Bryant University

HONORS THESIS

Life Insurance Purchase Behavior Analysis for Retired People

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Abstract

Life insurance is an important need for many people in the United States. It is an insurance that the purchaser will never get to receive the benefit, instead, upon death, their beneficiaries will receive it to supplement their income. This study will be analyzing the Health and Retirement Study dataset in order to identify and model the variables that are most related and/or correlated to the purchasing behavior of life insurance in the United States. Using different mathematical applications, such as linear modeling through R and correlations through Excel, the data has been scanned thoroughly to isolate potential significant variables. There is a lot of literature on life insurance itself and the purchasing behavior of life insurance, however, there is limited literature using the Health and Retirement Study dataset. Therefore, this is an opportunity to make new findings on this topic. The key findings show that there were seven variables, such as age and education level, that most correlated and related to the purchasing behavior of life insurance. Based on these findings, this study will provide some recommendations that can help life insurance companies better understand their market and utilize the findings accordingly.

Introduction

This Honors Thesis will take an in-depth analysis of the Health and Retirement Study dataset that covers a variety of citizens of the United States attributes such as age, gender, familial status, economic status, and many other variables and most importantly the status of owning life insurance over a 40 year period. This dataset includes more than a thousand entries and many more data points that were combed through to narrow down the large number of variables to around 20-30 key ones. From this point, the variables were then run through some linear modeling in order to calculate which variables are most statistically significant in determining the purchasing behavior for life insurance, and from there, they were narrowed down to the final 8 variables. From a preliminary outlook, my hypothesis was that the conclusions would support that age, familial status, number of dependents, and economic status would be the main variables that affect the purchasing behavior of life insurance. Using R and Microsoft Excel, the data was simplified and condensed into one that is easier and more efficiently utilized to analyze. An analysis was then done to determine which variables were most significant and implications and conclusions were drawn from these findings.

Literature Review

These articles included within my bibliography are meaningful for the overall topic of life insurance, however, some are not fully revolving around my topic and instead could dictate the general market around life insurance not only in the United States, but also around the world. All of these articles are related to the insurance industry and were very beneficial towards this study. These articles discuss the data analytics involved in the computations at insurance companies on top of articles that discuss profitability and behavior of consumers along with the actions taken by the insurance companies to best suit the consumers' needs while also benefitting ourselves.

Life insurance is a different type of insurance compared to health, property, and other financial insurances. It is an insurance that the insured person will never use themselves, but instead, it will go to their beneficiaries to support them financially after the insured's death. There are two types of life insurance: term life and whole life/cash value. There are many factors that affect people's decisions to purchase life insurance including age, number of dependents, income level, and marital status among many others. Rates are determined for premiums using many of these variables as well which also can affect purchasing behavior for cost-benefit analysis for consumers. There is typically a market premium for those who wish to purchase insurance at an older age. Throughout the past decade, there have been many theses and reports on life insurance in the United States concerning purchasing behavior and premium analysis, however there has not been any that have utilized the Health and Retirement Study data set up until this point. Therefore, this thesis will draw a conclusion that has not been previously found in another report while utilizing other dataset conclusions as a benchmark.

E.P. Davis claims that investing and the life insurance/pension fund markets are consistently growing over the past decade. With the growth of single parent families, two working parent families, and other non-traditional families, along with the increase in the average age of death, leading to older people that their families have to financially support, the demand for life insurance as a back-up source of funds has continued to grow even with the decline of traditional one working parent families. This trend is very important when looking at the variables that affect purchasing behavior as the trend of purchasing behavior is heavily influenced by socio-economic factors that can change the viewpoint and behavior of many people. The increase in knowledge across the social classes over the years in the United States has also increased the demand for life insurance as consumers are becoming more aware and informed about their financial options and decisions.

My thesis analyzes the Health and Retirement Study data set which allowed me to view the attributes and details about a large group of people in the United States that is a representation of the socio-economic, and ethnic divisions of the US population. Using the basic behavioral patterns for life insurance that has been researched in other papers, this study based the research results on those to compare the differences on using different data sets and how that also affects the purchasing behavior of life insurance.

Research Questions

This study looks to understand the supply, demand, and other variables that factor into the behaviors of purchasing life insurance from the data set that I have obtained through the Health and Retirement Study. There were 37 variables to analyze and narrow down the amount until there were enough factors to determine consistent data that supports a conclusion. The data is filled with consistent information that can be helped to determine the purchasing pattern for life insurance, and there was at first a focus on economic status, marital status, number of children, and health status until the data set was more intensely analyzed with models. These were useful in determining whether people buy life insurance or not and gave a more wholistic representation of the United States and their behavior with utilizing life insurance.

This study was an in-depth analysis of the more than 10,000 individuals available through the Health and Retirement Study which includes surveys spanning across 40 years in order to determine which variables are drivers for purchasing behavior of life insurance. The study only focuses on the most recent survey from 2016, however, since it was most representative of the current climate for life insurance. The age and spending by each sector are potential variables that were possibly needed in order to evaluate the set of retired individuals and were then used to create an overview of the supply, demand, and variables that influence consumers of life insurance.

This topic is very important to other scholars and researchers in this field as it will help give a general view on what factors influence the purchasing behavior for life insurance. Life insurance is an unsought product, meaning that people do not normally take the time to go and look for life insurance on a regular basis and few want to discuss it. This project will hopefully help many to better understand the variables involved with purchasing life insurance in order to give the companies more understanding of who they should target and what potential factors can predict who is more likely to buy life insurance and when they will. I will also be working with my mentor to potentially get this thesis published after going through many revisions and the processes of publishing a thesis.

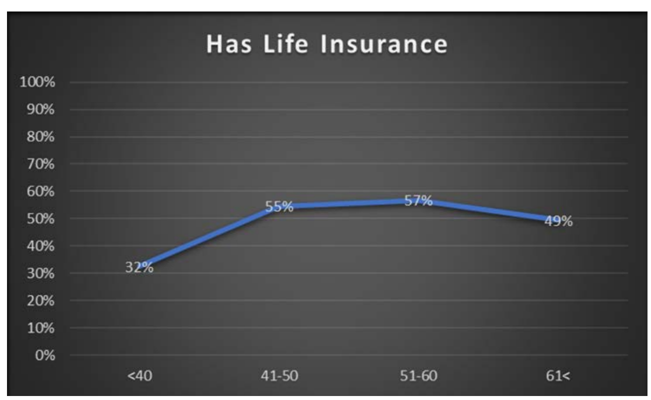
Research Methodology

This thesis is an empirical research project since it combs through the Health and Retirement Study Data Set in order to highlight certain variables. There was a use of linear modeling, as well as other statistical models, in order to help model the data in a more clear and concise form. On top of this, there is a referencing of other articles and journals that delve into the life insurance marketplace in order to get a better understanding of other factors and information that may not have been able to be found in the HRS Data Set. Microsoft Excel was used so that the data could be further refined and streamlined the data much more easily.

On top of this, Excel was used for Pivot Tables and for the correlation matrix. R was used to run both individual linear models and for the multiple linear models. This was all appropriate and relevant to the actuary field as Microsoft Excel and many programming applications are used every day by employees for insurance companies and this is also similar to market behavior teams who work for life insurance companies. Analyzing data and calculating variables that are most effective in determining purchasing behavior is crucial to the actuarial field in order to factor in different variables of the clientele and also the population as a whole for the premium and risk for the insurance companies. It can also help with the marketing sector for these companies to target those families/individuals who fall under a certain category of variables to increase profits.

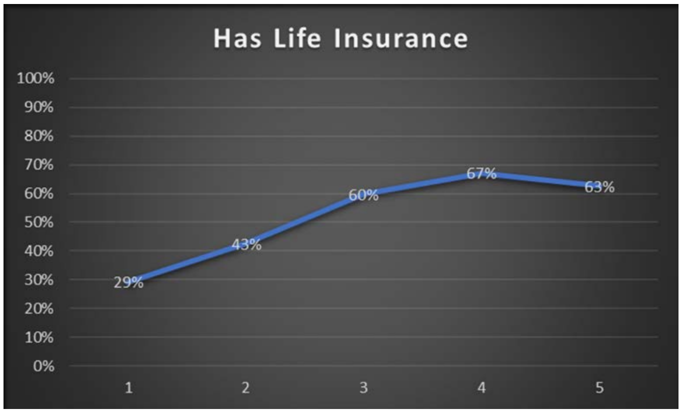
Findings

Out of the more than 20,900 individuals that responded to the survey, the data showed that 54% of them or around 11,300 have life insurance. This shows an even spread of the respondents that have life insurance. Once the data was refined into the 37 variables after an initial look through of all variables, each of the 37 variables were run through a linear model singularly with the presence of life insurance acting as the dependent variable. This was an important step as it would show if the variables chosen were significant for the purchasing behavior of life insurance. Each individual regression can be seen in Appendix A. The variables that showed that they had the most significance out of the 37 isolated variables were age, health status, education level, marital status, weight, if they had Medicare, if they had Long Term Care insurance, and how many times they visited the doctor within the past two years. The preliminary results show that this did not support my initial hypothesis. However, it did follow what previous reports have found in which certain variables such as age and education level are significant in determining purchase behavior of life insurance.

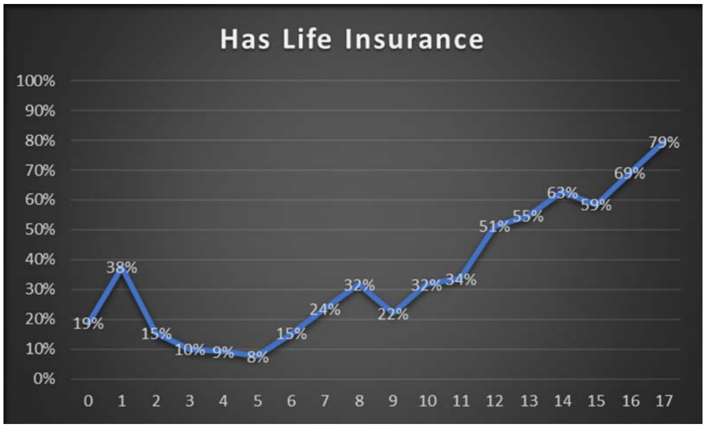


After the eight variables were finalized, they were again analyzed through a linear model using R. The benchmark to test the significance was 99%, meaning if the regression showed that the p-value was below .01, then it was deemed significant for the purchasing behavior of life insurance. For the variable of age, the data was sorted using a pivot table on Excel in order to group the ages. This was then graphed in order to see visually was the trend and correlation would be for age. This showed that as the age group increased, there was a positive correlation for having life insurance.

For the variable health rating, the respondents could respond with a scale of 1 to 5 with 1 representing poor health and 5 representing excellent health. The data showed again that there was a positive trend and correlation between health and having life insurance. There were similar results for the respondents' weight.

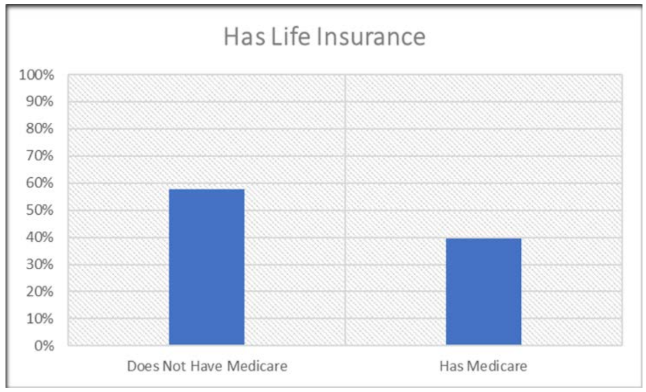


An interesting, but expected result was that the higher the education level, then there would be a greater chance of having life insurance. The data showed that this was indeed true, however it showed an extremely high percentage of those who had finished college and pursued a higher degree. There were around 80% of people who had life insurance that completed college and went on to pursue a master's degree or doctorate.

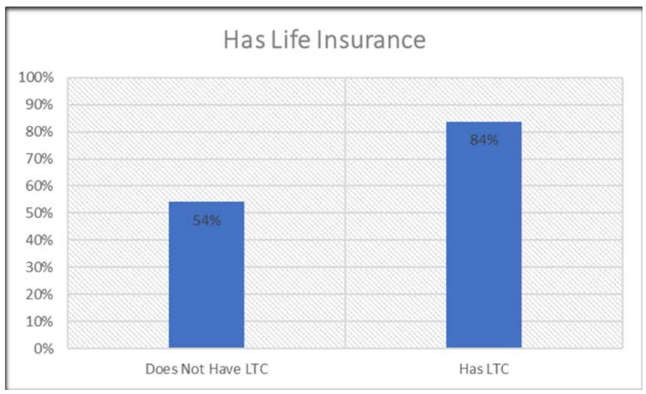


The data for marital status showed that those who were married had the highest chance of having life insurance, and those who were single had the least chance of having life insurance. This was reasonable as those who are single likely do not have many, if any, dependents and therefore would have less reason or need to purchase life insurance. Contrastingly, those who are married have their partner to support and possibly children, therefore, they would theoretically have a greater need for life insurance.

Another interesting finding from the analysis was that there was a negative correlation between having Medicare and having life insurance. Those who did not have life insurance had a greater chance of having Medicare and vice versa.



This was different, however for having long term care insurance as that was found to be positively correlated. The two graphs show the difference, with the graph of long-term care insurance showing just how large the gap was for that variable.



All of these variables showed interesting findings and also were found to be significant when determining the purchasing behavior of life insurance, whether that was positively or negatively. There was, however, one of the final eight variables that was completely different. The variable, number of times seen a doctor withing the past two years, showed that it was not significantly related to the purchasing behavior of life insurance after it was analyzed using a linear model on R. It had a p-value of 0.195 which was well above the threshold of 0.01. This would possibly be significant if using a different threshold or confidence interval, but for this study it did not meet the requirements.

After these variables were analyzed individually, it was analyzed on R using a multiple regression approach. The seven final variables were the independent variables with having life insurance acting as the dependent variable. The linear model can be found in Appendix B. It showed that age, health status, education level, marital status (only single and married), weight, having Medicare, and having long term care insurance were significant in determining the purchase behavior of life insurance. This is important as it shows that each variable alone is significant, and when paired together they remain significant regardless of the interactions that is present.

Once the variables were confirmed through the multiple regression, those variables were then put into Microsoft Excel and a correlation matrix was run. This matrix showed that all of the variables were positively correlated with only having Medicare negatively correlated. It also showed that education level, health status, having Medicare, and having long term care insurance were the most correlated to having life insurance. This was important when looking at the implications and conclusions.

	LifeIns	*Age*	*Education*	*Health*	*Weight*	*Medicare*	*LTC*
LifeIns	1						
Age	0.042574083	1					
Education	0.304792324	0.013971261	1				
Health	0.207594115	-0.058589754	0.27632141	1			
Weight	0.067063874	-0.016391882	0.04262468	-0.090794795	1		
Medicare	-0.113471946	0.183453886	-0.107761558	-0.265960735	0.02388766	1	
LTC	0.143617148	0.031803247	0.096872884	0.055648332	0.010933227	0.000333	1

Implications and Conclusions

There were some limitations to this study. Firstly, there was a data limitation. The data itself did not contain all variables that are potentially necessary such as gender. This could have impacted the data if included or could have greater expanded upon the conclusions reached. On top of this, there was a model limitation. For each of the variables, and even the multiple variable findings, some of the variables could have been not fully linear. This could have skewed the data possibly and could have affected the findings.

My research question was, what variables most affect or correlate to the purchasing behavior of life insurance? Some interesting findings that were concluded upon from the data were that both location of living, and economic status/wealth were not found to be significant. For the location variable, not enough respondents stated which state they lived in. This led to not enough data to definitively conclude something either for or against it. For economic status/wealth, however, it was supported through the data that they were not significant in determining the purchase behavior of life insurance. The p-value for salary earned was 0.381 which was extremely high and shows that salary did not significant affect purchase behavior within my constraints and thresholds. The p-value of net earnings was 0.485 which was even higher and showed that it was not significant in determining purchase behavior. The hypothesis stated that economic status would be significant, and the data supported the opposite.

The variables that were indeed significant in determining the purchase behavior of life insurance were health status, marital status, education level, the presence of Medicare, and the presence of long-term care insurance. These variables were most significant out of the seven variables isolated. For health status, the higher the level of perceived health, then the higher the chance of owning life insurance. This shows that those who believe they are healthy wish to insure that health in the off chance that anything goes wrong with their life. It also shows that those who have low perceived health do not put as much stock or thought into life insurance. It could also be more expensive for those with poor health and this could lead to different allocation of their funds which would not include life insurance.

For marital status, there was a significant disparity between those who were married and those who were single regarding the purchase of life insurance. Those who were married had a much higher chance of owning life insurance than those who were single. This can be explained by the fact that married individuals have more dependents than single people in most cases. Those who are married are more likely to purchase life insurance in order to help their spouse and possibly children financially in the event of their passing. For those who are single, they do not have as many dependents; they possibly have dependents of children or elderly parents, however.

For education level, the findings were almost identical to the hypothesis. The findings showed that the more education one receives, the greater the chance that they own life insurance. This can be explained by a higher salary for those who are more educated in most cases and also the level of information that they know about life insurance increases as they receive more education. The presence of Medicare was the only variable that was negatively correlated to owning life insurance. There was a higher chance of someone owning life insurance if they did not own Medicare and vice versa. This could be explained by the fact that those who own Medicare are over the age of 65 and therefore do not have many, if any, dependents to worry about and they theoretically have saved enough over their career to not need life insurance. Contrastingly, those without Medicare are younger than 65 and could still have years of their career left and dependents to support financially in the event of their passing.

Lastly, there was a positive correlation for the presence of long-term care insurance. Those who owned long-term care insurance were more likely to own life insurance. This is explained by the fact that long-term care insurance and life insurance go hand in hand. If someone purchases long-term care insurance, then they are most likely worried about future problems that could be very costly. Similarly, they would then be more willing to purchase life insurance in the event of their death to support their dependents financially for expenses that they would need to afford.

There are a few implications that can therefore be drawn from these findings. The Some of these implications are strictly analytical and show that some variables are more important than others in determining the purchase behavior of life insurance. Applying these findings to the life insurance industry can show further implications. Four implications were drawn when looking at the life insurance industry.

The first implication is that life insurance companies should target those with long-term care insurance or possibly offer a bundle deal of life insurance and long-term care insurance. This will allow life insurance companies to greater penetrate the market and target those who have long-term care insurance as these people typically will purchase life insurance. They should still target those without long term care insurance however it seems as if the two insurances are paired by many customers and a bundle would attract more new customers and entice old customers to remain with the company.

The next implication stems from the fact that the data showed that those who are more highly educated have a higher chance of purchasing life insurance. This means that life insurance companies can target those who are more highly educated for their product. On top of this however, it shows that those who are less educated could possibly not know or fully understand what life insurance is and how beneficial it can be. Therefore, it would be useful for insurance companies and possibly the government to advocate and inform the public of the uses and benefits of life insurance. This will help many millions of Americans possibly protect themselves again risk even more and also help insurance companies bring in new customers.

The next implication revolves around owning Medicare. Since those who do not own Medicare have a higher chance of owning life insurance, life insurance companies can target their marketing towards this group of people. The data did show that those with Medicare still own life insurance with about 40% of them owning it. This means that it is still a viable market for life insurance companies to target and sell life insurance to.

The last implication that was drawn from the findings and this study focuses on the fact that economic status was found to not be significant in determining the purchase behavior of life insurance. This is a surprise for many as life insurance can be expensive and also many do not view it as a necessity. This means that life insurance companies should focus their efforts on marketing similar packages to all of the classes, specifically the lower class. It can be found that those in the lower class are most at risk with deaths of the main money making member of their families as they will have to work even more than they currently do to make up for the lost income. Therefore, those of the lower class could be a market with untapped potential for life insurance companies that will greatly benefit the American society as a whole if those in the lower class can have a support netting of finances in the unfortunate event of a death.

Overall, many more implications can be drawn from these findings. There are also other variables that can be looked at and incorporated into the study that was not previously used. This study could be expanded to become a cross-decade study of the HRS dataset to look at trends in the American population regarding life insurance over time. That could have more implications that are very significant. This study, however, has many findings that can be implemented and tested by life insurance companies nationwide to benefit not only their own company, but also the United States population as a whole.

Appendices

Appendix A – Individual Regressions

```
lm(formula = LifeIns ~ Age, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-2.054 -1.869 -1.798  2.131  6.274 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 2.513300   0.081745  30.746  < 2e-16 ***
Age         0.005466   0.001224   4.464 8.09e-06 ***
```

```
lm(formula = LifeIns ~ Health, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-3.322 -1.883 -1.403  2.117  6.597 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  2.16327    0.04175   51.81   <2e-16 ***
Health       0.23983    0.01326   18.08   <2e-16 ***
```

```
lm(formula = LifeIns ~ Education, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-2.026 -1.855 -1.818  2.121  7.158 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.025757   0.050927  59.414  < 2e-16 ***
Education   -0.012201   0.002809  -4.343 1.44e-05 ***
```

```
lm(formula = LifeIns ~ Race, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-1.916 -1.916 -1.916  2.084  5.084 

Coefficients: (1 not defined because of singularities)
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)    2.916      0.128   22.79   <2e-16 ***
RaceTRUE          NA         NA      NA       NA    
```

```
lm(formula = LifeIns ~ Children, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-3.870 -1.841 -1.799  2.159  6.201 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  2.79892    0.03525  79.400   <2e-16 ***
Children     0.02092    0.00736   2.842   0.0045 ** 
```

```
lm(formula = LifeIns ~ Military, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-2.187 -1.885 -1.482  2.115  6.519 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  2.38067    0.12872  18.495  < 2e-16 ***
Military     0.10084    0.02691   3.747 0.000181 ***
```

```
lm(formula = LifeIns ~ Religion, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-2.019 -1.841 -1.815  2.159  6.184 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  2.79004    0.04972   56.12   <2e-16 ***
Religion     0.02546    0.01686    1.51    0.131    
```

```
lm(formula = LifeIns ~ MaritalStatus, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-2.687 -1.661 -1.661  1.954  6.339 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)   2.533185   0.024320  104.16   <2e-16 ***
MaritalStatus 0.128208   0.007427   17.26   <2e-16 ***
```

```
lm(formula = LifeIns ~ EmotionalProblems, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-2.133 -1.807 -1.807  2.193  6.519 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)        3.214630   0.040319  79.731   <2e-16 ***
EmotionalProblems -0.081535   0.008975  -9.085   <2e-16 ***
```

```
lm(formula = LifeIns ~ Depression, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-2.129 -1.784 -1.784  2.216  6.561 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.215590   0.035759   89.92   <2e-16 ***
Depression  -0.086301   0.008234  -10.48   <2e-16 ***
```

```
lm(formula = LifeIns ~ EverSmoke, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-2.035 -2.035 -1.658  1.965  6.342 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.12974    0.05472  57.191  < 2e-16 ***
EverSmoke   -0.09440    0.01527  -6.183 6.84e-10 ***
```

```
lm(formula = LifeIns ~ SmokeNow, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-2.227 -1.830 -1.830  2.170  6.170 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.32672    0.04759   69.91   <2e-16 ***
SmokeNow    -0.09931    0.01105   -8.99   <2e-16 ***
```

```
lm(formula = LifeIns ~ EverDrinkAlcohol, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-2.333 -1.750 -1.750  2.250  6.250 

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)    
(Intercept)      2.677489   0.024239 110.462   <2e-16 ***
EverDrinkAlcohol 0.072865   0.007289   9.997   <2e-16 ***
```

```
lm(formula = LifeIns ~ DaysAlc, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-1.754 -1.748 -1.747  2.252  6.253 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 2.7472461  0.0250155 109.822   <2e-16 ***
DaysAlc     0.0007882  0.0083673   0.094    0.925    
```

```
lm(formula = LifeIns ~ Weight, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-1.940 -1.880 -1.834  2.115  6.612 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  2.9852002  0.0326775  91.353  < 2e-16 ***
Weight      -0.0005977  0.0001554  -3.846  0.00012 ***
```

```
lm(formula = LifeIns ~ Height, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-2.181 -1.836 -1.836  2.164  6.250 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  2.40586    0.18705   12.86   <2e-16 ***
Height       0.08610    0.03634    2.37   0.0178 *  
```

```
lm(formula = LifeIns ~ Height2, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-1.824 -1.823 -1.821  2.177  6.179 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  2.8242482  0.0264337 106.843   <2e-16 ***
Height2     -0.0003431  0.0034828  -0.099    0.922    
```

```
lm(formula = LifeIns ~ CurrentJob, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-7.211 -1.903 -1.736  2.041  6.264 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 2.680076   0.019404  138.12   <2e-16 ***
CurrentJob  0.055867   0.003793   14.73   <2e-16 ***
```

```
lm(formula = LifeIns ~ RetireYR, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-2.285 -1.920 -1.919  2.080  6.081 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 2.828e+00  9.761e-02  28.973   <2e-16 ***
RetireYR    4.572e-05  3.295e-05   1.388    0.165    
```

```
lm(formula = LifeIns ~ Salary, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-2.527 -2.234  1.473  1.766  5.473 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 3.234e+00  1.630e-01  19.841   <2e-16 ***
Salary      2.930e-07  3.337e-07   0.878    0.381    
```

```
lm(formula = LifeIns ~ Earnings, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-2.373 -2.220  1.627  1.780  5.627 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 3.219e+00  1.220e-01  26.392   <2e-16 ***
Earnings    1.547e-07  2.215e-07   0.698    0.485    
```

```
lm(formula = LifeIns ~ EarningWhenLeft, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-2.084 -1.853 -1.849  2.150  6.150 

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)    
(Intercept)     2.850e+00  4.740e-02  60.113   <2e-16 ***
EarningWhenLeft 2.343e-07  1.381e-07   1.696     0.09 .  
```

```
lm(formula = LifeIns ~ HealthProb, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-2.036 -1.782 -1.782  2.218  6.472 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.099622   0.032446  95.531  < 2e-16 ***
HealthProb  -0.063514   0.008072  -7.868 3.82e-15 ***
```

```
lm(formula = LifeIns ~ Medicare, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-1.934 -1.934 -1.807  2.066  6.319 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  2.965636   0.025333 117.064  < 2e-16 ***
Medicare    -0.031685   0.007086  -4.472  7.8e-06 ***
```

```
lm(formula = LifeIns ~ PremiumsMO, data = Train)

Residuals:
   Min     1Q Median     3Q    Max
-2.155 -2.074  1.845  1.926  5.927

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 3.073e+00  4.101e-02  74.940   <2e-16 ***
PremiumsMO  8.182e-06  8.361e-06   0.979    0.328
```

```
lm(formula = LifeIns ~ LTC, data = Train)

Residuals:
   Min     1Q Median     3Q    Max
-2.561 -1.931 -1.301  2.069  6.699

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.14358    0.05170   41.46   <2e-16 ***
LTC          0.15746    0.01073   14.68   <2e-16 ***
```

```
lm(formula = LifeIns ~ TimesSeenDoctorIn2Yrs, data = Train)

Residuals:
   Min     1Q Median     3Q    Max
-2.383 -1.814 -1.810  2.187  6.190

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)           2.810e+00  1.531e-02  183.48   <2e-16 ***
TimesSeenDoctorIn2Yrs 5.740e-04  4.814e-05   11.92   <2e-16 ***
```

```
lm(formula = LifeIns ~ Inheritance10k, data = Train)

Residuals:
   Min     1Q Median     3Q    Max
-2.234 -1.855 -1.818  2.151  6.182

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)    2.818e+00  1.669e-02 168.867  < 2e-16 ***
Inheritance10k 4.167e-04  8.299e-05   5.021 5.18e-07 ***
```

```
lm(formula = LifeIns ~ Inheritance100k, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-1.631 -1.614 -1.598  2.372  6.700 

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)    
(Intercept)      2.6309748  0.0186199 141.299   <2e-16 ***
Inheritance100k -0.0003313  0.0001538  -2.154   0.0313 *  
```

```
lm(formula = LifeIns ~ Inheritance500kormore, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-2.008 -1.511 -1.501  2.484  6.499 

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)    
(Intercept)           2.5008593  0.0193806 129.039   <2e-16 ***
Inheritance500kormore 0.0005074  0.0001984   2.557   0.0106 *  
```

```
lm(formula = LifeIns ~ AnyInheritance, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-2.764 -2.749  1.236  1.236  5.531 

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)    
(Intercept)     3.7639573  0.0334771 112.434   <2e-16 ***
AnyInheritance -0.0002955  0.0003076  -0.961    0.337    
```

```
lm(formula = LifeIns ~ ReceiveLifeInsSettlement, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-3.816 -1.256 -1.256  1.464  5.744 

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)    
(Intercept)               1.93607    0.16521  11.719  < 2e-16 ***
ReceiveLifeInsSettlement  0.32001    0.04075   7.854 2.17e-14 ***
```

```
lm(formula = LifeIns ~ State, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-2.586 -1.997  1.414  2.003  6.003 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  2.50639    0.15650  16.016  < 2e-16 ***
State        0.09814    0.02537   3.868 0.000116 ***
```

```
lm(formula = LifeIns ~ Married, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-2.140 -2.140  1.860  1.860  6.034 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  2.92283    0.11329  25.800   <2e-16 ***
Married      0.04339    0.02337   1.857   0.0633 .  
```

```
lm(formula = LifeIns ~ Cohort, data = Train)

Residuals:
   Min     1Q Median     3Q    Max 
-2.080 -1.861 -1.752  2.139  6.248 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.134768   0.043408  72.216  < 2e-16 ***
Cohort      -0.054709   0.008541  -6.406 1.53e-10 ***
```

Appendix B – Final Variable Regressions and Multiple Regressions

```
lm(formula = LifeIns ~ Age, data = Train)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.7066 -0.5592  0.4265  0.4408  0.5549 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 0.307258   0.092629   3.317 0.000918 ***
Age         0.004754   0.001744   2.726 0.006440 ** 
```

```
lm(formula = LifeIns ~ Education, data = Train)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.7558 -0.4970  0.2442  0.3995  1.1240 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.123977   0.034166  -3.629 0.000288 ***
Education    0.051749   0.002528  20.471  < 2e-16 ***
```

```
lm(formula = LifeIns ~ MaritalStatus, data = Train)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.6342 -0.5245  0.3658  0.3658  0.5908 

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)    
(Intercept)                 0.52454    0.01614  32.498  < 2e-16 ***
MaritalStatusMarried        0.10964    0.01920   5.709 1.21e-08 ***
MaritalStatusNever Married -0.11537    0.02552  -4.520 6.36e-06 ***
MaritalStatusSeparated     -0.09184    0.03754  -2.447   0.0145 *  
MaritalStatusWidowed       -0.07717    0.04280  -1.803   0.0715 .  
```

```
lm(formula = LifeIns ~ Health, data = Train)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.7378 -0.5486  0.2622  0.4514  0.6406 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 0.264850   0.022951   11.54   <2e-16 ***
Health      0.094586   0.006968   13.57   <2e-16 ***
```

```
lm(formula = LifeIns ~ Weight, data = Train)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.8951 -0.5502  0.4163  0.4464  0.4899 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 4.770e-01  2.056e-02    23.2  < 2e-16 ***
Weight      4.185e-04  9.733e-05     4.3 1.75e-05 ***
```

```
lm(formula = LifeIns ~ Medicare, data = Train)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.5783 -0.5783  0.4217  0.4217  0.6041 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.57834    0.00816  70.879  < 2e-16 ***
Medicare    -0.18246    0.02498  -7.306  3.3e-13 ***
```

```
lm(formula = LifeIns ~ LTC, data = Train)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.8373 -0.5406  0.4594  0.4594  0.4594 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 0.540604   0.007929  68.177   <2e-16 ***
LTC         0.296698   0.031961   9.283   <2e-16 ***
```

```
lm(formula = LifeIns ~ TimesSeenDoctorIn2Yrs, data = Train)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.5624 -0.5608  0.4380  0.4396  0.6360 

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)    
(Intercept)            0.5623738  0.0082185  68.428   <2e-16 ***
TimesSeenDoctorIn2Yrs -0.0003968  0.0003061  -1.296    0.195    
```

```
lm(formula = LifeIns ~ Age + Education + MaritalStatus + Health +
    Weight + Medicare + LTC + TimesSeenDoctorIn2Yrs, data = Train)

Residuals:
    Min      1Q  Median      3Q     Max
-1.3405 -0.4521  0.1791  0.3975  1.1377

Coefficients:
                             Estimate Std. Error t value Pr(>|t|)
(Intercept)                -6.544e-01  9.791e-02  -6.684 2.65e-11 ***
Age                         7.167e-03  1.657e-03   4.326 1.55e-05 ***
Education                   4.091e-02  2.583e-03  15.838  < 2e-16 ***
MaritalStatusMarried        9.720e-02  1.821e-02   5.338 9.93e-08 ***
MaritalStatusNever Married -8.827e-02  2.405e-02  -3.670 0.000246 ***
MaritalStatusSeparated     -2.665e-02  3.533e-02  -0.754 0.450751
MaritalStatusWidowed       -4.664e-02  4.027e-02  -1.158 0.246824
Health                      5.288e-02  7.243e-03   7.302 3.40e-13 ***
Weight                      4.440e-04  9.064e-05   4.898 1.01e-06 ***
Medicare                   -8.540e-02  2.463e-02  -3.467 0.000531 ***
LTC                         2.266e-01  2.997e-02   7.559 4.97e-14 ***
TimesSeenDoctorIn2Yrs       2.254e-04  2.894e-04   0.779 0.436117
```

```
lm(formula = LifeIns ~ Age + Education + MaritalStatus + Health +
    Weight + Medicare + LTC, data = Train)

Residuals:
    Min      1Q  Median      3Q     Max
-1.3389 -0.4522  0.1799  0.3969  1.1582

Coefficients:
                             Estimate Std. Error t value Pr(>|t|)
(Intercept)                -6.493e-01  9.768e-02  -6.647 3.40e-11 ***
Age                         7.141e-03  1.656e-03   4.312 1.66e-05 ***
Education                   4.104e-02  2.577e-03  15.923  < 2e-16 ***
MaritalStatusMarried        9.683e-02  1.820e-02   5.320 1.10e-07 ***
MaritalStatusNever Married -8.854e-02  2.405e-02  -3.682 0.000234 ***
Health                      5.188e-02  7.127e-03   7.280 3.99e-13 ***
Weight                      4.425e-04  9.062e-05   4.883 1.09e-06 ***
Medicare                   -8.388e-02  2.455e-02  -3.417 0.000640 ***
LTC                         2.268e-01  2.997e-02   7.566 4.72e-14 ***
```

Appendix C – Correlation Matrix

	LifeIns	*Age*	*Education*	*Health*	*Weight*	*Medicare*	*LTC*
LifeIns	1						
Age	0.042574083	1					
Education	0.304792324	0.013971261	1				
Health	0.207594115	-0.058589754	0.27632141	1			
Weight	0.067063874	-0.016391882	0.04262468	-0.090794795	1		
Medicare	-0.113471946	0.183453886	-0.107761558	-0.265960735	0.02388766	1	
LTC	0.143617148	0.031803247	0.096872884	0.055648332	0.010933227	0.000333	1

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