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# Economic Inequality and U.S. Public Policy Mood Across Space and Time

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## Abstract

While classic theories suggest that growing inequality will generate mass support for redistribution, recent research suggests the opposite: increases in inequality in the United States are associated with decreases in support for redistribution among both low and high income citizens. We reconsider this conclusion. First, we examine the methods of this research, and find that the claims made are not robust to important corrections in model specification. We then utilize a distinct methodological approach, leveraging spatial variation in local inequality, and examine average differences in preferences across geographic context. Here we find a small, but positive relationship of inequality to support for redistribution. In both our reexamination of previous work and our extensions, we find little support for the claim that inequality reduces the demand for redistribution.

## Keywords

public opinion, inequality, time series, redistribution, public mood

Is objective variation in inequality across space and/or time related to variation in citizens' preferences for a larger or smaller government role in

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economic activities? If so, what is the qualitative nature of this relationship? Perhaps the most well-known, and intuitive, hypothesis is that of Meltzer and Richard (1981; hereafter MR), who hypothesize that increases in inequality will be associated with increases in support for government redistribution. According to the MR model, as inequality increases, the income distribution is increasingly positively skewed, which in turn increases the returns to the median citizen from higher levels of redistribution. Inequality thus shifts the overall distribution of preferences in favor of greater government action. On the whole, the MR model has met with limited empirical support (e.g., Kenworthy & McCall, 2008; Kenworthy & Pontusson, 2005; Lubker, 2007; Moene & Wallerstein, 2001). Within the literature, the United States serves as a particularly salient case of the weakness of the MR model, as income inequality is high and redistribution low relative to many other advanced industrial democracies (Alesina & La Ferrara, 2005; Kenworthy & Pontusson, 2005). Indeed, the United States has experienced rather uninterrupted growth in income inequality since the late 1970s (see Figure 1), which lays the foundation for one of the key puzzles in the study of American politics: Why has rising inequality over the past three decades gone unchecked by mass politics?

Leading research suggests that the answer to this puzzle may be found in how the American public actually responds to income inequality. Kelly and Enns (2010; hereafter KE) find that over-time increases in aggregate inequality are associated in the long term with *decreases* (rather than increases) in support for government redistribution. Although counterintuitive, this finding is reinforced by Luttig (2013; hereafter LG), who finds similar results with different measures of inequality. KE ground their findings within a theoretical model offered by Benabou (2000), which focuses on the aggregate effect of the increasing opposition of higher income voters to redistribution as a function of rising inequality. The main finding of KE appears to gel with the "unequal democracy" thesis that increases in inequality are self-reinforcing through political mechanisms related to the differential access of wealthier citizens to the levers of government policymaking and their interests in protecting the (unequal) status quo (e.g., Bartels, 2008; Gilens, 2012; Gilens & Page, 2014). Appeals to the unequal democracy thesis, however, are discomfited by KE's finding of a negative relationship of inequality and policy liberalism for both high- *and* low-income Americans. This latter finding not only conflicts with the Benabou model, but also the narrative that inequality has grown because political elites and representative institutions fail to respond to the interests of the poor while heeding those of the rich.

If correct, the implication of KE's finding is that inequality is self-reinforcing *and* that democratic processes are responsive to the interests of both the rich and the poor. Thus, while the implications with respect to the self-reinforcing nature of inequality are consistent with the unequal democracy perspective, problems of representation are tempered because both low- and high-income citizens respond to inequality with a preference for limited government. To make sense of this latter finding, KE suggest the possibility of the manipulation of lower income citizens' attitudes by economic and political elites, as well as media frames emphasizing individualism. This attempt to make sense of lower class opposition to redistribution is further aided by experimental evidence of "last place aversion" (Kuziemko, Buell, Reich, & Norton, 2014), cross-national evidence of the linkages between lower class status, national identification, and opposition to redistribution (Shayo, 2009), and the corpus of research on system justification (Jost, Banaji, & Nosek, 2004). In sum, KE's findings, as well as others', offer a solution to a key puzzle in American politics: income inequality has grown unabated because the American public as a whole has responded to growing inequality with a demand for less redistribution.

In this article, we question the evidence for this conclusion and present a reconsideration of the relationship of inequality to public opinion, including (a) a reevaluation of recent research, specifically that of KE and LG; and (b) the presentation of results from new analyses using a different reference point for inequality, namely, spatial rather than temporal variation. We are motivated by three observations. First, the findings of KE and LG are counterintuitive and conflict with other work in the literature. For example, scholarship finds that higher levels of *perceived inequality* are associated with greater support for government redistribution (Fong, 2001; Hayes, 2013), higher levels of inequality in immediate environments decrease beliefs in meritocratic ideology among the poor (Newman, Johnston, & Lown, 2015), and lower income citizens support redistributive policies when the distributional benefits are clear (Franko, Tolbert, & Witko, 2013). Second, and perhaps most important, we believe that there are important problems with the error-correction models (ECMs) as specified in KE and LG that cast doubt on their conclusions. Last, we are skeptical more generally of empirical approaches analyzing the effect of national-level, aggregate inequality on public opinion given citizens' general lack of awareness of national-level statistics (e.g., Lawrence & Sides, 2014).

In the present article, we first reexamine the models of KE and LG and demonstrate that the relationship of over-time inequality to public mood in the United States is not as robust as previous work suggests. Second, we build on the current literature by leveraging an alternative source of variation in inequality: spatial variation in *local* inequality.[1] Utilizing six national datasets in the United States, each containing a very large sample of respondents, we find that local inequality weakly *increases* support for redistribution and social welfare. Taken together, we view our findings as an important contribution to the ongoing conversation in political science concerning rising inequality and its relationship to public opinion. The work of KE and LG promises a partial answer to the puzzle of unabated inequality growth: inequality has gone unchecked over the past decades because increases in inequality cause the American public in the long term to want less redistribution. We find that this explanation lacks strong empirical support; indeed, our results may suggest just the opposite conclusion.

## Reexamination of Time-Series Analyses

It is well-known that regressing one non-stationary time series on a second non-stationary series dramatically inflates the Type I error rate, and that one solution to this problem is to difference *both* series and estimate the model on the resulting "white-noise" series (Granger & Newbold, 1974).[2] The problem with this approach is that it only allows the estimation of "short-term" relationships between series: the effects of *differences* in one variable from one period to another on similar differences in some other variable. For example, if inequality rose sharply from last year to this year, do we expect to observe a corresponding change in public opinion over the same period? Often, however, we believe that two series may have a "long-term" or equilibrium relationship. At a conceptual level, two series display a long-term relationship with one another when random shocks to either series that drive them apart dissipate over time. More formally, a long-term relationship exists between two non-stationary series when some linear combination of the two is stationary, and thus errors around this combination are randomly distributed about zero. This situation is known as cointegration (Engle & Granger, 1987).

To overcome the limitation of the traditional approach's focus on short-term dynamics, both KE and LG utilize ECMs, the general form for which is as follows:

$$\Delta Y_t = Y_{t-1} + X^1_{t\text{-}1} + \Delta X^1_t + \cdots + X^k_{t\text{-}1} + \Delta X^k_t + e_t. \tag{1}$$

In theory, ECMs allow for the estimation of both short-term and long-term relationships between series. In Equation 1, the coefficients on the differenced X represent short-term effects of the X on Y. The coefficients on the level X represent the long-term relationships between the X and Y, and the coefficient on the level Y is the error-correction mechanism, which is an estimate of the rate at which the equilibrium among the series is restored. For example, a coefficient of –.5 on the Level Y implies that shocks to the equilibrium dissipate at a rate of 50% per period. Importantly, ECMs assume that the non-differenced series on the right-hand side are stationary. This assumption can be justified in two cases: when the Y and X on the right-hand side are actually stationary series (De Boef & Keele, 2008) *or* when a linear combination of the Y and the X is stationary, and thus the series are cointegrated (Engle & Granger, 1987). When neither condition is met, ECMs are subject to the same problems of inflated Type I errors that plague simple regressions of non-stationary series (Grant & Lebo, 2015).

In the context of these considerations, consider Figure 1, which plots the dynamics of U.S. policy mood liberalism and those of U.S. national inequality as measured by the Gini coefficient—the two focal variables of KE: our primary concern is that the strong upward trend in inequality over time guarantees non-stationarity on the right-hand side, and thus a substantially increased probability of Type I errors. Consider that the trend in inequality is a *deterministic* portion of the series, and thus cannot explain the dynamics of mood over time. It is thus impossible for the trend portion of the series to be cointegrated with the mood series, and this is the essence of the problem: the inequality series must be non-stationary because of the trend, but that trend cannot be cointegrated with mood in principle. Put simply, there is a significant concern that the finding of a negative relationship between inequality and mood in both KE and LG is spurious—the result of a failure to detrend the inequality series prior to estimation. More simply, Figure 1 suggests skepticism regarding any long-term relationship of mood to inequality because the two obey fundamentally distinct long-term dynamics: one is a sinusoid and one an upward trend.

We need not speculate, however. A demonstration of the potential for spurious findings resulting from the inequality trend in this *specific context* can be obtained through simulation. Specifically, we created 1,000 new series, each composed of (a) the exact same trend present in the actual Gini series for the United States, and (b) randomly drawn stochastic shocks to the trend at each point in time. More concretely, we estimated the trend component of inequality from the KE data shown in Figure 1. We then created 1,000 new series, each of which begins with the same trend but substitutes randomly drawn "shocks" at each time period for the true stochastic component of the Gini series. Each of the 1,000 new series is thus nothing but a common trend and noise.[3] Each observation for each new "inequality" series is thus composed of a trend component that is common across all 1,000 series and a random component that is unique to each series. This allows us to examine how the KE model performs in a context where we know for sure (i.e., by construction) that "Gini" and mood are unrelated. Given the observed Gini series in Figure 1, we repeated the simulation for both a linear and a quadratic

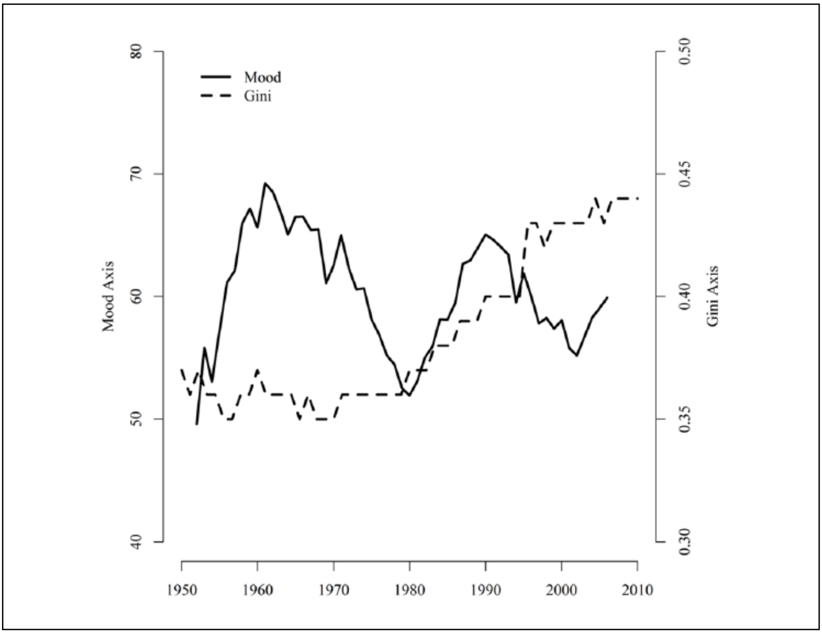


**Figure 1.** Inequality and policy mood in the United States.

trend. We then estimated KE's primary model examining the long-term relationship of mood to inequality 1,000 times for each type of trend, but substituting our newly created series for the Gini series one at a time, and keeping everything else in the model identical. Recalling again that the trend is deterministic and cannot explain variation in public mood, our new series should in theory be unrelated to public mood, because all stochastic variation is purely random by construction.

Instead, we find substantially inflated probabilities of Type I errors for both types of trend.[4] When using a linear trend for the Gini series, we reject the null hypothesis with a two-tailed test 22% of the time, and we reject the null with a one-tailed test (implicitly used by KE in their article) a striking 54% of the time. The problem is even more pronounced if we examine a quadratic trend for the Gini series. In this case, we reject the null with a one-tailed test about 35% of the time, and reject the null with a two-tailed test more than 83% of the time. In contrast, when we substitute noise series *without* trends for the Gini series, there is no inflation of Type I errors, which is exactly what we should find when estimating the relationship of a noise series to mood. These results strongly suggest that the trend in inequality inflates

Type I errors, and models utilizing the uncorrected inequality series do not provide valid hypothesis tests. Both the general theory of ECMs and our simulations within the specific context of inequality and mood suggest that a reconsideration of this relationship is worthwhile; indeed, critical, given the importance of these articles' conclusions.

## A Reexamination of KE and LG

We begin with a reexamination of KE's and then LG's models of the relationship between (real, rather than simulated) U.S. inequality and public policy mood over time using their publicly available data. The most important models in KE are those in columns 3 and 4 of their Table 1, and columns 3 and 4 of their Table 2. The first of these examines the relationship of inequality to public mood controlling for several alternative hypotheses, the second replicates this model but substitutes aggregate welfare preferences for public mood,[5] and the latter two estimate the mood model separately for low- and high-income citizens. Our strategy is as follows. For each model, we first reestimated the KE results. As noted above, the problem with these models is that they do not extract the trend in inequality observed throughout the time period, potentially generating spurious associations between inequality and aggregate preferences. We thus provide two additional specifications for each model. In the first, we extracted a *linear trend* from the Gini series, and then substituted this version for the original series. In the second, we extracted a *quadratic trend*, and again estimated an otherwise identical model.

We present our reanalysis of KE in our Table 1. We begin with the key model estimates from KE's Table 1, column 3. The first column in *our* Table 1 contains a true replication of this model, while the second presents estimates after extracting linear and quadratic trends from the inequality series, respectively. We perfectly replicate KE's estimates in the first column. As expected on the basis of visual inspection of Figure 1, however, the deterministic (trend) component of the Gini series dominates its total variance. The linear trend accounts for 80% of the overall variance in the series, while the quadratic trend accounts for 94%. Consistent with this, we find no statistically significant association of inequality to public mood when using either of these trend-extracted Gini series (i.e., columns 2 and 3 of our Table 1). It is again important to emphasize that the extraction of the deterministic component of the Gini series should have no (biasing) consequences for the discovery of a true relationship between inequality and mood to the extent that one exists. Trends cannot explain changes of this sort, and thus it would be a mistake to think that this approach somehow obscures the true relationship between the series by throwing the proverbial baby out with the bathwater.[6]

**Table 1.** Reexamination of Kelly and Enns (2010), Short-Term and Long-Term Estimates for Inequality.

| | | Original model | | Linear trend | | Quadratic trend | | w/control for party of President | |
|---|---|---|---|---|---|---|---|---|---|
| Model | Inequality variable | *B* | *SE* | *B* | *SE* | *B* | *SE* | *B* | *SE* |
| Table 1, Column 3, | Differenced | −29.56 | 37.59 | −57.33 | 42.58 | −31.08 | 45.61 | — | — |
| All citizens, mood | Lagged | −18.00* | 9.44 | −53.92 | 41.42 | −25.79 | 46.08 | — | — |
| Table 1, Column 4, | Differenced | −180.68 | 115.68 | −227.73* | 133.49 | −96.02 | 141.96 | — | — |
| All citizens, welfare | Lagged | −228.69** | 94.38 | −284.71* | 160.82 | 37.80 | 169.66 | — | — |
| Table 2, Column 3, | Differenced | −22.56 | 55.18 | −49.19 | 69.28 | −19.85 | 71.03 | — | — |
| Low income, mood | Lagged | −64.57** | 25.97 | −92.07 | 73.64 | −59.82 | 74.98 | — | — |
| Table 2, Column 4, | Differenced | −41.01 | 44.14 | −94.02 | 56.86 | −80.20 | 58.81 | −30.01 | 61.23 |
| High income, mood | Lagged | −61.98** | 24.38 | −140.92** | 66.15 | −124.81* | 71.19 | −41.58 | 76.21 |
| Variance in inequality explained by trend | | | | 80% | | 94% | | 94% | |

*Note.* $n$ = 54 for row 1; $n$ = 33 for row 2; $n$ = 50 for rows 3 and 4. The dependent variable is public mood liberalism for rows 1, 3, and 4. The dependent variable is welfare liberalism for row 2. Entries are ordinary least squares (OLS; first two models) and generalized least squares (GLS; second two models) regression coefficients and standard errors (*SE*). The first column contains exact replications. The second column uses the residuals from a regression of Gini on time as a substitution for the original Gini series. The third and fourth columns use the residuals from a regression of Gini on time and time-squared as a substitution for the original Gini series. The fourth column additionally controls for the party of the sitting President.

$^{*}p < .10$. $^{**}p < .05$.

**Table 2.** Reexamination of Luttig (2013), Short-Term and Long-Term Estimates for Inequality.

| Model | Inequality variable | Original model | | Linear trend | |
|---|---|---|---|---|---|
| | | *B* | *SE* | *B* | *SE* |
| Table 1, Model 1, | Differenced | −35.73 | 21.46 | −60.32** | 24.73 |
| All citizens, mean over median | Lagged | −14.81** | 7.23 | −57.87** | 28.28 |
| Table 1, Model 2, | Differenced | 4.43 | 33.00 | −21.10 | 42.07 |
| Low income, mean over median | Lagged | −31.28** | 13.35 | −63.40 | 45.85 |
| Table 1, Model 3, | Differenced | 2.94 | 27.90 | −44.61 | 35.28 |
| High income, mean over median | Lagged | −35.73** | 10.94 | −97.64** | 40.06 |
| Table 2, Model 4, | Differenced | −15.13 | 10.20 | −25.45* | 12.88 |
| All citizens, skew | Lagged | −10.05** | 4.59 | −27.84* | 16.36 |
| Table 2, Model 6, | Differenced | 5.99 | 8.38 | 2.31 | 13.98 |
| High income, 95/50 | Lagged | −8.10** | 2.93 | −9.02 | 18.41 |

*Note.* $n$ = 39 for all models. The dependent variable in all models is public mood liberalism. Entries are ordinary least squares (OLS) regression coefficients and standard errors (*SE*). The first column is a replication of the original. The second column uses the residuals from a regression of inequality on time as a substitution for the original series. A linear trend explains 97% of the variance in the mean over median measure of inequality, 97% of the variance in the skew measure, and 98% of the variance in the 95/50 ratio.
*$p$ < .10. **$p$ < .05.

The second row of our Table 1 reexamines KE's analysis of the welfare dependent variable (in their Table 1, column 4; substituted for the policy mood dependent variable). Our estimates in the "Original Model" columns are slightly different from KE, because we chose to include controls for unemployment and inflation. The substantive finding is nonetheless identical to KE: a negative and statistically significant long-term relationship of inequality to aggregate welfare preferences. Once again, however, we find no statistically significant relationship once the trends are removed. In the model that extracts a linear trend, the relationship between inequality and welfare mood is only significant if we extend the alpha level to .10, and in the quadratic trend model, the relationship is insignificant with either a standard (.05) or extended (.10) alpha level.

Finally, in the third and fourth rows of our Table 1, we reexamine KE's models that break the public into low- and high-income subsets (in their Table 2, columns 3 and 4), and examine the relationship of mood to inequality within each separately. Recall that KE find the same relationship for both low- and high-income citizens. With respect to low-income citizens, we replicate the core finding of a negative and significant relationship between lagged inequality and mood, but fail to find any statistically significant relationship once the trends are extracted from the inequality series. The results for high-income citizens are somewhat less clear. First, we again replicate KE in the first column. In this case, however, the relationship of inequality to mood remains statistically significant after extracting the linear trend. The relationship is significant after extracting the quadratic trend only if we extend the alpha level to .10. This is perhaps suggestive of a pattern consistent with Benabou (2000) in that the relationship is both negative and exists only for high-income respondents.

These results for high-income citizens, however, are not robust to an extended set of controls. KE estimate a final set of models that constitute a robustness check by including controls for the party of the President (they report these estimates in a supplemental appendix). They find a negative relationship between party and mood such that liberalism is higher following Republican presidencies. The association of inequality to mood is robust to this control with their specifications. As shown in the fourth column of our Table 1, it is *not* robust once the trend in inequality is removed. For high-income respondents, once Presidential partisanship is controlled, inequality has no statistically significant relationship to mood with either alpha level. Thus, while we do not entirely rule out a relationship of inequality to mood among high-income citizens using KE's preferred model, our confidence in this relationship is low, because it is not robust to additional controls suggested by KE.

We turn now to LG, who estimates the relationship of mood to inequality using a distinct set of inequality measures motivated by Lupu and Pontusson (2011). The latter argue that the relationship of inequality to redistribution is conditional on the structure of inequality. Specifically, when inequality manifests as divergence between the rich and the middle and lower classes, support for redistribution should be higher, because middle-income citizens are more likely to identify with low-income citizens. Conversely, when the structure of inequality binds the middle and upper classes against low-income citizens, demand for redistribution should be lower. LG provides several examinations of the relationship of mood to inequality, including breaking mood into low- and high-income components as per KE, with the following measures of inequality as the primary independent variables: the ratio of mean income to median income, distributional skew measured as the ratio of two income percentile ratios (95-50 to 50-20), and the ratio of the 95th percentile to the 50th percentile (utilized for high-income mood only). The ratio of mean to median income is a measure of overall inequality, and LG uses this measure as a conceptual replication of KE (who use the Gini coefficient).

Distributional skew is a measure of the structure of inequality. High values of this measure indicate that the middle class is closer to the poor, suggesting greater aggregate support for redistribution, while low values indicate the middle class is closer to the rich, suggesting less support. Finally, LG uses the 95 to 50 ratio as a measure of the distance between the rich and middle class, and expects that higher values of this measure will be associated with decreased support for redistribution among the rich, because they will feel more socially distant from the middle class.

Our Table 2 contains both the replicated "original model" reported in LG, and additional models that extract linear trends from the respective measures of inequality.[7] As with KE, a trend accounts for most of the variance in mean-over-median inequality (97%). However, in contrast to KE's results with the Gini coefficient, the long-term relationship of inequality to mood remains negative and statistically significant for both the overall model and for high-income citizens, although it does not remain significant for low-income citizens. This suggests empirical support for the Benabou (2000) model. Finally, we reexamine LG's Table 2 Models 4 and 6, which look at the relationship of distributional skew to mood for all citizens, and the relationship of the 95 to 50 ratio to mood for high-income citizens only.[8] A linear trend accounts for 97% of the variance in the overall skew measure, and 98% of the variance in the 95 to 50 ratio measure of inequality. The relationships in LG's Table 2 do not attain standard levels of statistical significance once the linear trend is removed. The relationship of skew to mood for all citizens is significant only if we extend the alpha level to .10.

To summarize, our reexaminations of KE and LG suggest the following conclusions. First, as suggested by Figure 1, most of the variance in inequality is accounted for by a deterministic trend over time. This is true for all measures of inequality examined. Often, the trend accounts for more than 95% of the variance in inequality. Second, the relationship of mood to inequality is not as clear as previous findings suggest. With respect to KE, once the trend in inequality is removed, we find no statistically significant relationship between inequality and either mood or welfare support for the public considered as a whole. Our results may suggest a relationship of Gini to mood among rich citizens; however, this finding is only significant with an extended alpha level, and is not robust to additional controls suggested by KE. With respect to LG, our results are mixed. On one hand, we find a significant relationship of mean-over-median inequality to mood for all citizens after extracting the trend in inequality. On the other hand, we find that this result may be driven largely by high-income citizens, because the relationship of inequality to mood among low-income citizens is not robust to the extraction of the linear trend. We also find no statistically significant relationship of the structure of inequality to mood after extracting the trend. Overall, then, our reexaminations of KE and LG weaken the claim that inequality and public mood are in a long-term relationship such that rising inequality is associated with greater opposition to social welfare. They also cast doubt on the claim that low-income citizens respond to increasing inequality by becoming more conservative, which is perhaps the most surprising finding of this research program. There is, however, some suggestion that inequality may promote conservatism among relatively wealthy members of the public—a conclusion that is consistent with the Benabou (2000) model, and with recent work on belief in meritocracy among the rich in response to local inequality (Newman et al., 2015).

As a more general matter, our sense is that the lack of stochastic variation in inequality over time, combined with the relatively few years available as data points, presents a particularly difficult problem for time-series analyses of this sort. That is, our claim is not that the conclusions of KE and LG are wrong, but rather that we have insufficient information at this point in time to achieve the level of efficiency in estimates necessary to be confident in their claims. An alternative is to examine the relationship of inequality to mood using a different reference point for comparison—one that exploits variation in inequality across space rather than time.

## Local Inequality as an Alternative Approach

To reconsider the relationship between income inequality and public policy mood, we turn to spatial variation in local inequality. We view such an approach as promising for several reasons. First, in contrast to the over-time data, there is substantial stochastic variation in local income inequality. Second, there is good reason to believe that the local level constitutes a more plausible arena than the national level to expect an effect of inequality on public opinion. One of the key assumptions of the MR model that has been questioned by scholars is that citizens are actually aware of the true level of aggregate inequality in their country (Kenworthy & McCall, 2008; Kenworthy & Pontusson, 2005). Over-time analyses require an even more questionable assumption: Citizens are aware of *changes* in national inequality from year-to-year. This seems tenuous at best.

First, scholarship finds that citizens in general suffer from political innumeracy (Lawrence & Sides, 2014), defined as ignorance of politically relevant numbers related to aggregate population demographics, macroeconomic statistics, the federal budget, and public policy. For example, research finds that citizens are largely innumerate with respect to estimating the size of national racial minority populations (Alba, Rumbaut, & Marotz, 2005;

Nadeau, Niemi, & Levine, 1993), the immigrant population (Citrin & Sides, 2008), Jews (Theiss-Morse, 2003), and gays and lesbians (Morales, 2011). Turning to aggregate economic conditions, citizens have also been found to be innumerate with respect to national unemployment and inflation rates (Sigelman & Yanarella, 1986), as well as federal budget spending on welfare (Kuklinski, Quirk, Jerit, Schwieder, & Rich, 2000).

Building on this work, and perhaps most important for present purposes, existing scholarship finds that this innumeracy holds when it comes to citizens' perception of aggregate inequality. For example, recent research demonstrates that citizens substantially underestimate the degree of earnings inequality in society (Norton & Ariely, 2011), and that this tendency is particularly pronounced in the United States (Kiatpongsan & Norton, 2014). Innumeracy about inequality is also evident when it comes to citizens' awareness of changes over time. For example, in an analysis of eight Organization for Economic Co-operation and Development (OECD) nations, Kenworthy and McCall (2008) find that over-time perceptions of income inequality tend to track poorly with actual trends. This finding is further corroborated by more detailed analyses focusing specifically on the United States, where scholarship finds that although American citizens evince a basic recognition of the fact of elevated *levels* of inequality in the nation, their perceptions of national inequality *over time* bears little relationship to actual year-to-year changes in aggregate inequality (Bartels, 2008; McCall, 2005). For example, Bartels (2008) finds that perceptions of inequality show little fluctuation between the mid-1970s to 1990 despite this being a period of increasing inequality, and that minor declines in perceived inequality occurred during the late 1990s when inequality was spiking upward. Perhaps most remarkable, Bartels demonstrates that despite the drastic growth in inequality from the late 1970s to the 2000s, Americans' perceptions of the prevalence of inequality were no greater at the end of George W. Bush's first term than during the Ford Administration. McCall (2005) uncovers year-to-year findings similar to Bartels', although finds limited evidence that mass media coverage of inequality can increase the linkage between Americans' *intolerance* of inequality and actual inequality growth (see also McCall, 2013). Media facilitation aside, the general picture painted by this research is one of substantial inaccuracy in citizens' perceptions of levels of, and over-time changes in, national economic inequality.

In response to this, a promising thread of research has emerged demonstrating that although citizens fail to accurately perceive various macroeconomic conditions or temporal dynamics in aggregate inequality, they do perceive relative spatial variation in subnational and local economic conditions. For example, recent work finds that Americans' perception of inequality strongly corresponds to variation in state-level inequality (Xu & Garand, 2010), that yearly variation in state-level estimates of perceived inequality systematically relate to yearly changes in state-level inequality (Franko, 2014), and that citizens' perceptions of local economic conditions track with actual variation in county and zip code economic conditions (Newman, Velez, Hartman, & Bankert, 2014). Furthermore, research suggests that citizens tend to rely upon their local context in generating estimates of aggregate conditions. For example, citizens who reside in local contexts with larger minority populations are more likely to estimate larger national minority populations (Citrin & Sides, 2008; Nadeau et al., 1993), and citizens appear to use local unemployment rates to inform their estimates of national economic conditions (Hansford & Gomez, 2011; Newman et al., 2014). Last, recent research in Argentina demonstrates that citizens' perception of the national income distribution is strongly linked to their income relative to those in their neighborhood (Cruces, Perez-Truglia, & Tetaz, 2013), and work in the United States demonstrates that citizens' perception of inequality in society is strongly related to the level of income inequality in their local county of residence (Newman et al., 2015). In short, if we are to find a relationship between objective variation in inequality and public opinion, this research suggests local-level geographic variation as the most likely arena.

## *Spatial Variation in Local Inequality and Public Opinion*

Our analysis of local inequality utilizes U.S. Census data merged with six large national surveys from 2006 to 2011, one each year from the Cooperative Congressional Election Study's Common Content (CCES; Ansolabehere, 2010a, 2010b, 2010c, 2012, 2013). Each CCES is an Internet-based survey conducted by the private survey research firm YouGov, and contains a large sample of adult U.S. citizens: 2006 CCES, $N$ = 36,500; 2007 CCES, $N$ = 10,000; 2008 CCES, $N$ = 32,800; 2009 CCES, $N$ = 13,800; 2010 CCES, $N$ = 55,400; 2011 CCES, $N$ = 20,150.[9] These large sample sizes, assuming unbiasedness, allow for efficient estimates of key model parameters, which are particularly important given the uncertainty in the literature surrounding both the magnitude and the direction of inequality's influence on mass preferences. In addition to the benefits afforded by their size, each survey provides geocodes for all respondents' county and zip code of residence, as well as multiple items for measuring respondents' preferences over government intervention in economic matters. Together, these six surveys provide a close to ideal data source for obtaining efficient estimates of the association of local inequality to public opinion, and assessing the robustness of such estimates across time.

We operationalize income inequality in four distinct ways to ensure that our results are robust to alternative measures and treatments of the concept. First, we rely upon the commonly used *Gini coefficient* for which county- and zip-level estimates are available through the American Community Surveys (ACS) of the U.S. Census Bureau.[10] The Gini varies from 0 (complete equality) to 1 (one household possesses all the resources in a region), and is thus a measure of resource dispersion across the units of a population. Our second measure of inequality compares the median household income of the top 20% of households within a region to the median income of the bottom 20% of households. The ACS (and the Census) measures income in an ordinal fashion, and thus we are unable to calculate familiar ratio measures of inequality. Instead, we calculated the median income *category* separately for the top 20% and the bottom 20% of households within a region, and then subtracted the latter from the former. Higher values of this measure, thus, indicate a large gap between the typical high- and low-income households within a region, and thus greater inequality. The correlation between this measure and the Gini coefficient at the zip code level is .63, and at the county level, the correlation is .64.

Our third measure offers a distinct conceptualization and approach to inequality that we believe could be particularly relevant to mass preference formation. Different measures of contextual inequality likely correspond with different day-to-day experiences of and exposure to uneven dispersions of wealth. For example, higher values of Gini correspond to movement toward the theoretical maximum of one household holding all of the wealth within a defined local area. While residing within a context where income is held by a slim minority of the residents may indeed serve as a powerful stimulus influencing residents' economic attitudes, there are other distributional configurations that may be as or more influential. One such distribution is a polarized bimodal distribution, in which a large proportion of low-income households reside in proximity to a large proportion of high-income households, with relatively few in the middle. Indeed, this is equivalent to the common idea of a "hollowed out" middle class. In contrast to a high value of Gini, where the contact with the wealthy minority and exposure to their wealth is questionable, the cohabitation of sizable lower and upper income populations within a small geographical area may serve as a more powerful day-to-day manifestation and reminder of inequality. To capture such a polarized, bimodal distribution, we estimate the percent of households in an area whose annual earnings are *Below25K*, whose earnings are *Above100K*, and the interaction of the two *Below25K* × *Above100K*.[11] The inclusion of an interaction between these two variables captures the effect of residing in an area where both the lower and upper income population are sizable, and thus, presumably, contact between the rich and poor is more frequent, and income inequality is more salient.

Finally, we draw on the theorizing of Lupu and Pontusson (2011) and LG and examine how the structure of inequality, in interaction with the income level of citizens, predicts policy attitudes. Following these authors, we constructed a measure of distributional skew, calculated as follows:

$$\text{Skew} = \frac{\left(\begin{array}{l}\text{Ratio of median income category for top 20\%}\\ \text{of households to median income category of households}\\ \text{between the 40th and 60th percentiles}\end{array}\right)}{\left(\begin{array}{l}\text{Ratio of median income category of households}\\ \text{between the 40th and 60th percentiles to median}\\ \text{income category of households in the bottom 20\%}\end{array}\right)}.$$

This measure captures the relative position of the middle class to the upper and lower classes in a given area. Higher values indicate that the middle class is closer to the lower class, and smaller values indicate that the middle class is closer to the upper class. Consistent with Lupu and Pontusson (2011) and LG, we would expect a positive relationship between this measure and policy liberalism.

To measure policy liberalism, we rely upon a five-item scale for the 2006 CCES ($\alpha = .78$), a five-item scale for the 2007 CCES ($\alpha = .77$), a six-item scale for the 2008 CCES ($\alpha = .79$), a six-item scale for the 2009 CCES ($\alpha = .85$), a seven-item scale for the 2010 CCES ($\alpha = .86$), and a two-item scale for the 2011 CCES ($r = .40$). Each of these scales is comprised of items tapping respondents' preferences over the scope of government efforts in (a) regulating economic activity, (b) spending on social services and welfare, and (c) taxation, and thus corresponds closely with the "mood" concept as defined by Stimson (1991; Ellis & Stimson, 2012). The high scale reliabilities across our datasets indicate that, despite tapping preferences over a range of government activities, these items appear to be strongly capturing a single dimension related to the size and scope of government in the economic domain. For each CCES survey, we averaged these items and coded the variable to range from low to high support for active government involvement (for simplicity, hereafter "policy liberalism"). Full question wordings for all items are contained in the online appendix.

All of our analyses included an identical set of controls. At both the zip code level and the county level, to control for the potential effects of non-inequality-related economic conditions, we include measures of median income, education (i.e., the percent of residents with a college degree), and unemployment. To control for the local demographic makeup of the population, we include controls for percent Black population, percent Hispanic population, and percent foreign-born population. To control for local political culture, we include the percent of the respondent's county voting for the Republican candidate in the most recent U.S. Presidential Election (we use the 2008 Election for the 2007 CCES). Finally, to control for thermostatic responses to prior government activity (e.g., Stimson, 1991; Wlezien, 1995), we include controls for the change in the percent of households receiving public assistance and supplemental security income from 2000 to the relevant period for each CCES survey. Each of these variables, except Republican voting percentages (obtained from the Atlas of U.S. Presidential Elections), was obtained from the ACS and the U.S. Census Bureau. For ease of interpretation, all context variables were recoded to have a mean of 0 and standard deviation of .5. Thus, a 1-point change in a contextual variable represents a 2 standard deviation change in that variable.

At the individual level, we control for several variables deemed important by prior research on individual support for social welfare spending and redistribution (e.g., Alesina & Giuliano, 2011; Alesina & La Ferrara, 2005; Fong, 2001; Rehm, 2009): age, gender, race, education, income, employment status, home ownership, marital and parental status, union membership, residence in the South, right-wing political affiliation,[12] and religiosity. All individual-level variables were coded to range from 0 to 1 prior to analysis.

## Results: Inequality and Preferences in the Aggregate

We begin with a consideration of the relationship of our first three measures of inequality to aggregate preferences (we turn to the Lupu & Pontusson, 2011, and LG hypotheses in the next section). We estimated the following model for each of the county-level analyses that follow, where the $\alpha_{0j}$ are random effects for zip or county, and the $\beta_{0k}$ are random effects for state. The zip-level models include one additional random intercept for county.

$$y_{ijk} = \alpha_{0j} + \beta_{0k} + \sum_{l=1}^{L} \beta_l \text{IND.LEVELCONTROL}_{lijk} + \varepsilon_{ijk}; \quad \varepsilon_{ijk} \sim N(0, \sigma_1^2)$$

$$\alpha_{0j} = \gamma_0 + \gamma_1 \text{INEQ}_j + \sum_{l=2}^{L} \gamma_l \text{GEOLEVELCONTROL}_{lj} + \delta_j; \delta_j \sim N(0, \sigma_2^2)$$

$$\beta_{0k} = \pi_0 + \theta_k ; \theta_k \sim N(0, \sigma_3^2)$$

All models were estimated via maximum likelihood. We estimated 12 models for *each* year of CCES data: 6 each focusing on the zip level and six each focusing on the county level—2 each for each of the three measures of inequality discussed above, with the 2 models differing only by the inclusion or exclusion of right-wing political affiliation. With respect to the latter, each of the two modeling choices is theoretically defensible. First, it might be reasonable to *exclude* political affiliation from all models if we assume that variation in affiliation is a function of inequality (e.g., partisanship as a "running tally," Fiorina, 1981). If true, then inclusion of affiliation will bias the estimates for inequality downward, because one pathway through which inequality transmits its influence is "controlled" (i.e., a post-treatment bias). Second, it might be reasonable to *include* affiliation if we assume that affiliation is exogenous to inequality *and* that affiliation influences both inequality and the dependent variable. The latter pathway from affiliation to preferences is highly likely given standard models in political behavior (e.g., Cohen, 2003; Lavine, Johnston & Steenbergen, 2012; Lenz, 2012; Zaller, 1992), and the former pathway from affiliation to *geographical location* has some empirical support (Bishop, 2008). Political affiliation, in contemporary U.S. politics, is highly cultural in content (Ellis & Stimson, 2012; Feldman & Johnston, 2014; Hetherington & Weiler, 2009), and people may cluster by affiliation because they prefer to be among and associate with others that share their broad cultural and moral outlooks. The truth is probably a mix of these two "pure" models, and thus we estimate both, assuming that models including affiliation will be underestimates of the true effect of inequality, and models excluding affiliation will be overestimates. If the results largely converge across the two model types, then one's preferred model will matter little for substantive conclusions reached by the present article. As we will see below, this is indeed the case.

Full tables of regression estimates are included in the online appendix. We focus our discussion of the results on the estimates for inequality across geounits and across years. Our estimates are highly efficient, and thus rather than discussing statistical significance, we highlight the substance of the estimates. Figure 2 plots the estimates of the marginal effect of inequality across the various models. The *y*-axis is categorical and displays the year of CCES data from which a given estimate is derived. The *x*-axis represents the marginal effect of inequality, which refers to the expected change in *policy liberalism* for a 2 *standard deviation* change in inequality. The solid circles are estimates from models that include right-wing affiliation as a control ("ideology" in the figures), and the empty circles contain estimates from models excluding this control variable.

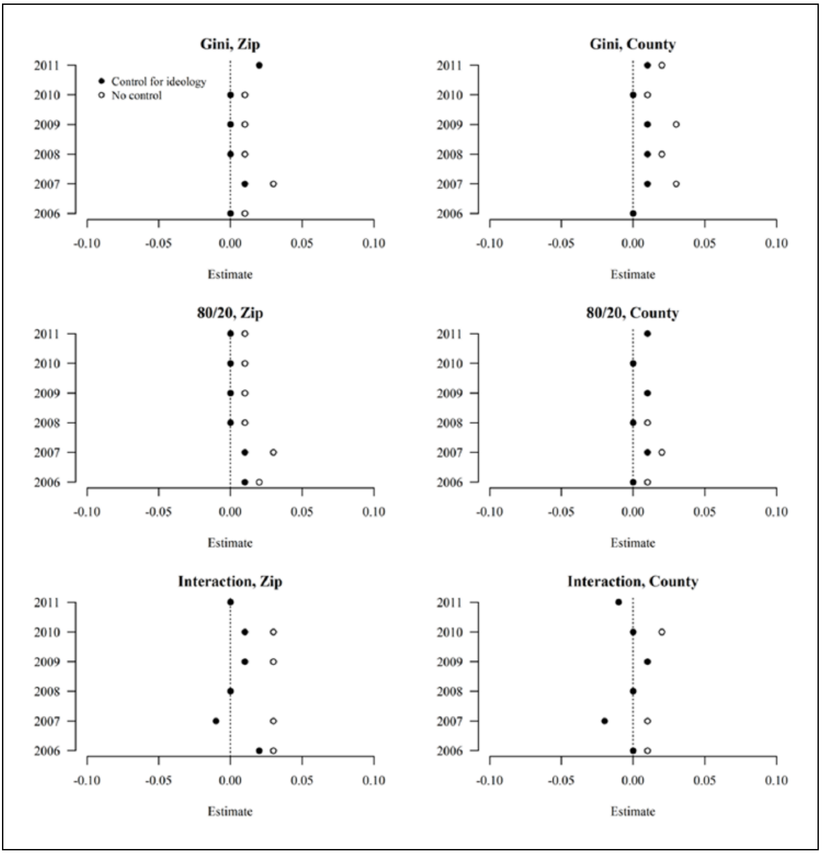


**Figure 2.** Marginal effect estimates for three measures of inequality at two geolevels.
*Note.* Dots correspond with point estimates for the marginal effect of a 2 standard deviation change in each measure of inequality on preferences for a larger government role in economic policy matters. Estimates are provided for each of 6 years from 2006 to 2011 with (solid) and without (open) control for political identity (i.e., partisanship and ideology). Rows with only one solid circle indicate identical estimates with and without control for identity.

The results are relatively clear and consistent: spatial variation in inequality is only weakly and inconsistently related to aggregate liberalism. Furthermore, when a relationship does exist, it is nearly always *positive* such that inequality *increases* liberalism. Recall that the dependent variable is always coded from 0 to 1, thus, even when estimates are statistically significant, they are *substantively* minimal. Consider that the largest effect observed across the 12 models is .03, which means that policy preferences in zip codes with inequality levels 1 *standard deviation* above the mean are expected to be 3 percentage points more liberal than in zip codes with inequality levels 1 *standard deviation* below the mean. Although there is an average increase in effect sizes moving from models controlling for political identity to those that do not, the latter effects are also substantively small.

To get a better sense of the effect sizes, we can compare the largest effect of inequality to that of other common variables used to explain social welfare attitudes included in our models. We will generously assume the largest estimated effect in our lenient model specification is the "true" relationship of inequality to liberalism, and double it to estimate the effect of inequality for a 4 standard deviation change: 6 percentage points. Compare this effect to that of right-wing affiliation (.37-.77), income (.10-.15), religiosity (.15-.25), gender (.04-.11), and race (Black respondents: .05-.25): even with our most generous treatment of the role of inequality, it falls toward the bottom of the range of effect sizes across these important variables. It is important to neither oversell nor undersell this result. On one hand, spatial variation in inequality is often related to social welfare liberalism, at least under lenient model specifications, and this relationship is in the direction expected by classic theorizing. On the other hand, the relationship is small compared with the most common variables used in the public opinion literature to explain such preferences. Inequality might matter, but not very much, and not in the self-reinforcing way suggested by recent research. Instead, when the public responds to inequality at all, the response is a call for greater redistribution and social welfare.

## *Results: Income-Based Heterogeneity and the Structure of Inequality*

We turn now to tests of the geographical equivalents of LG's tests regarding the structure of inequality over time and its relationship to policy liberalism across income levels. These analyses thus utilize our measure of distributional skew as the key independent variable, as described above. To examine the possibility of income-based heterogeneity, we divided each of our six CCES samples into five income categories.[13] We estimated separate models for each category of income, which allows the association of skew with preferences to vary (potentially) in a non-linear fashion. Importantly, by estimating separate models for each income group, we simultaneously control for all other interactions of control variables and income, ensuring that any variation in the association of skew and preferences is not merely picking up on variation for a correlated variable. Because the results above are largely identical across years, and to ensure similarly efficient estimates after breaking down the data by income, we combined the 6 years into a single dataset, and included "fixed" effects (dummy variables) for year in all models to account for average differences in the dependent variable across datasets and across years. This also controls for potential differences due to the construction of the dependent variable across years. Finally, we again estimate our models both controlling and not controlling for political affiliation, and again consider these to be lower and upper bounds on the association of inequality to preferences.

The results for all four models are shown in Figure 3. In this case, the *y*-axis now represents income category membership within a given CCES year. As with the full sample models above, the estimates show a consistent pattern: there is no substantively meaningful relationship of variation in local inequality with preferences. In this case, the findings imply that income *does not* consistently moderate this association—the estimates vary in a rather random fashion about 0 and are substantively small. There are a few statistically significant marginal effects of inequality on preferences, but these are quite small in magnitude, never exceeding 3 percentage points for a 2 *standard deviation* change in inequality, and there is no consistent pattern of statistical significance across the four models (see online appendix for full regression tables). At a local level, the structure of inequality shows no consistent relationship to policy liberalism across income categories.

## Conclusion

The present article has reconsidered the relationship between variation in inequality and citizen preferences for a larger government role in economic matters. Recent research reports the counter-intuitive finding of a *negative* relationship between inequality growth and aggregate preferences for government activism, and finds that this relationship is driven by *both* rich and poor citizens (i.e., liberal policy mood; KE; LG). A reconsideration of these models suggests that year-to-year variation in inequality may provide insufficient information for an examination of the question of interest. Indeed, nearly all variation in aggregate inequality from year-to-year was found to be deterministic—that is, explained by an upward trend. After extracting the trend, we find much weaker evidence for a negative relationship of inequality to mood, and our results suggest that this relationship, to the extent it exists, is likely driven by high-income citizens. In other words, the key finding that both low-income and high-income citizens become more conservative as a result of inequality—suggesting a self-reinforcing mechanism for inequality—does not find support in our reanalysis.

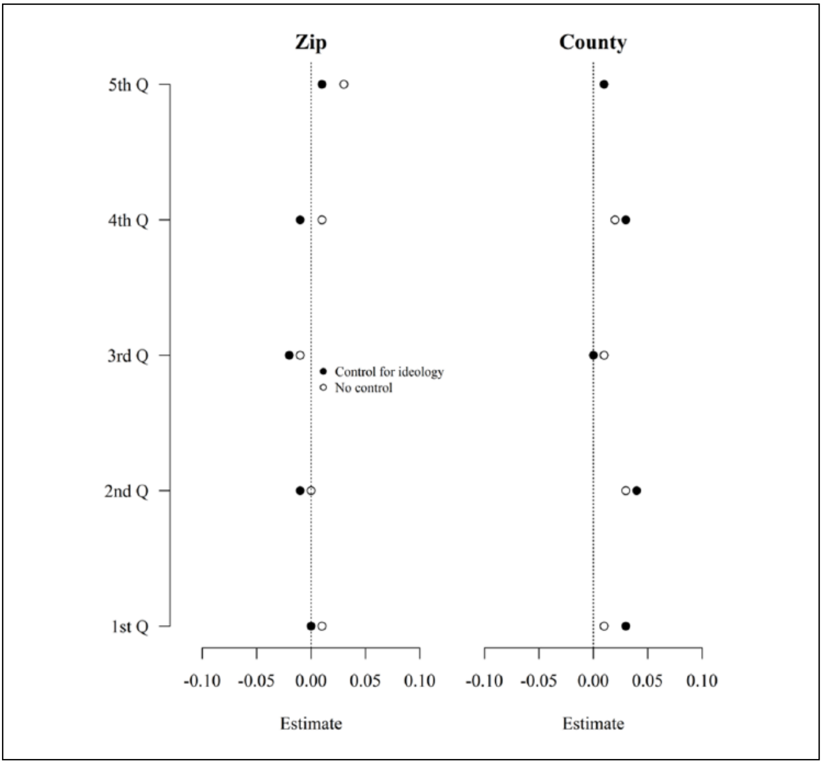


**Figure 3.** Marginal effect estimates for structure of inequality across income.
*Note.* Dots correspond with point estimates for the marginal effect of a 2 standard deviation change in the structure of inequality on preferences for a larger government role in economic policy matters for each of five quintiles of income. Higher values of the inequality measure correspond with greater relative distance of the middle class from the upper class.

A major alternative to temporal variation is spatial variation in inequality at a relatively local level. In our second set of analyses, we examined the relationship of four distinct measures of inequality to policy liberalism, at both the zip code and the county levels of analysis in the United States, across 6 years of data, and across models with both strict and lenient assumptions regarding politically motivated geographical sorting, and obtained highly efficient estimates of the association of local inequality to preferences. We also examined how the relationship of variation in inequality to preferences might be heterogeneous across levels of income and the structure of inequality itself. At best, our results suggest a weak, although *positive* relationship between inequality and policy liberalism. We did not find any consistent evidence for a relationship of the structure of inequality to aggregate opinion across income.

Where do our findings leave the literature on inequality, public opinion, and unequal democracy? Does this mean that inequality does not matter much to opinion? Not necessarily. There are other pathways by which aggregate inequality can influence preferences that do not necessitate, nor even predict, an empirical relationship between objective variation in inequality (of whatever form) and preferences. First, as discussed in the introduction, most of the temporal variation in inequality within the United States is deterministic—explained by a strong upward trend. This is similar to saying that the inequality series is akin to a single observation, namely, the observation that inequality has increased substantially in the United States since the 1970s. This observation, as a *narrative*, can itself influence mass preferences through standard models of opinion formation. For example, as suggested by the Occupy Wall Street protests, growth in inequality over time has become a more salient topic of elite discourse. Inevitably, partisan elites will shape interpretations of this fact itself (e.g., the extent to which the data are reliable, misinterpreted, etc.), its underlying causes (e.g., changes in returns to education, the decline of unions, etc.), and thus policy recommendations, around their ideological interests, and feed these interpretations to co-partisans within the mass public. In this sense, the objective fact of *a* change in inequality over time may indeed matter, but heterogeneously so, and conditional on political predispositions and attention to elite discourse. In our view, this is a more reasonable expectation for how changes in inequality over time can influence preferences. Consider: *even if* citizens are highly aware of changes in inequality at the aggregate over large spans of time, it seems implausible that they are aware of changes occurring from year to year, especially given how little stochastic variation exists in the series.

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## Notes

1. The bulk of empirical research focuses on nation-level estimates of inequality and public opinion, and employs cross-national analyses (e.g., Finseraas,

2009), time-series analyses within one nation (e.g., Kelly & Enns, 2010 [KE]; Kenworthy & McCall, 2008; Kenworthy & Pontusson, 2005), or time-series cross-sectional analyses (e.g., Moene & Wallerstein, 2001).

2. This logic extends to fractionally integrated series and fractional differencing (Lebo, Walker, & Clarke, 2000).
3. The noise component for the series was drawn from a normal distribution with a mean of 0 and a standard deviation equal to the standard deviation of the stochastic component of the true Gini series.
4. See the online appendix for both the code to reproduce the simulations, and the distributions of *t* values from which these Type I error rates were calculated.
5. Column 4 of Table 3 in KE is not actually a direct replication of column 3 (i.e., simply substituting welfare for mood). Rather, this model excludes the controls present in the model for mood. We include these controls in our reanalysis as they are stated to be important by KE, and are included in all other models. Excluding these controls generates the same conclusions as including them.
6. Although it is the case that a trend in one series cannot account for variance in another series, it is possible that public recognition of this trend—looking back on the history of inequality from the present context—*does* have an influence on preferences over social welfare *in the present context*. In other words, citizens might respond to the *fact* of the trend with preferences distinct from those that would be present with a different history of inequality. This, however, is not the hypothesis tested in KE, and cannot be tested via these methods. In this sense, it is best to think of the trend in Gini as a single observation of the world, that is, an observation of one realized pattern of inequality in one history. We only emphasize this point because it is intuitive to think that extracting the trend in Gini would somehow impede the ability to pick up on long-term relationships between these series, but this is incorrect.
7. In no case did a quadratic trend explain significantly more variance than the linear trend alone.
8. Luttig's (2013) Model 5 finds no relationship of low-income mood to the 50 to 20 ratio of inequality, so we do not consider it further here.
9. YouGov utilizes proximity matching to match panel respondents to the target sample. Non-response is mitigated by matching multiple panel respondents to each member of the target sample, and reassigning redundant matches within a given study to other open studies utilizing PollingPoint.
10. Given that our surveys span from 2006 to 2010, we tried to index the measurement of our contextual variables as close in time as possible to opinion measurement in the surveys. That said, the unavailability of data at varying geographic levels from the Census Bureau for certain years often limits perfect matching of contextual and opinion data in time. For our analysis of the 2006 Cooperative Congressional Election Survey's Common Content (CCES), we used the 2005-2009 American Community Surveys (ACS) of the U.S. Census Bureau 5-year estimates to obtain our county-level independent variables and the 2007-2011 ACS 5-year estimates to obtain our zip-level independent variables. For our

analysis of the 2007, 2008, 2009, 2010, and 2011 CCES, we used the 2007-2011 ACS 5-year estimates to obtain our county- and zip-level independent variables. In short, aside from the use of zip data from the 2007-2011 ACS to analyze social welfare policy attitudes in the 2006 CCES, all of our analyses involve indexing contextual measures and opinion measurement as contemporaneous as is possible with available Census data.

11. The US$25,000 and US$100,000 thresholds were chosen because they represented the closest categories of the ordinal ACS household income measure to one-half and two-times the median U.S. household income, respectively. These figures also seem face-valid with respect to operationalizing "poor" and "wealthy" households. Indeed, below 25K and above 100K correspond, roughly, with the 15th and 80th percentiles of income in the contemporary United States. We note, however, that this measure is not a perfect representation of the Lupu and Pontusson hypothesis, because we are restricted to using income categories rather than a continuous measure of income.
12. Right-wing political affiliation was calculated as the average of partisanship and ideology because the two are highly correlated, and many people place themselves at the midpoint of the ideology measure despite ideological leanings one way or the other.
13. Given the categorical coding of income in each survey, the five income groups are not true quintiles, as the five categories do not each contain exactly 20% of the sample. Nonetheless, the percentages are reasonably close to 20% in all cases.

## Supplemental Material

The online appendices are available at http://apr.sagepub.com/supplemental.

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