Does It Matter Where You Came From? Ancestry Composition and Economic Performance of US Counties, 1850–2010

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Abstract

What impact do immigrants and their descendants have in the short and long term? We develop the first measures of the country-of-ancestry composition and GDP per worker for US counties from 1850 to 2010. We show that ancestry groups have different impacts on county productivity. Groups from countries with higher economic development, with cultural traits that favor cooperation, and with a long history of a centralized state have a greater positive impact on county GDP per worker. Ancestry diversity is positively related to county GDP per worker, while diversity in origin-country culture or economic development is negatively related.

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1 Introduction

What impact will immigrants and their descendants have in their new homes in the short and long term? The answer depends on the attributes they bring with them, what they pass on to their children, and how they interact with other groups. As the immigration debate intensifies, it is increasingly important to understand whether immigrants have a persistent impact on their new homes and how and why this impact differs across groups. When people move to a new place, they leave behind the complex interactions of institutions, culture, and geography that determine economic outcomes in their homeland. They bring with them their own human capital and their cultural values, norms, and knowledge and experience of institutions. These values and experiences help shape the way they interact with others, the values they teach their children, the institutions they form in their new home, and their incentives for investing in human and physical capital. Because immigrants pass on many traits to their children, the effects of immigration do not end in the first generation and they may become even more important as new groups change the society around them to reflect their own values.[1]

This paper uses the large and diverse migration to and within the United States over a century and a half to study the effect of the changing ancestry mix on local economic development. To perform our analysis, we build two unique new data sets. Using individual records from the US census going back to 1850, we construct the country-of-ancestry composition of the population of of each US county. Crucially, we produce an objective measure of the ancestry composition of the full population, not just of first-generation immigrants, and so we are able to capture the long-term impact of groups and their descendants as they come to the US and move within it.[2] Second, we create a measure of the GDP of each county going back to 1850 that includes agriculture, manufacturing, and services, and so we capture the change in the

[1]A substantial body of research has shown the persistence of traits between the first and second generation of immigrants (see, for instance, the reviews by Fernández (2010) and Bisin and Verdier (2011)). Beyond the second generation, the persistence varies across cultural attitudes and countries of origin, but even for faster moving traits, differences remain by the fourth generation (Giavazzi, Petkov, and Schiantarelli, 2014).

[2]Note that we do not rely on self-reported ethnicity—available only since 1980—which also reflects the evolving nature of ethnic identity as a social construct.

sectoral composition of output.

We address three central questions: Do ancestry groups have different effects on local development? If so, which characteristics brought from the country of origin explain why groups have different effects? As groups come together and interact, what is the impact of ancestry diversity? Importantly, we focus on whether the mix of ancestries matters, not the impact of increased total population from immigration or internal population growth. Our work shows unequivocally that groups have different economic impacts, these impacts are closely related to characteristics in the origin country, and that overall diversity has both positive and negative consequences, depending on the form of diversity.

It is always a challenge to separate the economic effects of people and what they bring with them from the economic effects of a place's characteristics. For example, if ancestry groups from high-income countries are attracted to high-income places, in a cross-section it would be easy to confuse the importance of the place with the importance of ancestry. Our long panel allows us to control for unobservable county characteristics and hence separate out the effects of the evolving ancestry composition from time invariant characteristics of a county. Doing so removes the endogeneity that arises if certain ancestry groups are attracted to places with particular characteristics. In addition, it is possible that ancestry groups with particular endowments are more willing to move in response to short-term county-specific economic shocks, creating a form of short-term reverse causality. We address this potential source of endogeneity by creating an instrument for each county's share of a given ancestry using the share in the past and growth in that ancestry nationally, excluding the county's state. Doing so removes any county-ancestry specific pull factors. The validity of the instrument relies on the past shares being uncorrelated with current shocks. We are thus careful to use it only in dynamic estimation models where we can test for—and reject—the presence of serial correlation in the error term.[3]

[3]Peri (2012) follows a similar approach by creating an instrument for first generation immigrants' effect on productivity at the state level. The immigration (Card, 2001) and local development (Bartik, 1991) literature have used the past distribution as an instrument, although frequently without addressing that the exclusion restriction for an instrument which uses past information requires it to be uncorrelated with the error term, so requires the absence of serial correlation. We also present dynamic panel GMM results (Holtz-Eakin, Newey, and Rosen, 1988; Arellano and Bond, 1991) that address the identification issue in a closely related way, as well as the potential issue of Nickell (1981) bias.

We first show that ancestry groups have different effects on county GDP per worker, even after after we control for county-specific fixed effects, race, and other observables. The effects of different groups are correlated with characteristics of the country of origin. As a summary measure of what groups could bring with them, we construct the average origin GDP per person in each county. When internal or external migration results in a county's residents coming from 1% higher GDP per person countries on average, county GDP per worker increases by 0.3% in the first decade and 0.6% in the long run. The impact grows over time, reaching its peak only after several decades. It seems that it takes time for new groups to have an effect when they move.

The relationship between origin GDP and county GDP shows that there must be be something important for economic development that is transportable and inheritable. We examine possible origin characteristics that might explain the relationship. What appears to matter most for local economic development are cultural characteristics that capture the ability of people to productively interact with others (Tabellini, 2010). Moreover, it also matters whether immigrants came from a country with a long history of a centralized state not subject to foreign domination (Putterman and Weil, 2010). Origin political institutions that may change rapidly and may not be deeply embedded in the immigrants beliefs or values, such as constraints on executive power or political participation, are not important for the impact of immigrants once we control for their experience of a strong state. Over the long-term, the human capital of migrants is not significantly associated with local economic development once other endowments are controlled for, perhaps because public schooling reduces educational differences and schooling policies respond endogenously to immigration flows (Bandiera et al., 2015).

Diversity has both positive and negative effects. Immigrants and their descendants must interact with other groups from different backgrounds, and the full impact of a migration depends on these interactions. When ancestry diversity increases, so does GDP per worker. Despite the often negative views that greet new groups, more diversity is actually good for growth. Yet when groups have important cultural differences that may affect their ability to interact with others, diversity has a negative effect on local economic development. The results suggest that when groups have to share a place and work together, diversity is good, as long as there is a degree of agreement in terms of cultural values that facilitate exchange and production. We provide evidence that the positive effect of ancestry diversity on development is partly explained by the fact that greater ancestry fractionalization is associated with a richer menu of locally available skills. More diverse places can have greater specialization and returns from trade.

The structure of the paper is as follows: after discussing the relationship with the literature in Section 2, we describe the evolution of ancestry and its construction in Section 3 and describe the construction of county level GDP in Section 4; Section 5 contains the main results, while Section 6 concludes.

2 Relationship with the literature

Our work focuses on the effect of the ancestry mix on local economic development in the short and long run and sits at the intersection of several different strands of research on immigration, the historical causes of development, and the effect of diversity on economic outcomes. Our focus on the long-run economic effects of immigrants *and* their descendants distinguishes our work from the many contributions that focus on the experience of first-generation immigrants and their short-run effect on the labor market.[4] In addressing the long term consequences of migration in the US, our work is complementary to the recent paper by Sequeira, Nunn, and Qian (2017), who analyze how immigration to the United States during the Age of Mass Migration affected the prosperity of counties in 2000. We differ fundamentally from their contribution, because we focus on the effect of changes in the *mix* of the ancestries rather than the effect of the total size of historical migratory flows. Our work is also related, albeit less closely, to Burchardi, Chaney, and Hassan (2016), who find that if a county has a larger stock of ancestry from a given country, it is more likely to have a foreign investment link with that country today. They focus on explaining bilateral investment links and do not assess the effect this has on county level development, which is the focus of our investigation.

We also contribute to the vast literature on the historical roots of economic de-

[4]The literature on the effect of immigration is vast; see Borjas (2014) for a review, as well as the work of Borjas (1994), Card (2001), Ottaviano and Peri (2012), and Peri (2012). See also Abramitzky and Boustan (2017), who put more recent work on immigration into its historical context and Hatton and Williamson (1998), who provide evidence from the Age of Mass Migration.

velopment.[5] Because the different factors for development evolve endogenously in a place, it is difficult to disentangle fundamental causes. To deal with this problem, an important subset of the literature focuses on the impact of immigrants. In particular, we build on Putterman and Weil (2010) who reconstruct the share of a country's ancestors in 2000 who migrated from each origin since 1500. They conclude that adjusting for migration flows greatly enhances the ability of historical variables, such as the experience of early development or early institutions, to explain differences in current economic performance. Another strand of this literature examines the impact of European colonists (Acemoglu, Johnson, and Robinson, 2001; Glaeser et al., 2004; Albouy, 2012; Easterly and Levine, 2016). The distinguishing feature in our work is the long panel which allows us to cleanly distinguish the effects of immigrants from those of the places they move. In addition, we analyze which attributes brought by immigrants affect economic performance in the long run, a difficult yet important task (Easterly and Levine, 2016). Our examination of inherited culture is related to that of Algan and Cahuc (2010), who use the trust of different cohorts and generation of migrants in the United States to instrument for the changing trust in the origin country and assess its effect on economic development.[6] A distinguishing feature of our contribution is that we use the change of ancestry over time in US counties to identify the effect on local development of attributes brought from the country of origin.

Finally, our finding that diversity has both positive and negative effects contributes to the growing literature that examines ethnic diversity. A substantial body of work suggests that various forms of ethnic diversity hinder economic performance by impeding the diffusion of new ideas or by harming investment in public goods.[7] Yet other work suggests diversity can have positive consequences.[8] Our results support

[5] The literature here is vast and cannot be adequately surveyed here. See the reviews by Acemoglu, Johnson, and Robinson (2005), Nunn (2009), Spolaore and Wacziarg (2013), and Alesina and Giuliano (2015).

[6] On the importance of culture for economic outcomes see Guiso, Sapienza, and Zingales (2006), Guiso, Zingales, and Sapienza (2008) Tabellini (2010), Fernández (2010), Alesina and Giuliano (2015), and Bisin and Verdier (2011).

[7] See Spolaore and Wacziarg (2009) on barriers to diffusion and Alesina, Baqir, and Easterly (1999), Miguel and Gugerty (2005), and Easterly and Levine (1997) on ethnicity and local public spending.

[8] Ashraf and Galor (2013) find that the relationship between genetic diversity and country-level economic development is nonlinear, first increasing, then decreasing, resulting in an interior optimum level of diversity. Putterman and Weil (2010) find that the standard deviation of state history generated by the

recent work that suggests group diversity by itself may be good because of the gains from trade and specialization associated with it, but there are negative consequences if groups differ along important dimensions such as culture (Desmet, Ortuño-Ortín, and Wacziarg, 2015) or income (Alesina, Michalopoulos, and Papaioannou, 2016). The advantage of our approach is that by using ancestry rather than ethnicity, which may be endogeneous (Michalopoulos, 2012), and a panel to examine changes in diversity, we can more cleanly separate out the positive and negative consequences of diversity. Moreover, we focus on the effects of changes in the stock of ancestries and not on those induced only by greater diversity of first-generation immigrants, as in Ager and Brückner (2013) and Ottaviano and Peri (2006).

3 Ancestry in the United States

In the United States, there have been immense changes in overall ancestry and its geographic distribution since 1850. In this section, we describe how we construct a measure of the geographic distribution of ancestry over time and briefly discuss its evolution. Our estimates are the first consistent estimates of the stock of ancestry over time for the United States at both the national and county level, because they start with the census micro-samples and keep track of internal migration and population growth, in addition to new immigrant flows. Finally, our measure of ancestry is distinct from self-reported ethnicity available in the census since 1980, which also reflects the evolving nature of ethnic identity as a social construct.

3.1 Constructing an ancestry measure

Our approach is to build an estimate of the ancestry share in each county using census questions that ask every person to identify the state or country where he or she was

post-1500 population flows is positively related to the income of countries today. Ager and Brückner (2013) show that fractionalization of first-generation immigrants across counties in the United States from 1870 to 1920 is positively related to economic growth, while polarization is negatively related. Alesina, Harnoss, and Rapoport (2013) present evidence of a positive relationship between birthplace diversity of immigrants and output, TFP per capita, and innovation. Ottaviano and Peri (2006) find increased first-generation immigrant diversity is good for wages across US cities between 1970 and 1990.

born. From 1880 to 1970 the census also asked for the place of birth of the person's parents. For someone whose parents were born in the United States, we assign that person the ancestry for the children under five in the parents' birth county or state in the closest census year to her birth. This method allows for some groups to have faster population growth than others past the second generation. If the parents come from two different countries, we assume that they contribute equally to the ancestry of their children. The ancestry share for each period therefore depends on the ancestry share in the past, since internal migrants bring their ancestry with them when they move from state to state and pass it on to their children. We proceed iteratively, starting with the first available individual census information in 1850 and using the first census in 1790 updated with immigration records as the initial distribution. Appendix A gives the full details.

Accumulating this information over time for a geographic area gives, in expectation, the fraction of the people in a given area whose ancestors come from a given country. We therefore do not just capture 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 the counties where people from different countries originally settled.

We can construct ancestry at the county level until 1940. Starting in 1950, the census reports data only for somewhat larger county groups, whose definition changes slightly over time. Because of this aggregation, our analysis centers on the 1154 county groups that allow us to maintain a consistent geographical unit of analysis from 1850 to 2010. We continue to use county to refer to county groups, except where the specific number of groups is important.

The county or county group is the smallest unit for which this sort of demographic accounting makes sense. The county is also a useful unit because it is the only consistent sub-state administrative district. While the exact powers held by counties vary somewhat by state, counties are generally judicial and police districts with the county sheriff as the top law enforcement official. Many infrastructure and transportation decisions are also made at the county level. In addition, all local decisions are made at the county level or within the county, because counties contain cities, towns, and education districts that decide even more local matters.[9] Therefore, if ancestry affects individual outcomes, local goods, or has externalities that relate to in-person interactions, the county will capture them.

Because the contributions of African Americans and the legacy of slavery are so central to understanding ancestry in the United States, our analysis gives a special treatment to race. The census has recorded racial characteristics since 1850, and we use it to form separate ancestries for African Americans and Native Americans. We allow for distinct ancestries within racial groups when the information is available, and so recent Nigerian immigrants or immigrants from the West Indies, for instance, are treated as distinct from African Americans who are descendants of former slaves. We emphasize that any finding we make regarding African Americans cannot distinguish African culture and institutions from the brutal history of slavery and the cultural, economic, and political repression that continued for more than a century following the Civil War.

While nativity was a central concern in the early censuses, other distinctions within country of origin, such as religion or regional origin, were not generally or consistently recorded. Therefore, we cannot distinguish sub-national groups, even though the distinctions between them may be very important. For example, many Russian immigrants were Jewish, but since we cannot distinguish these immigrants, all Russians are recorded as a single group. Similarly, the census does not identify the African origin countries of the slave population in 1850.

While ancestry, as we define it, is objective, ethnicity and race are to a large extent social constructs (Nagel, 1994). The concept of ethnicity is continually evolving as groups define themselves and are defined by other groups. Ethnicity not only changes over time, but it may not be the same concept across the country at a given time. The social construction of ethnicity does not make it any less powerful, but it is necessarily an endogenous and fluid measure that responds to circumstances. Ancestry appears to be the primary input in forming ethnicity (Waters, 1990), and so we would expect the two to be highly related. Indeed, our measure of ancestry predicts the self-reported

[9] For a description of the role of counties, see the National Association of Counties `http://www.naco.org/sites/default/files/documents/Counties-Matter.pdf`, accessed 1 August 2017.

ethnicity or ancestry in the 2000 census very well (see Appendix A.5).

3.2 Ancestry since 1850

American ancestry has become increasingly diverse over time, and we provide a brief description here of the overall trends in composition necessary to understand our results. Figure 1 illustrates this growing diversity by showing the share of each group that make up more than 0.5% of the population for 1870, 1920, 1970, and 2010. One important finding from our work is that the United States has not had a single majority group since 1870, when waves of German and then Irish immigration finally pushed the English below 50%.

Starting in the 1870s, successive waves of immigration rapidly transformed the ancestral makeup of the United States. Older ancestral groups were still expanding, but not nearly as fast as the newer groups, and so, in a relative sense, the older groups declined substantially in importance. The share of descendants from England fell continuously and rapidly until the 1920s. The new immigrants were diverse, with large groups from southern Europe (particularly Italy), eastern Europe (particularly Poland and Russia), northern and central Europe, including the Austrians and Germans, and from Scandinavian countries.

Immigration restrictions that started in the 1920s severely slowed immigration until the 1960s. These restrictions were only gradually relaxed, and so changes during this period mostly represent internal differences in population growth and demographic structure. Beginning in the 1960s, new groups from Mexico, Central America, and South America started to arrive. The share of Mexican descendants in Figure 1 grew substantially between 1970 and 2010. A large number of immigrants from Asia arrived as well. By 2010, the United States had become much more diverse in origin, with substantial populations from countries in Asia, Europe, Africa, and Central and South America. In 2010, descendants of immigrants from England represented just 25% of the population, followed by people of German (12.6%), African American (11.4%), Mexican (7.4%), Irish (6%), and Italian (3.8%) ancestry.

The maps in Figures 2 and 3 show where the largest groups settled and moved over the years. They indicate a tendency to spread out over time, although the geographical and time dimensions of the spreading differ by group. For example, the Germans arrived early, started in a few areas around Milwaukee, Pennsylvania, and Texas, and subsequently spread to the entire Midwest and West. The Irish, followed, and while initially concentrated in the cities of the Northeast, dispersed widely throughout the entire United States. Italians came later, initially settled mostly in New York and Boston, and eventually spread throughout the Northeast but not far beyond, except for a presence in California and around New Orleans. The Great Migration of African Americans from the South to the cities throughout the country can be clearly seen by comparing 1920 in Figure 2 to 1970 in Figure 3. Because the maps do not depict cities well, the importance of the Great Migration is less visually obvious. African Americans are still highly concentrated geographically and have not experienced the slow diffusion that characterizes the descendants of the Germans and Irish. Finally, the maps show the diffusion of people of Mexican ancestry from the border regions of the Southwest to other areas of the country. The heterogeneity in time and space in the way ancestries spread provides us with the main source of identification to assess the effect on local development of the mix of attributes brought by immigrants.

4 County GDP from 1850–2010

To understand the impact of ancestry on economic performance, we construct a county-level measure of GDP per worker. Starting in 1950, the census began measuring income at the county level. Before then, it recorded county-level information only on manufacturing and agriculture. The main challenge is to provide an estimate of county level GDP for services, construction, and mining. It is very important to include these components to capture both the geographical distribution and time profile of local GDP. The full details for how we construct our measure of county-level GDP are in Appendix B, but we describe it briefly below. The basic idea is to combine the geographic distribution of employment in service industries, as reported in the census micro-samples, with historical wages to form an estimate of county services GDP. We then combine these estimates with manufacturing value added and agricultural output adjusted for intermediate inputs to form a measure of county GDP.

To obtain county-specific measures of GDP for services, construction and mining, we use the employment and occupation information collected by the census micro-samples for each year to construct employment by broad service category (trade, transportation and public utilities, finance, professional services, personal services, and government), construction and mining. We then calculate nominal valued added per worker in each industry based on national accounts and adjust this value added per worker using the local wage relative to the national wage. This adjustment allows the productivity of a worker in each sector to vary by location.[10] Another way to describe this procedure is that we distribute national GDP in an industry according to the wage bill of each county relative to the national wage bill in that industry. We have the full wage bill for the 1940 census, and we use the same allocation for the adjacent decades of 1950 and 1930, when there is much sparser wage information. For decades before 1930, we have information on wages within each sector only at the state level (or for the major city within a state). For these periods, we combine this historical information with the detailed wage distribution available for the full sample in 1940 to obtain a wage distribution that is specific to a given state and allows for differences between urban and rural areas.

The census reports income at the county level starting in 1950 and no longer reports manufacturing and agricultural output in the same way. Using the overlap in 1950 between our measure of nominal GDP by county and income in each county from the census, we construct a ratio of GDP to income at the county level. We use this county-level ratio to get an estimate of GDP from 1960 onward. Effectively, we use the growth rate of income at the county level to approximate the growth rate of county-level GDP. We then calculate GDP for the same county groups used in constructing the distribution of ancestries. We convert nominal GDP to real GDP using the price deflator from Sutch (2006). In our analysis, we generally allow for census division specific year effects that absorb any census division differences in the evolution of the GDP deflator. Then we divide real GDP by the number of workers in each county, calculated by summing all persons who indicate an occupation in the census micro-samples.

Ours is the first measure of GDP at the county level, as opposed to a combined measure of manufacturing and agriculture. By aggregating at the national level and

[10]We show in Appendix B that this approach is exactly what one ought to do under the assumption of perfect competition in output and factor markets and a constant returns to scale Cobb Douglas production function. This result holds even if the output market is monopolistically competitive, provided the markup is common across the United States.

at the state level, we can compare our measure to other calculations and thus provide some validation of our approach. Both the level and the growth rate at the national level closely track the GDP per capita from Sutch (2006) (see Figure A-1 in the appendix). Our shares of GDP also closely match the shares calculated in the National Income and Product Accounts starting in 1929, although without the volatility of the Great Depression (see Figure A-2 in the appendix). When we aggregate at the state level, our state GDP per capita closely compares to estimates of state income per capita in 1880, 1900, 1920, and 1940, as shown in Figure A-3 in the appendix.

5 Does ancestry matter and why?

Combining our measure of the ancestry makeup of each county with our measure of county GDP, we ask whether ancestry matters for local economic development and, if so, which attributes brought by the immigrants from the country of origin play an important role.

What is crucial about our empirical approach is that, unlike most other studies of ethnicity or ancestry, we have at our disposal a panel of consistent data. The availability of panel data allows us to evaluate how important ancestry composition is for economic development, controlling for time-invariant county characteristics, and examine how changes in the ancestry mix affect outcomes over time. Throughout the analysis, we limit the sample to 1870–2010 for two reasons: (1) the US Civil War (1861–1865) changed the economic landscape, making comparisons between the pre-war and post-war periods difficult; and (2) the iterative construction means that from 1870 onward the ancestry shares are based on more decades of micro-sample information.

We start by asking whether groups have different effects using an unrestricted linear specification in which each ancestry is allowed to have its own effect on county GDP per worker (Section 5.1). We then examine which origin characteristics are correlated with these unrestricted ancestry effects (Section 5.2). To address additional questions of endogeneity and compare origin characteristics, we next turn to a more parsimonious approach that uses the ancestry-weighted average origin characteristic in a county (Section 5.3.1). We finally allow for higher order functions of the ancestry shares to matter to address the role of diversity (Section 5.4).

5.1 Do ancestry groups have different economic effects?

We begin by testing whether ancestries are different along any economically relevant dimension. Denote with π^a_{ct} the share of the population of county c at time t whose ancestors came from a particular country-of-origin a out of all possible ancestries A. Note that the sum of all shares in a county is 1 by definition, and so we examine how composition matters, not how the size of the population matters. We estimate variations of:

$$y_{ct} = \theta_c + \theta_{dt} + \sum_{a=1}^{A} \alpha_a \pi^a_{ct} + \gamma X_{ct} + \epsilon_{ct}, \tag{1}$$

where each ancestry can have its own unrestricted effect on log county GDP per worker (y_{ct}) after controlling for county fixed effects (θ_c) and census-division-specific year effects (λ_{dt}) and other possible controls (X_{ct}). If ancestry composition does not matter, then all of the α_a coefficients will be equal (we use the English as the excluded reference ancestry).

Table 1 shows the results for many variations of equation (1), all of which strongly reject the hypothesis that ancestry composition does not matter. All estimates include county fixed effects, so the fixed characteristics of the place of settlement is controlled for. We include different combinations of year, year-division, or year-state effects in the first three columns. The remaining columns add county trends, two lags of county GDP, and additional controls. The table shows the F-statistic for the joint test that all α_a are equal (each ancestry matters equally for GDP).[11] To examine whether the results are purely driven by race, we also separately test the hypothesis that all ancestries other than African American and Native American have equal coefficients. Below each F-statistic we report its p-value. They are all zero to more decimal places than can fit in the table, strongly rejecting the hypothesis of equal effects.

The last column also includes other possible explanatory variables, such as population density and county-level education (measured first by literacy and then, after 1940, by average years of education). These variables represent potential channels through

[11] Since individual effects for very small ancestry groups cannot be precisely estimated, we include only the ancestries that make up at least 0.5% of the population in 2010, which accounts for 93% of the population. In the estimation, we use people of English origin as the reference point and omit their fraction from the regression. The test, therefore, is whether the coefficients for the other ancestry are jointly zero.

which ancestry may be related with economic development. The ancestry coefficients continue to be jointly significantly different from one another, even after including these controls, and so ancestry composition seems to matter beyond its relationship to education or urbanization.

5.2 What origin characteristics explain why ancestry groups have different effects?

In this section, we examine which country of origin characteristics help explain why ancestry groups have different economic effects. We first introduce our origin variables. We then examine whether the ancestry effects are correlated with origin characteristics.

The main limiting factor in the analysis of origin attributes is the availability of information for a broad range of countries over long time periods. Unlike our data on ancestry and county GDP, which we have carefully constructed based on micro data to be consistent across time and space, the cross-country data is not always available or reliable, particularly in the distant past. The full details of the construction of and sources for the origin variables are in Appendix D.[12]

To reflect the changing nature of what immigrants could bring with them, when the characteristics of the origin country are time varying, we weight them by the time of arrival of immigrant groups (see Appendix C for our creation of the conditional arrival density for all groups). In addition, we measure most origin variables as their difference from the United States at arrival. As time goes by, differences at arrival are likely to diminish, and so we allow these differences to depreciate the longer an immigrant group has been in the US. Formally, given a country-of-origin measure $\hat{\mathrm{z}}_\tau^a$ for ancestry a at the time τ of arrival and $\hat{z}_\tau^{US}$ measure in the US, we form the arrival-weighted origin attribute Z_t^a at time t:

$$\mathrm{Z}_t^a = \sum_{\tau=0}^{t} (\hat{z}_\tau^a - \hat{z}_\tau^{US})(1-\delta)^{t-\tau} F_t^a(\tau), \qquad (2)$$

[12] We only show results for origin variables that cover over 99% of the population in every county. Summary statistics for these variables appear in appendix Table A-2.

where $F_t^a(\tau)$ is the arrival density of group a up to time τ, which is 0 for $\tau > t$, and δ is the rate of depreciation of the importance of the origin.

As a summary variable for positive economic attributes, we form the Arrival-Weighted Origin GDP as the difference in log GDP per person in the country of origin and the log GDP per person in the United States at the time of immigration, depreciated at 0.5% per year, which implies that 40% of the difference between the origin country and the US disappears in 100 years. We show that the particular rate of depreciation does not affect our results, and they are largely the same if we simply use log origin GDP per person fixed in 1870. Origin GDP is a useful summary variable, since it captures whether an ancestry has been exposed to the mix of characteristics that led to economic development in the ancestral homeland and thus helps understand whether ancestry groups carry a portion of what matters for economic success with them.

Following Tabellini (2010), we use the World Values Survey (WVS) to construct a composite measure of cultural values that enhance productive social interactions by taking the first principal component of these values at the individual level from the WVS.[13] In order to obtain a time-varying measure of culture, we separate the individual WVS answers by birth cohort (born before 1925, 1925–1949, 1950–1974, after 1975). This procedure allows us to capture, albeit imperfectly, the changing cultural values inherited from the country of origin by different waves of immigrants. We then take differences from the United States depreciated at 0.5% per year to form the arrival-weighted Principal Component of Culture using equation (2). We obtain similar results using arrival-weighted Trust constructed in the same way.

For institutions, we use the state history variable from Putterman and Weil (2010) that reflects for how long a particular state had a centralized government free of foreign domination in 1500 (State History in 1500). Because State History in 1500 is fixed at a point in time, it does not vary by time of arrival. We also measure the constraints on the executive power in the country of origin at the time of arrival of various immigrant

[13]Tabellini (2010) focuses on answers from the WVS that measure: (i) generalized trust; (ii) the respect of others as a desirable characteristic children should have; (ii) obedience as a desirable children's characteristic; (iv) feeling of control of one's own fortune. The basic idea is that trust, respect, and control are cultural traits that enhance productive social interaction, while obedience is not a useful trait in a society that values independence.

waves (Executive Constraints at arrival). Finally, we construct Migrant Education at arrival by using literacy and years of education (after 1930) of immigrants from the census.

Figure 4 shows how a selection of arrival-weighted origin variables in 2010 relates to the individual ancestry effects we estimate in Table 1 column 5. We show 2010 arrival-weighted variables to capture the full experience of each immigrant group.

Origin variables associated with economic development in the home country are positively associated with the estimated ancestry effects. Ancestry groups from countries that are richer, arrived with more education, come from countries with longer state history, and have more constraints on executive power tend to have a large effect in their new homes. Groups from countries with a greater culture of cooperation (Principal Component of Culture) or more generalized trust (Trust) also have larger effects. We show several other variables, including some that have negative relationships, in Appendix Figure A-4.

5.3 A parsimonious representation of origin characteristics

In this section, we introduce a more parsimonious representation of the origin characteristics by constructing an ancestry-weighted average of origin endowments. We start by examining origin country GDP per person in Section 5.3.1, and then we turn to more specific origin characteristics in Section 5.3.2. We define the county average endowment as:

$$z_{ct} = \sum_{a=1}^{A} \pi_{ct}^{a} Z_{t}^{a} \tag{3}$$

for arrival-weighted origin characteristic Z_t^a defined as in equation (2) in the previous section. We can think of z_{ct} as the average or predicted value, across origin countries a, of the endowment of a given characteristic, Z_t^a. We use the lowercase italics to help denote the endowment variable weighted by the ancestry share, and uppercase letters for the endowment characteristic itself. When the country of origin characteristic is time invariant, the county-level average endowment will change only because of changes in ancestry composition.

Our typical regression takes the general form:

$$y_{ct} = \theta_c + \lambda_{dt} + \beta z_{ct} + \gamma X_{ct} + \epsilon_{ct}. \quad (4)$$

In some specifications z_{ct} will be a vector of the ancestry-weighted values of the endowment of several characteristics and in most specifications X_{ct} will include two lagged values of y_{ct}. Note that, implicitly, we are imposing the restriction that the ancestry coefficients in the unrestricted model of equation (1) are proportional to one or more elements of the endowment vector.

5.3.1 Origin development and county development

Table 2 shows a series of estimates of equation (4) for ancestry-weighted *Origin GDP per capita.* All of the estimates include census-division-specific year effects. Because much of the variation in the effect of ancestry is likely to be felt across regions, including census-division-year effects removes some variation but ensures that the estimates are not driven purely by differential regional trends.[14]

When we use fixed effects to control for all of the time invariant aspects that may affect economic development in column 1 of Table 2, the coefficient on *Origin GDP* is positive and significant at the 1% level. The estimates imply that when the people who make up a county come from places that are 1% richer, county GDP per worker is 0.3% higher. While the association of *Origin GDP* with local GDP is positive and significant in column 1 with fixed effects, the association is negative and significant in column 2 without county fixed effects. The negative coefficient illustrates just how important having a panel is. Cross-sectional regressions, even ones controlling for regional differences, may deliver severely biased results. The negative coefficient is likely particular to the settlement of the United States, but the possibility of bias in a cross-section is a more general problem.[15] Allowing for county effects also controls

[14]We use census divisions instead of states, since states vary tremendously in size and census divisions are much more similar in terms of geographic and population size. States such as Rhode Island also have very few county groups, and so including a fixed effect for them removes almost all variation.

[15]The primary driving force behind this correlation is the historical legacy of settlement, starting with the English. While the English are a large portion of the population in much of the United States, they are disproportionately present in rural areas in the poor South and Appalachian states, which received little immigration after their first settlement. Later immigrants, such as the Italians or Irish, while poor

for an arbitrarily complicated spatial correlation.

Because the effect of changes in ancestry may take some time to be fully felt, in columns 3 through 5 of Table 2 we show a dynamic specification including two lags of county GDP per worker.[16] There is evidence of severe serial correlation in column 1, according to the Arellano and Bond (1991) test. By including previous periods of the dependent variable county GDP per worker, we can remove the serial correlation as well as examine how the impact of ancestry evolves. The dynamic model suggests that the effects of a permanent change in the ancestry mix are felt about half within a decade, and half over the long term.[17] The long-term effect is now quite large: if the people who make up a county come from places that are 1% richer, county GDP per worker is 0.6% higher.

Columns 4 and 5 examine possible variations by including race and allowing for neighbors to have an effect. We permit African Americans and Native Americans to have an unrestricted coefficient, because the information at the origin level for African Americans and Native Americans is necessarily speculative and we would like to understand the differential effect that race has from ancestry.[18] The coefficient on *Origin GDP* remains significant, although it is now smaller, suggesting that while race is an important part of ancestry, it is not the only part. In column 5, we include a one decade-lag of a county group's neighbors' average *Origin GDP* and county GDP.[19] Because

when they arrived, went to cities and prosperous areas, especially in the Northeast. Finally, the Great Migration of African Americans shifted them from the poor rural South to growing urban areas.

[16]In the appendix we show that Nickell (1981) bias due to T being relatively short (around 14) does not affect these results. Note, moreover, that *t* indexes decades.

[17]The coefficient of first lag is highly significant and sizable (.44), while the one for the second lag is smaller and significant at the 10% level. While the second order lag is only sometimes significant across the different specifications, excluding it often causes the Arellano and Bond (1991) test of serial correlation to fail to reject the hypothesis of no serial correlation of ϵ_{ct}, and so we standardize on including two lags. The long-run multiplier, in a single equation context, is $\beta/(1-\rho_1-\rho_2)$, where β is the coefficient of each ancestry-weighted endowment variable, and ρ_1 and ρ_2 are the coefficients on the lags of county GDP.

[18]Where available, we assign the values of Ghana, a West African country that was at the heart of the slave trade, to African Americans, and typically use overall US values for Native Americans. The results are nearly identical if we also allow those with African ancestries from the West Indies to have their own independent effect.

[19]We lag the variables one decade to avoid the obvious identification problem of reflection: if neighboring county's affect each other simultaneously, then it requires an identification assumption to separate a county effect from a neighbor effect. A lag implicitly assumes that it takes a decade for a shock in one county to affect its neighbors, which seems the most sensible assumption. Note that fixed effects are far

the fixed effects already allow for an arbitrary fixed spatial relationship, the standard issue of spatial correlation is small, and adding a spatial lag variable has no additional effect.

The inclusion of county-specific effects eliminates endogeneity that may arise if certain ancestries are attracted to places with particular time-invariant characteristics omitted from the specification. However, it is also possible that ancestries with particular endowments are more willing to move in response to short-term county-specific economic shocks to GDP, creating a form of reverse causality. We use a variant of the instrumenting strategy developed in the immigration (Card, 2001; Peri, 2012) and local-development (Bartik, 1991) literature to show that this form of endogeneity does not affect our results.

Immigrants tend to go where there are already immigrants from their country (Bartel, 1989). Growth of native groups similarly occurs in places where there are already populations of that ancestry. We build on these observations to create an instrument for ancestry based on the past stock of ancestry.

We form our instrument starting with the population $P^a_{c,t-1}$ of ancestry a in county c at time $t-1$. We predict the c's population at time t as: $\tilde{P}^a_{c,t} = P^a_{c,t-1}(1 + g^a_{(-s(c))t})$, where $g^a_{(-s(c))t}$ is the growth rate of ancestry a from $t-1$ to t in all states except the state containing county c. Summing over all the ancestries gives the predicted total population in each county, $\tilde{P}_{c,t}$. The predicted share of ancestry a's population in each county is then $\tilde{\pi}^a_{c,t} = \tilde{P}^a_{c,t}/\tilde{P}_{c,t}$. We then form predicted ancestry-weighted variables $\tilde{z}_{ct}$ using equation (3) using $\tilde{\pi}^a_{c,t}$ instead of $\pi^a_{c,t}$.

We use the predicted *Origin GDP* formed using the past ancestries and their national growth rates (excluding the state of the destination county) as an instrument. To meet the exclusion restriction, the instrument must be uncorrelated with the error term at t in equation (4). By construction, $\tilde{z}_{ct}$ does not use any county specific information from decade t and, by using the growth rate excluding a county's state, does not use any information from surrounding counties either. However, $P^a_{c,t-1}$ may be correlated with the error term in $t-1$, ϵ_{ct-1}. This would invalidate the instrument if there is serial correlation (Cov $(\epsilon_{ct}, \epsilon_{ct-1}) \neq 0$). Because there is no evidence of serial correlation

more flexible for spatial correlations than the standard functional form assumptions of spatial lags. The only concern is whether shocks may propagate spatially, which does not seem to be the case.

in the errors of our dynamic specification in column 3 using the Arellano and Bond (1991) test, it is legitimate to use $\tilde{z}_{ct}$ as an instrument.

Using our instrument for *Origin GDP* in column 6, our estimates are very close to those obtained when we do not instrument, and so we can conclude that our results are not driven by short-term endogenous migration. The first stage regression suggests that the instrument is highly correlated with *Origin GDP* (the p value of the t statistic is 0 to at least five decimal places). In Appendix E and Table A-3, we discuss and show additional variations using GMM that deal with instrumenting in a dynamic panel when T is short.

About half of the impact of a permanent change in ancestry takes place immediately in Table 2, and half over the long term. We can go further and calculate the impulse-response function of an innovation in *Origin GDP* obtained by estimating a two-variable panel vector autoregression that allows ancestry to affect county GDP and county GDP to affect *Origin GDP*. The results are reported in Figure 5 under two opposite identification assumptions: either county-level GDP per worker affects *Origin GDP* with a lag, or the converse is true.[20] Innovations in *Origin GDP* have a significant and sizable initial effect on county GDP, which grows until about the third decade. County GDP has an inconsequentially small effect on *Origin GDP*, suggesting that differential ancestry migration because of shocks is not a concern, as our instrumental results suggested. These results suggest some of the ancestry effect must be relatively immediate, but more than half of the effect shows up only after several decades.

In Appendix Table A-4, we examine whether these results are robust to some other specifications. We first show that our results do not change when we allow the difference on arrival to depreciate faster or slower. When we allow the effect of ancestry to differ between metropolitan and non-metropolitan areas, there is some statistically weak evidence that the effect is slightly smaller in a metropolitan county. When we allow the coefficients to differ before and after 1940, the coefficient of *Origin GDP* does not differ economically and statistically between the two sub-periods. Clustering errors at the state-year level does not affect the significance of our results. The overall conclusion is that the coefficients appear to be largely stable over time and

[20]The coefficients for the estimation, which involve two lags, are in Appendix Table A-3.

cross-sectionally. Finally, a possible concern is that immigrants may be a selected group with, say, greater willingness to take risks (see, for example, Abramitzky, Boustan, and Eriksson (2012)). To the extent that such selection is true of all immigrants, it does not affect the internal validity of our results. Yet immigrants from different countries or times may select themselves differently. To address this concern, we include the value of the ancestry-weighted Gini coefficients in the origin country at the time of arrival (weighted by arrival density) in our standard regressions (see Table A-4, column 6). The idea is that selection issues may be more important for origin countries that have a more unequal income distribution. Including the *Origin Gini* leaves the coefficient on *Origin GDP* largely unchanged, so differential selection does not seem to affect our results.

We briefly examine some possible mechanisms through which ancestry works. Our examination is limited by data that are available at a county level over a long time. Table A-5 shows the relationship between our ancestry summary measure, *Origin GDP,* and county-level education and political participation, measured as the fraction of the adult population that voted in the most recent presidential election. Both are likely to be at least partially an outcome of ancestry and we show that *Origin GDP* positively affects each of them. But when we include each of them with *Origin GDP,* the coefficient on *Origin GDP* barely changes and remains significant, suggesting that, while these variables may explain some of the importance of ancestry, other avenues matter as well.

5.3.2 Origin characteristics and county development

Which specific attributes and characteristics brought from the origin country help explain the association between ancestry and development? Table 3 takes a selection of the endowment measures and examines which measures are significant by themselves and in combination with each other. Given the significance of lagged values of county GDP, we focus only on the dynamic specification and always include county fixed effects and census-division-year effects. Each of the culture, institution, and human-capital variables are significant when included one at the time in Table 3 (columns 1 through 6). When we include the ancestry-weighted measures of culture, institutions, and human capital together, the coefficients on *Principal component of culture* and *State History in 1500* remain highly significant, while the *Migrant education* coefficient is not significant (column 7). This may be because public schooling reduces educational differences and schooling policies respond endogenously to immigration flows (Bandiera et al., 2015). The coefficients of *Executive constraint at arrival* and *Political Participation* have small and not significant coefficients when added to the specification with *State History in 1500.* These variables represent political institutions that may change more rapidly and with which immigrants may have more limited experience, and so it makes sense that they have little effect in the United States. The importance of early political centralization for development is consistent with the results obtained by Michalopoulos and Papaioannou (2013) and Gennaioli and Rainer (2007).[21]

These results suggest that multiple endowments play a role in development, although we should not over-interpret them to conclude that these are the only endowments that matter. Still, when our summary measure, *Origin GDP,* is included with measures of culture, human capital and institutions in column 8, it is not significant and small, and the results do not change for *Principal component of culture* and *State history in 1500*. It appears that these imperfect measures of endowments capture the different dimensions of economically significant endowments fairly well.

5.4 The positive and negative impact of diversity

Until now we have examined the effect on county-level GDP per worker of the ancestry weighted average of the attributes people in a county brought from their respective countries of origin. However, the diversity of ancestries may be as important for local development as the average of those attributes. We use several measures of diversity. One is the standard fractionalization index that measures the probability that any two individuals chosen from a population will not be of the same group:

$$frac_{c,t} = 1 - \sum_{a=1}^{A} (\pi_{ct}^{a})^2. \tag{5}$$

[21]We obtained very similar results using *Trust* instead of *Principal Component of Culture*, but we prefer the specification with *Principal Component,* as it is based on multiple complementary cultural traits that denote the ability to interact with others. *Thrift* did not play a significant role when included.

Recent work has generalized this index by allowing it to incorporate measures of distance between groups (Bossert, D'Ambrosio, and La Ferrara, 2011). Weighted fractionalization measures how far groups are from each other on average along a particular dimension. The generalized fractionalization index is:

$$frac^{w}_{c,t} = 1 - \sum_{j=1}^{A} \sum_{k=1}^{A} \pi^{j}_{ct} \pi^{k}_{ct} s^{jk}_{t}, \tag{6}$$

where the w stands for a "weighted" fractionalization and s^{jk} is a measure of similarity between countries of origin. [22] The standard fractionalization index is just the weighted fractionalization index when members of different groups are assumed to be completely dissimilar ($s^{jk} = 0$ for $i \neq j$).

Table 4 reports the results when we include measures of fractionalization. Column 1 shows the fixed-effects estimates, including fractionalization, origin-GDP-weighted fractionalization, and *Origin GDP*. The coefficient of *Origin GDP* remains significant. The coefficient of fractionalization is positive and significant, while the coefficient of origin-GDP-weighted fractionalization is negative and significant.[23] Fractionalization seems to be the relevant measure of diversity. When we include polarization in column 2, it does not seem to have an independent effect.[24] The results are essentially unaltered when we instrument for the weighted endowment variable, fractionalization, and origin-GDP-weighted fractionalization using the predicted values of ancestry shares described in Section 5.3.1 (column 3).

In column 4 of Table 4, we replace ancestry-weighted *Origin GDP* with our deep

[22]The definition of s^{jk} is based on the difference of some country-of-origin measure z between group j and group k as $s^{jk}_{t} = 1 - |z^{j} - z^{k}|/r$, where $r = \max_{j\in\{1...A\}} z^{j} - \min_{j\in\{1...A\}} z^{j}$ is the range of values that z can take. As two groups become more similar along the z dimension, their similarity approaches 1.

[23]We have explored allowing for a quadratic term in fractionalization and weighted fractionalization. In our preferred dynamic specification, the quadratic term is not significant, and we have not found an internal optimum in any specification and so do not report these results.

[24]Polarization measures how far a county is from being composed of only two equally sized groups. Ager and Brückner (2013) found that polarization was negatively related to economic growth across counties in the US from 1870 to 1920, while fractionalization was positively related to growth. Their measures of polarization and fractionalization are calculated by dividing the population into first-generation immigrants from different countries, African Americans, and all second- or higher- generation whites together. Our calculations treat ancestry groups as distinct even past the first generation.

endowment variables and Origin-GDP-weighted fractionalization with attribute-weighted fractionalization created from the distinct endowment variables. The *Principal component of culture* and *State history* remain positive and significant. Culture-weighted fractionalization is the only weighted fractionalization variable with a coefficient that is significant at conventional levels. The sign of the coefficient is negative, suggesting that fractionalization of cultural attributes is particularly problematic. Ancestry fractionalization continues to have a positive effect on local development, and its coefficient is highly significant.

These results capture different effects of diversity. The positive effect of fractionalization is consistent with the notion that it is beneficial for people with new skills, knowledge, and ideas to come into a county. Moreover, if they bring different tastes, the newcomers may open up new opportunities for trade. Yet, if those new groups are substantially different along important dimensions, such as level of development of the country of origin or culture, these differences may create conflict and prevent agreement on growth enhancing policies at the local level. Our results suggest that the effect of diversity depends on the dimension one emphasizes and thus help account for the different results obtained by the rich literature on diversity we discussed in the introduction.

One possible explanation for the positive effect of fractionalization is that greater ancestry fractionalization brings with it a richer skill mix. We construct a measure of skill variety by using the occupational data from the individual census records. We divide occupations into either 10 or 82 categories. To capture the variety of skills available in a county, we construct a Constant Elasticity of Substitution (CES) aggregate of the occupations in each county. We impute the distributional share parameter and the elasticity of substitution between different skills using the full distribution of wages in 1940. We discuss our construction of the index in Appendix F.

As shown in Table 5, for a reasonable range of elasticities of substitution and for both the broad and narrow occupational classifications, ancestry fractionalization is positively correlated with occupational variety and negatively correlated with origin-GDP-weighted fractionalization, controlling for *Origin GDP*. Moreover, the index of occupational variety is positively and significantly related to county GDP when we include it in our standard equation containing *Origin GDP* and fractionalization. The coefficient of ancestry fractionalization is smaller and less significant relative to its value in the basic specification of Table 4, column 1. The results suggest that the positive effect of ancestry fractionalization reflects, at least in part, the richer mix of skills associated with a county's increasing degree of ancestry diversity.

6 Conclusion

The endowments brought by immigrants matter for economic development. Over the long term, counties with ancestry groups coming from countries at a higher level of development are more productive. The effects build over several decades, suggesting that new immigrants take some time to make their mark on their new homes. Cultural traits that enhance immigrants' ability to interact with others (such as trust) and coming from a country with a long history of centralized and independent government appear to be the most important explanations for the impact of ancestry. Ancestry diversity also improves productivity, while diversity in the cultural values reduces it. It seems that when groups have to share a place and work together, diversity is good, as long as there is a degree of agreement in terms of cultural attitudes that facilitate exchange, production, and the ability to agree in the public sphere.

The complex mosaic of ancestry in the United States has changed profoundly over time, and it is still evolving as new immigrants come and people move internally. Our results provide novel evidence on the fundamental and recurring question of whether the United States acts as a "melting pot," quickly absorbing new immigrant groups, or whether immigrant groups maintain distinct identities in at least some dimensions. The significance and persistence of our ancestry measure's effect are difficult to explain in a pure assimilationist view and are more consistent with approaches that emphasize the persistence of traits across generations. Our results show that this process generates important long-run consequences for local economic development.

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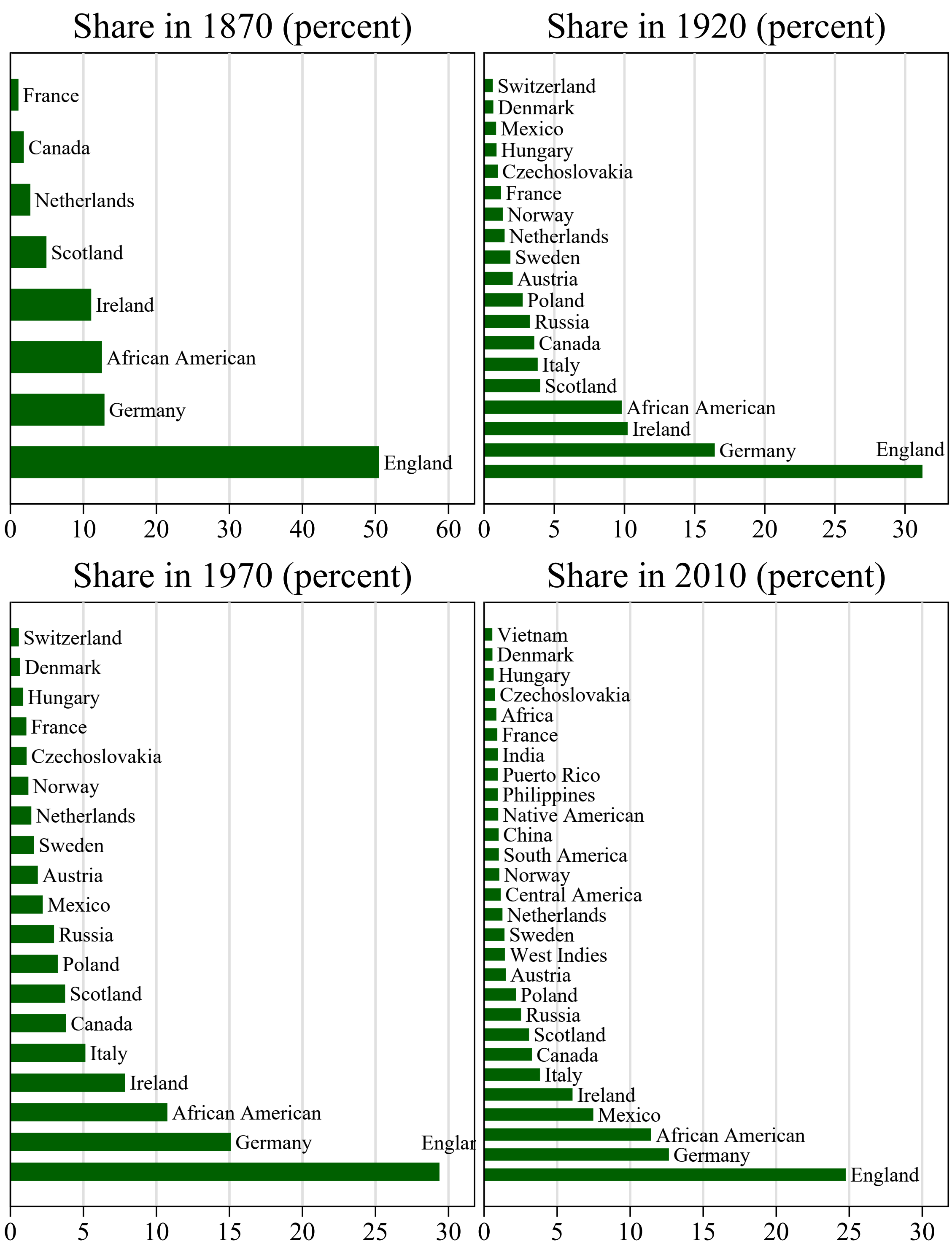
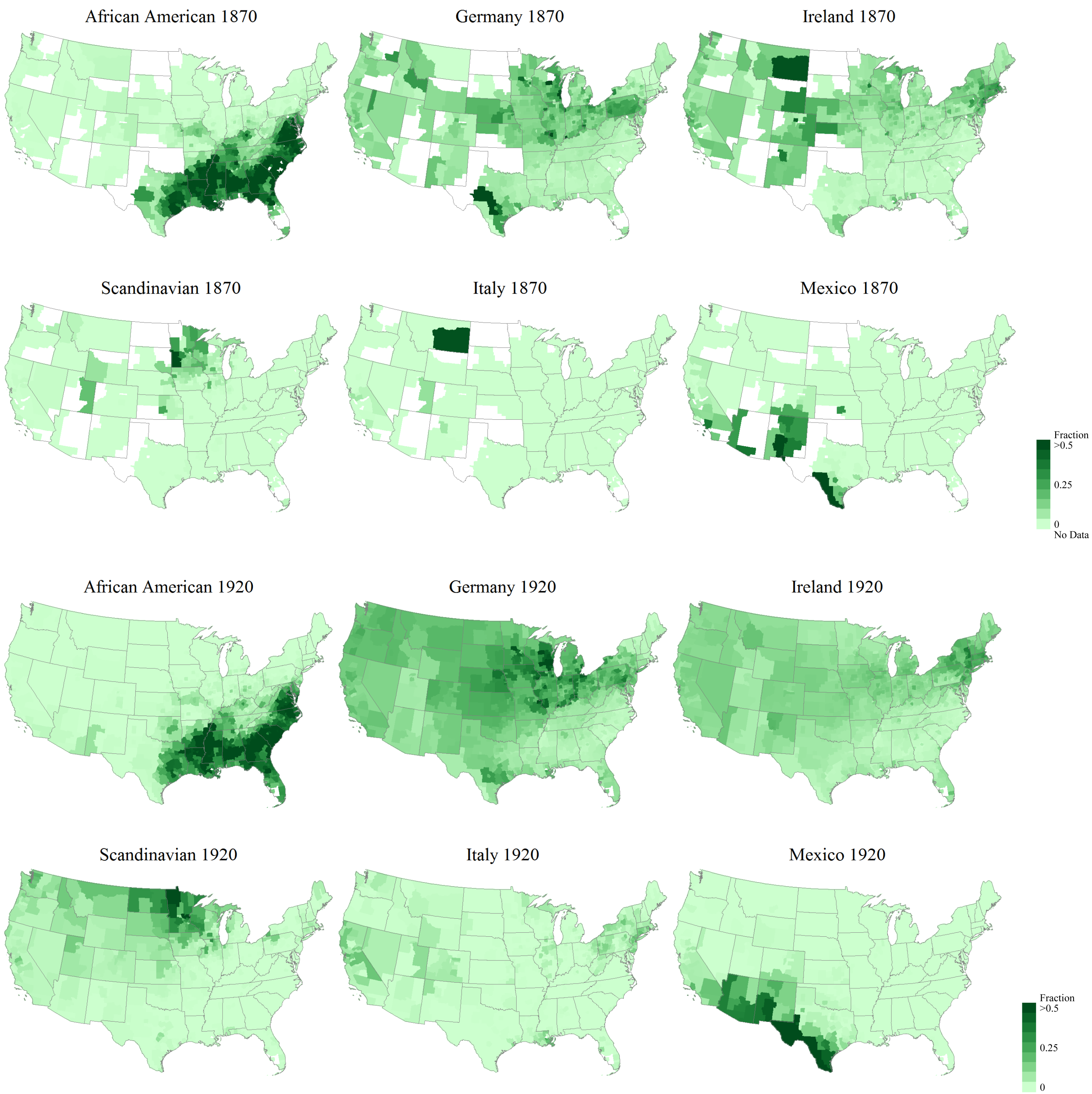
Figure 1: Ancestry share in the United States: 1870, 1920, 1970, and 2010



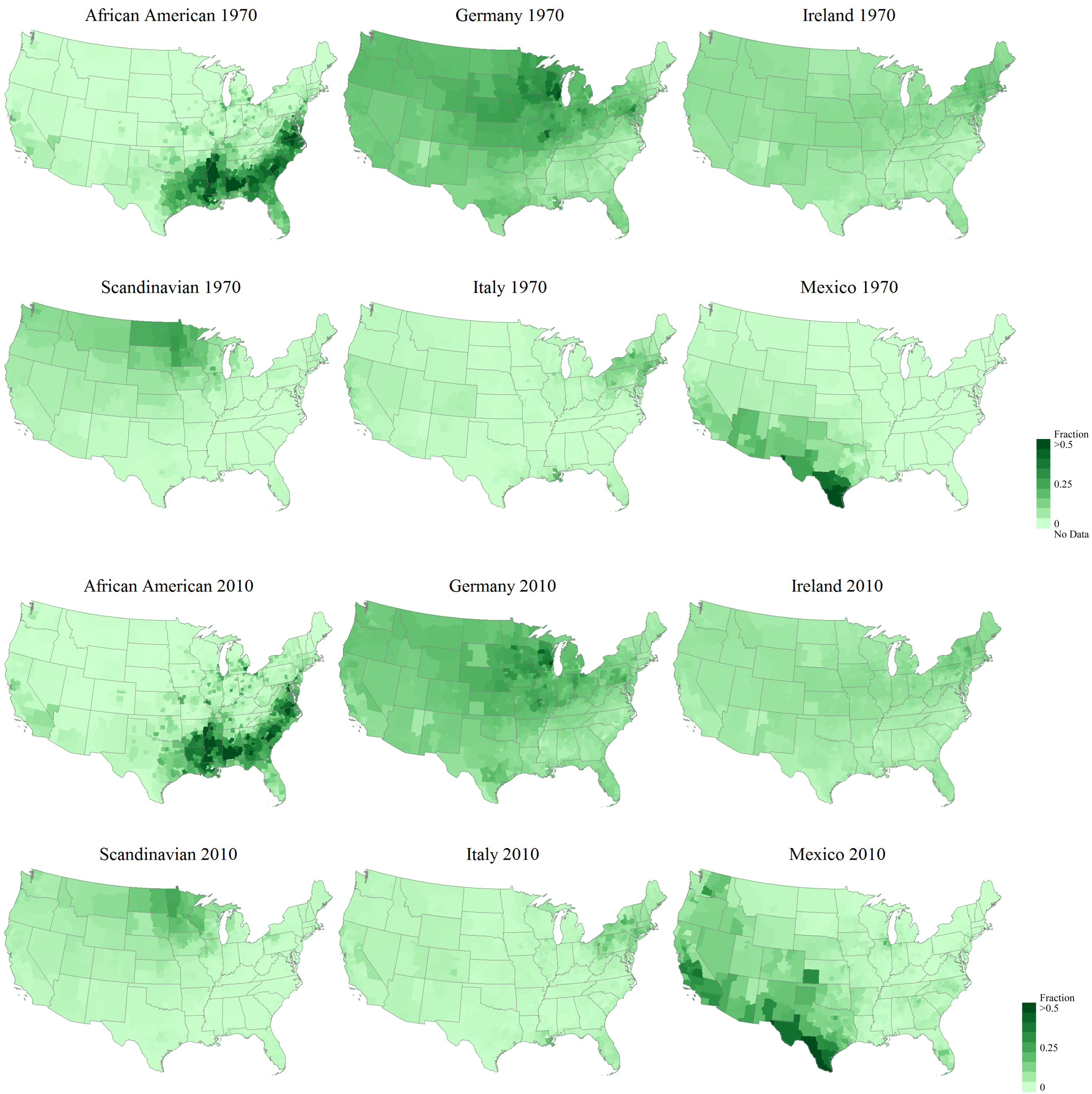
Notes: This figure showsaggregate ancestry shares in the United States for ancestries with greater that 0.5% of the population. Ancestry shares are created by summing the share in each county weighted by county population in each year. See Section 3 and Appendix A for the ancestry construction.

Figure 2: Select ancestries in the United States: 1870 and 1920



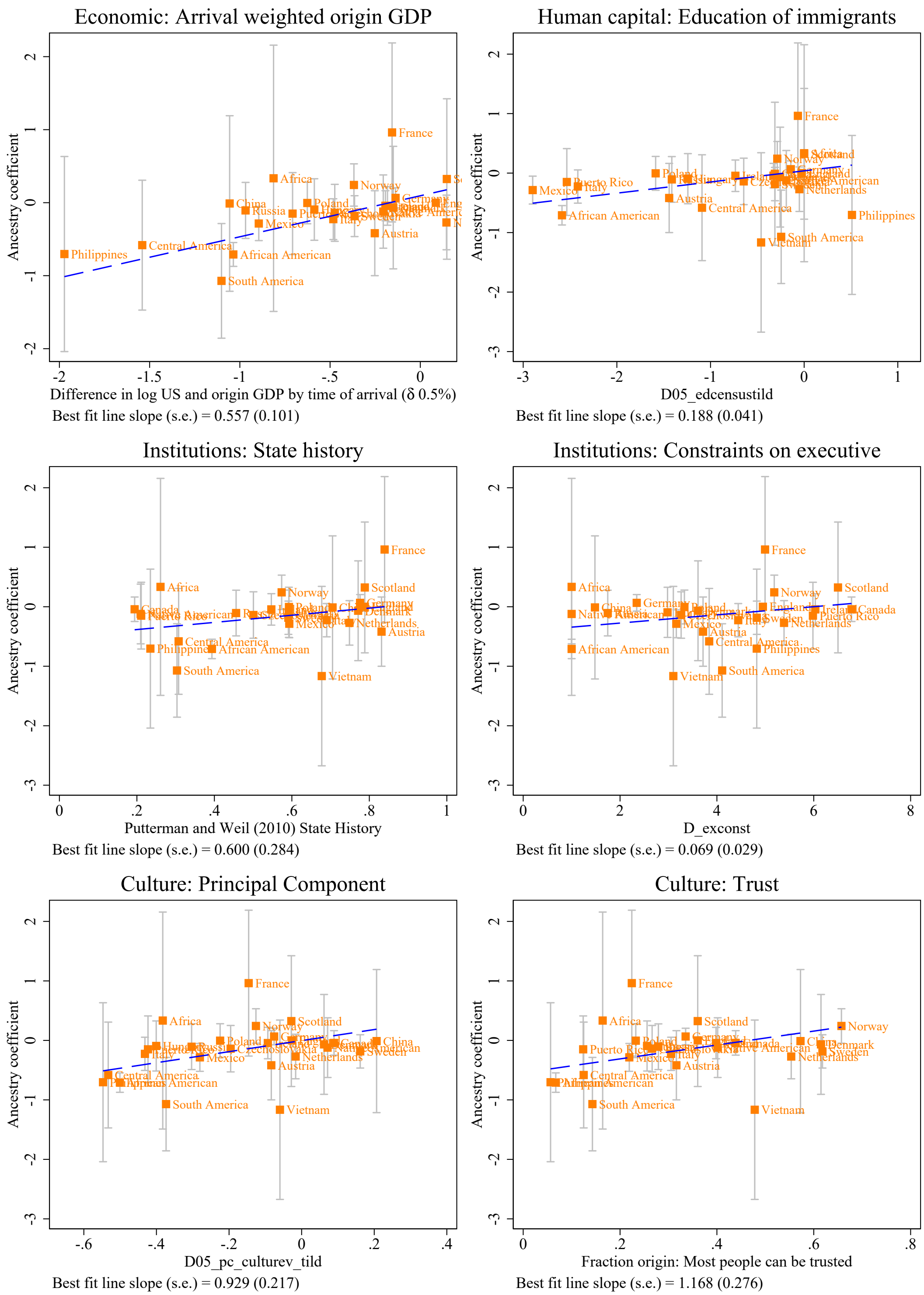
Notes: This figure shows the geographic distribution of select groups. Scandinavian is the combined Norway and Swedish ancestries. See Section 3 and Appendix A for the ancestry construction.

Figure 3: Select ancestries in the United States: 1970 and 2010



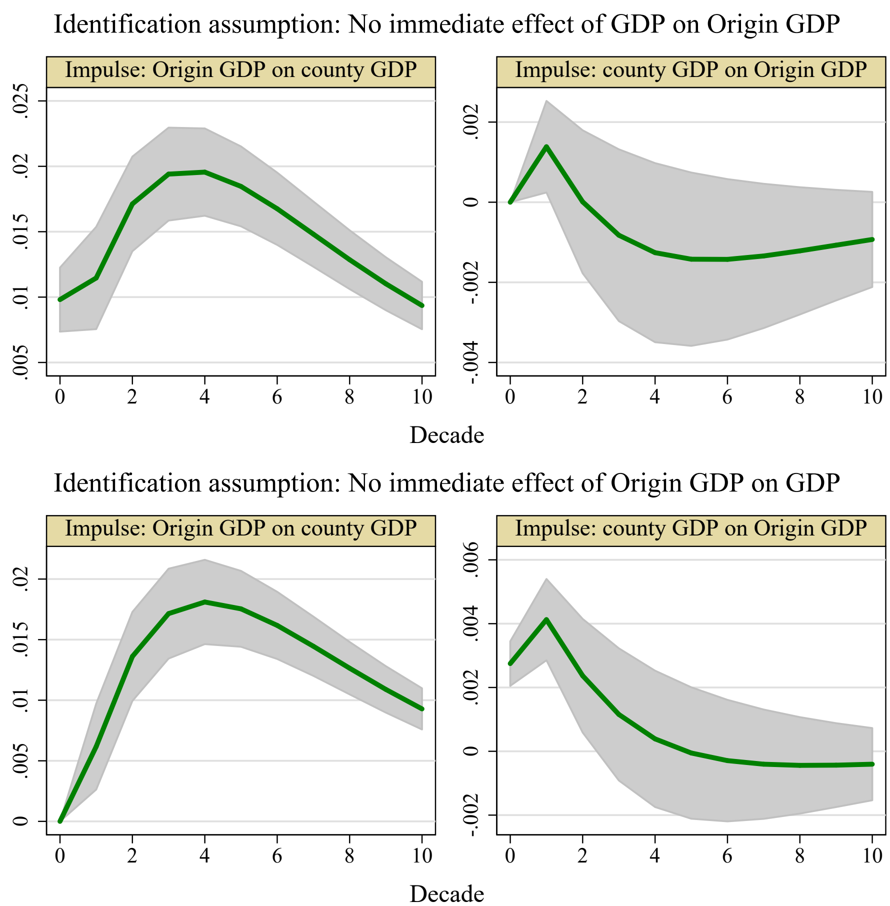
Notes: This figure shows the geographic distribution of select groups. Scandinavian is the combined Norway and Swedish ancestries. See Section 3 and Appendix A for the ancestry construction.

Figure 4: Ancestry and endowments from the country of origin



Notes: This figure shows the relationship between variables in the country of origin and the coefficients estimated for large ancestry groups in the log county GDP per worker equation (1), including county group fixed effects, census division by year effects, and two lags of county GDP per worker (column 5 in Table 1). Time-varying origin country measures are constructed as the immigrant arrival-weighted density of that country as in equation (2) (see Appendix C for sources and calculation of arrival density and Appendix D for the sources of the origin variables).

Figure 5: Impulse responses of log county income and ancestry-weighted *Origin GDP*



Notes: This figure shows impulse responses of a panel vector autoregression examining the co-evolution of ancestry weighted *Origin GDP* and county GDP. See Appendix E and Table A-3 for the VAR coefficients. The impulses are calculated using two Cholesky decompositions: (1) No immediate effect of county GDP per worker on ancestry weighted *Origin GDP*, but *Origin GDP* can immediately affect county GDP, (2) No immediate effect of *Origin GDP* on county GDP, but county GDP can immediately affect *Origin GDP*. The size of the impulse is the standard deviations of the residuals in each equation. Shaded areas are the 95% confidence intervals based on Monte Carlo simulation.

Table 1: County GDP per worker and individual ancestries

	Dependent variable: Log(County group GDP per worker)						
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
F(All ancestry =0)	25.32	10.69	13.90	8.192	9.365	5.260	7.592
p-value	0	0	0	0	4.94e-08	0	0
F(non-AA anc. =0)	16.05	8.833	8.624	6.291	3.444	4.026	3.317
p-value	0	0	0	0	0	3.57e-10	1.41e-07
County group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes						
Division X Year		Yes		Yes	Yes	Yes	Yes
State X Year			Yes				
County group trends				Yes		Yes	
Two lags of county GDP					Yes	Yes	Yes
Education and pop. density							Yes
R^2 (within)	0.938	0.947	0.962	0.963	0.970	0.977	0.969
R^2 (between)	0.378	0.424	0.485	0.0148	0.799	0.00332	0.804
Observations	18,447	18,447	18,447	18,447	16,144	16,144	15,916
County groups	1,149	1,149	1,149	1,149	1,146	1,146	1,146

Notes: This table tests whether ancestries have different effects on county GDP per worker. Each column shows the results from a regression including the fraction of every ancestry except the English (the excluded group), allowing each ancestry to have its own effect on county GDP per worker. The F-tests test the joint hypothesis that the coefficients on all ancestries are jointly zero and so equal to the English. Education is the fraction literate before 1940 and average years of education after. The Non-AA F tests whether all ancestries except African Americans and Native Americans are jointly insignificant. All regressions contain county-group fixed effects and different versions of year effects. Standard errors are allowed to cluster at the county-group level.

Table 2: County GDP per worker and country-of-origin GDP

	Dependent variable: Log(county GDP per worker)					
	Static		Dynamic			
	FE	OLS	FE	FE with Race	FE	IV-FE
	[1]	[2]	[3]	[4]	[5]	[6]
Origin GDP	0.310***	-0.172***	0.331***	0.152***	0.319***	0.354***
(ancestry weighted)	(0.0431)	(0.0409)	(0.0253)	(0.0290)	(0.0340)	(0.0302)
Decade lag			0.445***	0.436***	0.444***	0.442***
log county GDP			(0.0161)	(0.0163)	(0.0169)	(0.0162)
Two decade lag			0.0286*	0.0270*	0.0281*	0.0307*
log county GDP			(0.0167)	(0.0160)	(0.0166)	(0.0161)
Neighbor's Origin GDP					0.0104	
(one decade lag)					(0.0102)	
Neighbor's log county GDP					0.0193	
(one decade lag)					(0.0383)	
Division X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County group FE	Yes		Yes	Yes	Yes	Yes
Race				Yes		
Long-run effect	0.310	-0.172	0.629	0.283	0.604	0.671
Observations	16,713	16,713	14,415	14,415	14,415	13,252
County groups	1149		1146	1146	1146	1146
R^2 (within)	0.950	0.887	0.968	0.968	0.968	
R^2 (between)	0.113		0.472	0.486	0.446	
AB test serial corr.	6.01e-07		0.309	0.269		0.37

Notes: This table examines whether country-of-origin endowments as summarized by *Origin GDP* (the ancestry-weighted log difference between origin GDP per person and US GDP per person at the time of arrival, depreciated at a rate of 0.5% per year) matters for county GDP per worker in variations of equation (4). In the dynamic columns, the long-run effect is the the coefficient on *Origin GDP* divided by $(1 - \rho_1 - \rho_2)$, with the ρ's denoting the coefficients on the lag dependent variable. Column 1 includes fixed effects, column 2 does not. Columns 3–6 include two lags of the dependent variable (log county GDP per worker). Column 4 includes the fraction African American and Native American separately (the coefficients are not reported). Column 5 includes the average of the county's neighbors' *Origin GDP* and county GDP in the previous decade. Column 6 instruments for *Origin GDP* using the *Origin GDP* constructed using ancestry in the previous decade growing at the national growth rate excluding the county's state (see Section 5.3.1). The AB test is the p-value for the Arellano and Bond (1991) test for serial correlation (the test is for second-order serial correlation in the first difference of the residuals, which provides information on first-order serial correlation in the levels of the residuals). All regressions include census division by year fixed effects and standard errors clustered at the county group level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: County GDP per worker and ancestry-weighted origin characteristics

	Dependent variable: Log(County group income per worker)									
	FE	FE	FE	FE	FE	FE	FE	FE	FE	IV-FE
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Principal Component	0.818***						0.480***	0.573***	0.596***	0.405**
of culture	(0.0645)						(0.146)	(0.169)	(0.198)	(0.184)
State history		1.139***					0.610***	0.690***	0.707***	0.480***
in 1500		(0.0953)					(0.0988)	(0.114)	(0.141)	(0.145)
Migrant education			0.132***				0.0126	0.0152	0.0157	0.0443
at arrival			(0.0117)				(0.0256)	(0.0250)	(0.0252)	(0.0303)
Executive constraint				0.117***				0.00134		
at arrival				(0.0125)				(0.0155)		
Political participation					0.0329***			-0.00761		
at arrival					(0.00282)			(0.00588)		
Trust						2.039***				
						(0.164)				
Origin GDP									-0.0769	
									(0.0682)	
Decade lag	0.444***	0.447***	0.448***	0.453***	0.450***	0.445***	0.441***	0.440***	0.440***	0.439***
log county GDP	(0.0162)	(0.0162)	(0.0162)	(0.0163)	(0.0159)	(0.0161)	(0.0162)	(0.0163)	(0.0163)	(0.0165)
Two decade lag	0.0302*	0.0280*	0.0308*	0.0301*	0.0297*	0.0304*	0.0292*	0.0292*	0.0294*	0.0318**
log county GDP	(0.0167)	(0.0165)	(0.0169)	(0.0168)	(0.0170)	(0.0167)	(0.0164)	(0.0163)	(0.0163)	(0.0160)
Observations	14,415	14,415	14,415	14,415	14,415	14,415	14,415	14,415	14,415	14,398
County groups	1146	1146	1146	1146	1146	1146	1146	1146	0.968	1146
R^2 (within)	0.968	0.968	0.967	0.967	0.967	0.968	0.968	0.968	0.968	
R^2 (between)	0.492	0.515	0.529	0.495	0.506	0.494	0.485	0.486	0.490	
AB test serial corr.	0.322	0.299	0.416	0.540	0.573	0.317	0.397	0.387	0.401	0.237

Notes: This table examines which of multiple possible endowments from the origin country matter for county GDP. FE refers to fixed effects. IV-FE usesinstruments constructed using ancestry in the previous decade growing at the national growth rate excluding the county's state (see Section 5.3.1). The AB test is the p-value for the Arellano and Bond (1991) test for serial correlation. All regressions include census division by year fixed effects, county-group fixed effects, and standard errors are clustered at the county group level. Sources for origin variables are in Appendix D. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: County GDP per worker and diversity

	Dep. Variable: Log(County group income per worker)			
	FE	FE	IV-FE	FE
	[1]	[2]	[3]	[4]
Fractionalization	0.435***	0.454***	0.426***	0.494***
	(0.0777)	(0.0838)	(0.102)	(0.0934)
Origin GDP weighted	-0.477**	-0.513***	-0.589**	
fractionalization	(0.191)	(0.194)	(0.233)	
Origin GDP	0.283***	0.277***	0.288***	
	(0.0342)	(0.0369)	(0.0424)	
Migrant education				0.0401
at arrival				(0.0289)
Principal Component				0.328**
of culture				(0.143)
State history				0.313*
in 1500				(0.168)
Education weighted				1.009**
fractionalization				(0.422)
P.C culture weighted				-1.253***
fractionalization				(0.305)
State history weighted				-0.429*
fractionalization				(0.233)
Polarization		0.0311		
		(0.0441)		
Decade lag	0.439***	0.439***	0.437***	0.434***
log county GDP	(0.0165)	(0.0164)	(0.0167)	(0.0164)
Two decade lag	0.0283*	0.0284*	0.0303*	0.0297*
log county GDP	(0.0161)	(0.0161)	(0.0158)	(0.0159)
Observations	14,415	14,415	14,398	14,415
Division X Year	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes
County groups	1146	1146	1146	1146
R^2 (within)	0.968	0.968		0.968
R^2 (between)	0.539	0.535		0.550
AB test serial corr.	0.500	0.503	0.680	0.728

Notes: This table examines whether diversity of ancestry or ancestry attributes matters for county GDP. The creation of fractionalization and weighted fractionalization is described in Section 5.4. IV-FE uses instruments constructed using ancestry in the previous decade growing at the national growth rate excluding the county's state (see Section 5.3.1).The AB test is the p-value for the Arellano and Bond (1991) test for serial correlation (the test is for second-order serial correlation in the first difference of the residuals, which provides information on first-order serial correlation in the levels of the residuals). All regressions include census division by year fixed effects, and standard errors cluster at the county group level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Ancestry, occupational mix, and county GDP

Dependent variable:	Occ. Mix (broad, $\sigma = 1.5$)	Log(GDP p.w.)	Occ. Mix (narrow, $\sigma = 2$)	Log(GDP p.w.)
	[1]	[2]	[3]	[4]
Origin GDP	0.00488***	0.274***	0.00101***	0.260***
	(0.00123)	(0.0478)	(0.000222)	(0.0376)
Fractionalization	0.00864**	0.179**	0.00212***	0.0761
	(0.00356)	(0.0823)	(0.000787)	(0.0787)
Origin GDP weighted fractionalization	-0.0203**	0.251	-0.00509**	0.427*
	(0.00963)	(0.210)	(0.00190)	(0.235)
Occupation Mix (broad, $\sigma = 1.5$		5.370***		
		(0.412)		
Occupation Mix (narrow, $\sigma = 2$)				27.22***
				(2.436)
Decade lag dependent variable	0.741***	0.397***	0.707***	0.390***
	(0.0252)	(0.0251)	(0.0225)	(0.0283)
Two Decade lag dependent variable	0.0285	0.0369*	0.0487**	0.0345
	(0.0206)	(0.0207)	(0.0183)	(0.0212)
Observations	14,179	14,250	14,250	14,216
Division X Year	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes
County groups	1145	1145	1145	1145
R^2 (within)	0.835	0.968	0.969	0.968
R^2 (between)	0.625	0.324	0.139	0.259
AB test serial corr.	0.332	0.514	0.166	0.144

Notes: This table shows the relationship between county GDP per worker, the county occupation mix, and ancestry-weighted *Origin GDP*. The occupational mix in a county is measured as the Constant Elasticity of Substitution Aggregator with the elasticity σ and weights determined by the relative wages within occupations in 1940 (see Appendix F for the creation of the CES aggregator). Broad occupations are the first digit of the IPUMS codes, resulting in 10 categories, while narrow occupations are more detailed, resulting in 82 occupational categories after dropping the non-occupational response. All regressions include county group fixed effects and division-by-year effects, and they cluster standard errors at the county-group level.