Stochastic Reserves for Life Insurance: Modeling the Impact of a Pandemic

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Abstract

It is important to recognize the impact of the COVID-19 pandemic on different aspects of society and to analyze its effects to forecast future scenarios. The goal of this project was to analyze the impact of a pandemic on the reserves of a life insurance company. Reserve calculations were completed with pre-pandemic and post-pandemic factors to provide comparative data. The pandemic inputs impacted interest rates, mortality rates, infection rates, and lapse rates, and accounted for different regions of the US.

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Chapter 1: Introduction

The job of an actuary is to analyze and mitigate risk by studying past events and planning for future events. Actuaries are constantly looking to analyze outcomes and their effects on society or specific industries to better predict the future. However, there are some unexpected events that can simply never be predicted. A global pandemic is such an event, and it has affected many facets of society. The coronavirus pandemic has harmed many aspects of society from economics to public health. It is important to ask: what are the effects of a pandemic, how can they be measured, and how can we better plan for an event like this in the future?

The life insurance industry is one of many that have been impacted by the global pandemic. Life insurance companies pay close attention to their actuarial reserves, which are the amount of money that the company must hold in order to pay all future claims. Reserve calculations utilize many different inputs and information that the life insurance company receives from each person that they insure. In order to analyze the effects of a global pandemic on reserve calculations, additional inputs can be brought into the calculations and compared to the original reserves. These inputs reflect the impacts of a pandemic on public health and the economy.

The goal of this project was to analyze the impact of a pandemic on the reserves of a life insurance company. A model was developed in order to calculate stochastic reserves with variable inputs according to the disease and population being studied. The current COVID-19 pandemic was used as an example pandemic in the model created. The results of the model allowed for statistical analysis on the impact of the pandemic on a life insurance company. This model also allows for studies of other pandemics with different inputs, statistics and other populations.

Chapter 2: Background

2.1 Life Insurance Overview

2.1.1 Life Insurance Fundamentals

The overall concept of life insurance must first be explained. Individuals purchase a life insurance policy from a company. The purchaser is the insured and the company is the insurer. The life insurance policy is an agreement or contract in which the insured makes payments to the insurer in exchange for a promise that a benefit will be paid to a named beneficiary upon the insured's death. We will consider two main types of life insurance: term and whole life. Term insurance is a policy that expires after a set number of years, but these policies can be renewed. Whole life insurance policies last the entirety of the insured's life span.

There are several key pieces of information that a life insurance company needs to know about the insured. The first piece of information is the age of the person holding the policy when it was issued. The next element is the gender of the insured. Additionally, policyholders are generally grouped into different risk classes based on their health and lifestyle. Examples of risk classes are preferred, standard, or substandard. The gender, age, and risk class are used together to determine the specific mortality assumptions that are used for each policyholder. The next piece of information is the state or region in which the insured lives. The lifestyle and population density of certain regions gives the insurer information about how the policyholders' environment affects their lives. The life insurance company would also need to be aware of the age of the policy and the current age of the policyholder. These figures tell the insurer when the policy was issued, how many years are left in the policy, and the age of the policyholder today. An insurance company may offer many different types of insurance including whole life insurance and various term insurance policies. A company may also offer different death benefits such as $100,000, $500,000, and $1,000,000. The insured chooses the type and amount of their policy. Lastly, policyholders can choose to pay their premium with a single lump sum or an annual payment. All of these pieces of information are important for the insurance company's records.

2.1.2 Defining Premiums and Reserves

The premiums of a life insurance policy are the payments that the insured pays to the company. The calculation of these premiums can be done with basic first principles and can be demonstrated with an example. A given policy offers $B upon the death of the insured and the coverage lasts for three years. The policyholder will pay a premium at the beginning of each year and the benefit will be paid at the end of the year of death if death occurs within the three year coverage period; otherwise, no benefit is payable. First, we will define some basic first principles.

$$q_t = Probability\ of\ Dying\ in\ Year\ t \tag{2.1}$$

$$p_t = Probability\ of\ Living\ in\ Year\ t \tag{2.2}$$

The discount factor for a cash flow is v. A cash flow is discounted one year when it is multiplied by the discount factor v. To calculate the present value of the death benefit in our example policy, we must multiply the death benefit cash flow by the probability that the person dies in a given year and then discount back to time 0. This is completed for each of the three years. This concept will be reflected in the following formula:

$$Actuarial\ Present\ Value\ (Benefit) = (B \cdot q_1 \cdot v) + (B \cdot p_1 \cdot q_2 \cdot v^2) + (B \cdot p_1 \cdot p_2 \cdot q_3 \cdot v^3) \tag{2.3}$$

Similarly, we can find the present value of the premiums paid where the premium amount equals P, shown in the equation below. The premiums being paid are contingent on the fact that the policyholder lives.

$$Actuarial\ Present\ Value\ (Premiums) = P + (P \cdot p_1 \cdot v) + (P \cdot p_1 \cdot p_2 \cdot v^2) \tag{2.4}$$

The calculation of the premium is based on the following actuarial principle, combining the two prior formulas.

$$Actuarial\ Present\ Value\ (Benefit) = Actuarial\ Present\ Value\ (Premiums)$$

$$(B \cdot q_1 \cdot v) + (B \cdot p_1 \cdot q_2 \cdot v^2) + (B \cdot p_1 \cdot p_2 \cdot q_3 \cdot v^3) = P + (P \cdot p_1 \cdot v) + (P \cdot p_1 \cdot p_2 \cdot v^2) \tag{2.5}$$

This principle indicates that you can solve for P by factoring out the P and dividing the present value of the benefit by the present value of the premiums.

$$P = \frac{(B \cdot q_1 \cdot v) + (B \cdot p_1 \cdot q_2 \cdot v^2) + (B \cdot p_1 \cdot p_2 \cdot q_3 \cdot v^3)}{1 + (p_1 \cdot v) + (p_1 \cdot p_2 \cdot v^2)} \tag{2.6}$$

Actuarial reserves calculations are essential for any life insurance company. Actuarial reserves are the amount of money that the insurance company must have in order to pay all future claims. This amount is offset by the premiums that an insurance company expects to receive from policyholders in future years. One formula for actuarial reserves is as follows.

$$Reserves = Actuarial\ Present\ Value\ (Benefit) - Actuarial\ Present\ Value\ (Premiums) \tag{2.7}$$

The reserves for time 0 would be equal to zero as shown in the premium calculations. At time 0, the present value of the benefit is equal to the present value of the premiums. However, the reserves can change as the policy ages and as such the reserves calculations are vital for insurance companies so they can be sure they have enough to pay all claims. Using the example policy from above, the reserves at time 1, considering the remaining two years of benefits and premiums, are shown below.

$$Reserves = (B \cdot q_2 \cdot v) + (B \cdot p_2 \cdot q_3 \cdot v^2) - (P + (P \cdot p_2 \cdot v)) \tag{2.8}$$

Here is a numerical example showing how to solve for premium and reserves at time 1 for just one policy. The insured pays premium P at the beginning of each year and the benefit received at the end of the year of death is $1,000 and the interest rate is 5%. The following table gives the probability of dying and the probability of living through a given year.

t	**q_t**	**p_t**
1	.05	.95
2	.06	.94
3	.07	.93

Table 1: Probability for sample benefit and reserves calculations

To solve for the premium, we use formula 2.6:

$$P = \frac{\left(1000 \cdot 0.05 \cdot (\frac{1}{1.05})\right) + \left(1000 \cdot 0.95 \cdot 0.06 \cdot (\frac{1}{1.05})^2\right) + \left(1000 \cdot 0.95 \cdot 0.94 \cdot 0.07 \cdot (\frac{1}{1.05})^3\right)}{1 + \left(0.95 \cdot (\frac{1}{1.05})\right) + \left(0.95 \cdot 0.94 \cdot (\frac{1}{1.05})^2\right)} \tag{2.9}$$

This calculation shows that P is equal to $56.48 and the insured pays this premium at the beginning of every year. Now we can calculate the reserves at time 1. Time 1 is now the starting point for picking p's and q's from the table. We can use formula 2.8:

$$Reserves = \left(1000 \cdot 0.06 \cdot (\frac{1}{1.05})\right) + \left(1000 \cdot 0.94 \cdot 0.07 \cdot (\frac{1}{1.05})^2\right) - (P + \left(P \cdot 0.94 \cdot \left(\frac{1}{1.05}\right)\right)) \tag{2.10}$$

At time 1, the reserves are equal to $9.79. This is the amount of money the insurance company must have on hand to fund this individual policy.

2.1.3 Deterministic vs Stochastic Reserves

There are different approaches to calculating actuarial reserves: deterministic and stochastic. Using a deterministic reserves method gives a single best estimate on the amount of money that should be on hand. Alternatively, the stochastic reserves approach provides a distribution of estimates. The statistics of this distribution allow an insurance company to analyze different outcomes, their probabilities and how they can best protect the company from catastrophic loss (Carrato, McGuire, Scarth 2016).

Deterministic reserves can be calculated using one simple equation as shown above in Formula 2.7. Stochastic reserves calculations are a bit more complicated. A Monte Carlo simulation can be used to develop the stochastic reserves for each policy. The Monte Carlo process simulates an event many times in order to find the distribution of results. Each time the event is simulated, a random number is generated and is compared to the probability of a certain event occurring. If the random number is less than or equal to the probability of the event occurring, the event is recorded as a success. The outcome is recorded for each iteration to form a distribution of results. The average of these iterations can be found to compare the results to the single best estimate given by the deterministic reserves (Kenton 2020).

2.2 Effects of the COVID-19 Pandemic on Life Insurance

In order to demonstrate the model, the COVID-19 pandemic was used as an example. The effects of the COVID-19 pandemic have materialized within many different areas of society. In addition to the evident effects on citizens' health, widespread economic effects have been observed throughout the United States as well. The direct outcomes of the pandemic can be linked to changes in the life insurance industry. Life insurance companies rely on steady interest rates, mortality rate and lapse rate studies, and economic stability to accurately predict the reserves they need to have on hand to pay out their future claims. The COVID-19 pandemic has affected all of these aspects in various ways.

2.2.1 Impact on Interest Rates

The most important factor in the premium and reserving calculations that life insurance companies perform are the interest rates. All cash flows are discounted at a single chosen interest rate and it is important to pick a proper rate in these calculations. The COVID-19 pandemic ushered in a large drop in interest rates over the course of 2020. The benchmark Treasury rates fell nearly 100 basis points between February and March, which is about 1% (Schilling 9). These rates have not risen back to normal levels over the course of the Spring and Summer. As of the end of July, the 30-year, 20-year, and 10-year Treasury rates were down 77, 130, and 98 basis points respectively compared to the February rates (Schilling 9). These large drops in interest rates are direct effects of the coronavirus pandemic and should be taken into account by the life insurance industry.

2.2.2 Impacts on Mortality due to COVID-19 Infection Rates

Mortality rates play a large role in the premium and reserve calculations that life insurance companies perform as well. The health effects for those unfortunate enough to contract the disease include an increase in these mortality rates over the short-run, and adverse health-effects for the rest of their lives. The increase in mortality rates is driven by the infection rate of the disease. The infection rate is the probability of a person developing a disease. Once the person has been infected, the probability that they pass away increases. The number of people who have been infected and the people who have died from the disease are available on the CDC website and vary by age groups. This data is shown in the two tables below with the number of COVID-19 cases and the number of COVID-19 deaths split by age groups.

Age Group	Percentage	Count
0 - 4 Years	1.7	81,175
5 - 17 Years	6.5	305,307
18 - 29 Years	23.1	1,083,747
30 - 39 Years	16.9	792,093
40 - 49 Years	15.5	727,726
50 - 64 Years	20.9	982,707
65 - 74 Years	7.7	360,200
75 - 84 Years	4.4	206,863
85+ Years	3.3	156,341

Table 2: COVID-19 Cases by age group, Retrieved September 13, 2020. Data from 4,868,895 cases. Age group was available for 4,696,159 (96%) cases (CDC, 2020).

Age Group	Percentage	Count
0 - 4 Years	< 0.1	31
5 - 17 Years	< 0.1	49
18 - 29 Years	0.5	735
30 - 39 Years	1.3	1,896
40 - 49 Years	3.2	4,577
50 - 64 Years	15.7	22,236
65 - 74 Years	21.2	30,060
75 - 84 Years	26.4	37,453
85+ Years	31.6	44,875

Table 3: Deaths due to COVID-19 by age group, Retrieved September 13, 2020. Data from 141,926 cases. Age group was available for 141,912 (96%) cases (CDC, 2020).

The calculation of the mortality and infection rate for each age group is fairly simple.

$$Mortality\ rate = \frac{\#\ of\ deaths}{\#\ of\ infections} \tag{2.11}$$

$$Infection\ rate = \frac{\#\ of\ infections}{US\ Population} \tag{2.12}$$

The older age groups see a larger increase in mortality, if the disease is developed. The infection rates for these age groups stay fairly steady, but are larger for the youngest and oldest age groups (CDC 2020). Although many people have recovered from COVID-19, long lasting effects have also been observed in patients. These lasting effects include damage to the heart and lungs, and they cause an increase in mortality over the long run (Rees 2020). All of these rates are taken into account within a life insurance company's calculation.

2.2.3 Impacts on Lapse Rates

Lapse rates are also important in calculations performed by insurance companies. A policyholder lapses on their policy when they fail to pay the premium, and therefore, they forfeit the insured benefit. It has been concluded that lapse rates vary with rates of unemployment and economic health. Adjmal Sirak concluded that the event of becoming unemployed "increases the lapse rate by over 75%" (Sirak 15). COVID-19 has caused many negative effects on the United States economy including a large spike in unemployment rates. Official unemployment tripled in the first month of the pandemic from 4.4% to 14.7%. The U-6 rate, which refers to the unemployment rate including all full-time and part-time workers rose from 8.7% to 22.8%. These rates have since decreased, but still remain very high at 11.1% and 18.0% respectively. The subsequent initial unemployment claims, meaning the new claims of unemployment, totaled 54.1 million from March 14 to July 25 (Schilling 6). This increase in unemployment leads us to conclude that the COVID-19 pandemic has caused an increase in the lapse rate for life insurance policies.

2.2.4 Regional Impacts due to COVID-19

Different regions of the US have different infection rates due to population density and social distancing guidelines. High population density is a large contributor to a greater infection rate because there are more people in a smaller area. When the pandemic first hit the US, it was more difficult to slow the spread in these areas with high population density, such as large cities. Some states have created different mandates and guidelines that affect the infection rates. State mandates, such as mask mandates, help to decrease the infection rate by slowing the spread between people. In the heat map below, distinct regions are visible based on the total cases for each state as of September 28, 2020.

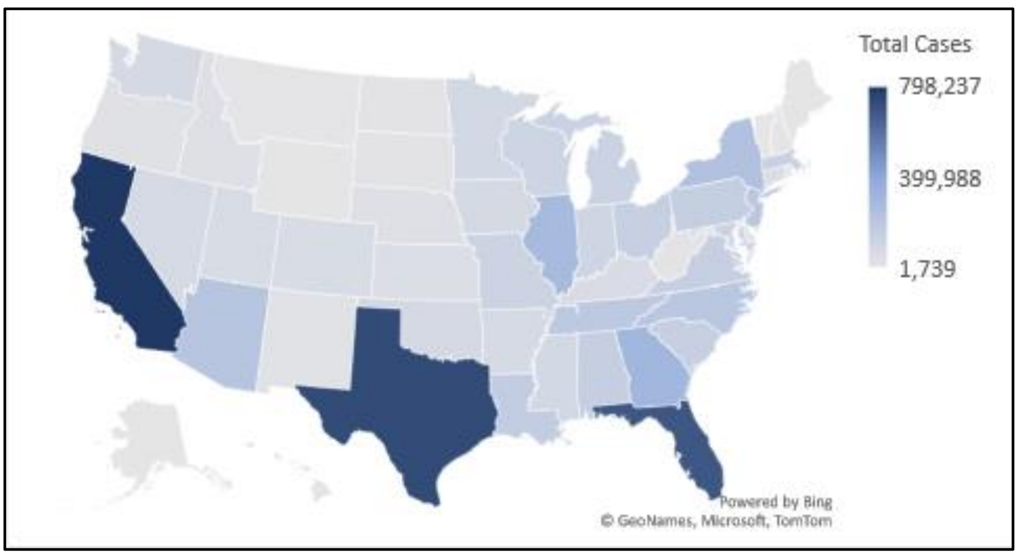

Figure 1: Heat map of COVID-19 cases by state (CDC 2020)

The northwest region of the country is very light due to rather small population densities. The southeast region is darker, highlighting a higher population density and lenient distancing and mask mandates. Differing regions must be taken into account by insurance companies.

Chapter 3: Methodology

3.1 Life Insurance Policy Block

In our model, the life insurance company has 5,000 policyholders. The development of the key characteristics of each policyholder is predominately random assignment; however, this was done on a stratified basis to ensure a reasonable mix across age groups, region, policy type, risk class, and benefit amount. The first column contains the age of the policyholder. The number of people in each age group were predetermined and then each policyholder in the group was assigned a random number between the two ages.

Breakdown of Policy Block by Age Group				
20-30	31-40	41-60	61-80	81-90
500	1000	1500	1500	500

Table 4: Ages of Policy Block

The next column contains the gender of the policyholder, male or female. Each policyholder was assigned a random number, either one for male or two for female.

The next column contains the region in which the policyholder lives, and this was done similarly to gender, using a random number generator. The next column is the type of insurance that the policyholder has. There are four different types: whole life, 10-year term, 20-year term and 30-year term. Using random numbers and the index function, approximately 25% of the policyholders were assigned to each type. There are also some restrictions on types that can be sold to certain individuals. Policyholders over the age of 60 are not allowed to purchase 30-year contracts due to the unpopularity of these contracts with older individuals. The next two columns show the age of the policy and the current age of the policyholder. Our insurance company was established eight years ago, so the age of each policy ranges between 0 and 8. Random number generators were used to assign a policy age to each policyholder.

The benefit for each policy is shown next. There are three benefit amounts: $100,000, $500,000 and $1,000,000. A random number generator was used to assign each policyholder a benefit amount. The next column contains the risk class assigned to the policyholder. The three risk classes are standard, preferred and substandard, and these account for 70%, 20% and 10% of the population, respectively. The last two columns indicate the premium type that is being paid, whether it is an annual payment, or a lump sum paid at issue. The 10, 20 and 30-year term policies can only be paid for with annual premiums, however the whole life premium can be either annual payments or a lump sum payment. The payment type was assigned accordingly, using random number generators to assign either annual or a lump sum payment for the whole life policies. All of this information is vital to the premium and reserving calculations.

3.2 Calculating Premiums

The first step in building our model was to calculate the premium for each policy using first principles. The Actuarial Present Value includes the probability of death as well as the probability of the policy lapsing and uses a single interest rate of 5% to discount cash flows. For each policy, the mortality rates are determined by the age and gender of the policyholder. The mortality tables used are from the SOA website. In order to calculate the premiums, we used Excel VBA. We looped through each policy and calculated the discounting factor for the benefit and the discounting factor for the premiums to then calculate the premium amount.

The discounting factor for the benefit is calculated by completing the following process:

$$benefit\ discounting\ factor = \frac{q_1}{1+i} + \frac{(1-q_1)(q_2)(1-l_2)}{(1+i)^2} + \cdots + \frac{(1-q_1)(1-q_2)\ldots(1-q_{t-1})(q_t)(1-l_2)(1-l_3)\ldots(1-l_t)}{(1+i)^t} \quad (3.1)$$

The q is the mortality rate, *l* is the lapse rate, *i* is the interest rate, and t is the last year of the policy. For each year, the product was added together to get the overall discounting factor as shown in the equation above. The benefit is assumed to be payable at the end of the year in which the policyholder dies. In our model, the policyholder cannot lapse in the first year as the premium is paid at the beginning of the year. The lapse rates are not incorporated into the equations until year two. In the equation above, the l_2 represents the policyholder lapsing in year two, therefore not paying their second premium.

Similarly, the discounting factor for the premium was calculated by completing the following process:

$$premium\ discounting\ factor = 1 + \frac{(1-q_1)(1-l_2)}{1+i} + \frac{(1-q_1)(1-q_2)(1-l_2)(1-l_3)}{(1+i)^2} + \cdots + \frac{(1-q_1)\ldots(1-q_{t-1})(1-l_2)\ldots(1-l_t)}{(1+i)^{t-1}} \quad (3.2)$$

The q is the mortality rate, *l* is the lapse rate, *i* is the interest rate, and t is the last year of the policy. The premiums are collected at the beginning of the year, as opposed to the death benefits that are given at the end of the year. The probabilities for each year are discounted back to time 0 using the discount factor v, with the first premium collected at time 0.

After we calculate the two discounting factors, the discounting factor for the benefit is then multiplied by the benefit amount for the policy. The policies in our policy block have either lump sum premium payments at the beginning of their policy period or annual premium payments for each year of their policy. For lump sum payments, the premium is calculated using formula 3.3.

$$Premium = benefit\ discount\ factor\ *\ benefit \tag{3.3}$$

For annual premium payments, using formula 2.4 from section 2.1.1, the premium is calculated using formula 3.4.

$$Premium = \frac{benefit\ discount\ factor * benefit}{premium\ discount\ factor} \tag{3.4}$$

3.3 Calculating Deterministic Reserves

The second step in building our model was to calculate the deterministic reserves for each policy using first principles. The code for the deterministic reserves was also written in excel VBA, similar to the premium calculations. Each policy was assigned a policy age at the start of our model, which tells us how long ago the policy was issued. The reserves are then calculated for the remaining years of the policy. As opposed to the premium calculation, which looped through each year of the policy starting at when it was issued, the reserves calculation loops through the remaining years starting at the policy age. Since we receive premiums at the beginning of the year, we calculated the reserves right after receiving the premium for the year of the policy age. This means the premium that was just received is not considered within the reserves. Similar to the premium code, in VBA, we looped through each policy and calculated the discount factor for the benefit and the discount factor for the premium.

The discounting factor for the benefit is calculated using the same process as for the premium calculation except the policy age is now time 0. Formula 3.5 shows the process below.

$$benefit\ discounting\ factor = \frac{q_{n+1}}{1+i} + \frac{(1-q_{n+1})(q_{n+2})(1-l_{n+2})}{(1+i)^2} + \cdots + \frac{(1-q_{n+1})(1-q_{n+2})\ldots(1-q_{t-n-1})(q_{t-n})(1-l_{n+2})(1-l_{n+3})\ldots(1-l_{t-n})}{(1+i)^{t-n}} \quad (3.5)$$

The q is the mortality rate, *l* is the lapse rate, *i* is the interest rate, t is the last year of the policy, and n is the policy age.

The premium discounting factor is calculated similar to the premium calculation. We looped through each year of the policy, with policy age equal to time 0. Formula 3.6 shows the process below.

$$premium\ discounting\ factor = 0 + \frac{(1-q_{n+1})(1-l_{n+2})}{1+i} + \frac{(1-q_{n+1})(1-q_{n+2})(1-l_{n+2})(1-l_{n+3})}{(1+i)^2} + \cdots + \frac{(1-q_{n+1})\ldots(1-q_{t-n-1})(1-l_{n+2})\ldots(1-l_{t-n})}{(1+i)^{t-n-1}} \quad (3.6)$$

The q is the mortality rate, *l* is the lapse rate, *i* is the interest rate, t is the last year of the policy, and n is the policy age. In this equation, the premium discounting factor for the first year is 0 because we are calculating the reserves right after we have received the premium for the current year.

After we calculate the two discounting factors, the discount factor for the benefit is multiplied by the benefit amount for this policy and the discount factor for premium is multiplied by the premium calculated for the policy. For lump sum payments, since we have already received the only payment for the policy, the reserves are equal to the benefit multiplied by the benefit discounting factor, as shown in formula 3.7.

$$Reserves = benefit\ discount\ factor\ *\ benefit \tag{3.7}$$

For annual premium payments, following the logic of formula 2.7 from section 2.1.2, the reserves are calculated using formula 3.8 below.

$$Reserves = (benefit\ discount\ factor * benefit) - (premium\ discount\ factor * premium) \tag{3.8}$$

Although the deterministic calculations will not be used directly in the analysis of this project, they were essential and serve as the baseline for the stochastic runs. In order to determine the correct amount of iterations for the stochastic runs, we compared the sum of the deterministic reserves to the sum of the stochastic reserves. We wanted to ensure that the percent difference between the deterministic and stochastic was less than 0.5%. We also did this comparison for each policy. On the individual policy level, we wanted to ensure that the percent difference was less than 15%. By doing this, we determined that one million was the necessary amount of iterations for our stochastic reserves.

3.4 Stochastic Reserves

After coding for the deterministic reserves, the next step was to build a stochastic model for reserves. A Monte Carlo simulation was used to calculate the reserves for each policy. The simulation was built in excel VBA, similar to the premium and deterministic reserves calculations. The code loops through each policy and runs the Monte Carlo simulation a specified number of iterations to determine an average outcome.

The simulation models what could happen with the life insurance policy beginning at the current time and looping through each year until the policy expires or another event causes the simulation to end. Each year, the simulation begins by generating two random numbers. The first random number is compared to the probability of the policyholder lapsing on the policy based on their age and the duration of their policy. If the random number is less than or equal to the given probability, the policy lapses and the simulation ends for that iteration. When a policy lapses, no death benefit is paid, so the present value of the death benefit is zero. If the policy does not lapse, the simulation continues, and the next random number is compared to the mortality rate based on the policyholder’s age, gender, and risk class. If the random number is less than or equal to the mortality rate, the insured dies, and the simulation ends. In this case, the death benefit is paid out and is discounted back to time 0, which is the policy age.

If the policy does not lapse and no death benefit is paid in a given year, the policy continues onto the next year. The term policies expire after a given number of years from issue, 10, 20, or 30, and the whole life expires after the policyholder is 120-years old specified by the mortality tables. The loop tests mortality and lapse random numbers against the probabilities and continues until a death or lapse occurs, or the policy expires. If the policy does not lapse in a given year, the premium is discounted back to time 0 and is added onto the previous years’ premiums. The process is the same for each year except for the current year, the first year of the loop. Since reserves are calculated right after the premium is collected, there is no premium discounted back in the first year of the loop. The reserves are calculated after the simulation is complete, using formula 2.7.

At the end of each iteration, the value for the reserves is calculated and are added together. After the given number of iterations is complete, the sum of reserves is divided by the number of iterations to find the average reserves. This number is directly compared to the deterministic reserves that were calculated. With a large enough quantity of iterations, the stochastic reserves average value will converge to the deterministic value.

3.5 Deterministic Reserves with Pandemic Inputs

The COVID-19 pandemic had large impacts on the inputs for reserve calculations performed by life insurance companies. Our model works to predict these impacts of a global pandemic on the reserves based on what has happened with COVID-19.

3.5.1 Impacts on Interest Rates

The economic effects of the pandemic are just as important to analyze as the health and safety impacts. Interest rates plummeted in March and have continued to stay low over the course of 2020. Our model includes a decreased interest rate for two years following the introduction of the disease into society. We predict that the duration of the pandemic is two years. We expect that the interest rate will rise back to normal levels as the economy heals. The decreased interest rate is 100 basis points below the interest rate used in the premium calculations as the US has seen drops of approximately 100 basis points in various interest rates in 2020 (Schilling 9).

3.5.2 Impacts on Mortality due to COVID-19 Infection Rates

The model also includes an increase in mortality for the duration of the pandemic. For each age group, the mortality rate was calculated given that a policyholder has contracted the disease based on CDC data. To incorporate this mortality rate into our model, we created a mortality rate multiplier for each age group. First, the average mortality of all the values pertaining to the given age group in the standard tables was found. Then, the mortality rates calculated from CDC data were divided by the average found from the tables. The result is the multiplier used to increase mortality for policyholders who contracted the disease in the first year of the pandemic. In the second year, the mortality rate is multiplied by the multiplier and divided by two. Due to the fact that hospitals have become more equipped to handle COVID-19 cases and new treatments have been used to treat the disease, the extra mortality used in year one was decreased in year two. It is easily deduced that a person who contracts COVID-19 now is more likely to live than someone who contracted the disease in March, which accounts for the decrease in extra mortality in the second year.

The infection rate of the disease was an important input for our model and was coupled with the mortality rate. The mortality multiplier was factored in for policyholders that contract the disease, so the probability that a policyholder gets the disease must be accounted for. In our deterministic model, the regular mortality taken from the table and the mortality with the given multiplier are weighted together. The infection rate is multiplied by the mortality with the multiplier and is added to one minus the infection rate multiplied by the regular mortality. This weighted mortality is used for the first year. In the second year the same process is used, but the mortality with the multiplier is divided by two to account for the improvement in care for Coronavirus patients.

	Age							
	20 - 30	**31 - 40**	**41 - 50**	**51 - 60**	**61 - 70**	**71 - 80**	**81 - 90**	**91 - 100**
Infection Rate	0.0254	0.0197	0.0167	0.0167	0.0166	0.0158	0.0287	0.0287
Mortality Rate If Infected	0.00068	0.0024	0.0063	0.0226	0.0835	0.1811	0.287	0.287
Mortality Multiplier If Infected	1.15114	3.08793	4.44796	6.98628	9.80085	8.06186	3.96304	1.24445

Figure 2: Infection & Mortality Inputs in Excel Model

Although our age groups do not line up exactly with the age groups from the CDC data, we generalized the infection and mortality rates to even age groups that made sense for our policy block. Since the COVID-19 pandemic is just used as an example in our model, the data does not have to be exact. The data was generalized to account for drastically changing data of the COVID-19 pandemic.

After two years, there is an extended mortality multiplier to account for long-lasting conditions caused by COVID-19. About 30% of people that contract COVID-19 experience damage to the heart or lungs or develop a lasting condition (Rees 2020). Some of these conditions include Myocarditis and other heart conditions. Based on the prognosis for Myocarditis given by Kühl, U., & Schultheiss, we determined the mortality for these conditions to be 40% (Kühl, U., & Schultheiss 2012). This extended mortality is the probability that there are lasting effects, 30%, multiplied by the mortality of the lasting effects, 40%. In our model, after the first two years the normal mortality rate from the table and the mortality with the extended mortality multiplier are weighted together. This method is used for all years after the pandemic to account for the lasting effects of COVID-19.

Long Term Effects	
% of people experience long term effects	0.3
Long Term Mortaility rate for effects	0.4
Extended Mortality Multiplier	1.12

Figure 3: Long Term Effect Inputs in Excel Model

3.5.3 Regional Impacts on Infection Rates

Throughout the United States, different regions, states, and even cities have introduced different COVID-19 guidelines and rules based on population densities and political opinions. The differing amount of social distancing and population density have resulted in varying levels of success in stopping the spread of the disease. For example, the low population density and strict travel and social distancing restrictions in Maine have interrupted the spread of coronavirus within the state. Maine has seen the second lowest amount of COVID-19 cases overall since March 2020. Other states with larger population densities and lenient social distancing guidelines have seen much larger numbers of the COVID-19 cases, such as Texas and Florida (CDC, 2020). In our model, the policyholders are split into four different regions. These regions vary in population density, social distancing measures, and guidelines. An infection rate multiplier was used for each region, either less than one to decrease the infection rates or greater than one to increase the infection rates. It was important to take into account the varying levels of infection throughout the country.

Social Distancing by Region (Population Density, mandates, closures etc)	1	2	3	4
Infection Rate Multiplier	0.5	0.75	1.25	1.5

Figure 4: Regional Inputs in Excel Model

3.5.4 Impacts on Lapse Rates

The last input for our model was a multiplier for the lapse rates. The pandemic ushered in a large increase in the unemployment rate in the United States. The official unemployment almost tripled at the start of the COVID-19 pandemic in March of 2020, going from 4.3% to 14.7%. The event of becoming unemployed increases a policyholder's probability of lapsing on their policy by 75% (Sirak 15). Taking the increase of unemployment, 10.3%, and multiplying by 75%, we get 7.725%. This percentage becomes our lapse rate multiplier within the model, increasing the lapse rates during the two year duration of the pandemic by 7.725%. To illustrate further, if we have 1,000 policyholders at the start of the pandemic, we would expect 103 or 10.3% to become unemployed. Of those 103 we would expect 77 or 75% of them to lapse on their policy because they have become unemployed. Overall, we expect an extra 77 out of 1000 policyholders to lapse due to COVID-19 effects on the economy. In our model, the lapse rates will be multiplied by 1.07725, which is the lapse rate multiplier calculated in this section.

Economy Effects		
Rate of Lapsing Policies Multiplier	1.07725	
Interest Rates	5%	4%
	non-pandemic	during pandemic

Figure 5: Economic Inputs in Excel Model, Lapse Rate Multiplier, and Interest Rates

3.6 Pandemic Inputs in Stochastic Reserves

The next step was to create the stochastic model with the pandemic inputs. The model with inputs is similar to the original stochastic code with no pandemic inputs. Each year, the simulation begins by generating three random numbers. The first random number is used to determine if the policyholder lapses in the given year. The random number is compared to the probability that the policyholder lapses. If the random number is less than or equal to the probability, the policy lapses that year and the simulation ends. The second random number is used to determine if the policyholder has contracted the disease. The random number is compared to the infection rate for the policyholder's given age group. If the random number is less than or equal to the probability of infection, the policyholder is labeled as an infected policyholder and is treated differently throughout the rest of the simulation. The third random number is used to determine if the policyholder dies in the given year. The random number is compared to the mortality rate for that year, and if the random number is less than or equal to the probability of death, then the policyholder dies. This mortality rate depends on if the policyholder is infected and in what year of the policy it is in.

In the first year of the loop, the model checks if the policyholder is infected using the infection random number as mentioned. If the policyholder is infected, they are labeled as an infected policyholder and the mortality random number is compared to the mortality rate times the mortality rate multiplier if infected as mentioned in section 3.4. If the policyholder is not infected, the mortality random number is compared to the normal mortality rate for the policyholder. In the first year, we assume the premium has just been paid, so the policyholders cannot lapse, similar to the model without pandemic inputs.

The second year of the loop has a similar process as the first, however we also checked if the policyholder lapsed. First, the lapse random number is compared to the lapse rate times the lapse rate multiplier mentioned in 3.4. If the random number is less than or equal to the modified probability of lapsing, then the model exits the loop and starts the next iteration. If the policyholder does not lapse, the model checks if the policyholder was infected in the previous year. If so, the mortality random number is compared to the modified mortality rate for year two, which is the mortality rate times the mortality rate multiplier divided by two. This will determine if the policyholder dies or continues to the next year. If the policyholder was not previously infected, the infection random number is compared to the infection rate. If this determines the policyholder is infected, then it follows the same process and compares the mortality random number to the modified mortality rate for year two. Lastly, if the policyholder has not been infected in year one or year two, the mortality random number is compared to the normal mortality rate for the policyholder.

For the rest of the years in the policyholder's term, the process is the same. First, the lapse random number is compared to the normal lapse rate. No lapse rate multiplier is applied after the two-year duration of the pandemic. Next, the model checks if the policyholder was infected during years one or two. If so, the mortality random number is compared to the mortality rate times the extended mortality multiplier mentioned in section 3.4 to take into account the lasting effects of the disease. If the policyholder has not been infected, the model compares the mortality random number with the normal mortality rate for the policyholder.

In any year, if the policyholder lapses, there is no death benefit, and the loop is exited. If the policyholder dies, the death benefit is discounted back to current time and the loop is exited. When the loop is exited due to a policy lapse, death or expiration, the iteration is complete, and a new iteration begins. At the end of each iteration, the value for the reserves is calculated and are added together. After the given number of iterations is complete, the sum of reserves is divided by the number of iterations to find the average reserves. The total iterations can be chosen within our model, and we used one million iterations. The one million iterations are completed for each of the 5,000 policyholders and an average number of reserves is returned within the excel sheet.

In our model, we seeded the random numbers in order to get the same random numbers every time we run the code for stochastic reserves with inputs. This method ensures that we get the same outcome every time in order to accurately compare pre-pandemic and post-pandemic runs. After we built our stochastic model with the pandemic inputs, we ran the model once with all of the inputs as expected and discussed earlier in section 3.5. We also ran our model with inputs that will not affect the reserves. For example, the following placeholder inputs were used. The infection rate was set to zero so that no one would be infected with the disease. The pandemic interest rate was set to the normal 5% interest rate. The mortality and lapse rate multipliers were all set to one so that they would not affect the mortality and lapse rates. With all these inputs, the model runs what would happen if the pandemic did not happen. Due to the seeding of the random numbers, the same random numbers are used when the model is run with the pandemic inputs and with the placeholder inputs, so the values are comparable.

Chapter 4: Findings and Analysis

The overall goal of this project was to assess how the pandemic inputs affect the stochastic reserves of a life insurance company. It was important to first assess the accuracy of our model. To do this, we used comparisons from the stochastic results to the deterministic results. Next, we looked to assess how the pandemic inputs affected the stochastic reserves. The pandemic caused an increase in mortality, lower interest rates, higher lapse rates and lasting health effects. There are many ways to analyze how the inputs of the pandemic are affecting individual policies, as well as groups of policies with similar characteristics. In this chapter, we will look in depth at the accuracy of our model and how the stochastic reserves are changing due to the COVID-19 pandemic.

4.1 Accuracy of Model

Assessing the accuracy of our model was vital in order to analyze the overall results. Manipulating the number of iterations completed in the stochastic reserves code improved the accuracy of these reserves when compared to the deterministic results. The first run of stochastic reserves was completed with just 10,000 iterations. These runs proved not to be accurate enough. The percent differences between the stochastic and deterministic reserves on the policy level ranged from 0 - 220%. A similar range of percent differences between deterministic and stochastic occurred with and without the pandemic inputs applied.

The mean and standard deviation for the percent difference between stochastic and deterministic reserves for pre-pandemic runs with 10,000 iterations were 11.55% and 22.38%

respectively. Similarly, the post-pandemic runs had a mean percent difference of 11.56% and standard deviation of 22.70%. The large mean and standard deviation help to further demonstrate the inaccuracy of using only 10,000 iterations.

To ensure greater accuracy, the amount of iterations for stochastic reserves was increased to 1,000,000. The increase in iterations drastically decreased the range of percent differences seen on the policy level to 0 - 15%. The mean percent difference between stochastic and deterministic reserves decreased from 11.55% with 10,000 iterations to 0.68% with 1,000,000 iterations for pre-pandemic runs. A similar drop was seen for post-pandemic runs, from 11.56% to 0.97%. There is also a decrease in the standard deviation proportionate to the decrease in the mean. For pre-pandemic runs, the standard deviation dropped from 22.38% with 10,000 iterations to 1.08% with 1,000,000 iterations. Similarly, the standard deviation dropped from 22.70% to 1.15% for post-pandemic runs. The decrease in mean and standard deviation help to emphasize the improved accuracy with 1,000,000 iterations.

The comparison of stochastic reserves with 10,000 iterations and 1,000,000 iterations can be seen in the graph below. The percent difference for each policy with 10,000 iterations is overlaid with the percent difference for each policy with 1,000,000 iterations. The orange bars are the 10,00 iterations and the blue bars are the 1,000,000 iterations. The large range for 10,000 iterations can be easily seen in Figure 6, compared to the smaller range for the larger number of iterations.

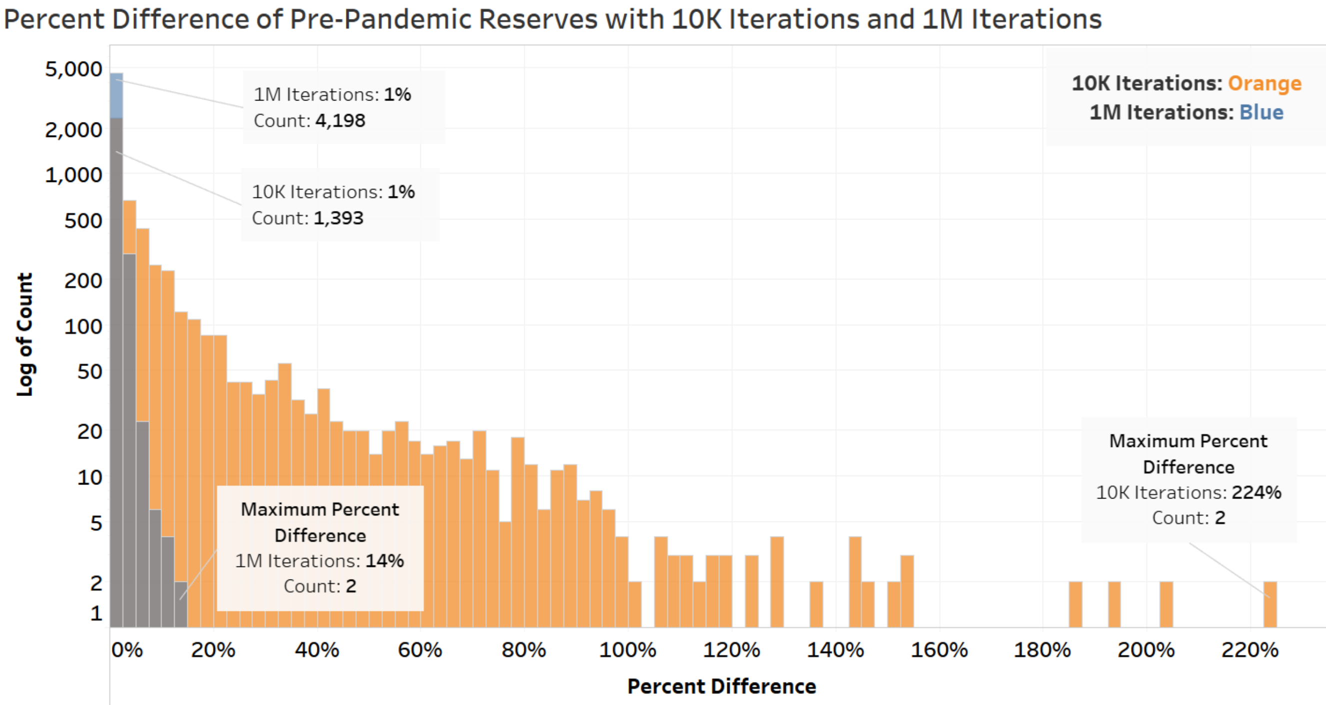

Figure 6: Percent Difference Between Pre-Pandemic Deterministic and Stochastic Reserves with 10K Iterations and 1M Iterations

Although there is a large increase in accuracy from 10,000 to 1,000,000 iterations, there are still policies with percent differences from deterministic to stochastic as large as 15%. These larger differences are not concerning in the context of the model. All of these differences are due to random variation and are occurring in policies with younger policyholders. These policyholders have relatively small values of reserves. A small change in the present value of premiums or benefit can cause a large percent difference between stochastic and deterministic reserves. This concept is more easily explained with an example. Policyholder 327 is a 26-year-old female with a $100,000 policy and is in a standard risk class. The policyholder makes annual payments and is in the first year of a 10-year term policy. The deterministic reserves are $24.45, and the stochastic reserves are $20.67. The percent difference in stochastic and deterministic reserves is 15.58%, however, there is only a $4 difference in the reserves. Overall, this percent difference seems large on the policy level, but the $4 compared to our total reserves is extremely small. It is 0.0000017% of the total stochastic reserves.

There are also slightly larger mean and standard deviations between stochastic and deterministic reserves for post-pandemic runs. The pandemic inputs provide more variation in the possible outcomes for the stochastic reserves. The code generates 3 random numbers, however, in the pre-pandemic reserve calculations the random number generated to determine infection is not used. In the post-pandemic reserve calculations, all 3 random numbers are used, creating the possibility for larger variation on the policy level and accounts for the slightly larger values appearing for post-pandemic runs.

4.2 Impacts of the Pandemic

With the pandemic modifications, we expected the stochastic reserves to increase, both on the policy level and the total reserves for the company. The total stochastic reserves for the company with no pandemic inputs was found simply by adding all the reserves for each policy together. The total stochastic reserves pre-pandemic is $216,795,901. After applying inputs and using the seeded random numbers, we found the total stochastic reserves post-pandemic are $224,512,830. The stochastic reserves increased by $7,716,929 or 3.6%. On the policy level, there was an increase in reserves for every policy.

In order to see how the stochastic model was working on an individual policy level, we printed out each iteration for one policy from the stochastic pre-pandemic and the stochastic post-pandemic reserves. Below are histograms that show each of the 1,000,000 iterations for policyholder 23 in our policy block. This policyholder is a 32-year-old standard female with 6 years left on her 10-year term coverage. The benefit amount is $100,000 and premium payments are annual. This policyholder was chosen because the percent increase post-pandemic for this policy was similar to the average of the percent increase for all 5,000 policies. The percent increase for this policy was 5.26% and the average for all policies was 5.12%. This average of 5.12% is larger than the overall percent increase of 3.6% because it does not take into account the weights associated with policy amount. Examining the totals in each bin of the histograms, it can be seen that there is a slight shift of reserves to the right. For example, in the pre-pandemic histogram, the -10K-0 bin contains 937,862 iterations. This bin in the post-pandemic histogram decreases by 4,675 to 933,187 iterations. The iterations are shifting from negative to positive reserves and show that there are more benefits being paid out post-pandemic. Each bin after the -10K-0, increases from pre-pandemic to post-pandemic. For example, the last bin of 90K-100K increases from 511 to 527 for pre-pandemic to post-pandemic, respectively.

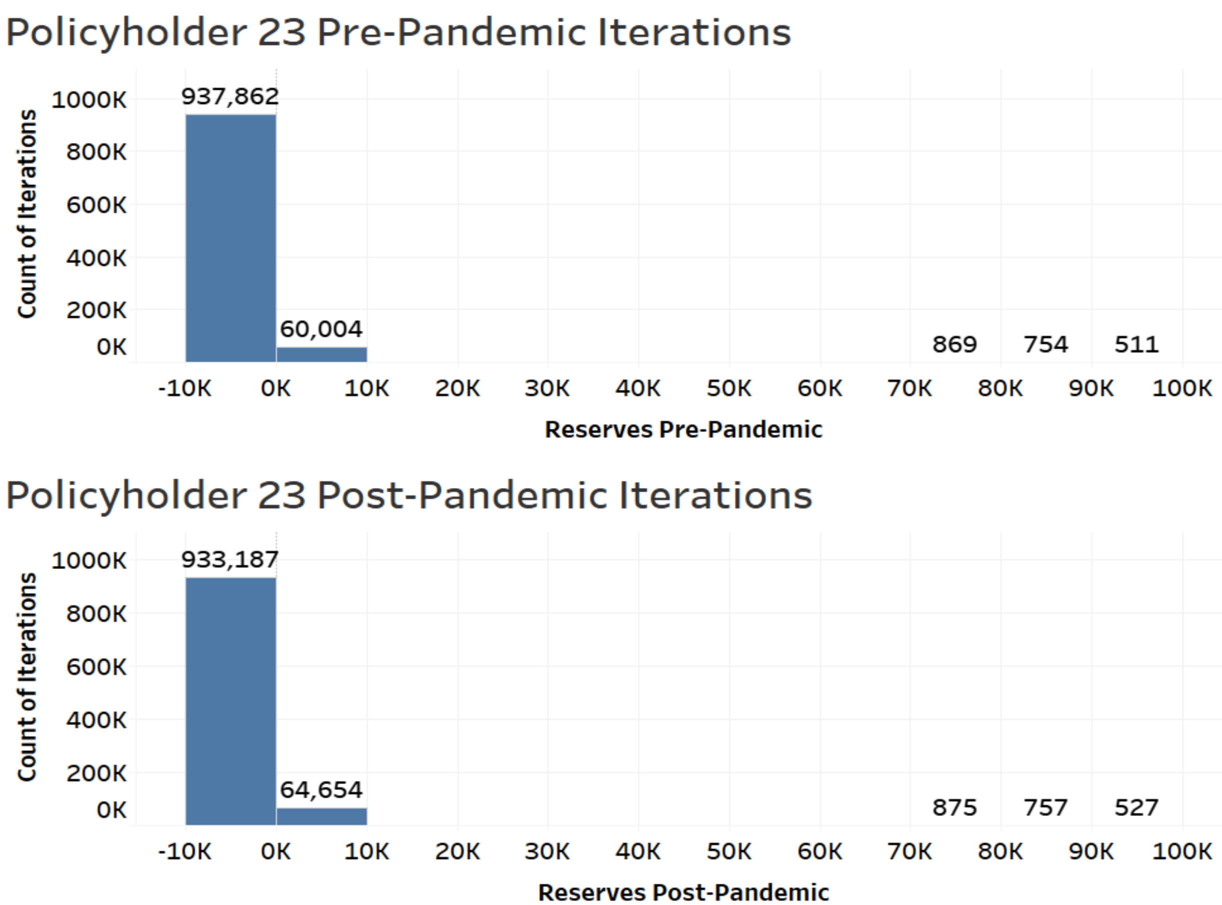

Figure 7: Histograms of Pre-Pandemic and Post-Pandemic Stochastic Reserve Iterations

Another way to show the impact of the pandemic inputs is through a deterministic waterfall. This waterfall effect is shown when specific inputs are layered on one by one. In our case, we started by adding the mortality and infection rate first, as we predicted it would have the largest impact. Next, we added in the infection rate multiplier. Then, the lapse rate multiplier followed by the change in interest rate, and lastly the extended mortality. The change in reserves from one input to the next for one specific policyholder are shown in figure 8. This policyholder was chosen because the pandemic inputs caused a large increase in their reserves. Policyholder 2877 is a 65-year-old preferred female living in region four with three years left on her 10-year term policy. The benefit amount is $500,000 and annual premium payments are made. The overall percent increase in reserves post-pandemic for this policy is 18.34%. The pre-pandemic reserves are $3,746 and the post-pandemic reserves are $4,433. Overall, this is an increase of $687, but it is more interesting broken down by the layering of the inputs. For example, by just layering in the mortality and infection rate, the reserves increased by $411. There was also a $205 increase by layering in the infection rate multiplier. This policyholder lives in region four which had the largest infection rate multiplier, so we expected a large percent increase from this input. For this policy, the reserves are increased each time by layering in another input, except for the lapse rate multiplier. It is important to note that the lapse rate multiplier actually causes a decrease in reserves. This is due to the fact that more policies are lapsing. Although we are not receiving premium payments, we are also not paying out as many benefits, so this causes a decrease.

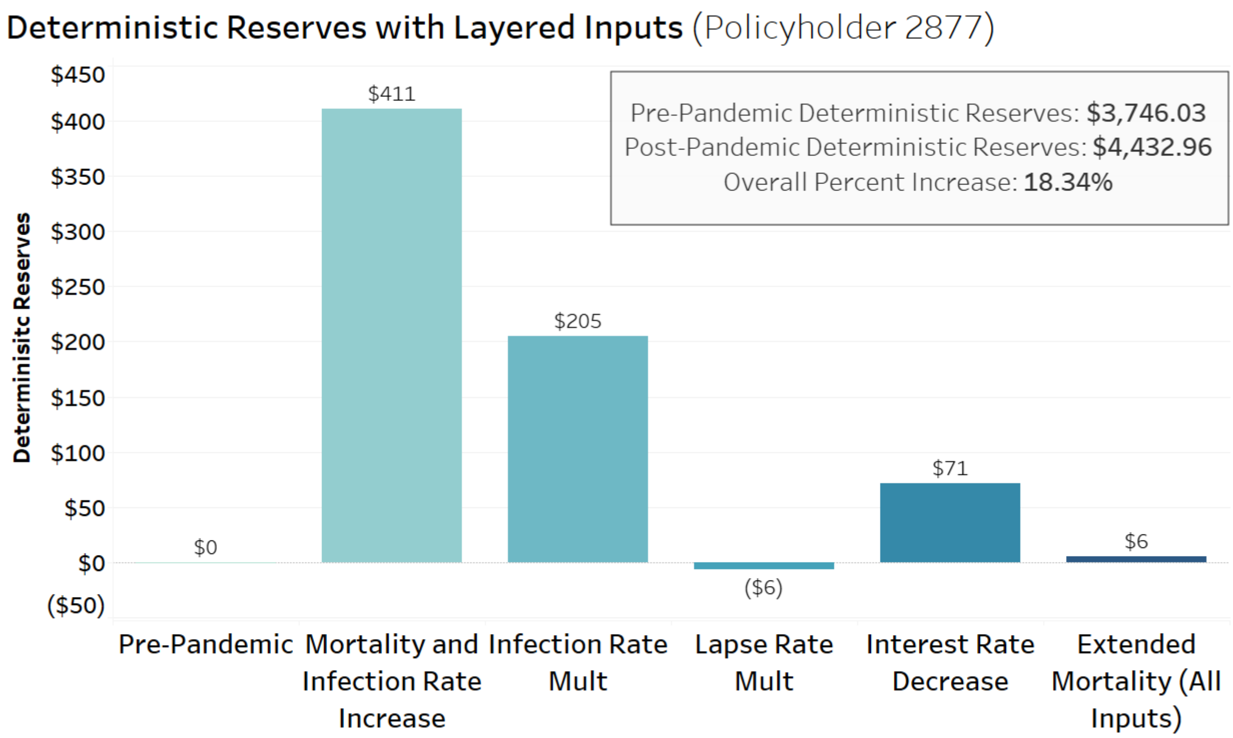

Figure 8: Deterministic waterfall for policyholder 2877 with layered pandemic inputs

Next, Policyholder 50 is examined for changes in reserves from one input to the next. This policyholder is dissimilar to policyholder 2877 shown in figure 8 in that the pandemic inputs had very little effect on the value of the reserves. Policyholder 50 is a 28-year-old standard female living in region 3 with 2 years left on a 10-year term policy. The benefit is $100,000 and annual payments are made. The overall percent increase in reserves post-pandemic for this policy is 0.95%. The pre-pandemic reserves are $40.41 and the post-pandemic reserves are $40.79. Figure 9 shows how each input affects the reserves. Policyholder 50 had a much smaller percent difference in pre-pandemic and post-pandemic reserves than policyholder 2877, despite similarities in many attributes. Both participants are preferred females with a small number of years left on their 10-year term policies, however there is one difference that accounts for the much smaller percent change in Policyholder 50's reserves.

The difference in the two policyholders that is causing Policyholder 50 to have a much smaller percent increase in reserves is the age. The mortality rates in the tables are smallest for the youngest policyholders and increase as the age of the policyholder increases. Also, the mortality multiplier that is applied if the disease is contracted is largest for the policyholders between 61-70, which means the largest multiplier is applied to policyholder 2877. The smallest mortality multiplier is applied to ages 20-30, which means the smallest multiplier is applied to policyholder 50. This accounts for the much smaller increase in reserves for Policyholder 50.

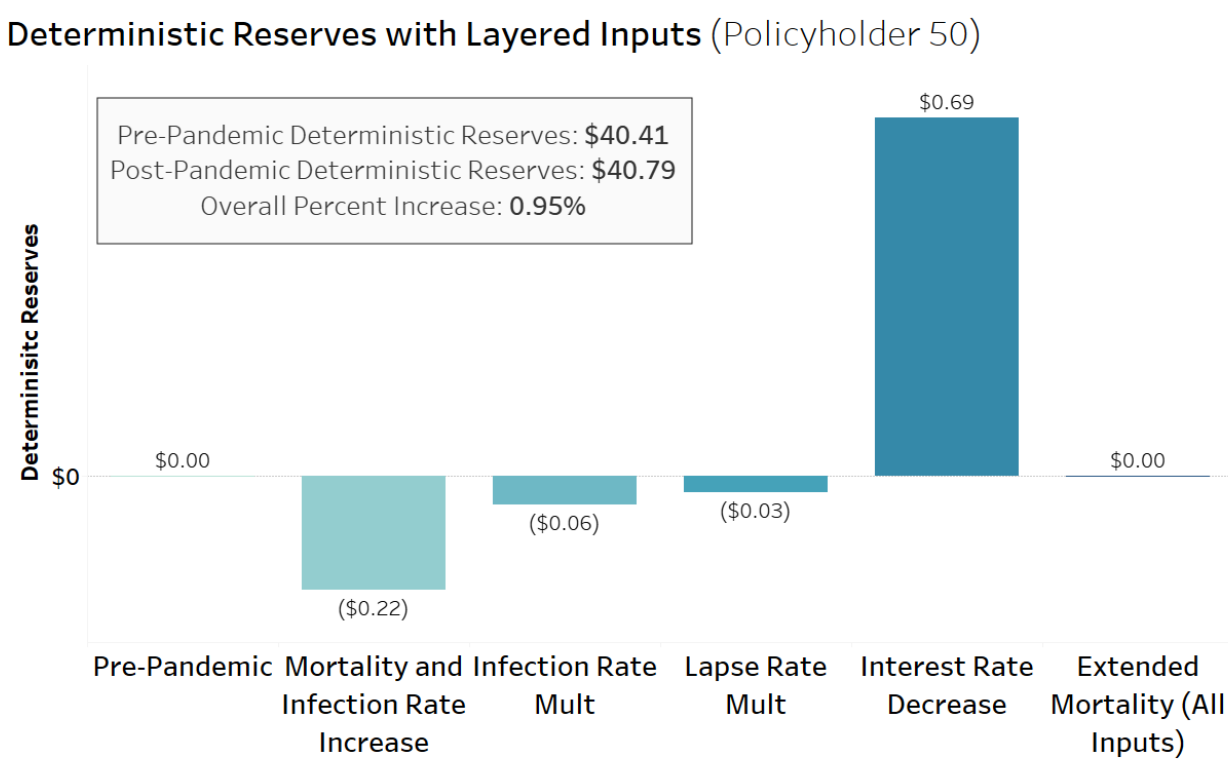

Figure 9: Deterministic Waterfall for Policyholder 50 with layered pandemic inputs

4.2.1 Policy Type

There are many factors to consider when looking at the overall results. The first is the policy type. The model has four different types of policies: 10-year term, 20-year term, 30-year term, and whole life. Figure 10 shows the average percent increase for the policies of each type.

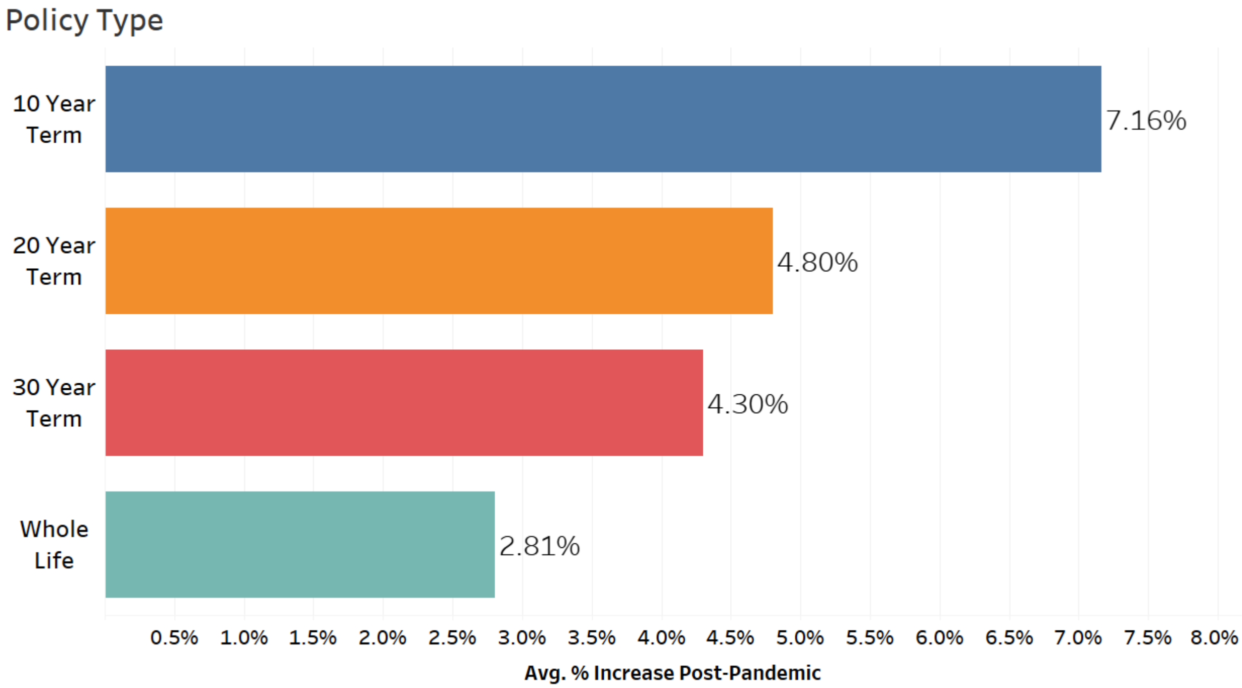

Figure 10: Average Percent Increase in Reserves by Policy Type

We see the largest increase for the 10-year term policies with an average of 7.16%. As the length of the policy increases, the impact of the pandemic decreases. This is due to the inputs that mainly affect the first two years. The infection rates, added mortality, and the lapse rate multiplier affect the two years of the pandemic and the largest changes occur during that time. For the 10-year term policies, there is less time for the reserves to converge back to pre-pandemic levels. The changes in the first two years do not impact the total reserves as severely for policies with many years left.

4.2.2 Regions

Another characteristic to examine was the region in which the policyholders lived. There are four regions, each assigned an infection rate multiplier based on population densities and political opinions. Figure 11 shows the average percent increase for policies in each region.

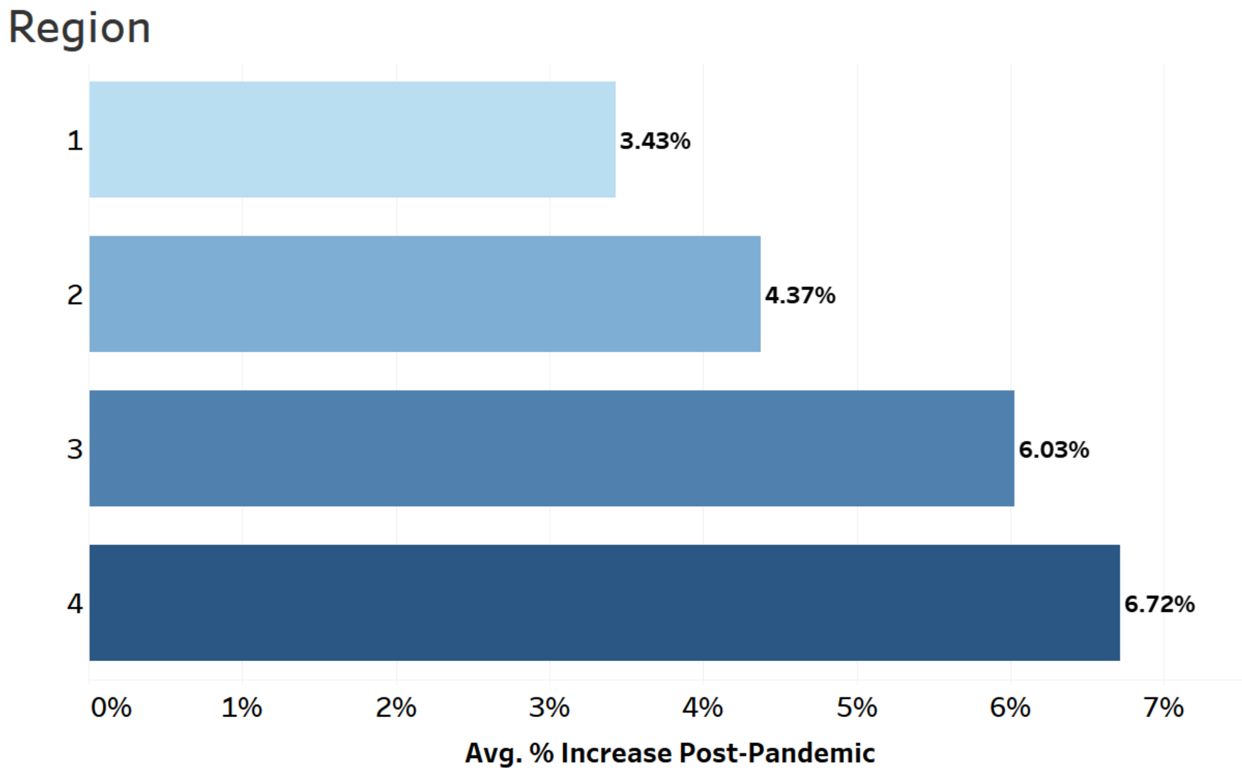

Figure 11: Average Percent Increase in Reserves by Region

These results are exactly what we expected based on the multipliers assigned to each region. The first region has the smallest bar, indicating that policies associated with region one showed the smallest average percent increase in reserves. This region also had the smallest infection rate multiplier at 0.5. It is also seen that region four has the largest bar, indicating that policies associated with region four showed the largest average percent increase in reserves. This region had the largest infection rate multiplier at 1.5. It is clear that as the infection rate multiplier increases, the average percent increase in reserves also increases. This input is important in order to distinguish regions in which the pandemic is being handled differently and regions that would naturally be impacted more by the pandemic.

4.2.3 Current Age and Year Left in Policy

Another characteristic to analyze is the age of the policyholders. The percent difference for each age group must be categorized again by the number years left in the policy to account for the construction of the policy block. No one over the age of 60 was allowed to obtain a 30-year policy and this is reflected in the percent differences between stochastic and deterministic for each age group. Figure 12 shows the percent increases by number of years left in the policy and by age group.

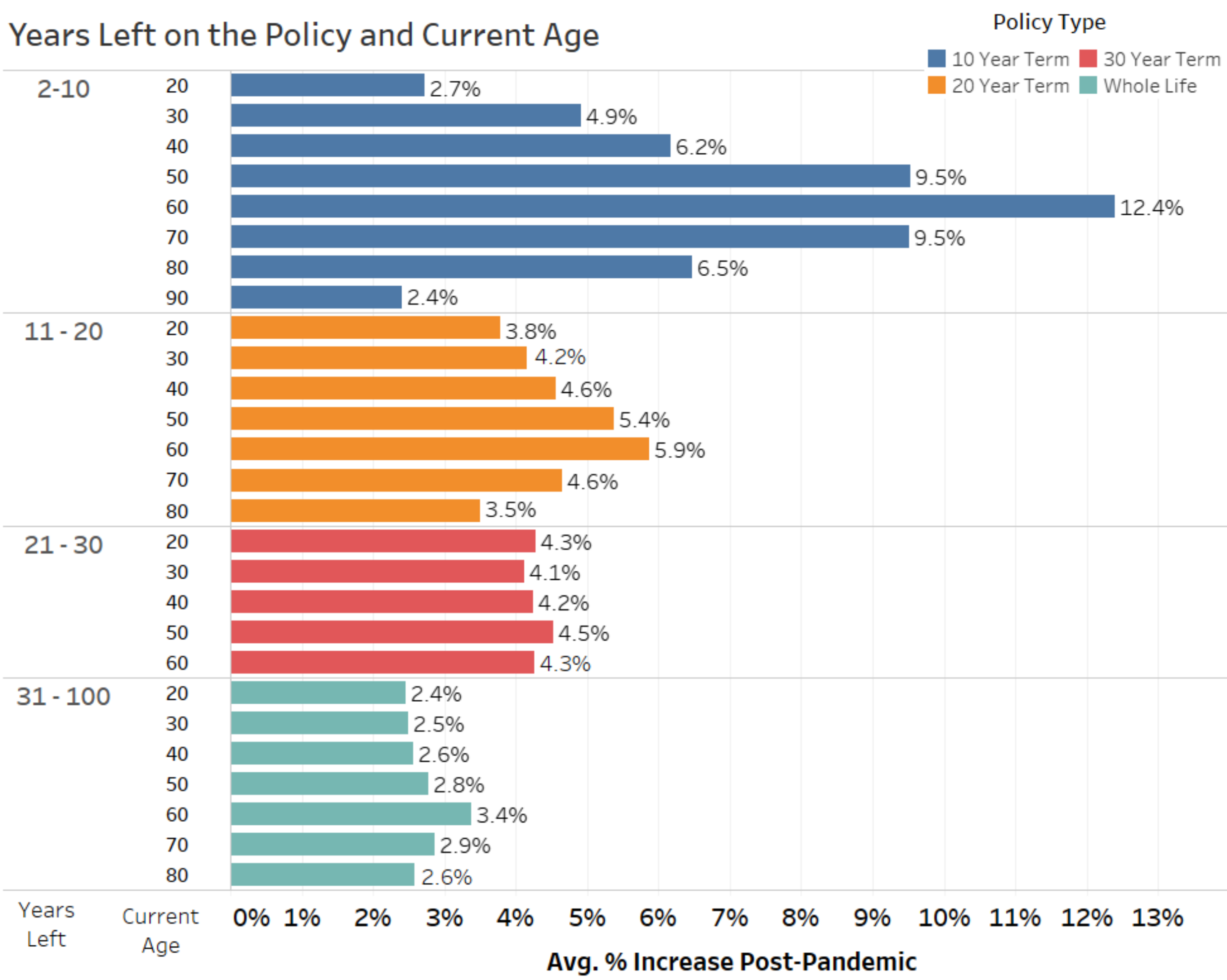

Figure 12: Percent Increase in Reserves by Number of Years Left on the Policy and Current Age

The graph shows that the policies with a lower number of years left are impacted more by the pandemic inputs. This is largely due to the pandemic inputs impacting the first two years after the pandemic begins. The policies with a larger amount of years left are able to recover after the impacts of the first two years. These results are consistent with the results seen in Figure 10, showing that the policy types with larger numbers of years are impacted less harshly by the pandemic inputs.

The graph also illustrates how the pandemic inputs affect each age group. These results are exactly as expected based on the mortality multipliers used for each age group. The multipliers increase mortality rates in policyholders who have contracted the disease. It is expected that the multipliers will increase the reserves. The largest multiplier was applied to the 60-70 age group. The bar representing 60-year old policyholders in each color is the largest, showing the largest percent increase for policyholders in the 60-70 age range. The multipliers increase steadily over the first five age groups and then steadily decrease back down over the remaining three age groups. This trend can be seen in each color in Figure 12.

4.2.4 Annual vs Lump Sum Premium

The last interesting characteristic to investigate is the payment form of the policy. All policies either pay premiums annually or as a large lump sum at the time they purchase the policy. Figure 13 shows the average percent increase after the pandemic inputs are applied to each group.

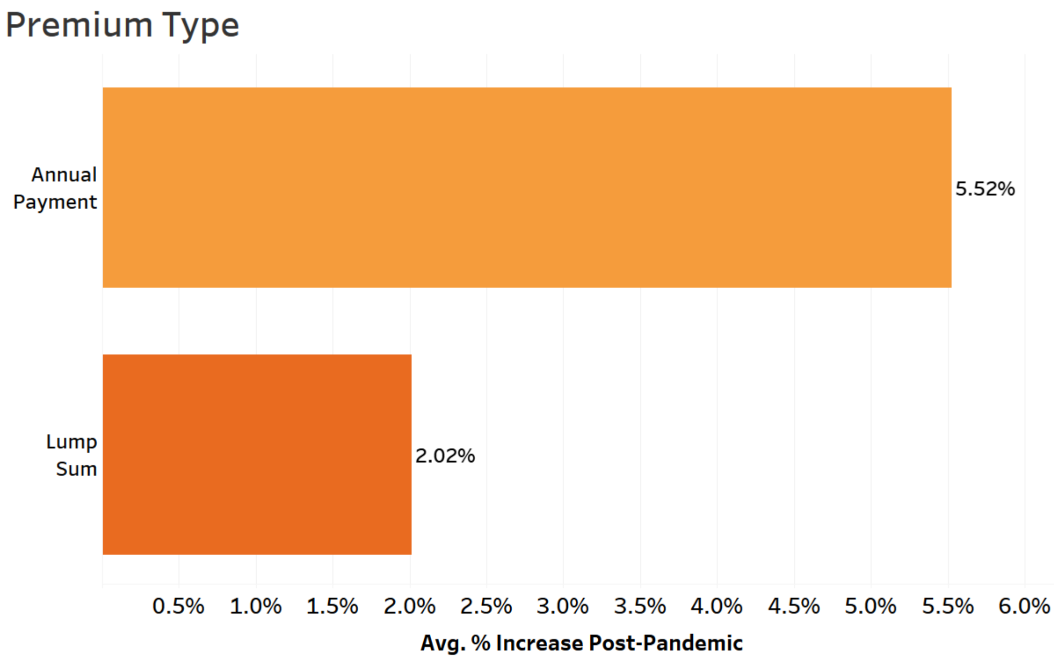

Figure 13: Percent Increase in Reserves by Premium Type

The pandemic inputs have a much larger impact on reserves for the annual payments than the lump sum payments. This result is consistent with the actuarial reserves equation. The impacts of the pandemic affect the present value of the benefit and the premiums in the reserves calculation. For policies with annual payments, the impact of the pandemic increases the present value of future benefits and decreases the present value of future premiums. For policies with lump sum premium payments, the impact of the pandemic only affects the present value of future benefits, so there is a lesser impact on reserves.

4.3 New Premium

After examining the effects of the pandemic on the life insurance company, we created a solution for the company to protect itself from the global pandemic. To account for the increase in reserves, the company could increase premiums when the policy was sold. The premium calculations described in section 3.1 were completed again, this time with the pandemic inputs built in. We assume that we know when the pandemic will hit and how far along each policy is into their term. This new premium calculation is completed for each policy, starting with normal inputs at time 0 and adding the pandemic inputs when the pandemic hits at each policy age. After following this process, the average increase in the new premium from the old premium is 1.22%.

The goal of this new premium is to bring the value of the total reserves down to pre-pandemic levels while using pandemic inputs. The deterministic and stochastic reserves calculations were run again, using pandemic inputs and the new premium. Although the total reserves did decrease with the new premium, it was still larger than the pre-pandemic reserves. To account for larger post-pandemic reserves, we took the extra premium received in each year and deposited it into a bank account that accumulates until the pandemic hits. To find the account balance for each policy, we took the difference between the new premium and old premium and accumulated it to the policy age using the pre-pandemic interest rate of 5%. These amounts were totaled to find the current value of the bank account. At the time of the pandemic, we withdrew the money and subtracted it from the reserves as it was money that we have already collected.

After completing this process, the final value of deterministic reserves is $218,069,444.84 and is only 0.52% larger than the pre-pandemic deterministic reserves. The total stochastic reserves is $218,851,260.63 and is only 0.88% larger than the pre-pandemic stochastic reserves. This method of increasing premiums and accumulating excess premiums in an account was successful in decreasing post-pandemic reserves. In using this method, the company would help protect itself from loss due to a pandemic. Without this protection, the company's reserves would increase by 3.56%. This process ensures an increase of only 0.88%.

Chapter 5: Conclusion

It is essential to analyze the impacts of events that occur in today's society to better predict the future and minimize risk associated with random events. The coronavirus pandemic has affected many aspects of society and it is important to investigate the significance of the impacts on unique industries. The model created and explained in this paper allows for the study and analysis of the effects that COVID-19 has had on the life insurance industry.

The overall goal was to create a stochastic model that could use inputs from any pandemic to estimate the reserves for a life insurance policy block with differing types of insurance. The COVID-19 pandemic is a great example of how many different factors can cause changes in life insurance reserves. We used the COVID-19 statistics to show how this model works. However, there are other past pandemics and possibly future pandemics in which this model can be used. It is a great tool to have and use in order to fully understand the impacts of a pandemic and which factors can impact the reserves the most.

In the analysis chapter, we discussed each input and factor on its own as well as layered one by one to show the true impact. All of the COVID-19 inputs impacted the reserves as expected. The increase in mortality coupled with the infection rate of the disease caused the largest increase in reserves out of all the inputs. Overall, the pandemic inputs increased the reserves amount for every policy. The overall results for the 5000 policies are shown in table 5.

Pre-Pandemic	Post-Pandemic	Difference	% Difference
$216,486,831.99	$224,512,830.06	$7,716,928.63	3.6%

Table 5: Overall Reserve Results

After analyzing the impacts of the pandemic on the reserves, we produced a possible solution to this problem. In order to protect the life insurance company from a pandemic, we introduced a new premium calculation to ensure the reserves do not increase as drastically when a pandemic hits. We increased each policy's premium by implementing the same pandemic inputs as used in the reserve calculations into the premium calculations. Table 6 shows the results of using the process explained in section 4.3.

Increase in Total Post-Pandemic Stochastic Reserves	
Old Premium	New Premium
3.6%	0.88%

Table 6: New Premium Method Results

Actuaries are always looking to analyze the outcomes of events and their effects on society or specific industries to better plan for the future. Pandemics, specifically the COVID-19 pandemic, are a good example of unexpected events that are difficult to plan for in an insurance company. From public health to the economy, COVID-19 affected society as a whole. This model can be implemented with other statistics or populations in order to better plan for the future despite other unexpected events that may occur.

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