Published in final edited form as:

J Abnorm Psychol. 2007 May ; 116(2): 378–394.

Nonnormality and Divergence in Posttreatment Alcohol Use:

Reexamining the Project MATCH Data “Another Way”

Katie Witkiewitz,

Department of Psychology, University of Illinois at Chicago

Han L. J. van der Maas,

Department of Psychology, University of Amsterdam

Michael R. Hufford, and

invivodata Corporation

G. Alan Marlatt

Addictive Behaviors Research Center, Department of Psychology, University of Washington.

Abstract

Alcohol lapses are the modal outcome following treatment for alcohol use disorders, yet many alcohol researchers have encountered limited success in the prediction and prevention of relapse. One hypothesis is that lapses are unpredictable, but another possibility is the complexity of the relapse process is not captured by traditional statistical methods. Data from Project Matching Alcohol Treatments to Client Heterogeneity (Project MATCH), a multisite alcohol treatment study, were reanalyzed with 2 statistical methodologies: catastrophe and 2-part growth mixture modeling. Drawing on previous investigations of self-efficacy as a dynamic predictor of relapse, the current study revisits the self-efficacy matching hypothesis, which was not statistically supported in Project MATCH. Results from both the catastrophe and growth mixture analyses demonstrated a dynamic relationship between self-efficacy and drinking outcomes. The growth mixture analyses provided evidence in support of the original matching hypothesis: Individuals with lower self-efficacy who received cognitive behavior therapy drank far less frequently than did those with low self-efficacy who received motivational therapy. These results highlight the dynamical nature of the relapse process and the importance of the use of methodologies that accommodate this complexity when evaluating treatment outcomes.

Keywords

alcohol relapse; drinking trajectories; growth mixture modeling; catastrophe modeling; self-efficacy

Alcohol relapse has been described as a discrete phenomenon and as a process of behavior change (Brownell, Marlatt, Lichtenstein, & Wilson, 1986; Miller, 1996). More recent conceptualizations of relapse have defined *lapse* as the initial setback (e.g., a discrete drinking episode) after a period of abstinence, *prolapse* as a return to abstinence or moderate drinking goals, and *relapse* as a dynamic process of continual lapses and prolapses (e.g., Donovan, 1996; Witkiewitz & Marlatt, 2004). The characterization of the alcohol relapse process as a dynamic and “complex” phenomenon has been described by several authors (Brownell et al., 1986; Hufford, Witkiewitz, Shields, Kodya, & Caruso, 2003; Marlatt, 1996; Shiffman, 1989), yet the most commonly used statistical analyses to assess alcohol treatment outcomes (e.g., multiple regression, repeated measures analysis of variance [ANOVA]) do not account for

complexity in the observed data. For example, the use of a continuous linear model a unit change in some risk factor predicts a unit change in drinking behavior, but in reality an ostensibly insignificant change in risk often corresponds with sudden changes in drinking. Drawing from this clinical and empirical observation, we propose that the alcohol relapse process is best characterized as a nonlinear dynamical system, and we evaluate two methods for testing dynamical models of alcohol consumption following treatment.

The complexity of the alcohol relapse process is easily observed by examining the between and within-person distributions of post-treatment drinking frequency. Figure 1A is the observed frequencies for percentage of drinking days in the 12th month following treatment for 478 people who had at least one drink. Figure 1B is an image of the observed trajectories of percentage of drinking days (rescaled on a 0 to 1.0 scale) in a random sample of 50 (out of 478) people longitudinally over the first 12 months following treatment. As seen in these graphs, there is significant heterogeneity in drinking behavior between and within individuals. Aggregating these data (between individuals or within individuals across time) for the purpose of statistical analysis produces sampling distributions that are highly skewed.

Researchers may adjust for the nonnormality in treatment outcomes, either by dichotomizing their data and then relying on an *any drinking* definition of relapse or by using mathematical transformations (e.g., arcsine transformation; Project MATCH Research Group, 1997). Both of these adjustments are problematic: An *any drinking* definition of relapse has lower predictive validity and clinical utility (Maisto, Pollock, Cornelius, Lynch, & Martin, 2003; Witkiewitz, 2005), and scale-free mathematical transformations do not eliminate floor or ceiling effects in a sampling distribution and thus violate many assumptions of commonly used statistical tests. Alternative distributions (e.g., zero-inflated Poisson models) or alternative methods (e.g., event history or mixture models) may be more appropriate. More important, the fact that drinking outcomes are often highly skewed with floor effects (e.g., nondrinking) is clinically meaningful. By transforming the drinking outcome variables and/or by using the wrong statistical analyses to assess drinking outcomes, the behavior of interest is not accurately characterized by the analyses of the observed data. Given the nonnormality of posttreatment drinking, it is possible that the statistical methods used to test alcohol treatment hypotheses are not sensitive to the underlying complexity of drinking behavior.

One example of a well-conceived study with null findings was a large multisite investigation, Project Matching Alcohol Treatments to Client Heterogeneity (Project MATCH), which was designed to test 16 empirically based a priori “matching hypotheses.” Each hypothesized match included one or more pretreatment client attributes interacting with treatment assignment (cognitive-behavioral [CBT], motivation enhancement [MET], or 12-step facilitation [TSF]) in the prediction of posttreatment response. The analysis of the MATCH data demonstrated all three treatments were equally effective in reducing alcohol use, however only one of the 16 primary hypotheses was supported. Project MATCH was “the largest, statistically most powerful, psychotherapy trial ever conducted” (Project MATCH Research Group, 1997, p. 25), and the lack of empirical support for the majority of primary and secondary matching hypotheses elicited a great deal of discontent. As part of their response to the widespread disappointment, the Project MATCH Research Group (1999) stated: “[I]f only we had examined the data in another way, the results might have been different” (p. 69). The current study was designed to test two different, but complementary, statistical methods for analyzing the Project MATCH data “in another way.” More specifically, we were interested in examining whether the use of analyses that treated the relapse process as a nonlinear dynamical system would improve our ability to test one of the proposed matching hypotheses.

Alternative Characterizations of Drinking Outcomes: Dynamical Systems Models

As described above, drinking outcome data may be uniquely suited for two alternative methodologies that do not require multivariate normal distributions: latent growth mixture modeling (LGMM) and catastrophe models (CT). As described below, LGMM and CT are based in two different traditions, yet both approaches fit within the paradigm of nonlinear dynamical systems modeling (van der Maas, in press). This section provides a brief overview of each modeling approach.

Latent Growth Mixture Modeling

The estimation of LGMM is an extension of finite mixture modeling (see B. Muthén & Shedden, 1999), with the addition of a continuous latent growth process. Basically, LGMM attempts to identify common patterns of growth across time. In traditional latent growth curve modeling, it is assumed that all individuals in a given sample come from a single population with one mean growth pattern, and the variability around that mean growth is captured by the variance of the growth factors (i.e., random effects). LGMM allows for more than one mean growth pattern, assuming unique mean growth for each unobserved subpopulation. Empirical studies applying LGMM to alcohol use have identified four common patterns of drinking trajectories (Jackson & Sher, 2005; White, Johnson, & Buyske, 2000), characterized as nondrinking, chronic drinking, increasing and decreasing drinking over time.

In general, LGMM is becoming increasingly popular in substance abuse research (Hill, White, Chung, Hawkins, & Catalano, 2000; B. Muthén & Muthén, 2000; White et al., 2000). One explanation for why substance use is so amenable to LGMM is the tendency for substance use behavior to be bimodal, with most individuals drinking heavily or abstaining. LGMM is also a useful approach for analyzing treatment outcome data because of the tendency for there to be nonresponders or nonspecific responses across different treatment conditions, in which both nonresponders and nonspecific responses can distort specific treatment effects. For example Muthén and colleagues (2002) used LGMM to characterize the effectiveness of a school-based intervention for classroom aggression in which subgroups of individuals were initially more aggressive. LGMMs were specified that accommodated both normative (nonaggressive) and non-normative (aggressive) patterns. Another modeling approach that may be specifically applicable for treatment outcome studies is called *complier-average causal effect* (CACE) modeling, which can be used to assess mixtures of treatment effects among compliers in the treatment group as compared with potential control group compliance variability (Jo, 2002).

Catastrophe Theory (CT)

As a complement to growth mixture modeling, catastrophe modeling can be used to study nonlinear relationships between variables and discontinuity in behavior resulting from this nonlinearity (Boker, 2001; Thompson & Stewart, 2002). One type of catastrophe model, the cusp catastrophe model (Thom, 1975), may be particularly useful for characterizing the nonnormality and discontinuity often observed in treatment outcome data (Clair, 1998; Hufford et al., 2003). Catastrophe theory is based on the topology of discontinuous change (Thom, 1975), and it is used to study behavior of a system that is driven toward equilibrium states. A standard example is to consider the transformation of the chemical H₂O from a solid to a liquid state (Stewart & Peregoy, 1978), in which ice and liquid represent the two stable states. As temperature increases at a continuous rate, solid H₂O begins to melt (disequilibrium), and there is a discontinuous change from solid to liquid.

The cusp catastrophe model (one of the seven catastrophe types described by Thom, 1975, and the simplest catastrophe model that shows discontinuities), is characterized by three states: two

stable states and one unstable state. The movement between these states depends on specific critical points as well as two variables controlling those critical points. The area between the two critical points is defined as the *region of indeterminacy* because the state of the behavior cannot be known unless prior status is also known. In the water example, the critical points under normal conditions are 0°C and 100°C; however at higher and lower atmospheric pressure the critical points shift accordingly. When water changes into ice, a process called a *phase transition*, the gradual decrease in temperature generates a sudden and qualitatively distinct substance. Two distinguishing properties of phase transitions within a cusp catastrophe model are *hysteresis* and *indeterminacy*. Hysteresis is evident when the transition between stable states depends on the direction of the transition between the critical points. Indeterminacy is related to hysteresis because in between the two critical points it is impossible to know the direction of change without knowing the prior status. For example, under certain levels of pressure, ice melts at 0 °C and water freezes at -4 °C (hysteresis). Under these same circumstances, if the temperature of the water is -2 °C, then without knowledge of prior status one would not know whether the water was about to freeze or if it had just melted (indeterminacy).

As applied to alcohol relapse, it is hypothesized that at critical points of relapse risk factors there are sudden changes in drinking behavior. Thus, individuals with the same level of absolute risk may display qualitatively distinct behavior, depending on the direction of change and prior status. On the basis of this conceptualization, the alcohol relapse process is not viewed as a continuous process whereby an individual drinks incrementally greater amounts following the first lapse; rather, as others have described, the process is more discontinuous in which a person can oscillate between an initial lapse, continuous heavy drinking (relapsed), and light or nondrinking (prolapsed). Risk-factor related hysteresis and the bimodality of drinking behavior are two reasons why traditional linear models may be inappropriate for analyzing drinking outcomes. Cusp catastrophe models differ from linear modeling approaches by taking into account the variability surrounding the critical points of the cusp function, whereas traditional approaches would treat this random variation as error.

Hufford and colleagues (2003) used a cusp catastrophe model to predict 6-month drinking behavior in two samples of individuals with alcohol abuse and/or dependence. The catastrophe model was compared with a standard linear regression model, with both models including alcohol dependence, self-efficacy, depression, alcohol use severity, family history, family conflict, and stress, in the prediction of alcohol consumption 6 months following treatment. The catastrophe model provided a substantially better fit to the data, predicting greater than 50% of the variance in total alcohol consumption. The best fitting linear models predicted less than 20% of the variance in total alcohol consumption.

Hufford and colleagues (2003) conceptualized the behavioral variable as total number of drinks and the control variables as proximal and distal risk factors. *Distal risk* was defined as a predisposing factor that increases the probability of relapse, such as family history of alcoholism, comorbid substance abuse, and severity of alcohol dependence. *Proximal risk* included any factor that immediately precipitated drinking, such as emotional states, self-efficacy, level of family conflict, and psychological distress.

Using the example from Hufford et al. (2003), we provide in Figure 2 a three-dimensional representation of the relapse cusp catastrophe model. In the three-dimensional model, the upper surface represents the range of possible drinking responses (here labeled 0%-100% abstinent), and the control plane represents the range of proximal and distal risk factors. Distal risk was defined as the *splitting parameter*, which follows the *z*-axis and corresponds to greater separation of drinking behavior (called the *bifurcation set*). Proximal risk, on the *x*-axis, was defined as the *normal parameter* and predicts the direction of the change in drinking behavior,

depending on the previous state and level of the splitting parameter. If distal risk is high and proximal risk is low, then an individual is more likely to be drinking lightly or abstaining; however, if distal risk is high and proximal risk is high, then the individual is more likely to be drinking frequently. If distal risk is low, then proximal risk will be linearly related to drinking, such that a unit increase in proximal risk will correspond to the same unit increase in drinking (shown as Path A). But if distal risk is high, then proximal risk is nonlinearly related to drinking (see Figure 2) and small changes in proximal risk predicts either sudden lapse (Path B) or prolapse (Path C). In two-dimensions (for example, looking at the relationship between proximal risk and the behavior of interest at only the highest level of distal risk), the cusp catastrophe model is simply an S-shaped response function.

A review of the empirical literature and clinical experience demonstrate the qualitative characteristics of the cusp catastrophe model, as described by Thom (1975) and others (Gilmore, 1981), can be applied to the relapse catastrophe model. *Multimodality* is indicated by the presence of more than one mode of the behavior based on specific values of the control parameters. As described above, one common characteristic of alcohol treatment outcome data is the presence of strong floor effects, where the majority of individuals at any one discrete time point are not drinking and the other mode is notoriously characterized by heavier drinking patterns (Sutton, 1979). *Sudden jump*, or rapid change in behavior at degenerate critical points, is illustrated by the cliché “fall off the wagon.” In the opposite direction, Miller, Walters, and Bennett (2001) identified sudden gains, called “quantum changes,” in the process of recovery from alcohol problems.

As described above, *hysteresis* may occur when the change in the behavioral variable corresponds with different values of the control parameters, depending on the direction of the change in the value of the input variable. For example, Hodgins, el Guebaly, and Armstrong (1995) showed an increase in negative affect was related to major drinking episodes, whereas a decrease in negative affect predicted lighter drinking episodes at different levels of negative affect. *Divergence*, the dependency on initial conditions with respect to which mode of behavior is likely after the bifurcation point, is the characteristic of a catastrophe model that is most consistent with the relationship between drinking and distal risk factors. Distal risk may determine whether an individual will relapse or maintain abstinence at increasing levels of proximal risk (Hufford et al., 2003).

The current study was designed to test specific hypotheses about the dynamical nature of the relapse process and the discontinuous relationships between a specific relapse risk factor, self-efficacy, and alcohol lapses by using both growth mixture and catastrophe methodology (Hartelman, 1997; Ploeger, van der Maas, & Hartelman, 2002). To this end, the data from a multisite trial of alcohol treatment outcomes (Project MATCH Research Group, 1997) were reanalyzed to assess the following: (a) discontinuity in drinking behavior at baseline, 6- and 12-months following treatment; (b) the patterns of drinking trajectories following treatment; and (c) the relationship between one of the original matching hypotheses (described below) and treatment outcomes across the different treatment conditions. It was hypothesized that the two modeling approaches would provide unique, yet complementary, explanations of the observed data and that these findings would shed light on the dynamics of posttreatment drinking (LGMM provides information about within and between person drinking dynamics over time, whereas the catastrophe models assess between person dynamics at a single point in time). Further, we hypothesized that the added complexity of the analytic approach would provide a more sensitive test of the matching hypotheses than the methods originally used by Project MATCH (1997).

Specifically, we revisited the original Project MATCH matching hypothesis that clients with lower baseline self-efficacy would have better outcomes if they received cognitive-behavior

therapy (CBT) as compared with those who received motivation enhancement therapy (MET; DiClemente et al, 2001, p. 241). Individuals higher in self-efficacy were hypothesized to have good outcomes, regardless of the treatment received. This interaction was defined by treatment assignment as a moderator for the relationship between self-efficacy and drinking outcome. *Self-efficacy* is defined as the degree to which an individual feels confident and capable of performing a certain behavior in a specific situational context (Bandura, 1977), and it is a specific treatment target in CBT, but not in MET. The Project MATCH Research Group (1997) hypothesized individuals with lower baseline self-efficacy would have better outcomes following CBT than MET, to the extent that CBT was effective in targeting self-efficacy (DiClemente et al., 2001; Project MATCH Research Group, 1997).

In general, higher levels of self-efficacy are consistently predictive of improved alcohol treatment outcomes (Connors, Maisto, & Zywiak, 1996; Greenfield et al., 2000; Project MATCH Research Group, 1997); however the relationship between self-efficacy and relapse risk is likely to be more complex and predominantly reciprocal. That is, lower self-efficacy predicts increased relapse risk and experiencing a lapse will initially decrease self-efficacy for abstinence. Analyses of smoking relapse dynamics have demonstrated nonlinearity and discontinuity in the relationships between self-efficacy and urges to smoke (Gwaltney, Shiffman, Balabanis, & Paty, 2005) and changes in self-efficacy in the progression from lapse to relapse (Shiffman et al., 2000).

In the original study (Project MATCH Research Group, 1997) and follow-up analyses of the self-efficacy matching hypothesis (DiClemente et al., 2001), the results supported the expected significant relationship between baseline self-efficacy and posttreatment drinking throughout the 1-year follow-up. However, there was no evidence that this relationship was moderated by treatment assignment. Thus, there were no significant differences in posttreatment drinking between treatment groups, and the self-efficacy matching hypothesis was not supported. In a discussion of the findings, DiClemente and colleagues (2001) made the following statement: "If future research were to seek self-efficacy matching effects, very different treatment parameters or more complex and multidimensional matching hypotheses should be considered" (p. 255). The current study was designed to accomplish this goal by testing two complex models of the self-efficacy matching hypothesis and by examining the alcohol relapse process as a dynamical system.

Method

Sample

Project MATCH was designed to test the hypothesis that certain client variables would predict a differential response to three types of therapy. Participants ($n = 1,726$) were recruited from nine research units and randomly assigned to one of three treatments (CBT, 12-step facilitation [TSF], or MET). All three treatments were provided in aftercare ($n = 774$) or outpatient ($n = 952$) settings. Follow-up assessments were conducted at 3, 6, 9, 12, and 15 months after the initial therapy session.

For the current study, only those treated in the outpatient condition were included in the analyses. The primary reason for focusing on the outpatient sample is because the type of treatment and number of treatment sessions were controlled by the Project MATCH investigators, whereas the aftercare participants received varying lengths of varying types of inpatient treatment prior to their participation in the Project MATCH study. Also, there was marginal support for the self-efficacy matching hypothesis during treatment in the aftercare sample. In the outpatient sample, none of the self-efficacy matching hypotheses were supported in analyses of drinking frequency.

Measures

Alcohol consumption—The criterion variable used in this investigation was the percentage of days abstinent (PDA) assessed with the Form-90 instrument (Miller & Del Boca, 1994). The primary goal of the Form-90 interview is to gather accurate information regarding a person's drinking behavior over a 90-day period prior to the interview. The intraclass correlation coefficient for PDA in a substance abusing sample was .85. For the growth mixture analyses, the scale of the PDA variable was reversed to represent percentage of drinking days (PDD), which allowed us to treat zero as nondrinking (explained below) and values greater than zero as drinking.

Self-efficacy—The confidence score of the Alcohol Abstinence Self-Efficacy Scale (AASE; DiClemente et al., 1994) was used as the measure of self-efficacy in the current analyses. The AASE is a 20-item measure of self-reported temptations and confidence in ability to abstain across 20 hypothetical situations (e.g., “When I am being offered a drink in a social situation”). The AASE is scored using a 5-point Likert-type scale, with item responses ranging from 1 (*not at all confident*) to 5 (*extremely confident*). The internal consistency of the total AASE at baseline was good ($\alpha = .92$; DiClemente et al., 2001). The 6- and 12-month AASE scores also had good reliability (6-month: $\alpha = .98$; 12-month: $\alpha = .97$).

Statistical Analyses

The Project MATCH Research Group used two primary analysis strategies for investigating the self-efficacy patient-treatment matching hypothesis (Longabaugh & Wirtz, 2002). First, they estimated a series of latent growth curve models with self-efficacy, treatment group (CBT vs. MET), and the Self-Efficacy $\times$ Treatment Group interaction entered as covariates. The matching hypothesis was supported if the interaction and/or the interaction by time effect (linear and quadratic) were significant (Project MATCH Research Group). Second, separate tests of “causal chains” were conducted to test for mediators of the primary matching variables. For the self-efficacy matching hypothesis, the causal chain was designed to test the hypothesis that the Treatment Group $\times$ Baseline Self-Efficacy interaction would be related to the change in self-efficacy following treatment, which in turn would predict treatment outcome. For example, if the chain was supported, then individuals with low baseline self-efficacy would have better outcomes following CBT, and the better outcomes would be mediated by changes in self-efficacy.

For the current study, the cusp catastrophe models were designed to test the causal chain hypothesis by assessing (a) the extent to which individuals report qualitatively different drinking outcomes following CBT and (b) whether these different outcomes were influenced by baseline self-efficacy and the change in self-efficacy ratings following treatment. The primary self-efficacy MATCH hypothesis was tested with a two-part latent growth mixture model. The LGMM provided a test of divergence in drinking and determined whether the difference in mean growth trajectories was related to self-efficacy, treatment group, and the Treatment Group $\times$ Baseline Self-Efficacy interaction.

Catastrophe models—Catastrophe theory was originally used to describe a deterministic system (Thom, 1975), and fitting a stochastic catastrophe model to noisy data has been a challenge for researchers. It is important to note that catastrophe modeling has received a great deal of criticism (Sussman & Zahler, 1978). One of the main criticisms of previous catastrophe research is the reliance on theoretical descriptions of the behavior without empirical data or analytic tests of the hypotheses derived from catastrophe theory. Over the past 25 years, analytic approaches have been proposed for estimation of cusp catastrophe models in the behavioral sciences (Cobb, 1981; Guastello, 1982; Oliva, Desarbo, Day, & Jedidi, 1987), and these approaches have subsequently been tested and improved.

Hufford and colleagues (2003) used the Guastello (1982) polynomial regression approach because the alternative approaches required too large of a sample size, but the authors questioned the appropriateness of the polynomial regression equations as a test of the catastrophe model. Likewise, Alexander, Herbert, DeShon, and Hanges (1992) and Hartelman (1997) provided simulations of Cobb's (1981) general multivariate methodology for estimating catastrophe models (GEMCAT; see Oliva et al., 1987), and Guastello's (1982) catastrophe modeling techniques. The results from these analyses supported the Cobb approach as the superior method (Wagenmakers, van der Maas, & Molenaar, 2005), whereas the Guastello approach capitalized on chance variation in the data and tended to overfit the catastrophe regardless of the true distribution of the data. In general, the Guastello and GEMCAT techniques are limited by the fact that they are unable to distinguish stable and unstable equilibrium, which is a critical component of cusp model fitting.

The Cobb (1981) approach is a parameter estimation technique based on a multimodal probability density function. The form of the cusp (response) surface is

$$f(z | \alpha, \beta) = C(\alpha, \beta) \exp(\alpha z + \beta z^2 - 1 / 4^4), \quad (1)$$

where z indicates the behavior variable (dependent variable), β and α represent two control parameters (called the splitting and normal parameters, respectively), and $C(\alpha, \beta)$ is an integration constant (Ploeger et al., 2002). The stochastic model is estimated with maximum likelihood estimation, in which the log-likelihood is maximized through multiple iterations. Cuspsfit, a Windows executable program, improves on Cobb's method by providing greater computational efficiency and the ability to simultaneously estimate linear, logistic, and cusp catastrophe models (Hartelman, 1997). The catastrophe model fit via Cuspsfit provides a methodology to test hypotheses about the behavior of a stochastic system that is consistent with deterministic catastrophe theory (Wagenmakers, Molenaar, Grasman, Hartelman, & van der Maas, 2005) and provides an empirical test of stable and unstable states.

One of the more difficult aspects of stochastic catastrophe modeling is the identification of proper control parameters for the model. In previous studies (Hufford et al., 2003), we have experienced great success with proximal and distal risk as the normal and splitting control parameters, respectively. In the current study, we were interested in further evaluating the role of self-efficacy in the relapse process. Thus, we conceptualized baseline self-efficacy as a distal risk factor (splitting parameter) and change in self-efficacy as a proximal risk factor (normal parameter) because of the temporal relationships between the measurement of self-efficacy and lapse events, in which the change in self-efficacy was considered the most proximal to lapse. Together, both measures of self-efficacy were included as control parameters in models of baseline, 6- and 12-month drinking frequency (PDA). For the baseline model, the pretreatment self-efficacy ratings served as the only control parameter. In the 6- and 12-month models, baseline self-efficacy and the change in self-efficacy from baseline to 6- and 12-months following baseline, respectively, served as the control parameters.

The decision to use a catastrophe model, instead of other alternative nonlinear dynamical system models, was based partially on graphical exploration of the data, which demonstrated extreme bimodality in drinking behavior for relatively continuous changes in the normal parameter (self-efficacy change) over certain ranges of the splitting parameter (baseline self-efficacy). There are numerous ways to graph these data, and we present two different methods. As shown in Figure 3A, we present a kernel regression of the three-way scatterplot for 12-month PDD as the behavioral variable (higher values on the y-axis represent heavy drinking), baseline self-efficacy (z -axis), and change in self-efficacy (x -axis). The bimodality in drinking is particularly relevant for individuals with low or high baseline self-efficacy. Individuals with low baseline self-efficacy or negative change in self-efficacy (indicating lower self-efficacy after treatment) are drinking most frequently, whereas individuals with higher baseline self-

efficacy and greatest improvements in self-efficacy over time were drinking least frequently. Likewise, in Figure 3B we show the histograms for 6-month PDD for three levels of self-efficacy. As seen in Figure 3B, the bimodality is the highest for individuals who report low self-efficacy.

The linear and logistic models each included self-efficacy and change in self-efficacy as predictors of PDA. In the logistic models, PDA was divided by using a median split into two groups (low and high PDA). In the linear models, PDA was treated as a continuous variable. All models were tested separately for each treatment group. The differences between the linear, logistic, and cusp models were compared with the Bayesian information criterion (BIC; Schwarz, 1978). BIC is an information theoretic method used in model selection to approximate the amount of information lost by the estimated model given the maximum likelihood, sample size, and number of parameters in the estimated and comparison models. Lower values of BIC indicate a better fitting model, and simulations have shown that the BIC provides consistent estimates of model fit at various sample sizes (Andrews & Currim, 2003; Myung, 2000).

Growth mixture models—The software program Mplus Version 3.12 (L. Muthén & Muthén, 2004) was used to estimate the LGMMs. Mplus is a general statistical modeling program that accommodates estimation of several forms of covariance structure models, latent class models, multilevel models, growth curve models, mixture models, et cetera. For LGMM, Mplus uses maximum likelihood estimation via an accelerated expectation-maximization algorithm. Automatically generated starting values with random perturbations were used to prevent convergence to local rather than global optima.

To accommodate the large number of individuals who were not drinking at any one time point (45% abstinent at 6-months and 46% abstinent at 12-months following treatment, but only 31% abstinent at both 6- and 12-months), we used a two-part modeling approach (E. C. Brown, Catalano, Fleming, Haggerty, & Abbott, 2005; Carlin, Wolfe, Brown, & Gelman, 2002; B. Muthén, 2001; Olsen & Schafer, 2001). The first part, called the *u-part*, was a latent class growth analysis of the likelihood of being classified as a drinker or a nondrinker. The second part, called the *y-part*, was a growth mixture analysis of the continuous drinking trajectories in those individuals who were classified as drinkers in the *u-part* of the model. The *u-part* is estimated by using a latent class growth analysis to allow for both random and structural zeros (Carlin et al., 2001; B. Muthén, 2001; Olsen & Schafer, 2001). Random zeros include those individuals who drink infrequently following treatment and report no drinking at certain, but not all, time-points. Structural zeros include those individuals who never drink following treatment (although, it is important to note that individuals who never drink after treatment may still be defined by random zeros because assignment to group in the two-part model is probabilistic). The *y-part* is estimated as a growth mixture model to allow for multiple classes of continuous growth, which provides a means for testing hypotheses on the basis of individuals with similar drinking trajectories over time. The *u-* and *y-parts* (i.e., *two-part*) are estimated simultaneously within a latent growth mixture modeling framework (see B. Muthén, 2001).

The analysis of the primary matching hypothesis proposed by the original Project MATCH Research Group (1999) was examined by using the two-part growth mixture model, where the random effects in both the *y-* and *u-parts*, as well as the probability of latent class membership, were regressed on the baseline self-efficacy ratings, treatment group designation, and the Treatment Group $\times$ Self-Efficacy interaction.¹ A series of unconditional two-part growth mixture models were estimated to determine the appropriate number of classes and the shape of the growth trajectories. Alternative variance assumptions were tested systematically by constraining the variance-covariance structure to be equal across classes (class invariant) versus letting the structure vary across classes (class varying). The same alternative variance-covariance structures were tested across treatment groups within the context of a multiple-

groups analysis for the CBT versus MET group comparison. These tests were conducted to assess measurement invariance of the growth mixture model across groups and over time.

Second, a conditional two-part growth mixture model was estimated for the CBT versus MET treatment group comparison. In this model, the growth parameters were regressed on baseline self-efficacy, treatment group, and the Self-Efficacy $\times$ Treatment Group interaction. These parameters were allowed to vary across latent growth classes. In addition, a multinomial logistic regression was conducted within Mplus to assess the relationship between the self-efficacy and treatment covariates in the prediction of latent class membership. Covariates were mean centered to enhance interpretability of coefficients (Aiken & West, 1991).

For the current study, one to four class models were compared by using the BIC, classification accuracy, class prevalence greater than 5% of sample (Jackson, Sher, & Schulenberg, 2005), the Lo-Mendell-Rubin likelihood ratio test (LRT) for k versus $k - 1$ classes (Lo, Mendell, & Rubin, 2001), class interpretability and inspection of pseudoclass plots for all classes to check the scatter of observations. Classification accuracy was measured by using the entropy statistic measure given by Ramasway, DeSarbo, Reibstein, and Robinson (1993), with entropy values close to 1 (range = 0 to 1), indicating higher classification precision.

Missing data—For both the latent growth mixture and catastrophe models, the patterns of missing data and the relationship between missing data and study variables were analyzed to assess the nature of the missing data. Missing data analyses with pattern mixture models revealed nonsignificant relationships between missingness on variables included in the model and any other variables included in the analyses. There were also no systematic relationships between missingness and demographic characteristics, treatment site, or treatment assignment. Given these tests and the precedent set by previous Project MATCH analyses, data were assumed to be missing at random (MAR), and the missing data mechanism was treated as ignorable (Allison, 2002).

Cusppfit uses a quasi-Newton iteration method and will not execute if any data are missing, therefore the incomplete cases needed to be imputed or deleted. Given the robustness of case deletion under the assumption of MAR (Allison, 2002) and the sensitivity of catastrophe models to initial conditions (which may be impacted by the added uncertainty of imputed values), we chose to use the deletion method for the catastrophe analyses. All analyses in Mplus were conducted using maximum-likelihood with robust standard errors, which allows missing data under the assumption of MAR.

Results

The following section is organized by the different sets of analyses that were conducted to test the proposed models. We begin with a general description of the data. Following, we present the catastrophe analyses which provide a test of the hypothesis that drinking is discontinuous following treatment. We also conduct a test of whether self-efficacy is a factor controlling discontinuous drinking behavior in the catastrophe model and whether there are differential effects of baseline self-efficacy across the three treatment groups. Finally, we provide the results from analyses of two-part growth mixture models, which were designed to test the

¹The analysis of the moderating effects proposed by the original Project MATCH Research Group (1999) could be examined using one of two different modeling approaches. Treatment assignment and the Treatment Assignment $\times$ Baseline Self-Efficacy interaction could be treated as covariates of the random effects in a two-part growth mixture model. Alternatively, treatment assignment could be treated as a “known class” of individuals in the context of the growth mixture model, similar to a multiple-groups structural equation model (B. Muthén et al., 2002). Because there is little consensus in the field regarding which approach is preferable, we chose to conduct the analyses by using both approaches. The findings were consistent with either modeling approach, but the former approach is presented in the current study because it more closely replicates the Project MATCH analyses.

hypotheses that posttreatment drinking frequency is multimodal and unique drinking trajectories can be predicted from baseline self-efficacy and treatment assignment.

Preliminary Analyses

The means and standard deviations for PDA and the correlation between PDA and self-efficacy (r_{se}) for each time point, organized by treatment group, are presented in Table 1. Repeated measures ANOVAs were conducted to evaluate mean differences between treatment groups on posttreatment PDA with self-efficacy entered as a covariate. Consistent with the original Project MATCH analyses, the difference between treatment groups was not significant, $F(2, 833) = .34, p = .71$, and the Treatment Group $\times$ Self-Efficacy interaction was also not significant, $F(1, 833) = .68, p = .41$.

Catastrophe Models

Three models (cusp catastrophe, linear, and logistic models) were tested separately for each of the three outpatient treatment groups. For the baseline linear, logistic, and cusp models, baseline self-efficacy was entered as a predictor of baseline PDA. For the 6- and 12-month linear and logistic models, the predictors included baseline self-efficacy and the change in self-efficacy from baseline to the 6- and 12-month time points, respectively. For the 6- and 12-month cusp catastrophe models, baseline self-efficacy was entered as the splitting parameter and the change in self-efficacy from baseline to the 6- and 12-month time points were entered as the normal parameter, respectively. Lower values of BIC indicate a better fitting model and, as shown in Table 2, all three cusp models provided a better fit to the data than the comparison linear and logistic models at baseline, 6-, and 12-months posttreatment. In addition to the linear and logistic model comparisons, we also estimated each of the cusp models with the control parameters constrained to zero (a constraint that is similar to an intercept-only model in multiple regression). The results from these analyses provide further support for the influence of posttreatment self-efficacy as a control parameter in the cusp catastrophe model. As shown, the 6-month and 12-month constrained cusp models provided a worse fit to the data than the full cusp models based on the BIC. The constrained cusp model provided a better fit to the data than the full cusp model at baseline, suggesting a small influence of pretreatment self-efficacy on bimodality in drinking.

The standardized cusp coefficients for each of the catastrophe models are presented in Table 3. These coefficients represent the relative weight of each of the control parameters in relation to the observed variation around the critical points in the cusp model. As shown in Table 3, the coefficients across all treatment groups are consistently small at baseline, again suggesting very little influence of self-efficacy on the critical points of pretreatment drinking frequency. At 6- and 12-month follow-ups, the coefficients for baseline self-efficacy (β_{SE_b}) were large and in the positive direction in the CBT model. Comparatively, the coefficients for baseline self-efficacy in the MET and TSF models were near zero. For all three treatment groups, the 6- and 12-month coefficients for the proximal measures of self-efficacy (α_{SE_6-b} and α_{SE_12-b}) were large and in the positive direction, indicating greater positive changes in self-efficacy associated with higher levels of PDA (i.e., higher probability of being in the abstaining mode of the cusp).

Growth Mixture Models

Unconditional growth mixture models—The goal of the unconditional model selection procedure was to evaluate several growth mixture models by using a systematic process of increasing the number of classes, including additional growth factors, and by adjusting the variance-covariance structure on the basis of parameter estimates in models of increasing complexity. LGMMs cannot be identified without some parameter restrictions (B. Muthén & Shedden, 1999). Systematically varying parameter restrictions allows for model building,

whereas evaluating increases or decreases in model fit and overall interpretation of the estimated models.

As recommended by B. Muthén (2001), the u- and y-parts of the two-part model were first estimated separately to determine the number of classes and growth functions. Shown in Table 4, the three-class models provided a good fit to the observed data in the u- and y-part models on the basis of BIC, the entropy statistic, and significant LRT. In both models, the estimation of a fourth class did not add substantial information to the three-class models, and the frequency of class membership for the fourth class was less than 5%; thus, to avoid overextraction (Bauer & Curran, 2003), a three-class model was retained for all remaining analyses.

The u-part was specified to have random intercept and linear slope parameters, and the variance of the intercept was also estimated. For model identification the variance of the u-part slope was constrained to zero; this constraint is often needed in two-part modeling (K. Masyn, personal communication, July 11, 2006). The fit of the y-part was best with random intercept, linear, and nonlinear (quadratic) slope parameters. For model identification, the variance of the quadratic slope parameter was constrained to zero. For all models, the classes were identified by using the means of the growth factors alone, with the variance components estimated as invariant across latent classes. As is often the case in growth mixture modeling, freeing the variances across latent classes led to model nonconvergence (Colder, Campbell, Ruel, Richardson, & Flay, 2002; Jackson et al., 2005; B. Muthén, 2001). The combined two-part, three-class model was identified and provided a good fit to the observed data on the basis of entropy (.75), Vuong-Lo-Mendell-Rubin adjusted likelihood ratio test ($LRT = 204.55, p = .006$), AIC, BIC, visual inspection of pseudoclass plots (Bandein-Roche et al., 1997), and interpretability of classes.

Conditional growth mixture models—Building from the unconditional two-part model, we estimated a conditional growth mixture model to test the matching hypothesis for the self-efficacy variable in the CBT and MET conditions. Prior to estimating the conditional models with covariates, we established that the unconditional growth mixture model was invariant across groups by estimating the model with treatment assignment entered as a “known class.” The model specification was consistent across treatment groups and the fit was not appreciably worse when equality constraints were imposed, thus providing support for the hypothesis of invariance.

In the conditional model, baseline self-efficacy, treatment group, and the Treatment Group $\times$ Self-Efficacy interaction were included as predictors of the random effects in the y-parts for each of the latent classes, meaning within each latent class the relationship between the continuous growth parameters and covariates were estimated separately. To be consistent with the Project MATCH analyses, baseline PDD and the Time $\times$ Baseline PDD interaction were also included as covariates. As shown in Table 4, the overall model fit was substantially improved from the unconditional models, which were based on AIC and BIC. The entropy decreased, which is often the case in two-part models (B. Muthén, 2001). The trajectories for the CBT versus MET models are shown in Figure 4. The three classes are labeled as a *frequent drinking class* (21%), *infrequent drinking class* (69%), and an *inconsistent drinking class* (11%; percentages do not sum to 100 as a result of rounding error). Inspection of the individual observed trajectories assisted us in labeling the third class as inconsistent because individuals who had a high likelihood of being classified as “inconsistent drinkers” showed the most erratic drinking frequencies, with many people transitioning from 0% drinking days to 100% drinking days in adjacent months.

The means and standard deviations for the within-class random effects and the relationships between covariates and the random effects within classes are shown in Table 5. The top part

of Table 5 provides the means (*Ms*) and standard deviations (*SDs*) for each of the random effects within class for the y- and u-parts of the model, which were used in combination with Figure 4 to label the classes. Frequent drinkers (21% of the sample) had an average initial PDD of .73 (*SD* = .07), with a significantly increasing linear slope ($M = .03$, *SD* = .02) and a significantly decreasing quadratic slope ($M = -.004$, *SD* = .002). Thus, individuals who were most likely classified as frequent drinkers had higher PDD, increasing PDD over time with a slight quadratic decrease in PDD. Individuals likely classified as inconsistent drinkers (11% of the sample) showed no significant trends in growth over time. Individuals classified as infrequent drinkers (69%) had a very low initial PDD of .13 (*SD* = .02), significantly increasing PDD over time ($M = .02$, *SD* = .009) and significantly decreasing quadratic slope ($M = -.002$, *SD* = .001). Thus, the growth patterns of the infrequent and frequent drinking classes were very similar, albeit at very different mean initial levels, which is further supported by looking at the mean intercept of the u-part, in which the majority of infrequent drinkers are nondrinkers (u-part intercept = 0.00), and the u-part intercept for the frequent drinkers is significantly greater than 0.00 ($M = 6.44$, *SD* = 1.14).

Shown in the bottom half of Table 5, the within-class comparisons were used to evaluate the relationship between self-efficacy and drinking across treatments (CBT was coded 0 and MET is coded 1) within each drinking class. Significant estimates are interpreted as the within-class variation in growth predicted from covariates; thus within the inconsistent drinking class higher PDD was associated with MET ($B = .28$, *SE* = .18), the rate of change of PDD was greatest for CBT ($B = -.11$, *SE* = .05), and nonlinear growth was associated with being in MET ($B = .01$, *SE* = .004). Higher self-efficacy was also associated with a greater rate of change within the inconsistent drinking class ($B = .08$, *SE* = .05). No other significant effects of covariates were found within the other two classes.

Of greater relevance to the Project MATCH matching hypothesis, the between-class comparisons were used to describe differences in the relationship between self-efficacy and drinking across treatments with drinking behavior partitioned into the unique class trajectories identified by the LGMM. Comparing across classes, all three covariates were significant predictors of class assignment based on a multinomial logistic regression analysis conducted within Mplus. Compared with the inconsistent drinking class, lower self-efficacy (odds ratio [OR] = .59) and being randomly assigned to MET (OR = 3.12) increased the odds of being in the frequent drinking class. Relative to the infrequent drinking class being assigned to CBT (OR = .43) increased the odds of being in the inconsistent drinking class. Also relative to the infrequent drinking class having lower baseline self-efficacy (OR = .49), and the interaction between self-efficacy and treatment (OR = 2.34) increased the odds of being in the frequent drinking class. To further evaluate the interaction effect, Figures 5A and 5B show the centered self-efficacy variable (*x*-axis) and intercept for PDD in the growth model (*y*-axis) for the infrequent (Figure 5A) and frequent (Figure 5B) drinking classes. The interpretation of the interaction effect is the relationship between PDD and baseline self-efficacy is negative for individuals assigned to MET and positive for individuals assigned to CBT within the frequent drinking class, but not in the infrequent drinking class. Thus, among frequent drinkers, individuals with low pretreatment self-efficacy had relatively better outcomes if they were assigned to CBT, as compared with MET. Frequent drinkers with high baseline self-efficacy had better outcomes if assigned to MET.

Discussion

In the current study, we evaluated two complementary models of alcohol lapses that accommodated nonlinearity, discontinuity, and individual heterogeneity in the relapse process during the first 12 months following alcohol treatment. Consistent with previous investigations (Hufford et al., 2003), the results from these analyses provided evidence that alcohol relapse

can be characterized with nonlinear dynamical systems theory. In addition, the current results identified self-efficacy as a critical predictor of lapse dynamics.

Support for the Dynamic Model of Relapse

In the catastrophe models, the proximal measures of self-efficacy were the strongest control parameters for all models, which provides support for the hypothesis that self-efficacy is an important proximal risk factor in the relapse process (Witkiewitz & Marlatt, 2004). Secondary analyses looking at the relationship between these proximal measures of self-efficacy and posttreatment drinking trajectories within the two-part, three-class growth mixture model were conducted and the results were fully consistent with the catastrophe analyses. Specifically, changes in self-efficacy, as well as the absolute levels of self-efficacy, following treatment were significantly related to outcome, particularly in distinguishing the most frequent drinking class from the inconsistent and infrequent classes. Baseline and 6-month self-efficacy were the best predictors of class membership, with higher self-efficacy predicting a greater likelihood of membership in the infrequent drinking class, in comparison to both the frequent and inconsistent drinking classes. The self-efficacy measure at 12 months did not predict likelihood of class membership, but it was significantly related to the average growth within the infrequent drinking class. Thus, the variation in growth trajectories were predicted from earlier measures of self-efficacy (baseline and 6 months), and 12-month self-efficacy was an important predictor of drinking frequency among those who were drinking infrequently following treatment.

Synthesizing both methodologies, we hypothesize the three drinking trajectories identified in the growth mixture analyses are analogous to the three states of the relapse cusp catastrophe model. The inconsistent drinking class could be described as an “unstable state” trajectory, whereas the frequent and infrequent drinking classes represent the “stable states” of the relapse cusp model. These distinctions considered, it is interesting to revisit the role of self-efficacy as a dynamic predictor of relapse. Baseline self-efficacy was a significant predictor of the growth parameters within the frequent and infrequent drinking classes but not within the inconsistent drinking class. Looking back at the relapse cusp model in Figure 2, baseline self-efficacy as the normal parameter (distal risk) would be expected to be strongly related to drinking behavior outside of the cusp in the response surface (i.e., responses that are mostly abstinent and mostly drinking) but not strongly related to drinking within the cusp where there is discontinuity in drinking responses.

Was Project MATCH Right After All?

In the original Project MATCH analyses, there was a lack of support for nearly all of the matching hypotheses, including the hypothesis that individuals lower in baseline self-efficacy would have better outcomes if they were randomly assigned to CBT. In the current analyses we found support for this hypothesis by using two distinct, yet corresponding, statistical methodologies.

The results from the catastrophe models provided support for the Project MATCH causal chain hypothesis and also suggested that bifurcation in drinking following treatment can be characterized as a process driven by a nonlinear interaction of self-efficacy change and baseline self-efficacy. Comparing three treatment groups (CBT, MET, and TSF) at baseline and at 6- and 12-months following treatment, the configuration of self-efficacy and change in self-efficacy in a catastrophe model provided a better fit to the PDA outcome than did comparison linear and logistic models of the same parameters. An inspection of the coefficients in the cusp model across treatment groups suggested baseline self-efficacy was a valid control parameter in the CBT group, but not in the MET or TSF groups, whereas the proximal measure was a valid control parameter in both groups. We interpret this finding as support for a more complex matching hypothesis. Specifically, baseline self-efficacy is an important predictor of divergent

drinking for individuals who receive CBT. Thus, clinicians administering CBT may need to be more fully aware of a client's vulnerability to small decreases in self-efficacy.

The results from the conditional growth mixture models also provided support for the original self-efficacy matching hypotheses. Baseline self-efficacy was related to different outcomes depending on whether the individual was randomly assigned to CBT or to MET, and this relationship was moderated by levels of drinking frequency. Levels of drinking frequency were characterized by three unique patterns of growth, defined as *infrequent drinking*, *frequent drinking*, and *inconsistent drinking*. Among the frequent drinkers, individuals with lower baseline self-efficacy who were assigned to MET reported greater than 20% more drinking days on average, in comparison to the frequent drinkers who were assigned to CBT. This interaction was significant on the basis of the multinomial logistic regression analysis, and it was in the direction hypothesized by the Project MATCH Research Group. It is interesting to note that the interaction was disordinal, with the reverse relationship for the frequent drinkers assigned to CBT. Individuals who had higher levels of baseline self-efficacy and who drank frequently following treatment were drinking less frequently if they were assigned to MET in comparison to those assigned to CBT. This effect was not expected and should be followed up in future research. One explanation is the abstinence violation effect (Marlatt & Gordon, 1985), which predicts individuals who are overconfident at the beginning of treatment would experience a larger lapse when they do drink.

Of those individuals in the infrequent and inconsistent drinking classes, there were no significant Attribute $\times$ Treatment interactions, but there were interesting Class $\times$ Treatment differences. As expected, lower baseline self-efficacy was predictive of an increased likelihood of being assigned to the frequent drinking class, in comparison to both the inconsistent and the infrequent drinking classes. Increased likelihood of membership in the frequent drinking class was predicted from assignment to MET, and individuals who had been assigned to CBT had a higher likelihood of being in the inconsistent drinking class. An inspection of the individual drinking patterns in the inconsistent drinking class showed considerable unevenness and jumping within individuals across time. This Treatment $\times$ Outcome interaction would be expected from learning-based theories of cognitive-behavioral treatments (Carroll, 1996; Marlatt & Gordon, 1985), in which relapse, including lapses and prolapses, is considered a learning process. Thus, individuals are expected to make mistakes (e.g., lapse) and to learn from these mistakes (prolapse).

Limitations and Future Directions

At the time, Project MATCH was one of the most methodologically rigorous psychotherapy outcome trials ever conducted, yet there were several limitations that are relevant to the current study, primarily those related to the measurement of drinking behavior and self-efficacy. Form-90 uses retrospective, self-reported information for estimating the PDA of each participant. An individual's retrospective reconstruction of behavior and events is often shown to have biases (Bradburn, Rips, & Shevell, 1987). Recounts of relapse, in particular, may be highly influenced by a person's schemas about addictive behavior (Shiffman et al., 1997). For those who did not have a single drink following treatment it may not be difficult to recount the number of days they were abstinent (100%), but those who drank occasionally may have a much higher incidence of biased reporting. The static measurement of self-efficacy in the AASE does not provide an ideal test of self-efficacy in a dynamic context. Unfortunately, the spacing of measurements in Project MATCH did not allow us to assess the influence of self-efficacy immediately preceding lapse, which would have been a more sensitive measure of proximal risk. Future research should address these questions by using measures that incorporate the dynamics of momentary changes in self-efficacy (Gwaltney et al., 2002).

The interpretations of the results from this study need to be considered preliminary, and interpretations of the findings must be tempered by the limitations of catastrophe and growth mixture modeling (Alexander et al., 1992; Bauer & Curran, 2003; Sussman & Zahler, 1978). Catastrophe models are less parsimonious than are linear models, and the variables controlling the cusp catastrophe can be difficult to identify. That is, the definition of what controls the system may be different for each individual. In general, the research design of Project MATCH is not particularly suited for dynamical systems modeling. To provide a stronger test of relapse as a dynamical system, the behavior of the system would need to be measured over a sufficient amount of time to allow for the dynamics of the system to unfold. Ideally, a catastrophe model would be tested a priori using an experimental design (van der Maas & Molenaar, 1992).

Another major limitation of Cuspsfit was the cross-sectional nature of the data being evaluated in that we were only capable of assessing interindividual differences in drinking behavior at varying levels of self-efficacy. The theoretical tenets of catastrophe theory assume within-person changes in system states, whereas we assessed system states at the between-person level and therefore our conclusions with regard to system transitions are preliminary. Adding the growth mixture modeling allowed us to delve deeper into the intraindividual changes in drinking at varying levels of self-efficacy, but transitioning between drinking states between time points was not parameterized with the mixture model. Given these limitations, we recommend a replication of this study with other potential data structures (e.g., multiple assessments of a single individual over time) or alternative methodologies (e.g., latent Markov transition models).

Latent growth mixture models are limited by the inability of the model to empirically determine the “right” number of latent trajectory classes, if such classes exist. Rather, researchers must specify the number of latent classes and compare the fit statistics across models of different numbers of latent classes. Under some circumstances (e.g., poorly specified structural models) LGMM incorrectly rejects a one-class model, when the data are simulated from one homogeneous population (Bauer & Curran, 2003). It is also important to note that growth mixture model estimation and evaluation of model fit is a hotly debated topic, and there are widespread disagreements among researchers in the area who have yet to establish uniform guidelines for testing or evaluating mixture models (see Bauer & Curran, 2003, and the series of commentaries in the same issue of *Psychological Methods*). We have estimated and interpreted the models in the current study on the basis of the best available methods to date, but we recommend future researchers conduct a thorough literature search to determine the most recent best practices in growth mixture modeling.

Additionally, the distributional assumptions of growth mixture models are such that the random effects are assumed to be normally distributed within class, and given the high levels of nonnormality in alcohol consumption data it is always a concern that within-class normality cannot be assumed, particularly for classes with smaller numbers of individuals who are likely classified in the class (e.g., the inconsistent drinking class in the current study). In the current study, we conducted skewness and kurtosis tests of within-class normality and found the inconsistent drinking class did violate the skewness test, indicating nonnormality. To our knowledge, the robustness of the within-class normality assumption in growth mixture modeling has not been systematically studied. We are currently exploring the use of the beta distribution as an alternative for handling nonnormal data within class (Smithson & Verkuilen, 2006).

There are also mechanistic explanations for why the cusp models provide a better fit than linear or logistic models (Sussman & Zahler, 1978) and why the three-class mixture model may fit the data better than a one-class growth curve model (Bauer & Curran, 2003). For example, both models are susceptible to variation based on measurement error, scaling of the independent

and dependent variables, and sampling bias. In addition, the fit of the catastrophe models was evaluated by comparing the BIC of the cusp model to the BIC of the linear and logistic models; however, the distributional assumptions across each model are different with the BIC of the linear and logistic models being based on normal probability density functions and the BIC of the cusp model being based on a multimodal probability density function. We are encouraged by the consistency of model fit comparisons across different specifications, time-points, and treatment groups, but the struggle to find a better measure of model comparison for nonnested catastrophe, linear, and logistic models remains a large research need. Both catastrophe and growth mixture models are also susceptible to local maxima and minima as well as to saddle points. In the current study, we attempted to minimize the likelihood of optimizing on local minima/maxima by running all models with multiple random starting values.

The current study focuses exclusively on the relationship between self-efficacy and treatment outcomes, but other dynamic relapse risk factors are likely to be equally important predictors of the bifurcation in drinking behavior following treatment. Commonly identified dynamic risk factors in the relapse process include the following: coping (McKay, 1999), stress (Brady & Sonne, 1999; S. A. Brown, Vik, Patterson, Grant, & Schuckit, 1995), craving (Rohsenow & Monti, 1999; Tiffany & Conklin, 2000), social support (Barber & Crisp, 1995), and negative affect (Hodgins et al., 1995). The assessment of these factors as predictors in the relapse catastrophe and growth mixture models could provide added insight into the dynamics of a relapsing system.

There are many methodological possibilities for future research that would use the techniques presented in this study. For example, the analysis of momentary data, in which a single individual is measured over several time-points on multiple days, would provide a more fine-grained assessment of the self-efficacy-relapse relationship. Extensions of growth mixture modeling, including piecewise growth mixture modeling and latent Markov models with regime switching, could be used to test the hypothesis of sudden jumps in drinking over time. Event history models, which can be used to track the occurrence and timing of lapse episodes, may provide an alternative means for assessing individuals who fall in and out of lapse states. We hope the promising findings in this study will stimulate alcohol researchers to consider using both nonlinear dynamical and growth mixture models in the description and prediction of the relapse process. To start, there are 15 other primary matching hypotheses that may be suitable for reanalysis (Project MATCH Research Group, 1999).

Summary and Conclusions

Alcohol relapse following treatment has been described as complex for almost 30 years (Brownell et al., 1986; Donovan, 1996; Marlatt & Gordon, 1985; Sutton, 1979), but during that time the methods used to evaluate drinking behavior following alcohol treatment have not advanced far beyond general linear modeling techniques. In the current study, we sought to evaluate two novel methodologies for assessing the nonlinearity and discontinuity in drinking lapses, and by taking into account these dynamics we found support for a hypothesis that was previously rejected when tested using a linear modeling strategy. The methods presented in the current study require further refinement, and testing hypotheses with these methods may be difficult for applied researchers who are less familiar with the software programs and modeling assumptions. Nonetheless, we encourage future investigations of relapse as a nonlinear dynamical system.

Acknowledgements

This research was supported by National Institute of Alcohol Abuse and Alcoholism Grant R21 AA013942-01. We thank the Project MATCH Research Group and Janice Vendetti for providing the data to conduct this research.

References

- Aiken, LS.; West, SG. Multiple regression: Testing and interpreting interactions. Sage; Newbury Park, CA: 1991.
- Alexander R, Herbert G, DeShon R, Hanges P. An examination of least-squares regression modeling of catastrophe theory. *Psychological Bulletin* 1992;111:366–374.
- Allison, P. Missing data. Sage; Thousand Oaks, CA: 2002.
- Andrews RL, Currim IS. Retention of latent segments in regression-based marketing models. *International Journal of Research in Marketing* 2003;20:315–321.
- Bandeem-Roche K, Miglioretti DL, Zeger SL, Rathouz PJ. Latent variable regression for multiple discrete outcomes. *Journal of the American Statistical Association* 1997;92:1375–1386.
- Bandura A. Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review* 1977;84:191–215. [PubMed: 847061]
- Barber JG, Crisp BR. Social support and prevention of relapse following treatment for alcohol abuse. *Research on Social Work Practice* 1995;5:283–296.
- Bauer DJ, Curran PJ. Distributional assumptions of growth mixture models: Implications for over-extraction of latent trajectory classes. *Psychological Methods* 2003;8:338–363. [PubMed: 14596495]
- Boker, SM. Differential structural equation modeling of intraindividual variability. In: Collins, LM.; Sayer, AG., editors. *New methods for the analysis of change*. American Psychological Association; Washington, DC: 2001. p. 3-28.
- Bradburn NM, Rips LJ, Shevell SK. Answering autobiographical questions: The impact of memory and inference on surveys. *Science* April 10;1987 236:157–161. [PubMed: 3563494]
- Brady KT, Sonne SC. The role of stress in alcohol use, alcoholism treatment, and relapse. *Alcohol Health and Research* 1999;23:263–271.
- Brown EC, Catalano RF, Fleming CB, Haggerty KP, Abbott RD. Adolescent substance use outcomes in the Raising Healthy Children Project: A two-part latent growth curve analysis. *Journal of Consulting and Clinical Psychology* 2005;73:699–710. [PubMed: 16173857]
- Brown SA, Vik PW, Patterson TL, Grant I, Schuckit MA. Stress, vulnerability and adult alcohol relapse. *Journal of Studies on Alcohol* 1995;56:538–545. [PubMed: 7475034]
- Brownell KD, Marlatt GA, Lichtenstein E, Wilson GT. Understanding and preventing relapse. *American Psychologist* 1986;41:765–782. [PubMed: 3527003]
- Carlin JB, Wolfe R, Brown CH, Gelman A. A case study on the choice, interpretation, and checking of multilevel models for longitudinal, binary outcomes. *Biostatistics* 2002;2:397–416. [PubMed: 12933632]
- Carroll KM. Relapse prevention as a psychosocial treatment: A review of controlled clinical trials. *Experimental and Clinical Psycho-pharmacology* 1996;4:46–54.
- Clair S. A cusp catastrophe model for adolescent alcohol use: An empirical test. *Nonlinear Dynamics, Psychology, and Life Sciences* 1998;2:217–241.
- Cobb L. Parameter estimation for the cusp catastrophe model. *Behavioral Science* 1981;26:75–78.
- Colder CR, Campbell RT, Ruel E, Richardson JL, Flay BR. A finite mixture model of growth trajectories of adolescent alcohol use: Predictors and consequences. *Journal of Consulting and Clinical Psychology* 2002;70:976–985. [PubMed: 12182281]
- Connors GF, Maisto SA, Zywiak WH. Understanding relapse in the broader context of post-treatment functioning. *Addiction* 1996;91(Suppl):S173–S190. [PubMed: 8997791]
- DiClemente, CC.; Carbonari, JP.; Daniels, JW.; Donovan, D.; Bellino, L.; Neavins, T. Self-efficacy as a matching hypothesis: Causal chain analysis. In: Longabaugh, RH.; Wirtz, PW., editors. *Project MATCH: A priori matching hypotheses, results, and mediating mechanisms*. Government Printing Office; Washington, DC: 2001. p. 239-257. NIAAA Project MATCH Monograph Series, No. 8
- DiClemente CC, Carbonari JP, Montgomery RP, Hughes SO. The Alcohol Abstinence Self-Efficacy Scale (AASE). *Journal of Studies on Alcohol* 1994;55:141–148. [PubMed: 8189734]
- Donovan DM. Marlatt's classification of relapse precipitants: Is the Emperor still wearing clothers? *Addiction* 1996;91(Suppl):S131–S137. [PubMed: 8997787]
- Gilmore, R. *Catastrophe theory for scientists and engineers*. Dover; New York: 1981.

- Greenfield SF, Hufford MH, Vagge LM, Muenz LR, Costello ME, Weiss RD. The relationship of self-efficacy expectancies to relapse among alcohol dependent men and women: A prospective study. *Journal of Studies on Alcohol* 2000;61:345–351. [PubMed: 10757147]
- Guastello SJ. Moderator regression and the cusp catastrophe. *Behavioral Science* 1982;27:259–272.
- Gwaltney CJ, Shiffman S, Balabanis MH, Paty JA. Dynamic self-efficacy and outcome expectancies: Prediction of smoking lapse and relapse. *Journal of Abnormal Psychology* 2005;114:661–675. [PubMed: 16351387]
- Gwaltney CJ, Shiffman S, Paty JA, Liu KS, Kassel JD, Gnys M, et al. Using self-efficacy judgments to predict characteristics of lapses to smoking. *Journal of Consulting and Clinical Psychology* 2002;70:1140–1149. [PubMed: 12362964]
- Hartelman, P. Stochastic catastrophe theory. Unpublished doctoral dissertation. University of Amsterdam; Amsterdam, the Netherlands: 1997.
- Hill KG, White HR, Chung JJ, Hawkins JD, Catalano RF. Early adult outcomes of adolescent binge drinking: Person and variable-centered analyses of binge drinking trajectories. *Alcoholism: Clinical and Experimental Research* 2000;24:892–901.
- Hodgins DC, el Guebaly N, Armstrong S. Prospective and retrospective reports of mood states before relapse to substance use. *Journal of Consulting and Clinical Psychology* 1995;63:400–407. [PubMed: 7608352]
- Hufford MH, Witkiewitz K, Shields AL, Kodya S, Caruso JC. Applying nonlinear dynamics to the prediction of alcohol use disorder treatment outcomes. *Journal of Abnormal Psychology* 2003;112:219–227. [PubMed: 12784831]
- Jackson KM, Sher KJ. Similarities and differences of longitudinal phenotypes across alternate indices of alcohol involvement: A methodologic comparison of trajectory approaches. *Psychology of Addictive Behaviors* 2005;19:339–351. [PubMed: 16366806]
- Jackson KM, Sher KJ, Schulenberg JE. Conjoint developmental trajectories of young adult alcohol and tobacco use. *Journal of Abnormal Psychology* 2005;114:612–626. [PubMed: 16351384]
- Jo B. Statistical power in randomized intervention studies with noncompliance. *Psychological Methods* 2002;7:178–193. [PubMed: 12090409]
- Lo Y, Mendell NR, Rubin DB. Testing the number of components in a normal mixture. *Biometrika* 2001;88:767–778.
- Longabaugh, RH.; Wirtz, PW. Project MATCH hypotheses. Results and causal chain analyses. NIAAA; Rockville, MD: 2002. National Institute on Alcohol Abuse and Alcoholism [NIAAA] Project MATCH Monograph Series No. 8
- Maisto SA, Pollock NK, Cornelius JR, Lynch KG, Martin CS. Alcohol relapse as a function of relapse definition in a clinical sample of adolescents. *Addictive Behaviors* 2003;28:449–459. [PubMed: 12628618]
- Marlatt GA. Taxonomy of high-risk situations for alcohol relapse: Evolution and development of a cognitive-behavioral model. *Addiction* 1996;91(Suppl):S37–S50. [PubMed: 8997780]
- Marlatt, GA.; Gordon, JR. Relapse prevention: Maintenance strategies in the treatment of addictive behaviors. Guilford Press; New York: 1985.
- McKay JR. Studies of factors in relapse to alcohol, drug, and nicotine use: A critical review of methodologies and findings. *Journal of Studies on Alcohol* 1999;60:566–576. [PubMed: 10463814]
- Miller WR. What is relapse? Fifty ways to leave the wagon. *Addiction* 1996;91(Suppl):15–27.
- Miller WR, Del Boca FK. Measurement of drinking behavior using the Form 90 family of instruments. *Journal of Studies on Alcohol* 1994;12:112–118.
- Miller WR, Walters ST, Bennett ME. How effective is alcohol treatment in the United States? *Journal of Studies on Alcohol* 2001;62:211–220. [PubMed: 11327187]
- Muthén, B. Two-part growth mixture modeling. 2001.
- Muthén B, Brown CH, Masyn K, Jo B, Khoo ST, Yang C, et al. General growth mixture modeling for randomized prevention interventions. *Biostatistics* 2002;3:459–475. [PubMed: 12933592]
- Muthén B, Muthén L. Integrating person-centered and variable-centered analysis: Growth mixture modeling with latent trajectory classes. *Alcoholism: Clinical and Experimental Research* 2000;24:882–891.

- Muthén B, Shedden K. Finite mixture modeling with mixture outcomes using the EM algorithm. *Biometrics* 1999;55:463–469. [PubMed: 11318201]
- Muthén, L.; Muthén, B. *Mplus user's guide*. 3rd ed.. Authors; Los Angeles: 2004.
- Myung IJ. The importance of complexity in model selection. *Journal of Mathematical Psychology* 2000;44:190–204. [PubMed: 10733864]
- Oliva TA, Desarbo WS, Day DL, Jedidi K. GEMCAT: A general multivariate methodology for estimating catastrophe models. *Behavioral Science* 1987;32:121–137.
- Olsen MK, Schafer JL. A two-part random effects model for semi-continuous longitudinal data. *Journal of the American Statistical Association* 2001;96:730–745.
- Ploeger A, van der Maas HLJ, Hartelman PA. Stochastic catastrophe analysis of switches in the perception of apparent motion. *Psychonomic Bulletin & Review* 2002;9:26–42. [PubMed: 12026951]
- Project MATCH Research Group. Matching alcoholism treatments to client heterogeneity: Project MATCH posttreatment drinking outcomes. *Journal of Studies on Alcohol* 1997;58:7–29. [PubMed: 8979210]
- Project MATCH Research Group. A study to remember: Response of the Project MATCH Research Group. *Addiction* 1999;94:66–69. [PubMed: 10665098]
- Ramasway V, DeSarbo W, Reibstein D, Robinson W. Empirical pooling approach to marketing mix elasticities with PIMS data. *Marketing Science* 1993;12:103–124.
- Rohsenow DJ, Monti RM. Does urge to drink predict relapse after treatment? *Alcohol Research & Health* 1999;23:225–232. [PubMed: 10890818]
- Schwarz G. Estimating the dimensions of a model. *The Annals of Statistics* 1978;6:461–464.
- Shiffman, S. Conceptual issues in the study of relapse. In: Gossop, M., editor. *Relapse and addictive behavior*. Routledge; New York: 1989. p. 149–179.
- Shiffman S, Balabanis MH, Paty JA, Engberg J, Gwaltney CJ, Liu KS, et al. Dynamic effects of self-efficacy on smoking lapse and relapse. *Health Psychology* 2000;19:315–323. [PubMed: 10907649]
- Shiffman S, Engberg JB, Paty JA, Perz WG, Gnys M, Kassel JD, Hickcox M. A day at a time: Predicting smoking lapse from daily urge. *Journal of Abnormal Psychology* 1997;106:104–116. [PubMed: 9103722]
- Smithson MJ, Verkuilen J. A better lemon squeezer? Maximum likelihood regression with beta-distributed dependent variables. *Psychological Methods* 2006;11:54–71. [PubMed: 16594767]
- Stewart IN, Peregoy PL. Catastrophe theory modeling in psychology. *Psychological Bulletin* 1983;94:336–362.
- Sussman HJ, Zahler RS. A critique of applied catastrophe theory in the applied behavioral sciences. *Behavioral Science* 1978;23:383–389.
- Sutton SR. Interpreting relapse curves. *Journal of Consulting and Clinical Psychology* 1979;47:96–98. [PubMed: 429669]
- Thom, R. *Stabilité structurelle et morphogénèse [Structural stability and morphogenesis]*. Fowler, H., editor. Benjamin; Reading, MA: 1975.
- Thompson, M.; Stewart, HB. *Nonlinear dynamics and chaos*. Wiley; Hoboken, NJ: 2002.
- Tiffany ST, Conklin CA. A cognitive processing model of alcohol craving and compulsive alcohol use. *Addiction* 2000;95(Suppl 2):S145–S153. [PubMed: 11002909]
- van der Maas, HLJ. The dynamical and statistical properties of cognitive strategies: Relations between strategies, attractors and latent classes. In: Newell, K.; Molenaar, P., editors. *Dynamical systems in development*. Erlbaum; Mahwah, NJ: p. xx-xx.(in press)
- van der Maas HLJ, Molenaar PCM. Stages of cognitive development: An application of catastrophe theory. *Psychological Review* 1992;99:395–417. [PubMed: 1502272]
- Wagenmakers EJ, Molenaar PCM, Grasman RP, Hartelman P, van der Maas HLJ. Transformation invariant stochastic catastrophe theory. *Physica D* 2005;211:263–276.
- Wagenmakers, EJ.; van der Maas, HLJ.; Molenaar, PCM. Fitting the cusp catastrophe model. In: Everitt, B.; Howell, D., editors. *Encyclopedia of Behavioral Statistics*. 1. Wiley; New York: 2005. p. 234–249.
- White HR, Johnson V, Buysse S. Parental modeling and parenting behavior effects on offspring alcohol and cigarette use: A growth curve analysis. *Journal of Substance Abuse* 2000;12:287–310. [PubMed: 11367605]

- Witkiewitz K. Defining relapse from a harm reduction perspective. *Journal of Evidence-Based Social Work* 2005;2:191–206.
- Witkiewitz K, Marlatt GA. Relapse prevention for alcohol and drug problems: That was Zen, this is Tao. *American Psychologist* 2004;59:224–235. [PubMed: 15149263]

Figure 1.

A: Observed drinking frequencies during 12th month following treatment. B: Observed drinking trajectories for random sample of 50 individuals, who drank at least once following treatment.

Figure 2.
Canonical form of the relapse cusp catastrophe model.

Figure 3.

A: Scatterplot with kernel regression of percent drinking days at 12 months, baseline self-efficacy, and change in self-efficacy from baseline to 12 months following treatment. B: Histograms of percentage of drinking days at 6 months for three levels of self-efficacy.

Figure 4.
Estimated means of two-part, three-class growth mixture model.

Figure 5.

A: Interaction between self-efficacy and treatment assignment on percentage of drinking days for infrequent drinking class. B: Interaction between self-efficacy and treatment assignment on percentage of drinking days for frequent drinking class. CBT = cognitive-behavioral treatment; MET = motivation enhancement treatment.

Table 1

Descriptive Statistics for Primary Dependent and Independent Variables

Variable	CBT				MET				TSF			
	N	M	SD	r _{se}	N	M	SD	r _{se}	N	M	SD	r _{se}
PDA-B	301	.33	.29	.05	316	.35	.29	.03	335	.35	.31	.12
PDA-M1	292	.79	.30	.20*	309	.75	.30	.06	323	.79	.31	.18*
PDA-M2	291	.75	.33	.17*	303	.73	.33	.05	321	.77	.33	.17*
PDA-M3	290	.74	.32	.17*	300	.74	.32	.05	320	.76	.33	.19*
PDA-M4	290	.73	.32	.17*	299	.74	.31	.10	321	.77	.33	.16*
PDA-M5	288	.73	.34	.16*	293	.74	.32	.13	319	.76	.34	.16*
PDA-M6	286	.70	.34	.15	291	.73	.33	.12	319	.76	.33	.15
PDA-M7	285	.71	.34	.17	290	.71	.35	.09	318	.74	.34	.12
PDA-M8	285	.72	.35	.17	286	.72	.35	.12	312	.75	.35	.11
PDA-M9	286	.72	.34	.16	286	.74	.34	.11	311	.75	.34	.13
PDA-M10	286	.71	.35	.13	286	.72	.35	.08	313	.74	.34	.11
PDA-M11	280	.72	.35	.10	283	.72	.35	.08	312	.74	.34	.12
PDA-M12	279	.72	.35	.11	281	.72	.35	.11	311	.74	.35	.10

Note. CBT = cognitive-behavioral therapy; MET = motivational enhancement therapy; TSF = 12-step facilitation therapy; r_{se} = correlation between baseline self-efficacy and drinking frequency; PDA = percentage of days abstinent for baseline (B) and follow-up assessments (M1-M12).

*
p < .05.

Table 2

Fit Statistics for Linear, Logistic, and Cusp Models

Model	Baseline			6 month			12 month		
	k	BIC	R ²	k	BIC	R ²	k	BIC	R ²
Linear Logistic Cusp Constrained cusp	3	(n = 297) 860.6	.002	4	CBT (n = 259) 806.4	.17	4	(n = 226) 839.8	.19
	4	862.5	.01	5	698.9	.22	5	719.9	.22
	6	762.5		6	539.3		6	513.9	
	4	752.0		4	553.4 MET		4	540.4	
Linear Logistic Cusp Constrained cusp	3	(n = 307) 888.7	.001	4	(n = 262) 797.8	.15	4	(n = 262) 818.6	.18
	4	892.3	.006	5	708.6	.19	5	694.3	.25
	6	793.4		6	538.8		6	483.1	
	4	783.1		4	544.9 TSF		4	493.4	
Linear Logistic Cusp Constrained cusp	3	(n = 319) 927.3	.01	4	(n = 286) 881.3	.15	4	(n = 288) 905.4	.20
	4	921.8	.02	5	775.6	.20	5	740.6	.31
	6	775.4		6	496.5		6	458.4	
	4	769.7		4	504.7		4	487.8	

Note. R² is interpreted only for the linear and logistic models. Constrained cusp indicates a model in which control parameters were constrained to zero. k = number of parameters; BIC = Bayesian information criterion; CBT = cognitive- behavioral therapy; MET = motivation enhancement therapy; TSF = 12-step facilitation therapy.

Table 3

Standardized Parameter Estimates for Cusp Models Across Treatment

Treatment group	Baseline model		6-month model		12-month model	
	β	α	β	α	β	α
Baseline	$\beta_{se,b}$	$\alpha_{se,b}$	$\beta_{se,b}$	$\alpha_{se,6b}$	$\beta_{se,b}$	$\alpha_{se,12,b}$
CBT	.05	.04	.15	.25	.18	.30
MET	.02	-.09	.05	.22	-.02	.21
TSF	.11	.09	.08	.21	.02	.30

Note. β = splitting parameter coefficient; α = normal parameter coefficient; $\beta_{se,b}$ = standardized cusp coefficient for self-efficacy at baseline; $\alpha_{se,6-b}$ = standardized cusp coefficient for the change in self-efficacy from baseline to 6 months; $\alpha_{se,12-b}$ = standardized cusp coefficient for the change in self-efficacy from baseline to 12 months; CBT = cognitive-behavioral therapy; MET = motivation enhancement therapy; TSF = 12-step facilitation therapy.

Table 4

Model Fit for Unconditional and Conditional Growth Mixture Models

Model	AIC	BIC	Entropy	LMR	
				aLRT	p
Unconditional u-part					
1-class	7,232.5	7,246.4	1.00		
2-class	6,898.3	6,926.1	.43	323.89	<.005
3-class	6,806.4	6,848.1	.62	93.22	<.005
4-class	6,800.9	6,856.5	.66	90.53	<.005
Unconditional y-part					
1-class	-3,939.3	-3,856.0	1.00		
2-class	-4,567.9	-4,466.0	.92	613.43	<.005
3-class	-4,925.4	-4,804.9	.92	352.20	<.005
4-class	-5,276.3	-5,137.3	.93	345.88	.20
Unconditional two-part					
1-class	5,574.2	5,676.1	1.00		
2-class	5,136.5	5,266.2	.60	438.63	.03
3-class	4,928.5	5,090.7	.75	204.55	.006
Conditional CBT vs. MET	3,190.8	3,482.7	.88	218.03	.04

Note. The four-class, two-part unconditional model did not converge. AIC = Akaike's information criterion; BIC = Bayesian information criterion; LMR = Lo-Mendell-Rubin likelihood ratio; aLRT = adjusted likelihood ratio; CBT = cognitive-behavioral therapy; MET = motivation enhancement therapy.

Table 5

Parameter Estimates for Conditional Growth Mixture Models

Random effect	Frequent drinkers ^a		Inconsistent drinkers ^b		Infrequent drinkers ^c	
	M	SD	M	SD	M	SD
Intercept y-part	.73	.07*	.44	.14*	.13	.02*
Linear slope y-part	.04	.02*	-.03	.04	.02	.009*
Nonlinear slope y-part	-.004	.002*	.004	.003	-.002	.001*
Intercept u-part	6.44	1.14*	-2.25	.94*	.00	.00
Slope u-part	-.55	.11*	.64	.12*	-.06	.02*
Within-class regression		SE		SE		SE
Intercept						
Self-efficacy	.05	.05	-.19	.18	-.02	.02
Tx assignment	.03	.07	.28	.18*	.02	.03
Self-Efficacy × Tx	-.08	.07	-.20	.20	-.02	.03
Slope						
Self-efficacy	-.01	.02	.08	.05*	-.08	.01
Tx assignment	-.03	.03	-.11	.05*	-.01	.01
Self-Efficacy × Tx	-.01	.02	.04	.07	.002	.01
Nonlinear slope						
Self-efficacy	.001	.001	-.005	.004	.001	.001
Tx assignment	.002	.002	.01	.004*	.001	.001
Self-Efficacy × Tx	.002	.002	-.003	.005	-.001	.001

Note. N = 478. Percentages do not sum to 100 as a result of rounding error. Treatment (Tx) assignment is coded as follows: Cognitive-behavioral therapy = 0, motivation enhancement therapy = 1.

^a 21%.

^b 11%.

^c 69%.

* $p < .05$.