Identifying Policy Characteristics Leading to Benefit Exhaustion

A Major Qualifying Project submitted to the faculty of

Worcester Polytechnic Institute in partial fulfillment of the requirements for the

Bachelors Degree of Science in Actuarial Mathematics

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May 2014

Abstract

Over the past 147 years, Genworth has been a leading provider of life insurance, annuities, mortgage insurance, and long term care insurance (LTC). It has earned a reputation for growth and success, which is evident in its rankings in both the S&P 500 and Fortune 500. The company, although headquartered in Richmond, Virginia, has a presence in 25 countries as well as all 50 states. In regards to its LTC products, Genworth is the top supplier and has paid out over $9.8 billion in LTC claims.

Our team has worked with Genworth over the course of this project to develop a method for identifying which factors, measured by Genworth, have the greatest impact on whether a claimant will exhaust his or her benefits. Beginning with the 31,488 claims in the data provided by Genworth, we looked only at the 26,114 claims that had closed (which included the 3,948 claims that were closed due to benefit exhaustion). The dataset included a variety of information including age, gender, marital status, benefit period, state, diagnosis, etc., but was stripped of any personal information which might identify individual policyholders.

The method of research that we decided was most important to our project compares claims closed due to exhaustion versus total claims closed, with respect to the frequency of any given factor. Next, we created a graphic we could reproduce for each factor based on this method. To verify that our method was viable, we tested all factors, including ones that we believed to not be relevant to the study. This gave us an indication of how much noise there might be when looking at the factors that we did believe to be relevant.

From our study, we were able to classify the factors that we tested into 3 main groups—Predictive and Known during Underwriting, Not Predictive and Known during Underwriting, and Unknown during Underwriting. Although some of the factors may have had a strong

correlation to benefit exhaustion, they may not be useful to Genworth when writing new policies (primarily because they were not knowable at the time the policy was underwritten and issued). Overall, the factors that we found to be the most useful in determining benefit exhaustion are those that are both Predictive and Known during Underwriting.

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Background

Long Term Care Insurance (LTCI) helps to pay for costs associated with activities of daily living, and is for those with serious mental damage, such as Alzheimer's disease. Many people worry about who will be there to take care of them when something terrible happens. Long term care gives patients the assistance and guidance they need to perform activities such as bathing, eating, and even moving in and out of bed. At least 70% of people over 65 will need long term care services and support at some point (Genworth Financial, 2014).

It is important to note that while LTCI is used to help people cope with the cost of chronic illnesses and different disabilities; it is very different then having health care insurance or Medicare which deal with immediate medical costs. According to a study in 2012, fewer than 8 million Americans have signed up for Long term care Insurance.

Genworth Financial, Inc. is "a publicly traded global financial security company with more than $100 billion in assets and a presence in more than 25 countries. We're recognized in Standard & Poor's 500 Index of Leading U.S. companies and ranked in the Fortune 500" (Genworth Financial, 2014). This success did not happen overnight, and should not be considered fleeting, as Genworth has been evolving and thriving throughout the past 147 years.

Genworth wrote its first policy in 1871 as The Life Insurance Company of Virginia. In 1986, Life of Virginia was acquired by Combined Insurance, which became Aon in 1987. In 1996, Life of Virginia was sold to GE Capital. In May 2004, Genworth Financial was formed out of various insurance businesses of General Electric Company.

Genworth is known to help people during important transitions and moments in their life. They accomplish this by protecting and growing retirement income, creating security through life and long term care insurance, with financial advisory services, and by providing a safer, more secure path to homeowners (Genworth Financial, 2014). This project focuses on Genworth's involvement with long term care insurance which they are currently the largest seller of (Genworth Financial Inc (GNW), n.d.). In addition, Genworth's products also include annuities, life insurance, and mortgage insurance. Their life insurance policies can also be broken down into universal, term, and whole life policies (Genworth Financial, 2014).

Headquartered in Richmond, Virginia, Genworth conducts business in all fifty states with its other main U.S. locations in Lynchburg, VA; Phoenix, AZ; Pleasant Hill, CA; Raleigh, NC; San Rafael, CA; Stamford, CT; and Washington, DC (Genworth Financial, 2014). As of December 31, 2011, the Company had more than 15 million customers, with a presence in more than 25 countries (Higher rates can blunt long-term-care errors, Genworth CEO Says, 2013).

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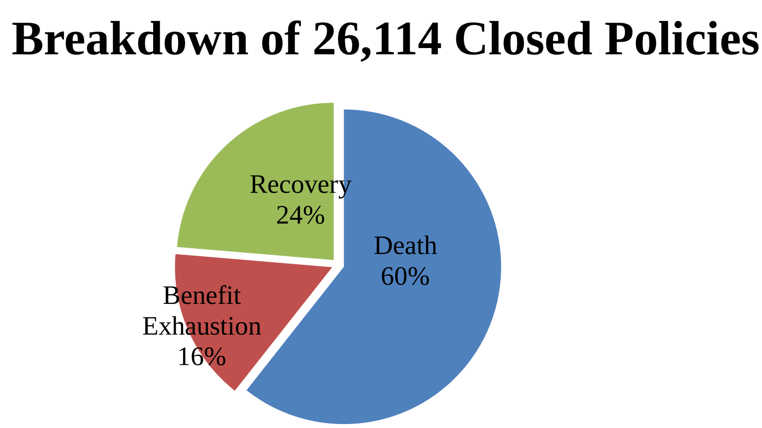
Data Description and Analysis

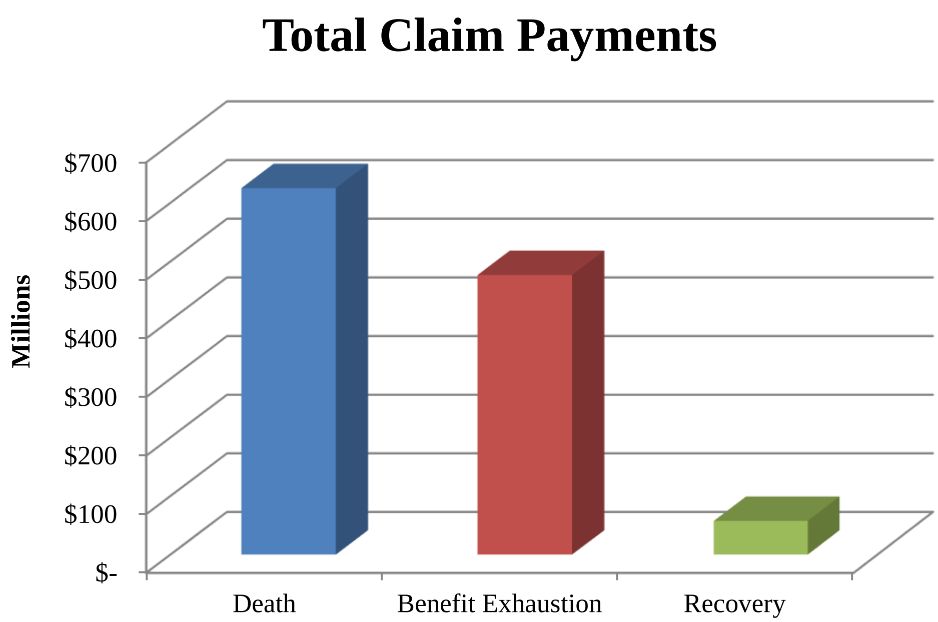
The claim source data provided to us by Genworth was a sample of their long term care insurance that contains any policy that opened a claim between 1994 and 2003. There are a total of 31,488 policies where 26,114 of these policies are closed. A policy is considered closed if Genworth is no longer making claim payments to it. Of those closed policies in our data set:

- 15,250 of them were due to death
- 3,948 of them were due to benefit exhaustion
- 5,954 of them were due to recovery
- The remaining 962 were split between 12 miscellaneous reasons

Our main focus in this study was on the 26,114 policies that were closed and the 3,948 policies that were closed due to benefit exhaustion. However, to understand why benefit exhaustion is so important, it is helpful to take a look at benefit exhaustion in comparison to the two other main close reasons, death and recovery. The following chart shows the percentage of policies closed due to each of the three main close reasons



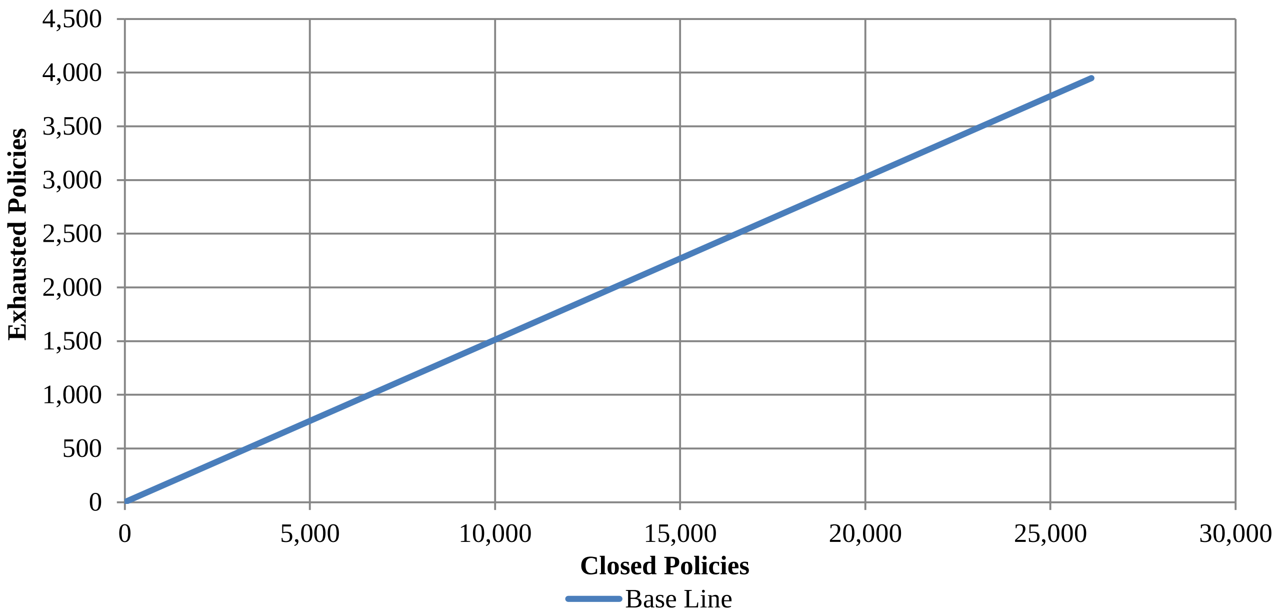
Examining this chart, it might not be immediately apparent why Genworth is so concerned about benefit exhaustion. It only accounts for 16% of all of the close reasons. However, when we break down these close reasons by total claim payments, it is evident that benefit exhaustion rivals death in losses.



The figure above shows that even though benefit exhaustion has the smallest percent of policies, the total claim payments that Genworth made to benefit exhaustion amount to significantly more than those made to claims closed due to recovery.

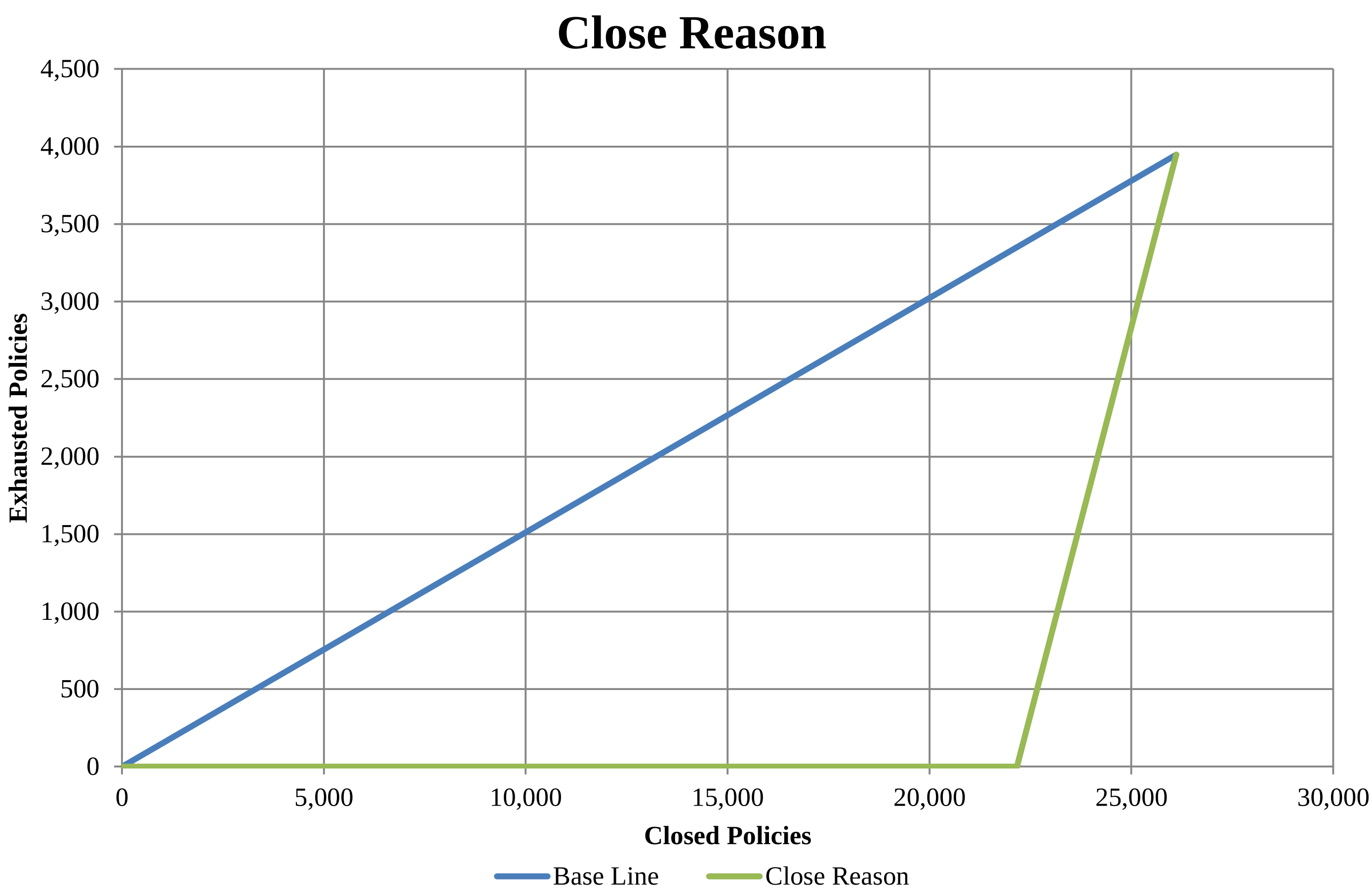
Frequency Correlation Method

The data that we were given included some information about each policy including, but not limited to, gender, total days on claim, issue age, original benefit claim coverage, and diagnosis codes. We wanted to analyze each of these factors to find out which ones could help predict benefit exhaustion. In order to do this we developed a method that we called the Frequency Correlation Method. This method started with the base line shown here:



This base line begins at the origin with zero closed policies and zero exhausted policies and then travels across the graph to the point where there are 26,114 closed policies and 3,948 exhausted policies. The line shown demonstrates an idealized situation where we could randomly sort the total 26,114 closed policies along the x-axis and then record the cumulative number of exhausted policies along the y-axis. A situation like that should result in the base line with a slope of approximately 0.15, roughly one exhausted policy for every seven closed policies.

Next, we wanted to think of different ways to sort the data based on the characteristics included in the data set. The first characteristic we decided to sort based on was the close reason which had the four options: death, recovery, benefit exhaustion, and other. First we sorted the policies based on the ones that closed due to death, recovery, or other, and then those that closed due to benefit exhaustion. Plotting this method results in the green line on the graph shown below. The first 22,166 policies that closed for reasons other than benefit exhaustion are depicted as the first part of the green line below that is found directly on the x-axis. This did not create any increase in the cumulative number of exhausted policies because none of them exhausted. The second part of the green line that leaves the x-axis are the remaining 3,948 policies that did close due to benefit exhaustion. This part of the line has a slope of one since every closed policy found here closed due to benefit exhaustion. In this case, the green line starts and ends at the same points as the base line, but it takes a very different path to get there. That different path is the ideal situation for a characteristic that would predict benefit exhaustion. If we were able to find another characteristic that, once sorted, created a graph similar to this close reason graph then we would know it was a predictive characteristic. Additionally, we noted that the area between the close reason line and the base line is the largest possible area that could occur between any factor line and the base line as this is the ideal predictive situation. As we move forward, we will be comparing the area between the factor line and the base line of other graphs back to this largest possible area as a percentage. For example, since this is the maximum possible area, the percentage of maximum possible area for the close reason graph is 100.0%.



Close Reason	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
Death	-	15,250	0.000000	-	15,250
Recovery	-	5,954	0.000000	-	21,204
Other	-	962	0.000000	-	22,166
Exhaustion	3,948	3,948	1.000000	3,948	26,114

Single Factor Charts

We decided to make graphs similar to the close reason graph shown above for each of the following characteristics (these are every useable field in the data file we received):

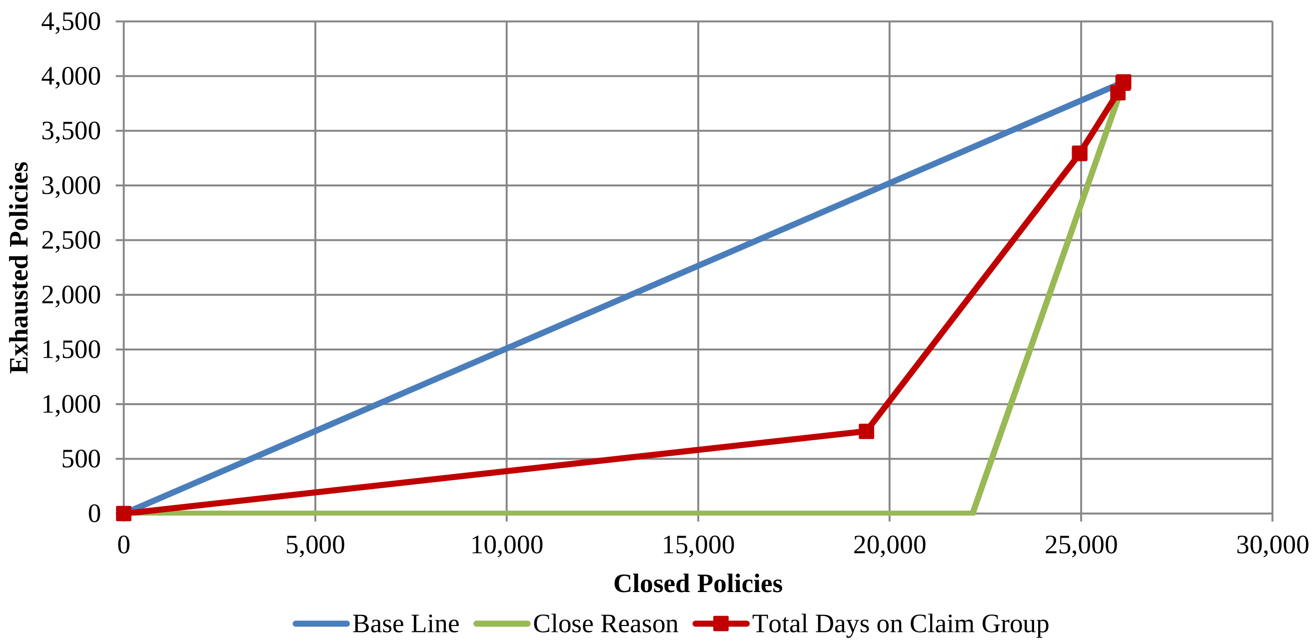
- Begin Duration
- Benefit Increase Option
- Benefit Period
- Claim Age
- Claim Age Group
- Claim ID
- Client Set Out of Force Date
- Close Reason
- Company
- Current Diagnosis Code
- Elimination Period
- End Duration
- Gender
- Initial Diagnosis Code
- Issue Age
- Marital Status
- Original Benefit Claim Coverage
- Plan Type
- Policy Status
- Replacement Indicator
- Risk Commenced Year
- U.S. Region
- Total Days on Claim

Total Days on Claim

One factor that turned out to be very predictive in regards to benefit exhaustion was Total Days on Claim. In the data, the Total Days on Claim ranged from 3 to 6000. Therefore we decided to group the number of days by 1000's thus resulting in six groups. Out of the 26,114 closed policies only 6 policies were in 5000-6000 Total Days on Claim group. For the purposes of our analysis, we decided to only include the first five "Total Days on Claim" groups.

Analysis showed that the longer a policy was on claim the more likely it was to exhaust their benefits. 3.9% of policies in Group 1, 45.6% of policies in Group 2, 55.6% of policies in

Group 3, 64.2% of policies in group 4, and 66.7% of policies in Group 5 closed due to benefit exhaustion. These percentages represent the slope of their respective red line segments. The first line segment represents policies with less than 1000 days on claim, the second line segment represents policies with between 1000-2000 days on claim, with the policies following this trend for all six groups. The percentage of maximum area given by this factor is an impressive 65.9%. However, we quickly realized that this factor was not as meaningful as it might appear. It is true that there is a meaningful correlation between benefit exhaustion and the total days a policy is on claim, but this is an obvious correlation, and it's not something that Genworth would know during the process of underwriting. Therefore, while the Total Days on Claim is definitely predictive, it would not be useful to Genworth for their underwriting process.



Total Days on Claim Group	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
1	753	19,393	0.038828	753	19,393
2	2,540	5,568	0.456178	3,293	24,961
6	3	6	0.500000	3,296	24,967
3	552	992	0.556452	3,848	25,959
4	88	137	0.642336	3,936	26,096
5	12	18	0.666667	3,948	26,114

Claim ID

One factor that is knowable during underwriting is claim ID (in point of fact, claim ID's are assigned at the time of claim, but it is essentially a random number associated with the policy, and in theory could be assigned at issue and then just not used if no claim ever arose). The point is, claim ID is a random number associated with a policy and we sorted the policies based on the third digit of this claim ID. We were confident that this would not be a predictive factor for benefit exhaustion since it was random but it was a good way to test our method. As we expected, claim ID only gave a 4.3% area which is shown below. There is, of course, no good reason why a third digit of "8" should indicate a different likelihood of benefit exhaustion than a third digit of "1", but random "noise" produced a slight result in that direction for this data. While this is not predictive, it does demonstrate that random noise can create an area of about 4% which is useful knowledge when looking at the areas of other characteristics.

Claim ID (3rd Digit)	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
8	355	2,611	0.135963	355	2,611
0	369	2,627	0.140464	724	5,238
6	359	2,552	0.140674	1,083	7,790
5	401	2,694	0.148849	1,484	10,484
4	382	2,560	0.149219	1,866	13,044
9	412	2,708	0.152142	2,278	15,752
7	405	2,581	0.156916	2,683	18,333
3	410	2,587	0.158485	3,093	20,920
2	429	2,661	0.161218	3,522	23,581
1	426	2,533	0.168180	3,948	26,114

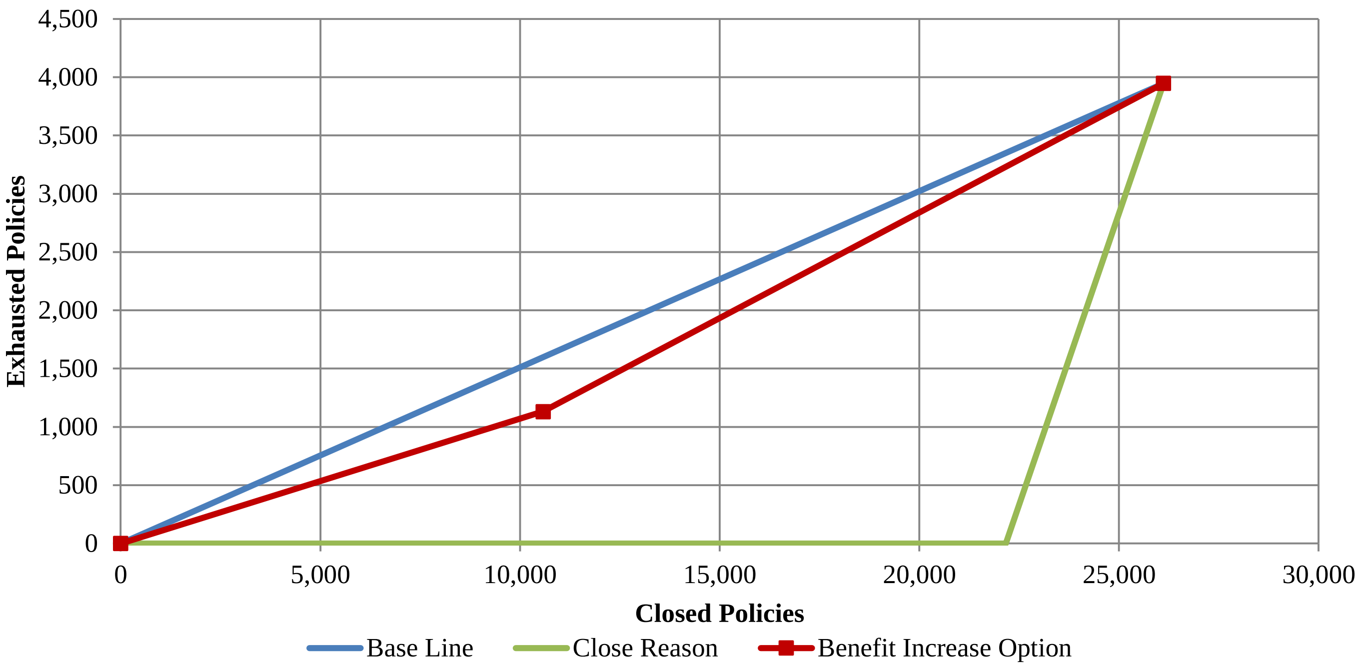
Benefit Increase Option

The first factor analyzed that was both Predictive and Known during Underwriting was benefit increase option (BIO). This option is given to policy holders while they are selecting their policy. It allows policy holders to pay an additional premium to increase the benefit coverage amounts at stated intervals during the life of the policy. There are usually a limited number of increase options offered to policy holders over the life of the policy. If you decide not to exercise this option one or more times when it is offered, you will lose any chances to increase your benefits in the future.

Of the total 26,114 closed policies 10,576 policies chose the benefit increase option, where 15,538 did not. Of the 10,576 who chose the option 1,132 closed due to benefit exhaustion. This means that around 10.7% of policies who elected for the BIO exhausted their benefits. This percentage is represented by the slope (0.107) of the first red line segment beginning at the origin and ending at the point (10,576, 1,132). 15,538 policies did not choose the BIO, and 2,816 of them closed due to benefit exhaustion. Therefore 18.1% of policies who did not choose the BIO exhausted their benefits. This percentage represents the slope of the second, steeper line segment.

Thus it can be concluded that policies in which the BIO was chosen tend to exhaust their benefits less frequently than those who do not elect this option. This conclusion follows logically because the policies with the BIO would presumably have a larger sum of potential benefits. Also policy holders who elected for the BIO would have been better able to prepare had they known they were going to begin using more benefits. The percentage of the maximum area given by this factor is 14.8%

Note that there are several types of Benefit Increase Option, but we did not find useful results when separating the data on that basis – a simple “yes or no” to the “do you have an increase option of some sort?” question produced the best results.



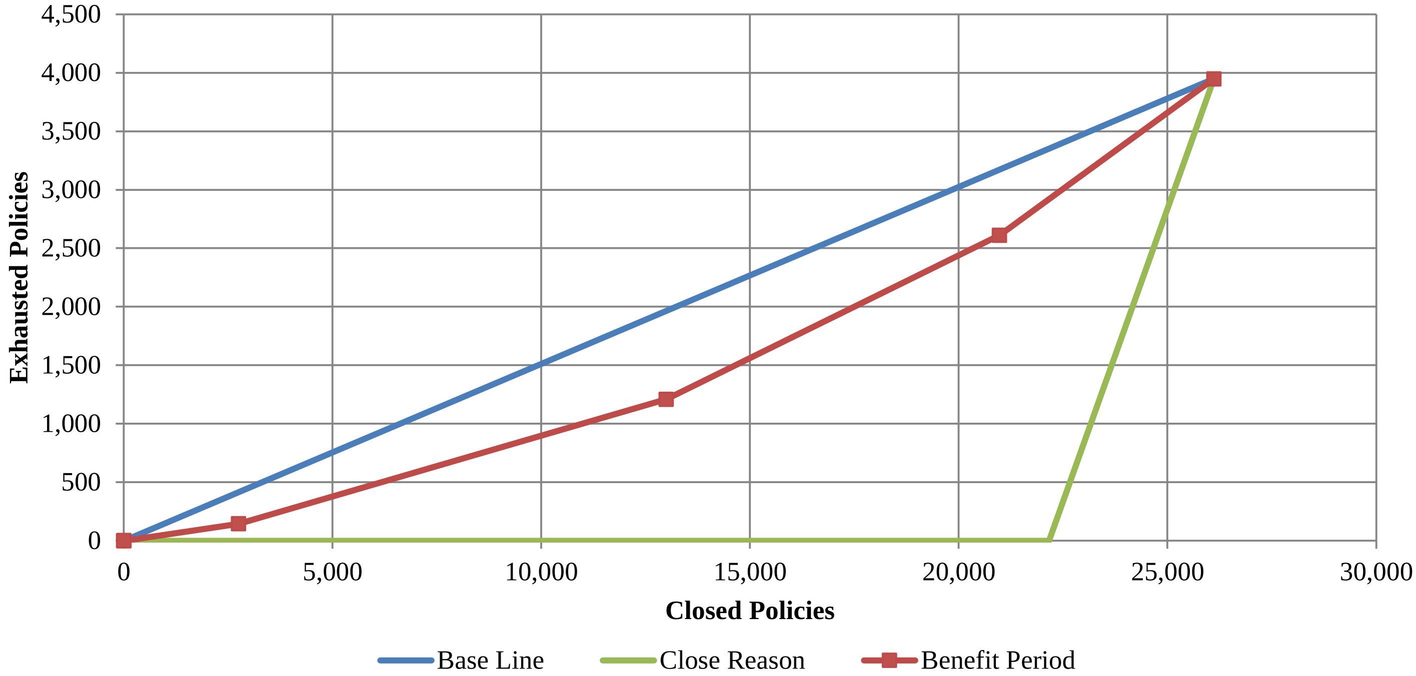
Benefit Increase Option	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
Yes	1,132	10,576	0.107035	1,132	10,576
No	2,816	15,538	0.181233	3,948	26,114

Benefit Period

The next factor analyzed that was both Predictive and Known during Underwriting was benefit period. Benefit period is the total amount of time (in continuous years) that benefits will be paid. In the data there were benefit periods ranging from 1 to 6 years. Out of the 26,114 closed policies, only 6 policies had either 1 or 5 year benefit periods so only benefit periods 2, 3, 4, and 6 years were included in the analysis.

Benefit Period	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
6	144	2,743	0.052497	144	2,749
4	1,065	10,248	0.103923	1,209	12,997
3	1,402	7,982	0.175645	2,611	20,979
2	1,337	5,135	0.260370	3,948	26,114

Analysis has shown that policies with shorter benefit periods are more likely to exhaust their benefits than policies with longer benefit periods. 5.2% of policies with a 6 year benefit period, 10.4% of polices with a 4 year benefit period , 17.6% of polices with a 3 year benefit period, and 26.0% of policies with a 2 year benefit period closed due to benefit exhaustion. As seen in previous graphs these percentages represent the slope of their respective red line segments. The first line segment represents policies with a 6 year benefit period, the second line segment represents policies with a 4 year benefit period, followed by policies with a 3 year benefit period, and a 2 year benefit period. The percentage of maximum area given by this factor is an impressive 28.2%. This result makes sense logically – shorter benefit periods result in a greater likelihood of exhausting policy benefits, and vice versa for longer benefit periods.

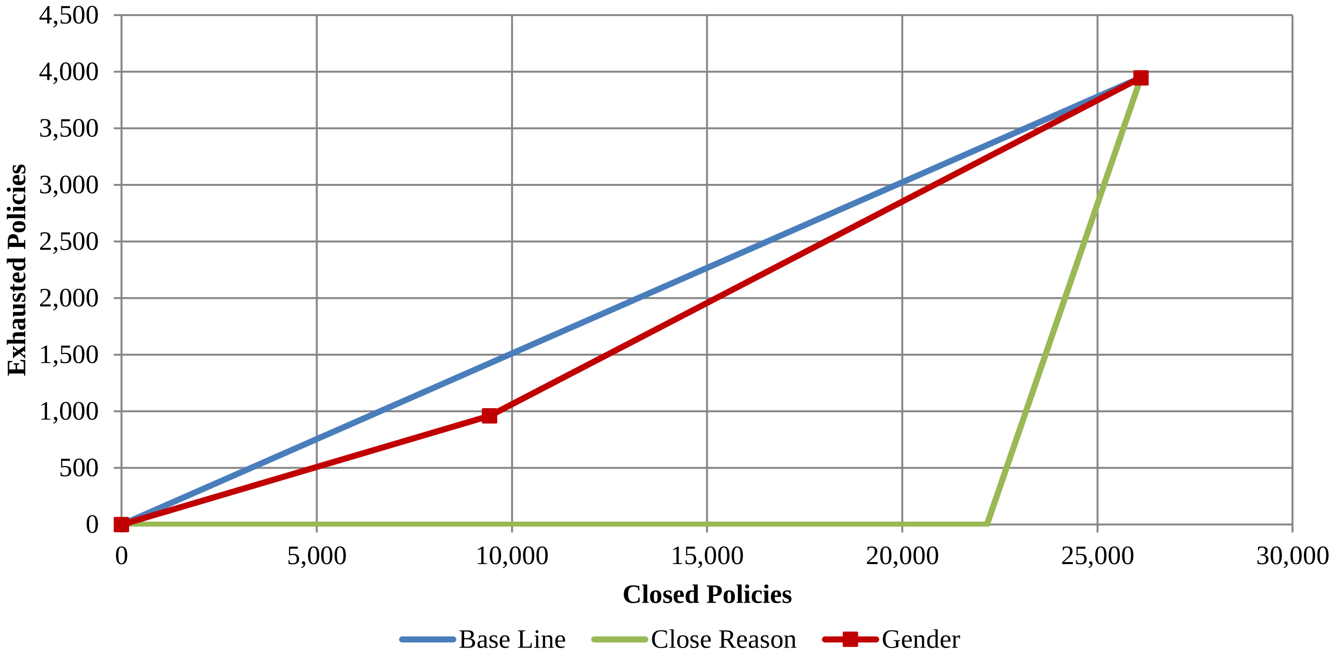


Gender

Gender was another factor that we found to be both Predictive and Known during Underwriting. Of the closed policies, 9,425 were males and 16,689 were females; and of the policies closed due to benefit exhaustion, 960 were males and 2,988 were females.

Gender	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
Male	960	9,425	0.101857	960	9,425
Female	2,988	16,689	0.179040	3,948	26,114

Looking at the graph, the first part of the red line segment represents males and the second part of the red line segment represents females. The slope of that the female portion of the line is steeper meaning females are more likely to exhaust their benefits. This is evident in the table as 17.9% of females exhausted their benefits, whereas 10.2% of males exhausted their benefits. This makes intuitive sense, as females generally have a longer lifespan than males. We found gender to be significant because the area between the gender line and the baseline is 13.9% of the total possible area.

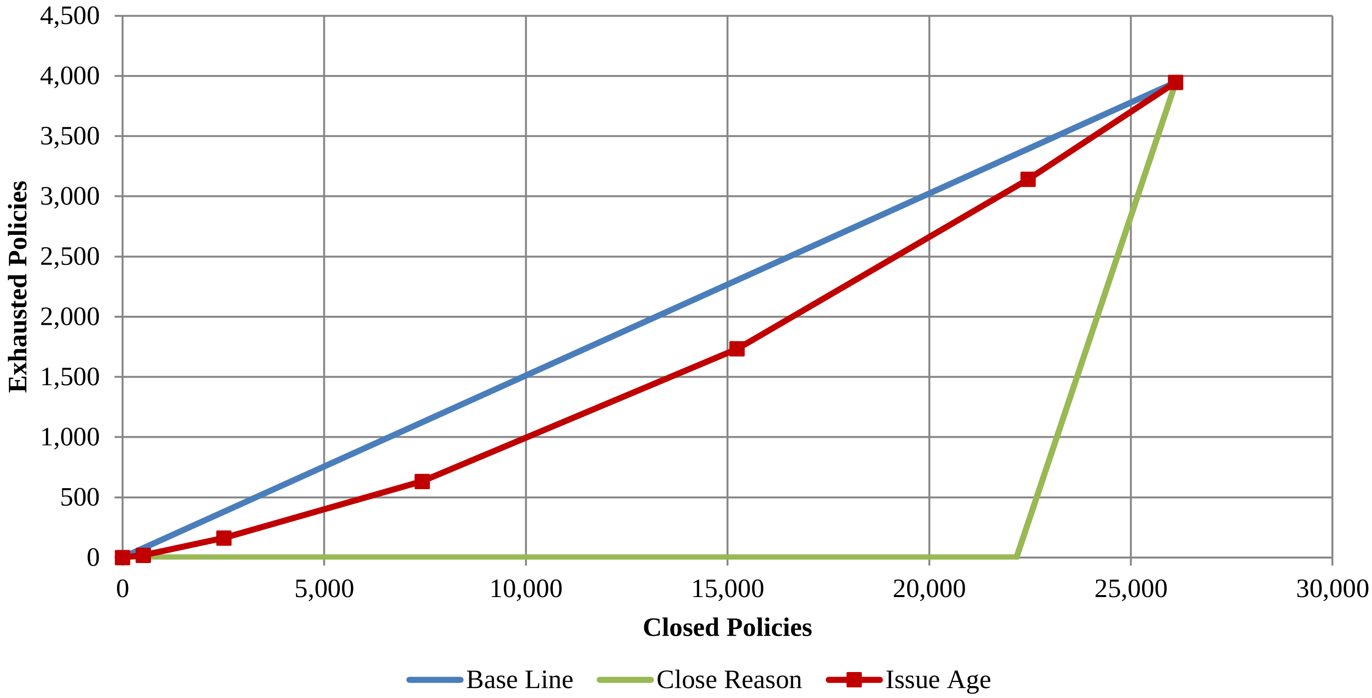


Issue Age

Next we looked at issue age, another of our factors we consider to be Predictive and Known during Underwriting. We grouped issue ages so that each group would have a significant number of closed policies and ranges no less than 5 years.

Issue Age	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
40-59	19	517	0.036750	19	517
60-64	143	1,997	0.071607	162	2,514
65-69	471	4,914	0.095849	633	7,428
70-74	1,101	7,812	0.140937	1,734	15,240
75-79	1,407	7,213	0.195064	3,141	22,453
80-94	807	3,661	0.220432	3,948	26,114

The chart shows that issue ages tend to follow a trend, as policies having younger issue ages are less likely to exhaust their benefits than policies with older issue ages. The slope of the 80-94 portion of the issue age line is about 7 times that of the 40-59 portion of the issue age line, with the line segments in the middle rising by age range. The percentage of area between the issue age line and the base line is 22.0%, which we consider to be predictive.

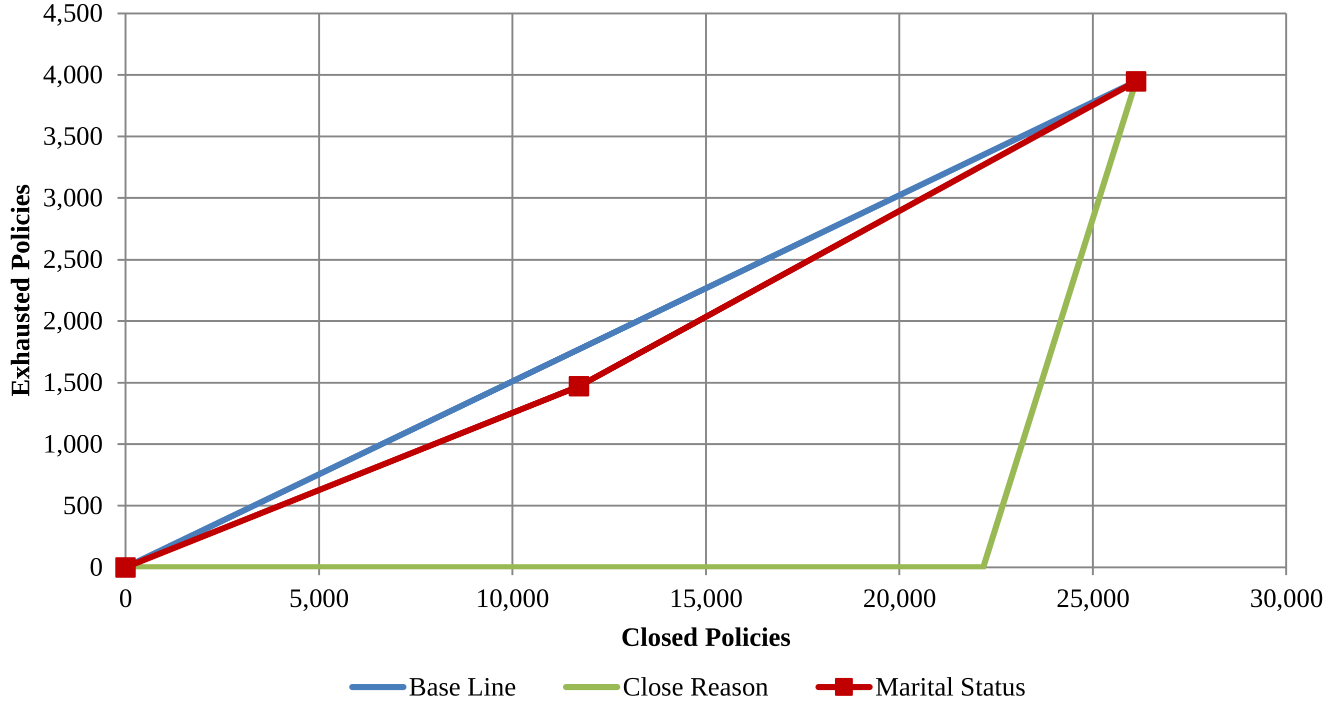


Marital Status

Our last factor that is both Predictive and Known during Underwriting is marital status. Of the 26,114 closed policies, 11,716 were married and 14,398 were single; and of the 3,948 policies closed due to benefit exhaustion, 1,471 were married and 2,477 were single.

Marital Status	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
Married	1,471	11,716	0.125555	1,471	11,716
Single	2,477	14,398	0.172038	3,948	26,114

From the graph, it was apparent that single policyholders are more likely to exhaust their benefits because the slope of the single line segment is slightly steeper than the slope of the married line segment. 17.2% of single policyholders exhausted their benefits whereas 12.6% of married policyholders exhausted their benefits. Marital status had the smallest percentage of area out of all our Predictive and Known during Underwriting factors at 9.0%; however, we still believe this to be significant.


4,500
4,000
3,500
3,000
2,500
2,000
1,500
1,000
500
0
Exhausted Policies
0
5,000
10,000
15,000
20,000
25,000
30,000
Closed Policies
Base Line
Close Reason
Marital Status

Key Predictive Factors

While the five factors just reviewed (Benefit Increase Option, Benefit Period, Gender, Issue Age, and Marital Status) were the most interesting and predictive, we created charts for every characteristic given in the data set. **All** of the charts can be found in the second section of the appendix.

Dual Factor Charts

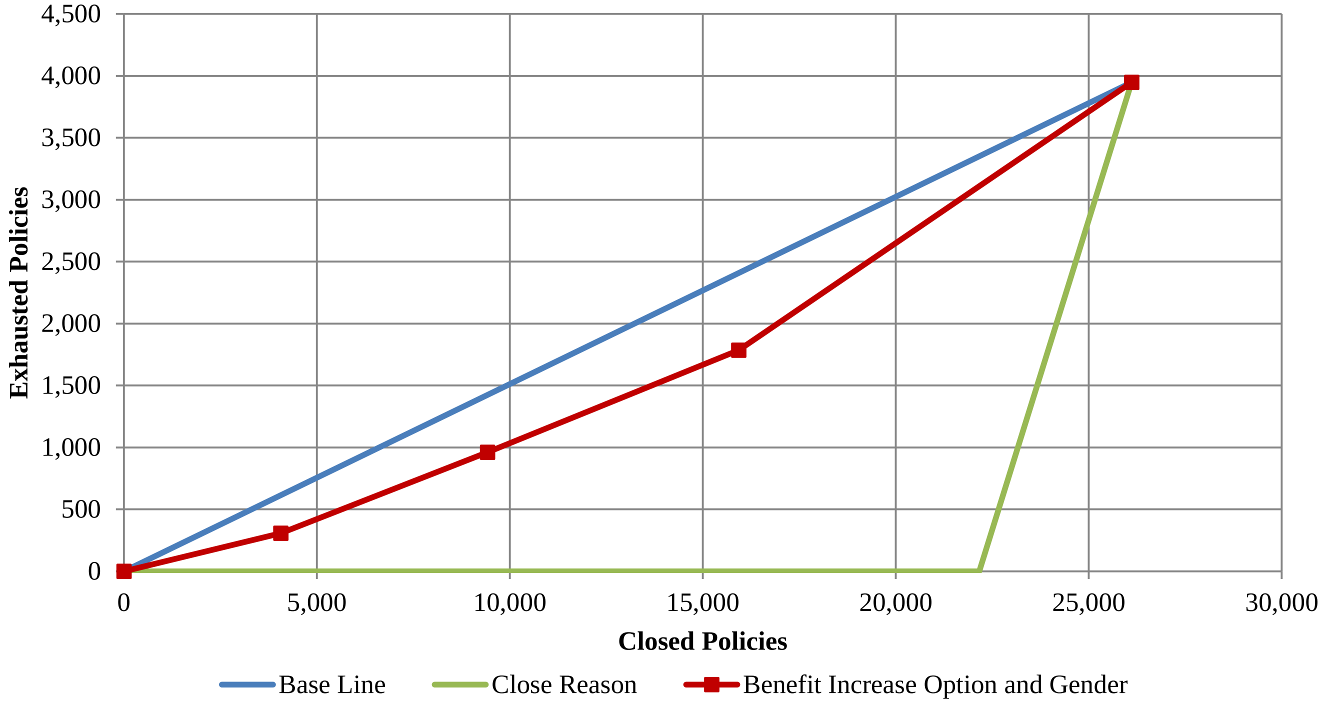
While the single factor charts are informative they were not satisfying enough. It was decided that it would be interesting to combine some of our key predictive factors we represented as single factor charts into dual factor charts in order to gain even more predictive results. To be successful, a “dual factor chart” needs to demonstrate a larger combined area than either single factor chart had separately, AND it would be good if the relative order of the single factors within the dual factor chart maintained the patter of the single factor charts. This will become clearer with some examples.

Gender and Benefit Increase Option

The first successful dual factor chart combined gender and benefit increase option. Individually, each factor had two options; Male and female for the gender chart, and yes and no for the benefit increase option chart. When we combine these two factors into one chart we have 4 four options; males with the benefit increase option, males without the benefit increase option, females with the benefit increase option, and females without the benefit increase option.

Favorably, by running our Frequency Correlation Method with these options our results followed logically. Males who choose the benefit increase option were least likely to exhaust their benefits followed by males who did not choose the benefit increase option. Next were the females who did choose the benefit increase option, and then the females who did not choose the benefit increase option. By combing these two factors into one chart we were successfully able to gain some additional predictive area. On their own gender and benefit increase option produced areas that were 13.9% and 14.8% respectively, but combined they generated an area that was 21.5% of the total maximum area.

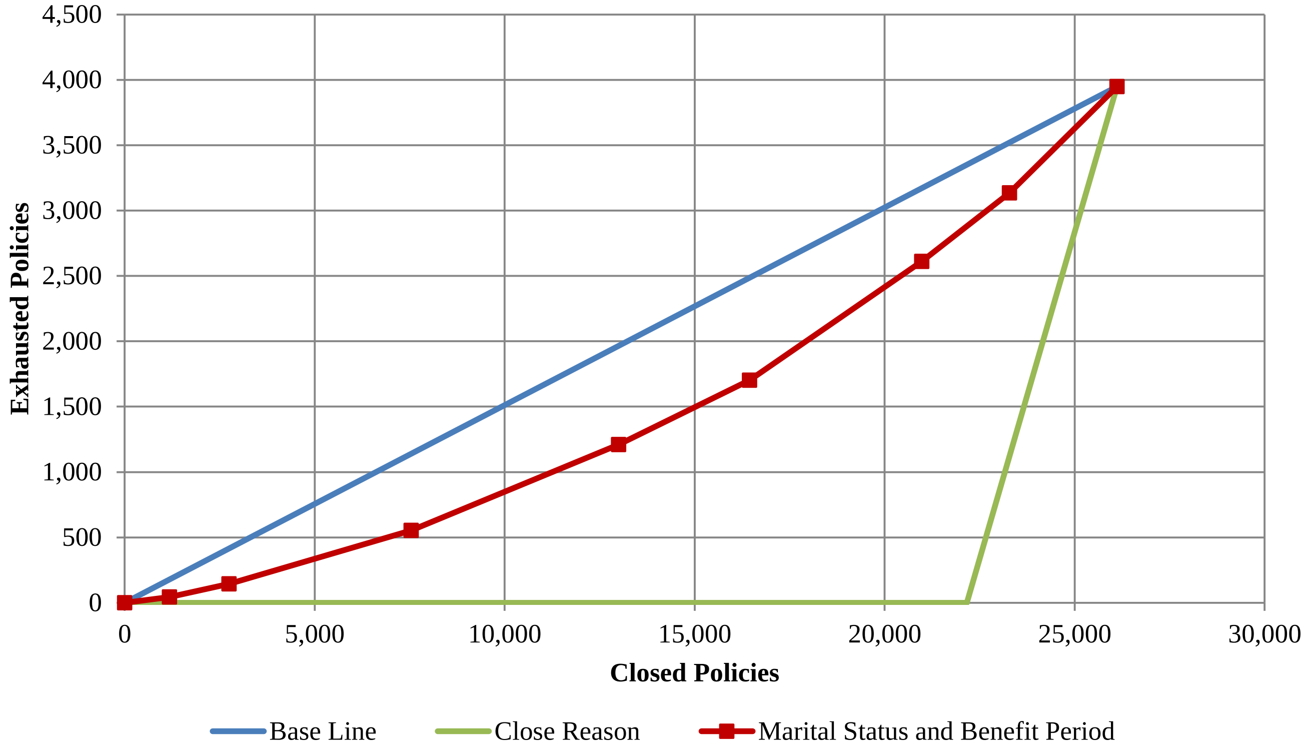
Gender and Benefit Increase Option	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
Male, Yes	307	4,066	0.075504	307	4,066
Male, No	653	5,359	0.121851	960	9,425
Female, Yes	825	6,510	0.126728	1,785	15,935
Female, No	2,163	10,179	0.212496	3,948	26,114



Benefit Period and Marital Status

Another example of our dual factor chart combined Benefit and Marital Status. Individually, marital status had two options; Married or Single. However, the Benefit Period had 4 options; 6,4,3, and 2 years. When we combined these two factors into one chart we were left with 8 different options; a benefit period combined with either a married or single marital status.

Analysis showed that our graph of these eight options followed logically. Single people were more likely to exhaust their benefits when compared to married people of the same benefit period. This pattern mirrored the trend we discovered when analyzing both the Benefit Period and Marital Status individually. By combining these two factors into one chart we were successfully able to gain some additional predictive area. On their own, Benefit Period and Marital Status produced area that were 28.2% and 9% respectively, but combined they generated an area that was 30.7% of the total maximum area.

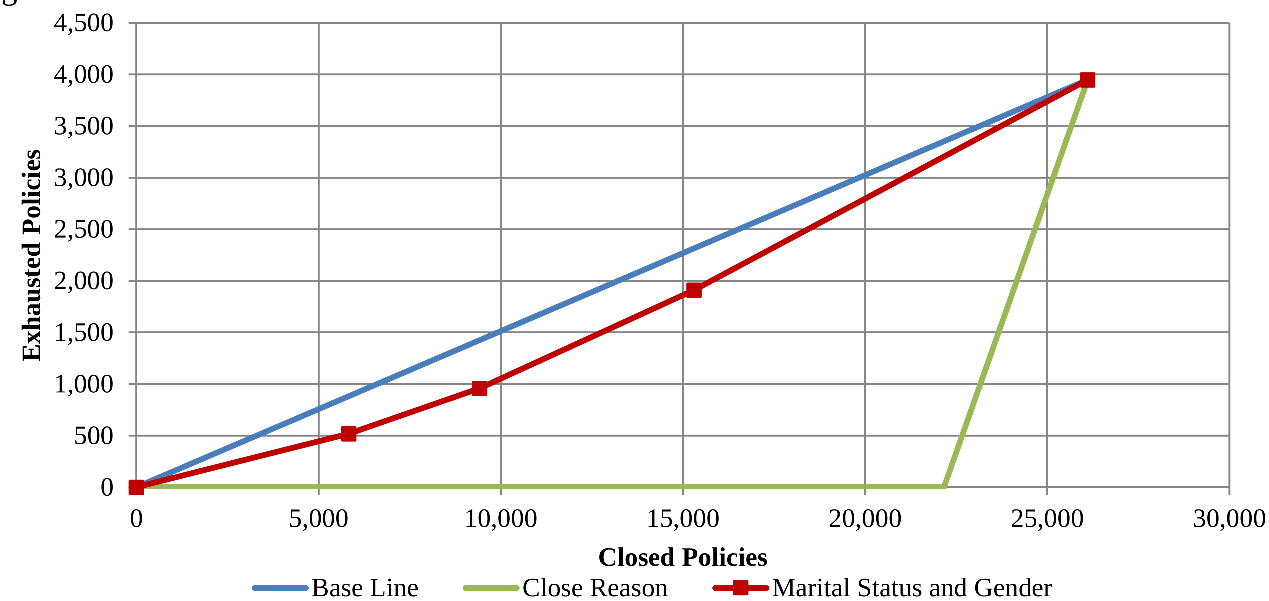


Benefit Period and Marital Status	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
6, Married	45	1,169	0.038494	45	1,175
6, Single	99	1,574	0.062897	144	2,749
4, Married	410	4,786	0.085667	554	7,535
4, Single	655	5,462	0.119919	1,209	12,997
3, Married	493	3,449	0.142940	1,702	16,446
3, Single	909	4,533	0.200529	2,611	20,979
2, Married	523	2,309	0.226505	3,134	23,288
2, Single	814	2,826	0.288040	3,948	26,114

Gender and Marital Status

Our final example of a successful dual factor chart combined Gender and marital status. Individually each factor had two options; Male and female for the Gender chart, and married or single for the marital status chart. When we combine these factors into one chart we are left with four options; a marital status factor accompanied by either the male or female gender factor.

Analysis showed that our graph of these four options followed logically. Similar to the previous dual-factor chart, single people tend to have a higher rate of exhaustion then married ones. Our individual factor analysis showed that females tend to exhaust their benefits at a higher rate than males, a pattern which is clear in the graph below as well. By combining these two factors into one chart we were successfully able to gain additional predictive area. On their own gender and marital status produced area that were 13.9% and 9% respectively, but combined they generated an area that was 16.6% of the total maximum area.



Gender and Marital Status	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
Male, Married	520	5,831	0.089179	520	5,831
Male, Single	440	3,594	0.122426	960	9,425
Female, Married	951	5,885	0.161597	1,911	15,310
Female, Single	2,037	10,804	0.188541	3,948	26,114

We decided to focus on these three dual factor charts; however, the remainder of them can be found in the third section of the appendix. It is important to note that there is only one dual factor chart concerning issue age. Issue age was difficult to combine with other factors to show conclusive prediction of benefit exhaustion since the ages did not fall into ascending order as we desired. The one example with issue age that is included in the appendix has the ages broken down differently than issue age independently, which we did not find useful to show that it was a predictive factor. Additionally, we attempted to make triple factor charts but the results were inconclusive (the desired maintaining of the single factor chart "ordering" did not happen).

Conclusion

Once we created the graphs for all the characteristics present in our data, we were able to find a percentage of maximum area for each of them. Those areas can be found in the table below. The top left section of this table, which is yellow, are the factors that were the key predictive factors. These five were the ones we used to make the dual factor charts and were both Predictive and Known during Underwriting. The bottom left section of the table are the factors that were known during underwriting but didn't have a predictive area, such as claim ID at 4.3%. Finally, the section on the right side of the graph are those that may seem predictive at first but aren't known at the time of underwriting so they aren't useful in order to help predict benefit exhaustion; total days on claim is a good example of this.

Known During Underwriting	
Predictive	• Marital Status (9.0%) • Gender (13.9%) • Benefit Increase Option (14.8%) • Issue Age (22.0%) • Benefit Period (28.2%)
Not Predictive	• Plan Type (0.0%) • Replication Indicator (0.8%) • Company (0.9%) • Elimination Period (2.3%) • Claim ID (4.3%) • Original Benefit Claim Coverage (5.8%) • U.S. Region (6.0%)

Unknown During Underwriting
• Risk Commenced Year (5.2%) • Claim Age Group (6.3%) • Policy Status (11.7%) • Claim Age (12.0%) • Begin Duration (17.7%) • Initial Diagnosis Code (31.1%) • End Duration (22.0%) • Client Set Out of Force Year (23.2%) • Current Diagnosis Code (39.8%) • Total Days on Claim (65.9%) • Close Reason (100.0%)

In conclusion, we found that not all of the factors that we were given to use are available to predict benefit exhaustion at the time of underwriting. Even if a factor is available at time of underwriting it is not a guarantee that it will demonstrate predictive abilities. The most predictive factor is benefit period where policies with shorter benefit periods tend to exhaust more frequently. This is followed by issue age, benefit increase option, gender, and marital status, respectively. When we created dual factor charts by combining those five key predictive factors the result tends to be more predictive than the factors individually. This is shown in the table below where the first line is benefit increase option at 14.8% and gender at 13.9% individually and then their combined dual factor area of 21.5%. This pattern follows all the way down the table.

Benefit Increase Option - 14.8%	Gender - 13.9%
Benefit Increase Option & Gender - 21.5%	
Benefit Increase Option - 14.8 %	Benefit Period - 28.2%
Benefit Increase Option & Benefit Period - 31.8%	
Issue Age - 22.0%	Benefit Period - 28.2%
Issue Age & Benefit Period - 34.7%	
Issue Age - 22.0%	Marital Status - 9.0%
Issue Age & Marital Status - 23.6%	
Marital Status - 9.0%	Benefit Period - 28.2%
Marital Status & Benefit Period 30.7%	
Marital Status - 9.0%	Gender - 13.9%
Marital Status & Gender 16.6%	
Benefit Increase Option - 14.8%	Marital Status - 9.0%
Marital Status & Benefit Increase Option - 18.4%	
Benefit Period - 28.2%	Gender - 13.9%
Benefit Period & Gender - 33.4%	

Overall, this process should allow Genworth Financial to be able to better predict which of their policies are likely to exhaust their benefits. Knowing that information will help them to refine their underwriting process which will help them succeed economically as well as to leave fewer policy holders with exhausted benefits when they still need help to care for themselves.

Acknowledgements

We would like to thank our advisor, Professor Jon Abraham, for his support and guidance during this project. In addition, we would like to acknowledge Genworth Financial for allowing us to complete this project and our liaison at Genworth, Daniel Borland, for assisting us with any questions we encountered.

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Higher rates can blunt long-term-care errors, Genworth CEO Says. (2013, December 4). Retrieved from Investment News: http://www.investmentnews.com/article/20131204/FREE/131209962

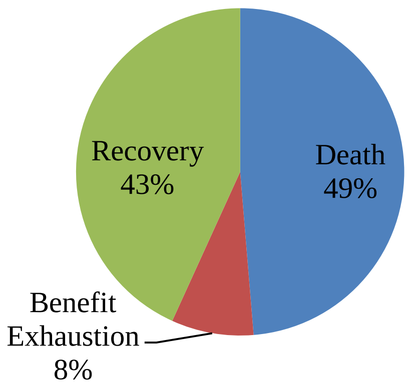
Appendix

Section 1: Data Analysis Graphs

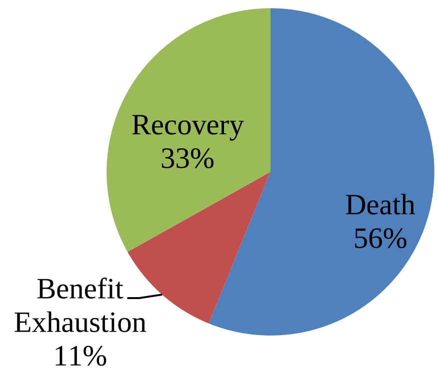
The consecutive pages contain graphs breaking the data into various divisions including issue age, gender, and close reason. These graphs gave an introductory look into the data.

Issue Age Graphs

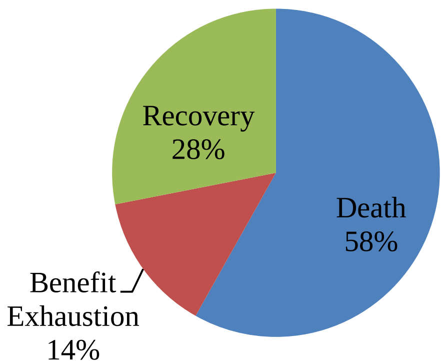
45-69 Closed Reason Breakdown



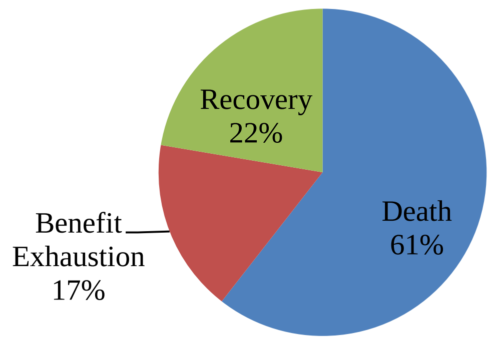
70-74 Closed Reason Breakdown



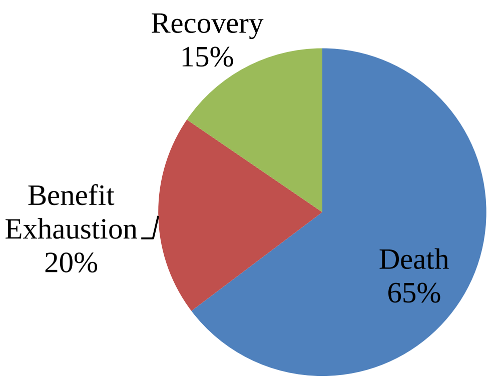
75-79 Closed Reason Breakdown



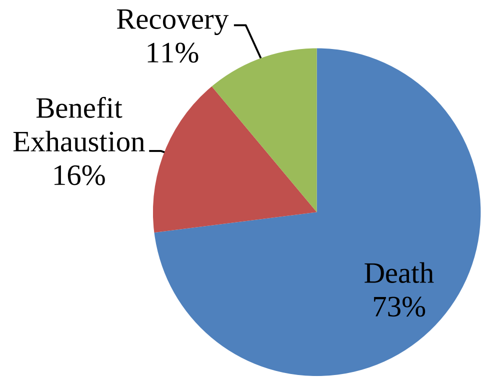
80-84 Closed Reason Breakdown



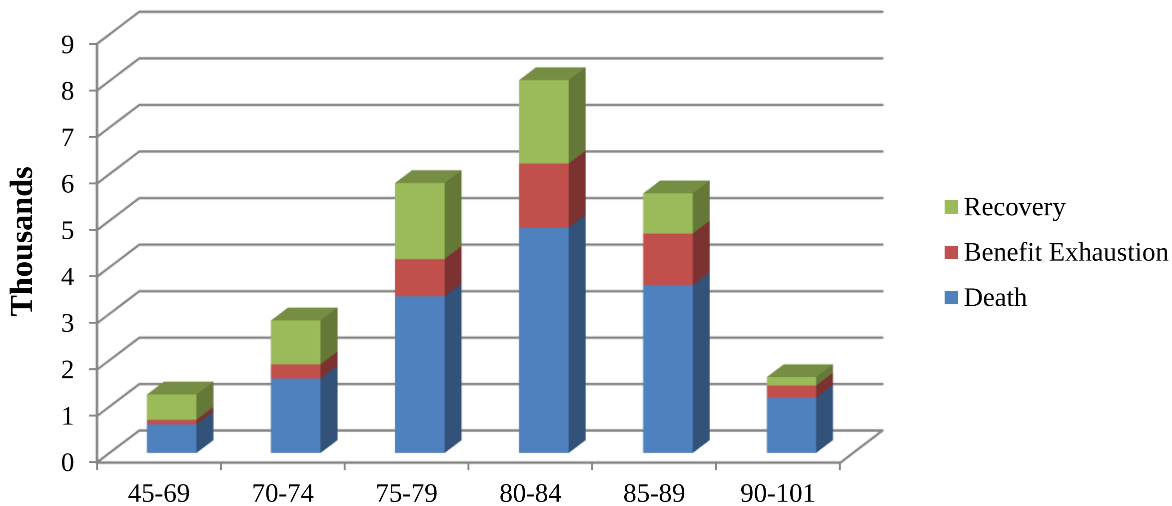
85-89 Closed Reason Breakdown



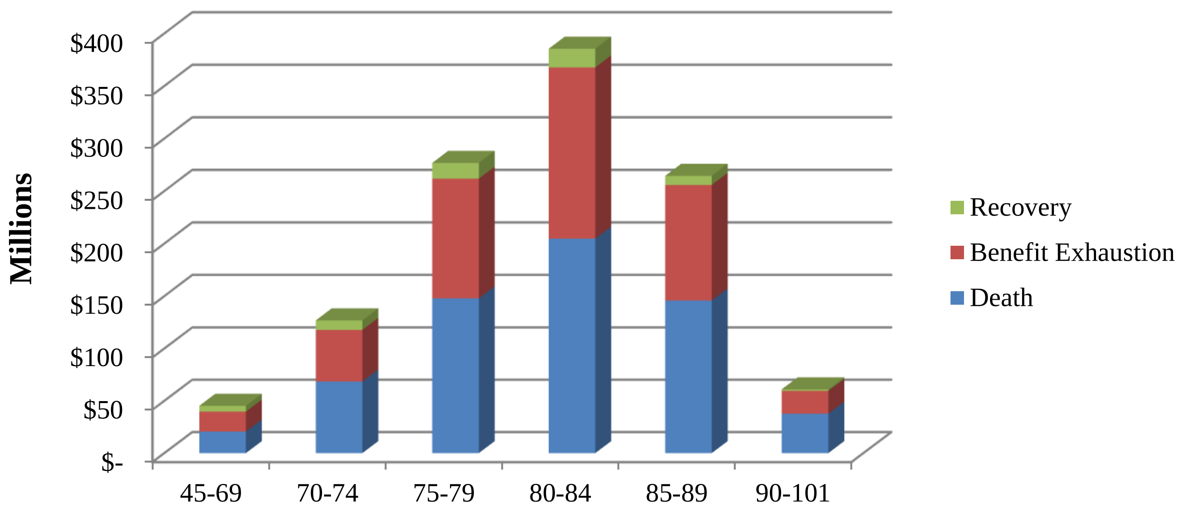
90-101 Closed Reason Breakdown



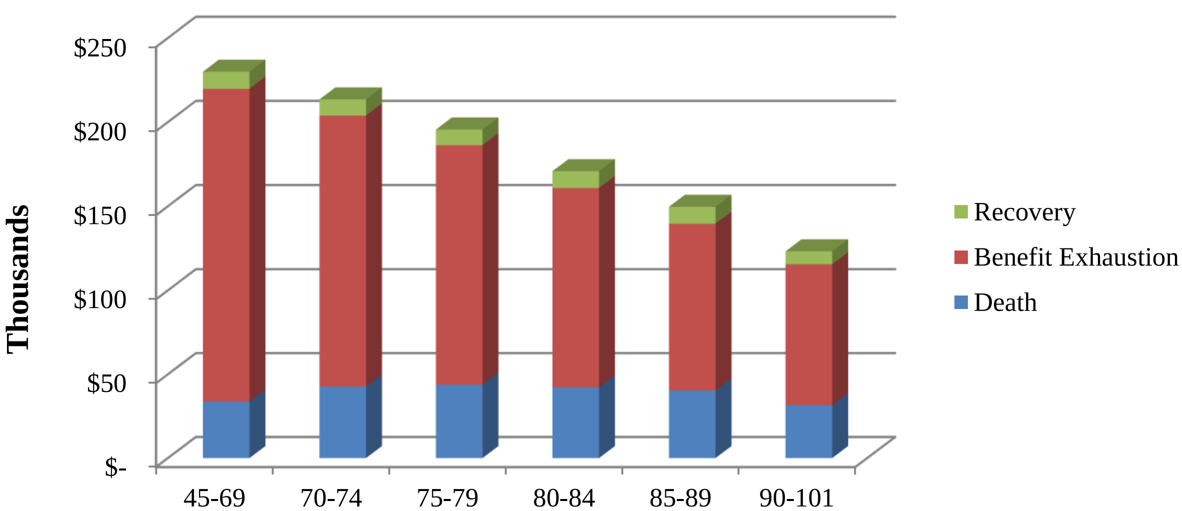
Number of Closed Policies



Total Claim Payments

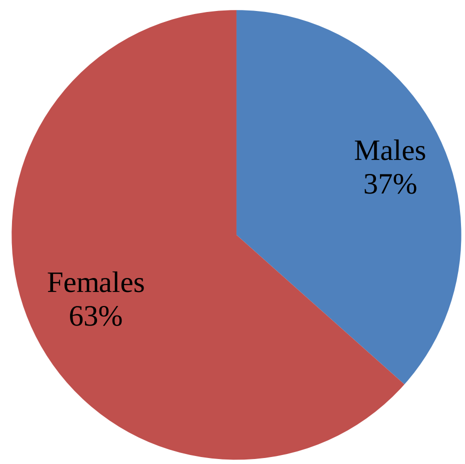


Average Total Claim Payments

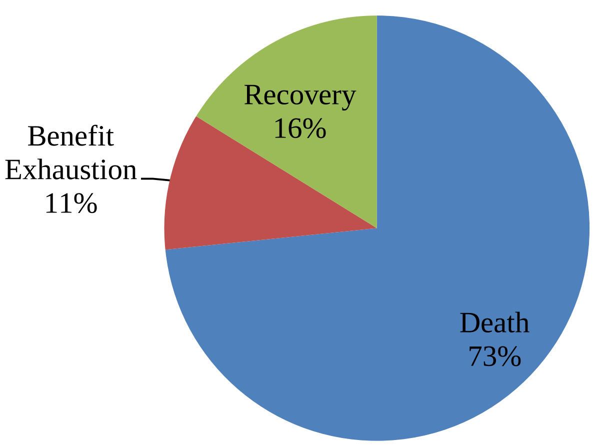


Gender Graphs

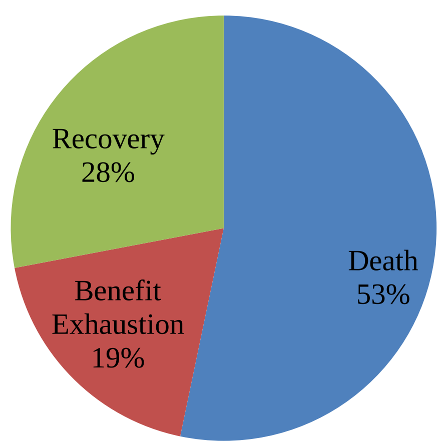
Closed Policies of Males vs. Females due to Death, Recovery, and Benefit Exhaustion

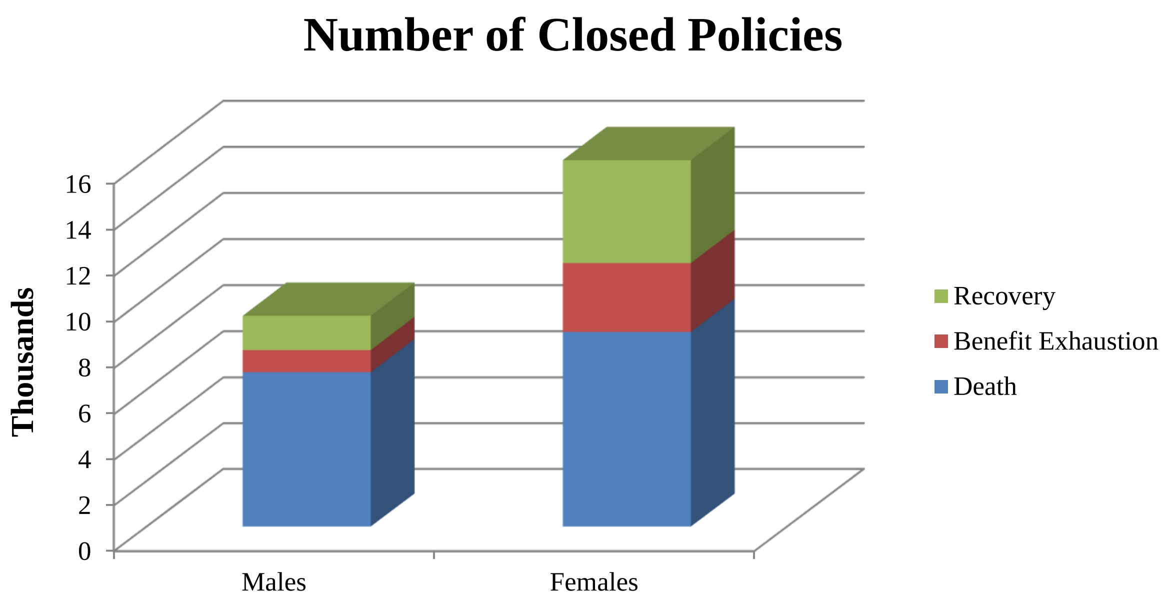


Male Closed Reason

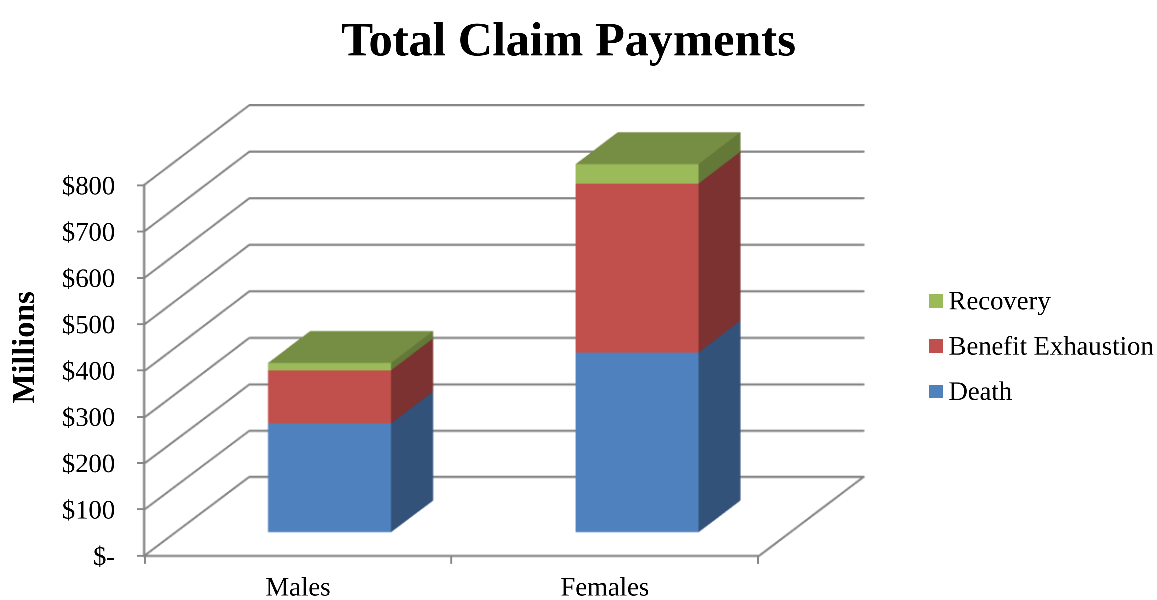


Female Closed Reason

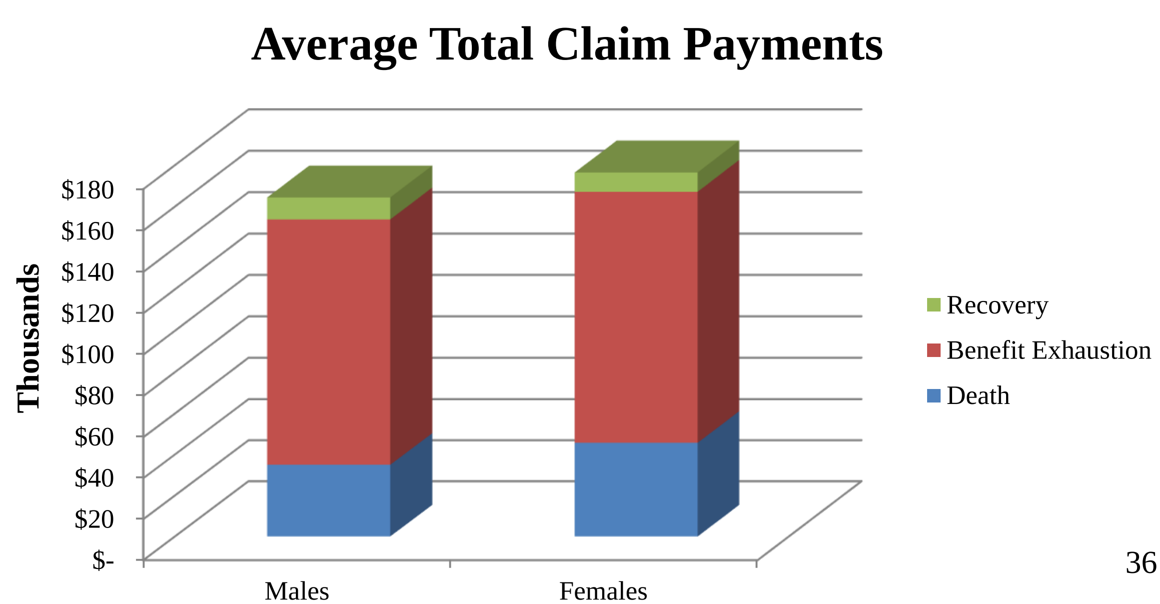




Number of Closed Policies
Thousands
16
14
12
10
8
6
4
2
0
Males
Females
Recovery
Benefit Exhaustion
Death

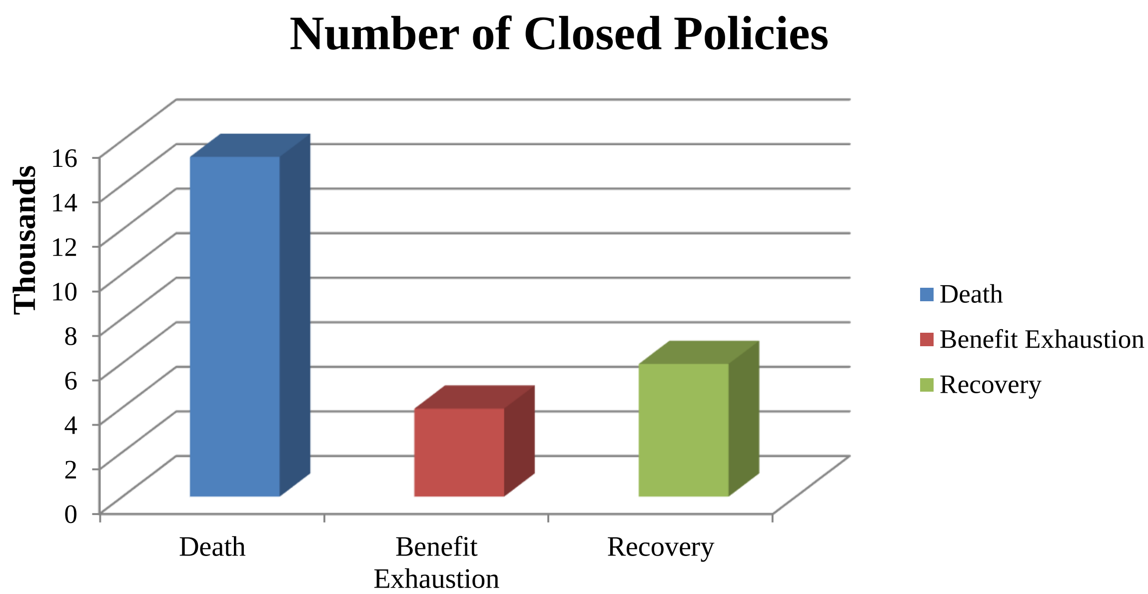


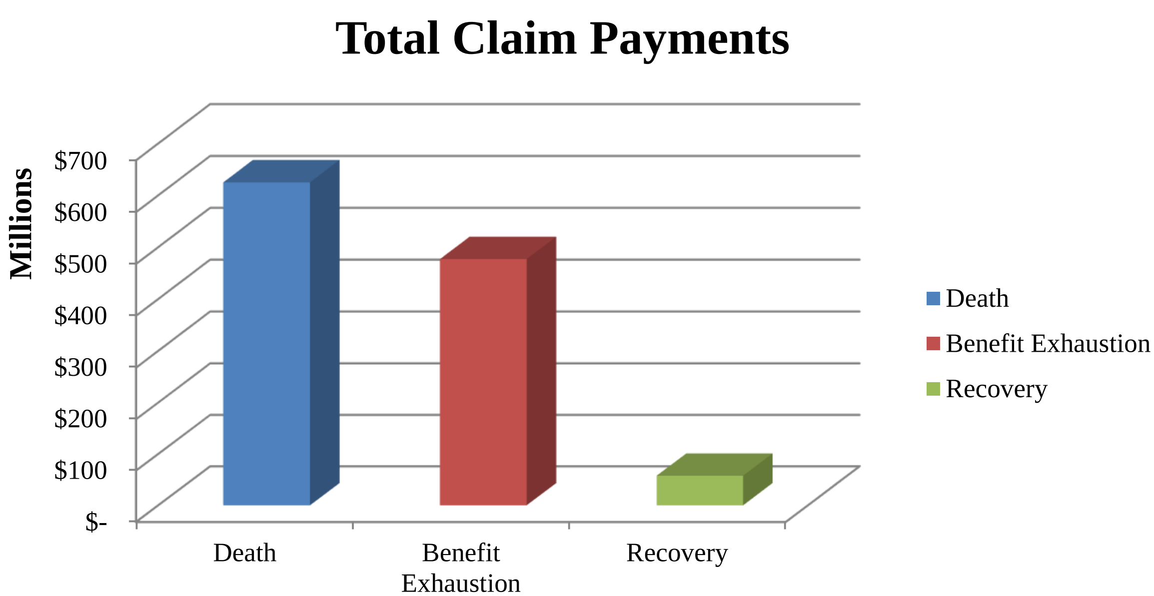
Total Claim Payments
Millions
$800
$700
$600
$500
$400
$300
$200
$100
$-
Males
Females
Recovery
Benefit Exhaustion
Death

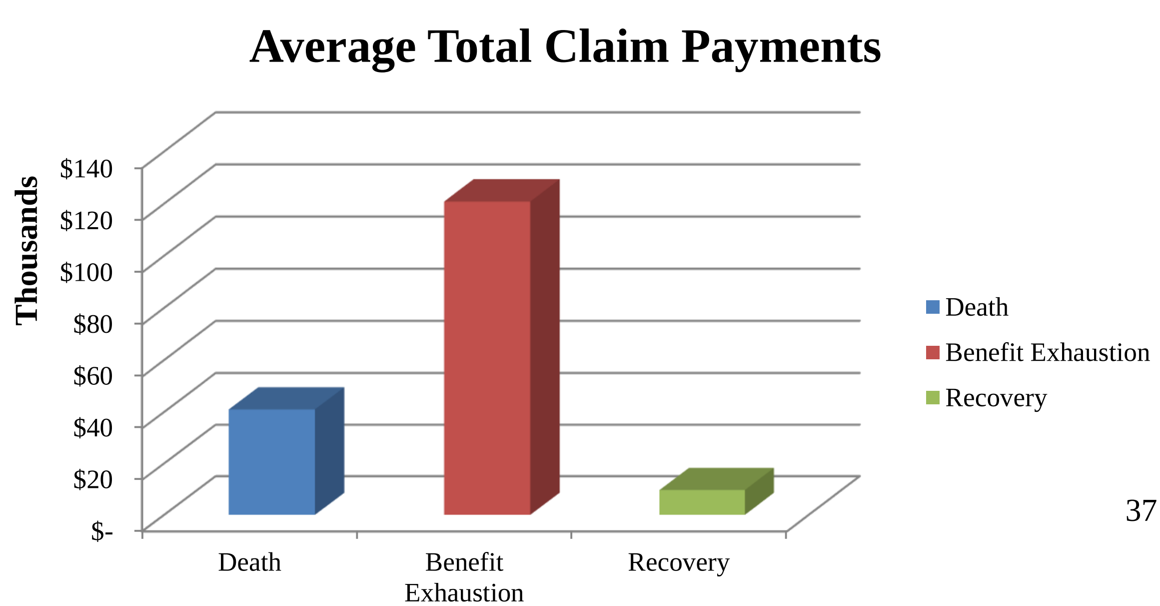


Average Total Claim Payments
Thousands
$180
$160
$140
$120
$100
$80
$60
$40
$20
$-
Males
Females
Recovery
Benefit Exhaustion
Death

Close Reason Graphs



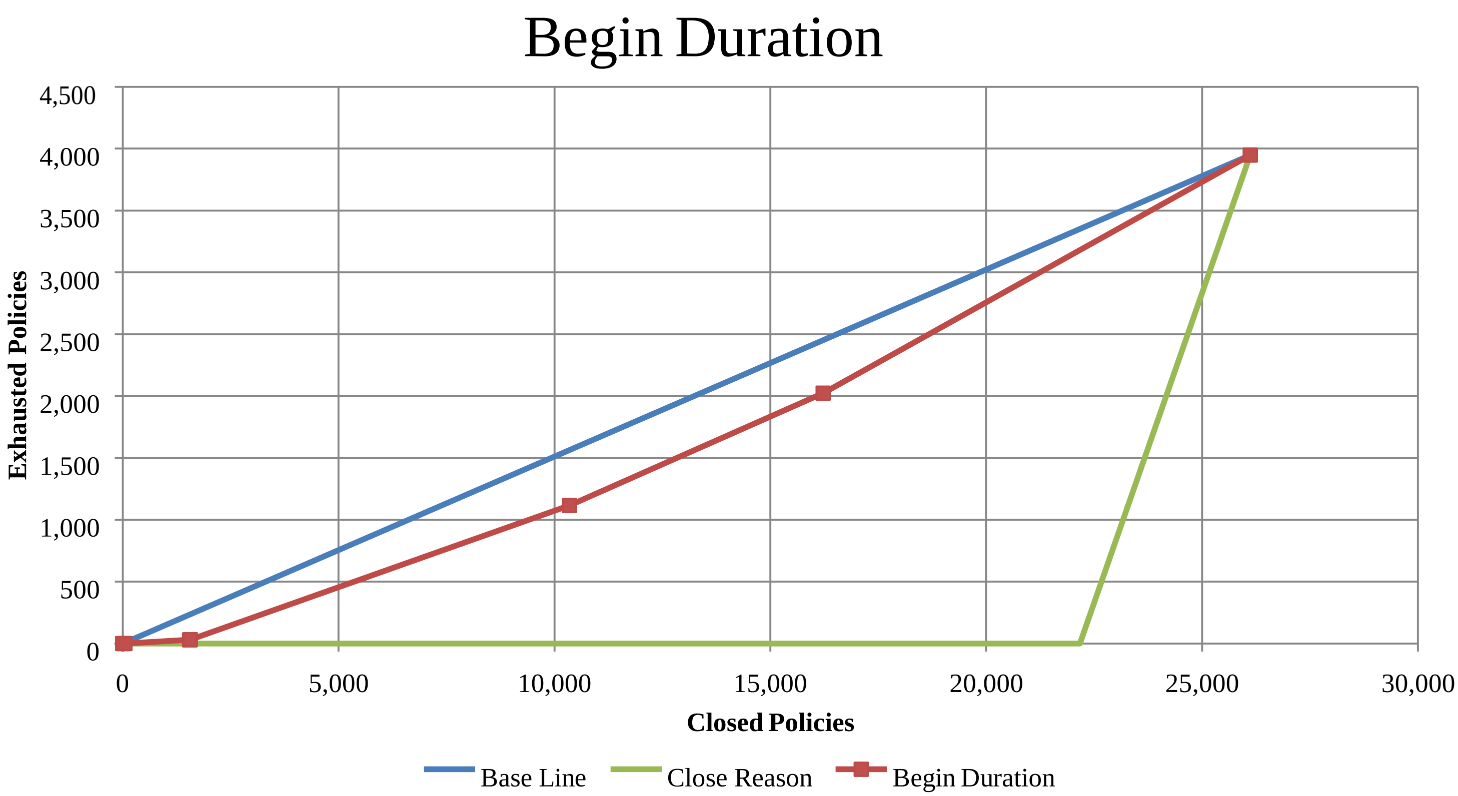




Section 2: Single Factor Graphs

The consecutive pages contain the single factor charts for the following characteristics:

- Begin Duration
- Benefit Increase Option
- Benefit Period
- Claim Age
- Claim Age Group
- Claim ID
- Client Set Out of Force Date
- Close Reason
- Company
- Current Diagnosis Code
- Elimination Period
- End Duration
- Gender
- Initial Diagnosis Code
- Issue Age
- Marital Status
- Original Benefit Claim Coverage
- Plan Type
- Policy Status
- Replacement Indicator
- Risk Commenced Year
- U.S. Region
- Total Days on Claim

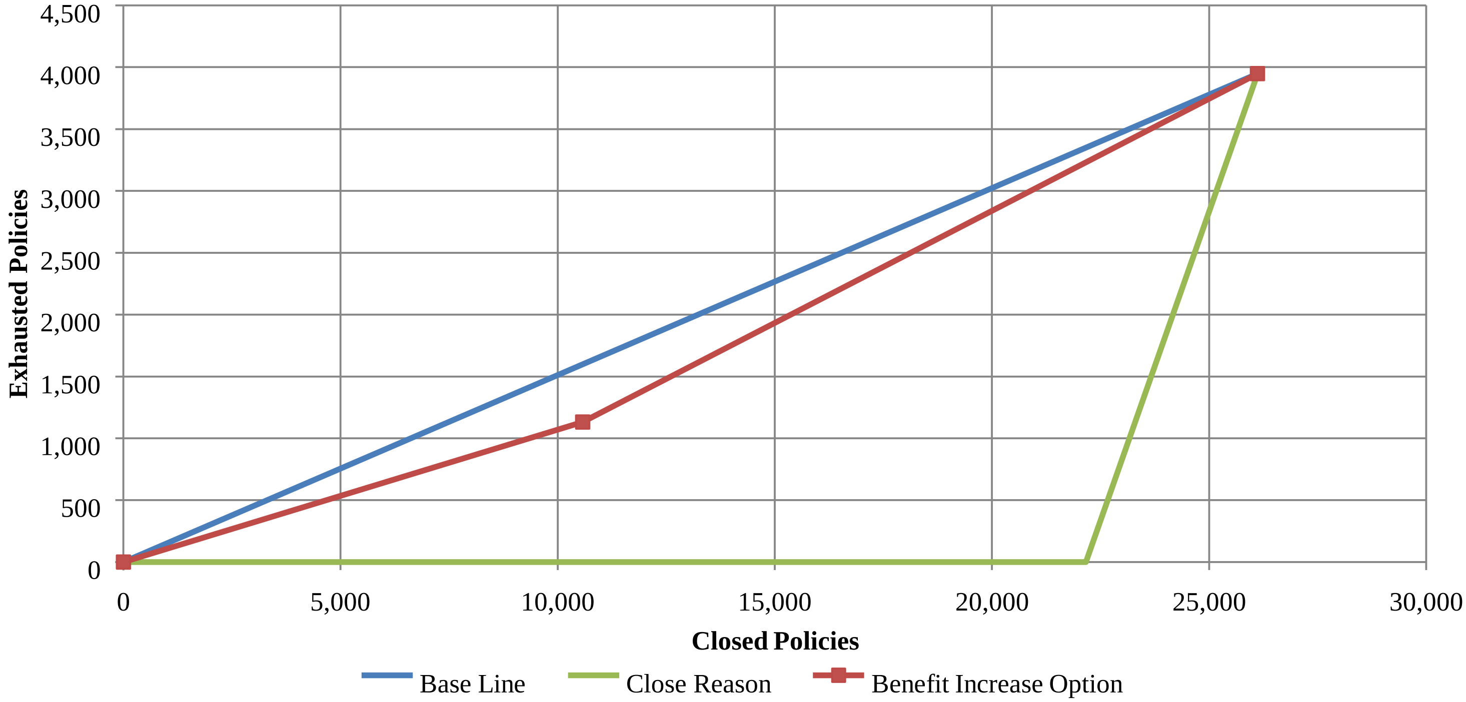


Begin Duration	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
21 to 25	-	53	0.000000	-	53
16 to 20	30	1,497	0.020040	30	1,550
Blank	1	17	0.058824	31	1,567
11 to 15	1,085	8,783	0.123534	1,116	10,350
1 to 5	908	5,873	0.154606	2,024	16,223
6 to 10	1,924	9,891	0.194520	3,948	26,114

Percentage of Maximum Area
17.7%

Predictive
Unknown during Underwriting

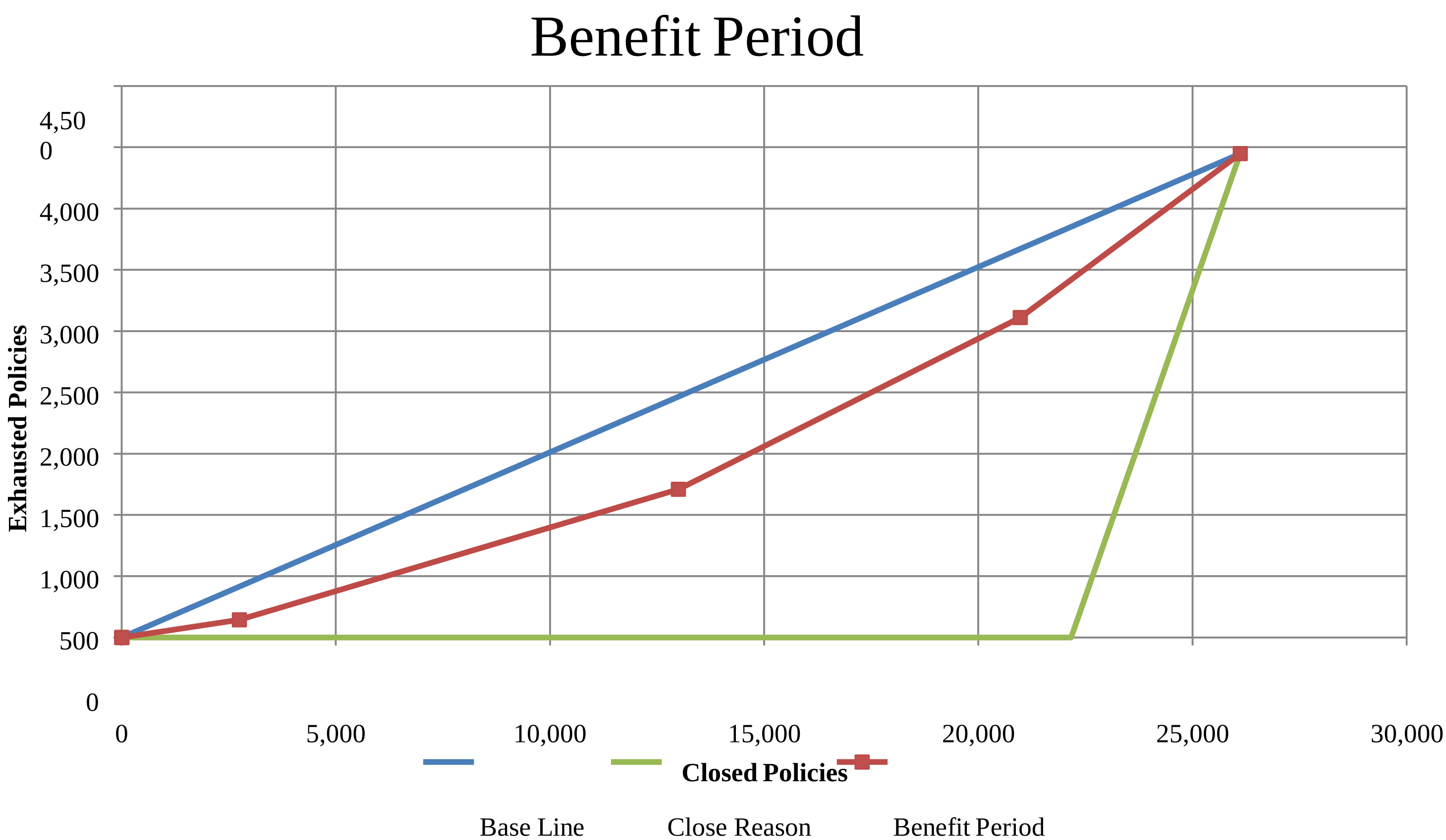
Benefit Increase Option



Percentage of Maximum Area
13.9%

Benefit Increase Option	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
Yes	1,132	10,576	0.107035	1,132	10,576
No	2,816	15,538	0.181233	3,948	26,114

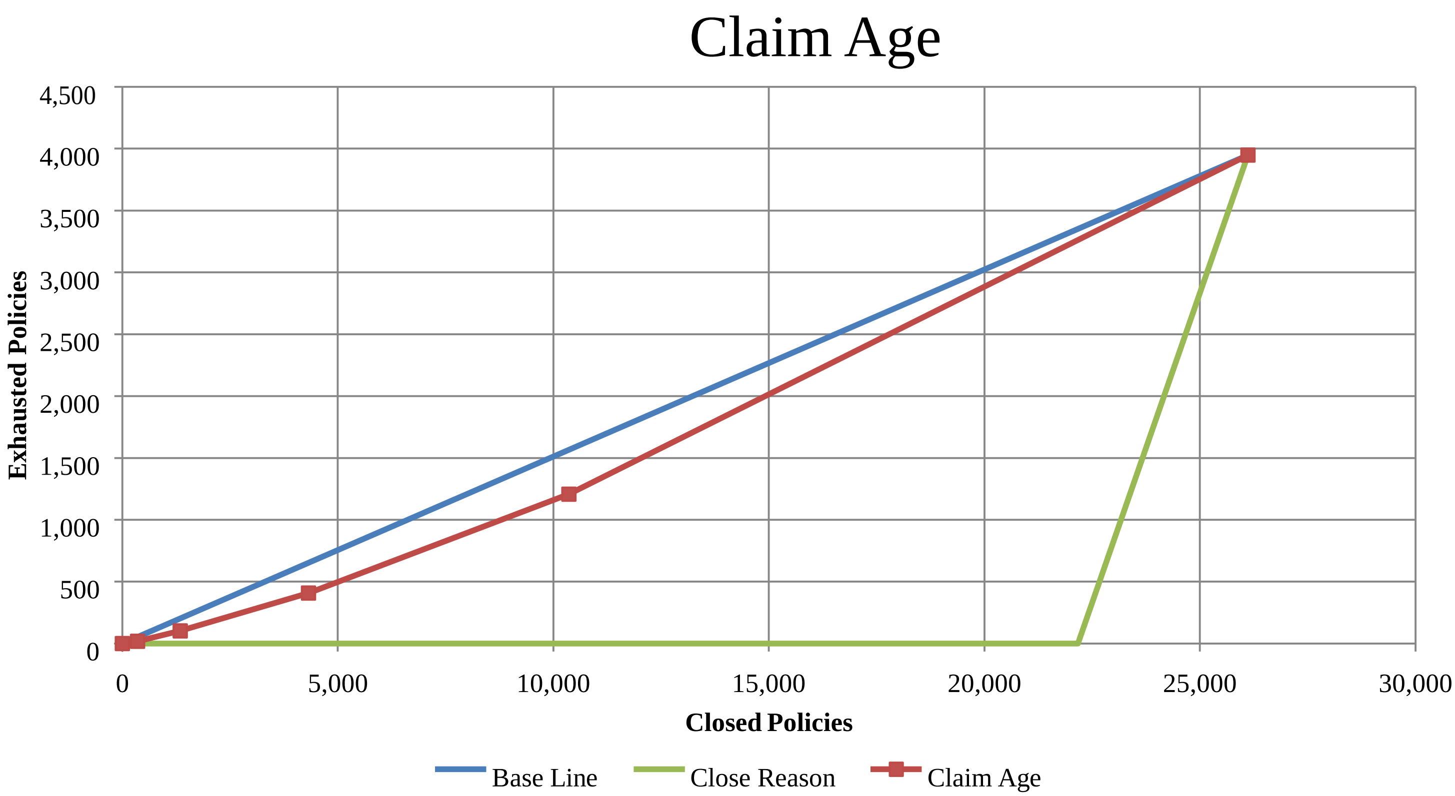
Predictive
Known during Underwriting



Benefit Period	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
1	-	4	0.000000	-	4
5	-	2	0.000000	-	6
6	144	2,743	0.052497	144	2,749
4	1,065	10,248	0.103923	1,209	12,997
3	1,402	7,982	0.175645	2,611	20,979
2	1,337	5,135	0.260370	3,948	26,114

Percentage of Maximum Area
28.2%

Predictive
Known during Underwriting



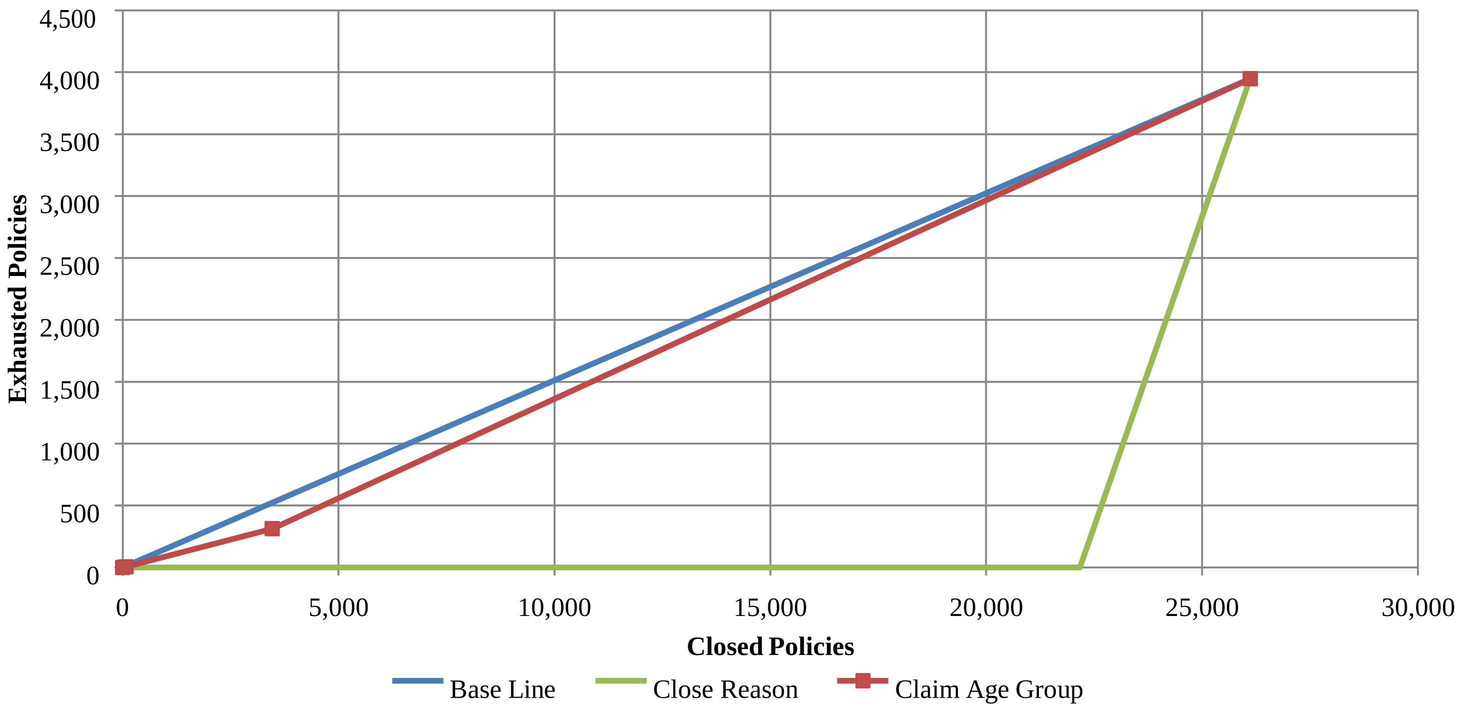
Claim Age	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
45-64	18	353	0.050992	18	353
65-69	84	988	0.085020	102	1,341
70-74	306	2,977	0.102788	408	4,318
75-79	799	6,041	0.132263	1,207	10,359
80-100	2,741	15,755	0.173977	3,948	26,114

Percentage of Maximum Area
12.0%

Predictive

Unknown during Underwriting

Claim Age Group

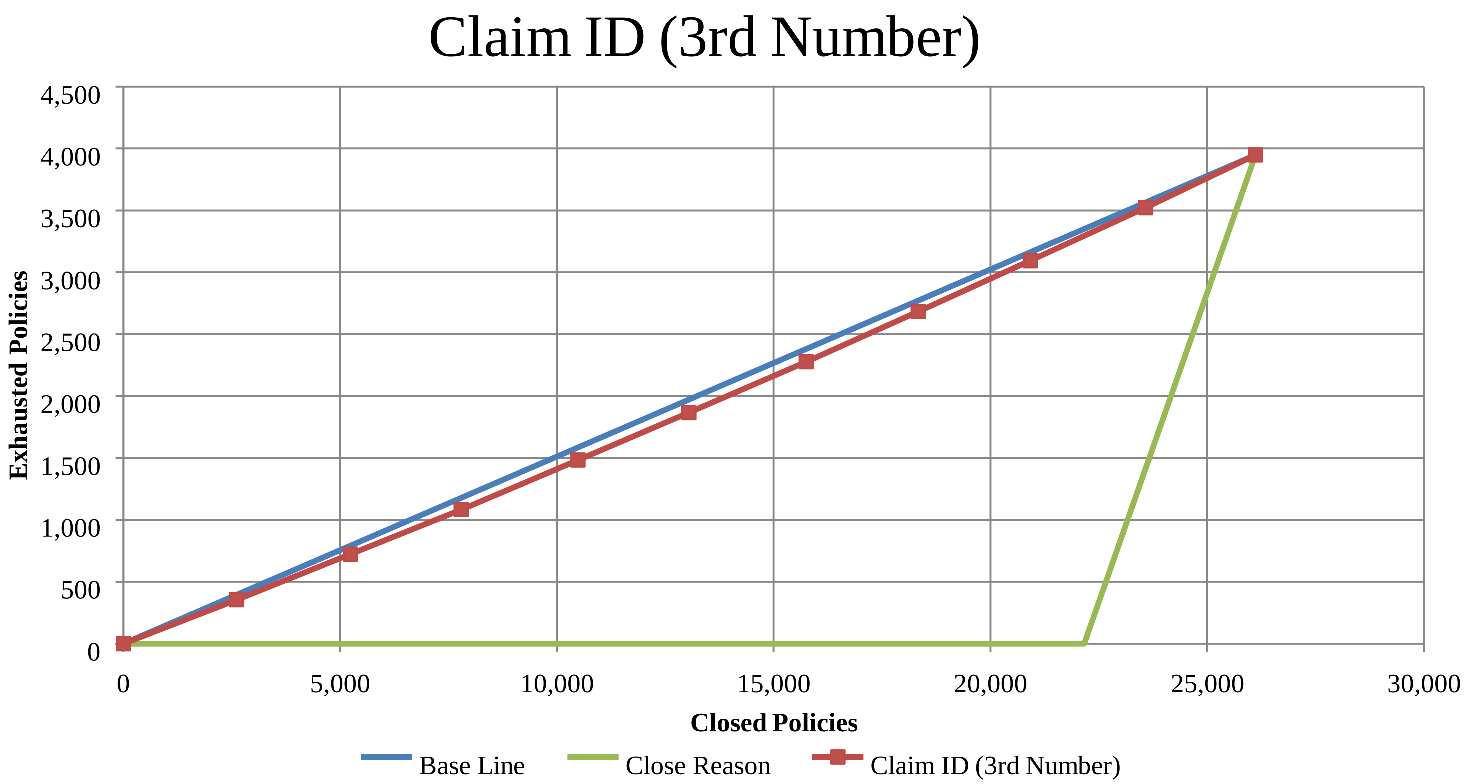


Claim Age Group	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
60-	5	77	0.064935	5	77
60-74	308	3,386	0.090963	313	3,463
75+	3,635	22,651	0.160479	3,948	26,114

Percentage of Maximum Area
6.3%

Not Predictive

Unknown during Underwriting

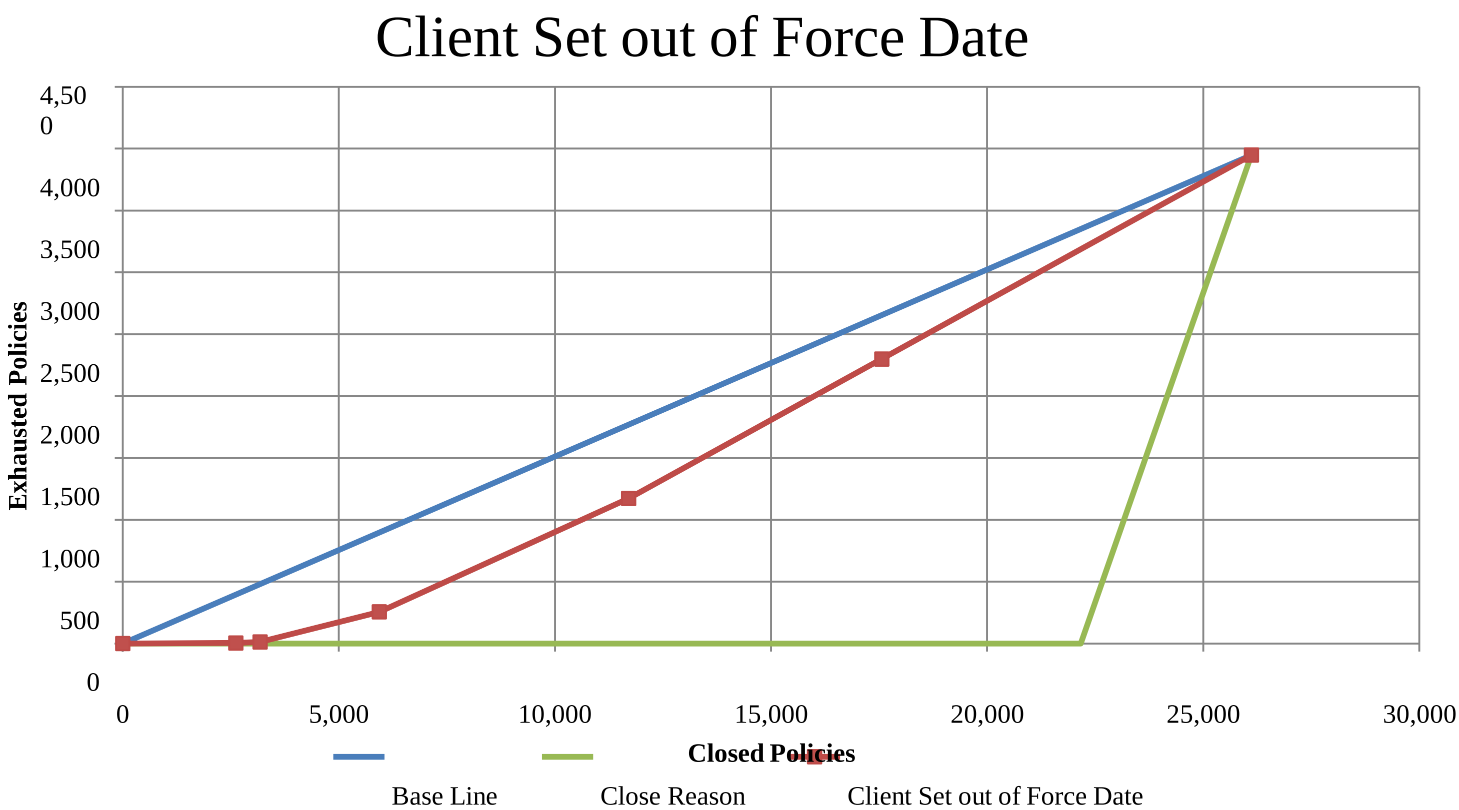


Claim ID (3rd Number)	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
8	355	2,611	0.135963	355	2,611
0	369	2,627	0.140464	724	5,238
6	359	2,552	0.140674	1,083	7,790
5	401	2,694	0.148849	1,484	10,484
4	382	2,560	0.149219	1,866	13,044
9	412	2,708	0.152142	2,278	15,752
7	405	2,581	0.156916	2,683	18,333
3	410	2,587	0.158485	3,093	20,920
2	429	2,661	0.161218	3,522	23,581
1	426	2,533	0.168180	3,948	26,114

Percentage of Maximum Area
4.3%

Not Predictive
Known during Underwriting

Client Set out of Force Date



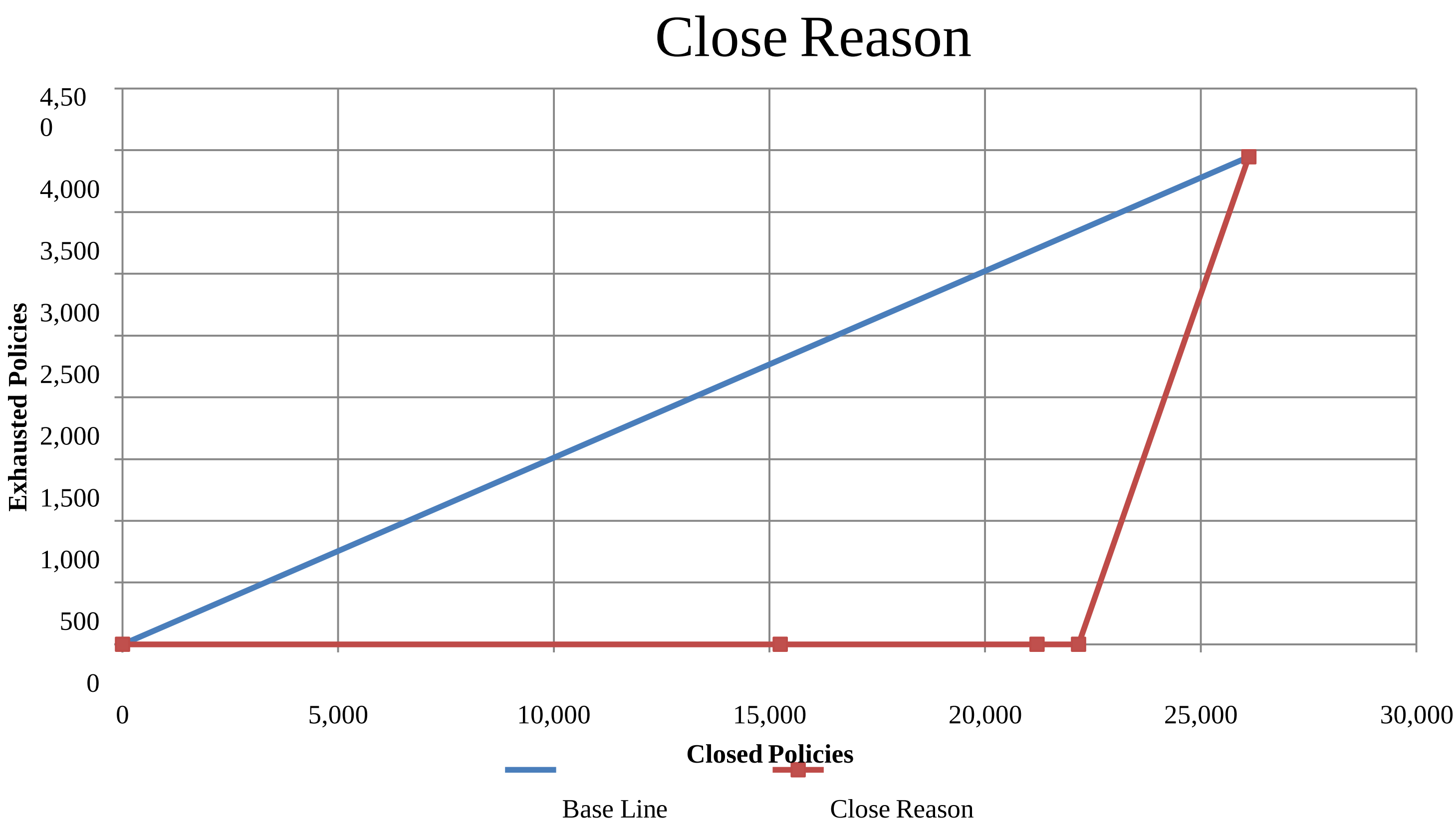
Client Set out of Force Date	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
Blank	4	2,617	0.001528	4	2,617
1995-1998	9	561	0.016043	13	3,178
1999-2002	243	2,756	0.088171	256	5,934
2003-2006	917	5,770	0.158925	1,173	11,704
2011-2013	1,127	5,858	0.192386	2,300	17,562
2007-2010	1,648	8,552	0.192703	3,948	26,114

Percentage of Maximum Area
23.2%

Predictive

Unknown during Underwriting

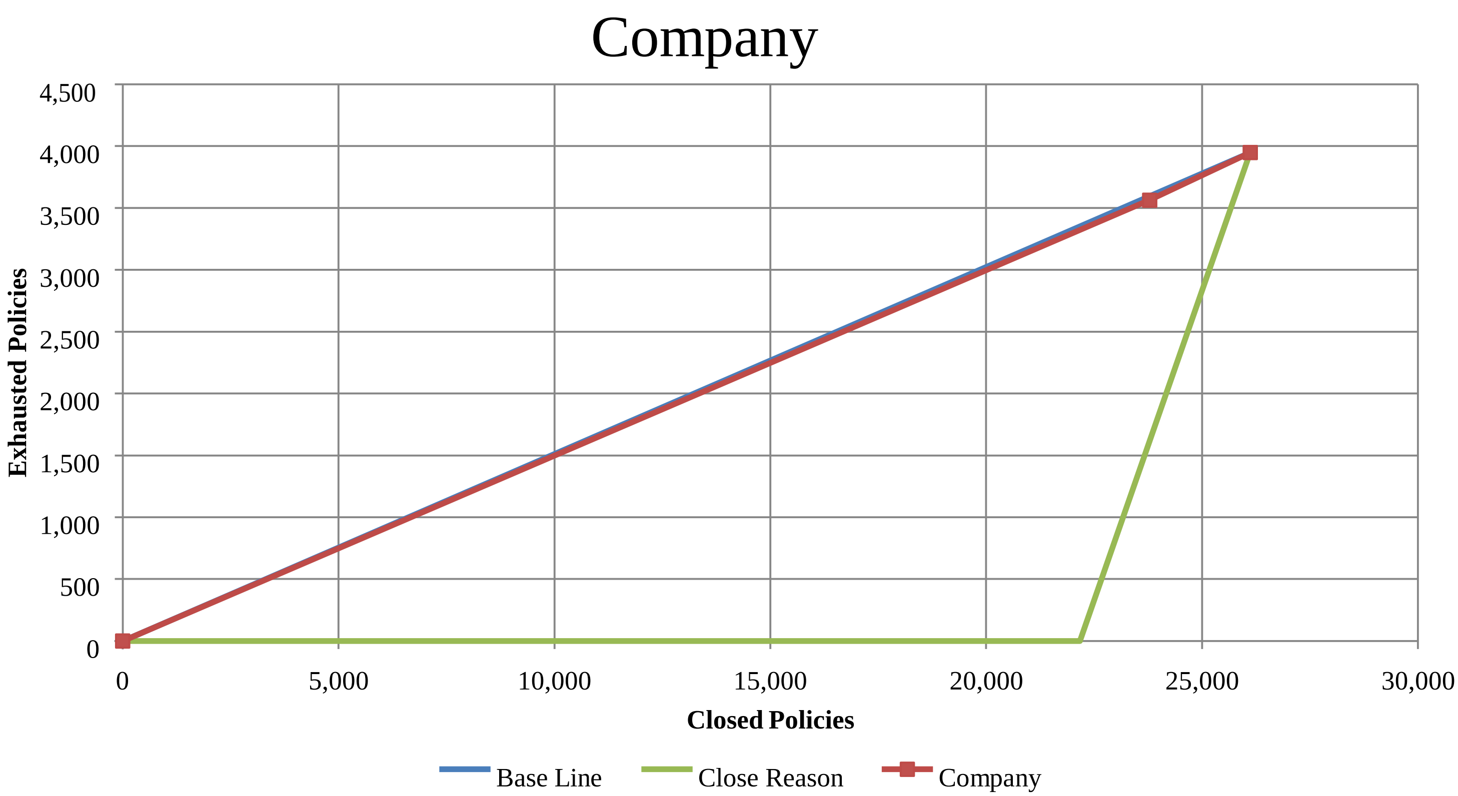
Close Reason



Close Reason	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
Death	-	15,250	0.000000	-	15,250
Recovery	-	5,954	0.000000	-	21,204
Other	-	962	0.000000	-	22,166
Exhaustion	3,948	3,948	1.000000	3,948	26,114

Percentage of Maximum Area
100.0%

Predictive
Unknown during Underwriting

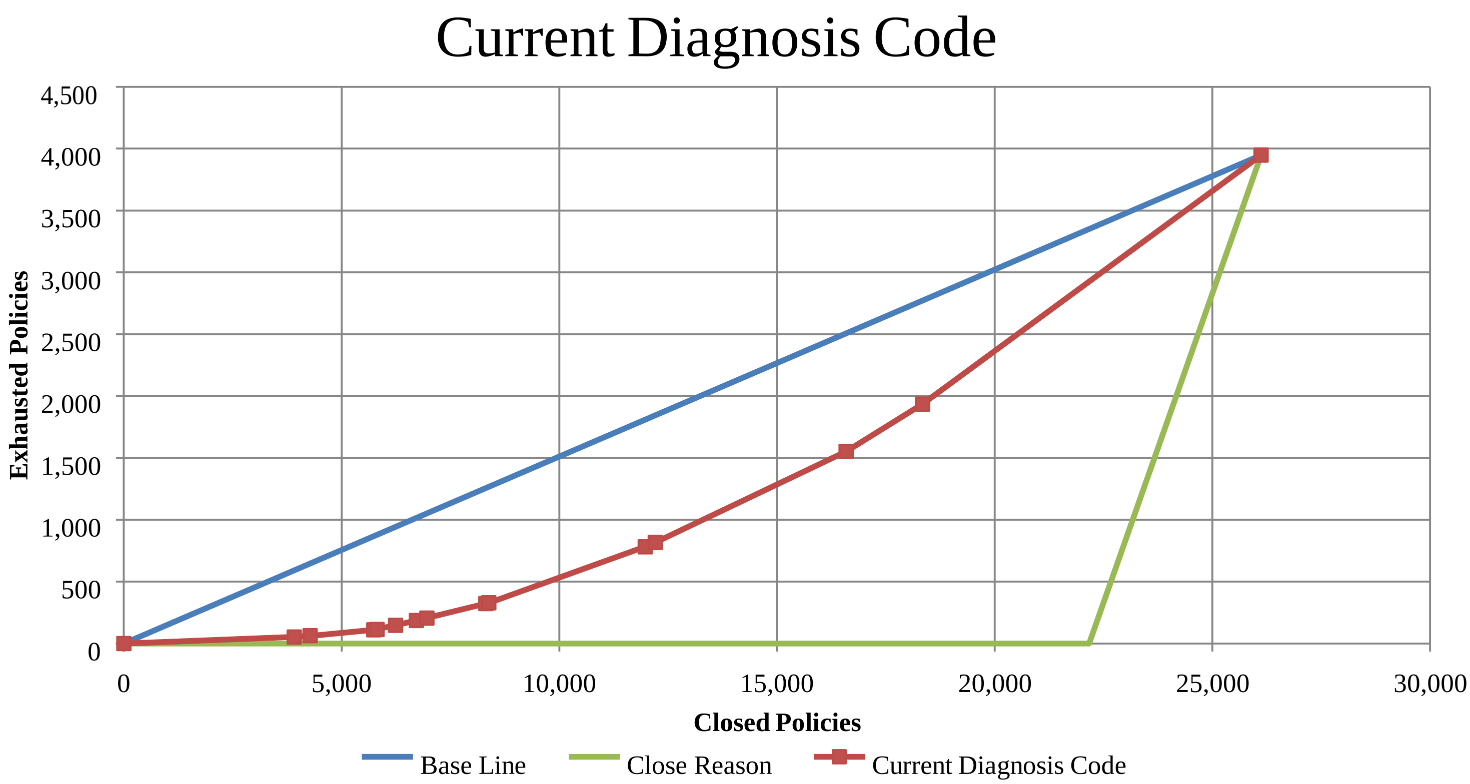


Percentage of Maximum Area
1.0%

Company	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
31	3,563	23,786	0.149794	3,563	23,786
40	385	2,328	0.165378	3,948	26,114

Not Predictive

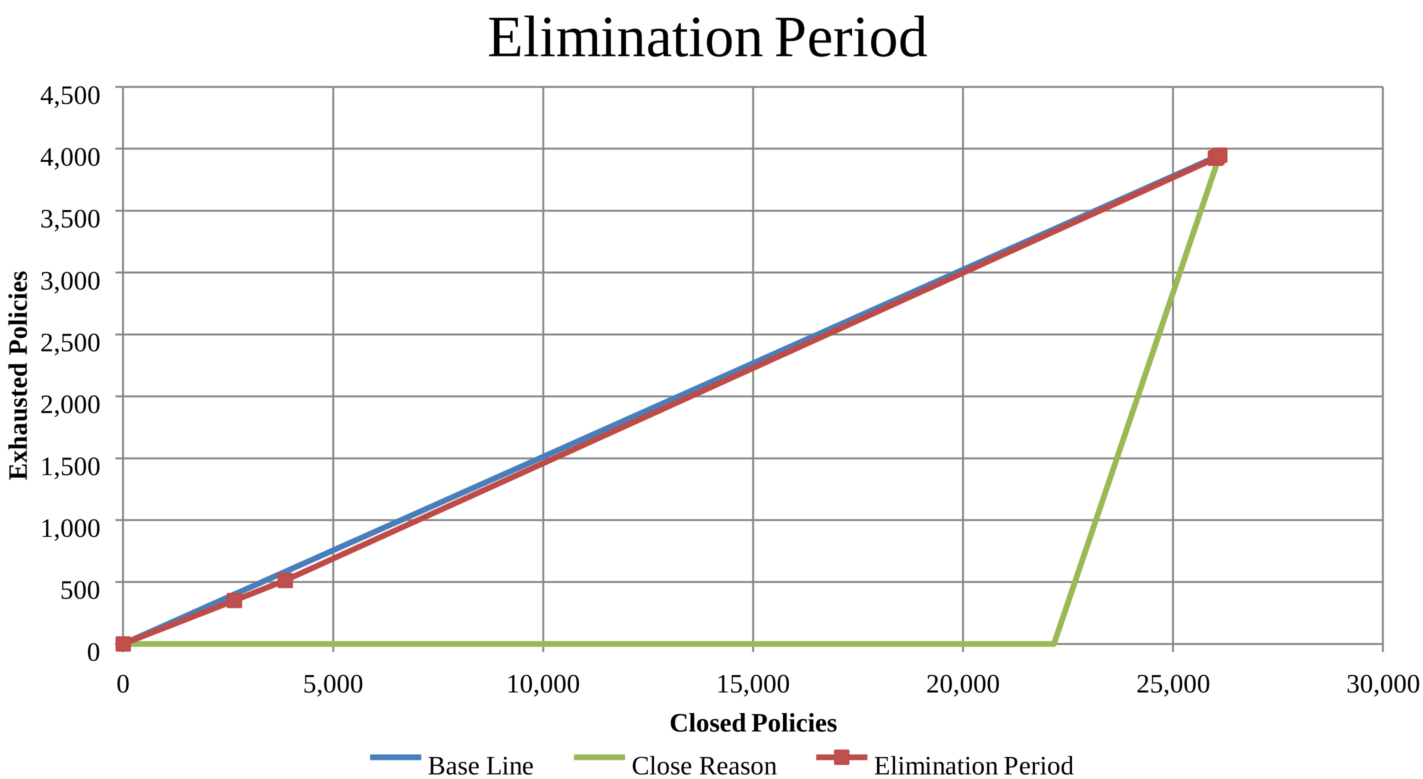
Known during Underwriting



Current Diagnosis Code	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
2	53	3,745	0.014152	53	3,913
9	10	362	0.027624	63	4,275
17	48	1,466	0.032742	111	5,741
4	3	72	0.041667	114	5,813
10	33	426	0.077465	147	6,239
1	39	477	0.081761	186	6,716
16	20	242	0.082645	206	6,958
8	117	1,356	0.086283	323	8,314
12	6	68	0.088235	329	8,382
13	453	3,590	0.126184	782	11,972
3	35	230	0.152174	817	12,202
7	736	4,383	0.167922	1,553	16,585
6	382	1,756	0.217540	1,935	18,341
5	2,013	7,773	0.258973	3,948	26,114

Percentage of Maximum Area
39.8%

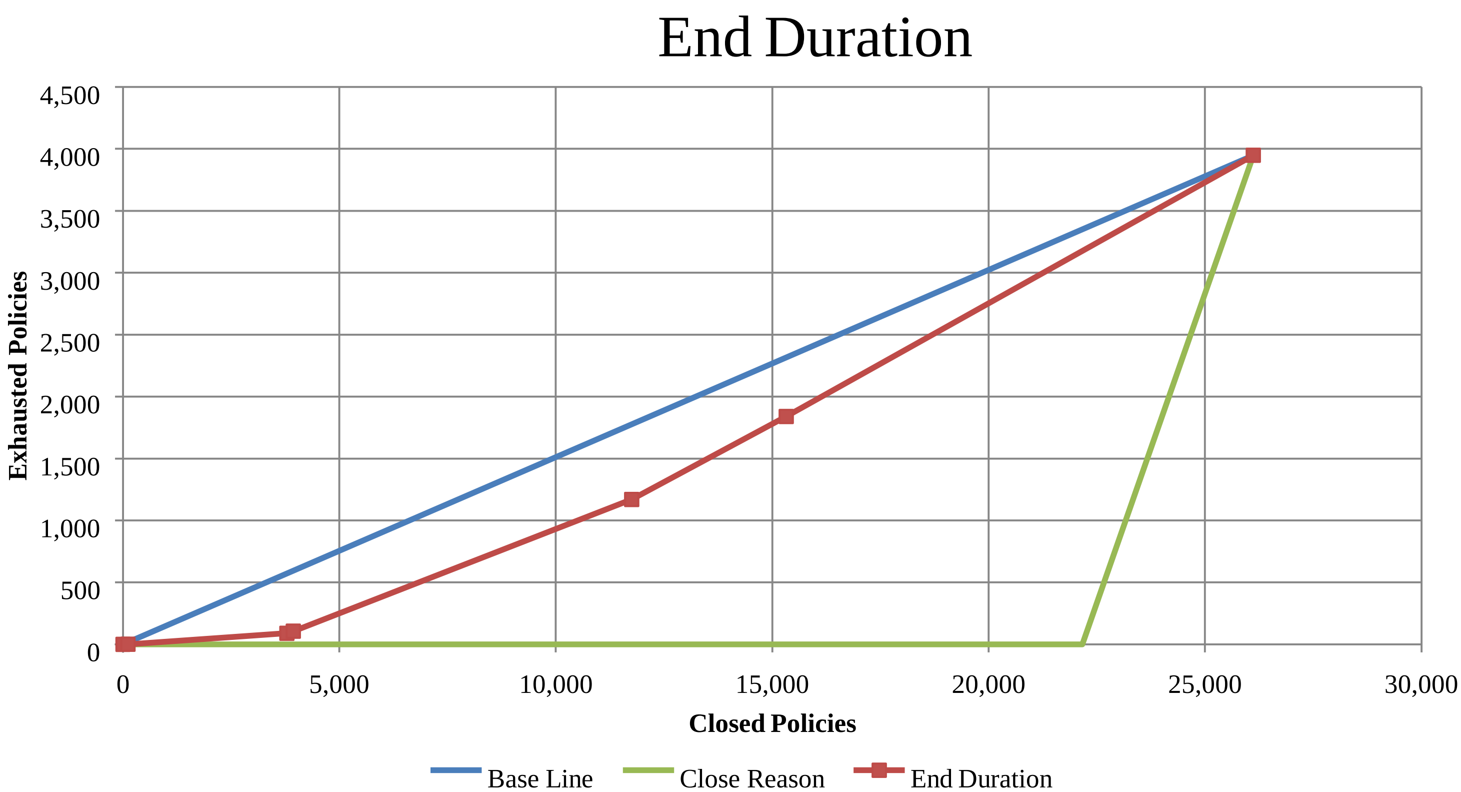
Predictive
Unknown during Underwriting



Elimination Period	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
50	351	2,650	0.132453	351	2,650
0	162	1,210	0.133884	513	3,860
100	3,411	22,150	0.153995	3,924	26,010
30	1	6	0.166667	3,925	26,016
20	6	32	0.187500	3,931	26,048
90	17	66	0.257576	3,948	26,114

Percentage of Maximum Area
2.3%

Not Predictive
Unknown during Underwriting

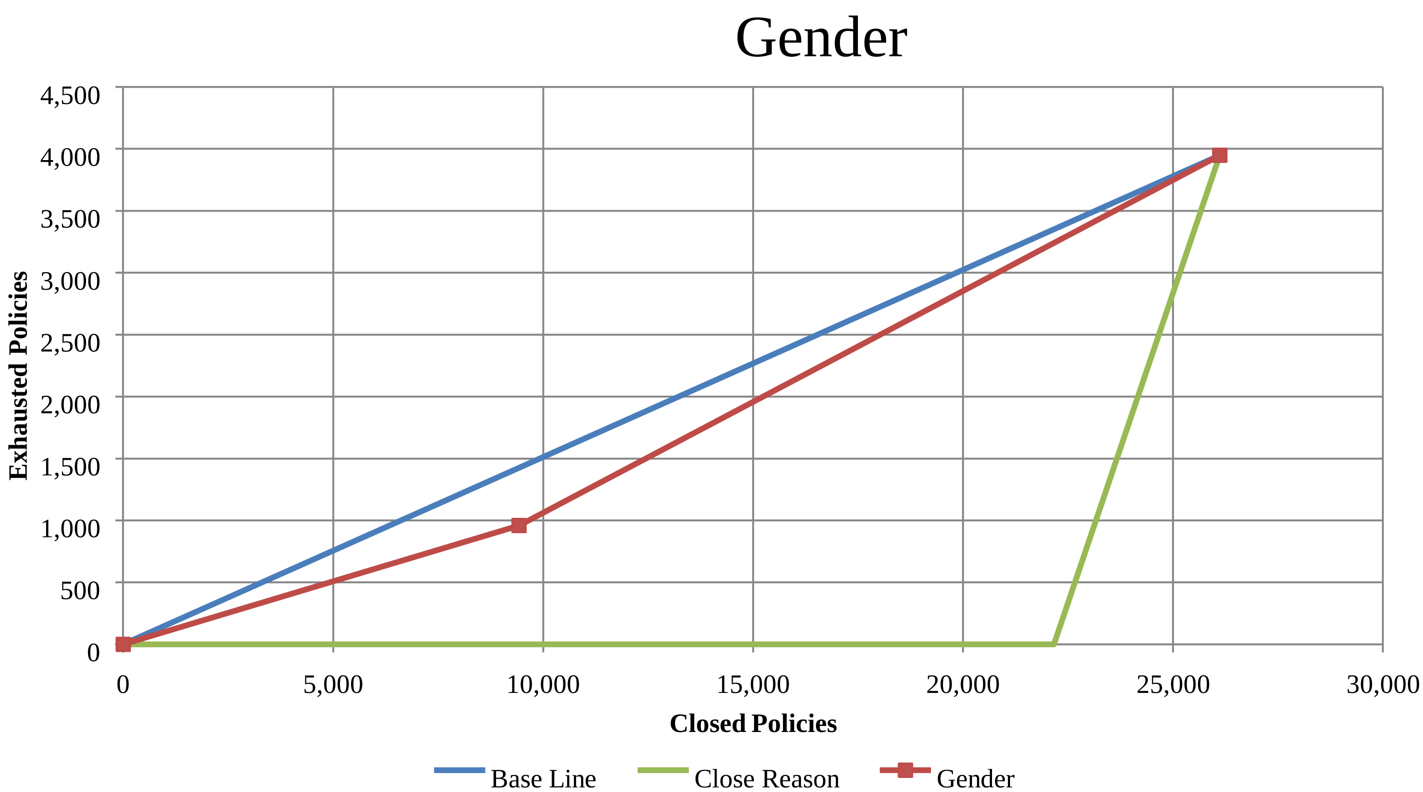


End Duration	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
Blank	1	114	0.008772	1	114
1 to 5	88	3,672	0.023965	89	3,786
21 to 25	18	148	0.121622	107	3,934
6 to 10	1,063	7,820	0.135934	1,170	11,754
16 to 20	670	3,570	0.187675	1,840	15,324
11 to 15	2,108	10,790	0.195366	3,948	26,114

Percentage of Maximum Area
22.3%

Predictive

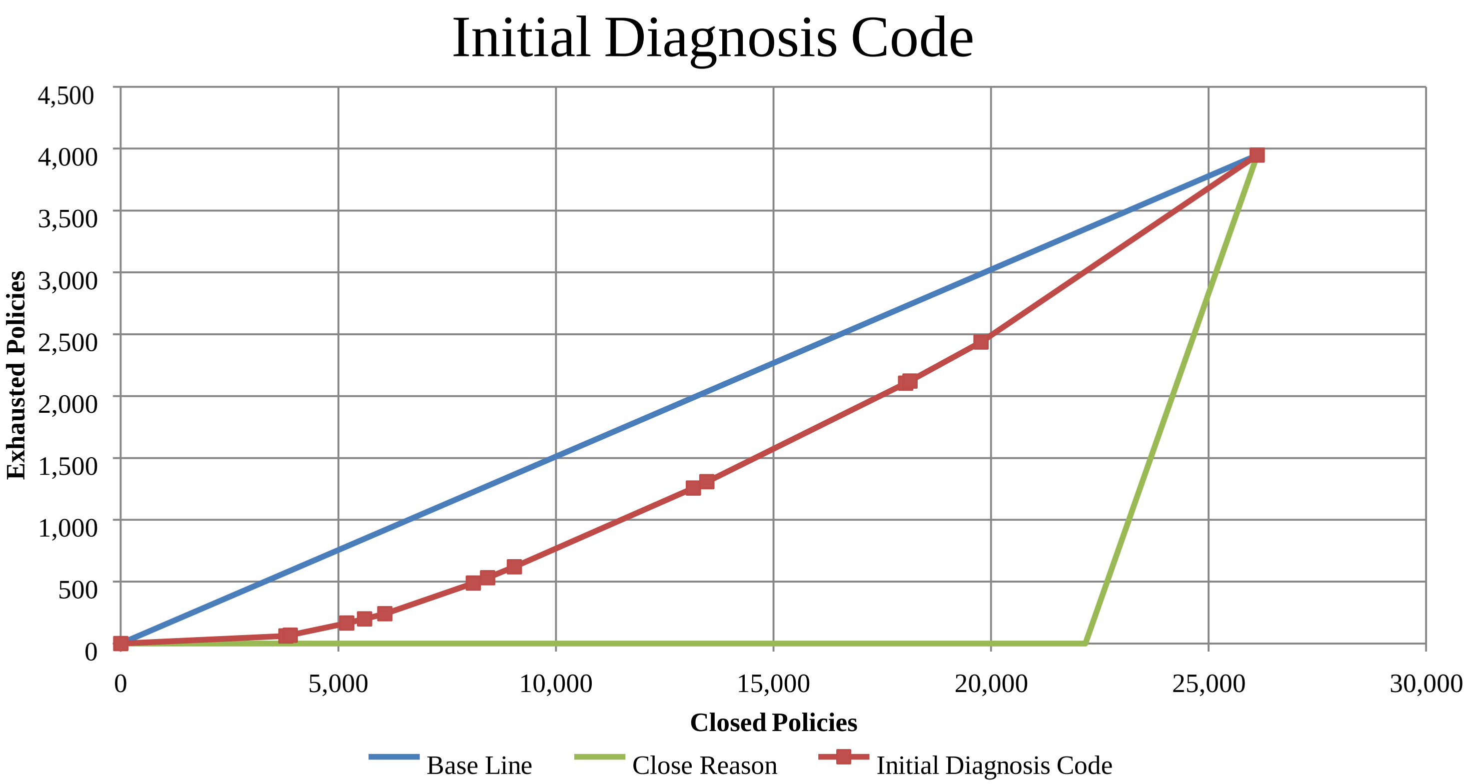
Unknown during Underwriting



Gender	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
Male	960	9,425	0.101857	960	9,425
Female	2,988	16,689	0.179040	3,948	26,114

Percentage of Maximum Area
13.9%

Predictive
Known during Underwriting

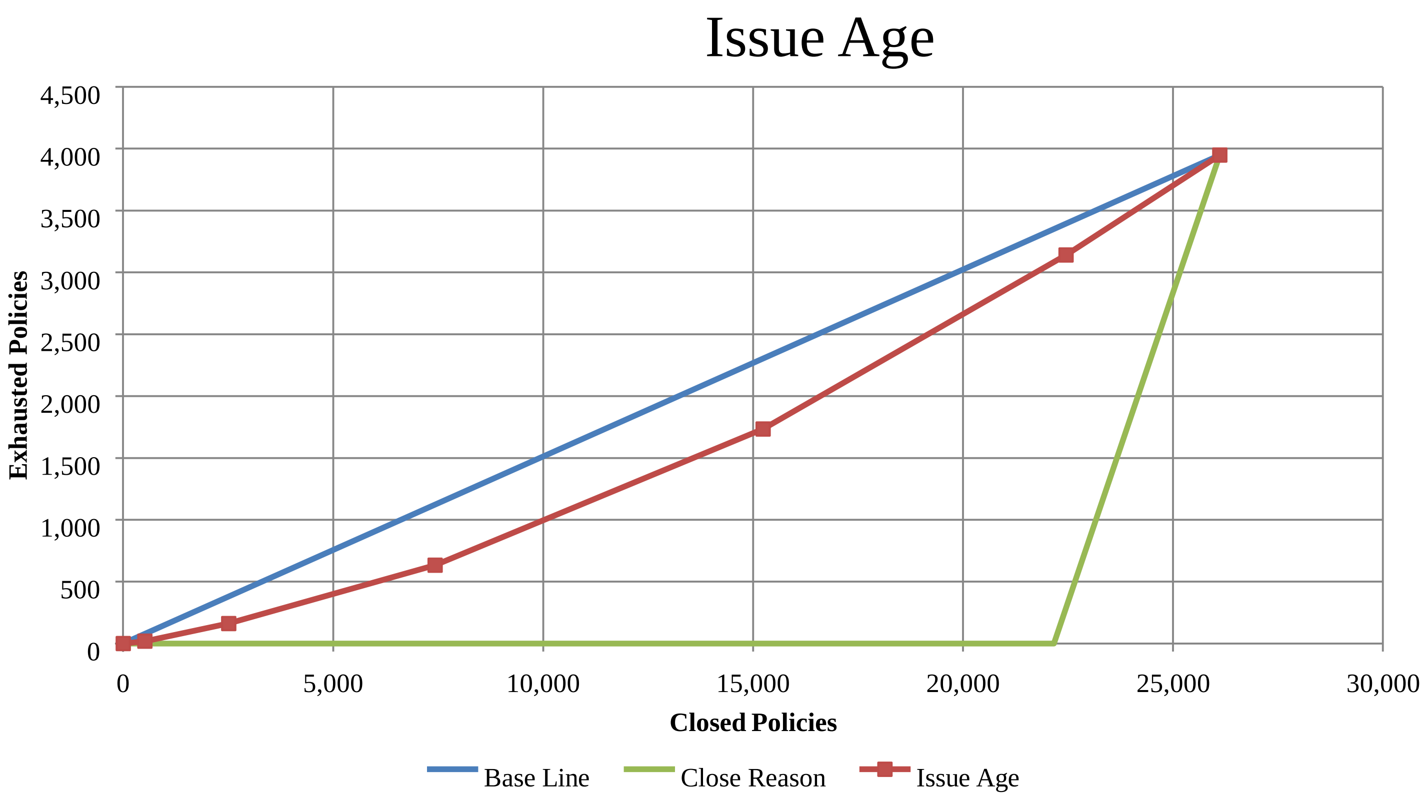


Initial Diagnosis Code	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
2	61	3,628	0.016814	61	3,796
4	7	99	0.070707	68	3,895
8	98	1,297	0.075559	166	5,192
10	33	411	0.080292	199	5,603
9	42	466	0.090129	241	6,069
17	248	2,034	0.121927	489	8,103
16	43	327	0.131498	532	8,430
1	88	615	0.143089	620	9,045
13	637	4,113	0.154875	1,257	13,158
3	52	310	0.167742	1,309	13,468
7	795	4,566	0.174113	2,104	18,034
12	18	101	0.178218	2,122	18,135
6	315	1,633	0.192897	2,437	19,768
5	1,511	6,346	0.238103	3,948	26,114

Percentage of Maximum Area
31.1%

Predictive

Unknown during Underwriting

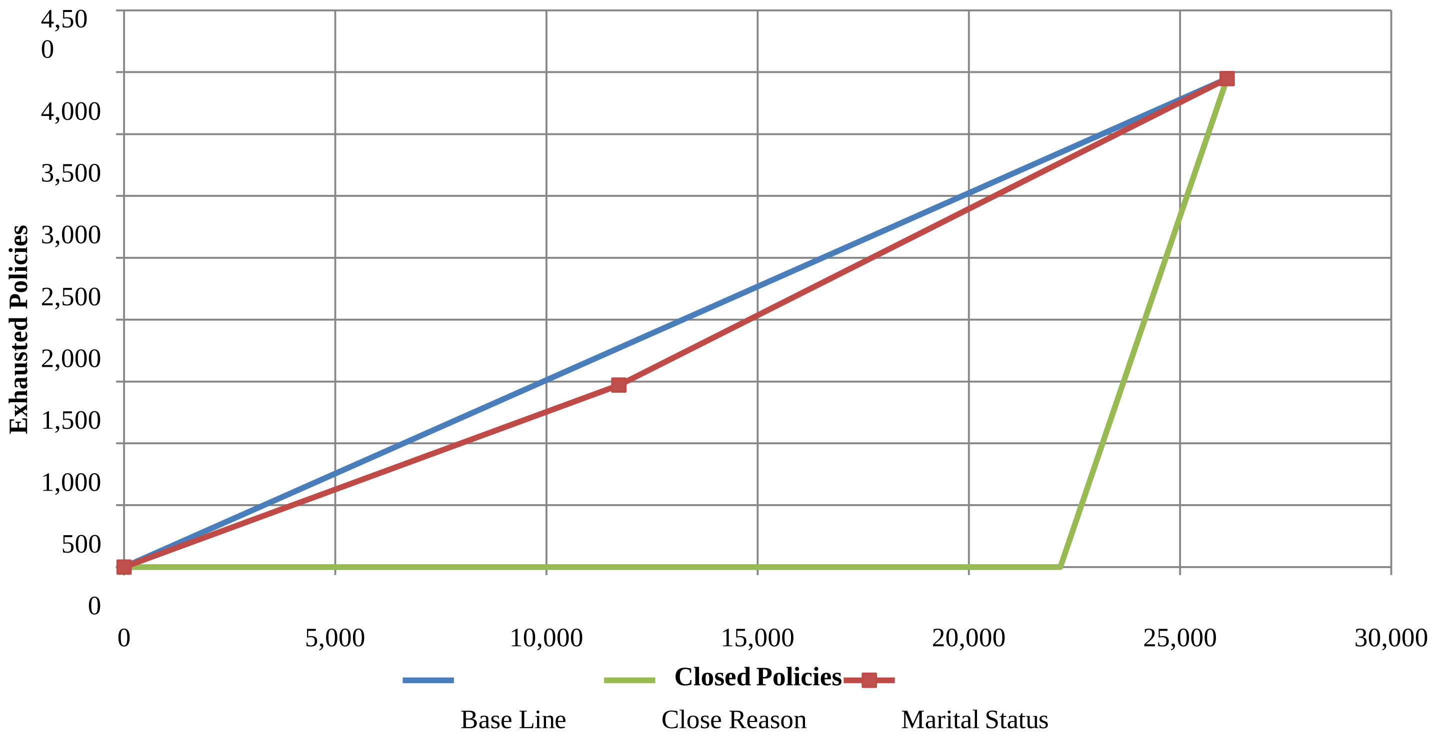


Issue Age	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
40-59	19	517	0.036750	19	517
60-64	143	1,997	0.071607	162	2,514
65-69	471	4,914	0.095849	633	7,428
70-74	1,101	7,812	0.140937	1,734	15,240
75-79	1,407	7,213	0.195064	3,141	22,453
80-94	807	3,661	0.220432	3,948	26,114

Percentage of Maximum Area
22.0%

Predictive
Known during Underwriting

Marital Status



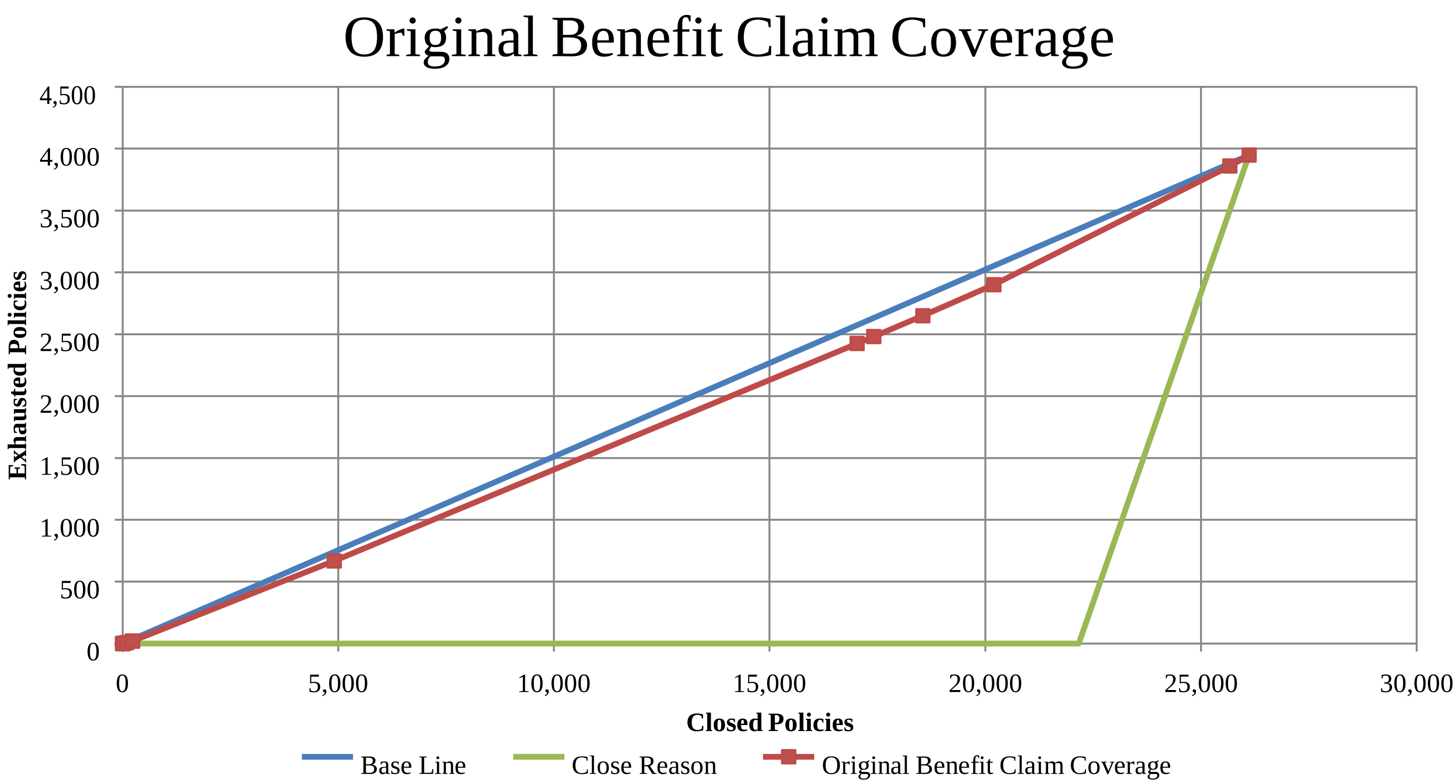
Marital Status	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
Married	1,471	11,716	0.125555	1,471	11,716
Single	2,477	14,398	0.172038	3,948	26,114

Percentage of Maximum Area

9.0%

Predictive

Known during Underwriting

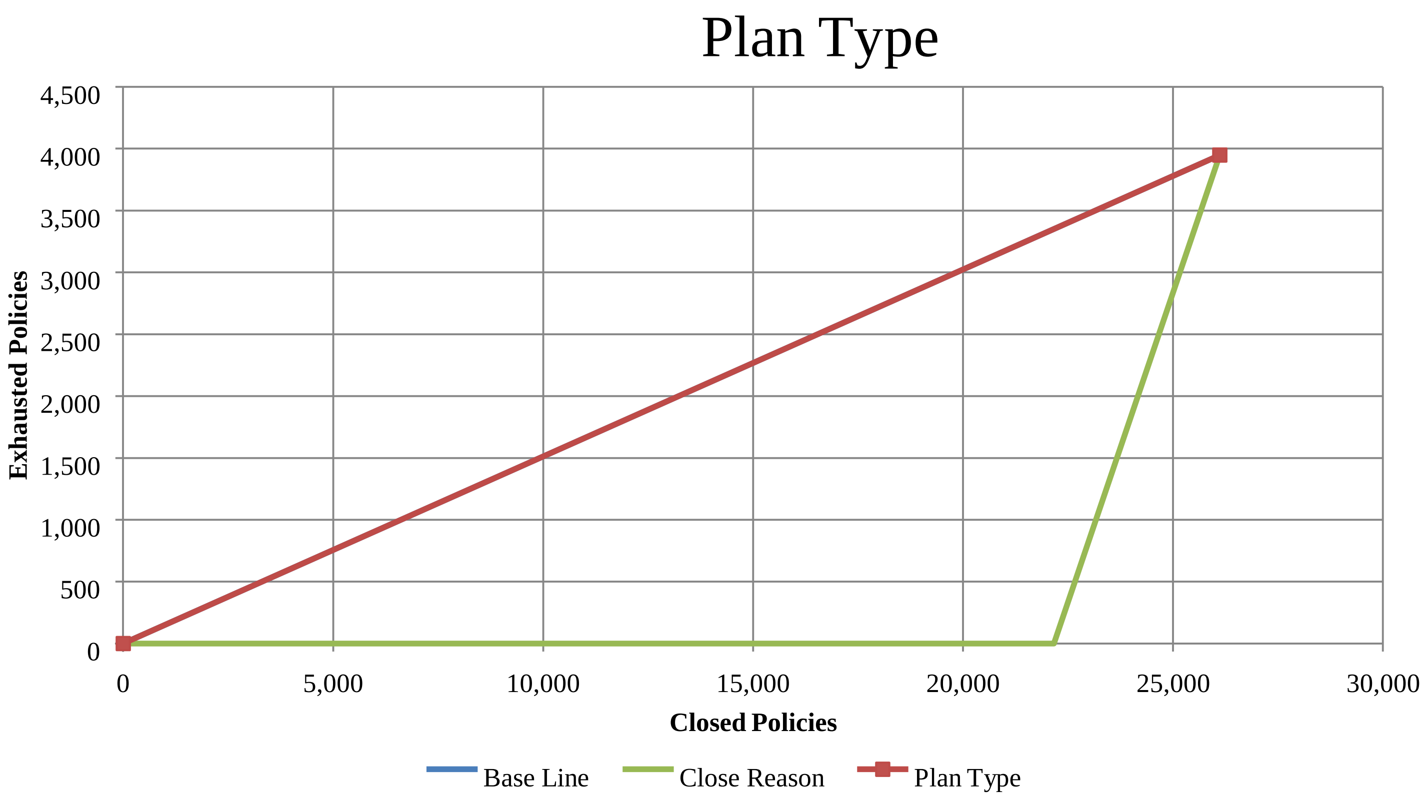


Original Benefit Claim Coverage	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
$225-$250	-	10	0.000000	-	10
$275-$300	-	-	0.000000	-	10
$325-$350	-	2	0.000000	-	12
$300-$325	1	21	0.047619	1	33
$250-$275	6	64	0.093750	7	97
$175-$200	12	127	0.094488	19	224
$0-$25	1	8	0.125000	20	232
$75-$100	648	4,677	0.138550	668	4,909
$100-$125	1,757	12,119	0.144979	2,425	17,028
$200-$225	56	385	0.145455	2,481	17,413
$125-$150	169	1,139	0.148376	2,650	18,552
$150-$175	250	1,645	0.151976	2,900	20,197
$50-$75	960	5,469	0.175535	3,860	25,666
$25-$50	88	448	0.196429	3,948	26,114

Percentage of Maximum Area
5.8%

Not Predictive

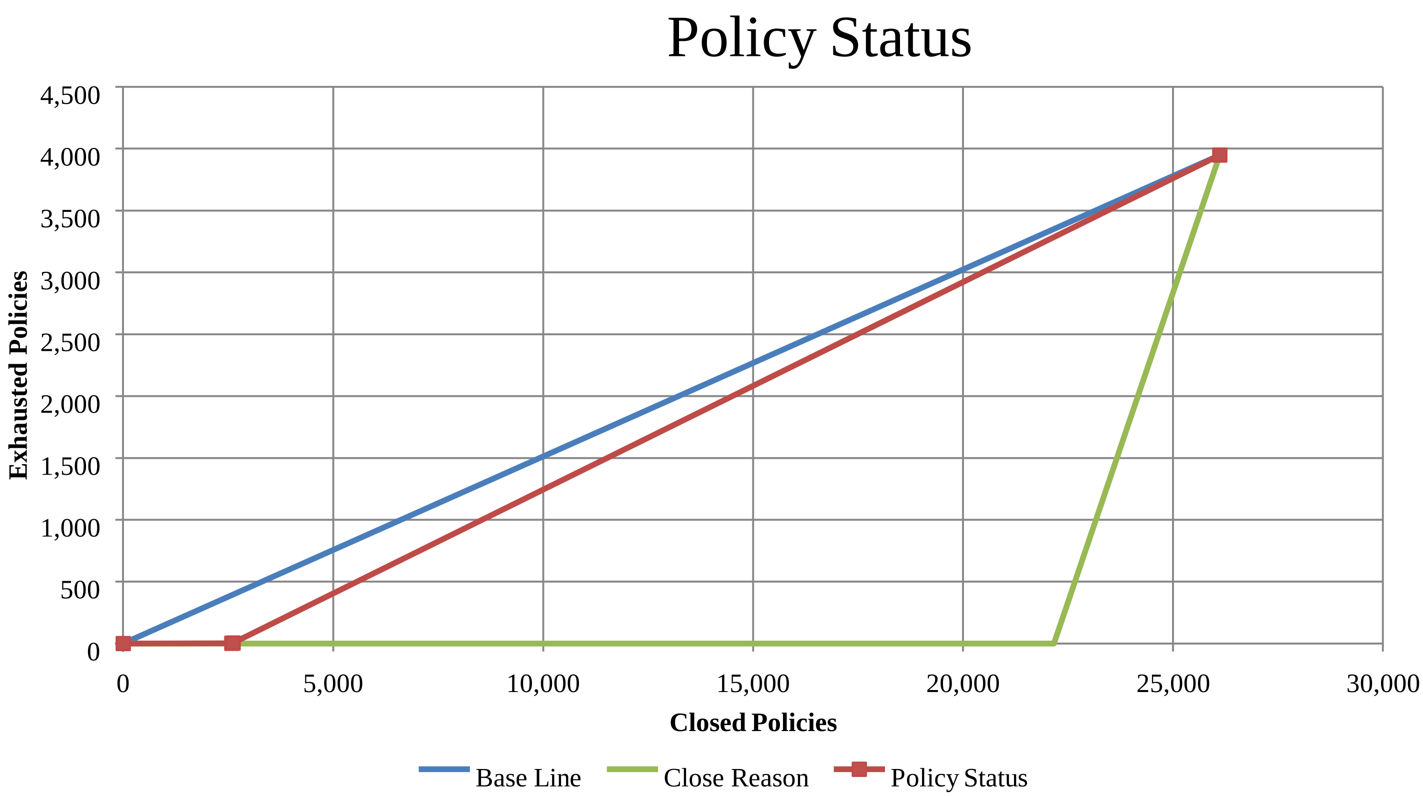
Known during Underwriting



Plan Type	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
PCS	3,948	26,114	0.151183	3,948	26,114

Percentage of Maximum Area
0.0%

Not Predictive
Known during Underwriting



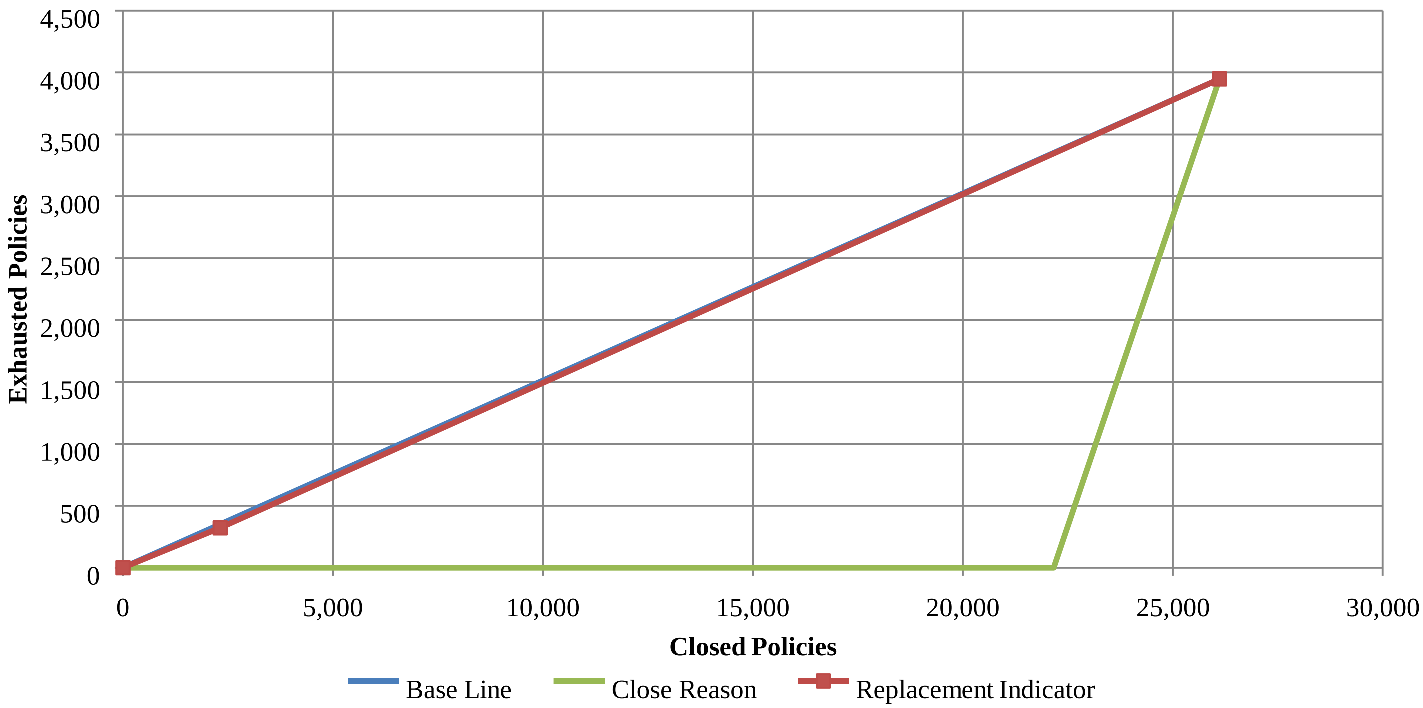
Policy Status	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
A	2	2,587	0.000773	2	2,587
F	2	30	0.066667	4	2,617
T	3,944	23,497	0.167851	3,948	26,114

Percentage of Maximum Area
11.7%

Predictive

Unknown during Underwriting

Replacement Indicator

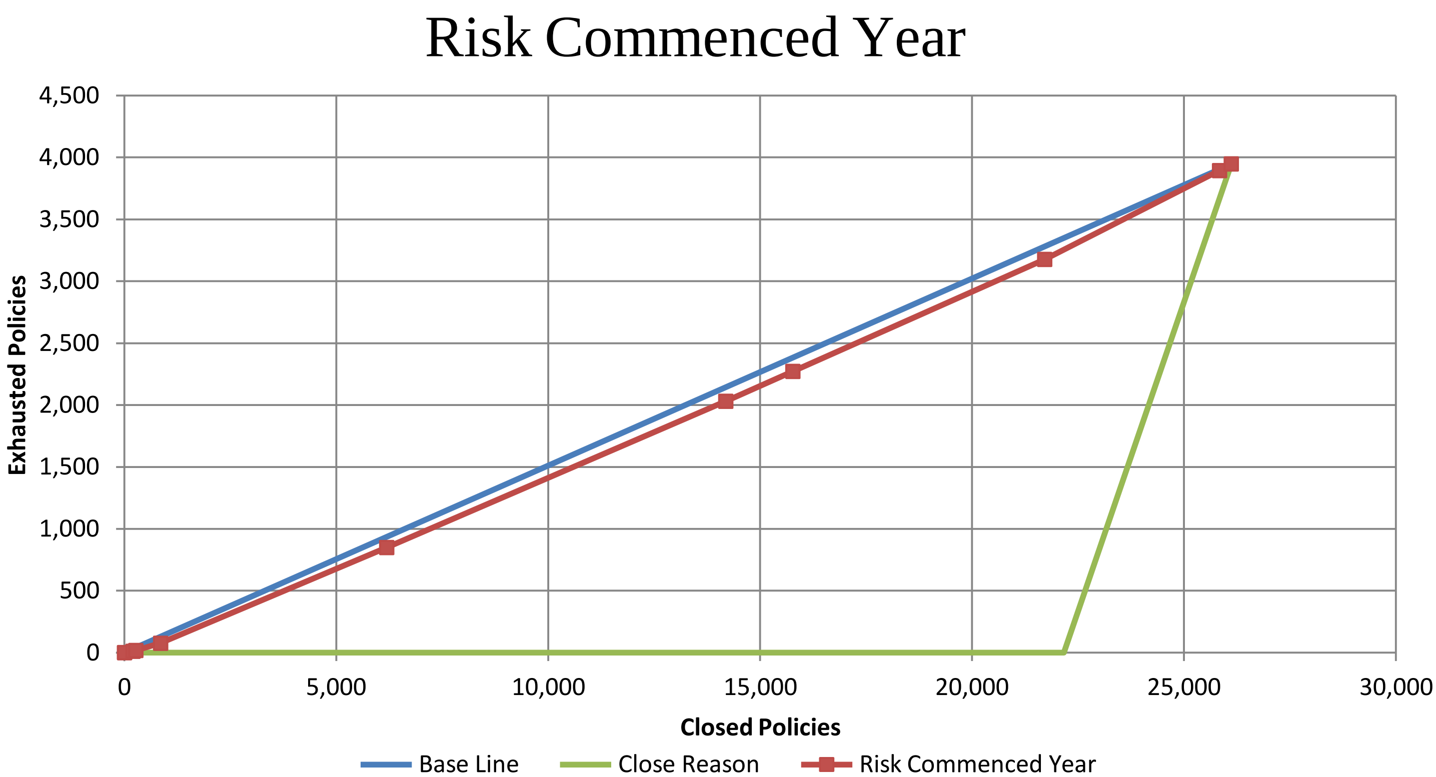


Replacement Indicator	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
Yes	322	2,317	0.138973	322	2,317
No	3,626	23,797	0.152372	3,948	26,114

Percentage of Maximum Area
0.8%

Not Predictive

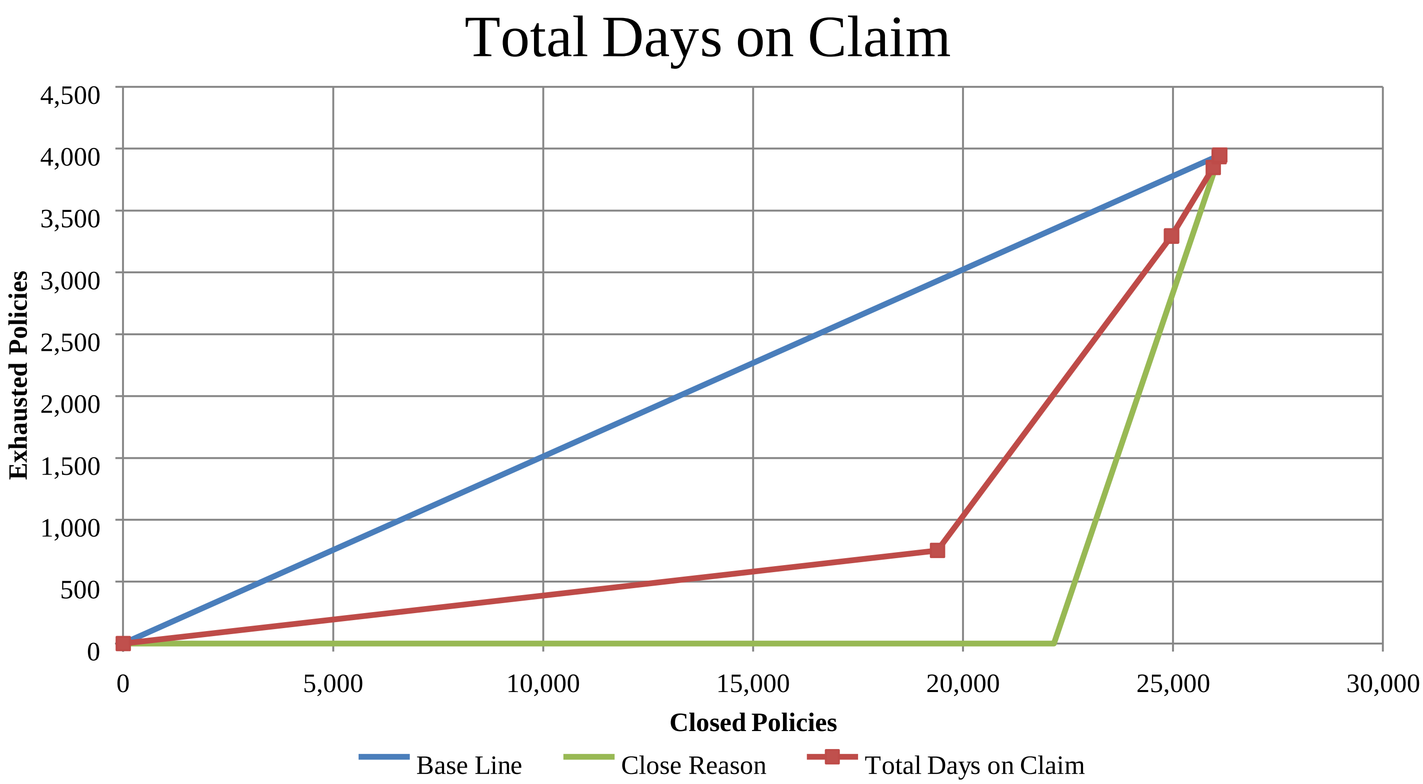
Known during Underwriting



Risk Commenced Year	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
2003	-	3	0.000000	-	3
2000	11	199	0.055276	11	202
2002	6	65	0.092308	17	267
2001	59	585	0.100855	76	852
1995	773	5,336	0.144865	849	6,188
1996	1,182	7,999	0.147768	2,031	14,187
1994	241	1,583	0.152243	2,272	15,770
1997	905	5,941	0.152331	3,177	21,711
1998	717	4,126	0.173776	3,894	25,837
1999	54	277	0.194946	3,948	26,114

Percentage of Maximum Area
5.2%

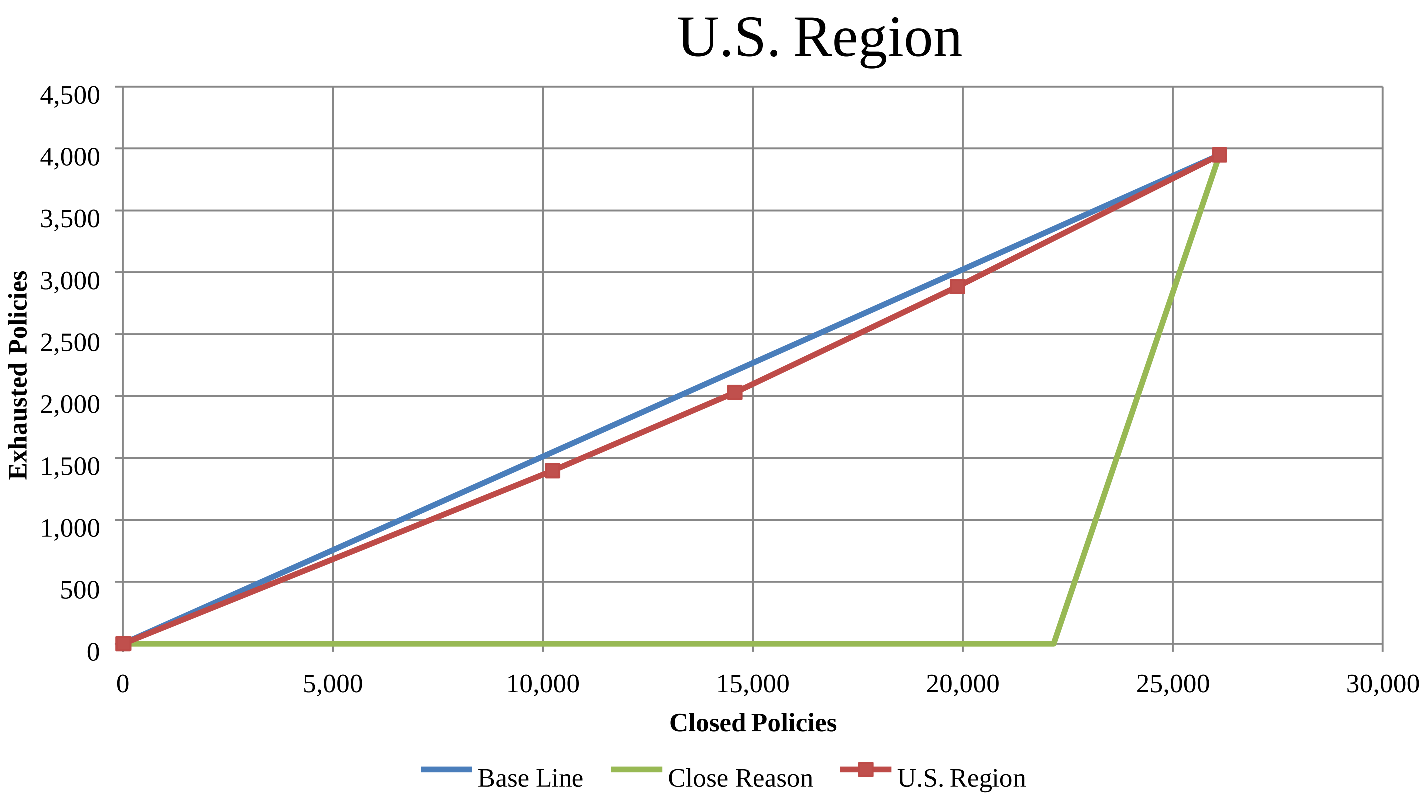
Not Predictive
Unknown during Underwriting



Total Days on Claim	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
1	753	19,393	0.038828	753	19,393
2	2,540	5,568	0.456178	3,293	24,961
6	3	6	0.500000	3,296	24,967
3	552	992	0.556452	3,848	25,959
4	88	137	0.642336	3,936	26,096
5	12	18	0.666667	3,948	26,114

Percentage of Maximum Area
65.9%

Predictive
Unknown during Underwriting



U.S. Region	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
#N/A	2	22	0.090909	2	22
South	1,395	10,210	0.136631	1,397	10,232
Midwest	633	4,340	0.145853	2,030	14,572
West	855	5,298	0.161382	2,885	19,870
Northeast	1,063	6,244	0.170243	3,948	26,114

Percentage of Maximum Area
6.0%

Not Predictive

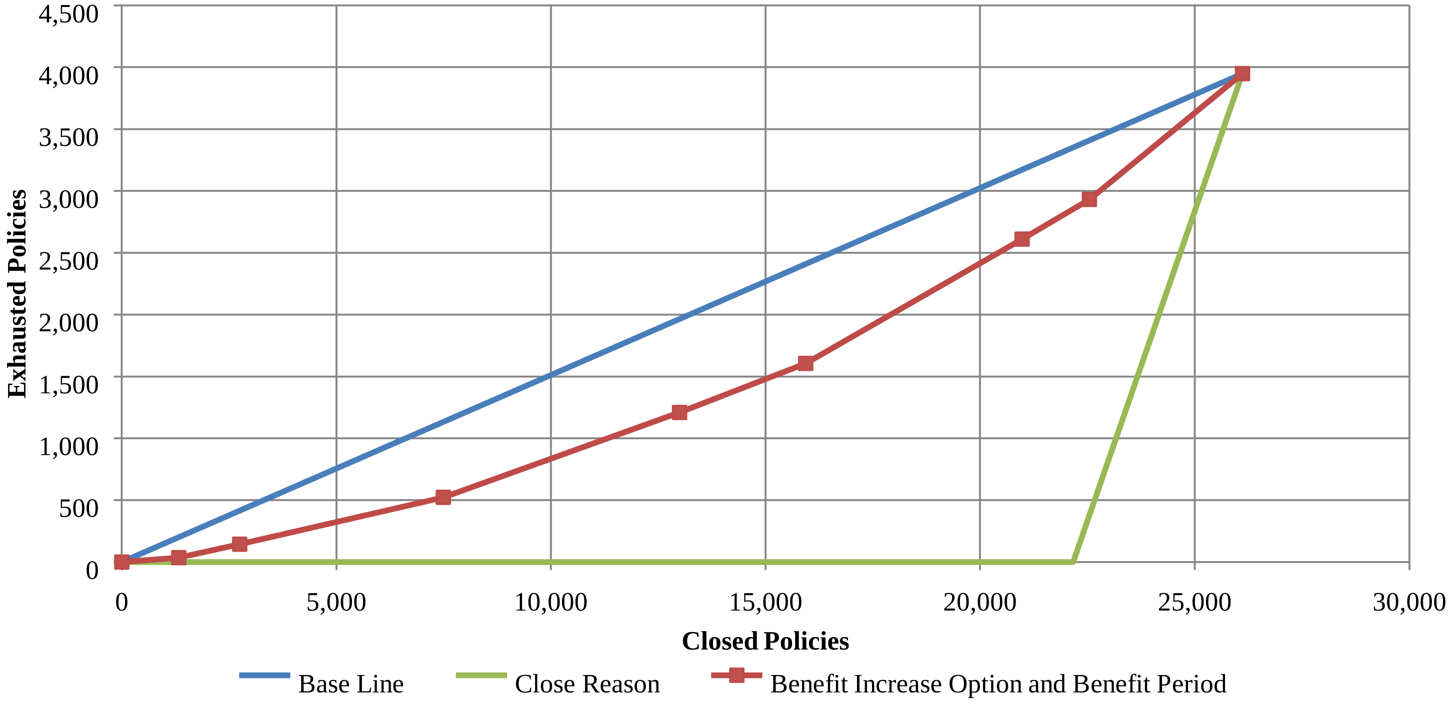
Known during Underwriting

Section 3: Dual Factor Graphs

The consecutive pages contain the dual factor charts for the following characteristics:

- Benefit Increase Option and Benefit Period
- Benefit Increase Option and Gender
- Benefit Increase Option and Marital Status
- Gender and Benefit Period
- Issue Age and Marital Status
- Marital Status and Benefit Period
- Marital Status and Gender

Benefit Increase Option and Benefit Period

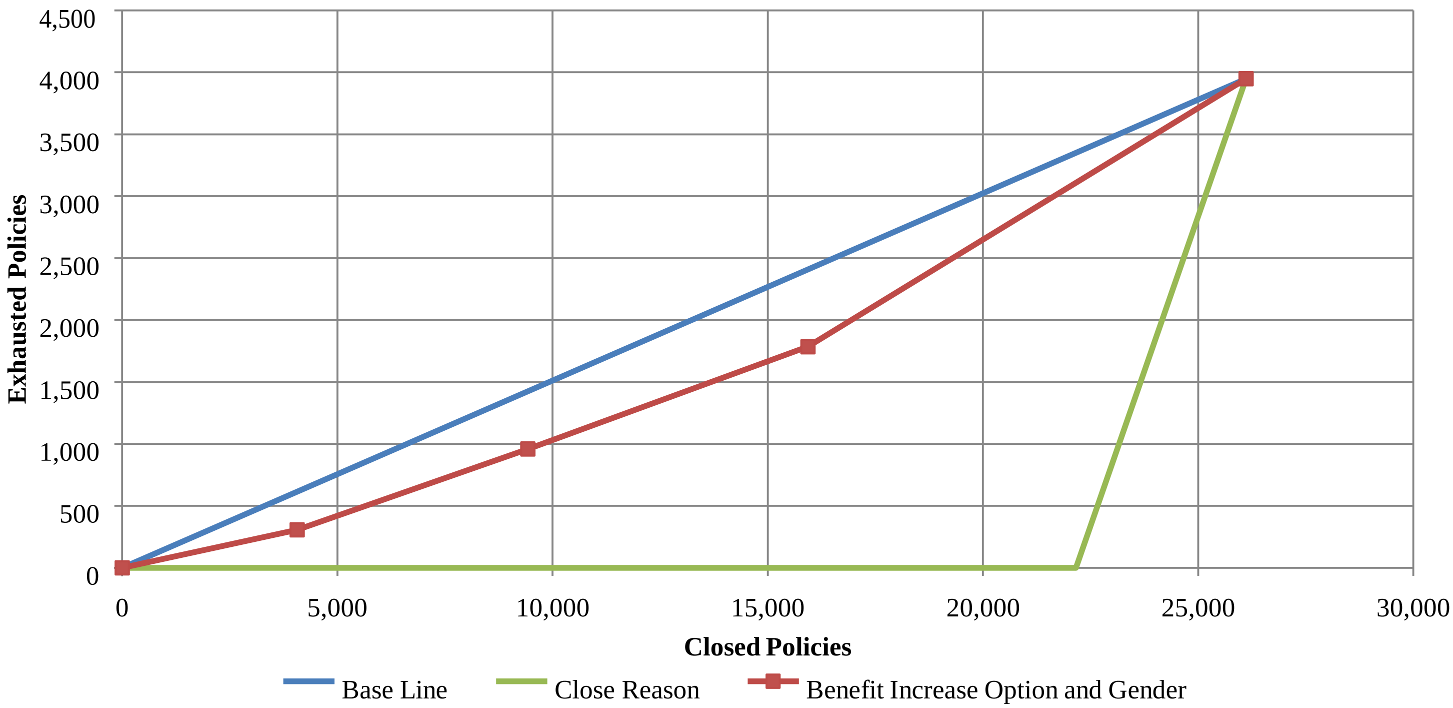


Benefit Increase Option and Benefit Period	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
Yes, 6	35	1,323	0.026455	35	1,329
No, 6	109	1,420	0.076761	144	2,749
Yes, 4	379	4,743	0.079907	523	7,492
No, 4	686	5,505	0.124614	1,209	12,997
Yes, 3	397	2,938	0.135126	1,606	15,935
No, 3	1,005	5,044	0.199247	2,611	20,979
Yes, 2	321	1,566	0.204981	2,932	22,545
No, 2	1,016	3,569	0.284674	3,948	26,114

Percentage of Maximum Area
31.2%

Predictive
Known during Underwriting

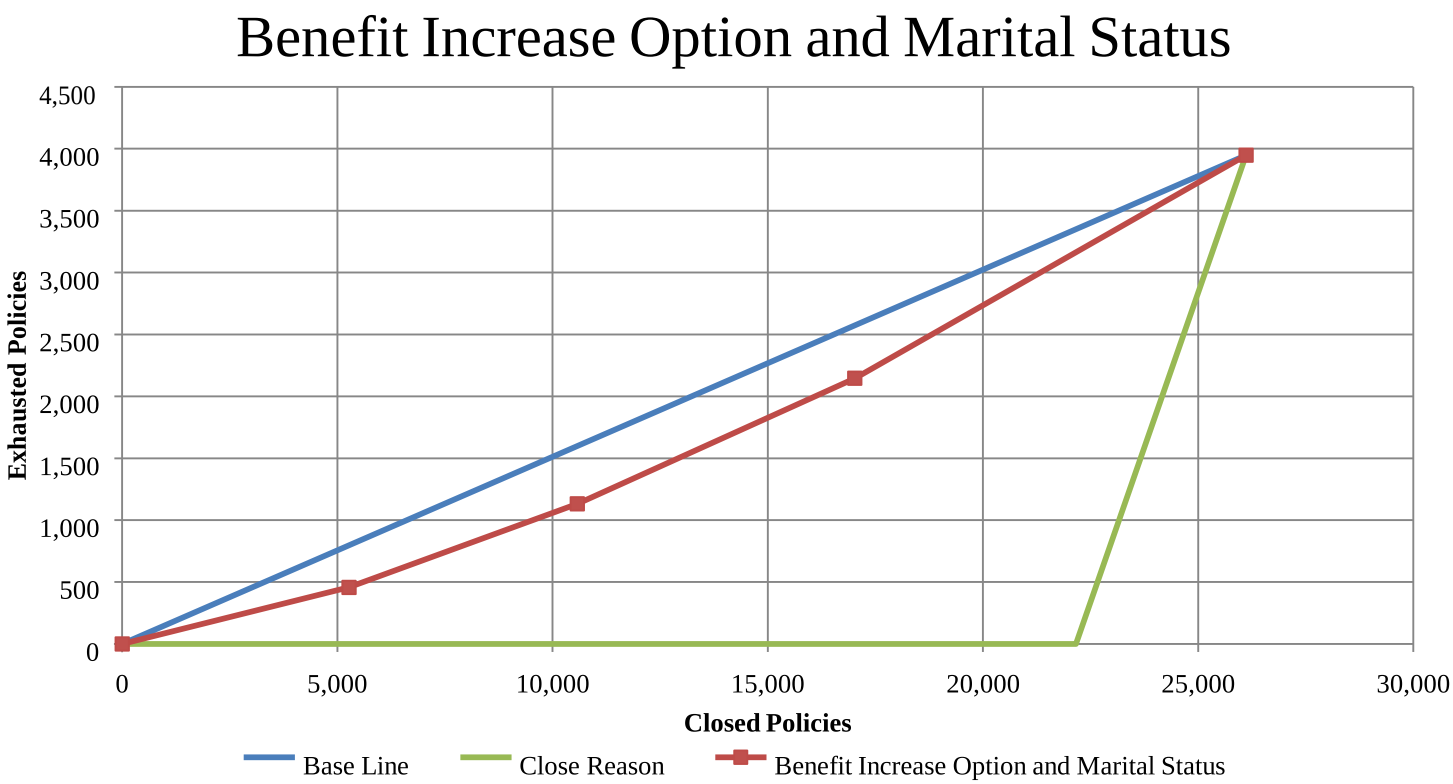
Benefit Increase Option and Gender



Benefit Increase Option and Gender	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
Yes, Male	307	4,066	0.075504	307	4,066
No, Male	653	5,359	0.121851	960	9,425
Yes, Female	825	6,510	0.126728	1,785	15,935
No, Female	2,163	10,179	0.212496	3,948	26,114

Percentage of Maximum Area
21.5%

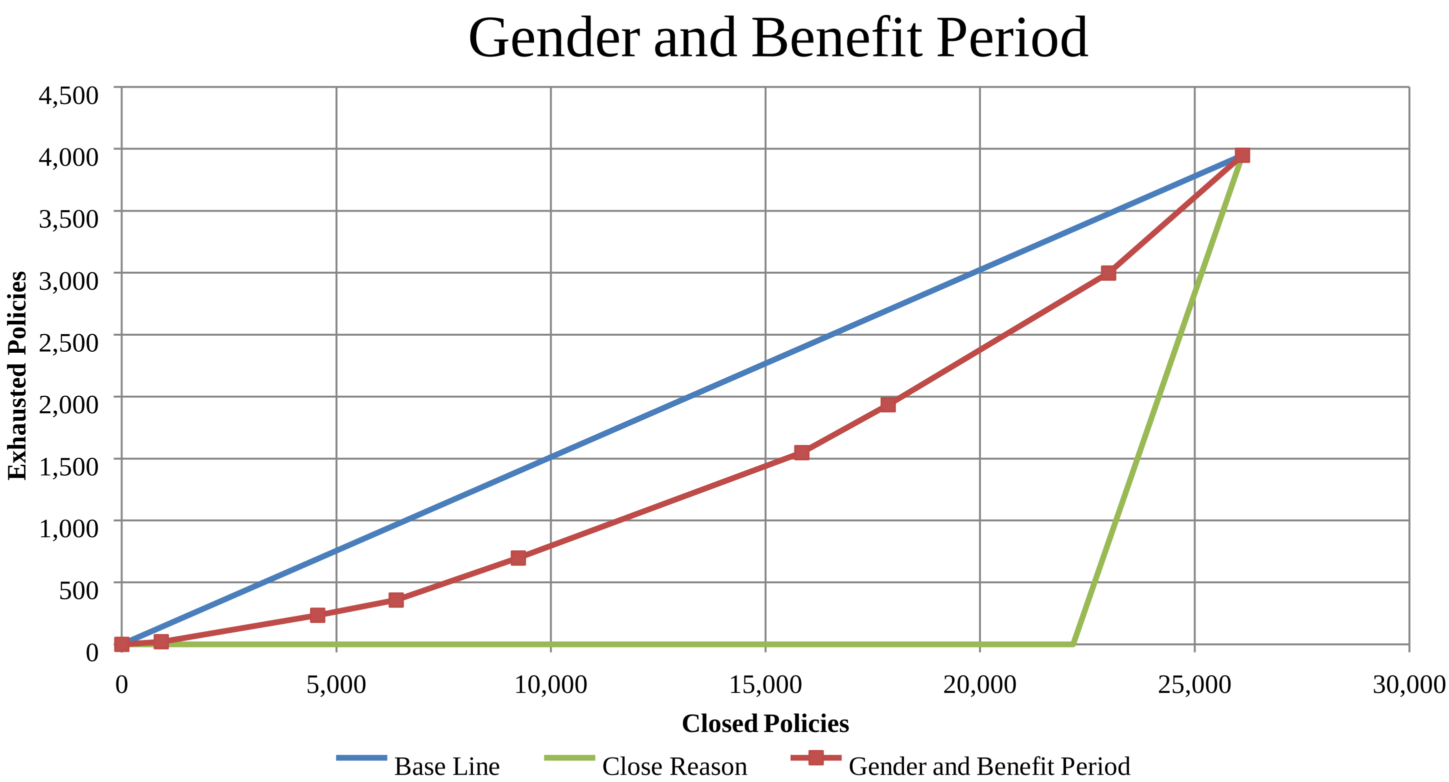
Predictive
Known during Underwriting



Benefit Increase Option and Marital Status	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
Yes, Married	457	5,270	0.086717	457	5,270
Yes, Single	675	5,306	0.127214	1,132	10,576
No, Married	1,014	6,446	0.157307	2,146	17,022
No, Single	1,802	9,092	0.198196	3,948	26,114

Percentage of Maximum Area
18.0%

Predictive
Known during Underwriting

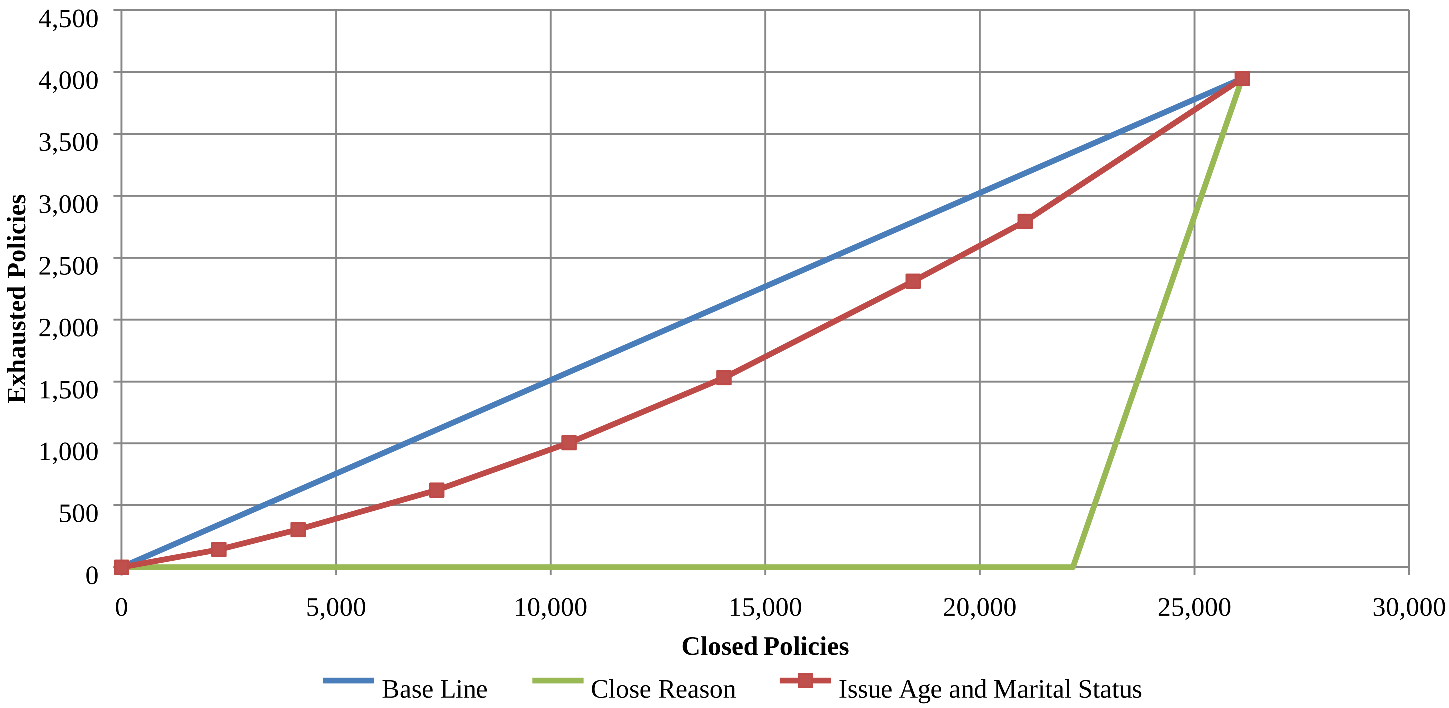


Gender and Benefit Period	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
Male, 6	21	915	0.022951	21	921
Male, 4	214	3,645	0.058711	235	4,566
Female, 6	123	1,828	0.067287	358	6,394
Male, 3	339	2,847	0.119073	697	9,241
Female, 4	851	6,603	0.128881	1,548	15,844
Male, 2	386	2,015	0.191563	1,934	17,859
Female, 3	1,063	5,135	0.207011	2,997	22,994
Female, 2	951	3,120	0.304808	3,948	26,114

Percentage of Maximum Area
33.4%

Predictive
Known during Underwriting

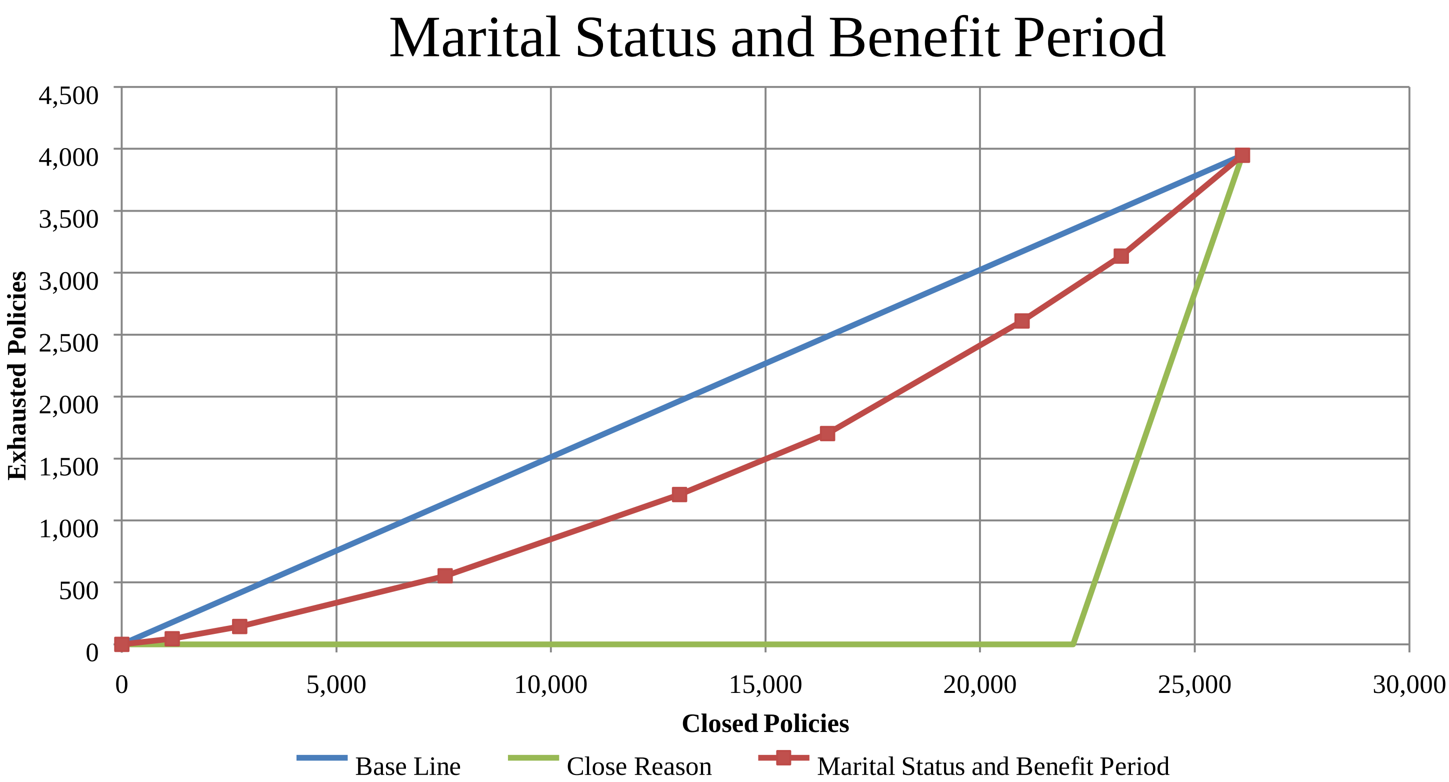
Issue Age and Marital Status



Issue Age and Marital Status	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
42-66, Married	143	2,268	0.063051	143	2,268
42-66, Single	161	1,847	0.087168	304	4,115
67-71, Married	319	3,231	0.098731	623	7,346
67-71, Single	383	3,082	0.124270	1,006	10,428
72-76, Married	525	3,609	0.145470	1,531	14,037
72-76, Single	779	4,410	0.176644	2,310	18,447
77-96, Married	484	2,608	0.185583	2,794	21,055
77-96, Single	1,154	5,059	0.228108	3,948	26,114

Percentage of Maximum Area
23.3%

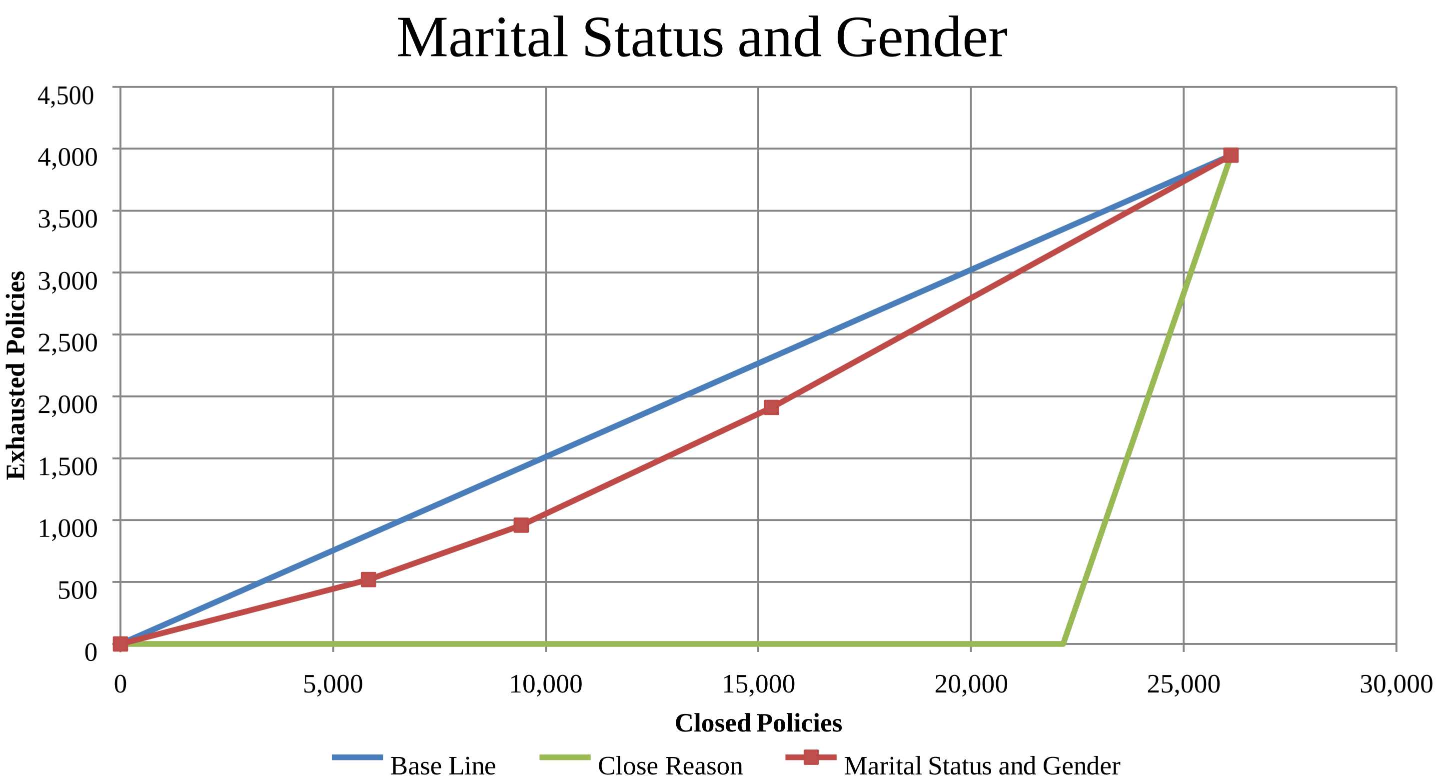
Predictive
Known during Underwriting



Marital Status and Benefit Period	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
Married, 6	45	1,169	0.038494	45	1,175
Single, 6	99	1,574	0.062897	144	2,749
Married, 4	410	4,786	0.085667	554	7,535
Single, 4	655	5,462	0.119919	1,209	12,997
Married, 3	493	3,449	0.142940	1,702	16,446
Single, 3	909	4,533	0.200529	2,611	20,979
Married, 2	523	2,309	0.226505	3,134	23,288
Single, 2	814	2,826	0.288040	3,948	26,114

Percentage of Maximum Area
30.7%

Predictive
Known during Underwriting



Marital Status and Gender	Count of Exhausted Policies	Count of Closed Policies	Slope	Total Exhausted Policies	Total Closed Policies
				-	-
Married, Male	520	5,831	0.089179	520	5,831
Single, Male	440	3,594	0.122426	960	9,425
Married, Female	951	5,885	0.161597	1,911	15,310
Single, Female	2,037	10,804	0.188541	3,948	26,114

Percentage of Maximum Area
16.6%

Predictive
Known during Underwriting