Ancestry Diversity and Local Public Spending in the U.S. since 1870 *

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Abstract

We study the changing country-of-ancestry composition of U.S. counties since 1870 and its relationship with local public spending on education and the police. We show that ancestry diversity increased rapidly from 1870 to 1930 and at a slower pace after 1960. The areas experiencing the fastest recent increase in diversity were the least diverse in 1960. We examine how different diversity measures relate to local public spending. Increases in origin-country cultural or GDP weighted fictionalization are associated with reductions in education expenditure. Increases in racial fractionalization, instead, are associated with increases in education expenditures and decreases in police expenditures.

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1 Introduction

Over four centuries, successive waves of immigrants from different countries with diverse histories and cultures came to North America, often displacing by disease and force the Native Americans. Some immigrants were searching for better economic opportunities or were seeking religious or political freedom. Others were forcibly brought as slaves. In this process, the United States of America (U.S.) became one of the most diverse countries in the world. These successive immigrant waves and their descendants negotiated economic and political relationships among themselves where they settled. The outcomes of these negotiations shaped a wide range of public policy decisions, including local spending decisions.

Despite the importance of these relationships, studying how group differences affect public sending decisions has been hampered by limited available data and reached different conclusions. The typical study uses broad racial and ethnic groupings. These groupings assume that the only differences that matter are by race, origin continent, or broad linguistic group. Yet immigrants from each origin country brought distinct cultural attributes, and economic and institutional experiences, so combining all "Whites" into one group is likely missing something important. Similarly, combining all Hispanics, Asians, or African Americans misses the many differences within these groups. Other studies rely on first generation immigrants which assumes that all differences disappear by the second generation.

In this paper, we use the novel data set created by Fulford, Petkov, and Schiantarelli (2020), which measures since 1870 the fraction of every county's population that is descended from ancestors who migrated from a particular foreign country, to analyze the evolution of diversity at the local level and to assess its relationship with local public spending on education and the police. We use the ancestry data to construct different measures of diversity: fractionalization across all ancestries; ancestry fractionalization weighted by differences in origin-country attributes such as cultural measures of social cooperation (Tabellini, 2010) or origin-country GDP per capita; and racial fractionalization combining ancestries into broad racial and ethnic groups. We use these data to describe—for the first time—the full complexity of the evolution of U.S. diversity across space and time. We also construct police and teacher employment per capita in each county since 1870 using individual decennial census records and county education and police expenditures since 1960. Together with our long ancestry panel, we are thus able to examine what kinds of diversity matter for public expenditures and whether these relationships change over time. Spending on education and the police have been the subject of a rich debate, both in the past and more recently. Bringing new evidence to bear on their relationship with diversity is, therefore, a valuable and topical exercise.

We first examine how national and local diversity evolved since 1870. Ancestry fractionalization at the national level increased rapidly from 1870 to 1930, but then stopped increasing as immigration restrictions were introduced in the mid-1920s. Ancestry fractionalization began to increase again in 1960, but at a much slower pace despite the waves of immigration since then. For local expenditure decisions, it is local diversity that is likely to matter, since it is local groups that must come to agreement. We document that the average county is typically less fractionalized than the nation overall because groups tend to concentrate. Still, average county fractionalization also increased rapidly until the 1930s. More recently, average county fractionalization has been increasing at a faster pace than national fractionalization as descendants of previous immigrants dispersed and new immigrants settled in more varied places. We show that the counties with the largest increase in fractionalization since 1960 were the least fractionalized in 1960.

We then document that the cross-sectional relationship between expenditures and diversity are highly time and measure dependent. For example, in cross-sections in each year before 1950, highly culturally or racially diverse areas had fewer teachers per capita, a relationship that changes sign or disappears after 1950. Before 1950, more culturally or ancestry fractionalized areas employed more police, but more racially fractionalized areas employed fewer police. Since then, more racially and culturally fractionalized areas employ more police and spend more on police. These results suggest that cross-sections are unlikely to reveal deep relationships between local expenditures and diversity.

We use our long panel to analyze how these local diversity changes relate to local expenditure changes. The panel allows us to control for time invariant local characteristics and examine whether the relationship can be given a causal interpretation. In addition, we control for time varying local characteristics such us the age structure of the population and county GDP per capita. Fixed effects regressions estimated over the entire sample, for the pre-1940, and post-1960 periods suggest that increases in origin-culture (or origin-GDP) weighted fractionalization is associated with decreases in teachers per capita, a decrease in education expenditures per capita, and a decrease in the share of local spending devoted to education. On the other hand, increases in racial fractionalization tend to be associated with increases in the resources devoted to education. We also find that a larger the share of African Americans is significantly associated with fewer teachers per capita before 1940 and higher share of education spending after 1960. Unweighted ancestry fractionalization is either not significant or positive and significant for the per capita measures after 1960. Perhaps surprisingly, increases in racial fractionalization are associated with decreases in police expenditures. Increases in cultural fractionalization or unweighted ancestry fractionalization are associated with increases in police expenditure when they are significant.

These results continue to hold even when we instrument our fractionalization measures with a shift-share instrument based on county ancestry from the previous decade growing at the national rate excluding the state in which a county is located. They also hold when we: (1) use origin GDP per capita at the time of arrival as an alternative group distance measure; (2) restrict the sample to urban areas; (3) include an income inequality measure; and (4) include outcomes such as education or crime that might be directly affected by education or police expenditures.

In summary, our results are the first to fully characterize the full range of U.S. diversity over space and time and the association of various measures of fractionalization with local spending. We show that fractionalization measures based on standard racial and ethnic groupings do not reduce education spending. Instead, it appears to be deeper origin cultural or economic differences which are responsible for difficulty reaching agreement on education spending. Once we control for these differences, racial fractionalization is generally positively related to education expenditures and negatively related to police expenditures.

In the next section we review the relevant literature to put our results in context. In Section 3, we summarize the nature of the data we use, starting with a brief outline of the construction of the county-level ancestry data from 1870 to 2010. In Section 4, we describe the various diversity measures we employ and discuss their cross-sectional dispersion and evolution over time. We also describe the evolution of expenditure on education and the police and their cross-sectional correlation with our diversity measures. Section 5 contains our panel data estimation results, instrumental variable results, and robustness exercises as well as a detailed comparison with previous findings. Section 6 concludes the paper.

2 Literature Review

The literature on the relationship between public expenditures and diversity is vast and complex but not conclusive.[1] There are several ways in which diversity may affect public spending: (1) Different groups may have different preferences over the types of public goods (Alesina, Baqir, and Easterly, 1999; Alesina and La Ferrara, 2000). (2) Groups may value spending that benefits other groups less (Alesina, Baqir, and Easterly, 1999), so diverse areas may have lower spending on truly public goods. (3) Public spending may be used for patronage (Cox and McCubbins, 1986; Erie, 1988; Alesina, Baqir, and Easterly, 2000), so diverse areas may have greater resources devoted to benefiting particular groups. (4) Spending choices may react directly to increased diversity. For example, education spending may increase if it is used as a nation building tool to create a more educationally and culturally homogeneous country (Bandiera et al., 2019), although Goldin and Katz (2008; 2011) emphasize the negative effect of diversity on the high school movement (see Black and Sokoloff (2006) for a history of education that places these developments in context). In addition, the perceived threat from increased diversity may cause increased police expenditures (Jackson and Carroll, 1981; Brown and Warner, 1992; Morris and LeCount, 2020) to help maintain social control and suppress ethnic conflict (Montalvo and Reynal-Querol, 2005).

[1]See the review in Alesina and Ferrara (2005). In addition to the papers quoted below, see also La Porta et al. (1999) and Alesina et al. (2003) for related contributions.

The empirical relationship between diversity and public expenditure is mixed. Alesina, Baqir, and Easterly (1999) find a negative cross-sectional relationship between racial fractionalization and the share of public spending on education. The Alesina, Baqir, and Easterly (1999) racial fractionalization is based on self-reported census divisions into Black, Asian, White, Native American and "Other" which they use as a proxy for Hispanic. Gisselquist (2014) uses the same data and documents that there is mixed support for a negative association. Across Japanese cities, Miyazaki (forthcoming) finds little relationship between increases in ethnic fractionalization and education spending but a negative relationship with spending on infrastructure. Boustan et al. (2013) finds an increase in racial heterogeneity is associated with larger expenditures in a municipal panel from 1970 to 2000. The evidence in Tabellini (2020) suggests that the influx of immigrants from 1910 to 1930 lowered public spending and tax rates, and that the political impacts were larger the greater the cultural distance between immigrants and natives. At a micro level, Beach and Jones (2017) present evidence that increases in city council diversity lower public spending. Meanwhile, there is evidence that diversity matters for local development, but that the kind of diversity matters.[2] For instance, Fulford, Petkov, and Schiantarelli (2020) find that measures of fractionalization have a positive effect on local development at the county level in the period 1870-2010, consistent with the results in Ottaviano and Peri (2005b), but origin-culture fractionalization has a negative effect.[3]

Diversity's impact on local spending decisions may be measure, time, and context dependent. One reason is that the relationship between expenditures and diversity depends on the diversity of voters, not just the population. After Reconstruction, African Americans largely lost the ability to vote in Southern states after the Civil War and experienced a decline in school resources (Margo, 1990). Despite the unequal resources, African Americans continued to make progress in education and narrow the racial education gap (Collins and Margo, 2006). Nonetheless, poor school quality

[2]See Alesina, Spolaore, and Wacziarg (2000), Ottaviano and Peri (2005b; 2005a) on the benefits of diversity for productivity. See Lazear (2001; 1999) for an analysis of the trade-off in production between the benefits of variety and the cost of communication associated with greater diversity.

[3]See also Sequeira, Nunn, and Qian (2019) and Burchardi et al. (2020) on the related issue of the effect of immigration on county level economic growth and innovation andCampo et al. (forthcoming) for the role of diversity in attracting immigrant inventors. The literature on the economic effect of diversity at the country level is enormous and we cannot do justice to it here. For an original contribution on the effect of birthplace diversity (our main focus) and a review of the literature see Alesina, Harnoss, and Rapoport (2016).

substantially hampered human capital accumulation and increased wage inequality (Carruthers and Wanamaker, 2017). Partly as a response, many African Americans moved from the rural South to the cities in rest of the country, altering the political equilibrium there (Tabellini, 2019; Calderón, Fouka, and Tabellini, 2020).[4] The 1965 Voting Rights Act, which limited the ability of states to disenfranchise African Americans, helped shift state expenditures towards higher African American share counties (Cascio and Washington, 2014).

Our work showing the evolution of ancestry is also related to an important demography, sociology, and economic literature which is too vast to give full justice to. Omi and Winant (2015) and Cornell and Hartmann (2006) provide some context for understanding ethnicity and race in the U.S. while Hirschman (2005) and Abramitzky and Boustan (2017) provide context for immigration in U.S. history. Roediger (2005) examines the changing white identity of immigrants. The social importance of race and ethnicity extends to many economic areas. One of the most prominent is "redlining"—the exclusion of groups, including immigrants and especially African Americans, from housing, access to credit, and other services. This practice contributed to the Black-white wealth gap (Hardy, Logan, and Parman, 2018) and other geographic differences that persist today (Aaronson et al., 2021).

3 Data

Our main data set provides an objective measure of the geographic distribution of ancestry since 1850. We focus our analysis from 1870 onward during which we have measures of the resources devoted to education and police. Fulford, Petkov, and Schiantarelli (2020) and the associated online appendix provide a complete discussion of the data set's construction, but we describe it briefly here. We build an estimate of each county's ancestry share using individual records from the decennial census when they are available starting in 1850. We construct the expected ancestry

[4]The Great Migration may have altered the political equilibrium directly by changing the electorate and indirectly by changing the political preferences of other groups. Ramos-Toro (2021), for example, examines the legacy of Civil War refugee camps and the transmission of political preferences from African Americans to white Americans.

mix for each person based on where and when he or she was born or on her parents' birthplace.[5] Since the country (or state) of birth of each individual is recorded in the census, for first generation immigrants born outside the United States, the expected ancestry mix is straightforward since we know exactly where they came from. This is also true for the children born in the U.S. from first generation immigrants from 1880 to 1970, as we observe the birth place of a person's parents. If the parents are born in the U.S. (or their country of origin is not recorded), we assign the child the expected ancestry mix of the children under five in the parents' birth state, or in the child's residence county if the child has not moved states, in the closest census year to the child's birth. This method allows for some groups to have faster population growth than others past the second generation. The ancestry mix for each period therefore depends on the ancestry share in the past, since internal migrants bring their ancestry mix with them when they move from state to state and pass it on to their children. Fulford, Petkov, and Schiantarelli (2020) start with the 1790 census, update it with immigration records from 1800 to 1850, then proceed iteratively from the first census with micro-records in 1850.

Accumulating this information over time for a geographic area gives the share of the people in a given area whose ancestors come from a given country. Therefore, we capture not just the fraction of first generation immigrants, but instead keep track of the ancestry of everyone, accounting for internal migration, the age structure of the population, differential population growth across ancestries, and local variations in where people from different countries originally settled. Because of the way the census ancestry data were reported after 1940, we aggregate to 1154 county groups which we use as our main unit of analysis. We continue to use county to refer to county groups, except where the specific number of groups is important.[6]

[5]The expected ancestry mix is a vector of all possible ancestries for each person describing that person's share of each ancestry. A first generation migrant has a one for their origin country and zero everywhere else. Second generation migrants received a mix from their parents (with equal weights). Third generation migrants have a more diffuse mix from their place of birth. The expected ancestry mix is only meaningful in a probabilistic sense at the individual level past the second generation. But by accumulating over a geographic area's population, we can obtain population shares for each ancestry.

[6]There are 1154 county groups as opposed to 3143 counties. Our county groupings approximately correspond to 1980 Public Use Microdata Areas (PUMAs). See the Appendix in Fulford, Petkov, and Schiantarelli (2020) on the criteria used in creating the county groups.

There are several advantages to this approach over the more common use of self-reported ancestry or coarser measures that only consider broad racial or ethnic categories. First, it allows us to go back to 1870 and to consider the evolution of ancestry over a long period of time. For comparison, the census first asked questions about self-reported ancestry in 1980 and has changed its approach several times since then. Second, it provides an objective measure of ancestry, attempting to measure something that could in principle be measured exactly: the share of a county's population descended from people who lived in another region of the world. Subjective measures of ethnicity or ancestry, such as those asked by recent censuses, may be affected by local circumstances, may differ by region and over time, and may change as an individual's perception of the link to her parents' origin country evolves (Liebler et al., 2017). Such self-identification is powerful, but is at least as much an outcome of complex social processes as it is a driver of them. Third, because our ancestry measure is at the county level, we appropriately captures the increasingly complex mix of ancestries. Recent self-reported measures force individuals to choose one or two identities with which they most associate, so tend understate ancestry diversity. While it is interesting to study the circumstances of identity formation in a particular place and time, our data allow us to study the evolving intermix of all ancestries across the entire continental U.S.

While these data have a number of advantages, they are not well suited to answer other questions. First, while we capture the ancestry distribution across county groups, we cannot say anything about settlement patterns within them and cannot study the role of intermarriage within a county.[7] Second, because the data are constructed from origin-country questions in the census, they do not capture within origin regional or religious differences, and so miss some important facets of group differences. Finally, the census does not distinguish among the African origin countries of the slave population in 1850.

In addition to the ancestry data, we create measures of the resources devoted to education and the police. For the entire 1870 to 2010 period, we construct teachers or police per capita, based on the full count individual census records on occupation (Ruggles et al., 2010). In addition, starting

[7]Residential segregation within cities has been the focus of many studies of group settlement (Cutler, Glaeser, and Vigdor, 1999; Massey and Denton, 1988; Logan and Parman, 2017).

in 1957, the Census of Governments, conducted every five years, provides information on education and police expenditures. When available, expenditures are a more accurate measure of the resources spent on education or policing, as they include also capital expenditures and expenditures on administrative personnel not classified as teachers and policemen. But the employment based measures allow us to go further back in time.

We also include several controls in various regressions, including the demographic structure of the population. Moreover, we make use of the measure of county group GDP per capita created by Fulford, Petkov, and Schiantarelli (2020). We also employ measures of county literacy rates prior to 1940 and years of education from the National Historical Geographic Information System (Minnesota Population Center, 2011). We use crime data from the Uniform Crime Reporting program and its predecessors maintained by the FBI. The collection and processing of these data has well documented issues (Maltz and Targonski, 2002), so we treat these data with caution. Finally, in some specifications we use the ratio between median and mean income as an income inequality measure (United States Census Bureau, 2012).

4 Diversity and public expenditures since 1870

In this section, we examine how diversity and public expenditures have evolved over time and geographically. We then show how their cross-sectional relationship has evolved. The next section uses the panel to study how changes in diversity affect public expenditures.

American ancestry has grown increasingly diverse over time. Figure 1 illustrates this growing diversity by showing the shares of the groups that make up more than 0.5 percent of the population in 1870 and 2010. In 1870, descendants from Great Britain were still the majority, but they had lost their majority status by 1880. The U.S. has become more diverse since then. Figure 1 shows the striking variety of origin countries that had significant population shares by 2010. Since 1970, for instance, there has been an increase in the immigrants from Asia and Central America that now represent the majority of inflow to the U.S.

4.1 Measuring diversity

We focus on three ways to measure diversity. One way to characterize the growing diversity of the U.S. is by calculating how fractionalized it has become. The standard fractionalization index measures the probability that any two individuals chosen from a population will not be of the same group:

$$frac_{c,t} = 1 - \sum_{a=1}^{A} (\pi_{ct}^{a})^2, \tag{1}$$

where π_{ct}^{a} is ancestry a's population share in county c at time t. When one group is very large, two people meeting are very likely to be the same, so fractionalization approaches 0; when there are many small groups, fractionalization approaches 1.

To understand the importance of racial differences, we also define a coarser measure, *Racial fractionalization,* which is fractionalization based on larger groupings, consisting of the Black, Native American, Asian and Pacific Islanders, European and other, and Latin American ancestries. A variant of this measure has been extensively used in the literature on diversity. Unlike objectively defined ancestry, any broader grouping necessarily involves some judgment about which groups are importantly distinct. We follow current discourse which tends to view Hispanic ethnicity as of similar importance to racial classifications and group all immigrants from Mexico, Central America and South America under Latin American ancestries. This choice is fraught with difficulties because the Hispanic ethnicity contains descendants from indigenous peoples, from European immigrants, and from people of African descent. More generally, ethnicity and who is part of a "white majority" are socially evolving concepts (Roediger, 2005). For instance, Italian immigrants when they came in large numbers starting around 1900 were not considered part of the "white majority" and it took time for this perception to evolve. Yet it is possible that these wide groupings may play an important role in the political equilibrium that determines local expenditure decisions.

Finally, we measure diversity based on cultural or economic attributes from the origin country. Recent work has generalized the fractionalization index by allowing it to incorporate measures of distance between groups (Bossert, D'Ambrosio, and La Ferrara, 2011). Define a measure of similarity based on the difference of some country-of-origin measure z between group j and group k as $s_c^{jk} = 1 - |z_t^j - z_t^k|/r_t$ where r is the maximum value the difference can take. As two groups become more similar along the z dimension, their similarity approaches one. Then a generalized fractionalization index is:

$$frac_{c,t}^{w} = 1 - \sum_{j=1}^{A}\sum_{k=1}^{A} \pi_{ct}^{j}\pi_{ct}^{k} s_t^{jk} \tag{2}$$

where the w stands for a "weighted" fractionalization. The standard fractionalization index is just the weighted fractionalization index when members of different groups are assumed to be completely dissimilar ($s_t^{jk} = 0$ for $i \neq j$).

We measure cultural fractionalization using differences in origin culture, as measured in the World Value Survey, along dimensions that are key for social cooperation (Tabellini, 2010).[8] We follow Tabellini (2010) and take the principal component of these cooperation measures to create a single social cooperation measure. We also use origin GDP per capita at the time of arrival as another summary measure of similarity across countries. In both cases, we allow for the origin value to vary over time and for assimilation or convergence following Fulford, Petkov, and Schiantarelli (2020). Formally, we construct z_t^j using an attribute $\hat{z}_\tau^j$ at time of arrival τ, take the difference from the U.S. value, $\hat{z}_\tau^j - \hat{z}_\tau^{US}$, and depreciate the difference at a rate δ per year.w[9] Weighting by the density of immigrants from ancestry j at arrival time, F_τ^j, yields an arrival-weighted measure:

$$\mathrm{z}_t^j = \sum_{\tau=0}^{t} (\hat{z}_\tau^j - \hat{z}_\tau^{US})(1-\delta)^{t-\tau} F_\tau^j.$$

This approach allows ancestries that have, on average, been in the U.S. longer to have converged to the U.S. average and so contribute less to diversity. We focus on a depreciation rate of 0.5 percent per year, implying that 40 percent of the original distance is eliminated in 100 years, but

[8]Tabellini (2010) uses answers on (1) generalized trust; (2) the respect of others as a desirable characteristic children should have; (3) obedience as a desirable children's characteristic; (4) feeling of control of one's own fortune, to build a proxy of cultural characteristics that favor cooperation. When enough data are available, we use the attitudes of older cohorts in the WWS to proxy for attitudes back in time. For a theoretical and empirical discussion of the evolution of cultural heterogeneity in the U.S. between 1972 and 2018 using the General Social Survey data, see Desmet and Wacziarg (2021).

[9]See Giavazzi, Petkov, and Schiantarelli (2019) for an investigation of the evolution of traits across generation of immigrants to the U.S and whether or not they converge to those of the long established groups.

we examine different degrees of convergence.

In constructing attribute-weighted ancestry measures, an obvious problem is what value to assign to the descendants of slaves brought forcibly to the U.S. (a distinct ancestry from recent immigrants from individual African countries which have separate ancestries). No option is really satisfactory in light of the paucity of data on origin attributes and the likely impact of slavery on attitude formation. We use the measures created by Fulford, Petkov, and Schiantarelli (2020) and described in the online appendix of that paper. More precisely, for origin-GDP weighted fractionalization, we use data on GDP for the West African country of Ghana for which there is information for 1870. West Africa was the main source region for slaves brought to North America. For symmetry, we use the 2009-2014 wave of the World Value Survey for Ghana (the earliest one available) to construct culture-weighted fractionalization, assuming that today's cultural attitudes are informative about past attitudes. In practice, allowing for time-varying attitudes across birth cohorts and convergence , African Americans in 2010 receive nearly the same numerical value as recent immigrants from Ghana or Turkey. The value is slightly lower than Italy and slightly higher than India. We examine our results' sensitivity to some of these assumptions by including the Fraction Black directly in some specifications, allowing for different depreciation rates, and using origin GDP rather than origin culture as a group distance measure.

4.2 Diversity since 1870

The top dashed line in Figure 2 shows how overall ancestry fractionalization in the U.S. as a whole has changed over time. In 1870, the probability of two randomly chosen people in the U.S being from different ancestries was nearly 70 percent. The large waves of migration over the next 50 years pushed the probability over 80 percent by 1920. Following the slowdown in migration after 1924, fractionalization stabilized, but began increasing slowly again in the 1970s, although at a pace lower than during the 1870-1920 period. Fractionalization was nearly 90 percent in 2010.

The overall diversity of the U.S. hides large geographical differences within it. A different and more informative way to calculate overall fractionalization is to start from fractionalization at the county level and then average across counties weighted by population. This approach captures the diversity the average person experiences locally. (Table 1 shows the unweighted mean which evolves nearly identically.) The lower solid line in Figure 2 measures average county fractionalization which is generally about 10 percentage points lower than overall fractionalization. People are more likely to live within counties composed more of their own group than overall fractionalization would suggest. The average American county continues to become increasingly diverse after 1960. Groups have been spreading out and the new migrants are going to more varied places, so average county fractionalization has increased at a faster pace compared to overall U.S. fractionalization over the last fifty years.

Figure 3 shows the geography of ancestry fractionalization in 1870, 1920, 1960 and 2010. A darker shade represents areas with higher levels of fractionalization. White areas in 1870 are counties for which population levels is too low to be able to calculate meaningful statistics. The maps get darker overall with time, showing the overall increase in fractionalization and its spread to new areas. Across the populous northeastern corridor from Washington, D.C. to Boston, fractionalization has hardly changed in the last five decades, despite the immigration waves since 1960. Similarly, California is not notably more fractionalized in 2010 than it was in 1960.

Instead, fractionalization increased the most in areas that were the least fractionalized in 1960. Figure 4 shows the change in fractionalization across county groups compared to their fractionalization in 1960. There is a clear downward slope as fractionalization in the least fractionalized county groups increased the most. This increasing homogeneity is evident in the maps in Figure 3. Fractionalization increased across Appalachian states (western Virginia, West Virginia, western North Carolina, Kentucky, and Tennessee). Fractionalization also increased sharply across the broader area surrounding Atlanta, Georgia, through Florida and some areas of Texas.

For each of the diversity measures discussed in the previous section, Table 1 provides descriptive statistics of the mean and standard deviation across country groups in each decade. The mean ancestry fractionalization in column 2 follows a similar path to the population-weighted mean in Figure 2 (we do not weight by population in the regressions). The evolution of *Racial fractional-*

ization is similar. Racial fractionalization increases monotonically over most of the period, with the exception of the period between 1930 and 1950. The cross-sectional standard deviation falls until 1970 and increase slightly after that.

Culture-weighted fractionalization increases until about 1930. But after that the amount of convergence we allow for as a result of assimilation matters as the immigration rate slows. Allowing differences to depreciate at 0.5 percent per year—implying that 40 percent of the original distance is eliminated in 100 years—culture-weighted fractionalization peaks in 1930 then declines and is constant for the last several decades. Two competing trends explain this path. The substantial increase in immigration in more recent decades tends to increase cultural fractionalization. On the other hand, the larger existing population is slowly homogenizing. If we had chosen a smaller depreciation rate of 0.2 percent per year— implying around 20 percent of the original distance is eliminated after 100 years—then culture-weighted fractionalization falls after the peak in 1930, but increases in the last three decades as immigration increased. Origin-GDP-weighted fractionalization (with differences relative to the U.S. depreciating at 0.5 percent per year), reaches its peak in 1920, decreases until 1970, and then increases after that. This path likely reflects that the distance between source countries of immigration after 1970 is larger in terms of log GDP per capita that in terms of our culture measure.

4.3 Public expenditures on police and education

There have been large secular increases in education and police employment and spending. Tables 2 and 3 provide descriptive statistics of these variables across county groups and nationally over time. Since 1870, the proportion of the population employed in teaching in the average county group has increased more than six fold and the proportion employed as police by more than seven fold. Since 1960, education expenditures per capita have more than doubled in real terms. Yet education's total expenditure share has decreased from 52.2 to 44.5 percent in the average county as other expenditures increased more rapidly. On the other hand police expenditures per capita have more than tripled and police's total expenditure share increased from 3.7 to 5.2 percent.

Based on Table 2, it appears that education is a necessity among public expenditures since 1960. County income and tax receipts have been increasing. Education expenditures have also grown. But the share spent on education has decreased. On the other hand, police expenditures appear to be a luxury.

The standard deviation across county groups of police and education employment increased since 1870, as did the standard deviation of expenditures since 1960. Counties are making different decisions over time and across space. We next explore how these choices are related to diversity and income.

4.4 The cross-sectional relationship between diversity and public expenditures

We briefly describe the cross-sectional relationship between diversity measures and public expenditure measures here. In the next section, we use the panel to remove persistent county characteristics. The cross-sectional results help understand the geography of diversity, public expenditures, and GDP per person at a given time. Are the most diverse areas spending the most of education or police? How about the highest GDP areas? How do these relationships change over time?

Figures 5 and 6 present the year-by-year cross-sectional relationship between these diversity measures and resources devoted to education and police. The coefficients plotted in each panel show how increasing that diversity measure by one standard deviation is associated with an increase in employment or expenditure across county groups in that year. A positive coefficient shows that more diverse county groups devote greater resources in that year. We also include the coefficient from regressions showing the relationship of (log) income per capita. These coefficients show whether higher income counties devote more resources to education and police.

These simple year-by-year regressions show that more fractionalized county groups employ more teachers per capita since 1870 and spend more per capita since 1960. Before 1950, more culturally or racially fractionalized county groups employed fewer teachers and spent less on education per capita. This relationship starts to change after 1950, so that, by 2010, the most culturally fractionalized county groups employ more teachers and spend much more on education. In contrast, more diverse county groups by any measure spend a smaller share on spending on education after 1960.

While higher income county groups employ more teachers in most years and spend more, they devote a smaller share of total spending to education until 2010. Within years, as across them, education appears to be a necessity.

More ancestry fractionalized and culturally fractionalized county groups devote more resources to police, by whatever measure, but the association becomes less strong and it even becomes negative for employment in 2010. The association with racial fractionalization is mostly negative up to 1950, while it becomes positive and strongly statistically significant after 1950. Contrary to education expenditures, higher income counties devote a greater share of overall spending to police.

5 Diversity's impact on public expenditures

In this section, we go beyond bivariate cross-sectional correlations and examine the relationships in more richly specified models estimated using our panel. In our regressions, we control for county fixed effects and include a basic set of controls such as the fraction of the population above 65, the fraction 18 and under, and the log of county GDP per capita. We also explore several additional variations including: the impact of limiting the sample to only urban counties, including the Black population share, including a measure of inequality when it is available since 1960, and including measures of education and crimes per capita. Both of these last measures are potential outcomes of spending and may be affected by diversity directly.[10] Finally, we build an instrument based on ancestry in the past that deals with some potential endogeneity issues, due, for instance, to reverse causality.

[10]We include education as a control for police spending in our basic specification.

5.1 Panel results

Table 4 shows multivariate regressions of our various measures of resources invested in education on our measures of diversity. Education has been used in the literature as an example of a type of expenditure that, in addition to a private return, also generates positive externalities and, hence, a public return (Alesina, Baqir, and Easterly, 1999). Each regression includes county fixed effects, year fixed effects, and the controls described above.[11] In the core results, in addition to ancestry fractionalization and racial fractionalization, we use culture-weighted ancestry fractionalization with a depreciation rate equal to 0.5 percent, but our results are robust to using Origin GDP per capita to capture dissimilarity or a different depreciation rate (see Tables A-7 and A-8 in the appendix). Distances in Origin GDP can be thought of as a summary measure of the economic, institutional and cultural differences of each immigrant groups relative to the US. The correlation between ancestry fractionalization, culture-weighted fractionalization, and racial fractionalization is positive but not very high (see Table A-1 in the appendix), so we have the variation necessary to estimate the separate effect of each diversity dimension.

Culture-weighted fractionalization is negatively and mostly significantly related to all measures of the resources devoted to education in Table 4. Moreover, the coefficient indicates a meaningfully large relationship. The mean proportion of teachers increased from 0.32 percent in 1870 to 2.3 in 2010, while the share of education expenditures declined from 52 percent in 1960 to 45 percent in 2010 (see Tables 2 and 3). Using the coefficients in columns (2) and (3) for the different subperiods and recalling that the fractionalization variables are in units of standard deviation, a one standard deviation increase in culture-weighted fractionalization is associated with a 5 percentage point decrease in the proportion of teachers in the 1870–1940 sample and a 13 percentage point decrease in the 1960-2010 sample. Similarly, a one standard deviation increase in culture-weighted fractionalization is associated with a 7 percent decrease in education expenditure per capita in column (4) and nearly 3 percentage points decrease in the share of education expenditure relative

[11] The sign of GDP per capita is mostly positive and significant for the per capita measures of education except in the share of education spending, where it is negative. The coefficient of fraction of 18 and under is consistently positive and significant, while the coefficient of the fraction 65 and older is mostly negative and significant.

to total expenditure in the 1960-2010 period in column (5).

Conversely, there is no evidence of a negative association between ancestry fractionalization or racial fractionalization and the resources devoted to education. Actually, the association tend to be positive either for racial fractionalization or ancestry fractionalization or both, although which is significant depends on the period and measure.

These conclusions are largely robust to variations in the included controls and sample. The results for culture-weighted fractionalization are similar when we restrict the sample to metropolitan counties (see Table A-3 in the appendix). Because all of the panel results already include fixed effects, we already remove any persistent fixed urban or rural differences. However, restricting to counties which contain a metropolitan area allows the year effects and the effect of fractionalization to be specific to these areas which are also the most populous. In Table A-3, the culture-weighted fractionalization coefficients are still negative and significant, while fractionalization is positive or not significant. The racial fractionalization coefficient is negative for teachers per capita after 1960 but positive for the share of expenditures. These results suggest that racial group differences may have a somewhat different effect in cities than rural areas, but that cultural differences have a similar effect.

Including measures of the stock of education (literacy until 1930, years of education after), does alter some results for education in appendix Table A-4, but the key conclusions still hold. The amount of education is partly a function of previous expenditures on education, so including education as a control assesses diversity's impact on education expenditures outside of any channel that works through education.

The corresponding results for police are in Table 5. Expenditure on the police, insofar as it contributes to public safety, has a public good aspect, but the literature has emphasized that historically it has been also a vehicle for patronage hiring (Cox and McCubbins, 1986; Erie, 1988; Alesina, Baqir, and Easterly, 2000) or for enforcing group boundaries (Jackson and Carroll, 1981; Brown and Warner, 1992; Morris and LeCount, 2020). Racial fractionalization is negatively and significantly associated with all measures of resources spent on police, while the ancestry fractionalization and cultural fractionalization coefficients are typically positive when they are significant. The results for the metropolitan counties are similar (see appendix Table A-9). Including a measure of crime in does not change the results (see appendix Table A-10). Beyond its statistical significance in Table 5, the racial fractionalization coefficient in each regression implies a meaningfully large effect. The average county group employed 0.350 percent of its population as police in 2010, so a one standard deviation increase in racial fractionalization from 1960-2010 in column (3) is associated with a 13 percent lower police employment share. In sum, while there is some evidence that certain diversity measures are positively associated with police spending, it is ancestry based fractionalization measures that have a positive relationship, not racial fractionalization.

The legacy of slavery and of the struggles to overcome *de jure* and *de facto* discrimination faced by the Black community may mean that the impact of the Black population share is distinct from overall racial and ancestry fractionalization. Appendix Tables A-5 for education and A-11 for police report the results obtained when the fraction Black is included as an additional regressor. This addition does not alter the conclusions for the three fractionalization measures included in our basic specification. The fraction Black is correlated with these measures (see Table A-1), but the correlation is not high in the panel. For the education results in Table A-5, the coefficient on the fraction Black is negative and significant in the 1870-1940 sample and positive after 1960. This result, which we will discuss more below, is consistent with political disenfranchisement loosening after the 1965 Voting Rights Act (Cascio and Washington, 2014). For police in Table A-11, the coefficient on the fraction Black is not significant.

We examine this issue from a different direction by allowing the diversity measures to have different impacts in southern states than in the rest of the country (we use the South region as defined by the Census which includes the states east of Texas and Oklahoma and south of Delaware). Appendix Tables A-6 and A-12 show the results for education and police expenditures. The education results for the rest of country are very similar to the main results. Allowing all coefficients to be different, including the year effects and controls, the diversity variables appear to have a much smaller impact in the South. Some coefficients are statistically significant but they are generally smaller and not consistently of the same sign across measures and time periods. We draw two limited conclusions: the first is that, as the cross-section results emphasized, diversity's impact is region and time period specific, with our our overall results driven by what happens in the counties outside the South. Second, we cannot conclude that diversity does not matter in the South, only that, after controlling for county specific fixed effects, the changes over time there do not appear to be sufficient to derive precise conclusions about the relationship between education spending and diversity. Table A-12 for police expenditures, on the other hand, suggests that the relationship between diversity and police spending in the South and rest of country appear to be fairly similar, although the coefficients are not as consistently significant.

We also examine how including a measure of income inequality affects the results for education and police spending. For the period 1960-2010, we can construct the ratio between the mean and median income in a county. This ratio is closely related to the Gini coefficient in the cross-section when both are available (the correlation is 0.7, for instance, in 2010). Including this income inequality measure, there is essentially no change in the estimated coefficients of the fractionalization variables or their significance (see appendix Table A-2). Its sign is almost always positive in the education equation and negative in the police equation in the panel. A positive sign is largely consistent with the results for local spending in the municipal panel and for school district spending in Boustan et al. (2013). If we use only the cross-sectional variation (by omitting the county group dummies) the sign of the mean-to-median-income ratio is negative as in Alesina, Baqir, and Easterly (1999). This difference again highlights the importance of having a panel.

A key advantage over other work is our ability to examine multiple forms of diversity at the same time. However, when we put each of our three fractionalization measures in separate regressions, the sign and significance patterns from the multivariate panel regressions continue to mostly hold. Tables A-13 and A-14 in the appendix show these results.

5.2 Instrumental variable results

Do these results have a causal interpretation going from fractionalization to local expenditure choices? We have purposely avoided placing such a causal interpretation on the results so far. The results in Tables 4 and 5 include fixed effects, so persistent unobservable differences between counties are removed and we control for the age structure of the population and for local economic development, captured in the regressions by county group GDP per worker. Yet changes in the outcomes themselves could cause changes in diversity. For example, an increase in education expenditures might cause an increase in ancestry or racial fractionalization by attracting members of different ancestries or racial/ethnic groups, which would explain the positive association. If this reverse causation were operative, we would expect the negative coefficient of cultural ancestry fractionalization on education to under-estimate its true effect, while the positive coefficient of racial fractionalization or ancestry fractionalization to over-estimate it. Another alternative is that both changes in diversity and changes in expenditure are caused by some third factor such as an unobservable change in the attitudes of the existing population or a change in the structure of the economy that attracts a racially diverse population and makes education expenditures more valuable.

To examine the importance of these factors, we employ an instrument that breaks the contemporaneous relationship between our diversity variables and the outcomes. More precisely, we employ a "shift-share" instrument that uses the allocation of ancestries from a previous decade to predict the share in the current decade using the national growth rate of that ancestry, excluding the growth in the county group's state. By construction, this instrument removes contemporaneous shocks that might affect both the diversity and the outcome, so removes reverse causality or third factor effects that operate within one decade.[12]

Table 6 shows the education results. The first stage regression suggests that the instruments are not weak as judged by the Kleibergen and Paap (2006) test as implemented in Schaffer (2005).

[12] Jaeger, Ruist, and Stuhler (2018) examine some of the necessary equilibrium conditions for such a shift-share instrument to be valid. We allow for serial correlation which addresses some possible problems below.

The results are quite similar to the results without instrumenting in Table 4. Culture-weighted fractionalization is negative and significant in all time periods and for all education expenditure measures. Racial fractionalization is positive and significant. Ancestry fractionalization is also positive and significant except in column 5, where it has a negative sign.

The coefficients in Table 6 when instrumenting are generally slightly larger in absolute value than the corresponding coefficients in Table 4. The increases suggest that either there is a measurement error that gives rise to attenuation bias, or the reverse causality or omitted factors are tending to act in the opposite direction to the causal effect of diversity changes. For example, if an increase in culture-weighted fractionalization tends to make agreement on education more difficult while at the same time an increase in education spending attracts migrants with diverse backgrounds, then the panel without instrumenting will tend to underestimate the negative direct effect of culture-weighted fractionalization. The fact that the coefficient on culture-weighted fractionalization becomes more negative when instrumenting is consistent with either attenuation bias or reverse causality. The increase in the size of the positive racial fractionalization coefficient, when instrumenting, suggests that attenuation bias from measurement error is likely to be more important than any upward bias from reverse causality. In any case, the combined effect of these two types of biases appears to be relatively minor.

Table 7 shows the same instrumental variable regressions for police expenditures. As in Table 5 without instrumenting, the racial fractionalization coefficient is consistently negative and significant and the ancestry fractionalization coefficient is either positive and significant or not statistically different from zero. Culture-weighted fractionalization has a positive coefficient for 1870-1940 for police employment but it becomes negative for the 1960-2010 period. The coefficients are generally larger in absolute value in Table A-16 than in Table 5 but the differences are not generally large.

Using a function of the past ancestry distribution as an instrument for the present requires the absence of serial correlation in the error term. In appendix Tables A-15 and A-16 we include a lag of the dependent variable to help remove this dependence if it is there. We show the results with and without instrumenting, since including a lagged dependent variable affects the size of the main coefficients. The results we obtain are mostly similar and lead to the same general conclusions.[13]

5.3 Discussion and relation with the literature

The panel results differ from the cross-section results in Figures 5 and 6. For instance, in the cross-section, more fractionalized counties devote a smaller share of their resources to education and a greater share to police, using any of our fractionalization measures. Yet controlling for fixed county differences, as racial fractionalization increases, counties devote a greater share to education and less to police (or the same, depending on the regression). These differences suggest the presence of strong and persistent county effects which cannot be controlled for in the cross-section. Moreover, the instrumental variable estimates confirm the sign of the coefficients of the fractionalization variables, so there is evidence supporting a causal effect of fractionalization on local expenditure outcomes.

How do our results compare with those obtained in the literature? Ours is the only paper that focuses on ancestry diversity and can use an objective measure of ancestry. Moreover, it is the only paper that can study diversity over a long period of time, using census based measures of occupations, such as teachers and policeman. For this reason, it can explore dimensions of diversity that other papers could not. Most of the literature has focused exclusively on the post-war period and has been based on a coarser measure of racial and ethnic fractionalization, distinguishing between non-Hispanic White, Black, Asian and Pacific Islander, Native Americans, and Hispanic. Alesina, Baqir, and Easterly 1999, using this type of measure, find a robust negative cross-sectional correlation between racial fractionalization and the share of spending on road, sewerage and education, and a positive one with expenditure on the police. They do not find evidence of a significant role of racial fractionalization for the share of spending on road, sewerage, education or the police,

[13] Including a lag dependent variable in a fixed effect regression with a relatively short panel introduces Nickell (1981) bias. Because the persistence is not large in most specifications and our time dimension of 15 decades is substantial, the bias is likely to be small and we ignore it rather than move to more complicated dynamic panels estimation methods with their own limitations.

using the change between 1990 and 1960. Our cross-sectional results since 1950 in Figures 5 and 6 are thus consistent with cross-sectional results in the literature (Alesina, Baqir, and Easterly, 1999; Ajilore and Smith, 2011). Yet subsequent analyses have suggested that these cross-sectional results are less consistent across types of expenditures (Gisselquist, 2014).

We do not find evidence supporting racial fractionalization having a negative a negative role for education spending. However, our results on the effect of culture or origin-GDP weighted ancestry fractionalization on education are supportive of the arguments that diversity hinders spending on some public goods, but the channel does not appear to be racial fractionalization. Boustan et al. (2013) also examine racial fractionalization while studying the effect of income inequality in a panel of U.S. municipalities from 1970-2000. As discussed earlier, we find similar results for income inequality. We differ in finding that racial fractionalization tends to have a negative relationship with police spending while Boustan et al. (2013) find a positive relationship. Our results suggest that it is different measures of fractionalization, such as ancestry or culture-weighted fractionalization, that are positively associated with police spending. Holding these measures constant, increases in racial fractionalization either decrease or do not change police spending.[14]

Our results for the 1870-1940 period suggest that culture-weighted fractionalization has a negative effect on the percentage of teachers in the population, which is not supportive of an interpretation of education as a nation building exercise to homogenize culturally diverse immigrants. Bandiera et al. (2019), instead, present evidence that the introduction of compulsory education by states in the age of Mass Migration occurs earlier as the percentage of immigrants from countries with low civic capital increases. They proxy low civic capita by the absence of compulsory education requirements in the origin country. Our result is more consistent, instead with the emphasis in Goldin and Katz (2008) on the negative effect of heterogeneity on investment in education.[15]

[14]One reason for differing results is that municipal expenditures may not form a consistent unit for expenditure purposes. Many municipalities make only minor police expenditures, leaving policing to the county, and do not make education expenditures which are made at the school district level (Auxier, 2020). Our approach aggregates all local expenditures at the county level, so incorporates municipal expenditures as well as school district expenditures, state, and federal transfers.

[15]See especially Chapter 6 and the discussion and results in Table 6.1 for levels (in 1910 and 1928) and long differences of state graduation rates as a function, among other things, of the percentage of Catholics, used as a proxy for heterogeneity. Both the choice of the proxy for heterogeneity and also the use of graduation rates as a dependent

Our conclusions continue to hold even if we restrict the estimation periods to the 1910–1930 or 1870–1920 that approximate the periods considered in Goldin and Katz (2008) and Bandiera et al. (2019), respectively. Yet teachers per capita is an imperfect measure of education spending for the reasons already explained and culture or GDP weighted fractionalization is distinct from a measure of diversity based on compulsory education in the country of origin, so the different conclusions may arise from differences in measurement.

Our results are consistent with the idea that the role of diversity may change over time, which is likely to be particularly important for African Americans. African Americans were denied effective franchise in many states after Reconstruction. During this period, racial diversity may not have meant electoral diversity, so public expenditures did not reflect the views of African Americans. Calderón, Fouka, and Tabellini (2020) emphasize that the Great Migration lead to political empowerment of African American outside the South and affected positively the attitude of white voters towards civil rights. Ramos-Toro (2021) also discusses the transmission of political preferences from African Americans to white Americans, analyzing the legacy of the Civil War refugee camps.[16] Cascio and Washington (2014) show that the 1965 Voting Rights Act increased transfers of state funds toward counties with higher Black population shares in states that restricted voting through literacy tests.

Because of this complex history, we allow the Black population share to have an independent effect in Tables A-5 and A-11. As we have already discussed, including the Black population share does not affect the conclusions for the other fractionalization variables much. Importantly, the coefficient on the Black share on education is negative in the pre-1940 sample and positive in the post-1960 sample, suggesting that the 1965 Voting Rights Act made a significant difference in the ability of the Black community to affect education spending positively. This ability was

variable, an outcome measure of state level investment in education, is open to debate.

[16]See Desmet, Gomes, and Ortuño-Ortín (2020) for a theoretical discussion and cross country evidence that, while overall fractionalization worsens public goods outcomes, local interaction mitigates this negative association. Fouka and Tabellini (2021) provide evidence that Mexican immigration to the U.S. affected positively white Americans' attitudes and behaviors towards Black Americans.See also Giuliano and Tabellini (2020) who argue that historical immigration affected the ideology of today's Americans through a process of horizontal transmission from immigrants to natives.

absent or limited earlier, which may have contributed to the exodus of better-educated Blacks from the South. Tabellini (2019) finds, using a shift-share instrument similar to ours, that the influx of Blacks to the rest of the country during the first Great Migration, had a negative effect on tax revenues and public spending due to the fall in property values. Our results for 1870-1940 suggest a positive effect of racial fractionalization on the number of teachers, which is not necessarily inconsistent with a fall in total spending, an issue our paper does not address.

6 Conclusion

The complex mosaic of ancestry in the U.S. has changed profoundly over time and it is still evolving as new migrants enter and people move internally. We use the quantitative mapping of U.S. counties' ancestry distribution from 1870 to 2010 to provide the first complete description of U.S diversity across time and space. The movement of people into the U.S. and within it has generated a complex and evolving pattern of ancestry fractionalization across counties. Both immigration flows and internal movements of population have contributed to an increasingly widespread experience of diversity. Since 1960, the least fractionalized countries have experienced the greatest increase in fractionalization.

The robustly negative and significant association between culture-weighted fractionalization (or origin-GDP-weighted fractionalization) and resources devoted to education in all our panel results is consistent with stories that emphasize difficulty agreeing on investment in public goods in a more diverse environment. However, racial fractionalization is generally positively and significantly associated with education expenditure. Thus, racial and broad ethnic divisions are not the key source of disagreement that prevent investment in education. Racial fractionalization is robustly negatively and significantly associated with police expenditure, while ancestry based measures of fractionalization, when significant, tend to be positively associated with police spending. In sum, fractionalization has different dimensions and narratives which focus only on racial differences are missing a more complex story.

After the protests for racial justice during the summer in 2020, there were calls to alter police funding in favor of other spending priorities such as education or other social programs. Debates and negotiations about expenditure and resource allocation at the local level have characterized the U.S. throughout its history. Whether communities can reach a new spending equilibrium with the many cleavages that divide them will depend on many factors. Our results emphasize that one factor that may make agreement on spending that is socially beneficial harder are group differences in traits such as trust and respect for others or differences in origin-country economic development which underlie our measure of attribute-weighted fractionalization. Yet trust and other cultural attitudes may also evolves from interacting with others in the social, political, and economic sphere. Studying the endogenous formation of these traits is, therefore, an important task for future research.

References

Aaronson, Daniel, Jacob Faber, Daniel Hartley, Bhashkar Mazumder, and Patrick Sharkey. 2021. “The long-run effects of the 1930s HOLC "redlining" maps on place-based measures of economic opportunity and socioeconomic success.” *Regional Science and Urban Economics* 86:103622.

Abramitzky, Ran and Leah Boustan. 2017. “Immigration in American Economic History.” *Journal of Economic Literature* 55 (4):1311–45.

Ajilore, Olugbenga and John Smith. 2011. “Ethnic fragmentation and police spending.” *Applied Economics Letters* 18 (4):329–332.

Alesina, Alberto, Reza Baqir, and William Easterly. 1999. “Public Goods and Ethnic Divisions.” *The Quarterly Journal of Economics* 114 (4):1243–1284.

———. 2000. “Redistributive Public Employment.” *Journal of Urban Economics* 48 (2):219–41.

Alesina, Alberto, Arnaud Devleeschauwer, William Easterly, Sergio Kurlat, and Romain Wacziarg. 2003. “Fractionalization.” *Journal of Economic Growth* 8 (2):155–194.

Alesina, Alberto and Elliana La Ferrara. 2005. “Ethnic Diversity and Economic Performance.” *Journal of Economic Literature* 43 (3):762–800.

Alesina, Alberto, Johann Harnoss, and Hillel Rapoport. 2016. “Birthplace Diversity and Economic Prosperity.” *Journal of Economic Growth* 21:101–138.

Alesina, Alberto and Eliana La Ferrara. 2000. “Participation in Heterogeneous Communities.” *The Quarterly Journal of Economics* 115 (3):847–904.

Alesina, Alberto, Enrico Spolaore, and Romain Wacziarg. 2000. “Economic Integration and Political Disintegration.” *American Economic Review* 90 (5):1276–1296.

Auxier, Richard C. 2020. “What Police Spending Data Can (and Cannot) Explain amid Calls to Defund the Police.” Urban wire: The blog of the Urban Institute, The Urban Institute. URL `https://urbn.is/2YmpvzG`.

Bandiera, Oriana, Myra Mohnen, Imran Rasul, and Martina Viarengo. 2019. “Nation-building Through Compulsory Schooling during the Age of Mass Migration.” *The Economic Journal* 129:62–109.

Beach, Brian and Daniel B. Jones. 2017. “Gridlock: Ethnic Diversity in Government and the Provision of Public Goods.” *American Economic Journal: Economic Policy* 9 (1):112–36.

Black, Sandra E. and Kenneth L. Sokoloff. 2006. “Chapter 2 Long-Term Trends in Schooling: The Rise and Decline (?) of Public Education in the United States.” Elsevier, 69–105.

Bossert, Walter, Conchita D’Ambrosio, and Eliana La Ferrara. 2011. “A Generalized Index of Fractionalization.” *Economica* 78 (312):723–750.

Boustan, Leah, Fernando Ferreira, Hernan Winkler, and Eric M. Zolt. 2013. “The Effect of Rising Income Inequality on Taxation and Public Expenditures: Evidence from U.S. Municipalities and School Districts, 1970–2000.” *The Review of Economics and Statistics* 95 (4):1291–1302.

Brown, M. Craig and Barbara D. Warner. 1992. “Immigrants, Urban Politics, and Policing in 1900.” *American Sociological Review* 57 (3):293–305.

Burchardi, Konrad B., Thomas Chaney, Tarek Alexander Hassan, Lisa Tarquinio, and Stephen J. Terry. 2020. “Immigration, Innovation, and Growth.” Working Paper 27075, NBER.

Calderón, Álvaro, Vasiliki Fouka, and Marco Tabellini. 2020. “Racial Diversity, Electoral Preferences, and the Supply of Policy: the Great Migration and Civil Rights.” Working Paper 20-017, Harvard Business School BGIE Unit. URL `https://ssrn.com/abstract=3447469`.

Campo, Francesco, Mariapia Mendola, Andrea Morrison, and Gianmarco Ottaviano. forthcoming. “Cultural diversity, Innovation, International Migration.” *Journal of the European Economic Association* .

Carruthers, Celeste K. and Marianne H. Wanamaker. 2017. “Separate and Unequal in the Labor Market: Human Capital and the Jim Crow Wage Gap.” *Journal of Labor Economics* 35 (3):655–696.

Cascio, Elizabeth U. and Ebonya Washington. 2014. “Valuing the Vote: The Redistribution of Voting Rights and State Funds following the Voting Rights Act of 1965.” *The Quarterly Journal of Economics* 129 (1):379–433.

Collins, William J. and Robert A. Margo. 2006. “Chapter 3 Historical Perspectives on Racial Differences in Schooling in the United States.” Elsevier, 107–154.

Cornell, Stephen and Douglas Hartmann. 2006. *Ethnicity and race: Making identities in a changing world*. Sage Publications.

Cox, Gary W. and Mathew D. McCubbins. 1986. "Electoral Politics as a Redistributive Game." *The Journal of Politics* 48 (2):370–389.

Cutler, David M., Edward L. Glaeser, and Jacob L. Vigdor. 1999. "The Rise and Decline of the American Ghetto." *Journal of Political Economy* 107 (3):455–506.

Desmet, Klaus, Joseph Flavian Gomes, and Ignacio Ortuño-Ortín. 2020. "The geography of linguistic diversity and the provision of public goods." *Journal of Development Economics* 143:102384.

Desmet, Klaus and Romain Wacziarg. 2021. "The Cultural Divide." *The Economic Journal* 131:2058–2088.

Erie, Steven P. 1988. *Rainbow's End: Irish-Americans and the Dilemmas of Urban Machine Politics, 1940–1985*. Berkeley: University of California Press.

Fouka, Vasiliki and Marco Tabellini. 2021. "Changing Ingroup Boundaries: The Effect of Immigration on Race Relations in the US." Discussion Paper 14311, IZA Institute of Labor Economics.

Fulford, Scott L., Ivan Petkov, and Fabio Schiantarelli. 2020. "Does it matter where you came from? Ancestry composition and economic performance of US counties, 1850–2010." *Journal of Economic Growth* 25:341–380.

Giavazzi, Francesco, Ivan Petkov, and Fabio Schiantarelli. 2019. "Culture: Persistence and Evolution." *Journal of Economic Growth* 24 (2):117–154.

Gisselquist, Rachel M. 2014. "Ethnic divisions and public goods provision, revisited." *Ethnic and Racial Studies* 37 (9):1605–1627.

Giuliano, Paola and Marco Tabellini. 2020. "The Seeds of Ideology: Historical Immigration and Political Preferences in the United States." Working Paper 27238, NBER.

Goldin, Claudia and Lawrence F. Katz. 2008. *The Race between Education and Technology*. Cambridge, Massachusetts: The Belknap Press of Harvard University Press.

———. 2011. *Mass Secondary Schooling and the State: The Role of State Compulsion in the High School Movement*. University of Chicago Press, 275–310.

Hardy, Bradley L., Trevon D. Logan, and John Parman. 2018. "The Historical Role of Race and Policy for Regional Inequality." Framing paper, The Hamilton Project. URL `https://www.hamiltonproject.org/papers/the_historical_role_of_race_and_policy_for_regional_inequality`.

Hirschman, Charles. 2005. "Immigration and the American Century." *Demography* 42 (4):595–620.

Jackson, Pamela Irving and Leo Carroll. 1981. "Race and the War on Crime: The Sociopolitical Determinants of Municipal Police Expenditures in 90 non-Southern U.S. Cities." *American Sociological Review* 46 (3):290–305.

Jaeger, David A, Joakim Ruist, and Jan Stuhler. 2018. "Shift-Share Instruments and the Impact of Immigration." Working Paper 24285, NBER. URL `http://www.nber.org/papers/w24285`.

Kleibergen, Frank and Richard Paap. 2006. "Generalized reduced rank tests using the singular value decomposition." *Journal of Econometrics* 133 (1):97–126.

La Porta, Rafael, Florencio Lopez-de Silanes, Andrei Shleifer, and Robert Vishny. 1999. "The quality of government." *The Journal of Law, Economics, and Organization* 15 (1):222–279.

Lazear, Edward P. 1999. "Culture and Language." *Journal of Political Economy* 107 (6):S95–S126.

———. 2001. "Globalisation and the Market for Team-Mates." *The Economic Journal* 109 (454):15–40.

Liebler, Carolyn A., Sonya R. Porter, Leticia E. Fernandez, James M. Noon, and Sharon R. Ennis. 2017. "America's Churning Races: Race and Ethnicity Response Changes Between Census 2000 and the 2010 Census." *Demography* 54 (1):259–284.

Logan, Trevon D. and John M. Parman. 2017. "The National Rise in Residential Segregation." *The Journal of Economic History* 77 (1):127–170.

Maltz, Michael D. and Joseph Targonski. 2002. "A Note on the Use of County-Level UCR Data." *Journal of Quantitative Criminology* 18 (3):297–318.

Margo, Robert A. 1990. *Race and Schooling in the South, 1880–1950: An Economic History*. University of Chicago Press.

Massey, Douglas S. and Nancy A. Denton. 1988. "The Dimensions of Residential Segregation." *Social Forces* 67 (2):281–315.

Minnesota Population Center. 2011. "National Historical Geographic Information System: Version 2.0." Minneapolis, MN, University of Minnesota. Available: `http://www.nhgis.org`, accessed 1 August 2014.

Miyazaki, Takeshi. forthcoming. "Does ethnic diversity affect public goods provision? Evidence from boundary reform of local governments." *Applied Economics* .

Montalvo, José G. and Marta Reynal-Querol. 2005. "Ethnic Polarization, Potential Conflict, and Civil Wars." *The American Economic Review* 95 (3):796–816.

Morris, R. C. and Ryan Jerome LeCount. 2020. "The Value of Social Control: Racial Resentment, Punitiveness, and White Support for Spending on Law Enforcement." *Sociological Perspectives* 63:697–718.

Nickell, Stephen. 1981. "Biases in Dynamic Models with Fixed Effects." *Econometrica* 49 (6):1417–1426.

Omi, Michael and Howard Winant. 2015. *Racial Formation in the United States*. New York: Routledge, third edition ed.

Ottaviano, Gianmarco I.P. and Giovanni Peri. 2005a. "Cities and cultures." *Journal of Urban Economics* 58 (2):304–337.

———. 2005b. "The economic value of cultural diversity: evidence from US cities." *Journal of Economic Geography* 6 (1):9–44.

Ramos-Toro, Diego. 2021. "Self-Emancipation and Progressive Politics: The Legacy of Civil War Refugee Camps."

Roediger, David R. 2005. *Working Toward Whiteness: How America's Immigrants Became White: The Strange Journey from Ellis Island to the Suburbs*. Basic Books.

Ruggles, Steven, J. Trent Alexander, Katie Genadek, Ronald Goeken, Matthew B. Schroeder, and Matthew Sobek. 2010. "Integrated Public Use Microdata Series: Version 5.0 [Machine-readable database]."

Schaffer, Mark E. 2005. "XTIVREG2: Stata module to perform extended IV/2SLS, GMM and AC/HAC, LIML and k-class regression for panel data models." Statistical Software Components, Boston College Department of Economics, revised 26 June 2020.

Sequeira, Sandra, Nathan Nunn, and Nancy Qian. 2019. "Immigrants and the Making of America." *The Review of Economic Studies* 87 (1):382–419.

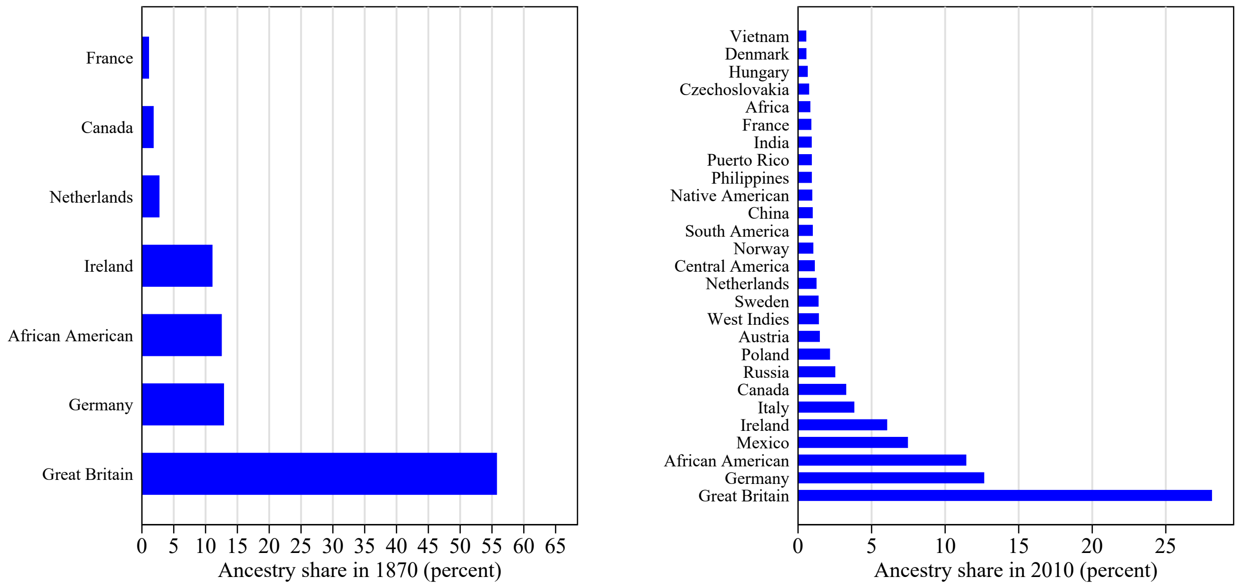
Tabellini, Guido. 2010. "Culture and Institutions: Economic Development in the Regions of Europe." *Journal of the European Economic Association* 8 (4):677–716.

Tabellini, Marco. 2019. "Racial Heterogeneity and Local Government Finances: Evidence from the Great Migration." Working Paper 19-006, Harvard Business School.

———. 2020. "Gifts of the Immigrants, Woes of the Natives: Lessons from the Age of Mass Migration." *Review of Economic Studies* 87 (1):454–486.

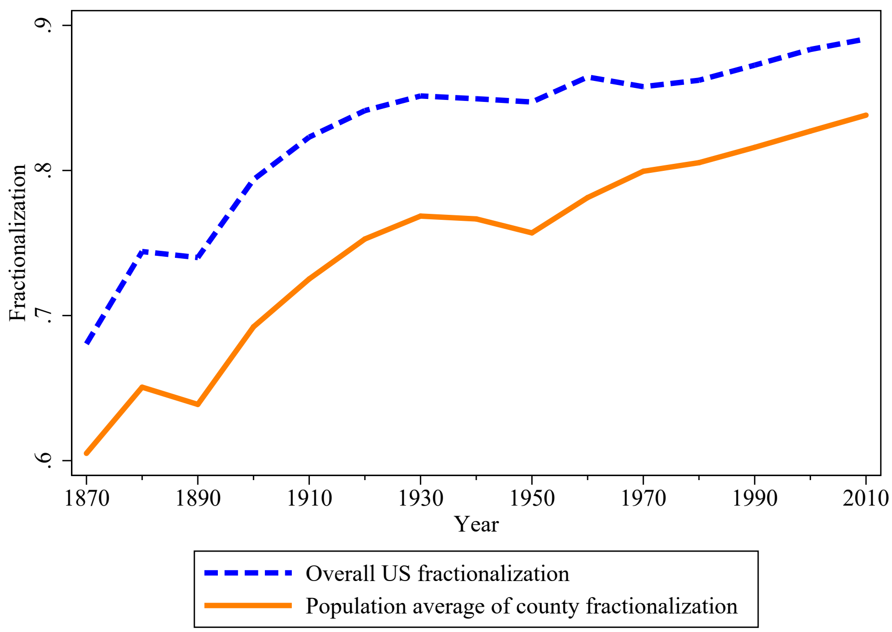
United States Census Bureau. 2012. "County and City Data Book Consolidated File: County Data, 1947-1977 (ICPSR07736-v2)." Inter-university Consortium for Political and Social Research [distributor].

Figure 1: Ancestry share in the United States: 1870 and 2010



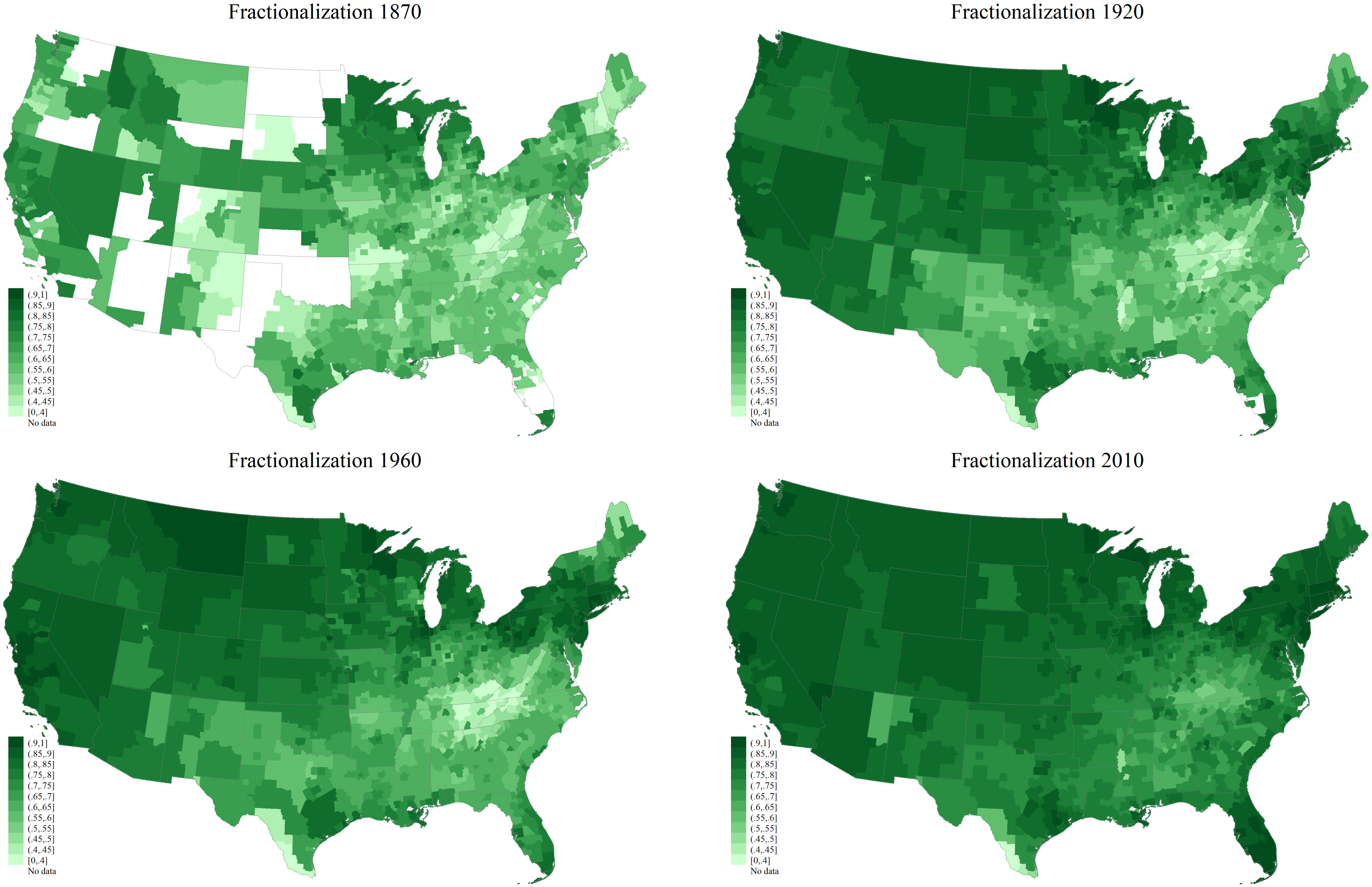
Notes: Aggregate ancestry shares in the U.S. for ancestries with greater that 0.5% of the population. Ancestry shares are created by summing the share in each county weighted by county population in each year. Great Britain is combined England, Welsh, and Scotland ancestries.

Figure 2: Ancestry fractionalization in the United States



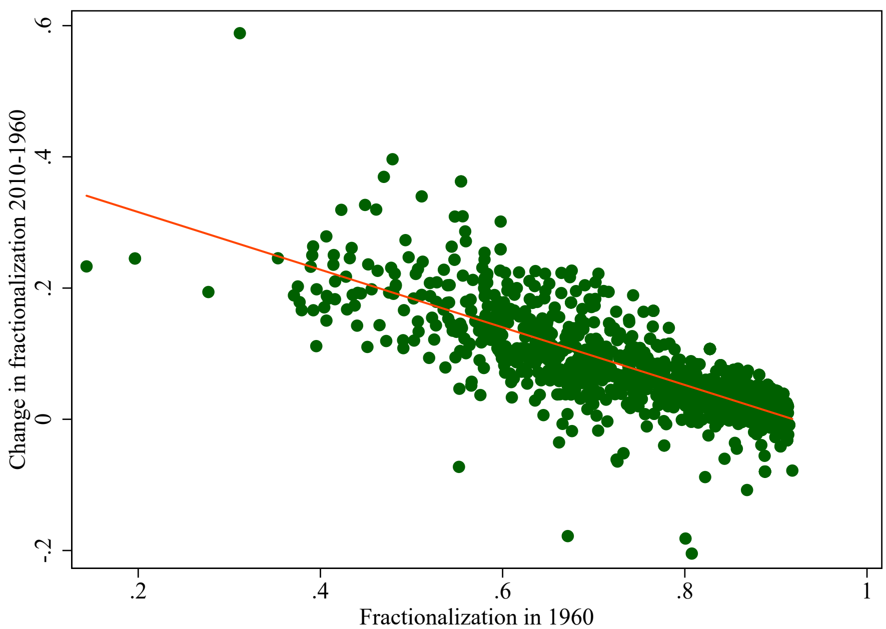
Notes: Overall U.S. Fractionalization is the probability that two people chosen at random from the U.S. will be from different groups: $frac_t = 1 - \sum_{a=1}^{A} (\pi_t^a)^2$ while the population average of county fractionalization is the probability that two people chosen at random from a randomly chosen county will be of different ancestries: $\sum_c (Pop_{c,t}/Pop_{US,t}) frac_{c,t}$.

Figure 3: Fractionalization in 1870, 1920, 1960, 2010



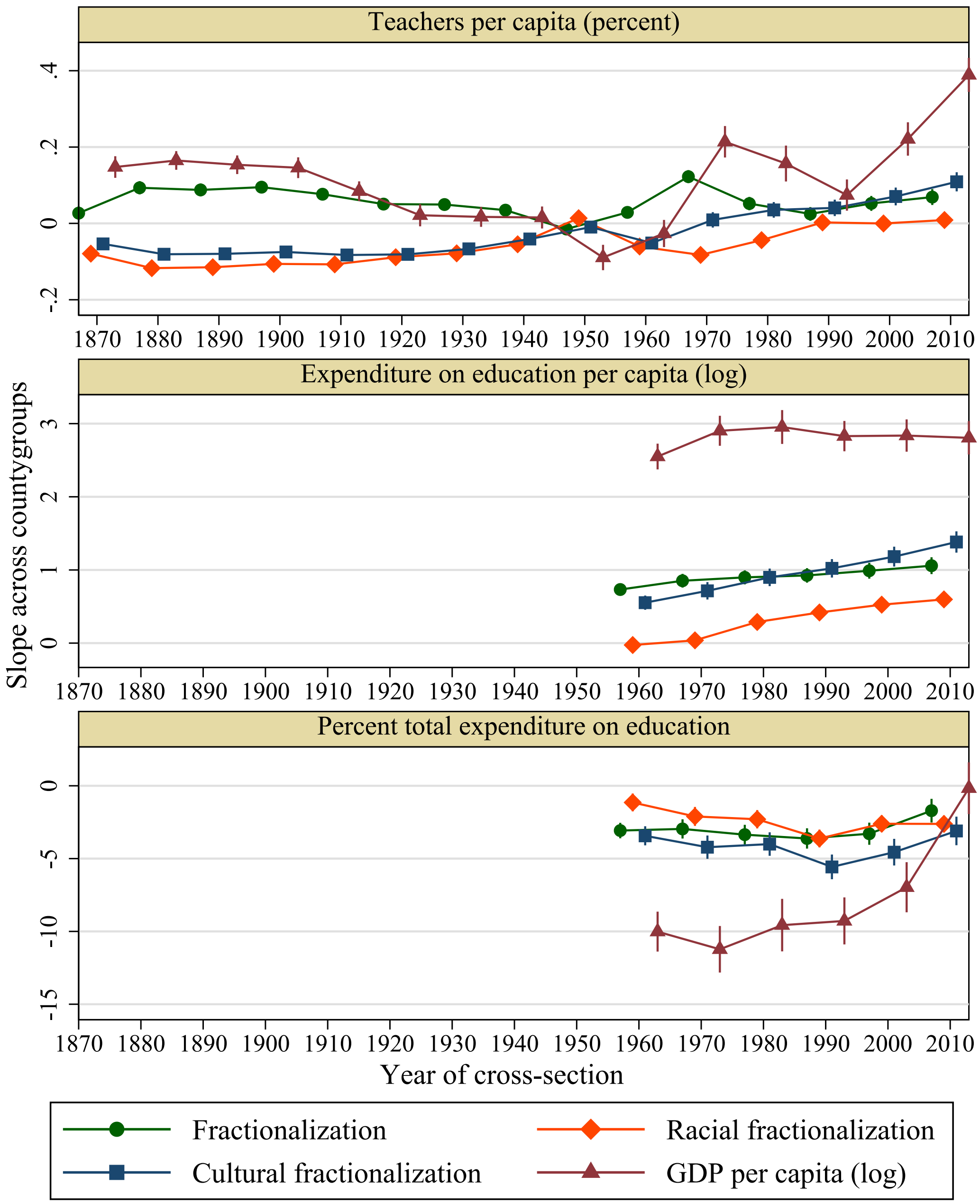
Notes: Fractionalization within each county group. Source: Authors' calculations.

Figure 4: Change in fractionalization 1960-2010 by fractionalization in 1960



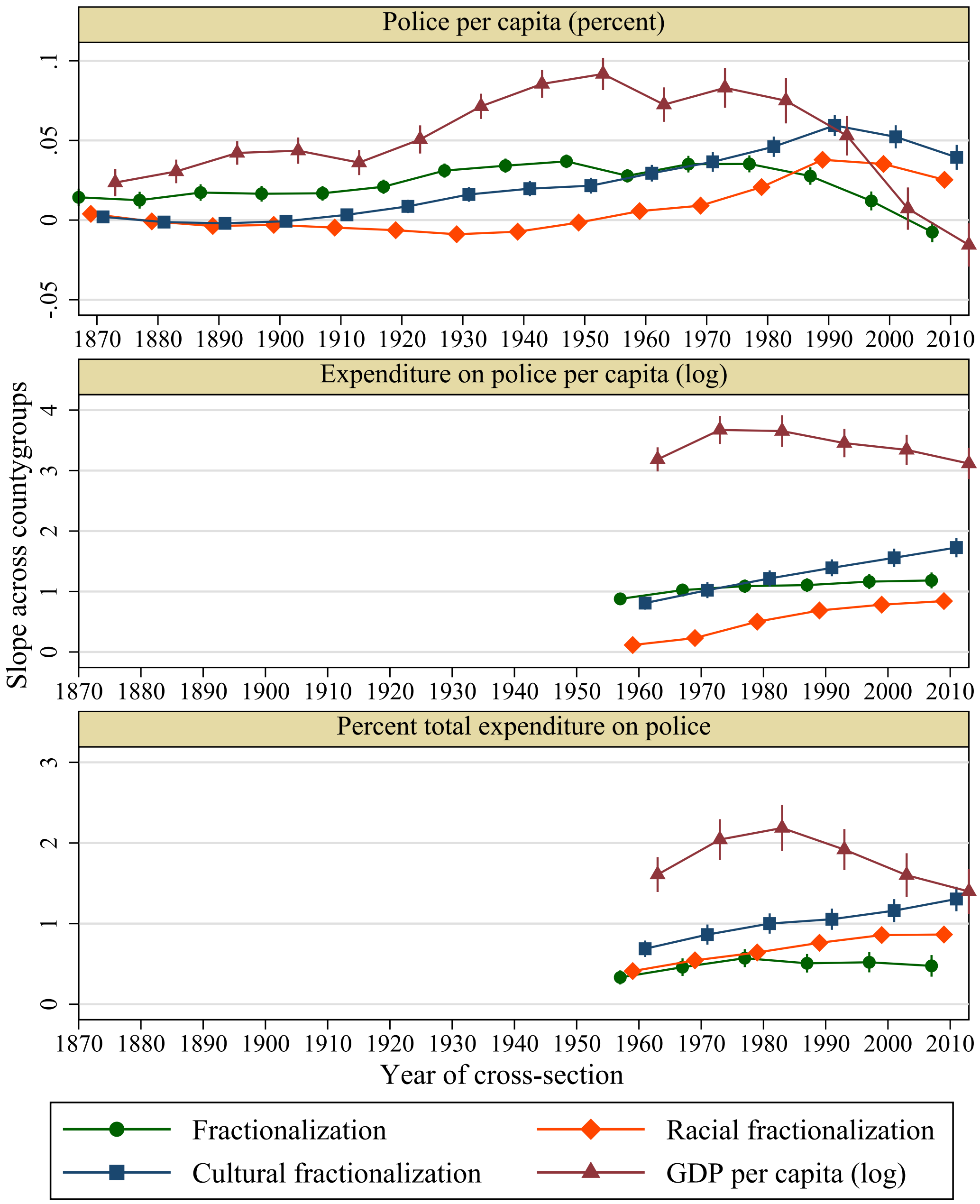
Notes: Best fit line from an unweighted linear regression. Source: Authors' calculations.

Figure 5: Education expenditure correlation across county groups by year



Notes: Shows the cross-sectional coefficient β_t in each year from the regression: Educ. per capita$_{i,t} = \theta_t I(\text{year}_t) + \beta_t \text{Fractionalization}_{i,t} \times I(\text{year}_t) + \varepsilon_{i,t}$. All fractionalization variables are normalized (z-score) by the standard deviation across all county groups and time periods.

Figure 6: Police expenditure correlation across county groups by year



Notes: Shows the cross-sectional coefficient β_t in each year from the regression: Police. per capita$_{i,t} = \theta_t I(\text{year}_t) + \beta_t \text{Fractionalization}_{i,t} \times I(\text{year}_t) + \varepsilon_{i,t}$. Bars show 95 percent confidence intervals. Fractionalization variables are normalized (z-score) by the standard deviation across all county groups and time periods.

Table 1: Fractionalization measures over time

	Fractionalization		Racial fractionalization		Culture (0.05%) fractionalization		Culture (0.2%) fractionalization		Origin GDP fractionalization	
Year	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
1870	0.608	0.110	0.168	0.186	0.095	0.067	0.093	0.065	0.117	0.069
1880	0.661	0.110	0.171	0.184	0.099	0.063	0.098	0.061	0.124	0.069
1890	0.644	0.113	0.164	0.183	0.100	0.063	0.100	0.061	0.120	0.066
1900	0.693	0.115	0.162	0.180	0.107	0.059	0.108	0.057	0.125	0.065
1910	0.717	0.121	0.167	0.182	0.115	0.054	0.118	0.053	0.128	0.059
1920	0.739	0.125	0.170	0.178	0.120	0.049	0.125	0.050	0.132	0.051
1930	0.749	0.125	0.178	0.173	0.120	0.045	0.129	0.047	0.130	0.046
1940	0.751	0.124	0.175	0.168	0.115	0.043	0.127	0.046	0.124	0.043
1950	0.738	0.130	0.176	0.164	0.105	0.041	0.119	0.046	0.114	0.042
1960	0.754	0.131	0.196	0.162	0.108	0.039	0.127	0.045	0.114	0.038
1970	0.782	0.106	0.199	0.156	0.105	0.032	0.126	0.039	0.114	0.032
1980	0.790	0.104	0.233	0.163	0.103	0.032	0.126	0.039	0.115	0.033
1990	0.800	0.101	0.264	0.168	0.101	0.030	0.127	0.038	0.118	0.034
2000	0.814	0.094	0.309	0.173	0.101	0.028	0.129	0.036	0.125	0.035
2010	0.826	0.088	0.345	0.173	0.101	0.026	0.131	0.034	0.128	0.035

Notes: Mean and standard deviation over county groups (unweighted). Culture fractionalization is the difference between the origin principal component of culture (Tabellini, 2010) and the U.S. principal component of culture at arrival depreciated at 0.5% or 0.2% per year. Origin GDP is the difference between arrival log GDP per person and U.S. log GDP per person depreciated at 0.5% per year. Source: Authors' calculations using ancestry data in Fulford, Petkov, and Schiantarelli (2020).

Table 2: Education employment and spending over time

	Percent teachers in population			Expenditure on education per capita (2015 $1,000)			Percent county expenditure on education		
Year	Mean	S.D.	National	Mean	S.D.	National	Mean	S.D.	National
1870	0.319	0.169	0.340						
1880	0.441	0.201	0.455						
1890	0.520	0.196	0.522						
1900	0.548	0.192	0.538						
1910	0.600	0.186	0.593						
1920	0.651	0.184	0.638						
1930	0.841	0.182	0.814						
1940	0.882	0.163	0.862						
1950	0.795	0.227	0.770						
1960	1.247	0.228	1.207	1.84	4.52	1.20	52.2	9.8	44.4
1970	1.837	0.272	1.815	3.11	7.65	2.08	53.3	9.9	45.4
1980	2.025	0.338	1.974	2.75	6.84	1.81	47.9	8.8	41.7
1990	2.161	0.343	2.114	3.70	9.26	2.39	47.9	9.2	40.7
2000	2.126	0.339	2.086	4.68	11.88	3.03	48.6	9.2	42.7
2010	2.236	0.377	2.199	4.69	12.01	2.87	44.6	9.7	39.0

Notes: Mean and standard deviation over county groups (unweighted). National is the population weighted mean. Source: Authors' calculations using Census of Governments and IPUMS.

Table 3: Police employment and spending over time

	Percent police in population			Expenditure on police per capita (2015 $1,000)			Percent county expenditure on police		
Year	Mean	S.D.	National	Mean	S.D.	National	Mean	S.D.	National
1870	0.040	0.042	0.047						
1880	0.049	0.038	0.056						
1890	0.048	0.039	0.060						
1900	0.054	0.038	0.066						
1910	0.044	0.038	0.062						
1920	0.049	0.041	0.067						
1930	0.085	0.056	0.110						
1940	0.111	0.058	0.133						
1950	0.131	0.094	0.155						
1960	0.150	0.069	0.174	0.187	0.555	0.138	3.66	1.33	5.11
1970	0.190	0.078	0.217	0.316	0.947	0.244	3.78	1.42	5.32
1980	0.251	0.093	0.267	0.360	1.028	0.261	4.64	1.55	6.01
1990	0.313	0.115	0.329	0.488	1.392	0.352	4.69	1.56	5.99
2000	0.334	0.118	0.346	0.587	1.579	0.418	4.91	1.65	5.90
2010	0.350	0.136	0.355	0.640	1.722	0.443	5.16	1.74	6.02

Notes: Mean and standard deviation over county groups (unweighted). National is the population weighted mean. Source: Authors' calculations using Census of Governments and IPUMS.

Table 4: Multiple diversity measures and education expenditures

Dependent variable:	Teachers per capita			Exp. educ. per capita (log)	Percent total exp. educ.
Period	1870-2010	1870-1940	1960-2010	1960-2010	1960-2010
	(1)	(2)	(3)	(4)	(5)
Fractionalization	0.0892***	0.00978	0.138***	0.0453***	-0.724
	(0.00958)	(0.00773)	(0.0201)	(0.0134)	(0.567)
Racial fractionalization	0.0360***	0.0386***	0.0314**	0.00522	2.342***
	(0.00980)	(0.0102)	(0.0138)	(0.0122)	(0.434)
Culture-weighted fractionalization (0.5%)	-0.0928***	-0.0516***	-0.127***	-0.0692***	-2.669***
	(0.00690)	(0.00577)	(0.0246)	(0.0173)	(0.695)
Fraction age 65 and older	-1.127***	3.119***	-1.424***	0.0585	-2.016
	(0.196)	(0.235)	(0.285)	(0.212)	(6.811)
Fraction 18 and younger	0.392***	0.746***	1.271***	1.368***	40.17***
	(0.108)	(0.0971)	(0.255)	(0.180)	(6.603)
log GDP per capita	0.110***	0.0667***	0.258***	0.305***	-2.483**
	(0.0135)	(0.00857)	(0.0460)	(0.0339)	(1.136)
Observations	16,709	8,710	6,854	6,346	6,346
R-squared	0.929	0.773	0.751	0.878	0.302
Year FE	Yes	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes	Yes
With Controls	Yes	Yes	Yes	Yes	Yes

Notes: Controls include: fraction age 65 and older, fraction 18 and younger, and log GDP per capita. Fractionalization variables are normalized (z-score) by the standard deviation across all county groups and time periods. Standard errors are clustered at the county group level.

Table 5: Multiple diversity measures and police expenditures

Dependent variable:	Police per capita			Exp. police. per capita (log)	Percent total exp. police
Period	1870-2010	1870-1940	1960-2010	1960-2010	1960-2010
	(1)	(2)	(3)	(4)	(5)
Fractionalization	0.0167***	-0.000365	0.00306	0.0501***	0.311***
	(0.00305)	(0.00157)	(0.00701)	(0.0176)	(0.0856)
Racial fractionalization	-0.0233***	-0.0169***	-0.0463***	-0.111***	-0.173***
	(0.00315)	(0.00252)	(0.00496)	(0.0128)	(0.0604)
Culture-weighted fractionalization (0.5%)	0.00628**	0.0171***	-0.00769	0.0439*	-0.149
	(0.00283)	(0.00166)	(0.00857)	(0.0233)	(0.103)
Years education	0.0156***	0.00771***	0.0341***	0.0624***	-0.181**
	(0.00186)	(0.00113)	(0.00586)	(0.0154)	(0.0794)
Fraction literate	0.0516***	-0.0220***			
	(0.0120)	(0.00675)			
Fraction age 65 and older	-0.0734	-0.624***	-0.150	-1.116***	-4.555***
	(0.0620)	(0.0511)	(0.0949)	(0.242)	(1.132)
Fraction 18 and younger	-0.0444	-0.160***	-0.0277	-0.00508	-4.036***
	(0.0295)	(0.0220)	(0.0909)	(0.211)	(0.990)
log GDP per capita	0.0178***	0.00742***	0.0229	0.553***	0.878***
	(0.00383)	(0.00173)	(0.0186)	(0.0452)	(0.207)
Observations	16,709	8,710	6,854	6,346	6,346
R-squared	0.768	0.623	0.576	0.911	0.365
Year FE	Yes	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes	Yes
With Controls	Yes	Yes	Yes	Yes	Yes

Notes: Controls include: Years education (1940 and after), fraction literate (before 1940), fraction age 65 and older, fraction 18 and younger, and log GDP per capita. Fractionalization variables are normalized (z-score) by the standard deviation across all county groups and time periods. Standard errors are clustered at the county group level.

Table 6: Instrumented diversity measures and education expenditures

Dependent variable:	Teachers per capita			Exp. educ. per capita (log)	Percent total exp. educ.
Period	1870-2010	1870-1940	1960-2010	1960-2010	1960-2010
	(1)	(2)	(3)	(4)	(5)
Fractionalization	0.122***	0.0230*	0.218***	0.0242	-2.753***
	(0.0133)	(0.0125)	(0.0325)	(0.0236)	(0.854)
Racial fractionalization	0.0419***	0.0595***	0.0293*	0.0421***	3.474***
	(0.0110)	(0.0191)	(0.0175)	(0.0153)	(0.513)
Culture-weighted fractionalization (0.5%)	-0.0975***	-0.0588***	-0.152***	-0.0769***	-3.266***
	(0.00834)	(0.00886)	(0.0335)	(0.0259)	(0.945)
Weak Id. F-statistic	144.4	50.43	260.2	236.3	236.3
Observations	16,543	8,542	6,853	6,345	6,345
Year FE	Yes	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes	Yes
With Controls	Yes	Yes	Yes	Yes	Yes

Notes: Controls include: fraction age 65 and older, fraction 18 and younger, and log GDP per capita. Fractionalization variables are normalized (z-score) by the standard deviation across all county groups and time periods. Standard errors are clustered at the county group level. The Weak Id. reports the Kleibergen and Paap (2006) weak identification Wald rk F-statistic as implemented in Schaffer (2005).

Table 7: Instrumented diversity measures and police expenditures

Dependent variable:	Police per capita			Exp. police per capita (log)	Percent total exp. police
Period	1870-2010	1870-1940	1960-2010	1960-2010	1960-2010
	(1)	(2)	(3)	(4)	(5)
Fractionalization	0.0244***	-0.00177	0.0279***	0.161***	0.894***
	(0.00389)	(0.00250)	(0.0108)	(0.0276)	(0.137)
Racial fractionalization	-0.0253***	-0.0209***	-0.0518***	-0.103***	-0.182**
	(0.00360)	(0.00391)	(0.00633)	(0.0162)	(0.0817)
Culture-weighted fractionalization (0.5%)	0.00415	0.0209***	-0.0438***	0.00141	-0.625***
	(0.00339)	(0.00214)	(0.0123)	(0.0346)	(0.156)
Weak Id. F-statistic	146.3	52.10	262.6	236.4	236.4
Observations	16,543	8,542	6,853	6,345	6,345
Year FE	Yes	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes	Yes
With Controls	Yes	Yes	Yes	Yes	Yes

Notes: Controls include: Years education (1940 and after), fraction literate (before 1940), fraction age 65 and older, fraction 18 and younger, and log GDP per capita. Fractionalization variables are normalized (z-score) by the standard deviation across all county groups and time periods. Standard errors are clustered at the county group level. The Weak Id. reports the Kleibergen and Paap (2006) weak identification Wald rk F-statistic as implemented in Schaffer (2005).

Appendix For Online Publication

Table A-1: Correlations among diversity measures

Overall correlation

	Fract.	Racial fract.	Culture fract. (0.5%)	Culture fract. (0.2%)	Origin GDP fract. (0.5%)	Fraction Black
Fractionalization	1.000					
Racial fractionalization	-0.052	1.000				
Culture fract. (0.5%)	0.119	0.699	1.000			
Culture fract. (0.2%)	0.237	0.746	0.970	1.000		
Origin GDP fract. (0.5%)	0.001	0.819	0.937	0.898	1.000	
Fraction Black	-0.334	0.754	0.748	0.722	0.819	1.000

Residual correlation

	Fract.	Racial fract.	Culture fract. (0.5%)	Culture fract. (0.2%)	Origin GDP fract. (0.5%)	Fraction Black
Fractionalization	1.000					
Racial fractionalization	0.133	1.000				
Culture fract. (0.5%)	0.445	0.591	1.000			
Culture fract. (0.2%)	0.472	0.631	0.986	1.000		
Origin GDP fract. (0.5%)	0.381	0.721	0.924	0.896	1.000	
Fraction Black	-0.044	0.251	0.243	0.241	0.257	1.000

Notes: This table shows the correlation across diversity measures. The first panel shows the overall correlation across county groups and time. The second shows the residual correlation after removing countygroup fixed effects and year effects. Source: Authors' calculations.

Table A-2: Multiple diversity measures, education and police expenditures, and inequality

Dependent variable:	Teachers per capita	Exp. educ. per capita (log)	Percent total exp. educ.	Police per capita	Exp. police. per capita (log)	Percent total exp. police
Period	1960-2010	1960-2010	1960-2010	1960-2010	1960-2010	1960-2010
	(1)	(2)	(3)	(4)	(5)	(6)
Fractionalization	0.140***	0.0479***	-0.674	0.000537	0.0489***	0.298***
	(0.0201)	(0.0134)	(0.567)	(0.00694)	(0.0174)	(0.0858)
Racial fractionalization	0.0285**	1.16e-05	2.242***	-0.0423***	-0.109***	-0.152**
	(0.0139)	(0.0124)	(0.438)	(0.00488)	(0.0130)	(0.0604)
Culture-weighted	-0.125***	-0.0660***	-2.607***	-0.0101	0.0429*	-0.160
fractionalization (0.5%)	(0.0246)	(0.0171)	(0.693)	(0.00843)	(0.0234)	(0.103)
Mean inc./Median inc.	0.124**	0.223**	4.265**	-0.174***	-0.0833	-0.908***
	(0.0617)	(0.0945)	(2.005)	(0.0271)	(0.0841)	(0.272)
Fraction age 65 and older	-1.489***	-0.0619	-4.314	-0.0573	-1.071***	-4.060***
	(0.288)	(0.219)	(6.885)	(0.0948)	(0.247)	(1.128)
Fraction 18 and younger	1.272***	1.374***	40.28***	-0.0284	-0.00632	-4.049***
	(0.254)	(0.179)	(6.600)	(0.0898)	(0.211)	(0.985)
log GDP per capita	0.267***	0.324***	-2.123*	0.00842	0.545***	0.793***
	(0.0460)	(0.0329)	(1.150)	(0.0181)	(0.0446)	(0.205)
Years education				0.0348***	0.0630***	-0.175**
				(0.00576)	(0.0153)	(0.0788)
Observations	6,853	6,346	6,346	6,853	6,346	6,346
R-squared	0.751	0.879	0.303	0.582	0.911	0.366
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes	Yes	Yes
With Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Controls include: fraction age 65 and older, fraction 18 and younger, and log GDP per capita for both education and police, and average years of education for police. Inequality is measured as the ratio between the mean and median family income. Fractionalization variables are normalized (z-score) by the standard deviation across all county groups and time periods. Standard errors are clustered at the county group level.

Table A-3: Multiple diversity measures and education expenditures, metro counties only

Dependent variable:	Teachers per capita			Exp. educ. per capita (log)	Percent total exp. educ.
Period	1870-2010	1870-1940	1960-2010	1960-2010	1960-2010
	(1)	(2)	(3)	(4)	(5)
Fractionalization	0.0927***	-0.000541	0.143***	0.0265	0.134
	(0.0163)	(0.0124)	(0.0329)	(0.0226)	(1.201)
Racial fractionalization	-0.0307**	0.0173	-0.0370**	-0.00808	3.153***
	(0.0133)	(0.0154)	(0.0187)	(0.0167)	(0.586)
Culture-weighted	-0.0514***	-0.0184**	-0.127***	-0.0921***	-6.378***
fractionalization (0.5%)	(0.0102)	(0.00903)	(0.0340)	(0.0270)	(1.122)
Fraction age 65 and older	-0.661**	2.349***	0.407	1.676***	20.75
	(0.320)	(0.359)	(0.395)	(0.278)	(13.64)
Fraction 18 and younger	0.441**	0.378**	2.232***	2.617***	44.74***
	(0.175)	(0.159)	(0.401)	(0.303)	(12.02)
log GDP per capita	0.144***	0.0542***	0.567***	0.283***	-3.636*
	(0.0307)	(0.0137)	(0.0641)	(0.0491)	(1.916)
Observations	7,459	3,912	3,038	2,560	2,560
R-squared	0.941	0.766	0.823	0.892	0.261
Year FE	Yes	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes	Yes
With Controls	Yes	Yes	Yes	Yes	Yes

Notes: Controls include: fraction age 65 and older, fraction 18 and younger, and log GDP per capita. Metro counties are counties that include an MSA using the 2010 metropolitan statistical area definition. Fractionalization variables are normalized (z-score) by the standard deviation across all county groups and time periods. Standard errors are clustered at the countygroup level.

Table A-4: Multiple diversity measures and education expenditures, with education controls

Dependent variable:	Teachers per capita			Exp. educ. per capita (log)	Percent total exp. educ.
Period	1870-2010	1870-1940	1960-2010	1960-2010	1960-2010
	(1)	(2)	(3)	(4)	(5)
Fractionalization	0.0551***	-0.00352	0.0498**	-0.00817	-1.319**
	(0.00938)	(0.00717)	(0.0195)	(0.0138)	(0.568)
Racial fractionalization	0.0216**	0.0190*	0.0578***	0.0208*	2.515***
	(0.00947)	(0.0103)	(0.0139)	(0.0118)	(0.429)
Culture-weighted fractionalization (0.5%)	-0.0412***	-0.0120*	-0.0240	-0.0117	-2.029***
	(0.00824)	(0.00673)	(0.0248)	(0.0176)	(0.708)
Years education	0.0645***	-0.0445***	0.265***	0.152***	1.695***
	(0.00681)	(0.00546)	(0.0171)	(0.0134)	(0.480)
Fraction literate	0.609***	0.270***			
	(0.0436)	(0.0346)			
Fraction age 65 and older	-0.737***	4.000***	-1.160***	0.199	-0.453
	(0.197)	(0.241)	(0.269)	(0.196)	(6.853)
Fraction 18 and younger	0.262**	0.703***	1.689***	1.614***	42.91***
	(0.107)	(0.0965)	(0.245)	(0.174)	(6.678)
log GDP per capita	0.0910***	0.0658***	-0.0834*	0.104***	-4.721***
	(0.0133)	(0.00853)	(0.0473)	(0.0359)	(1.264)
Observations	16,709	8,710	6,854	6,346	6,346
R-squared	0.932	0.786	0.767	0.885	0.305
Year FE	Yes	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes	Yes
With Controls	Yes	Yes	Yes	Yes	Yes

Notes: Controls include: Years education (1940 and after), fraction literate (before 1940), fraction age 65 and older, fraction 18 and younger, and log GDP per capita. Metro counties are counties that include an MSA using the 2010 metropolitan statistical area definition. Fractionalization variables are normalized (z-score) by the standard deviation across all county groups and time periods. Standard errors are clustered at the county group level.

Table A-5: Multiple diversity measures and education expenditures, with fraction Black

Dependent variable:	Teachers per capita			Exp. educ. per capita (log)	Percent total exp. educ.
Period	1870-2010	1870-1940	1960-2010	1960-2010	1960-2010
	(1)	(2)	(3)	(4)	(5)
Fractionalization	0.0792***	0.00170	0.185***	0.0946***	0.0978
	(0.0117)	(0.00906)	(0.0212)	(0.0141)	(0.626)
Racial fractionalization	0.0427***	0.0431***	-0.0150	-0.0465***	1.478***
	(0.0108)	(0.0104)	(0.0156)	(0.0131)	(0.478)
Culture-weighted fractionalization (0.5%)	-0.0839***	-0.0415***	-0.172***	-0.123***	-3.568***
	(0.00925)	(0.00769)	(0.0256)	(0.0187)	(0.733)
Fraction Black	-0.133	-0.183**	0.999***	1.128***	18.82***
	(0.0847)	(0.0759)	(0.165)	(0.151)	(4.498)
Fraction age 65 and older	-1.095***	3.264***	-1.427***	0.0497	-2.163
	(0.199)	(0.245)	(0.281)	(0.207)	(6.841)
Fraction 18 and younger	0.392***	0.747***	1.359***	1.479***	42.02***
	(0.108)	(0.0969)	(0.254)	(0.177)	(6.629)
log GDP per capita	0.109***	0.0683***	0.316***	0.366***	-1.465
	(0.0133)	(0.00863)	(0.0472)	(0.0351)	(1.143)
Observations	16,709	8,710	6,854	6,346	6,346
R-squared	0.929	0.774	0.753	0.882	0.307
Year FE	Yes	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes	Yes
With Controls	Yes	Yes	Yes	Yes	Yes

Notes: Controls include: fraction age 65 and older, fraction 18 and younger, and log GDP per capita. Fractionalization variables are normalized (z-score) by the standard deviation across all county groups and time periods. Standard errors are clustered at the countygroup level.

Table A-6: Multiple diversity measures and education expenditures, in South and rest of country

Dependent variable:	Teachers per capita			Exp. educ. per capita (log)	Percent total exp. educ.
Period	1870-2010	1870-1940	1960-2010	1960-2010	1960-2010
	(1)	(2)	(3)	(4)	(5)
Outside south:					
Fractionalization	0.0961***	-0.0180*	0.241***	0.0283	3.734***
	(0.0142)	(0.0109)	(0.0341)	(0.0273)	(0.968)
Racial fractionalization	0.0383***	0.0289**	0.0518***	0.0245*	2.990***
	(0.0119)	(0.0131)	(0.0164)	(0.0143)	(0.499)
Culture-weighted	-0.0892***	-0.00648	-0.191***	-0.0542**	-6.123***
fractionalization (0.5%)	(0.0132)	(0.0115)	(0.0317)	(0.0239)	(0.907)
In South:					
Fractionalization	0.0156	-0.0313***	0.00416	-0.0451**	-1.081
	(0.0142)	(0.0101)	(0.0282)	(0.0192)	(0.852)
Racial fractionalization	0.0529***	0.0107	0.00296	-0.0541**	-0.591
	(0.0194)	(0.0186)	(0.0281)	(0.0221)	(0.885)
Culture-weighted	-0.0186	0.0289**	0.0209	0.0716**	0.166
fractionalization (0.5%)	(0.0168)	(0.0135)	(0.0425)	(0.0285)	(1.390)
Observations	16,709	8,710	6,854	6,346	6,346
R-squared	0.933	0.790	0.759	0.884	0.321
Year FE	Yes	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes	Yes
With Controls	Yes	Yes	Yes	Yes	Yes

Notes: Controls include: fraction age 65 and older, fraction 18 and younger, and log GDP per capita. Fractionalization variables are normalized (z-score) by the standard deviation across all county groups and time periods. Standard errors are clustered at the countygroup level. We interact the South dummy with all controls and year effects, allowing the effects to be different in the South and Not South.

Table A-7: Multiple diversity measures and education expenditures, with lower depreciation of culture

Dependent variable:	Teachers per capita			Exp. educ. per capita (log)	Percent total exp. educ.
Period	1870-2010	1870-1940	1960-2010	1960-2010	1960-2010
	(1)	(2)	(3)	(4)	(5)
Fractionalization	0.0844***	0.00860	0.103***	0.0124	-1.149**
	(0.00996)	(0.00814)	(0.0197)	(0.0138)	(0.561)
Racial fractionalization	0.0334***	0.0371***	0.0151	-0.0144	2.105***
	(0.0102)	(0.0105)	(0.0139)	(0.0123)	(0.445)
Culture-weighted fractionalization (0.2%)	-0.0885***	-0.0534***	-0.0488**	0.00274	-1.650**
	(0.00828)	(0.00685)	(0.0231)	(0.0170)	(0.652)
Fraction age 65 and older	-1.169***	3.022***	-1.336***	0.121	-0.778
	(0.195)	(0.237)	(0.285)	(0.210)	(6.825)
Fraction 18 and younger	0.342***	0.729***	1.341***	1.435***	40.49***
	(0.109)	(0.0978)	(0.257)	(0.181)	(6.629)
log GDP per capita	0.114***	0.0667***	0.296***	0.339***	-2.026*
	(0.0136)	(0.00856)	(0.0461)	(0.0346)	(1.147)
Observations	16,709	8,710	6,854	6,346	6,346
R-squared	0.929	0.772	0.749	0.878	0.300
Year FE	Yes	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes	Yes
With Controls	Yes	Yes	Yes	Yes	Yes

Notes: Controls include: fraction age 65 and older, fraction 18 and younger, and log GDP per capita. Fractionalization variables are normalized (z-score) by the standard deviation across all county groups and time periods. Standard errors are clustered at the county group level.

Table A-8: Multiple diversity measures and education expenditures, with Origin GDP fractionalization

Dependent variable:	Teachers per capita			Exp. educ. per capita (log)	Percent total exp. educ.
Period	1870-2010	1870-1940	1960-2010	1960-2010	1960-2010
	(1)	(2)	(3)	(4)	(5)
Fractionalization	0.0837***	0.00419	0.126***	0.0880***	-0.836
	(0.00932)	(0.00720)	(0.0186)	(0.0120)	(0.524)
Racial fractionalization	0.0689***	0.0529***	0.103***	0.149***	4.046***
	(0.0114)	(0.0118)	(0.0207)	(0.0175)	(0.563)
Origin GDP fractionalization (0.5%)	-0.115***	-0.0615***	-0.146***	-0.232***	-3.448***
	(0.00868)	(0.00749)	(0.0245)	(0.0184)	(0.670)
Fraction age 65 and older	-1.110***	3.328***	-1.451***	-0.0959	-2.876
	(0.197)	(0.234)	(0.284)	(0.206)	(6.709)
Fraction 18 and younger	0.398***	0.736***	1.319***	1.316***	40.88***
	(0.109)	(0.0974)	(0.253)	(0.173)	(6.629)
log GDP per capita	0.114***	0.0708***	0.296***	0.290***	-1.956*
	(0.0136)	(0.00869)	(0.0447)	(0.0309)	(1.116)
Observations	16,709	8,710	6,854	6,346	6,346
R-squared	0.929	0.772	0.751	0.885	0.305
Year FE	Yes	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes	Yes
With Controls	Yes	Yes	Yes	Yes	Yes

Notes: Controls include: fraction age 65 and older, fraction 18 and younger, and log GDP per capita. Fractionalization variables are normalized (z-score) by the standard deviation across all county groups and time periods. Standard errors are clustered at the county group level.

Table A-9: Multiple diversity measures and police expenditures, metro counties only

Dependent variable:	Police per capita			Exp. police. per capita (log)	Percent total exp. police
Period	1870-2010	1870-1940	1960-2010	1960-2010	1960-2010
	(1)	(2)	(3)	(4)	(5)
Fractionalization	0.00686*	0.00338	-0.0271**	-0.00502	0.0527
	(0.00405)	(0.00274)	(0.0118)	(0.0253)	(0.189)
Racial fractionalization	-0.0149***	-0.0230***	-0.0498***	-0.109***	-0.169*
	(0.00431)	(0.00509)	(0.00681)	(0.0163)	(0.0942)
Culture-weighted fractionalization (0.5%)	0.0161***	0.0191***	0.0220*	0.142***	0.222
	(0.00381)	(0.00269)	(0.0133)	(0.0366)	(0.206)
Years education	0.0135***	0.0100***	0.0221**	0.0189	-0.337**
	(0.00392)	(0.00263)	(0.00948)	(0.0233)	(0.152)
Fraction literate	0.0326	-0.0195			
	(0.0222)	(0.0128)			
Fraction age 65 and older	-0.414***	-0.742***	0.125	-1.389***	-10.53***
	(0.0987)	(0.0977)	(0.186)	(0.363)	(2.368)
Fraction 18 and younger	-0.180***	-0.208***	0.153	-0.503	-10.02***
	(0.0516)	(0.0381)	(0.166)	(0.356)	(1.959)
log GDP per capita	0.0159**	0.00801**	0.0687*	0.453***	0.945**
	(0.00790)	(0.00324)	(0.0364)	(0.0792)	(0.412)
Observations	7,459	3,912	3,038	2,560	2,560
R-squared	0.744	0.690	0.530	0.910	0.280
Year FE	Yes	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes	Yes
With Controls	Yes	Yes	Yes	Yes	Yes

Notes: Controls include: Years education (1940 and after), fraction literate (before 1940), fraction age 65 and older, fraction 18 and younger, and log GDP per capita. Metro counties are counties that include an MSA using the 2010 metropolitan statistical area definition. Fractionalization variables are normalized (z-score) by the standard deviation across all county groups and time periods. Standard errors are clustered at the countygroup level.

Table A-10: Multiple diversity measures and police expenditures, with crime control

Dependent variable:	Police per capita	Exp. police. per capita (log)	Percent total exp. police
Period	1960-2010	1960-2010	1960-2010
	(1)	(2)	(3)
Fractionalization	0.00208	0.0476***	0.303***
	(0.00709)	(0.0175)	(0.0852)
Racial fractionalization	-0.0465***	-0.108***	-0.167***
	(0.00505)	(0.0128)	(0.0606)
Culture-weighted	-0.00547	0.0435*	-0.150
fractionalization (0.5%)	(0.00866)	(0.0233)	(0.103)
Years education	0.0351***	0.0592***	-0.190**
	(0.00593)	(0.0155)	(0.0798)
Fraction age 65 and older	-0.120	-0.982***	-4.151***
	(0.0958)	(0.236)	(1.129)
Fraction 18 and younger	-0.0201	0.122	-3.653***
	(0.0911)	(0.209)	(0.993)
log GDP per capita	0.0220	0.572***	0.934***
	(0.0187)	(0.0457)	(0.208)
Crimes per 100,000 (log+10)	0.00133	0.0225***	0.0674***
	(0.00191)	(0.00560)	(0.0205)
Observations	6,790	6,346	6,346
R-squared	0.578	0.912	0.369
Year FE	Yes	Yes	Yes
County group FE	Yes	Yes	Yes
With Controls	Yes	Yes	Yes

Notes: Controls include: Years education (1940 and after), fraction literate (before 1940), fraction age 65 and older, fraction 18 and younger, and log GDP per capita. Fractionalization variables are normalized (z-score) by the standard deviation across all county groups and time periods. Standard errors are clustered at the county group level.

Table A-11: Multiple diversity measures and police expenditures, with fraction Black

Dependent variable:		Police per capita		Exp. police. per capita (log)	Percent total exp. police
Period	1870-2010	1870-1940	1960-2010	1960-2010	1960-2010
	(1)	(2)	(3)	(4)	(5)
Fractionalization	0.0145***	-0.000748	0.00998	0.0555***	0.252**
	(0.00394)	(0.00168)	(0.00748)	(0.0194)	(0.0977)
Racial fractionalization	-0.0216***	-0.0166***	-0.0523***	-0.115***	-0.120*
	(0.00364)	(0.00240)	(0.00549)	(0.0144)	(0.0712)
Culture-weighted fractionalization (0.5%)	0.00800**	0.0176***	-0.0146	0.0380	-0.0848
	(0.00372)	(0.00181)	(0.00906)	(0.0244)	(0.110)
Fraction Black	-0.0312	-0.00944	0.121*	0.0993	-1.095
	(0.0339)	(0.0170)	(0.0673)	(0.166)	(0.888)
Years education	0.0136***	0.00796***	0.0307***	0.0574***	-0.128
	(0.00180)	(0.00111)	(0.00632)	(0.0163)	(0.0813)
Fraction literate	0.0478***	-0.0228***			
	(0.0118)	(0.00700)			
Fraction age 65 and older	-0.0674	-0.619***	-0.154	-1.120***	-4.517***
	(0.0638)	(0.0492)	(0.0945)	(0.241)	(1.129)
Fraction 18 and younger	-0.0445	-0.160***	-0.0229	-9.21e-06	-4.092***
	(0.0295)	(0.0219)	(0.0902)	(0.212)	(0.990)
log GDP per capita	0.0178***	0.00752***	0.0348*	0.562***	0.776***
	(0.00382)	(0.00173)	(0.0205)	(0.0477)	(0.215)
Observations	16,709	8,710	6,854	6,346	6,346
R-squared	0.768	0.623	0.576	0.911	0.365
Year FE	Yes	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes	Yes
With Controls	Yes	Yes	Yes	Yes	Yes

Notes: Controls include: Years education (1940 and after), fraction literate (before 1940), fraction age 65 and older, fraction 18 and younger, and log GDP per capita. Fractionalization variables are normalized (z-score) by the standard deviation across all county groups and time periods. Standard errors are clustered at the county group level.

Table A-12: Multiple diversity measures and police expenditures, in South and rest of country

Dependent variable:	Police per capita			Exp. police. per capita (log)	Percent total exp. police
Period	1870-2010	1870-1940	1960-2010	1960-2010	1960-2010
	(1)	(2)	(3)	(4)	(5)
Outside south:					
Fractionalization	0.00665*	-0.00221	0.00570	-0.0336	0.336**
	(0.00342)	(0.00170)	(0.0108)	(0.0301)	(0.139)
Racial fractionalization	-0.0125***	-0.00752**	-0.0412***	-0.100***	-0.0533
	(0.00355)	(0.00316)	(0.00543)	(0.0139)	(0.0652)
Culture-weighted fractionalization (0.5%)	0.0143***	0.0157***	0.00272	0.129***	-0.0426
	(0.00334)	(0.00219)	(0.0104)	(0.0285)	(0.128)
In South:					
Fractionalization	0.0201***	0.00666**	-0.0148	-0.0244	0.191
	(0.00605)	(0.00311)	(0.0117)	(0.0265)	(0.126)
Racial fractionalization	-0.0355***	-0.0255***	-0.0364***	-0.0569*	-0.108
	(0.00775)	(0.00450)	(0.0106)	(0.0293)	(0.164)
Culture-weighted fractionalization (0.5%)	-0.00396	0.00755***	-0.0142	0.0468	-0.277
	(0.00691)	(0.00269)	(0.0172)	(0.0430)	(0.214)
Observations	16,709	8,710	6,854	6,346	6,346
R-squared	0.774	0.640	0.583	0.916	0.379
Year FE	Yes	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes	Yes
With Controls	Yes	Yes	Yes	Yes	Yes

Notes: Controls include: Years education (1940 and after), fraction literate (before 1940), fraction age 65 and older, fraction 18 and younger, and log GDP per capita. Fractionalization variables are normalized (z-score) by the standard deviation across all county groups and time periods. Standard errors are clustered at the county group level. We interact the South dummy with all controls and year effects, allowing the effects to be different in the South and Not South.

Table A-13: Individual diversity measures and education expenditures

Dependent variable:	Teachers per capita			Exp. educ. per capita (log)	Percent total exp. educ.
Period	1870-2010	1870-1940	1960-2010	1960-2010	1960-2010
	(1)	(2)	(3)	(4)	(5)
Fractionalization	0.0260***	-0.0309***	0.0796***	0.0117	-1.699***
	(0.00771)	(0.00549)	(0.0162)	(0.0111)	(0.489)
Racial fractionalization	-0.0157*	-0.0142	0.0112	-0.0121	1.402***
	(0.00800)	(0.00872)	(0.0130)	(0.0110)	(0.406)
Culture-weighted fractionalization	-0.0481***	-0.0379***	-0.0149	-0.0350***	-1.760***
	(0.00447)	(0.00353)	(0.0197)	(0.0135)	(0.550)
Observations	16,709	8,710	6,854	6,346	6,346
Year FE	Yes	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes	Yes
With Controls	Yes	Yes	Yes	Yes	Yes

Notes: Controls include: fraction age 65 and older, fraction 18 and younger, and log GDP per capita. Fractionalization variables are normalized (z-score) by the standard deviation across all county groups and time periods. Standard errors are clustered at the county group level.

Table A-14: Individual diversity measures and police expenditures

Dependent variable:	Police per capita			Exp. police. per capita (log)	Percent total exp. police
Period	1870-2010	1870-1940	1960-2010	1960-2010	1960-2010
	(1)	(2)	(3)	(4)	(5)
Fractionalization	0.0172***	0.00932***	-0.00920	0.0522***	0.198***
	(0.00220)	(0.00113)	(0.00564)	(0.0136)	(0.0650)
Racial fractionalization	-0.0175***	-0.000651	-0.0479***	-0.0897***	-0.174***
	(0.00281)	(0.00233)	(0.00478)	(0.0125)	(0.0580)
Culture-weighted fractionalization	0.00291	0.0120***	-0.0287***	0.0182	-0.0182
	(0.00204)	(0.00119)	(0.00672)	(0.0173)	(0.0748)
Observations	16,709	8,710	6,790	6,346	6,346
Year FE	Yes	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes	Yes
With Controls	Yes	Yes	Yes	Yes	Yes

Notes: Controls include: fraction age 65 and older, fraction 18 and younger, and log GDP per capita. Fractionalization variables are normalized (z-score) by the standard deviation across all county groups and time periods. Standard errors are clustered at the countygroup level.

Table A-15: Instrumented diversity measures and education expenditures, with lag dependent variable

Dependent variable:	Teachers per capita			Exp. educ. per capita (log)	Percent total exp. educ.
Period	1870-2010	1870-1940	1960-2010	1960-2010	1960-2010
	(1)	(2)	(3)	(4)	(5)
Panel A: No instrument					
Fractionalization	0.0744***	0.00513	0.136***	-0.0101	-2.011***
	(0.00736)	(0.00697)	(0.0188)	(0.0155)	(0.631)
Racial fractionalization	0.0223***	0.0380***	0.0167	-0.0332***	3.019***
	(0.00629)	(0.00850)	(0.0123)	(0.0121)	(0.450)
Culture-weighted fractionalization (0.5%)	-0.0663***	-0.0436***	-0.123***	-0.00234	-2.717***
	(0.00519)	(0.00467)	(0.0230)	(0.0229)	(0.850)
Lag dependent variable	0.447***	0.435***	0.144***	0.209***	0.224***
	(0.0135)	(0.0189)	(0.0152)	(0.0185)	(0.0196)
Panel B: Shift-share instrument					
Fractionalization	0.0987***	0.00717	0.213***	-0.0996***	-4.401***
	(0.0102)	(0.0105)	(0.0302)	(0.0329)	(1.233)
Racial fractionalization	0.0234***	0.0670***	0.0132	0.00409	4.976***
	(0.00686)	(0.0142)	(0.0158)	(0.0152)	(0.571)
Culture-weighted fractionalization (0.5%)	-0.0674***	-0.0465***	-0.150***	0.0255	-5.320***
	(0.00609)	(0.00626)	(0.0308)	(0.0391)	(1.375)
Lag dependent variable	0.446***	0.447***	0.144***	0.234***	0.211***
	(0.0136)	(0.0181)	(0.0155)	(0.0200)	(0.0197)
Weak Id. F-statistic	741.8	132.6	260.4	49.88	47.61
Observations	15,549	7,545	6,853	5,288	5,288
Year FE	Yes	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes	Yes
With Controls	Yes	Yes	Yes	Yes	Yes

Notes: Controls include: fraction age 65 and older, fraction 18 and younger, and log GDP per capita. Fractionalization variables are normalized (z-score) by the standard deviation across all county groups and time periods. Standard errors are clustered at the county group level. The Weak Id. reports the Kleibergen and Paap (2006) weak identification Wald rk F-statistic as implemented in Schaffer (2005).

Table A-16: Instrumented diversity measures and police expenditures, with lag dependent variable

Dependent variable:	Police per capita			Exp. police per capita (log)	Percent total exp. police
Period	1870-2010	1870-1940	1960-2010	1960-2010	1960-2010
	(1)	(2)	(3)	(4)	(5)
Panel A: No instrument					
Fractionalization	0.00913***	-0.00125	-0.00174	0.0885***	0.518***
	(0.00255)	(0.00144)	(0.00656)	(0.0197)	(0.106)
Racial fractionalization	-0.0208***	-0.0126***	-0.0426***	-0.149***	-0.145**
	(0.00216)	(0.00223)	(0.00438)	(0.0145)	(0.0715)
Culture-weighted	0.00555***	0.0117***	-0.000902	0.0207	-0.365***
fractionalization (0.5%)	(0.00210)	(0.00131)	(0.00805)	(0.0289)	(0.133)
Lag dependent variable	0.470***	0.392***	0.176***	0.218***	0.189***
	(0.0256)	(0.0384)	(0.0221)	(0.0215)	(0.0217)
Panel B: Shift-share instrument					
Fractionalization	0.0137***	-0.00326	0.0185*	0.258***	1.493***
	(0.00317)	(0.00248)	(0.00980)	(0.0366)	(0.200)
Racial fractionalization	-0.0215***	-0.0160***	-0.0464***	-0.148***	-0.0556
	(0.00250)	(0.00328)	(0.00569)	(0.0187)	(0.103)
Culture-weighted	0.00412*	0.0166***	-0.0325***	-0.0324	-1.160***
fractionalization (0.5%)	(0.00248)	(0.00186)	(0.0115)	(0.0484)	(0.233)
Lag dependent variable	0.468***	0.385***	0.168***	0.199***	0.179***
	(0.0258)	(0.0383)	(0.0224)	(0.0216)	(0.0222)
Weak Id. F-statistic	668.5	132.9	267.5	48.63	49.22
Observations	15,549	7,545	6,853	5,288	5,288
Year FE	Yes	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes	Yes
With Controls	Yes	Yes	Yes	Yes	Yes

Notes: Controls include: Years education (1940 and after), fraction literate (before 1940), fraction age 65 and older, fraction 18 and younger, and log GDP per capita. Fractionalization variables are normalized (z-score) by the standard deviation across all county groups and time periods. Standard errors are clustered at the county group level. The Weak Id. reports the Kleibergen and Paap (2006) weak identification Wald rk F-statistic as implemented in Schaffer (2005).