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Dynamic Association Between Negative Affect and Alcohol Lapses Following Alcohol Treatment

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Abstract

Clinical research has found a strong association between negative affect and returning to alcohol use after a period of abstinence. Yet little is known about the probability of a lapse given a particular level of negative affect or whether there is a reciprocal relationship between negative affect and alcohol use across time. The goal of the current study was to examine the association between negative affect and drinking behavior in the 1st year following alcohol treatment. The authors applied an associative latent transition analysis to the Project MATCH outpatient data (n = 952) and then replicated the model in the Project MATCH aftercare data (n = 774). Changes in drinking following treatment were significantly associated with current and prior changes in negative affect, and changes in negative affect were related to prior changes in drinking (effect size range = 0.13–0.33). The results supported the hypothesis that negative affect and alcohol lapses are dynamically linked and suggest that targeting the relationship between negative affect and alcohol use could greatly decrease the probability of lapses and improve alcohol treatment outcomes.

Keywords

negative affect; alcohol relapse; depression; anger; associative latent transition analysis

The earliest theories of alcohol and drug dependence included descriptions of negative affect, avoidance of aversive states, and pleasure seeking as primary motives for substance use (Solomon & Corbit, 1974; Wikler, 1948). Experiencing negative affect has been linked to reinitiation of drug use (i.e., a lapse) following periods of abstinence. Several studies have shown that self-reported negative mood predicts substance use treatment outcomes (e.g., Cooney, Litt, Morse, Bauer, & Gaupp, 1997; Hodgins, el-Guebaly, & Armstrong, 1995; Kessler et al., 1997; Zywiak, Connors, Maisto, & Westerberg, 1996), and higher rates of relapse (i.e., a return to heavy drinking) have been observed among individuals with comorbid affective disorders (Conner, Sorensen, & Leonard, 2005; Curran, Flynn, Kirchner, & Booth, 2000; Hasin et al., 2002; Hodgins, el-Guebaly, Armstrong, & Dufour, 1999; Kodl et al., 2008). Cognitive–behavioral or pharmacological treatment of depression and/or anxiety in conjunction with alcohol treatment has been shown to decrease negative affective symptoms and improve drinking outcomes (e.g., Kushner et al., 2005; Nunes & Levin, 2004; Turner & Wehl, 1984).

Several theories have been put forward to explain the relationship between negative affect and alcohol use. The self-medication hypothesis (Khantzian, 1997) proposes that individuals

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use alcohol to reduce dysphoria, and several studies have demonstrated that alcohol can reduce negative affective states (e.g., Armeli et al., 2003; Kushner et al., 1996). Baker, Piper, McCarthy, Majeskie, and Fiore (2004) proposed that the avoidance of negative affect during withdrawal produces the primary motive for resumption of drug use. Several brain systems and neurotransmitters have been implicated as playing key roles in the reinforcing effects of drugs, acute withdrawal symptoms, and negative reinforcement associated with drug addiction. The prefrontal cortex, hypothalamic-pituitary-adrenal axis, basal forebrain, nucleus accumbens, amygdala, and several neurotransmitters, including dopamine and serotonin systems, endocrine systems, opioid peptides, corticotropin-releasing hormone (CRH), glutamate and gamma-aminobutyric acid, have been found to be related to decreases in reward function after repeated administration of a drug, maintenance of drug dependence, and relapse to drug-taking behavior in animals (Bruijnzeel & Gold, 2005; Heinz, Goldman, Gallinat, Schumann, & Puls, 2004; Koob, 2000; Le Moal & Koob, 2007).

A major emphasis of human research on relapse has focused on gaining a better understanding of what predicts a lapse. Yet little is known about how negative affect is related to alcohol lapses following treatment. That is, do lapses result in an individual feeling more depressed or angry or anxious? Or do changes in negative affect cue an individual to resume drinking (Cooper, Frone, Russell, & Mudar, 1995; Leigh, 1989)? Or perhaps both processes are working concurrently such that negative affective states and drinking form a feedback loop whereby changes in one reciprocally influence changes in the other.

Given the high degree of discontinuity that is often observed in drinking behavior following treatment (Witkiewitz, van der Maas, Hufford, & Marlatt, 2007), it is also important to examine whether abrupt shifts in drinking (e.g., "falling off the wagon") predict a qualitative change in negative affect. We designed the current analyses to test the temporal relationship between negative affective states and drinking states following treatment using a modified associative latent transition analysis (ALTA; Flaherty, 2008b), which allowed for testing the dynamic questions proposed above.

ALTA is a type of latent class model in which the focus is on studying two dynamic processes that are hypothesized to be associated both in degree of a characteristic (e.g., affect and alcohol use are related) and in degree of change (e.g., changes in affect are associated with changes in alcohol use). Parallel-process (i.e., cross-domain) growth models have also been used to examine changes in two behaviors over time; however, these methods require the estimation of a continuous growth trajectory. ALTA can be used to examine changes in drinking behavior and negative affect across time without assuming a smooth, continuous growth trajectory; thus, the relationship between the two processes can be examined in terms of both stability and qualitative change. The difference between ALTA and a parallel-process growth model is the underlying assumption of the nature of the latent variable. Growth models assume that the latent variables that underlie the change in behavior over time (e.g., intercept, linear slope) are continuous, whereas ALTA assumes that the latent variables are categorical and that change in behavior over time is characterized by discrete state changes. Several studies have found a continuous relationship between negative affect and alcohol use, but no studies have examined whether discrete change in one predicts change in the other. The goal of the current analyses was to examine stability and transitions between negative affect states and drinking behavior states across time in the 1st year following treatment. We conducted analyses to determine whether negative affect and drinking behavior are completely independent processes across time or whether they are associated processes at a single point in time and/or prospectively across time. We were also interested in describing the probabilities of posttreatment drinking and affect conditional on prior drinking and affective states.

Method

The data for this study are from Project MATCH (Matching Alcoholism Treatments to Client Heterogeneity; Project MATCH Research Group, 1993), a multisite, randomized clinical trial. The trial recruited 1,726 participants with alcohol use disorders and randomly assigned them to three treatments: cognitive behavioral therapy, motivational enhancement therapy, and twelve-step facilitation. Project MATCH recruited participants from outpatient and aftercare programs at nine clinical research sites across the United States. In the outpatient arm (n = 952), participants were recruited from the community or outpatient treatment centers. Participants in the aftercare arm (n = 774) were recruited from intensive day hospital or inpatient treatment centers. Models were first estimated in the outpatient arm and then replicated in the aftercare arm. The model parameters were statistically equivalent across both samples, and only the results from the outpatient sample are presented below.[1] The outpatient sample was 28% female, 80% White, 12% Hispanic, and 6% Black (Tonigan, 2003), with an average age of 38.9 years (SD = 10.9 years).

Upon meeting inclusion and exclusion criteria, participants were given an intake diagnostic evaluation and baseline assessment measures. Follow-up drinking assessments were conducted immediately posttreatment and 3, 6, 9, and 12 months following treatment. Follow-up psychosocial assessments were administered posttreatment and 6 and 12 months following treatment. A comprehensive list of all assessments can be found in previous Project MATCH publications (Project MATCH Research Group, 1993, 1997).

Measures

The reliability and validity of measures used in Project MATCH were adequate (see Connors et al., 1994). Self-reported drinking data were corroborated via collateral informants and biochemical measures. Measures relevant to the current study are described below.

Drinking consequences—The Drinker Inventory of Consequences (DrInC; Miller, Tonigan, & Longabaugh, 1995) was used to assess consequences experienced as a result of drinking in the last 3 months. The DrInC asks the respondent to report on a 4-point Likert-type scale (0 = *never*, 3 = *daily*) the frequency and severity of 45 drinking consequences, with higher DrInC scores indicating more frequent and severe consequences. For the analysis, DrInC scores were divided into three categories: (a) few or no consequences (DrInC score less than 10), (b) medium consequences (DrInC score greater than or equal to 10 and less than 40), and (c) high consequences (DrInC score greater than or equal to 40). This categorization was based on the distribution of DrInC scores as well as previous mixture analyses of the DrInC measure (Wu & Witkiewitz, 2008).

Drinking intensity—Average standard drinks per drinking day (DDD) were assessed with the Form 90 (Miller and Del Boca, 1994). The primary goal of the Form 90 is to gather information regarding a person's drinking behavior over a 90-day period by a calendar method. For the current study, DDD over the previous 30-day period was categorized into (a) nondrinking, defined as zero DDD; (b) moderate drinking, defined as 5 or fewer DDD for men and 4 or fewer DDD for women; and (c) heavy drinking, defined as more than 5

[1]Two multiple-group associative latent transition analysis (ALTA) models were tested with treatment arm entered as *knownclass*. The constrained model, in which parameters were constrained to be equal across treatment arms, did not fit significantly worse than the unconstrained model and was much more parsimonious. In addition, separate ALTA models were estimated with treatment arm as a predictor of the ALTA parameters, and consistent with the multiple-group analysis, there were no significant effects of treatment arm. Please contact Katie Witkiewitz for copies of the results from the aftercare sample. The ALTA Mplus syntax is also available from Witkiewitz.

DDD for men and more than 4 DDD for women. This categorization was based on the definition of heavy drinking provided by the National Institute on Alcohol Abuse and Alcoholism (2004).

Drinking frequency—Percent drinking days (PDD) was also derived from the Form 90 interview (Miller & Del Boca, 1994). For the current study, PDD was categorized into (a) nondrinking, defined as 0% drinking days in the 30 days prior to assessment; (b) infrequent drinking, defined as drinking less than 50% of the days in the 30 days prior to assessment; and (c) frequent drinking, defined as drinking 50% or more of the days in the 30 days prior to assessment. Alternative definitions of infrequent drinking were considered (e.g., <30% days abstinent = infrequent drinking); however, an inspection of the distribution of drinkers who drank at least once at each time point demonstrated strong bimodality, with a local minimum at 50%. The average PDD of those included as infrequent drinkers ranged from 17% (*SD* = 12%) to 24% (*SD* = 11%), whereas PDD of frequent drinkers ranged from 84% (*SD* = 17%) to 88% (*SD* = 15%).

Number of alcohol dependence symptoms was included as a covariate because previous research has shown a strong relationship between dependence symptoms and drinking class transitions (Witkiewitz, 2008). Dependence was defined as the number of current alcohol dependence symptoms (range = 0–9), based on the Structured Clinical Interview for the *Diagnostic and Statistical Manual of Mental Disorders* (Spitzer & Williams, 1985). In the outpatient sample, participants (*n* = 952) had a mean of 5.76 (*SD* = 1.93) symptoms, which was less than the number of symptoms in the aftercare sample (*M* = 6.8, *SD* = 1.9).

Negative affect—Negative affect was measured by two indicators: the Beck Depression Inventory (BDI; Beck, Steer, & Garbin, 1988) and the State–Trait Anger Expression Inventory (STAXI; Spielberger, 1988). The BDI is a 21-item self-report scale that inquires about a variety of symptoms of depression. Participants are asked to respond on a scale of 0–3 how much each statement best describes the way they have been feeling during the past 2 weeks including today. Total scores on the BDI can range from 0 to 63. The STAXI is a 44-item self-report questionnaire that includes items representing how often participants have an angry temper and how often they feel angry. The STAXI comprises eight subscales (State–Anger, Trait–Anger, Trait–Temperament, Trait–Reaction, Anger–In, Anger–Out, Anger–Control, Anger–Expression), which combine to create a total anger score. Consistent with previous MATCH publications (Waldron, Miller, & Tonigan, 2001), we used the total anger score.

Negative affect was defined by categorical latent class variables at each time point that were indicated by derived categories for the observed BDI and STAXI scores at each time point. In the outpatient sample, the BDI scores ranged from 0 to 43 at baseline (*n* = 896; *M* = 9.84, *SD* = 7.97), 0 to 39 at posttreatment (*n* = 859; *M* = 6.97, *SD* = 7.31), and 0 to 45 at 6 and 12 months (*n* = 819; *M* = 7.16, *SD* = 7.49; and *n* = 825; *M* = 7.09, *SD* = 7.65, respectively). On the basis of the distribution of scores and recent psychometric studies of the BDI (Rissmiller, Biever, Mishra, & Steer, 2006; Seignourel, Green, & Schmitz, 2008), we chose a categorization scheme that divided the sample into low BDI (total scores less than 10), moderate BDI (total scores between 10 and 18), and high BDI (scoring 19 or higher). It is important to note that the pretreatment BDI scores of participants in MATCH (outpatient, *M* = 9.84; aftercare, *M* = 10.57) are lower than BDI scores observed in prior studies (e.g., BDI = 12.0, *SD* = 10.4; Hodgins et al., 1995; BDI = 14.81, *SD* = 9.9; Rubin, Stout, & Longabaugh, 1996).

The STAXI scores ranged from 15 to 57 at baseline (*n* = 896; *M* = 29.46, *SD* = 7.25), 15 to 59 at posttreatment (*n* = 854; *M* = 26.93, *SD* = 6.6), 15 to 60 at 6 months (*n* = 827; *M* =

26.46, *SD* = 7.04), and 15 to 53 at 12 months (*n* = 832; *M* = 25.61, *SD* = 6.63). The STAXI total scores were divided into three categories according to the distribution of scores in the sample: low anger (below 23), moderate anger (between 24 and 31), and high anger (above 32).

It is important to note that categorizing a continuous variable into a categorical variable can sacrifice power and result in a loss of information (MacCallum, Zang, Preacher, & Rucker, 2002), but for the current study, it was helpful to categorize these variables to reduce information loss. (When a skewed continuous variable is an indicator of a latent class variable, there is often a large proportion of individuals in one class and smaller proportions in other classes, capturing sample-specific modes in the data.) Also, in our experience estimating these models, the results are consistent whether using continuous or categorical indicators of the latent variable; however, the models with continuous indicators tend to be less stable with more convergence problems.

Data Analyses

We used the software program Mplus (Version 5.1; L. Muthén & Muthén, 2007) to estimate all models. We estimated model parameters by an expectation-maximization algorithm using a maximum likelihood estimator with robust standard errors. We estimated models using automatically generated starting values with random perturbations (100 random sets with 80 optimizations) to reduce likelihood of convergence to local optima (Hipp & Bauer, 2006).

Missing data are always a concern in longitudinal research. In Project MATCH, data were missing for at most 81 participants on each of the drinking outcomes and for at most 133 participants on the negative affect measures. Those with missing data were included in all analyses via the maximum likelihood estimator with robust standard errors, which computes the covariance matrix for all individuals (*n* = 952) on the basis of their observed data. Mplus allows for missing data that are missing at random but only for endogenous variables. For the models with covariates, the sample size was reduced to 872. We also conducted attrition analyses to assure there were no significant differences on any of the study variables between those with missing data and those with complete data.

ALTA is an extension of latent transition analysis (LTA) and the latent class model. The latent class model (Goodman, 1974; Lazarsfeld & Henry, 1968) is a measurement model in which observed items are indicators of an unobservable categorical latent variable. The categories of the latent variable are referred to as classes, which are thought to represent unobservable subgroups in a population. Thus, the classes are defined by an individual’s pattern of responses to each item, and individuals with similar patterns of responding are considered part of the same subgroup. The parameters of the latent class model help to define the latent classes: (a) Latent class proportions indicate how many people are expected to be in each class; (b) response probabilities are the probabilities of responding to an item, given that one is expected to be in each latent class (probabilities closer to 1.0 indicate a strong correspondence between latent class membership and endorsement of the item). For an extensive description of the latent class model, we recommend several books on the topic (Hagenaars & McCutcheon, 2002; Lazarsfeld & Henry, 1968; McCutcheon, 1987).

LTA is essentially a longitudinal latent class analysis in which separate latent class models are estimated at multiple time points. LTA includes the estimation of an additional parameter, the transition probability, which is an estimate of the probability of transitioning between latent classes. As described in more detail elsewhere (Flaherty, 2008a, 2008b), the ALTA model incorporates two associated processes, which are each represented by separate LTAs that are jointly conditioned on one another. Expected class membership of one latent transition process at each time point is conditioned on prior and concurrent class membership of the other latent transition process. One of the primary goals of the ALTA model is to jointly condition subsequent states on prior and concurrent states, thus allowing for a full association between the two processes. In addition, ALTA can be used to determine whether one process predicts the transition probabilities for another process. This model is hierarchical and requires higher order interaction terms (Bray, 2007), which are not easily identified in Mplus.[2] Thus, in the current study, we focused on the main effects of prior and concurrent behavior on subsequent and concurrent behavior. Using the estimates from this model, we calculated several conditional probabilities: (a) initial probability of negative affect state, (b) initial probability of drinking state conditional on initial negative affect state, (c) subsequent negative affect states conditional on prior negative affect and drinking, and (d) subsequent drinking conditional on prior levels of drinking and both prior and concurrent negative affect.

Given the timing of assessments for alcohol use (posttreatment and 3, 6, 9, and 12 months) and negative affect (posttreatment and 6 and 12 months), we were forced either to discard two time points (3- and 9-month alcohol use) or to incorporate the intermediate measures of alcohol use in a modified ALTA model. To be consistent with the original ALTA model (Flaherty, 2008a), we initially conducted the analyses without the intermediate time points[3] and compared the estimates to the model with the intermediate alcohol use measures. The pattern of results was consistent across models, and thus we report the results from the model that used the full information available from the data. Including the intermediate measures of alcohol use, we defined the conditional probabilities of subsequent alcohol use (for each period) as (a) alcohol use (3 and 9 months) conditioned on prior level of alcohol use (posttreatment and 6 months) and prior level of negative affect (posttreatment and 3 months) and (b) alcohol use (6 and 12 months) conditioned on concurrent negative affect (6 and 12 months), prior level of alcohol use (3 and 9 months), and prior level of negative affect (posttreatment and 6 months).

Testing of the modified ALTA models proceeded in several stages. First, we estimated latent class models of drinking outcome and negative affect indicators separately at each time point to determine the appropriate number of classes necessary to model each construct. We determined the suitable number of classes using the most accepted methods for class enumeration in mixture modeling (Bauer & Curran, 2003; B. Muthén, 2003): the Lo–Mendell–Rubin likelihood ratio test (LRT) and the boot-strapped likelihood ratio test (BLRT; Lo, Mendell, & Rubin, 2001; Nylund, Muthén, & Asparouhov, 2007), as well as the sample-sized adjusted Bayesian Information Criterion (aBIC), which has been shown to be superior in latent class model simulations (Henson, Reise, & Kim, 2007). Second, we estimated latent transition models for each process separately to further simplify the measurement structure and deal with estimation problems by imposing parameter restrictions. Parameter restrictions in LTA models are often necessary if the available information from the data is smaller than the number of parameters being estimated (Lanza & Collins, 2008). The goal of these analyses was to identify a more parsimonious model that did not fit significantly worse than the less restricted model and to reduce empty cells in the transition probability matrices by fixing very small transition parameters (τ) at zero. One to two parameter restrictions were imposed at a time, and we compared the more restricted model with a less restricted model using the scaled chi-square difference test (Satorra,

[2]The Mplus software, in its current iteration (Version 5.1), does not easily identify a model with higher order interaction terms, which is an inherent feature of Flaherty's ALTA software. Despite this limitation of Mplus, we were still able to free all restrictions on the odds ratios, such that odds of subsequent behavior were free to vary across all classes of prior and concurrent behavior, and thus the models presented herein are conceptually similar to the ALTA model proposed by Flaherty (2008a).

[3]In addition, we estimated models without the intermediate time point using the Flaherty ALTA software. Conditional probabilities obtained via the ALTA software were fully consistent with the results from Mplus, and conclusions were the same across programs.

2000), which is necessary when comparing models that are estimated by maximum likelihood estimation with robust standard errors (L. Muthén & Muthén, 2007).

After fitting the individual LTA models, we estimated four modified ALTA models to test associations between latent class variables. As described in more detail by Flaherty (2008a, 2008b), the four modified ALTA models provide an opportunity to examine whether the negative affect latent class variable and drinking latent class variable were (a) completely independent, (b) related cross-sectionally but not longitudinally, (c) related longitudinally but not cross-sectionally, or (d) fully associated. The full-association model is the least restricted model and allows for all cross-sectional and longitudinal parameters between latent class variables to be estimated. The most restricted model, the independence model, constrains all cross-sectional and longitudinal parameters to be equal across the classes of the drinking and negative affect variables, forcing the processes to be independent. We used the scaled chi-square difference test to evaluate whether the independence model fit as well as the less restricted models. If the more restricted model fit significantly worse, then the less restricted model was retained.

We conducted two sets of modified ALTA models.[4] In the first set, we examined the relationship between posttreatment and 6-month drinking and negative affect, with the addition of the 3-month drinking outcomes mediating the relationship between posttreatment and 6-month negative affect. In the second set of analyses, we applied the same modeling framework to assess the association between 6- and 12-month drinking and negative affect, with 9-month drinking outcomes mediating 6- and 12-month negative affect. Additionally, for all models, we included treatment group; baseline DDD, PDD, BDI, and STAXI; gender; and number of dependence criteria as covariates. Figure 1 and Figure 2 provide an abbreviated illustration of the variables in the modified ALTA model. The circles represent latent variables (including measurement errors and residual variances), and squares represent observed variables.

Results

Preliminary Analyses

We estimated one- to four-class latent class models for the negative affect and drinking outcomes separately at each time point. For negative affect, the three-class model provided the best fit based on the aBIC, LRT, and BLRT, with good classification based on the entropy statistic. The item probabilities helped to define the classes, which could be characterized as low negative affect (i.e., high probability of response to lowest BDI and STAXI categories), anger only (i.e., high probability of endorsing moderate to highest STAXI category and lowest BDI category), and high negative affect (i.e., high probability of endorsing the highest BDI and STAXI categories). It is interesting to note that a depression-only class did not emerge from the data. In the four-class model, the additional class could be defined as moderate anger and moderate depression, but this model did not fit significantly better than the three-class model. For the drinking outcomes, a three-class model provided the best fit based on aBIC, LRT, and BLRT at all three time points. The three classes could be characterized as nondrinking with moderate drinking consequences (i.e., individuals who were not drinking currently but reported consequences of prior

[4]This modeling framework was chosen for pragmatic reasons: to reduce model complexity by limiting the number of cells in the contingency table. For each model set, there were 243 response patterns and 19,699 cells in the contingency table. Each model took approximately 30 min to run on a 3.0-GHz, 32-GB server. The model with all time points (posttreatment and 3, 6, 9, and 12 months) had 405 patterns and over 30 billion cells, which was too computationally intensive (i.e., the computer did not have enough memory to estimate the model).

drinking), moderate infrequent drinking with few drinking consequences, and heavy frequent drinking with high drinking consequences.

Negative Affect LTA

After estimating the individual latent class analysis models, we evaluated the latent transition models for each process separately. The negative affect LTA consisted of three latent classes that characterized BDI and STAXI scores over time. Latent transition probabilities indicated that most transitioning between posttreatment and 6 months occurred between the high negative affect and anger-only classes, with 15% transitioning from anger only to high negative affect and 17% transitioning from high negative affect to anger only. Only 2% of those initially classified as anger only were expected to transition to low negative affect. From Months 6 to 12, 17% of those initially classified as anger only transitioned to the low negative affect class. An additional 16% transitioned from high negative affect to anger only. The low negative affect class remained the most stable, with 90% and 91% of individuals remaining low negative affect from posttreatment to 6 months and 6 to 12 months, respectively. Those expected to transition out of low negative affect were more likely to transition to high negative affect (3 to 9 months, 8%; 6 to 12 months, 7%) than to anger only (2% at both time points). Owing to the small probability of transitioning from low negative affect to anger at each time point, these τ parameters were fixed at zero in subsequent models. The probability of transitioning from anger to low negative affect from posttreatment to 6 months was also fixed at zero.

Alcohol Use LTA

The three-class LTA indicated that most individuals were expected to remain in the same drinking class over time. As expected, the largest transition occurred from immediately posttreatment to 6-month follow-up, with 22% transitioning from nondrinking to heavy drinking and 27% transitioning from nondrinking to moderate drinking. From 6 to 12 months, the largest transitions were from the moderate drinking class and the heavy frequent drinking class to the nondrinking class, 17% and 20%, respectively. These results provide strong evidence for discontinuity in posttreatment alcohol use, when individuals transition between qualitatively distinct states from one time point to the next.

Modified ALTA Model Results

We examined four modified ALTA models at each period (Time Period 1 = posttreatment to 6 months; Time Period 2 = 6 to 12 months) corresponding to the full-association, cross-sectional, longitudinal, and independence models. Across both periods, the full-association model provided the best fit to the data and fit significantly better than all comparison models based on the Satorra-Bentler (Satorra, 2000) chi-square difference test for nested model comparisons. For Time Period 1, the independence model fit significantly worse than the cross-sectional and longitudinal models: cross-sectional, $\Delta\chi^2(3) = 28.81$, $p < .0001$, $\phi = .17$;[5] longitudinal, $\Delta\chi^2(6) = 40.31$, $p < .0001$, $\phi = .20$; and the cross-sectional, longitudinal, and independence models all fit significantly worse than the full-association model: cross-sectional, $\Delta\chi^2(10) = 32.32$, $p = .0004$, $\phi = .18$; longitudinal, $\Delta\chi^2(7) = 57.10$, $p < .0001$, $\phi = .24$; independence, $\Delta\chi^2(13) = 95.64$, $p < .0001$, $\phi = .32$. For Time Period 2, the cross-sectional, longitudinal, and independence models all fit significantly worse than the full-association model: cross-sectional, $\Delta\chi^2(10) = 104.49$, $p < .0001$, $\phi = .33$; longitudinal, $\Delta\chi^2(7) = 16.60$, $p = .02$, $\phi = .13$; independence, $\Delta\chi^2(13) = 27.72$, $p = .009$, $\phi = .17$. Thus, across both periods, negative affect and alcohol use were related cross-sectionally and

[5] Phi, or ϕ, is an effect size estimate for chi-square where $\phi = .10$ is considered a small effect and $\phi = .30$ is considered a medium effect, as suggested by Cohen (1988, pp. 224–225).

longitudinally. Significant associations between alcohol use and negative affect classes for the full-association models are provided in Figure 1 and Figure 2.

To further examine the relationship between negative affect and alcohol use classes, we examined the class proportions, posterior probabilities of class membership, and ALTA parameter estimates. Estimated class proportions, shown in Table 1, indicated that individuals were fairly evenly distributed across the negative affect classes at each time point. The initial distribution of negative affect classes is presented in the first column. At posttreatment, more individuals were classified as high anger (42%), followed by low negative affect (32%) and high negative affect (26%); and at 6 months, more were classified as low negative affect (37%), followed by high anger (34%) and high negative affect (29%). The cross-sectional probabilities that describe initial drinking conditional on initial negative affect, as seen in Table 1, indicated that the probability of heavy drinking at any one time point was greatest for those expected in the high negative affect class (posttreatment, 60%; 6 months, 67%). The probability of moderate drinking was near zero for those expected in the high negative affect class, whereas 20% and 43% of those expected in the low negative affect class were expected to be classified as moderate drinkers at posttreatment and 6 months, respectively. Those expected to be classified in the anger-only class had a high probability of being classified in the nondrinking class at both time points and were less likely to be classified as moderate drinkers, compared with those expected to be classified in the low negative affect class.

Selected estimates for the longitudinal association between alcohol class and negative affect class, in which negative affect at Months 6 and 12 is conditional on prior alcohol use class and prior negative affect class, are provided in Table 2. Those classified as non- or moderate drinkers had a lower probability of expected membership in the high negative affect class compared with heavy drinkers, particularly among those who were also expected in the low negative affect class at the prior time point. Importantly, heavy drinking appears to predict higher negative affect at a subsequent time point: Twenty-four percent of those who were classified as low negative affect posttreatment and heavy drinking at Month 3 were expected to be members of the high negative affect class at Month 6. Conversely, those who were initially classified as high negative affect and then classified as non- or moderate drinking at the subsequent time point were more likely to be classified as low negative affect at Month 6 (14% and 30%, respectively) and Month 12 (14% and 17%, respectively) than those who continued to be classified in the heavy drinking class (6 months, 3%; 12 months, 6%).

One remaining question is whether changes in drinking would be related to a change in negative affect. Selected estimates (not shown in Table 2) indicated that of those classified as low negative affect posttreatment who were initially classified as nondrinking at Month 3 and then experienced a lapse (transitioned from nondrinking at Month 3 to heavy drinking at Month 6; $n \approx 127$),[6] 36% were expected to be classified as high negative affect at Month 6. Only 8% of those who were low negative affect at Month 3 ($n \approx 307$) were expected to be classified as high negative affect at Month 6, given that they remained nondrinking from Months 3 to 6. Of those who were classified as high negative affect posttreatment and heavy drinking at Month 3 ($n \approx 173$), 12% were likely to be classified as low negative affect, given nondrinking at Month 6, whereas of those who remained classified as heavy drinkers, only 4% were likely to be classified as low negative affect. These same relationships were not evident in the 6- to 12-month period. Taken together, initial transitions to heavier drinking were associated with a greater probability higher negative affect, and transitions out of

[6]These sample sizes represent the approximate number of individuals classified within each group based on the estimated posterior probabilities. It is important to note that all unconditional analyses were based on a total sample size of 952 and conditional analyses (with covariates) were based on a sample size of 872.

heavy drinking were associated with a greater probability of lower negative affect but only in the first 6 months following treatment.

Finally, the probability of subsequent drinking class conditional on prior drinking class and both prior and concurrent negative affect classes was examined. As seen in Table 3 and Table 4, expected membership in the low negative affect and anger-only classes was associated with a lower probability of heavy drinking, and high negative affect was generally more associated with a higher probability of heavy drinking. A few additional observations are worth noting. First, among those who were expected to be heavy drinkers at Month 3 ($n \approx 402$) or Month 9 ($n \approx 322$), the probability of remaining in the heavy drinking class at Month 6 or 12 was greater than 93% for those expected to be classified in the high negative affect class in Months 6 and 12. The probabilities of nondrinking at Months 6 and 12, given heavy drinking at Months 3 and 9, were 25% and 30% among those with low negative affect at Months 6 and 12, respectively. It is interesting that regardless of negative affect, there was a near-zero probability of expected membership in the moderate drinking class at subsequent time points, given heavy alcohol use at the prior time point.

For those who were expected to be moderate drinkers in Month 3 ($n \approx 221$) and Month 9 ($n \approx 262$), there was a higher probability of staying classified as a moderate drinker at Months 6 and 12 if also classified as low negative affect at Months 6 and 12. High negative affect in Month 6 or 12 was related to a higher probability of moderate drinking at prior time points, predicting heavy drinking at subsequent time points between Months 3 and 6 or Months 9 and 12. This was especially the case for individuals who were expected to be low negative affect at posttreatment and high negative affect at Month 6.

For those expected to be nondrinkers at Month 3 ($n \approx 328$) and Month 9 ($n \approx 367$), the probability of maintaining nondrinking was 82% among those expected to be in the anger-only class at Month 6 and 89% among those who were classified as high negative affect in Month 6 and low negative affect at Month 12. Those individuals who transitioned from low to high negative affect had the highest probabilities of subsequent heavy drinking at 6 and 12 months, following prior nondrinking (28% and 37%, respectively). The probability of subsequent nondrinking after prior moderate drinking was greatest for those individuals who were expected to remain in the low negative affect class across time.

Covariate Analyses

Treatment assignment and gender were not related ($p > .20$) to negative affect or alcohol use class membership. Baseline BDI and STAXI scores were significantly related to the negative affect classes at both posttreatment and 6 months ($p < .0005$). As expected, individuals with higher BDI and STAXI scores at baseline were significantly less likely to be classified in the low negative affect class compared with the high negative affect class (e.g., posttreatment: odds ratio $[OR]_{BDI} = 0.87$, 95% confidence interval [CI] = 0.83–0.91; $OR_{STAXI} = 0.77$, 95% CI = 0.72–0.82). For the alcohol measures at posttreatment, higher baseline DDD predicted a lower likelihood of membership in the moderate drinking class compared with the heavy drinking class (OR = 0.91; 95% CI = 0.84–0.99), and a higher number of dependence criteria predicted a greater likelihood of being classified as nondrinking compared with heavy drinking (OR = 1.13; 95% CI = 1.02–1.26), which is consistent with prior research (Witkiewitz, 2008). At 6 months, more baseline dependence symptoms predicted a lower likelihood of membership in the moderate drinking class relative to the nondrinking class (OR = 0.79; 95% CI = 0.69–0.89) and a low negative affect class relative to the high negative affect class (OR = 0.85; 95% CI = 0.74–0.99).

Discussion

The current study examined the reciprocal relationship between negative affect (defined by depressive symptoms and anger expression) and alcohol use (defined by intensity, frequency, and consequences) during the 1st year following outpatient alcohol treatment. The results provided support for a dynamic association between the two processes over time. The comparisons between cross-sectional, longitudinal, and full-association ALTA models demonstrated that independence between the two processes could not be assumed. Changes in drinking states following treatment were significantly associated with current and prior changes in negative affect, and changes in negative affect were significantly associated with prior changes in drinking state (effect size range = 0.13 [small] to 0.33 [medium]). Overall, the results showed that individuals who reported higher negative affect or increased negative affect over time had the highest probability of heavy and frequent drinking following treatment and had a near-zero probability of moderate drinking. Heavier and more frequent alcohol use predicted a greater probability of high negative affect and increased negative affect over time, whereas nondrinking predicted a greater probability of decreased negative affect over time.

The results from the current study have numerous clinical implications. Primarily, the results replicate prior studies (Curran et al., 2000; Hasin et al., 2002; Kodl et al., 2008), which have shown that alcohol use and negative affect are highly related. The current results have also extended this research by identifying high negative affect (including both anger and depression) as particularly related to drinking behavior, whereas low negative affect and high anger (without depression) were related to moderate and nondrinking. In addition, the results provide evidence that reducing negative affect following alcohol treatment could increase a client's chances of maintaining abstinence or returning to nondrinking following a lapse (Brown, Evans, Miller, Burgess, & Mueller, 1997; Brown & Ramsey, 2000; Ramsey, Engler, & Stein, 2005). If the client experiences a lapse, then an intervention focused on decreasing negative affect could help the client return to abstinence. (For example, in Table 3 and Table 4, one can see that 25% and 30% of individuals who transitioned from heavy drinking to nondrinking at 6 and 12 months, respectively, also transitioned from high negative affect to low negative affect, whereas only 6% of individuals who did not transition out of high negative affect were expected to transition from heavy drinking to nondrinking.) The finding that high levels of depressive symptoms (but not high levels of anger) increased the probability of heavy drinking suggests that treating depressive symptoms following a lapse may be especially important. We did not find significant relationships between either treatment assignment or gender and the negative affect or drinking latent classes. The lack of significant differences across treatment groups is not surprising given the lack of treatment main effects that have been observed in the Project MATCH data (Project MATCH Research Group, 1997). Gender has been shown to predict higher rates of relapse attributed to negative affect in some studies (e.g., Zywiak et al., 1996), although other studies have found no gender differences in the relationship between negative affect and alcohol relapse (e.g., Hodgins et al., 1995). It could be the case that gender predicts a linear relationship between negative affect and alcohol lapses, but gender is not related to the discontinuous transitions that were examined in the current study.

The relationship between negative affect and alcohol lapses has been a subject of scientific inquiry for almost 30 years (e.g., Marlatt & Gordon, 1980). The results from the current study provide evidence for bidirectionality and potentially a feedback loop between negative affect and posttreatment alcohol use. A feedback loop is a mechanism by which a system controls behavior within itself. For example, a negative feedback loop helps to maintain the stability of the system. In the current study, we observed that individuals who maintained non- or moderate drinking were most likely to report low negative affect or anger only (without high depression). Thus, low negative affect maintains the stability of the system, and high negative affect (with depression) might create a bifurcation point for heavy drinking. A positive feedback loop creates change within the system and relates to divergence in behavior of the system. In the current study, changes in negative affect predicted qualitative changes in drinking behavior. This feedback system is also supported by neurobiological evidence linking negative affect with initiation and reinstatement of heavy drinking. Thus, a primary future direction should be to develop treatments that specifically target the relationship between affect and alcohol use (e.g., Kranzler, Armeli, Feinn, & Tennen, 2004). For example, MTIP, a CRH receptor antagonist, was found to block the relationship between a stressor and alcohol reinstatement in alcohol-dependent Marchegian Sardinian rats (Gehlert et al., 2007). Likewise, preliminary data (Bowen et al., 2008; Hsu et al., 2008) from an efficacy trial of mindfulness-based relapse prevention indicated that mindfulness training significantly moderated the relationship between posttreatment BDI scores and posttreatment alcohol use (control group, $r = .50$, $p < .0005$; mindfulness group, $r = -.01$, $p = .98$). Previous research has also established a relationship between positive mood changes, CRH, and mindfulness training (Harte, Eifert, & Smith, 1995), suggesting that targeting CRH (either chemically or behaviorally via mindfulness training) could be a next step for treating comorbid affective and alcohol use disorders.

The present study has several important limitations. First and foremost, the current study is a secondary data analysis, and the original study used retrospective self-report measures of drinking behavior, consequences, and negative affect. Using latent variable modeling and including multiple indicators of drinking and affect reduce the impact of measurement error, but in vivo assessment, affective manipulation, additional measures of affect (e.g., anxiety), and physiological data would greatly increase confidence in the findings. Second, the timing of assessments reduced our ability to examine all transitions that could have occurred between time points (e.g., changes in negative affect in the months between the assessment intervals could not be examined) but also allowed us to modify the ALTA model to incorporate a mediating variable. Although we see this model as an extension of ALTA, to our knowledge no studies have examined mediation within the ALTA modeling framework. Considering the importance of studying mechanisms of change within treatment outcome research (Kazdin & Nock, 2003), it seems a necessary step to further develop methods for estimating mediation in ALTA models. It is also important to note that the models presented above were estimated with Mplus, not with the software originally developed for ALTA modeling (Flaherty, 2008a). More work needs to be conducted to examine similarities and differences between the Mplus models and the ALTA software parameterization and assumptions (Flaherty, 2008a). Third, the techniques used in this study relied on correlational data, and there was no manipulation of negative affect or alcohol use to provide the opportunity to test causal relationships. Future research could examine the associative relationship between affect and drinking behavior following a negative mood induction (e.g., Cooney et al., 1997) or a programmed lapse. Fourth, no information about concurrent depression treatment or diagnosis was provided in the data set, and such information could potentially impact the results. For example, it could be the case that individuals with low negative affect who maintained nondrinking were receiving ongoing treatment for depression. Finally, Project MATCH and clinical trials in general have been criticized for lacking external validity (e.g., Bühringer, 2006; Humphreys & Weiner, 2000), and thus results from the current study might not generalize to individuals who are more severely depressed or more dependent on alcohol. Acknowledging this limitation, we are currently in the process of replicating the current analyses in the Relapse Replication and Extension Project data (Lowman, Allen, Stout, & The Relapse Research Group, 1996), which included a more diverse, community sample.

The primary strengths of the current study include the use of an innovative method, ALTA modeling, for examining relationships between negative affect and alcohol use. ALTA provides the opportunity to examine systems-level research questions, such as those proposed in the current study, within a single comprehensive model, thus controlling for multiple influences and collinearity between processes. In addition, the replication of the results in two samples provides further evidence of the validity of the findings and the utility of the ALTA model. The current findings provide further validation of the important role of negative affect in the prediction of alcohol treatment outcomes and also provide evidence that changes in drinking predict changes in negative affect. Future research on the combined treatment of comorbid alcohol use and affective disorders needs to be conducted. In particular, preclinical research on the brain systems that are implicated in both negative affect and drinking processes could potentially lead to significant treatment advances.

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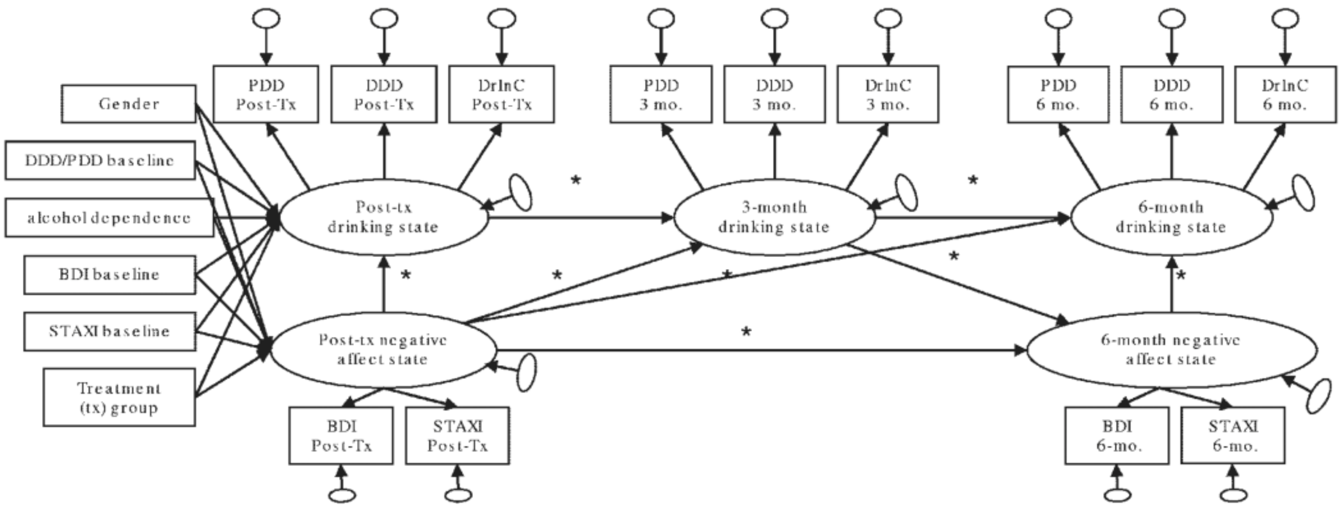

Figure 1.

Associative latent transition model for Time Period 1 (posttreatment to 6 months; $n = 872$). Asterisks indicate that at least one multinomial logistic regression estimate for the path is significant at $p < .05$. PDD = percent drinking days; DDD = drinks per drinking day; DrInC = Drinker Inventory of Consequences; BDI = Beck Depression Inventory; STAXI = State–Trait Anger Expression Inventory.

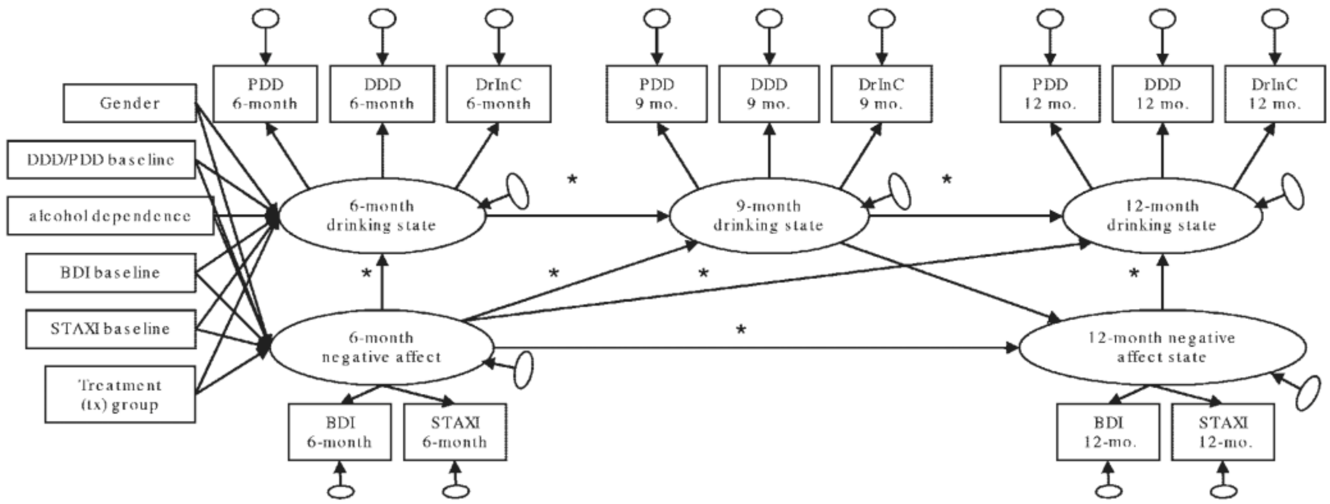

Figure 2.
Associative latent transition model for Time Period 2 (6 months to 12 months; *n* = 872). Asterisks indicate that at least one multinomial logistic regression estimate for the path is significant at $p < .05$. PDD = percent drinking days; DDD = drinks per drinking day; DrInC = Drinker Inventory of Consequences; BDI = Beck Depression Inventory; STAXI = State–Trait Anger Expression Inventory.

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Table 1

Estimated Class Proportions and Cross-Sectional Relationship Between Negative Affect (NA) and Alcohol Use in the Outpatient Sample (n = 872)

Time Period 1: Posttreatment drinking				Time Period 2: Month 6 drinking			
Posttreatment NA	**Non ($n \approx 538$)**	**Moderate ($n \approx 102$)**	**Heavy ($n \approx 312$)**	**Month 6 NA**	**Non ($n \approx 337$)**	**Moderate ($n \approx 264$)**	**Heavy ($n \approx 351$)**
Low NA ($n \approx 307$; $p = .32$)	.60	.20	.20	Low NA ($n \approx 352$; $p = .37$)	.40	.43	.17
Anger only ($n \approx 399$; $p = .42$)	.65	.09	.26	Anger only ($n \approx 327$; $p = .34$)	.41	.25	.34
High NA ($n \approx 246$; $p = .26$)	.39	.01	.60	High NA ($n \approx 273$; $p = .29$)	.23	.10	.67

Note. Data represent initial probability of drinking state conditional on initial negative affect state; *p* values indicate initial probability of negative affect state. Models are covariate adjusted. Non = nondrinking class.

Table 2

Longitudinal Relationship Between Negative Affect (NA) and Alcohol Use in the Outpatient Sample (n = 872)

	Low NA posttreatment, NA Month 6			Anger posttreatment, NA Month 6			High NA posttreatment, NA Month 6				Low NA Month 6, NA Month 12			Anger Month 6, NA Month 12			High NA Month 6, NA Month 12		
Drinking Month 3	**Low**	**Anger**	**High**	**Low**	**Anger**	**High**	**Low**	**Anger**	**High**	**Drinking Month 9**	**Low**	**Anger**	**High**	**Low**	**Anger**	**High**	**Low**	**Anger**	**High**
Non	.90	.02	.08	.08	.76	.16	.14	.20	.66	Non	.90	.02	.08	.20	.64	.16	.14	.17	.69
Moderate	.91	.01	.08	.09	.73	.18	.30	.12	.58	Moderate	.91	.03	.06	.19	.69	.12	.17	.35	.48
Heavy	.70	.06	.24	.02	.79	.19	.04	.22	.75	Heavy	.85	.04	.11	.10	.70	.20	.06	.17	.76

Note. Subsequent negative affect conditional on prior drinking and prior negative affect. Models are covariate adjusted. Anger = anger only; non = nondrinking class.

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Table 3

Longitudinal Relationship Between Alcohol Use and Negative Affect (NA) for Posttreatment to Month 6 in the Outpatient Sample (n = 872)

	Nondrinking Month 3, drinking Month 6			**Moderate drinking Month 3, drinking Month 6**			**Heavy drinking Month 3, drinking Month 6**		
NA posttreatment to Month 6	**Non**	**Moderate**	**Heavy**	**Non**	**Moderate**	**Heavy**	**Non**	**Moderate**	**Heavy**
Low NA	.72	.23	.05	.13	.85	.02	.24	.00	.76
Anger only	.80	.11	.08	.19	.78	.03	.19	.00	.81
High NA	.63	.10	.27	.34	.51	.14	.06	.00	.94
Low to high NA	.69	.03	.28	.22	.57	.21	.07	.00	.93
High to low NA	.64	.10	.27	.04	.93	.03	.25	.00	.75

Note. Selected estimates of drinking conditional on prior levels of drinking and both prior and concurrent negative affect. Models are covariate adjusted. Non = nondrinking class.

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Table 4

Longitudinal Relationship Between Alcohol Use and Negative Affect (NA) for Month 6 to Month 12 in the Outpatient Sample (n = 872)

	Nondrinking Month 9, drinking Month 12			Moderate drinking Month 9, drinking Month 12			Heavy drinking Month 9, drinking Month 12		
NA Months 6 to 12	**Non**	**Moderate**	**Heavy**	**Non**	**Moderate**	**Heavy**	**Non**	**Moderate**	**Heavy**
Low NA	.80	.18	.02	.14	.84	.02	.12	.03	.85
Anger only	.82	.16	.03	.15	.84	.01	.15	.04	.81
High NA	.67	.11	.22	.19	.62	.19	.06	.00	.94
Low to high NA	.56	.07	.37	.21	.65	.14	.02	.00	.97
High to low NA	.89	.09	.02	.13	.86	.01	.30	.08	.62

Note. Selected estimates of drinking conditional on prior levels of drinking and both prior and concurrent negative affect. Models are covariate adjusted. Non = nondrinking class.