Team InnoVision

United States Health Insurance

Adverse Disruptors in the Healthcare Industry

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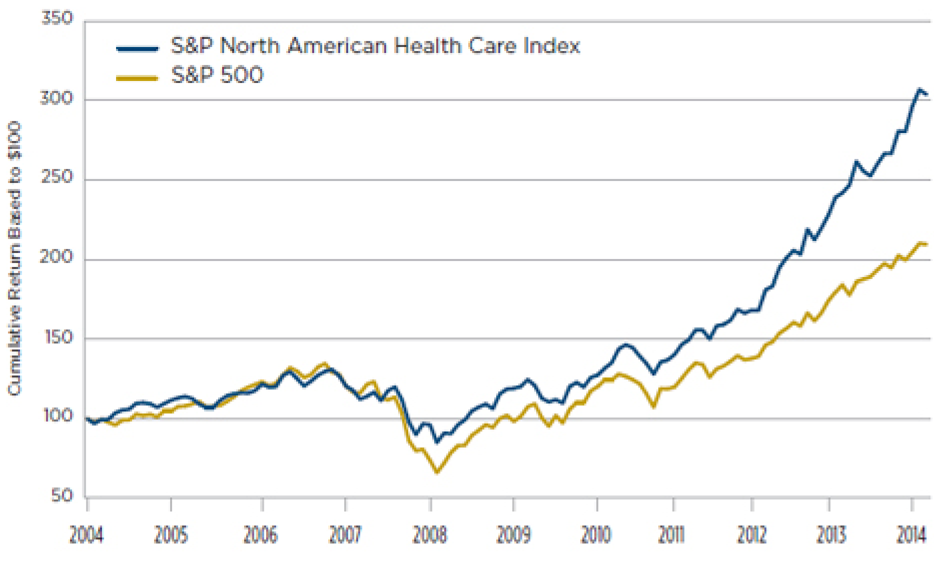
1.0 Executive Summary

In the current market, many variables are radically changing and undergoing a turbulent transformation. The United States population is aging, health care reform is a constant topic for government officials, yet through all of this, healthcare companies have been outperforming the market. After careful analysis, our team has identified two potential disruptors:

- Pandemic outbreak
- Potential repeal of Obamacare

We first looked at an infrequent yet possible outcome of an epidemic outbreak. The results vary heavily based on several different factors, (e.g. an outbreak in the heavily populated Manhattan area would be vastly more detrimental than an outbreak in an isolated region such as Alaska(however we saw the extremity of the potential losses as high as $80 billion. This would create significant unforeseen increases in liabilities and if not prepared for, could blindside the company.

Lastly, given the current state of the election, a Republican government is a strong possibility, resulting in the likely repeal of Obamacare given the party's political standpoints. The healthcare industry has been booming since the introduction of the Affordable Care Act(ACA) which draws concern to the negative impacts if the repeal presented itself as a reality. After investigation of the effects of a repeal, we saw what was essentially a demographic reversion with a large increase in the uninsured population being observed. With less policyholders in force, we can expect to see a heavy negative impact on the company's financials.



(Pipeline to Innovation: Healthcare Fund Insight, 2015)

Each disruptor would modify the baseline demographic and claim costs assumptions based on the detailed approaches mentioned in the latter parts of this report. In a pandemic scenario, claim costs associated with infections and deaths drives the claim cost higher, leading to negative financial impacts. Using a slightly different approach, the repeal of Obamacare would have limited impacts on the claim costs yet negatively influence the insured demographics and limit the potential revenue streams your company is expecting.

The increase in liabilities due to pandemics were estimated at $80.2 billion for the year in which the hypothetical pandemic took place. Similarly a reduction of insured demographics caused by a hypothetical repeal of ObamaCare is expected to reduce our business volume by 3.7%.

2.0 Purpose and Background

The purpose of this study is to analyze potential significant disruptors that could affect the company's financials negatively, but to also quantify the impact these disruptors would have on the company in the next 5 years. The goal is to create a framework of possible scenarios that may arise, and how these would affect the company. The company can then make informed knowledgeable decisions to manage and mitigate the risk that lies ahead.

Demographics have been modeled and projected for numerous years, however the way this has been done has varied depending on the study purpose and data availability. The most common approach used by the US Census Bureau is the Cohort Component method, which blocks the population into certain age groups of equal intervals. This allows for a simple shift from one group to the next over a period of time equivalent to the length of each age group. On the other hand, The Lewin Group uses a cell-based method that divides the population up into subgroups based on certain factors such as socioeconomic class, age, sex etc. The model then produces estimates of the effect of changes on individual subgroups, which can be aggregated to see the total population trends.

Additionally, in recent studies on health insurance expenditures, we have also observed an increase in the popularity of microsimulation models, which aims to estimate the projected life trajectory of individuals in a large, representative sample of the target population. Rather than choosing one method over the other, we felt each model has its own drawbacks and created a hybrid model based on the cohort-component model and cell-based model. Unfortunately, the lack of complete, seriatim-level data dictated that we could not construct a microsimulation model.

The SOA published a study in 2011 titled "Potential Impact of Pandemic Influenza On the U.S. Health Insurance Industry". The study explored the shock impact that a pandemic would have, and the toll it would have on the healthcare industry. However certain components needed to be adjusted as many things have changed within the last 5 years, and will continue to do so for the next 5. Our pandemic model built upon the 2011 SOA study by introducing mortality assumptions based on gender, age group, health status and state.

Finally, while much research has been done on the implementation of the Affordable Care Act, much of it incorrectly predicted that it would be quite taxing on the healthcare industry. Several conjectures and predictions were made on the effect the ACA would have when implemented, and the SOA published a study on it . However, there is a vast lack of readily available data predicting the effect of the ACA being repealed. While one could assume that there would simply be a general reversion to the past, time lag contributes to be a significant factor, and further investigation needed to be taken to predict the effect this would have on the company.

3.0 Data

3.1 Data Sources Used

Statistics regarding the demographic composition of the United States, divided by age, state, and insurance coverage, was obtained from the U.S. Census Bureau through both its censuses, intercensal estimates, and surveys particularly designed to obtain information on health insurance coverages. Since granular data divided by all five demographic characteristics of interest (age, gender, self-reported health status, health insurance coverage, and state of residence) is not publically available, data regarding the distribution and correlation of gender and self-report health status with each other and the other three existing variables were required to break the data to the desired level of granularity. Industry studies such as the *Profile of Uninsured Persons in the United States* conducted by Pfizer Inc. and statistical data collected by the Washington State government using the *Behavioral Risk Factor Surveillance System* were used to assist the process of generating population estimates for refined demographic cells. Publicly available databases such as the Human Mortality Database and Public Use Files (PUFs) provided by the Centre of Disease Control and Prevention were also used to extract key assumptions such as mortality in our model.

Many industry studies on health coverage distribution and healthcare expenditure were used in our model-construction processes as guidelines and references. Notably, results from the *Study of the Effect of a Flu Pandemic on Insured Mortality Using the Delphi Method* (conducted by the Society of Actuaries) were used as a target of comparison to ensure the accuracy and validity of our own model.

3.2 Data Validation

To ensure the consistency of our data, we have tried to use data from as few sources as possible. Most data were obtained from the U.S. Census Bureau. This ensures the consistency of variable categorization, and reduces the potential for major discrepancies for different statistical estimates. We have also reconciled the population on an aggregate level between different surveys conducted by the U.S. Census Bureau and any other sources we have used.

We eliminated all sources whose aggregate figures deviated from the corresponding U.S. Census Bureau estimates by more than 5%.

4.0 Method Analysis and Models

There are a plethora of potential disruptors your company faces in the coming five years. We created an exhaustive list, and chose the most impactful disruptors based on the combination of the severity these events would have if they were to occur, along with the likelihood of such events happening. These two criterion still provided a vast measure to categorize disruptors, however with careful deliberation we arrived at two that were not only placed on opposite ends of the spectrum, but we felt were essential to prepare for, and could prove vastly detrimental if ignored. As mentioned above, the disruptors we feel need to be prepared for are a possible pandemic, and the potential repeal of Obamacare.

4.1 Base Model

The disruptor's effects were decomposed between demographic and claim cost components. Current demographics of the United States health industry census was projected up to years 2017 - 2021 based on the 2014 estimated demographics. Similarly the claim costs assumptions were developed and projected for years 2017 - 2021. The baseline liability for the next five years was conjoined between the two aforementioned components.

4.1.1 Demographics

Modelling the impacts of disruptors was based on the composition of demographics and claim costs. The current demographic estimates of the United States was taken from the Income, Poverty and Health Insurance Coverage in the United States surveys conducted by the U.S. Census Bureau during the years 2002-2014, and projected up to years 2017 - 2021 using a cell-based model that estimates the population shifts between different demographic cells divided by age group, state of residence, health insurance coverage, self-reported health status, and gender.

We investigated the use of a microsimulation model, however seriatim data is needed for a microsimulation model, but decided against it due to the lack of seriatim-level data and relevant assumptions such as the detailed transition rates between insurance segments, divided by single years of age. Thus, we decided to construct a hybrid model that partially retained the property of microsimulation models that projects the trajectory of each individual in its sample population, but used demographic cells as our highest level of granularity.

The key equation that underlies the year-by-year projection of each demographic cell is:

population in year (x+1) = (population in year x) + (births) - (deaths) + (net health deterioration) + (population entering the age group) - (population leaving the age group) + (net insurance coverage movement)

The order in which these movements are applied are: deaths, aging, health deterioration, age group movements, insurance coverage movement, and births. Deaths and births are calculated directly from previous year population estimates, whereas aging and health deterioration are assumed to occur simultaneous and are both based on after-death population. Insurance coverage transitions are calculated on the estimated population net of all other movements.

For our demographic projection model, a major challenge was to ensure that the effects of correlating factors such as health status and age on mortality, morbidity, etc. are isolated. In order to do this, a base set of assumptions are obtained from aggregate estimates derived from the overall U.S. population, then a series of adjustments are applied to account for/remove the effect of each variable within our scope of consideration.

The transition rates were broken into a base rate, which represents the natural transitions assuming no changes, and an excess rate which accounts for shifts due to singular occurrences that would not be repeated. The data from years 2009-2014 was used to identify the base transition rates by finding the least squares estimates of the transition rates subject to certain constraints, such as a lower bound of 0% and an upper bound of 100%. Before the optimization process takes place, excess transition rates are estimated from historical legislative/economic changes, and the excess movements are removed from the population estimates to be used as input to the optimization process. We only used 6 years of data because our estimates of excess rates are increasingly inaccurate retrospectively and loses credibility regarding the final product. The diagonal elements of the transition matrix (e.g. uninsured-to-uninsured transition), account for the outflow of population from a particular insurance coverage segment, whereas the non-diagonal entries on row i, column j represent the expected % of insurance segment i transferring to segment j in one year. The *lsqlin* function that MatLab's optimization toolbox offers was used for this optimization (please refer to the demographic model spreadsheet for codes and matrix inputs). Once the estimated transition matrix has been obtained, the net annual insurance coverage movements can then be calculated by matrix multiplication.

Factors to consider when identifying transition rates were based in part on the cohort-component model, as we were looking at yearly intervals, and both births and deaths had to be considered. However, cohort component looks at bigger time intervals, allowing for a direct transition between groups; we had intervals that weren't uniform (0-18, 19-24, then intervals of 10 years, then 65+). Furthermore, certain areas, such as the moment someone enters the 65+ category, were more complex due to retirement and becoming Medicare-eligible. Therefore, a special set of insurance coverage transition rates were developed for the aged population (ages 65+).

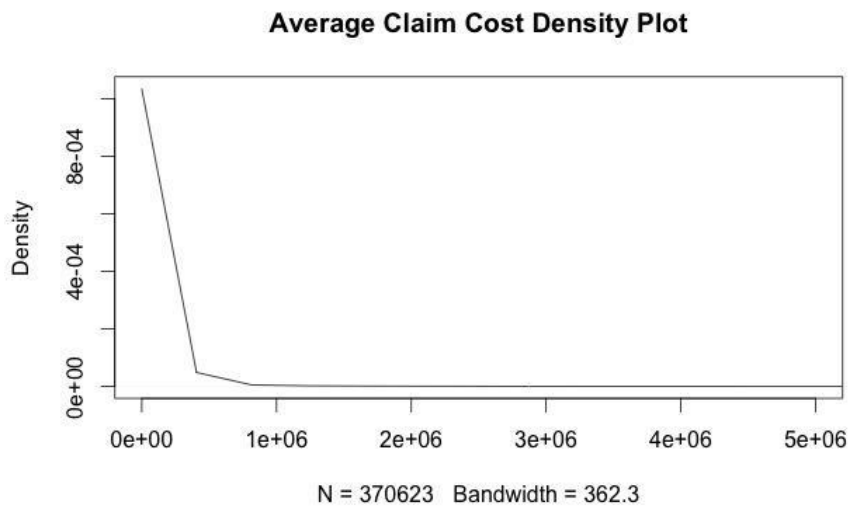
Further pieces incorporated into the model were fertility rates that varied by state, the human mortality database records and the assumption of no mortality improvement. The arising problem of age versus health status needed to be addressed. If the health status of a certain cohort is assumed to be constant as the cohort ages, the overall health status of the U.S. population would be expected to improve indefinitely due to the higher mortality rates of people with poor health and the continuous influx of new-borns whose health status is expected to exceed that of the total population. The age of the policyholder therefore needs to be considered because an individual who gets older should naturally be more likely to become unhealthy. So a health deterioration factor was implemented, using a relative index that correlated mortality and health status, which was calibrated by age.

Finally, once the model was built, it had to be tested for accuracy. To do so we used a combination of actual to expected(A/E) ratios by projecting the 2013 data to 2014 to test against the actual results. The A/E ratio was calculated for each cohort individually, and then for each group, and then for all pairs of demographic characteristics . Any significant outliers were examined as an accuracy and reasonability check, and the model was calibrated correspondingly to ensure the A/E ratio for population divided by all pairs of characteristics are within 3% of 100%. Please refer to the “Model Accuracy Test - A-E 2014” tab for detailed model accuracy testing calculations and all tabs ending with “adj.” for the model calibrations.

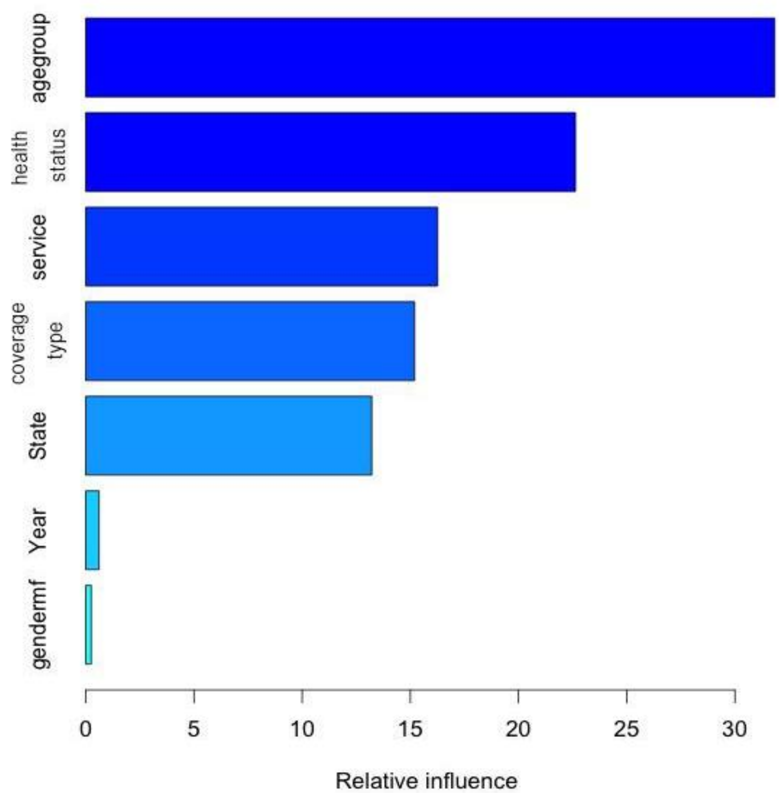
4.1.2 Claim Costs

Original claim costs were from the CMS Health Expenditures by Age and Gender report(Age and Gender, 2010) segregated by age, gender, service, and coverage from 2002 - 2010. To add state and health status, we included the claim costs by states(National Health Expenditure by Resident State, 2010) and used service by state and state by health factors (SOA Obamacare Study, 2011) to scale the severity of the claim costs by the state and health status. Weighting the claim costs based on severity and population in each group, the claim costs for 2002 - 2010 with increased member characteristics was developed. The National Health Expenditure Index was used to trend the claim costs to 2011 - 2014.

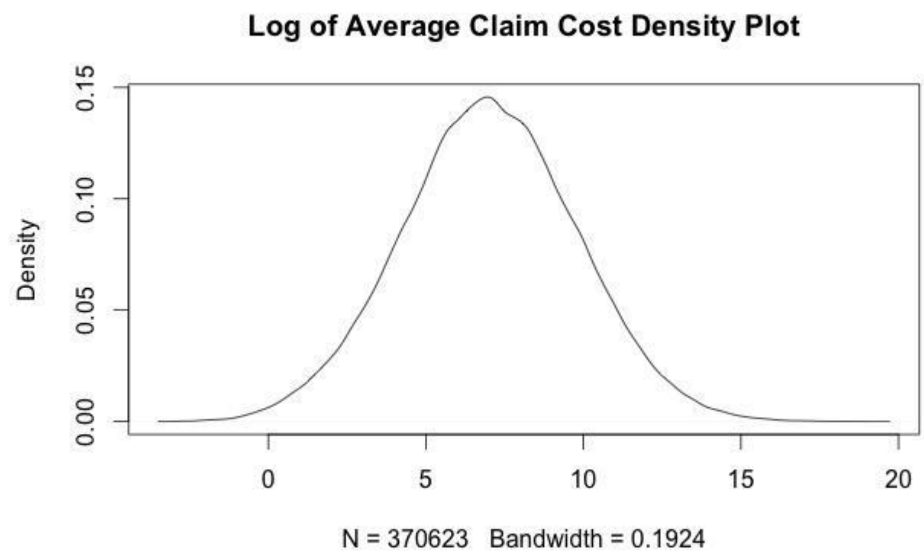
The claim distribution was observed to be a left skewed positive distribution and following traits of the gamma or inverse gaussian.



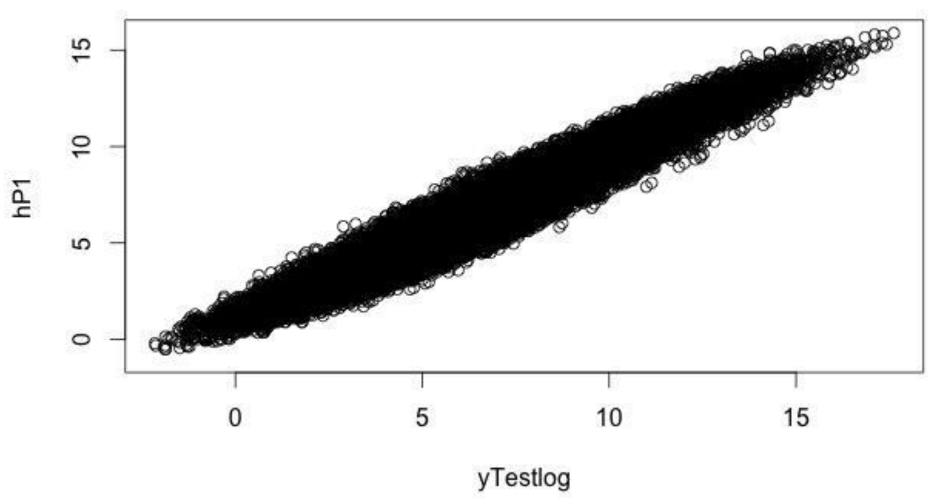
We then adopted the gradient boosting method(GBM), which produces the significance of each variable on the overall claim costs. The graph below demonstrates the relative influence of each variable on the claim costs.



The claim costs were then unskewed by taking the log of the average claim costs, and GBM was applied. The following graph shows the density distribution of log of claim costs, with a clear normal trend. Therefore, gaussian GBM was applied with 800 tree nodes and 2.5% learning rate.



2002 - 2013 historical claim costs by groups were utilized as the training set and 2014 data as the testing and fitting set. A graph of the 2014 actual versus predicted values below shows a linear trend and depicts that the model is correct.



This revised model projects the claim costs for the years 2015 - 2021. Despite the increasing trend in historical claim costs, the projected claim costs remained the same. This is due to the fact that Year is used as a numeric variable. This results in that as Year increases by one, the impact of it on the projected value is low.

Therefore, with the model limitation and time constraints, we have decided to adopt linear trending on the historical claim costs. The average increase per year is around 6%. The Main factors that are driving the increase in claim costs include the following:

1. The increase in prescription drugs. The increase is due to changes in availability of approved pharmaceutical ingredients, leading to scarcity of ingredients, much tighter control at FDA, and mergers and acquisitions of generic drug industries.
2. There are significant increases in outpatient costs and personal care costs.

A model assumption was used that the premiums of that year are equivalent to expected claim costs. Hence the expected claim costs minus the actual realized claim costs would be the profit during that year.

4.2 The Repeal of Obamacare

4.2.1 Past Effect of ACA

Though the Affordable Care Act had vast impact across the board in regards to healthcare companies, levels of coverage, and insurance as a whole, one of the vital effects was the change in the demographic population. A lot of the base analysis of Obamacare was used in calculating the excess rates used in the base model, as there were several legislative implementations that created demographic shifts. One such example was the Health Insurance Mandate that caused a drastic decrease in the uninsured population as members of the population wanted to avoid incurring tax penalties. For each historic year, a 5x5 matrix was created to estimate the excess rates due to such changes, which was then utilized in the baseline model.

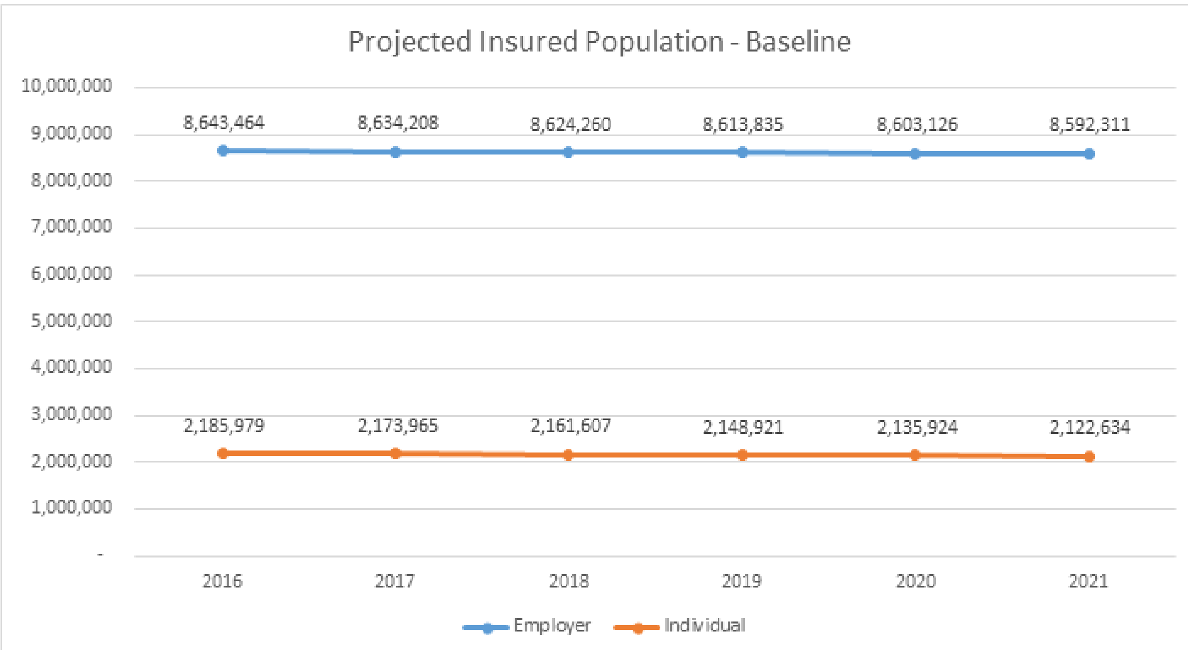
4.2.2 Potential Political Reform

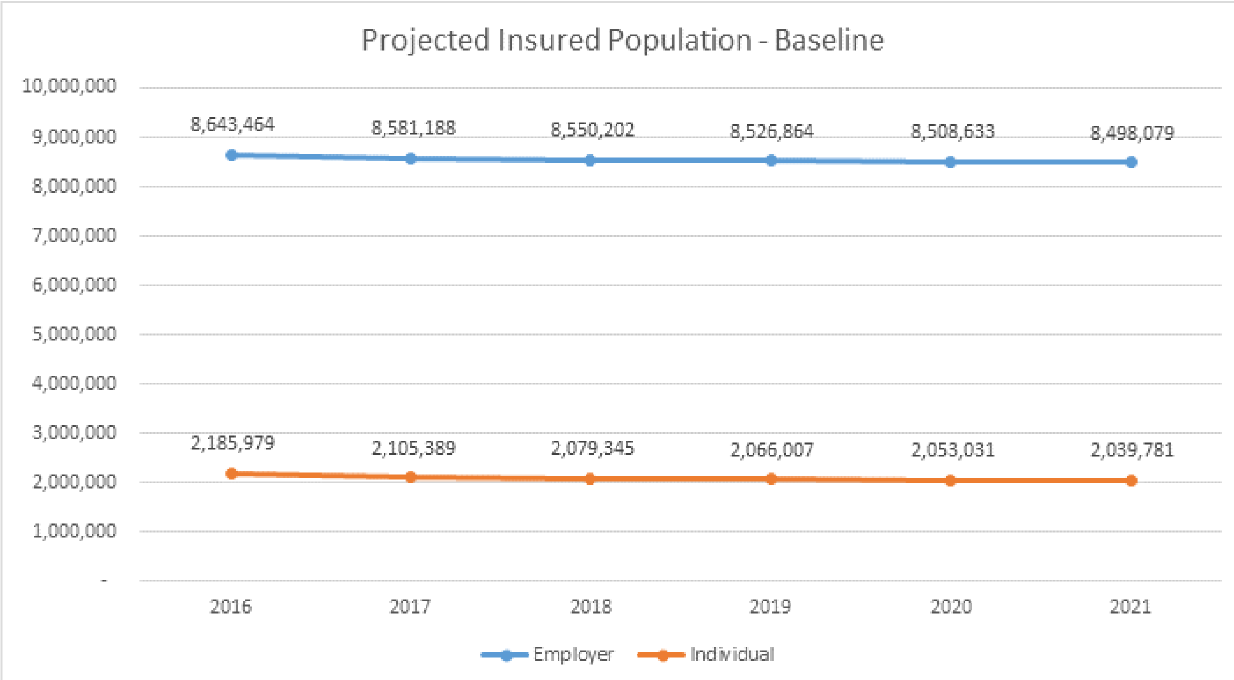
As aforementioned, there is a very large likelihood of a Republican victory, which could mean a repeal of Obamacare. There are several effects of this, but we isolated 3 vital points that are both potential and significant. The first is a large reversion back to pre-mandate demographics. As seen in 2014, a large shift was observed from the uninsured population to all forms of insurance. If this mandate were removed, it's natural to expect many policyholders that had only bought insurance to avoid the tax penalty would shift back to being uninsured. However, we predict there would be some lag as it is human tendency to push things such as cancellations off to a later time. We estimate that approximately half of the specified policyholders would immediately cancel their insurance when possible, and the rest would slowly phase out over 3 years.

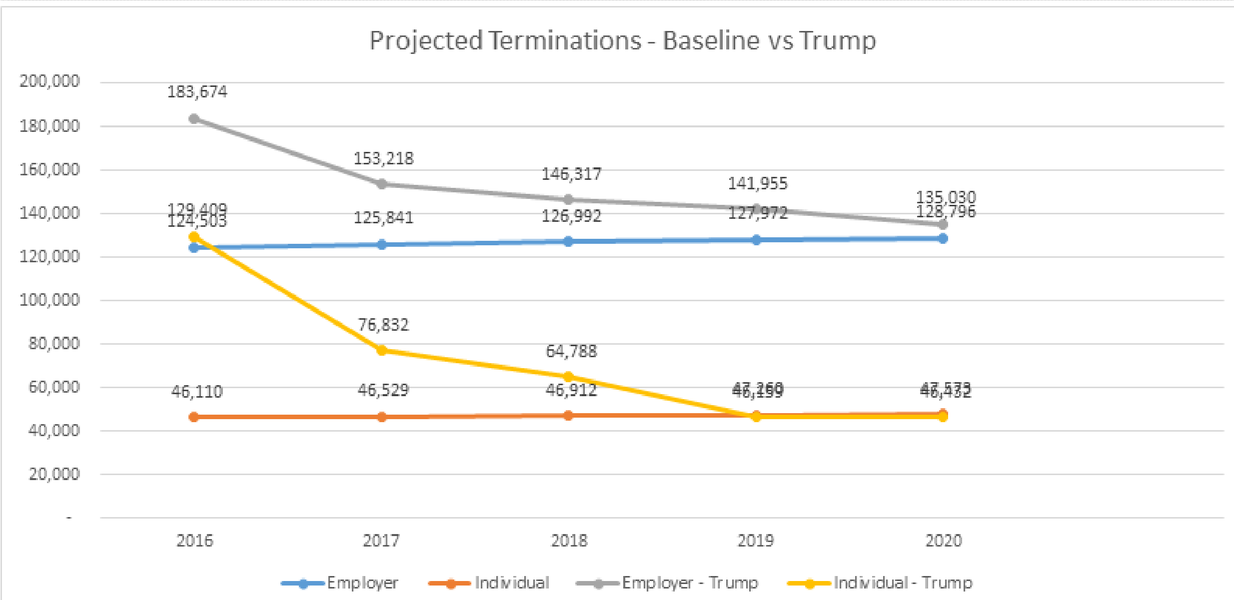
On the other hand, Donald Trump has declared in his proposed plan that he wants insurance premiums to be tax deductible for individual insurance. Many policyholders will jump at the benefits of this and might now see individual insurance as worth it. We predict that this would minorly offset the shift back to the uninsured population from those with individual insurance, as they have more incentive to stay under their plans.

Lastly, though we see the general trend pushing back towards the uninsured population, Donald Trump has stated that he would allow insurance sellers to have free access to buyers, regardless of the state. We foresee a slight shift from the uninsured population to the insured population as a result of increased access to different plans.

As a result of the large decrease in business, we predict a 3.7% decrease in the first year alone after the repeal of the Affordable Care Act, which will have a drastic effect on the company's financials, unless plans are made to prepare for this possibility.







4.3 Pandemic Outbreak

Starting from 2000, epidemic influenza has been a major concern to healthcare industry such as the SARS outbreak, H1N1 and H5N1 Ebola outbreak, and Zika outbreak. From historical pandemics particularly in recent years, the epidemic has a particularly rapid growth rate on the onset but gradually decreases when the proper protocol is put in place. Although some pandemics may not have a long duration, its impact to the healthcare industry may be extremely severe. A widespread epidemic can cause controversy among the population affected. During outbreaks, there is an expectation to have a significant increase in health care costs due to increasing in demands for inpatient, outpatient, and other medical services. The occurrence of a pandemic is categorized as one of our three disruptors because of its unpredictability and severe negative impact.

After carefully studying the SOA's published Pandemic Modeling report(Toole, J. June 2010), we decided that the pandemic disruptor acts as a scenario shock on top of our overall demographic assumptions. Additionally, there is a shock on claim costs in which it looks at the infected population and applies an additional claim cost assumption due to the fact that an affected individual has an increased likelihood of claims subtracting the recovery rate. Among the claim cost shocks there is a segregation between high and low risk of attaining the disease. In our base demographic model we have already included assumptions on morbidity, mortality, and claim cost projections. The assumption is that the pandemic will only last for one year, hence for the five year projection, there is an application of the pandemic mortality, morbidity, and claim cost adjustments only for the affected year.

The assumption changes followed the study's(Toole, J. June 2010) references and methods, where we adjusted accordingly to fit our base model. We introduced mortality assumption based on gender, age group, health status and states.

5.0 Conclusion

After examining the possible disruptors, there is a very strong possibility for the company to experience adverse losses in the upcoming years. The increase in liabilities due to pandemics were estimated at $80.2 billion for the year in which the hypothetical pandemic took place. Similarly a reduction of insured demographics caused by a hypothetical repeal of ObamaCare is expected to reduce our business volume by 3.7%.

Baseline Versus Disruptors Aggregate Claim Costs - Linear Model

($ In Millions)	2017	2018	2019	2020	2021
Baseline Assumption	503,733	536,642	571,837	609,458	648,863
With Health Care Legislation Disruptor	503,705	536,971	572,157	609,379	648,763
Pandemic Disruptor	583,933	536,642	571,837	609,458	648,863

A pandemic, though however unlikely is very much so a possibility and a catastrophe of such magnitude should be prepared for in the event of an outbreak. Something to consider is the introduction of deductibles or co-payments, as many policyholders might panic and induce unnecessary checkups incurring more costs for the company. These would cause policyholders to exercise more rational A few possibilities that should be investigated to mitigate losses are, or an excess of loss reinsurance policy, which would be relatively expensive compared to the potential loss that could be experienced.

The other quite concerning possibility is a Republican government repealing the Affordable Care Act and the Insurance Mandate. It will result in an expected 3.7% decrease in business in a single year, as the effect of a sole event that can be predicted is something that should not be ignored. The staggering loss of policyholders is something that can be investigated, to see if there are incentives of some sort to convince them to stay. The initial work in terms of attracting clients has been done, but retention of these policy holders is vital.

The other factor to think of is the cross-state boundary being abolished by Donald Trump. On one hand, the company will now have access to a vast majority of the population that wasn't reached before hand. Steps should be taken to investigate which areas would prove most profitable, and should be focused on for marketing and advertising. On the other hand, the company would now face a stark increase in competition, and an area of focus would again be how to retain current policyholders, but in this case from leaving to other healthcare companies, as opposed to going uninsured altogether.

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