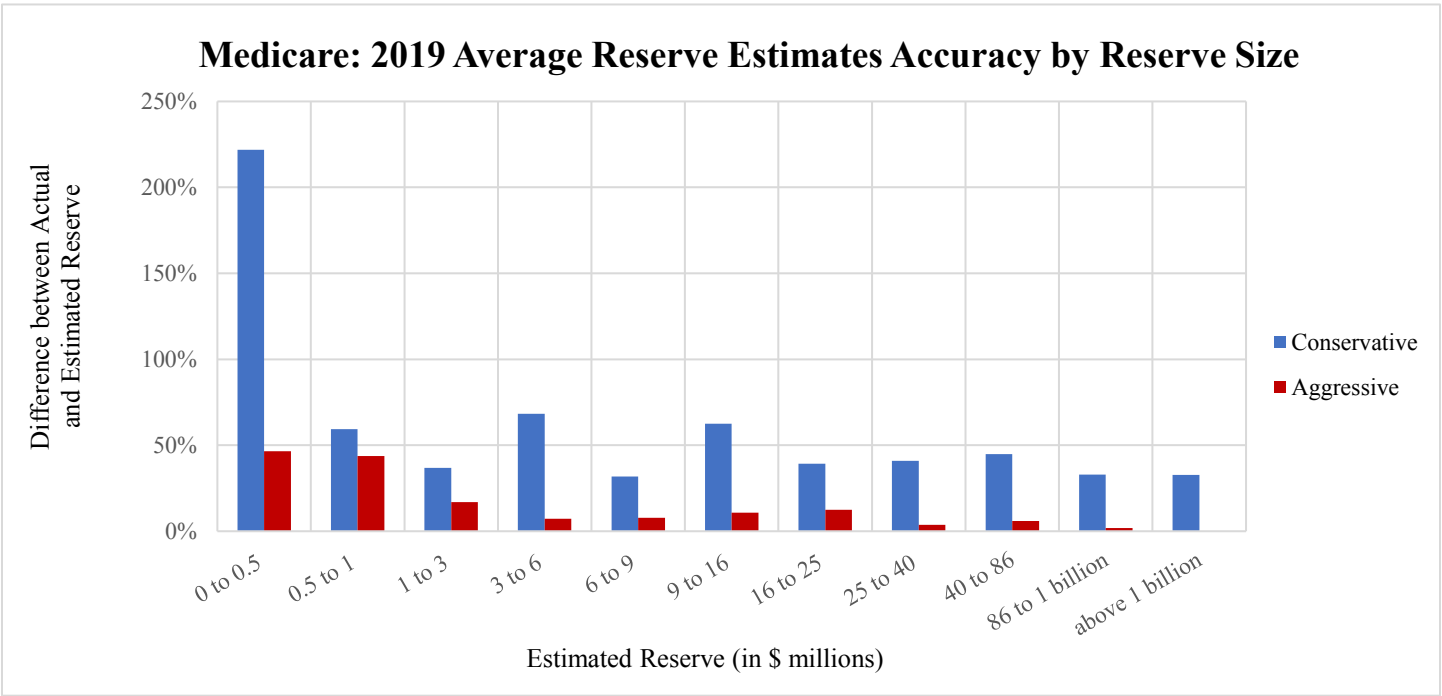
Appendix L.1: Total Reserve Estimate Accuracy and Conservativeness by Reserve Size



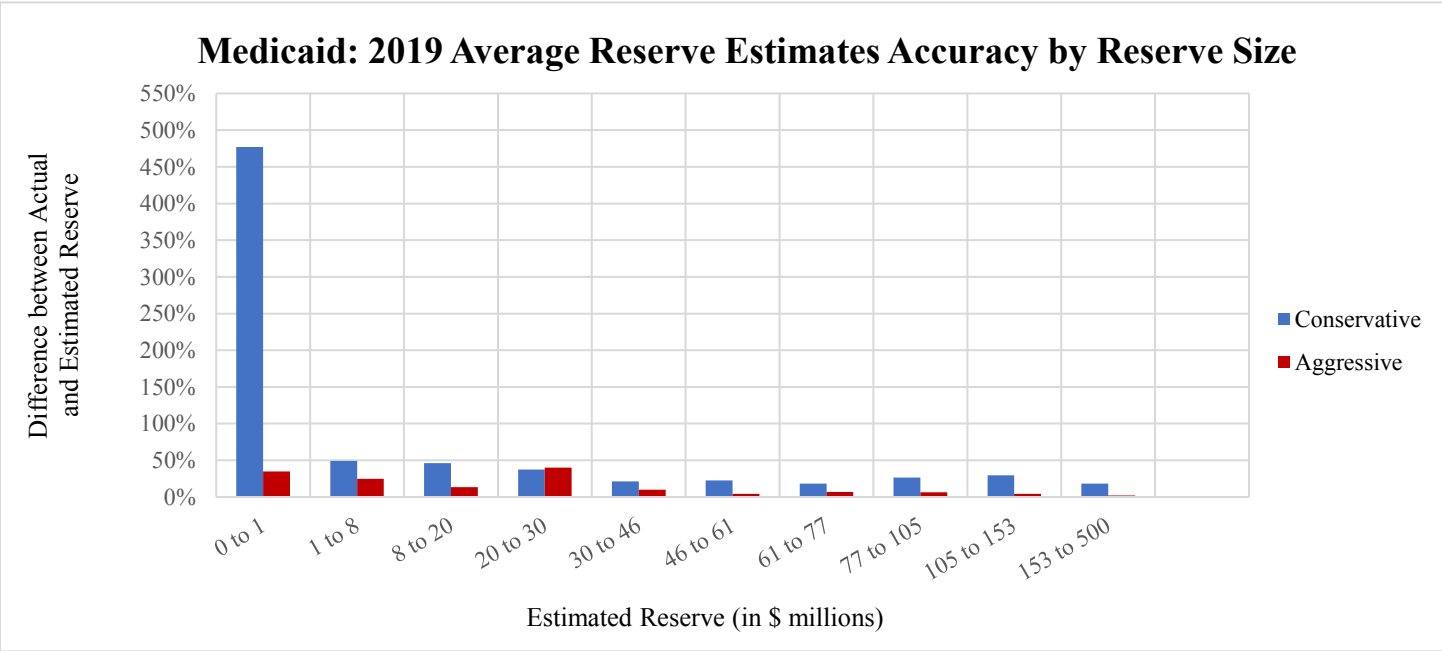
Appendix L.2: Medical Reserve Estimate Accuracy and Conservativeness by Reserve Size



Appendix L.3: Medicare Reserve Estimate Accuracy and Conservativeness by Reserve Size

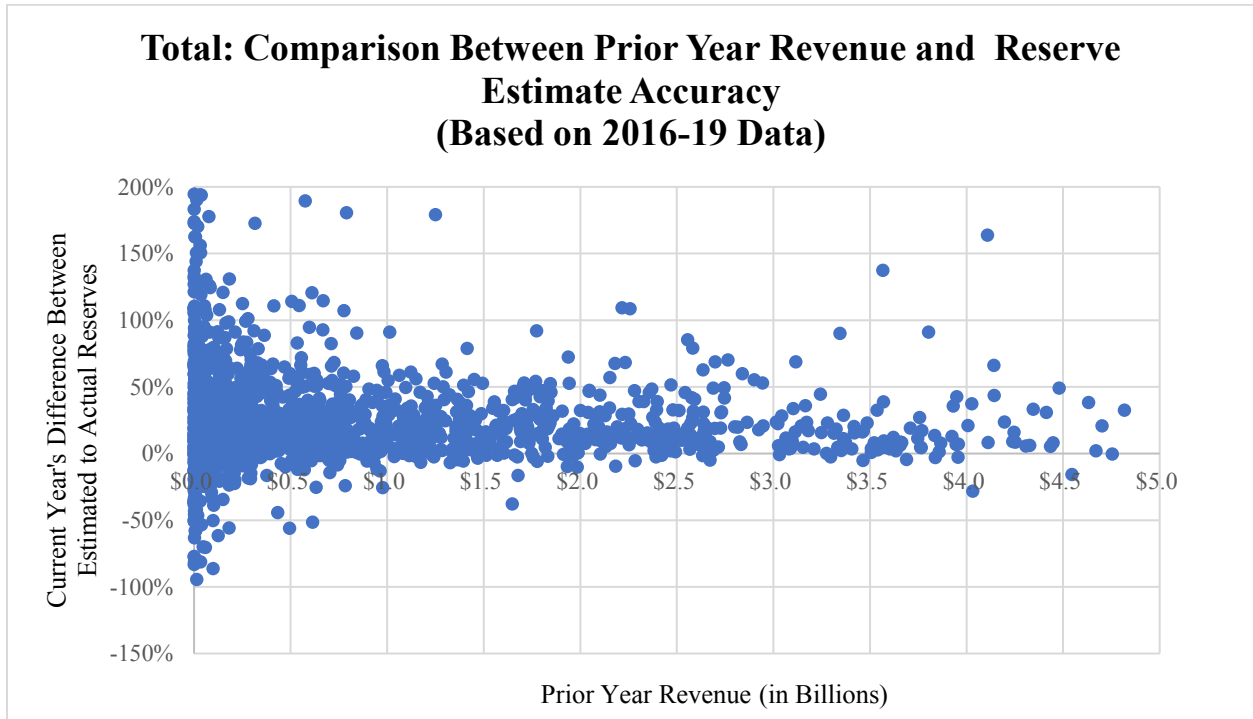


Appendix L.4: Medicaid Reserve Estimate Accuracy and Conservativeness by Reserve Size



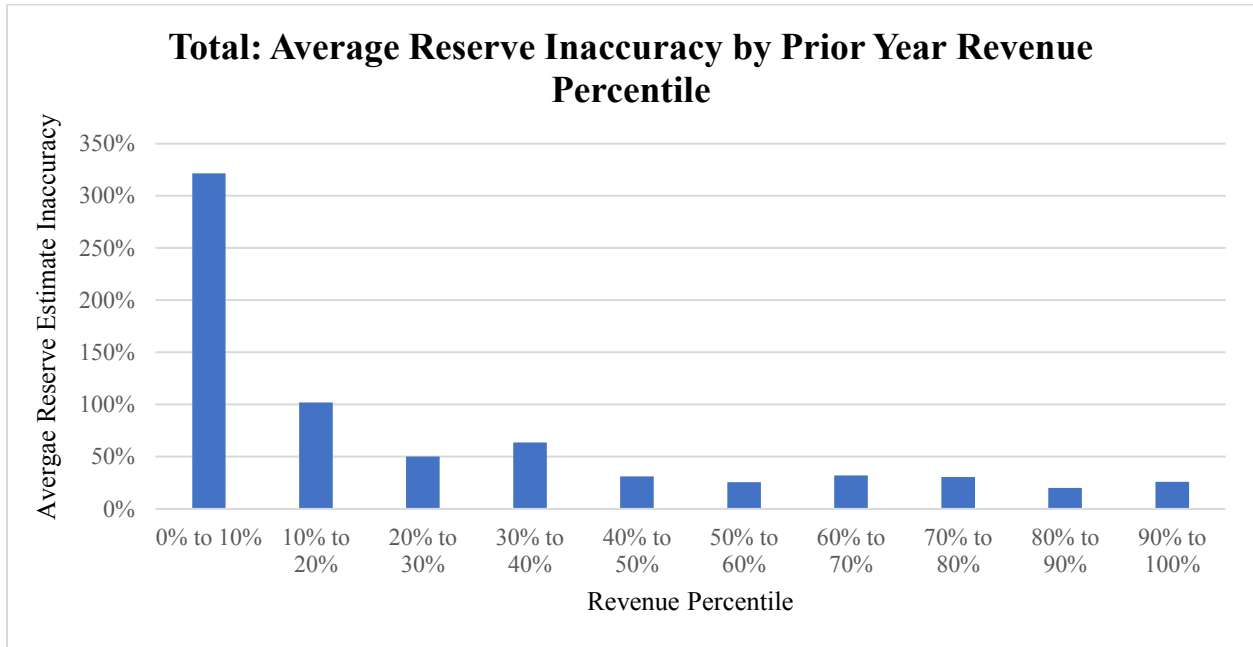


Appendix M: Prior Year Revenue versus Reserves Percent Accuracy

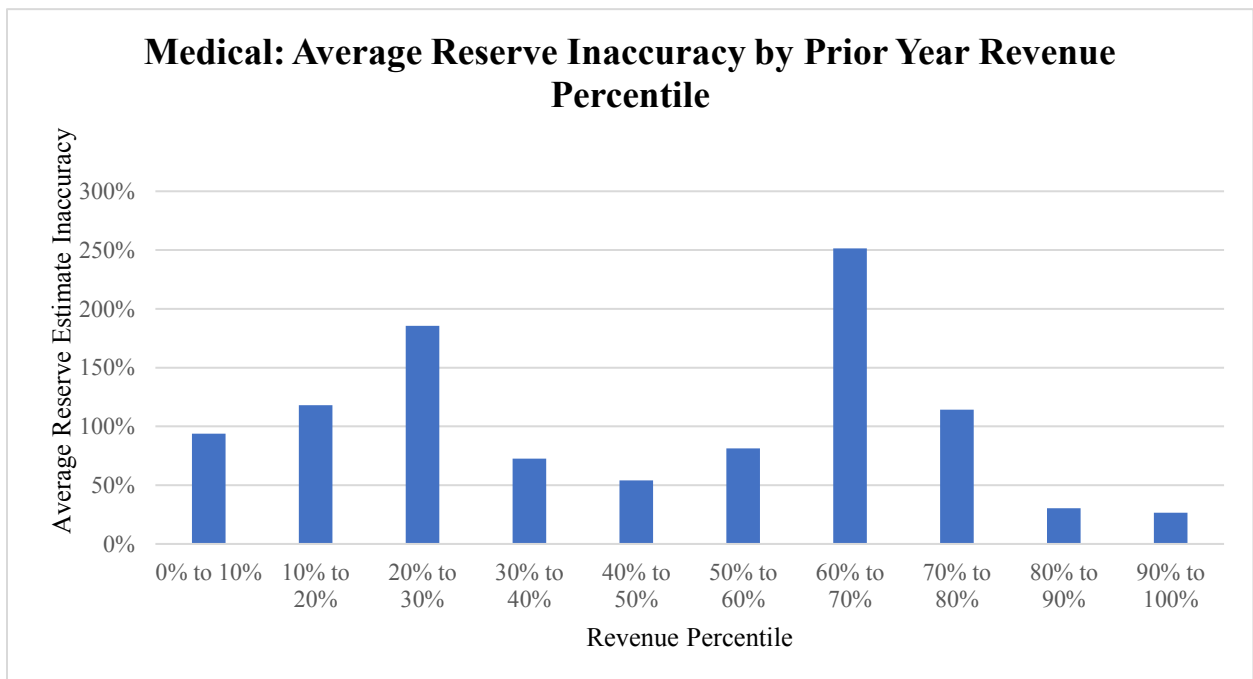


## Appendix N: Revenue versus Average Reserve Accuracy

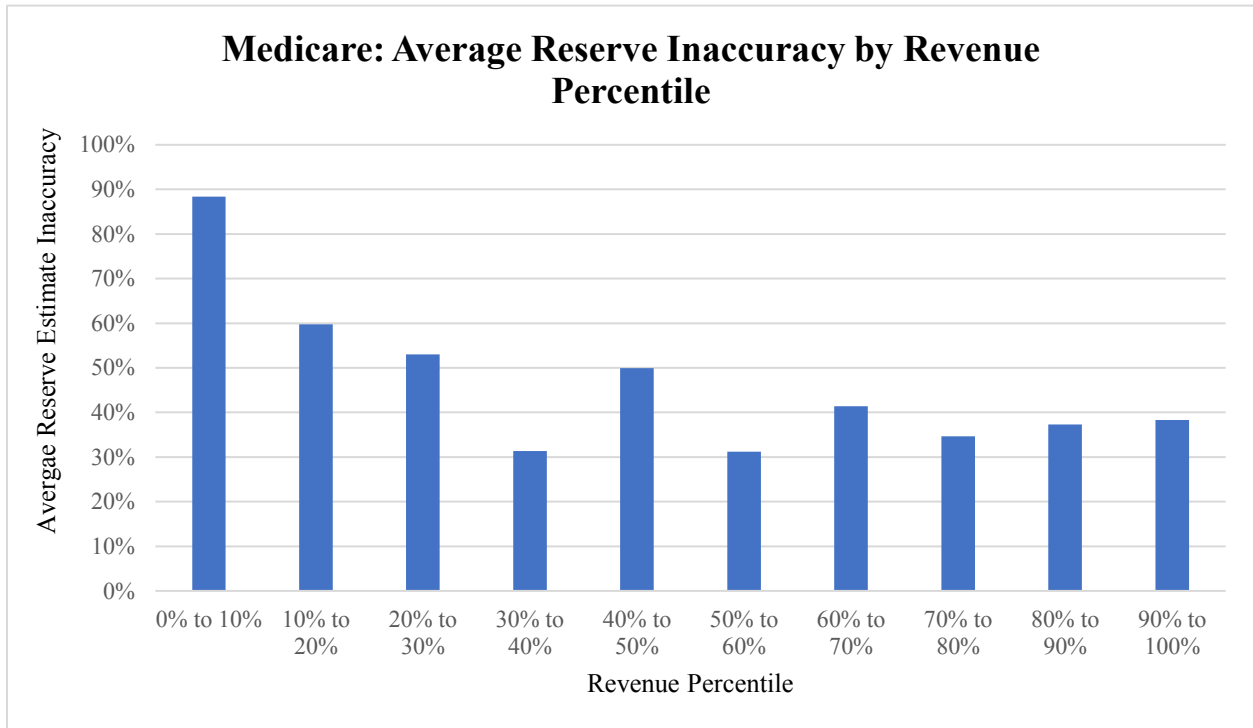
Appendix N.1: Total Reserve Accuracy by Prior Year Revenue



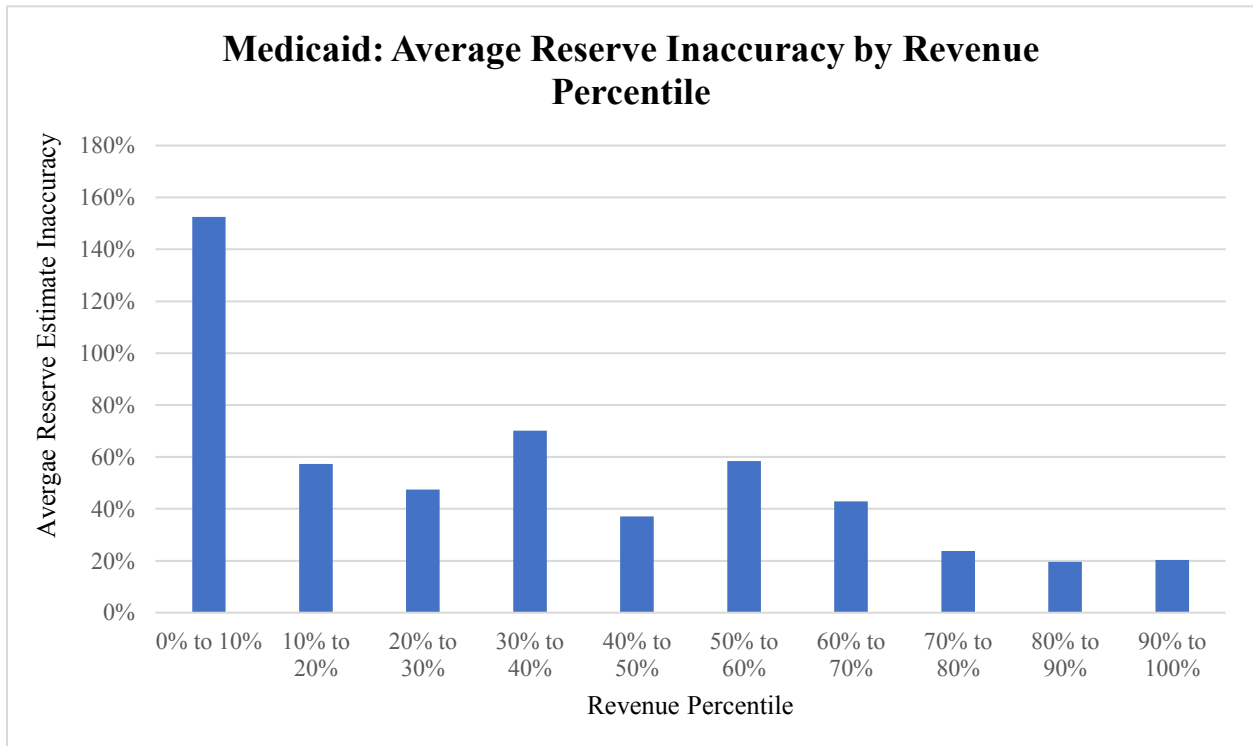
Appendix N.2: Medical Reserve Accuracy by Prior Year Revenue



Appendix N.3: Medicare Reserve Accuracy by Prior Year Revenue

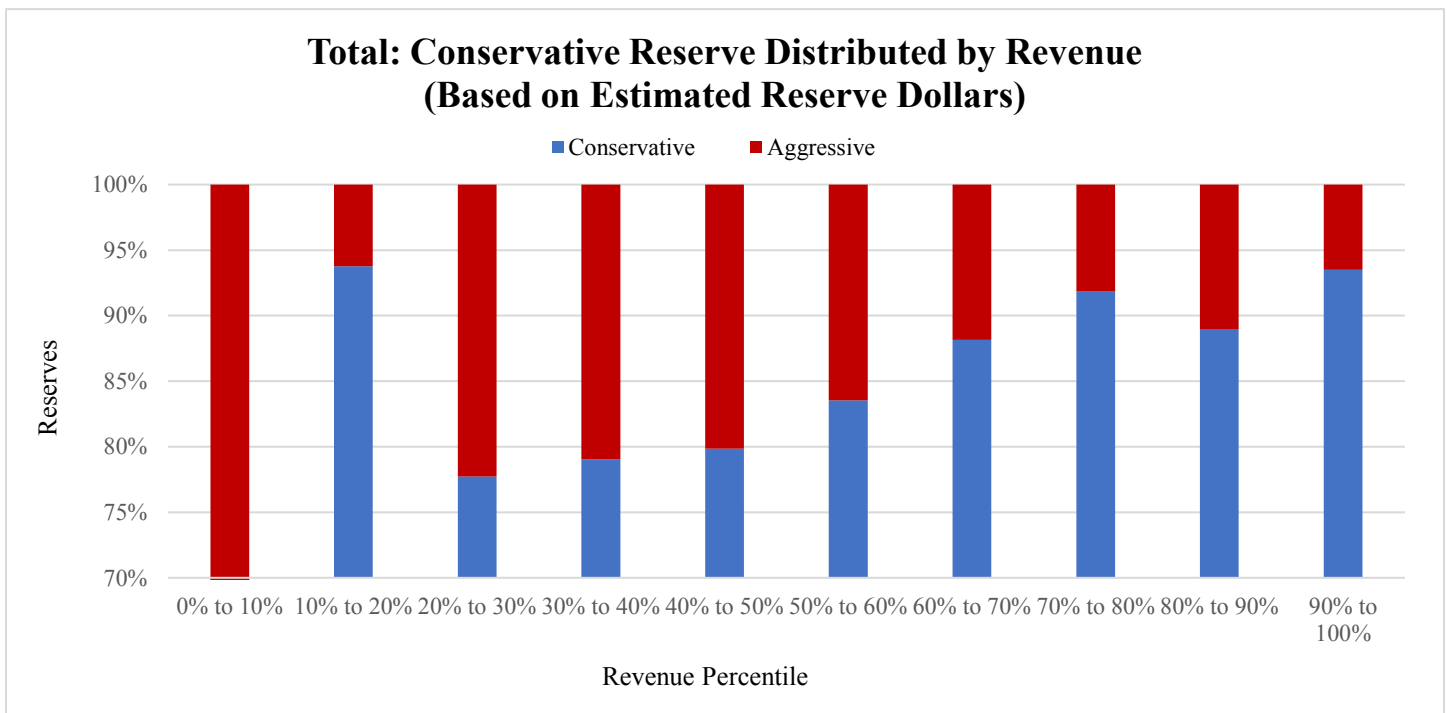
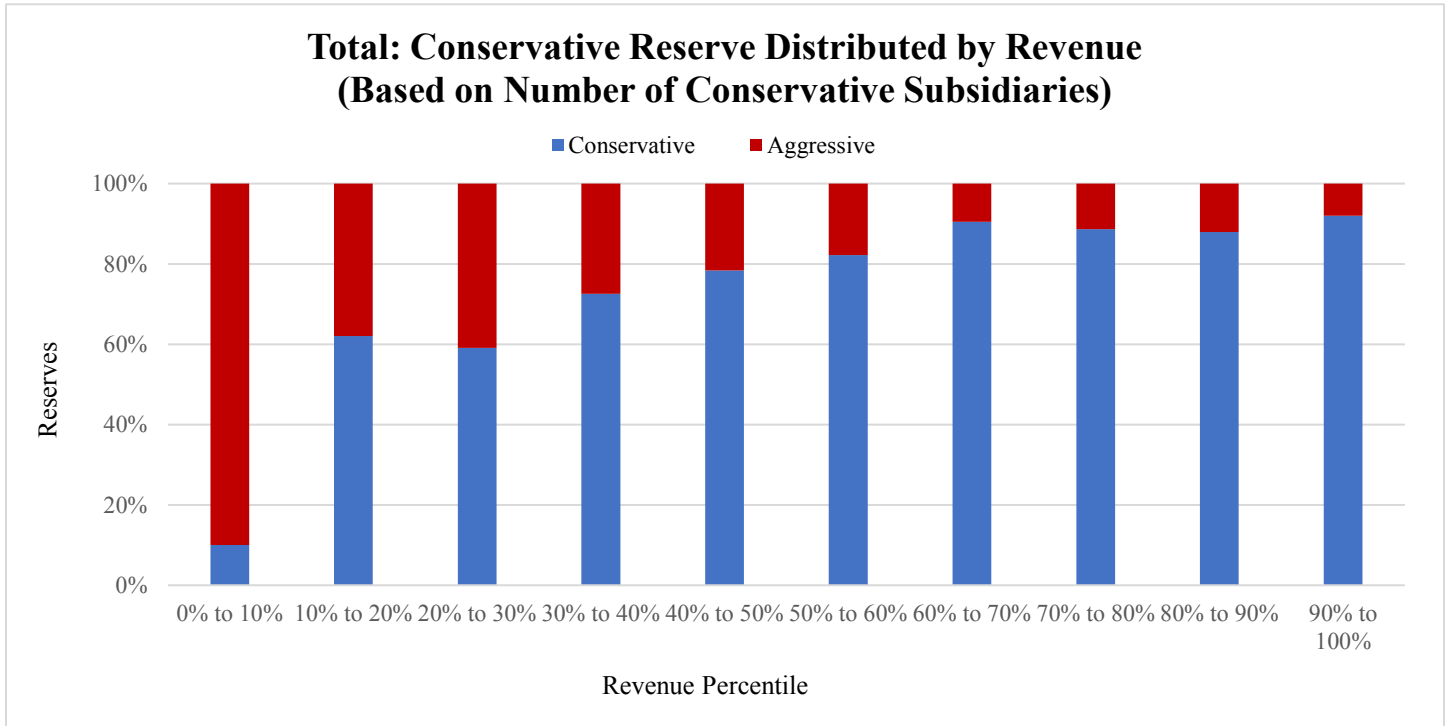


Appendix N.4: Medicaid Reserve Accuracy by Prior Year Revenue



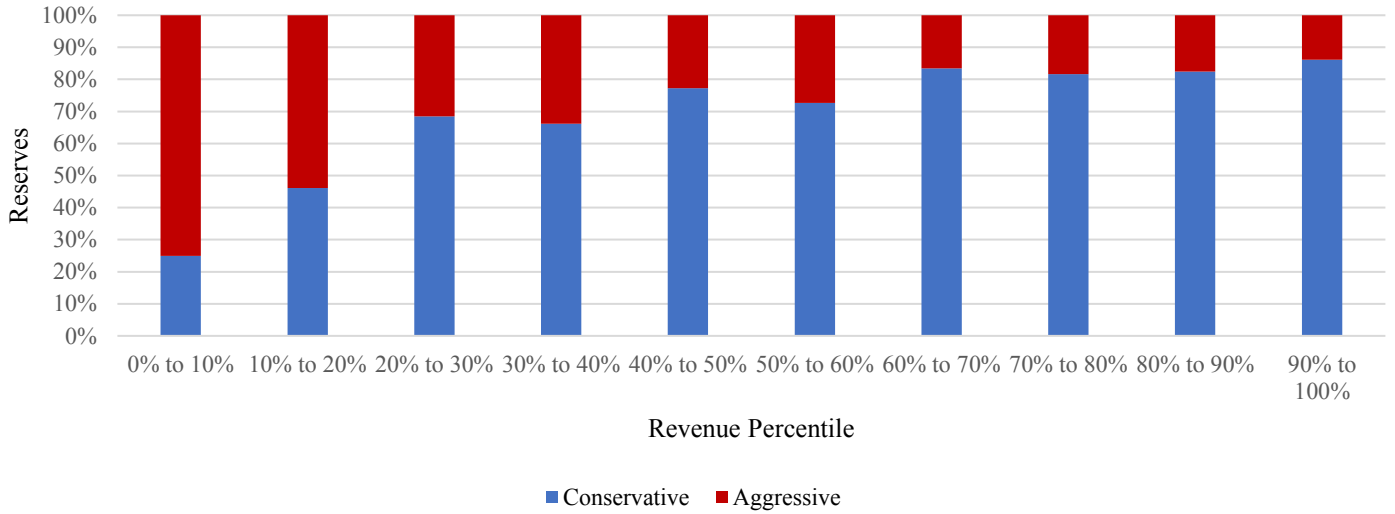
## Appendix O: Revenue versus Reserve Conservativeness

### Appendix O.1: Total Reserve Conservativeness by Revenue

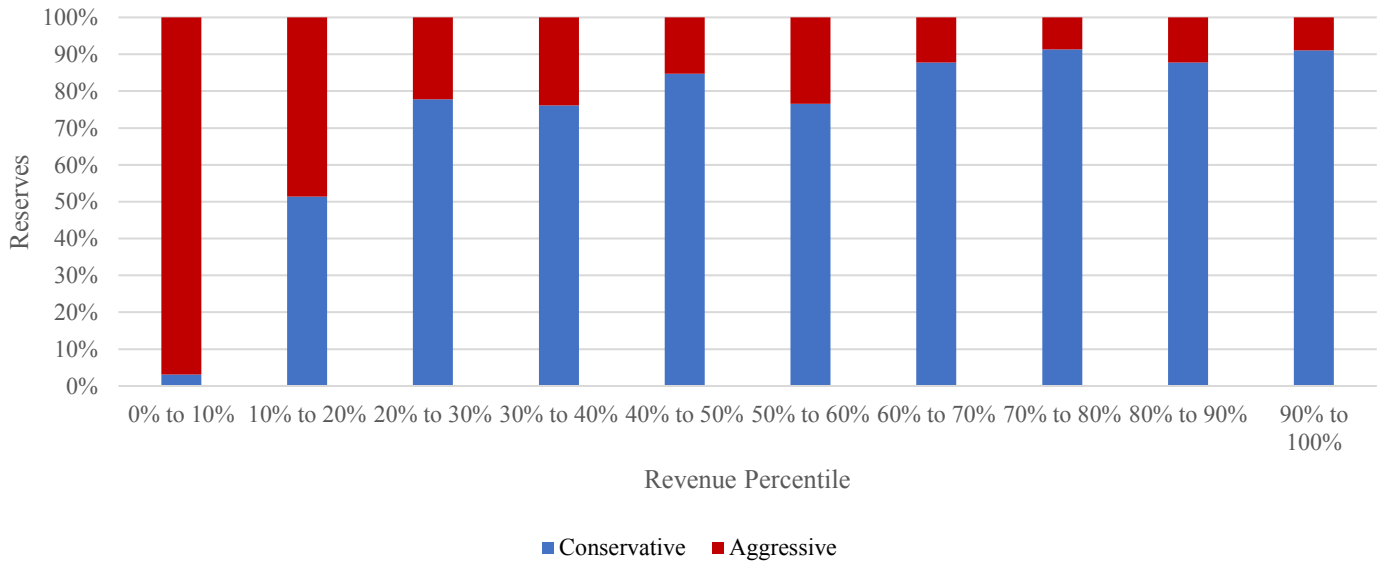


Appendix O.2: Medical Reserve Conservativeness by Revenue

**Total: Conservative Reserve Distributed by Revenue  
(Based on Number of Conservative Subsidiaries)**

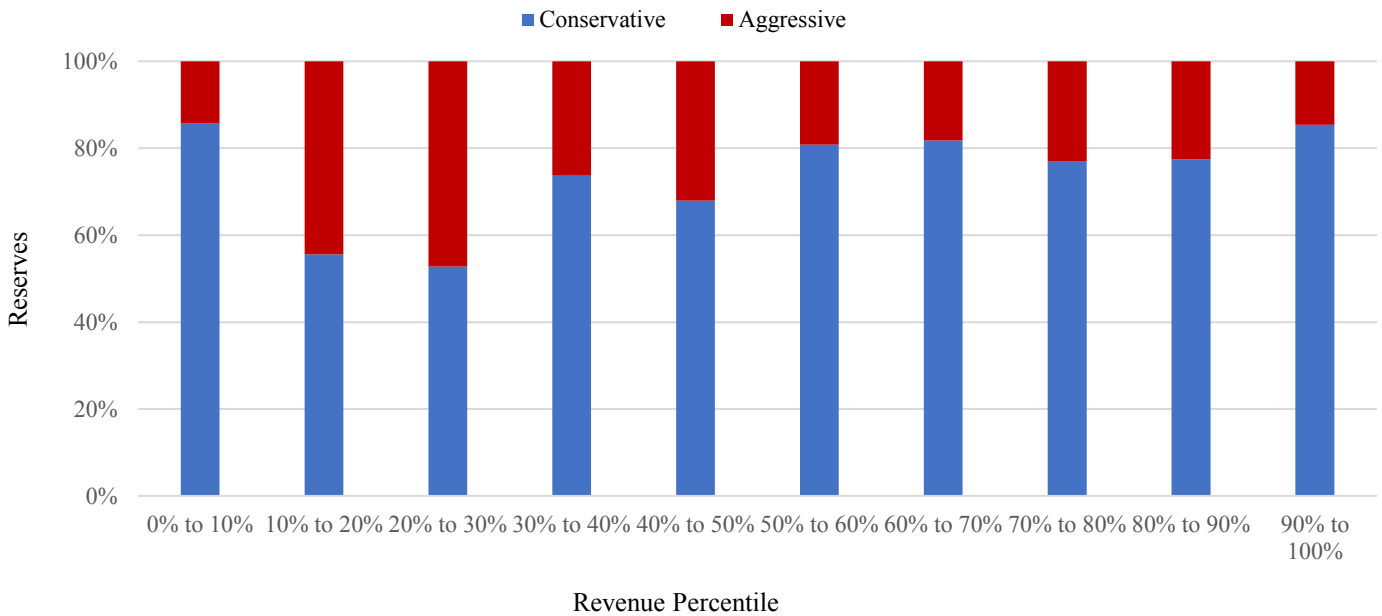


**Total: Conservative Reserve Distributed by Revenue  
(Based on Estimated Reserve Dollars)**

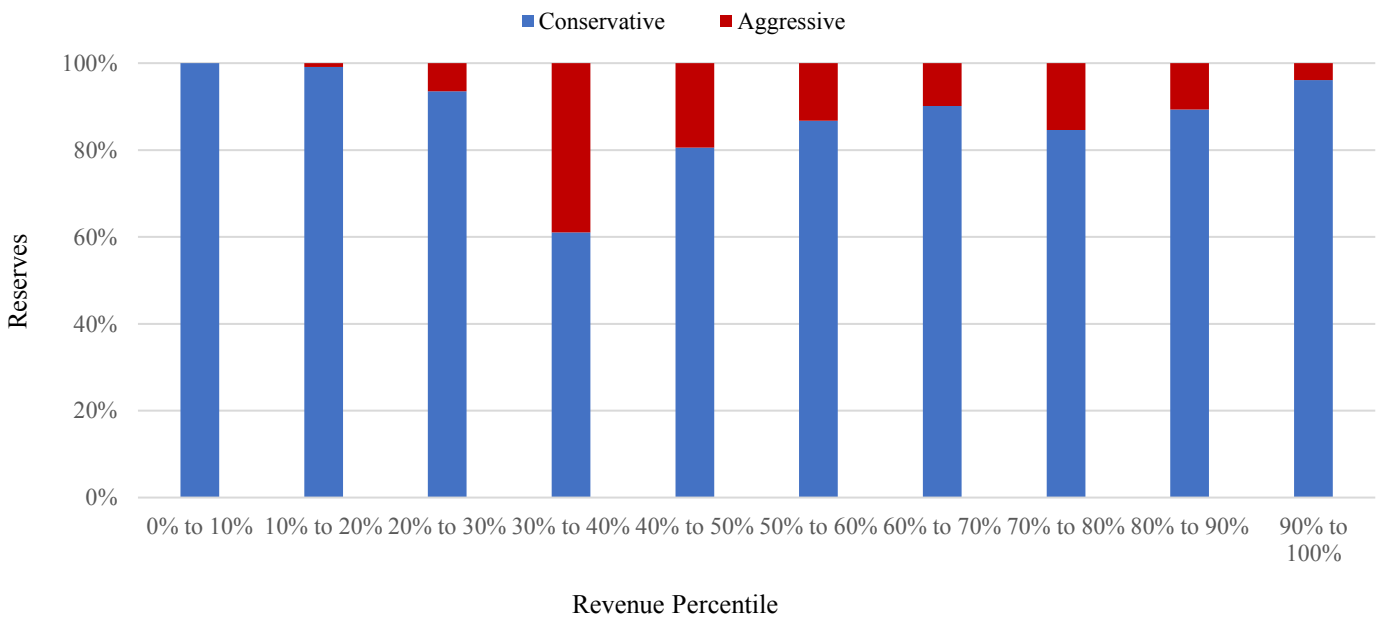


Appendix O.3: Medicare Reserve Conservativeness by Revenue

**Medicare: Conservative Reserve Distributed by Revenue  
(Based on Number of Conservative Subsidiaries)**

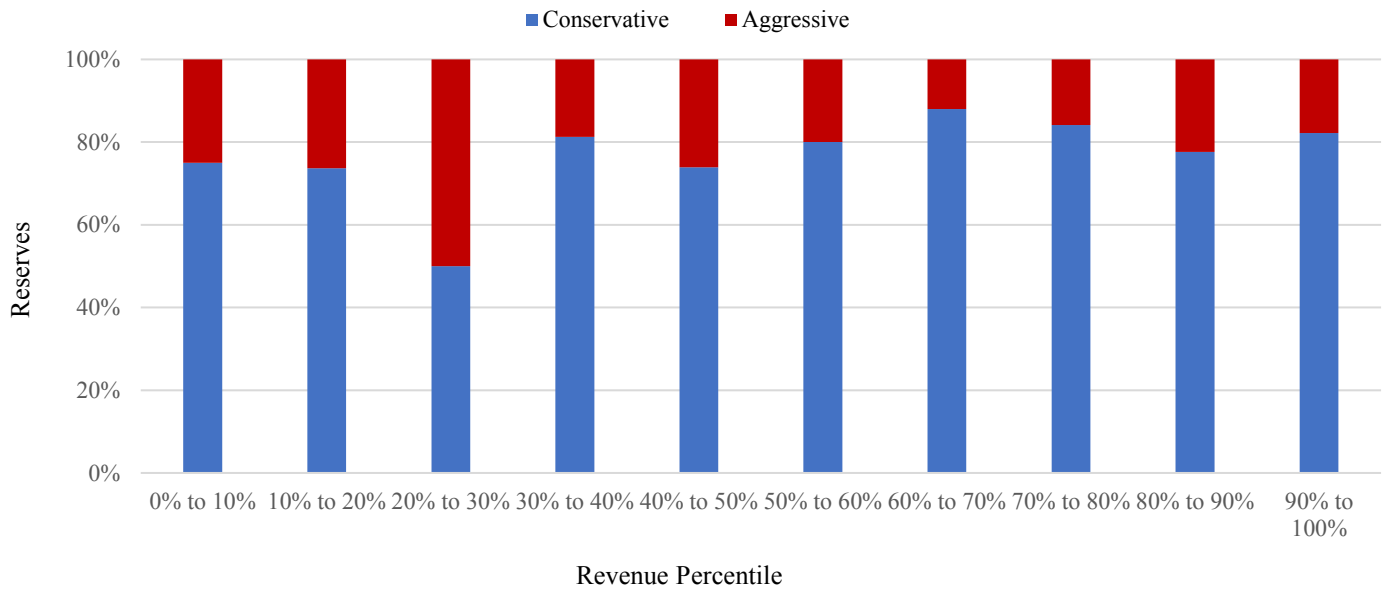


**Medicare: Conservative Reserve Distributed by Revenue  
(Based on Estimated Reserve Dollars)**

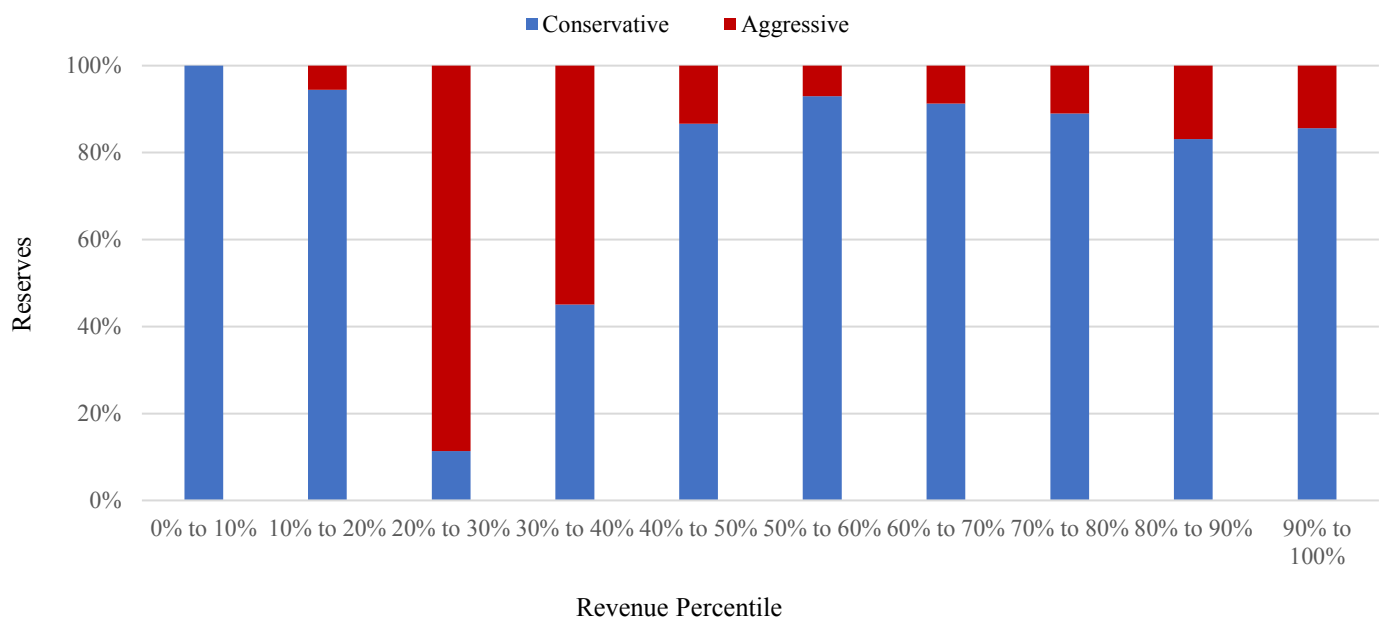


Appendix O.4: Medicaid Reserve Conservativeness by Revenue

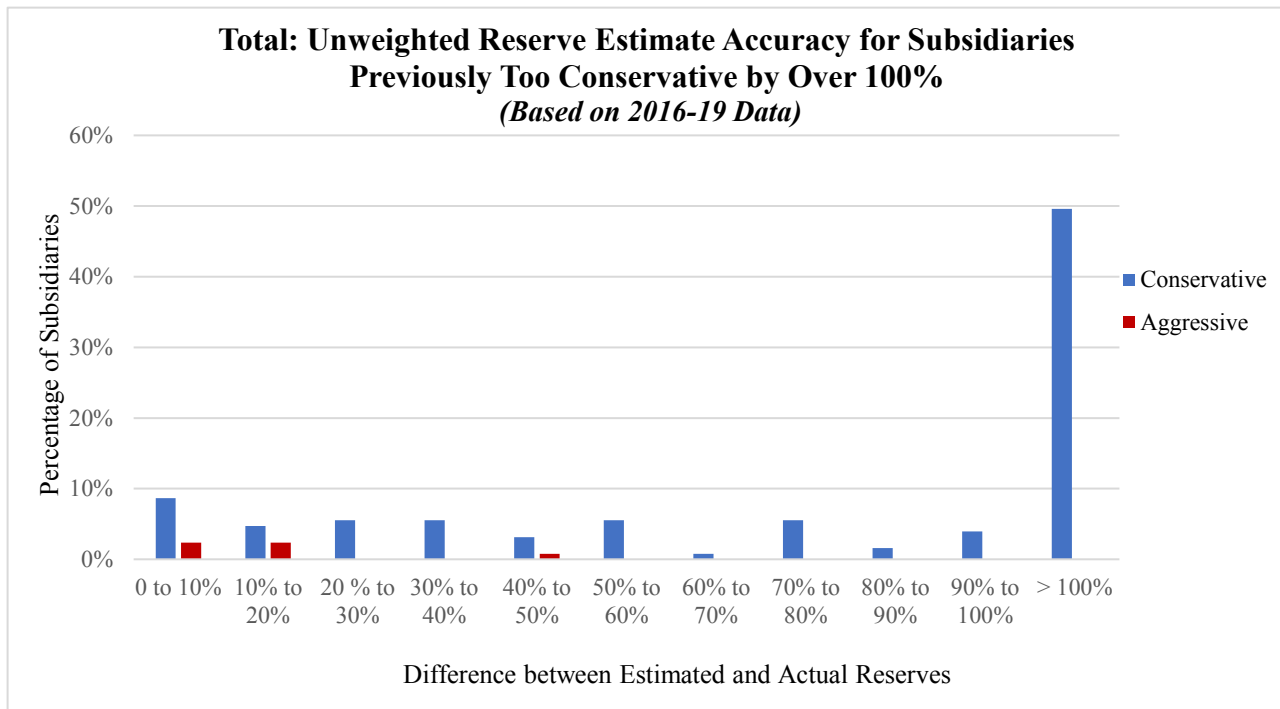
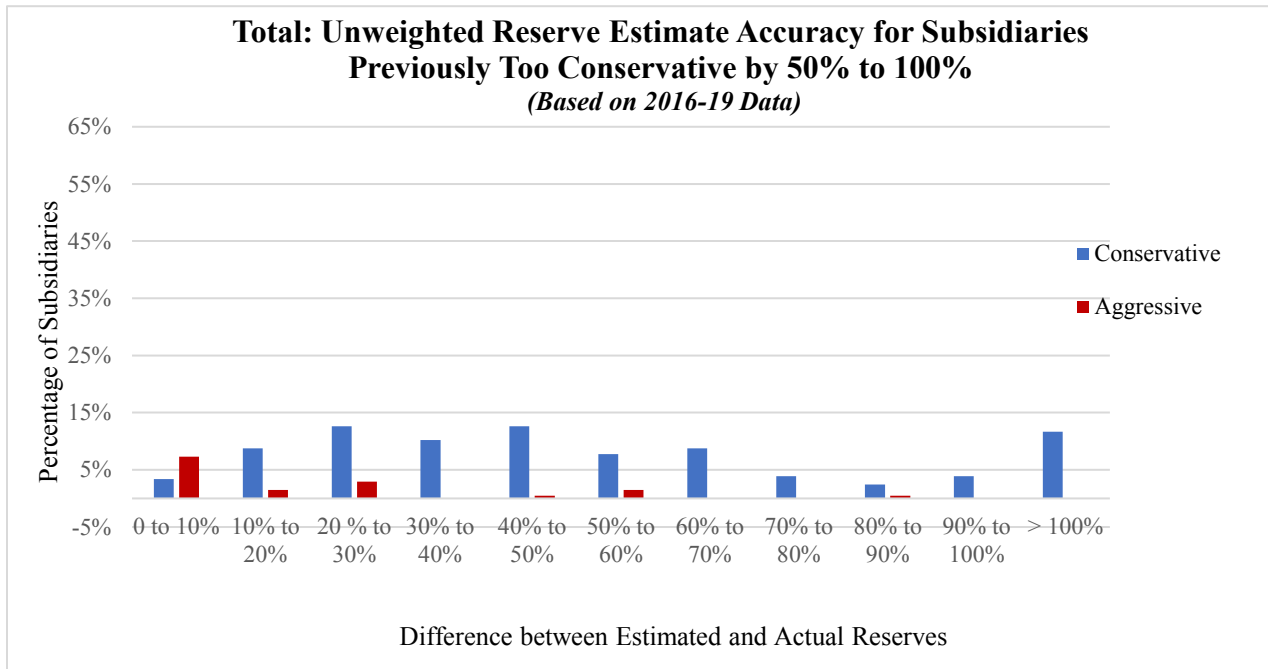
**Medicaid: Conservative Reserve Distributed by Revenue  
(Based on Number of Conservative Subsidiaries)**



**Medicaid: Conservative Reserve Distributed by Revenue  
(Based on Estimated Reserve Dollars)**

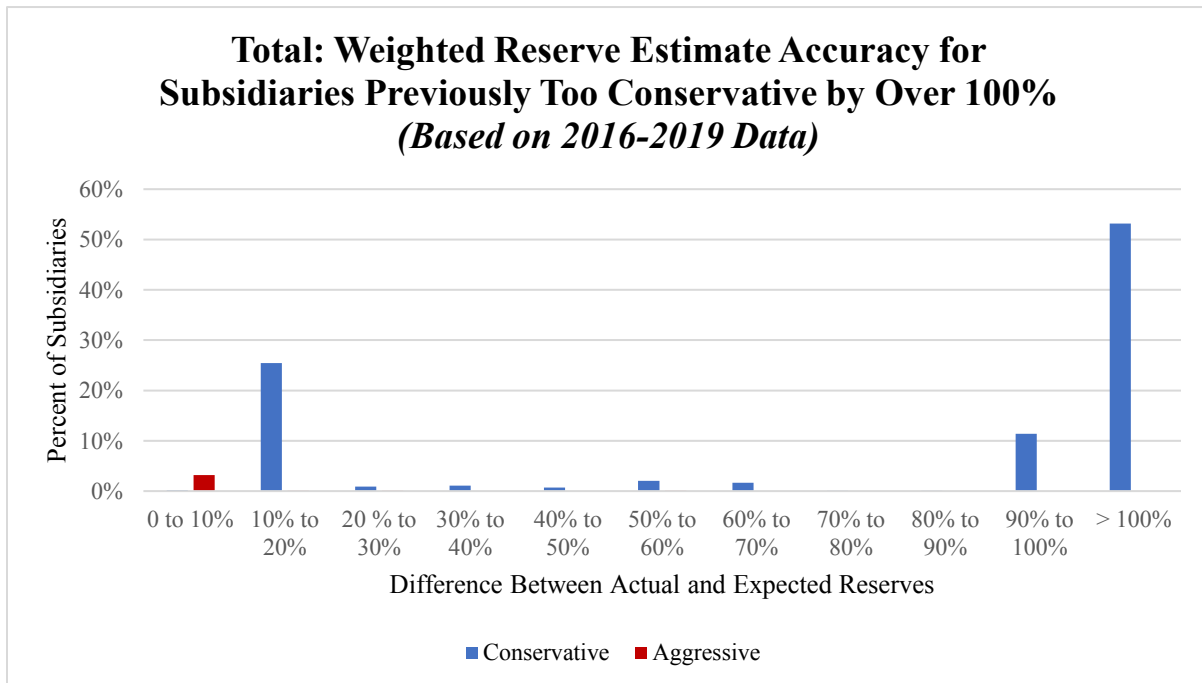
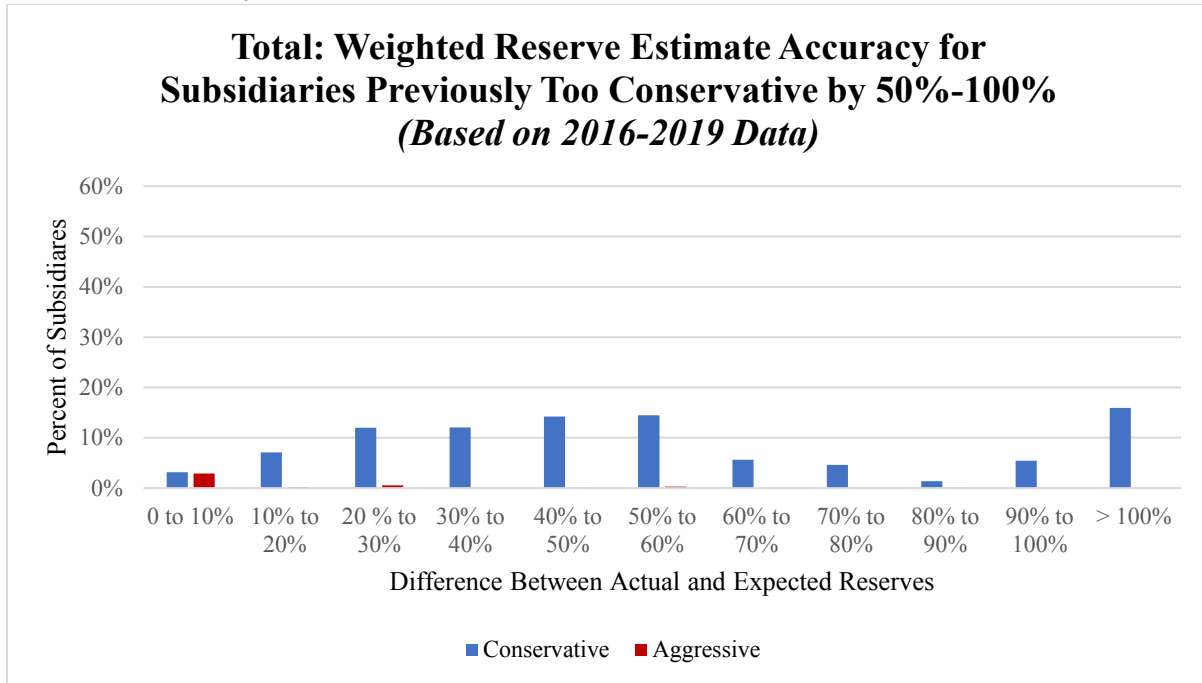


Appendix P: Unweighted 50-100% Extremely Conservative Distribution versus Unweighted 100%+ Extremely Conservative Distribution





Appendix Q: Weighted 50-100% Extremely Conservative Distribution versus Weighted 100%+ Extremely Conservative Distribution



## Appendix R: Prediction Model Calculations Example

The tables below walk through our prediction model calculations for the subsidiary C1653. C1653 was in 2018 reserve accuracy grouping 3, meaning, it was extremely conservative in 2018. Note that due to rounding differences, some of the calculations may not be exact.

Original Transition Matrix	-2	-1	1	2	3
3	5%	6%	10%	29%	51%

Attribute	Grouping and Event	Probability of Grouping	Probability for All Subsidiaries	Scale Factor	Transition Groupings to Apply Scale Factor
Switchers Conservativeness	0 P(Switching)	21%	14%	$.39/.21 = .67$	-2, -1
	0 P (Not Switching)	79%	86%	$.61/.79 = 1.09$	3, 2, 1
Switchers Accuracy	1 P(Switching)	19%	21%	$.19/.21 = .91$	1, -1
	1 P (Not Switching)	81%	79%	$.81/.79 = 1.02$	3, 2, -2
RBC Ratio	>200% P (Conservative)	84%	83%	$.84/.83 = 1.00$	3, 2, 1
	>200% P (Aggressive)	16%	17%	$.16/.17 = .98$	-2, -1
Reserve Size Conservativeness	1 P (Conservative)	83%	87%	$.83/.87 = .95$	3, 2, 1
	1 P (Aggressive)	17%	13%	$.17/.13 = 1.31$	-2, -1
Reserve Size Accuracy	1 P (Inaccuracy)	60%	55%	$.60/.55 = 1.09$	3, 2, -2
	1 P (Accuracy)	40%	45%	$.40/.45 = .89$	1, -1
Reserving Variance	1 P (Remaining Extremely Conservative)	49%	45%	$.49/.45 = 1.07$	3
Extremely Conservative 3 Year Trend	2 P (Remaining Extremely Conservative)	55%	39%	$.55/.39 = 1.4$	3
Public vs Private Conservativeness	N P (Conservative)	82%	83%	$.82/.83 = .98$	3, 2, 1
	N	18%	17%	$.18/.17 =$	-2, -1

	P (Aggressive)			<b>1.09</b>	
<b>Public vs Private Accuracy</b>	N P (Accurate)	<b>46%</b>	<b>42%</b>	.46/.42 = <b>1.1</b>	<b>1, -1</b>
	N P (Moderate)	<b>32%</b>	<b>35%</b>	.32/.35 = <b>.92</b>	<b>2, -2</b>
	N P (Inaccurate)	<b>22%</b>	<b>23%</b>	.22/.23 = <b>.95</b>	<b>3</b>
<b>Extremely Aggressive Adjustment</b>	N/A, 2018 estimate is not more than 50% too aggressive				

<b>New Transition Matrix</b>	<b>-2</b>	<b>-1</b>	<b>1</b>	<b>2</b>	<b>3</b>
<b>3</b>	.05* .67* 1.02* .98* 1.31* 1.09* 1.09* .92 =5%	.06* .67* .91* .98* 1.31* .89* 1.09* 1.1 =5%	.1* 1.09* .91* 1.00* .95* .89* .98* 1.1 =9%	.29* 1.09* 1.02* 1.00* .95* 1.09* .98* .92 =31%	.51* 1.09* 1.02* 1.00* .95* 1.09* 1.07* 1.4* .98* .95 =83%

5%+5%+9%+31%+83%=133%

<b>New Transition Matrix Probability Adjusted</b>	<b>-2</b>	<b>-1</b>	<b>1</b>	<b>2</b>	<b>3</b>
<b>3</b>	5%/133%= <b>3%</b>	5%/133%= <b>4%</b>	9%/133%= <b>7%</b>	31%/133%= <b>23%</b>	83%/133%= <b>63%</b>

## 8.0 References

Odomirok, Kathleen C, et al. “Part IV. Statutory Filings to Accompany the Annual Statement.”

*Financial Reporting Through the Lens of a Property/Casualty Actuary*, Casualty Actuarial Society, 2014, pp. 282.