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The Alcohol Policy Environment, Enforcement, and Consumption in the U.S

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Abstract

Introduction and Aims—Many studies of alcohol policies examine the presence or absence of a single policy without considering policy strength or enforcement. We developed measures for the strength of 18 policies (from Alcohol Policy Information System) and levels of enforcement of those policies for the 50 U.S. states, and examined their associations with alcohol consumption.

Design and Methods—We grouped policies into four domains (underage alcohol use, provision of alcohol to underage, alcohol serving, general availability) and used latent class analysis (LCA) to assign states to one of four classes based on the configuration of policies—weak except serving policies (6 states), average (29 states), strong for underage use (11 states), and strong policies overall (4 states). We surveyed 1,082 local enforcement agencies regarding alcohol enforcement across five domains. We used multilevel LCA to assign states to classes in each domain and assigned each state to an overall low (15 states), moderate (19 states), or high (16 states) enforcement group. Consumption outcomes (past-month, binge, and heavy) came from the Behavioral Risk Factor Surveillance System.

Results—Regression models show inverse associations between alcohol consumption and policy class, with past-month alcohol consumption at 54% in the weakest policy class and 34% in the strongest. In adjusted models, the strong underage use policy class was consistently associated with lower consumption. Enforcement group did not affect the policy class and consumption associations.

Discussion and Conclusions—Results suggest strong alcohol policies, particularly underage use policies, may help to reduce alcohol consumption and related consequences.

Keywords

alcohol; policy; enforcement; consumption; binge

INTRODUCTION

A host of alcohol regulations and policies, such as minimum legal drinking ages (MDLA), taxes, and restrictions on availability, have been implemented to prevent and reduce alcohol use and misuse and associated negative consequences. Strong evidence indicates that many of these restrictions can influence alcohol use and related problems [1]; however, much of this evidence comes from earlier studies that assessed effects of alcohol policies by simply measuring the existence of a policy (i.e., “present” or “not present”; e.g., [2–4]). Yet, a given alcohol policy may vary across states or other jurisdictions [5–6]. For example, each state in the U.S. has some form of an age-21 MLDA, but the potential strength of the MLDA laws varies by state [6].

A number of studies have examined variability of specific state-level alcohol policies. Mosher and associates [5] rated state-level responsible beverage service (RBS) training laws along five components and found that only two of the 23 states with RBS laws had strong overall RBS laws and the majority of other states were considered to have weak laws. Fell and associates [6] did a similar analysis of the strength of numerous U.S. MLDA and companion laws (e.g., keg registration, blood alcohol content limits for underage drivers), using a scoring system that considered whether provisions of the law decreased or increased the likelihood of youth drinking. Using this scoring system they found large variability in the strength of laws across states. Naimi et al. [7] developed implementation ratings for 29 state-level alcohol policies. Using concepts such as applicability and enforceability, each policy was given an implementation rating ranging from 0.0 (no policy) to 1.0 (full implementation) using a modified Delphi approach with a panel of 10 alcohol policy experts. Erickson and colleagues [8] rated the strength of 18 state-level alcohol policies using a coding protocol that considered policy reach, enforceability, and deterrence. Each of these teams identified variability in the strength of individual policies across states.

In addition to within-policy variability in strength across states, there is also between-policy variability in terms of their effectiveness (e.g., alcohol excise taxes may create a stronger effect than bans on Sunday alcohol sales). A primary challenge to combining policies for assessment of their effects is determining how to ‘weight’ the different types of policies. A simple sum or average equally weights each policy included in the index. By ignoring this, a small (i.e., potentially less effective) policy contributes equally to the index as a large (i.e., potentially more effective) policy. A recent paper by Nelson and colleagues [9] rated the efficacy of 47 different state policies in the US on a scale that allowed a comparative assessment of all of these policies relative to one another. A subsequent paper by this research team used these ratings to create multiple aggregate measures of 29 alcohol policies for each state [7] and found that states with more restrictive policies had lower rates of alcohol consumption.

Enforcement of policies also likely plays an important role. Multiple theories describe why and how enforcement modifies behavior (e.g., [10–11]), and empirical data across a variety of policy areas confirms that increased enforcement strengthens the effects of alcohol policies (e.g., 12–14). Despite this, enforcement is often not included in alcohol policy

evaluation research. The reasons for the lack of inclusion are varied, but difficulty operationalizing enforcement and collecting the data are possible explanations.

In this study we describe a statistical approach to aggregate multiple state alcohol policies to create a measure of the overall state-level alcohol policy environment that incorporates the strength of specific policies in each state. We use a statistical clustering model that creates clusters or classes of states that have similar policy profiles and provides descriptive information to facilitate interpretation of these profiles. An important difference of this approach is that states that would have similar quantitative scores through the use of a sum or average can look quite different using these clusters or classes. We examined how this alcohol policy environment measure correlates with measures of alcohol consumption and the role of enforcement in these associations.

METHODS

We created measures of state-level alcohol policy and enforcement, and identified measures of alcohol consumption and covariates drawn from multiple data sources.

Individual policy measures

We examined all state-level policies included in the Alcohol Policy Information System (APIS) database (<http://alcoholpolicy.niaaa.nih.gov>) for 2009 with the exception of those pertaining to Pregnancy and Alcohol, Vehicular Insurance, and Health Care Services and Financing which were outside the scope of this study. To create strength scores for each type of policy in each state, we categorized the strength of each policy on a scale from “most restrictive” to “least restrictive” in all 50 states. To determine a policy’s strength or restrictiveness, we considered how the components of a particular policy may affect its reach, enforceability, and/or implementation. We examined 19 policies; however, we were unable to create strength scores for three policies (blood alcohol content (BAC) limits) because they had no meaningful variation across states and we separated one policy (false identification) into three individual policies. Hence, we created strength scores for a total of 18 policies, with a range from 2 to 6 categories per policy (Table 1; see [8] for full description of the process).

Enforcement measure

We surveyed 1,082 local law enforcement agencies regarding their alcohol enforcement practices. We used a multi-stage sampling strategy to select a sample of representative agencies from each state, selecting 40 agencies in large states and 20 agencies in small states (large and small state designation was determined by number of agencies per state using a median split; median=300). We also sampled based on proportion of agencies with county sheriff versus municipal police, and ensuring equal number of small and large agencies. We surveyed, via telephone or online, an officer from each agency who was most knowledgeable about his/her agency’s alcohol-related enforcement activities (see [15] for a complete description of survey methods). Using multilevel latent class analyses [16] to determine state-level enforcement measures, we assigned states to classes in five enforcement domains based on multiple indicators per domain: underage use (six indicators), underage provision

(six indicators), underage compliance checks (seven indicators), drinking-driving (four indicators), and overservice (i.e., sales to obviously intoxicated patrons; seven indicators). The underage compliance checks and overservice domains had two classes each (high and low) and the other three domains had three classes each (generally characterized as high, moderate, and low). We coded the two-class domains as high=3 vs. low=1, and the three-class domains as high=3, moderate=2, and low=1. For each state, we created an overall sum scores across the five domains (range=5–15). We then created a three-level variable from the sum measure, using approximate tertiles based on the distribution: low (sum=5–7; 15 states), moderate (sum= 8–9; 19 states), or high (sum=10–15; 16 states).

Consumption measures

Consumption measures (past-month, binge, and heavy) came from the 2009 Behavioral Risk Factor Surveillance System (BRFSS). The BRFSS is a nationally representative household random-digit dial telephone survey of adults aged 18 years and older in all US states (n~400,000). Past-month drinking was defined as having at least one alcoholic drink (beer, wine or liquor) in the past 30 days. Binge drinking was defined as five or more drinks for men or four or more drinks for women on one occasion in past 30 days. Heavy drinking was defined as drinking on average more than 1 drink per day for women, more than 2 drinks per day for men. Each drinking measure was coded as 0=no, 1=yes at the individual level.

Individual-level demographic measures

Individual-level demographic measures were taken from the 2009 BRFSS and used as covariates in our analysis. Education was measured based on the question “What is the highest grade or year of school you completed” (a five-level variable collapsed to: 0=high school graduate or less, 1=some college or college graduate). Age was measured as a continuous variable (open ended question: What is your age?). Race/ethnicity was measured using a calculated variable (by BRFSS) based on responses to two questions “Which one of these groups would you say best represents your race? (seven response choices)” and “Are you Hispanic or Latino? (yes/no)”. The calculated variable had five categories which we reduced to four: White, non-Hispanic; Black, non-Hispanic; Hispanic; Other (multi-racial or other race, non-Hispanic). All BRFSS data were weighted to be representative of state populations. Further details about the BRFSS and the survey methodology are available at www.cdc.gov/brfss.

State-level demographic measures

We included three state-level demographic measures as covariates in our analysis. State total population was a count variable and state unemployment rate was a continuous variable, both drawn from the 2010 U.S. Census. Religiosity, measured as the percent of the state population who attend worship at least one time per week, was collected as part of the U.S. Religious Landscape Survey in 2007–2008 by the Pew Research Center.

Analyses

We conducted a multi-step analysis to examine how the state alcohol policy environment was associated with alcohol consumption. First, we conducted a latent class analysis (LCA)

to develop a measure of the strength/restrictiveness of the overall state alcohol policy environment. LCA allows a limited number of indicators, so we categorized the alcohol policies into four domains: underage alcohol use, provision of alcohol to underage, alcohol server policies, and general alcohol availability (Table 1; we excluded the open container policy because it did not fit conceptually with the other policies). We summed the policy strength scores (after standardization with mean=0, standard deviation=1) for all the policies in a given domain to create a domain sum score (Table 1). The domain sum scores were used as indicators in the LCA models. We conducted two-class, three-class, four-class, and five-class solutions and selected the best-fitting model based on standard criteria including model fit (using the Akaike Information Criteria [AIC], Bayesian Information Criteria [BIC]), posterior probabilities, interpretability, theoretical soundness and prevalence in each class [17].

Second, we conducted unadjusted state-level analyses relating policy class to weighted state-level alcohol consumption prevalences (past-month, binge, and heavy; all from 2009 BRFSS, N=50). For this analysis (and the subsequent multilevel regressions), we used a classify-analyze approach [18], assigning each state to the policy class with the highest posterior probability and using this assigned class as the alcohol policy environment measure.

Third, we conducted adjusted multilevel logistic regression analyses (state-level policy class; individual-level consumption outcomes). We separately regressed each of the dichotomous alcohol outcome variables on policy class (coded as dichotomous variables with the largest class as the referent), adjusting for all individual and state-level covariates. Finally, we re-estimated each regression model with the enforcement measure added to determine whether enforcement class was associated with alcohol consumption or the policy-alcohol consumption association. All regression models were conducted in MPlus v7 [16] using mixture modelling with a MLR estimator (maximum likelihood estimation with robust standard errors). We accounted for clustering of individuals within states and included appropriately-scaled individual BRFSS weights [19].

RESULTS

Our chosen latent class model for the alcohol policy environment measure was the four class model based on several factors. First, although the five- and six-class models had lower adjusted BICs, the additional classes identified in these models were not clearly distinct (Table 2). Hence, the four-class model was most interpretable theoretically. Also, the entropy and the average posterior probabilities were highest for the four-class model. The high average posterior probabilities, ranging from 0.90 to 1.0, also suggest the classify-analyze approach was reasonable. We did compute likelihood ratio tests to compare the different models, however, the tests were not useful (all non-significant) which suggests using other criteria for assessing model fit. Figure 1 presents a profile plot of the four classes. Class 1 had 6 states and was characterized by weak policies except for relatively strong server policies. Class 2 was the largest class with 29 states and was characterized as having average policy scores across all four domains. Class 3 had 11 states and was characterized by strong underage use policies but otherwise average policies. Finally, Class 4 was the smallest class

with just four states and was characterized by strong policies overall. Table 3 shows which states were assigned to each class.

Table 4 shows the alcohol consumption measures (raw, unadjusted) for the states in each policy class. An inverse association appears for all three alcohol consumption outcomes. The four states in the strongest policy class had lower rates of past-month, binge, and heavy alcohol consumption. Likewise, the six states in the policy class with the weakest policies had higher rates of all types of alcohol consumption.

Table 4 also summarizes the association between policy class and alcohol consumption outcomes using fully adjusted multilevel regression models. Compared to the class with average policy strength (largest class; 29 states), the class with strong underage use policies (Class 3) had consistently negative and significant associations with all three alcohol consumption measures.

Unlike the unadjusted models, however, Class 3 rather than Class 4 had the lowest average rates of alcohol consumption. For past-month and binge drinking, Class 4 (compared to Class 2) had negative associations with binge drinking but these are not statistically significant. Comparisons between Class 1 and the referent class were variable and only significant for past month drinking.

Individual-level covariates in adjusted models were significant with very few exceptions (data now shown in tables). Among the state-level covariates, church attendance was consistently negatively associated with alcohol consumption measures, unemployment was negatively associated with past month and binge drinking (non-significant in heavy drinking model), and total population had mixed results.

When the enforcement measures were added to the adjusted models, effects of policy class were unchanged for all three consumption outcomes. There was some significant relationships between enforcement and the consumption outcomes—states in the low enforcement group, compared to the high group, had higher levels of past-month, binge, and heavy consumption (comparisons between moderate and high groups were not significant). The percentage difference in consumption for the low group versus high group was 2.4% for past-month, 6.7% for binge, and 10.1% for heavy.

DISCUSSION

The current results build on and extend a growing body of research that seeks to examine the effects of combinations of alcohol control policies rather than individual or isolated policy effects. The use of strength scores is a key element as it provides much richer measures of alcohol control policies, allowing for between-state variability for specific types of policies to be incorporated in the measure. Numerous distinct and complementary approaches to assessing variability in specific policies across jurisdictions have now been proposed [6–8], and each has concluded that such variability exists.

The novel aspect of these analyses is the model that was used to combine policies into an overall measure. Results suggest states can be grouped by their alcohol control policies into

classes or clusters that are distinct, and these classes are associated with alcohol consumption. Focusing on the four states with the strongest alcohol control policies, we see that although they have much stronger policy ratings for underage and availability policies, they are similar to the other classes on strength of server policies. Further exploration might determine whether this is a reflection of a deliberate process by policymakers in these states and, if so, what information or context is responsible. Another interesting aspect to these classes is how the six states with the weakest policies mirror the six states with the strongest policies. Once again, determining whether this is intentional and associated with a specific policymaking orientation or approach could provide important information about the legislative process and guide advocacy work.

Differences in consumption between classes do not appear to be merely the effects of more versus fewer policies. The largest class has policies that are approximately the average strength for all four policy domains. By using this class as the referent, differences in alcohol consumption can be specifically tied to the qualitative differences of the classes. Although in unadjusted models we saw a gradient where classes with stronger policies tended to have lower consumption, this did not completely hold in the adjusted models. The class with the strongest policies was not significantly associated with alcohol consumption in adjusted models. This may be in part due to the small size of this class (four states), as the associations were in the negative direction as would be expected (for past month and binge drinking) but did not reach statistical significance. When we compare the average policy class to the class that is also average on underage provision, server, and availability but stronger on underage use, we do see significant associations between strong underage use policies and lower rates of consumption. It may be that strong underage use policies are associated with lower alcohol consumption when all other policies are invariant. This was also the only comparison that showed differences on the heaviest alcohol consumption outcome; these heavy drinking behaviors might be more represented in youth and most sensitive to these underage use policies.

We saw minimal effects for our aggregate measure of alcohol enforcement. We hypothesized that enforcement would be associated with lower alcohol consumption and that it would moderate the association between policy class and consumption such that policy effects would be stronger in states with higher enforcement. We found no moderating effects, and enforcement was only associated with binge drinking when comparing states with the strongest enforcement versus those with the weakest enforcement. The biggest concern interpreting these mostly null findings is the measure of enforcement. The measure is based on enforcement activities of local law enforcement in each state, combined using multilevel latent class analysis, and then aggregated across enforcement domains. This measurement model assumes that law enforcement activities across communities in a state are consistent or correlated and that our sample of communities in each state are representative and of adequate size. Either of these assumptions may be invalid. Also, a number of additional measures of state-level alcohol enforcement, such as alcohol enforcement by state-level alcohol beverage control offices and drink-driving enforcement by state highway patrol agencies, were not included. States with strong enforcement by these excluded agencies may show lower enforcement by local agencies and bias this measure. Future work specifically focusing on enforcement measurement is needed.

The current study has a number of limitations. Our analyses reflect policies and enforcement in one year (2009); policies and enforcement practices certainly change over time, and longitudinal analyses to capture these changes are needed in future studies. Given that the data are cross-sectional, we are not able to make claims of directionality or causality. The sample size is also constrained to 50 states which affect both statistical power and model stability for the latent class analyses. The main outcome analyses were multilevel regression using BRFSS outcomes, so while the individual-level sample size is quite adequate, the primary predictor is still measured at the state level and restricted to that sample size and degrees of freedom. This also limited the number of state-level covariates we could include in the model. In addition, some types of alcohol policies, such as advertising restrictions and penalties for drinking-driving, are not included. As described above, the enforcement measure, while derived from a multilevel latent class analysis of a large sample of law enforcement agencies and covering multiple enforcement domains, does not incorporate enforcement activities for all alcohol enforcement agencies in each state. In addition, enforcement data were self-report. Finally, we used a classify-analyze approach for latent class models which does not take into account uncertainty in class membership; however, given high average posterior probabilities in our analyses, the bias due to this uncertainty is likely minimal.

In conclusion, we found that U.S. states can be grouped into four homogeneous classes based on their alcohol control policies, with over half of the states reporting average strength policies across all domains. The states with stronger policies, particularly underage use policies, tended to have less alcohol consumption, and the relatively small numbers of states in these classes suggests opportunities for policymakers in other states to address longstanding and continued high levels of alcohol consumption and related consequences.

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Figure 1.
Policy Latent Class Analysis: Probabilities for 4-class model

Table 1

Policies and domains with range of strength scores

Domains/Policies	Range of strength scores	
	Original	Standardized
Underage alcohol use domain	8–17	–6.76 – 5.97
Underage: possession	1–5	–1.05 – 1.23
Underage: consumption ¹	1–4	–1.48 – 1.09
Underage: internal possession ¹	1–2	–0.43 – 2.27
Underage: purchasing	1–2	–3.36 – 0.29
False identification: Users ¹	1–2	–2.27 – 0.43
Use/Lose: Driving privileges	1–4	–1.52 – 1.29
Provision of alcohol to underage domain	5–13	–4.65 – 5.43
Keg registration	1–5	–1.09 – 2.61
Underage: furnishing	1–3	–1.09 – 1.14
Hosting underage drinking parties	1–4	–0.82 – 1.85
False ID: Suppliers ²	1–2	–0.99 – 0.99
False ID: Retailers ^{1,2}	1–2	–0.65 – 1.51
Alcohol server domain	3–12	–3.02 – 5.44
Age of server: on-premise	1–4	–0.88 – 2.26
Age of server: off-premise	1–4	–1.00 – 1.46
Beverage service training	1–4	–1.14 – 1.71
General availability domain	3–8	–2.71 – 4.03
Sunday sales	1–3	–0.63 – 2.69
Control system ¹	1–3	–0.71 – 1.57
Beer taxes	1–3	–1.37 – 1.43
Polices not used in domains or sum scores		
Adult BAC ³	--	
Youth BAC ³	--	
Boating BAC ³	--	
Open Container ⁴	1–2	

¹ Small categories collapsed before summing² Three separate 2-category policies were created for false id: users, retailers, suppliers.³ No meaningful variability across states⁴ Not included in a domain because conceptually distinct

Table 2

Latent class growth curve model fit statistics

Number of classes	AIC	BIC	Adjusted BIC	Entropy	Smallest class size	Likelihood ratio test (p-value) ^I
2	909	934	893	.63	34%	0.401
3	909	943	887	.75	2%	0.081
4	905	949	876	.93	8%	0.367
5	904	957	869	.92	8%	0.558
6	908	971	868	.92	7%	0.822

^I Compares model with the model with one less class (p<.05 indicates model fits better than model with one less class)

Table 3

Description of four policy classes

Class	Description of Class	Number of states	States
1	Weak policies except for server policies	6	DE, NV, NM, NY, VT, WY
2	Average for all policies	29	AK, AR, CA, CT, FL, GA, HI, IL, IN, IA, KY, LA, ME, MD, MA, MN, MS, MT, NE, NJ, ND, OH, OK, RI, TX, VA, WA, WV, WI
3	Strong underage use but otherwise average	11	AZ, CO, ID, KS, MI, MO, NH, OR, PA, SD, TN
4	Strong policies overall	4	AL, NC, SC, UT

Table 4

Alcohol consumption by policy class

Class	Description of Class	Past-month		Binge		Heavy	
		Raw percent	Estimate: fully adjusted model [/]	Raw percent	Estimate: fully adjusted model [/]	Raw percent	Estimate: fully adjusted model [/]
1	Weak policies except for server policies	53.5%	-0.130 [*]	11.6%	-0.082	5.5%	0.027
2	Average for all policies	48.7%	REF	11.2%	REF	4.8%	REF
3	Strong underage consumption/possession but otherwise average	47.6%	-0.145 [*]	10.4%	-0.102 [*]	4.4%	-0.130 [*]
4	Strong policies overall	34.4%	-0.090	8.0%	-0.100	3.6%	0.014

* p<.05

[/] Estimates are regression coefficients from multi-level models controlling for sex, age, race, marital status, education (at individual level) and state population, percent unemployment and religiosity (at state-level)

REF: referent group