Block Dental

Team 19 Executive Summary

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I. Introduction

The current loss ratio of Block Dental is 88%, and the following report will describe strategies to decrease this loss ratio to 70% in three years.

II. Analyzing the data

In our analysis of the given "Renewal Training data", we looked to see if the win rates were intuitive for each factor. For *Loss ratio band (loss ratio)*, we see that a higher loss ratio is correlated with higher win rate since a customer with high losses is benefiting from the high payout relative to premium and is likely to renew their policy. For *Rate band (net dental renewal increase)*, a higher rate increase is associated with a lower win rate since customers will not renew their policies if they can find cheaper alternatives elsewhere. For *Channel*, we found that groups that buy through a General Agent, who is hired by the group to find a policy to fit their needs, renew more often since the agent finds an appropriate policy. For *State*, the state the group is in has a slight effect on win rate but nothing intuitive. Slight variation may be related to the availability of dental insurers in the state, legislation, average population age, or other demographics. For *SIC Code,* we see relatively small changes in win rate except in companies with an SIC code of 1 or 33. Companies in agricultural production crops only renewed their policies 16% of the time and companies in the metal industry never renewed their policies among the 57 groups we insured.

Assuming the same amount of utilization, other factors that may cause one group to have a higher loss ratio is the average age of the group. Older groups may need more dental services and treatments like root canals or implants compared to just cavities for younger groups, resulting in higher claims and loss ratios.

In the past, some groups with a higher loss ratio may have had a lower rate increase because they may be loyal, returning customers whom we have years of data on. Hence, their losses have stabilized and are more predictable than those of new customers. As a result, these groups are valuable, and it makes sense to charge them a lower rate in hopes of retaining them for years to come.

II. Developing a renewal probability model

After using R to analyze the factors in the "renewal training data," we concluded that "Net dental renewal increase" and "Channel" were the best predictors of Stage which we encoded as "1" for "Closed Won" and "0" for "Closed Lost". Using these two factors to train a logistic regression model, the resulting test error was .14. It is necessary to consider at least two factors because there is not a big enough relationship between Stage and a single factor. Thus, we need at least two predictors to come up with a more accurate probability model for renewal. The generated renewal win rate curve is shown in *Figure 2.1.*

III Pt 1. Strategy for maximizing profit

First, we assumed that expenses and claims will remain the same throughout the years. Another assumption is that renewals each year are independent from each other. In our strategy, we first used our model to calculate a probability using "Channel" and our chosen "Net Dental Renewal Increase" for each rate brand. From this, we got an indicator variable, "Predicted Win/Loss" which is "1" if the probability $\geq$ 0.5 and "0" otherwise. Then, we calculated Expected Premiums and an overall Loss Ratio for Block Dental for the year using the aforementioned rate increases. Using these loss ratios, we found the corresponding Loss Ratio band, applied the probability renewal model using new "Net Dental Renewal Increase" values for the next year, and repeated the same steps as in 2020 to get 2021 and 2022 expected premiums, claims, and loss ratios. We then adjusted the rate increases for each LR band to reach our desired profitable loss ratio. The chosen rate increases as well as expected financials can be found in *Figures 3.1* and *3.2.*

III Pt 2. Strategy for maximizing revenue

To maximize revenue, we want to find the optimal rate increase where we do not lose clients according to our probability model. For this strategy, our methodology for calculating expected premiums, claims, and LR are the same, including our assumptions, but we adjusted the rate increases for the purpose of maximizing premiums by 2022. We started by increasing each LR band by an amount that would not cause groups to leave. Then, we decreased the rate increase in the years after that. This results in premiums of 144 million compared to 121 million in premiums from maximizing profit. This also resulted in a lower loss ratio of .64 compared to .67 when maximizing profit.

IV. Final strategy

To decrease the loss ratio to 70% in three years, our final strategy is to have rate increases on a continuous scale instead of a specific number per band. Our previous strategies assumed the same increase for each LR band but this allows us to be more specific. Since our target loss ratio is 0.7, we took any group that has a LR greater than this and subtracted .7 from it. We then divided that by 3 to get our rate increase/yr for that group. This leads to naturally diminishing increases over time assuming claims will stay the same. We do experience a lower win rate since groups with very high loss ratios leaving due to this approach, but we see that it realistically optimizes profit much more than the other two approaches. Although this approach depends on each group's unique loss ratio, large rate increases for certain companies may arise. Thus, we decided to implement a cap on the rate increases at 20%. This allowed us to hit our target loss ratio of .7 while retaining about 87% of our customers. We wanted to avoid large rate increases for State Insurance filing reasons as well as maintaining a higher win rate. Our expected financials for this strategy can be seen in *Figure 4.1.*

V. Final implications

An assumption we made was that a company's decision to renew with us is unaffected by other years. One of our predictors is net increase and in the real world, we can expect that if a customer has had their rates increased yearly, they will likely leave for another insurer. But, this is not something our model can take into account yet. Other ways to reduce loss ratio can be in the policy design themselves, like decreasing the policy maximum or increasing deductibles. This could discourage some people from using dental services unless really needed if they face a higher deductible than is worth their trouble. An additional, but indirect, method could be to encourage healthy dental practices among customers through incentive programs or ad campaigns. Lastly, a trade-off we experience by not incorporating more factors into our model is giving up accuracy for model simplicity and interpretability.

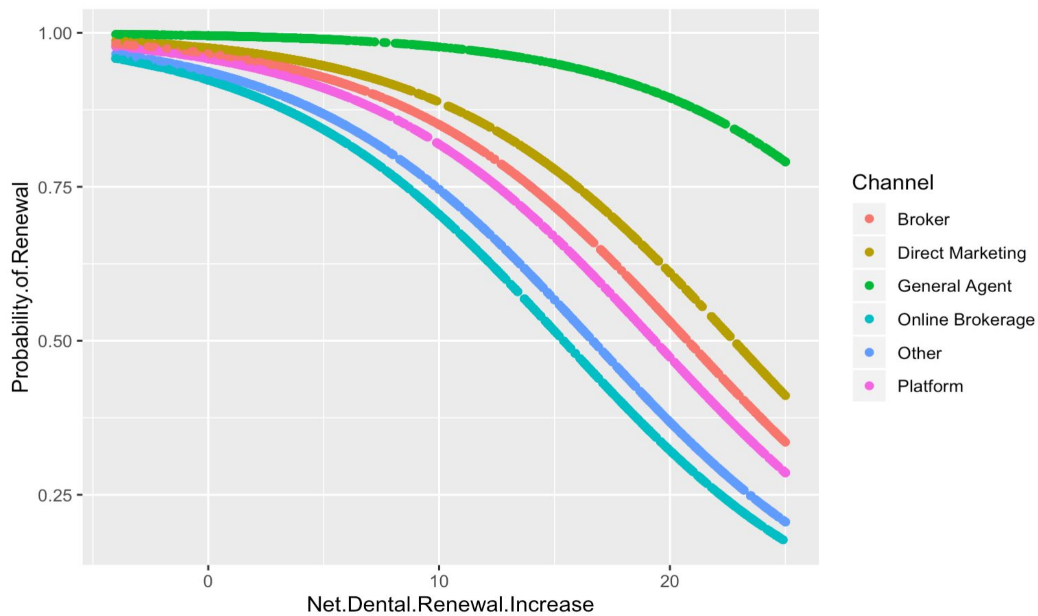

Figure 2.1

Loss Ratio (%)	Rate Increase Yr 1 (%)	Rate Increase Yr 2 (%)	Rate Increase Yr 3 (%)
(0,25]	0	0	0
(25,50]	0	0	0
(50,75]	5	5	5
(75,100]	10	10	10
(100,150]	15	15	15
(150,9999]	20	15	15

Figure 3.1

	2020	2021	2022
Expected Premiums	$108.9 million	$117.7 million	$126.3 million
Expected Claims	$84.8 million	$84.8 million	$84.8 million
Expected Payoff	$24.1 million	$32.9 million	$41.5 million
Expected Loss Ratio	77.9%	72.1%	67.1%
Win %	95%	95%	95%

Figure 3.2

	2020	2021	2022
Expected Premiums	$98.5 million	$104.1 million	$108.5 million
Expected Claims	$74.4 million	$74.4 million	$74.4 million
Expected Payoff	$24.1 million	$29.7 million	$34.1 million
Expected Loss Ratio	75.50%	71.48%	68.56%
Win Loss %	87.54%	87.54%	87.54%

Figure 4.1