

# Economic Inequality and Class Consciousness in the United States\*

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## Abstract

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\*Revision history and the materials needed to reproduce the analyses of this paper can be found [on Github here](#).

One of the most important questions underlying recent research on economic inequality and democracy is whether inequality in democratic contexts is self-correcting or instead self-reinforcing. Rational choice arguments have long maintained that, where economic inequality is higher, the benefit of more redistributive policies to the median voter and to those with below-median incomes will be greater, leading them to demand and achieve the adoption of higher taxes and more government spending to ameliorate unequal conditions between those with higher and lower incomes (see, e.g., Meltzer and Richard 1981).

[unequal democracy / relative power stuff]

A prominent recent study, Newman, Johnston, and Lown (2015, hereafter NJL), argues in favor of the former, more optimistic view. It contends that simply being exposed to high levels of local income inequality prompts those with lower incomes to become more likely to view the United States as divided into haves and have-nots and to see themselves as among the have-nots, that is, to become more likely to achieve a class consciousness vital to contesting the fairness of the economic system and mobilizing in favor of redistribution.

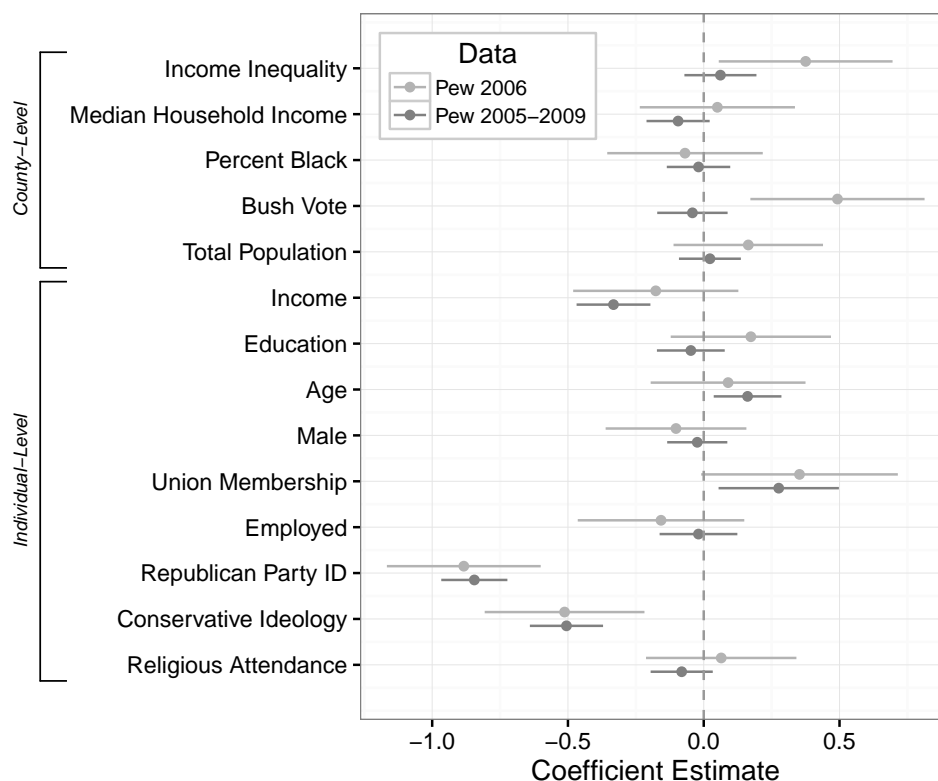
An important step in the process of conducting sound research is striving to utilize all available data. Researchers should seek to conduct their analysis on the entirety of data that they have at their disposal. Doing so provides a number of benefits: it increases the likelihood that the sample utilized captures the true distribution of the underlying population, and it affords greater leverage in testing the implications of one's hypothesis. While the issue of selection bias cannot be avoided simply by including all available data, limiting analysis to a particular dataset, particularly when alternatives are available, may cast doubt on the inferences drawn from that analysis. By including all relevant data researchers are better able to observe the implications of their theory, thus providing greater support for the hypotheses

they advance.

NJL claims to employ “an additional national data set conducted by the Pew Research Center in 2006 containing a unique set of questions tapping perceptions of economic hierarchy and inequality and respondents perception of their own position within such a hierarchy” (Newman, Johnston, and Lown 2015, 336). In reality, these questions are not unique to the 2006 dataset, but are instead present in a number of Pew surveys, including some used in the paper’s earlier analysis. Perhaps it is by coincidence that, as shown in Figure 2, the coefficient of interest only achieves statistical significance when using the 2006 data. As illustrated, no other dataset produces a statistically significant coefficient for Gini according to the authors’ model. This provides a clear illustration of the importance of including all relevant data; failure to do so can lead to biased results.

The authors’ use of this severely truncated data has implications beyond the coefficient of interest as well. While Figure 1 clearly demonstrates that a more careful inclusion of all data produce results that run counter to the findings of Newman et al, including all available data drastically changes the entire model, not merely the coefficient for Gini. Figure 1 provides estimates of the coefficients from Newman et al’s Table 2 (p. 336) with a sample that includes data from the 2005, 2006, 2007, and 2009 surveys they use earlier in their article. When all relevant data is included, the results are drastically different. Not only does the primary variable of interest (Gini coefficient) lose statistical significance, but others do as well. Having voted for Bush is no longer a statistically significant predictor of believing America is divided into the haves and have-nots, but income becomes strongly negative and significantly associated with the same belief. Additionally, union membership gains statistical significance, indicating that belonging to a union increases the likelihood an individual

Figure 1: Local Inequality and the Perception of America as Divided into ‘Haves’ and ‘Have-Nots’: Results Using All Available Data

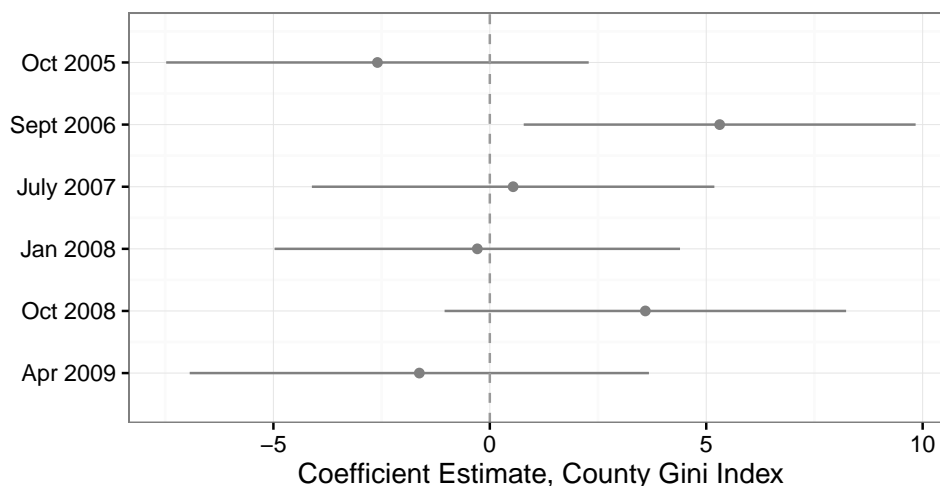


*Notes:* Dots indicate estimates; whiskers represent 95% confidence intervals. Results from replications of the model presented in Table 2 of Newman, Johnston, and Lown (2015) on the 2006 Pew survey analyzed in that article and on pooled data from the six Pew surveys that included the same item and were conducted in the time period the article examines. The statistically significant result for county income inequality in the 2006 survey presented in that article is not evident when all of the available data are examined.

perceives that have/have-not division. Ultimately, Figure 1 provides graphical representation of the dangers of not including all available data. By limiting their analysis to the sole dataset that produced a statistically significant coefficient for inequality, the authors have disguised the true relationship in order to support their theory. A properly crafted analysis reveals findings that are far less surprising; the wealthy are less likely to see America as divided into the haves and have-nots, while union members are more likely to do so. These

findings counter the primary argument advanced by NJL, and lend strong evidence to the claim that “we should be willing to take whatever information we can acquire so long as it helps us learn about the veracity of our theory,” while illustrating the pitfall of picking and choosing data that confirm our theory, while ignoring data that does not (King, Keohane, and Verba 1994, 31).

Figure 2: Local Inequality and the Perception of America as Divided into ‘Haves’ and ‘Have-Nots’: Results Using Each Available Dataset

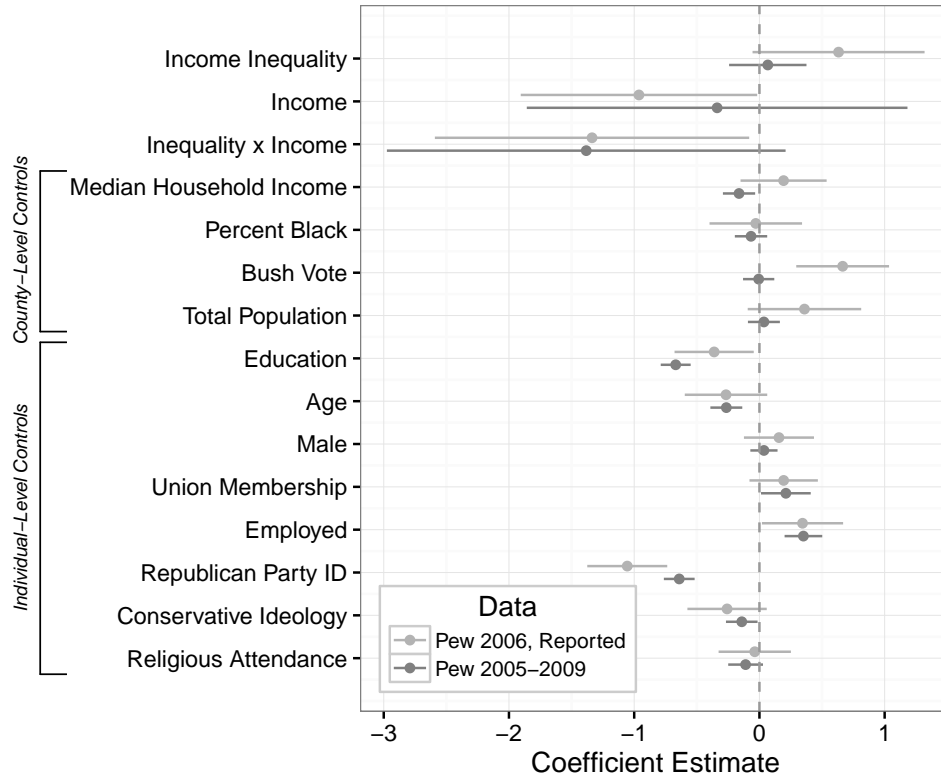


*Notes:* Dots indicate estimates; whiskers represent 95% confidence intervals. Results for county income inequality from replications of the model presented in NJL Table 2 on data from each of six available surveys conducted in the in the time period examined in that article. Of the six surveys, the only one that yields a statistically significant result is the 2006 survey presented in the article.

practice

Regarding the influence of income inequality on awaking the class consciousness, NJL concluded that people with lower income are more likely to identify as “have-nots” when they live in contexts of greater income inequality. The main empirical evidence for this argument was a negative and statistically significant interactive term. However, the significance of interactive term is not an appropriate criterion for judging the conditional effect in inter-

Figure 3: Local Inequality and Self-Identification as a ‘Have-Not’: Results Using All Available Data



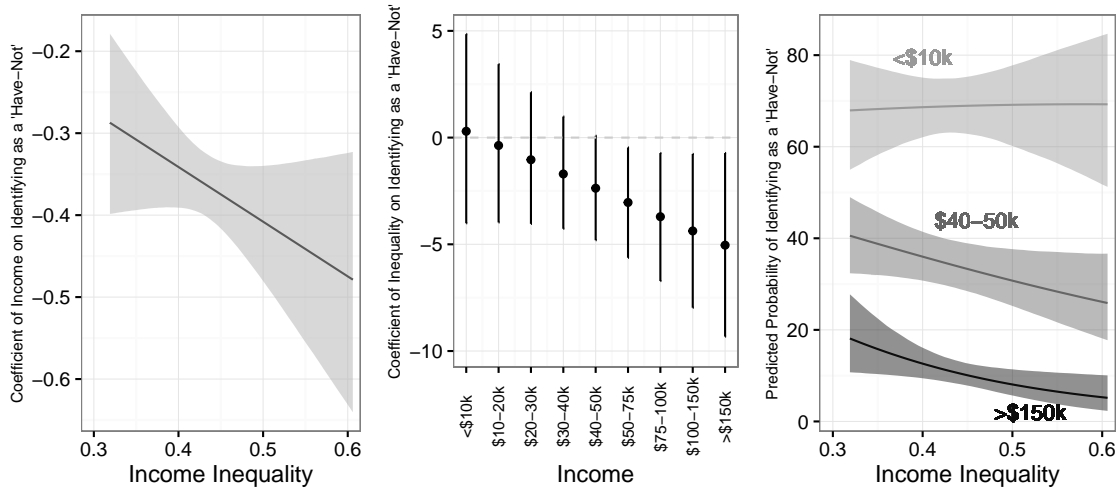
*Notes:* Dots indicate estimates; whiskers represent 90% confidence intervals. Results obtained by replicating the analysis from NJL Table 3 on pooled data from the six Pew surveys that included the same item conducted in the time period examined in that article. The published NJL analysis, purportedly of the 2006 Pew survey, is not reproducible because it includes more parameters than observations; the reported results are depicted here.

actions, regardless the aforementioned selection bias in the data. It only implies the effect of inequality on identifying “have-nots” when the income is zero, but it does not offer any direct information about the situation when income is not zero. In NJL’s measure, there is even no category for zero income; the smallest category is “less than ten thousand.” In this case, the significant interactive term has even less substantive meaning.

To detect the conditional effect of inequality in the non-zero income conditions, one needs to calculate the marginal effect of inequality (see more technical details in Brambor, Clark,

and Golder 2006). We did the calculation again based on all the available data, controlling for the panel difference with least square fixed effect. The result is visualized in the leftest panel of Figure 4. The solid line represents the estimate of the effect of inequality affecting the log likelihood to identify as “have-nots” led by income, and the shadow indicates the 95% confidence intervals. Only when the intervals of a higher inequality does not overlap the intervals of lower inequality can one say the effect of inequality is different from zero, while such pattern was not shown in the plot at all. To interpret this more substantively, we also calculated the predicted probability of identification for people with the lowest, median, and highest income at different inequality levels. The result is presented in the rightest panel of Figure 4, and no significant effect can be identified, either. In conclusion, with an appropriate interpretation of the empirical evidence, NJL’s argument is actually rejected.

Figure 4: Conditional Effects of Income and Local Inequality on Self-Identification as a ‘Have-Not’



*Notes:* Dots and solid lines indicate estimates; whiskers and shaded regions represent 95% confidence intervals. Income is estimated to have a negative effect on identifying as a have-not that is strong, statistically significant, and larger in magnitude as local income inequality increases. There is no support, however, for the conclusion reached in NJL that lower income people are more likely to identify as have-nots when they live in contexts of greater income inequality.

## References

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