




Alcohol use trajectories among U.S. adults during the first 42 weeks of the COVID-19 pandemic

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Abstract

Background: This study characterized the prevalence, drinking patterns, and sociodemographic characteristics of U.S. adult subpopulations with distinct drinking trajectories during the COVID-19 pandemic's first 42 weeks.

Methods: Adult respondents ($n = 8130$) in a nationally representative prospective longitudinal study completed 21 biweekly web surveys (March 2020 to January 2021). Past-week alcohol drinking *frequency* (drinking days [range: 0 to 7]) and *intensity* (binge drinking on usual past-week drinking day [yes/no]) were assessed at each timepoint. Growth mixture models identified multiple subpopulations with homogenous drinking trajectories based on mean drinking days or binge drinking proportional probabilities across time.

Results: Four drinking frequency trajectories were identified: *Minimal/stable* (72.8% [95% CI = 71.8 to 73.8]) with <1 mean past-week drinking days throughout; *Moderate/late decreasing* (6.7% [95% CI = 6.2 to 7.3]) with 3.13 mean March drinking days and reductions during summer, reaching 2.12 days by January 2021; *Moderate/early increasing* (12.9% [95% CI = 12.2 to 13.6]) with 2.13 mean March drinking days that increased in April and then plateaued, ending with 3.20 mean days in January 2021; and *Near daily/early increasing* (7.6% [95% CI = 7.0 to 8.2]) with 5.58 mean March drinking days that continued increasing without returning to baseline. Four drinking intensity trajectories were identified: *Minimal/stable* (85.8% [95% CI = 85.0% to 86.5%]) with <0.01 binge drinking

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probabilities throughout; *Low-to-moderate/fluctuating* (7.4% [95% CI = 6.8% to 8%]) with varying binge probabilities across timepoints (range:0.12 to 0.26); *Moderate/mid increasing* (4.2% [95% CI = 3.7% to 4.6%]) with 0.39 April binge drinking probability rising to 0.65 during August–September without returning to baseline; *High/early increasing trajectory* (2.7% [95% CI = 2.3% to 3%]) with 0.84 binge drinking probability rising to 0.96 by June without returning to baseline. Males, Whites, middle-aged/older adults, college degree recipients, those consistently working, and those above the poverty limit were overrepresented in various increasing (vs. minimal/stable) frequency trajectories. Males, Whites, nonmarried, those without college degree, 18 to 39-year-olds, and middle aged were overrepresented in increasing (vs. minimal/stable) intensity trajectories. **Conclusions:** Several distinct U.S. adult sociodemographic subpopulations appear to have acquired new drinking patterns during the pandemic's first 42 weeks. Frequent alcohol use assessment in the COVID-19 era could improve personalized medicine and population health efforts to reduce drinking.

KEYWORDS

alcohol use trajectories, COVID-19 pandemic, epidemiology

INTRODUCTION

Aggregate population-wide estimates of U.S. alcohol sales and mean adult drinking levels were slightly elevated during the first several months of the COVID-19 pandemic compared to past years (Lee et al., 2021; Pollard et al., 2020). Whether drinking increases have persisted later into the pandemic is unknown yet important for determining whether funding and population health promotion programming dedicated to mitigating alcohol use should be elevated among the various national public health priorities requiring attention during this pandemic.

While aggregate population-wide drinking estimates are informative, they could obscure clinically important heterogeneity and volatility in person-level drinking trajectories (Muthen & Muthen, 2000). Stress, lack of alternative sources of enjoyment, reduced healthcare access, institutional racism, economic distress, and alcohol delivery services during the pandemic might have increased drinking for some subpopulations (Huckle et al., 2021; McPhee et al., 2020). Closure of bars and fewer social gatherings might reduce drinking for other subpopulations (Garnett et al., 2021; Jackson, Merrill, et al., 2021). Although cross-sectional research finds that individuals retrospectively report having changed their drinking during the pandemic (Capasso et al., 2021; Garnett et al., 2021), longitudinal characterization of drinking trajectories during the pandemic is lacking.

The numerous patterns and timing of changes in drinking complicates efforts to identify common alcohol use trajectory patterns and, in turn, inform requisite alcohol-related public health strategies. Growth mixture models (GMMs) are person-centered analyses that can identify a parsimonious set of alcohol use trajectories that sufficiently explain inter-individual variability in the intercepts and

slopes of drinking across time (Muthen & Muthen, 2000). Applying GMMs to nationally representative longitudinal drinking data collected during the pandemic could provide evidence that would assist behavioral and public health practitioners seeking to help individuals and subpopulations who: (a) decreased their drinking during the pandemic and could benefit from further support to sustain it, (b) require intervention to prevent increased drinking patterns established during the pandemic from persisting, and (c) are persistently involved in problematic drinking.

Evidence of whether particular demographic groups are overrepresented in subpopulations with increasing or decreasing trajectories could also inform strategies for reducing alcohol-related health disparities and precision prevention. Prior to the pandemic, it has been well-documented that the prevalence and consequences of heavy alcohol use are overrepresented among certain U.S. subpopulations defined by race/ethnicity, income, employment, education, and other demographic variables that are proxies for disproportionate exposure to racism, economic disadvantage, and other social determinants of alcohol use (Bellis et al., 2016; Schmidt et al., 2010). In the absence of data on the social mechanisms of alcohol use disparities, leveraging demographic data to identify if certain demographic populations are at high risk of escalating drinking trajectories during the pandemic can provide initial impetus for mechanistic research on alcohol disparities. GMM is particularly useful for this purpose. GMM provides a single set of estimates for an association between a demographic characteristic and drinking trajectories that considers the simultaneous association with both baseline (intercept) drinking and the pattern of changes in drinking over time (slopes). As such, GMM can provide a parsimonious characterization of these associations, which could offer clues into how the social determinants of health could alter drinking patterns throughout the pandemic

differentially across subpopulations within the United States. Such evidence would clarify whether national funding for science and health services to promote health equity should be allocated to alcohol use relative to other funding priorities. Additionally, these data can also inform for whom drinking intervention programs, detailed alcohol use surveillance, and public health messaging campaigns should be emphasized. Specifically, the data can inform how outreach and dissemination of alcohol mitigation resources and tools might prioritize or be tailored to resonate with specific communities overrepresented with increasing alcohol use trajectories during the pandemic.

This nationally representative prospective intensive longitudinal study examined drinking trajectories over the first 42 weeks of the COVID-19 pandemic among U.S. adults. In addition to describing aggregate population-wide estimates, GMMs identified distinct subgroups, prevalence, and sociodemographic characteristics of U.S. adults with respect to distinct drinking trajectories during the pandemic.

MATERIALS AND METHODS

Participants and procedures

The Understanding America Study (UAS) is a nationwide, probability-based online panel of noninstitutionalized adults regularly surveyed on social, economic, and health issues (Alattar et al., 2018). UAS uses address-based random probability sampling and is

regularly refreshed with two-stage adaptive sampling to increase national representativeness detailed elsewhere (Alattar et al., 2018). Annually, panel recruitment rates range 15% to 20% and retention rates have been approximately 95%. Each survey contains updated sampling weights using a two-step procedure with poststratification ranking algorithms to increase demographic national representativeness and adjust for oversampling of California residents at a 2.6:1 ratio (Alattar et al., 2018). Initial panel recruitment completed by postal mail and phone contact involves identity verification, written informed consent, and demographic information surveys (later updated quarterly).

All UAS panel members were invited to the Coronavirus in America longitudinal survey consisting of a March 10, 2020 baseline (wave 1; 1 day before COVID-19 was declared a global pandemic by WHO) and biweekly follow-ups starting April 1, 2021 (Kapteyn et al., 2020). A nested stratified design randomized participants to respond on a preassigned day across a 14-day period with 13-day response windows for each respective follow-up. Surveys were self-administered web questionnaires. Participants without internet service or devices were provided internet-enabled tablets. This study used 21 biweekly surveys waves (03/10/2020 to 01/20/2021; see dates in Figure 1). For each survey, best practices in survey structure are used and data validation checks are made flagging inconsistent responses, time spent per question, item nonresponse rates, and whether respondents changed their initial response to a particular question (Kapteyn et al., 2020). Quality assurance data check results provided no indication of concerns, consistency of results for each timepoint

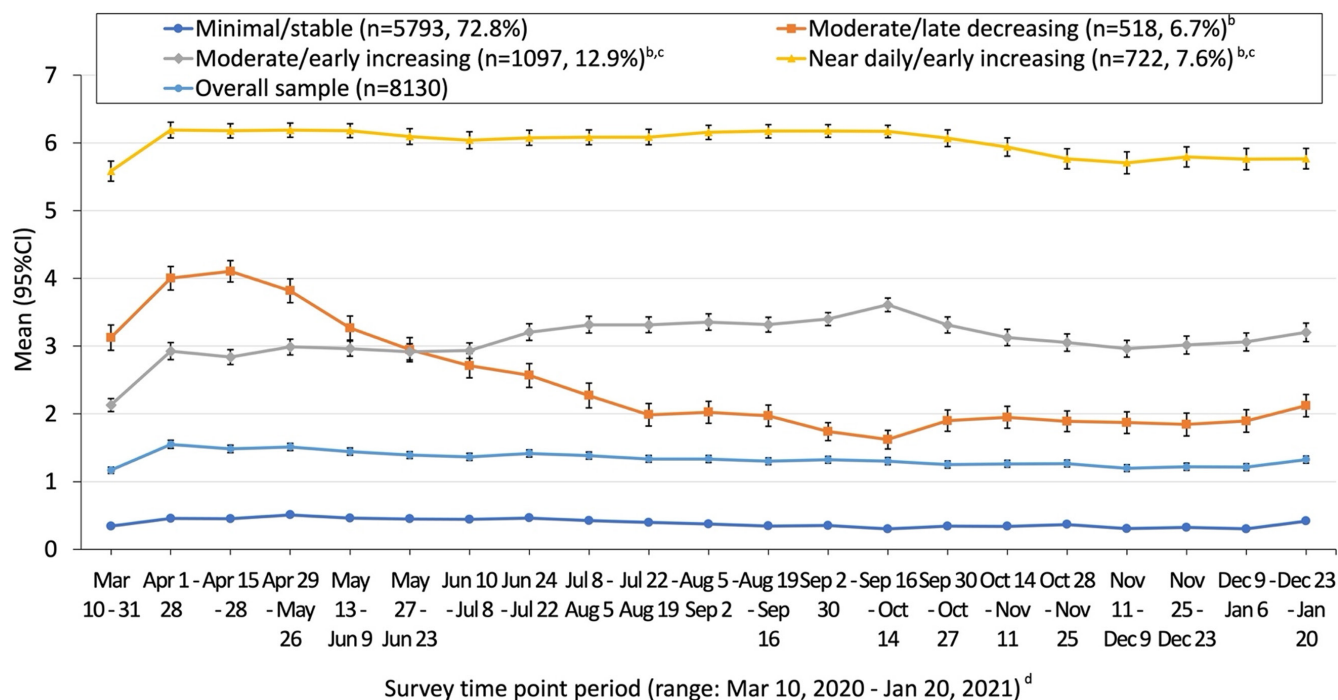


FIGURE 1 Past-Week No. Drinking Days Across Time Overall and by Trajectory Groups

^aRespective latent trajectory linear slope, $p < .05$.

^bRespective latent trajectory quadratic slope, $p < .05$.

^cPeriods overlap because survey invitations are staggered across 2-weeks and respondents have up to 14 days to complete survey.

with other national data sources and are publicly available for download at uasdata.usc.edu. University of Southern California's Institutional Review Board approved this study.

Measures

Demographics

Participants self-reported baseline sex (female or male), race/ethnicity (Hispanic, Non-Hispanic Black, Non-Hispanic White, Non-Hispanic Asian, Non-Hispanic Other [American Indian, Alaska Native, Pacific Islander combined due to small frequencies]), age (18 to 39, 40 to 50, 51 to 64, 65+ years), currently married (yes/no), annual household income (above vs. below federal poverty threshold), and highest education (college degree: yes/no), residing in California (vs. other states). Employment was assessed each wave and responses across were coded into one 4-level variable (consistently working [stable full-time or stable part-time], job loss/reduced time [transition from full/part-time to unemployed or full-time to part-time at any point during follow-up] or consistently not working [unemployed, disabled, on sick/other leave, or retired across all waves], or other).

Drinking outcomes

Drinking frequency at each wave was measured using a past-week alcohol drinking days item (range: 0 to 7). Beginning wave 3 (April 15–April 28), a drinking intensity item assessing number of drinks on a typical past-week drinking day (0 to 15+) was administered and recoded to a 0/1 dichotomous binge-type drinking proportional probability variable per federal definitions (NIAAA, 2004; ≥ 4 drinks females/ ≥ 5 drinks males vs. ≤ 3 drinks females/ ≤ 4 drinks males or no drinking).

Data analysis

After descriptive analyses of aggregate samples, GMMs (Muthen & Muthen, 2000) identified multiple homogenous trajectory subgroups using mean, variance, and covariance patterns of person-level repeated measurements of estimated latent intercepts, linear slopes, and quadratic slopes. For drinking days (negative binomial link) and binge-type drinking (binary logit), we estimated separate series of GMMs involving successively increasing numbers of latent trajectories. Selecting models with best-fitting number of trajectories was guided by Akaike Information Criterion (AIC), entropy values (Nylund et al., 2007), and Lo–Mendell–Rubin (LMR) likelihood ratio tests. To ensure a global solution, each class model was replicated using multiple start values and different random starts. As the default model option, GMM random effects (i.e., variation around the mean trajectory within classes) and residual variances (i.e., the variance of

the difference between the observed and estimated value for each individual at each time point) were constrained to be equal for each class. Descriptions of each trajectory in final GMMs were based on: (a) tests of whether estimated linear/quadratic slopes significantly differed from zero, and (b) past-week drinking day means and binge drinking probabilities at each timepoint using trajectory variables. The auxiliary BCH/DCAT method was performed to estimate individual associations between each sociodemographic variable (i.e., distal categorical variable; DCAT option) and probability of trajectory group membership (Asparouhov & Muthén, 2014). Significance of differences was reported based on the overall and pair-wise Chi-square/df values from the auxiliary procedure. Sensitivity analyses were conducted to examine the consistency of GMM results when using a subset of timepoints and compare the results of demographic associations with latent trajectories derived from GMM versus associations with trajectories derived using growth curve modeling. Analyses used Mplus Version 8 (Muthen & Muthen, 2015) with full information maximum likelihood estimation accounting for missing data in the study variables across waves, complex analysis accounting for nesting and sampling structure (i.e., the nesting of participants by their state), and nationally representative sampling weights (i.e., poststratification weights, generated through a ranking algorithm, were used in all analyses to align the sample to the U.S. adult population, in terms of distribution for sex, race/ethnicity, age, education, and geographic location [more information is available at uasdata.usc.edu/page/weights]). Benjamini–Hochberg two-tailed *p*-values were corrected for multiple tests to maintain study-wise false discovery rate of 0.05 (Benjamini, 1995).

RESULTS

Descriptive results

Study samples

Among 8547 UAS panel respondents invited for the Coronavirus in America survey, 8151 completed ≥ 1 survey, of whom, 8130 and 7833 provided drinking frequency and intensity data at ≥ 1 timepoints, respectively, which constituted the two analytic samples. There was variability across waves in response rates (Mean = 75.6% [SD = 3.3%]; range = 67.1% to 84.7%) and in total surveys completed per respondent (mean = 15.64 [SD = 6.65], range = 1 to 21). Depicted in Tables 1 and 2, samples were 52% female, 18% Hispanic, 12% Black, 61% White, 5% Asian, 4% other race/ethnicity, 53% married, 45% with college degree, 19% to 20% below poverty threshold, 54% with consistent working status throughout follow-up, and 7% to 8% with employment loss or reduction during follow-up. Collapsing across waves, 129,102 (drinking frequency), and 123,619 (intensity) observations were analyzed, weighted past-week number of drinking days prevalence varied (0 [57.9%], 1 [11.4%], 2 [9.0%], 3 [6.8%], 4 [4.1%], 5 [3.4%], 6 [1.6%], and 7 [5.9%] days). Table S1 details drinks per drinking day distributions.

TABLE 1 Demographic characteristics of overall sample and by trajectory group for no. drinking days outcome^a

Variables	By no. drinking days trajectory group				p-value for group difference ^d	
	Overall (n = 8130)	Minimal/stable trajectory (n = 5973)	Moderate/late decreasing trajectory (n = 518)	Moderate/early increasing trajectory (n = 1097)		Near daily/early increasing trajectory (n = 722)
Female sex	52.0 (50.9 to 53.0)	55.8 (54.5 to 57.2)	53.6 (49.2 to 57.9)	46.7 (43.6 to 49.8) ^e	32.3 (28.5 to 36.1) ^e	<0.001
Race/ethnicity						<0.001
Hispanic	18.4 (17.6 to 19.2)	19.7 (18.6 to 20.7)	20.4 (16.9 to 23.9)	13.5 (11.3 to 15.6) ^e	5.8 (3.9 to 7.7) ^e	
White	60.7 (59.7 to 61.8)	58.1 (56.8 to 59.4)	61.0 (56.7 to 65.3)	68.8 (65.6 to 71.7) ^e	84.1 (81.2 to 87.2) ^e	
Black	12.0 (11.3 to 12.7)	12.2 (11.4 to 13.1)	10.6 (7.9 to 13.3)	10.7 (8.8 to 12.7)	6.0 (4.0 to 7.9) ^d	
Asian	5.1 (4.6 to 5.6)	5.8 (5.2 to 6.4)	4.9 (3.1 to 6.8)	2.3 (1.4 to 3.3) ^e	1.1 (0.3 to 2.0) ^e	
Other ^b	3.8 (3.4 to 4.2)	4.2 (3.7 to 4.7)	3.0 (1.5 to 4.6)	4.7 (3.4 to 6.1)	2.9 (1.6 to 4.3)	
Age, year						<0.001
18 to 39	41.1 (40.0 to 42.2)	41.2 (39.9 to 42.5)	49.0 (44.7 to 53.3) ^e	38.3 (35.2 to 41.4)	23.3 (20.0 to 26.6) ^e	
40 to 50	17.6 (16.8 to 18.4)	17.3 (16.3 to 18.2)	22.0 (17.8 to 26.2)	22.1 (19.5 to 24.7) ^e	12.7 (10.0 to 15.4) ^e	
51 to 64	22.4 (21.5 to 23.3)	22.7 (21.6 to 23.8)	21.8 (19.2 to 24.5)	21.8 (19.2 to 24.4)	27.4 (23.8 to 31.1) ^e	
65+	18.9 (18.0 to 19.7)	18.9 (17.8 to 19.9)	8.0 (5.6 to 10.4) ^e	17.8 (15.4 to 20.2)	36.6 (32.6 to 40.5) ^e	
Currently married	52.9 (51.8 to 54.0)	51.5 (50.1 to 52.8)	52.9 (48.7 to 57.2)	55.3 (52.3 to 58.4)	60.0 (56.0 to 64.0) ^e	<0.001
Received college degree	44.8 (43.7 to 45.9)	41.1 (39.8 to 42.4)	57.9 (53.5 to 62.2) ^e	55.6 (52.5 to 58.7) ^e	59.3 (55.3 to 63.3) ^e	<0.001
Below federal poverty level	19.5 (18.6 to 20.4)	22.4 (21.2 to 23.5)	16.9 (13.6 to 20.2)	10.4 (8.5 to 12.3) ^e	7.7 (5.5 to 9.9) ^e	<0.001
California resident	12.3 (11.6 to 13.0)	12.4 (11.6 to 13.2)	11.2 (8.6 to 13.8)	11.6 (9.7 to 13.5)	13.2 (10.5 to 15.8)	0.65
Employment during follow-up ^c						<0.001
Consistently employed	53.9 (52.8 to 54.9)	52.0 (50.7 to 53.4)	67.9 (63.8 to 71.9) ^e	58.7 (55.6 to 61.8) ^e	52.6 (48.5 to 56.7)	
Job loss or reduced time	8.7 (8.1 to 9.3)	8.8 (8.1 to 9.5)	11.4 (8.6 to 14.1) ^e	9.2 (7.4 to 11.0)	5.8 (3.9 to 7.7)	
Consistently not working	34.9 (33.9 to 36.0)	36.8 (35.5 to 38.0)	19.7 (16.2 to 23.1) ^e	28.0 (25.2 to 30.9) ^e	39.9 (35.9 to 43.9)	
Other	2.5 (2.2 to 2.8)	2.4 (2.0 to 2.8)	1.2 (0.3 to 2.1)	4.1 (2.9 to 5.4)	1.7 (0.7 to 2.8)	

^aWeighted percentages (95% CIs).^bNative American (American Indian, Alaska Native), Native Hawaiian, or Pacific Islander.^cConsistently working: stable full-time or stable part-time job across all survey waves. Job loss/reduced time: Transition from full/part-time to unemployed (7.2%) full-time to part-time (1.5%) at any point during follow-up. Consistently not working: unemployed, disabled, on sick/other leave, or retired throughout all survey waves. Other: Mixed, other labor force status, changes from not-working to working, changes from part-time to full-time job positions, or others.^dCalculated based on Chi-square/df from the overall test of auxiliary model for each covariate.^eProportion of demographic subgroup in respective trajectory group significantly different from the Minimal/stable drinking trajectory group from pair-wise Chi-squared tests ($p < 0.05$).

TABLE 2 Demographic characteristics of overall sample and by trajectory group for binge drinking outcome^a

Variables	By binge drinking trajectory group					p-value for group difference ^d
	Overall (n = 7833) ^c	Minimal/stable trajectory (n = 6807)	Low-to-moderate/fluctuating trajectory (n = 533)	Moderate/mid increasing trajectory (n = 298)	High/early increasing trajectory (n = 195)	
Female sex	52.0 (51.0 to 53.1)	53.7 (52.4 to 54.9)	56.4 (52.2 to 60.6)	43.7 (38.1 to 49.4) ^e	32.3 (25.7 to 39.0) ^e	<0.001
Race/ethnicity						<0.001
Hispanic	18.4 (17.5 to 19.2)	17.6 (16.7 to 18.6)	19.7 (16.3 to 23.1)	22.6 (17.8 to 27.3)	12.7 (7.9 to 17.4)	
White	60.8 (59.7 to 61.9)	61.6 (60.4 to 62.8)	59.1 (55.0 to 63.4)	61.6 (56.0 to 67.1)	73.4 (67.1 to 79.7) ^e	
Black	11.9 (11.2 to 12.6)	11.3 (10.5 to 12.1)	13.3 (10.4 to 16.2)	11.0 (7.4 to 14.5)	7.5 (3.8 to 12.1)	
Asian	5.1 (4.6 to 5.6)	5.4 (4.8 to 5.9)	3.5 (1.9 to 5.0)	1.0 (0.01 to 2.1) ^e	2.0 (0.01 to 3.9) ^e	
Other ^b	3.8 (3.4 to 4.3)	4.1 (3.6 to 4.6)	4.4 (2.6 to 6.1)	4.0 (1.8 to 6.2)	4.5 (1.5 to 7.4)	
Age, year						<0.001
18 to 39	41.0 (39.9 to 42.1)	38.6 (37.5 to 40.0)	54.9 (50.7 to 59.2) ^e	44.5 (38.8 to 50.1) ^e	32.8 (26.1 to 39.5)	
40 to 50	17.9 (17.1 to 18.8)	17.3 (16.6 to 18.0)	18.1 (14.8 to 21.3)	27.1 (22.1 to 32.2) ^e	23.1 (18.2 to 28.0) ^e	
51 to 64	22.2 (21.3 to 23.1)	22.9 (21.9 to 23.9)	19.8 (16.4 to 23.1)	19.6 (15.1 to 24.1)	26.4 (20.1 to 32.7) ^e	
65+	18.9 (18.0 to 19.7)	20.8 (19.8 to 21.8)	7.2 (5.0 to 9.4) ^e	8.8 (5.6 to 12.0) ^e	17.8 (12.3 to 23.2)	
Currently married	53.0 (51.9 to 54.1)	53.9 (52.7 to 55.2)	44.3 (40.0 to 48.5) ^e	44.3 (38.6 to 49.9) ^e	49.5 (42.3 to 56.6)	<0.001
Received college degree	45.0 (43.9 to 46.1)	47.0 (45.8 to 48.3)	48.3 (44.0 to 52.5)	40.0 (34.3 to 45.5) ^e	35.6 (28.8 to 42.4) ^e	<0.001
Below federal poverty level	19.4 (18.5 to 20.2)	19.2 (18.2 to 20.2)	20.2 (16.8 to 23.7)	19.3 (14.7 to 23.8)	16.7 (11.3 to 22.1)	<0.001
California resident	12.2 (11.4 to 12.9)	12.4 (11.6 to 13.1)	11.5 (8.9 to 14.0)	11.2 (7.9 to 14.5)	8.7 (4.5 to 12.8)	0.29
Employment during follow-up ^c						<0.001
Consistently employed	53.6 (52.5 to 54.7)	52.9 (51.6 to 54.1)	60.7 (56.5 to 64.8) ^e	58.3 (52.7 to 63.9)	52.7 (45.6 to 59.9)	
Job loss or reduced time	9.0 (8.4 to 9.7)	9.0 (8.3 to 9.7)	12.8 (9.9 to 15.7) ^e	8.8 (5.6 to 12.0)	6.1 (2.7 to 9.5)	
Consistently not working	34.8 (33.8 to 35.9)	35.7 (34.5 to 36.9)	24.3 (20.6 to 27.9) ^e	28.1 (22.9 to 33.2)	37.9 (31.0 to 44.9)	
Other	2.6 (2.2 to 2.9)	2.4 (2.1 to 2.8)	3.0 (1.6 to 4.5)	4.8 (2.4 to 7.3)	3.2 (0.07 to 5.7)	

^aWeighted percentages (95% CIs).^bNative American (American Indian, Alaska Native), Native Hawaiian, or Pacific Islander.^cConsistently working: stable full-time or stable part-time job across all survey waves. Job loss/reduced time: Transition from full/part-time to unemployed (7.5%) full-time to part-time (1.5%) at any point during follow-up. Consistently not working: unemployed, disabled, on sick/other leave, or retired throughout all survey waves. Other: Mixed, other labor force status, changes from not-working to working, changes from part-time to full-time job positions, or others.^dCalculated based on Chi-square/df from the overall test of auxiliary model for each covariate.^eProportion of demographic subgroup in respective trajectory group significantly different from the Minimal/stable binge drinking trajectory group from pair-wise Chi-squared tests ($p < 0.05$).

Aggregate population-wide drinking

In the overall sample, mean past-week drinking days increased slightly from 1.17 in March 2020 to 1.48 to 1.55 in April, then gradually declined throughout the remainder of the year, with mean drinking days ranging from 1.20 to 1.33 across the four final timepoints (Figure 1). Across all timepoints, mean proportional probability of past-week binge drinking in the aggregate sample was 0.06 (SD = 0.004) and fairly stable (range: 0.05 to 0.07; Figure 2).

Drinking frequency trajectories

Fit statistics of drinking frequency GMMs with 1- to 5-class specifications detailed in Table S2 supported a 4-class model (AIC = 169,053.72, Entropy = 0.96, LMR p -value < 0.001). Depicted in Figure 1, the final GMM yielded a: (i) *Minimal/stable* (72.8% [95% CI = 71.8 to 73.8] prevalence; linear slope, $p = 0.13$; quadratic slope, $p = 0.29$) with <1 mean past-week drinking days across all timepoints; (ii) *Moderate/late decreasing* (6.7% [95% CI = 6.2 to 7.3]; linear slope, $p < 0.001$; quadratic slope, $p < 0.001$) with 3.13 mean March past-week drinking days, temporary increases in April, reductions from May to July, and leveling off thereafter (June-January range: 1.62 to 2.71); (iii) *Moderate/early increasing* (12.9% [95% CI = 12.2 to 13.6]; linear slope, $p < 0.001$; quadratic slope, $p < 0.001$) with 2.13 March mean past-week drinking days that increased to 2.93 by April without returning to baseline, ending 2020 with 3.20 mean days;

and (iv) *Near daily/early increasing* (7.6% [95% CI = 7.0 to 8.2]; linear slope, $p < 0.001$; quadratic slope, $p < 0.001$) with 5.58 March past-week drinking days that increased to 6.19 in April and never returned to baseline.

Demographic composition of drinking frequency trajectory groups differed (Table 1). Notable results of pairwise comparisons to the *Minimal/stable* trajectory include: (a) 18 to 39-year olds and those with job loss or job time reduction were more prevalent in the *Moderate/late decreasing* trajectory, (b) men, Whites, middle-aged/older adults, and those above the poverty threshold were more prevalent in one or both of the increasing trajectories, (c) those consistently employed were more prevalent in the *Moderate/late decreasing* trajectory or *Moderate/early increasing* trajectories, and (d) those with college degree were more prevalent in all three drinking trajectories.

Drinking intensity trajectories

GMMs for past-week binge drinking indicated a 4-class model was optimal (AIC = 27,427.07, Entropy = 0.91, LMR p -value < 0.001; each GMM's fit statistics reported in Table S3). Depicted in Figure 2, the final model included a: (i) *Minimal/stable* (85.8% [95% CI = 85.0 to 86.5] prevalence; linear slope, $p = 0.11$; quadratic slope, $p = 0.32$) with consistent <0.01 binge-type drinking probabilities across timepoints; (ii) *Low-to-moderate/fluctuating* (7.4% [95% CI = 6.8 to 8.0]; linear slope, $p = 0.26$; quadratic slope, $p = 0.78$) with varying binge

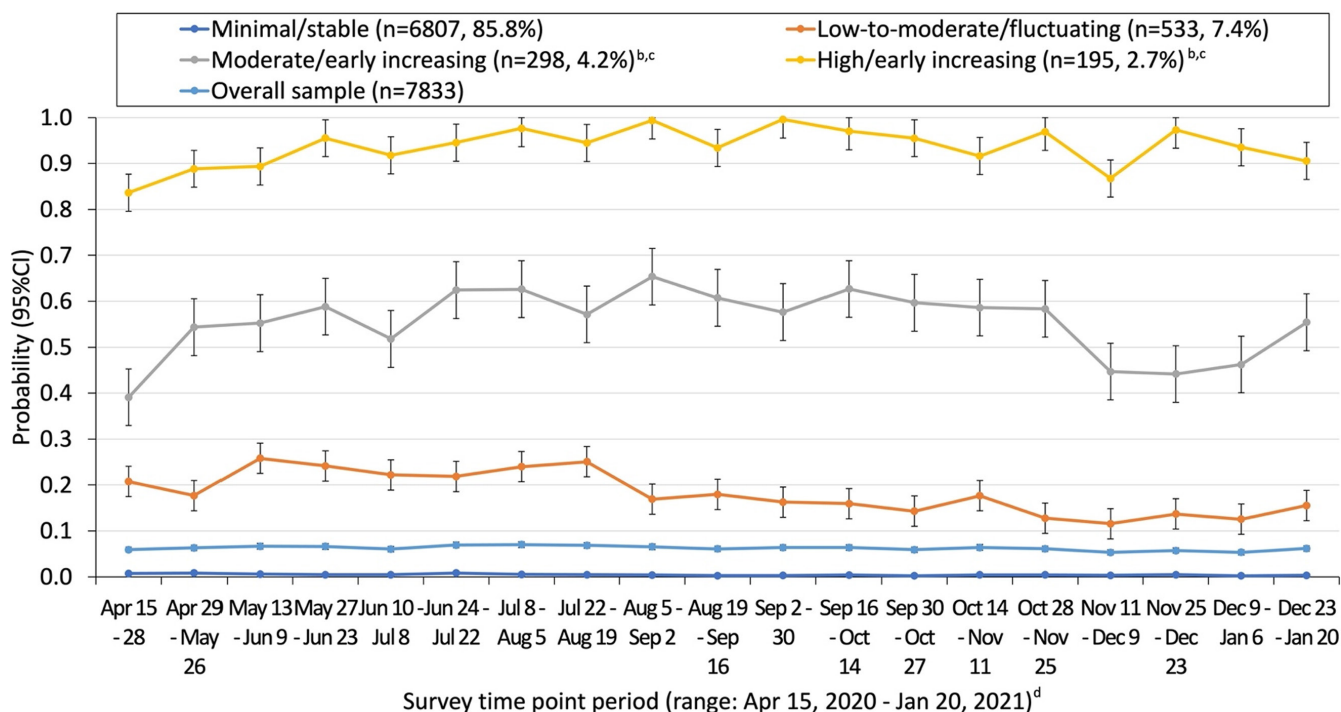


FIGURE 2 Binge Drinking Across Time Prevalence Overall and by Trajectory Groups

^aRespective latent trajectory linear slope, $p < .05$.

^bRespective latent trajectory quadratic slope, $p < .05$.

^cPeriods overlap because survey invitations are staggered across 2-weeks and respondents have up to 14 days to complete survey.

drinking probabilities across timepoints (range: 0.12 to 0.26) lacking systematic trends; (iii) *Moderate/mid increasing* (4.2% [95% CI = 3.7 to 4.6]; linear slope, $p < 0.001$; quadratic slope, $p < 0.001$) with a 0.39 April binge drinking probability, that rose by May to 0.59, peaked at 0.65 during August–September without returning to baseline; and (iv) *High/early increasing* (2.7% [95% CI = 2.3 to 3.0]; linear slope, $p < 0.001$; quadratic slope, $p < 0.001$) with an 0.84 April past-week binge drinking probability that rose to 0.96 by June without returning to baseline.

Demographics of binge drinking trajectory groups varied (Table 2). Notable pairwise comparisons to the *Minimal/stable trajectory* group were: (a) males, 40 to 50-year-olds, or college degree nonrecipients were more prevalent in the two trajectories with the highest binge probabilities across follow-up (*Moderate/mid increasing* and *High/early increasing*), (b) 18 to 39 year-old or nonmarried respondents were more prevalent in the *Low-to-moderate/fluctuating* and *Moderate/mid increasing* trajectories, and (c) those with job loss or job time reduction were more prevalent in the *Low-to-moderate/fluctuating* trajectory.

Sensitivity and supplemental analyses

To determine whether the results were consistent across different modeling approaches and time points, we conducted additional sensitivity analyses. These analyses showed that the GMM trajectories were consistent regardless of whether data were drawn from a subsection of the timepoints versus all timepoints (see Figures S1 to S2). Sensitivity analyses also showed that the model fit and effect sizes for demographic associations with drinking trajectories were comparable when using GMM versus growth curve modeling approaches to estimate drinking trajectory growth processes (see Tables S4 and S5). To verify that nondrinkers were classified correctly, we manually identified 988 (12.1%) nondrinkers who reported 0 days of past-week drinking across all time points. All 988 of these participants were correctly identified as the lowest drinking frequency trajectory group from the GMM analysis. We also report monthly trends of U.S. COVID-19 cases alongside UAS population-wide alcohol use descriptive statistics aggregated by month for descriptive purposes (see Table S6).

DISCUSSION

This study of U.S. drinking trajectories across the first 42 weeks of the COVID-19 pandemic advances the literature in three respects. First, it follows up previously published aggregate population-wide estimates obtained April–June 2020 (McKetta et al., 2021; Pollard et al., 2020) by demonstrating that modest increases in mean drinking frequency early in the pandemic largely dissipated by late 2020. Second, we provide new estimates tracking binge drinking during the pandemic, which is an important health indicator over and above. Third, GMMs revealed that aggregate population-wide

drinking estimates likely obscure heterogeneity in person-level drinking trajectories by identifying sizeable subpopulations with divergent changes in drinking patterns during the pandemic.

Most U.S. adults maintained stable patterns of minimal/no drinking in this study, including subpopulations averaging less than one drinking day per week (72.8%) or with negligible binge-type drinking probabilities across follow-ups (85.8%). These results support pre-2020 data indicating that most U.S. adults either do not drink or use alcohol infrequently and in nonheavy intensity patterns (Esser et al., 2020), and do not indicate major change in the trend of a nondrinker/minimal drinker majority during the pandemic's first 42 weeks.

Two subpopulations who collectively constituted 20.5% of adults increased their drinking frequency at some point during the pandemic. Two subpopulations with a combined 6.9% prevalence increased their probability of binge drinking during the pandemic. These four increasing trajectory subpopulations never returned to their baseline (March 2020) drinking levels throughout follow-up and ended January 2021 with either moderate or high drinking frequencies or binge drinking probabilities (March 2020). Existing research and theory identifies stress, lack of nonalcohol alternative options for enjoyment, reduced contact with health care professionals or other sources of support, and easy access to alcohol delivery as possible causes of increased drinking during the pandemic (Acuff et al., 2020; Garnett et al., 2021; Huckle et al., 2021; McPhee et al., 2020). If heightened drinking patterns acquired during the pandemic were to persist, risk of alcohol use disorder occurrence or exacerbation, alcohol-related injury, and other alcohol-related health problems might become a public health concern.

One subpopulation (6.7%) in this study that tended to drink moderately frequently in March 2020 appreciably reduced their drinking frequency later in pandemic. This pattern differed from the other drinking trajectories, especially the *Moderate/early increasing* group. The *Moderate/late decreasing* trajectory's drinking frequency was approximately one day per week higher than *Moderate/early increasing* trajectory at the pandemic's outset, and then later in the pandemic the two drinking trajectories crossed over one another, ending the follow-up period at one day per week lower drinking frequency. It is plausible that this subpopulation might have normally drank in social contexts and reduced their drinking due to social distancing, state-specific intermittent closure of bars and restaurants, or being deterred from socializing due to concern over virus exposure (Garnett et al., 2021). Consistent with this explanation, average drinking levels reduced from March to June 2020 in U.S. states with higher COVID-19 disease burden and more extensive stay-at-home policies issued early in the pandemic (McKetta et al., 2021). However, the decline in mean drinking frequency among this subpopulation continued through summer and into September 2020 when many U.S. regions loosened stay-at-home orders and business closure mandates, which might indicate continued apprehension to resume prepandemic activities, especially when there were heightened cautions about easing such restrictions. Furthermore, alcohol availability was likely affected in different regions across the country, as some retailers have indicated remaining open in order

to relieve the burden on hospitals and mitigate the number of patients being admitted for withdrawal symptoms. Another possibility is that pandemic triggered self-examination and a decision to reduce drinking in this subpopulation, which has been reported in UK samples (Jackson, Merrill, et al., 2021; Jackson, Garnett, et al., 2021). Research identifying drivers of drinking reductions during the pandemic might illuminate protective factors that could potentially be bolstered as targets in future alcohol use intervention.

In demographic comparisons, young adults were overrepresented in both the decreasing drinking frequency trajectory and in subpopulations with increasing probabilities of binge drinking at some point during the pandemic. These data align with previous evidence indicating that younger (vs. older) adults are more likely to engage in heavy drinking on an episodic basis (Keys and Miech, 2013) and the current results suggest possible amplification of such patterns during the pandemic. Because postsecondary education, dating, socializing, residence transitions, and unstable employment are particularly salient for this age group (Arnett, 2000), they might have been especially vulnerable to psychosocial disruptions during the pandemic. Older adults were overrepresented in subpopulations with high drinking levels at the beginning of the pandemic who further increased their drinking, which is notable given increasing trends of older adult binge drinking in recent years (Han et al., 2017). Additionally, those experiencing a job loss or reduction from full to part time were overrepresented in trajectories with reduced drinking frequency and low-to-moderate binge prevalence during the pandemic, perhaps indicating their reduced disposable income had an impact on their alcohol purchasing patterns. While it is plausible that stress associated with employment instability provoked increased drinking, the study did not find this group to be more common in any of the increasing drinking trajectories, and aggregation by demographics may mask high-risk profiles (e.g., a person with alcohol use disorder who relapses significantly due to job loss). However, the study design was not suited to isolate the temporal and causal association of job instability and drinking, which should be addressed further. White participants were overrepresented and Black and Hispanic racial/ethnic minority groups were underrepresented in several subpopulations with increasing drinking trajectories. A limitation is the insufficient sample size to separate out American Indian and Alaska Natives, who historically have substantially elevated drinking prevalence (Chartier & Caetano, 2010) and merit further surveillance.

This descriptive study did not examine mechanisms underlying differences in demographic differences in trajectories. These disparities should not be assumed as being innate features of each group in question, and rather effects of social determinants of health. Demographic differences in alcohol use trajectories could be mediated by cross-population variation in experiences of discrimination, financial instability, housing uncertainty, food uncertainty, unstable childcare, social support, having family members who may have become ill due to COVID-19, and many other fluctuating factors during the pandemic. Each of these putative mechanisms merit further research and could explain some of the demographic associations

with alcohol use trajectories demonstrated herein. In addition to research, the study's practice implications are that funding, social policies, programming, and outreach designed to mitigate alcohol use should be prioritized and perhaps targeted to communities overrepresented in trajectories with increasing drinking. For instance, alcohol prevention messaging using terminology and themes relevant to young adults or older adult populations might be fruitful.

No other nationally representative datasets with biweekly alcohol use measures are available as a comparison to this study, leaving unclear whether these observations are unique to the pandemic context. Drinking frequency increases from March to April during the first U.S. COVID-19 outbreak and most trajectory groups could reflect typical within-year seasonality in drinking. Drinking may have been lower in early March and higher in late March and throughout April due to a "spring break" like attitude, as some groups did not have to get up early to commute or go to school; however, such seasonal trends have not been previously observed (Cho et al., 2001). Another explanation of early drinking increases is measurement reactivity effects, whereby respondents might have become more comfortable disclosing drinking over time. This type of reactivity is liable to be uncommon for UAS panel members accustomed to disclosing sensitive information from previous surveys. Additionally, the different trajectory subpopulations identified exhibited distinct patterns and timing of change from May onward, which is inconsistent with population-wide systematic seasonality or measurement effects. Hence, it is possible that the results may reflect naturalistic changes in drinking specific to the pandemic. Future research should examine the impact of inter- and intra-state variation in local COVID-19 mitigation policies and waves of COVID-19 cases on U.S. adult drinking across time.

There are boundaries in interpreting the GMM results. GMMs prioritize parsimony by identifying the minimal number of trajectories that incrementally improve data fit. While the final GMM's entropy values were high, not all respondents are likely to have trajectories closely matching one of the four subpopulation's prototypical patterns. Some speculate about the possibility of individuals in long-term recovery who might return to heavy substance use during the pandemic and there is initial evidence of individuals who entered the pandemic as regular smokers that later quit smoking (Jackson, Garnett, et al., 2021; Volkow, 2020). Although this study did not identify distinct trajectories involving either extreme drinking escalation or abrupt cessation during the pandemic, it does not indicate that such cases did not exist. Rather, the results indicate that such cases were rare and heterogeneous. This, however, does not diminish their validity and warrants the potential for more cases such as these to be explored further and investigate the volatility in drinking outcomes during the pandemic or other public health and social crises. Furthermore, the approach used to generate the GMMs and identify how many classes best fit the data places equality constraints the variance parameters of each class. It is possible that the true phenotypic expression of different subtypes of drinking trajectories during the pandemic might, in actuality, be more or less variable for particular phenotypes. In comparison to the moderate or high drinking

trajectories, fewer people in minimal drinking trajectory phenotypes might be expected to exhibit drinking patterns that deviate from their group's prototypical drinking pattern. Even though this study's GMMs produced favorable fit statistics, it is possible that between-group variance equality constraints misfit the data and could alter the nature of GMM trajectories yielded (Sijbrandij et al., 2020).

This study had limitations. First, alcohol use was self-reported and subject to measurement error, although recall error is mitigated by the frequent assessments and a recall period limited to 7 days. Second, while UAS uses probability-based address sampling and includes sampling weights to correct for oversampling of California residents and other sampling error sources, participants are noninstitutionalized and may not be representative of populations with unstable housing or other circumstances that interfere with longitudinal research participation and retention. Third, survey nonresponse might have impacted the findings; although, GMM is less impacted by missing data than other methods because it uses person-specific data to estimate latent intercepts and slopes. Fourth, the drinking intensity measure addresses drinks per typical drinking day and categorized responses on the basis of heavy, binge-type drinking thresholds for simplicity and alignment with certain federal definitions which has limits. Drinks per typical drinking day measures are less precise for individuals with substantial intra-week vacillation in drinking intensity and do not distinguish multiple-bout versus single-bout per day patterns. Fifth, lack of prepandemic data limited the ability to adjust for prepandemic trends. Finally, some factors such as seasonality may be associated with alcohol use trend within a calendar year. Future research exploring seasonal effects in relation to variation in U.S. adult drinking trend data is needed to parse trends that are specific to the pandemic versus those that are enduring.

In conclusion, this intensive longitudinal study of U.S. adult drinking identified several demographically-distinct subpopulations with diverging drinking trajectories during the first 42 weeks of the COVID-19 pandemic. While population-wide aggregate mean drinking increases during the pandemic were modest and time-limited, escalating drinking in certain U.S. adult subpopulations raises public health concerns. This study's identification of a sizeable subpopulation that reduced their drinking during the pandemic raises a scientific opportunity to illuminate drivers of drinking reductions that could potentially be bolstered as targets in future alcohol use intervention and a clinical opportunity to reinforce drinking reductions to promote long-term change. The unique demographic composition of the different drinking trajectories reported here provides insight into the patient characteristics and sociodemographic communities who might benefit from intervention to counteract drinking increases or reinforce drinking reductions. Given that drinking might either increase or decrease for substantial portions of the population during the pandemic, repeated assessment of patients' drinking warrants consideration in clinical settings.

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CONFLICT OF INTEREST

AML, JC, LAR, RLP, ERP, BPL, JPD, JH, HJ, JPW, JOL, and RCW report no disclosures. NT discloses institutional grant support from Gilead Sciences, Genentech-Roche and GSK.

AUTHOR CONTRIBUTIONS

AML conceptualized the study and drafted portions of the manuscript; JC performed the analyses and drafted portions of the manuscript; AML, JC, LAR, RLP, BPL, ERP, NT, JPD, JH, HJ, JPW, JOL, and RCW interpreted the results and critically reviewed and revised the manuscript. RCW integrated comments and reviews from authors. All authors approved the manuscript.

DATA AVAILABILITY STATEMENT

JC had full access to all the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

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