Socioeconomic Determinants of 2020 U.S. Presidential Election County-Level Voter Turnout

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1 Introduction and Motivation

Every four years, hundreds of millions of Americans cast their ballots for the next president of the United States in the most prominent instance of American participatory democracy. Voter turnout, or the ratio of the number of votes cast in an election to the voting-age or voting-eligible population or number of registered voters, is regarded as important indicator of the health of popular democracy (Woolley and Peters 2024). Barriers to voting, such as strict voter ID laws, purging voter rolls, and reducing early voting times, have been a pressing concern for as long as voting has existed but are especially relevant today ("Voter Suppression" 2024). Social scientists and policymakers are interested in determinants of voter turnout and potential interventions to increase voting.

In this project, we curate a county-level dataset of voter turnout in the 2020 U.S. presidential election and a variety of socioeconomic and demographic characteristics. We hypothesize that socioeconomic and demographic factors provide significant predictive power in predicting voter turnout at the county level. We also hypothesize that poor_share2010 (the poverty rate in 2010) is positively and statistically significantly associated with voter turnout. To assess these hypotheses, we first conduct a baseline linear regression with all continuous predictors and no interaction terms (Section 4.1). We also conduct regularization and model selection using LASSO (Section 4.2), explore a model with an interaction term (Section 4.4), and construct a model with state random effects (Section 4.5).

2 Data Description and Exploratory Data Analysis

The dataset combines election data from the MIT Election Lab, population data from the U.S. Census Bureau, and socioeconomic and demographic predictors from Opportunity Insights. The turnout rate data is calculating by dividing the number of votes cast in the 2020 U.S. presidential election in each county (MIT Election Data and Science Lab 2018) by the voting-eligible population (U.S. citizens age 18 and up) (US Census Bureau 2020). The resulting turnout rate should be a proportion between 0 and 1. The exception for the election data is Alaska, whose data is organized by election districts. Estimates for Alaska election data by county equivalent (borough and Census area) are derived from another source (cinyc 2021).

The predictors (county-level demographic and socioeconomic characteristics) are from Opportunity Insights, a Harvard-based research lab studying economic opportunity in the United States (Chetty et al. 2022). For predictors labeled with years, the data is for the labeled year(s) or the 5-year period ending in the labeled year. Basic descriptions of the predictors can be found in Table 1 and more detailed descriptions can be found here. Datasets for FIPS state and county codes are also used to merge the data sources (US Census Bureau 2023).

2.1 Descriptive Statistics

The dataset contains 3,141 observations and 21 variables, 19 of which (all except county and FIPS code) will be used as predictors. All predictors except state are continuous. For each of our continuous variables, we summarize the number of missing values, mean, median, standard deviation, interquartile range, minimum value, and maximum value (Table 1).

2.2 Pre-Processing

Most variables have either zero or a small fraction of observations missing. The exception is ln_wage_growth_hs_grad, which has 21.8% of its observations missing. To handle the missing data, we drop the ln_wage_growth_hs_grad variable altogether and drop the counties that have missing data in at least one of the remaining variables, leaving 2,999 observations and 18 predictors.

There is one invalid value for turnout rate greater than 1, so we set it equal to 1. There are a few invalid values for mean math scores less than 0, so we set them equal to 0.

Variable	Description	Missing	Mean	Median	SD	IQR	Min	Max
frac_coll_plus2010	Proportion of people age 25 or older with a bachelor's degree or higher	0	0.19	0.17	0.09	0.09	0.04	0.71
foreign_share2010	Proportion of residents that are foreign-born	0	0.04	0.02	0.06	0.04	0	0.72
med_hhinc2016	Median household income	1	48,981	47,127	13,398	14,687	20,171	129,150
poor_share2010	Proportion of residents below the federal poverty line	0	0.16	0.15	0.06	0.08	0	0.53
share_white2010	Proportion of residents that are White non-Hispanic	0	0.78	0.86	0.2	0.27	0.03	0.99
share_black2010	Proportion of residents that are Black non-Hispanic	0	0.09	0.02	0.15	0.1	0	0.86
share_hisp2010	Proportion of residents that are Hispanic	0	0.08	0.03	0.13	0.07	0	0.96
share_asian2010	Proportion of residents that are Asian non-Hispanic	21	0.01	0	0.02	0.01	0	0.43
gsmn_math_g3_2013	Mean 3rd grade math test scores (grade level)	73	3.21	3.24	0.78	0.98	−0.66	6.58
rent_twobed2015	Median gross rent for two-bedroom housing units	76	692.34	642.51	205.04	195.93	236	2,085.23
singleparent_share2010	Proportion of households with children that have a single parent	0	0.31	0.3	0.09	0.1	0	0.81
traveltime15_2010	Proportion of workers age 16 or older who do not work at home that have a commute shorter than 15 minutes	0	0.4	0.38	0.14	0.19	0.1	0.99
emp2000	Proportion of residents age 16 or older that are employed	0	0.57	0.58	0.08	0.1	0.24	0.84
ln_wage_growth_hs_grad	Difference in log average hourly wage for high school graduates between 2010−2014 and 2005−2009	684	0.08	0.07	0.14	0.13	−0.72	0.91
popdensity2010	Residents per square mile	1	262.67	45.3	1,774.99	96.74	0.04	70,583.6
ann_avg_job_growth_2004_2013	Average annualized job growth rate	5	0	0	0.01	0.02	−0.08	0.12
job_density_2013	Jobs per square mile	2	124.24	18.47	862.85	43.3	0.02	36,663.2
turnout.rate	Proportion of voting-eligible residents (citizens 18 and over) who voted in the 2020 presidential election	0	0.66	0.66	0.11	0.14	0.19	1.58

Table 1: Descriptions and descriptive statistics of the continuous predictors in the dataset.

2.3 Exploratory Graphs

Figure 1 shows the number of counties or county equivalents for each state in the dataset. The counts range from 1 in the District of Columbia to about 225 in Texas.

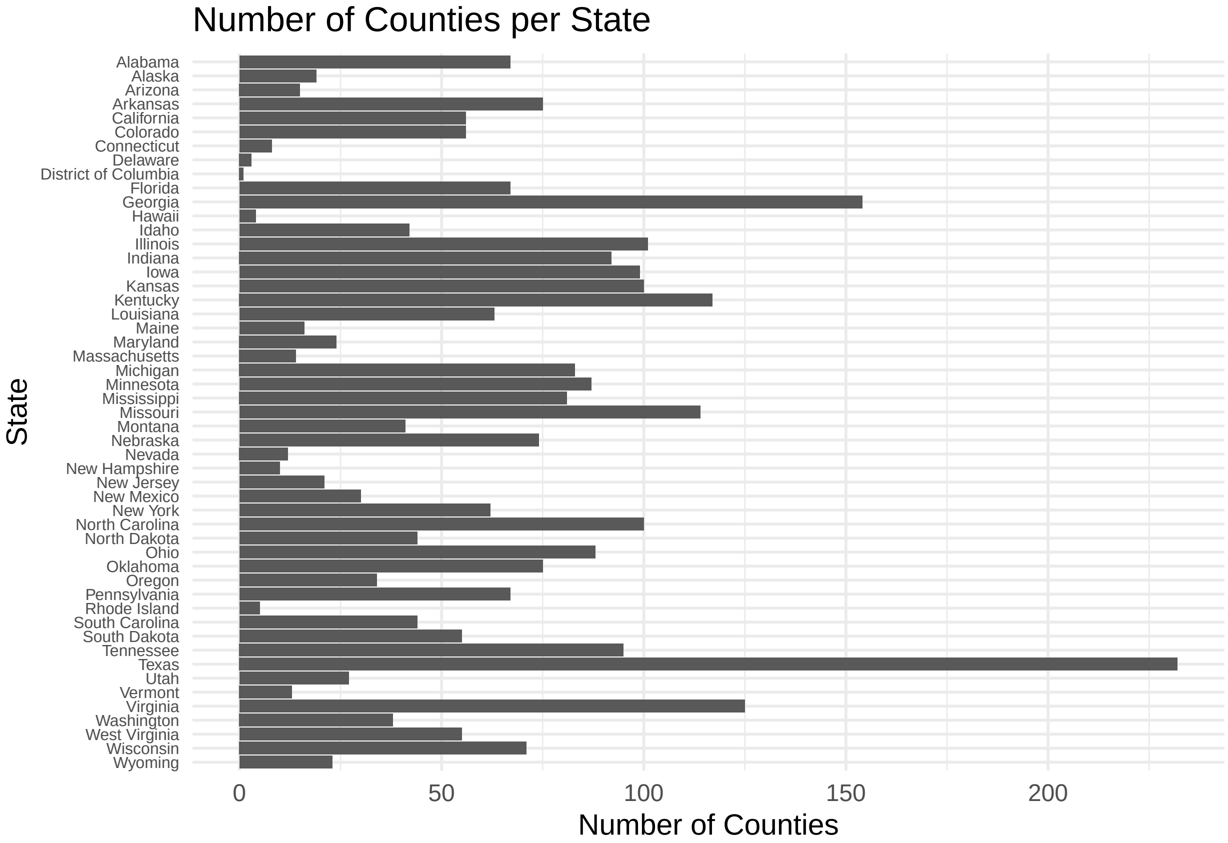


Figure 1: Bar chart showing the number of counties or county equivalents per state in the dataset.

The histogram of turnout rate (Figure 2) shows an approximately normal distribution. Most counties have turnout rates between 0.45 and 0.85, with few extreme values.

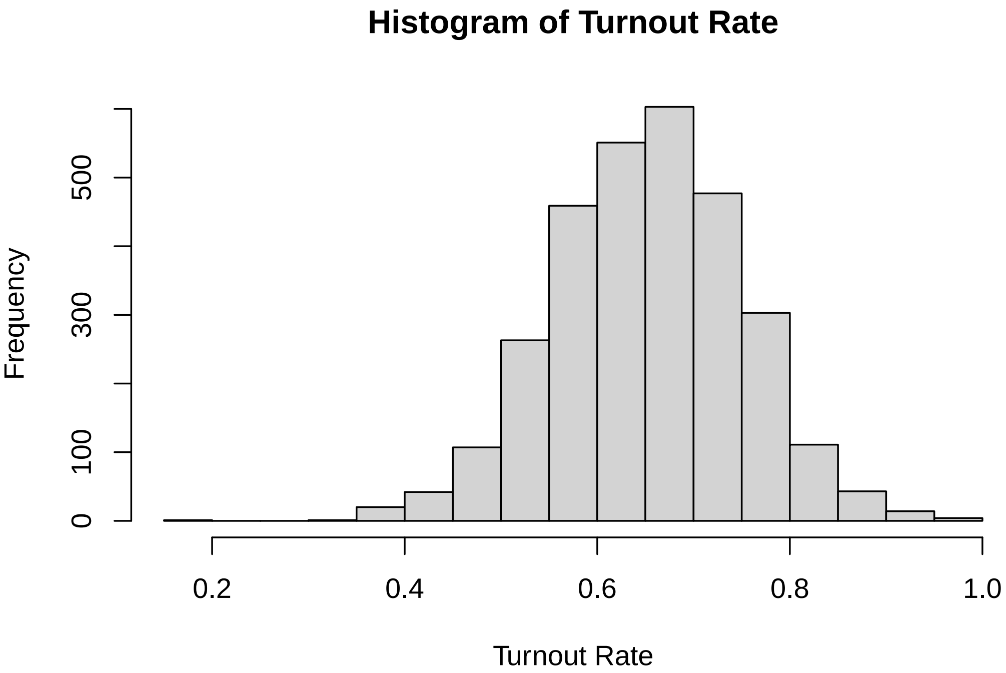


Figure 2: Histogram of turnout rate for counties shows an approximately normal distribution.

To see the relationship between voter turnout and one predictor variable hypothesized to be associated with it, we plot the 2010 poverty rate against the 2020 turnout rate for each county (Figure 3). There is a moderate negative association between the variables ($r = -0.571$).

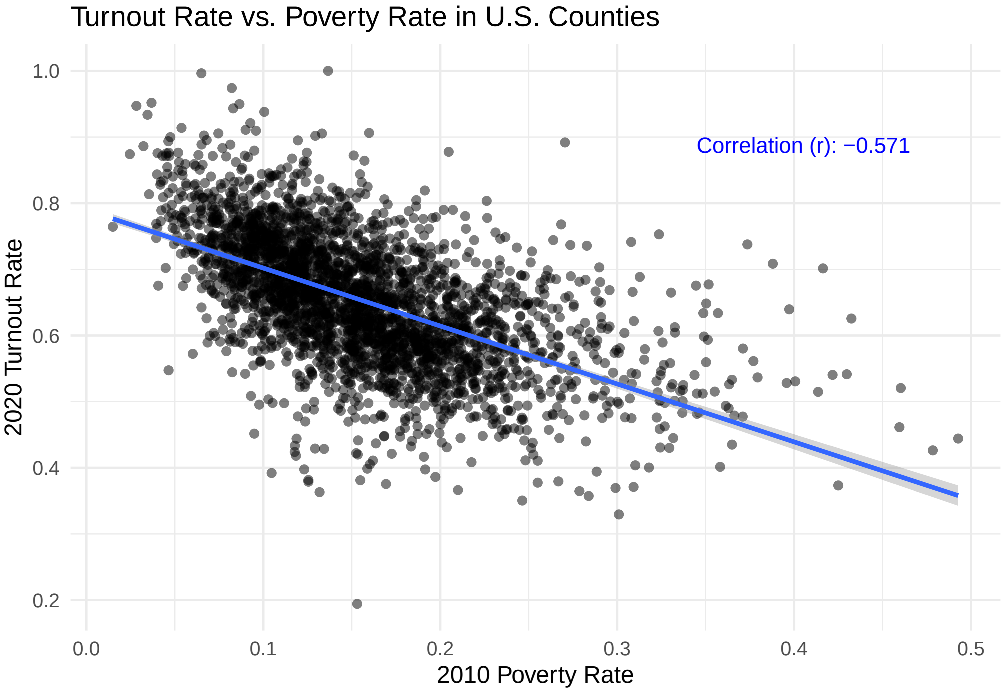


Figure 3: Scatterplot of poverty rate vs. turnout rate. The negative association between the two variables aligns with the theory that socioeconomic disadvantage is associated with lower electoral participation.

3 Methods

We start by conducting a linear regression between the outcome variable (voter turnout) and the continuous predictor variables (all socioeconomic and demographic characteristics in the dataset) as a baseline model. We assess the statistical significance of the coefficient estimates with t-tests, where the t-statistic is the estimate divided by the standard error. We assess the predictive power of the model overall with an F-test, which compares two nested models (where the p_1 predictors in one model are a subset of the $p_2 = p_1 + k$ predictors in the other model). The extra-sums-of-squares F-test statistic is

$$F = \frac{(SSE_1 - SSE_2)/k}{SSE_2/(n - p_2 - 1)},$$

where n is the number of observations. To assess the overall predictive power of a model, we compare it to the intercept-only model, which has no predictors.

To combat overfitting and conduct model selection, LASSO is used. The loss function that LASSO aims to minimize is

$$\sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j|$$

for a dataset with n observations and p predictors. Considering that OLS regression minimizes the sum of squared residuals, the LASSO loss function introduces a term proportional to the sum of the absolute values of the coefficients, penalizing large coefficient estimates. λ is a tuning parameter that controls the strength of the penalty. Unlike ridge regression, LASSO can shrink coefficients to 0 and act as a form of model selection.

We also explore the effect of adding an interaction term to the model. An interaction term is a product of two existing predictors that allows the effect of one predictor to vary based on the value of another predictor. To assess the impact on the model of adding this interaction term, we again use an extra-sums-of-squares F-test, but using the model with and without the interaction term as the nested models.

Lastly, we account for state-level variation in voter turnout by adding state random effects to the model. In both fixed effects and random effects models, a categorical variable is used and an estimates is made for each level of the variable (in this case, `state`). While a fixed effects model in this case would allow the coefficient for each state to vary freely, a random effects model assumes the states come from the same distribution and takes this distribution into account when estimating the effect of each state, assigning more structure to the data.

4 Results

4.1 Baseline Model

We first fit a simple linear regression model containing all predictors except state and no interaction terms. The model output is shown in Table 2.

The baseline model has significantly more explanatory power than an intercept-only model ($F = 147.4, p < 10^{-15}$) and demonstrates several significant relationships. The model explains approximately 44% of the variance in voter turnout between counties ($R^2 = 0.442$, adjusted $R^2 = 0.439$). The statistically significant positive predictors are college-educated share ($\hat{\beta} = 0.372$), foreign-born share ($\hat{\beta} = 0.110$), White population share ($\hat{\beta} = 0.042$), Black population share ($\hat{\beta} = 0.059$), and employment ($\hat{\beta} = 0.114$). On the other hand, poverty rate has a strong negative effect in the model, with a one percentage point increase in poverty rate associated with a 0.576 percentage point decrease in turnout ($p < 10^{-15}$). Other significant negative predictors are Hispanic population share ($\hat{\beta} = -0.051$), Asian population share ($\hat{\beta} = -0.506$), single parent share ($\hat{\beta} = -0.062$), travel time ($\hat{\beta} = -0.043$), and job growth ($\hat{\beta} = -0.707$). Median household income, math scores, two-bedroom rent, population density, and job density are not significantly related to turnout at the $\alpha = 0.05$ threshold. This initial exploration suggests that socioeconomic conditions significantly shape local electoral participation.

Variable	**Estimate**	**SE**	***t*-value**	***p*-value**
(Intercept)	0.608	0.0329	18.5	2.4e−72
`frac_coll_plus2010`	0.372	0.026	14.3	5.44e−45
`foreign_share2010`	0.11	0.0496	2.23	0.026
`med_hhinc2016`	1.3e−07	2.54e−07	0.51	0.61
`poor_share2010`	−0.576	0.0404	−14.3	1.08e−44
`share_white2010`	0.0423	0.0208	2.03	0.0421
`share_black2010`	0.0591	0.0208	2.83	0.00462
`share_hisp2010`	−0.0511	0.0249	−2.06	0.0398
`share_asian2010`	−0.506	0.0917	−5.52	3.71e−08
`gsmn_math_g3_2013`	−0.000993	0.00214	−0.464	0.643
`rent_twobed2015`	−7.02e−06	1.43e−05	−0.492	0.623
`singleparent_share2010`	−0.0617	0.0246	−2.51	0.012
`traveltime15_2010`	−0.0425	0.0117	−3.63	0.000283
`emp2000`	0.114	0.0273	4.17	3.17e−05
`popdensity2010`	−2.26e−07	5.51e−06	−0.041	0.967
`ann_avg_job_growth_2004_2013`	−0.707	0.107	−6.62	4.12e−11
`job_density_2013`	−4.92e−06	1.13e−05	−0.434	0.665

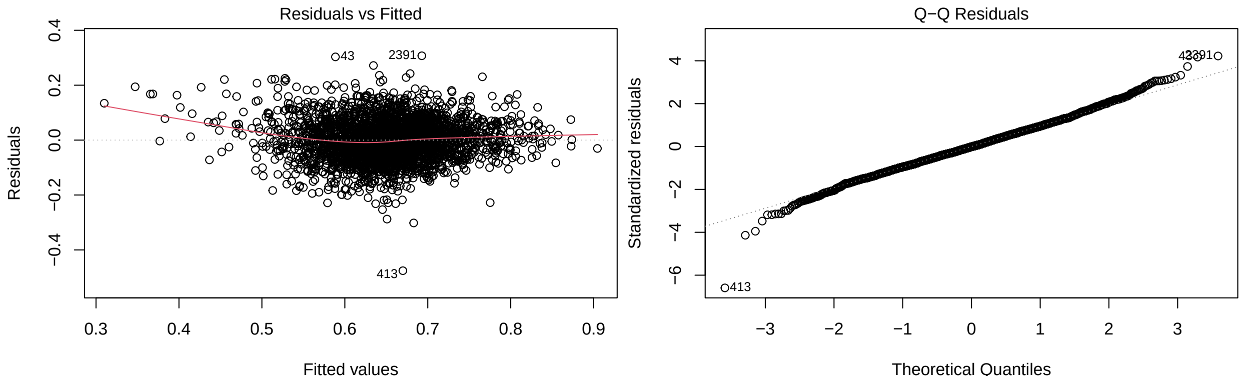
Table 2: Baseline model output.

4.1.1 Diagnostics

We conduct diagnostics for the baseline model to assess its suitability for linear regression. Below we assess the assumptions required for OLS linear regression:

- **Existence of Variance:** Residuals are reasonably dispersed, confirming the existence of variation in the dependent variable.
- **Linearity:** The residuals vs. fitted values plot (Figure 4a) does not show pronounced curvature, suggesting linearity is generally satisfied.
- **Independence:** Spatial correlation may exist between neighboring counties; external tests (like Moran's I) should be considered for future analyses.
- **Homogeneity (Homoscedasticity):** Some fanning in the residuals vs. fitted values plot (Figure 4a) suggests heteroscedasticity. Robust standard errors or alternative modeling approaches may be warranted.
- **Normality:** The Q-Q plot (Figure 4b) shows mostly normal residuals, with minor deviations in the tails.

Overall, while the model is a decent fit, improvements—such as using robust errors or accounting for spatial autocorrelation—could refine our inference.



(a) Residuals vs. fitted values plot.

(b) Q-Q residual plot.

Figure 4: Diagnostic plots for baseline model.

4.2 LASSO

To address potential overfitting and identify the most influential variables, we employ LASSO regularization, which penalizes large coefficient estimates and can shrink coefficients to 0 to conduct model selection. We use ten-fold cross-validation to select a penalty level that balances predictive accuracy and model parsimony, reaching an optimal λ of 2.769e−4. LASSO retains all predictors except `gsmn_math_g3_2013` and `rent_twobed2015` (Table 3). This aligns with earlier findings that these variables were not statistically significant in the baseline model.

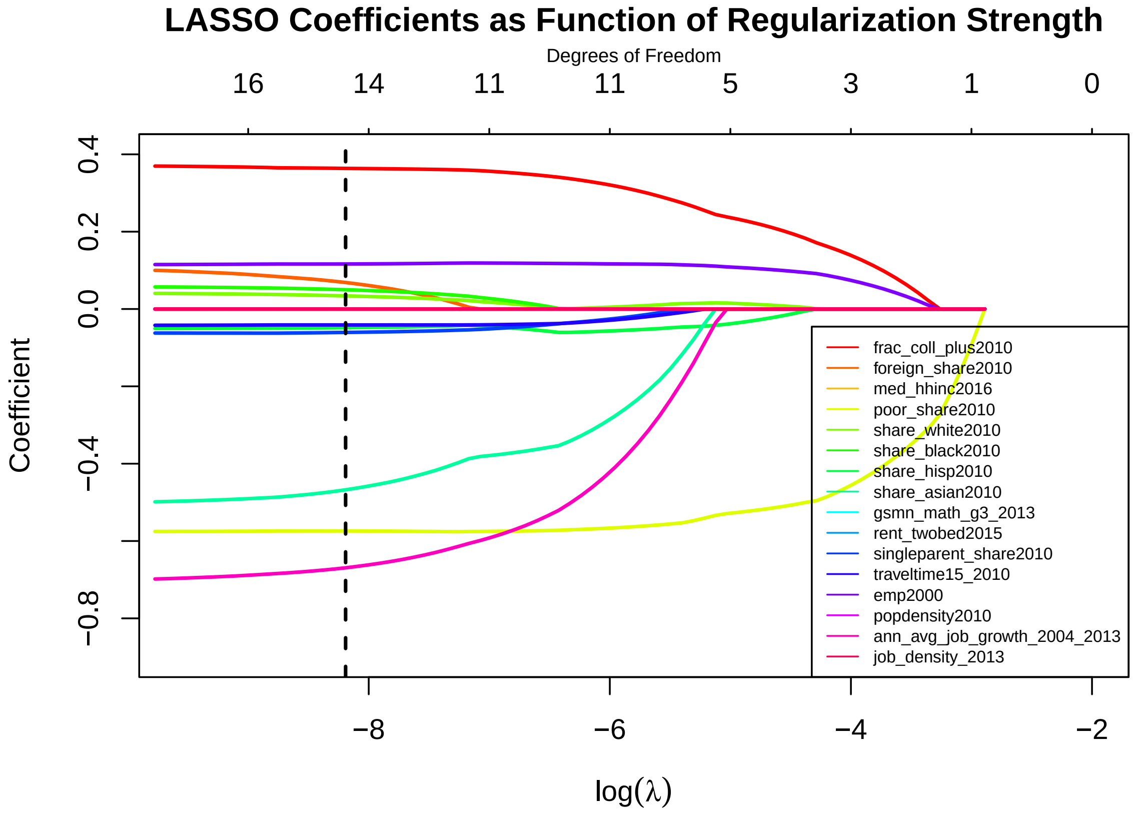


Figure 5: Coefficient values plotted against λ showing the effect of LASSO regularization. As λ increases, the coefficients shrink to 0.

Variable	Coefficient
(Intercept)	0.612
frac_coll_plus2010	0.363
foreign_share2010	0.0702
med_hhinc2016	4.44e−08
poor_share2010	−0.574
share_white2010	0.0339
share_black2010	0.0499
share_hisp2010	−0.0486
share_asian2010	−0.47
gsmn_math_g3_2013	0
rent_twobed2015	0
singleparent_share2010	−0.0605
traveltime15_2010	−0.0412
emp2000	0.116
popdensity2010	−8.43e−07
ann_avg_job_growth_2004_2013	−0.67
job_density_2013	−3.17e−06

Table 3: Coefficients after LASSO regularization with $\lambda = 2.769\text{e}{-4}$.

Figure 5 shows the relationship between λ and the coefficients of the predictors, visually demonstrating which variables are "important" enough to survive the LASSO penalty. As λ increases (moving right on the x-axis), the regularization strength increases and more predictors drop out of the model with coefficients of 0. The vertical dashed black line shows the chosen λ. Predictors with coefficients of 0 at the vertical line are dropped from the final model. At the chosen λ, most of the coefficients have not shrunk towards 0 very far compared to the left side of the graph (see Table 8 for a comparison of baseline model and LASSO coefficients).

4.3 Correlation Structure

Examining correlations among predictors helps identify potential multicollinearity and structure in the data. The heatmap in Figure 6 shows groups of variables that cluster together, indicating underlying socioeconomic dimensions. For instance, population density, job density, foreign share, Hispanic share, and Asian share are clustered together, possibly reflecting the tendency of densely populated cities to be racially diverse and have high foreign-born populations. Another cluster groups annual average job growth, proportion with a bachelor's degree or higher, and median two-bedroom rent, potentially capturing areas with highly educated residents that are areas of economic growth. These clusters may reflect underlying latent factors that shape voter turnout. One concern shown in the correlation matrix is the very high correlation between population density and job density ($r = 0.991$). Near-perfect collinearity can artificially inflate standard errors for coefficient estimates. In the baseline model, the coefficients for population density and job density were both not statistically significant (Table 2), so we should be wary of this result and consider removing one of the predictors.

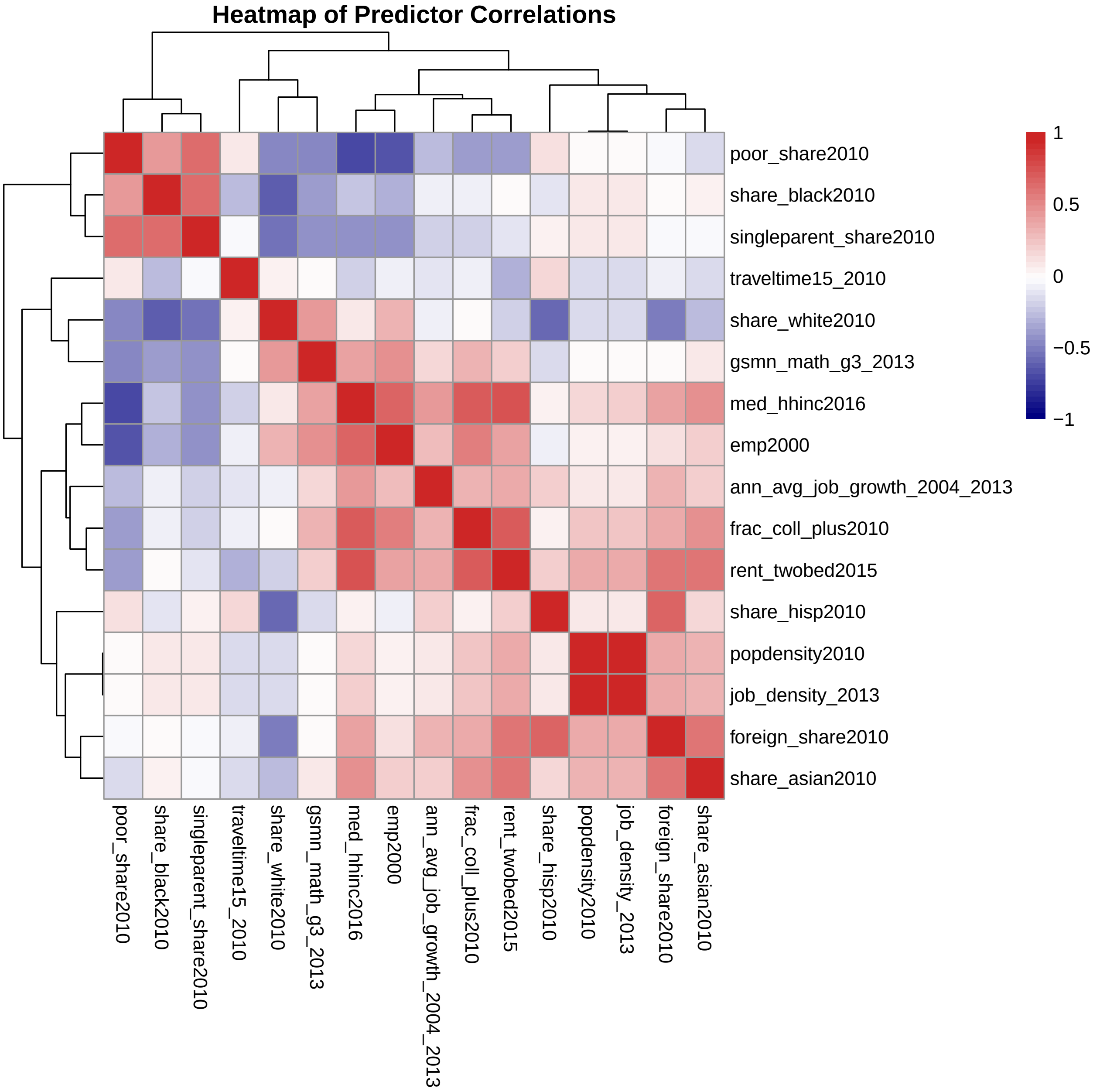


Figure 6: Heatmap of the correlation matrix of the continuous predictors.

4.4 Interaction Terms

We test whether adding an interaction term between education and poverty (`frac_coll_plus2010:poor_share2010`) to the LASSO-regularized model improves model performance. To do so, we use an extra-sums-of-squares F-test.

A highly significant test result ($F = 94.894$, $p < 10^{-15}$) suggests the interaction between college education fraction and poverty share is highly significant, indicating that the effect of education on turnout may depend on the poverty context of the county (and vice versa).

4.5 State Random Effects

We run a final model excluding the variables zeroed out by LASSO and adding state random effects to control for unobserved state-level heterogeneity. The model output for the continuous predictors and the state random effects estimates are shown in Tables 4 and 5, respectively.

Variable	**Estimate**	**SE**	***t*-value**	***p*-value**
(Intercept)	0.551	0.0295	18.7	0
`frac_coll_plus2010`	0.241	0.0209	11.5	0
`foreign_share2010`	−0.0646	0.0438	−1.48	0.14
`med_hhinc2016`	9.15e−07	2.07e−07	4.42	9.97e−06
`poor_share2010`	−0.36	0.0347	−10.4	0
`share_white2010`	0.0908	0.0195	4.66	3.18e−06
`share_black2010`	0.0955	0.0208	4.58	4.56e−06
`share_hisp2010`	0.00265	0.0246	0.107	0.914
`share_asian2010`	−0.461	0.0878	−5.25	1.53e−07
`singleparent_share2010`	−0.0884	0.0204	−4.33	1.46e−05
`traveltime15_2010`	−0.0881	0.0114	−7.7	1.33e−14
`emp2000`	0.11	0.025	4.41	1.02e−05
`popdensity2010`	5.38e−06	4.48e−06	1.2	0.23
`ann_avg_job_growth_2004_2013`	−0.697	0.0915	−7.62	2.62e−14
`job_density_2013`	−1.18e−05	9.18e−06	−1.29	0.199

Table 4: Output of model with state random effects (continuous predictors only).

With state fixed effects, the adjusted R^2 improves to approximately 0.646, suggesting that differences between states explain a significant portion of turnout variation (see Section 7.2). However, we focused instead on the random effects model, which is particularly appropriate given the hierarchical structure of our data, where counties are nested within states, and helps prevent overfitting in states with few counties. The variance components show significant state-level variation (state intercept variance = 0.0026), indicating meaningful differences in baseline turnout rates across states that cannot be explained by our county-level predictors alone. The residual variance (0.0038) suggests there remains substantial within-state variation between counties.

After controlling for state-level factors through random effects, education, poverty, and various demographic characteristics remain significant predictors. Notably, poverty and time-to-work maintain their negative associations with turnout, while educational attainment consistently shows a positive association.

The random effects components provide important insights into the structure of voter turnout variation:

- The state-level variance (0.00246) indicates modest but meaningful differences between states. With a

standard deviation of approximately 0.05, we can expect about 95% of state-level effects to fall within ±10 percentage points of the overall mean, reflecting differences in state election policies, political culture, and other state-specific factors.
- The residual variance (0.00336) represents within-state variation between counties. Being larger than the state-level variance, this suggests that counties within the same state show more variation than states differ from each other. About 95% of county-level deviations fall within ±11.6 percentage points of their state's mean.
- Approximately 42.3% of the unexplained variation in turnout rates is attributable to state-level differences (calculated as the ratio of state variance to total variance), indicating that state-level factors play an important but not dominant role in determining turnout rates.

This random effects approach allows us to model state-specific deviations while still estimating common coefficients for our predictors across all states, providing a more nuanced understanding than either pooled OLS or fixed effects would allow. This final specification suggests that while local socioeconomic conditions are important determinants of turnout, broader state-level contexts—potentially including differences in election administration, political culture, and institutional factors—also substantially shape the electoral participation landscape.

5 Discussion and Conclusion

Our analysis shows that socioeconomic and demographic factors strongly influence county-level voter turnout. Education and certain demographic features (e.g., Black population share) are robust, positive predictors of turnout, while higher poverty rates, longer travel times, and certain population characteristics (e.g., Asian population share) are negatively associated. LASSO regularization supports the exclusion of non-influential predictors, refining the model and reinforcing the significance of key variables. Incorporating interaction terms and state fixed effects further refines our understanding, revealing that the influence of education on turnout may be contingent on the economic context and that state-level factors account for substantial variation across the U.S. counties.

There are some limitations to our findings. One important caveat is that these associations between county-wide factors and voter turnout do not imply anything about the individuals within counties. Concluding that, for instance, highly educated people are more likely to vote solely based on the data presented here would an example of the ecological fallacy, where inferences about individuals are made based on inferences about groups containing those individuals (Freedman 1999). Another limitation is that there is a somewhat arbitrary time lag between the measurement of the predictors and the outcome (the socioeconomic and demographic factors are measured between 2000 and 2016, but the voter turnout rate is measured in 2020). We posit that these predictors do not change much from year to year, which is an assumption that could be tested with more data. Additionally, there may be other characteristics that impact county-level voter turnout, such as age, that are not captured in our data. Regardless, these findings have implications for policymakers and organizations interested in increasing voter participation. Interventions that improve socioeconomic conditions, reduce poverty, enhance education, and consider unique state-level political climates could foster higher electoral engagement, but more research should be done at the individual level or experimental level to reach more statistically sound conclusions.

6 Bibliography

Chetty, Raj, John Friedman, Nathaniel Hendren, Maggie R. Jones, and Sonya R. Porter. 2022. "Replication Data for: The Opportunity Atlas: Mapping the Childhood Roots of Social Mobility." Harvard Dataverse. https://doi.org/10.7910/DVN/NKCQM1.

cinyc. 2021. "Alaska Presidential Results by County Equivalent, 1960-2020." *RRH Elections*. https://rrhelections.com/index.php/2021/04/13/alaska-presidential-results-by-county-equivalent-1960-2020/9/.

Freedman, David. 1999. "Ecological Inference and the Ecological Fallacy." *International Encyclopedia of the Social & Behavioral Sciences* 6 (4027-4030): 1–7.

MIT Election Data and Science Lab. 2018. "County Presidential Election Returns 2000-2020." Harvard

Dataverse. https://doi.org/10.7910/DVN/VOQCHQ.

US Census Bureau. 2020. "B05003: Sex by Age by Nativity and Citizenship Status." https://data.census.gov/table/ACSDT5Y2020.B05003?t=Citizenship&g=010XX00US$0500000&y=2020&d=ACS%205-Year%20Estimates%20Detailed%20Tables&moe=false&tp=true.

———. 2023. "American National Standards Institute (ANSI), Federal Information Processing Series (FIPS), and Other Standardized Geographic Codes." *Census.gov*. https://www.census.gov/library/reference/code-lists/ansi.html.

"Voter Suppression." 2024. https://www.brennancenter.org/issues/ensure-every-american-can-vote/voter-suppression.

Woolley, John, and Gerhard Peters. 2024. "Voter Turnout in Presidential Elections." *The American Presidency Project*. https://www.presidency.ucsb.edu/statistics/data/voter-turnout-in-presidential-elections.

7 Appendix

7.1 State Random Effects

The estimates for the state random effects are shown in Table 5.

State	Intercept	State	Intercept	State	Intercept
Alabama	0.544	Kentucky	0.528	North Dakota	0.541
Alaska	0.553	Louisiana	0.545	Ohio	0.517
Arizona	0.589	Maine	0.612	Oklahoma	0.46
Arkansas	0.445	Maryland	0.504	Oregon	0.656
California	0.588	Massachusetts	0.563	Pennsylvania	0.528
Colorado	0.629	Michigan	0.598	Rhode Island	0.501
Connecticut	0.508	Minnesota	0.61	South Carolina	0.545
Delaware	0.547	Mississippi	0.545	South Dakota	0.545
District of Columbia	0.529	Missouri	0.512	Tennessee	0.475
Florida	0.59	Montana	0.616	Texas	0.521
Georgia	0.524	Nebraska	0.567	Utah	0.581
Hawaii	0.611	Nevada	0.59	Vermont	0.571
Idaho	0.584	New Hampshire	0.549	Virginia	0.55
Illinois	0.517	New Jersey	0.567	Washington	0.649
Indiana	0.472	New Mexico	0.56	West Virginia	0.46
Iowa	0.579	New York	0.489	Wisconsin	0.593
Kansas	0.526	North Carolina	0.587	Wyoming	0.533

Table 5: State random effects intercept estimates.

7.2 State Fixed Effects

We run a model excluding the variables zeroed out by LASSO and adding state fixed effects to control for unobserved state-level heterogeneity. The model output for the continuous predictors and the state fixed effects estimates are shown in Tables 6 and 7, respectively.

Variable	**Estimate**	**SE**	t**-value**	p**-value**
(Intercept)	0.534	0.0298	17.9	3.6e−68
frac_coll_plus2010	0.24	0.0211	11.4	2.33e−29
foreign_share2010	−0.056	0.0446	−1.26	0.209
med_hhinc2016	9.68e−07	2.09e−07	4.64	3.7e−06
poor_share2010	−0.347	0.0349	−9.97	4.95e−23
share_white2010	0.0974	0.0198	4.92	9.21e−07
share_black2010	0.104	0.0212	4.91	9.73e−07
share_hisp2010	0.0031	0.0249	0.125	0.901
share_asian2010	−0.52	0.095	−5.48	4.72e−08
singleparent_share2010	−0.0894	0.0205	−4.36	1.32e−05
traveltime15_2010	−0.091	0.0116	−7.85	5.76e−15
emp2000	0.11	0.0252	4.38	1.22e−05
popdensity2010	5.03e−06	4.51e−06	1.11	0.265
ann_avg_job_growth_2004_2013	−0.698	0.0918	−7.6	3.88e−14
job_density_2013	−1.07e−05	9.24e−06	−1.16	0.247

Table 6: Output of model with state fixed effects (continuous predictors only).

State	**Estimate**	**SE**	***t*-value**	***p*-value**	**State**	**Estimate**	**SE**	***t*-value**	***p*-value**
Alaska	0.0161	0.0184	0.873	0.383	Montana	0.0762	0.0124	6.13	9.75e−10
Arizona	0.0521	0.0175	2.98	0.00286	Nebraska	0.025	0.0108	2.32	0.0205
Arkansas	−0.0994	0.00992	−10	2.74e−23	Nevada	0.0537	0.0187	2.87	0.00418
California	0.0492	0.0121	4.06	5e−05	New Hampshire	0.00639	0.0201	0.318	0.751
Colorado	0.0888	0.0115	7.74	1.36e−14	New Jersey	0.0268	0.0156	1.71	0.0872
Connecticut	−0.0424	0.0223	−1.91	0.0568	New Mexico	0.0212	0.015	1.41	0.157
Delaware	0.00291	0.0343	0.0848	0.932	New York	−0.0549	0.0111	−4.94	8.3e−07
District of Columbia	−0.0488	0.0596	−0.819	0.413	North Carolina	0.0447	0.00925	4.83	1.44e−06
Florida	0.0482	0.0105	4.59	4.61e−06	North Dakota	−0.00176	0.0125	−0.141	0.888
Georgia	−0.0194	0.00855	−2.27	0.0232	Ohio	−0.0265	0.00995	−2.67	0.00767
Hawaii	0.109	0.0399	2.73	0.00644	Oklahoma	−0.0836	0.0105	−7.93	2.99e−15
Idaho	0.043	0.0121	3.57	0.000368	Oregon	0.118	0.0129	9.19	7.15e−20
Illinois	−0.0258	0.0097	−2.66	0.00789	Pennsylvania	−0.0151	0.0105	−1.43	0.152
Indiana	−0.0722	0.00995	−7.26	4.97e−13	Rhode Island	−0.0554	0.0274	−2.02	0.0432
Iowa	0.0377	0.0101	3.74	0.000189	South Carolina	0.000997	0.0113	0.0881	0.93
Kansas	−0.0158	0.0101	−1.56	0.119	South Dakota	0.00321	0.0118	0.273	0.785
Kentucky	−0.0159	0.00944	−1.68	0.0928	Tennessee	−0.0691	0.00959	−7.21	7.02e−13
Louisiana	0.00109	0.0103	0.106	0.916	Texas	−0.0202	0.0093	−2.18	0.0297
Maine	0.0753	0.0166	4.54	5.89e−06	Utah	0.0405	0.014	2.89	0.00391
Maryland	−0.0418	0.0143	−2.92	0.00355	Vermont	0.0311	0.0181	1.72	0.086
Massachusetts	0.0211	0.0178	1.18	0.238	Virginia	0.0065	0.009	0.723	0.47
Michigan	0.0559	0.0101	5.56	2.93e−08	Washington	0.111	0.0125	8.92	7.76e−19
Minnesota	0.0689	0.0103	6.68	2.81e−11	West Virginia	−0.085	0.0111	−7.67	2.35e−14
Mississippi	0.00126	0.00972	0.13	0.897	Wisconsin	0.0513	0.0106	4.84	1.36e−06
Missouri	−0.0311	0.00943	−3.29	0.000997	Wyoming	−0.00924	0.015	−0.617	0.537

Table 7: State fixed effects estimates.

7.3 Comparison of Coefficient Estimates for Baseline, LASSO-Regularized, and State Fixed Effects Models

Table 8 compares coefficient estimates for the baseline model (no interaction terms or regularization), LASSO-regularized model, and model with LASSO-omitted predictors and state fixed effects. We can see that most of the estimates for the LASSO model are close to the corresponding estimates for the baseline model, but interestingly, LASSO actually increased the absolute value of some coefficients (such as employment).

Variable	**Baseline**	**LASSO**	**Random**	**Fixed**
(Intercept)	0.608	0.612	0.551	0.534
`frac_coll_plus2010`	0.372	0.363	0.241	0.24
`foreign_share2010`	0.11	0.0702	−0.0646	−0.056
`med_hhinc2016`	1.3e−07	4.44e−08	9.15e−07	9.68e−07
`poor_share2010`	−0.576	−0.574	−0.36	−0.347
`share_white2010`	0.0423	0.0339	0.0908	0.0974
`share_black2010`	0.0591	0.0499	0.0955	0.104
`share_hisp2010`	−0.0511	−0.0486	0.00265	0.0031
`share_asian2010`	−0.506	−0.47	−0.461	−0.52
`gsmn_math_g3_2013`	−0.000993	0	0	0
`rent_twobed2015`	−7.02e−06	0	0	0
`singleparent_share2010`	−0.0617	−0.0605	−0.0884	−0.0894
`traveltime15_2010`	−0.0425	−0.0412	−0.0881	−0.091
`emp2000`	0.114	0.116	0.11	0.11
`popdensity2010`	−2.26e−07	−8.43e−07	5.38e−06	5.03e−06
`ann_avg_job_growth_2004_2013`	−0.707	−0.67	−0.697	−0.698
`job_density_2013`	−4.92e−06	−3.17e−06	−1.18e−05	−1.07e−05

Table 8: Comparison of coefficients for quantitative predictors in the baseline, LASSO, state random effects, and state fixed effects models.