Variation in the Drinking Trajectories of Freshman College Students

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Abstract

Recently, Del Boca, Darkes, Greenbaum, and Goldman (2004) examined temporal variations in drinking during the freshmen college year and the relationship of several risk factors to these variations. Here, using the same data, we investigate whether a single growth curve adequately characterizes the variability in individual drinking trajectories. Latent growth mixture modeling identified five drinking trajectory classes: Light-Stable, Light-Stable + High Holiday, Medium-Increasing, High-Decreasing, and Heavy-Stable. In multivariate predictor analyses, gender (i.e., more females) and lower alcohol expectancies distinguished the Light-Stable from other trajectories; only expectancies differentiated the High-Decreasing from the Heavy-Stable and Medium-Increasing classes. These findings move us closer to identification of individuals at risk for developing problematic trajectories and to development of interventions tailored to specific drinker classes.

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The extent of college student drinking and the serious concern it engenders has been highlighted by a National Institute on Alcohol Abuse and Alcoholism report (NIAAA, 2002; see also Goldman, Boyd, & Faden, 2002), as well as by the popular press. Extrapolations from available datasets have suggested that each year 1,400 students die, 600,000 are physically assaulted, 500,000 are injured, and 70,000 are sexually assaulted, in conjunction with alcohol use (Hingson, Heeron, Zakocs, Kopstein, & Wechsler, 2002). The drinking patterns associated with this level of adverse consequences demands close research attention using a variety of methodological approaches, but the existing database, although growing, still has limitations.

Much of the most direct information on college drinking comes from three multiyear national surveys--Monitoring the Future (MTF), the Core Institute Project (CORE), and the College Alcohol Study (CAS)--that focus on the overall prevalence of alcohol use across college campuses (see O'Malley & Johnston, 2002, for a detailed description of each survey), supplemented by additional longitudinal data from research on specific campuses (e.g., Baer, Kivlahan, Blume, McKnight, & Marlatt, 2001). The methodology used in these studies was designed to reveal macro-level trends in consumption over periods of years, rather than detailed information about ongoing drinking. Further, what we know about temporal changes in alcohol use comes primarily from cross-sectional comparisons of successive respondent cohorts, rather than from repeated measurements of the same individuals. In panel surveys using longitudinal designs to track individual change, the interval between assessments has been at least one year (e.g., Baer et al., 2001; Schulenberg, O'Malley, Bachman, Wadsworth, & Johnston, 1996; Tucker, Orlando, & Ellickson, 2003), an approach that does not permit examination of short-term (e.g., week-to-week) changes in drinking practices and their development over time.

Conversely, the small subset of longitudinal studies that have assessed alcohol use at a more micro-level (e.g., daily use) usually have been limited to relatively brief time spans (e.g., 28 days, Rabow & Neuman, 1984; Rabow & Duncan-Schill, 1995).

We recently applied latent growth curve (LGC) modeling to a dataset that included information on daily fluctuations in drinking behavior across an entire year of college for three successive cohorts of incoming students (Del Boca, Darkes, Greenbaum, & Goldman, 2004). The data indicated that the nature of alcohol use by students could not be easily captured by widely spaced assessments of drinking or even by closely spaced assessments confined to a relatively brief time span; alcohol use was not evenly distributed across the typical week, nor across the academic year. Most drinking occurred toward the weekend (Thursday through Saturday), and was heavier during the initial weeks of the Fall and Spring semesters, and lowest during midterm and final exam weeks. Additionally, the heaviest drinking occurred during holiday periods when students tended to be away from campus (e.g., New Year’s, Spring Break).

A LGC model with four growth factors--intercept, slope, quadratic (drinking evidenced a shallow u-shaped function across the school year), and holiday (representing time-specific peak drinking weeks; specifically, Thanksgiving, Christmas, New Year’s, and Spring Break occurred)--adequately fit the data. No significant cohort effects were found for any of the four LGC factors across the three years of data collection. When several well-established antecedent and proximal risk factors for heavy drinking were tested simultaneously, gender, type of residence, and alcohol expectancies predicted growth factors in the LGC model. Male students and those who lived off campus had higher overall consumption levels. Alcohol expectancies significantly predicted all four growth factors: Higher expectancy scores predicted higher initial drinking and holiday consumption, as well as the recovery of drinking to initial levels following a shallow initial decline. It was evident, therefore, that individual difference factors could manifest themselves during periods when influential external contingencies also were operating.

Because our previous report focused on temporal variability in overall drinking levels during the freshman year, the results were based on an LGC model that assumed that individual curves were relatively homogeneous. A single growth curve, however, may not adequately characterize the variations in individual trajectories. For example, the slight linear slope in the aggregate LGC model may mask the presence of distinct participant subgroups, with some students increasing their drinking over time, while others decreased their alcohol use. Studies have identified multiple latent developmental trajectories as early as sixth grade (e.g., Greenbaum & Dedrick, 2003; Li, Duncan, & Hops, 2001). Beginning with the young adult years, multiple trajectory classes that reflect different courses (i.e., increases, decreases, stability) have been found consistently (e.g., Muthén & Muthén, 2000; Schulenberg et al., 1996). It remains unknown whether heterogeneous growth patterns characterize proximal fluctuations in drinking within a single college year. Here we applied latent growth mixture (LGM) modeling to examine this possibility, using the same data analyzed by Del Boca et al. (2004).

Method

Participants

Participants were a random sample of 301 University of South Florida freshmen, stratified on gender and family history of alcoholism, recruited from approximately 6,000 incoming students who were screened during mandatory summer orientation sessions over three successive years. The sample included slightly disproportionate percentages of each gender (males comprised 47%) when compared to the freshmen population (43-44% of incoming students were male during the three years), but was otherwise demographically similar.

Participants' ages ranged from 17 to 20 (M = 18.40, SD = 0.47); 71% described themselves as Caucasian, 9% as African American, 12% as Hispanic, and 8% as "Other" (compared to 71%, 10%, 11%, and 8%, respectively, in the population).

Data from 237 participants (79%) who reported consuming at least 1 drink during the academic year were used for this study. Abstainers were excluded because they did not exhibit the behavior of interest and would contribute little to an analysis of change (i.e., such participants had no trajectory other than a flat line). Their exclusion also reduced the skewness of the distributions of the drinking variables. This analysis sample was demographically similar to the larger sample: 48% male; 52% FH+; 73% Caucasian, 8% African American, 12% Hispanic, and 7% "Other"; mean age, 18.42 years (SD = 0.45). Study dropout in the subsample was about 8%.

Procedure

Incoming freshmen were screened for age, drinking history, family history of alcoholism, and interest in study participation during mandatory summer orientation sessions. Over a 3-year period, virtually all attendees (about 6,000) completed the survey, and approximately 80% indicated interest in participating in the study. A stratified, random sample of students who indicated interest in participation, and who also reported a positive or negative family history of alcohol problems (see below; about 57% of those screened), were enrolled.

During an intake session in early Fall, participants completed instruments assessing personal history and lifestyle variables, personality, alcohol expectancies, drinking patterns, alcohol-related problems, current affect related to several life domains (e.g., work, family, and school), and illicit drug use. Measures (described below) drawn from this baseline assessment were used to predict class membership in the LGM analyses. Alcohol expectancies, affect, lifestyle variables, illicit drug use, alcohol use and alcohol problems were reassessed during later in-person sessions held in December and April, and during five telephone interviews conducted in interim months. Only the longitudinal drinking data are used in this study. Participants were paid for completing assessments and earned as much as $75 if all study requirements were met.

Measures

Gender, race/ethnicity, and residential living arrangement (dormitory, off campus with significant other/peers, off campus with parents) were assessed by the *Personal Experiences Questionnaire*, created specifically for this project.

A *Timeline Followback* interview (*TLFB*: Sobell & Sobell, 1994) assessed daily alcohol consumption. The reliability and validity of the *TLFB* procedure is well established (Sobell & Sobell, 1994; Tonigan, Miller, & Brown, 1997), and its concordance with data derived from other methods has been excellent over relatively short time intervals (Leigh, 2000). Using customized calendars highlighting national and local holidays, college and community events, and other noteworthy occurrences, participants were trained to estimate the number of standard drinks (i.e., 12 oz. of beer; 5 oz. of wine or wine cooler, or 3.5 oz. of fortified wine; a mixed drink or 1 shot [1.5 oz.] of 86-100 proof hard liquor) consumed each day on a calendar commencing 30 days earlier and ending “yesterday” (the day before the interview). Subsequent followback drinking assessments began on the previous interview date and ended “yesterday,” producing a continuous daily drinking record for the 32 weeks of the academic year.

Although daily drinking data were collected, as in our prior study (see Del Boca et al., 2004)**,** weekly estimates were computed due to the cyclic weekly pattern and the overly sparse data matrix for longitudinal analysis that the daily data provided (i.e., the large number of zeroes due to abstinent days). Weekly quantity distributions were highly nonnormal (Skew M = 3.71, SD = 0.65; Kurtosis M = 17.83, SD = 7.53). According to Bauer and Curran (2003; 2004), nonnormality can produce spurious extraction of latent trajectory classes. Therefore, the data were natural log transformed and a constant of 1.00 was added to each score before transformation [Ln (X + 1)], resulting in improved normality of the distributions (Skew *M* = 1.36, *SD* = 0.21; Kurtosis *M* = 0.62, *SD* = 0.62).

Weekly consumption values were present for 96% of the possible data points. Complete data were obtained for all 32 weeks from 67% of the sample; an additional 23% were missing one or more daily data points in three or fewer weeks. Most missing values were due to the small proportion of participants who did not complete the study (8% in the analysis sample, which accounted for 75% of the missing data). The number of weeks in which drinking data was missing for each participant was calculated; because this continuous variable was highly skewed (ranging from 0 to 30, with a median of 0), a dichotomous measure was created that contrasted those with complete data (67%) with those who had one or more missing values (33%).

The *Alcohol Expectancy Questionnaire* (*AEQ*: Brown, Goldman, Inn, & Anderson, 1980), comprising 68 True-False items about expected effects of alcohol, was administered, but only the 9-item Social/Physical Pleasure scale (e.g., “Drinking adds a certain warmth to social occasions”) was used in the analyses because it had predicted multiple growth factors in Del Boca et al. (2004) and has consistently predicted drinking in college students (e.g., Darkes, Greenbaum, & Goldman, 2004). The reliability and predictive validity of the AEQ are well established (e.g., Goldman et al., 1997); in this study, coefficient alpha for the Social/Physical Pleasure scale was .81.

The 11-item Sensation Seeking subscale of the 99 True-False items of the *Zuckerman-Kuhlman Personality Questionnaire Form III* (*ZKPQ III*: Zuckerman, Kuhlman, Joireman, Teta, & Kraft, 1993) assessed sensation seeking. Coefficient *alphas* ranging from .73 to .83 have been reported (Zuckerman et al., 1993). Sensation seeking tendencies have been a robust predictor of college student drinking (e.g., Darkes, Greenbaum, & Goldman, 1998).

Four items in the screening questionnaire assessed family history of alcoholism. Respondents indicated if either biological parent, or any grandparent, experienced any of several alcohol-related problems (e.g., legal, physical). Participants were classified as positive (FH+) if at least one first-degree relative (mother or father) had alcohol problems, and categorized as negative (FH-) if both parents and all four grandparents did not evidence any alcohol problems.

Analytic Strategy

Latent growth mixture (LGM) modeling (Muthén & Shedden, 1999; Muthén et al., 2002) was used to identify the form and number of latent trajectory classes that best fit the data and to test potential predictors of class membership. Unlike conventional latent growth curve (LGC) models, which assume that growth trajectories in the sample arise from a single multivariate normal distribution, LGM models allow for heterogeneous trajectories by modeling a *mixture* of distinct multivariate normal distributions, each referred to as a latent class. Individuals within each latent class share the same growth factors and have similar growth curve patterns.

The starting point for these analyses was the single-curve latent growth model from Del Boca et al. (2004). Subsequently, a series of unconditional (i.e., no covariates or outcomes) LGM models with two to five classes was inspected. For each LGM class model tested, polynomial (i.e., linear, linear + quadratic) growth curve models were posited with both fixed and random effects. Following Del Boca et al. (2004), a time-specific holiday factor (representing Thanksgiving, Christmas, New Year's, and Spring Break holiday weeks) was also included in the tested models. Selection of a final model was based on conceptual considerations (e.g., interpretability) and statistical fit indices that included information criteria (i.e., Akaike information criterion, Akaike, 1987 [AIC]; Bayesian information criterion, [BIC], Schwartz, 1978; sample-size adjusted BIC, [SSABIC], Sclove, 1987), Lo-Mendell-Rubin's adjusted likelihood ratio test (LRT; Lo, Mendell, & Rubin, 2001), and entropy measures (Ramaswamy, DeSarbo, Reibstein, & Robinson, 1993).

Multiple criteria were used to evaluate the LGM models because each type of index provides information about different aspects of model fit. The information criterion indices are goodness-of-fit measures that incorporate various penalties for model complexity (e.g., number of parameters in the model). Comparisons between competing models assessed relative fit to the data; lower observed criterion values are indicative of improved fit. Lo-Mendell-Rubin's (2001) LRT statistic, as implemented in Mplus Version 2.13, was used to compare mixture models with differing numbers of latent classes; a significant chi-square value ($p < .05$) indicates that the specified model is unlikely to be generated by a model with one less class. Entropy (Ramaswamy et al., 1993), a standardized summary measure of the classification accuracy of placing participants into classes based on their model-based (i.e., posterior) probabilities, can range from 0.00 to 1.00; higher values indicate better classification.

We sought a (better fitting) model with smaller information criterion values, larger entropy, and a significant Lo-Mendell-Rubin adjusted likelihood ratio test. Additionally, auxiliary information in the form of theoretically meaningful covariate predictors of class membership was incorporated in view of Muthén's (2003) recommendation that, "The estimated prediction of class membership is a key feature in examining predictions of theory. If classes are not statistically different with respect to covariates that, according to theory, should distinguish classes, crucial support for the model is absent" (p. 373).

Between-class differences in the growth factors were tested using a nested model procedure in which the fit of the model with freely estimated growth factors was compared to that of a restricted model in which the specific growth factors tested were constrained to be equal. Potential predictors of class membership (covariates) were well established antecedent (e.g., gender) and proximal (e.g., residence) risk factors for heavy drinking. Significance of the covariate effects was tested by *pseudo-z* statistics based on the ratios of the estimated covariate parameter coefficients divided by their standard errors. Based on LGM's assumption of within-class normality conditional on covariates (Muthén, 2003), and following Bauer and Curran's (2004) recommendations regarding diagnostic testing for model misspecification, a final check on model selection involved examination of residuals for significant outliers and time trends.

We chose LGM modeling due to its advantages over methods used in much prior research to investigate heterogeneity of drinking patterns. To advance beyond the limitations of conventional cluster analysis, LGM models utilize: (a) maximum likelihood estimation to obtain the estimated probabilities of class membership to account for the probabilistic nature of class assignment; (b) dynamic (i.e., longitudinal) data rather than point estimates to identify latent classes; (c) latent variables to reduce measurement error; (d) structural models that include contextual variables; and (e) all participants' data, even if incomplete.

Results

Latent Class Enumeration

As noted, tested models ranged from a 1-class latent growth curve model to a 5-class mixture model. Growth factor variances and residual variances of the observed variables were constrained to be equal across classes. Models were tested with both linear-only and linear and quadratic growth factors. After 3 classes were extracted, the linear-only model performed somewhat better than the quadratic model on the BIC and adjusted LRT, and, based on parsimony, was selected over the quadratic model. Additionally, in our initial models, within-class coefficients for the holiday factor were constrained to be equal across all four holiday weeks. We then specified a model where the coefficients for the holiday effect were freely-estimated and, using a nested model procedure, tested the freely-estimated versus the constrained model and found the freely-estimated model fit significantly better, χ^2 (3, N = 237) = 28.44, $p <$ .05, with all of the freely-estimated holiday loadings being significant (*psuedo*-*z*s > 2.00). Results of the information criterion and adjusted LRT fit indices and entropy values for the fitted mixture models are displayed in Table 1.

Based on empirical and substantive considerations, the 5-class linear model was selected as optimal. Figure 1 graphically displays the predicted trajectories of the five classes, and Table 2 provides the equations for the five growth trajectories and the estimated class proportions in the population. Based on the functional form of the growth curves, the classes were labeled: (a) Classes 1 and 2, "Light-Stable" and "Light-Stable + High Holiday," were two trajectory classes of light drinkers who differed from each other in the magnitude of their consumption during holiday weeks; (b) Class 3, "Medium-Increasing," was comprised of participants with moderate levels of drinking at study entry, who increased consumption over time; (c) Class 4, "High-Decreasing," represented students who began the year with relatively high levels of drinking, but declined significantly as the year progressed; and (d) Class 5, "Heavy-Stable," included those who drank the heaviest and did so consistently over the course of the year.

Class Differentiation

The 5-class model had the smallest values for two of the three indices (the AIC and the SSABIC), an adjusted LRT probability of .15 (for the 5-class model not to have been generated by a “true” 4-class solution), and an entropy value of .84. Despite the smaller BIC, higher entropy, and a lower *p* value for the adjusted LRT of the 4-class linear solution, the 5-class linear model was selected. Indeed, the only difference between the two models was attributed to a new trajectory in the 5-class model that emerged from the previous model’s large class of relatively light drinkers.

Our decision to adopt the 5-class model was supported by an examination of the specific growth factors for the two Light-Stable classes, which indicated that only the holiday factor was significantly different. Between-group differences in the holiday growth factor could not be tested by the nested model procedure because the constrained model (where the holiday factors were equal) represented a degenerate solution (i.e., the two classes specified did not differ in any of the potential growth factors, i.e., intercept, slope, and holiday). However, a test of holiday differences was provided by calculating a 95% confidence interval for the two holiday effects under the alternative hypothesis of two distinct classes. Non-overlapping confidence intervals indicated that the two holiday factors were significantly ($p < .05$) different from each other, Light-Stable + High Holiday $M = 1.44$, $SE = 0.16$, 95% CI = 1.12 to 1.75; Light-Stable $M = 0.29$, $SE = 0.07$, 95% CI = 0.16 to 0.43. Hence, we opted for the 5-class, rather than the 4-class model because the High Holiday trajectory represented a group of novice college drinkers potentially at risk for holiday alcohol consequences; as noted by Muthén (2003), “a growth mixture model is an important tool for early detection of likely membership in a problematic class” (p. 374).

Examination of the remaining between-class comparisons among the growth factors indicated that the intercept and slope parameters for the other three drinking classes were all significantly different from each other, Medium-Increasing vs. High-Decreasing intercept, χ^2 (1, $N = 237$) = 43.92, $p < .001$; Medium-Increasing vs. Heavy-Stable intercept, χ^2 (1, $N = 237$) =

75.02, $p < .001$; High Decreasing vs. Heavy-Stable intercept, χ^2 (1, N = 237) = 35.01, $p < .001$; Medium-Increase vs. High-Decreasing slope, χ^2 (1, N = 237) = 88.36, $p < .001$; Medium-Increasing vs. Heavy-Stable slope, χ^2 (1, N = 237) = 21.05, $p < .001$; High Decreasing vs. Heavy-Stable slope, χ^2 (1, N = 237) = 36.13, $p < .001$.

Estimated population average probabilities of class membership for each class were derived from the model-based probabilities for all participants to be in each of the five classes (each participant has a probability for membership for each of the five classes that sums to 1.00); these provide more detailed information about the distinctiveness among the classes than the summary entropy measure. The lowest probability of correct classification (.775) occurred for the High-Holiday class; corresponding probabilities for the other classes ranged from .895 to .958. The two highest misclassification probabilities, accounting for almost half (44%) of all misclassifications, occurred between the Light-Stable and the Light-Stable + High Holiday classes: Individuals classified in the latter group had a .177 probability of placement in the Light-Stable class; Light-Stable participants had a .066 probability of assignment to the High Holiday class. Thus, the decline in entropy from the 4- to 5-class mixture model was likely caused by the relative blurring of the Light-Stable and Light-Stable + High Holiday classes.

In brief, the analyses supported the distinctiveness of the five classes. Each class differed from the others with respect to at least one model parameter. Overall, the probabilities associated with class assignment indicated that the classes were well differentiated, although this proved to be less evident in the case of the two Light classes.

Observed Drinking Trajectories

To better understand the drinking patterns associated with the five latent trajectories in their original (untransformed) drinking metric (standard drinks/week), participants were categorically assigned to classes using their highest model-based (posterior) probability of class membership. The sample-based class trajectories of observed drinking values are depicted in Figure 2. Because the figure presents untransformed values, the differences between the Heavy-Stable class, which was characterized by extreme values in the drinking distributions, and the four remaining classes appear very pronounced. As shown in the figure, consumption tended to fluctuate from week to week, and all groups (except the Light-Stable class) showed at least some increase in alcohol use during holiday weeks when students were typically away from campus.

Examination of the actual reported amounts consumed across weeks in the academic year provided an additional perspective on the drinking behavior of students assigned to the identified classes. Participants in the Light-Stable and Light-Stable + High Holiday groups reported consuming comparable quantities at study entry (*M*s = 1.57 [*SD* = 5.22] and 1.54 [*SD* = 3.10] standard drinks, respectively, during Week 1). With the exception of the heavier holiday drinking by the latter group, this low level of alcohol use remained consistent across the weeks in the academic year. However, the difference between these two groups in terms of Holiday drinking was considerable. Light-Stable + High Holiday drinkers consumed an average of 6.14 ($SD = 2.49$) standard drinks per week during the four holiday periods, compared with only 1.12 ($SD = 1.16$) for those in the Light-Stable group, $t = 13.33$; $df = 140$, $p < .001$. Further, the total weekly quantities for the High Holiday group were not attributable to an increase in the frequency of light or moderate drinking occasions. Consistent with the view that this class comprises an at-risk group of freshmen drinkers, twelve of the 14 participants (86%) in this class engaged in heavy drinking (i.e., consumed more than 5 drinks per occasion) at least once during the four holiday weeks; the mean number of heavy drinking episodes for these 12 students was 2.25, and the average amount consumed was 6.57 standard drinks.

Despite the variability in weekly consumption, participants in the High-Decreasing and Medium-Increasing classes exhibited very different overall trends in drinking patterns. At study entry, the Decreasing group consumed an average of 5.75 (SD = 5.84) standard drinks per week. During the Fall, students in this group averaged 6.11 (SD = 3.36) drinks per week (excluding holiday weeks); however, the mean level of consumption declined significantly during the Spring (M = 3.51, SD = 1.64), t = 5.49, df = 41, $p < .001$. In contrast, those in the Medium-Increasing group consumed 4.03 (SD = 5.44) standard drinks during Week 1, and 3.47 (SD = 1.81) drinks per week, on average, during the first semester, but increased significantly to 6.91 (SD = 2.96) drinks per week during the second term, t = 5.81, df = 17, $p < .001$. Whereas the average drinking quantity per week during the Fall was significantly greater for High-Decreasing than for the Medium-Increasing, students, t = 3.22, df = 61, $p < .001$, the reverse occurred during the Spring, t = 5.71, df = 58, $p < .001$. Despite these differences, students assigned to the two classes did not differ significantly in their holiday alcohol use.

Finally, freshmen in the Heavy-Stable class evidenced a much higher level of drinking than those in the other classes across the entire academic year, averaging 17.19 (SD = 6.92) drinks/week during non-holiday periods. During holidays, these participants increased their consumption levels to an overall mean of 26.56 (SD = 10.84) standard drinks per holiday week. These amounts are substantial, and very likely place these students at heightened risk.

Covariate Analyses

The unconditional 5-class LGM model was expanded to include antecedent and proximal risk factors as predictors of class membership in a series of weighted (i.e., based on each participant's probability of being in each class) multinomial logistic regressions. In these analyses, to provide latent class comparisons and maintain model identification, it was necessary to designate one of the latent classes as a reference class. Within this framework, three sets of comparisons were of interest. First, to determine which variables were associated with increased levels of college drinking, we identified those covariates that predicted membership in any of the heavier drinker classes as compared with the class that drank the least, the Light-Stable drinkers (the largest class). Second, the High-Decreasing class was compared to the Medium-Increasing class, using the former class as the reference group. Third, to investigate factors involved in desistence, comparisons were made between the Heavy-Stable and High-Decreasing classes. In these analyses, the Heavy-Stable class was the reference class.

Specific covariates included the following: (a) gender (1 = female), (b) race/ethnicity (1 = white), (c) residence (0 = living at home, 1 = living off-campus or in a dormitory), (d) sensation seeking, (e) Social/Physical Pleasure alcohol expectancies, (f) family history of alcoholism (1 = yes), and (g) missingness (1 = presence of at least one missing drinking data point), which served as a control for possible differences between participants with complete versus incomplete data. Due to missing data on the covariate, sample size for the prediction analyses was reduced from 237 to 235, 234, or 230, depending on the model tested. Initial regression analyses tested a series of univariate predictor models, one for each covariate. Subsequently, all covariates from the univariate analyses that met at least a marginal level of significance ($p < .10$) were entered into a multivariate logistic model, which assessed each covariate effect conditioned on the others in the model. For these analyses, a significance level of $p < .05$ was applied.

Light-Stable versus Others. For comparisons with the Light-Stable class, univariate regression models indicated that among the covariates, gender, alcohol expectancies, sensation seeking, and missingness were at least marginally significant ($p < .10$). Although missingness significantly predicted class membership, model parameter estimates were not biased, assuming missing at random (MAR, i.e., missing values can be predicted by observed variables in the data set, Little & Rubin, 1987).

The four covariates that were associated with class differences in the univariate analyses were entered into a multivariate logistic regression. Using a nested model comparison, the covariate model was a significant improvement in model fit compared to the 5-class unconditional model, (χ^2 (16, N = 234) = 300.96, $p < .001$) and for the observed variables averaged an R^2 = 11.2% for each class and, overall, accounted for an R^2 = 55.9%. Table 3 displays the resulting covariate means and proportions for each latent class and the significant differences between the Light-Stable reference group and the other classes. For alcohol expectancy, the Light-Stable class had significantly lower mean expectancy scores than all other classes, *pseudo-z* = 3.20, 4.20, 4.03, 3.66, respectively, *p*s < .001. Gender also was a significant predictor of class membership; this difference was restricted to the Heavy-Stable comparison, however, with the percentage of females in the Heavy-Stable class significantly lower than for the Light-Stable class, *pseudo-z* = 2.41, $p < .05$. Sensation seeking and missingness were not significant predictors in any of the class comparisons.

Medium-Increasing versus High-Decreasing. In the univariate logistic regression analyses comparing the Medium-Increasing and High-Decreasing classes, only alcohol expectancies significantly predicted class membership, while sensation seeking was marginally related. Thus, alcohol expectancies and sensation-seeking were included in the multivariate prediction model. However, only expectancies remained significant, with the Medium-Increasing class having higher scores, *pseudo-z* = 2.00, $p < .05$.

High-Decreasing versus Heavy-Stable. A similar pattern was found for covariates predicting the High-Decreasing versus Heavy-Stable classes. In the univariate tests, alcohol expectancy was significant, and Sensation Seeking scores were marginally related to class membership. In the multivariate model, only expectancy significantly distinguished the classes, with lower scores for the High-Decreasing class, *pseudo*-z = 4.03, $p < .001$.

To summarize, several risk factors differentiated the classes in univariate analyses. Because of shared variance among the covariates, however, only gender and alcohol expectancies were significant predictors in multivariate analyses. Expectancy was the strongest and most consistent factor associated with class membership.

Analysis of Residuals

Bauer and Curran (2004) have recommended using residual diagnostics to examine model misspecification as an adjunct to model fit indices in identifying the optimal number of latent classes. Therefore, as a further check on the adequacy of the final 5-class model (with Light-Stable as the reference class, and gender, alcohol expectancies, sensation seeking, and missingness as covariates), which assumes multivariate normality of the observed dependent variables conditional on predictors and class (Muthén, 2003), residuals were examined using Q-Q norm and trend plots based on a pseudo-class diagnostic for latent growth mixture models (Wang, Brown, & Bandeen-Roche, in press). Wang and her colleagues note, that under the assumption of within-class normality conditional on covariates, if the selected model is misspecified, then the residuals from the pseudo-class assignment will not behave as a standard normal variable. In these analyses, individuals were randomly assigned to pseudo-classes based on their model-based (posterior) probabilities, and standardized residuals were calculated. Normality of the distributions was examined with Q-Q norm plots. Additionally, mean structures of the growth curves were examined with residual trend plots across the 32-week period. Visual inspection of the Q-Q norm plots suggested no serious departure from the normality assumption.

However, a higher preponderance of residuals towards the low end of the distribution for the Light-Stable class, typical of a “floor” effect, was observed. Therefore, compared with other classes, a relatively larger proportion of Light-Stable participants were abstainers on most weeks. Examination of the 32-week time trend plots of the mean residuals for each class indicated no significant residual outliers (i.e., all zs < 1.96), nor any systematic residual patterns across time. Hence, these plots supported the adequacy of the 5-class solution.

Discussion

Latent Classes of Freshmen Drinkers

As anticipated, this application of LGM modeling to the data originally analyzed by Del Boca et al. (2004) indicated that multiple latent trajectory classes were embedded within the single latent growth curve that best described the overall pattern of drinking across the first college year. Based on empirical criteria and substantive considerations, we chose a 5-class model as optimal. The classes can be described as: (a) freshmen who began as and remained light drinkers throughout the year (Light-Stable); (b) those who drank little across the year, with the exception of holiday weeks when drinking substantially increased (Light-Stable + High Holiday); (c) students who entered as moderate drinkers, but increased consumption across the year (Medium-Increasing); (d) those who began in the upper range, but decreased their drinking over time (High-Decreasing); and (e) participants who entered as relatively heavy drinkers and continued to drink at that level throughout the year (Heavy-Stable).

In addition to providing a more detailed picture of the variation among freshmen drinkers, these results reinforced our earlier finding that alcohol use was not continuous throughout the academic year, but instead was influenced by external contingencies (e.g., school schedules, holidays). Contingency-driven drinking occurred, at least to some degree, in all but the Light-Stable class. As shown by our Light-Stable + High Holiday class, even generally light drinkers may consume large quantities on occasion. If one adds together the students who drink heavily *on occasion*, it becomes evident that concerns related to alcohol use are present at some point in their college careers for a relatively large segment of the student community.

These spikes in drinking may help to explain why students apparently overestimate the rate of heavy drinking among their peers (NIAAA, 2002). Students' estimates may seem distorted when compared to *average* drinking levels, but when compared to salient, event-driven heavier drinking periods, such estimates may be more accurate. As case studies of fatal drinking instances among students show, serious consequences sometimes may befall very inexperienced drinkers who respond to situational pressures to drink heavily. In our study, the Light-Stable + High Holiday drinkers were primarily young women for whom circumscribed Holiday increases in consumption might result in relatively high blood alcohol concentrations and increased risk of harm proximal to these events. Conversely, the Heavy-Stable drinkers consumed significantly larger amounts of alcohol per week than the other classes across the entire year. Such consistent heavy drinking likely increases their potential for more chronic long-term negative outcomes.

Distinctiveness of Latent Classes

The five trajectory classes differed statistically in terms of the parameters of the growth mixture models (entry level drinking, changes over time, and the amount of additional drinking during holiday weeks). Beyond identifying individual differences in initial drinking, which could have been detected without examining longitudinal change, the incremental value of LGM modeling was that it identified classes that also varied by the amount of change that occurred during the year and during time-specific holiday weeks. Hence, the identified classes reflect differences that would not be apparent from a cross-sectional analysis of initial drinking only.

There is reason to believe, therefore, that the trajectory groupings were reliably distinctive; that is, individual *patterns* fell into latent classes, and these classes may be usefully examined for characteristics that may reflect different etiological pathways and long-term outcomes. Of the covariates studied, gender and alcohol expectancy significantly predicted class membership in the multivariate models. Not surprisingly, the Heavy-Stable included more males than the Light-Stable class; it is well-established that males tend to consume more alcohol than females.

Prediction by Expectancies

Expectancy scores at entry, the most powerful predictors in the study, significantly discriminated between the two heaviest drinking classes, students who decreased their drinking and those who maintained the same drinking level. This association also may reflect the well known cross-sectional correlation between expectancies and initial drinking levels. However, previous research has consistently indicated that expectancies exert a causal influence on alcohol use, although the evidence regarding the effect of expectancies on drinking trajectories is somewhat mixed. Because alcohol expectancy has been theorized to exert a proximal influence on drinking, it seems likely that time-based fluctuations in expectancy could differentially affect the course of drinking over an immediately subsequent time period. Future research using LGM should determine the temporal boundaries of the expectancy-drinking association.

Alcohol expectancy measured at intake into the study also effectively distinguished between the light drinker classes with respect to future holiday drinking. These two classes were not distinguishable by their initial drinking levels or by change in alcohol use over the freshmen year, differing significantly only in the magnitude of the holiday factor. The Light Stable + High Holiday group drank approximately six times more (in terms of standard drinks) during holiday than during non-holiday weeks. As alcohol tolerance in light drinkers is generally low, the large relative increase in drinking on holidays suggests increased risk for negative outcomes. Hence, expectancy may have an important practical application in identifying incoming students who are light drinkers, but may be at risk for alcohol-related consequences.

Methodological Considerations

Recently, Bauer and Curran (2003; 2004) recently have suggested that three data conditions may lead to spurious estimation of latent growth mixture classes; (a) misspecification (nonnormality of residuals) of the within-class model; (b) nonnormality of the observed variables; and (c) nonlinearity. In the current study, residual diagnostics indicated no misspecification of the within-class model; transformation of the observed variables produced distributions that were only mildly nonnormal, and nonlinearity, although present, accounted for only a small amount of model misfit. Nevertheless, we acknowledge that our results may not reflect “true” participant classes, but may merely be parsimonious ways of describing a complex population distribution (Bauer & Curran, 2004). Additionally, the generalizability of our findings is limited, and independent replication of our findings would be essential for generalizing to other college and young adult drinkers.

These issues cannot be resolved at present. LGM is a new technique that will continue to evolve. As Bauer and Curran (2003; 2004) suggest, indices of model fit may not provide sufficient evidence for population heterogeneity. Further, no consensus currently exists as to which fit index should be used for selecting the “best” model; the (at least) three commonly used different indices often yield contradictory “best” models. Until decision rules are clarified, ambiguity in model selection will persist, and LGM results should be regarded as somewhat preliminary. Within this context, we have reported both a single-class (see Del Boca et al., 2004) and, here, a 5-class LGM solution for the same data. We believe that both models are heuristic, and neither represents "truth" (see also Cudeck & Henly, 2003). In the single-class model, we were concerned with *aggregate changes* in drinking for our freshmen sample as a function of time. Heterogeneity was modeled as individual differences in the growth parameters, and important correlates of the growth factors were identified, which presumably could inform the development of strategies aimed at changing the level of a specific growth factor (e.g., slope, holiday factor) for the entire sample. In this paper, we also modeled heterogeneity in growth, but our focus was on identifying important *individual differences* in drinking trajectories, so that correlates of potentially problematic classes could be considered in attempts to alter the course of similar drinkers in the sample. Given the limitations of our sample and the LGM approach, however, the development of specific targeted strategies should await replication of the current findings.

Research and Policy Implications

The fate of our trajectory classes as the students move into later college years, and beyond, remains to be explored. Do the curves continue on the same paths? Do the potentially riskier drinking patterns evolve into subsequent life problems? Sher (1996) has suggested that college drinking problems are transitory, but additional research with more detailed assessment is warranted. Assessment using the current methodology (as well as others such as computer-assisted momentary assessment) is informative in ways that traditional methods are not. This approach is labor intensive and expensive, however, and more extended applications of the methodology require that preliminary work establishes an empirical basis to explore further.

Policy and prevention possibilities arise, however, even from the present one-year findings. Students are not all alike; as suggested by the NIAAA Task Force on College Drinking (2002), multiple strategies to prevent problems associated with drinking are required. For some students, such as our Heavy-Stable group, efforts might best be made to reduce ongoing drinking, although such efforts may be both time consuming and resource intensive. Other patterns, such as that seen in our Light Stable + High Holiday group, suggest that harm reduction efforts focused at high-risk time periods might be more efficient and cost effective. In addition, our preliminary results suggest that one might use expectancy as a means of distinguishing those who are more likely to drink heavily at peak periods from among the larger group of light drinkers. Overall, our results, although of limited generalizability, suggest the possibility that approaches targeted to specific trajectory classes, identified via frequent monitoring and LGM analysis, might lead to more efficiency and economy.

Conclusions are tempered somewhat by the study's relatively small sample, which was recruited from a single university. Conventional rules of thumb, based on power estimates for the RMSEA statistic (McCallum, Browne, & Sugawara, 1996), suggest that at least 200 cases are needed to adequately test latent variable models. Preliminary work by Brown (2003) on LGM models indicates that even more participants are needed to achieve conventional power of .80. These considerations lead to the inevitable suggestion for future research, using larger and more diverse samples of participants and institutions, to enhance statistical power and generalizability. Finally, a broader range of biopsychosocial risk processes may be needed to relate behavioral patterns to their biological and genetic underpinnings.

References

Akaike, H. (1987). Factor analysis and the AIC. *Psychometrika, 52*, 317-332.

Baer, J. S., Kivlahan, D. R., Blume, A. W., McKnight, P., & Marlatt, G. A. (2001). Brief intervention for heavy drinking college students: 4-year follow-up and natural history. *American Journal of Public Health, 91*, 1310-1316.

Bauer, D.J., & Curran, P.J. (2003). Distributional assumptions of growth mixture models: Implications for the overextraction of latent trajectory classes. *Psychological Methods, 8*, 338-363.

Bauer, D. J., & Curran, P. J. (2004). The integration of continuous and discrete latent variable models: Potential problems and promising opportunities. *Psychological Methods, 9*, 3-29.

Brown, E. C. (July, 2003). *Estimates of statistical power for latent trajectory class enumeration in the growth mixture model*. Unpublished doctoral dissertation, University of South Florida.

Brown, S.A., Goldman, M.S., Inn, A., & Anderson, L. (1980). Expectations of reinforcement from alcohol: Their domain and relation to drinking patterns. *Journal of Consulting and Clinical Psychology, 48*, 419-426.

Cudeck, R., & Henly, S. J. (2003). A realistic perspective on pattern representation in growth data: Comment on Bauer and Curran (2003). *Psychological Methods, 8*, 378-383.

Darkes, J., Greenbaum, P. E., & Goldman, M. S. (1998). Sensation seeking – disinhibition and alcohol use: Exploring issues of criterion contamination. *Psychological Assessment, 10*, 71-76.

Darkes, J., Greenbaum, P. E., & Goldman, M. S. (2004). Alcohol expectancy mediation of biopsychosocial risk: Complex patterns of mediation. *Experimental and Clinical Psychopharmacology, 12*, 27-38.

Del Boca, F. K., Darkes, J, Greenbaum, P. E., & Goldman, M. S. (2004). Up close and personal: Temporal variability in the drinking of individual college students during their first year. *Journal of Consulting and Clinical Psychology*, *72*, 155-164.

Goldman, M. S., Boyd, G. M., & Faden, V. (Eds.) (2002). College drinking, what it is and what to do about it: A review of the state of the science. *Journal of Studies on Alcohol, Supplement #14* .

Goldman, M.S., Greenbaum, P.E., & Darkes, J. (1997). A confirmatory test of hierarchical expectancy structure and predictive power: Discriminant validation of the alcohol expectancy questionnaire. *Psychological Assessment*, *9*, 145-157.

Greenbaum, P. E., & Dedrick, R. F. (2003, March). *Developmental trajectories of substance use among adolescents with serious emotional disturbance: Predictors, outcomes, and parallel processes*. Paper presented at the annual meeting of A System of Care for Children's Mental Health: Expanding the Research Base, Tampa, FL.

Hingson, R.W., Heeron, T., Zakocs, R.C., Kopstein, A., & Wechsler, H. (2002). Magnitude of alcohol-related mortality and morbidity among U.S. college students ages 18-24. *Journal of Studies on Alcohol*, *63*, 136-144.

Leigh, B. C. (2000). Using daily reports to measure drinking and drinking patterns. *Journal of Substance Abuse*, *12*, 51-65.

Li, F., Duncan, T. E., & Hops, H. (2001). Examining developmental trajectories in adolescent alcohol use using piecewise growth mixture modeling analysis. *Journal of Studies on Alcohol*, *62*, 199-210.

Little, R.J., & Rubin, D.B. (1987). *Statistical analysis with missing data*. New York: Wiley.

Lo, Y., Mendell, N., & Rubin, D. B. (2001). Testing the number of components in a normal mixture, *Biometrika, 88*, 767-778.

McCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods*, *1*, 130-149.

Muthén, B. O. (2003). Statistical and substantive checking in growth mixture modeling: Comment on Bauer and Curran (2003). *Psychological Methods*, *8*, 369-377.

Muthén, B. O, Brown, C. H., Masyn, K. Jo, B., Khoo, S.T., Yang, C. C., Wang, C. P., Kellam, S. G., Carlin, J. B., & Liao, J. (2002). General growth mixture modeling for randomized preventive interventions, *Biostatistics*, *3*, 459-475.

Muthén, B. & Muthén, L. (2000). Integrating person-centered and variable-centered analysis: Growth mixture modeling with latent trajectory classes. *Alcoholism: Clinical and Experimental Research*, *24*, 882-891.

Muthén, B. O., & Shedden, K. (1999). Finite mixture modeling with mixture outcomes using the EM algorithm. *Biometrica, 55*, 463-469.

National Institute on Alcohol Abuse and Alcoholism. (2002*). A call to action: Changes the culture of drinking at U.S. Colleges* (NIH Publication No. 02-5010). Rockville, MD: U. S. Department of Health and Human Services.

O'Malley, P. M., & Johnston, L. D. (2002). Epidemiology of alcohol and other drug use among American college students. *Journal of Studies on Alcohol, Supplement #14*, 23-39.

Ramaswamy, V., DeSarbo, W., Reibstein, D., & Robinson, W. (1993). An empirical pooling approach for estimating marketing mix elasticities with PIMS data. *Marketing Science, 12*, 103-124.

Rabow, J., & Duncan-Schill, M. (1995). Drinking among college students. *Journal of Drug and Alcohol Education*, *40*, 52-64.

Rabow, J., & Neuman, C. A. (1984). Saturday night live: Chronicity of alcohol consumption levels among college students. *Substance and Alcohol Actions/Misuse*, *5*, 1-7.

Schulenberg, J., O'Malley, P.M., Bachman, J.G., Wadsworth, K.N., & Johnston, L.D. (1996). Getting drunk and growing up: Trajectories of frequent binge drinking during the transition to young adulthood. *Journal of Studies on Alcohol, 57,* 289-304.

Schwartz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics*, *6*, 461-464.

Sclove, S. L. (1987). Application of model-selection criteria to some problems in multivariate analysis. *Psychometrika*, *52*, 333-343.

Sher, K. J. (1996, June). *The course of alcohol problems in adolescence and young adulthood: Perspectives from a high-risk, prospective study*. Plenary address presented at the annual meeting of the Research Society on Alcoholism, Washington, DC.

Sobell, L.C., & Sobell, M.B. (1994). *Timeline Followback (TLFB) User's manual.* Toronto: Addiction Research Foundation.

Tonigan, J. S., Miller, W. R., & Brown, J. M. (1997). The reliability of Form 90: an instrument for assessing alcohol treatment outcome. *Journal of Studies on Alcohol, 58,* 358-364.

Tucker, J. S. Orlando, M, Ellickson, P. L. (2003). Patterns and correlates of binge drinking trajectories from early adolescence to young adulthood. *Health Psychology*, *22*, 79-87.

Wang, C.-P., Brown, C. H., & Bandeen-Roche, K. (In press). Model diagnostics for General growth mixture models: Examining the impact of a preventive intervention on differential pathways to aggressive behavior. *Journal of the American Statistical Association.*

Zuckerman, M., Kuhlman, M.D., Joireman, J., Teta, P., & Kraft, M. (1993). A comparison of three structural models of personality: The big three, the big five, and the alternate five. *Journal of Personality and Social Psychology, 65,* 757-768.

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Table 1

Fit Indices and Entropy of the Growth Mixture Models

	Fit Indices				
Growth Model	AIC	BIC	SSABIC	Entropy	Adjusted LRT
1-class	16,760.587	16,927.054	16,774.911	---	---
2-class	16,713.437	16,897.244	16,729.252	.894	.46
3-class	16,727.699	16,908.000	16,743.216	.899	.06
4-class	16,618.346	16,809.090	16,634.759	.905	.07
5-class[a]	16,610.990	16,812.138	16,628.298	.844	.15

Note. AIC = Akaike Information Criteria, BIC = Bayesian Information Criteria, SSABIC = Sample Size Adjusted Bayesian Information Criteria, LRT = Lo-Mendall-Rubin Likelihood Ratio Test. In the final 5-class solution, all variances were fixed except for the intercept factor. Holiday loadings were freely estimated. All models included correlated errors for weeks 1 – 4.

[a] No additional class could be found.

Table 2

Growth Factor Parameter Estimates and Model-Based (Posterior) Probabilities for the Unconditional 5-Class Mixture Model

	Growth Factor Parameter Estimates			
Class	Intercept	Slope	Holiday	Model-based Probability
1. Light-Stable	0.266	0.000	0.294	0.533
	(0.026)	(0.000)	(0.066)	
2. Light-Stable + High Holiday	0.378	0.000	1.438	0.088
	(0.054)	(0.000)	(0.158)	
3. Medium-Increasing	0.695	0.037	0.597	0.083
	(0.200)	(0.010)	(0.187)	
4. High-Decreasing	1.720	-0.028	0.672	0.197
	(0.107)	(0.006)	(0.125)	
5. Heavy-Stable	2.606	0.000	0.637	0.099
	(0.099)	(0.000)	(0.091)	

Note. Standard errors are in parentheses below parameter estimates.

Table 3.

Covariates Associated With Latent Class Membership: Mean Differences between Latent Trajectory Classes (Reference Class = Light–Stable)

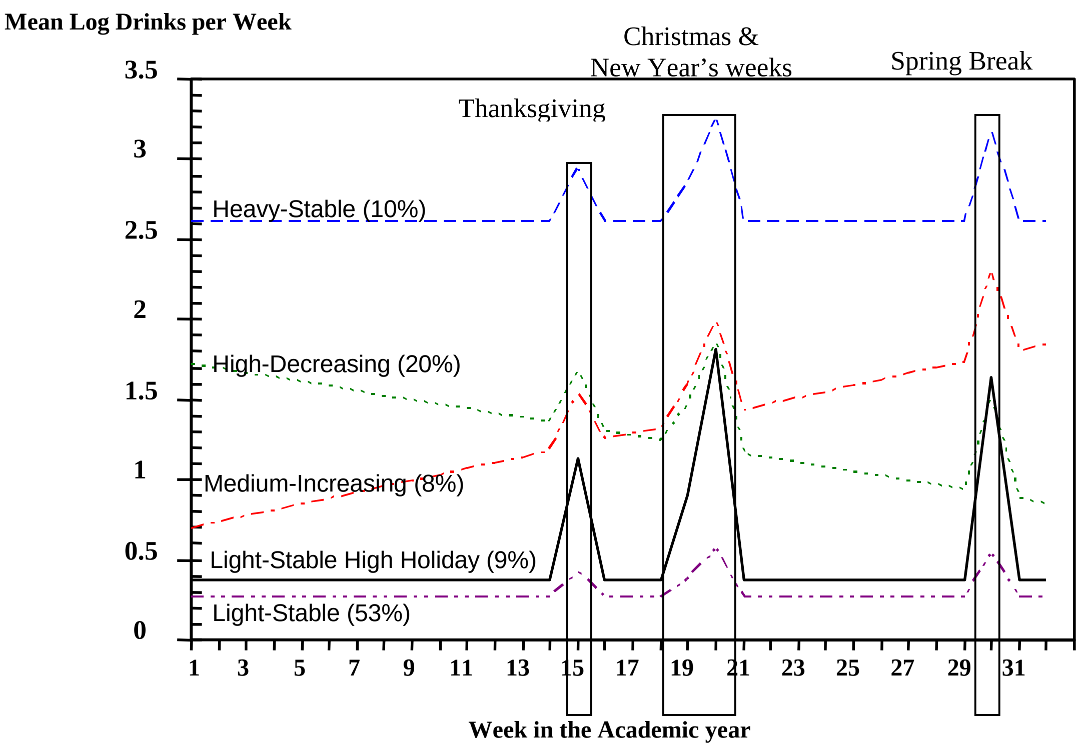
Class	Alcohol Expectancies	Sensation – Seeking	% Female	% With at Least One Missing Data Point
1. Light-Stable	13.51 [a]	5.48	59.6 [a]	30.7
2. Light-Stable + High Holiday	15.67 [b]	7.44	74.3 [a]	9.9
3. Medium – Increasing	16.29 [b]	7.50	36.3 [a]	33.6
4. High-Decreasing	16.36 [b]	6.98	40.6 [a]	43.1
5. Heavy-Stable	16.89 [b]	7.01	18.4 [b]	53.9

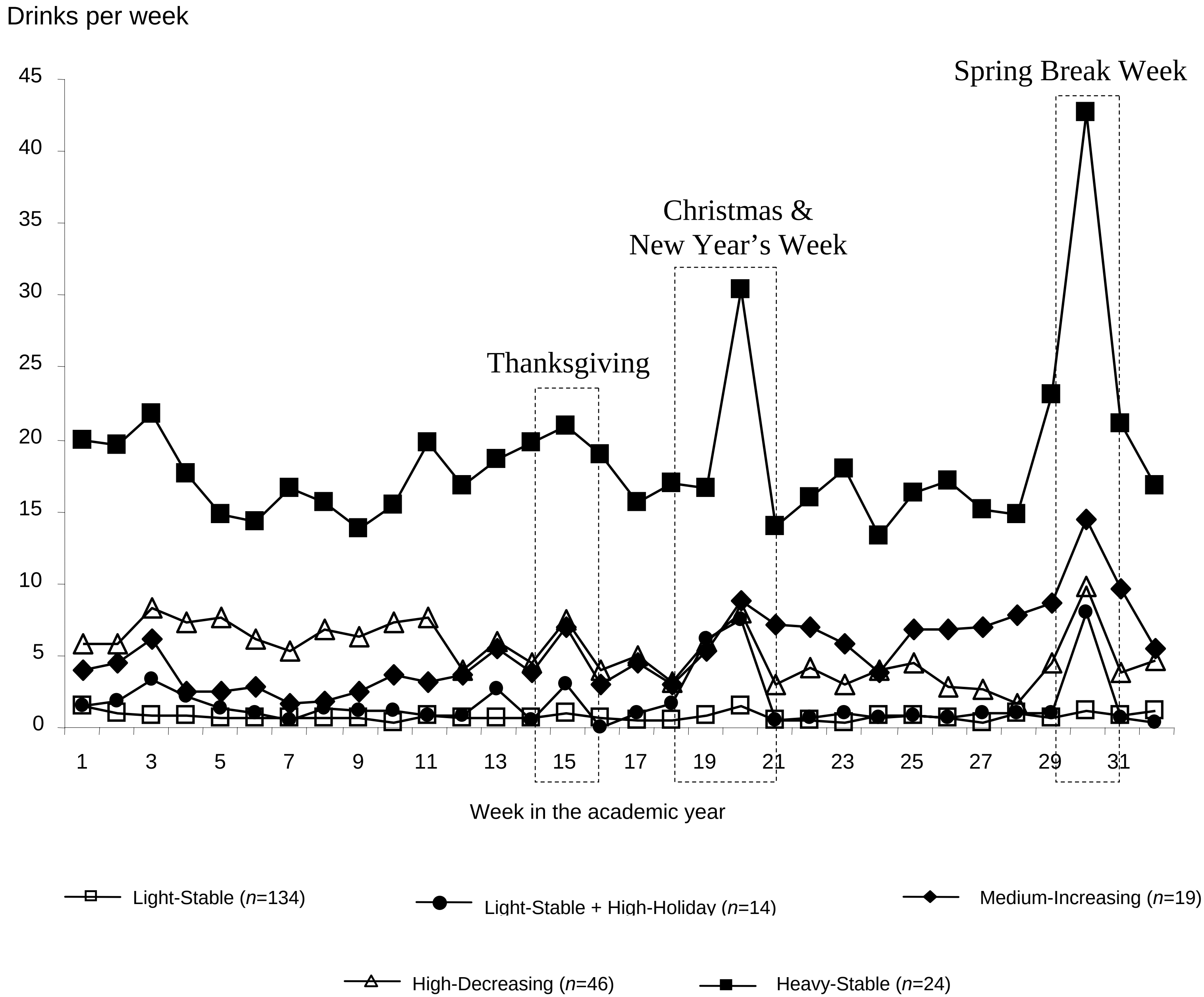
Note: A significant mean difference ($p < .05$) between the reference class and another class is noted by a different superscripted letter within that column.

Figure Captions

Figure 1. Fitted drinking trajectory classes from the unconditional model (without adjustment for covariates).

Figure 2. Mean Weekly Quantity of Alcohol Consumed across the Academic Year by Class.


Mean Log Drinks per Week
3.5
3
2.5
2
1.5
1
0.5
0
Christmas &
New Year's weeks
Spring Break
Thanksgiving
Heavy-Stable (10%)
High-Decreasing (20%)
Medium-Increasing (8%)
Light-Stable High Holiday (9%)
Light-Stable (53%)
1
3
5
7
9
11
13
15
17
19
21
23
25
27
29
31
Week in the Academic year


Drinks per week
45
40
35
30
25
20
15
10
5
0
Spring Break Week
Christmas &
New Year's Week
Thanksgiving
1
3
5
7
9
11
13
15
17
19
21
23
25
27
29
31
Week in the academic year
Light-Stable (n=134)
Light-Stable + High-Holiday (n=14)
Medium-Increasing (n=19)
High-Decreasing (n=46)
Heavy-Stable (n=24)