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Drinking Trajectories Following an Initial Lapse

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Abstract

Relapse following alcohol treatment is a major problem for individuals who are alcohol dependent, yet little is known about the course of drinking after the initial lapse. In the current study, discrete-time survival analysis and latent growth mixture modeling were used to evaluate the time to first lapse and the trajectories of post-lapse drinking in a sample of 563 individuals who received community alcohol treatment. Results showed a decreasing risk of lapsing over time. After the initial lapse, three trajectory subgroups provided a parsimonious representation of the heterogeneity in post-lapse drinking frequency and quantity, with the majority of individuals reporting light, infrequent drinking. Covariate analyses incorporating demographics, distal risk factors, time-to-first lapse, and coping behavior as predictors of time-to-lapse and post-lapse drinking trajectories indicated alcohol dependence and coping behavior were the strongest predictors of lapsing and post-lapse drinking behavior.

KEYWORDS: alcohol treatment outcomes, relapse, growth mixture modeling, post-treatment drinking trajectories, alcohol dependence

Drinking Trajectories Following the Initial Post-Treatment Lapse

Approximately 17.6 million Americans meet criteria for alcohol abuse or dependence (Grant, Dawson, Stinson, Chou, Dufour, & Pickering, 2004), and 12.5% of individuals who meet criteria for alcohol abuse or dependence (2.2 million Americans) will receive treatment for an alcohol problem (National Institute of Alcohol Abuse and Alcoholism, NIAAA, 1998). Of those who receive treatment, the majority of individuals will have at least one drink in the first 12-months following treatment (Maisto, Pollock, Cornelius, Lynch, & Martin, 2003), yet few studies have examined what happens after the initial post-treatment lapse (Stout, 2000). To our knowledge no empirical studies have systematically quantified individual patterns of drinking following the initial post-treatment drinking episode. Considering the majority of individuals do lapse following treatment, it is important to gain a better understanding of the drinking patterns following an initial lapse. Furthermore, can the frequency and severity of drinking following a lapse episode be predicted from pre-treatment characteristics?

Understanding Alcohol Lapses

The high likelihood of a lapse following treatment has been described by several authors (Donovan, 1996; Hunt et al., 1977; Sutton, 1977). Detailed investigations of the relapse process have highlighted the large variation in drinking behavior between individuals (Delucchi, Matzger & Weisner, 2004), as well as the erratic drinking behavior within individuals over time (Warren, Hawkins & Sprott, 2003). Yet, very little is known about the variation in post-lapse drinking patterns and how these patterns may be predicted from pre-treatment characteristics.

Several biological, physiological, and psychosocial factors have been put forward as potential risk factors in the relapse process. Shiffman (1989) and others (Donovan, 1996; Witkiewitz & Marlatt, 2004) have classified risk factors based on their timing and mechanisms of action in predicting lapses. *Distal risks* are factors that present an underlying susceptibility to heavy drinking, including family history of alcohol use disorders (Craig, Krishna & Poniarski, 1997), age of first drink (McGue, Iacono, Legrand, Malone, & Elkins, 2001), and severity of physical dependence (Heather, Stallard, & Tebbutt, 1991). Unlike distal risk, which is stable over time and presents a constant level of risk, *proximal risks* are considered malleable and often act as a catalyst or immediate trigger of alcohol craving, alcohol-seeking, or alcohol use (Brownell et al., 1986; Chung et al., 2001; Marlatt & Gordon, 1985; Shiffman, 1989; Witkiewitz & Marlatt, 2004). One proximal risk factor, ineffective coping behavior, is particularly troubling because individuals who are unable to implement effective coping strategies are more likely to use alcohol as a means to cope with a variety of high-risk situations (e.g., negative affective states, social pressure to drink, the presence of alcohol cues; see Chung, Langenbucher, Labouvie, Pandina, & Moos, 2001; Cooper, Frone, Russell, & Mudar, 1995; Litt, Kadden, Cooney, & Kabela, 2003; Timko, Finney, & Moos, 2005). The importance of coping behavior in preventing relapse has led to the implementation of coping skills training as a major component of nearly all empirically-supported treatments for alcohol use disorders (Kadden & Cooney, 2005). Yet, there is scant evidence that implementation of effective coping strategies following coping skills training is a mediating mechanism of improved outcomes (e.g., Litt et al., 2002; Morganstern & Longabaugh, 2000). Given these discrepant findings it is critical to gain a better understanding of individual variation in the coping-drinking relationship following treatment.

Identifying Heterogeneity in the Lapse Process

Over the past decade social scientists have moved in the direction of using advanced longitudinal data analytic techniques (Collins & Sayer, 2001) to investigate the course of human behavior across time. Recently, methodology has been developed that allows researchers great flexibility in the parameterization of population heterogeneity beyond the conventional mixed effects models. Unlike structural equation models, these new models combine both *person-centered* and *variable-centered* approaches (Bates, 2000; Muthén, 2000; Nagin & Tremblay, 2001). Longitudinal variable-centered approaches describe the relationships between variables in the prediction of outcomes modeled as a function of time and covariates. Longitudinal person-centered approaches describe the relationships between people by exploring the similarities and differences in response patterns over time across individuals. Latent growth mixture modeling (Muthén, 2001; Muthén & Shedden, 1999) provides a combined modeling focus by identifying discrete typologies of mean growth trajectories in the population (using a categorical latent variable with categories often referred to as latent classes or mixture components) as well as individual heterogeneity within each trajectory type (using continuous latent variables as random effects). Furthermore, measured covariates of both trajectory type and variability within type can be investigated (Muthén, 2001), although covariates are not needed to fit the model. Growth mixture modeling has been applied to several areas of clinical psychology, such as delinquency (Raskin-White, Bates & Buyske, 2001); conduct disorder (Schaeffer, Petras, Ialongo, Poduska, & Kellam, 2003); and substance abuse (Colder, Campbell, Ruel, Richardson, Flay, 2002; Hill, White, Chung, Hawkins, & Catalano, 2000; Jackson & Sher, 2006; Li, Duncan, & Hops, 2001; Orlando, Tucker, Ellickson, & Klein, 2004; Raskin-White, Johnson, & Buyske, 2000).

The current study aims to delineate patterns in post-treatment drinking behavior using a sample of individuals who reported on monthly alcohol consumption during the first 12 months following community alcohol treatment. The first goal of the present study was to use discrete-time survival analysis to assess the time-to-first-lapse following alcohol treatment. The second goal was to use latent growth mixture modeling to investigate common patterns and individual differences in trajectories of drinking after the initial post-treatment drink. The third goal was to describe differences in time-to-lapse and post-lapse drinking trajectories using relapse risk factors as predictors within a general latent variable framework (Muthén, 2001). In the current investigation we used growth mixture models to identify common trajectories (each with its own normally distributed growth process) and then investigate hypotheses that individual membership in trajectory sub-groupings as well as the individual variability in level and shape of the trajectories would be associated with distal risk factors, time-to-first lapse, and coping behavior.

Current Study

Method

The data for this study is from the Relapse Replication and Extension Project (RREP; Lowman, Allen, Stout, & the Relapse Research Group, 1996) which was sponsored by the NIAAA and conducted by researchers at three research sites: Brown University (Providence, Rhode Island), Research Institute on Addictions (Buffalo, New York), and the University of New Mexico (Albuquerque, New Mexico). All three sites met the shared design elements requested by the NIAAA including identical assessment measures and the inclusion of research participants treated in standard treatment programs.

Participants. In order to be eligible for participation in the RREP, recruited individuals needed to meet the following criteria: at least 18 years of age (21 at RIA); meet Diagnostic Interview Survey criteria for alcohol abuse or dependence within the past 6 months without more severe concurrent drug diagnoses; not have used intravenous drugs within the past 6 months; not have major comorbid psychiatric diagnoses; and provide informed consent to participate.

The total sample size of the RREP was 563 participants. Brown recruited 300 participants from six facilities in the Providence area, RIA recruited 142 participants from eight programs in the Buffalo area, and UNM recruited 121 participants from one outpatient program in the Albuquerque area. Combined across all three sites, the participants were 41.2% female; ranged in age from 18 to 64 years old (M = 34.33, SD = 8.72); and identified as Caucasian (67.3%), African American (16.0%), Hispanic (8.9%), American Indian (2.6%), and “other” (5.2%).

Measures. Baseline assessments were conducted during the admission process and the assessment intervals were based on a post-admission timeline. Drinking frequency was assessed bi-monthly for twelve months following admission. Demographics and distal risk factors (e.g., family history of abuse) were assessed at baseline only, and proximal risk factors (e.g., coping skills) were assessed at baseline, 6- and 12-months following admission. Only the instruments described below were included in the primary analyses for the current study.

Pre- and post-treatment drinking behavior was assessed using the Form 90 (Miller, 1996) which gathers self-reported information on daily alcohol use between each assessment interval, beginning at three months pre-admission and assessed bi-monthly for 12 months following treatment. Frequency of drinking (Percentage of drinking days; PDD) and quantity of drinking (drinks per drinking day; DDD) were both derived from the Form-90. The reliabilities of PDD and DDD in the total sample were adequate (PDD: $\alpha = .94$; DDD: $\alpha = .90$).

Individuals in the RREP received different lengths of treatment and reported their first lapse at various times during the 12-month follow-up assessment period. Starting the growth model at intake would present a treatment length bias and starting the growth model at the end of treatment would present a time-to-first lapse bias. Thus, it was determined that calendar time did not provide an appropriate time-scale for the growth models; rather, time was defined as *the amount of time since the first lapse*. Consequently, the first time of measure for the growth process of interest was the first month following the month of first lapse. The last time of measure for the growth process was defined as the seventh month following the month of the initial lapse. The selection of the seventh post-lapse month was based on the frequency of lapsing in the first five months following treatment (61%) and thus the high frequency of individuals providing data throughout the seven months following their initial lapse. Prior to running the growth models, the time-to-first lapse for all participants was estimated using a discrete-time survival model, as described below.

Demographic characteristics (age, gender, ethnicity and years of education) and several distal risk factors (family history of alcoholism, age of first drink, and drinking history) were assessed by self-report, forced-choice, binary items on the Comprehensive Drinker Profile (CDP; Miller & Marlatt, 1984). Alcohol dependence was assessed using the Alcohol Dependence Scale (ADS), a 25-item measure of alcohol dependence symptoms (Skinner & Horn, 1984). Coping was assessed using the Coping Behaviors Inventory (CBI; Litman, Stapleton, Oppenheim, & Peleg, 1983) a measure with four subscales (positive thinking, negative thinking, avoidance or distraction, seeking social support) representing the frequency of using each type of coping behavior in order to prevent drinking. The CBI was administered at baseline, 6 months, and 12 months; and produced reliable scores at all three administrations (α = .95; .94; .95, respectively). All subscales of the CBI were averaged into a single coping composite measure for each time of administration, with higher scores indicating more frequent use of coping strategies. Each coping composite was then entered into an initial growth model with the baseline coping scores estimated as the random intercept. This coping intercept (coping at baseline) was used as a covariate in the discrete-time survival models. For the growth mixture models we estimated a second growth model of the coping scores by using time scores that estimated a random intercept at the month of first lapse. We then entered the change between the two intercepts (coping at first month of lapse subtracted from coping at baseline) as a covariate in the growth mixture models.

Data Analyses

Model estimation. The software program Mplus version 4.2 (Muthén & Muthén, 2006) was used to estimate the discrete-time survival and growth mixture models. Mplus utilizes full information maximum likelihood (FIML) estimation under the assumption of missing at random (MAR) with robust standard errors (called the MLR estimator in Mplus). Automatically generated starting values with random perturbations (100 random sets of starting values with 50 full optimizations) were used to increase confidence in the final maximum likelihood value, which was replicated in the optimized runs for all reported models (Hipp & Bauer, 2006; Muthén & Muthén, 2006).

For the discrete-time survival models we were interested in estimating the hazard probabilities for first lapse corresponding to each one-month time period beginning at treatment intake. The hazard probability for a given time period, t, is estimated by the proportion of individuals under observation who are known to have not experienced any drinking lapse prior to time period t that then experience their first drinking lapse during time period t. We were further interested in testing the effects of covariates on the hazard probabilities. Initially, we estimated a conditional model where the log hazard odds (i.e., logit hazard probabilities) varied as a linear function of the covariates. This is sometimes referred to as the proportional hazard odds model. We also assessed evidence for time-varying effects of each covariate by relaxing the proportional hazard odds constraint and using a scaled likelihood ratio test to compare fit relative to the proportional hazard odds model. (For more on discrete-time survival analysis in a latent variable framework, see Muthén & Masyn, 2005).

For the growth mixture models, the relative fit of models with varying numbers of classes were assessed using the two most accepted and widely cited methods (Bauer & Curran, 2003a; Muthén, 2003). First, models with differing number of classes were compared using the sample-size adjusted Bayesian Information Criterion (aBIC, Sclove, 1987), which is a criterion for assessing relative model fit based on the log-likelihood of the estimated model given the observed data as well as the complexity of the model based on both the number of parameters and sample size. In a recent study the aBIC was shown to be the best likelihood-based indicator of model fit for latent variable mixture models (Henson, Reise, & Kim, 2007). Second, the bootstrapped likelihood ratio test (BLRT) and adjusted likelihood ratio test (LRT) were used to test the fit of $k - 1$ classes against k classes, with a significant p-value indicating the null hypothesis of $k - 1$ classes should be rejected in favor of at least k classes (Lo, Mendell, & Rubin, 2001; McLachlan & Peel, 2000; Nylund, Muthén & Asparhouhov, in press). In addition, we evaluated the classification precision as indicated by estimated posterior class probabilities, summarized by the entropy measure given by Ramaswamy and colleagues (1993). Entropy values closer to 1.0 indicate higher classification precision. Finally, models with varying numbers of classes were evaluated and compared according to substantive utility, distinctiveness, and interpretability of the resultant class sets.

Missing data. Missing data were included in the discrete-time survival and growth mixture modeling specification using the FIML estimator with robust standard errors (MLR). Mplus version 4.2 allows for missing data that is MAR in endogenous variables. For the discrete-time survival models hazard probabilities for the entire sample (n =563) were included via MLR under the MAR assumptions and the models with covariates included those individuals with complete data on all covariates (n =439). For the growth mixture models observed drinking at each time point was endogenous to the latent growth factors, therefore the complete data of those who lapsed (*n* =395) was included via MLR under the MAR assumption. For the conditional growth mixture models two methods were used to handle missing data in the covariates. First, the complete case data on covariates were included in the growth mixture models with a total sample size of 331. Second, the multiple imputation methods developed by Schafer (1997) were incorporated into a growth mixture model in Mplus, in which covariate values were imputed where missing. Five imputed data sets were combined into a single set of parameter estimates using the average of the squared standard errors across data sets and the variation in between-analysis parameter estimation (Muthén & Muthén, 2004; Schafer, 1997). The differences between the models estimated using complete case data and the parameters estimated with multiply imputed values were negligible and the results from the complete case data are reported below.[1] There were no significant differences on any of the study variables between those with missing data and those with complete data.

Hypothesis testing. The first stage of the analyses for the current study involved estimating discrete-time survival models to determine the average hazard probabilities over time, to test the proportional hazard odds assumption for the covariate effects, and to test the significance of the covariate effects.

The second stage of the analyses consisted of estimating a series of unconditional two-part, parallel process growth mixture models for the two drinking outcomes with one model for each class enumeration (i.e., estimating one- through five-class models). The two-part modeling strategy was used because the majority of individuals were not drinking at any given time-point, even following the first lapse, thus two-parts needed to be estimated: drinking vs. not-drinking and how much/often drinking, when drinking. Essentially, a two-part model allows the researcher to simultaneously estimate a logistic growth model of binary indicators (i.e., drinking or not-drinking) with a growth model for the continuous outcomes among those who reported drinking at the time of measurement. As described by Olsen and Schafer (2001) “it is natural to view a semi-continuous response as a result of two processes, one determining whether the response is zero and the other determining the actual level if it is non-zero. The two processes are distinct and may be influenced by covariates in different ways” (p. 730).

Figure 1 provides a reduced version of the unconditional two-part parallel process model (in the estimated model all observed variables included residual variances and latent variable variances and covariances were estimated as described in this section). The quantity and frequency outcomes were linked at zero (a zero value for PDD necessarily indicated a zero value for DDD), thus only one logistic growth model was estimated for the binary indicators (any drinking vs. not). Two growth models for the continuous quantity and frequency indicators were estimated in parallel (growth models for PDD and DDD). For both DDD (quantity outcome) and the binary drinking indicator outcomes, the linear slope was sufficient to explain a significant amount of variation, but for PDD (frequency outcome) the quadratic slope was also significant and greatly improved the fit of the model to the observed data. For each class we evaluated the direction and significance of the means and variances of the random intercepts and slopes to gain a better understanding of the trajectory forms across classes. For the frequency outcomes, the variance on the quadratic factor as well as the covariances between the quadratic factor and the intercept and slope factors were fixed at zero. For the binary outcomes, variance of the slope was fixed at zero for model identification, which is often a necessary constraint in two-part models. The variances of the intercepts and linear slope factors as well as the covariance between the intercepts and linear slope factors were constrained to be class-invariant for all three processes.

For all analyses, the treatment site was incorporated into the analyses by adjusting the standard errors using a sandwich estimator for the within site dependence of observations (Muthén & Muthén, 2006). Intraclass correlation coefficients for the site effect ranged from .007 to .026 for drinking quantity (DDD) and from .005 to .037 for drinking frequency (PDD).

The third stage of analyses was designed to test specific hypotheses about the relationship between distal risk, coping, and time-to-first lapse in the prediction of drinking trajectories and trajectory class membership. The goals of the covariate analyses were twofold: (1) to assess the degree to which baseline measures and distal risk predicted trajectory class membership; and (2) to evaluate the associations of distal risk and baseline risk factors with drinking frequency and quantity *within* trajectory classes. Overall significance of each covariate in predicting class membership was tested using a scaled likelihood ratio test[2] comparing the log likelihood difference in the (null) model with a zero path from the covariate to the latent class variable with the (alternative) model with a freely estimated path from the covariate to the latent class variable. A multinomial logistic regression was used to estimate the associations between the covariate and latent class membership so each covariate association was characterized by $K-1$ regression coefficients where K was the number of latent class. Each coefficient represented the change in the log odds of being in a given class, k ($k=1,\ldots,K-1$), relative to the reference class, K, for a one unit change in the covariate. The significance of the separate regression coefficient was tested by calculating the estimated coefficient divided by its standard error and then comparing that ratio to the standard z-distribution. The sign and significance of the coefficients as well as the corresponding odds ratios and class probabilities were calculated for each covariate. In addition, we incorporated covariates as predictors of within-class variation in growth trajectories using standard linear regression. In these models, the relationship between covariates and the intercept and slope random effects were evaluated by the significance of the Wald statistic and the 95% confidence interval for each regression coefficient.

In comparison to previous longitudinal analyses of post-treatment drinking (see Godley, Dennis, Godley, & Funk, 2004; Miller, Westerberg, Harris, & Tonigan, 1996), the growth mixture modeling approach provided several advantages. Of primary focus to the current study, these models allowed for more flexible estimation of population heterogeneity in post-lapse drinking trajectories through a finite mixture of random effects, with each mixture component (latent class) representing an empirically dominant pattern of drinking behavior among a subgroup of individuals. In addition, by estimating covariate effects on the latent growth factors, rather than the drinking indicators themselves, the attenuation caused by time-specific and measurement error in observed drinking outcomes is reduced.

Results

Discrete-time Survival Model

For these analyses, the outcome event was the month in which the first lapse occurred, which was defined as the first follow-up month where PDD and DDD were greater than zero. For the unconditional survival model, the marginal hazard probabilities were highest in the first two months of follow-up (.21-.28), then .08-.13 for the third through the seventh month, and dropped to the range .03-.06 for the remaining months. For the conditional survival model, none of the covariates individually showed significant time-varying effects, so the conditional model under the proportional hazard odds assumption was retained. Model results are given in Table 1. Only ADS total score and the estimated coping intercept score at baseline were significant predictors of time-to-first-lapse. The confidence interval for the odds ratio of the ADS score included 1.00, indicating a potentially null effect of ADS on time-to-first-lapse. Higher coping scores at intake corresponded to lower hazard probabilities of lapsing during the first year of follow-up (hOR = .39). Figure 2 displays the estimated mean hazard and survival probabilities from the conditional model, as seen in the figure there is a decreasing risk of lapsing over time. Time-of-first-lapse was included as a covariate in the growth mixture models, as described next.

Latent Growth Mixture Models

All analyses were first conducted with demographic characteristics as predictors of class membership and random effects within class. Gender was significantly related to class membership and was included in all models as a covariate. No other demographic variables were related to drinking trajectories. One- to five-class two-part trajectory models were estimated using Mplus. As shown in Table 2, the three-class model appeared to strike the best balance between parsimony and fit, providing a significantly better fit than the two-class model based on the LRT/BLRT. The rate of decrease in the aBIC slows considerably comparing differences from two to three classes (ΔaBIC = 126.56) versus three to four classes (ΔaBIC = 38.09). The three-class model had the highest entropy of all class enumerations. Also, the four-class model did not fit significantly better than the three-class model based on the LRT (p = 26) or BLRT (p = .67). The five-class model also did not provide a better fit than the four-class model based on the LRT/ BLRT. Based on these empirical results along with an assessment of each of these models with regards to substantive distinctness of the resultant classes, the results from the three-class models are presented below.[3]

Shown in Figures 3a and 3b, the estimated trajectories for the 3-classes can be described as (1) a frequent heavy drinking trajectory (6%); (2) A "prolapsing" trajectory characterized by frequent drinking following the first lapse and a return to less frequent drinking (12%); and (3) an infrequent moderate drinking trajectory (82%)[4].

It is important to note that the two-part model identifies any non-drinking as a missing observation and therefore the continuous drinking trajectories are based on an individual's potential drinking outcomes, observed for those that are drinking during those time periods and unobserved for those not drinking. The data proportions for the binary (drinking vs. not-drinking) part of the two-part model indicate that roughly a quarter of those people who had an initial lapse are abstinent at any given time-point (ranging from 18% abstinent in the first post-lapse month to 26% in months five and six). These rates of abstinence are in addition to the 30% of individuals who continuously abstained during the 12 months following treatment.

Risk Factors and Lapse Trajectories: Conditional Growth Mixture Models

Four conditional three-class growth mixture models incorporating the covariates (month of first lapse, gender, family history, ADS total scores, years of drinking problem, and coping) were estimated with a variety of between-class and within-class variable constraints. In conditional Models #1 and #2 class membership was regressed on month of first lapse, gender, family history, years of drinking problem, ADS total scores, and coping using a multinomial logistic regression model within the Mplus program. This model expressed the probability that individual i is a member of class k as a function of the covariate x. Setting one of the classes as a reference class allows for estimation of the log odds of class membership for each covariate. Conditional Model #1 also included regressions of the growth parameters on the covariates, with the regression coefficients constrained to be invariant across classes. This model served as the full conditional model, which was compared to several alternative models (described below) in which parameters were systematically constrained to zero.

Overall fit and model comparisons for conditional Models #1-4 are shown in Table 2 and the individual parameter estimates for the covariate effects are shown in Table 3. Conditional

Model #1 provided the best fit to the data in comparison to the other conditional models based on aBIC and the scaled χ^2 difference tests. In conditional Model #2 the regression paths of the growth factors on the covariates were constrained at zero, providing a test of within-class differences on covariates. Conditional Model #2 fit significantly worse than conditional Model #1 (scaled χ^2diff (Δdf=30) = 107.93, $p < .0005$) indicating the importance of including the growth factor regressions in the model. Conditional Models #3 constrained the between class regressions to zero, which provided a test of the growth factors regressed on covariates without covariates predicting class membership. Model #3 also fit significantly worse than Model #1 (scaled χ^2diff (Δdf=12) = 28.57, $p = .005$). For Model #4 the regression coefficients of the growth factors and the between class membership on the covariates were constrained to zero. Model #4 fit significantly worse than Model #1 (scaled χ^2diff (Δdf=42) = 135.09, $p < .0005$).

Given all comparisons conditional Model #1 was chosen as the best representation of the observed data. As shown in Table 3, the results from Model #1 indicated several significant relationships between the covariates and the within-class growth factors. ADS score was significantly related to the within-class intercept and slope of the quantity (DDD) growth processes, indicating that higher alcohol dependence is related to heavier drinking in the first month following lapse and a greater increase in drinking quantity over time. Time-to-first-lapse was significantly related to the intercept of the frequency process, suggesting that individuals who lapse earlier are drinking more frequently in the first post-lapse month. Gender was significantly related to the intercept of the quantity process, such that males reported drinking greater amounts in the month following lapse. The change in coping over time was significantly related to the intercept of drinking frequency and the slope of drinking quantity in the negative direction, suggesting that a decrease in coping scores from baseline to the month following the first lapse was associated with more frequent drinking and a greater increase in drinking quantity over time following the first lapse. Likewise, coping was negatively related to the intercept of the categorical process indicating a decrease in coping is related to increased likelihood of drinking. All other covariate predictions were non-significant.

Results from the multinomial logistic regression of class membership regressed on the covariates indicated some differences between classes based on covariates. The odds ratios for the covariates effects on class membership from conditional Model #1 (which controlled for covariate effects on the growth factors) are provided in Table 4. Earlier lapse was associated with membership in the prolapsing class of individuals, who were drinking frequently initially and then decreased their drinking frequency over time. Individuals with higher alcohol dependence were most likely to be classified in the frequent heavy drinking class.

Discussion

The current study evaluated the time-to-lapse and individual trajectories of drinking frequency and quantity following an initial post-treatment drinking episode. We observed three common patterns of post-lapse drinking, which could be characterized as infrequent moderate drinking, prolapse drinkers (heavier drinking with decreased frequency over time), and frequent heavy drinking. The estimated post-lapse drinking trajectory class prevalence suggested that the majority of individuals were best classified as infrequent moderate drinkers or abstainers following treatment. Only a small percentage (6%) of individual's displayed a frequent heavy drinking trajectory. Another small subset of individuals returned to less frequent drinking after an initial period of sustained frequent drinking (12%). Thus, the majority of individuals report a return to abstinence or infrequent drinking following the initial lapse, and only a small percentage of individuals could be reliably classified as continuously frequent heavy drinkers following treatment.

The effects of distal risk, gender and coping scores were incorporated into the model and provided added insights into the time-to-lapse and post-lapse drinking process. Distal coping, as measured by the intercept of coping scores following treatment, was not related to the drinking growth processes within class, but did predict time-to-first-lapse. Proximal coping, assessed by the change in coping following treatment, was significantly related to within-class drinking frequency at the time of the first lapse and the change in quantity of drinking following the first lapse in the negative direction. That is, better coping skills over time were related to less frequent drinking at the time-of-first-lapse and lighter drinking over time following the first lapse.

Alcohol dependence scores were predictive of time-to-first-lapse, drinking quantity at the time of initial lapse and increase in drinking quantity over time, as well as class membership. Individuals with higher alcohol dependence scores experienced earlier lapses, had the worst drinking outcomes within class and were most likely classified as the heaviest, most frequent drinkers. Since the hazard probability of first lapse was influenced by baseline coping skills and alcohol dependence scores, there is evidence of additional indirect effects of ADS total scores and coping skills on post-lapse drinking outcomes mediated by the timing of first lapse.

Time-to-first-lapse was related to class membership: individuals who lapsed earlier had a higher probability of being classified as individuals who initially drank heavily and frequently and then reported decreased drinking frequency over time. Years of drinking problem duration and family history were not significantly related to the within class drinking outcomes and did not predict class membership. An optimistic interpretation of this finding is that individuals who have a family history or who have been suffering from a drinking problem for many years are not doomed to have the worst outcomes following treatment, although to the extent that these distal risk factors are also related to alcohol dependence is important to consider.

Implications and Limitations

The results from these analyses support a conceptualization of the relapse process as highly variable between and within individuals. Further, these results contradict the conceptualization of alcoholism as a *relapsing* condition (Litman, 1986). In all models the largest class could be described as an infrequent drinking class and only a very small proportion of the sample represented a stable frequent drinking trajectory. The results from the covariate analyses of the estimated drinking classifications are consistent with clinical intuition and previous empirical findings.

Both baseline coping and the change in coping following treatment were related to post-treatment drinking outcomes. Baseline coping predicted the time-to-first-lapse and the change in coping from baseline to the month-of-first-lapse predicted drinking frequency in the first post-lapse month and the change in drinking quantity over time. These findings highlight the importance of teaching effective coping skills during treatment, as well as the need to provide follow-up/aftercare sessions that emphasize the importance of coping skill acquisition and utilization. As described by McLellan (2002), “many of those who develop addiction disorders suffer multiple relapses following treatments and are thought to retain a continuing vulnerability to relapse for years or perhaps a lifetime” (p. 249). McLellan (2002) suggests alcohol dependence and addiction, in general, may be more accurately treated using a chronic illness model, in which continuing care is necessary to maintain long-term successful outcomes. The findings from the current study support the observations of McLellan (2002) and others (Maisto, Sobell & Sobell, 1980) who have emphasized the importance of post-treatment aftercare.

Based on the current study and previous research we suggest coping skills training be a major focus of aftercare interventions. McKay and colleagues (1996) identified coping strategies as being critical in the promotion of abstinence and termination of lapses in a sample of alcohol dependent males followed for 30-months. Coping has also been shown to be a predictor of stable remission from an alcohol use disorder over a 16-year period (Moos & Moos, 2005, 2006).

One limitation of the current study is the reliance on the information provided by the RREP data. The self-report instruments used in the RREP to assess the domains of relapse risk factors and drinking outcomes may not provide the most accurate depiction of the complex forces interacting within a relapsing system. For example, the Form 90 uses retrospective information for measuring drinking behavior and studies have shown that an individual's reconstruction of behavior may contain biases (Bradburn, Rips, Shevell, 1987). It is possible that some variability in drinking trajectories could be explained by self-report bias.

The results from the growth mixture analyses presented in this study need to be interpreted with a certain amount of caution (Bauer & Curran, 2003a; Bauer & Curran, 2004). In general, we regard our modeling approach as exploratory and all of the estimated models need to be replicated in a new dataset, preferably by different investigators. One of the main limitations of mixture modeling, and other statistical techniques, is the inability of researchers to ever know the "true" underlying distribution in the population (Cudeck & Henly, 2003). Rather, growth mixture models can be used to approximate the true structure of the data, but the resulting model will always be making an approximation. We view the analyses conducted in the current study as one approach of many that may prove useful in studying drinking patterns over time and as stated by Bauer and Curran (2003b): "All of our models are wrong, and it is quite possible that there is no 'right' model to discern whatsoever. The real task at hand is to decide which model is most useful" (p. 388). The goal of the current analyses was to summarize and evaluate models of post-treatment drinking behavior. The growth mixture models presented in this study provide an interesting and potentially useful representation of the population heterogeneity in the relapse process. The usefulness of these results does not hinge on whether the trajectory subgroups we reported reflect "true" or actual subpopulations of post-lapse drinkers. Furthermore, these results are consistent with theories of relapse (Donovan, 1996) and provide direction for future research.

Future Directions

This study focused specifically on drinking frequency and quantity however models of drinking-related problems could also be estimated with growth mixture models. An important extension of the current study is to examine other substances and non-substance relapse using growth mixture modeling. There are many methodological possibilities for future research using the analytic techniques presented in this study. For example, these techniques could be applied to momentary data, where a single individual is measured over several time-points on multiple days. Modeling relapse using a general latent variable modeling framework allows for several additional hypotheses to be tested using a variety of different model specifications. For example, piecewise growth mixture modeling could be used to measure discontinuity in growth trajectories (see Colder et al., 2002), which would allow for a test of drinking trajectories that is consistent with the hypotheses of discontinuous models of alcohol relapse (Hufford et al., 2003).

In summary, growth mixture modeling techniques can help identify multiple trajectory profiles of post-treatment drinking based on relapse risk factors. Based on these results, coping skills training should continue to be a major focus of relapse prevention and aftercare interventions. Individuals with higher alcohol dependence scores should either be provided more intensive treatment, more aftercare options, or advised of the potential for a poor prognosis given their alcohol dependence. With a basic consideration of the dynamic relationship between risk factors and relapse vulnerability, researchers and clinicians may design experimental studies and treatments accordingly.

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Footnotes

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[1] Results from the multiple imputation are available from the first author.

[2] A scaled likelihood ratio test is necessary when testing the difference in log likelihoods from nested models estimated using robust maximum likelihood procedures (Muthén & Muthén, 2006).

[3] Results from the 1-, 2-, 3-, and 5-class models are available from the first author.

[4] The “moderate drinking trajectory” was defined as a midpoint between the infrequent and frequent drinking trajectories and does not necessarily reflect the definition of moderate drinking provided by NIAAA (see Dufour, 1999) or the Department of Health and Human Services (DHHS, 1995).

Table 1

Hazard Odds Ratios (95% Confidence Intervals) for Time-to-First-Lapse (LL = -862.25, # free parameters = 17)

Covariate	hOR	95% CI
Gender	1.15	(0.89, 1.49)
Family history	0.99	(0.98, 1.01)
Years of drinking problem	1.02	(1.00, 1.03)
ADS Total scores	0.99*	(0.97, 0.99)
Coping at baseline	0.39*	(0.21, 0.71)

Note. * $p < 0.05$; *hOR* = Hazard Odds Ratio.

Table 2

Model Fit for Two-Part Parallel Process Latent Growth Mixture Models

Outcome k-class model	Log-likelihood (# free parameters)	Entropy	aBIC	LRT	BLRT p-value
1-class	-6942.38 (32)	--	13985.84	--	--
2-class	-6853.77 (40)	.66	13833.90	173.78, p < .0005	177.21, p < .0005
3-class	-6777.86 (48)	.80	13707.34	154.88, p = .005	157.94, p <.0005
4-class	-6746.18 (56)	.70	13669.25	72.35, p = .26	73.78, p = .67
5-class	-6698.79 (64)	.71	13599.72	104.86, p = .08	106.93, p = .67
Nested Model Comparisons	**Log-likelihood (# free parameters)**	**Entropy**	**aBIC**	**Scaling Factor**	**Scaled χ^2 difference vs. Conditional #1 (df)**
Conditional #1	-5402.18 (90)	.85	11041.07	1.49	
Conditional #2	-5451.29 (60)	.85	11060.39	1.78	107.93(30), $p < .0005$
Conditional #3	-5420.68 (78)	.83	11046.51	1.52	28.57 (12), $p = .005$
Conditional #4	-5478.89 (48)	.84	11084.02	1.80	135.09(42), $p < .0005$

*Note. a*BIC = sample size adjusted Bayesian Information Criterion; LRT = adjusted likelihood ratio test; BLRT = bootstrapped likelihood ratio test. For aBIC, smaller values indicate a better fitting model. Conditional model #1 includes both class membership and growth factors regressed on covariates; conditional model #2 includes only class membership regressed on covariates; conditional model #3 includes only growth factors regressed on covariates; for conditional model #4 the regression coefficients of the growth factors and the between class membership on the covariates were constrained to zero. Scaled χ2 difference testing for nested conditional models based on formulas given by Satorra and Bentler (1999), see http://www.statmodel.com/chidiff.shtml (last accessed June 17, 2007) for details.

Table 3

Parameter Estimates for Growth Factors Regressed on Covariates

	Continuous Process				Categorical Process
	PDD Intercept	PDD Slope	DDD Intercept	DDD Slope	Intercept
Covariate	B (SE)	B (SE)	B (SE)	B (SE)	B (SE)
Gender	-.04 (.04)	-.01 (.01)	-2.94 (1.13)*	-.08(.26)	-.28 (.36)
Family history	.002 (.003)	-.001 (.001)	.004 (.05)	-.02 (.01)	-.01 (.02)
Years of drinking	.00 (.002)	.00 (.001)	-.002 (.07)	.00 (.02)	.01 (.02)
ADS total scores	.003 (.003)	.001 (.001)	.22 (.08)*	.03 (.02)*	.03 (.02)
Month of lapse	.02 (.01)*	-.002 (.003)	-.01 (.22)	.07 (.08)	.11 (.08)
Coping	-.09 (.02)*	-.004 (.01)	.41 (.58)	-.28 (.16)*	-.87 (.22)*

Note. * $p < .05$; B = unstandardized regression coefficient, SE = standard error, PDD = % drinking days; DDD = Drinks per drinking day

Table 4

Odds Ratios (95% confidence intervals) for Comparisons between Three Trajectory Sub-Groups

Covariates	Infrequent moderate drinking vs. prolapse drinking reference group	Frequent heavy drinking vs. prolapse drinking reference group	Infrequent moderate drinking vs. frequent heavy drinking reference group
Gender	1.34 (.60 – 2.99)	.55 (.10 – 3.06)	2.47 (.52 – 11.58)
Family history	.98 (.93 – 1.03)	.99 (.92 – 1.06)	.99 (.94 – 1.04)
Years of drinking problem	1.00 (.95 – 1.06)	.99 (.91 – 1.08)	1.01 (.94 – 1.08)
ADS Total scores	1.02 (.97 – 1.07)	1.12 (1.02 – 1.23)*	.91 (.84 – .98)*
Month of first lapse	1.67 (1.24 – 2.25)*	1.61 (1.10 - 2.37)*	1.03 (.80 – 1.34)
Coping	.82 (.47 – 1.41)	1.03 (.46 – 2.31)	.79 (.39 – 1.58)

Note. * $p < .05$

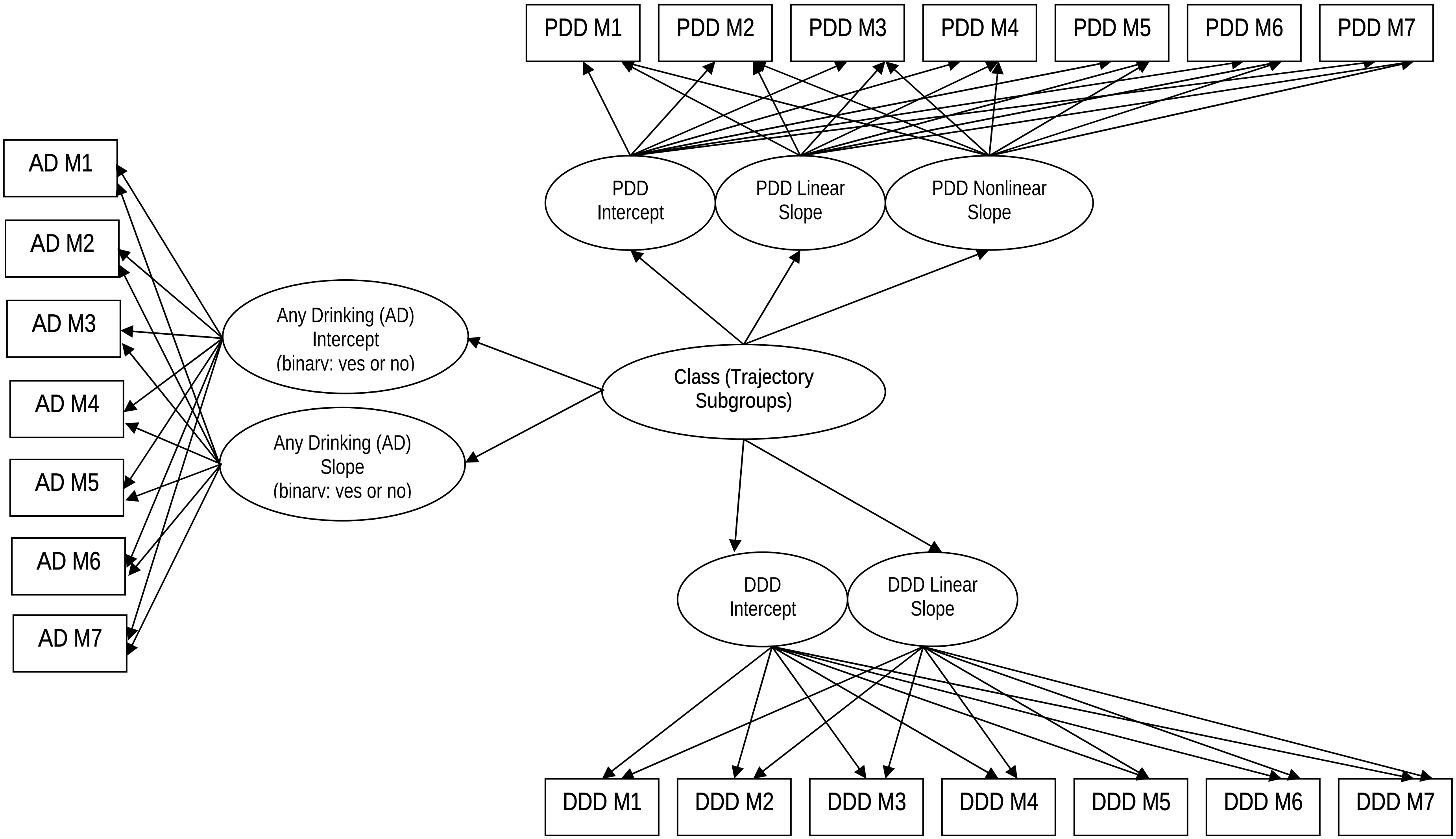
Figure Captions

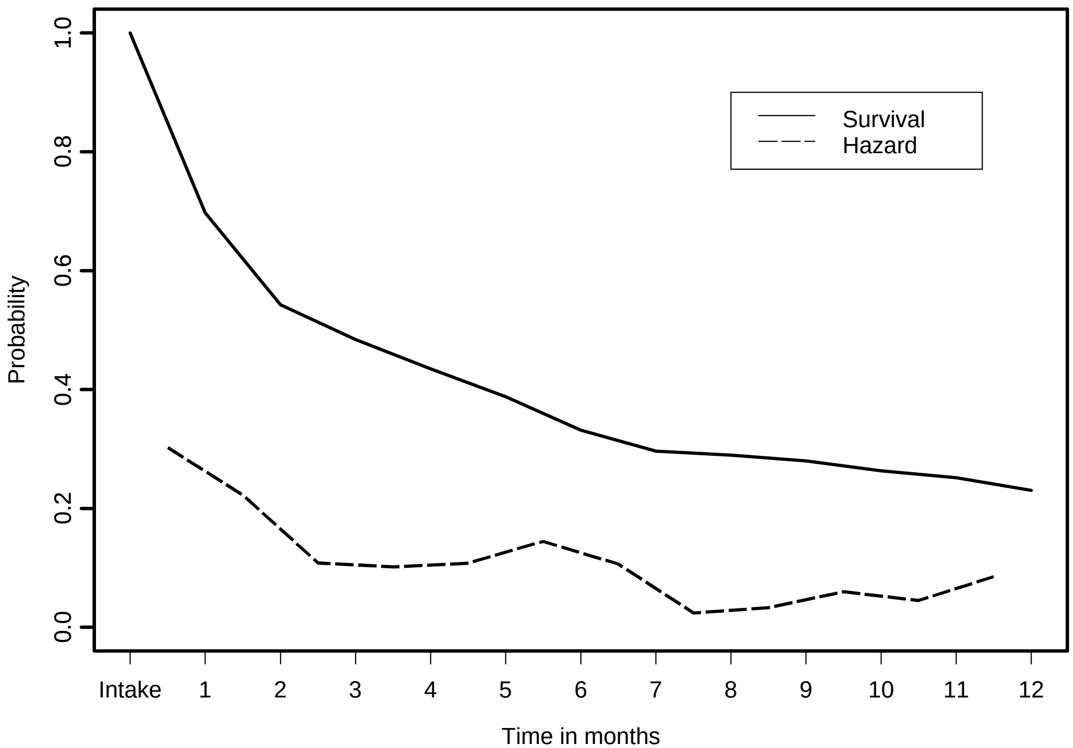
Figure 1. Unconditional two-part, parallel process growth mixture model

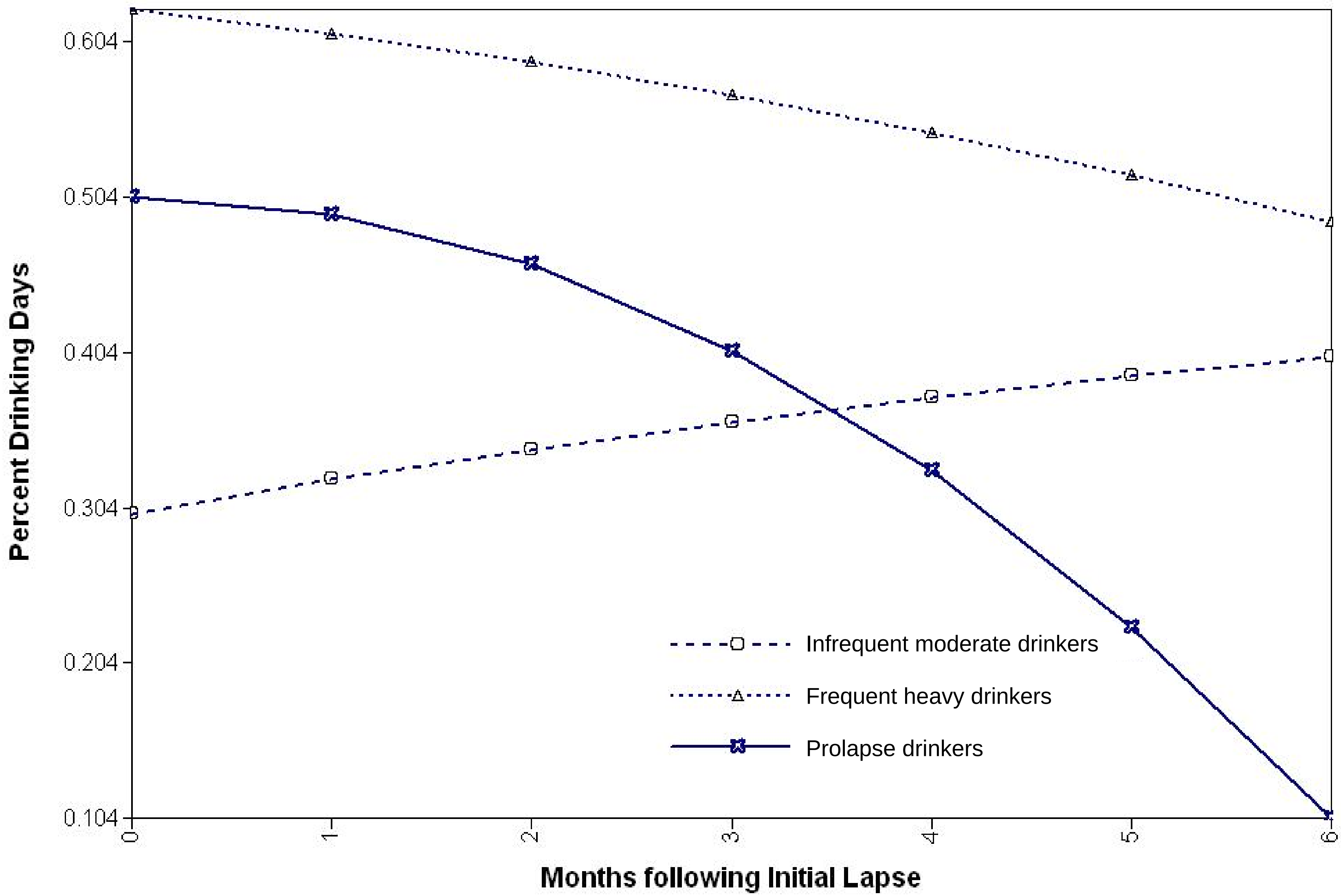
Figure 2. Estimated mean hazard and survival probabilities for time-to-first-lapse

Figure 3a. Trajectory subgroups for 3-class growth mixture model - percent drinking days (PDD)

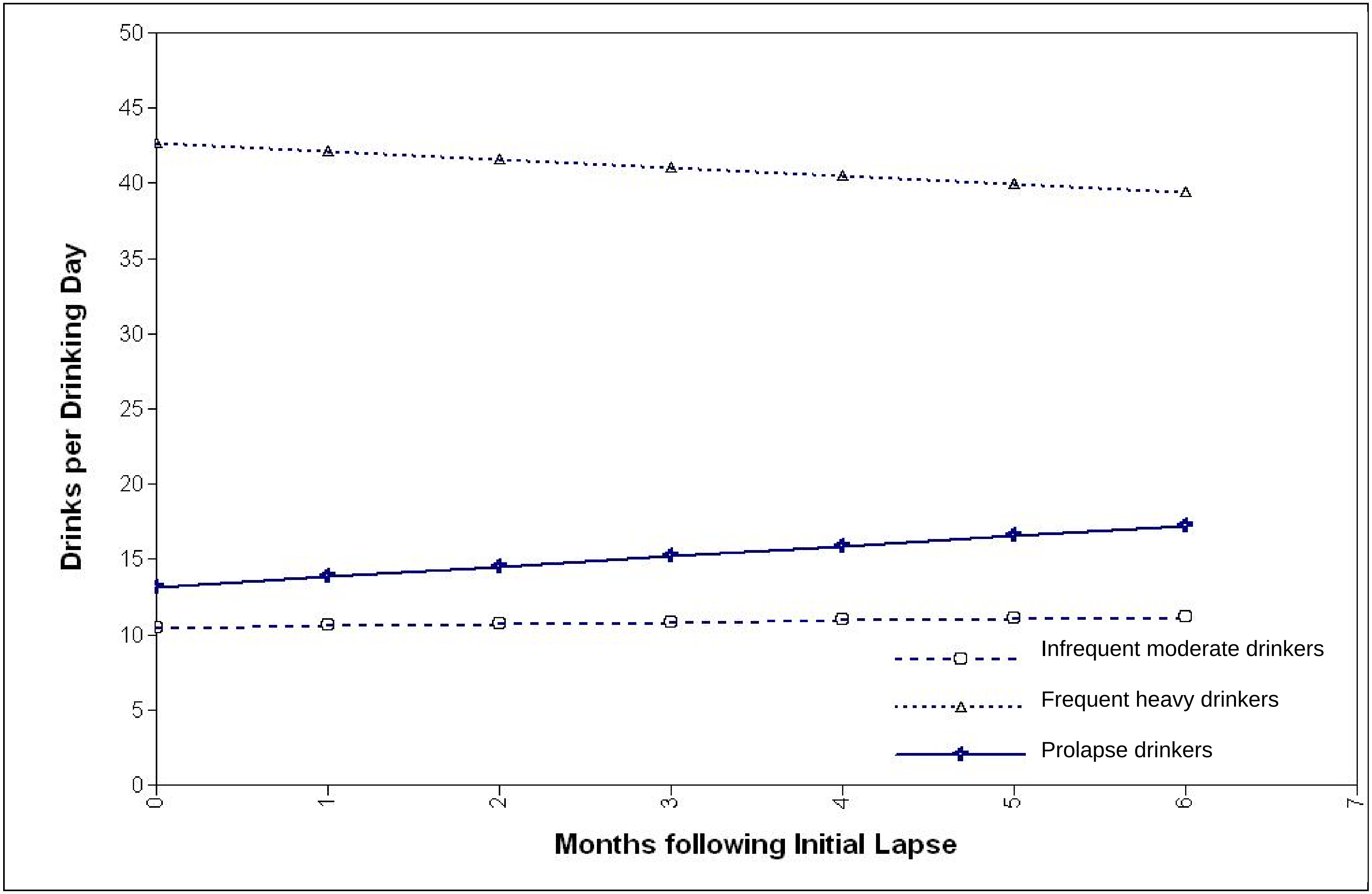
Figure 3b. Trajectory subgroups for 3-class growth mixture model – drinks per drinking day (DDD)


PDD M1
PDD M2
PDD M3
PDD M4
PDD M5
PDD M6
PDD M7
PDD Intercept
PDD Linear Slope
PDD Nonlinear Slope
AD M1
AD M2
AD M3
AD M4
AD M5
AD M6
AD M7
Any Drinking (AD) Intercept (binary: yes or no)
Any Drinking (AD) Slope (binary: yes or no)
Class (Trajectory Subgroups)
DDD Intercept
DDD Linear Slope
DDD M1
DDD M2
DDD M3
DDD M4
DDD M5
DDD M6
DDD M7


Survival
Hazard
Probability
0.0
0.2
0.4
0.6
0.8
1.0
Intake
1
2
3
4
5
6
7
8
9
10
11
12
Time in months



Percent Drinking Days
0.604
0.504
0.404
0.304
0.204
0.104
0
1
2
3
4
5
6
Months following Initial Lapse
Infrequent moderate drinkers
Frequent heavy drinkers
Prolapse drinkers


Drinks per Drinking Day
50
45
40
35
30
25
20
15
10
5
0
0
1
2
3
4
5
6
7
Months following Initial Lapse
Infrequent moderate drinkers
Frequent heavy drinkers
Prolapse drinkers