Dynamic Pricing Analysis

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Abstract

This paper presents a methodology that represents a significant enhancement to current pricing practices. The goal of this methodology is to estimate the impact that a rate change will have on a company's policyholder retention and the resulting profitability of this transformed book of business. The paper will present the basics of this methodology as well as where future work will need to be done to bring this methodology into mainstream pricing. The work that the authors have done in this area has focused on Private Passenger Auto Insurance but these techniques could be applied to other lines of business.

Introduction

There is a wealth of actuarial literature regarding appropriate methodologies for using exposure and claims data in order to calculate indicated rates. Techniques have been developed to address difficult issues such as small volumes of data, years that are particularly immature and high excess layers of coverage. All of these techniques ultimately produce a set of actuarially indicated rates and rating factors. When it comes to deciding on the rates and rating factors that will actually be used in the marketplace, however, a new dynamic begins to enter the picture.

A revised set of rates will impact the profitability of the companies' book of business in a number of different ways. There is the obvious impact that the revised rates will have on the premiums that policyholders are paying. There is also the more intangible impact of the policyholder reaction to the rate change. A rate change exceeding a certain threshold will likely send a customer shopping for an alternate insurer. Depending on the alternative premiums that are available in the market, that customer may decide to insure with another company. If a rate change produces a large number of such non-renewals within the company's book of business, the revised rates could impair the intended benefits of the rate change. Alternatively, if the non-renewals that occur are in classes of business that are particularly unprofitable for the company, its profitability could actually be enhanced by the non-renewal activity.

Companies often have a number of ad hoc "rules of thumb" for determining the amount of a rate change that the market will bear, but very few rigorous models exist that attempt to estimate the likely customer reaction to a rate change. An approach to pricing that considers not only the impact of the new rates on the average premium charged, but also on the renewal behavior of policyholders can thus be a significant step forward for determining appropriate prices and likely future profitability. The question that must be asked is "Are there a family of models that can model the renewal behavior of policyholders?"

Actuarially Sound Rates

This paper will present methodologies that will allow the consideration of the impact of policyholder retention in the pricing process. As such, the rates that are being considered in such an approach may not be the same as the actuarially indicated rate. However, since no actuarial method produces an indicated rate that is precisely correct in all situations, there will always be a reasonable range of actuarially sound rates. The methodologies presented in this paper demonstrate how the decision regarding which rate to implement can be made with more rigor than is possible with the current approaches used in the industry.

I. Agent Based Modeling

A. What is It?

A family of techniques that has been successfully applied to model similar behavior in the past is called Agent Based Modeling. Simply put, in using these techniques, models are built which contain factors, agents and rules. Factors are the quantitative measures of the system that is being modeled. In the example of modeling customer reaction to rate changes, the factors would encompass the rates and rating factors for a company and its competitors. It would also include the loss potential of various classes of business that would be used to determine profitability of those business classes. The agents in the model are the units between which interactions take place. In the modeling of rate change reactions, agents would consist of customers, competitors, insurance agents, etc. The rules describe how the different agents in the model will interact.

One of the problems encountered in applying agent based modeling to insurance is with nomenclature. We have agents in the model and agents who are selling policies. To complicate matters even further, the insurance agents are one of the agents in the model. Throughout this paper, in order to assure that the terminology is succinct, an agent in the model will be referred to as an economic agent while an agent selling insurance will be referred to as an insurance agent.

Economic agent behavior is assigned rules, based on a combination of historical data, surveys, focus groups, and analysis. The models are run under various scenarios and the results can be used to help determine a strategic direction with insights that cannot be discerned with the current "rules of thumb" type approach.

An example of a successful application of economic agent based modeling is the modeling of changes in retirement behavior, measured by retirement ages, in response to law changes. In an article in *Behavioral Dimensions of Retirement Economics* by Robert Axtell and Joshua Epstein[1], the changes in retirement behavior since 1961 were successfully modeled. In 1961, the minimum age at which a worker could receive Social Security benefits was reduced from 65 to 62. It was expected that the average retirement age would reduce somewhat quickly to the lower age as a result of this change in benefits.

The actual experience however, was somewhat different. Peoples' average retirement ages did move towards younger ages but the transformation took nearly three decades, which was much longer than expected. What was missing from the original estimations that caused the actual experience to differ so greatly?

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[1] Robert L. Axtell and Joshua M. Epstein, 1999, "Coordination in Transient Social Networks: An Agent-Based Computational Model of the Timing of Retirement." *Behavioral Dimensions of Retirement Economics*: 161-186

The original models were predicated on the assumption that the primary factor that influenced retirement age was the laws surrounding Social Security benefits. Reality, however, is more complicated than that. After researching the factors that influenced retirement ages, it was determined that a major factor in the decision to retire is the retirement decisions of other people in an individual's social network. By constructing models that consider these social interactions, a set of economic agents and rules were developed that accurately predicted the retirement age decisions of a population of individuals. This seemingly complex decision making of individuals could thus be accurately modeled, in the aggregate, with the proper alignment of economic agents and straightforward decision rules.

B. Constructing a Model of Insurance Retention

If models can be constructed that accurately predict the retirement decisions of a population, it is not difficult to imagine the construction of models that accurately predict the decisions of a group of policyholders to remain with their current insurer or to switch from their current insurer to another. In order to construct such a model, the first step is to describe the process that an insured will utilize in deciding to renew his policy or switch to another insurer.

1. The insured receives his renewal notice approximately 45 days prior to policy expiration.
2. If the premium decreases or increases modestly, the insured will likely renew the policy with his current insurer.
3. If the premium increases significantly, the insured will likely begin shopping around.
4. The insured will do some market research by calling other insurance agents or getting quotes over the phone or internet.
5. Depending upon the savings that can be realized, the insured will either stay or move.

This is a rather simple model as it relies solely on price as the factor upon which the decision is made. In reality, the process is more complex as other factors, such as quality of service, brand name recognition and financial stability enter into the decision as to where to buy insurance. However, many recent studies have shown that price is the most significant factor. Thus, once models can be constructed that accurately model behavior based on price, more complex models can subsequently be constructed that would consider elements other than price. Methods used to modify the basic model in consideration of these other elements will be discussed further in section II.F.

Throughout this paper, private passenger auto insurance will be used as an example line of business. These techniques could apply to other lines as well.

C. Economic Agent Based Approach versus Current Approach

The current "rules of thumb" approach may have been good enough at one time. It may also be true that this approach will be acceptable today in a situation where the rate change is simple. An example would be a rate change that applies only to the base rates. However, one of the trends for virtually all lines of business is that rate structures have become more refined over time. Using automobile insurance as an example, the number of different possible combinations of rate classes is so great that it is not possible to assess all of the changes that individual policyholders will experience in a rate change where base rates, territorial factors, driver classification factors and accident surcharges all change at the same time.

The economic agent based approach requires a model that analyzes the impact of a rate change at the individual insured level, taking into account class, territory, etc. The rate impact on detailed classifications can be assessed and thus the likely behavior of members of each of the classifications can also be assessed. By combining this retention information with information regarding the profitability of each of these individual classes, a powerful tool is built. This tool can be used to test a number of different rate scenarios in order to determine an optimal combination of profitability and retention.

For the application we created, the ABM modeling approach has advantages over traditional economic approaches to estimating buyer elasticity of demand. Traditional approaches would require empirical studies of policyholder reaction to rate changes and then the construction of elasticity curves from this analysis. While traditional approaches are useful during both a stable economic and competitive environment these conditions rarely exist for an extended period of time. The ABM approach allows for the ability to separate the impacts of the economy on a policyholder's propensity to shop and the level of price competition on the policyholder's ability to find an alternate policy at a lower price.

Another advantage of the ABM approach is that it allows for the modeling of emergent behavior. These are behavioral impacts, which may seem irrational at an individual level but are exhibited when the behavior of a group is analyzed as a whole. An example of this phenomenon is the observed behavior of groups of insured to leave when they are presented with a rate decrease. This seems irrational at an individual level but this phenomenon is accepted as regularly occurring

An additional key issue to note is that, while the model operates at the individual insured level, the goal of the model is to project the aggregate behavior of an entire book of policyholders. Thus, precise modeling of the behavior of each individual insured is not required in order to accurately model the overall behavior of a book of policyholders.

II. An Actual Model in Operation

A. The Economic agents in the Model

In constructing such a model, the first decision that must be made is "what are the appropriate economic agents to include in the model?" In the case of the retention/profitability model, there are four economic agents in the model. These economic agents are

1. The policyholders
2. The company that is considering changing its rates
3. The other companies that form the competition in the state
4. The insurance agents who are selling policies

B. The Factors in the Model

As previously mentioned, factors are the quantitative measures of the system that is being modeled. For a retention model, factors would comprise the companies new and old rate sets as well as the rates of market competitors. In addition, the claims frequencies and severities by major risk class will also need to be entered into the model. The methodology used to process this information will be described more fully in section II D.

C. The Rules for Interaction

Once the economic agents in the model are determined, the rules for interaction must then be determined. Using the structure of the model described above, the rules required for the model can be developed.

1. Policyholder/Company Interaction

   When the policyholder receives his renewal notice, a number of factors will determine his likelihood of shopping for an alternate insurer. These include the amount of a rate increase that he sees, his satisfaction with the handling of a claim (if this occurred during the most recent policy period), his satisfaction with policyholder service that he may have received throughout the policy period (e.g. for a change in vehicle), past rate changes that the policyholder experienced and position in the underwriting cycle. The focus of this paper is the amount of rate increase that the policyholder experiences and the impact that the change has on the policyholders propensity to shop and switch his policy.

   The likelihood to shop is related to the concept of the price elasticity of demand. Since auto insurance is a mandatory product in most states, a significant increase in price does not normally cause a driver to forego purchasing insurance, but instead causes him to shop. At what amount of rate change does the decision to shop occur? The decision of whether to seek an alternate insurer can be expressed as a probability function describing the relationship between the dollar (or percentage) change in an individual insured's premium and the likelihood of that insured researching the premiums of alternate insurers. We will refer to this function as the shopping function. The shopping function could be expressed either as a discrete function or a continuous function. The following would be a simple example of such a function

Premium Increase	Likelihood of Shopping
$0 and below	2%
$1 to $50	5%
$51 to $100	25%
$101 to $200	70%
$201 to $300	85%
$301 and above	100%

2. Policyholder/Competitor Interaction

If the rate increase is significant enough, and the policyholder decides to shop for coverage from another insurer, the rates of those insurers will come into play. If the policyholder finds that the price he has with his current insurer is less expensive than the prices charged by other companies, then the policyholder is unlikely to move coverage to another company. If, however, the price charged by the other companies is significantly less than that charged by the current insurer, the likelihood of the policyholder moving coverage to one of the other companies would be significant. Similar to the shopping function, the likelihood of a policyholder moving from one company to another can be described by a probability function. This function would describe the likelihood that a policyholder would move to another company given the amount of savings that could be realized. We will refer to this function as the switching function.

Similar to the shopping function, the switching function could be expressed either as a discrete function or a continuous function. The following would be a simple example of such a function

Premium Savings	Likelihood of Switching
$0 and below	2%
$1 to $50	15%
$51 to $100	40%
$101 to $200	95%
$201 to $300	98%
$301 and above	100%

The shopping and switching functions shown above are for illustration purposes only and are not based on independent research performed by the authors. The functions also show the probability based on the dollar amount of change. Work done by the authors has shown that both the dollar amount and percentage change are important predictors of shopping and switching behavior. The process required to develop shopping and switching functions is described later in this paper

3. Policyholder/Agency interaction

Whether the policyholder uses an insurance agent or buys coverage directly from the company is likely to have an impact on the likelihood of switching from one company to another. For policyholders using an independent insurance agent, alternative quotes can be obtained from the policyholders' own insurance agent. Thus, the likelihood of switching is probably greater with an independent insurance agent than with a direct insurance agent since it is easier for the customer to obtain alternative quotes from the independent agent. This would be addressed in the model by having one shopping function used for shopping for alternative quotes via the policyholders own insurance agent and a separate shopping function, with higher threshold amounts, that would be used for determining whether the policyholder will seek alternative quotes from other insurance agents or through other direct writers.

Insurance agents may also influence the behavior of their customers. For example, an insurance agent who considers a particular insurer to be a good business partner due to strong policyholder and claim service or a favorable commission structure may try to keep policies with that particular company, regardless of rates being offered by competitors.

The direct sale of insurance could have a significant impact on these functions. One of the reasons that direct sale of insurance is becoming more prevalent is that policyholders have better access to competitive information and indeed have the ability to purchase a policy via the Internet. As purchasing coverage directly from a company becomes more popular, the likelihood of switching from one company to another should increase as the effort required to comparison shop a policy will be reduced. The direct sale of insurance increasing the amount of price shopping that occurs, increases the need to perform the type of modeling that is described in this paper.

In order to keep the presentation in the paper more straightforward, the illustrations in this paper do not consider policyholder/insurance agent interaction.

D. Model in Operation

In order to develop and utilize such a model, the following information must be input to the model.

1. Current rates and rating factors of the company used to determine premiums
2. Proposed rates and rating factors of the company
3. Rates and rating factors of key competitors - These should be the largest companies in the state as these are the companies from which policyholders are most likely to get quotes. In addition, as policyholders of companies using independent insurance agents are likely to get an initial quote from the insurance agent, the most common competitors in insurance agents offices should also be used in the model.
4. The profitability of the different classes of business for the company
5. The current in force distribution of policyholders in the various rate classes

With this information put into the model, it can be run to test alternative proposed rating structures. This is done by creating a virtual marketplace and applying a Monte-Carlo simulation to the individual policyholders in the marketplace. The model will first generate a group of policyholders consistent with the companies' policyholder distribution across key classes (age, gender, marital status, etc.). The current and proposed rates of the company will then be used to determine the amount of rate change that the individual policyholders will experience. The premium change, in combination with the shopping function, will determine the probability of each individual policyholder shopping. The simulation is then run which results in certain individual policyholders deciding to shop. The policyholders that decide to shop will go into the market to seek alternative quotes and will thus determine the possible savings by switching to another company. The savings, in combination with the switching function will determine the probability that an individual policyholder will switch. A second simulation is then run which results in certain individual policyholders deciding to switch to another company. In addition, certain policyholders of the competitors will shop their policies as well. While there are a number of factors driving this behavior, our model assumes that all policyholders of the competitors are likely to shop with equal probability. The model will be run for multiple iterations until the results converge to an equilibrium level of retention and profitability.

Essentially the model tracks the distribution of policyholders across various rate classes before and after the rate change. The model then combines this information with the profitability by class in order to produce an estimate of the total profitability that will be realized under each rate scenario as well as the volume of business that will be written under each scenario.

E. Example of Determining Customer Retention

An example will help to clarify the operation of the model. This example describes how the model will work for an individual policyholder. Consider an example driver with the following characteristics

Age	35-44
Gender	Female
Marital Status	Married
Single Car/Multi-Car	Multi-Car
Driving Record	Clean
Number of Years Loss Free	5
Vehicle usage	Drive to Work < 10 miles
Rating Territory	12
Liability Limit	100/300/50
Comprehensive Deductible	100
Collision Deductible	250
Vehicle Model Year	1996

In addition, the following premiums apply for this policyholder.

Current Premium	\$500
New Premium	\$555
Premiums of Competitors	
Competitor #1	\$619
Competitor #2	\$452
Competitor #3	\$544
Competitor #4	\$592

Since the policyholder experiences a \$55 increase in premium, the shopping function would predict that 25% of these policyholders will shop. When they shop, they learn that a savings of \$103 is possible and 95% of the policyholders will switch for this amount of savings. Via the simulation, the rate increase will cause 24%(=25%x95%) of policyholders to leave the company. If there were 250 policyholders with the above characteristics, the simulation would be expected to result in the company losing 60 of these policyholders due to the rate change. If these policyholders were expected to earn an annual profit of 15% (i.e. this assumes that total losses and expenses are \$472 per policy) at the higher rate level, the following table describes the expected premium and profit at the higher rate level

Current Premium	\$125,000 (=\$500x250)
Premium after rate change	\$105,450 (=\$555x190)
Profit after rate change	\$15,818 (=\$555x190x15%)

These results can be compared to the results of no rate change and a 9% rate increase to a premium of \$545. Note that with a 0% change, the profit would be 5.6% of premium and with a 9% increase, the profit would be 13.4 % of premium (again assuming that total losses and expenses are \$472 per policy). In addition, the 9% increase would result in losing only 2% of policyholders as 5% would shop for alternatives and 40% of those would switch companies for the \$93 savings that could be achieved.

Premium with 0% change	\$125,000 (=\$500x250)
Profit with 0% change	\$7,000 (=\$500x250x5.6%)
Premium after rate change	\$132,300 (=\$540x245)
Profit after rate change	\$17,728 (=\$540x245x13.4%)

Obviously, the 9% rate increase is preferable as it produces a larger total profit. These results for each individual class will be accumulated in order to determine the total projected premium and profit for a specific rate scenario. The volume/profit tradeoff under each scenario can thus be reviewed in order to determine the rate structure that is considered best for the company.

F. Aggregation of Results

The example in the previous section was simplistic from a number of different perspectives. First, it dealt with a single combination of risk classes while a company's book of business is comprised of numerous different risk classes. Obviously, each such combination will have its own premium. Second, the shopping and switching functions in the example are also simplistic. The example functions shown describe the behavior of one combination of risk classes, however, the shopping and switching functions need to be more specific to the behavior of different risk classes in order for the model to accurately estimate the behavior of an entire book of business.

Constructing a more comprehensive model requires that the rate change, competitive position and shopping and switching propensities of different risk classes are known. The complexities of current rate structures requires that a thorough modeling framework be developed in order to model results at the individual class level and then aggregate the results across all of the possible combinations of driver class, territory, driving record, number of times renewed, etc. However, at its basis, the process involves aggregating results at the individual class level as described in section E.

By constructing models for different rate change scenarios, the retention and profitability of these different scenarios can be examined. The following three examples show how different rate scenarios can be analyzed in order to provide greater insight into their impact on retention and profitability.

1. Different scenarios with same overall rate change
   A company is targeting a 5% overall rate increase, but there are three specific sets of changes that are being considered for implementation.

   Scenario 1
   Only changing territorial base rates.
   This option would have rate changes vary by territory but not across other rating variables.

   Scenario 2
   Changing territorial base rates so that the territorial relativities are the same as Scenario 1. Changing a policy renewal discount to give a greater discount to policyholders that have been insured by the company for six or more years since the loss data of the company indicates that a greater discount is justified. Currently, all policyholders receive a 5% discount after three years. The proposed rate structure adds a 10% discount after six years. In this scenario, the territorial base rates would be offset in order to make up for the increase in the renewal discount and thus maintain the targeted 5% increase.

   Scenario 3
   Changing territorial base rates so that the territorial relativities are the same as Scenario 1.

Changing a policy renewal discount to give a greater discount to policyholders that have been insured by the company for six or more years since the loss data of the company indicates that a greater discount is justified.
Changing the Multi Car discount to give a greater discount to multi car policies since the loss data of the company indicates that a greater discount is justified. Again, the territorial base rates would be offset in order to maintain the overall 5% increase

As you move from scenario 1 to scenario 3, policyholders will experience more extreme rate changes. For instance, consider a territory in scenario #1 in which all coverage base rates are increased by 5%. All policyholders will experience a 5% increase unless there is a change in policy characteristics such as a change in vehicle or driving record. However in scenario #2, base rates need to increase by 7% in order to make up for the greater discount for policyholders insured for six or more years. Policyholders insured for five or fewer years will experience a 7% increase while policyholders insured for six or more years will experience a 2% increase (7% base rate increase combined wit a 5% greater discount). This demonstrates the more extreme rate changes experienced in scenario 2 versus scenario 1.

Thus, policyholders will experience the most extreme rate changes in scenario #3 and thus more policyholders will tend to shop their policies in this scenario. What impact will this have on the book of business in terms of retention and profitability? By applying the techniques mentioned previously, the following table can be produced to compare the modeled results of these different scenarios.

Scenario	Premium	Retention	Loss Ratio	Operating Result
1	149,134	88.5%	66.5%	$3,672
2	151,263	88.6%	65.5%	$5,318
3	154,412	88.7%	64.4%	$7,031

As this table demonstrates, Scenario 3 yields the best profit since the company is retaining more of the more profitable multi-car, renewal policies.

2. Different overall rate changes
A company is considering different base rate changes. The three options being considered are for a 3% overall rate increase, a 5% overall rate increase and a 7% overall rate increase. Which scenario will produce the best profit? Will the highest rate change produce unacceptably low retention values? A similar table to the previous table can be presented that compares these different scenarios.

Scenario	Premium	Retention	Loss Ratio	Operating Result
+3%	151,885	88.5%	65.92%	$4,678
+5%	153,606	87.5%	64.46%	$6,980
+7%	155,336	86.9%	63.02%	$9,283

The above table shows that the operating result projected under the +7% scenario produces the greatest profit. This is because the reduction in the retention is more than offset by the increase in premium and so the total premium is greatest under the +7% scenario. The question then remains as to whether the 86.9% retention is acceptable to the company. This decision will need to be based on the growth goals of the company. The decision process will vary from company to company.

3. Effect of rating plan changes

Most companies offer a discount for renewing a policy with one company. Is a company better off taking a deeper discount on the older more profitable policies in order to retain them for a longer period of time at a less profitable level? Or is the company better off by offering less of a discount in order to maintain a higher profitability but suffer somewhat in policyholder retention? Retention modeling allows for these types of questions to be answered. For example, consider a situation in which a company is concerned that its current rate structure is too heavily discounted for policies with longer renewal persistency. It is considering two rate changes of +5% overall. In one scenario, it is making no changes to its renewal discount. In another scenario, it is reducing the discount for policies at the sixth and greater renewals.

Scenario 1

# Times Renewed	Rate Change	Premium (000's)	Retention	Loss Ratio	Operating Result
0-2	+5%	57,064	84.8%	67.5%	856
3-5	+5%	34,050	90.4%	67.0%	681
6-8	+5%	25,153	90.5%	63.2%	1,459
9+	+5%	36,437	91.8%	55.3%	4,992
Total	+5%	152,704			7,988

Scenario 2

# Times Renewed	Rate Change	Premium (000's)	Retention	Loss Ratio	Operating Result
0-2	+3%	56,383	85.2%	68.6%	230
3-5	+3%	34,791	90.6%	67.3%	591
6-8	+7%	25,902	90.3%	61.7%	1,880
9+	+7%	36,830	91.2%	53.8%	5,598
Total	+5%	153,906			8,299

The above examples show that the improvement in profitability more than outweighed the loss of premium due to lower retention on policies at six and subsequent renewals and thus the company would be in a better financial position with the lower discount. These calculations could be run over a number of years in order to determine what the lifetime value of this group of insureds will be. The discussion of lifetime customer value is outside the scope of this paper but readers are referred to the paper by Feldblum[2] on the subject.

These three examples demonstrate the power of these modeling techniques. The decision making process that companies have historically utilized require that judgments be made regarding the impact of the rate change on retention, however, these judgments were largely based on anecdotal information regarding customer reaction to a rate change. In addition, these decisions are often based on review of a limited number of risks reviewed as part of a competitive analysis. The modeling techniques described in this paper combine a quantitative specification of how customers do react to a rate change with a review of thousands of different risks (potentially, a company's entire book of business) in order to model customer retention and the resulting impact on profitability. These techniques also allow for modeling over multiple time periods. Modeling over multiple time periods has the advantage of projecting results over more than a one-year time horizon in order to see if there will be any negative consequences of taking less than the indicated rate change in the current year. However, it also requires estimates of future competitive position and this adds more uncertainty to the model.

G. Parameterization of the Switching and Shopping Functions

The switching and shopping functions are the most difficult elements of the model to parameterize. Possible sources for this information are the following:

1. Industry studies - Industry studies of the relationship between customer loyalty and price have been done and these could be used to determine appropriate probabilities for these functions.
2. Surveys of policyholders - A company could survey its own policyholders to determine the likelihood of shopping and switching policies at various price levels. Work done by the authors has shown the following to be significant predictors of retention

   - Amount of Rate Change
   - Competitive position
   - Driver Age
   - Multi Car/Single Car
   - Existence of other policies (e.g. existence of a homeowners policy)
   - Number of Times Renewed
   - Channel (Agency company versus a direct writing company)

3. Actual company experience - by matching rate change histories with renewal data, a company could determine the likelihood of a policyholder switching based on actual company data.

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[2] Sholom Feldblum, 1996, "Personal Automobile Premiums: An Asset Share Pricing Approach for Property/Casualty Insurance", *Proceedings of the Casualty Actuarial Society*: 190-296.

The industry data could be used as a starting point for determining these functions, but this approach has two main disadvantages. First, the industry studies will, by definition, describe average policyholder behavior for the entire industry. As mentioned earlier, the likelihood of a policyholder moving is different for a company selling policies directly as compared to one that is selling via insurance agents. Other dynamics will also cause differences in the shopping behavior of the policyholders of different companies. Thus, once a model is developed using industry data, it should be enhanced with company specific switching and shopping functions. This could be accomplished via the surveys and company experience discussed above to determine the appropriate functions. The second disadvantage of using industry studies as a starting point is that these studies were not designed for the specific purpose of developing shopping and switching functions and thus will not have all of the required data.

Once the basic shopping and switching functions have been developed, they need to be tested. This can be accomplished by running a historical rate change through the model and comparing the modeled results to the actual results to test model performance. The testing may be done at a fairly detailed level or at a more aggregate level depending on the intended use of the model. It is the experience of the authors that survey data will predict actual retention behavior of a group of policyholders quite well for certain dimensions of a company's rate structure but will under performs in other dimensions. Thus the process of back-testing the model in order to tune the shopping and switching functions to a company's actual experience is critical to the accurate performance of the model.

H. Future Enhancements

As is the case with any modeling exercise, it generally starts with a simple example and then more complexity is added in order to improve the accuracy of the basic model as the technique matures. The basic model presented here could be enhanced in the following ways.

1. Refinement of shopping and switching functions

   The sample shopping and switching functions presented in this paper are very simplistic and are merely designed to demonstrate the concept of how such models could work. In reality, modeling of behavior is much more complicated than the functions presented in this paper. Proper design of these functions is critical to model development.

   In order to assess the shopping function, policyholder surveys will probably be required. Analysis of a company's retention data will not give information about all of the policyholders that decide to "test the waters" for another insurer. Such a survey should be directed at a proper cross section of the policyholder base in order to assess the effect of age, gender, current premium level, etc on the propensities to shop and switch. This survey could arm the company with a detailed shopping function that would be fully indicative of its policyholder base.

The switching function could be determined through a combination of data analysis and surveys. The advent of insurance market websites provides a single source of information regarding the premium of the prior company and the premium of the new company to which the policyholder switched. Data from such market websites probably holds the most promise for determining the switching function. A survey could also be conducted on policyholders of a company that cancel voluntarily to determine the premium savings that were required in order for them to switch to a different insurer.

Alternatively, one overall survey could be conducted that would attempt to determine both the shopping and the switching functions. Similar surveys have shown that a policyholder generally underestimates the amount of premium that he actually pays, unless he has a copy of his last renewal notice in front of him,. Thus, while such surveys would provide the quickest method of determining the shopping and switching functions, they should be verified with actual data analysis for a company.

The specificity of the shopping and switching functions is also an area that is of key concern. Different policyholders will have different shopping and switching propensities. For instance, the more often a policyholder renews with his current insurer, the less likely he is to shop his policy, regardless of price changes. In addition, if a policyholder has more than one type of policy with a given company, he is less likely to shop his policy. Regional differences in shopping behavior also affect the propensity to shop. The work done by the authors has shown these to be some of the more critical factors in predicting the shopping and switching behavior. Increasing the specificity of these functions will improve the performance of the model especially when the rate change is less uniformly distributed by rate class.

2. Build brand name into the model
Individual companies' policyholder retention rates can differ quite dramatically. The reasons for these differences are varied and have an impact on an individual company's shopping and switching functions. The different levels of policyholder service offered by insurers also have an impact on retention. Companies operating within a particular market niche will have different shopping and switching functions than companies operating across the entire market. For instance, a company whose marketing strategy is to emphasize lower prices is probably attracting a more price-sensitive customer than a company that is emphasizing policyholder service. These types of different marketing strategies should be reflected in the model via shopping and switching functions that are geared towards a company's own marketing strategy. Thus, the shopping and switching functions should be company-specific. The techniques mentioned previously in this paper should be applied to develop company-specific shopping and switching functions.

3. Changing data structures to support retention modeling
Data structures in company databases could be modified in order to better track the impact of rate changes on a policyholder and thus better assess the shopping and switching functions.

One example of additional data that should be captured is premium data on policyholders that did not renew policies. Usually, these policyholders are eliminated from most "actuarial" databases and thus information allowing the assessment of the likelihood of policyholder non-renewal is lost.

A second example of an additional data element is an indicator to tell whether there was a change in policy characteristics that caused a change in premium. For instance, the policyholder may have replaced a car or had an accident in the previous year causing an increase in the premium. It is likely that the policyholder will be less likely to shop their policy if a premium increase is due to one of these reasons, however, the authors are not aware of any published studies examining this phenomenon. Perhaps a $50 increase in premium due to a rate increase is just as likely to cause someone to shop as is a $50 increase due to the policyholder receiving a moving violation. By assessing the different causes of premium increases and the associated changes in retention rates, this issue can be better understood.

4. Factors other than price producing shopping behavior
   As previously mentioned, the shopping and switching functions predict customer movement based solely on rate activity. There are other factors that could cause the policyholders to shop for an alternative insurer. These include the policyholder not being satisfied with claim service or policy service throughout the year. This could be included in the retention model by estimating the number of policyholders that will require claim service or policy service throughout the year and estimating the percentage of these policyholders that will be unsatisfied with this service and thus shop for alternatives. The number of policyholders that will require claim service and policy service can be based on the company's internal data. The percentage of policyholders dissatisfied with service can be estimated through survey data.

   An alternative would be to predict some amount of random shopping based on the same type of company data as mentioned in the previous paragraph. This random shopping could likely form an accurate estimate of the impact of non-price factors on retention.

5. Impact of Internet/Direct Advertising
   The internet has created a new era of consumerism. The level of insurance price comparison-shopping that can be accomplished via the internet was previously unheard of. Consumers can now receive several comparable quotes through a single internet quoting service. Online comparisons are also available through individual company websites such as Progressive. Also contributing to the increase in comparison-shopping is the dramatic increase in TV and direct mail advertising urging policyholders to shop their policies. These advertising campaigns could lead to a rise in spontaneous shopping by policyholders

Retention modeling is still in a nascent stage of development. The five areas mentioned here are areas where some of the more significant work is required in order to bring retention modeling into the mainstream of pricing practice. However, as work in these areas progresses, retention modeling techniques will become more accepted and accurate.

III. Conclusion

An old adage is that "You can't stop progress". One of the ways that rate structures have progressed is that they have become more and more refined over time. The advances in computing power have allowed analysis of new data elements and provide the ability to discern patterns in the data that simply could not be recognized using single dimensional cross cuts of data that, at one time, were the norm.

While improved technology has produced tremendous advances in determining proper premiums for individual policyholders, it has made the assessment of the impact of rate activity a very difficult matter. It is now time to use the progress in computing power to address this problem as well. By using information on the elasticity of demand to estimate policyholder retention, rate structures can be determined that will produce the optimal combination of policyholder growth and profitability.

This paper has presented the framework for a modeling methodology that can be used to find this optimal combination. However, much more work in this area needs to be done. Future papers to be presented by the authors will focus on more specific shopping and switching functions and a case study of modeled results versus actual results from an actual rate change.