Inequality and Redistribution
Evidence From US Counties and States, 1890-1930.

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Abstract
Does economic inequality affect redistributive policy? This paper turns to US county and state data on land inequality over the period 1890-1930 to help address this fundamental question in political economy. To facilitate causal inference, the identification strategy uses indicators of weather risk—rainfall, growing degree days, and topographical variability--as instruments for land inequality. The evidence consistently suggests that greater inequality is significantly associated with less redistribution.

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I. INTRODUCTION

Does economic inequality affect redistributive policy? This fundamental question in political economy has spawned a vast literature with often contrasting answers. Approaches that aggregate preferences based on the median voter predict a positive relationship between inequality and redistribution (Meltzer and Richard [1981])[2]. However, models that use alternative formulations of the social contract to aggregate preferences sometimes predict a negative correlation. Political participation can vary by wealth and education levels, and the decisive "voter" may be wealthier than the median. In this case, because the decisive agent is a net loser from redistribution, he can block redistribution as inequality increases, engendering a negative relationship between inequality and redistribution[3].

Models that endogenize the social contract posit causation between inequality, political institutions and redistributive policy. Small groups are better able to solve the collective action problem and derive more concentrated benefits from political intervention [Olson (1956), Stigler (1971)]. Thus, a common intuition in many of these models is that because of the threat of higher taxation in highly unequal societies, a small elite might manipulate the political process in order to limit the political participation of the median voter. The elite can thus implement the redistributive policies that favor their economic interests—policies that also determine the subsequent level of inequality[4]. As a result, high levels of inequality can coexist with low levels of redistribution.

But despite these theoretical advances, the empirical literature has made limited progress in identifying the direction and mechanisms through which inequality might affect redistributive policy. Many cross country studies find no relationship between inequality and government transfers as a share of GDP, or in some cases the correlation is negative (Rodriguez [1998])[5]. Moreover, there are considerable impediments to causally interpreting many of the results in the empirical literature. Redistributive policies--education expenditures and tax policies for instance--can shape inequality, making reverse causality a likely feature of the data. Likewise, latent institutional and political characteristics can shape both redistributive policies and inequality, leading to omitted variable bias. Inconsistency is also likely because of errors in measuring inequality across extremely heterogeneous countries and periods.

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[2] Greater inequality implies that the median voter is poorer than the average voter; and in a democracy, this difference between the median and mean voter can lead to increased redistribution. Recent books in economics with several chapter length surveys include Drazen [2004], Persson and Tabellini [2005] and Ray [2005].

[3] In extreme inequality, the large number of poor can impose redistribution . See Benabou [2004] for a synthesis of these class of models.

[4] Bourguignon and Verdier [2000], Pineda and Rodriguez [2000], Acemgolu and Robinson [2000, 2006] and Acemoglu et. al [2006] are recent examples in this literature. In contrast, Alesina and Angeletos [2005] argue that a negative relationship between inequality and redistribution may also be driven by societal differences in the preference for fairness, and perceptions about the relative importance of luck versus talent in shaping outcomes.

[5] See Perotti [1994, 1996], and the reviews by Persson and Tabellini [2005] and Benabou [1996].

The political and economic forces in the United States over the period 1890-1930 provide a helpful environment to study these issues. And this paper turns to the detailed and relatively informative economic and political data from this era to develop empirical tests and stylized facts to assess the contrasting theoretical predictions on inequality and redistributive policy[6]. More so than is the case currently in the US, redistributive policy was determined by local governments. In 1930, the federal government accounted for about 0.35 percent of total revenues allocated to public elementary and secondary schools; even state governments accounted for only 17 percent of the total; while counties and other local governments contributed 82 percent of total education revenues (US Census [1976]).

To study the impact of inequality on policy outcomes, I measure economic inequality, proxied by the Gini coefficient, using the distribution of farm sizes in each county. Although the structure of economic production in the United States was fast changing over this period, agriculture remained an important economic activity[7]. And with limited access to financial instruments for most of the population, and still relatively low levels of urbanization, farms and other real assets remained principal stores of wealth throughout this period. Thus, the concentration of land ownership is an imperfect but important indicator of wealth inequality during this period of rich cross county and state variation in redistributive policies[8].

The concentration of landownership also permit the use of weather risk measures as instruments to help causally interpret the relationship between inequality and redistribution. Weather is a major determinant of risk in agricultural production, and farmers dislike risk (Moscardi and de Janvry [1977], Binswanger [1980]). These two facts have helped spawn an influential and large literature in agricultural economics on weather risk, the optimal scale of agricultural production and the distribution of farm sizes (surveys include Eastwood et. al [2004] and Ray [1998]). I thus use the standard deviation of surface elevation, rainfall and growing degree days—observed at the county level—as instruments [9].

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[6] In an influential paper, Goldin and Katz (2001) also examine public policy outcomes during this time period.

[7] Although declining over the period, the rural population at the end of the sample period was still substantial, at around 44 percent in 1930. Likewise, about 23 percent of all households lived on farms in 1930 (Historical Statistics of the United States Table Aa716-775).

[8] The expansion of the federal government beginning with the Depression, and the Civil Rights Era of the 1960s make post 1930 data less useful [Besely (2005), Walker and Vatter (1997)]. For instance, the distribution of education funding in 2004 is quite different: the breakdown between federal, state and local revenues for education is 9, 47 and 44 percent respectively(US census:http://www.census.gov/govs/www/school04.html). Also, land inequality is unfortuately a less informative indicator of wealth inequality in the modern period. That said, in an important paper Alesina et. al (1999) examines public expenditures and ethnic heterogeneity using contemporary US data.

[9] Related to this approach is Vollrath [2006] who, building on Engerman and Sokoloff [2002], use mean rainfall outcomes to examine landownership concentration in 1860 US county data. Other examples that use rainfall and more general weather shocks as part of their identification strategy include Miguel, Satyanath and Sergenti [2004] in the case of Africa and growth; Ramcharan [2007] in the case of windstorms, earthquakes and exchange rates; see Ronsenzweig and Wolpin [2000] for a recent critical survey of some of these “natural” approaches to identification.

At both the state and county level, as well as across a variety of redistributive indicators and estimators, the results suggest that greater inequality is associated with less redistribution. The IV estimates are also considerably larger than OLS, and they suggest an economically large impact. For instance, in the 1930 cross section of about 3000 counties, a one standard deviation increase in inequality is associated with an 18 percent decline in per capita education expenditures. These estimates are also robust across very different time periods. In the 1930 and 1920 cross sections, a one standard deviation increase in inequality is associated with a 9 percent and 23 percent decrease in tax revenues respectively.

The underlying mechanism behind this negative relationship also resembles the channels suggested in the literature. In more urban counties, where the presence of manufacturing and other sectors make it less likely that the concentration of agricultural land ownership translates into political power, the negative impact of inequality on redistributive policy is smaller. There is more direct albeit tentative evidence at the state level. Higher levels of inequality are associated with less political competition in both congressional and gubernatorial elections. And there is less redistribution in states with less political competition.

Therefore, taken together, the statistical evidence is not consistent with the Meltzer Richard idea that redistributive policy may be decided by the "one person on vote" political mechanism with full political participation. This idea has helped shape thinking on the relationship between inequality and economic growth, and this evidence may have broader implications for these models [Bertola (1993), Alesina and Rodrik (1994) and Persson and Tabellini (1994). In particular, these results lend credence to the idea that economic elites might disproportionately shape policy outcomes, and is consistent with research that suggest economic inequality can yield socially inefficient policies [Acemoglu and Robinson (2000, 2006) and Bourguignon and Verdier (2000), as well as earlier work on state capture and the private interest theory of regulation Olson (1956); Stigler (1971)].

This paper is organized as follows. Section II discusses the empirical framework and data, while Section III presents the main results. Section IV focuses on the mechanism, and Section V concludes.

II. Data and Empirical Framework

A. An Overview of the Data

The Sample Period: 1890-1930

Political and economic features of the United States during this era, as well as the availability of data on redistributive policy, inequality and other key variables can help empirically assess the relationship between inequality and redistribution. During this era redistributive policy was determined primarily at the local level. Table 2 makes this point: unlike the modern era, federal and even state governments accounted for only a small fraction of total education revenues[10]. Figure 1 more generally illustrates this pattern of public expenditures. During the sample period, local government expenditures accounted for the largest share of total government expenditures in the United States, with the share of Federal expenditures rising dramatically with the onset of the Depression and World War II [Brownlee (1996)]. Thus, given the federalism of the period, redistributive policies differed significantly across states and counties.

Historical narratives also suggest that redistributive policy was keenly contested. Across many regions the rise of the railroad and rapid industrialization pitted the economic interest of industrialists and large land owners against small farmers, and especially in the South, poor blacks and landless farmers (Brogan [1999], Degler[1983], Foner and Garraty (1991)]. In Texas for example, one dollar of the poll tax was earmarked for education expenditures, simultaneously disenfranchising the poor, and reducing taxes on capital and land needed to fund education—a key redistributive public good. Direct taxation for education was also capped at 35 cents on a hundred dollar of real property valuation (Newton and Gambrell [1935]) [11].

Redistribution

I use a variety of common variables at both the county and state levels to help measure redistributive policies. At the county level, there are per capita education expenditures in 1930; per capita tax revenue in 1930 and 1920. The state level provides a larger and more diverse set of measures. These include per capita education expenditures in 1890 and 1910; per capita welfare expenditures, 1890-1910; total expenditures, 1890-1910 and ad valorem taxes—real estate and property taxes, 1890-1900. Table 3 summarizes the county and state level measures of redistribution. There are clear regional differences, as states and counties in the Southern and Border regions redistributed significantly less than the national average.

Inequality: The Concentration of Land Ownership

The main measures of wealth inequality are based on the distribution of farm sizes for each of the decennial census years 1890-1930. The distribution of farm sizes is an imperfect but useful indicator of wealth concentration over this period. Although the structure of economic production in the United States was fast changing, agriculture remained an important economic activity[12]. Moreover, with limited access to financial instruments for most of the population, and still relatively low levels of urbanization, farms and other real assets remained principal stores of wealth throughout this period.

[10] All Tables and Figures are in the Appendix.

[11] Many states and counties also limited education funding from direct taxation. See Pearson and Fuller [1969] for a survey of state education funding policies during this period.

[12] The value of agricultural output as a percent of national income ranged from 18 percent in 1890 to about 10 percent in 1930, while about 22 per cent of households lived on farms [Historical Statistics of the United States (1976)].

The data are collected by the U.S. Census Bureau and are observed at the county level; in some specifications I aggregate up to the state level. The US Census provides information on the number of farms falling within a particular acreage category or bin, ranging from 20-49 acres up to 1000 acres—see Table 1. I establish the main results using the Gini coefficient to summarize the farm acreage data. The Gini coefficient is a measure of concentration that lies between 0 and 1, and higher values indicate that larger farms account for a greater proportion of total agricultural land—the ownership of agricultural wealth is unequally distributed, and skewed towards large farms. Conversely, smaller Gini values suggest that the total farm acreage—agricultural wealth—is relatively equally distributed among farms of different sizes. The box plot in Figure 2 helps convey the regional variation[13]. It illustrates for example the relative equality of the North East. But the median level of inequality among Southern and Pacific counties were very similar, although more dispersed in the former.

Figures 3-5 provide a first look at the relationship between inequality and redistribution. Figures 3 and 4 are respectively scatter plots of inequality and county level per capita education expenditures and tax revenue, observed in 1930. Figure 5 uses the log of per capita ad valorem taxes observed at the state level in 1890 as the dependent variable. At both the county and state level, in both the beginning of the sample and 40 years later, increased inequality is associated with less expenditures on education, less overall tax revenue and less tax revenue collected on real property. Taken together, these simple correlations suggest that higher inequality can lead to less redistribution. However, reverse causality, measurement error and unobserved county and state heterogeneity preclude causal interpretation—issues the next section addresses.

B. Empirical Framework and Identification Strategy

In a simple linear formulation of the relationship between inequality and redistribution, suppose y_i measures the extent to which county $i's$ policies are redistributive; y_i for example could be per capita education expenditures in county i. And let INQ_i denote the level of wealth inequality in county i, and X_i be a vector of observables that may also determine county $i's$ preference for redistribution:

$$y_i = \beta INQ_i + X_i\alpha + \varepsilon_i \tag{1.1}$$

The parameters β and α are to be estimated and ε_i is a residual term. In this linear model, evaluating the various theoretical predictions on the impact of inequality on redistribution hinges on the sign and magnitude of β --the conditional correlation between INQ_i and y_i. However, theoretical arguments suggest that OLS estimates of β can be biased.

[13] In all box plots, the shaded rectangle represents the interquartile range, which contains the median—the solid line. The ends of the vertical lines extend to a maximum of 1.5 times the interquartile range. Dots beyond this range are possible outliers.

Specifically, redistribution can itself affect the distribution of wealth (Bourguignon and Verdier [2000]). Higher levels of redistribution for example can lower inequality, imparting a negative bias on the OLS estimate of β. Likewise, models of endogenous political institutions (Acemgolu and Robinson [2000, 2006]) suggest that these institutions both affect inequality and redistribution, and are also shaped by inequality and redistribution, again leading to biased OLS estimates. At the same time, measures of inequality are computed from survey data and are prone to measurement error, which can bias OLS estimates of β towards zero.

Weather is a major determinant of risk in agricultural production, and to help facilitate causal inference, I use measures of weather risk as instruments for farm concentration. An influential literature in agricultural economics on the optimal scale of agricultural production, the distribution of farm sizes and weather risk motivate this approach. Recent surveys include Eastwood et. al [2004]; Ray [1998] and Binswanger, Denninger and Feder [1995]; while Heady [1952] and Johnson [1947] review these issues with examples drawn from American agriculture in the sample period.

The underlying logic rests on the idea that weather patterns—storms, droughts, large air and soil temperature variations--are a powerful source of spatially covariant risk (Moscardi and de Janvry [1977], Binswanger [1980]). Furthermore, the variety and effectiveness of risk mitigation measures are closely related to farm size, which in turn can magnify productivity differentials across farm sizes, and increase the drive for farm consolidation [Rosenzweig and Binswanger (1993)]. Some mitigation measures for example lower average farm productivity. And wealthier farmers—those with larger farm sizes—can bear additional risk, and achieve higher levels of productivity, eventually tilting the distribution of land towards large farms.

For instance, compared to wealthy farmers, poor farmers may insure against variable precipitation by allocating a larger share of labor to non farm employment. And this difference in the choice of labor allocation in response to risk can magnify differences in the size of farm plots. In addition, some risk mitigating measures may be difficult on smaller farms. Diversifying production across crops, as well as livestock to hedge against negative weather shocks may be less effective on smaller plots. As a result, frequent weather shocks may disproportionately trim the number of small farms, again leading to the further concentration of land among bigger farms.

The Dust Bowl of the 1930s provides a concrete illustration of how weather shocks might shape farm size distributions. Hansen and Libecap (2004) suggests that the distribution of farm sizes played a crucial role in turning the severe drought that gripped the Great Plains in the 1930s into a disaster, shaping the subsequent distribution of farm sizes. Before the shock, small farms accounted for a large share of agricultural production in the arid Mid Western States. But in part due to limited credit access, small farms did not optimally invest in erosion control techniques. Their large numbers also induced a common pool problem, as small farms did not internalize the impact of blowing sand on their neighbors. When the rains failed, the concentration of small farmers magnified the catastrophe, eventually leading to the consolidation of agricultural production into larger units. That is, although history "predetermined" farm sizes in the Great Plains with the Homestead Act of 1862, which provided 160 acres for a nominal $18 fee, the inherent variability of precipitation in that region exerted a powerful impact on farm sizes in the long run[14].

To implement the instrumental variables strategy, I measure the intrinsic weather risk of agricultural production in a given county using the standard deviation rainfall, growing degree days or heating units and elevation observed at the county level—Table 4 summarizes the data across geographic regions. The weather data are collected from 20,000 National Weather Service monitoring stations, beginning around 1900, while the elevation data are compiled from US Geological Survey relief maps[15].

Droughts and floods can destroy livestock and crops. And the variability of rainfall captures a key component of precipitation risk at the county level. In addition to precipitation, temperature variability can also harm agricultural production. Plant growth depends on the ambient and soil temperatures. After seeds are planted, the number of growing degree days determine the time needed for plant maturity and harvest (McMaster and Wilhelm [1997])[16]. And large fluctuations in a county's growing degree days can introduce considerable uncertainty into the choice of crops, the timing of plantings and harvests, and ultimately yield and income.

The variability of surface elevation can also delineate spatially covariant weather risk. Weather patterns and soil characteristics fluctuate less over relatively flat surfaces. While substantial changes in elevation can induce large differences in precipitation outcomes, soil productivity and crop types. Thus, rainfall, growing degree days and topographical variability capture important and distinct features of weather risk—and are likely to be key determinants of the distribution of farm sizes across counties.

Figures 6-8 support the first step in the identification strategy. Consistent with the discussion on farm size and weather risk, these figures depict a robust correlation between the concentration of farm sizes observed in 1930 for the 2966 US counties in the sample, as measured by the Gini coefficient, and the log of the standard deviation of growing degree days, rainfall and the standard deviation of elevation respectively. In all cases, counties with greater weather risk also have more unequal farm size distributions.

[14] To be sure, rather than concentrating land area among large farmers, alternative approaches suggest that spreading production across disparate climatic regions may be the optimal diversification response to spatially covariant weather risk. Towsend [1993] for example develops these ideas using examples drawn from Medieval village economies. I revisit the logic behind the identification strategy in the Robustness Section.

[15] The data were purchased from Weather Source, and the data appendix provides more detail on how these variables are constructed.

[16] Growing degree days are calculated as the difference between the average and base daily temperatures (Griffin and Honeycutt [2000]). The appendix provides more detail.

While Figures 6-8 are supportive of the identification strategy, I do not wish to overstate the case for weather risk in identifying the impact of inequality on redistributive policy. Climatic variability can affect other economic outcomes, such as agricultural productivity, that might also influence redistributive policies. Thus, the estimation strategy conditions on a wide variety of plausible demographic and economic control variables in order to render the exclusion restriction assumption plausible. Specifically, the baseline specification controls for other plausibly exogenous variables that might also be related to both redistribution and weather outcomes: state fixed effects, as well as county area and total population. The augmented specification includes potentially relevant but endogenous demographic and economic controls: the percent of a county's population that is classified as native born white; black; the percent living in urban areas; population density; as well as the average level of farm productivity—simple summary statistics in Table 5[17]. There are still weaknesses in this approach, and the robustness section considers alternative controls and instruments.

That said, the first stage conditional correlation between the weather risk variables and the Gini measure of land concentration is large and robust (Table 6) [18]. From the base specification in column 2, all three variables are positive, and individually and jointly significant (p-value=0.00). A one percent increase in rainfall variability is associated with a 0.1 standard deviation increase in the Gini coefficient; the estimated impacts of growing degree days variability and terrain variability are also similar. These results are little changed in the augmented specification (column 3).

Moreover, the conditional median point estimates in column 4—which are less sensitive to outliers—are significant and nearly identical to conditional mean OLS results. The dummy variable approach—equals 1 for Southern counties and zero otherwise—indicates that the weather risk variables do affect farm size variation differently across regions. From column 5, the impact of weather risk on farm size concentration is significantly larger in Southern counties: the interaction term between this dummy variable and topographical variation is positive and significant. But the impact remains significant for Northern counties as well (p-value=0.00).

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[17] Average farm productivity can be endogenous since it can depend on education levels, which itself is determined by redistributive policies. Likewise, endogeneity can also arise in this augmented specification because demographic groups can migrate in response to the provision of public goods (Rhode and Strumpf [2003]). The Data Appendix defines these variables more precisely and list their sources. Table 6 provides common summary statistics across geographic regions.

[18] Following Rappaport [1999], and Levy et. al [2005] in all cross county regressions, I report standard errors corrected for potential spatial correlation. In particular, I weight the error covariance matrix using quadratic weighting for counties less than a 150 kilometers apart. Typically, correcting for spatial correlation produces errors about 5-10 larger than the heteroscedaticty errors. The Appendix provides more detail, but see also Conley [1998] and the survey by Cressie [1993] on spatial data.

III. MAIN RESULTS

A. County Level Data

Per Capita Education Expenditures

Education is a key redistributive good and the results in Table 7 uniformly suggest that greater inequality is significantly associated with less per capita education expenditures. Moreover, the IV estimates—which are about thrice as large as the OLS estimate (column 2)--imply that the impact of inequality is economically very large[19]. From the baseline IV specification (column 3), a one standard deviation increase in inequality is associated with a 17 percent decline in per capita education expenditures. This impact remains statistically and economically significant (p-value=0.00) after controlling for a range of demographic and economic county characteristics (column 4); in this case, the point estimate is about 6 percent larger than in column 3.

Unlike other parts of the US, the post belllum South was heavily dependent on agriculture, and its political and social system rigidly enforced race and class distinctions. I use state dummy variables in the estimation and control for a host of economic and demographic observables, nevertheless these results may still be solely driven by unobserved historical, political, economic and social differences between Northern and Southern counties. To allow the impact of inequality to differ between the North and South, I interact inequality with a dummy variable that takes on the value of one if a county is located in a Southern or Border state, and zero otherwise. The interaction term is not significant, suggesting that inter regional differences are not the main source of these results.

Texas provides a helpful case study to gauge the robustness of these findings. It is the largest state in the continental U.S., and has a very diverse physical geography, spanning nearly eleven degrees of latitude and over thirteen degrees of longitude. There is thus substantial variation in weather risk and land inequality among its 235 counties. The historical record also reveals that inequality and redistributive policies were closely connected. Direct taxation for education was capped at 35 cents on a hundred dollar valuation as Conservative Democrats—large landowners, ranchers and industrialists —fought over redistributive policy with poor tenant farmers and blacks—the main constituents of the Populist Party (Newton and Gambrell [1935] and Miller [1986]).

From column 6, in what is perhaps the cross section with the least amount of unobserved heterogeneity, a one standard deviation increase in inequality is associated with a 39 percent decrease in per capita education spending. However, the potential for biased estimates and inference exist because the instruments generate only weak identification in

[19] The significantly larger (in absolute value) IV estimates highlight the possibly large attenuation bias imparted by errors in measuring in inequality.

this sub sample[20]. To address the challenges posed by these potentially weak instruments, I also report results using limited information maximum likelihood estimators (LIML) (column 7), since the latter is known to have better small sample properties and be more robust to weak instruments[21]. Both the LIML (column 7) and 2SLS estimates are very similar.

Per Capita Tax Revenue

Education as well as most other public goods were funded primarily from local taxes in this era. And tax revenue is also an important indicator of cross county variation in redistributive preferences and the overall size of government[22]. Using the log of per capita tax revenue collected at the county level as the dependant variable, the results in Table 8 show that despite the distortions possible from the Depression, higher inequality is associated with significantly less tax revenues in the 1930 cross section; likewise, the IV estimates are also considerably larger than the OLS point estimate (column 2).

In particular, the baseline IV specification in column 3 suggests that a one standard deviation increase in inequality is associated with a 5.3 percent decline in per capita tax revenues. Adding other demographic and economic controls increases the point estimate by about 64 percent, and the coefficient is now significant at the 10 percent level (p-value=0.06) (Column 4). Interacting inequality with the North-South interaction term (column 5) indicates no significant difference in impact across the two regions. Column 6 restricts the sample to Texas, again revealing a significant relationship.

Although these results appear robust, the period around 1930 witnessed many significant economic and social events. The economic and political repercussions of the 1929 stock market crash was just beginning to be felt in 1930. This era was also a period of rapid technological change, as tractors and mechanized production replaced animal power on farms (Gardner [2002]). From columns 7 and 8 of Table 8, there is evidence that the negative relationship between inequality and redistribution may generalize to other time periods. In the 1920 cross section, a one standard deviation increase in inequality is associated with an 18 percent decrease in tax revenue—larger than the 1930 point estimate. Column 8 again shows that this relationship is relatively stable across the main geographic regions. Indeed, the state level data, which extend from 1890-1930 across a wider set of redistributive variables closely resemble the county level results, and for concision are in Appendix II.

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[20] Based on the definition proposed by Stock and Yogo (2001) that a 5 percent hypothesis test rejects no more than 15 percent of the time, the critical value for the weak instrument test based on the first stage F-statistic is 11.59.

[21] See Mackinnon and Davidson [1993] and the survey by Stock et. al [2002]). Separately, although developed under the maintained assumption of homoscedasticity, the weak instrument robust conditional likelihood ratio test suggested by Moreira (2003) yields a confidence interval of [-10.14, 0-.99] for the LIML estimate of the Gini coefficient—the p-value is 0.01.

[22]For example, in cross county work Cameron [1978] and Blais et. al [1993] use tax revenue as a share of GDP to help measure redistributive intent.

IV. ROBUSTNESS

A. Semi Parametric Results

The evidence appears consistent with those theories that predict a negative relationship between inequality and redistribution. But many of these theories suggest a relationship that may be more complex than the linear specification considered in Equation (1.1). In explaining why Western countries extended the franchise, Acemoglu and Robinson [2000] observe that higher inequality can actually lead to higher temporary redistribution in order to avoid political revolution. Only when revolutions are difficult to foment, do higher inequality imply less redistribution. Likewise, because of the productivity benefits from a more educated workforce, some parameter values in the Bourguignon and Verdier [2000] model predict that elites may actually increase funding for education in more unequal societies.

I consider a semi-parametric estimation strategy to help capture the possible non linearities in the relationship between inequality and redistribution. Specifically, this strategy treats redistribution as a possibly non linear function of inequality, $f\left(INQ_i\right)$, with the control variables entering linearly:

$$y = f\left(INQ_i\right) + X_i\alpha + \varepsilon_i \tag{1.2}$$

Thus, while it may be hard to empirically measure the difficulty of inciting revolutions, or the extent of education externalities, this functional form flexibility can help identify changes in the magnitude and direction of the relationship between inequality and redistribution that would otherwise be masked in the linear specification.

I implement this approach using optimal tenth order differencing to estimate the baseline representation of Equation (0.2) for the 1930 cross-section of US counties (Blundell and Duncan [1998] and Yatchew [2003]). Intuitively, this modular approach first removes the direct and indirect impact of inequality--the non parametric variable in Equation (0.2)--allowing an estimate of α; after estimating α, standard non parametric methods to analyze $f\left(INQ_i\right)$ are available. Figure 9 depicts the relationship between inequality and the log of per capita education expenditures, $f\left(INQ_i\right)$, using local weighted regression (LOWESS) smoothing (Hardle [1990]). The corresponding linear specification is shown using the dashed line.

Although the theory suggests that the relationship between inequality and redistribution can be non-monotonic, the slope of the function $f\left(INQ_i\right)$ is negative over the entire sample: increased inequality appears to uniformly imply less education expenditures. Moreover, the evidence in Figure 9 further suggests that the linear specification adequately represents the relationship between education expenditures and inequality[23]. In contrast, the semi parametric approach identifies some subtle but significant changes in the magnitude of the relationship between inequality and per capita tax revenue (Figure 10). In particular, the linear specification significantly overestimates the negative impact of inequality on tax revenue for low levels of inequality. But over the support of inequality in the sample, the slope of the semi parametric model is consistently negative, again suggesting that a marginal increase in inequality is associated with less redistribution.

B. Alternative Identification Strategies

Standard overidentification tests do not reject the weather risk instruments. But these statistical tests often have low power in identifying violations of the exclusion restriction. And although the empirical strategy has conditioned on a wide range of variables, weather risk may still affect policy outcomes through unobserved channels, such as crop choice or the demand for redistributive policies to help insure against weather shocks. Thus, this subsection gauges the robustness of the identification strategy.

Mean Rainfall

Engerman and Sokoloff [2002] also argue that intrinsic land and weather characteristics can explain differences in farm sizes or inequality across North and South America. But rather than emphasize weather risk as the main impetus for farm consolidation, they focus on crop choice. Crops suited for plantation agriculture such as sugar cane, tobacco and rice thrive in warm regions with regular and heavy rainfall. In contrast, Engerman and Sokoloff [2002] claim that grain—wheat and barley—which are better suited to more temperate climates, exhibit less economies of scale[24]. Thus, because of their suitability for grain production, temperate regions may have enjoyed a more equitable distribution of wealth as smaller farms proliferated among settlers.

To gauge the sensitivity of the IV strategy to this complementary approach to weather and farm size distribution, I add the mean level of rainfall to the instrument list. The first stage, reported in column 2 of Table 10 for 1930, is consistent with the Engerman and Sokoloff hypothesis. The mean annual rainfall coefficient is positive and significant at the 10 percent level; and both the mean and standard deviation of rainfall are jointly significant at the 5 percent level. But from column 3, the estimated impact of inequality on per capita education expenditures is only slightly higher when mean rainfall is added to the instrument list. Likewise, using per capita tax revenues in 1930 as the dependant variable, columns 4 reveals that incorporating the Engerman and Sokoloff hypothesis into the IV strategy yields estimates that closely resemble those obtained earlier.

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[23] Under the null hypothesis of linearity, the heterosecdasticy robust specification test statistic, which is distributed as N(0,1), is 0.54.

[24] Virginia tobacco for example requires rainfall between 23 to 31 inches per annum, while Nebraska wheat usually thrives in regions that receive between 14 to 21 inches of rain per annum

Crop Choice

The crops grown in a county can also directly shape the distribution of farm sizes. Although agriculture was rapidly becoming mechanized during this period, cereal production such as wheat and rye were still subject to less economies of scale than other crops such as apples and other fruits, which often required large orchards in order for production to be profitable (Gardner [2002]). Therefore, cross county differences in the types of crops grown can also be a credible source of exogenous variation in land inequality. And to further gauge the robustness of the main results, Table 10 reports 2SLS results based on the value of fruits and nuts; cereals; and vegetables as a share of the total value of agricultural output in each county.

The first stage results in column 5 of Table 10 indicate that counties with agricultural production concentrated in fruit production or vegetables also had higher levels of land inequality. The coefficient on cereals is negative, suggesting that greater cereal production occurred in less unequal environments, but this variable is individually not significant. However, all three variables are jointly significant (F-Statistic=35.73). The 2SLS estimate of the impact of land inequality on education expenditures (column 6) is smaller than that obtained using the weather risk variables, but remains negative and robust (p-value=0.00), and is about double the OLS result reported in Table 7. The impact on per capita tax revenue is also larger than the OLS results in Table 8, but is not significant (p-value=0.18).

1890 Inequality

The recent literature on local average treatment effects (Imbens and Angrist [1994]) observes that even for valid instruments, IV estimates can be sensitive to the choice instruments. In this case, beyond weather risk, the cross section variation in land inequality was also shaped by historical Federal polices such as the aforementioned Homestead Act of 1862, the timing of migration patterns, transportation and other factors. And these alternative sources of variation in land inequality could yield different estimates of the impact of inequality on redistributive policy. For example, in counties where Federal land polices disproportionately determined land distribution patterns, those residents may have had a more favorable view of government intervention than residents in counties where weather risk was the major determinant.

Therefore, to crudely gauge how well these results might generalize, I use land inequality in 1890 to instrument inequality outcomes in 1930 and 1920. There is evidence of robust persistence in inequality from the first stage F-Statistic—columns 5-7 of Table 10--reflecting in part geographic but also historical land policies and settlement patterns. And the results in columns 5-7 suggests that the results may generalize: the estimated relationship between inequality and redistributive policy remains large, negative and robust. But there are important caveats: although the instrument is observed 30-40 years prior and reverse causality is less likely to be a source of bias, persistent unobserved variables that shape both inequality and redistribution—like political institutions—can still render this IV approach inconsistent.

V. Mechanism

Economic Structure: Urbanization

Cross county differences in urbanization can help in understanding the negative relationship between the concentration of agricultural land ownership and redistribution. Economic activity in more urban counties is likely to be distributed across agriculture, manufacturing and other sectors. Because of the presence of these other possibly more economically important sectors, the concentration of agricultural land ownership is less likely to translate into political power in more urban counties. Alternatively, concentrated land ownership in heavily rural counties implies that a few landowners control the majority of economic production, which can allow the landed elite to implement their preferred redistributive policies. Urbanization then might help determine the extent to which agricultural land ownership translates into political power.

To empirically implement this idea, I interact the Gini coefficient measure of land inequality with the percent of the population living in urban areas. Columns 2-4 of Table 11 suggest that the negative impact of agricultural land inequality is significantly more muted in more urban counties. From column 2, a one standard deviation increase in inequality is associated with an 18 percent decline in per capita education expenditures for a county at the median level of urbanization, but a 13 percent decline for a county at the 75th percentile urbanization. Columns 3 and 4 reveal a similar pattern using per capita tax expenditures in both 1930 and 1920.

Economic Structure: Manufacturing

The remaining columns of Table 11 interact land inequality with the per capita number of manufacturing establishments. There is evidence that the importance of land inequality in shaping redistributive policies is more limited in counties where manufacturing dominates the economic structure. At the median level of per capita manufacturing, a one standard deviation increase in inequality is associated with an 18 percent decline in per capita education expenditures. But at the 90th percentile, a similar increase in inequality is associated with only an 11 percent drop. Again, these results are replicated when using tax revenues in 1930 as well as 1920.

Taken together, the evidence in Table 11 hints at the possible political mechanism underlying the negative relationship between inequality and redistributive policy. But rather than reflecting the extent to which land inequality might translate into political power, the interaction terms might capture the purely economic factors that shape redistributive policy. More urban counties might be wealthier or have larger tax bases, making them less dependant on agriculture to fund redistributive policy.

Diffusion of Power: Small Farms

To more intuitively capture the relative importance of small farms in agriculture, and by extension, the possible diffusion of political power within a county, I construct an alternative measure of land concentration. Farm sizes in the census data range from between 3-9 acres to over 1000 acres, and using the mid point of these ranges, I create the ratio of the total number of acres of agricultural land operated by farms under 500 acres versus the total number of acres of land found on farms classified as being 500 acres and above. Unlike the Gini coefficient, higher values of the land ratio suggest that agricultural land—and possibly agricultural production—is relatively concentrated among smaller farms. As a result, the relative economic importance and political influence of a few big land holders are likely to be small when this ratio is large.

The evidence in Table 12 appears consistent with this prediction: there is an economically large positive correlation between the relative importance of small farms and redistributive policies. I obtain these correlations using the weak instrument robust LIML estimator, since from the first stage F-Statistic, the instruments may only generate weak identification. The LIML estimates suggest that a one standard deviation increase in the ratio of small to large farms' land area is associated with a 76.7 percent increase in per capita education expenditures (column 2)—about 4 times as large as the impact estimated using the Gini coefficient. The impact is nearly identical with the log of per capita tax revenues as the dependent variables (column 3); and both estimates do not appear to significantly differ between Northern and Southern counties. The relative importance of small farms also appears positive and large in the 1920 cross section (column 4), but is not significant.

Political Competition

State level data yield political variables that might better help in understanding the negative impact of inequality on redistribution. In particular, I focus on the impact of inequality on political competition; and in turn, the role of political competition on redistribution. Historical narratives motivate this approach. There was redistributive conflict between the planter oligarchy, poor whites and blacks in the post Reconstruction South[25]. And despite transferring de jure political power to the poor, some historians observe that by not fundamentally reforming the economic structure of the South—breaking up large plantations and redistributing land to peasant farmers—Reconstruction left de facto political power with the old elite.

Turning to the data, I measure political competition using standard two party indices common in the literature (Rusk [2001])[26]. Specifically, political competition is defined as 1 minus the difference between the absolute value of the Democratic and Republican

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[25] Consider the following election appeal from 1870 in Georgia: "Let the slave-holding aristocracy no longer rule you. Vote for a constitution which educates your children free of charge; relieves the poor debtor from his rich creditor; allows a liberal homestead for your families; and more and more than all, places you on a level with those who used to boast that for every slave they were entitled to three fifths of a vote in congressional representation," (Brogan [1998]).

[26] During this period, third parties had little political influence, as the Democratic and Republican parties consolidated their electoral dominance in the post Civil War period. For electoral support for the Populist Party declined after 1896; Theodore Roosevelt's "Bull Moose Party" in the 1912 elections is an important exception to two party electoral competition during this period.

candidates vote shares in a particular state's race: $\left(1-\left|DEM\% - REP\%\right|\right)$: higher values indicate more competitive races. I focus primarily on congressional and gubernatorial elections[27]. And because of the possible impact on political competition on redistributive policy and thus, inequality, I continue with the instrumental variables approach. But at the state level, the IV strategy produces weak identification, and I rely on the weak instrument robust LIML estimator; I also report the Moeria (2003) weak instrument robust conditional likelihood ratio test of the significance of the Gini Coefficient.

Table 13 suggests that over the period 1890 through 1930, states with higher levels of inequality also had less competitive gubernatorial and congressional elections. Specifically, the LIML estimates are less robust at the gubernatorial level, and are significant at conventional levels only in 1910 and 1920; for congressional elections, the LIML estimates are significant at the 10 percent level except in 1910. The point estimates are however economically large. In 1920 for example, a one standard deviation increase in inequality is associated with a 1.51 standard deviation decline in the competitiveness of congressional elections. Likewise, in 1910 a similar increase in inequality is associated with a 0.67 standard deviation decline in the competitiveness of gubernatorial elections.

Table 14 documents a large robust positive relationship between political competition and redistributive polices. A one standard deviation increase in the competitiveness of congressional elections within a state is associated with a 50 percent increase in per capita ad valorem taxes in 1900. In 1910, a similar increase in the competitiveness of gubernatorial elections imply a 66 percent rise in per capita education expenditures. Taken together, the results in Tables 13 and 14 tentatively suggest that inequality may have influenced electoral institutions, and these institutions in turn may have shaped redistributive policies.

VI. CONCLUSION

Using a wide range of estimators and specifications, the empirical evidence based on US county and state data over the period 1890-1930 suggests that economic inequality can negatively affect redistributive policy. Moreover, the instrumental variables approach, which uses indicators of weather risk as instruments, yield economically large estimates. There is also tentative evidence that inequality negatively affects political competition, and that increased political competition is associated with greater redistribution.

These results support the idea that economic elites can shape policy outcomes in excess of what the simple median voter framework would suggest, and may have

[27] Unlike presidential elections, which can often revolve around national issues, congressional races better reflect local political and economic sentiments, such as preferences for local taxes and education expenditures (Gimpel [1993]). There is also the added advantage that congressional districts can be gerrymandered, which can produce rich variation in county level measures of political competition.

implications for the broader question of inequality's impact on economic growth and development. In particular, thee evidence is consistent with those models that suggest high levels of inequality can generate socially inefficient policies [Acemoglu and Robinson (2000, 2006) and Bourguignon and Verdier (2000), and earlier work on state capture and the private interest theory regulation [Olson (1956); Stigler (1971)].

However, recent research suggests mechanisms that might be observationally equivalent to those identified in the data. Rajan [2006] for example notes that inequality might shape the initial constellation of payoffs from different economic policies across interest groups or constituencies. And rather than emphasizing coercive political power, heterogeneous payoffs might itself prevent agreement on redistributive policies. Likewise, Alesina and Angeltos [2005] hypothesize that underlying differences in perceptions of fairness can also produce a stable negative relationship between inequality and redistribution. Therefore, these results add to rather than settle the debate on inequality and redistribution.

VII. APPENDIX

A. Computing Standard Errors

Nearby counties may share similar unobserved features—histories or cultural characteristics for example—that shape redistributive policies. As a result, the correlation in the error term in Equation (1.1) between county i and county j may be proportional to the distance between the two counties. We thus follow Conley [1998], Levy et. al [2005] and Rappaport [1999], and assume a spatial structure to the error covariance matrix. Specifically, for county pairs further than a 150 kilometers apart—measured as the distance between the counties' geographic center-- we assume independence. Meanwhile, for county pairs less than 150 km apart, we use quadratic weighting:

$$E\left(\varepsilon_i \varepsilon_j\right) = \left[1 - \left(\frac{dis\tan ce_{ij}}{150}\right)^2\right] \rho_{ij}$$

$$\widehat{\rho_{ij}} = e_i e_j$$

B. Tables and Figures

Table 1: Variables' Definitions and Sources

Variable	Source	Definition
Land Inequality (Gini Coefficient)	United States Bureau of Census; Inter-University Consortium for Political and Social Research (ICPSR) NOs: 0003, 0007,0008,0009,0014,0017	The number of farms are distributed across the following size (acres) bins: 3-9; 10-19 acres; 20-49 acres; 50-99 acres; 100-174;175-259;260-499;500-999; 1000 and above. We use the mid point of each bin to construct the Gini coefficient; farms above 1000 acres are assumed to be 1000 acres.
Per Capita Education Expenditures (County Level, 1932)	Rhode and Strumpf [2005]	The exact definition is "School government cost payments operations and maintenance"
Per Capita Tax Revenues (County Level, 1932 & 1922)	Rhode and Strumpf [2005]	Taxes collected by all local governments—county, minor civil divisions, school districts, etc.—within the county
State Level Data: Per Capita Education and Welfare Expenditures (1890, 1900); Per Capita Total Expenditures (1890-1910); Ad Valorem Taxes (1890-1900)	Socio-Economic, Public Policy and Political Data for the United States, 1890-1960 (ICPSR 0015)	
Population Density; Urban Population; Fraction of Native White Population; Fraction of Black Population; Fraction of Population Between 7 and 20 years; County Area; County Population	United States Bureau of Census; Inter-University Consortium for Political and Social Research (ICPSR) NOs: 0003, 0007,0008,0009,0014,0017	
Average Level of Agricultural Productivity; Share of Fruit and Nuts; Cereal; and Vegetables.	United States Bureau of Census; Inter-University Consortium for Political and Social Research (ICPSR) NOs: 0003, 0007,0008,0009,0014,0017	The total value of crops; implements and machinery; land and buildings divided by total farm population. Shares are deflated by the total value of crops in each county.
Annual Standard Deviation of Rainfall; Annual Mean Rainfall	Weather Source 10 Woodsom Drive Amesbury MA, 01913 (Data Compiled from the National Weather Service Cooperative (COOP) Network	The COOP Network consists of more than 20,000 sites across the U.S., and has monthly precipitation observations for the past 100 years. However, for a station's data to be included in the county level data, the station needs to have a minimum of 10 years history and a minimum data density of 90 percent: ratio of number of actual observations to potential observations. If one or more candidate stations meet the above criteria the stations' data are averaged to produce the county level observations. If no candidate station exists within the county, the nearest candidate up to 40 miles away in the next county is substituted. The arithmetic mean and standard deviation level of rainfall are computed from the monthly data for all years with available data.

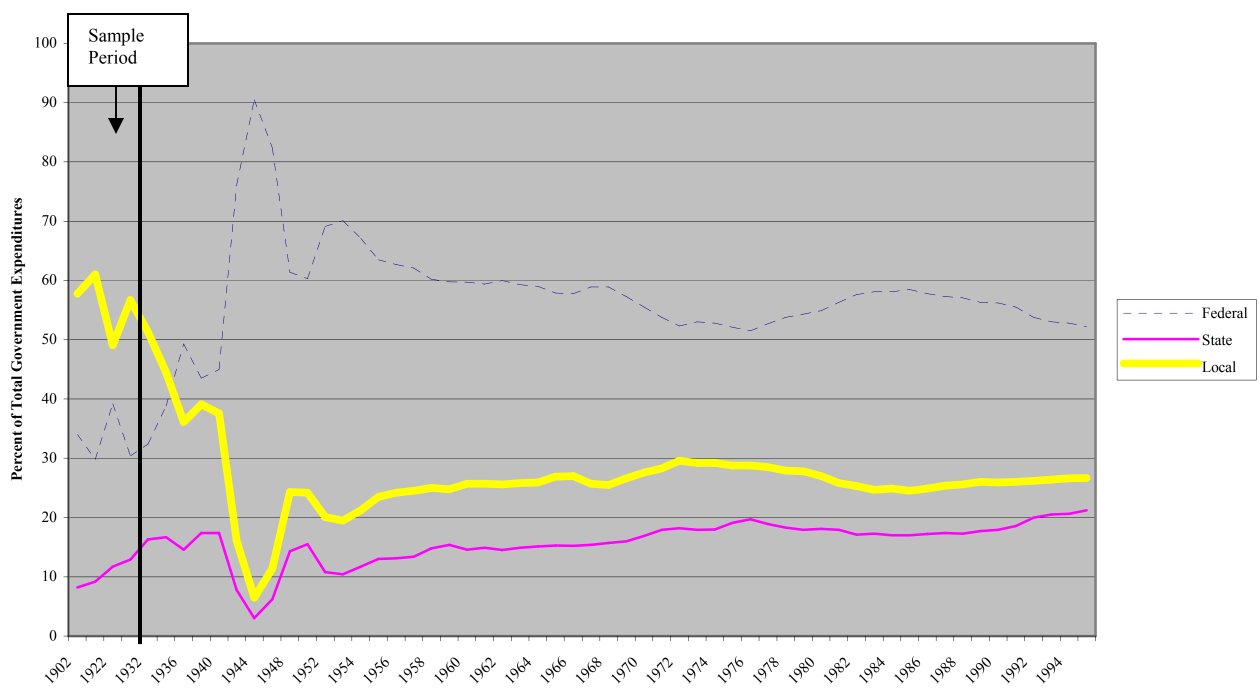
Annual Standard Deviation Growing Degree Days	Weather Source 10 Woodsom Drive Amesbury MA, 01913 (Data Compiled from the National Weather Service Cooperative (COOP) Network	Computations are similar to rainfall. Growing degree days (GDD) derived by taking the average of the daily high and low temperature each day and subtracting the baseline temperature, which for most counties is 10 degrees Celsius. For example a day with a high of 20C and a low of 16C would correspond to 8 GDD.
Weighted Standard Deviation of Elevation	Weather Source 10 Woodsom Drive Amesbury MA, 01913	The number of square miles of each county's land area is listed from below 100 meters, 0-100 meters;100-200 meters; the bins increase in increments of 100 meters up to 5000 meters. The weighted standard deviation is then computed, with the weight being the share of land area in each elevation category.

Table 2. Decomposition of Education Expenditures by Government Level

Year	Federal	State	Local
2004	9.0%	47.0%	44.0%
1940	1.8%	30.3%	67.9%
1930	0.3%	16.9%	82.7%
1920	0.3%	16.5%	83.3%
1910	---	15.0%	72.3%
1900	---	17.3%	67.7%
1890	---	18.2%	67.8%

Source: Historical Statistics of the United States (H 486-491) and US Census (http://www.census.gov/govs/www/school04.html).

Figure 1: Total Government Expenditures, by Level: 1902-1995



Source: Historical Statistics of the United States Millennial Edition Online; Table Ea10-23.

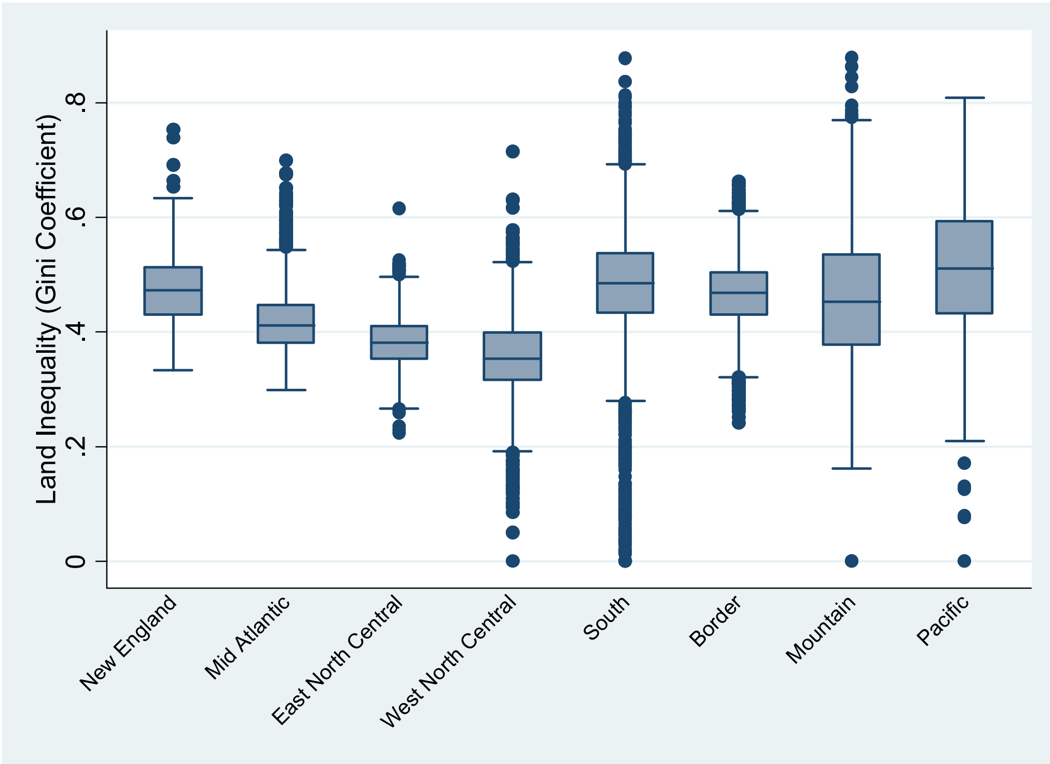
Table 3: County Level Redistribution Measures, Summary Statistics by Region, 1930

	Full Sample	New England	Middle Atlantic	East North Central	West North Central	South	Border	Mountain	Pacific
	Per Capita Education Expenditures								
Mean	14.32	15.13	19.02	17.27	17.35	7.79	9.19	25.4	27.11
Standard Deviation	8.82	3.11	6.71	3.42	9.46	3.57	3.87	8.5	8.98
	Per Capita Tax Revenues								
Mean	10.93	2.23	10.12	10.23	13.10	8.21	6.69	19.44	22.91
Standard Deviation	8.83	1.94	6.03	4.31	7.32	7.03	4.02	12.61	15.27

State Level Redistribution Measures, Summary Statistics by Region

	Full Sample	New England	Middle Atlantic	East North Central	West North Central	South	Border	Mountain	Pacific
	Per Capita Welfare Expenditures								
Mean	589.21	954.31	935.14	701.90	584.84	249.70	325.94	605.90	724.11
Standard Deviation	675.55	963.59	1090.43	722.04	511.86	193.29	266.09	571.82	747.54
	Per Capita Ad Valorem Taxes								
Mean	435.07	509.625	492.75	456.80	474.14	165.50	270.66	628.62	710.83
Standard Deviation	217.26	169.50	190.60	75.22	95.18	59.40	98.10	191.50	162.66
	Per Capita Total Expenditures								
Mean	4410.63	5377.08	5784.52	4528.38	4316.28	2249.86	2948.82	5673.09	6820.23
Standard Deviation	2456.16	2466.28	3041.87	1320.96	1182.80	1070.27	1496.24	2455.72	3350.67

Figure 2: Land Inequality, Box Plots, by Region, 1890-1930



The shaded rectangle represents the interquartile range, which contains the median—the solid line. The ends of the vertical lines extend to a maximum of 1.5 times the interquartile range. Dots beyond this range are possible outliers.

Figure 3: The Log of Per Capita Education Expenditures Vs Inequality (County Level), 1930

Figure 4: The Log of Per Capita Tax Revenues Vs Inequality (County Level), 1930

Figure 5: The Log of Per Capita Ad Valorem Tax Revenues (State Level) Vs Inequality, 1890

Table 4. Summary Statistics, The Log Standard Deviation of Growing Degree Days and Elevation.

	New England	Middle Atlantic	East North Central	West North Central	South	Border	Mountain	Pacific
	Growing Degree Days	Growing Degree Days	Growing Degree Days	Growing Degree Days	Growing Degree Days	Growing Degree Days	Growing Degree Days	Growing Degree Days
Mean	5.51	5.69	5.68	5.79	6.07	5.88	5.63	5.69
Standard Deviation	0.37	0.38	0.26	0.26	0.44	0.37	0.35	0.35
Min	5.14	5.18	5.22	5.32	5.05	5.20	4.79	5.12
Max	7.36	7.14	6.60	7.00	7.64	7.51	7.20	6.80

Summary Statistics, The Log Standard Deviation of Rainfall.

	New England	Middle Atlantic	East North Central	West North Central	South	Border	Mountain	Pacific
Mean	2.10	1.93	1.84	1.81	2.19	2.07	1.23	1.96
Standard Deviation	0.34	0.24	0.21	0.31	0.26	0.20	0.31	0.67
Min	1.54	1.49	1.24	1.05	1.06	1.28	0.54	0.46
Max	3.31	3.04	2.83	2.82	3.27	3.00	3.79	3.33

Summary Statistics, The Standard Deviation of Elevation.

	New England	Middle Atlantic	East North Central	West North Central	South	Border	Mountain	Pacific
Mean	98.07	87.01	32.29	41.24	43.09	57.59	276.69	320.55
Standard Deviation	63.12	47.45	20.99	29.57	45.32	46.31	135.12	170.76
Min	0	0	0	0	0	0	3.367	33.26
Max	232.17	277.04	131.62	417.53	301.13	370.04	652.68	811.23

Figure 6: Inequality Vs The Log of the Standard Deviation of Growing Degree Days, 1930

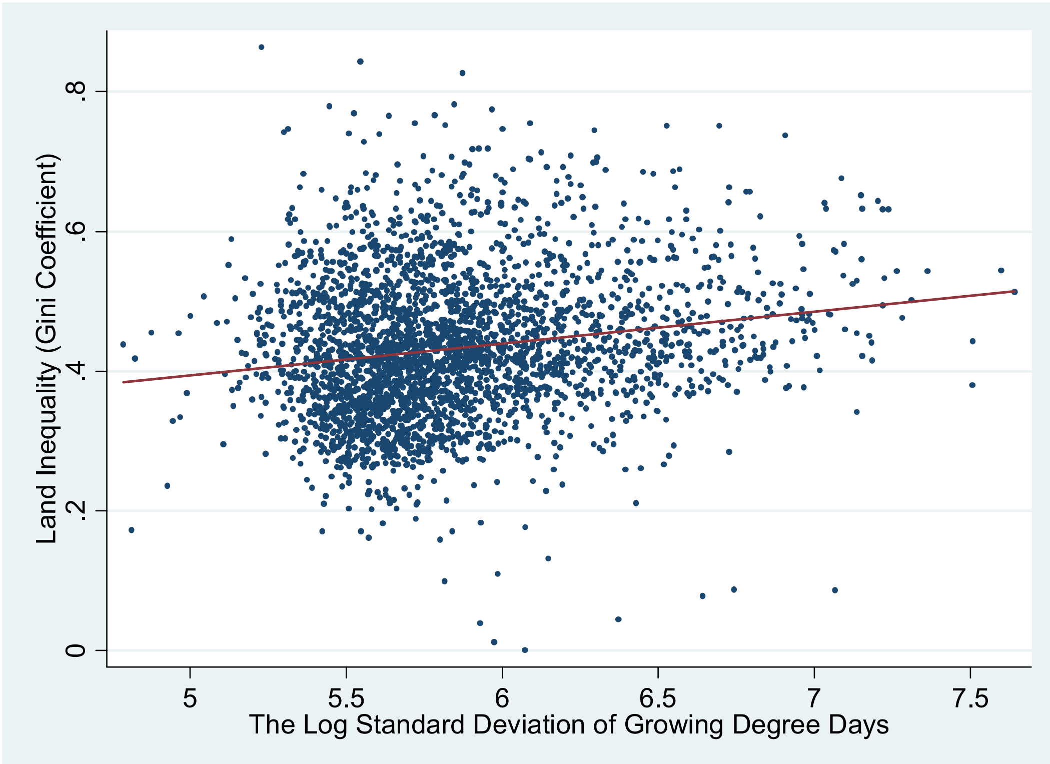


Figure 7: Inequality Vs The Log of the Standard Deviation of Rainfall, 1930

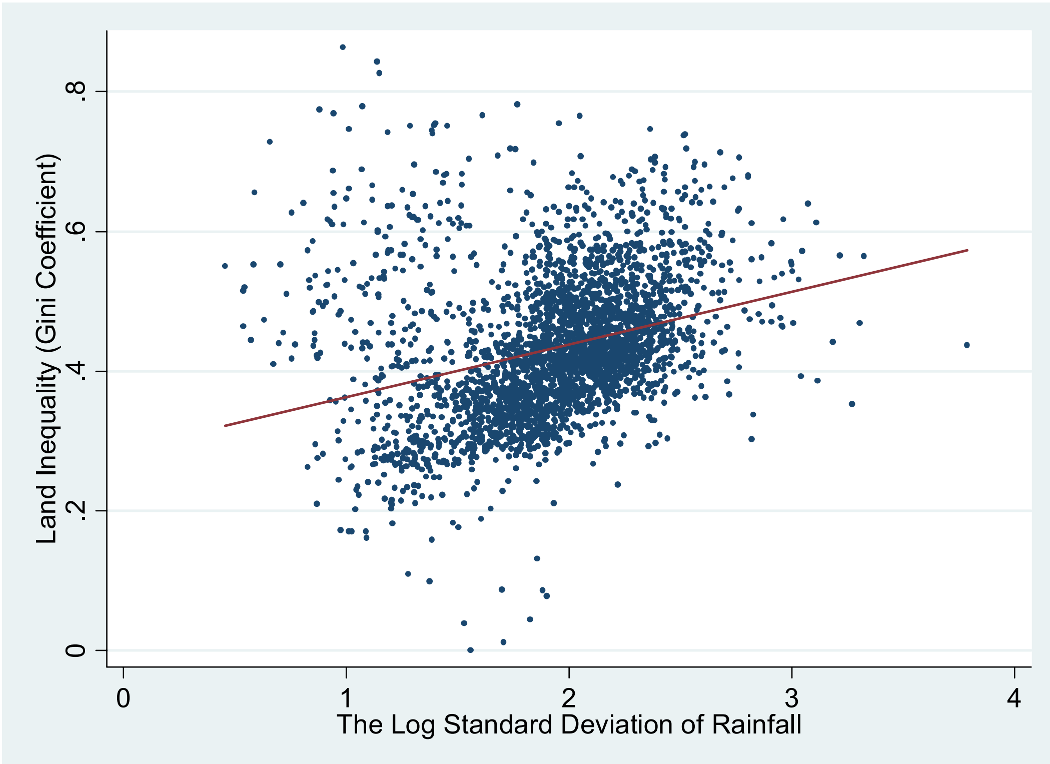


Figure 8: Inequality Vs The Standard Deviation of Elevation, 1930

Table 5. Covariates, Summary Statistics, 1930

Variable	Mean	Std. Dev.	Min	Max
Average Farm Productivity	3990.28	4750.97	261.58	96953.66
Percent of Population in Urban Areas	21.33	25.73	0.00	100.00
Population Density	67.60	835.01	0.10	36613.96
Fraction of the Population White Native Born	0.82	0.18	0.14	1.00
Fraction of the Population Black	0.11	0.18	0.00	0.86
Faction of the Population Between Ages 7-20	0.30	0.04	0.10	0.40
Total Population	39447.80	134923.00	52.00	3982123.00
Total Area, Square Miles	4361.54	21652.33	11.00	545971.00

Table 6. Dependant Variable: Land Inequality (Gini Coefficient), County Level Data 1930 (First Stage)

	(2) Baseline Controls (OLS)	(3) Augmented Controls (OLS)	(4) Augmented Controls (Median Regression)	(5) Augmented Controls (OLS)
Elevation (Standard Deviation)	0.015***	0.017***	0.018***	0.015***
	[0.004]	[0.004]	[0.002]	[0.005]
Rainfall (Log Standard Deviation)	0.032***	0.014**	0.020***	0.012
	[0.008]	[0.008]	[0.005]	[0.009]
Growing Degree Days (Log Standard Deviation)	0.010**	0.010**	0.011***	0.011
	[0.005]	[0.004]	[0.003]	[0.007]
Elevation*Southern Counties Dummy (Log Standard Deviation)	---	---	---	0.014***
	---	---	---	[0.007]
Rainfall*Southern Counties Dummy (Log Standard Deviation)	---	---	---	0.010
	---	---	---	[0.016]
Growing Degree Days* Southern Counties Dummy (Log Standard Deviation)	---	---	---	-0.0004
	---	---	---	[0.008]
Observations	2966	2966	2966	2966
R-squared	0.57	0.62		0.62
F Test: Weather Risk Variables=0	17.72	13.13	51.65	11.61
p-value	0.000	0.000	0.000	0.000

Table 1 provides definitions and sources of variables. Standard errors in brackets are corrected for spatial correlation—See Appendix; * significant at 10%; ** significant at 5%; *** significant at 1%. All specifications include state and regional dummy variables; county area; and log of total population. The Southern Counties Dummy Variable takes on the value of 1 if a county is located in a Southern or Border state, and zero otherwise; column 5 linearly includes this variable. The augmented specification also includes the average level of agricultural productivity; population density; urban population; the fraction of the population that is native white; the fraction of the population that is black population; and the fraction that is between 7 and 20 years old—Table 1 provides definitions and sources. The First Stage F-Statistic tests whether the elevation, rainfall and growing degree days variables jointly equal zero.

Table 7. Dependant Variable: The Log of Per Capita Education Expenditures, Observed at the County Level Data in 1930

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS (Baseline Specification)	2SLS (Baseline Specification)	2SLS (Augmented Specification)	2SLS (Augmented Specification)	2SLS (Texas) (Baseline)	LIML (Texas) (Baseline)
Land Inequality	-0.558***	-1.640***	-1.828***	-2.249***	-3.694***	-3.909**
	[0.12]	[0.463]	[0.4293]	[0.724]	[1.350]	[1.652]
Land Inequality*Southern Counties Dummy Variable	---	---	---	1.983	---	---
	---	---	---	[1.934]	---	---
Observations	2966	2966	2966	2966	225	225
R-squared	0.76	0.74	0.75	0.75	0.12	0.12
Overidentification Test	---	0.20	2.17	2.09	1.67	0.949
p-value	---	0.654	0.337	0.351	0.435	0.622
First Stage F-Statistic (p-value)	---	19.34 (0.00)	15.82 (0.00)	21.47 (0.00)	3.35 (0.02)	3.35 (0.02)

All specifications include state and regional dummy variables; county area; and log of total population. The Southern Counties Dummy Variable takes on the value of 1 if a county is located in a Southern or Border state, and zero otherwise; column 5 linearly includes this variable. The augmented specification also includes the average level of agricultural productivity; population density; urban population; the fraction of the population that is native white; the fraction of the population that is black population; and the fraction that is between 7 and 20 years old—Table 1 provides definitions and sources. The Gini Coefficient is used to measure land inequality. Column 7 uses the Limited Information Maximum Likelihood (LIML) estimator. Standard errors in brackets are corrected for spatial correlation—See Appendix; * significant at 10%; ** significant at 5%; *** significant at 1%. The First Stage F-Statistic tests the hypothesis that the conditional correlation between both the weather risk variables and the inequality measure is zero. The Overidentifcation Test is the Hansen J Statistic—distributed as Chi Square with two degrees of freedom.

Table 8. Dependant Variable: The Log of Per Capita Tax Revenue, Observed at the County Level Circa 1933 and 1920

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS (Baseline Specification) 1930	2SLS (Baseline Specification) 1930	2SLS (Augmented Specification) 1930	2SLS (Augmented Specification) 1930	2SLS Texas (Baseline Specification) 1930	2SLS (Augmented Specification) 1920	2SLS (Augmented Specification) 1920
Land Inequality	-0.115	-0.417	-0.874*	-1.101**	-3.338*	-1.776***	-2.693***
	[0.187]	[0.552]	[0.538]	[0.687]	[1.784]	[0.617]	[1.025]
Land Inequality*Southern Counties Dummy Variable	---	---	---	0.270	---	---	1.191
	---	---	---	[1.561]	---	---	[1.872]
Observations	2966	2966	2966	2966	225	3015	3015
R-squared	0.77	0.77	0.81	0.81	0.13	0.76	0.76
Overidentification Test	---	3.95	4.12	0.60	2.58	2.14	3.73
p-value	---	0.047	0.127	0.741	0.275	0.343	0.155
First Stage F-Statistic (p-value)		19.34 (0.00)	15.82 (0.00)	21.47 (0.00)	3.35 (0.02)	20.19 (0.00)	20.19 (0.00)

All specifications include state and regional dummy variables; county area; and log of total population. The Southern Counties Dummy Variable takes on the value of 1 if a county is located in a Southern or Border state, and zero otherwise; columns 5 and 8 linearly include this variable. The augmented specification also includes the average level of agricultural productivity; population density; urban population; the fraction of the population that is native white; the fraction of the population that is black population; and the fraction that is between 7 and 20 years old; the average level of agricultural productivity is not available for 1920—Table 1 provides definitions and sources. The Gini Coefficient is used to measure land inequality. Standard errors in brackets are corrected for spatial correlation—See Appendix; * significant at 10%; ** significant at 5%; *** significant at 1%. The First Stage F-Statistic tests the hypothesis that the conditional correlation between both the weather risk variables and the inequality measure is zero. The Overidentifcation Test is the Hansen J Statistic—distributed as Chi Square with two degrees of freedom.

Figure 9: Per Capita Education Expenditures, County Level Data 1930; Semi Parametric Specification

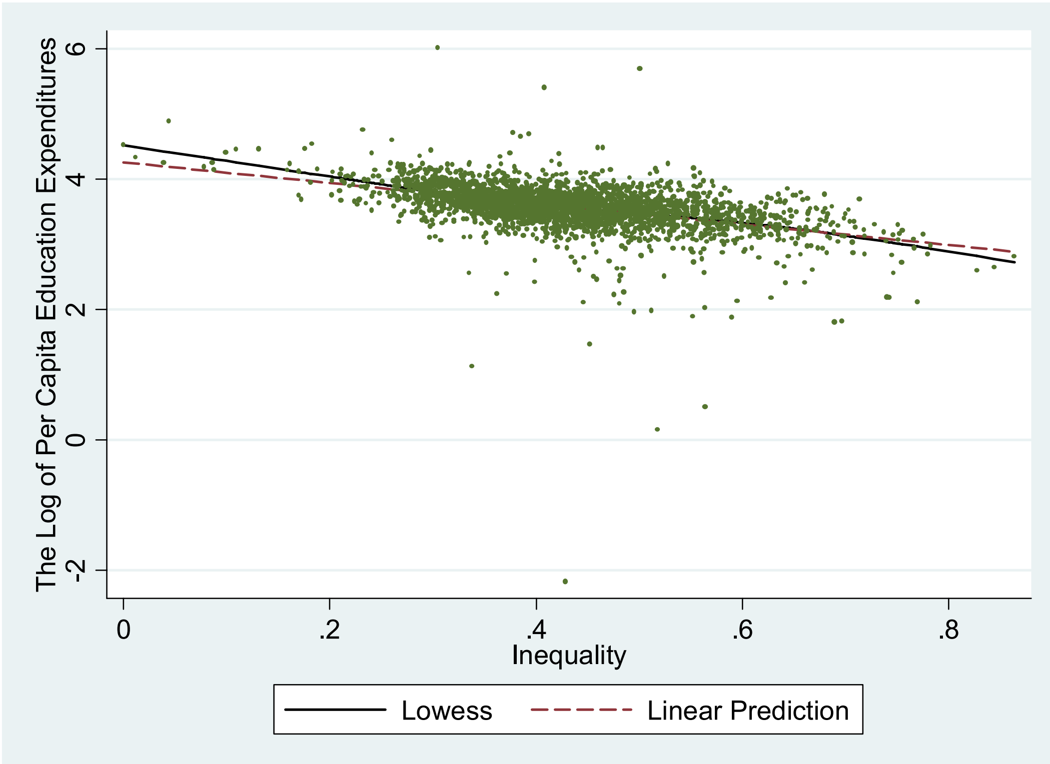


Figure 10: Per Capita Tax Revenue, County Level Data 1930; Semi Parametric Specification

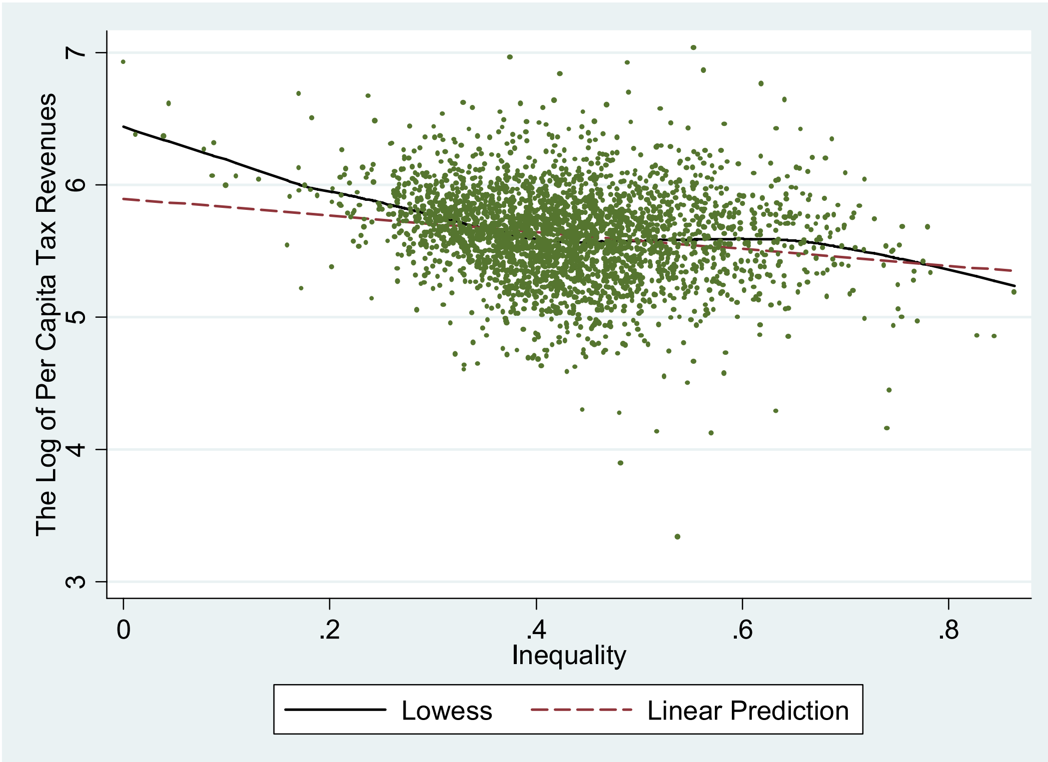


Table 10. Alternative Identification Strategies

	Mean Rainfall			*Crop Choice*			*1890 Land Inequality*	
(1)	(2) (OLS)	(3) (2SLS)	(4) (2SLS)	(5) (OLS)	(6) (2SLS)	(7) (2SLS)	(8) (IV)	(9) (IV)
	(First Stage) Land Inequality (1930)	Per Capita Education Expenditures (1930)	Per Capita Tax Revenues (1930)	(First Stage) Land Inequality (1930)	Per Capita Education Expenditures (1930)	Per Capita Tax Revenues (1930)	Per Capita Education Expenditures (1930)	Per Capita Tax Revenues (1930)
Land Inequality	---	-1.903***	-0.967**	---	-0.989***	-0.549	-3.011***	-1.623***
	---	[0.490]	[0.552]	---	[0.293]	[0.413]	[0.624]	[0.583]
Elevation (Standard Deviation)	0.016***	---	---	---	---	---	---	---
	[0.004]	---	---	---	---	---	---	---
Rainfall (Log Standard Deviation)	0.009	---	---	---	---	---	---	---
	[0.007]	---	---	---	---	---	---	---
Rainfall (Annual Average)	0.004*	---	---	---	---	---	---	---
	[0.003]	---	---	---	---	---	---	---
Growing Degree Days (Log Standard Deviation)	0.011**	---	---	---	---	---	---	---
	[0.004]	---	---	---	---	---	---	---
Fruits and Nuts				0.002***	---	---		
				[0.001]	---	---		
Cereals				0.0007	---	---		
				[0.001]	---	---		
Vegetables				0.002***	---	---		
				[0.007]	---	---		
R-squared	0.63	---	---	0.64	---		---	---
Observations	2966	2966	2966	2966	2966	2966	2528	2528
Overidentification Test	---	2.67	4.49	---	2.42	0.63	---	---
p-value	---	0.445	0.213	---	0.30	0.73	---	---
F-Statistic (p-value)	12.52 (0.00)	12.52 (0.00)	12.52 (0.00)	35.73 (0.00)	23.78 (0.00)		97.90 (0.00)	97.90 (0.00)

All specifications include state and regional dummy variables; county area; and log of total population; the average level of agricultural productivity (in 1930 only); population density; urban population; the fraction of the population that is native white; the fraction of the population that is black population; and the fraction that is between 7 and 20 years old. Columns 3-4 use average annual rainfall as well as the standard deviation of elevation, and the log standard deviation of rainfall and growing degree days as instruments for Land Inequality. Columns 6-7 use the agricultural shares (value) of fruits and nuts; cereals; and vegetables as instruments. Columns 8-9 use Land Inequality in 1890 as the **only** instrument. Table 1 provides definitions and sources. The Gini Coefficient is used to measure Land Inequality. Standard errors in brackets are corrected for spatial correlation—See Appendix; * significant at 10%; ** significant at 5%; *** significant at 1%. The First Stage F-Statistic tests the hypothesis that the conditional correlation between both the instruments and the inequality measure is zero. The Overidentifcation Test is the Hansen J Statistic—distributed as Chi Square with two degrees of freedom.

Table 11. Inequality And The Economic Structure, County Level Data

(1)	(2) (2SLS)	(3) (2SLS)	(4) (2SLS)	(5) (2SLS)	(6) (2SLS)	(7) (2SLS)
	The Log of Per Capita Education Expenditures, 1930	The Log of Per Capita Tax Revenues, 1930	The Log of Per Capita Tax Revenues, 1920	The Log of Per Capita Education Expenditures, 1930	The Log of Per Capita Tax Revenues, 1930	The Log of Per Capita Tax Revenues, 1920
Land Inequality	-2.049***	-1.444***	-2.437***	-2.184**	-0.594	-2.168***
	[0.471]	[0.596]	[0.644]	[1.043]	[1.345]	[0.933]
Land Inequality*Urbanization	0.020*	0.052***	0.067***	---	---	---
	[0.012]	[0.014]	[0.014]	---	---	---
Land Inequality*Per Capita Manufacturing Establishments	---	---	---	760.021***	622.030	576.931**
	---	---	---	[204.564]	[923.276]	[301.112]
Observations	2966	2966	3015	2460	2460	2838
Overidentification Test	1.60	1.50	0.86	2.16	2.60	2.26
p-value	0.450	0.473	0.649	0.339	0.272	0.324

All specifications include state and regional dummy variables; county area; and log of total population; the average level of agricultural productivity (only in 1930); population density; urban population; the fraction of the population that is native white; the fraction of the population that is black population; and the fraction that is between 7 and 20 years old; columns 5-7 also linearly include the per capita number of manufacturing establishments; the average level of agricultural productivity is not available for 1920—Table 1 provides definitions and sources. The Gini Coefficient is used to measure land inequality. Standard errors in brackets are corrected for spatial correlation—See Appendix; * significant at 10%; ** significant at 5%; *** significant at 1%. The First Stage F-Statistic tests the hypothesis that the conditional correlation between both the weather risk variables and the inequality measure is zero. The Overidentifcation Test is the Hansen J Statistic—distributed as Chi Square with two degrees of freedom.

Table 12. An Alternative Measure of Concentration: The Relative Importance of Small Farms.

	(2) (LIML)	(3) (LIML)	(4) (LIML)
	Dependant Variable: Per Capita Education Expenditures (1930)	Dependant Variable: Per Capita Tax Revenues (1930)	Dependant Variable: Per Capita Tax Revenues (1920)
Ratio of Small to Large Farms (Land Area)	0.022**	0.020*	0.041
	[0.011]	[0.012]	[0.031]
Ratio of Small to Large Farms (Land Area) * Southern Counties Dummy Variable	-0.014	-0.022	-0.076
	[0.018]	[0.018]	[0.074]
Observations	2937	2937	2944
R-squared	0.93	0.92	0.58
Overidentification Test	0.01	0.22	0.01
p-value	0.924	0.637	0.961
F-Statistic (p-value)	8.48 (0.00)	8.48 (0.00)	7.21 (0.00)

The “Ratio of Small to Large Farms Land Area” is defined as: the ratio of total land on farms less than 500 acres in size versus total land on farms equal to or above 500 acres. All specifications include state and regional dummy variables; county area; and log of total population; the average level of agricultural productivity (except Column 4); population density; urban population; the fraction of the population that is native white; the fraction of the population that is black population; and the fraction that is between 7 and 20 years old;—Table 1 provides definitions and sources. The Southern Counties Dummy Variable takes on the value of 1 if a county is located in a Southern or Border state, and zero otherwise; all columns linearly include this variable. Standard errors in brackets are corrected for spatial correlation—See Appendix; * significant at 10%; ** significant at 5%; *** significant at 1%. The First Stage F-Statistic tests the hypothesis that the conditional correlation between both the weather risk variables and the “Ratio of Small to Large Farms Land Area” is zero. The Overidentifcation Test is the Anderson-Rubin Test Statistic—distributed as Chi Square with one degree of freedom.

Table 13. Inequality and Political Competition, State Level Data

	(2) LIML	(3) LIML	(4) LIML	(5) LIML	(6) LIML	(7) LIML	(8) LIML	(9) LIML	(10) LIML
	Gubernatorial Competition					Congressional Competition			
	1890	1900	1910	1920	1930	1900	1910	1920	1930
Land Inequality	-0.145	-3.044	-2.475*	1.552*	-0.796	-3.864*	-3.317	-3.848*	-4.889*
	[0.469]	[2.013]	[1.342]	[0.823]	[0.507]	[1.987]	[2.299]	[2.239]	[2.885]
Observations	41	45	47	47	44	48	47	45	44
Overidentification Test	1.90	0.93	0.01	0.02	1.06	0.53	0.57	0.03	0.09
p-value	0.168	0.334	0.904	0.90	0.303	0.467	0.450	0.870	0.769

All specifications include regional dummy variables; county area; and log of total population. The First Stage F-Statistic tests the hypothesis that the conditional correlation between both the weather risk variables and the inequality measure is zero. The Overidentifcation Test is the Andersen Rubin Statistic—distributed as Chi Square with one degree of freedom. Standard errors are heteroscedasticy robust; * significant at 10%; ** significant at 5%; *** significant at 1%. LIML is the Limited Information Maximum Likelihood Estimator.

Table 14. Political Competition and Redistribution, State Level Data

	(2) (2SLS)	(3) (2SLS)	(4) (2SLS)	(5) (2SLS)	(6) (2SLS)	(7) (2SLS)	(8) (2SLS)
	The Log of Per Capita Ad Valorem Taxes 1900	The Log of Per Capita Total Expenditures 1900	The Log of Per Capita Welfare Expenditures 1900	The Log of Per Capita Education Expenditures 1900	The Log of Per Capita Total Expenditures 1910	The Log of Per Capita Welfare Expenditures 1910	The Log of Per Capita Education Expenditures
Congressional Competition	2.731***	2.297***	2.327***	1.516**	---	---	---
	[0.585]	[0.508]	[0.574]	[0.635]	---	---	---
Gubernatorial Competition	---	---	---	---	1.702***	1.421***	2.529***
	---	---	---	---	[0.586]	[0.534]	[0.631]
Observations	44	44	44	44	47	47	47
Overidentification Test	2.31	2.68	1.80	0.20	0.88	0.48	0.64
p-value	0.128	0.102	0.180	0.656	0.348	0.487	0.424

All specifications include regional dummy variables; county area; and log of total population. The First Stage F-Statistic tests the hypothesis that the conditional correlation between both the weather risk variables and the inequality measure is zero. The Overidentifcation Test is the Hansen J Statistic—distributed as Chi Square with one degree of freedom. Standard errors are heteroscedasticy robust; * significant at 10%; ** significant at 5%; *** significant at 1%.

C. State Level Data

In this appendix I use state level data to explore the relationship between inequality, political competition and redistribution. A wider spectrum of redistributive policy variables are available at the state level, with some extending back to 1890. Despite the risk of aggregation bias, and the limited degrees of freedom, this additional information is an important robustness check. As Tables A1 and A2 reveal, the main results are little changed: inequality remains negatively associated with both less redistribution

Using a relatively parsimonious base specification which controls for state area and population as well as region fixed effects, columns 2-3 of Table A1 document a large negative and robust relationship between inequality and per capita education expenditures both in 1890 and 1910. In the 1890 cross section for example, a one standard deviation increase in inequality is associated with a 57 percent decline in per capita education expenditures—the estimated magnitude is similar for 1900.

Likewise, with per capita welfare expenditures as the dependant variable, the impact of inequality is negative and economically large in each of the three decennial years from 1890 through 1910 with available data (Columns 4-6). A similar pattern repeats itself in Columns 2-4 of Table A2, where total per capita expenditures is the dependant variable. However, inequality is not just associated with less per capita spending, but also with the share of public expenditures allocated to education. From Column 5 of Table A2, a one standard deviation increase in inequality is associated with a 0.53 standard deviation decline in the ratio of education spending to total expenditures in 1910.

Moreover, higher inequality is also associated with significantly lower tax revenue. Columns 7 and 8 use per capita ad valorem tax revenues—mainly taxes collected on real property--as the dependant variable; data are available only for 1890 and 1900. In both years the impact of inequality is negative and significant. For instance, in the 1900 cross section, a one standard deviation increase in inequality is associated with a 65 percent decline in per capita ad valorem taxes.

Table A1. Inequality and Redistribution, State Level Data,

	(2) (2SLS)	(3) (2SLS)	(4) (2SLS)	(5) (2SLS)	(6) (2SLS)
	Per Capita Education Expenditures, 1890	Per Capita Education Expenditures, 1900	Per Capita Welfare Expenditures, 1890	Per Capita Welfare Expenditures, 1900	Per Capita Welfare Expenditures, 1910
Inequality	-4.356**	-14.758***	-5.229***	-9.142***	-7.994***
	[1.870]	[4.689]	[1.152]	[2.850]	[2.999]
Observations	43	48	45	45	48
R-squared	0.92	0.91	0.98	0.97	0.98
First Stage F-Statistic (p-value)	27.25 (0.00)	6.35 (0.00)	29.53 (0.00)	15.59 (0.00)	6.35 (0.00)
Overidentifcation Test (p-value)	1.974 (0.16)	0.00 (0.99)	0.21 (0.64)	2.01(0.16)	0.34 (0.58)

All specifications include regional dummy variables; county area; and log of total population. The First Stage F-Statistic tests the hypothesis that the conditional correlation between the weather risk variables and the inequality measure is zero. The Overidentifcation Test is the Hansen J Statistic—distributed as Chi Square with one degree of freedom. Standard errors are heteroscedasticy robust; * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A2. Inequality and Redistribution, State Level Data

(1)	(2) (2SLS)	(3) (2SLS)	(4) (2SLS)	(7) (2SLS)	(8) (2SLS)	(9) (2SLS)
	Per Capita Total Expenditures 1890	Per Capita Total Expenditures 1900	Per Capita Total Expenditures 1910	Education Expenditures, As a Share of Total Expenditures, 1910	Per Capita Ad Valorem Taxes, 1890	Per Capita Ad Valorem Taxes, 1900
Land Inequality	-4.850***	-9.466***	-9.294**	-0.033*	-5.241***	-11.425***
	[0.999]	[2.662]	[3.659]	[0.018]	[1.059]	[2.999]
Observations	45	45	48	48	45	45
R-squared	0.98	0.98	0.99	0.72	0.98	0.98
First Stage F-Statistic (p-value)	29.53 (0.00)	6.35 (0.00)	6.35 (0.00)	6.35 (0.00)	29.53 (0.00)	15.59 (0.00)
Overidentifcation Test (p-value)	1.37 (0.24)	2.25 (0.13)	0.50 (0.48)	0.89 (0.35)	1.57 (0.21)	1.97 (0.16)

All specifications include regional dummy variables; State area; and log of total population. The First Stage F-Statistic tests the hypothesis that the conditional correlation between both the weather risk variables and the inequality measure is zero. The Overidentifcation Test is the Hansen J Statistic—distributed as Chi Square with one degree of freedom. Standard errors are heteroscedasticy robust; * significant at 10%; ** significant at 5%; *** significant at 1%.

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