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Event History Analysis of Behavior Modification*

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Abstract

This paper examines the antecedents of behavior modification in the context of smoking cessation behavior. Event history analysis is used as a useful research method for investigating a dynamic process. This method is especially useful for understanding the process in which individuals move from one qualitative state to another and identifying the variables which affect this process. A partially parametric model, called proportional hazard model, is used to quantify the relationship between transition rate and a set of explanatory variables. Theoretical and methodological implications are then drawn and discussed.

I . Introduction

How can one modify one's behavior? If so, how can one maintain the modified behavior? These are questions relevant to every aspect of our life. There have been many studies that try to explain one's behavior, but relatively few studies on changing and maintaining the changed behavior. As behavior becomes habitual or addictive, it will be more difficult to modify. Even though one may succeed in modifying behavior temporarily, maintaining the modified behavior will be more difficult. Such behavior runs a wide gamut from addictive behaviors like alcoholism, smoking, drug abuse to minor habits like trembling legs while talking. Though they differ in their scope and nature, there are common characteristics. One's intention might be in one direction, while attitudes or habits point in the opposite direction. Then there will be a conflict between

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intention and habit. Thus one's attitudes or intentions are not enough to explain one's behavior. What are the factors that are associated with maintaining the modified behavior? This study tries to address this question in the context of quitting smoking (Yi 1996). Smoking cessation behavior has been suggested as an example of the use of behavior modification technique in marketing (Nord and Peter 1980).

People's smoking cessation behaviors are a phenomena which occur in time as discrete or qualitative changes such as smoking/nonsmoking, or abstinence/ relapse. Many studies in this area have depended upon static research methods which ignore the temporal dimensions of the problem. The most widely used methods are the logit, probit, log-linear models for contingency tables, and linear regressions with dummy dependent variable (e.g., Agresti 1990, Everitt 1977, Magidson 1994, Malhotra 1984, Yi 1996). These are based on the idea that units under study are classified by exhaustive, mutually exclusive outcomes representing either an equilibrium state - smoke/ not smoke or an unalterable classification of determination- abstinence/relapse. However, the assumption of equilibrium is rarely supported substantively. Most behavior can be best characterized by a chain of changes which occur over time. Also for many researchers and practitioners, the interest lies as much in the process of change as in its outcome. Thus, the usual static methods are not satisfactory, as they provide no clue to the time path of change.

In static analysis, the actual timing of relapse events within an individual is ignored, and the multiple spells of abstinence or relapse over time are not taken into account. In order to extrapolate beyond a given interval, one needs more assumptions. However, the nature of smoking cessation can be best characterized by a chain of smoking states which can occur over time. Smoking behavior is dynamic, and people can move relatively frequently between states, and show progression of outcomes rather than unalterable properties. Such problems can be overcome if one abandons the equilibrium assumption and uses methods which explicitly incorporate time, known generally as dynamic methods (Carroll 1983, Tuma and Hannan 1984). As Raffalovich and Knoke (1983) argue cogently, methods for analysis of historic change should faithfully mirror the processes that generate the phenomena under investigation. Otherwise, research findings might be confounded such that it is difficult to make meaningful substantive interpretations of the results.

In this study, we adopt a dynamic method of analysis in order to investigate smoking cessation behavior over time: event history analysis (Allison 1984, Tuma and Hannan 1984). The purpose of the study is to understand the process by which ex-smokers move from one qualitative state to another, and to identify the variables which affect this process. The model belongs to a broad class of dynamic models known as finite-state, continuous-time stochastic models (Massy, Montgomery, and Morrison 1970). The finite-state characteristic of the model indicates that an individual can occupy only a countable number of possible states. These states are required to be mutually exclusive and exhaustive; that is, at every point in time a unit must occupy only one qualitative state.

The set of all possible states are known as the state space and is denoted by a state-space variable (Allison 1984). Here smoke/ not smoke are used as the state space. It is, however, important to recognize that the state space is a construction of the investigator, and depends upon the substantive questions of interest (Carroll 1983). It does not arise naturally from the data, and different investigators can often construct different state spaces. For example, data on smoking behavior might be analyzed as two-state process of movement between the states of smoking and nonsmoking as in this study. Yet another investigator might analyze the data as a multi-state problem of never smoke, smoke never quit, smoke quit, relapse after quit etc. The designation of state spaces therefore depends on substantive motivations.

The model to be used in the study is depicted in a continuous form, as opposed to discrete time. This means that changes between states can occur at any point in time. Discrete-time models, in contrast, constrain the occurrence of changes to only specified times, which are usually separated by intervals of equal duration. In the past, it has been thought that discrete-time models are preferable to continuous-time models because most longitudinal social-science data are collected in panel form with waves of equal duration. Such reasoning is based upon the measurement property of the data, and allows the data to dictate the form of the model. The form of the model should depend upon the substantive realism, rather than the data form (Coleman 1981). In the current context, the continuous time model seems to be favored substantively over concrete time. Transitions between the states, i.e. smoking and nonsmoking, are likely to occur at any time, rather than occur only at fixed time points.

II. Event History Analysis

In this section, fundamental elements of event history analysis will be examined briefly. This is motivated to facilitate the subsequent expositions in the paper. It is assumed that the process of movement is the first order and that there is individual difference which effect each variable. The exact meanings and implications of these assumptions will become clear later in the section.

1. State Space

The state space may be defined as Y(t), an integer-valued variable which indicates the state occupied by an individual at time t. In the present study with two states, Y(t) can take only two values, each an arbitrarily chosen integer assigned exclusively to a particular state. Two states, i.e. smoke/ not smoke, are used. Since we use ex-smokers as subjects, these can be called relapse/ abstinence. Implicit is the assumption that the process is first order. The states do not consider the past history, and the current state is used. It does not differentiate the abstinence with prior relapse experience from the abstinence without prior relapse. Thus possible states are two, abstinence and relapse. If the process is higher order, we may need to adopt more than two states, e.g. abstinence after relapse, abstinence without relapse experience, smoking without any abstinence experience, relapse after abstinence, etc. All states are recurrent, i.e. they may be visited repeatedly.

2. State Probability and Transition Probability

The state probability is the probability of occupying each state, or the proportion of units occupying each state. Since we are concerned with a dynamic process, the state probabilities are functions of time. The sum of all state probabilities will equal unity, since state space is mutually exclusive and exhaustive. Obviously the state probabilities will depend upon time in many temporal processes. When a process reaches such a point where state probabilities no longer change with increases in time, the process is said to have reached an equilibrium.

Unlike state probabilities, which are unconditional and calculated for a single moment in time, transition probabilities are conditional upon the state occupied and calculated relative to two time points. That is to say, transition probabilities describe the probabilities of specific changes in the state-space variable across two points in time. Obviously the transition probabilities will vary depending upon the length and characteristics of the interval between two times. In general, a transition probability can be defined as

$$p_{jk}\ (t,\ t+\triangle Dt) = \Pr[Y(t+\ \triangle t)=k \mid Y(t) = j]$$

if two points in time are defined as t and t + $\triangle t$ such that $\triangle t$ is always positive. So it gives the probability of occupying state k at t + $\triangle t$, given that state j was occupied at time t.

3. Transition Rates

The central feature of the model is the instantaneous transition rate, often referred to simply as the rate. Rate is defined as the transition probability over a unit of time where the unit is infinitesimal. More formally, the rate between two state j and k is defined as

$$r_{jk}(t) = \lim p_{jk}(t,\ t+\ \triangle t)/\triangle t.$$

The transition rate will be always nonnegative, although it is unbounded above. Even where the transition rate is constant, the probability of leaving a state can be shown to decline exponentially with time spent in this state. This is one of the main advantages of modeling social processes in terms of transition rates instead of probabilities of change (Tuma, Hannan, and Groenveld 1979). In this study, two transition rates are investigated, i.e., relapse rate and return-to-abstinence rate.

4. Population Heterogeneity

The model given above assumes population homogeneity; that is the rate of transition is assumed to be the same for all members of a population. However, it is likely that the process of smoking cessation behavior will differ from person to person. That is, transition rates are likely to depend upon exogenous properties of individuals, exhibiting population heterogeneity. A straightforward extension specifies the transition rate as an explicit function of exogenous variables which differ across individuals.

$$r_{jkt}(t) = f\ (\beta_{jk}\ X_i\ )$$

The usual functional forms are linear form and log-linear forms. However, linear forms can predict negative rates, which is not desirable. The log-linear form gives the following equations.

$$\ln\ r_{ijk}\ (t) = \beta_{jk}\ X_i$$

$$r_{ijk}(t) = \exp(\ \beta_{jk}\ X_i\ )$$

5. Time Dependence

It is assumed that rates will vary over time. This time dependence may be based on changing exogenous factors(measured or unobserved) or on variations in parameters associated with exogenous factors. There are four types of time, i.e. historical time, age, experience, or duration. In the context of smoking cessation behavior, and duration, i.e. time since entering current state, shows relevance (Freeman, Carroll, and Hannan 1983). For example, the longer one has been in the current state, the less likely is one to leave the state. This variation with duration is frequently called semi-Markov model (Coleman 1981). On the other hand, time-independent or time-stationary model does not allow rates to vary with time.

There are several approaches to time dependence, e.g. measured changes in X(t), periodization, nuisance function, and parametric models for r(X,t). As well as the measured changes in exogenous variables, a nuisance function will be incorporated in order to capture the time dependence.

6. Data Requirements

Data requirements for event history analysis are more stringent than usual quantitative techniques. At a minimum, information must exist for all individuals on their initial or starting state, their final or destination state, and the exact times of entry and exit from each state. These four state and time variables define a spell, the basic unit in an event history analysis. Individuals can provide multiple spells if they make several stage-changes during the period of investigation. For example, if an individual goes through abstinence, relapse and abstinence, then there are two spells for him/her.

Event history analysis presumes that observations have been collected in continuous time, that is, that the exact sequence and timing of events and corresponding levels of exogenous variables are known. However, such comprehensive information is hardly obtained. With less than adequate data, much information is necessarily lost, and the analysis suffers. Ideally the data records should contain information concerning the characteristics of each individuals which are thought to affect the rate, denoted by X variables. These variables are assumed to be exogenous and are measured contemporaneously with the duration of the spell. Most frequently, the exogenous variables are measured at the starting time of each spell.

Ⅲ. Hypotheses

There are many contending theories on motives and incentives in cigarette smoking and cessation (Clark 1977, Schachter 1978, William 1972). These are beyond the scope and interest of the current study though. Smoking cessation behavior has been suggested as an example of behavior modification in marketing (Nord and Peter 1980). Several hypotheses about the smoking cessation behavior are suggested and rationales or relevant theories will be discussed in this section. Since our interest lies in two distinct transition rates, the hypotheses will be made in terms of a transition rate.

1. Relapse Rate

1.1 Self--Efficacy

Self-efficacy theory is an integrative framework that accounts for the behavioral and psychological changes resulting from different efforts (Bandura 1977). Self-efficacy is proposed as a common cognitive mechanism that underlies psychological change. With respect to smoking, self-efficacy can be defined as the confidence in one's ability to remain abstinent in a given situation (McIntyre, Liechtenstein, and Mermelstein 1983). People will use many techniques to quit smoking, and they will differ in producing personal efficacy. According to the theory, perceived efficacy will direct one's behavior. Bandura(1977) claims that given skills and incentives, efficacy expectations are major determinant of people's choice of activities, how much effort they will expand, and of how long they will sustain effort in dealing with stressful situations. So self-efficacy is hypothesized to decrease the relapse rate.

H1: Self-efficacy is negatively associated with the relapse rate.

1.2 Need for a New Behavior

Another important predictor would be a specific need for a new behavior (here quitting). Ex-smokers will differ in their need for quitting smoking. For example, some people may have a greater need for quitting smoking than others. Most human behavior is motivated to satisfy the various needs. It is likely that a person who feels a high need for quitting will be more resistant to the temptation to smoke after he/she quits smoking than one with a low need. The need for quitting smoking can be instantiated by the number of reasons to quit smoking given by each individual. Also the need for quitting will determine the effort level exerted by each individual during the abstinence spell, this would then subsequently affect the relapse rate. Thus, a need for quitting smoking is hypothesized to be negatively related to relapse rate.

H2: The need for quitting is negatively associated with the relapse rate.

1.3 Past Behavior: Intensity vs Length

In the habitual behavior like smoking, the effect of past behavior is expected to be important (Triandis 1977). Triandis argues that habit is one of the most important factors in explaining one's behavior. Habit can be captured by the intensity of past smoking behavior, which can be instantiated by the average nicotine intake per day for each individual. Nevertheless, there is an alternative representation of the habit. That is the length of the past smoking behavior, i.e. how long one has been smoking. The longer one has kept a habit, the less likely is one to abandon the habit. Past smoking history is thus expected to be related to the relapse rate, but two aspects of past smoking behavior can affect the relapse rate, i.e. intensity and length. These are to be investigated by testing the following hypotheses.

H3: The intensity of the past smoking behavior is positively related to the relapse rate.

H4: The length of the past smoking behavior is positively related to the relapse rate

1.4 Stress Management: Absolute and Relative Level

It is often argued that smoking is used as a means of stress management by people. People use smoking when they feel stress, and they come to believe that smoking helps them manage their stress according to this theory. By the associative learning process, people will feel like smoking when they feel stress or tension according to this view. If an ex-smoker experiences the stress during the abstinence spell, he might feel the temptation to smoke, leading to relapse. Or the change in stress might be more relevant, rather than the absolute level of stress. It has been found that people are sensitive to change rather than the absolute level. In the context of the current study, an increase in stress might even be attributed to quitting smoking by some individuals. Then they might choose to relapse in order to reduce the stress which they perceive to have been increased by quitting.

H5: The frequency of hassle is positively related to the relapse rate.

H6: The change in hassle frequency is positively related to the relapse rate.

1.5 Withdrawal Symptom: Craving

Quitting smoking is abstaining from doing a behavior, i.e. smoking. It can be conceptualized as a behavior in that it changes the status. Maintaining smoking is to keep the current state, and status quo. On the other hand, quitting is changing the status from smoking to nonsmoking, and affects the status. Thus it is consistent with a concept of an action. So it can be construed as a positive action, rather than a negative one of not doing something. There are several symptoms reported after quitting smoking. It is likely that people with more symptoms regard quitting as passive actions, and that they are more prone to relapse. One important symptom is the craving for smoking during the abstinence period. It is hypothesized that the degree of craving, a withdrawal symptom, is positively associated with relapse.

H7: The craving for smoking during abstinence is positively related to the relapse rate.

2. Return-to-abstinence Rate

In a dynamic analysis like this study, an individual can go through multiple states during the given period. Thus, one may have relapsed, but can return to abstinence again. Since these transitions are not symmetric, several hypotheses are proposed regarding the return-to-abstinence rate. Of course, the relevant variables will not be necessarily the same for both rates.

2.1 Need for a New Behavior

Although one may have relapsed to smoking, the need for quitting will still exist in one's mind. To the extent that the need is felt by each individual, he or she will feel pressure toward returning to abstinence. Also this might make one feel uncomfortable at smoking, resulting in quitting smoking again. Thus, a need for quitting is hypothesized to be positively associated with the return to abstinence.

H8: The need for quitting is positively related to the return-to-abstinence rate.

2.2 Relapse Symptom: Body Mass Index and Lung Health

One might be sensitive to the health status during the relapse period or spell. The relevant ones in the context of smoking are related to the body mass index and the lung status. Since relapsers had tried to quit smoking befire but returned to smoking, they will be paying attention to changes in their health status, and will consider them as relapse symptoms. In this sense, they will be affected by the change in health status during relapse spell, rather than by the absolute level of the health status. Thus changes in health status are hypothesized to be positively related to return-to-abstinence.

H9: Change in body mass index is positively associated with the return-to-abstinence rate.

H10: Change in lung health is negatively associated with the return-to- abstinence rate.

IV. Data

Subjects were recruited from a number of formal smoking-cessation programs in the San Francisco Bay and Sacramento Delta regions of California. The recruitment process involves two steps. First, the participants were given "agreements to be contracted" forms, and interested candidates were free to mail their forms in. After 3 months had passed, each candidate was called to determine her current smoking status. Those stating they maintained abstinence were invited to join Northern California Smoking Relapse Study(NCRCS). In order to corroborate the self-reported smoking status, saliva thiocayante(SCN) was used. For the current study, all female ex-smokers were used. A further detailed description can be found elsewhere (Swan et al. 1985, Yi 1996).

1. Measures

The dependent variable in this study is the rate of transition into two states: abstinence and relapse. Abstinence is defined as no reported smoking and SCN corroboration. And, relapse is defined as reported smoking in any amount at any time before an examination or an SCN value greater than or equal to 120 ug/ml. UNEMPLOY measures the employment status at the intake. QUITREAS is the number of reasons for quitting. Subjects were asked to indicate any or all of 12 commonly cited reasons for wanting to quit prior to their most recent attempt at cessation. The number of reasons checked was then computed for each participant.

Self-efficacy is measured by asking the subjects to self-rate the likelihood of returning to smoking in 19 situations commonly encountered in daily life. SITULIKE is the sum of likelihoods of relapse in these situations. Since relapse is highly likely, SITULIKE is the reverse measure of self-efficacy. Average nicotine intake per day is also measured by DOSE. The years of smoking history is indicated by YRSMOKR. CRAVING is the withdrawal symptom assessed in the study.

Hassles, lung health, and body mass index are measured at six and twelve months after intake. Since each of the two spells ended with either the six or 12 month assessment, the values corresponding to the spell were used instead of intake value. Change for frequency in hassles was computed as the difference in value from beginning to the end of the spell. CHFREQ is the variable corresponding to this. Change in body mass index(BMI) and lung health was computed as relative change, i.e. the difference from beginning to the end of the spell divided by the value at the beginning of the spell. These are indicated by CHBMI and CHLUNG. Table 1 provides the brief description of the variables used in this study. Table 2 and 3 provides some descriptive statistics for the variables. There are 192 spells for abstinence, and 59 spells for relapse.

Construction of event histories for the NCRCS was complicated by two factors: (a) the independent verification of subjects' self-reported smoking status via SCN test ; and (b) the systematic updating of data on possible causative factors in the process. Each interview begins a new spell(except the final twelve-month interview, for which no follow-up information is available). The interview procedure immediately verifies the starting state via the SCN test, and provide new measurement on coincident variables. Coding starting time as interview data rather than time of entry into state eliminates problems of length-bias and

Table 1. Description of Variables in the Analysis

Variables	Brief Description
UNEMPLOY	0= employed, 1= unemployed
QUITREAS	number of reasons to quit
SITULIKE	sum likelihoods for situations
DOSE	daily nicotine intake
YRSMOKR	years of smoking history
CRAVING	craving for smoking
FREQUEN	frequency of hassles
CHFREQ	change in hassle frequency
BMI	body mass index
CHBMI	change in body mass index
ABLUNG	lung health status
CHLUNG	change in lung health

*Dummy variables are 1 if the definition of the variable is satisfied.

Table 2. Descriptive Statistics for Abstinence Spells

Variable	Minimum	Maximum	Mean	s.d.
UNEMPLOY	0.00	1.00	0.22	0.41
QUITREAS	1.00	12.00	6.41	2.47
SITULIKE	1.00	64.00	9.75	9.78
DOSE	0.27	86.4	22.56	14.11
YRSMOKR	-21.34	32.73	-0.10	10.71
CRAVING	1.00	7.00	5.36	1.47
FREQUEN	3.00	69.00	21.88	11.18
CHFREQ	-1	3.67	0.00	0.57

Table 3. Descriptive Statistics for Relapse Spells

Variable	Minimum	Maximum	Mean	s.d.
QUITREAS	1.00	12.00	6.56	2.50
BMI	19.77	42.20	24.67	4.06
CHBMI	-0.29	0.36	-0.01	0.10
ABLUNG	0.00	1.00	0.63	0.49
CHLUNG	-1.00	1.00	-0.03	0.45

attribution of measured characteristics to earlier time points. It can be noted that each subject can be represented by at most two spells since there are two follow-up interviews.

V. Method

A partially parametric model, called proportional hazard model, is used to analyze the data. The goal of our analysis is to quantify the relationship between transition rate and a set of explanatory variables. These variables, often called covariates or prognostic factors, usually represent either measurements of inherent differences among subjects or constitute a set of indicator variables representing different treatment groups. The model is formulated in terms of the effects of covariates on rates. No parametric assumptions are made about the shape of survival curve. The form of the model is as follows:

$$r(t) = \exp(bX)\ h_o(t)$$

where $h_o(t)$ is assumed to be the same for all units at any specific point in time t, but otherwise may be of any form. This is called a 'nuisance function'. The model is called proportional hazards model, since rate is not known exactly (because $h_o(t)$ is unobserved) but for any two cases at the same time, rate are proportional to each other.

$$r_i\ (t)\ /\ r_j\ (t) = \exp(\beta X_i)\ /\ \exp(\beta X_j)$$

This leads to a simpler estimation based on such ratios, which cause $h_o(t)$ to cancel out. The model implicitly contain two assumptions. The first assumption is the multiplicative relationship between the nuisance function and function of covariates(proportionality). Thus the ratio of rates for two units with different sets of covariates does not depend upon time. The second assumption is the log-linear form for the relationship between the rate and covariates. It can be noted that there is no intercept term in the first term involving covariates in the model. There is no way of distinguishing the intercept, since it cancels out as $h_o(t)$. Nevertheless, we can regard $h_o(t)$ as the changing intercept, which will be helpful for interpretation.

Estimation of the parameters is done in the following way. First sort cases by time of events t(i), and assume all events occur at distinct times(no ties). Then at the time of i-th event, among all cases, the probability for this case to fail is this one:

$$PL_i = r(X_{(i)}, t_{(i)}) / \Sigma r(X_j\ t_{(i)}) = \exp(\beta X_{(i)}) / \Sigma \exp(\beta X_j)$$

,where R(t) is the set of all cases at risk of event at time t, called risk set. This is called "partial likelihood" by Cox (1972). Assuming that cases are independent, we can solve partial likelihood(PL) as maximum likelihood(ML). Maximization of the partial likelihood function yields estimates of b which are consistent and efficient.

BMDP2L is used to estimate the proportional hazards model. The model is a run for each transition rate, i.e. for relapse rate and return-to-abstinence rate. As mentioned above, only female ex-smokers were used in this study, based upon prior research that shows the substantial difference across sex. The starting status is abstinence for a model of relapse rate, which is indicated by the variable SS. On the other hand, the starting status for a model of return-to-abstinence is relapse, and the response is abstinence. Time is measured by the duration, i.e. the time between starting time and finishing time of the spell.

Ⅵ. Results

The results by BMDP2L provide the logarithm of the maximized partial likelihood function and the global chi-square statistic(and its p-value). The global chi-square statistic tests the hypothesis that all coefficients are identically zero. This statistic is defined as follows

$$U'(0)\ I^{-1}(0)\ U(0)$$

where U(0) is the vector of first derivatives of the partial likelihood function evaluated at β=0, and I(0) denotes the observed information matrix (the negative of the matrix of second order partial derivatives) evaluated at β=0. The global chi-square has asymptotic chi-square distribution with degrees of freedom equal to the number of covariates in the model.

Table 4. Results for the Relapse Rate (N=192)

Variable	Coeff.	Odds Ratio	chi-square
UNEMPLOY	.878	2.407	8.04***
QUITREAS	-.105	.900	3.46*
SITULIKE	.016	1.02	2.71*
DOSE	.017	1.017	3.97**
YRSMOKR	-.004	.996	.08
CRAVING	.272	1.313	6.79***
FREQUEN	.014	1.014	1.48
CHFREQ	.092	.433	1.10

global chi-square =29.23, d.f.=8, p-value=.000
* significant at the .10 level
** significant at the .05 level
*** significant at the .01 level

The results for a relapse rate are summarized in Table 4. The global chi-square is 29.23 with 8 d.f. The p-value is .000, indicating that the vector of coefficients is different from zero. The number of cases is 192 for this estimation. For each covariate, the computed parameter estimates, their asymptotic standard errors and the coeff./s.e. ratio are given by BMDP2L. The regression coefficient indicates the relationship between the rate and covariate. A positive coefficient increases the rate of relapse, and therefore indicates negative relationship with survival. A negative coefficient has the reverse interpretation.

PL estimates are efficient and consistent, but they are not necessarily asymptotically normal. Thus, the coefficient / standard error ratio is only approximately normal. The simulation results reported in Tuma and Hannan (1984) shows that a normal test may even be conservative, and that a normal test loses exactness as percentage of censored cases increases. It also found that a normal approximation is reasonably good for an average sample size. In this study a PL joint test is adopted instead of the single normal test.

While partial likelihood from PL estimation is not strictly a likelihood in the usual sense, joint or log likelihood(LR) tests are possible. If we have two partial likelihoods for nested models 1 and 2, say PL1 and PL2, then the LR chi-square is as follows;

$$\chi^2 \text{ LR} = -2 \ln (PL1 / PL2)$$

This will be approximately chi-squared with d.f. equal to difference in the number of parameters. This is the same as χ^2 LR for MLE, and recommended over the t- ratio test based on s.e. In order to test the hypotheses, we need to assess each coefficient. Thus the χ^2 LR is calculated for each parameter estimate. This is done by comparing the model with that covariate and the model without the covariate. Then χ^2 LR is calculated by minus twice log likelihood ratio. This will be chi-square with d.f. 1.

Column 4 in Table 4 provides this chi-square statistic to be used for evaluating the significance of each estimate. The significance of each coefficient is indicated by three levels, i.e., .10, .05, and .01. We will interpret them as weak support, support, and strong support respectively for significance when they are in the hypothesized sign.

Table 5 provides the results for return-to-abstinence rate. The number of valid spells is 59. The global chi-square statistic is 6.07 with d.f. 5. The p-value is .299, indicating the overall insignificance of the model. This is in contrast with the p-value of .000 for relapse rate model. Thus we can not reject that all coefficients are identically zero according to this statistic. The individual χ^2 LR for each covariate is , however, reported in column 4 as in Table 4. This test shows that one coefficient, i.e. that for CHBMI, is significant at .01 level.

Table 5. Results for the Return-to-abstinence Rate (N=59)

Variable	Coeff.	Odds Ratio	chi-square
QUITREAS	.139	1.150	1.82
BMI	.030	1.031	.21
CHBMI	2.476	11.894	7.63***
ABLUNG	.079	1.082	.02
CHLUNG	-.784	.457	2.26

global chi-square =6.07, d.f.=5, p-value= .299

***significant at the .01 level

Ⅶ. Discussion

β in the model has usual regression interpretation on log of rate. In other words, e^{β} is a multiplicative or relative effect, same as odds ratio in logit model. If we add one unit to Xp, rate is multiplied by exp(βp). Algebraically ratio of rates for two cases is

$$r_{jk}\ (X_1,\ X_2,\ \ldots,\ X_{p+1},\ t)\ /\ (X_1,\ X_2,\ \ldots,\ X_p,\ t) = \exp\ (\beta p).$$

This is especially useful when Xp is a dummy. It gives the ratio of rates for Xp =1 vs Xp =0. For example in Table 4, the odds ratio is 2.407 for UNEMPLOY, a dummy variable for employment status. So the relapse rate for the unemployed is 2.407 times the relapse rate for the employed. Column 4 in Table 4 and 5 provides these results.

Let us turn to the interpretation of the results in terms of the hypotheses. The significance of each parameter estimate is tested by the likelihood chi-square rather than by t-ratio. H1 on self-efficacy is weakly supported with the χ^2 of 2.71, as can be confirmed in Table 4. As mentioned above, we will use .01, .05, .10 level significance as strong support, support, weak support respectively. Of course, the sign needs to be in the expected direction in order to be used as supportive evidence. As SITULIKE variable is the reverse of self-efficacy, the positive sign of SITULIKE implies the negative relationship between rate of transition and self-efficacy. So a person with a higher self-efficacy is less likely to relapse, although the evidence is a little weak. H2 on need for quitting gets a weak support with coefficient -.105. So a person who has a higher need for quitting tends to have a lower relapse rate than a person with a lower need for quitting. In maintaining abstinence, one will have to exert effort to overcome the temptation to smoke. The cognitive reasons for quitting will be of help to the abstiners in justifying the effort exerted.

H3 and H4 are to investigate two alternative explanations of past smoking history effects on relapse. The past habit can be represented either by the intensity or the length. If we look at the covariates DOSE and YRSMOKR, we can see that YRSMOKR is not significant with χ^2 of .08. On the other hand, DOSE has χ^2 of 3.97, which is significant at .05 level. So intensity of the past smoking behavior seems to be related to the relapse rate, giving support for H3. The person who used to have a higher nicotine intake per day seems to relapse to smoking more than the person with a low daily nicotine consumption in the past.

The effect of stress on relapsing is hypothesized by H5 and H6. They hypothesized the effect of stress either by an absolute level or by relative change, respectively. But neither effect was supported by the data. Both FREQUEN and CHFREQ are not significant even at .10 level. So the argument that smoking is used as a means of stress management is not supported by this analysis.

An effect of a withdrawal symptom, i.e. craving, is found. In H7, we had hypothesized that craving for smoking during abstinence is positively related to the relapse rate. This is strongly supported by χ^2 of 6.79 for CRAVING. To summarize the findings for a relapse rate, employment status, intensity of past smoking behavior, craving for smoking, need for quitting, and self-efficacy are found to be significant covariates.

Looking at the rate of return-to-abstinence, only the change in body mass index is found to be a significant covariate with χ^2 of 7.63. H8 on the effect of the need for quitting, and H10 on the change in the lung's health level are not supported. H9 on the effect of change in the body mass index is strongly supported. As the subjects are composed of all females, the effect of the body mass index change seems to be understandable. The subjects are likely to be sensitive to weight, which is related to the body mass index. To sum up the findings for a return-to-abstinence rate, change in body mass index is found to be another significant covariate.

This study used the transition rate analysis to model the dynamic process of a smoking cessation behavior. The model of a return to abstinence after relapse indicates the possible presence of an asymmetric process. The empirical data reveals a lack of symmetry with respect to significant covariates for each transition rate. The transition rate analysis has the advantage of modeling a relatively neglected aspect of the dynamic process. Also the use of biological corroboration will provide more reliable data than self-reports are able to.

A limitation on the study involves the measurement of the timing of events. The NCRCS ascertained the date of the event to the nearest month. Strictly speaking, the study adopting an event history analysis should specify the date of transition as accurately as possible. However, there is a trade-off between the practicality of collecting data and the faithfulness to the underlying process. It can also be noted that the number of events for a model of return-to-abstinence is quite small (N=59). As NCRCS excluded individuals who relapsed within 3 months after cessation, the study is deficient in the number of individuals of whom returned to abstinence. Thus, results from the model of the return-to-abstinence rate should be interpreted with caution and should avoid making general accusations to prevent misinterpretations be made.

References

Agresti, Alan *Categorical Data Analysis*, New York: Wiley, 1990.

Allison, P. *Event History Analysis*, Beverly Hills, CA, Sage, 1984.

Bandura, A. "Self-efficacy: Toward a Unifying Theory of Behavioral Change," *Psychological Review*, 84 (2), 1977, pp. 191-215.

Caplan, N., R. D., Cobb, S., French, J. R. P. "Relationships of Cessation of Smoking and Job Satisfaction, Personality, and Social Support," *Journal of Applied Psychology*, 60, 1975, pp. 211-219.

Carroll, G. R. "The Analysis of Discrete Dependent Variables: A Didactic Essay," *Quality and Quantity*, 17, 1983, pp. 425-460.

Clark, Robert R. *Smoking: A Social Interaction Theory of Cigarette Smoking and Quitting*, Oceanside, NY, Davor Science Pub, 1977.

Clee, Mona A. and Robert A. Wickland "Consumer Behavior and Psychological Reactance," *Journal of Consumer Research*, 6 (March), 1980, pp. 389-405.

Coleman, J.S. *Longitudinal Data Analysis*, New York, Basic Books, 1981.

Cox, D. R. "artial Likelihood," *Biometrika*, 62, 1975, pp. 269-276.

Dixon, W. J. *BMDP Statistical Software*, Berkely, CA, University of California Press, 1981.

Dunn, William L., Jr. *Motives and Incentives in Cigarette Smoking*, Williamsburg, VA, 1972.

Eisinger, Richard A. "Nicotine and Addiction to Cigarettes," *British Journal of Addiction*, 66, 1971, pp. 150-156.

Everitt, B. S. *The Analysis of Contingency Table*, London: Chapman & Hall, 1977.

Festinger, Leon *A Theory of Cognitive Dissonance*, Evanston, Row, 1957.

Freeman, John, Glenn R. Carroll, and Michael Hannan "The Liability of Newness: Age Dependence in Organizational Death Rates," *American Sociological Review*, 48, 1983, pp. 692-710.

Fishbein, Martin and Icek Ajzen *Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research*, Reading, Addison-Wesley, 1975.

Goodman, Leo A. *Analyzing Qualitative/categorical Data*, Abt Books: Cambridge, MA, 1978.

Green, Paul E. *Analyzing Multivariate Data*, Hillsdale, IL: Dryden Press, 1978.

Jarvik, K., M. E. "Biological Factors Underlying the Smoking Habit." In Jarvik et al., *Research on Smoking Behavior, NIDA Research Monograph No.17*, U.S. Department of Health, Education, and Welfare. DHEW. Publication No. (ADW) 78 581, 1977.

Joreskog, K. G. and D. Sorbom *LISREL*, Chicago: National Education Resources, 1993.

Knoke, D. and P. J. Burke *Log-linear Models*, Beverly Hills, CA, Sage, 1980.

Leventhal, Howard and Paul Cleary "The smoking Problem: A Review of Research and Theory in Behavior Risk Modification," *Psychological Bulletin*, 88, 1980, pp. 390-405.

Magidson, Jay "Multivariate Statistical Models for Categorical Data," in Richard P. Bagozzi, *Advanced Methods of Marketing Research*, Cambridge, MA, Blackwell, 1994, pp. 79-117.

Malhotra, Naresh K. "The Use of Linear Logit Models in Marketing Research," *Journal of Marketing Research*, 21, 1984, pp. 20-31.

Massy, William F., David B. Montgomery, and Donald Morrison *Stochastic Models of Buying Behavior*, Cambridge, MA, MIT Press, 1970.

Nord, Walter R. and J. Paul Peter "A Behavior Modification Perspective on Marketing," *Journal of Marketing*, 44 (2), 1980, pp. 36-50.

Pomerleau, U., Ovide, F. "Behavioral Factors in the Establishment, Maintenance, and Cessation of Smoking." In Norman A. Kransnegor, *The Behavioral Aspects of Smoking*, 1979.

Schachter, Stanley "Nisbett's paradox." In William L Dunn, Jr., *Smoking Behavior: Motives and Incentives*, Washington, V.H. Winston and Sons, 1973.

________ "Pharmacological and Psychological Determinants of Smoking," *Annals of Internal Medicine*, 88, 1978, pp. 104-114.

Swan, Gary, R.H. Roseman, S.D. Parker, and C.E. Denk "Identification of

Variables Associated with Maintenance of Nonsmoking in Ex-Smokers: The Northern California Smoking Relapse Study," Final Report, Menlo Park, CA, SRI International, 1985.

Triandis, Harry *Interpersonal Behavior*, Monterey, CA: Brooks/ Cole, 1977.

Tuma, Nancy B. and M. T. Hannan *Social Dynamics: Models and Methods*, New York: Academic Press, 1984.

Tuma, Nancy B., M. T. Hannan, and L. Groeneveld "Dynamic Analysis of Event Histories," *American Journal of Sociology*, 84, 1979, pp. 820-854.

Yi, Youjae "An Investigation into Selected Antecedents of Behavior Modification," *Seoul Journal of Business*, 2, 1996, pp. 165-187.