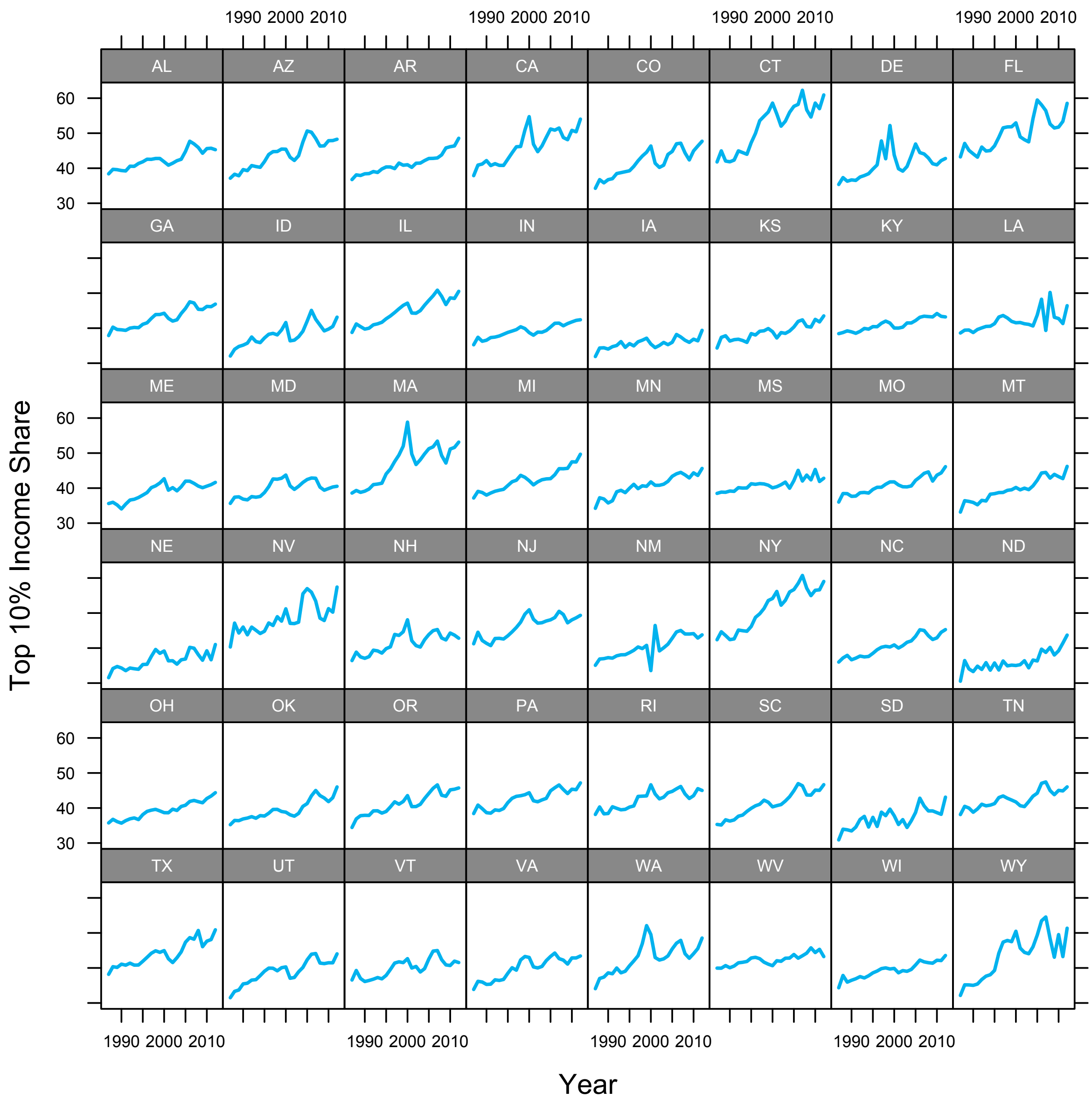
Appendix A: Additional Materials and Analyses

Figure A.1: Trends in State Top 10% Income Share, 1987-2012



Source: Frank et al. (2015).

Table A.1: The Effect of State Income Inequality on Public Perceptions of Growing Inequality, Top 1% Income Share State Ideology Subsamples

	Δ Perceptions of Growing Inequality			
	Liberal States		Conservative States	
	b	*(se)*	*b*	*(se)*
Error Correction Rate				
Perceived Inequality$_{t-1}$	-0.78***	(0.05)	-0.82***	(0.07)
Long-Run Coefficients				
Top 1% Income Share$_{t-1}$	0.94***	(0.23)	0.93***	(0.20)
Unemployment Rate$_{t-1}$	0.66**	(0.21)	0.45	(0.28)
Poverty Rate$_{t-1}$	0.51*	(0.23)	0.22	(0.18)
Policy Liberalism$_{t-1}$	1.53	(2.45)	6.76*	(3.36)
Median Income$_{t-1}$	-0.01	(0.11)	-0.11	(0.12)
Percent White$_{t-1}$	2.03	(1.64)	1.23	(1.85)
Short-Run Coefficients				
Δ Top 1% Income Share	0.45**	(0.16)	0.73***	(0.14)
Δ Unemployment Rate	0.38*	(0.19)	0.18	(0.31)
Δ Poverty Rate	0.19	(0.15)	0.24*	(0.11)
Δ Policy Liberalism	1.84	(1.61)	3.42	(2.93)
Δ Median Income	-0.06	(0.09)	0.01	(0.08)
Δ Percent White	0.15	(0.82)	1.71	(1.98)
Constant	-154.17	(152.53)	-23.59	(140.99)
N	525		600	
Wald Chi^2	722.05		333.09	

$^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Entries are mean-group estimator coefficients with standard errors in parentheses. Each model specification includes a time trend—these estimates are not included in the table. Liberal states are identified as those that have above average policy liberalism scores and conservative states are those that are below the mean.

Table A.2: The Effect of State Income Inequality on Public Perceptions of Growing Inequality, Top 10% Income Share State Ideology Subsamples

	Δ Perceptions of Growing Inequality			
	Liberal States		Conservative States	
	b	*(se)*	*b*	*(se)*
Error Correction Rate				
Perceived Inequality$_{t-1}$	-0.77***	(0.05)	-0.81***	(0.06)
Long-Run Coefficients				
Top 10% Income Share$_{t-1}$	0.60**	(0.22)	0.88***	(0.15)
Unemployment Rate$_{t-1}$	0.24	(0.15)	0.26	(0.20)
Poverty Rate$_{t-1}$	0.67***	(0.20)	0.26	(0.17)
Policy Liberalism$_{t-1}$	0.81	(2.53)	7.18*	(3.60)
Median Income$_{t-1}$	0.01	(0.11)	-0.02	(0.12)
Percent White$_{t-1}$	2.07	(1.55)	1.79	(1.88)
Short-Run Coefficients				
Δ Top 10% Income Share	0.26	(0.16)	0.71***	(0.11)
Δ Unemployment Rate	0.20	(0.14)	-0.01	(0.23)
Δ Poverty Rate	0.28*	(0.14)	0.31**	(0.11)
Δ Policy Liberalism	1.96	(1.57)	4.91	(3.51)
Δ Median Income	-0.04	(0.09)	0.05	(0.08)
Δ Percent White	0.79	(0.87)	2.42	(2.13)
Constant	-169.90	(144.38)	-99.32	(145.02)
N	525		600	
Wald Chi^2	501.64		340.91	

$^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Entries are mean-group estimator coefficients with standard errors in parentheses. Each model specification includes a time trend—these estimates are not included in the table. Liberal states are identified as those that have above average policy liberalism scores and conservative states are those that are below the mean.

Table A.3: The Effect of State Income Inequality on Public Perceptions of Growing Inequality, Gini Coefficient State Ideology Subsamples

	Δ Perceptions of Growing Inequality			
	Liberal States		Conservative States	
	b	*(se)*	*b*	*(se)*
Error Correction Rate				
Perceived Inequality$_{t-1}$	-0.84***	(0.05)	-0.87***	(0.07)
Long-Run Coefficients				
Gini Coefficient$_{t-1}$	0.72***	(0.16)	0.73***	(0.13)
Unemployment Rate$_{t-1}$	0.27	(0.25)	0.24	(0.20)
Poverty Rate$_{t-1}$	0.19	(0.20)	0.21+	(0.13)
Policy Liberalism$_{t-1}$	-0.78	(2.24)	3.75	(3.09)
Median Income$_{t-1}$	-0.07	(0.10)	0.03	(0.11)
Percent White$_{t-1}$	1.41	(1.48)	0.06	(1.55)
Short-Run Coefficients				
Δ Gini Coefficient	0.56***	(0.11)	0.35**	(0.11)
Δ Unemployment Rate	-0.10	(0.15)	-0.54**	(0.20)
Δ Poverty Rate	0.03	(0.15)	0.26**	(0.09)
Δ Policy Liberalism	0.99	(1.57)	2.38	(2.66)
Δ Median Income	-0.07	(0.10)	0.05	(0.07)
Δ Percent White	-0.10	(0.99)	1.79	(2.10)
Constant	-101.99	(137.57)	40.92	(116.07)
N	525		600	
Wald Chi^2	379.39		280.01	

$^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Entries are mean-group estimator coefficients with standard errors in parentheses. Each model specification includes a time trend—these estimates are not included in the table. Liberal states are identified as those that have above average policy liberalism scores and conservative states are those that are below the mean.

Table A.4: The Effect of State Income Inequality on Public Perceptions of Growing Inequality, Including Per Capita Income

	Δ Perceptions of Growing Inequality					
	Top 1%		Top 10%		Gini	
	b	*(se)*	*b*	*(se)*	*b*	*(se)*
Error Correction Rate						
Perceived Inequality$_{t-1}$	-0.81***	(0.04)	-0.84***	(0.04)	-0.85***	(0.04)
Long-Run Coefficients						
Top 1% Income Share$_{t-1}$	1.01***	(0.16)				
Top 10% Income Share$_{t-1}$			0.72***	(0.15)		
Gini Coefficient$_{t-1}$					0.74***	(0.11)
Unemployment Rate$_{t-1}$	0.57***	(0.15)	0.41**	(0.15)	0.49**	(0.17)
Policy Liberalism$_{t-1}$	4.54+	(2.32)	3.58	(2.60)	1.72	(1.97)
Median Income$_{t-1}$	-0.22***	(0.06)	-0.17*	(0.07)	-0.11	(0.07)
Per Capita Income$_{t-1}$	-0.07	(0.32)	0.49	(0.33)	0.42	(0.30)
Percent White$_{t-1}$	2.93**	(1.09)	2.68*	(1.12)	1.13	(1.01)
Short-Run Coefficients						
Δ Top 1% Income Share	0.66***	(0.10)				
Δ Top 10% Income Share			0.50***	(0.10)		
Δ Gini Coefficient					0.44***	(0.10)
Δ Unemployment Rate	0.16	(0.17)	0.04	(0.20)	-0.37*	(0.18)
Δ Policy Liberalism	3.95*	(1.96)	4.65+	(2.44)	2.32	(1.81)
Δ Median Income	-0.13**	(0.05)	-0.12*	(0.05)	-0.06	(0.05)
Δ Per Capita Income	-0.25	(0.24)	0.22	(0.28)	0.24	(0.24)
Δ Percent White	1.31	(1.06)	1.46	(1.12)	0.41	(1.20)
Constant	-195.31*	(92.80)	-192.15*	(95.68)	-71.47	(85.54)
N	1200		1200		1200	
Wald Chi^2	553.35		536.23		525.12	

$^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: These results replicate the first model presented in Tables 1, 2, and 3 of the main text with the addition of a variable accounting for per capita income. Entries are mean-group estimator coefficients with standard errors in parentheses. Each model specification includes a time trend—these estimates are not included in the table.

Table A.5: The Effect of State Income Inequality on Public Perceptions of Growing Inequality Using Alternative Measure of State Ideology

	Δ Perceptions of Growing Inequality					
	Top 1%		Top 10%		Gini	
	b	*(se)*	*b*	*(se)*	*b*	*(se)*
Error Correction Rate						
Perceived Inequality$_{t-1}$	-0.77***	(0.04)	-0.75***	(0.04)	-0.81***	(0.04)
Long-Run Coefficients						
Top 1% Income Share$_{t-1}$	0.90***	(0.15)				
Top 10% Income Share$_{t-1}$			0.74***	(0.15)		
Gini Coefficient$_{t-1}$					0.67***	(0.11)
Unemployment Rate$_{t-1}$	0.72***	(0.18)	0.52***	(0.13)	0.31*	(0.14)
Policy Mood$_{t-1}$	0.12+	(0.07)	0.09	(0.06)	0.12*	(0.05)
Median Income$_{t-1}$	-0.03	(0.08)	-0.02	(0.07)	-0.00	(0.07)
Percent White$_{t-1}$	2.17+	(1.22)	2.41*	(1.15)	0.95	(1.13)
Short-Run Coefficients						
Δ Top 1% Income Share	0.60***	(0.09)				
Δ Top 10% Income Share			0.46***	(0.09)		
Δ Gini Coefficient					0.46***	(0.08)
Δ Unemployment Rate	0.43**	(0.14)	0.26*	(0.12)	-0.25*	(0.11)
Δ Policy Mood	0.07	(0.06)	0.04	(0.06)	0.09+	(0.05)
Δ Median Income	-0.01	(0.05)	-0.01	(0.05)	0.01	(0.05)
Δ Percent White	0.69	(1.08)	1.25	(0.98)	0.44	(1.41)
Constant	-141.70	(106.66)	-175.52+	(101.77)	-49.00	(93.11)
N	1200		1200		1200	
Wald Chi^2	535.81		549.23		627.97	

$^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: These results replicate the first model presented in Tables 1, 2, and 3 of the main text with Enns and Koch's (2013) measure of state policy mood used as an alternative to Caughey and Warshaw's (2016) measure of state policy liberalism. Entries are mean-group estimator coefficients with standard errors in parentheses. Each model specification includes a time trend—these estimates are not included in the table.

Appendix B: Estimating State Perceptions of Inequality Over Time

Since a central goal of this study is to better understand the public's perceptions of economic inequality while taking into account state economic and political context, a measure of perceptions over time for each state is required. A main barrier is that survey questions asking people about income inequality are rarely asked consistently from year to year. This is the case for survey research on inequality in general, which means measuring opinion within the states is an even greater challenge since many surveys conducted in the U.S. are designed to make inferences about the nation as a whole. So two main issues must be addressed in order to evaluate perceptions of inequality: (1) a survey question is needed, one asked regularly over time, that captures the extent to which individuals comprehend growing economic inequality; and (2) the question used should be included in a survey designed in such a way that it allows for estimates of opinion at the state level.

Fortunately, both issues can be resolved. While it is true that few survey questions consistently ask about income inequality, one question in particular has been asked by several polling organizations dating back to the 1980s. The relatively straightforward question asks if people believe "the rich are getting richer and the poor are getting poorer." Not only has the question been asked regularly over time, but it also uses a simple comparison—between those who are rich and those who are poor—to tap into perceptions of income differences. Additionally, the question does not ask about a specific time frame and does not mention any geographic context, allowing individuals to give their general view on the state of inequality without focusing exclusively on the national or local economic environment. Altogether, the question was asked on 34 national surveys during the 1987-2012 period, with an average of more than 1,500 respondents per survey and a combined total of over 53,000 individuals polled. Table B.1 provides more information on the polling organizations that conducted the surveys and the years the surveys were conducted, the exact question wording, coding, and sources. In addition to general web searches, the Roper Center's iPOLL Databank (`http://www.ropercenter.uconn.edu/data_access/ipoll/ipoll.html`) and the Polling the Nations database (`http://poll.orspub.com/`) were used to find all instances of the "rich getting richer" question being asked. With all of this survey data from national samples of American adults, the question now becomes how these national surveys can be used to estimate state-level opinion.

The most common approach to measuring state opinion in the absence of polls specifically designed to sample state populations (which are quite rare) is to use some form of disaggregation. Disaggregation generally involves combining many national surveys and then disaggregating responses by state. Since the common sample size of a national survey is around 1,000 respondents, the main drawback of this method is that a large number of surveys are required in order to produce accurate estimates of state opinion. Disaggregation is particularly problematic for this study since not nearly enough polls asked the rich-poor question to measure state opinion over time for every state. Recent advances in public opinion estimation, however, have given researchers an alternative to disaggregation when studying attitudes at the state-level. Multilevel regression and post-stratification (MRP) is a measurement strategy that allows for the estimation of state opinion using typical national opinion polls. Research has shown that MRP provides accurate estimates of state and local opinion even when using a single national survey (Lax and Phillips 2009*a*;*b*; 2012; Park, Gelman and Bafumi 2006). This is the approach taken here to create a unique measure of state-level perceptions of growing economic inequality.[1]

Estimating opinion using MRP involves two steps. The first is to model individual responses to the survey question of interest—in this case, whether the individual agrees or disagrees with "the rich are getting richer and the poor are getting poorer" statement—using multilevel regression. These models include basic demographic and geographic characteristics of the survey respondents. Similar to pervious work, this study uses the following characteristics to model perceptions of inequality: race (black, white, or other), gender (female or male), age (18-29, 30-44,

[1] See Lax and Phillips (2009*b*) for a review of the pros and cons of different approaches to measuring state opinion and a detailed discussion of the MRP process.

45-64, or 65+), education (less than high school graduate, high school graduate, some college, or college graduate), state of residence (all 50 states and D.C.),[2] the percentage of Republican Party identifiers in each state, the year of the survey (more on this below), and an indicator for each survey used to account for any potential differences across polls. The results of the model are then used to predict the probability of agreeing that inequality is growing for every possible individual type (e.g., a white female who is 30-44 years of age with some college education living in Ohio), resulting in a total of 4,896 predicted values. These probabilities are then used in the second step of the estimation, which is post-stratification. Post-stratification is the process of weighting each individual type probability estimate by the actual proportion of each type in the population using data from the U.S. Census.[3] This part of the procedure adjusts for any differences between the individuals surveyed in each state and the true state population.

The strategy for creating the over time state opinion estimates developed here departs from previous studies using MRP to measure attitudes over time. One potential strategy to account for change in opinion over time using MRP is to complete the steps described above for each year under analysis (see Enns and Koch 2013). This approach is most useful when the questions used to measure opinion are asked several times every year so that enough respondents from smaller states are used to have more precise over time estimates. While the "rich are getting richer" question is asked regularly, it is only asked more than once in a given year on a few occasions. When the survey questions being examined are not asked multiple times on an annual basis, an alternative option is to increase state sample sizes by combining surveys across multiple years. Rather than estimating state opinion for every year, surveys are pooled over specified blocks of time (e.g., a

[2] Although all available respondents from all states are included in the individual models, many surveys did not interview residents of Alaska and Hawaii. This means that most years do not have opinion estimates for these states and they are not included in the analysis presented in the main text.

[3] The Census's Public Use Microdata Samples are used for the post-stratification stage, which include the 1990 5% sample of population and housing, the 2000 5% sample of population and housing, and the five-year American Community Survey data are used for 2005-2011. Linear interpolation is used to estimate each population type for years between these surveys.

three- or five-year window) to increase the amount of information used when modeling opinion (see Pacheco 2011).

This study expands on these methods by using a completely pooled approach to estimate state opinion over time. In other words, all available survey questions for all available years are included in a single model of individual opinion (i.e., the first step of MRP). The procedure is relatively straightforward and only requires researchers to add a time component to their multilevel model. An indicator of time (in this case, the year the survey was conducted) is interacted with state of residence so that a random effect is allowed for every state-year combination.[4] This allows for unique estimates of opinion for each state over time by using all available information in one model. The result is a series of aggregate state opinion from 1987 to 2012 indicating the percentage of the public agreeing with the "rich are getting richer" statement.[5] This variable is used throughout this study to account for state-level perceptions of inequality.

Measurement Validity

To assess the accuracy of the state perceptions of inequality measure used in this study's analyses, a number of simulations were conducted to compare the estimates produced using multilevel regression and post-stratification (MRP) to those produced using the straightforward disaggregation method. The approach used here is similar to existing research that uses estimates based on the MRP procedure discussed in the main text (e.g., Lax and Phillips 2009*b*; Pacheco 2011), with the intention of demonstrating the general precision of MRP and its level of precision relative

[4] This is an extension of the initial MRP modeling strategy suggested by Lax and Phillips (2009*b*). Instead of only allowing a random effect for every state, a random effect is estimated for every state-year. The method extends the logic of partial pooling across states to partial pooling across states and time. It should be noted that simply adding a time component to the multilevel model without interacting the term with the state indicator (or some other geographic identifier) will not produce a dynamic opinion series.

[5] Due to survey data limitations (see Table B.1), estimates of perceived inequality could not be calculated for some years. Following previous studies (Pacheco 2014; Soroka and Wlezien 2010), linear interpolation is used to complete the time-series for these years.

to disaggregation. This is accomplished by first creating baseline estimates of state inequality perceptions that can be used as target values to evaluate the performance of MRP and disaggregation. The perceived inequality baseline values are created by simply pooling all of the available polling data used in this study (see Table B.1)—totaling over 50,000 observations—and then calculating the average response to the question asking about the difference between the rich and the poor in each state.[6]

The next step is to randomly sample the pooled survey responses to examine the performance of MRP and disaggregation estimates when using a range of sample sizes. Samples of 10%, 5%, and 2% of the pooled responses are used here, which correspond to sample sizes of approximately 5,000, 2,500, and, 1,000 total respondents, respectively. For each sample size, 200 simulations are conducted where a sample is drawn and state estimates of perceived inequality are produced using both the MRP procedure and the basic disaggregation method for each simulation. Finally, for each simulated estimate the values generated using MRP and disaggregation can be assessed for accuracy. First, each simulation is compared to the baseline state estimates by calculating the mean absolute error across all states and each set of simulations (i.e., the absolute difference between the baseline value and both the MRP and disaggregation estimates). Second, the average standard deviation for each set of simulations across all states is calculated to get a sense of the relative variation produced by each measurement method.

The results of the simulations are presented in Figure B.1. The top panel of the plot demonstrates the mean absolute error for the MRP and disaggregation measurement approaches across states and simulations for each sample size, and the bottom panel shows the average standard deviation of the MRP and disaggregation estimates for each sample size across states and simulation runs. The results of the simulations suggest that MRP creates more accurate estimates of state per-

[6] Even after pooling all available polling data, the overall number of observations in some states was still somewhat small. To ensure that the baseline estimates of perceived inequality are as accurate as possible, only those states with more than 300 respondents are included in the validation exercise. A total of 38 states meet this criterion and they are used as the basis of comparison for the MRP and disaggregation results.

ceived inequality than disaggregation and that the MRP estimates tend to have less fluctuation than the disaggregation method. Additionally, the relative accuracy and stability of the MRP estimates improves when sample sizes are smaller. For instance, the difference between the mean absolute error produced by MRP and disaggregation when using the 2% sample is around four times larger than the difference produced when using the 10% sample. In other words, the value of using MRP over disaggregation increases as the survey sample size decreases.

A separate analysis comparing MRP and disaggregation estimates of inequality perceptions for the 16 largest states was also conducted. The 16 largest states were used since the number of survey respondents per state-year becomes quite small—an average of less than 70 per year—as more states are included. For the states that are included in the analysis, the number of state-year responses is certainly not ideal. On the high end, California has an average of 280 respondents per year while New York and Texas have approximately 200 state-year respondents on average. On the low end, Indiana, Missouri, Tennessee, Virginia, and Wisconsin all have, on average, between 70 and 85 survey responses per year. Even when considering these limitations of the data, the correlation between the MRP and disaggregation perceptions of growing inequality measures for these larger states is 0.86. As shown in Figure B.2, the MRP and disaggregation measures follow similar trajectories over time in each state, with the most obvious difference being the much higher variance for the disaggregation measure of perceived inequality. This is consistent with the simulations discussed above, where the disaggregation method produces much larger swings in its point estimates when compared with the MRP estimates.

Additionally, the models presented in Tables 1, 2, and 3 of the main text were replicated using the disaggregation measure of inequality perceptions in place of the MRP measure, and the results are presented in Table B.2. The estimated effects are substantively comparable to those presented in the main text for most of the central variables being examined. However, the results from the models using the disaggregation measure of inequality perceptions should be interpreted with caution. As demonstrated in the simulations above, measures based on simple disaggregation, particularly when sample sizes are small (which is the case here), are much less accurate and have much larger variances relative to the measures produced by MRP. Also, these models only include a small sample of states that are not representative of the American states more broadly.

Table B.1: Survey Questions Used to Estimate Public Perceptions of Economic Inequality

Polling Organization & Question Wording	Year of Survey	Coding
ABC News: I'm going to read a few statements, for each, please tell me if you agree or disagree with it ... The rich are getting richer and everyone else is getting poorer.	1996	1 = agree; 0 = disagree
CBS News: These days, do you feel that the rich are getting richer and everyone else is getting poorer, or is that not the case?	2011	1 = rich getting richer; 0 = not the case
CBS News/New York Times: These days, do you feel that the rich are getting richer and everyone else is getting poorer, or is that not the case?	2011	1 = rich getting richer; 0 = not the case
Harris Poll: Now, we want to ask you about some things some people have told us they have felt from time to time. Do you tend to feel that ... The rich get richer and the poor get poorer?	1991, 1996, 1997, 2002-2005, 2007-2009, 2011	1 = yes, feel this way; 0 = no, don't feel this way
Marttila & Kiley: Now I am going to read you a series of statements that will help us understand how you feel about a number of things. Please tell me whether you completely agree, mostly agree, mostly disagree, or completely disagree with each statement I read ... Today it's really true that the rich just get richer while the poor get poorer.	1992	1 = completely agree or mostly agree; 0 = mostly disagree or completely disagree
Pew Values Survey: I'm going to read you some more statements on a different topic. Please tell me how much you agree or disagree with each of these statements ... Today it's really true that the rich just get richer while the poor get poorer. Do you completely agree, mostly agree, mostly disagree, or completely disagree?	1987-1989, 1991, 1992, 1997, 1999, 2002, 2003, 2007, 2008, (Social Trends Survey), 2009, 2012	1 = completely agree or mostly agree; 0 = mostly disagree or completely disagree
Princeton Survey Research Associates: Here are some statements on a different topic. Please tell me how much you agree or disagree with each of these statements ... Today it's really true that the rich just get richer while the poor get poorer.	1991, 1992 (5)	1 = completely agree or mostly agree; 0 = mostly disagree or completely disagree

Note: The Harris Poll also asked the question in 1992 (2), 1993, 1994, 1999, and 2000, and the Pew Values Survey asked the question in 1990 and 1994. The question could not be used for these particular survey years, however, because state of residence identifiers are not included in the data.

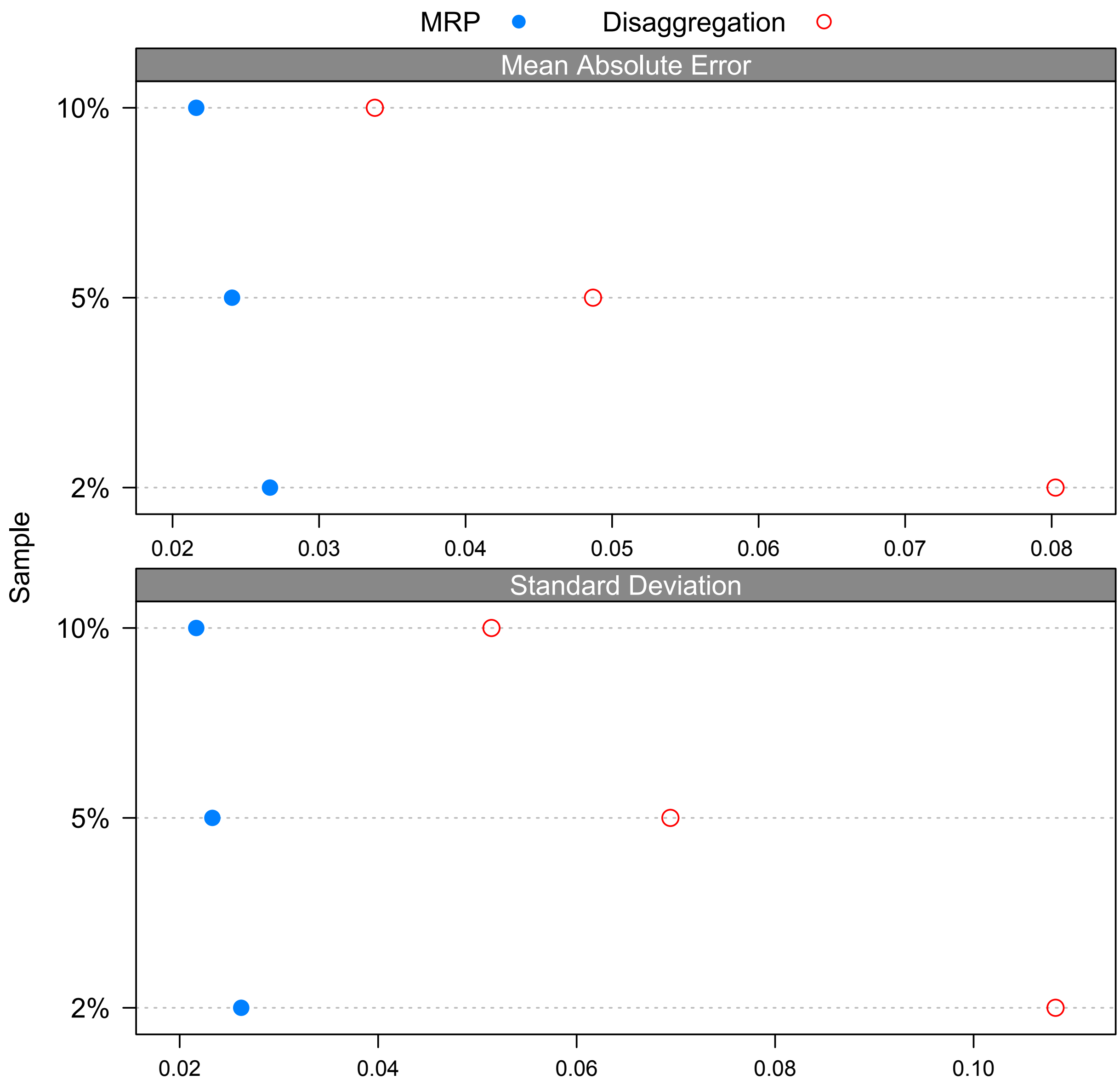
Source: The Harris Poll surveys were accessed through the Odum Institute's data archive (`http://www.odum.unc.edu/odum/`). The Pew Values Survey is available through the Pew Research Center's website (`http://www.people-press.org/values-questions/`). All other surveys were accessed using the Roper Center's iPOLL Databank (`http://www.ropercenter.uconn.edu/data_access/ipoll/ipoll.html`).

Table B.2: The Effect of State Income Inequality on Public Perceptions of Growing Inequality Using Disaggregation to Measure Perceptions

	Δ Perceptions of Growing Inequality (Disaggregation)					
	Top 1%		Top 10%		Gini	
	b	*(se)*	*b*	*(se)*	*b*	*(se)*
Error Correction Rate						
Perceived Inequality$_{t-1}$	-0.99***	(0.07)	-0.97***	(0.08)	-1.05***	(0.08)
Long-Run Coefficients						
Top 1% Income Share$_{t-1}$	2.57***	(0.58)				
Top 10% Income Share$_{t-1}$			1.51**	(0.51)		
Gini Coefficient$_{t-1}$					1.89***	(0.50)
Unemployment Rate$_{t-1}$	1.12+	(0.60)	-0.04	(0.55)	0.11	(0.39)
Policy Liberalism$_{t-1}$	13.98+	(7.29)	14.81+	(8.60)	8.68	(8.84)
Median Income$_{t-1}$	-0.43	(0.27)	-0.52	(0.32)	-0.09	(0.28)
Percent White$_{t-1}$	-2.06	(3.31)	-1.23	(3.29)	-0.83	(3.43)
Short-Run Coefficients						
Δ Top 1% Income Share	1.37**	(0.51)				
Δ Top 10% Income Share			0.67	(0.56)		
Δ Gini Coefficient					1.13**	(0.41)
Δ Unemployment Rate	0.53	(0.55)	-0.33	(0.47)	-1.13*	(0.49)
Δ Policy Liberalism	4.37	(4.64)	5.59	(5.29)	6.43	(5.67)
Δ Median Income	-0.32	(0.24)	-0.34	(0.27)	-0.20	(0.27)
Δ Percent White	-0.42	(2.38)	0.93	(2.45)	0.19	(1.68)
Constant	247.69	(291.59)	161.99	(288.15)	71.11	(303.19)
N	400		400		400	
Wald Chi^2	363.66		569.45		1028.86	

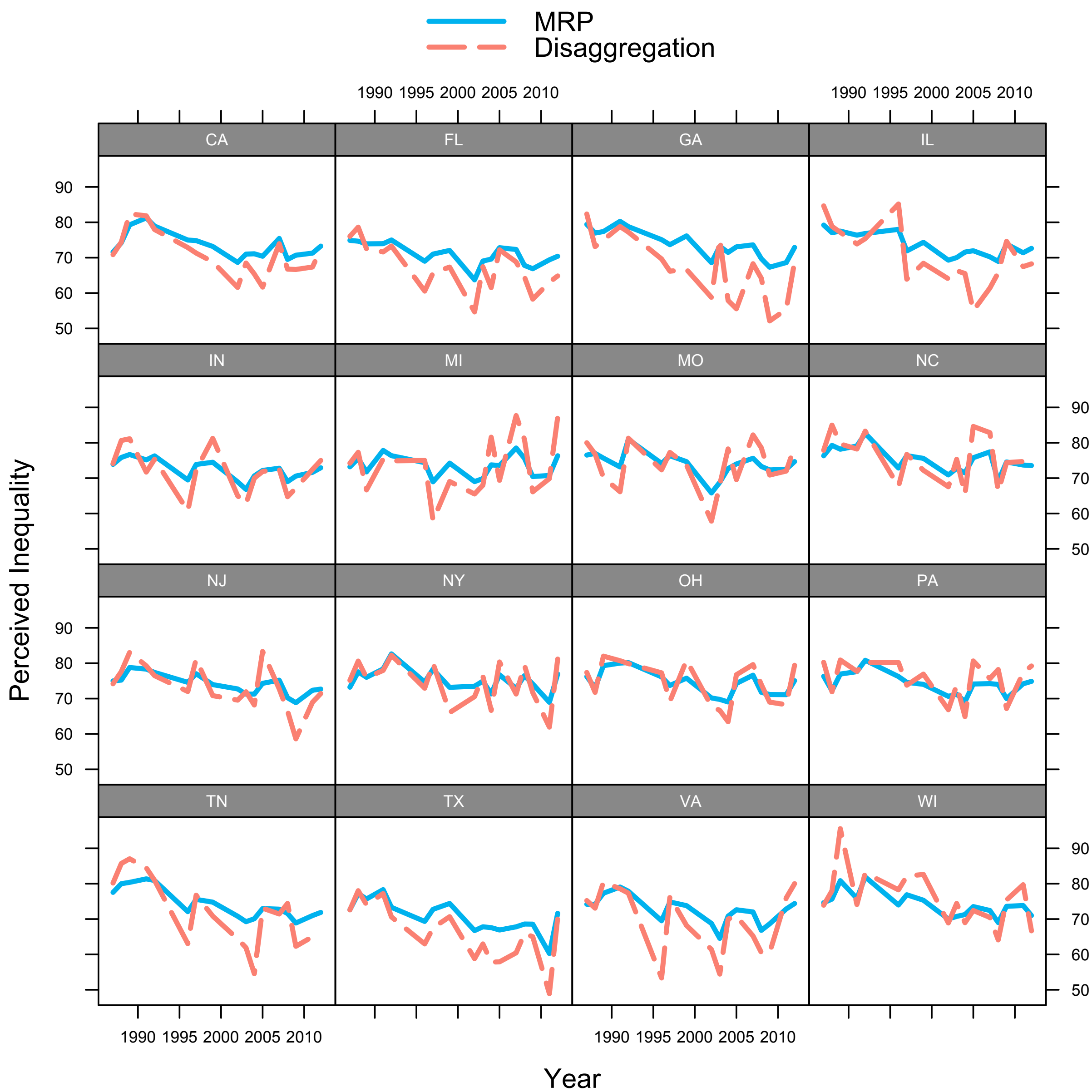
$^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: These results replicate the first model presented in Tables 1, 2, and 3 of the main text, with the difference being that the perceived inequality variable (i.e., the dependent variable) is measured using disaggregation rather than MRP. Entries are mean-group estimator coefficients with standard errors in parentheses. Each model specification includes a time trend—these estimates are not included in the table.

Figure B.1: Comparing Simulation Estimates of State Perceived Inequality Using MRP and Disaggregation



Note: The top panel plots the mean absolute error between a baseline target value and both the MRP and disaggregation measurement approaches across states and simulations for each sample size. The bottom panel shows the average standard deviation of the MRP and disaggregation estimates for each sample size across states and simulation runs. The MRP and disaggregation estimates were simulated 200 times for each sample size.

Figure B.2: Measures of State Perceived Inequality Over Time Using MRP and Disaggregation for the 16 Largest States



Note: The correlation between the MRP and disaggregation measures for the 16 states is 0.86. The states presented in the plot have a minimum average of 70 respondents per state-year.

Appendix C: Modeling Perceptions of State Income Inequality

Since this study examines aggregate perceptions of inequality over time at the state level, a modeling approach for time-series cross-sectional (TSCS) data is needed. To assess whether the public's understanding of inequality has followed objective measures of income inequality, an error correction model (ECM) is used to estimate the relationship between changes in perceived inequality and actual shifts in state income differences. The following equation, which includes only a single independent variable for clarity, is used to model perceptions of inequality:

$$\Delta y_{it} = b_0 + a_1 y_{i(t-1)} + b_1 \Delta x_{1it} + b_2 x_{1i(t-1)} + e_{it}$$

The ECM is employed here since it is one of the most general time-series models and allows researchers to account for both long- and short-term effects over time (De Boef and Keele 2008; Kelly and Enns 2010). In the above equation each observation is a particular state i in a given time period t. The first difference (denoted by the Δ symbol) of the dependent variable, perceptions of economic inequality, is regressed on a lagged version of the dependent variable and a lagged and differenced version of each explanatory variable. The effect of the independent variable on the dependent variable is represented by b_1 and b_2, with the former being an estimate of the short-term effect of the variable. The a_1 estimate—also referred to as the error correction rate—together with the b_2 coefficient provides the long-run effect of the variable. The total effect, or long-run multiplier, is estimated as $\frac{b_2}{-a_1}$. The main distinction to make between short- and long-term effects is that short-term effects occur immediately while long-term effects are distributed over time. When the effect of a variable is distributed over time, the long-run multiplier provides an estimate of the total effect of the variable for all periods.

When estimating the above equation, it is important to consider both over time dynamics and the potential for cross-sectional heterogeneity. One way to analyze TSCS data is to pool all states into a single model and attempt to control for cross-sectional differences using fixed effects or random intercepts. Both approaches, however, assume that the effect of each regressor in the model on the dependent variable is equal across states. If the effects are homogeneous, these models will produce accurate and consistent results. However, this homogeneity assumption is often not only conceptually inappropriate, but if the effects are not equivalent across groups the estimated model can lead to inconsistent results and misleading inferences (Frank 2009; Pesaran and Smith 1995). Furthermore, Pesaran and Smith (1995) show that incorrectly assuming effect homogeneity when using TSCS data is particularly problematic for dynamic time-series models (i.e., including a lagged dependent variable), which is the case for this analysis. An alternative approach, and the one used here, is to allow the coefficients, intercepts, and error variances to be uniquely estimated for each individual state, which produces consistent estimates when effects are heterogeneous. This is the model proposed by Pesaran and Smith (1995), referred to as the mean-group estimator, where separate time series models are estimated for each group (in this case, each state) and the effects are then averaged across all models to obtain a final set of estimates. More specifically, both the short-run (b_1) and long-run (b_2) mean-group coefficients, b_{MG}, are estimated by averaging the individual i coefficients from all N states:

$$b_{MG} = \frac{\sum_{i=1}^{N} b_i}{N};$$

and the standard errors of the MG coefficients are consistently estimated using (Pesaran and Smith 1995; Pesaran, Shin and Smith 1999):

$$se(b_{MG}) = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(b_i - b_{MG})^2}.$$

As a robustness check, the second model presented in Tables 1, 2, and 3 of the main text were replicated using fixed effects as an alternative to the mean-group estimator. The results are presented in Table C.1, and are largely consistent with the models discussed in the main text. The main difference between the two sets of results is that in the fixed-effect models, while the poverty rate is positive and statistically significant the significant effects are observed in the short-run rather than the long-run. Also, while the coefficients for state policy liberalism are positive (as expected) across all models, the estimates are not statistically different from zero when using the fixed-effects specification. Finally, while the estimated coefficients for the inequality indicators are significantly different from zero for both specifications, the magnitude of the coefficients are somewhat smaller in the fixed-effects models. In any case, the mean-group estimator is preferred over fixed-effects models for the reasons discussed above and the mean-group results are therefore the central focus of the analysis.

Stationarity tests were also conducted for each variable used in the analyses. In any time series model it is important to examine the order of integration of all variables used in the analysis to ensure that meaningful inferences can be made based on the model results. In general, each included variable should be of the same order—for example, all variables I(0) or all variables I(1)—meaning that only stationary variables should be used to model a stationary dependent variable and only non-stationary variables should be used to model a non-stationary dependent variable of the same order (see Enders 2015). The Fisher augmented Dickey-Fuller test, which is specifically designed for TSCS data, was used to assess whether the variables discussed above represent stationary series. The results of the tests indicate that nearly all variables for every state panel has a unit root (i.e., they are non-stationary series) with some exceptions. The panel unit-root tests for state poverty and citizen liberalism suggested that at least one series in the group was stationary. The two variables were more closely examined by conducting augmented Dickey-Fuller tests for each state separately to determine the balance of stationary and non-stationary series. The tests show that the poverty rate is stationary in three panels (Connecticut, Virginia, and Washington) and citizen liberalism is stationary in two (Alabama and South Carolina). Since these factors are potentially important in shaping perceptions of inequality, these states are simply excluded from the estimation when including these variables in the analyses.

Seeing that all of the series being used in the proposed analysis have unit roots, a central question is whether the measures of perceived inequality and objective inequality are cointegrated. If the variables are not cointegrated, then it would be unlikely to find a long-run relationship between changes in inequality and the public's perceptions of income differences. Using Pedroni's panel cointegration tests (Pedroni 2004) the null hypothesis of no cointegration between objective inequality and perceptions of inequality can be clearly rejected for all three measures of income inequality (i.e., the top 10% income share, top 1% income share, and the Gini coefficient).

Table C.1: The Effect of State Income Inequality on Public Perceptions of Growing Inequality, Fixed-Effects Models

	Δ Perceptions of Growing Inequality					
	Top 1%		Top 10%		Gini	
	b	*(se)*	*b*	*(se)*	*b*	*(se)*
Error Correction Rate						
Perceived Inequality$_{t-1}$	-0.50***	(0.03)	-0.50***	(0.03)	-0.52***	(0.03)
Long-Run Coefficients						
Top 1% Income Share$_{t-1}$	0.20***	(0.04)				
Top 10% Income Share$_{t-1}$			0.13**	(0.04)		
Gini Coefficient$_{t-1}$					0.19***	(0.04)
Unemployment Rate$_{t-1}$	0.35***	(0.06)	0.27***	(0.06)	0.24***	(0.06)
Poverty Rate$_{t-1}$	0.03	(0.05)	0.04	(0.05)	0.07	(0.05)
Policy Liberalism$_{t-1}$	0.36	(0.30)	0.26	(0.31)	0.30	(0.30)
Median Income$_{t-1}$	-0.03	(0.03)	-0.02	(0.03)	0.00	(0.03)
Percent White$_{t-1}$	0.02	(0.07)	-0.00	(0.07)	-0.06	(0.07)
Short-Run Coefficients						
Δ Top 1% Income Share	0.24***	(0.04)				
Δ Top 10% Income Share			0.15***	(0.04)		
Δ Gini Coefficient					0.17***	(0.05)
Δ Unemployment Rate	0.12	(0.08)	0.00	(0.07)	-0.10	(0.07)
Δ Poverty Rate	0.10*	(0.05)	0.11*	(0.05)	0.12**	(0.05)
Δ Policy Liberalism	0.68	(0.61)	0.71	(0.61)	0.85	(0.61)
Δ Median Income	0.00	(0.03)	0.01	(0.03)	0.03	(0.03)
Δ Percent White	-0.36*	(0.17)	-0.31+	(0.17)	-0.31+	(0.17)
Constant	33.64***	(7.00)	33.19***	(7.25)	32.23***	(7.09)
N	1125		1125		1125	

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: These results replicate the second model presented in Tables 1, 2, and 3 of the main text using fixed-effects models rather than the mean-group estimator. Entries are regression coefficients with standard errors in parentheses. Each model specification includes a time trend—these estimates are not included in the table.

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