

Improved estimates for individual and population-level alcohol use in the United States, 1984–2020

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Abstract

Aims: While nationally representative alcohol surveys are a mainstay of public health monitoring, they underestimate consumption at the population level. This paper demonstrates how to adjust individual-level survey data using aggregated alcohol per capita (APC) data for improved individual- and population-level consumption estimates.

Design and Methods: For the period 1984–2020, data on self-reported alcohol consumption in the past 30 days were taken from the Behavioral Risk Factor Surveillance System (BRFSS) involving participants (18+ years) in the United States (US). Monthly abstainers were reallocated into lifetime abstainers, former drinkers, and 12-month drinkers using the 2005 National Alcohol Survey data. To correct for under-coverage of alcohol use, we triangulated APC and survey data by upshifting quantity (average grams/day) and frequency (drinking days/week) of alcohol use based on national- and state-level APC data. Results were provided for the US as a whole and for selected states to represent different drinking patterns.

Findings: The corrections described above resulted in improved correspondence between survey and APC data. Following our procedure, national estimates of alcohol quantity increased from 45% to 77% of APC estimates. Both quantity and frequency of alcohol use were upshifted; by upshifting to 90% of APC, we were able to fit trends and distributions in APC patterns for individual states and the US.

Conclusions: An individual-level dataset which more accurately reflects the alcohol use of US citizens was achieved. This dataset will be invaluable as a research tool and for the planning and evaluation of alcohol control policies for the US. The methodology described can also be used to adjust individual-level alcohol survey data in other geographical settings.

Introduction

Data from nationally representative surveys provide a foundation for public health surveillance to investigate trends in alcohol consumption in different

sociodemographic subgroups and the general population. In almost all cases these surveys underestimate the overall level of consumption (Kilian et al., 2020; Midanik, 1988; Midanik, 1982). To correct for this under-reporting, the usual method used in epidemiological studies to estimate the

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burden of disease and mortality attributable to alcohol use (such as comparative risk assessments) involves the triangulation (i.e., combination) of alcohol per capita consumption (APC) and survey data (Manthey et al., 2019; Rehm et al., 2007); i.e. an upshifting of survey responses. APC is considered the most reliable indicator for the overall level of alcohol consumption in a jurisdiction (Gmel & Rehm, 2004). However, as it is mainly derived from social statistics (sales data, or production figures; Poznyak et al., 2013; Rehm et al., 2007), it only provides one measure of alcohol consumption volume, and does not allow for disaggregation into drinking patterns by different sociodemographic groups. This disaggregation must be done using population surveys (Manthey et al., 2019; Rehm et al., 2007) with survey data being used as a second indicator for level of drinking and to inform patterns of drinking across population subgroups. Survey estimates therefore need to be corrected to obtain realistic and representative alcohol use models for the general population (Rehm, Kilian, & Manthey, 2021; Rehm, Kilian, Rovira, et al., 2021). By triangulating APC and survey data, we can address both of their limitations and achieve a more accurate and representative estimate of alcohol consumption including that of different population subgroups. Triangulation is the standard procedure used in aggregate-level modelling (Manthey et al., 2019), and has been used to adjust drinking data for the United States (US) at the aggregate level, whereby drinking variables are adjusted for demographic subgroups and not for individuals (Subbaraman et al., 2020).

For policy modelling methods for which the unit of analysis is the *individual*, such as microsimulation, an adjusted individual-level dataset is required. Currently, a method does not exist to triangulate population-based surveys with APC data at the individual level. Microsimulation techniques have been introduced into the social sciences to understand if and how individual-level processes and interactions between individuals can better explain macro-level phenomena (Epstein & Axtell, 1996; Gilbert & Troitzsch, 1999). While such techniques hold promise, their application in alcohol research to date has been modest (for exceptions, see Giraldo et al., 2017; Gorman et al., 2006; Julien et al., 2020; Julien et al., 2021; Probst et al., 2020; Vu et al., 2020) and have tended to assess theory-focused hypotheses, usually based on artificial and small populations. They have yet to be used more widely in epidemiology or policy-modelling applications. However, the accuracy, empirical foundation, and representativeness of the input data is paramount for the usefulness of the model (e.g., Katikireddi et al., 2014); this requires an adjusted individual-level dataset.

This article describes how to construct an adjusted individual-level dataset that can be used for microsimulation modelling, the generation of macro-level consumption patterns to be used in model calibration and validation, and in the more conventional epidemiological modelling of alcohol-related harm. Accordingly, this contribution describes the process of triangulation of survey data to build an adjusted dataset based on identifiable individual drinking groups to be used in the modelling of the effects of alcohol control policies in the US, and in individual US states.

Methods

Behavioral Risk Factor Surveillance System (BRFSS) data 1984–2020

The Behavioral Risk Factor Surveillance System (BRFSS) is a state-based surveillance system of telephone surveys that collects data from US residents in 50 states and Washington DC regarding their health-related risk behaviors, chronic health conditions, and use of prevention services. It is the largest continuously conducted annual cross-sectional telephone survey system for alcohol use currently operating in the US (Centers for Disease Control, 2019). The BRFSS is notable for being the only state and nationally representative alcohol use dataset for the US that is freely available and covers the period from the 1980s to the present day; all other surveys either do not cover extended periods of time with annual surveys, and/or are not representative at the state and national level. However, long-term estimates of alcohol use are important in determining exposure risk for chronic conditions such as liver cirrhosis. Data collected from each state can then be pooled to produce nationally representative estimates. Accordingly, the BRFSS allows for consistency and comparability between states, and for the whole country. We used BRFSS data collected between 1984 and 2020 and the available sample (after removing missing alcohol consumption and demographic data) was 11,764 in 1984 and 330,446 in 2020. Sample sizes available in each year and detailed information about missing data in the BRFSS are available in the Supplementary Material (Tables S4 – S5).

BRFSS Alcohol Consumption Data

We included all adults (18 years of age or older) from the BRFSS data who answered telephone interview questions on the frequency and quantity of their alcohol consumption. We used the two core alcohol questions in the BRFSS to assess alcohol consumption among US adults. The first asks respondents: ‘During the past 30 days, how many days per week or per month did you have at least one drink of any alcoholic beverage?’ The second asks about the quantity of alcohol consumed: ‘On the days when you drank, about how many drinks did you drink on average?’. We first calculated average daily alcohol consumption by multiplying the number of drinking-days in the past month by the average number of drinks per drinking day, and then dividing this product by 30. To convert this into average grams of pure ethanol consumed per day we multiplied it by 14 grams, as per the US standard drink size (National Institute on Alcohol Abuse and Alcoholism [NIAAA], 2020). For illustration purposes to compare unadjusted and adjusted estimates, alcohol consumption was also categorized into the following four categories defined by the World Health Organization (WHO; World Health Organization, 2000): Abstainers (previous 12 months), Category I (up to 20 [women] or 40 [men] grams per day), Category II (21–40 [women] or 41–60 [men] grams per day), Category III (41–60 [women] or 61–100 [men] grams per day) and Category IV (61+ [women] or 101+ [men] grams per day).

National Alcohol Survey (NAS) Alcohol Consumption Data

The 2005 National Alcohol Survey (NAS; Alcohol Research Group, 2019) is a nationally representative survey consisting of 6,919 Computer Assisted Telephone Interviews (CATI) sampled using a Random Digit Dial (RDD) to landline phones. The target population of NAS surveys was the noninstitutionalized household adult population of the US and sampled adults aged 18 and older from 50 US States and Washington DC. Details about NAS series are reported elsewhere (Kerr et al., 2009; Kerr et al., 2013).

Data Sources for Alcohol Per Capita

APC data for the US and for individual states were based on surveillance reports by the NIAAA for 1977–2020 (Slater & Alpert, 2020). The surveillance reports use sales data for alcoholic beverages collected by the Alcohol Epidemiologic Data System for individual states and from the National Alcohol Beverage Control Association alongside reports from beverage industry sources. *Per capita* consumption is calculated using denominators from US Census population data. APC data were converted from liters per year to grams per day by assuming a density of 793 g/L (WHO, 2018).

Issues with the BRFSS in the estimation of individual-level alcohol consumption

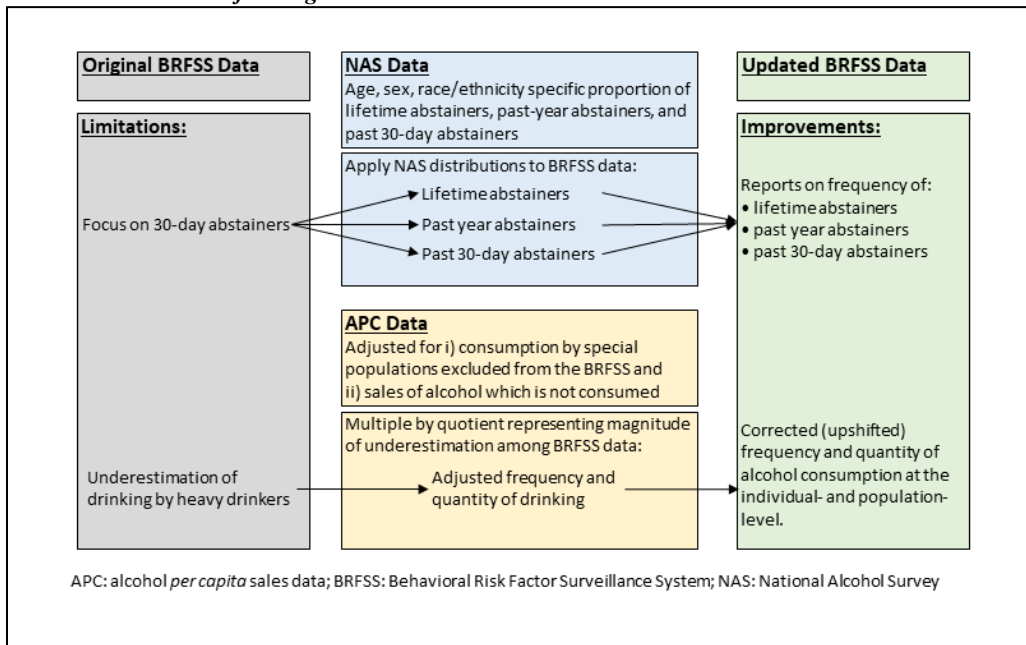
The BRFSS has two major problems when used to generate estimates of individual-level alcohol use. First, it does not provide an estimate for past-year abstainers given its time-frame of 30 days (as noted above, yearly data are necessary for triangulation), and it does not separate past year from lifetime abstainers (for more details on categories of abstainers, see Manthey et al., 2019). Distinguishing

between categories of abstainers is important, as these are differentially linked to burden of disease: past-year abstainers often quit drinking for health reasons and have higher health risks relative to lifetime abstainers (Rehm, Gmel, et al., 2017; Rehm, Sherk, et al., 2017). Second, as with almost all surveys, the BRFSS underestimates drinking by heavy drinkers and persons with alcohol use disorders in part due to its sampling frame, which excludes or underrepresents military personnel, institutionalized populations, or people with transient housing including the homeless (Shield & Rehm, 2012). In addition to sampling biases, survey estimates of level of consumption in a population may be affected by individual answering behaviours, including choosing not to respond to a survey, memory bias (Nguyen-Louie et al., 2016), problems in conceptualising own drinking behaviour based on standard drinks (Bond et al, 2014), and the tendency to present oneself in a positive light as a non-heavy drinker i.e., social desirability bias (Davis et al., 2010). The steps taken to address some of these limitations are outlined below.

Standard Procedures of Triangulation

Due to the above noted issues with the BRFSS individual-level survey data, triangulation was necessary to generate more realistic annual estimations of drinking behavior for the US and individual states. Triangulation refers to the combination of several data sources and is required due to the limited time frame of the BRFSS survey data, and the documented under-recording of drinking behavior in surveys. The standard procedures of triangulation are outlined in Figure 1.

Figure 1
Standard Procedures of Triangulation



We separated the group of 30-day abstainers as identified by the BRFSS between 1984 and 2020 into three subgroups: lifetime abstainers, abstainers over the past 12 months, and drinkers who drank in the past 12 months but abstained in the previous 30 days. To identify these subgroups, we used the 2005 NAS, described above, which distinguished between lifetime, past-year, past 30-day abstainers and current drinkers. Specifically, the distributions of each subgroup from the 2005 NAS (Tables S1 – S3) by age group (18–34, 35–64, and 65+ years), sex, and race/ethnicity (White, Black, Hispanic, and Other) were used to allocate the population of BRFSS 30-day abstainers to a new subgroup using proportional sampling. Within each age, sex and race/ethnicity subgroup, individuals were randomly assigned to one of three new subgroups such that the NAS proportions matched the simulated proportions of individuals in each category. Cumulative probabilities were calculated using the proportions in Table S2. For each BRFSS individual, a random number between 0 and 1 was sampled and compared to the category specific cumulative probability to assign a new drinking category.

Underestimation of Heavy Drinkers

Heavy drinkers excluded from usual household surveys can be divided into two categories: (a) the non-institutionalized civilian population (e.g. homeless individuals) and (b) institutionalized non-civilian populations, including military personnel who seem to have developed a drinking culture that is distinct from the civilian population (Shield & Rehm, 2012). Before triangulation we needed to adjust APC for groups that are excluded from the survey data (including active-duty military personnel and state and federal prison populations) but which contribute to the APC data. Between 1984 and 2020, these special populations constituted roughly 1% each of total US population (range 0.98% to 1.23%; Western & Travis, 2014). By assuming that these populations drink 50% more than the general population (Shield & Rehm, 2012), a downward adjustment to the APC was made with a uniform scale of 150% on the proportion of special populations (i.e., the adjusted APC = APC grams/day – [APC grams/day x 0.98% x 1.5]).

Standard procedures of triangulation are based on the average level of consumption (e.g., Rehm et al., 2010), without accounting for the individual level frequency and quantity that make up individual drinking patterns and serve as the foundation for average levels of alcohol use. To correct for the underestimation of heavy drinkers, the quantity of alcohol consumption (in average grams/day) from the BRFSS was upshifted to adjusted APC data. The proportion of drinkers in revised BRFSS data (corrected for overestimation of abstainers and for exclusion of military personnel and prisoners) was applied to BRFSS drinking data to calculate per capita consumption of the BRFSS cohort. To upshift the consumption distribution, a correction of 90% to adjusted APC was used, given that some of the alcohol sold is not consumed due to broken containers or containers being incompletely consumed (WHO, 2018). A ratio (r) was calculated by dividing the 90% adjusted APC by BRFSS average per capita consumption for each year, to

quantify the magnitude of underestimation of the BRFSS. The squared cube root of this ratio was multiplied by the frequency of alcohol consumption ($f_{\text{new}} = f_{\text{old}} * r^{2/3}$) and quantity (in grams/day; $q_{\text{new}} = q_{\text{old}} * r^{2/3}$) to create upshifted estimates. The upshifted frequency and quantity were curtailed to 30 days per month, and 200 grams/day, respectively (Gmel et al., 2013). A cube root of the ratio was used to allocate heavier drinkers a larger upshift, as heavier drinkers are thought to more commonly under-report their alcohol use (Boniface et al., 2014).

Scope of Results Presented

We present results not only for the US as a whole but also for five selected states: Colorado (CO), New York (NY), Minnesota (MI), Tennessee (TN), and Texas (TX). These states were selected to present the heterogeneity of US drinking cultures as they included “wet” (CO, MI), “moderate” (NY, TX) and “dry” (TN) states (Kerr, 2010).

Software Used

All analyses were performed in R (R Core Team, 2013), and code to generate adjusted data is available open-source at https://bitbucket.org/r01cascade/improved_individual_estimates/src/master/.

Results

Re-Allocating Drinking Status in the BRFSS

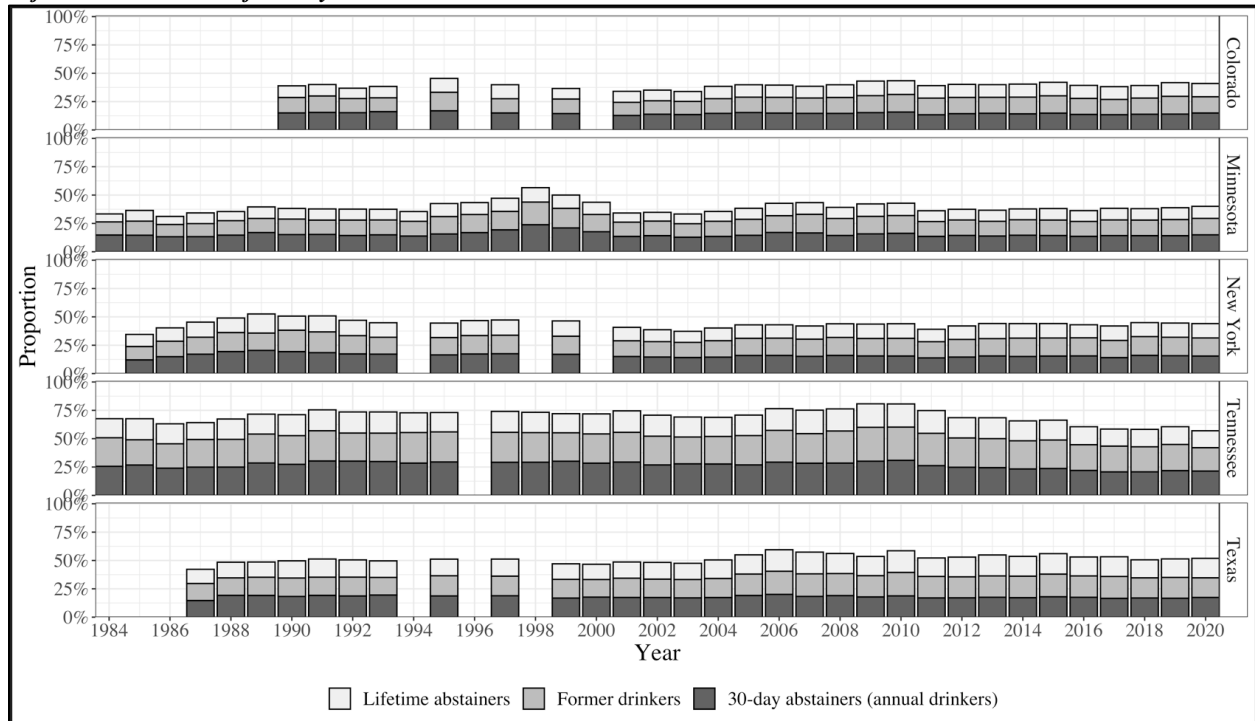
Adjusted distributions of 30-day abstainers are shown for Colorado, New York, Minnesota, Tennessee, and Texas in Figure 2. Initial estimates for 30-day drinking prevalence for the US ranged from 35.3% (1996) to 50.7% (1986) for women and 51.4% (1996) to 67.3% (1984) for men. After reallocating drinking status, annual prevalence of 12-month drinking for the US ranged between 60.0% (1996) and 71.0% (1984) for women and 69.8% (1996) and 79.6% (1984) for men. Tables S6 – S7 provide estimates for each year and state. The adjusted distributions were a good fit to the observed proportions from the National Alcohol Survey data (Table S8).

Comparison of Alcohol Grams Per Day in Adjusted and Unadjusted BRFSS Data

The adjusted data showed a clear elevation of coverage rates, moving closer to the numbers seen in APC data. Coverage (the proportion of APC consumption recorded in the survey) of the unadjusted and adjusted BRFSS to alcohol per capita (APC) sales data is displayed in Figure 3 and Tables S9 – S10 for the US and individual states. For the US, initial mean coverage was 45% ($SD = 4\%$) which increased to 77% ($SD = 2\%$) in the adjusted dataset for the US. A comparison of the mean grams per day observed in the initial BRFSS data compared to the adjusted data showed a smooth yet elevated curve (Figure 4) with state-level data showing similar trends (Figure S1). In sum, the results showed that we were able to establish an adjusted individual-level dataset and estimate annual population-level consumption that were consistent with both APC levels and the BRFSS survey distributions.

Figure 2

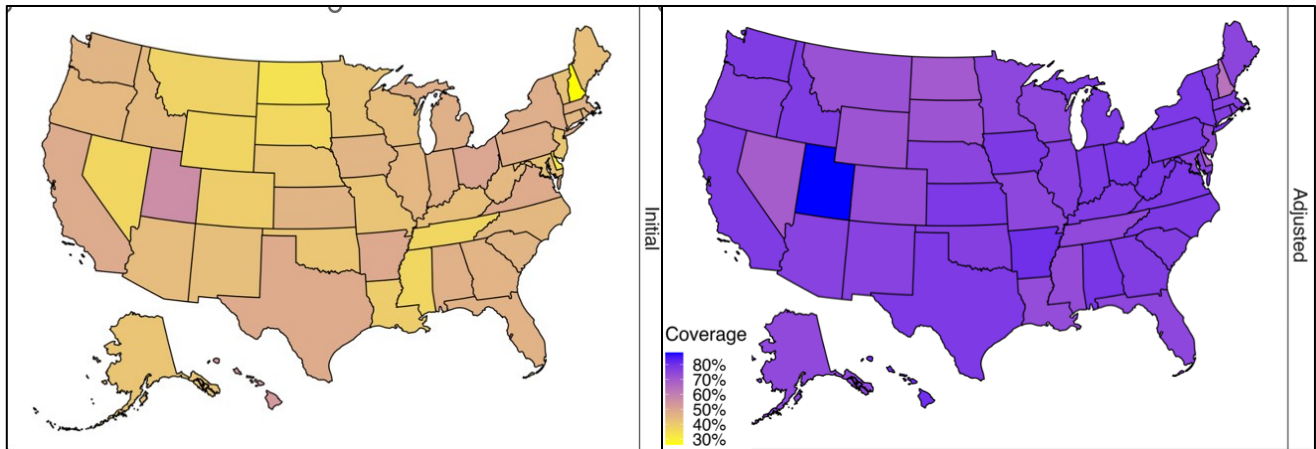
Adjusted Distributions of 30-Day Abstainers



Note: 30-day abstainers were re-allocated into lifetime abstainers, former drinkers and 30-day abstainers (annual drinkers) in the BRFSS 1984-2020 for Colorado, Minnesota, New York, Tennessee, and Texas. Data are missing in years where alcohol use data was not collected in the BRFSS in that state in that year (see Supplementary Material and (Yi et al., 2003) for details of available annual alcohol use data for each state).

Figure 3

Mean Coverage Rate Averaged Over Time (1984-2020) in US States: : Comparing past-30 days drinking volume among drinkers in initial and adjusted BRFSS and APC data



Note: Coverage refers to the proportion of APC consumption recorded in the survey data.

Comparison of Levels of Alcohol Use

The prevalence of individuals in each alcohol consumption category was compared for initial and adjusted data (Figure 5). Table 1 shows the proportion of individuals (averaged over time) in each alcohol consumption category for the US based on calculations using the initial and adjusted data. Due to representing monthly drinking behavior, annual prevalence of abstainers was higher in the initial data with a

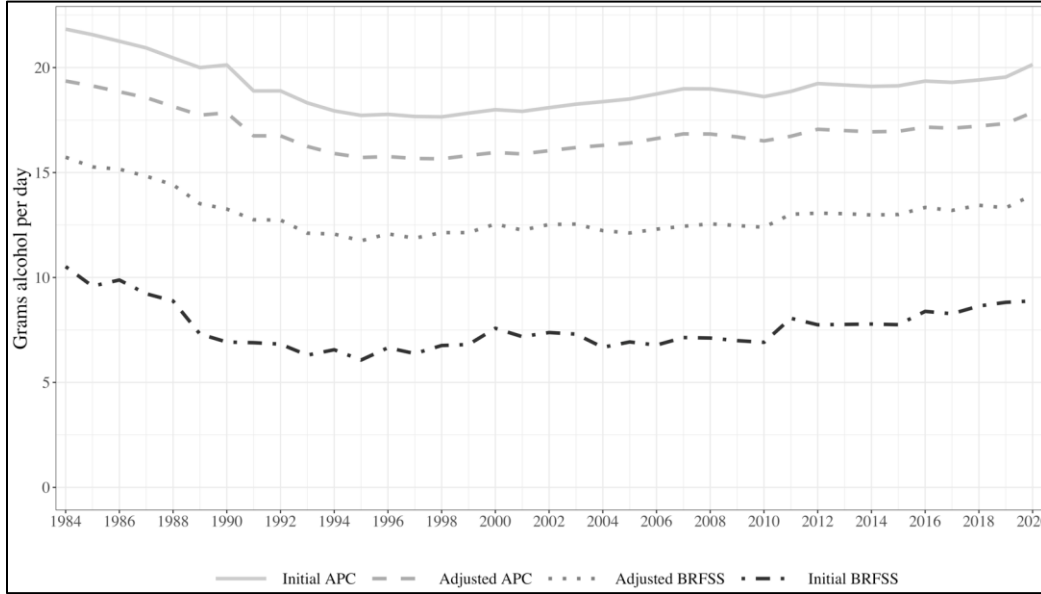
mean of 40.7% (men) and 56.0% (women) which reduced to 26.0% (men) and 34.5% (women) in the adjusted data. The largest relative changes were observed in the heaviest drinking category IV (60+ [women] and 100+ [men] grams/day), increasing by 0.6 percentage points for women (from 0.2% to 0.8%) and 1.2 percentage points for men (from 0.6% to 1.8%). Similarly, Table 2 shows initial and adjusted mean prevalence for frequency of drinking days.

The largest increases were seen for the highest category (25–30 drinks/month), increasing by 2.9 percentage points for

women (from 3.3% to 6.2%) and by 6.2 percentage points for men (from 8.5% to 14.7%).

Figure 4

Comparison of Initial and Adjusted BRFSS Data Compared to Initial and Adjusted APC Sales Data on Alcohol Consumption in the United States 1984-2020



Note: Adjusted BRFSS refers to the final adjusted value for the BRFSS after performing the upshifting procedure. Adjusted APC refers to the final adjusted value for APC after correcting for special populations and applying the 90% correction recommended by WHO.

Figure 5

Proportion of Individuals in Each Alcohol Consumption Category in Initial and Adjusted BRFSS Data

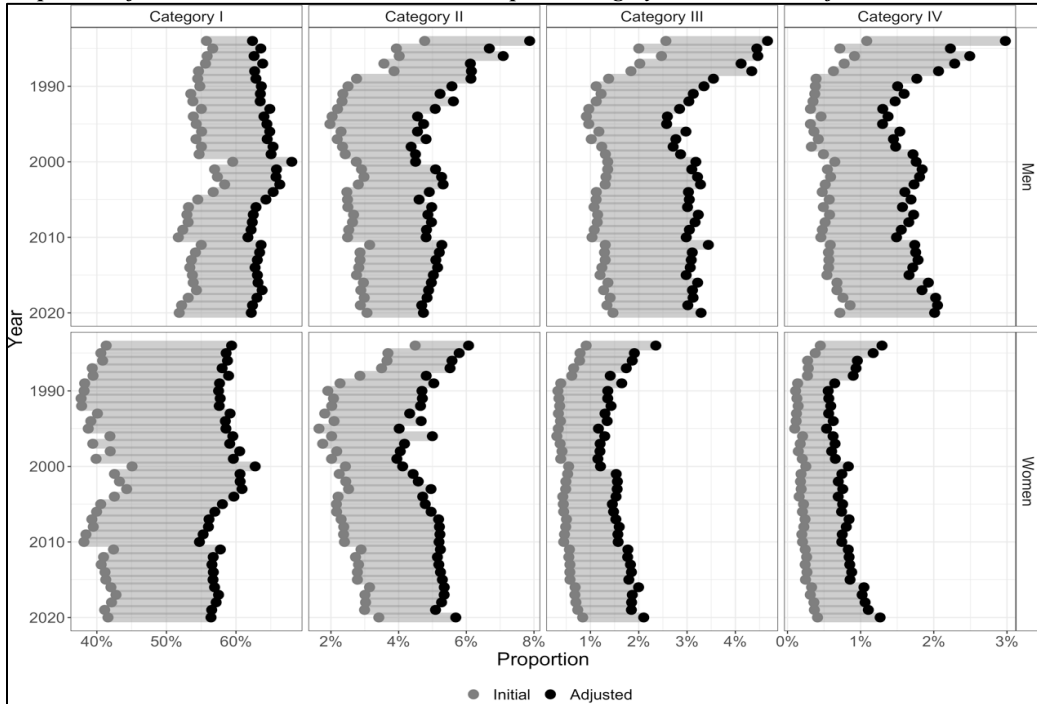


Table 1

Mean Proportion (1984-2020) of Individuals in each Category of Alcohol Consumption in the US in Initial vs Adjusted BRFSS Data

Sex	Category	Initial		Adjusted		Ratio
		Mean (%)	SD (%)	Mean (%)	SD (%)	
Women	Abstainer ¹	56.0	2.2	34.5	1.6	0.6
Women	I	40.6	1.8	58.1	1.7	1.4
Women	II	2.6	0.6	5.0	0.5	1.9
Women	III	0.5	0.2	1.6	0.3	3.2
Women	IV	0.2	0.1	0.8	0.2	4.0
Men	Abstainer ¹	40.7	2.3	26.0	1.7	0.6
Men	I	54.6	1.7	63.8	1.4	1.2
Men	II	2.8	0.6	5.2	0.8	1.9
Men	III	1.3	0.4	3.2	0.5	2.5
Men	IV	0.6	0.2	1.8	0.3	3.0

Note: Ratio represents the relative change from the initial to the adjusted proportion and is calculated by dividing the initial proportion by the adjusted proportion.

¹In the initial data abstainer refers to 30-day abstainer and after adjustment refers to 12-month abstainer.

Table 2

Mean Proportion (1984-2020) of Individuals by Categories of Alcohol Consumption Frequency in the US in Initial vs Adjusted BRFSS Data

Sex	Drinking frequency (days per month)	Initial		Adjusted		Ratio
		Mean (%)	SD (%)	Mean (%)	SD (%)	
Women	1-5	49.6	2.9	38.8	2.5	0.8
	6-10	6.4	0.8	11.6	0.6	1.8
	11-15	3.2	0.7	4.5	1.5	1.4
	16-20	1.8	0.5	2.0	1.2	1.1
	21-25	1.2	0.3	2.2	0.7	1.8
	25-30	3.3	0.9	6.2	1.6	1.9
Men	1-5	42.7	3.3	29.9	2.3	0.7
	6-10	10.4	1.0	14.1	1.0	1.4
	11-15	6.2	0.9	7.1	2.4	1.1
	16-20	3.7	0.7	3.7	2.3	1.0
	21-25	2.5	0.5	4.4	1.4	1.8
	25-30	8.5	2.0	14.7	2.6	1.7

Note: Ratio represents the relative change from the initial to the adjusted proportion and is calculated by dividing the initial proportion by the adjusted proportion. Drinking frequency is presented in categories, but the procedure was performed on continuous frequency data. Consumption frequency is number of drinking days per month.

Discussion

The triangulation procedures described above improve estimates for state- and national-level alcohol consumption patterns. The procedure identified allows for the adjustment and upshift of the frequency of drinking and grams per day. This decomposition for the individual level, to our knowledge, has been achieved here for the first time. Using this new methodology, we can show not only matching trends to APC over time for the entire US, but also for individual states selected for separate policy modeling.

Given that our method accounts for heavier drinkers underestimating their consumption in surveys more than lighter drinkers (Boniface et al., 2014), our estimates can suggest how much heavy drinking is currently being underestimated in the BRFSS survey. After applying our adjustment, the prevalence of individuals drinking in the heaviest drinking categories (over 60 or 100 mean grams per day for women and men, respectively) increased approximately three- to four-fold. When applying these proportions to the total US adult (18+) population in 2020 (Ruggles et al., 2020) this would result in an additional 1,520,493 men and 784,970 women in the US population drinking at the most hazardous levels.

The procedure in this article can be adapted to produce comparable estimates for alcohol exposure in different jurisdictions. However, it is based on several assumptions that require further discussion. First, it assumes that the APC is an ideal estimate for overall consumption level (Gmel & Rehm, 2004), an assumption which seems reasonable for the US and the individual states given extant literature (Poznyak et al., 2013; Subbaraman et al., 2020). Second, it may be reasonable to suspect that much of the difference between the survey’s results and the APC is due to alcohol consumed by relatively small groups of heavy drinkers not covered by the usual representative surveys, such as the homeless, the institutionalized, or military personnel (Gmel & Rehm, 2004; Rehm, 1998). If this reasoning is correct, then relatively little error is introduced by assuming that surveys can validly estimate abstainer rates. In this exercise, military personnel were excluded by the BRFSS as a special population as it constituted under 1% of the general population. By assuming these populations drink 50% more than the general population (Shield & Rehm, 2012), a downward adjustment to the APC was made. Further, we used the standard US drink definition of 14 grams, however the study period ranges back to 1984 where standard drinks may have contained less alcohol (Turner, 1990). The decision to cap grams per day at 200 grams, rather than an alternative amount could have impacted the results. However, we expect any impact of different capping thresholds to be minimal as after performing the upshift less than 1% of individuals in each year consumed over 150 grams per day.

Finally, an argument can be made that the current procedure may lead to an overestimation of alcohol-attributable burden, as relative risks used to estimate burden are based on similar subjective assessments to surveys. While the goal of the current article was not to estimate burden, recent research has shown that the upshifting may be justified (Stockwell et al., 2018). Further research to determine improved methods of upshifting for estimating alcohol-

attributable burden is necessary (Parish et al., 2017; Rehm, 2017).

A further limitation concerns individual-level heterogeneity in under-reporting, for example by different socio-demographic subgroups, and there is currently no evidence to suggest how groups might differentially under-report alcohol consumption. Therefore, while we produce representative results at the national- and state-level, microsimulation and other modeling methods using this data should exercise caution when producing subgroup summaries by socio-demographic indicators.

This work has important implications for future epidemiological research efforts and for informing policymaking. As almost all surveys fail to estimate the real consumption level of a population accurately, modelling is necessary, and is possible, as our research has shown. The adjusted individual-level US and state-level dataset is a useful research tool to aid planning and evaluation of alcohol control policies for the US. The method described is available open-source and can be applied in other jurisdictions to achieve more realistic individual- and population-level estimations of alcohol use.

Ethics Statement

Ethics approval was granted by the Human Research Ethics committees at the Centre for Addiction and Mental Health, Canada (approval 096/2018) and at the University of Sheffield, UK (Application # 011019).

Authors' Contributions

The idea for this study was based on the Calibrated Agent Simulations for Combined Analysis of Drinking Etiologies (CASCADE) project (led by RP, WK, JR), and the specific operationalization was conceptualized by JR. CB carried out the main statistical analyses and developed the open-source R code which was verified by KP. CB and JR led the original writing of the draft of the paper, with suggested revisions made by all other authors. All authors provided critical review on various versions and approved the final version of the manuscript. The funding bodies had no role in the study design, analysis, decision to publish, or preparation of the manuscript.

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References

- Alcohol Research Group (ARG). (2019). *National Alcohol Surveys*. Retrieved August 13, 2019 from <http://arg.org/center/national-alcohol-surveys/>
- Bond, J. C., Greenfield, T. K., Patterson, D., & Kerr, W. C. (2014). Adjustments for drink size and ethanol content: new results from a self-report diary and transdermal sensor validation study. *Alcoholism, Clinical and Experimental Research*, 38(12), 3060–3067. <https://doi.org/10.1111/acer.12589>
- Boniface, S., Kneale, J., & Shelton, N. (2014). Drinking pattern is more strongly associated with under-reporting of alcohol consumption than socio-demographic factors: Evidence from a mixed-methods study. *BMC Public Health*, 14(1), 1297. <https://doi.org/10.1186/1471-2458-14-1297>
- Centers for Disease Control. (2019). *Behavioral Risk Factor Surveillance System (BRFSS)*. <https://www.cdc.gov/brfss/>
- Davis, C. G., Thake, J., & Vilhena, N. (2010). Social desirability biases in self-reported alcohol consumption and harms. *Addictive Behaviors*, 35(4), 302–311. <https://doi.org/10.1016/j.addbeh.2009.11.001>
- Epstein, J. M., & Axtell, R. L. (1996). *Growing artificial societies: Social science from the bottom up*. The MIT Press. <https://mitpress.mit.edu/9780262550253/growing-artificial-societies/>
- Gilbert, N., & Troitzsch, K. G. (1999). *Simulation for the Social Scientist*. Open University Press.
- Giraldo, L. F., Passino, K. M., Clapp, J. D., & Ruderman, D. (2017). Dynamics of metabolism and decision making during alcohol consumption: Modeling and analysis. *IEEE Transactions on Cybernetics*, 47(11), 3955–3966. <https://doi.org/10.1109/tcyb.2016.2593009>
- Gmel, G., & Rehm, J. (2004). Measuring alcohol consumption. *Contemporary Drug Problems*, 31(3), 467–540. <https://doi.org/10.1177/009145090403100304>
- Gmel, G., Shield, K. D., Kehoe-Chan, T. A. K., & Rehm, J. (2013). The effects of capping the alcohol consumption distribution and relative risk functions on the estimated number of deaths attributable to alcohol consumption in the European Union in 2004. *BMC Medical Research Methodology*, 13(1), 24. <https://doi.org/10.1186/1471-2288-13-24>

- Gorman, D. M., Mezc, J., Mezc, I., & Gruenewald, P. J. (2006). Agent-based modeling of drinking behavior: A preliminary model and potential applications to theory and practice. *American Journal of Public Health, 96*(11), 2055–2060. <https://doi.org/10.2105/AJPH.2005.063289>
- Julien, J., Ayer, T., Bethea, E. D., Tapper, E. B., & Chhatwal, J. (2020). Projected prevalence and mortality associated with alcohol-related liver disease in the USA, 2019–40: A modelling study. *The Lancet Public Health, 5*(6), e316–e323. [https://doi.org/10.1016/S2468-2667\(20\)30062-1](https://doi.org/10.1016/S2468-2667(20)30062-1)
- Julien, J., Ayer, T., Tapper, E. B., Barbosa, C., Dowd, W. N., & Chhatwal, J. (2021). Effect of increased alcohol consumption during COVID-19 pandemic on alcohol-associated liver disease: A modeling study. *Hepatology, 75*(6), 1480–1490. <https://doi.org/10.1002/hep.32272>
- Katikireddi, S. V., Bond, L., & Hilton, S. (2014). Perspectives on econometric modelling to inform policy: a UK qualitative case study of minimum unit pricing of alcohol. *The European Journal of Public Health, 24*(3), 490–495. <https://doi.org/10.1093/eurpub/ckt206>
- Kerr, W. C. (2010). Categorizing US State drinking practices and consumption trends. *International Journal of Environmental Research and Public Health, 7*(1), 269–283. <https://doi.org/10.3390/ijerph7010269>
- Kerr, W. C., Greenfield, T. K., Bond, J., Ye, Y., & Rehm, J. (2009). Age-period-cohort modelling of alcohol volume and heavy drinking days in the US National Alcohol Surveys: Divergence in younger and older adult trends. *Addiction, 104*(1), 27–37. <https://doi.org/10.1111/j.1360-0443.2008.02391.x>
- Kerr, W. C., Greenfield, T. K., Ye, Y., Bond, J., & Rehm, J. (2013). Are the 1976–1985 birth cohorts heavier drinkers? Age-period-cohort analyses of the National Alcohol Surveys 1979–2010. *Addiction, 108*(6), 1038–1048. <https://doi.org/10.1111/j.1360-0443.2012.04055.x>
- Kilian, C., Manthey, J., Probst, C., Brunborg, G. S., Bye, E. K., Ekholm, O., Kraus, L., Moskalewicz, J., Sieroslowski, J., & Rehm, J. (2020). Why Is Per capita consumption underestimated in alcohol surveys? Results from 39 Surveys in 23 European Countries. *Alcohol and Alcoholism, 55*(5), 554–563. <https://doi.org/10.1093/alcac/agaa048>
- Manthey, J., Shield, K. D., Rylett, M., Hasan, O. S. M., Probst, C., & Rehm, J. (2019). Global alcohol exposure between 1990 and 2017 and forecasts until 2030: A modelling study. *Lancet, 393*(10190), 2493–2502. [https://doi.org/10.1016/s0140-6736\(18\)32744-2](https://doi.org/10.1016/s0140-6736(18)32744-2)
- Midanik, L. (1988). Validity of self-reported alcohol use: A literature review and assessment. *British Journal of Addiction, 83*(9), 1019–1030. <https://doi.org/10.1111/j.1360-0443.1988.tb00526.x>
- Midanik, L. T. (1982). The validity of self-reported alcohol consumption and alcohol problems: a literature review. *British Journal of Addiction, 77*(4), 357–382. <https://doi.org/10.1111/j.1360-0443.1982.tb02469.x>
- National Institute on Alcohol Abuse and Alcoholism. (2003). Recommended alcohol questions. Retrieved January 27, 2020, from <https://www.niaaa.nih.gov/research/guidelines-and-resources/recommended-alcohol-questions>
- National Institute on Alcohol Abuse and Alcoholism. (2020). What is a standard drink? Retrieved January 27, 2020, from <https://www.niaaa.nih.gov/what-standard-drink>
- Nguyen-Louie, T. T., Buckman, J. F., Ray, S., & Bates, M. E. (2016). Drinkers’ memory bias for alcohol picture cues in explicit and implicit memory tasks. *Drug and Alcohol Dependence, 160*, 90–96. <https://doi.org/10.1016/j.drugalcdep.2015.12.033>
- Parish, W. J., Aldridge, A., Allaire, B., Ekwueme, D. U., Poehler, D., Guy, G. P., Jr., Thomas, C. C., & Trogdon, J. G. (2017). A new methodological approach to adjust alcohol exposure distributions to improve the estimation of alcohol-attributable fractions. *Addiction, 112*(11), 2053–2063. <https://doi.org/10.1111/add.13880>
- Poznyak, V., Fleischmann, A., Rekke, D., Rylett, M., Rehm, J., & Gmel, G. (2013). The World Health Organization’s Global Monitoring System on Alcohol and Health. *Alcohol Research: Current Reviews, 35*(2), 244–249.
- Probst, C., Vu, T. M., Epstein, J. M., Nielsen, A. E., Buckley, C., Brennan, A., Rehm, J., & Purshouse, R. C. (2020). The Normative underpinnings of population-level alcohol use: An individual-level simulation model. *Health Education & Behavior: The Official Publication of the Society for Public Health Education, 47*(2), 224–234. <https://doi.org/10.1177/1090198119880545>
- R Core Team. (2013, 06/08/2017). *A language and environment for statistical computing*. R Foundation for Statistical Computing. Retrieved September 22, 2020 from <http://www.R-project.org/>
- Rehm, J. (1998). Measuring quantity, frequency, and volume of drinking. *Alcoholism: Clinical and Experimental Research, 22*(2 Suppl), 4s–14s. <https://doi.org/10.1097/0000374-199802001-00002>
- Rehm, J. (2017). Commentary on Parish et al. (2017): What is the best exposure for estimating alcohol-attributable burden of disease? *Addiction, 112*(11), 2064–2065. <https://doi.org/10.1111/add.13939>
- Rehm, J., Gmel, G. E., Sr., Gmel, G., Hasan, O. S. M., Imtiaz, S., Popova, S., Probst, C., Roerecke, M., Room, R., Samokhvalov, A. V., Shield, K. D., & Shuper, P. A. (2017). The relationship between different dimensions of alcohol use and the burden of disease – an update. *Addiction, 112*(6), 968–1001. <https://doi.org/10.1111/add.13757>
- Rehm, J., Kehoe, T., Gmel, G., Stinson, F., Grant, B., & Gmel, G. (2010). Statistical modeling of volume of alcohol exposure for epidemiological studies of population health: The example of the US. *Population Health Metrics, 8*, 3. <https://doi.org/10.1186/1478-7954-8-3>
- Rehm, J., Kilian, C., & Manthey, J. (2021). Future of surveys in the alcohol field. *Drug and Alcohol Review, 40*(2), 176–178. <https://doi.org/10.1111/dar.13180>
- Rehm, J., Kilian, C., Rovira, P., Shield, K. D., & Manthey, J. (2021). The elusiveness of representativeness in general population surveys for alcohol. *Drug and Alcohol Review, 40*(2), 161–165. <https://doi.org/10.1111/dar.13148>

- Rehm, J., Klotsche, J., & Patra, J. (2007). Comparative quantification of alcohol exposure as risk factor for global burden of disease. *International Journal of Methods in Psychiatric Research*, 16(2), 66–76. <https://doi.org/10.1002/mpr.204>
- Rehm, J., Sherk, A., Shield, K. D., & Gmel, G. (2017). *Risk relations between alcohol use and non-injury causes of death*. Centre for Addiction and Mental Health. <https://www.camh.ca/-/media/files/pdfs---reports-and-books---research/camh-risk-relations-between-alcohol-use-and-non-injury-causes-of-death-sept2017-pdf.pdf>
- Ruggles, S., Flood, S., Goeken, R., Grover, J., & Meyer, E. (2020). IPUMS USA: Version 10.0 [dataset]. Minneapolis, MN: IPUMS, 2020. As of July, 29 2020.
- Shield, K. D., & Rehm, J. (2012). Difficulties with telephone-based surveys on alcohol consumption in high-income countries: The Canadian example. *International Journal of Methods in Psychiatric Research*, 21(1), 17–28. <https://doi.org/10.1002/mpr.1345>
- Slater, M. E., & Alpert, H. R. (2020). *Surveillance Report# 115 Apparent Per Capita Alcohol Consumption: National, State, And Regional Trends, 1977–2018*. National Institute on Alcohol Abuse and Alcoholism. Retrieved October 23, 2020 from <https://pubs.niaaa.nih.gov/publications/surveillance115/CONS18.pdf>
- Stockwell, T., Zhao, J., Sherk, A., Rehm, J., Shield, K., & Naimi, T. (2018). Underestimation of alcohol consumption in cohort studies and implications for alcohol's contribution to the global burden of disease. *Addiction*, 113(12), 2245–2249. <https://doi.org/10.1111/add.14392>
- Subbaraman, M. S., Ye, Y., Martinez, P., Mulia, N., & Kerr, W. C. (2020). Improving the validity of the behavioral risk factor surveillance system alcohol measures. *Alcoholism: Clinical and Experimental Research*, 44(4), 892–899. <https://doi.org/10.1111/acer.14301>
- Turner, C. (1990). How much alcohol is in a 'standard drink'? An analysis of 125 studies. *British Journal of Addiction*, 85(9), 1171–1175. <https://doi.org/10.1111/j.1360-0443.1990.tb03442.x>
- Vu, T. M., Buckley, C., Bai, H., Nielsen, A., Probst, C., Brennan, A., Shuper, P., Strong, M., & Purshouse, R. C. (2020). Multiobjective genetic programming can improve the explanatory capabilities of mechanism-based models of social systems. *Complexity*, 2020, 1–20. <https://doi.org/10.1155/2020/8923197>
- Western, B., & Travis, J. (2014). *The Growth of Incarceration in the United States: Exploring Causes and Consequences*. National Research Council. The National Academies Press. <https://doi.org/https://doi.org/10.17226/18613>.
- World Health Organization. (2000). *International guide for monitoring alcohol consumption and related harm*. Retrieved May 20, 2019, from <https://apps.who.int/iris/handle/10665/66529>
- World Health Organization. (2018). Global status report on alcohol and health 2018. Retrieved May 20, 2019, from https://www.who.int/substance_abuse/publications/global_alcohol_report/en/
- Yi, H.-y., Chen, C. M., & Williams, G. D. (2003). State trends in drinking behaviors 1984–2001. *U.S. Alcohol Epidemiologic Data Reference Manual*, 7. https://pubs.niaaa.nih.gov/publications/DRM_02-5213/DRM_02-5213-Summary.pdf