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Age Cohort Affects on U.S. State-Level Alcohol Consumption Shares: Insights Using Attraction CODA

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Abstract

One of the most significant demographic changes predicted for this mid-century is in the age distribution of the U.S. population. Few aggregate empirical studies in the alcohol demand literature account for the entire age distribution of a jurisdiction in the statistical analyses. Herein, we propose the use of the attraction CODA empirical framework to model age cohort impacts to state-level beer, wine and spirits consumption shares in the U.S. for the years 2008 - 2020. This compositional construct, based in simplicial geometry, allows researchers to keep intact the entirety of states' age distributions without designed transformation. Age related results show that declines in states' beer shares are attributed to, mainly, proportional increases of states' 35-54 year-old cohorts. States with increasing older to elder population proportions experienced increases in wine shares and states' 35-54 year-old cohorts again, not younger populations, are key in driving the increased states' spirits consumption shares.

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1. Introduction

Few aggregate empirical studies in the alcohol demand literature account for the entire age distribution of a jurisdiction in the collective analyses. Freeman (2011) made the case that the relationship between age and alcohol consumption is genuinely complex and that there is value in examining all age cohorts on the right-hand-side (RHS). He argued that the proportions of a population that are too young or too old may modify the drinking behaviors of the in-between cohorts. Citing collinearity of state-level age-groupings and degrees of freedom issues, Freeman opted for Fair and Dominguez's (1991) polynomial distributed lag method of entering the entire age distribution of a jurisdiction on the RHS. The restrictions imposed on the age cohort proportions as suggested by Fair and Dominguez, however, mask the age-group specific impacts on alcohol consumption variation. Only implied coefficients for the age intervals can be recovered from the polynomial (quadratic) transformation. Freeman (2011) seemed more interested in the altered impacts to other economic condition coefficients in his models.

Age-group proportions (summing to one) by jurisdiction over time form an important compositional explanatory variable for alcohol consumption variation. Paired with the industry convention consumption components − beer, wine and spirits − we now have fashioned a compositional relationship that cannot be estimated with usual econometric methods. Modeling shares of the total for all of these variables has the advantage of exploiting relative competitive and demographic information implicit in the compositional vectors. By *relative information* we mean the complex pattern of interplay within the industry combined with the varying age makeup of consuming populations. Early work on specific compositional data analysis is credited to Aitchison (1986). Table 1 shows this variability of the two compositional vectors for the U.S. from 2008 to 2020. The simple story Table 1 tells is that proportionally the U.S. is getting older and volume consumption shares for wine and spirits are rising while beer consumption shares are in decline.

Table 1: Share comparison 2008-2020

	2008	**2020**	**%Change**
Beer	0.558	0.460	-17.56%
Wine	0.142	0.169	19.01%
Spirits	0.300	0.371	23.67%
Age 0-18	0.260	0.235	-9.62%
Age 19-25	0.092	0.085	-7.61%
Age 26-34	0.118	0.123	4.24%
Age 35-54	0.291	0.257	-11.68%
Age 55-64	0.113	0.131	15.93%
Age 65+	0.126	0.169	34.13%

- Beer, wine and spirits volume shares.
- For sources see Table 2.

The aim of this paper is to apply recent statistical methods that accommodate the compositional nature of both alcohol consumption shares (LHS) and age cohort proportions (RHS).[2] Two types of statistical models have been recently adapted to handle compositional variables - the Dirichlet covariate model and the Compositional Data Analysis (CODA) model. Both have been shown to outperform earlier modeling specifications when derived in the conventional *attraction* form (Morais et al., 2018a).[3] Attraction models are analogous to the utility concept in discrete choice modeling. Simply, consumer attraction to a component is modeled as a function of determinates impacting its proportional share (e.g., component taxation, consumer income and age cohorts herein). The compositional share of the dependent component is defined as its relative attraction to other competing components (Cooper, 1993). Morais et al. (2018a) strongly advocate for their adaptation of the attraction CODA model when: i) cross effects are important to consider, ii) the RHS contains compositions and iii) the property of Independence from Irrelevant Alternatives (IIA) becomes too restrictive. CODA models follow the subcompositional coherence property which does not imply IIA (van den Boogaart and Tolosana-Delgado, 2013).

Herein, we propose the use of the attraction CODA empirical framework to model impacts to state-level consumption shares of the U.S. alcoholic beverage industry for the years 2008 - 2020. This construct allows us to keep intact the entirety of states' age distributions without polynomial transformation. Age related results show that declines in states' beer shares are associated with proportional increases of states' 35-54 year-old cohorts. States with increasing older to elder population proportions are linked to increased wine shares and states' 35-54 year-old cohorts again, not younger populations, are key in driving the increased states' spirits consumption shares. The balance of this examination is divided into four sections. Section 2 describes the data, provides sources, presents descriptive statistics and variable analysis. Section 3 presents the empirical model and discusses the complex econometric issues. Section 4 interprets the empirical results with conclusions and future research directions drawn in section 5.

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[2] Kraus et al. (2022) form dependent compositions for individual alcohol consumption survey data and estimate using a multinomial logit model. The authors do not address the limitations from the IIA property inherent in multinomial logit estimation.

[3] Primarily, the performance comparisons are to aggregate multinomial logit specifications.

2. Data

Table 2 presents the descriptive statistics and sources for all variables. The data comprise a 13 year (2008-2020) panel for all 50 states and the District of Columbia.

Table 2: Variable descriptive statistics and sources

	Mean	STD	Source
Beer Share	0.488	0.074	The Beer Institute, The Brewer's Almanac
Wine Share	0.141	0.053	The Beer Institute, The Brewer's Almanac
Spirits Share	0.371	0.057	The Beer Institute, The Brewer's Almanac
Beer Tax	0.297	0.260	The Beer Institute, The Brewer's Almanac
Wine Tax	0.858	0.569	Tax Foundation
Spirits Tax	4.197	2.236	Tax Foundation
Income	48.189	7.844	U.S. Bureau of Economic Analysis
Age 0-18	0.244	0.023	U.S. Census Bureau, American Community Survey
Age 19-25	0.091	0.008	U.S. Census Bureau, American Community Survey
Age 26-34	0.120	0.014	U.S. Census Bureau, American Community Survey
Age 35-54	0.266	0.017	U.S. Census Bureau, American Community Survey
Age 55-64	0.130	0.012	U.S. Census Bureau, American Community Survey
Age 65 +	0.148	0.023	U.S. Census Bureau, American Community Survey

Consumption shares, the dependent composition, were derived from the state-level shipments data made available annually by The Beer Institute (2021), a national trade association.[4] Beer, wine and spirits shipments data were transformed into drink equivalents by converting total volumes to 12 ounce portions for beer, 5 ounces for wine and 1.5 ounces for spirits. Total drink equivalents for each component, by state and year, are then presented as shares of the total.[5] The Beer Institute compiles shipment volumes based on reporting from the individual states. Data reflect shipments and/or sales volumes determined by local tax payments and/or state reporting of malt, wine and spirits beverage shipments. Figure 1 depicts the trajectory of the three component shares, from 2008 to 2020, for the state of California. Note that beer's share of consumption has declined, spirits' share has increased, while wine's consumption share has remained relatively flat for the state.

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[4] *The Brewer's Almanac*, September 2021 revised version. The Beer Institutes' alcohol shipments data was also used by Yakovlev and Guessford (2013).

[5] See the appendix to this paper for a table presenting shares for all jurisdictions for the endpoint years 2008 and 2020.

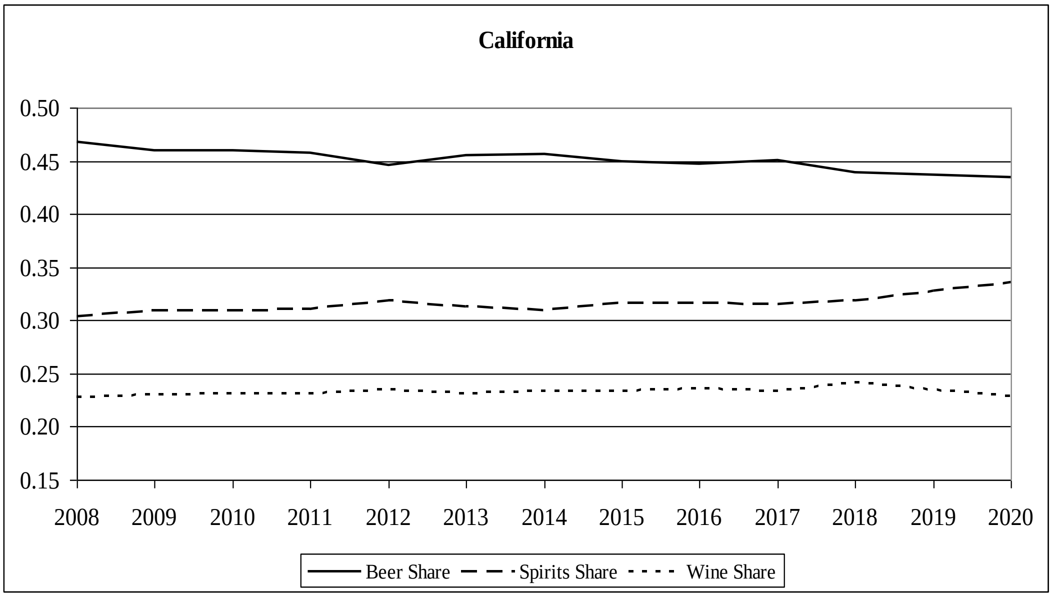

Figure 1: California alcohol consumption shares

Compiled tax data for this study is component, state and year specific. Again, The Beer Institute is the source for state-level beer excise tax data. Beer-specific excise tax burden by state and year are converted to 2020 dollars per gallon.[6] Generally, this rate includes state and local brewery production and specific sales taxes and fees aimed at malt based products. Interestingly, in some states (e.g. Pennsylvania), separate on-brewery-premise sales taxes are imposed. The Tax Foundation is the source of both wine and spirits state-level excise tax data.[7] For some control states (where government controls all sales) data were missing. For wine, data absent states included Mississippi, New Hampshire, Pennsylvania, Utah and Wyoming. For spirits, New Hampshire and Wyoming were missing data. In each missing data occurrence we relied on the state's statutory markup (e.g. 17.6 percent in Wyoming)[8] to impute specific tax revenue from reported state sales of wine and spirits. The totals were then converted to 2020 dollars per gallon of apparent consumption (from The Beer Institute) per state, per year. Disposable personal income is sourced from the U.S. Bureau of Economic Analysis (BEA), Personal Income and Outlays 2021 release. This state-level income measure represents per capita personal income available to persons for spending or saving (after-tax income), converted to thousands of 2020 dollars.

The entirety of the age distribution by state is sourced from The American Community Survey (ACS) based on data collected by the U.S. Census Bureau.

[6] Freeman (2011) used this tax data in his state-level analysis.

[7] Fogarty and Voon (2018) and Hart and Alston (2020) used Tax Foundation excise tax data in their respective studies.

[8] Wyoming Statute § 12-2-303.

ACS grouped population data are widely used by researchers across the academic spectrum. The ACS assembles populations by state and year into six age-range categories as shown in Tables 1 and 2. These six age-range categories form an explanatory compositional vector of proportions (summing to one) that is unique to each state-year observation, not each consumption component. Past examinations of aggregate alcohol demand were reluctant to include the complete age vector on the RHS citing collinearity and degrees of freedom issues. While compositional data models can accommodate shares data on the RHS, intercorrelation between the age-components may pose precision problems in estimation. Table 3 shows the correlation coefficients between income and the six age components.

Table 3: Income and age-component correlation coefficients

	Income	**Age 0-18**	**Age 19-25**	**Age 26-34**	**Age 35-54**	**Age 55-64**
Income	1.000					
Age 0-18	-0.433	1.000				
Age 19-25	0.042	0.466	1.000			
Age 26-34	0.497	-0.057	0.400	1.000		
Age 35-54	0.151	-0.084	-0.116	-0.128	1.000	
Age 55-64	-0.075	-0.589	-0.480	-0.450	-0.165	1.000
Age 65 +	-0.094	-0.561	-0.533	-0.359	-0.438	**0.726**

In addition, following Belsley et al. (2013), a variance decomposition proportions examination of the age groupings indicates a high level of collinearity between the two oldest age components. The last column of table 3 bolsters this test diagnostic. This issue will be addressed in the results section below.

3. Model

Models adapted to shares data, compositional data models, stem from simplicial geometry developed by Aitchison (1986). A dependent vector of shares is a composition of strictly positive proportions (summing to one) belonging to the simplex space where relative share comparison is most important. Hence, the compositional makeup of the data must be considered. Compositional models are classified as *transformation* models where they assume a Gaussian distribution for an isometric log-ratio (IRL) transformation of shares (Morais et al., 2018a).[9] These specifications are mathematically complex but allow for great flexibility in model development. RHS variables can be component specific, observation specific, cross-component interactive and can take a compositional or traditional form.

[9] IRL is preferred in this application because the resulting coordinates possess orthonormal error terms with non-constant (between) variance (Trinh et al., 2018). Moreover, other transformation methods developed may introduce collinearity among the transformed coordinates.

Compositions on the RHS can explain dependent share components individually or explain the complete LHS observation of shares. Moreover, dependent and explanatory compositional variables can have different dimensions. For example, herein alcohol consumption is made up of three components and these three components are explained by the same six age groupings by state-year observation.[10]

A *D* composition of alcohol consumption shares *S* is represented in simplex space by,

$$S^D = \left\{ S = \left(S_1, S_2, \ldots, S_D\right)'; \; S_j > 0; \; j, l, m = 1, \ldots, D; \; \sum_{j=1}^{D} S_j = 1 \right\}. \tag{1}$$

Usual regression applications are not particularly useful on the simplex. Therefore shares are transformed using IRL resulting in real unbounded coordinates in Euclidean space. Coordinates are defined,

$$irl(S) = V' \log(S) = S^* = \left(S_1^*, \ldots, S_{D-1}^*\right)', \tag{2}$$

where *V* represents the transformation (contrast) matrix (Pawlowsky-Glahn et al., 2015). Usual methods are now applicable to the coordinates and results in the simplex can be recovered with back (inverse) transformation,

$$irl^{-1}(S^*) = C\left(\exp(VS^*)\right)' = S, \tag{3}$$

where *C*(.) denotes the share closure operation (van den Boogaart and Tolosana-Delgado, 2013).

The concept of an *attraction* model comes from the marketing literature and is akin to the utility notion in discrete choice modeling (Cooper, 1993). The attraction to a component of a composition becomes a function of explanatory variables (typically demand related). A share *j* is defined as its relative attraction to competing shares given,

$$0 < S_{j,i} = \frac{A_{j,i}}{\sum_{l=1}^{D} A_{l,i}} < 1, \tag{4}$$

where $A_{j,i}$ is the attraction of share *j* at observation *i*. Following Morais et al., (2018a), expected share value in the simplex (attraction form) becomes,

[10] Morais et al. (2018b) cite an example where the LHS is a composition of GDP from three sectors explained by a composition of six categories of the labor force.

$$\mathrm{E}^{\oplus} S_{j,i} = \frac{\alpha_j \cdot \prod_{l=1}^{D} \prod_{k=1}^{K_X} X_{k,l,i}^{\beta_{k,j,l}} \cdot \prod_{\kappa=1}^{K_W} \beta_{\kappa,j}^{W_{\kappa,i}}}{\sum_{m=1}^{D} \alpha_m \cdot \prod_{l=1}^{D} \prod_{k=1}^{K_X} X_{k,l,i}^{\beta_{k,m,l}} \cdot \prod_{\kappa=1}^{K_W} \beta_{\kappa,m}^{W_{\kappa,i}}}, \tag{5}$$

where Table 4 denotes (in general form) all variables and notations. The complexity of this model is compounded by the potentially large number of parameters, therefore, N must be sufficiently large. The 'compositions' package in **R** was used to fit equation (5).[11]

Table 4: Expected shares model notations

Observations, indexed $i = 1, \ldots, N$ (N = 51 states x 13 years = 663) Components, indexed $j, l, m = 1, \ldots, D$
$\mathrm{E}^{\oplus}$, expected value in the simplex. α, model intercepts.
Explanatory variables that vary over components and observations, $X_{j,i}$ These can be traditional variables, dummy variables or composition vectors Index of type X variables, $k = 1, \ldots, K_X$ Estimated coefficients of the X type, β_k
Explanatory variables that vary over observation only, W_i These can be traditional variables, dummy variables or composition vectors Index of type W variables, $\kappa = 1, \ldots, K_W$ Estimated coefficients of the W type, β_κ

4. Results

State-level alcohol consumption shares ($S_{j,i}$) are modeled as a function of state-specific alcohol component-specific excise taxation ($X_{j,i}$), overall state-level per capita disposable income (W_i) and the composition of state-level population shares by ACS age-group (composition in W_i). State and year dummy variables are also included to control for state and temporal heterogeneity and correlation. While **R** estimation is performed in coordinate space, interpretation of the coefficient estimates is not straight forward because estimates are coupled to the log-ratio transformation of shares, not the shares directly. Morais et al. (2018b) show that relative measures, like elasticities, work best to interpret impacts on LHS compositional shares. Following Morais et al., (2018b) pp. 7-11, derived elasticities, on average, are presented in Tables 5 and 6. Statistical significance is linked to the underlying coefficient estimates. Mindful of the collinearity between the two oldest age components shown is section 2 above, we estimated two models − one unrestricted and in the second we combined the last two age-group components that were highly collinear (forming five components in the composition). Results presented are from the unrestricted version as combining the older age components

11 See van den Boogaart et al., (2014).

did not affect remaining coefficient estimates and resulting average elasticities in any meaningful way.

Table 5: Non-compositional variable elasticities

	Beer Tax	**Wine Tax**	**Spirits Tax**	**Income**
Beer Share	-0.0020	0.0014	0.0241**	-0.365*
Wine Share	0.0028*	-0.0100**	0.0118*	0.531**
Spirits Share	0.0006	0.0059*	-0.0358**	0.494**

- Underlying coefficients significant at (*) < 10%, (**) < 5%, (***) < 1% levels.

Two of three own-tax elasticities (on the diagonal of the first 3 columns in table 5) are negative and statistically significant at conventional levels. For example, a 1 percent increase in state spirits excise taxes per gallon decrease spirits' consumption share by 0.036 percent. Interestingly, four cross-tax elasticities are statistically significant and all positive. Again, a 1 percent increase in the spirits tax increases the beer consumption share by 0.024 percent. These cross-component results highlight one of the many strengths of the attraction CODA framework. Table 5 tax elasticities are comparable to those found in previous state-level alcohol consumption examinations, see Yakovlev and Guessford (2013)[12] and Kunce (2023a). The rather small, inelastic, tax elasticity estimates are common among aggregate data alcohol consumption studies.

All income elasticities are statistically significant at conventional levels. A 1 percent increase in disposable personal income decreases the beer consumption share by roughly 0.36 percent. State beer shares have been negatively impacted by real income increases over the 2008 - 2020 period. This result is consistent with others analyzing the same time period (e.g. Kunce, 2023a). Presumably, higher incomes induce preference shifts away from beer to other beverages. Alternatively, Swinnen (2017) pointed out that while higher income jurisdictions (countries) may be drinking relatively less beer, they are in turn drinking more expensive beer. In this case, preferences are shifting within component to perceived higher quality (price) products in less overall volume. Wine and spirits shares are shown to increase with increases in disposable personal income, though the impacts are inelastic. Interestingly, the wine income elasticity presented is roughly one-half the magnitude of what Kunce (2023a) found. Overall however, these results align with most previous wine and spirits consumption examinations (see the survey by Fogarty, 2010).

Results for compositional age components reveal complex yet interesting effects on state consumption shares. In Table 6, the elasticities in bold show the largest positive and negative impacts (all inelastic) to each specific component share. Note that the wine share did not have a statistically significant negative age

[12] This study did not model consumption shares. The analysis focused on per capita consumption volumes in three separate component models.

elasticity. Starting with beer, states with increasing populations in the 19 to 25 year-old cohort experienced increases in beer consumption shares. A 1 percent increase in this population component increased beer's share of consumption by 0.18 percent. The largest negative impact to state beer shares appeared in the 35 to 54 year age component. One explanation for this effect, coupled with the 55 to 64 year-old smaller positive impact, could be the historic growth of the small-beer industry in the U.S. from 2008 (Kunce, 2023b).

Table 6: Compositional age elasticities

	0-18	**19-25**	**26-34**	**35-54**	**55-64**	**65 +**
Beer Share	-0.059	**0.177***	0.055*	**-0.396****	0.115*	-0.132*
Wine Share	0.307*	-0.007	0.035	0.443**	0.219**	**0.653****
Spirits Share	0.073	**-0.218***	0.067*	**0.489****	0.142*	0.163

- Underlying coefficients significant at (*) < 10%, (**) < 5%, (***) < 1% levels.

This older adult cohort has, perhaps, not given up beer, they just prefer small-beer alternatives (Elzinga et al., 2015). Rather than consume 'suitcases' of big-beer's fizzy corn and rice water, this age component likely shifted preference to small-beer products consumed in lesser quantities. As anticipated, states with larger proportions of the elderly demographic exhibit smaller beer consumption shares.[13] Interestingly, states with proportionally larger populations of children experienced increases in wine consumption shares. This is the only statistically significant impact for this age cohort and it supports Freeman's (2011) notion that proportions of ages younger than normal drinking age may affect consumption of the latter. In any case, states with increased older population proportions have larger wine consumption shares. The estimated elasticity for the 65 plus component affecting wine shares is the largest in magnitude herein (see both Tables 5 and 6). This pattern likely indicates a tendency for the elderly to be more health conscious regarding alcohol consumption − drinking with meals or for simple pleasure not intoxication (Kraus et al., 2022). Lastly, Table 1 shows that the spirits component of our triangular simplex has experienced the largest change from 2008 − a 24 percent increase. Our results indicate that this increase is not necessarily coming from states with younger population proportions, rather it stems from states with larger shares of 35 to 64 year-olds. Kelley (2022) reported that 70 percent of those aged 35 to 54 imbibe − proportionally higher than any other ACS age cohort. Additionally, she made the case that growth of the spirits share is the result of increases in off-site sales of premium liquors and packaged ready-to-drink mixed cocktails.

[13] This old-age affect on beer consumption was a key finding in Kerr et al. (2004).

5. Conclusion

One of the most significant demographic changes predicted for this mid-century is in the age distribution of the U.S. population. A recent population turning point analysis published by the U.S. Census Bureau focuses on key demographic changes expected into the year 2060 (Vespa et al., 2020). Most notably, the proportion of the U.S. population aged 65 and above is expanding and is expected to be roughly one forth (0.25) by 2060. Moreover, the report projects that by 2034, those aged 65 and above will outnumber children (those aged 18 and below) for the first time in U.S. history. These projections raise interesting questions about the impact of such demographic changes to alcohol consumption patterns. Results herein suggest that more elderly populations favor wine and to a lesser extent spirits, but beer consumption shares will suffer. Compositional data analysis, as proposed in this paper, and its evolution would serve as a useful tool going forward. While alcohol production and consumption provides important economic throughput in the U.S., it is also valuable to recognize future patterns for alcohol consumption by age cohort given the strong correlation of age with unhealthy drinking behavior (Kanny et al., 2018). Understanding the impacts of an aging population serves the industry and policy makers alike.

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Appendix

Table A1: Shares of Beer, Wine and Spirits consumption for the years 2008 and 2020

		2008			2020	
State	**Beer**	**Wine**	**Spirits**	**Beer**	**Wine**	**Spirits**
Alabama	0.6479	0.0948	0.2573	0.5756	0.1060	0.3184
Alaska	0.4753	0.1498	0.3749	0.4002	0.1575	0.4424
Arizona	0.5693	0.1403	0.2904	0.4844	0.1397	0.3759
Arkansas	0.6152	0.0780	0.3068	0.5391	0.0852	0.3757
California	0.5078	0.2109	0.2813	0.4459	0.2340	0.3201
Colorado	0.5131	0.1290	0.3579	0.4387	0.1103	0.4510
Connecticut	0.4343	0.2162	0.3495	0.3383	0.2233	0.4384
Delaware	0.4661	0.1614	0.3725	0.3263	0.1323	0.5414
DC	0.3589	0.2482	0.3928	0.2432	0.2733	0.4835
Florida	0.5119	0.1662	0.3220	0.4266	0.1633	0.4101
Georgia	0.5903	0.1113	0.2985	0.5247	0.1175	0.3578
Hawaii	0.5475	0.1825	0.2700	0.4774	0.2166	0.3061
Idaho	0.5782	0.1341	0.2877	0.4763	0.1270	0.3967
Illinois	0.5571	0.1484	0.2945	0.4790	0.1799	0.3411
Indiana	0.5706	0.1022	0.3272	0.4563	0.1026	0.4410
Iowa	0.6494	0.0669	0.2837	0.5325	0.0735	0.3940
Kansas	0.6296	0.0644	0.3060	0.5481	0.0600	0.3920
Kentucky	0.5979	0.0780	0.3241	0.4815	0.0730	0.4455
Louisiana	0.6145	0.0886	0.2969	0.5099	0.0965	0.3935
Maine	0.5454	0.1478	0.3069	0.4501	0.1244	0.4254
Maryland	0.4913	0.1443	0.3644	0.4021	0.1591	0.4388
Massachusetts	0.4623	0.2249	0.3128	0.3473	0.2394	0.4132
Michigan	0.5495	0.1235	0.3270	0.4342	0.1243	0.4414
Minnesota	0.4998	0.1159	0.3843	0.4300	0.1166	0.4534
Mississippi	0.6677	0.0459	0.2864	0.5655	0.0482	0.3864
Missouri	0.5814	0.1060	0.3126	0.4517	0.1065	0.4418
Montana	0.6206	0.1050	0.2745	0.5636	0.1005	0.3359
Nebraska	0.6288	0.0738	0.2974	0.5084	0.0721	0.4195
Nevada	0.5002	0.1543	0.3456	0.4559	0.1891	0.3550
New Hampshire	0.4383	0.1593	0.4024	0.3989	0.1580	0.4431
New Jersey	0.4327	0.2180	0.3493	0.3356	0.2252	0.4392
New Mexico	0.6020	0.0952	0.3028	0.5708	0.1317	0.2975
New York	0.4904	0.1998	0.3098	0.4100	0.2219	0.3681
North Carolina	0.6121	0.1205	0.2674	0.5349	0.1117	0.3535
North Dakota	0.5847	0.0612	0.3541	0.4778	0.0605	0.4617
Ohio	0.6390	0.1082	0.2528	0.4979	0.1256	0.3766

Oklahoma	0.6572	0.0823	0.2605	0.5409	0.0822	0.3770
Oregon	0.5274	0.1711	0.3015	0.4627	0.1638	0.3736
Pennsylvania	0.6247	0.1015	0.2738	0.5636	0.1144	0.3220
Rhode Island	0.4781	0.1967	0.3252	0.3146	0.1931	0.4923
South Carolina	0.6180	0.0887	0.2933	0.5962	0.0925	0.3113
South Dakota	0.6258	0.0653	0.3089	0.6067	0.0756	0.3176
Tennessee	0.6192	0.0936	0.2872	0.4735	0.0896	0.4369
Texas	0.6760	0.0859	0.2381	0.5861	0.0796	0.3344
Utah	0.6042	0.0912	0.3046	0.5427	0.0794	0.3780
Vermont	0.5273	0.2148	0.2579	0.5004	0.2318	0.2678
Virginia	0.5773	0.1653	0.2574	0.4790	0.1848	0.3362
Washington	0.5137	0.1892	0.2971	0.4648	0.2030	0.3322
West Virginia	0.6955	0.0577	0.2468	0.6571	0.0542	0.2887
Wisconsin	0.5560	0.1029	0.3411	0.4627	0.1100	0.4274
Wyoming	0.5669	0.0705	0.3626	0.4525	0.0775	0.4700
United States	**0.5584**	**0.1423**	**0.2993**	**0.4598**	**0.1687**	**0.3715**