The Struggle to Keep Subscribers

Antonio Azcueta
ECON 482A
Autumn 2003
aazcueta@u.washington.edu

Executive Summary:

All businesses look for ways to maximize profit. In the business of newspapers, advertising pay generates the most profit for a company, but in order to maximize this profit, the number of subscribers has to be very high. I work to keep this circulation number up by retaining current subscribers. The purpose of this paper is to construct a model that would show me what types of customers were easier to retain. Using that information, I would focus more on retaining these peopled in order to maximize the number of canceling customers that I retain. I would also be able to see which customers were going to be harder to save. Using that information, perhaps we could develop new marketing tools to target these customers and make it easier to keep them..

The act of convincing a canceling customer to keep their subscription is called a save. In this paper, I look at several factors that affect the number of saves that I obtained in two weeks at work. I collected data from all customers who called me to cancel their subscription. Before analyzing any data, I believed that offering customers another promotional rate could save most customers who had previous promotions. It seemed logical because most of my saves came from using this technique alone. Since my left-hand-side variable is a dummy variable, I used the probit command in EVIEWS to estimate the β's in the model. One of the things I learned from the results of the probit model was that I was wrong. As it turned out, many people were not willing to keep the subscription even if I lowered the cost. The main factors that contributed to the number of saves obtained were those who had a service problem, have subscribed for over a year, and are weekend related.

Introduction:

The number of subscribers to a newspaper is vital for its survival in a world where more and more people turn to television and the Internet to stay informed. The majority of The Seattle Times Company's revenue comes from advertising. This large portion of the revenue increases as the number of subscribers increases. While sales representatives increase the number of subscribers to our newspapers through telemarketing, door-to-door, and kiosk sales, current subscribers are calling me, a customer service representative, to say that they are no longer happy with their subscription and do not wish to continue receiving the newspaper. It is a constant day-to-day struggle to maximize the number of sales and minimize the number of lost subscribers.

I assist customers with any billing or delivery issue that they have with their subscription to The Seattle Times or The Seattle Post-Intelligencer. It is also my job to minimize the number of customers that cancel their subscription. I am paid commission for obtaining saves. To get saves, I have to convince canceling customers to keep their subscription active. I do this by offering promotions and resolving any billing or delivery related problems. It is not an easy task and our superiors are only expecting a minimum of twenty percent ratio of saves to total opportunities.

My goal every day is to increase my number of saves so that I can increase the amount of commission I receive on my next paycheck. Additionally, an increase in the number of saves could make me look like a better representative to my superiors by increasing my ratio of saves to total opportunities. The problem is that I use the same techniques for each scenario. If someone has a delivery issue, I promise to have an appropriate route manager fix the problem. If they have a problem with the billing or simply the cost of the paper, I offer them our promotions. I wanted a model that would help me find out where new techniques would be most beneficial. It is with new techniques that I hope to increase my saves, and therefore my commission.

The Model:

Before collecting any data, I thought I already had a good idea of the type of subscribers that I could and could not save. For example, it seemed logical to assume that people that were previously on promotions called in because they do not want to pay full price. By offering them the lower rate again, I could easily get a save. I set out to construct a model that would really show me what types of subscribers I was saving. I hoped that it would also show me what types of subscribers I was not saving so that I could develop new techniques to use on them.

First, I tried to think of as many factors that would influence the number of saves I obtained. In each workweek, I worked on a Monday, Wednesday, and Friday. I ended up getting calls from sixty-six people that wished to cancel, and I saved twenty-two of them. At about thirty-three percent, that is actually good compared to previous weeks. I took down all pertinent information from the callers. I could not let the data collection process interfere with my duties at work, so the variables I chose were the ones that I could easily get from the customer without keeping them on the phone longer than normal. Most ended up being dummy variables.

I ended up with the following model:

$$\text{SAVED} = \beta_0 + \beta_1{*}\text{ZONE} + \beta_2{*}\text{PPROMO} + \beta_3{*}\text{SRVC} + \beta_4{*}\text{YRS} + \beta_5{*}\text{MOS} + \beta_6{*}\text{WEREL} + \beta_7{*}\text{TI} + \beta_8{*}\text{CURBAL} + \beta_9{*}\text{CM} + \beta_{10}{*}\text{CARD} + \beta_{11}{*}\text{MALE}$$

ZONE is the variable for whether or not the customer lives in the city of Seattle or not. PPROMO is the variable for whether or not the customer was previously on a promotion. SRVC is the variable for whether the customer has been having delivery problems. The variable YRS is for the total number of years the customer has subscribed to the paper. Many were subscribers for less than one year so I chose to add the variable MOS for the total number of months the customer has subscribed to the paper. WEREL is the variable that describes whether their service is mainly daily related (subscription included Monday through Thursday) or weekend related (subscription included Friday thru Sunday). TI describes the customer as either Times or Post-Intelligencer subscriber. CURBAL is the current balance on the account on the day of the call. CM is the variable for whether the customer is choosing a local community paper i.e. The Tacoma News Tribune and The Everett Herald. CARD shows if a customer renews their subscription automatically with a credit or debit card. MALE is the variable showing whether the caller was a male or female.

Results:

The results of the probit model were not exactly astonishing, but I did find a few surprises. The first real surprise came when I looked at the coefficients for YRS and MOS. I found it odd that the coefficient for YRS was positive while the coefficient for MOS was negative. It did not seem logical at first and I tried to find out why by looking into the data. I figured that if a longer subscription in years contributed to saves, so should a longer subscription in months. What I noticed was that when coding the number of years for a subscription, those customers who had been subscribers for less than one year were recorded as zero years. I concluded that people who have subscribed for at least a year were easier to save in comparison to those who subscribed for less than one year, resulting in the opposite signs for the coefficients.

Another interesting surprise was that those customers who live in Seattle do not contribute to the number of saves obtained. In fact, they were contributing to the number of subscription cancellations. This was odd because both the Seattle Times and P-I are more focused on the Seattle metro area than on its outlying suburban areas where there is competition from other newspapers. For whatever reason, the customers outside of Seattle are easier to save.

As far as other variables go, I could not think of other variables that would help explain the number of saves I would obtain. My model does not account for every reason that a customer would have for canceling their subscription. There are some reasons that prevent me from even attempting to get a save. For example, customers that are moving out of state are not going to buy a mail subscription for over twice as much as their new local paper. In addition, some people that call in say that they told our sales representative that they were not interested in the first place and refuse to pay the bill. These types of things are assumed to be spread out evenly between me and the other representatives. In any given week, I could get the vast majority of moving customers, but in the long run, it is assumed that everyone gets about the same amount. Furthermore, our performance in the long run should not be affected. A better model, therefore, could include observations throughout a whole month or maybe a year to account for different seasons.

Conclusion:

The variables that increased the probability of a cancellation were CM, CARD, and ZONE. These things would need to be researched by someone in a higher marketing position. Seattle residents should be easier to save since the paper is catered to them more. If there was some way to get better local coverage at a low cost to compete more with the other papers, we could save more subscriptions. Perhaps the customers paying automatically are unhappy with that type of billing. I cannot do much with these things.

The variables that increased the probability of a save were SRVC, YRS, and WEREL. These results make sense and I came up with some techniques noted below to increase my saves. There is no reason why we should lose a subscription due to a delivery issue that can easily be remedied, and we should be able to retain loyal subscribers. When someone wants to cancel due to a delivery issue, I have to convince him or her that it will be resolved immediately. If a long-time subscriber calls to cancel, I can remind them that we have appreciated their loyalty and would hate to lose their business. Hopefully, they will remember how much they have enjoyed the paper and change their mind. I can also obtain more saves by offering canceling daily-related customers a cheaper weekend related subscription. Sunday is a more popular paper so we should be able to keep customers on at least Sunday only.

In conclusion, I feel that my model did not turn out too bad. There are so many things that can contribute to the effectiveness of persuasion, and most of these things are not in my model. Still, I have a better understanding of what is going on and I believe that my performance will increase at work. As long as it does, this paper was a good idea.

Dependent Variable: SAVED
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 12/05/03   Time: 12:56
Sample: 1 66
Included observations: 66
Convergence achieved after 25 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.085793	0.766518	-0.111926	0.9109
ZONE	-0.898274	0.484665	-1.853391	0.0638
PPROMO	0.261320	0.573610	0.455570	0.6487
SRVC	8.556117	12859909	6.65E-07	1.0000
YRS	1.539819	0.872780	1.764270	0.0777
MOS	-0.135943	0.075732	-1.795066	0.0726
WEREL	0.733612	0.434513	1.688355	0.0913
TI	-0.191026	0.429812	-0.444441	0.6567
CURBAL	0.028284	0.021285	1.328790	0.1839
CM	-8.831353	5548720.	-1.59E-06	1.0000
CARD	-0.064576	0.764487	-0.084469	0.9327
MALE	-0.277229	0.395868	-0.700308	0.4837

Mean dependent var	0.333333	S.D. dependent var	0.475017
S.E. of regression	0.433555	Akaike info criterion	1.270179
Sum squared resid	10.15039	Schwarz criterion	1.668298
Log likelihood	-29.91591	Hannan-Quinn criter.	1.427495
Restr. log likelihood	-42.00994	Avg. log likelihood	-0.453271
LR statistic (11 df)	24.18805	McFadden R-squared	0.287885
Probability(LR stat)	0.011963		
Obs with Dep=0	44	Total obs	66
Obs with Dep=1	22		