### Appendix A. Measuring Electoral Class Bias

We draw on the Current Population Survey (CPS) Voter Supplements to construct our measure of electoral class bias (Brown et al. 1999; Hill and Leighley 1992; Rigby and Springer 2011; Rosenstone and Hansen 1993). The CPS has some limitations for our purposes, but also several properties that are unmatched by other sources. First, the survey asks questions about voting behavior and turnout and includes very large samples of Americans (over 100,000 respondents). Second, the CPS interviews thousands of individuals in every state allowing for representative estimation of turnout rates in each state, even in those states with small populations. Finally, questions about voting have been consistently asked for each presidential and midterm election for several decades. For these reasons the CPS data are used to construct the voter bias measures reported here.

Our measure captures disproportionate participation rates across income groups (Blakely et al. 2001; Mackenbach and Kunst 1997; Wichowsky 2012), providing an empirical measure of how much richer citizens participate in elections relative to others within their state. The class bias variable is created by first assigning all CPS respondents to a cumulative, within-state family income distribution. For instance, consider a CPS respondent who reports a family income of $50,000 to $59,999. If this income category consists of 10% of the state’s residents and 50% of the population falls below this income level, then this individual is assigned to 0.55 on the state’s cumulative income distribution (0.50 + [0.10/2]). This within state income position is then used as a determinant of voter turnout in the following OLS regression model:

|  |
| --- |
| *vote = b0 + b1(income position) + e,* |

where vote is coded as 1 if the individual reported voting and 0 if the person did not vote, and income position indicates each individual’s position on their state’s cumulative income distribution as described above. A unique regression model is specified for each state and each election year. Since both variables (vote and income) are bounded between 0 and 1, the resulting coefficient (b1) on the cumulative income scale is interpreted as the absolute difference in the probability of voting for the poorest and richest income group in each state.

Hence, the participation bias measure ranges from -1 to 1, with negative values indicating low-income individuals are more likely to vote than the rich, 0 meaning the rich and poor have an equal probability of voting, and positive values meaning the rich vote at a higher rate than the poor. A value of 0.33 (the average of the measure across all years and states), for example, indicates that the rich are 33% more likely to vote than the poor. This calculation is straightforward. Since income is scaled between 0 and 1 in every state, the average rate of turnout for the poorest group in a state is equal to *b0 + (b1 × income)*, or just the estimate of *b0* since the lowest income in any given state is 0 (i.e., *b1 ×* 0 = 0). Similarly, the average turnout rate for the rich is equal to *b0 +* (*b1 ×* 1). Therefore, the difference in the participation rates between the rich and poor will be equal to the estimate of *b1* since *b0* is a constant.

This measure has several distinctive characteristics. First, our measure includes information about the participation of all income groups. Many previous studies focus on lower class turnout, but this ignores the fact that turnout among middle and upper income citizens can vary as well. We capture disparities in participation rates of individuals from upper and lower income groups, rather than only the participation rates of lower income voters, which reflects that when outcomes are zero-sum, politicians must weigh the relative preferences and power of different groups. Second, our measure is based on a state-specific income distribution. Many previous studies use a single income threshold to determine which group is wealthy and which is poor (see Solt [2010] and Wichowsky [2012] for exceptions). Such measures ignore the fact that earning $30,000 in Oklahoma is quite different than an income of $30,000 in Connecticut.

### Appendix B. Components of State Policy Liberalism Index

Table B1: Descriptive Statistics for State Economic Policy Measures (Unstandardized) and Economic Policy Liberalism Index (Standardized)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Mean  | S.D.  | Min.  | Max.  |
|  |  |  |  |  |
|  |  |  |  |  |
| Top Corporate Tax Rate  | 6.56  | 3.00  | 0  | 13.8  |
| Top Income Tax Rate  | 6.02  | 3.79  | 0  | 19.8  |
| Minimum Wage  | 4.08  | 1.06  | 2.3  | 7.63  |
| Collective Bargaining Rights  | 3.58  | 1.83  | 0  | 6  |
|  |  |  |  |  |
| Economic Policy Liberalism  | 0  | 2.42  | -6.86  | 5.74  |

### Appendix C. Variable Descriptions

|  |  |  |
| --- | --- | --- |
| Variable Name | Description | Source |
|  |  |  |
| Congress Percent Democrat | Percent of seats in Congress held by Democrats | U.S. Census Bureau |
|  |  |  |
| Democratic President | Democratic control of the presidency | U.S. Census Bureau |
|  |  |  |
| Econ. Policy Liberalism | State economic policy liberalism | Multiple sources; see Appendix B |
|  |  |  |
| Gross State Product  | Gross state product (GSP) | U.S. Census Bureau |
|  |  |  |
| Left Gov. Power | Ideology of state legislature; higher values indicate a more liberal ideology | Berry et al. (1998) |
|  |  |  |
| Manufacturing, Percent GSP | Proportion of GSP from manufacturing | U.S. Census Bureau |
|  |  |  |
| Percent 65 or Older  | Percent of the state population that is 65 or older | U.S. Census Bureau |
|  |  |  |
| Percent Non-White  | Percent of the state population that is non-white | U.S. Census Bureau |
|  |  |  |
| Post-Cash Transfer Gini | State Gini coefficient after government transfers | Annual Social and Economic Supplement; see Kelly and Witko (2012) |
|  |  |  |
| Pre-Redistribution Gini  | State Gini coefficient prior to government transfers | Annual Social and Economic Supplement; see Kelly and Witko (2012) |
|  |  |  |
| Public Mood  | State public ideology; higher values indicate a more liberal ideology | Enns and Koch (2013) |
|  |  |  |
| Union Density | Percent of the state population that are union members | Hirsch and MacPherson (2003) |
|  |  |  |
| Voting Class Bias  | Income-based bias in state voter turnout; higher values indicate more upper-class bias | Current Population Survey; see Appendix A |
|  |  |  |

### Appendix D. Model Estimation

Given that our data contain both time series and cross-sectional variation, we need to use an estimation procedure that deals with the most commonly encountered issues with such a data structure. As is well-known, unit-effects are one of the most potentially problematic issues in TSCS analysis, and there are multiple strategies for dealing with unit-effects (Plumper et al. 2005; Stimson 1985; Wilson and Butler 2007). One of the most common strategies is to estimate a fixed-effects model in which a separate intercept is estimated for each unit (state in our analysis). The problem with such an approach, however, is that it becomes difficult to capture effects of variables that vary only or mostly across states rather than over time (Beck 2001). Another alternative, estimating a lagged dependent variable model with panel corrected standard errors, can be similarly problematic. Essentially, it is difficult using most common techniques to both account for unit effects in order to insure proper model specification and accurately capture between-unit effects.

To overcome this issue we use a mixed within and between estimator developed by Bartels (2008a). The model, using a simplified bivariate version, is structured as follows:

|  |
| --- |
| $$ΔY\_{ij}=γ00\_{}+α\_{1}Y\_{ij\left(t-1\right)}+β\_{1}ΔX\_{1ij}^{W}+β\_{2}X\_{1ij\left(t-1\right)}^{W}+γ\_{01}\acute{X}\_{1j}+u\_{0j}+e\_{ij}$$ |

The model has several notable features. First, two different versions of each explanatory variable are included in the model. $\acute{X}$$\acute{X}$ is the “between” version of the each variable, which is the state-specific mean. This version of the variable will, by construction, not vary over time but will capture the between unit effects of the variable. $X\_{ij}^{W}$$X\_{ij}^{W}$ is the “within” version of the variable, calculated as $X\_{ij}^{W}=X\_{ij}-\acute{X}\_{j}$$X\_{ij}^{W}=X\_{ij}-\acute{X}\_{j}$. Since the within-state mean is subtracted from the observed value at each time point, the “within” version captures only over time movement, removing any unit effects. Second, the model is estimated with a random intercept, which is why the error term is partitioned into a within-state (eij) and between-state (u0j) component. Finally, we account for dynamics in the within portion of the model by estimating an error correction model (ECM).

Regarding the error correction portion of the model, the key point to understand is that for each independent variable X we have up to two parameter estimates—β1 for the differenced variable and β2 for the lagged level of the variable. If either of these coefficient estimates indicates a statistically significant relationship, then it is appropriate to conclude that the explanatory variable has a relationship with the dependent variable (if β2 is significant then α1 must also be significant to conclude that a relationship is present). In this simple bivariate example, β1 provides an estimate of the initial change in the dependent variable produced in the short term by a shock to the independent variable. This is called the “short term” effect, not meaning that the effect is impermanent but that the effect occurs wholly at a specific point in time. β2 and α1 provide the information needed to estimate the slightly more complicated “long term” impact. This is also called the error correction component of the model. The long term impact is the portion of the connection between X and Y that does not occur at one particular point in time but is distributed temporally such that a portion of the impact is felt in each period over a time span. The size of this long run impact is a function not only of β2 but also of α1, which is known as the error correction rate. The total long-term impact of a shock to X on Y via the error correction component, the long run multiplier, is computed by dividing β2 by α1. The only departure from the standard error correction approach used in this analysis is that due to very different levels of gross state product or GSP per capita among states, we utilize the percentage change in GSP, or the GSP growth rate, rather than the raw differenced variable.[[1]](#endnote-1)

### Appendix E. Replication of Economic Policy Liberalism Analysis

|  |
| --- |
| **Table E1. Effect of Class Bias on Left Government Power and Economic Policy Liberalism** |
|  |  |  |
|  | ΔEcon. Policy Liberalism*t* (alternative measure) |
| ***Error Correction Rate***  |  |  |
| Econ. Policy Liberalism*t*-1  | -0.019\*\*\* | (0.004) |
|  |  |  |
| ***Within State Effects***  |  |  |
| Δ Voting Class Bias*t*  | -0.150 | (0.166) |
| Voting Class Bias*t*-1  | -0.058 | (0.152) |
| Δ Public Mood*t*  | -0.000 | (0.003) |
| Public Mood*t*-1  | -0.001 | (0.002) |
| Mood*t*-1 × Bias*t*-1  | -0.001 | (0.026) |
| Δ Gross State Product*t*  | 3.567\* | (1.880) |
| Gross State Product*t*-1  | 0.112 | (0.118) |
| Δ Percent Non-White*t*  | 0.152 | (0.411) |
| Percent Non-White*t*-1  | -0.489\*\*\* | (0.183) |
| Δ Percent 65 or Older*t*  | -4.537 | (8.369) |
| Percent 65 or Older*t*-1  | 0.181 | (1.057) |
| Δ Union Density | -0.259 | (0.415) |
| Union Density*t*-1 | -0.014 | (0.289) |
|  |  |  |
| ***Between State Effects***  |  |  |
| Voting Class Bias  | 3.045\*\* | (1.481) |
| Public Mood  | 0.030\*\* | (0.012) |
| Mood × Bias  | -0.078\*\* | (0.037) |
| Gross State Product  | -0.206 | (0.174) |
| Percent Non-White  | -0.044 | (0.062) |
| Percent 65 or Older  | 0.238 | (0.290) |
| Union Density | 0.114 | (0.113) |
|  |  |  |
| Constant  | -1.139\*\* | (0.480) |
|  |  |  |
| Observations  | 1500 |  |
| Wald2  | 121.242 |  |
| Random effects models with robust standard errors in parentheses. The delta symbol (Δ) indicates a first differenced variable and the *t*-1 subscript indicates that the variable has been lagged by one year. Within state effects represent the overtime effects of each variable while the between state effects represent the average effects of the variables across states. See Appendix D for a detailed discussion of the model estimation. The version of the Economic Policy Liberalism index examined here does not account for state collective bargaining rights (see Table B1) so that the effect of state union membership could be assessed.\* *p <* 0.10, \*\* *p <* 0.05, \*\*\* *p <* 0.01 |

###

### Appendix F. Exogeneity Tests

One of the central arguments of our study is that class bias in the electorate influences government responsiveness and as a result this unequal representation shapes the distribution of income. At the same time, we recognize the possibility that because income inequality may be associated with growing upper class bias in the interest system, inequality may indirectly lead to growing class bias in the longer-term. However, since we are interested in how less class bias would influence representation and ultimately inequality we still take class bias in turnout as a given, for the purposes of our analysis. We believe this approach is sound given that any influence inequality has on class bias will likely be observed over a relatively long period of time while our interest in the effect of class bias on inequality largely focuses on the short-term.

 To empirically check our modeling strategy in this regard, we conducted a set of exogeneity tests that assess the effect of income inequality on voting class bias. This is accomplished by replicating the models presented in Table 2 of the article, but instead of including each measure of income inequality (i.e., our two versions of the state Gini coefficient) as the dependent variable we include the measures as independent variables. We then use our measures of voting class bias as the dependent variable and examine whether income inequality affects class bias. The results are shown below in Table E1 with the effects of inequality highlighted in bold. Since none of the results indicate a statistically significant relationship between the Gini coefficient and class bias we can be confident in the results we present in the main text.

|  |
| --- |
| **Table F1: Exogeneity Tests of the Effect of Income Inequality on Voting Class Bias** |
|  |  |  |
|  | Δ Voting Class Bias*t* | Δ Voting Class Bias*t* |
| ***Error Correction Rate***  |  |  |
| Voting Class Bias*t-1* | -0.222\*\*\* | -0.220\*\*\* |
|  | (0.016) | (0.016)  |
| ***Within State Effects***  |  |  |
| Δ Pre-Redistribution Gini*t* | **0.071** |   |
|  | **(0.091)** |   |
| Pre-Redistribution Gini*t-1* | **-0.019** |   |
|  | **(0.098)** |   |
| Δ Post-Cash Transfer Gini*t* |  | **-0.036**  |
|  |  | **(0.093)**  |
| Post-Cash Transfer Gini*t-1* |  | **-0.042**  |
|  |  | **(0.102)**  |
| Δ Left Gov. Power*t*  | 0.013 | 0.012  |
|  | (0.010) | (0.010)  |
| Left Gov. Power*t*-1  | -0.010 | -0.009  |
|  | (0.006) | (0.007)  |
| Δ Econ. Policy Liberalism*t*  | -0.007 | -0.007  |
|  | (0.006) | (0.006)  |
| Econ. Policy Liberalism*t*-1  | 0.003\* | 0.003\*  |
|  | (0.002) | (0.002)  |
| Δ Democratic President*t*  | 0.001 | 0.002  |
|  | (0.004) | (0.004)  |
| Democratic President*t*-1  | 0.006\* | 0.006\*  |
|  | (0.004) | (0.003)  |
| Δ Congress Percent Democrat*t*  | 0.217\*\*\* | 0.201\*\*\* |
|  | (0.047) | (0.047)  |
| Congress Percent Democrat*t*-1  | 0.140\*\*\* | 0.132\*\*\* |
|  | (0.042) | (0.045)  |
| Δ Manufacturing, Percent GSP*t*  | 0.389\*\*\* | 0.397\*\*\* |
|  | (0.109) | (0.107)  |
| Manufacturing, Percent GSP*t*-1  | -0.026 | -0.029  |
|  | (0.032) | (0.035)  |
| Δ Gross State Product*t*  | -0.223 | -0.239  |
|  | (0.157) | (0.159)  |
| Gross State Product*t*-1  | -0.007 | -0.006  |
|  | (0.011) | (0.011)  |
| Δ Percent Non-White*t*  | 0.212\*\*\* | 0.217\*\*\* |
|  | (0.064) | (0.064)  |
| Percent Non-White*t*-1  | 0.089\*\*\* | 0.092\*\*\* |
|  | (0.028) | (0.028)  |
| Δ Percent 65 or Older*t*  | -0.921 | -0.826  |
|  | (1.321) | (1.336)  |
| Percent 65 or Older*t*-1  | 0.339\*\* | 0.327\*\*  |
|  | (0.139) | (0.154)  |
| ***Between State Effects***  |  |  |
|  Pre-Redistribution Gini |  **0.108** |  |
|  |  **(0.102)** |  |
|  Post-Cash Transfer Gini |  |  **0.155**  |
|  |  |  **(0.151)**  |
| Left Gov. Power  | 0.006 | 0.006  |
|  | (0.009) | (0.010)  |
| Econ. Policy Liberalism  | -0.000 | -0.000  |
|  | (0.001) | (0.001)  |
| Manufacturing, Percent GSP  | 0.006 | 0.010  |
|  | (0.022) | (0.022)  |
| Gross State Product  | -0.002 | -0.003  |
|  | (0.016) | (0.017)  |
| Percent Non-White  | -0.005 | -0.008  |
|  | (0.015) | (0.015)  |
| Percent 65 or Older  | -0.230\*\* | -0.199\*\*\* |
|  | (0.092) | (0.071)  |
| Constant  | -0.029 | -0.040  |
|  | (0.048) | (0.065)  |
| Observations  | 1500 | 1500 |
| Wald2  | 1138.066 | 974.731 |
| Random effects models with robust standard errors in parentheses. The delta symbol (Δ) indicates a first differenced variable and the *t*-1 subscript indicates that the variable has been lagged by one year. Within state effects represent the overtime effects of each variable while the between state effects represent the average effects of the variables across states. See Appendix D for a detailed discussion of the model estimation. |
| \* *p <* 0.10, \*\* *p <* 0.05, \*\*\* *p <* 0.01 |

### References to the Appendices

Bartels, Brandon. 2008. “Beyond ‘Fixed Versus Random Effects’: A Framework for Improving Substantive and Statistical Analysis of Panel, TSCS, and Multilevel Data.” *The Society for Political Methodology*, 1–42.

Bartels, Larry M. 1996. “Uninformed Votes: Information Effects in Presidential Elections.” *American Journal of Political Science* 40 (1): 194–230. doi:10.2307/2111700.

———. 2002. “Beyond the Running Tally: Partisan Bias in Political Perceptions.” *Political Behavior* 24 (2): 117–50.

Bartels, Larry M. 2003. “Democracy with Attitudes.” In *Electoral Democracy*, edited by Michael MacKuen and George Rabinowitz, 48–82. Ann Arbor, MI: University of Michigan Press.

Bartels, Larry M. 2005. “Homer Gets a Tax Cut: Inequality and Public Policy in the American Mind.” *Perspectives on Politics* 3 (1): 15–31.

———. 2007. “Homer Gets a Warm Hug: A Note on Ignorance and Extenuation.” *Perspectives on Politics* 5 (4): 785–90.

———. 2008. *Unequal Democracy: The Political Economy of the New Gilded Age*. Princeton, NJ: Princeton University Press.

Bartels, Larry M, Hugh Heclo, Rodney E Hero, and Lawrence R Jacobs. 2005. “Inequality and American Governance.” In *Inequality and American Democracy: What We Know and What We Need to Learn*, edited by Lawrence R Jacobs and Theda Skocpol, 88–155. New York, NY: Russell Sage Foundation.

Bartels, Larry M., and John Zaller. 2001. “Presidential Vote Models: A Recount.” *PS: Political Science & Politics* 34 (01): 9–20.

Hirsch, Barry T. and David A. MacPherson. 2003. “Union Membership and Coverage Database from the Current Population Survey: Note.” *Industrial & Labor Relations Review* 56(2):349– 354.

Page, Benjamin I., Larry M. Bartels, and Jason Seawright. 2013. “Democracy and the Policy Preferences of Wealthy Americans.” *Perspectives on Politics* 11 (01): 51–73.

1. This was necessary because even after adjusting gross state product by population the very different magnitudes of gross state product per capita can mask the relative magnitude of economic growth or decline. For example, in California a $2,000 dollar increase in per capita gross state product would actually represent much slower economic growth than a $2,000 increase in per capita gross state product in Alabama, because the latter has a much lower level of gross state product per capita. [↑](#endnote-ref-1)