Supporting Information for
"Urban Water Conservation Policies in the United States"

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1. Captions for Datasets S1 to S4
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Introduction

This supporting information document presents additional details of the data and analysis.

SI Text

Data

We used VWCI data for 195 cities in 45 states, as shown in Table S1.

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At the MSA level (Dataset S1, Table S1), our regression analysis used the following six covariates: ln(population), population growth rate between 2010 and 2014, the Köppen aridity index, the fraction of the municipal water supply coming from surface water (henceforth, surface-water fraction), the Cook Partisan Voting Index (PVI), and the per-capita real personal income (RPI) for 2014 normalized for inflation and regional variations in the cost of living. We used the natural logarithm of the population rather than the raw population because the raw population was skewed, with a sharp peak near 500,000, and a long tail at higher populations (Figure S1).

At the state level (Dataset S2, Table S2), our analysis used the following four covariates: PVI, RPI, the Köppen aridity index, and the surface-water fraction.

Analysis

Diagnostics

Our Monte Carlo analysis sampled four Markov chains, allowing each chain to warm-up and tune sampling parameters for the first 1000 iterations and then sampling each chain for 1000 more iterations, yielding a total of 4000 samples. Each sample is a vector of length 57, with values for each of the parameters α_0, β_j, γ_k, δ_{state}, σ, and ϕ, where j indexes over the six MSA-level covariates, k indexes over the four state-level covariates, and *state* indexes over 44 of the 45 states (leaving one out for identifiability). The samples approximate random draws from the joint posterior probability distribution of the parameters, given the priors and the observed data. Thus, the statistics of the sampled values approximate the statistics of the joint posterior distribution.

Collinearity among the predictor variables is diagnosed by observing correlations in the joint posterior probability distributions of the regression coefficients [*Stan Development Team*, 2016, pp. 288–293]. Inefficient sampling due to varying curvature in the log-probability manifold or poorly chosen priors can be diagnosed by irregularities in joint posterior distributions [*Stan Development Team*, 2016, pp. 316–321]. Pairwise correlation plots of the Monte-Carlo samples for the regression coefficients in our models of VWCI, requirements, and rebates (Figures S2–S4) are smooth with little correlation and give no cause for concern. In addition, the Hamiltonian Monte Carlo calculations proceeded without any divergences or exceessive tree depths after warm-up, and the Gelman-Rubin

$\hat{R}$ potential scale-reduction factor converged to ≤ 1.02 for each parameter [*Stan Development Team*, 2016].

Model Selection

We used several model-selection criteria in deciding whether to model the VWCI, requirements, and rebates as binomial or beta-binomial processes. At each joint sample of the model parameters in the Monte-Carlo process, we both computed the log-likelihood of the observed data under the sampled parameters and also generated posterior predictions obtained by drawing simulated observations from binomial or beta-binomial distribution at each joint sample of the model parameters.

Visual comparisons of distributions of posterior predictions to observed data and comparisons of the posterior predictions of mean, maximum, and minimum VWCI over the cities in our data set showed better agreement for the overdispersed β-binomial process than for a purely binomial one [*Gelman et al.*, 2014].

A separate test for overdispersion, which accounts for the danger of overfitting by introducing new free parameters, uses the Leave-One-Out cross-validation Information Criterion (LOO-IC) or the Widely Available Information Criterion (WAIC, also known as the Watanabe-Aikake Information Criterion), obtained by Pareto-smoothed importance sampling [*Vehtari et al.*, 2017]. Both information criteria favored the overdispersed beta-binomial distribution over a pure binomial, and also strongly favored hierarchical over single-level models (Tables S9–S14). Our choice to use very weakly informative priors in our model reduces the accuracy of our estimates of LOO-IC and WAIC [*Vehtari et al.*, 2017], but we do not worry overly about this potential inaccuracy both because the posterior prediction test yields the same results and because a pure binomial model gives very similar results to those presented here.

Results

Results of the analysis are summarized in Tables S15–S17.

Robustness Tests

We chose our explanatory variables based on theoretical considerations, as described in *Hess et al.* [2016]. To test the robustness of our analysis, we compared the results described above to several kinds of alternate regression analyses for the VWCI.

In the first series, we varied the interval over which we averaged the Köppen aridity index, considering the 30-year period 1985–2014, the 45 year period 1970–2014, the 20 year period 1995–2014, and the 10-year period 2005–2014. This tests for sensitivity to recent extreme events versus the longer-term average climate. There were no significant differences between the regressions using the four different intervals: the posterior distributions were nearly identical (Figure S5) and the information criteria differed by less than one tenth of the standard error (Tables S3 and S6).

Second, we performed regressions with additional or different explanatory variables (Figures S6–S7 and Tables S4–S5 and S7–S8). Population density has been found to correlate well with voting patterns, and thus might affect water conservation policies [*Rodden*, 2016]. We substituted 2010 population-weighted population density and the rate of change of population density from 2000–2010 [*Wilson et al.*, 2012] for total population. The results were similar to those of our original analysis, and produced slightly, but insignificantly, inferior information criteria scores.

We also considered that the area of an MSA might be important to collecting and distributing water, so we conducted regressions that included an additional explanatory variable representing the total area of the MSA as reported in the 2010 U.S. Census [*Wilson et al.*, 2012], the coefficient for area was consistent with zero and the information criteria scores were slightly and insignificantly inferior to our original analysis.

We also considered that in addition to mean personal income and relative purchasing power, the distribution of income might be important, so we performed regressions that included Gini indices of income inequality at both the MSA and the state levels, taken from the 2014 American Community Survey [*U.S. Census Bureau*, 2017]. The Gini index lies in the range zero (complete equality, with everyone receiving the same income) to one (complete inequality, with one person receiving all of the income and everyone else receiving nothing). In these regressions the coefficient for the state-level Gini index was positive and of comparable magnitude to the state-PVI coefficient, and the coefficient for the MSA-level Gini index was very small and consistent with zero. The information criteria scores were slightly and insignificantly inferior to our original model.

In order to test alternative model structures, we introduced interaction terms between aridity and PVI at both the state and MSA levels. As with the previous tests, introducing this term did not change the posterior distributions of the coefficients for the other covariates by very much and the information criteria scores were slightly, but insignificantly, worse.

All of these different analyses of VWCI consistently found that at the state level, the largest coefficients were for aridity and PVI, and at the MSA-level PVI, population (or population density), and population (or population-density) growth rates were positive and of comparable magnitude. The variations in coefficients across all of the alternate analyses were well within the 95% highest-density intervals of the posterior probability distribution.

In order to test that aridity and PVI were, in fact, significant We also performed regressions leaving out either the aridity or PVI covariates. These regressions produced information criteria scores that were inferior to the original regression by slightly more than one standard error in the case of PVI and by about one-third of the standard error in the case of aridity. We also observed that removing either one of these covariates did not significantly change the coefficients for any of the other covariates. This reinforces the evidence of the pairwise correlation plots that there are no problems with interdependence or multicollinearity among the covariates.

In all of these analyses, the MSA-level PVI, population, and population growth coefficients were positive and distinct from zero. The values and the ranking of these three coefficients changed, but by amounts that were well within the posterior probability distributions. The remaining MSA-level variables were consistent with zero.

The posterior distributions were considerably narrower than the prior distributions and lay well within those prior distributions, which indicates that they are not constrained by the priors. We tested this by varying the scales of the priors and by replacing the Cauchy priors on α_0, β, and γ with normal priors. The results were very similar to and consistent with the original analysis.

We also tested alternative regressions that used different normalizations for the MSA-level variables: In this alternative normalization, instead of taking the differences between the MSA-level variables and the state-level variables and scaling this difference to the state-level scales ($x_{\text{scaled}} = (x - w)/(2\sigma_w)$), we took the raw values for each MSA-level variable and scaled them to have zero-mean and a standard deviation of 0.5 across all 195 MSAs, without referring them to the state-level variables ($x_{\text{scaled}} = (x - \mu_x)/(2\sigma_x)$), as described in the main text.

We repeated all of the regressions described above using this alternative scaling of the MSA-variables (Figures S8–10 and Tables 9–14). The information criteria scores for these regressions were generally slightly, but insignificantly, inferior to the corresponding regressions using the original MSA-scaling and the posterior distributions of the regression coefficients differed in one important way: The coefficient for state-level PVI shifted to lower values, becoming consistent with zero, and its median was roughly one third of its value for the original scaling. The other regresion coefficients did not change much under the new scaling.

This result reveals an ambiguity in interpreting the role of PVI: Under the original scaling, PVI was important at both the state and MSA levels, leading to the interpretation that both the state-level PVI and the difference between the state-level and MSA-level PVI were well corelated with the propensity to adopt water-conservation policies. Under the alternative scaling, the coefficient for state-level PVI is consistent with zero (with an 85% probability of being positive) and the coefficient for MSA-level PVI is clearly positive, with an almost identical distribution as with the original scaling. Because the information criteria scores are only slightly different between the two analyses (the difference is roughly 5% of the standard error on the LOO-IC), there is no good reason to prefer one to the other and from a statistical perspective two alternative interpretations are equally plausible: That both the state-level PVI and the difference between the state- and MSA-level PVI are independently significant, or that the effect of the state-level PVI is not significantly different from zero, but that the MSA-level PVI is significant.

We conclude from this that the results of our analysis are robust against many changes of time-spans, explanatory variables, and assumptions about priors, except for the ambituity over the importance of state-level PVI.

Aside from state-level PVI, the effects of state-level aridity and MSA-level PVI, population, and population growth are robust and stable. Alternate model structures and alternate specifications of covariates were either markedly inferior (as measured by information criteria scores) or produced regression coefficients that were consistent with the original analysis.

Although many of the differences between information criteria were small, our original analysis produced the best score.

There are myriad other potential explanatory variables, but our concern that further exploration of alternative models might unintentionally become an exercise in "p-hacking" due to "garden of forking paths" effects [*Gelman and Loken*, 2014] led us to confine this analysis to our original set of variables, which we had previously chosen for theoretical reasons [*Hess et al.*, 2016].

Figures S1–S10

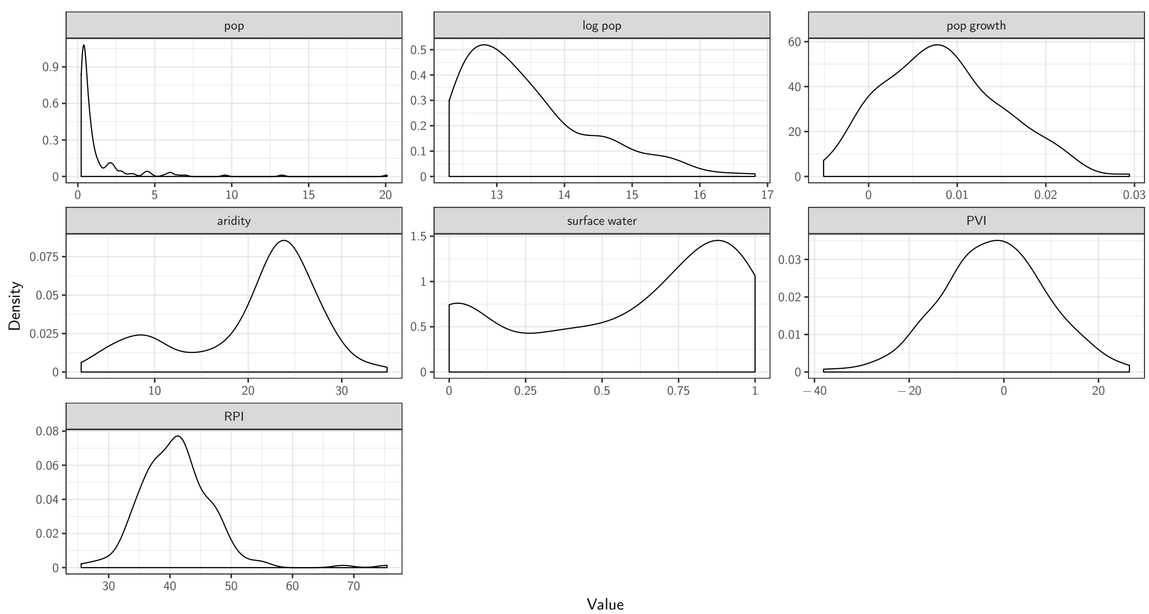

Figure 1. Kernel-density distribution of MSA-level covariates. Population in millions and RPI in thousands of chained 2009 dollars.

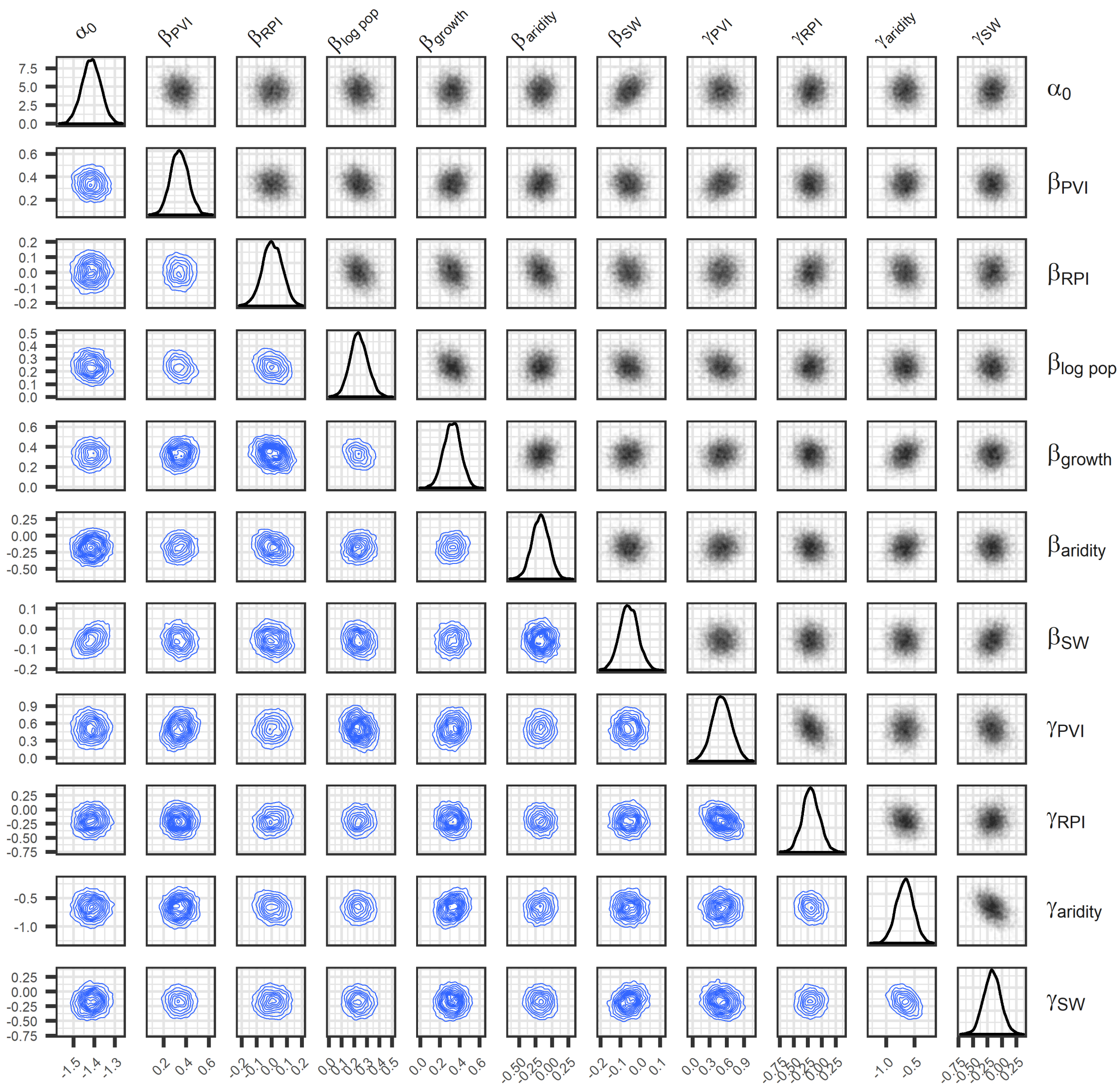

Figure 2. Correlation plot of posterior probability distribution of regression coefficients α, β, and γ for VWCI. The diagonal panels show the probability density for each coefficient, panels in the upper triangle show scatterplots of 4000 HMC samples, and panels in the lower triangle show joint probability density contours corresponding to the scatterplot in the upper triangle. Slight correlations are apparent, as between γ_{aridity} and γ_{SW}, γ_{PVI} and γ_{RPI}, and β_{SW} and α_0, but these are small enough not to pose problems apart from slightly increasing the uncertainty in the parameter estimates.

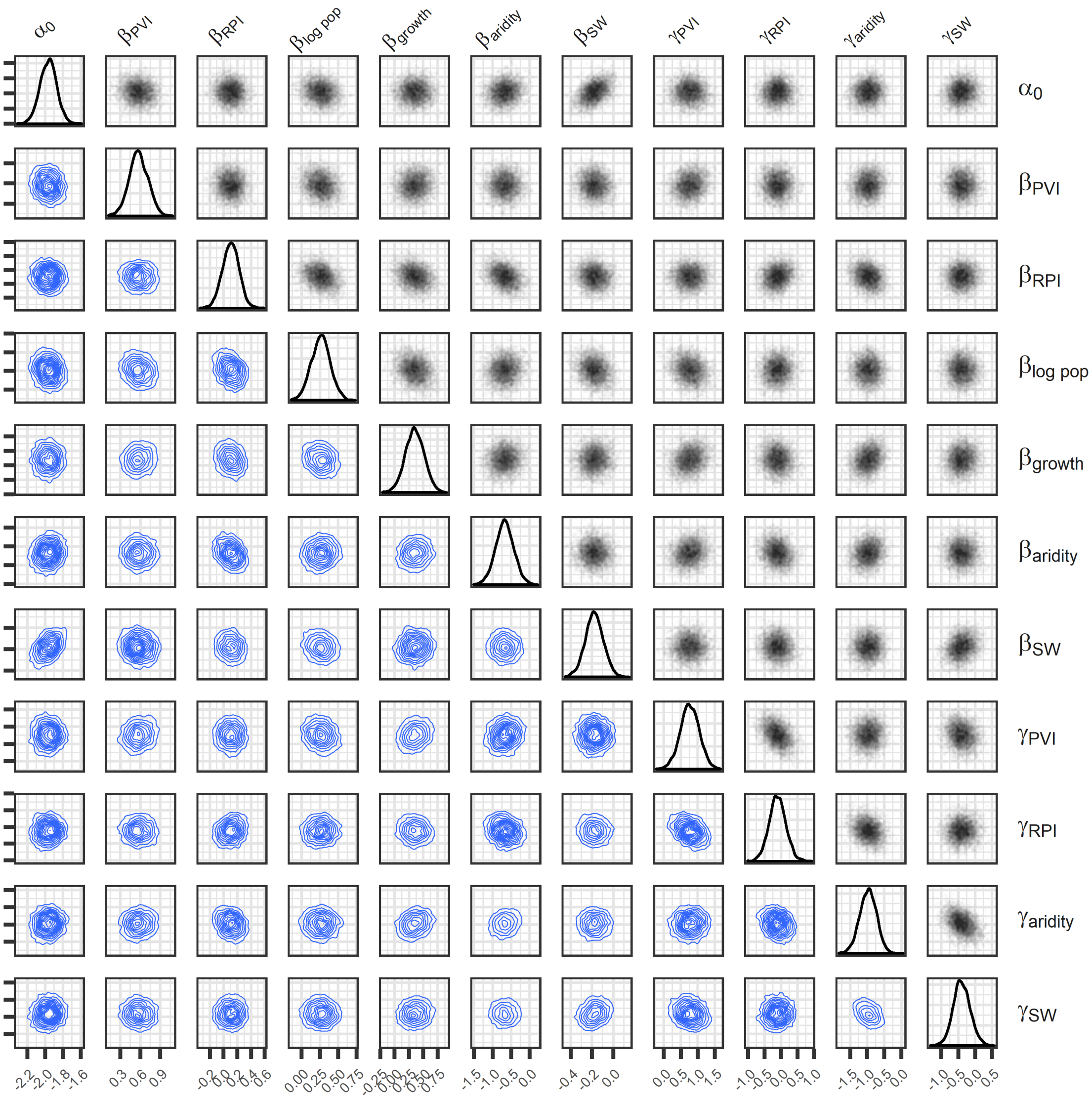

Figure 3. Correlation plot of posterior probability distribution of regression coefficients α, β, and γ for requirements.

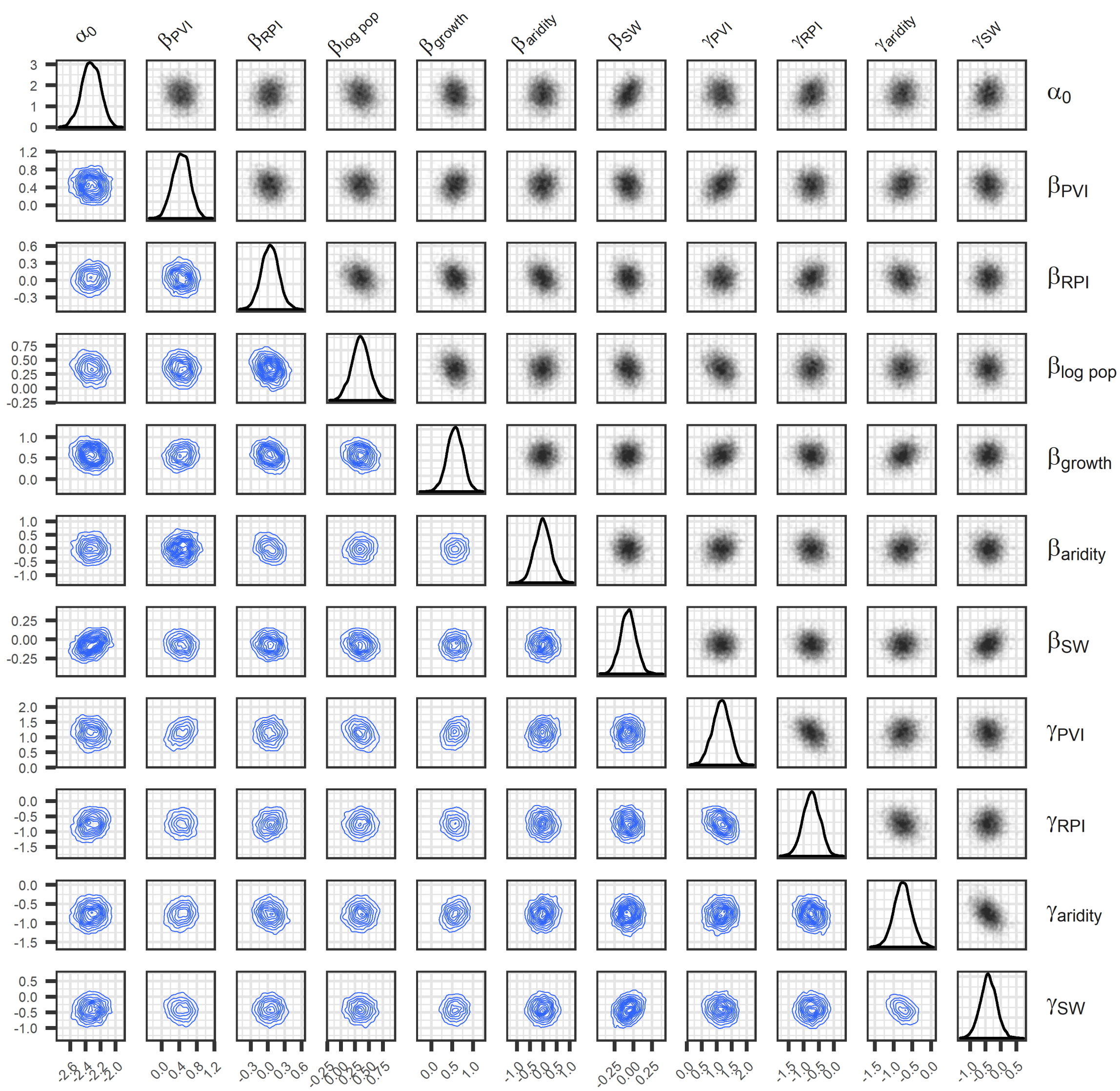

Figure 4. Correlation plot of posterior probability distribution of regression coefficients α, β, and γ for rebates.

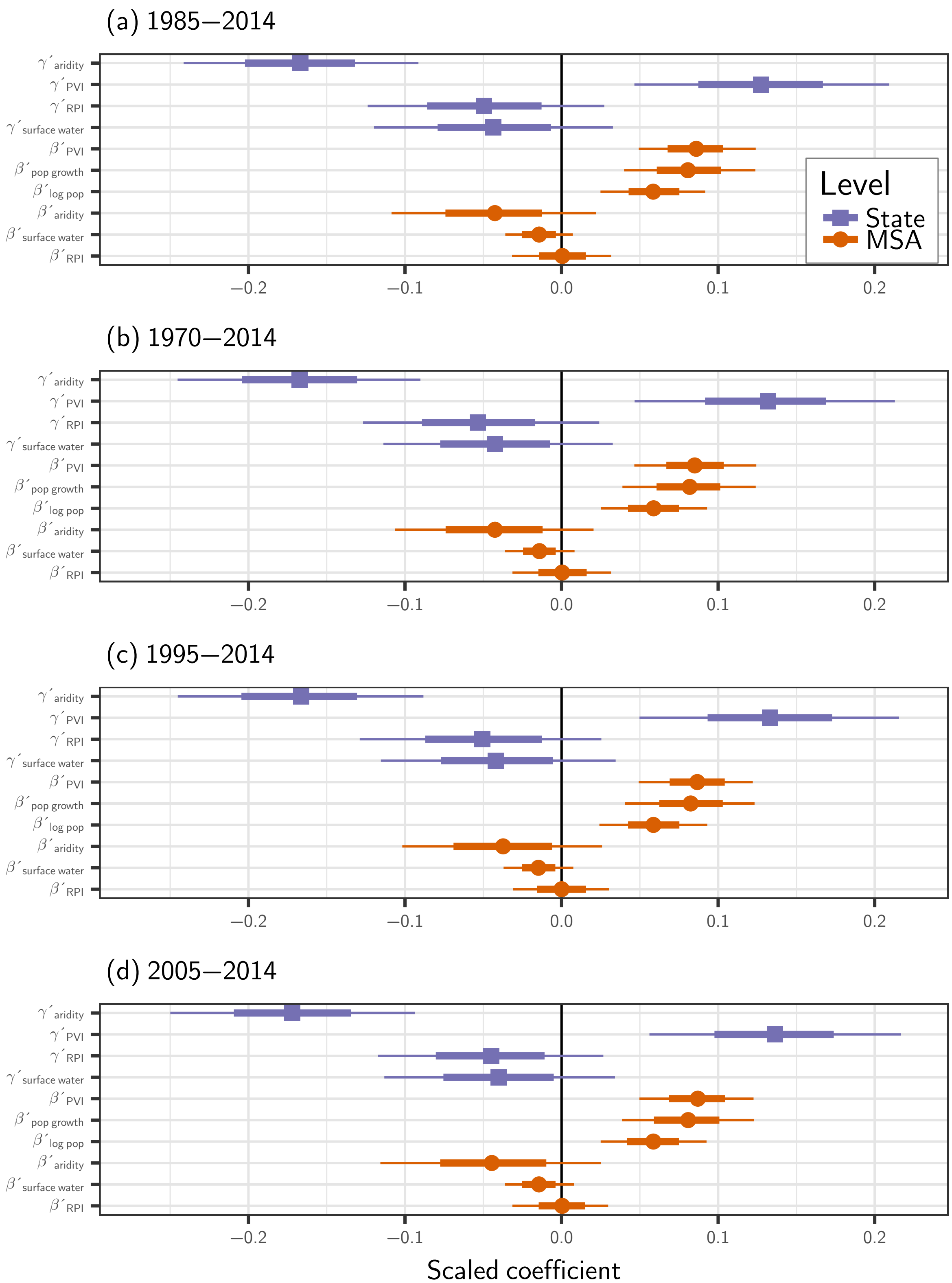

Figure 5. Regression coefficients for VWCI, averaging state and MSA aridity over different intervals.

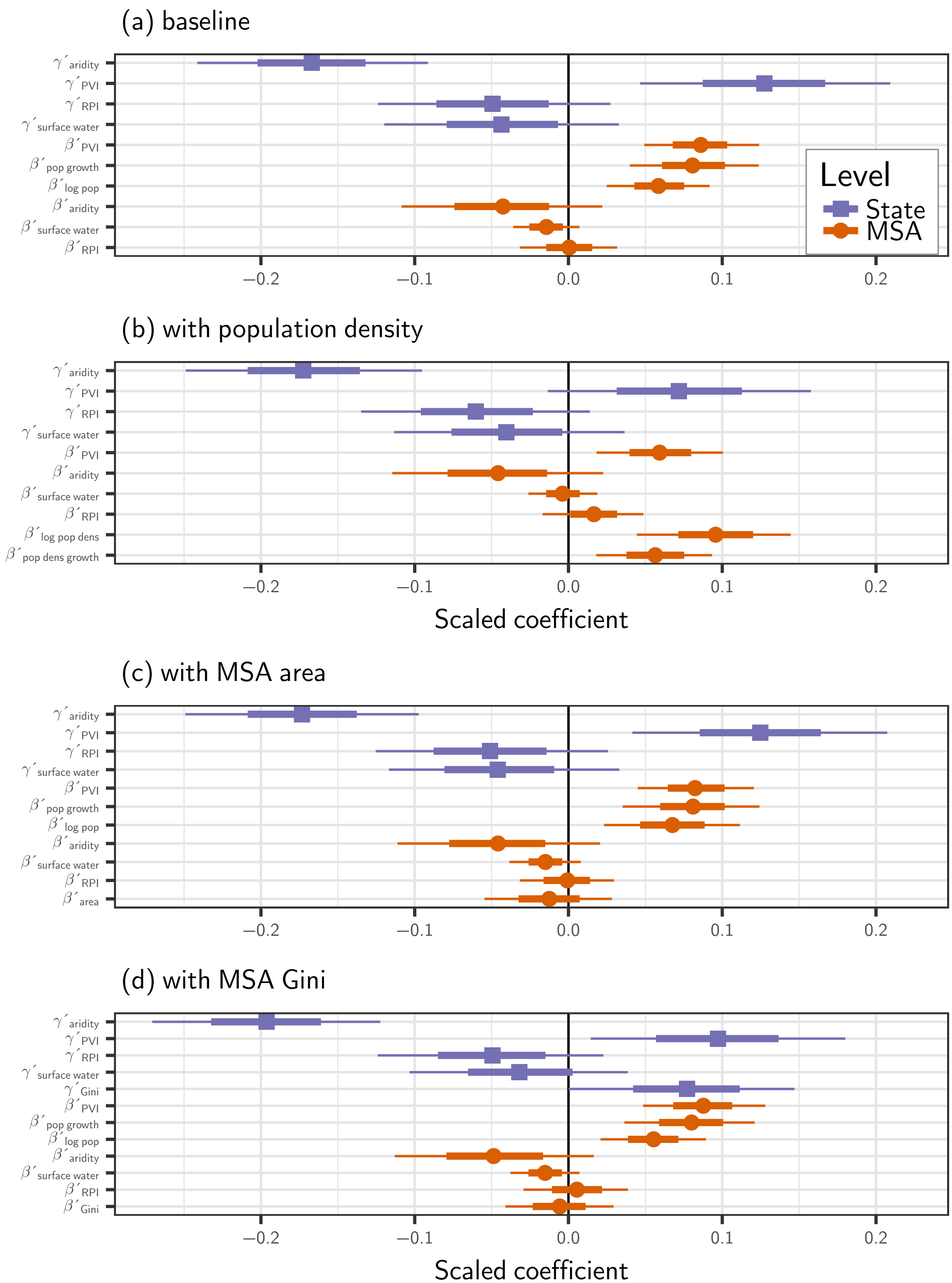

Figure 6. Regression coefficients for VWCI, with different covariates.

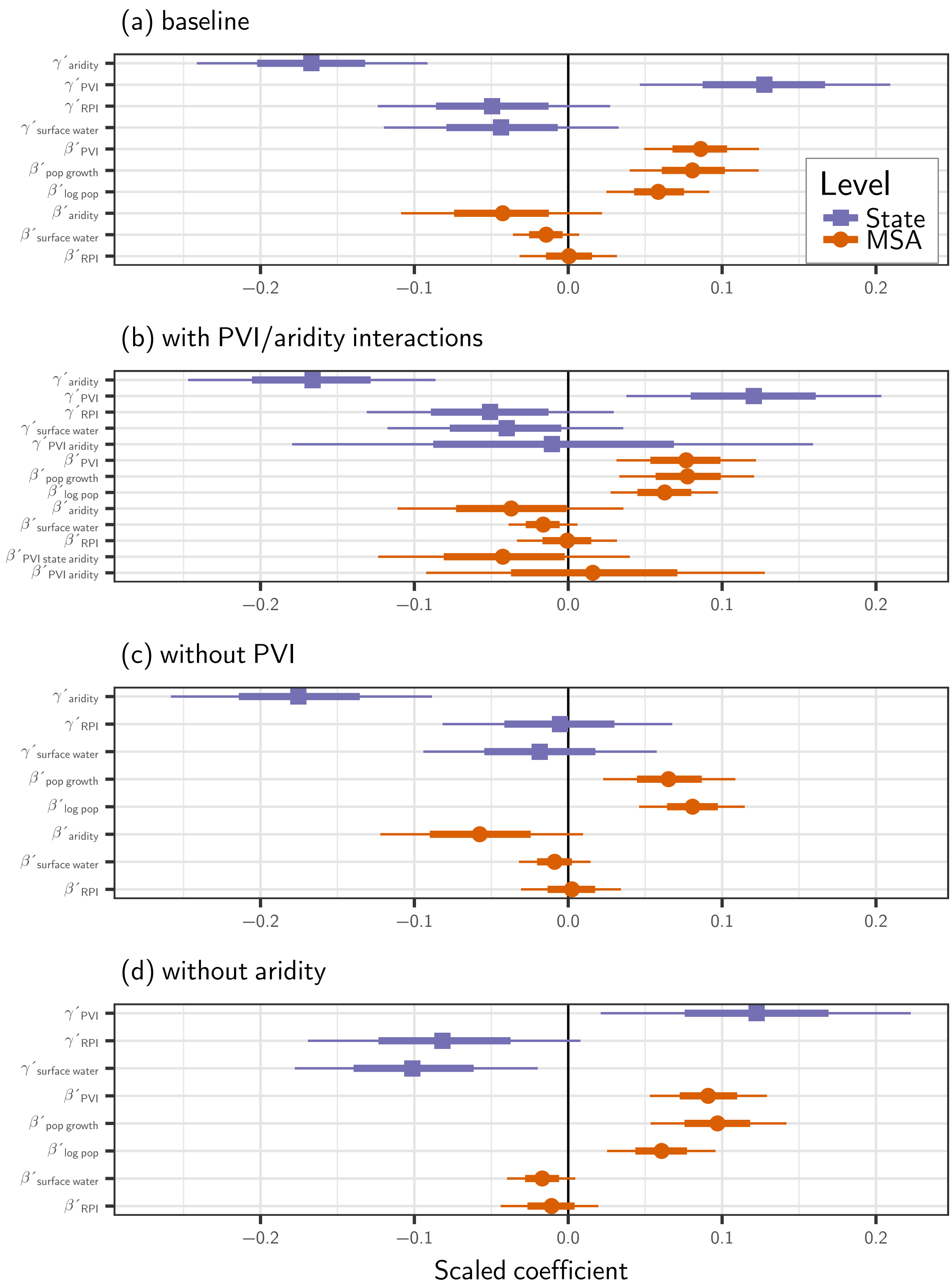

Figure 7. Regression coefficients for VWCI, with different covariates.

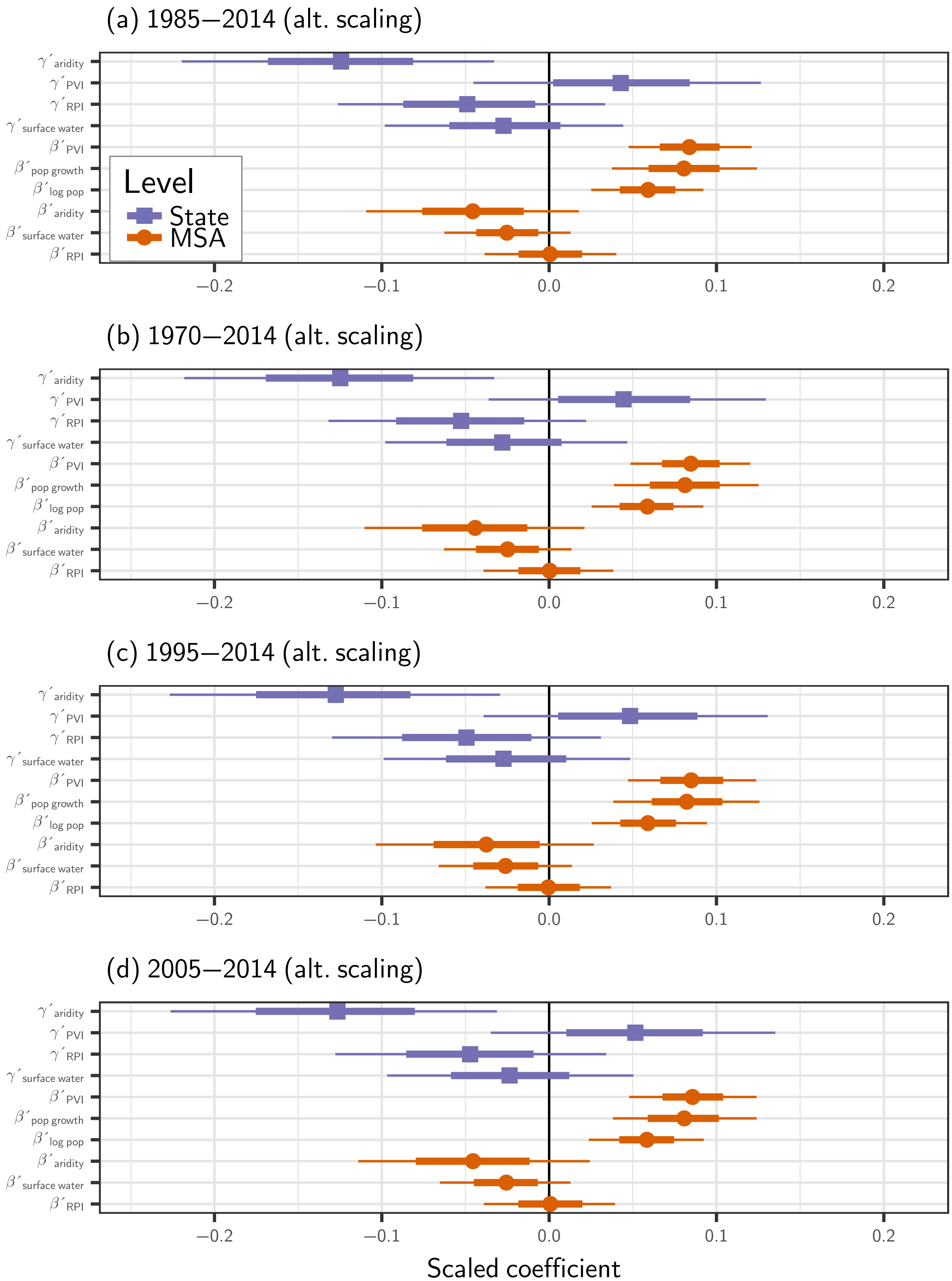

Figure 8. Regression coefficients for VWCI, averaging state and MSA aridity over different intervals, using alternative scaling of MSA-level variables.

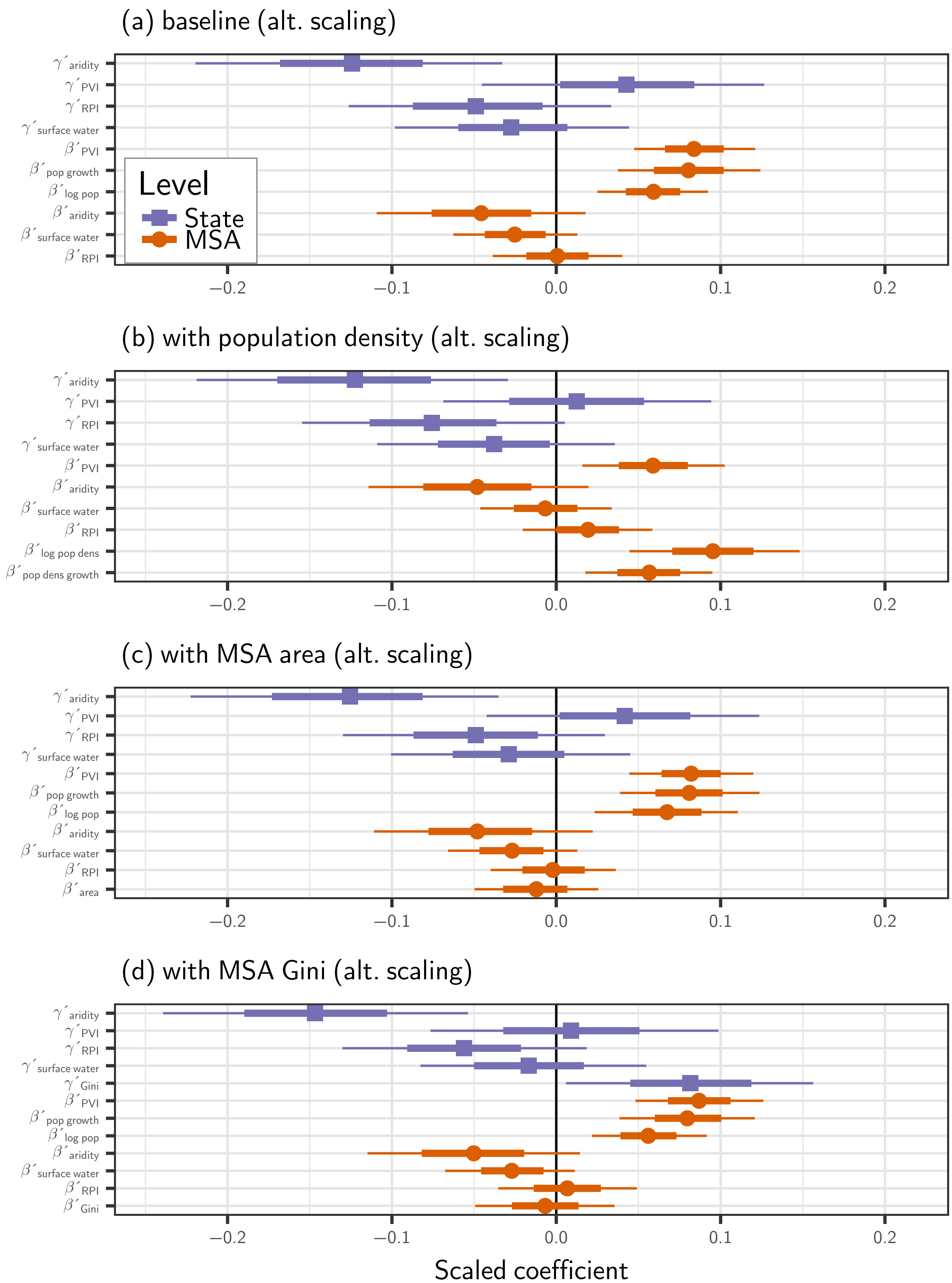

Figure 9. Regression coefficients for VWCI, with different covariates, using alternative scaling of MSA-level variables.

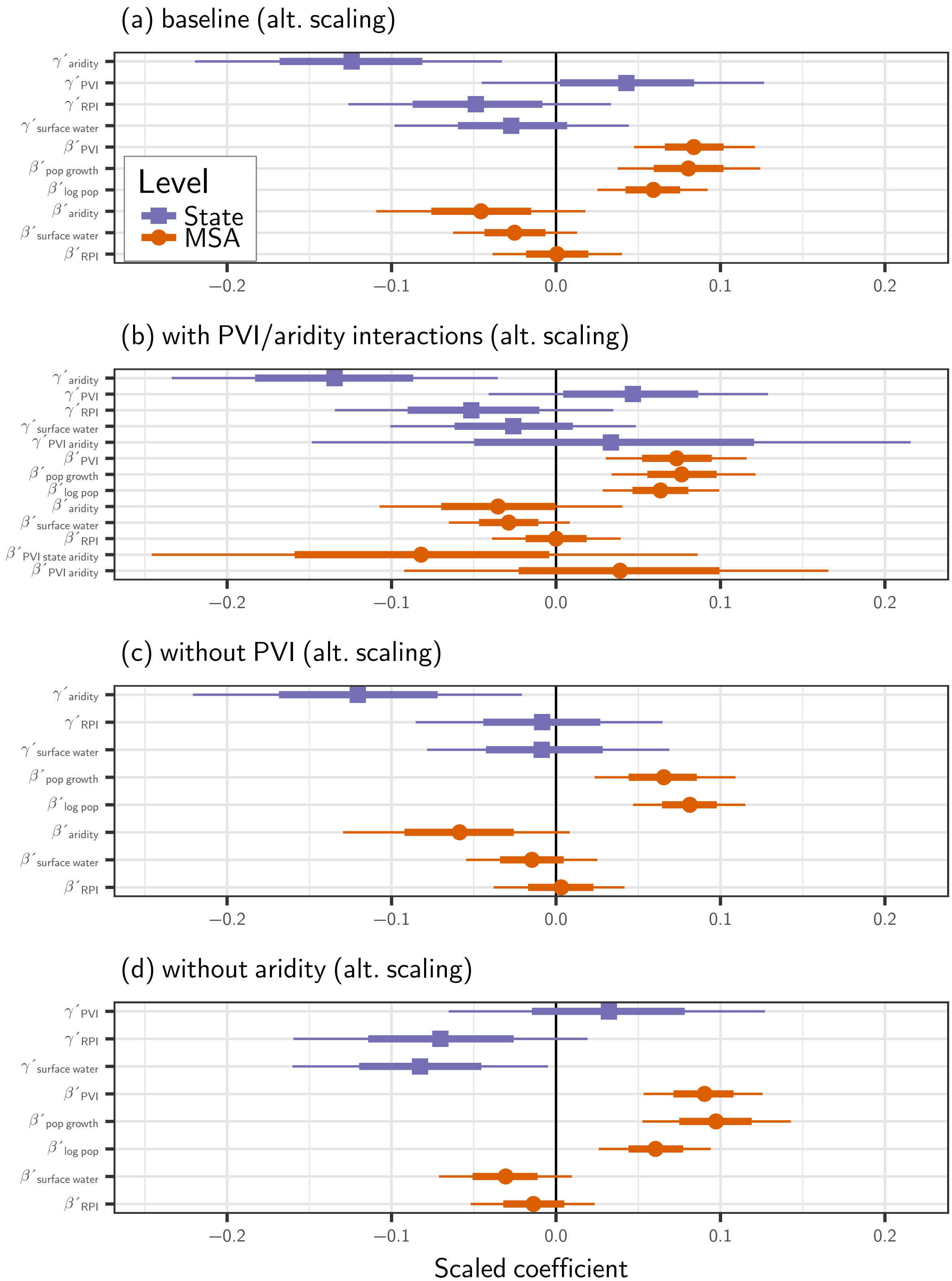

Figure 10. Regression coefficients for VWCI, with different covariates, using alternative scaling of MSA-level variables.

1 Tables S1–S17

Table S1 Caption

Table 1. Conservation scores and covariates for cities: VWCI = Vanderbilt Water Conservation Index (total # of conservation measures), Req. = # requirements, Reb. = # rebates, PVI = Cook Partisan Voting Index, Aridity = Köppen aridity index, RPI = per-capita real personal income (thousands of regionally adjusted chained 2009 dollars), Pop. = population (thousands), Growth = population growth rate (2010–2014), Surf. W. = surface-water fraction.

Table S2 Caption

Table 2. State-level covariates: PVI = Cook Partisan Voting Index, RPI = per-capita real personal income (thousands of regionally-adjusted chained 2009 dollars), Aridity = the Köppen aridity index, Surf. W. = the surface-water fraction.

Table S3

Model	LOO-IC	s.e.$_{IC}$	ELPD$_{LOO}$	s.e.$_{ELPD}$
hierarchical beta–binomial: 1995–2014	1247.8	20.2	-623.9	10.1
hierarchical beta–binomial: 1985–2014	1248.4	20.5	-624.2	10.3
hierarchical beta–binomial: 1970–2014	1248.8	20.4	-624.4	10.2
hierarchical beta–binomial: 2005–2014	1249.2	20.5	-624.6	10.2
hierarchical binomial: 1970–2014	1329.3	44.1	-664.6	22.1
hierarchical binomial: 1985–2014	1330.8	44.2	-665.4	22.1
hierarchical binomial: 1995–2014	1332.1	44.3	-666.1	22.1
hierarchical binomial: 2005–2014	1333.4	44.3	-666.7	22.1
single-level binomial: 2005–2014	1585.3	73.7	-792.6	36.8
single-level binomial: 1985–2014	1598.0	76.4	-799.0	38.2
single-level binomial: 1970–2014	1599.2	76.5	-799.6	38.2
single-level binomial: 1995–2014	1614.8	78.5	-807.4	39.3
single-level beta–binomial: 2005–2014	1719.6	89.6	-859.8	44.8
single-level beta–binomial: 1985–2014	1730.4	91.5	-865.2	45.8
single-level beta–binomial: 1970–2014	1738.0	92.9	-869.0	46.4
single-level beta–binomial: 1995–2014				

Table 3. Comparing different climatological averaging periods and models: LOO = leave-one-out cross-validation, LOO-IC = LOO information criterion, ELPD = expected log pointwise predictive density, and s.e. indicates the standard error of estimates of quantities. Lower values of the information criteria and greater (less negative) values of ELPD indicate superior model performance. Models are labelled by the time-period for averaging aridity and the structure of the statistical model.

Table S4

Model	LOO-IC	s.e.$_{\mathrm{IC}}$	ELPD$_{\mathrm{LOO}}$	s.e.$_{\mathrm{ELPD}}$
hierarchical beta–binomial: baseline	1248.4	20.5	-624.2	10.3
hierarchical beta–binomial: with MSA Gini coefficient	1251.1	20.1	-625.5	10.1
hierarchical beta–binomial: with MSA area	1252.3	20.6	-626.1	10.3
hierarchical beta–binomial: with PVI/aridity interactions	1254.0	21.4	-627.0	10.7
hierarchical beta–binomial: without aridity	1254.7	20.7	-627.4	10.4
hierarchical beta–binomial: with pop. density	1260.9	23.1	-630.4	11.6
hierarchical beta–binomial: without PVI	1269.2	21.4	-634.6	10.7
hierarchical binomial: without aridity	1328.5	43.7	-664.3	21.8
hierarchical binomial: baseline	1330.8	44.2	-665.4	22.1
hierarchical binomial: with MSA Gini coefficient	1336.2	44.2	-668.1	22.1
hierarchical binomial: with MSA area	1336.4	44.5	-668.2	22.2
hierarchical binomial: with PVI/aridity interactions	1337.3	46.5	-668.7	23.2
hierarchical binomial: with pop. density	1371.9	54.1	-685.9	27.0
hierarchical binomial: without PVI	1387.4	50.7	-693.7	25.4

Table 4. Comparing different models and sets of covariates with LOO-IC for hierarchical regressions. Models are labelled by the covariates that differ from the baseline case and the baseline and by the structure of the statistical model.

Table S5

Model	LOO-IC	s.e.$_{IC}$	ELPD$_{LOO}$	s.e.$_{ELPD}$
single-level binomial: with PVI/aridity interactions	1591.8	76.9	-795.9	38.4
single-level binomial: with MSA Gini coefficient	1593.7	78.7	-796.9	39.3
single-level binomial: baseline	1598.0	76.4	-799.0	38.2
single-level binomial: with MSA area	1602.5	76.7	-801.2	38.3
single-level binomial: with pop. density	1679.0	87.1	-839.5	43.6
single-level binomial: without PVI	1684.5	89.2	-842.3	44.6
single-level beta–binomial: baseline	1730.4	91.5	-865.2	45.8
single-level beta–binomial: with MSA Gini coefficient	1745.1	95.5	-872.6	47.8
single-level beta–binomial: with PVI/aridity interactions	1768.0	98.3	-884.0	49.1
single-level beta–binomial: with MSA area	1806.9	108.4	-903.5	54.2
single-level beta–binomial: without PVI	1832.9	101.8	-916.5	50.9
single-level beta–binomial: with pop. density	1834.0	100.5	-917.0	50.2
single-level binomial: without aridity	1850.3	112.1	-925.2	56.1
single-level beta–binomial: without aridity	2080.6	140.2	-1040.3	70.1

Table 5. Model Comparison with LOO-IC for single-level regressions and different sets of covariates.

Table S6

Model	WAIC	s.e.$_{IC}$	ELPD$_{WAIC}$	s.e.$_{ELPD}$
hierarchical beta–binomial: 1995–2014	1244.0	20.0	-622.0	10.0
hierarchical beta–binomial: 1985–2014	1244.1	20.2	-622.1	10.1
hierarchical beta–binomial: 1970–2014	1244.6	20.1	-622.3	10.0
hierarchical beta–binomial: 2005–2014	1245.3	20.1	-622.7	10.1
hierarchical binomial: 1970–2014	1317.0	43.5	-658.5	21.7
hierarchical binomial: 1985–2014	1317.7	43.5	-658.9	21.7
hierarchical binomial: 1995–2014	1319.1	43.6	-659.5	21.8
hierarchical binomial: 2005–2014	1319.1	43.4	-659.5	21.7
single-level binomial: 2005–2014	1584.8	73.5	-792.4	36.8
single-level binomial: 1985–2014	1597.5	76.4	-798.8	38.2
single-level binomial: 1970–2014	1598.9	76.5	-799.4	38.2
single-level binomial: 1995–2014	1614.0	78.4	-807.0	39.2
single-level beta–binomial: 2005–2014	1700.7	86.3	-850.4	43.1
single-level beta–binomial: 1985–2014	1716.6	89.5	-858.3	44.8
single-level beta–binomial: 1970–2014	1723.0	90.5	-861.5	45.2
single-level beta–binomial: 1995–2014	471976.3	79550.5	-235988.2	39775.2

Table 6. Model comparison: WAIC = widely applicable information criterion (also known as the Watanabe-Aikake Information Criterion), ELPD = expected log-probability density, and s.e. indicates the standard error of estimates of quantities. Lower values of the information criteria and greater (less negative) values of ELPD indicate superior model performance. Models are labelled by the time-period for averaging aridity and the structure of the statistical model.

Table S7

Model	WAIC	s.e.$_{\mathrm{IC}}$	ELPD$_{\mathrm{WAIC}}$	s.e.$_{\mathrm{ELPD}}$
hierarchical beta–binomial: baseline	1244.1	20.2	-622.1	10.1
hierarchical beta–binomial: with MSA Gini coefficient	1247.4	19.8	-623.7	9.9
hierarchical beta–binomial: with MSA area	1247.4	20.2	-623.7	10.1
hierarchical beta–binomial: without aridity	1248.5	20.2	-624.2	10.1
hierarchical beta–binomial: with PVI/aridity interactions	1248.7	20.9	-624.4	10.5
hierarchical beta–binomial: with pop. density	1258.5	23.0	-629.2	11.5
hierarchical beta–binomial: without PVI	1265.4	21.0	-632.7	10.5
hierarchical binomial: without aridity	1315.8	43.2	-657.9	21.6
hierarchical binomial: baseline	1317.7	43.5	-658.9	21.7
hierarchical binomial: with MSA area	1321.5	43.6	-660.8	21.8
hierarchical binomial: with MSA Gini coefficient	1322.4	43.4	-661.2	21.7
hierarchical binomial: with PVI/aridity interactions	1322.4	45.4	-661.2	22.7
hierarchical binomial: with pop. density	1361.6	53.8	-680.8	26.9
hierarchical binomial: without PVI	1372.7	49.8	-686.3	24.9

Table 7. Model comparison with WAIC for hierarchical regressions. Models are labelled by the covariates that differ from the baseline case and by the structure of the statistical model.

Table S8

Model	WAIC	s.e.$_{IC}$	ELPD$_{WAIC}$	s.e.$_{ELPD}$
single-level binomial: with PVI/aridity interactions	1590.5	76.6	-795.2	38.3
single-level binomial: with MSA Gini coefficient	1593.1	78.5	-796.6	39.3
single-level binomial: baseline	1597.5	76.4	-798.8	38.2
single-level binomial: with MSA area	1600.6	76.4	-800.3	38.2
single-level binomial: with pop. density	1678.7	87.1	-839.3	43.6
single-level binomial: without PVI	1684.2	89.2	-842.1	44.6
single-level beta–binomial: baseline	1716.6	89.5	-858.3	44.8
single-level beta–binomial: with MSA Gini coefficient	1726.2	93.0	-863.1	46.5
single-level beta–binomial: with PVI/aridity interactions	1745.1	95.6	-872.6	47.8
single-level beta–binomial: with MSA area	1769.3	100.0	-884.6	50.0
single-level beta–binomial: with pop. density	1814.3	98.1	-907.2	49.1
single-level beta–binomial: without PVI	1815.9	99.9	-907.9	49.9
single-level binomial: without aridity	1849.6	112.0	-924.8	56.0
single-level beta–binomial: without aridity	2058.0	137.5	-1029.0	68.7

Table 8. Model comparison with WAIC for single-level regressions and different sets of covariates.

Table S9

Model	LOO-IC	s.e.$_{\mathrm{IC}}$	ELPD$_{\mathrm{LOO}}$	s.e.$_{\mathrm{ELPD}}$
hierarchical beta–binomial: 1970–2014	1249.1	20.5	-624.5	10.2
hierarchical beta–binomial: 1985–2014	1249.3	20.5	-624.6	10.3
hierarchical beta–binomial: 1995–2014	1249.3	20.4	-624.7	10.2
hierarchical beta–binomial: 2005–2014	1250.3	20.4	-625.1	10.2
hierarchical binomial: 1970–2014	1330.1	44.2	-665.1	22.1
hierarchical binomial: 1985–2014	1330.3	44.1	-665.1	22.1
hierarchical binomial: 2005–2014	1332.6	44.1	-666.3	22.1
hierarchical binomial: 1995–2014	1333.3	44.2	-666.6	22.1
single-level binomial: 2005–2014	1586.2	73.7	-793.1	36.9
single-level binomial: 1985–2014	1599.0	76.4	-799.5	38.2
single-level binomial: 1970–2014	1599.8	76.8	-799.9	38.4
single-level binomial: 1995–2014	1614.6	78.5	-807.3	39.3
single-level beta–binomial: 2005–2014	1722.7	89.5	-861.3	44.7
single-level beta–binomial: 1985–2014	1737.7	92.2	-868.8	46.1
single-level beta–binomial: 1970–2014	1741.7	93.3	-870.9	46.6
single-level beta–binomial: 1995–2014	1758.2	95.4	-879.1	47.7

Table 9. Model comparison with LOO-IC for different climatological averaging periods and models, using the alternative scaling for MSA-level covariates.

Table S10

Model	LOO-IC	s.e.$_{\mathrm{IC}}$	ELPD$_{\mathrm{LOO}}$	s.e.$_{\mathrm{ELPD}}$
hierarchical beta–binomial: baseline	1249.3	20.5	-624.6	10.3
hierarchical beta–binomial: with MSA area	1252.3	20.6	-626.2	10.3
hierarchical beta–binomial: with MSA Gini coefficient	1252.8	20.4	-626.4	10.2
hierarchical beta–binomial: with PVI/aridity interactions	1252.9	21.2	-626.5	10.6
hierarchical beta–binomial: without aridity	1254.0	20.8	-627.0	10.4
hierarchical beta–binomial: with pop. density	1262.7	23.1	-631.4	11.5
hierarchical beta–binomial: without PVI	1268.1	21.2	-634.0	10.6
hierarchical binomial: without aridity	1329.9	43.9	-664.9	22.0
hierarchical binomial: baseline	1330.3	44.1	-665.1	22.1
hierarchical binomial: with PVI/aridity interactions	1334.3	45.9	-667.2	23.0
hierarchical binomial: with MSA area	1336.7	44.3	-668.3	22.2
hierarchical binomial: with MSA Gini coefficient	1339.2	44.5	-669.6	22.3
hierarchical binomial: with pop. density	1372.8	54.2	-686.4	27.1
hierarchical binomial: without PVI	1386.8	50.6	-693.4	25.3

Table 10. Model comparison with LOO-IC for hierarchical regressions using the alternative scaling for MSA-level covariates.

Table S11

Model	LOO-IC	s.e.$_{\text{IC}}$	ELPD$_{\text{LOO}}$	s.e.$_{\text{ELPD}}$
single-level binomial: with PVI/aridity interactions	1590.9	76.6	-795.4	38.3
single-level binomial: with MSA Gini coefficient	1591.8	78.2	-795.9	39.1
single-level binomial: baseline	1599.0	76.4	-799.5	38.2
single-level binomial: with MSA area	1601.9	76.6	-801.0	38.3
single-level binomial: with pop. density	1678.9	87.2	-839.4	43.6
single-level binomial: without PVI	1683.9	89.1	-842.0	44.6
single-level beta–binomial: baseline	1737.7	92.2	-868.8	46.1
single-level beta–binomial: with MSA Gini coefficient	1750.3	97.0	-875.1	48.5
single-level beta–binomial: with PVI/aridity interactions	1770.8	99.5	-885.4	49.8
single-level beta–binomial: with MSA area	1788.8	103.5	-894.4	51.7
single-level beta–binomial: without PVI	1817.6	100.4	-908.8	50.2
single-level beta–binomial: with pop. density	1833.4	99.9	-916.7	49.9
single-level binomial: without aridity	1850.4	112.0	-925.2	56.0
single-level beta–binomial: without aridity	2083.3	139.8	-1041.7	69.9

Table 11. Model comparison with LOO-IC for single-level regressions using the alternative scaling for MSA-level covariates.

Table S12

Model	WAIC	s.e.$_{\text{IC}}$	ELPD$_{\text{WAIC}}$	s.e.$_{\text{ELPD}}$
hierarchical beta–binomial: 1970–2014	1244.8	20.2	-622.4	10.1
hierarchical beta–binomial: 1985–2014	1245.1	20.2	-622.5	10.1
hierarchical beta–binomial: 1995–2014	1245.3	20.1	-622.6	10.0
hierarchical beta–binomial: 2005–2014	1246.0	20.0	-623.0	10.0
hierarchical binomial: 1985–2014	1317.6	43.4	-658.8	21.7
hierarchical binomial: 1970–2014	1317.7	43.5	-658.9	21.7
hierarchical binomial: 2005–2014	1319.1	43.3	-659.5	21.7
hierarchical binomial: 1995–2014	1319.1	43.4	-659.6	21.7
single-level binomial: 2005–2014	1585.3	73.5	-792.6	36.8
single-level binomial: 1985–2014	1598.4	76.3	-799.2	38.2
single-level binomial: 1970–2014	1599.1	76.6	-799.6	38.3
single-level binomial: 1995–2014	1614.1	78.4	-807.0	39.2
single-level beta–binomial: 2005–2014	1705.3	86.9	-852.7	43.4
single-level beta–binomial: 1985–2014	1721.3	89.8	-860.6	44.9
single-level beta–binomial: 1970–2014	1725.9	91.0	-863.0	45.5
single-level beta–binomial: 1995–2014	1741.8	92.6	-870.9	46.3

Table 12. Model comparison with WAIC for different climatological intervals, using the alternative scaling for MSA-level covariates.

Table S13

Model	WAIC	s.e.$_{\mathrm{IC}}$	ELPD$_{\mathrm{WAIC}}$	s.e.$_{\mathrm{ELPD}}$
hierarchical beta–binomial: baseline	1245.1	20.2	-622.5	10.1
hierarchical beta–binomial: with MSA area	1247.4	20.2	-623.7	10.1
hierarchical beta–binomial: with PVI/aridity interactions	1247.8	20.8	-623.9	10.4
hierarchical beta–binomial: without aridity	1248.0	20.3	-624.0	10.1
hierarchical beta–binomial: with MSA Gini coefficient	1248.6	20.0	-624.3	10.0
hierarchical beta–binomial: with pop. density	1260.1	22.9	-630.0	11.5
hierarchical beta–binomial: without PVI	1264.6	21.0	-632.3	10.5
hierarchical binomial: without aridity	1316.5	43.2	-658.3	21.6
hierarchical binomial: baseline	1317.6	43.4	-658.8	21.7
hierarchical binomial: with PVI/aridity interactions	1320.1	45.1	-660.1	22.6
hierarchical binomial: with MSA area	1321.7	43.4	-660.9	21.7
hierarchical binomial: with MSA Gini coefficient	1325.0	43.7	-662.5	21.8
hierarchical binomial: with pop. density	1361.0	53.7	-680.5	26.8
hierarchical binomial: without PVI	1371.9	49.7	-685.9	24.9

Table 13. Model comparison with WAIC for hierarchical regressions against absolute MSA covariates.

Table S14

Model	WAIC	s.e.$_{IC}$	ELPD$_{WAIC}$	s.e.$_{ELPD}$
single-level binomial: with PVI/aridity interactions	1589.3	76.4	-794.7	38.2
single-level binomial: with MSA Gini coefficient	1591.3	78.1	-795.6	39.1
single-level binomial: baseline	1598.4	76.3	-799.2	38.2
single-level binomial: with MSA area	1600.5	76.4	-800.2	38.2
single-level binomial: with pop. density	1678.2	87.2	-839.1	43.6
single-level binomial: without PVI	1683.6	89.1	-841.8	44.5
single-level beta–binomial: baseline	1721.3	89.8	-860.6	44.9
single-level beta–binomial: with MSA Gini coefficient	1730.6	94.3	-865.3	47.2
single-level beta–binomial: with PVI/aridity interactions	1744.8	96.1	-872.4	48.1
single-level beta–binomial: with MSA area	1761.8	97.6	-880.9	48.8
single-level beta–binomial: without PVI	1805.8	99.1	-902.9	49.6
single-level beta–binomial: with pop. density	1815.5	98.1	-907.7	49.1
single-level binomial: without aridity	1849.3	111.8	-924.7	55.9
single-level beta–binomial: without aridity	2056.3	136.4	-1028.2	68.2

Table 14. Model comparison with WAIC for single-level regressions against absolute MSA covariates.

Table S15 Caption

Table 15. Posterior probability distributions of regression coefficients for VWCI: mean, standard error of the mean, standard deviation of the posterior, quantiles of the posterior, and the Gelman-Rubin potential scale-reduction factor $\hat{R}$. γ coefficients correspond to state-level effects, β coefficients to MSA-level effects, δ coefficients represent state-level intercepts, α_0 is the overall intercept, and ϕ characterizes the overdispersion of the beta-binomial distribution. For more detail, see Materials and Methods.

Table S16 Caption

Table 16. Posterior probability distribution of regression coefficients for requirements

Table S17 Caption

Table 17. Posterior probability distribution of regression coefficients for rebates

Captions for Datasets S1–S4

Dataset S1: MSA-Level Data

This dataset contains MSA-level data: the FIPS (Federal Information Processing Standard) code for the MSA, the name of the MSA, the central city, state, latitude, longitude, VWCI, number of water-conservation requirements, number of rebate policies for water-conservation actions, the average annual precipitation (in millimeters) temperature (in Celsius), and Köppen aridity index, for the central city, the Cook Partisan Voting Index for the counties of the MSA, the 2014 population and average annual population growth rate from 2010–2014 for the MSA, the fraction of the municipal water supply derived from surface water, the BEA 2014 regional price parity and per-capita real personal income for the MSA (in chained regionally-adjusted 2009 dollars).

Dataset S2: MSA-Level Data Codebook

This dataset contains a codebook explaining the variable corresponding to each column in Dataset S1.

Dataset S3: State-Level Data

This dataset contains stae-level data: the FIPS code for the state, the abbreviation and name of the state, the average annual precipitation (in millimeters), temperature (in Celsius), and Köppen aridity index for the state, the state-level Cook Partisan Voting Index, the fraction of the state water supply derived from surface water, and the BEA 2014 state-level regional price parity and per-capita real personal income (in chained regionally-adjusted 2009 dollars).

Dataset S4: State-Level Data Codebook

This dataset contains a codebook explaining the variable corresponding to each column in Dataset S3.

Data Analysis Scripts S1

The zip file `scripts_S1.zip` contains R and Stan scripts to reproduce the regression analysis presented here. To reproduce the analysis, unzip the file with the scripts, copy Datasets S1 and S3 into the `data` subdirectory, and run the scripts `gilligan_vwci_ef_2017.R` and `gilligan_vwci_ef_si.R` in R.

This paper was produced with the following R packages:

- R version 3.4.4 (2018-03-15), `x86_64-w64-mingw32`
- Locale: `LC_COLLATE=English_United States.1252`, `LC_CTYPE=English_United States.1252`, `LC_MONETARY=English_United States.1252`, `LC_NUMERIC=C`, `LC_TIME=English_United States.1252`
- Running under: `Windows 10 x64 (build 16299)`
- Matrix products: default
- Base packages: base, datasets, graphics, grDevices, methods, parallel, stats, utils
- Other packages: bindrcpp 0.2, bitops 1.0-6, broom 0.4.3, cowplot 0.9.2, dplyr 0.7.4, egg 0.2.0, extrafont 0.17, fontcm 1.1, forcats 0.3.0, geosphere 1.5-7, ggmap 2.6.1, ggplot2 2.2.1.9000, ggrepel 0.7.0, ggthemes 3.4.0, gridExtra 2.3, hms 0.4.2, janitor 0.3.1, jgally 1.2.9.9999, jgmcmc 1.1.1, knitr 1.20, lazyeval 0.2.1, loo 1.1.0, lubridate 1.7.3, magrittr 1.5, maps 3.2.0, ncdf4 1.16, pacman 0.4.6, purrr 0.2.4, raster 2.6-7, RColorBrewer 1.1-2, RCurl 1.95-4.10, readr 1.1.1, readxl 1.0.0, rlang 0.2.0.9000, rstan 2.17.3, shiny 1.0.5, shinystan 2.4.0, sp 1.2-7, StanHeaders 2.17.2, stringr 1.3.0, tibble 1.4.2, tidyr 0.8.0, tidyverse 1.2.1, viridis 0.5.0, viridisLite 0.3.0, xtable 1.8-2, zoo 1.8-1
- Loaded via a namespace (and not attached): abind 1.4-5, arm 1.9-3, assertthat 0.2.0, base64enc 0.1-3, bayesplot 1.4.0, bindr 0.1.1, cellranger 1.1.0, cli 1.0.0, coda 0.19-1, colorspace 1.3-2, colourpicker 1.0, compiler 3.4.4, crayon 1.3.4, crosstalk 1.0.0, digest 0.6.15, DT 0.4, dygraphs 1.1.1.4, evaluate 0.10.1,

extrafontdb 1.0, foreign 0.8-69, GGally 1.3.2, glue 1.2.0, grid 3.4.4, gtable 0.2.0, gtools 3.5.0, haven 1.1.1, htmltools 0.3.6, htmlwidgets 1.0, httpuv 1.3.6.2, httr 1.3.1, igraph 1.2.1, inline 0.3.14, jpeg 0.1-8, jsonlite 1.5, labeling 0.3, lattice 0.20-35, lme4 1.1-15, mapproj 1.2-5, markdown 0.8, MASS 7.3-49, Matrix 1.2-12, matrixStats 0.53.1, mime 0.5, miniUI 0.1.1, minqa 1.2.4, mnormt 1.5-5, modelr 0.1.1, munsell 0.4.3, nlme 3.1-131.1, nloptr 1.0.4, pillar 1.2.1, pkgconfig 2.0.1, plyr 1.8.4, png 0.1-7, proto 1.0.0, psych 1.7.8, R6 2.2.2, Rcpp 0.12.16, reshape 0.8.7, reshape2 1.4.3, RgoogleMaps 1.4.1, rjson 0.2.15, rsconnect 0.8.8, rstudioapi 0.7, Rttf2pt1 1.3.6, rvest 0.3.2, scales 0.5.0.9000, shinyjs 1.0, shinythemes 1.1.1, splines 3.4.4, stats4 3.4.4, stringi 1.1.7, threejs 0.3.1, tidyselect 0.2.4, tools 3.4.4, withr 2.1.2, xml2 1.2.0, xts 0.10-2

References

Associated Press (2006). Many state legislative races are uncontested. Retrieved from `http://www.nbcnews.com/id/15446775/ns/politics/t/many-state-legislative-races-are-uncontested`.

Brown, K. P., & Hess, D. J. (2017). The politics of water conservation: Identifying and overcoming political barriers to successful policies. *Water Policy*, *19*, 304–321. `https://doi.org/10.2166/wp.2016.089`.

Carpenter, B., Gelman, A. Hoffman, M. Lee, D., Goodrich, B., Betancourt, M., Brubaker, M. A., Guo, J., Li, P., & Riddell, A. (2017). Stan: A probabilistic programming language. *Journal of Statistical Software*, *76*, 1–32. `https://doi.org/10.18637/jss.v076.i01`.

Chupp, B. A. (2011). Environmental constituent interest, green electricity policies, and legislative voting. *Journal of Environmental Economics and Management*, *62*, 254–266. `https://doi.org/10.1016/j.jeem.2011.03.008`.

CQ Press (2016). Voting and elections collection. Retrieved from `http://library.cqpress.com/elections/`.

Fiorina, M. P. (2016). *The (re)nationalization of Congressional elections* (Essays on Contemporary Politics 7). Stanford, CA: Hoover Institute. Retrieved from `https://www.hoover.org/sites/default/files/research/docs/fiorina_renationalizationofcongressionalelections_7.pdf`.

Fleck, J. (2016). *Water is for Fighting Over and Other Myths about Water in the West*. Washington, DC: Island.

Gelman, A., & Hill, J. (2007). *Data Analysis using Regression and Multilevel/Hierarchical Models*. New York, NY: Cambridge.

Gelman, A., & Loken, E. (2014). The statistical crisis in science. *American Scientist*, *102*, 460–465.

Gelman, A., Jakulin, A., Pittau, M. G., & Su, Y.-S. (2008). A weakly informative default prior distribution for logistic and other regression models. *Annals of Applied Statistics*, *2*, 1360–1383. https://doi.org/10.1214/08-AOAS191.

Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., & Rubin, D. B. (2014). *Bayesian Data Analysis*, 3rd ed. Boca Raton, FL: CRC.

Gleick, P. H. (2002). Water management: Soft water paths. *Nature*, *418*, 373–373, https://doi.org/10.1038/418373a.

Grant, D. and Vasi, I.B. (2016) Civil society in an age of environmental accountability: How local environmental nongovernmental organizations reduce U.S. power plants' carbon dioxide emissions. *Sociological Forum*, *32*, 94–115. https://doi.org/10.1111/socf.12318.

Hawkins, C. B., & B. A. Nosek (2012). Motivated independence? implicit party identity predicts political judgments among self-proclaimed independents. *Personality and Social Psychology Bulletin*, *38*, 1437–1452. https://doi.org/10.1177/0146167212452313.

Hess, D. J., Wold, C. A., Hunter, E., Nay, J. J., Worland, S., Gilligan, J., & Hornberger, G. M. (2016). Drought, risk, and institutional politics in the American Southwest. *Sociological Forum*, *31*, 807–827. https://doi.org/10.1111/socf.12274.

Hess, D. J., Wold, C. A., Worland, S. C., & Hornberger, G.M. (2017). Measuring urban water conservation policies: Toward a comprehensive index. *Journal of the American Water Resources Association*, *53*, 442–455. https://doi.org/10.1111/1752-1688.12506.

Hornberger, G. M., Hess, D. J., & Gilligan, J. (2015). Water conservation and hydrological transitions in cities in the United States. *Water Resources Research*, *51*, 4635–4649. https://doi.org/10.1002/2015WR016943.

Klarner, C. (2015). Competitiveness in state legislative elections: 1972–2014. *Ballotopedia*. Retrieved from https://ballotpedia.org/Competitiveness_in_State_Legislative_Elections:_1972-2014.

Maggioni, E. (2014). Water demand management in time of drought: What matters for water conservation. *Water Resources Research*, *51*, 215–139. https://doi.org/10.1002/2014wr016301.

Matsuura, K., & Willmott, C. J. (2015a). *Terrestrial Air Temperature: 1900–2014 Gridded Monthly Time Series (Version 4.01)* (Department of Geography, University of Delaware). Retrieved from http://climate.geog.udel.edu/~climate/html_pages/Global2014/README.GlobalTsT2014.html.

Matsuura, K., and Willmott, C. J. (2015b). *Terrestrial Precipitation: 1900–2014 Gridded Monthly Time Series (Version 4.01)* (Department of Geography, University of Delaware). Retrieved from http://climate.geog.udel.edu/~climate/html_pages/Global2014/README.GlobalTsP2014.html.

Maupin, M., Kenny, J., Hutson, S., Lovelace, J., Barber, N., & Linsey, K. (2014). *Estimated use of water in the United States in 2010* (USGS Circular 1405). Washington, DC: U.S. Geological Survey. Retrieved from https://doi.org/10.3133/cir1405.

Melillo, J. M., Richmond, T. C., & Yohe G. W. (Eds.). (2014). *Climate Change Impacts in the United States: The Third National Climate Assessment*. Washington, DC: U.S. Global Change Research Program. Retrieved from https://doi.org/10.7930/J0Z31WJ2.

Quan, C., Shuang, H., Torsten, U., Chunhua, Z., and Liu, Y.-S. (2013). Validation of temperature—precipitation based aridity index: Paleoclimatic implications. *Palaeogeography Palaeoclimatology Palaeoecology*, *386*, 86–95. https://doi.org/10.1016/j.palaeo.2013.05.008.

R Core Team (2016). *R: A Language and Environment for Statistical Computing*. Vienna: R Foundation for Statistical Computing.

Rodden, J. (2016). The geographic distribution of political preferences. *Annual Review of Political Science*, *13*, 331–340. https://doi.org/10.1146/annurev.polisci.12.031607.092945.

Saurí, D. (2013). Water conservation: Theory and evidence in urban areas of the developed world, *Annual Review of Environment and Resources*, *38*, 227–248.

https://doi.org/10.1146/annurev-environ-013113-142651.

Stan Development Team (2016). *Stan Modeling Language: User's Guide and Reference Manual*, version 2.14.0. Retrieved from http://mc-stan.org/documentation/.

Svara, J. H. (2003). *Two Decades of Continuity and Change in American City Councils*, Washington, DC: National League of Cities. Retrieved from http://www.skidmore.edu/~bturner/Svara%20citycouncilrpt.pdf.

Switzer, D., and Vedlitz, A. (2016). Green colored lenses: Worldviews and motivated reasoning in the case of local water scarcity. *Environment and Behavior*, *49*, 719–744. https://doi.org/10.1177/0013916516669391.

U.S. Bureau of Economic Analysis (2016a). Real personal income and regional price parities. In *Regional Economic Accounts Methodology* (Report RPP2016). Retrieved from http://www.bea.gov/regional/pdf/RPP2016_methodology.pdf.

U.S. Bureau of Economic Analysis (2016b). *RPI1: Real per-capita personal income.* Retrieved from http://www.bea.gov/iTable/index.cfm.

U.S. Census Bureau (2016). *Metropolitan and micropolitan statistical areas.* Retrieved from https://www.census.gov/data/datasets/2016/demo/popest/total-metro-and-micro-statistical-areas.html/.

U.S. Census Bureau (2017). Gini index of income inequality. In *2014 American Community Survey 1-Year Estimates.* Retrieved from https://www.census.gov/data/datasets/2016/demo/popest/total-metro-and-micro-statistical-areas.html/.

Vehtari, A., Gelman, A., & Gabry, J. (2017). Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. *Statistics and Computing*, textit27, 1413–1432. https://doi.org/10.1007/s11222-016-9696-4.

Vose, R. S., Applequist, S., Squires, M., Durre, I., Menne, M. J., Williams, C. N., Fenimore, C., Gleason, K., & Arndt, D. (2014). Improved historical temperature and precipitation time series for U.S. climate divisions, *Journal of Applied Meteorology and Climatology*, *53*, 1232–1251. https://doi.org/10.1175/JAMC-D-13-0248.1.

Wasserman, D. (2013). *Introducing the 2014 Cook Political Report Partisan Voter Index.* Cook Political Report. Retrieved from http://cookpolitical.com/story/5604.

Wilson, S. G. and Plane, D. A. and Mckun, P. J. and Fischetti, T. R. & Goworowska, J. (2016). *Patterns of Metropolitan and Micropolitan Population Change: 2000–2010* (Report No. C2010SR-01). Washington, DC: U.S. Census Bureau. Retrieved from https://www.census.gov/library/publications/2012/dec/c2010sr-01.html