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A DISCRETE-TIME HAZARD MODEL OF A NEW GOLF COURSE

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The influence of several covariates on golf course choice behavior are investigated using a discrete-time hazard model. This model is able to predict whether an individual will play a new golf course (probability) and, if so, when in terms of weeks after the course opens for play (timing). Results suggest that choice behavior is a function of the golfer's handicap, the academic standing of the golfer, the number of rounds played per month, and the innovativeness of the golfer

INTRODUCTION

Golf is a $20 billion industry in the U.S. and is expected to reach $40 billion by the year 2000 (Symonds 1989). While the National Golf Foundation (hereafter abbreviated as NGF) predicts that 3650 new golf courses will have opened by the year 2000 (NGF 1989), the nature of the golf industry is rapidly changing. The number of new membership golf courses is growing at a much slower rate than the number of new public or pay-as-you-play courses (Hick 1989).

Yet despite golf being the fastest growing sport in the U.S. (Nelson 1990) and recognizing that there are over 23 million golfers presently in the U.S. (NGF 1989), little is known about golf course choice behavior. In fact, very little research appears to have empirically or conceptually examined covariates which might be expected to influence golfers' choice behavior. Only the PGA (1994, 1996), NGF (1989) and Piper (1990) have investigated some of the determinants of golfers' choice behavior. However, these studies only examined a subset of covariates, provided only descriptive statistics, and did not examine new golf courses. This knowledge gap apparently applies to private as well as public courses. This paucity of research is surprising and quite disturbing considering that a significant amount of marketing is conducted each year by golf course marketers.

PURPOSE

The purpose of this study is to apply a discrete-time hazard model to predict choice behavior at a recently opened (i.e., new) public golf course. This model will enable one to examine the probability and the timing of choice. In other words, the researcher and marketing manager will not only be able to predict whether an individual plays a new golf course but also when an individual will play a new golf course. In addition, this model will help identify the attributes of an individual golfer which will influence choice behavior. It should be noted that this study examines the adoption of a particular public golf course and not the game of golf per se.

In an attempt to examine golfer's choice behavior as a function of time, this study begins with an investigation of golf course choice behavior as described in the past literature. This is followed by a brief overview of the innovativeness literature and the discrete-time hazard model as applicable in the domain of golf course choice behavior. Results and conclusions are presented with implications for golf professionals and course managers.

Golf Course Choice Behavior

There appears to be very little literature dealing with public golf course choice behavior. The only empirical studies on golf course consumers in general have been conducted by Piper (1990), the NGF (1989), and the PGA (1994, 1996). This is surprising given that golf is the fastest growing sport in the U.S.

Piper (1990) investigated the relationship between the demand for public golf courses and several demographic variables. Income and age were found to be inversely related with demand for public courses (as opposed to private membership courses).

The NGF and the PGA are responsible for the vast majority of empirical research on U.S. golfers. Findings suggest that most golfers consider price (i.e., greens fees) as the single most important factor in deciding which golf course to play. Other attributes found to influence choice intentions were the number of golfers on the course, the distance to the golf course from home, and the speed of play. While the NGF and PGA studies of U.S. golfers are useful, the results are only descriptive in nature.

Innovativeness

Though little consensus exists as to a suitable definition of innovativeness (Goldsmith and Hofacker 1991; Hurt et. al 1977; Mudd 1990) two broad conceptualizations of the innovativeness construct have been proposed. The temporal conceptualization or behavioral definition of innovativeness refers to the degree to which an individual is relatively earlier in adopting an innovation than other members of his/her social system (Baumgarten 1975; Robertson 1967; Robertson and Kennedy 1968; Robertson and Myers 1969; Rogers and Shoemaker 1971). This conceptualization represents an operational definition since it focuses on innovativeness as actual behavior rather than as a hypothetical construct (Hirschman 1980; Midgley and Dowling 1993).

The second conceptualization considers innovativeness as a hypothetical construct or a generalized personality trait which is possessed to a greater or lesser degree by all individuals (Midgley and Dowling 1978, 1993). Midgley (1976) and Midgley and Dowling (1978) define innovativeness as the degree to which an individual is receptive to new goods, services, and ideas and makes innovation decisions independently of the communicated experience of others. The depiction of innovativeness as an underlying personality trait has been well documented in the marketing literature (e.g., Goldsmith 1987; Hurt et. al 1977; Leavitt and Walton 1975; Raju 1980).

Though the depiction of innovativeness as a global trait has received much attention, some scholars (Goldsmith, Freiden and Eastman 1995) have delineated between innovativeness measured on a more abstract global level and that of a domain-specific nature. In other words, consumers may be innovators for certain product categories (e.g., trial of a new golf course), but not for other product domains (e.g., trial of a new breakfast cereal). Domain-specific innovativeness also appears to exhibit a stronger correlation with actual product purchase behavior than would global innovativeness, which is at a higher level of abstraction. Finally, Goldsmith et. al (1995) posit that domain-specific innovativeness traits mediate the influencing effect of global innovativeness on product purchase behaviors.

In an attempt to integrate the aforesaid conceptualizations, past researchers (Hirschman 1980; Midgley and Dowling 1978; Ridgway and Price 1994) have distinguished between inherent or innate innovativeness and actualized innovativeness. Actualized innovativeness is consistent with the temporal concept of innovativeness in that it deals with adoption of products, services, and ideas (i.e., measurable behavior) rather than the consumer's willingness to adopt (i.e., a predisposition to act in certain ways). Extant literature suggests that actualized innovativeness comprises two underlying dimensions---adoptive innovativeness and vicarious innovativeness (Hirschman 1980; Midgley and Dowling 1978; Ridgway and Price 1994). Adoptive innovativeness is the actual adoption of new products, while vicarious innovativeness refers to the process of active information search prior to the acquisition of new products.

Innate innovativeness reflects the desire of an individual to seek out new goods, services, or ideas. Innate innovativeness can be thought of as comprised of two components---innate adoptive innovativeness and innate vicarious innovativeness (Hirschman 1980; Midgley and Dowling 1978; Ridgway and Price 1994). Whereas, innate adoptive innovativeness is the willingness to adopt new products relatively earlier than others, innate vicarious innovativeness is the willingness to read about, shop for, and talk with others about new products. Ram and Jung (1994) suggest that innate innovativeness often results in actualized innovativeness. However, the relationship between innate innovativeness and actualized innovativeness is mediated by the presence of other intervening variables such as situational factors and innovation characteristics (Midgley and Dowling 1978; Midgley andDowling 1993).

Past research (e.g., Gatignon and Robertson 1985) has indicated that opinion leadership is positively correlated with product innovativeness and early adoption behavior. Further, early adoption is correlated with such characteristics such as venturesomeness, creativity, lower risk perception, and rapid decision making (Childers 1986; Midgley and Dowling 1993) which suggest less extensive search and more direct information gathering from mass media. Hence, opinion leaders would rely on media (external) sources as they are the innovators and early adopters for a particular product category.

Discrete-Time Hazard Model

Researchers in marketing have posed questions about the timing of events. Not only are they interested in whether or not an event will occur but also when it will occur. For example, diffusion of innovation researchers have been interested in not only whether or not an innovative product is adopted as well as when it will be adopted (e.g., Sinha and Chandrashekaran 1992).

A set of statistical techniques called hazard models can help researchers simultaneously explain whether or not an event occurs and, if so, when it does occur (Allison 1982; Blossfeld et. al 1989; Cox and Oakes 1984; Kalbfleisch and Prentice 1980; Miller 1981; Yamaguchi 1991). In other words, these models focus on the amount of time taken for an event to occur as well as the probability of occurrence. The variable of interest is the time between an initial and a target event. Hazard models allow the researcher to describe patterns of occurrence, compare these patterns among groups, and build statistical models of the probability of occurrence over time.

Despite the persuasive argument provided by Helsen and Schmittlein (1989) as to the applicability of these models for analyzing various marketing problems, few researchers have used these models in empirical research (exceptions include Jain and Vilcassim 1991; Richard and Allaway 1993; Sinha and Chandrashekaran 1992). Jain and Vilcassim (1991) employed a hazard model to investigate the time between product purchases. Richard and Allaway (1993) use a discrete-time hazard model to predict college basketball attendance. Sinha and Chandrashekaran (1992) utilized a hazard model to examine the diffusion of innovation process.

Prior to an application of the discrete-time hazard model to golf course choice behavior, a brief discussion of the model is warranted (for extensive discussions see: Allison 1982; Efron 1988; Laird and Oliver 1981; Guilkey and Rindfuss 1987; McLanahan 1988). In discrete-time hazard modeling studies the researcher is interested in a discrete random variable T that represents the time until an event occurs (playing a new golf course for the first time). Time, in this case, is measured by the number of weeks between the golf course opening and when the golfer plays the course for the first time.

Discrete-time hazard models focus on two related probabilities: the survivor probability, S_{ij}, and the hazard probability, h_{ij}. For the golf course choice problem, the survivor probability is the probability that individual i "survives" (i.e., does not play the new course) at least up to week j. The survivor function is the chronological pattern of these survivor probabilities over time. The hazard probability is the probability that individual i plays the new course in week j, conditional on not playing prior to that week (or the "risk" of playing at week j). The hazard function is the chronological pattern of these probabilities over time. Note that the target event of interest (playing a new golf course for the first time) is assumed to be non-repeatable; once it occurs it cannot occur again. Models for such repetitive events have been adequately discussed by past scholars (Allison 1984; Tuma and Hannan 1984; Yamaguchi 1991). A more extensive discussion of hazard modeling appears in the Appendix.

METHODOLOGY

Research Setting

The research setting is a medium size city in the southeast U.S. The city has three established golf courses. Of the three established golf courses, two of the three are public. A fourth golf course opened in the fall of 1994. The new golf course is public. This new golf course is the choice object of interest for this study. A discrete-time hazard model is utilized to predict if and when golfers choose to play the new golf course for the first time.

The Sample

A convenience sample of undergraduate Professional Golf Management (PGM) students from a major Southeastern university was selected for the study. The event of interest was playing a new public golf course that had opened in the area (i.e., choice behavior). The student golfers are predominately male, 18 to 22 years of age, Caucasian, and from middle to upper middle income families.

The Variables

Choice is assumed to be a function of several variables including the characteristics of the individuals (Louviere and Hensher 1983). These include the golfer's handicap, the academic standing (Freshman, Sophomore, Junior, and Senior), and the number of rounds played per month. Eight time dummy variables were utilized to capture the baseline hazard. The scale items and associated notations appear in Table 1.

TABLE 1
NOTATION AND SCALE ITEMS

Notation	Scale Items
D1	Time dummy for Week 1.
D2	Time dummy for Week 2.
D3	Time dummy for Week 3.
D4	Time dummy for Week 4.
D5	Time dummy for Week 5.
D6	Time dummy for Week 6.
D7	Time dummy for Week 7.
D8	Time dummy for Week 8.
HANDICAP	What is your golf handicap?
STANDING	What is your academic standing?
ROUNDS	How many rounds of golf do you play in a typical month?
INNOVATE1	In general, I am the last in my circle of friends to play a new golf course.
INNOVATE2	If I heard that a new golf course opened in my area, I would be interested enough to play it.
INNOVATE3	Compared to my friends, I do not play a lot of different golf courses.
INNOVATE4	In general, I am the last in my circle of friends to know when new golf courses open.
INNOVATE5	I will play a new golf course even if I have not heard a lot about it.
INNOVATE6	I know about new golf course openings before other people do.

There have been several attempts to develop a multi-item scale of innovativeness (e.g., Leavitt and Walton 1975; Hurt et. al 1977). Goldsmith and Hofacker (1991) developed a six item scale of innovativeness. In addition to exhibiting acceptable reliability and validity, the scale was found to be easy to administer and score (Goldsmith and Hofacker 1991).

The six items of the Goldsmith and Hofacker (1991) innovativeness scale were also included in this study. These items also appear in Table 1. These items used seven-point scales from "Strongly Agree" (7) to "Strongly Disagree" (1). Three of the items were positively worded while three items were negatively worded. The negative items were re-coded prior to data analysis.

Questionnaire Administration

The questionnaire was administered by personal interviews in Golf Merchandising courses composed of PGM majors. The personal interviews yielded 240 useable questionnaires. The self-administered questionnaire required approximately 10 minutes to complete. The questionnaire gathered data concerning the golfer's handicap, the academic standing of the golfer, and the number of rounds played per month. In addition, the six item innovativeness scale was included.

Each week, for eight weeks, after the initial questionnaire administration, students were asked to indicate whether they had played the new golf course. As such, longitudinal data was obtained concerning golf course choice behavior for eight weeks after the new course opened for play. It is interesting to note that by the end of the eight week period, approximately 82 percent of the subjects had played the new golf course at least once. In addition, subjects played the new golf course an average of one time per month.

The final sample consisted of 240 student golfers. Prior to parameter estimation, individuals were randomly assigned to either the estimation data set (175 individuals) or to the holdout data set (65 individuals). The parameters of two discrete-time hazard models derived from the estimation data set were used to assess predictive accuracy of the models in the holdout data set. Since hazard is assumed to be a conditional probability, the target event of interest is the individual's first round at the new golf course. Subsequent choice was not investigated in the study.

There may be a concern that early adoption of the golf course is not a function of innovativeness of the person in question but rather of the administration of the research instrument. This "error of inference regarding the cause of an observed effect", referred to as demand artifacts, can create false positive readings, and has been a major concern for marketing and consumer researchers (Sawyer 1975; Shimp et. al 1991; Darley and Lim 1993; Bone 1995;). Several preconditions exist for subjects to be demand biased. The most pertinent precondition is that the respondents must encode a demand cue that makes them conscious of the research hypothesis. However, Shimp et. al (1991) contend that though subjects will probably encode demand cues and even discern the research hypothesis in "simplistic experiments", the bulk of evidence suggests that subjects typically do not enact roles in a hypothesis-confirming fashion (for a detailed discussion on this issue refer to Shimp et. al 1991). Given that respondents do not typically engage in hypothesis confirmation behavior we can infer within the context of the present study, that there exists no evidence to believe that early adoption of golf course behavior is attributable to increased awareness of respondents arising out of administration of the questionnaire (i.e., presence of false positive reading). On the contrary, results discussed below seem to indicate that only 24 percent of all respondents (innovators) adopt and play the golf course during the first week, with the number gradually decreasing each week. Furthermore, the analysis of the hazard model results also suggest that innovativeness is a strong predictor of golf course choice behavior -- a fact which leads us to the conclusion that it is the innovativeness trait that causes a person to adopt and play a particular golf course.

RESULTS

Reliability And Factor Structure

The reliability and factor structure of the innovativeness scale is consistent with the results of Goldsmith and Hofacker (1991). The six item innovativeness scale was subjected to a Common Factor Analysis and a varimax rotation. The criterion used to generate factors was the average communality extracted as suggested by Hair et. al (1995). The resulting one factor solution explained 62.56 percent of the variance. No cross loadings equaled or exceeded 0.3 providing support for convergent and discriminant validity of the innovativeness scale. The alpha value for the innovativeness scale was 0.78. These findings lend support that the six item innovativeness scale shares a common core (Churchill 1979). Therefore, the innovativeness index for each golfer was derived after items of the scale were summed (after the negative items were re-coded) and averaged for each individual golfer. Larger values of the scale indicated higher levels of innovativeness.

Baseline Model Results

Table 2 presents the results for two discrete-time hazard models. Likelihood ratio tests (analogous to F tests in regression) were conducted to test the significance of the individual model parameters. The results of the likelihood ratio tests indicate that both models are significant with at least one parameter being significantly different from zero.

The baseline model is usually the first step during any data analysis. It serves three purposes. First, it provides a benchmark against which to compare the goodness-of-fit of more complex models using likelihood ratio tests (Kalbfleisch and Prentice 1980). Second, inspection of the parameters provides direct information on the shape of the overall logit-hazard profile and, therefore, provides a first suggestion of the temporal shape of the overall pattern of choice in the sample. Third, the baseline model can be used to answer substantive questions like: "As a group, are individuals more likely to play the new golf course early or late into the semester?" Because the baseline model contains no covariates (to distinguish members of the sample from each other) other than time dummies, this substitution yields the fitted hazard function for the entire sample, assuming a homogeneous population in which individuals are not distinguished by values of any covariates. The parameters represent the hazard probability in each time period under observation (i.e., the probability of playing in week 1, the probability of playing in week 2 given that the individual did not play in week 1, and so on). Patterns in the values of these parameters describe the temporal shape of the overall hazard function and, because of the flexibility of the parameterization, the hazard profile is free to adopt whatever shape best describes the pattern of probability of occurrence in the sample data.

Similarly, one can then calculate survival probabilities and use this information to calculate median lifetime. The median lifetime is an important summary statistic. When the survivor function equals 50 percent, half of the sample has played the new golf course for the first time and half have not. The median lifetime answers the descriptive question: "How many weeks will pass before the average individual in the sample will play the new golf course ?" The estimated median lifetime can be obtained by linear interpolation (see Miller 1981).

TABLE 2
DISCRETE-TIME HAZARD MODEL RESULTS

	Baseline Model Parameter $ (Standard Errors)	Full Model Parameter $ (Standard Errors)
D1	-2.4163*	-2.2657*
	(0.1747)	(0.9651)
D2	-1.8563*	-1.9308*
	(0.2357)	(0.9059)
D3	-3.4143*	-3.4223*
	(0.3282)	(1.0110)
D4	-2.4513*	-2.5146*
	(0.3773)	(1.0441)
D5	-1.1359*	-1.5587*
	(0.5065)	(0.6365)
D6	-1.0465*	-1.9181*
	(0.4177)	(0.7914)
D7	-0.7003*	-1.3109*
	(0.2417)	(0.5325)
D8	-0.4135*	-1.3546*
	(0.1385)	(0.6745)
HANDICAP	______	-0.3479*
		(0.1296)
STANDING	______	0.2719*
		(0.0615)
ROUNDS	______	0.3575*
		(0.1338)
INNOVATE	______	0.4671*
		(0.1759)
Log-Likelihood	-225.7700	-197.6700
Restricted Log-Likelihood	-245.5100	-245.5100
Likelihood Ratio Test	39.4740*	95.6730*
df	8	12
Classification Accuracy:		
Estimation	0.7718	0.8255
Holdout	0.7328	0.7730

*= Significant at the 0.05 level or less.

While it is useful to examine the parameters of the baseline model to study the dynamics of choice, plots of the hazard and survivor functions are often more instructive. By examining the plot of the hazard function, one can precisely pinpoint when individuals are most likely to play the golf course for the first time. Its magnitude for each week indicates the probability of playing for that week; the higher the hazard the greater the probability. In other words, the hazard probability is the probability that an individual plays the new course in a given week, conditional on not playing prior to that week. The hazard function is the chronological pattern of these probabilities over time.

The hazard plot in Figure 1 indicates the probability of playing for each week. As such, examining the hazard function plot for the baseline model in Figure 1 indicates that approximately 8 percent of the individuals play the new golf course during week 1. Of those non-players in week 1, approximately 13 percent played during week 2.

For the golf course choice problem, the survivor probability is the probability that an individual "survives" (i.e., does not play the new course) at least up to that week. The survivor function is the chronological pattern of these survivor probabilities over time. The survivor function plot in Figure 1 is a display of the probability of surviving (remaining a non-player) against time. At the beginning, 100 percent are surviving and the survival probability is 1.00. Over time, individuals play the new golf course and the survivor function drops steadily toward zero, because although some individuals are censored, the survivor function rarely reaches zero. One can also use the survivor plot to pinpoint the time an individual first played the new course. If the survivor plot plunges sharply between one week and the next, this implies that a large portion of non-players play in the intervening period. The most useful statistic of the survivor function plot is the median lifetime. The median lifetime of 5.0343 suggests that about five weeks will pass before the average individual plays the golf course for the first time.

Full Model Results

After adding covariates to the baseline model, the goodness-of-fit of the full model can easily be compared to that of the baseline model using the standard likelihood ratio test, based on the known asymptotic distributional properties of -2 times the log-likelihood (LL) statistic (-2LL). In order to estimate the parameters of the model, the maximum likelihood estimation technique requires the maximization of the log likelihood function. As discussed before the results of the likelihood ratio test suggest that at least one of the parameters is significantly different from zero. The -2LL decreased from 451.5400 for the baseline model to 395.3400 for the full model indicating that the model with the covariates significantly improves explanatory power (chi-square=56.2000, df=8, $p<0.0001$). With the estimation of two models, it is also useful to compare them on the basis of their Classification Accuracy on both the estimation and holdout data sets. In other words, the Classification Accuracy can be used to assess the goodness-of-fit and the predictive accuracy of the models. Classification Accuracy is a measure of how well a model correctly classifies observations (i.e., how well the models correctly classify golfers who played the new course versus those who did not play the new course).

The Classification Accuracies for the baseline and full model for the estimation and holdout data sets appear in Table 2.

Figure 1
Hazard Proabilities For The Baseline Model

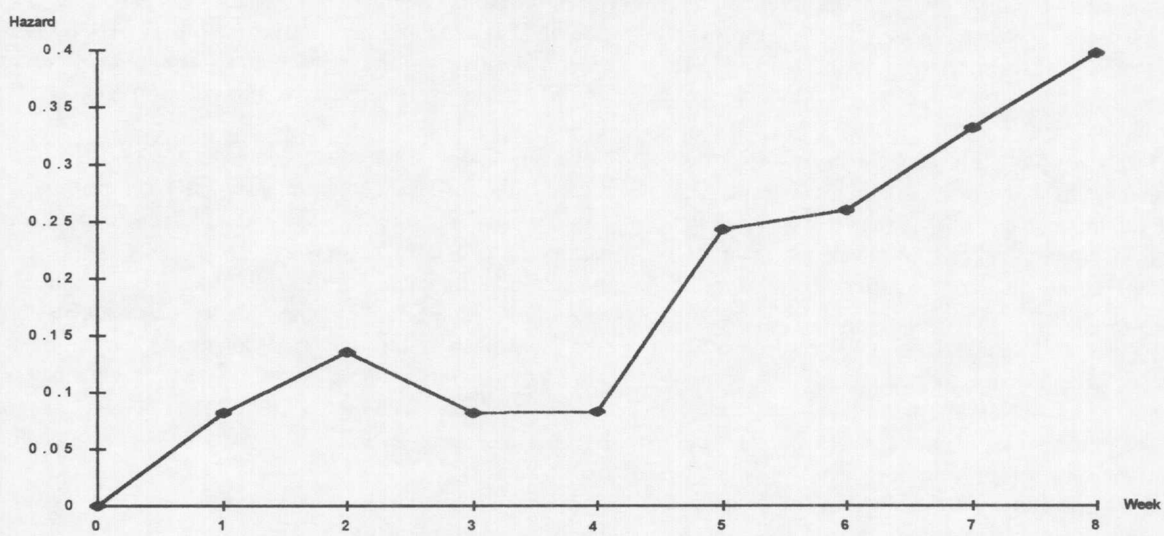
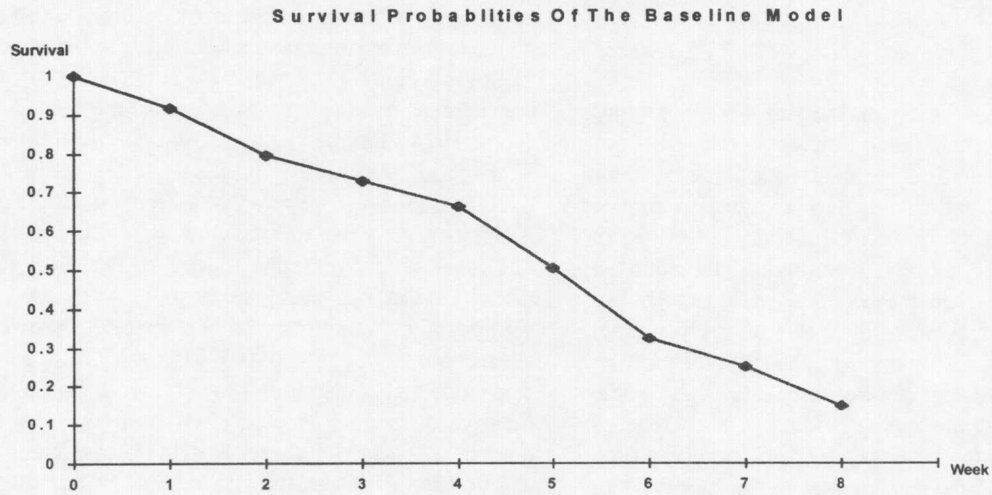


FIGURE 1 (CONTINUTED)



When compared to the proportional chance criterion (C_{pro}=0.625 or 50 percent that can be classified by chance plus a 25 percent cushion as suggested by Hair et al. 1995), a good fit and generalizability of the models appear tenable. Acceptable models are those that exceed the proportional chance criterion. While both models appear adequate for classifying observations, the full model offers an improvement over the baseline model. The improved Classification Accuracy also carries over to the holdout data set.

The hazard and survivor plots in Figure 2 can be interpreted in the same manner as they were in Figure 1, with one exception. The full model has "shift" parameters that account for differences in golfers related to academic standing, number of rounds played per month, golfer's handicap, and the innovativeness index. An examination of the hazard function plot for the full model (Figure 2) indicates that approximately 24 percent of the individuals played the new golf course during week 1. Of the non-players in week 1, approximately 26 percent played during week 2. The plot indicates the probability of playing for each week. The median lifetime for the full model of 2.6214 suggests that about two-and-one-half weeks will pass before the average individual plays the new golf course for the first time.

Asymptotic t-tests can be used for testing the zero restriction for individual parameters. A positive parameter increases the value of the hazard function and therefore indicates a negative relationship with survival. A negative parameter has the reverse interpretation.

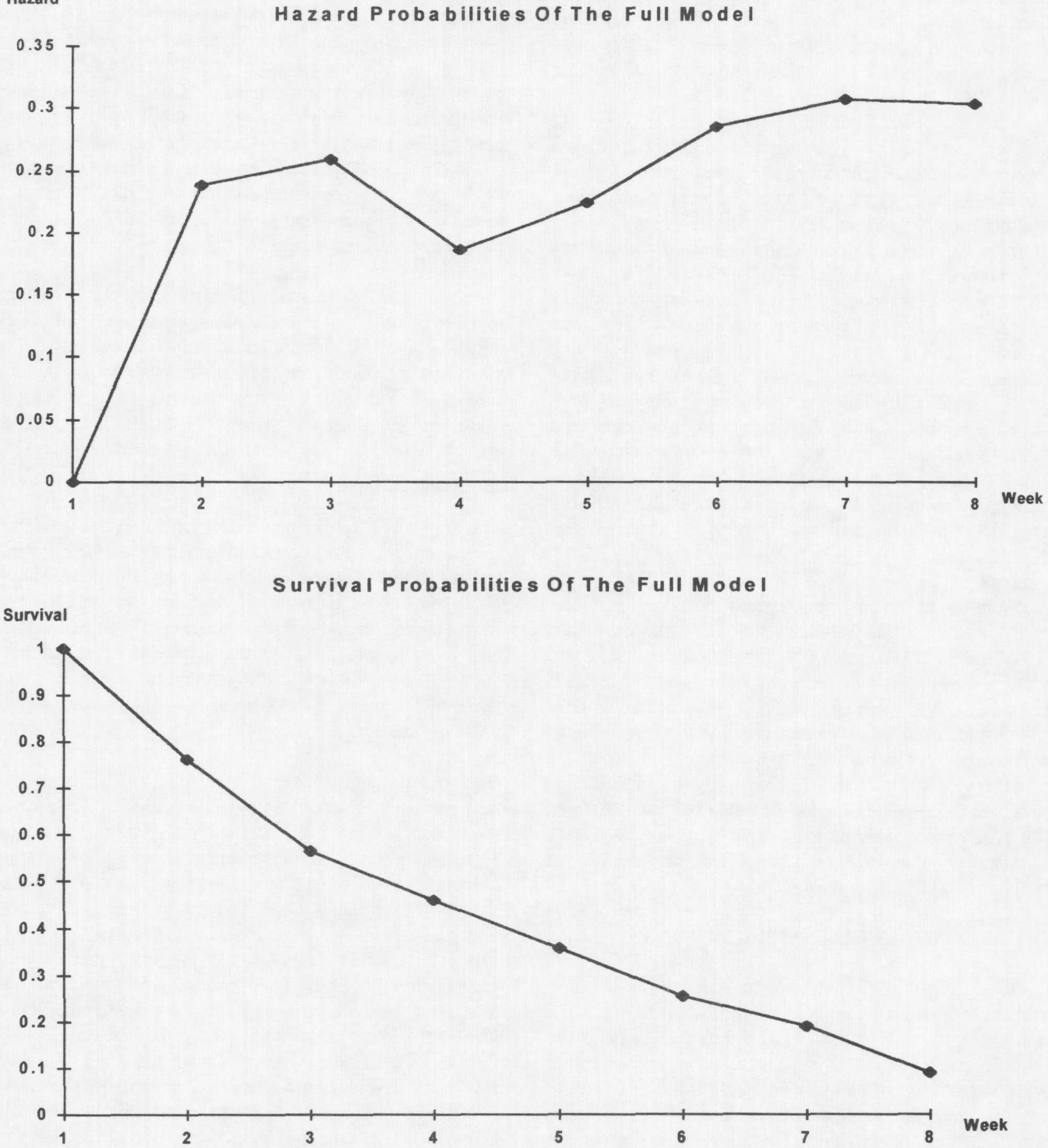
At the 0.05 level of significance, the full model has four significant parameters. The influence of academic standing (STANDING), number of rounds played per month (ROUNDS), and the innovativeness index (INNOVATE) exert a positive influence on choice. The golfer's handicap (HANDICAP) exerts a negative influence on choice.

However, since the parameters indicate the effects on logit-hazard, the easiest interpretation is to examine the exponentiated parameter. For example, the exponentiated parameter for STANDING is equal to 1.3125. This estimate indicates that for each year increase in academic standing, the odds of playing are 1.3125 times greater. The student golfers who have been at the university longer appear to be more willing to play the new golf course. A similar explanation for other variables such as ROUNDS, INNOVATE, and HANDICAP can be derived based on the exponentiated parameters.

Theoretical Implications

There appear to be several theoretical implications from this study. The scale developed by Goldsmith and Hofacker (1991) exhibits acceptable reliability and validity in a new

FIGURE 2



Hazard Probabilities Of The Full Model
Hazard
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
1
2
3
4
5
6
7
8
Week
Survival Probabilities Of The Full Model
Survival
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1
2
3
4
5
6
7
8
Week

research setting. As with other products and services, adopters of a new golf course can be categorized according to their degree of innovativeness. While innovativeness appears to be a product/service specific construct, this study provides further evidence that there are golfers possessing innovativeness to a greater or lesser degree. Thus, this study points to the existence of innovativeness as a domain specific construct.

It appears that choice of playing a new golf course is a function of several covariates including the golfer's handicap, the academic standing of the golfer, the number of rounds played per month, and the innovativeness of the golfer. Up until this point in time, golf professionals and course mangers have intuitively believed that low handicappers are more likely to play new courses for two reasons. First, low handicappers tend to play more in order to keep their handicap low and are more prone to getting bored by playing the same course all the time. Second, as the low handicapper plays the same course all the time it becomes less of a challenge because of familiarity. Since better players enjoy a real test more than those golfers just trying to get around the course without embarrassing themselves too badly, lower handicappers are more likely to try a course with which they are not familiar for the challenge its newness has to offer.

As suggested by Helsen and Schmittlein (1989), hazard models are useful for analyzing various marketing problems such as diffusion of innovation. Using the scales developed by Goldsmith and Hofacker (1991) and discrete-time hazard models is consistent with the view of innovativeness as a hypothetical construct and as behavior. Figures like those in Figure 1 and 2 can be developed to allow the researcher to examine the proportion of individuals who adopt a product/service in each time period. By operationalizing innovativeness as some function of time, the researcher can easily group individuals as to whether they are innovators (i.e., adopt early), laggards (i.e., adopt late), or something in between.

MANAGERIAL IMPLICATIONS

Traditionally, new golf course operators have focused their advertising efforts on the mid to high handicappers due to the fact that the majority of golfers fall into this range. The findings of the current study suggest an alternative approach based upon the level of innovativeness, skill, and frequency of play. This new approach should result in a faster adoption rate of the course as well as increased revenues from all the profit centers controlled by the new course operator.

While the current study does not specifically address the relationship between innovativeness, opinion leadership, and social activities, prior research suggests that innovators are high in opinion leadership (Gatignon and Robertson 1985; Green, Langeard and Favell 1974; Migley and Dowling 1978; and Robertson 1971), social participation (Gatignon and Robertson 1985; Green, Langeard and Favell 1974; Midgley and Dowling 1978; and Robertson 1971), income (Gatignon and Robertson 1985; Green, Langeard and Favell 1974; Midgley and Dowling 1978; and Robertson 1971), and upward social mobility (Robertson and Kennedy 1968). In light of the aforementioned research, it is noteworthy that golfers highest in innovativeness are also the opinion leaders, are the most socially active, are those with the lowest handicap, and have the lowest average of strokes over par per round (PGA 1996). Therefore, it may be in the best interest of the new course operator, contrary to traditional practices, to focus initial marketing efforts on this minority of golfers for several reasons.

First, golfers high in innovativeness tend to play a larger number of different courses than the average golfer. This suggests that these golfers are more predisposed to trying a variety of courses and may be more amenable to trying a new course. Second, golfers high in innovativeness tend to spend more, are less price sensitive, more fashion conscious, and intend to spend more on lessons than the average golfer (PGA 1996).

The implication for the new course operator is to look at the revenues from the entire facility and not just the number of rounds played. By properly stocking and merchandising the golf shop fashion area, the operator can significantly impact his revenues. In addition, the intention of high innovators to take more lessons and have the newest and best equipment suggests two additional profit centers that can be cultivated while the customer base is being built during the formative years of the course.

The second major finding of this study for the managers of new golf courses pertains to low handicappers. Traditionally, this group has not been targeted for recruitment due to it representing a very small percentage of all golfers as well as golf shop operators feeling that the low handicappers, due to their skill level, know exactly what they want and are not as easily influenced as high and middle handicappers. However, it is precisely this distinction that can make them a critical factor in the success of a new course. This study shows that low handicappers have a high innovativeness rating and the low handicappers in this study played the new course within 2.6 weeks of it opening even though there may have been barriers that would have suggested otherwise. Considering that those higher in innovativeness tend to be more knowledgeable, are opinion leaders, and have high social participation, it would be advisable to identify the low handicappers in the mens' clubs, women's clubs, and country clubs in the target area before the opening of the course. By inviting them to play the course, the manager of the new course quickly exposes the opinion leaders and the most respected (skilled) players of the surrounding community to the new facility. Not only would this enable the manager to take advantage of the low handicappers position within the golfing community but also elicit responses from this group as to what they feel needs to be improved to make the facility more appealing. The advantages are threefold.

First, it accelerates the adoption time of the low handicappers and may accelerate the adoption time of the middle and high handicappers due to word of mouth advertising by the opinion leaders in the community. Second, it contributes to putting the opinion leaders on the course operator's side and giving them a sense of partnership in offering suggestions as to how to improve the facilities. If the suggestions are implemented it not only improves the facility but also helps to neutralize any early negative word of mouth advertising that may have occurred if such a strategy were not used. This is crucial because ninety-one percent of dissatisfied customers never buy from the shop again and tell, on the average, nine other people about their dissatisfactory encounter (White House of Consumer Affairs, 1986).

Third, by exposing more people to the course sooner it is possible to begin building the client base faster and with less traditional advertising. This will improve the revenues during first year operations in two ways. By building a larger client base faster, an increased traffic flow will be created through the pro shop and the driving range which are two additional profit centers. In addition, by diverting the monies that would have been spent simply creating an awareness of the course (traditional advertising) to special promotional events, which tend to draw more people, the course operator can create more awareness of the course, increase the traffic flow in the pro shop, encourage the use of the practice facilities, and provide more lessons for the pros.

The third major finding of the current study concerning the likelihood of playing a new course is that those who play more rounds will tend to adopt a new course sooner. This finding is supported by recent research (PGA 1996). In examining the six male clusters from the PGA study, one finds that the number of different courses played varies directly with the number of rounds played. This suggests that those who play more rounds will be more likely to try a new course as opposed to those who play fewer rounds and limit their play to a smaller number of courses. The implication for the new course operator is that the course should be located in an area that is mainly comprised of those clusters of golfers who play a lot of rounds or that the course be easily accessible to a large geographic area that contains a significant number of golfers from the clusters of golfers who play a lot of rounds.

LIMITATIONS

There are two noteworthy limitations to this study. The sample used was an all male sample. This means that the results of the study cannot be generalized to female golfers because female golfers differ significantly from male golfers in terms of price sensitivity, competitiveness, fashion consciousness, perceived treatment, playing companions, and several other factors (PGA 1996). However, according to the cluster analysis done by the PGA resulting in six all male clusters and two all female clusters, the results may be generalized to the six male clusters which comprise 79.6 percent of all golfers in the United States or about 18,308,000 golfers.

In addition, the sample used was a student sample. While there has been much debate concerning the use of student samples and their generalizability to the general population, there are two reasons for accepting the use of a student sample in this particular study. First, Beltramini (1983) found that the attitudes of student samples and adult samples toward athletic/sports facilities did not differ significantly with the exception of price. This difference was explained by the disparity of income between the students and adults.

Second, this study is exploratory in nature. Calder et. al (1982) state that it is essential that attempts at progress be made with the realization that no one study, especially at the early stages of theory development, will be able to obtain a purity of external validity as proposed by Lynch (1982) and those holding to an inductionist approach as opposed to the falsification approach. The process that leads to theory development and acceptance is a cycle of testing, acceptance, rejection, and refinement. To insist on each study being perfect before it is conducted, especially in terms of external validity, would undermine the entire development process.

CONCLUSION

The current study combines the application of Hazard modelling techniques with diffusion and innovativeness literature in the realm of new golf course choice behavior. The results of the study presents some interesting findings and suggests some strategies for early revenue maximization. Specifically, this study suggests that by identifying and using the innovators in the golfing community the new course operator should be able to diffuse information about the new facility more quickly and in a more cost efficient manner. Interestingly, those golfers who are highest in innovativeness tend to be the lower handicappers. This suggests an appraoch contrary to the traditional practice of targeting the initial advertising efforts to the largest group of golfers, medium and high handicappers.

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APPENDIX

Event history data is collected on a sample of n individuals (i=1,2,...,n) drawn at random from the population of interest. The i^{th} individual has j_i records, at which point either the event occurs or the individual is censored.

The decision to play the new golf course depends on a variety of characteristics of the individual(s) (Louviere and Hensher 1983). Therefore, researchers have tried to identify covariates (predictors) that identify difference in hazard across subgroups of the population. Thus, consider P covariates (p=1,2,...,P), each of which characterizes members of the population on a specific dimension. These covariates can be categorical or continuous. As such, individual i's values for each of the P predictors in time period j is the vector $\mathbf{Z}_{ij}=[Z_{1ij}, Z_{2ij},..., Z_{Pij}]$. Because the values of some covariates may vary over time, the values of these covariates are recorded in every time period during data collection.

The discrete-time hazard model specifies that the hazard probability depends upon each individual's values on a vector of covariates and dummy time variables. Allison (1982) and Cox (1972) proposed that, because the h_{ij} are probabilities, they should be reparameterized so that they have a "logistic" dependence on the covariates and the time periods. This model represents the log-odds (odds is a quantity related to hazard in that it describes the chance of event occurrence versus it not occurring) of event occurrence as a function of covariates and dummy time variables. The discrete-time hazard model is therefore represented as:

$$h_{ij} = \frac{1}{1+e^{-[(\alpha_1 D_{1ij}+\alpha_2 D_{2ij}+\ldots+\alpha_J D_{Jij})+(\beta_1 Z_{1ij}+\beta_2 Z_{2ij}+\ldots+\beta_P Z_{Pij})]}} \quad (1)$$

where (D_{1ij}, D_{2ij},...,D_{Jij}) are a sequence of time dummy variables, indexing time periods (i.e., weeks). The symbol J refers to the last period observed for anyone in the sample. If j_i represents the last time period when individual i was observed (and at which time the individual was either censored or experienced the event of interest), then $J=j_i$. The time period dummies are defined identically for all individuals: $D_{1ij}=1$ when j=1 and $D_{1ij}=0$ when j takes on any other value (2 through J), $D_{2ij}=1$ when j=2 and $D_{2ij}=0$ otherwise, and so on. The "intercept" parameters (α_1, α_2,...,α_J) capture the baseline level of hazard in each time period (i.e., when the values for all the covariates are zero), and the "slope" parameters (β_1, β_2,...,β_P) describe the effects of the covariates on a baseline hazard function, albeit on a log-odds scale.

A more straightforward version of the model can be derived by taking logistic (logit) transformations of both sides of the equation, yielding the logit-hazard model:

$$\ln\left(\frac{h_{ij}}{1-h_{ij}}\right)=(\alpha_1 D_{1ij}+\alpha_2 D_{2ij}+\ldots+\alpha_J D_{Jij})+(\beta_1 Z_{1ij}+\beta_2 Z_{2ij}+\ldots+\beta_P Z_{Pij}) \quad (2)$$

Allison (1982) showed that the estimates of the parameters in equation (2) can be obtained from standard logistic regression software.

The above model assumes that the predictors are linearly associated with the logistic transformation of hazard (logit-hazard), and not with the hazard probabilities themselves. In other words, there is a hypothesized linear relationship between logit-hazard and the covariates and time dummies. One, therefore, interprets points on the logit-hazard function as describing the "conditional log-odds" of event occurrence in each time period, given no earlier occurrence of the event. To return to the metric of hazard we substitute back into equation (1). The survivor probabilities can be estimated from:

$$S_{ij}=S_{ij-1}(1-h_{ij}) \quad (3)$$

The notions of dummy variables and censoring require further explanation. The dummy variables serve as a series of "intercept" parameters, one for each time period. As such, the use of dummy variables (especially in the baseline model) provides a general profile of risk (i.e., experiencing the event) assuming a homogeneous population in which individuals are not distinguished by values of any covariates. In other words, the dummy variables capture the effect of time itself on the event of interest (i.e., playing a new golf course for the first time).

Censoring is a function of the data collection period. No matter how long the data is collected, some individuals will never experience the event of interest (i.e., play the new golf course). These individuals are said to be censored. In this situation, the researcher has incomplete information about event occurrence. If the individual's event time is censored, the researcher knows only that if the person ever experiences the event, he/she will do so after the data collection period. The researcher knows neither "when" or "whether" the event will ever happen. All the researcher knows is that by the end of the data collection period, the event has not occurred. Censored observations provide the researcher with useful information. One knows at least that the individual survived for a certain length of time and this useful information need not be discarded. Discrete-time hazard models incorporates those censored cases to make maximum use of information.

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