INEQUALITY AND REDISTRIBUTION: EVIDENCE FROM U.S. COUNTIES AND STATES, 1890–1930

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Abstract—Does economic inequality affect redistributive policy? This paper turns to U.S. county data on land inequality over the period 1890 to 1930 to help address this fundamental question in political economy. Redistributive policy was primarily decided at the local level during this period, making county-level data particularly informative. Examining within-state variation also reduces the potential impact of latent institutional and political variables. The paper also uses a variety of identification strategies, including historic variables as well as county weather and crop characteristics, as instruments for land inequality. The evidence consistently suggests that greater inequality is significantly associated with less redistribution. This negative relationship is especially large in heavily rural counties, where concentrated landownership implied that landed elites also controlled the majority of economic production.

I. Introduction

DOES economic inequality affect redistributive policy? The literature provides contrasting answers. Some approaches that aggregate preferences based on the median voter predict a positive relationship between inequality and redistribution (Meltzer & Richard, 1981).[1] Intuitively, because greater inequality implies that the median voter is poorer than the average voter, increased inequality is likely to engender greater redistribution in political systems that operate under strict majority rule. And building on this idea that high inequality can lead to costly redistribution and higher capital tax rates, several influential models predict that high inequality can lower economic growth (Bertola, 1993; Alesina & Rodrik, 1994; Persson & Tabellini, 1994).

However, models that incorporate credit market imperfections and allow variation in political participation across groups can yield a nonlinear relationship between inequality and redistribution (Benabou, 2000). Political participation might vary, for example, because small wealthy or educated groups might be better able to solve the collective action problem and derive more concentrated benefits from political intervention (Acemoglu & Robinson, 2008; Olson, 1965; Stigler, 1971). In this case, the politically decisive agent might be a net loser from redistribution, blocking redistribution as inequality increases. But for extreme levels of inequality, the large number of poor can impose redistribution. For example, in Bourguignon and Verdier (2000), education increases both the productivity and political participation of the poor. And for some parameter values, despite the productivity externality associated with education, elites might restrict redistributive education expenditures in order to preserve their political power and avoid higher future taxation. Galor, Moav, and Vollrath (2008) also provide conditions whereby high levels of inequality can coexist with little redistribution and underdevelopment.[2]

The empirical literature, however, 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, and in some cases, the correlation is negative.[3] There are also considerable impediments to causally interpreting many of the empirical results. 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.

To help assess the contrasting theoretical predictions on inequality and redistributive policy, this paper uses U.S. Census county and state economic and political data over the period 1890 to 1930. Agriculture was a key sector at the time, and I measure economic inequality, proxied by the Gini coefficient, using census data on the distribution of farm sizes in each county. The data are reasonably comparable within the cross section and across the sample periods. Also, because of the significant political and economic federalism in the United States over the sample period, county-level data might be especially informative, as redistributive policy was determined primarily by local governments (Walker & Vatter, 1997).[4] In 1930, the federal government accounted for just 0.35% of total revenues allocated to public elementary and secondary schools. Even

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[1] Recent books in economics with several chapter-length surveys include Drazen (2000), Persson and Tabellini (2002), and Ray (1998).

[2] Alesina and Angeletos (2005) also posit a negative relationship between inequality and redistribution. But in this case, the negative correlation is driven by societal differences in the preference for fairness, and perceptions about the relative importance of luck versus talent in shaping outcomes.

[3] See Perotti (1993, 1996), and the reviews by Persson and Tabellini (2002) and Benabou (1996). Recent work by Acemoglu et al. (2007) suggests a positive relationship between inequality and several measures of redistribution using Colombian data.

[4] In an influential paper, Goldin and Katz (2001) also examine public policy outcomes during this time period. Other papers that use U.S. data, albeit post-1960 data, to test political economy theories, include Alesina, Baqir, and Easterly (1999), as well as Besley, Persson, and Sturm (2005).

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state governments accounted for only 17% of the total, while counties and other local governments contributed 82% of total education revenues (U.S. Department of Commerce, 1976).[5]

Examining within-state variation reduces the potential impact of latent institutional and political variables, and the paper also uses a variety of identification strategies, each with its own advantages and limitations, in order to help causally interpret the relationship between inequality and redistribution. At the county level, for example, some specifications address reverse causality by instrumenting the impact of land inequality on redistribution in 1930 using the 1890 variation in land inequality. Yet although inequality in 1890 is unaffected by public policy forty years later, persistent latent political and institutional factors could still be a source of bias. Relying on arguments in agricultural economics that emphasize the role of local weather characteristics in shaping the optimal scale of agricultural production, the analysis also uses arguably exogenous variables such as the standard deviation of surface elevation, rainfall, and growing degree days—observed at the county level—as instruments.[6]

The various identification strategies—using data at both the state and county level, as well as across several redistributive indicators and time periods—all consistently suggest that greater inequality is associated with less redistribution. The estimates are also economically large. For instance, the IV estimates based on the weather variables as instruments suggest that in the 1930 cross section of about 3,000 counties, a 1 standard deviation increase in inequality is associated with an 18% decline in per capita education expenditures. In the 1930 and 1920 cross sections, a 1 standard deviation increase in inequality is associated with 9% and 23% decreases in tax revenues, respectively.

The structure of economic production in the United States was fast changing over this period but unevenly distributed across space, and the analysis also exploits the large cross-county variation in the economic importance of agriculture in the local economy relative to manufacturing.[7] The evidence indicates that in heavily rural counties, where concentrated landownership implied that landed elites may have controlled the majority of economic production and held greater sway over policy, the negative impact of inequality on redistribution was especially large. In contrast, there is evidence of greater redistribution in counties in which smaller farms dominated.

Table 1.—Decomposition of Education Revenue Sources, 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 U.S. Census (http://www.census.gov/govs/www/school04.html).

Taken together, these results are inconsistent with the idea that increasing inequality leads to greater redistribution. Instead, political economy models that emphasize a connection between economic inequality, credit market constraints, and differences in political influence across economic groups appear to offer the most attractive explanation for the negative correlation between inequality and redistribution found in the data (Benabou, 2000; Bourguignon & Verdier, 2000; Galor et al., 2009). These results also tentatively suggest that the negative correlation found between inequality and economic growth in cross-country data might stem from too little rather than too much productive distribution. This paper is organized as follows. Section II discusses the data, section III presents the main results, section IV considers the robustness of these results, section V focuses on the mechanism, and section VI concludes.

II. Data

A. *The Sample Period, 1890–1930*

The political and economic features of the United States during this era, as well as the availability of data on redistributive policy, land inequality, and other key variables, are particularly helpful in empirically assessing the relationship between inequality and redistribution. During this era, redistributive policy was determined primarily at the local level (table 1). Unlike the modern era, federal and even state governments accounted for only a small fraction of total education revenues. 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 Great Depression and World War II (Brownlee, 1996). In addition, there are no post-1950 U.S. Census land distribution data, and many key county-level redistributive variables are only sporadically available in the pre-1960 period.

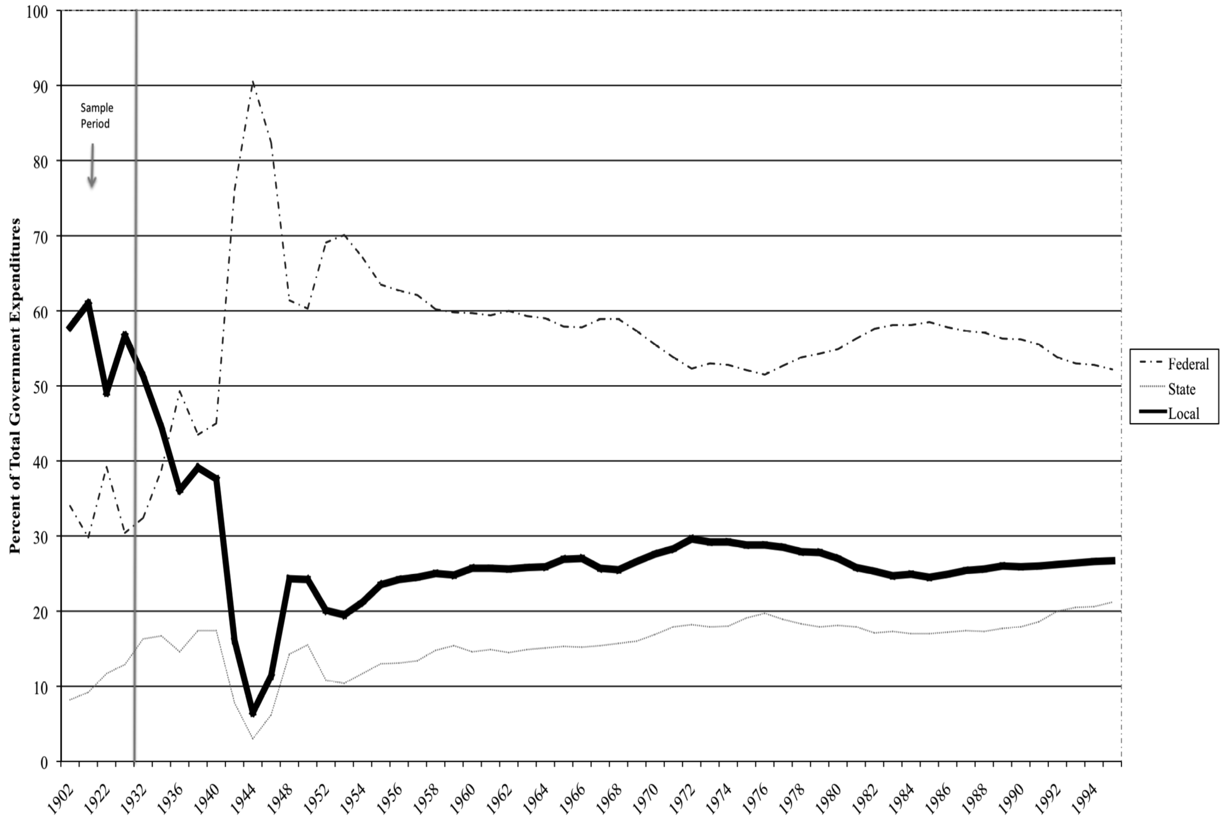
Historical narratives also suggest that redistributive policy was keenly contested. Across many regions, the rise of the railroad and rapid industrialization pitted the economic interest of industrialists and large landowners against small

[5] The distribution of education funding in 2004 is different. The breakdown between federal, state, and local revenues for education is 9%, 47%, and 44%, respectively (U.S. Census, http://www.census.gov/govs/www/school04.html).

[6] See, for example, Moscardi and de Janvry (1977), Binswanger (1981), and the surveys by Eastwood and others (2010) and Ray (1998). Other papers that use rainfall and more general weather shocks as part of their identification strategy include Miguel, Satyanath, and Sergenti (2004).

[7] Although declining over the period, the rural population at the end of the sample period was still substantial, at around 44% in 1930. About 23% of all households lived on farms in 1930 (U.S. Department of Commerce, 1976).

FIGURE 1.—TOTAL GOVERNMENT EXPENDITURES, BY LEVEL, 1902–1995



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

Source: U.S. Department of Commerce (1976).

farmers and, especially in the South, poor blacks and landless farmers (Brogan, 1999; Degler, 1984; Foner & Garraty, 1991). In Texas, for example, $1 of the poll tax was earmarked for education expenditures, simultaneously limiting the participation of the median voter and reducing taxes on capital and land needed to fund education—a key redistributive public good.[8] Direct taxation for education was also capped at 35 cents on $110 of real property valuation (Newton & Gambrell, 1935).[9] Thus, the federalism as well as the redistributive conflicts of the period induced rich cross county and state variation in policies.

B. *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 and 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 2 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.

C. *Inequality: The Concentration of Landownership*

The main measures of wealth inequality are based on the distribution of farm sizes for each of the decennial census years 1890 to 1930. The distribution of farm sizes is an imperfect but useful indicator of wealth concentration over this period. With limited access to financial instruments for most of the population, and still relatively low levels of urbanization, farms were important stores of wealth throughout this period. That said, although agriculture remained an important economic activity in the aggregate, its economic importance varied widely

[8] Public education was largely financed from local taxes during this period. And although blacks and the very poor often had less access to public education than other groups (Donohue, Heckman, and Todd, 2002), education was still widely viewed as a public good with significant redistributive content. In fact, many southerners, for example, argued that education was too redistributive (Wish, 1964), while more generally, Progressive era reformers emphasized the role of public education in redistributing wealth (Hofstadter, 1960).

[9] 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.

TABLE 2.—REDISTRIBUTION MEASURES, SUMMARY STATISTICS BY REGION, 1930

	Full Sample	New England	Middle Atlantic	East North Central	West North Central	South	Border	Mountain	Pacific
County-Level Redistribution Measures									
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									
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	1,090.43	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	4,410.63	5,377.08	5,784.52	4,528.38	4,316.28	2,249.86	2,948.82	5,673.09	6,820.23
Standard deviation	2,456.16	2,466.28	3,041.87	1,320.96	1,182.80	1,070.27	1,496.24	2,455.72	3,350.67

across counties.[10] And several specifications exploit the cross-sectional variation in the relative importance of agriculture compared to manufacturing in order to better understand the link between land concentration and redistribution.

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 U.S. Census provides information on the number of farms falling within a particular acreage category or bin, ranging from 20 to 49 acres up to 1,000 acres (see table 3). 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 toward 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. It illustrates, for example, the relative equality of the Northeast. But the median levels of inequality among southern and Pacific counties were very similar, although more dispersed in the former.

III. Empirical Framework and Results

A. *Empirical Framework*

This section uses a simple linear formulation to measure the impact of inequality on redistribution. Let y_i measure 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:

$$y_i = \beta INQ_i + X_i\alpha + \varepsilon_i. \quad (1)$$

The parameters β and α are to be estimated, and ε_i is a residual term. 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, OLS estimates of β can be biased. Redistribution can itself affect the distribution of wealth (Bourguignon & Verdier, 2000). Higher levels of redistribution, for example, can lower inequality, imparting a negative bias on the OLS estimate of β. Also, measures of inequality are computed from survey data and subject to measurement error, which can bias OLS estimates of β toward 0. Thus, the empirical strategy considers several approaches to estimate β more reliably.

This section uses measures of weather risk as instruments for land concentration. Weather is a major determinant of risk in agricultural production, and an influential literature in agricultural economics on the optimal scale of agricultural production, the distribution of farm sizes, and weather risk motivates this approach. More recent surveys include Eastwood, Lipton, and Newell (2010), Ray (1998), and Binswanger, Deininger, 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, and large air and soil temperature variations—are powerful sources of spatially covariant risk.[11]

[10] The value of agricultural output as a percentage of national income ranged from 18% in 1890 to about 10% in 1930, while about 22% of households lived on farms (U.S. Department of Commerce, 1976).

[11] See, for example, Moscardi and de Janvry (1977) and Binswanger (1981).

TABLE 3.—DEFINITIONS AND SOURCES OF VARIABLES

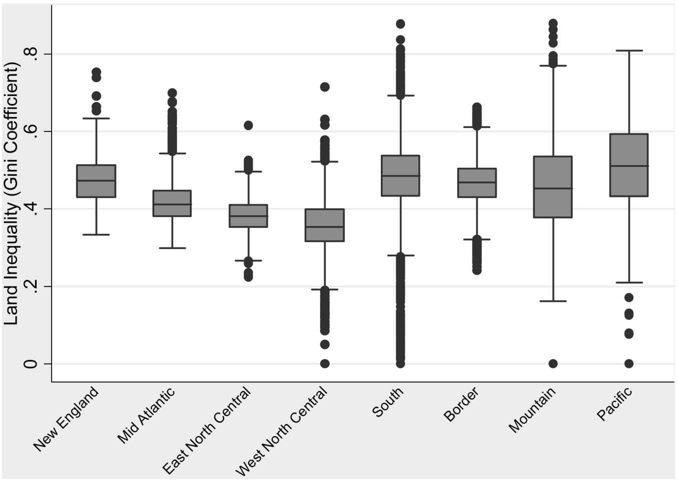
Variable	Source	Definition
Land inequality (Gini coefficient)	U.S. Bureau of Census; Inter-University Consortium for Political and Social Research (ICPSR) Nos. 0003, 0007, 0008, 0009, 0014, 0017	The number of farms are distributed across the following size bins (in acres): 3–9; 10–19; 20–49; 50–99; 100–174; 175–259; 260–499; 500–999; 1,000 and above. We use the midpoint of each bin to construct the Gini coefficient; farms above 1,000 acres are assumed to be 1,000 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 and 1922)	Rhode and Strumpf (2005)	Taxes collected by all local governments—county, minor civil divisions, school districts, and so on—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	U.S. 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	U.S. Bureau of Census; ICPSR Nos. 0003, 0007, 0008, 0009, 0014, 0017	Total value of crops, implements and machinery, and 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, 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 United States 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%: 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, Amesbury MA, 01913 (data compiled from the 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°C. For example, a day with a high of 20°C and a low of 16°C would correspond to 8 GDD.
Weighted standard deviation of elevation	Weather Source, 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 5,000 meters. The weighted standard deviation is then computed, with the weight being the share of land area in each elevation category.

And in the presence of imperfect credit markets, the variety and effectiveness of risk mitigation measures can be closely related to farm size.[12] Risk mitigation measures in turn can magnify productivity differentials across farm sizes, allowing very wealthy or large farmers to gain an advantage in agricultural production relative to very poor or small farmers (Rosenzweig & Binswanger, 1993). For example, 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, concentrating land holdings among bigger farms. Also, compared to wealthy farmers, poor farmers may insure against variable precipitation by increasing nonfarm employment. And this difference in labor allocation can magnify differences in the size of farm plots.

However, the impact of weather risk on land concentration can be ambiguous. While weather risk can have a positive effect on land inequality, as agricultural production becomes consolidated among larger plot sizes, the concentration of agricultural production among similarly sized large plots can eventually reduce land inequality. Also, the connection between land inequality and wealth inequality can be equally ambiguous if small farmers are fully compensated in the land transfer process (the appendix develops a simple example and discusses these issues). Moreover, 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

[12] See Rajan and Ramcharan (2008) for a discussion of access to finance and the general development of banking during this period.

FIGURE 2.—LAND INEQUALITY: BOX PLOTS, BY REGION, 1890–1930



Note: The shaded rectangle represents the interquartile range, which contains the median, shown as 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.

weather risk. Townsend (1993), for example, develops these ideas using examples drawn from medieval village economies.

Thus, the impact of weather risk on land concentration is an empirical question. To help measure intrinsic weather risk, I use the standard deviation of 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, and the elevation data are compiled from U.S. Geological Survey relief maps.[13]

Droughts and floods can destroy livestock and crops, and the variability of rainfall captures a key component of precipitation risk at the county level. 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 determines the time needed for plant maturity and harvest (McMaster & Wilhelm, 1997).[14] 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.

That said, because climatic variability can affect other economic outcomes that might also influence redistributive policies, 2SLS estimates based on these instruments can be biased. 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. The baseline specification controls for the plausibly exogenous variables that might also be related to both redistribution and weather outcomes: state dummies, as well as county area and total population. The augmented specification includes potentially relevant but endogenous demographic and economic controls that might affect either the demand for or the supply of redistribution: the percentage of a county's population that is classified as native-born white, black, the percentage living in urban areas, population density, the percentage between the ages of 7 and 20, and the average level of farm productivity (simple summary statistics are in table 5).[15]

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

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

[15] Average farm productivity can be endogenous since it can depend on education levels, which itself is determined by redistributive policies. Endogeneity can also arise in this augmented specification because de-

TABLE 4.—SUMMARY STATISTICS ON WEATHER

	New England	Middle Atlantic	East North Central	West North Central	South	Border	Mountain	Pacific
	Log Standard Deviation of Growing Degree Days and Elevation							
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
Minimum	5.14	5.18	5.22	5.32	5.05	5.20	4.79	5.12
Maximum	7.36	7.14	6.60	7.00	7.64	7.51	7.20	6.80
	Log Standard Deviation of Rainfall							
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
Minimum	1.54	1.49	1.24	1.05	1.06	1.28	0.54	0.46
Maximum	3.31	3.04	2.83	2.82	3.27	3.00	3.79	3.33
	Standard Deviation of Elevation							
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
Minimum	0.00	0.00	0.00	0.00	0.00	0.00	3.367	33.26
Maximum	232.17	277.04	131.62	417.53	301.13	370.04	652.68	811.23

TABLE 5.—COVARIATES, SUMMARY STATISTICS, 1930

Variable	Mean	s.d.	Minimum	Maximum
Average farm productivity	3,990.28	4,750.97	261.58	96,953.66
Percent of population in urban areas	21.33	25.73	0.00	100.00
Population density	67.60	835.01	0.10	36,613.96
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
Fraction of the population ages 7–20	0.30	0.04	0.10	0.40
Total population	39,447.80	134,923.00	52.00	3,982,123.00
Total area, square miles	4,361.54	21,652.33	11.00	545,971.00

The first-stage conditional correlations suggest that weather risk can concentrate land holdings (table 6).[16] From the base specification in column 2, all three variables are positive and individually and jointly significant (p-value = 0.00). A 1% 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. Moreover, the conditional median point estimates in column 3, which are less sensitive to outliers, are significant and nearly identical to conditional mean OLS results.

These results are little changed in the augmented specification. The weather variables continue to explain a significant fraction of the variation in land concentration (column 4). Column 4 also suggests that the racial composition of the county is related to land concentration. Both the fraction of the native white population and the fraction black population are negatively related to land concentration. Reflecting in part the various attempts to settle the white population such as the Homestead Act and the granting of similarly sized farm plots in the Upper Midwest, the impact of the native white population is over twice as large as the black population estimate. A 1 standard deviation increase in the native white population variable is associated with a 0.32 standard deviation decrease in land concentration. But the migration of population groups in response to land concentration, such as the movement of blacks out of the South in the 1920s, can affect the interpretation of these OLS results.[17] There is also evidence in column 5 that the weather risk variables affect farm size variation differently across regions, but the impact remains significant for northern counties as well (p-value = 0.00).

B. *Results*

Using the log of per capita education expenditures at the county level observed circa 1930 as the dependent variable, the evidence in table 7 suggests that greater inequality is

mographic groups can migrate in response to the provision of public goods (Rhode & Strumpf, 2003). The appendix defines these variables more precisely and list their sources.

[16] Following Rappaport (1999) and Higgins and others (2006) 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 150 kilometers apart. Typically, correcting for spatial correlation produces errors about 5% to 10% larger than the heteroskedasticity robust error. The appendix provides more detail, but see also Conley (1999) and the survey by Cressie (1993) on spatial data.

[17] There is also a positive significant correlation between rainfall and the fraction of the population that is black (0.48). However, the remaining weather variables are not significantly correlated with the ethnic variables.

TABLE 6.—DEPENDENT VARIABLE: LAND INEQUALITY (GINI COEFFICIENT), COUNTY-LEVEL DATA 1930 (FIRST STAGE)

(1)	(2) Baseline Controls (OLS)	(3) Augmented Controls (Median Regression)	(4) Augmented Controls (OLS)	(5) Augmented Controls (OLS)
Elevation (standard deviation)	0.015***	0.018***	0.017***	0.015***
	[0.004]	[0.002]	[0.004]	[0.005]
Rainfall (log standard deviation)	0.032***	0.020***	0.014**	0.012
	[0.008]	[0.005]	[0.008]	[0.009]
Growing degree days (log standard deviation)	0.010**	0.011***	0.010**	0.011
	[0.005]	[0.003]	[0.004]	[0.007]
Black population			−0.089***	
			[0.025]	
Native white population			−0.185***	
			[0.023]	
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	2,966	2,966	2,966	2,966
R^2	0.57		0.62	0.62
F test: Weather risk variables = 0	17.72	51.65	13.13	11.61
p-value	0.000	0.000	0.000	0.000

Note: Table 3 provides definitions and sources of variables. Standard errors in brackets are corrected for spatial correlation (see the appendix). Significant at * 10%, ** 5%, *** 1%. All specifications include state 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 0 otherwise; state dummies linearly absorb this variable in column 5. 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; and the fraction that is between 7 and 20 years old. The first-stage F-statistic tests whether the elevation, rainfall, and growing degree days variables jointly equal 0.

TABLE 7.—DEPENDENT VARIABLE: LOG OF PER CAPITA EDUCATION EXPENDITURES, OBSERVED AT THE COUNTY-LEVEL DATA IN 1930

(1)	(2) OLS (Baseline Specification)	(3) 2SLS (Baseline Specification)	(4) 2SLS (Augmented Specification)	(5) 2SLS (Augmented Specification)	(6) 2SLS (Augmented Specification)	(7) LIML (Texas) (Baseline)
Land inequality	−0.558***	−1.640***	−1.828***	−2.249***	−2.254***	−3.909**
	[0.121]	[0.463]	[0.4293]	[0.724]	[0.668]	[1.652]
Land inequality × southern counties dummy variable				1.983		
				[1.934]		
Land inequality × black population					4.341	
					[3.318]	
Black population					−2.0184	
					[1.614]	
Native white population					0.328**	
					[0.157]	
Observations	2,966	2,966	2,966	2,966	2,966	225
R^2	0.76	0.74	0.75	0.75	0.74	0.12
Overidentification test		0.20	2.17	2.09	2.739	0.949
p-value		0.654	0.337	0.351	0.437	0.622
First-stage F-statistic (p-value)		19.34 (0.00)	15.82 (0.00)	21.47 (0.00)	13.30 (0.00)	3.35 (0.02)

Note: All specifications include state, 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 0 otherwise; state dummies linearly absorb this variable in column 5. 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; and the fraction that is between 7 and 20 years old. Table 3 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 the appendix). Significant at * 10%, ** 5%, *** 1%. The first-stage F-statistic tests the hypothesis that the conditional correlation between both the weather risk variables and the inequality measure is 0. The overidentification test is the Hansen J-statistic, distributed as chi square with 2 degrees of freedom.

significantly associated with less redistribution. The baseline OLS estimate in column 2 implies that a 1 standard deviation increase in inequality is associated with a 5.6% decline in per capita education expenditures (p-value = 0.00). The 2SLS estimate in column 3 is about three times as large, suggesting that land concentration may have had an economically large impact on 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).

Unlike other parts of the United States, the postbellum South was heavily agricultural, and its political and social system rigidly enforced race and class distinctions. I use state dummy variables in the estimation and control for various economic and demographic observables; nevertheless, these results may still be driven solely 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 1 if a county is located in a southern or border state and 0 otherwise. The interaction term is not significant, suggesting that the state dummies and other controls may already absorb much of these interregional differences (column 5).

State-level evidence suggests that race and ethnic heterogeneity may have also shaped education expenditures (Goldin & Katz, 2001). To better understand the impact of the interplay between these factors and land concentration on education expenditures, column 6 of table 7 interacts land concentration with the share of the county population classified as black. Race and ethnic heterogeneity appear important. A 1 standard deviation increase in the share of the native white population is associated with about a 6% increase in per capita education expenditures. The point estimate on the black population share suggests a negative impact about six times larger in absolute value, but this variable is imprecisely estimated. The interaction term between the share of black population and land concentration is also not significant.[18]

Texas is a valuable case study to gauge the robustness of these findings. It is the largest state in the continental United States and has a diverse physical geography, spanning nearly 11° of latitude and over 13° 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 $100 valuation as conservative Democrats—large landowners, ranchers, and industrialists—fought over redistributive policy with poor tenant farmers and blacks—the main

[18] Interaction terms use the share of native white population; tenancy and sharecropping are also not significant, and these results are available on request.

constituents of the Populist party (Newton & Gambrell, 1935; Miller, 1986).

From column 7, in what is perhaps the cross section with the least amount of unobserved heterogeneity, a 1 standard deviation increase in inequality is associated with a 41% decrease in per capita education spending. Because the potential for biased estimates and inference exists since the instruments generate only weak identification in this subsample, column 7 uses the limited information maximum likelihood estimators (LIML).[19] LIML is known to have better small sample properties and be more robust to weak instruments.[20] The 2SLS estimate is about 5% smaller (available on request).

Because education as well as most other public goods were funded primarily from local taxes in this era, county tax revenue is another useful indicator of cross-county variation in redistributive preferences and the overall size of government.[21] Table 8 uses the log of per capita tax revenues, circa 1930, as the dependent variable. The baseline 2SLS estimate (column 3) is about four times larger than OLS (column 2), but both are imprecisely estimated. There is greater precision in the augmented specification (column 4), suggesting that a 1 standard deviation increase in inequality is associated with about a 9% decline in per capita tax revenues. 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.

Column 7 of table 8 uses the log of per capita tax revenues, observed circa 1920, as the dependent variable. In the 1920 cross-section, a 1 standard deviation increase in inequality is associated with an 18% decrease in tax revenue—larger than the 1930 point estimate. The different macroeconomic environments—the peak of the post–World War I boom in agriculture, compared with the onset of the Great Depression in 1930—as well as the declining economic importance of agriculture over the period might account for the larger estimate of β in the 1920 cross section.[22]

IV. Robustness of the Identification Strategy

Because standard overidentification can have low power in identifying violations of the exclusion restriction, this section further gauges the robustness of the identification strategy. For instance, despite conditioning 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. Also, the recent literature on local average treatment effects (Imbens & Angrist, 1994) observes that even for valid instruments, IV estimates can be sensitive to the instrument set. In this case, weather risk, historical federal policies such as the Homestead Act of 1862, the timing of migration patterns, transportation, and other factors all shaped land distribution. And these alternative sources of variation in land inequality could yield different estimates of the impact of inequality on redistributive policy. Perhaps in counties where federal land policies 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.

A. *1890 Inequality*

Land inequality is persistent, and columns 2 and 3 of table 9 use land inequality in 1890 to instrument the impact of land inequality on redistributive policies circa 1930. Because contemporary public policy is unlikely to affect the land distribution a generation earlier, reverse causality is less likely to be a source of bias. The IV results continue to suggest a negative relationship between inequality and redistributive policy and are consistently larger than their OLS counterparts. However, while the 1890 IV estimates are robust to reverse causality, omitted political, economic, and cultural characteristics remain potential sources of bias, especially given the strong persistence in inequality.

B. *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 consideration, this argument focuses 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 grains (wheat and barley), which are better suited to more temperate climates, exhibit fewer economies of scale.[23] 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 omit the measures of weather variability from the instrument set

[19] Based on the definition proposed by Stock and Yogo (2002) that a 5% hypothesis test rejects no more than 15% of the time, the critical value for the weak instrument test based on the first-stage F-statistic is 11.59.

[20] See Mackinnon and Davidson (1993). Separately, although developed under the maintained assumption of homoskedasticity, 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.

[21] For example, in cross-country work Cameron (1978) and Blais, Blake, and Dion (1993) use tax revenue as a share of GDP to help measure redistributive intent.

[22] Using state-level data, which extend from 1890 to 1930, the appendix considers the robustness of these results across other time periods.

[23] Virginia tobacco, for example, requires annual rainfall between 23 and 31 inches, while Nebraska wheat usually thrives in regions that receive between 14 and 21 inches of rain annually.

TABLE 8.—DEPENDENT VARIABLE: LOG OF PER CAPITA TAX REVENUE, OBSERVED AT THE COUNTY LEVEL, CIRCA 1933 AND 1920

(1)	(2) OLS (Baseline Specification)	(3) 2SLS (Baseline Specification) 1930	(4) 2SLS (Augmented Specification) 1930	(5) 2SLS (Augmented Specification) 1930	(6) 2SLS Texas (Baseline Specification) 1930	(7) 2SLS (Augmented Specification) 1920
Land inequality	−0.115	−0.417	−0.874*	−1.101**	−3.338*	−1.776***
	[0.187]	[0.552]	[0.538]	[0.687]	[1.784]	[0.617]
Land inequality × southern counties dummy variable				0.270		
				[1.561]		
Observations	2,966	2,966	2,966	2,966	225	3,015
R^2	0.77	0.77	0.81	0.81	0.13	0.76
Overidentification test		3.95	4.12	0.60	2.58	2.14
p-value		0.047	0.127	0.741	0.275	0.343
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)

Note: All specifications include state 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 0 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; and the fraction that is between 7 and 20 years old. The average level of agricultural productivity is not available for 1920. Table 3 provides definitions and sources. The Gini coefficient is used to measure land inequality. Standard errors in brackets are corrected for spatial correlation (see the appendix). Significant at * 10%, ** 5%, *** 1%. The first-stage F-statistic tests the hypothesis that the conditional correlation between both the weather risk variables and the inequality measure is 0. The overidentification test is the Hansen J-statistic, distributed as chi square with 2 degrees of freedom.

TABLE 9.—ALTERNATIVE IDENTIFICATION STRATEGIES

	Instrument: 1890 Land Inequality		Instrument: Rainfall (Annual Average)			Instrument: Crop Values		
(1)	(2) IV Per Capita Education Expenditures (1930)	(3) IV Per Capita Tax Revenues (1930)	(4) (OLS) (First-Stage) Land Inequality (1930)	(5) (IV) Per Capita Education Expenditures (1930)	(6) (IV) Per Capita Tax Revenues (1930)	(7) (OLS) (First-Stage) Land Inequality (1930)	(8) (2SLS) Per Capita Education Expenditures (1930)	(9) (2SLS) Per Capita Tax Revenues (1930)
Land inequality	−3.001***	−0.882*		−2.506**	−2.550*		−0.989***	−0.549
	[0.541]	[0.521]		[1.293]	[0.552]		[0.293]	[0.413]
Rainfall (annual average)			0.0008***					
			[0.0002]					
Fruits and nuts						0.002***		
						[0.001]		
Cereals						−0.0007		
						[0.001]		
Vegetables						0.002***		
						[0.007]		
R^2			0.63			0.64		
Observations	2,528	2,528	2,966	2,966	2,966	2,966	2,966	2,966
Overidentification test							2.42	0.63
p-value							0.30	0.73
F-statistic (p-value)	12.35 (0.00)	12.35 (0.00)				35.73 (0.00)	35.73 (0.00)	35.73 (0.00)

Note: All specifications include state 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; and the fraction that is between 7 and 20 years old. Columns 2 and 3 use land inequality in 1890 as an instrument. Columns 5 and 6 use average annual rainfall as an instrument for land inequality. Columns 8 and 9 use the agricultural shares (value) of fruits and nuts, cereals, and vegetables as instruments. Table 3 provides definitions and sources. The Gini coefficient is used to measure land inequality. Standard errors in brackets are corrected for spatial correlation (see the appendix). Significant at * 10%, ** 5%, *** 1%. The first-stage F-statistic tests the hypothesis that the conditional correlation between the instruments and the inequality measure is 0. The overidentification test is the Hansen J-statistic, distributed as chi square with 2 degrees of freedom.

TABLE 10.—SMALL FARMS AND THE SCALE OF AGRICULTURE

(1)	(2) (LIML) Dependent Variable: Per Capita Education Expenditures (1930)	(3) (LIML) Dependent Variable: Per Capita Tax Revenues (1930)	(4) (2SLS) Predominantly Larger Farms Dependent Variable: Per Capita Education Expenditures (1930)	(5) (2SLS) Predominantly Smaller Farms Dependent Variable: Per Capita Education Expenditures (1930)
Land inequality			−1.945*** [0.459]	−2.695** [1.309]
Ratio of small to large farms (land area)	0.022** [0.011]	0.020* [0.012]		
Ratio of small to large farms (land area) × southern counties dummy variable	−0.014 [0.018]	−0.022 [0.018]		
Observations	2,937	2,937	1,483	1,484
R^2	0.93	0.92	0.75	0.73
Overidentification test	0.01	0.22	2.954	2.842
p-value	0.924	0.637	0.228	0.251
F-statistic (p-value)	8.48 (0.00)	8.48 (0.00)	10.61 (0.00)	9.09 (0.00)

Note: 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 dummy variables, county area, and log of total population; 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; and the fraction that is between 7 and 20 years old. Table 3 provides definitions and sources. Columns 4 and 5 restrict the sample to counties having above and below the median number of farms of 1,000 acres. Standard errors in brackets are corrected for spatial correlation (see the appendix). Significant at * 10%, ** 5%, *** 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 0. The overidentification test is the Anderson-Rubin test statistic, distributed as chi square with 1 degree of freedom.

and use only the mean level of rainfall as an instrument. The first stage (column 4 of table 8) is consistent with the Engerman and Sokoloff hypothesis. The mean annual rainfall coefficient is positive and significant at the 1% level. And from columns 5 and 6, the IV estimates remain negative and statistically significant, and they are larger than the 2SLS weather risk estimates.[24]

C. Crop Choice

The crops grown in a county can directly shape the distribution of farm sizes, providing another credible source of exogenous variation in land inequality. Although agriculture was rapidly mechanizing during this period, cereal production such as wheat and rye were still subject to fewer 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). To further gauge the robustness of the main results, table 9 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 7 of table 9 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 8) is smaller than that obtained using the weather 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).

[24] However, because the IV estimates are relatively imprecise, Hausman-based tests indicate that the IV and weather risk 2SLS estimates are not statistically different.

V. Mechanism

A. Farm Sizes

To more intuitively capture the relative importance of small farms in agriculture, I construct an alternative measure of land concentration. Farm sizes in the census data range of between 3 and 9 acres to over 1,000 acres, and using the midpoint 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.

There is an economically large, positive correlation between the relative importance of small farms and redistributive policies (columns 2–4 of table 10). I obtain these correlation using the weak instrument robust LIML estimator, since from the first-stage F-statistic, the instruments may generate only weak identification. The LIML estimates suggest that a 1 standard deviation increase in the ratio of small to large farms' land area is associated with a 76.7% increase in per capita education expenditures (column 2)—about four 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).

TABLE 11.—INEQUALITY AND THE ECONOMIC STRUCTURE, COUNTY-LEVEL DATA

(1)	(2) (2SLS) Log of Per Capita Education Expenditures (1930)	(3) (2SLS) Log of Per Capita Tax Revenues (1930)	(4) (2SLS) Log of Per Capita Education Expenditures (1930)	(5) (2SLS) Log of Per Capita Education Expenditures (1930)
Land inequality	−2.049***	−1.444***	−2.184**	−0.594
	[0.471]	[0.596]	[1.043]	[1.345]
Land inequality × urbanization	0.020*	0.052***		
	[0.012]	[0.014]		
Land inequality × per capita manufacturing establishments			760.021***	622.030
			[204.564]	[923.276]
Land inequality × crop values shares				−3.852**
				[1.555]
Observations	2,966	2,966	2,460	2,520
Overidentification test	1.60	1.50	2.16	0.85
p-value	0.450	0.473	0.339	0.653

Note: All specifications include state 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; and the fraction that is between 7 and 20 years old. Columns 5 and 6 also linearly include the per capita number of manufacturing establishments and crop shares: ratio of crop values to the value of crops and manufacturing. The average level of agricultural productivity is not available for 1920. Table 3 provides definitions and sources. The Gini coefficient is used to measure land inequality. Standard errors in brackets are corrected for spatial correlation (see the appendix). Significant at * 10%, ** 5%, *** 1%. The first-stage F-statistic tests the hypothesis that the conditional correlation between both the weather risk variables and the inequality measure is 0. The overidentification test is the Hansen J-statistic, distributed as chi square with 2 degrees of freedom.

But rather than reflecting the political influence of large owners in curtailing the supply of education, these correlations might reflect the demand for education and the impact of technological differences in agricultural production. In particular, because the production technology on larger farms, such as plantations, might have relied primarily on unskilled labor, the demand for education might have been lower in counties where larger farms dominated. This technological-cum-demand channel would also generate a negative correlation between land concentration and education expenditures.

To help gauge the potential impact of this technological channel, columns 4 and 5 of table 10 estimate the baseline specification separately for counties with predominantly larger farms—those having greater than the median percentage of farms over 1,000 acres—as well as for counties with mainly smaller farms: below the median. Because the scale of agricultural production within each subsample is generally similar, the variation in the demand for education due to scale factors is likely to be limited among the counties in each subsample. From columns 4 and 5, the impact of land concentration on education remains negative and significant and is similar across the two subsamples.[25]

B. *Economic Structure: Urbanization*

Cross-county differences in urbanization might also help in understanding the negative relationship between land concentration 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 landownership is less likely to translate into the concentration of political power in more urban counties. Alternatively, concentrated landownership in heavily rural counties implies that few landowners control the majority of economic production, which might magnify their political influence over redistributive policies.

To empirically implement this idea, I interact the Gini coefficient measure of land inequality with the percentage of the population living in urban areas. Columns 2 and 3 of table 11 suggest that the negative impact of agricultural land inequality is significantly more muted in more urban counties. From column 2, for example, a 1 standard deviation increase in inequality is associated with an 18% decline in per capita education expenditures for a county at the median level of urbanization, but a 13% decline for a county at the 75th percentile urbanization.

C. *Economic Structure: Manufacturing Density and the Relative Importance of Agriculture*

Column 4 of table 11 interacts land inequality with the per capita number of manufacturing establishments. Low manufacturing density suggests that landed elites may have had greater control over economic production, increasing their political power and influence over redistributive policy. And at the median level of per capita manufacturing, a 1 standard deviation increase in inequality is associated with an 18% decline in per capita education expenditures. But at the 90th percentile, a similar increase in inequality is associated with only an 11% drop. Instead of manufacturing density, column 5 uses the ratio of crop values to the value of manufacturing and crops within the county to help measure the importance of agriculture relative to manufacturing in the local economy. The interaction term is again negative and robust.

[25] The results are also similar when the sample is split according to the land area of farms over 1,000 acres. The results are also robust when technological differences in farming and the demand for human capital are proxied by the capital intensity of agriculture—the per capita (farm population) value of mechanized farm equipment. These results are available on request.

TABLE 12.—STATE-LEVEL ELECTIONS DATA

A. Inequality and Political Competition

(1)	(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

B. Inequality and Percentage Democratic Vote in Gubernatorial Elections

(1)	(2) LIML 1890	(3) LIML 1900	(4) LIML 1910	(5) LIML 1920	(6) LIML 1930
Land inequality	119.441***	453.392**	191.138**	154.206	281.611
	[515.745]	[1,826.084]	[882.567]	[993.509]	[467.725]
Observations	41	45	47	47	44
Overidentification test	3.59	0.53	0.39	2.27	1.29
p-value	0.058	0.466	0.533	0.132	0.255

Note: All specifications include a south indicator variable, 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 0. The overidentification test is the Anderson Rubin statistic, distributed as chi square with 1 degree of freedom. Standard errors are heteroskedasticity robust. Significant at * 10%, ** 5%, *** 1%. LIML is the limited information maximum likelihood estimator.

D. Political Influence

The political variables available at the state level might also help in understanding the negative impact of inequality on redistribution. As the Texas example noted, elections were often centered around redistributive politics. And political participation among the landed elite might have been higher and more effective in states with greater levels of inequality. This impact on political participation can arise in part because greater inequality can concentrate the benefits of political participation and simplify the collective action problem among the landed. The landed elite may have also been able to block the participation of other groups. Landed elites, for example, were closely associated with the poll tax, literacy tests, and the other barriers that limited the political participation of groups that were most likely to benefit from redistribution in the post-Reconstruction South, such as blacks and poor whites.[26]

To help study these issues, I focus on the impact of inequality on political competition at the congressional and gubernatorial levels.[27] Political competition is measured using standard two party indices common in the literature: 1 minus the difference between the absolute value of the Democratic and Republican candidates vote shares in a particular state's race: $(1 - |DEM\% - REP\%|)$: higher values indicate more competitive races (Rusk, 2001). Because political competition is likely to be endogenous, I continue with the instrumental variables approach based on weather risk. At the state level, the IV strategy produces weak identification, and I rely on the weak instrument robust LIML estimator; I also report the Moreira (2003) weak instrument robust conditional likelihood ratio test of the significance of the Gini coefficient.

Table 12A suggests that over the period 1890 through 1930, states with higher levels of inequality also had less competitive gubernatorial and congressional elections. 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% level except in 1910. The point estimates are, however, economically meaningful. In the 1920 cross-section, a 1 standard deviation increase in inequality is associated with a 1.51 standard deviation decline in the competitiveness of congressional elections. In 1910, a similar increase in inequality is associated with a 0.67 standard deviation decline in the competitiveness of gubernatorial elections.

Landed elites were also often associated with the Democratic party. In the South, the landed aristocracy opposed the political and economic reforms advanced by the Republicans during this period and generally supported the Democratic party, while in the Midwest and other regions, the Populist party most often represented the interests of small agrarian interests rather than the landed elite (Goodwyn, 1978). Consistent with these historical narratives, the decline in political competition in table 12A may have

[26] Consider also 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, 1999).

[27] Unlike presidential elections, which 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.

provided an electoral advantage to Democratic candidates: there is a robust positive association between land inequality and the percentage of votes won by Democratic gubernatorial candidate, especially in the earlier part of the sample (Table 12B).

Table 13 documents a large, robust, positive relationship between political competition and redistributive policies. A 1 standard deviation increase in the competitiveness of congressional elections within a state is associated with a 50% increase in per capita ad valorem taxes in 1900. In 1910, a similar increase in the competitiveness of gubernatorial elections implies a 66% rise in per capita education expenditures. The results in tables 12 and 13 tentatively suggest that greater inequality may have given the landed elite disproportionate political influence, allowing them to shape redistributive policies.

VI. Conclusion

Using a wide range of estimators and specifications, the empirical evidence based on U.S. county and state data over the period 1890 to 1930 consistently suggests that economic inequality can negatively affect redistributive policy. These various approaches also yield economically large estimates and suggest that the negative impact of land inequality is larger in counties where landed elites may also have controlled much of economic production. There is also evidence that inequality is negatively associated with political competition and that increased political competition is associated with greater redistribution. Theories noting that imperfect credit markets and unequal political participation can combine to produce a negative relationship between inequality and redistributive policies appear to be the most attractive explanation for these empirical results (Benabou, 2000; Bourguignon & Verdier, 2000; Galor et al., 2009).

Moreover, the significant impact of land concentration on policy outcomes suggests that local political structures can have large economic consequences, even across environments that share similar constitutions and aggregate de jure political institutions (Acemoglu & Robinson, 2008; Rajan & Zingales, 2006; Olson, 1965; Stigler, 1971). Of course, because these results are obtained within a single country, they are silent on the relative importance of de jure political institutions such as democracy and constitutional checks and balances in shaping comparative development (see, for example, North, 1990, and North & Weingast, 1989).

Also, future research would perhaps provide a more complete understanding of the economic consequences of inequality. What, for example, is the legacy of the negative relationship between inequality and redistribution? Did the possible underinvestment in human capital have a significant impact on the economic outcomes of individuals across generations, as well as on political units like counties and states far into the future? Or did migration, as well as technological and economic change, limit the economic legacy of land inequality?

TABLE 13.—POLITICAL COMPETITION AND REDISTRIBUTION, STATE-LEVEL DATA

(1)	(2) (2SLS) Log of Per Capita Ad Valorem Taxes (1900)	(3) (2SLS) Log of Per Capita Total Expenditures (1900)	(4) (2SLS) Log of Per Capita Welfare Expenditures (1900)	(5) (2SLS) Log of Per Capita Education Expenditures (1900)	(6) (2SLS) Log of Per Capita Total Expenditures (1910)	(7) (2SLS) Log of Per Capita Welfare Expenditures (1910)	(8) (2SLS) Log of Per Capita Education Expenditures (1910)
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

Note: All specifications include a south indicator variable, 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 0. The overidentification test is the Hansen *J*-statistic, distributed as chi square with 1 degree of freedom. Standard errors are heteroskedasticity robust. Significant at * 10%, ** 5%, *** 1%.

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APPENDIX

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) between county i and county j may be proportional to the distance between the two counties. I thus follow Conley (1999) and Rappaport (1999) and assume a spatial structure to the error covariance matrix. Specifically, for county pairs farther than 150 kilometers apart, measured as the distance between the counties' geographic center, I assume independence. Meanwhile, for county pairs less than 150 kilometers apart, I use quadratic weighting:

$$E(\varepsilon_i \varepsilon_j) = \left[1 - \left(\frac{distance_{ij}}{150}\right)^2\right]\rho_{ij} \qquad \widehat{\rho_{ij}} = e_i e_j. \tag{A1}$$

Weather and Farm Sizes: A Simple Example

To illustrate the impact of weather variability on the distribution of farm sizes, this simple example builds on the more general theoretical framework in Rosenzweig and Binswanger (1993). The main intuition is that in the presence of risk aversion and capital markets constraints, very wealthy or large farmers can gain an advantage in agricultural production relative to very poor or small farmers.

Concretely, consider a simple two-period economy in which agricultural production requires a storable good (W), land (T), labor (L), and, according to a simple fixed proportion technology:

$$F = A \min \{\alpha W, T, L\}, \tag{A2}$$

where A is a weather-generated technological parameter that affects all agricultural production equally within a district (spatially covariant risk). In particular, with probability p, an adverse weather event occurs, normalized so that $A = 0$, while with probability $1 - p$, a positive weather outcome is realized, $A = \bar{A}$. The storable good (W) can also be consumed.

There are three farmers, each endowed with one unit of labor and land: the economy begins with no land inequality. However, they differ in their endowment of W. Poor farmers (P) are endowed with one unit of the storable asset, W_P, while middle (M) and rich (R) farmers have two and three units of this asset, respectively: $W_P = 1$, $W_M = 2$, $W_R = 3$. Farmers are also risk averse (log utility), and there is no discounting. Before A is realized in period 1, farmers must decide what fraction, α, of W to allocate to farming, with the residual $1 - \alpha$ available for period 2 consumption.

If credit markets are absent, agricultural production is too risky for the poor farmer. He would have to devote his total endowment of $W_P = 1$ to farming and would be left unable to smooth consumption if $A = 0$. The poor farmer would thus be better off selling his land and labor, becoming a tenant. The middle farmer lacks the capital to absorb the surplus land and labor. If he committed resources to the extra land, he would also not be able to smooth consumption if $A = 0$. Only the rich farmer can afford to absorb the poor farmer's land and labor.

However, the price of land transfer from poor to rich can depend on important economic and political details, such as employment opportunities in other sectors, de jure political institutions, and the de facto power of the rich. For example, a political system dominated by the rich might allow them to simply expropriate the land. Ransom and Sutch (2001) discuss the power of rich farmers during the sample period. Rajan and Ramcharan (2008) provide evidence that the wealthy may have constrained finance in the countryside in part to force the poor to supply land and labor at distressed prices. And Acemoglu and Robinson (2008) model the interplay between de jure and de facto power on factor prices. These details are important. But to close the example as simply as possible, I assume the rich simply absorb the land and labor of the poor. The poor consume only their endowment. This consolidation is optimal for the rich if the probability of a bad weather outcome is not too great:

$$\frac{\ln(2\bar{A} + 1) - \ln(\bar{A} + 1)}{\ln(2) + \ln(2\bar{A} + 1) - \ln(\bar{A} + 1)} > p. \tag{A3}$$

And the distribution of farm sizes goes from {1, 1, 1} to {0, 1, 2}.

The dust bowl of the 1930s provides a concrete illustration of some of these ideas. Hansen and Libecap (2004) suggest that the distribution of farm sizes played a crucial role in turning the severe drought that gripped the Great Plans 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 midwestern states. But in part due to limited credit access, small farms did not optimally invest in erosion control techniques. Their larger 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 large number of small farmers magnified the catastrophe, skewing agricultural production into larger units. That is, although history "predetermined" farm sizes in the Great Plains with the Homestead Act of 1862, the inherent variability of precipitation in that region exerted a powerful impact on farm sizes in the long run.