Does it matter where you came from? Ancestry composition and economic performance of U.S. counties, 1850-2010

Authors: Scott Lansing Fulford, Ivan Petkov, Fabio Schiantarelli

Boston College Working Papers in Economics, 2017

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

Scott L. Fulford, Ivan Petkov, and Fabio Schiantarelli*

January 2017

Abstract

The United States provides a unique laboratory for understanding how the cultural, institutional, and human capital endowments of immigrant groups shape economic outcomes. In this paper, we use census micro-samples to reconstruct the country-of-ancestry composition of the population of U.S. counties from 1850 to 2010 and describe its evolution. We also develop a county-level measure of GDP per worker over the same period. Using this novel panel data set, we show that the evolution of a county's ancestry composition is significantly associated with changes in county-level GDP. The cultural, institutional, and human capital endowments from the country of origin drive this relationship. We also use an instrumental variable strategy to identify the effect of endowments on local economic development. Finally, our results suggest that while ancestry diversity is positively related to county GDP, diversity in attributes is negatively related to county GDP. We show that part of this relationship is explained by the close link between occupational variety and ancestry diversity.

JEL classification: J15, N31, N32, O10, Z10
Keywords: Immigration, Ethnicity, Ancestry, Economic Development, Culture, Institutions, Human Capital

*Scott Fulford: Consumer Financial Protection Bureau, email: scott.fulford@cfpb.gov. The views expressed in this paper are those of the authors and do not necessarily represent the views of the CFPB or the United States. Most of this work was completed while Scott Fulford was on the faculty at Boston College. Ivan Petkov: Northeastern University, email: i.petkov@northeastern.edu. Fabio Schiantarelli: Boston College, email: schianta@bc.edu. The authors of this paper are a descendant of the Great Puritan Migration, a first generation Bulgarian, and a first generation Italian. We would like to thank Ethan Struby, Lauren Hoehn Velasco, and Ana Lariau Bolentini for their excellent research help, and Andrew Copland and Hayley Huffman for their editorial assistance. This work has benefited greatly from the comments of participants in the Boston College Macroeconomics Lunch, the Harvard University Economic History Seminar, the University of Delaware, the College of the Holy Cross Economics Department, the EIEF and EAP OECD seminars, the Brown University "Deeply Rooted Factors in Comparative Development" Conference, the 2015 Barcelona Summer GSE forum, the 50th Anniversary Essex University Economics Conference, and the NBER 2015 Political Economy Summer Institute. In addition, we gratefully acknowledge useful conversations with and suggestions from Alberto Alesina, Oded Galor, Nathan Nunn, Luigi Pascalli, Enrico Spolaore, Francesco Trebbi, and David Weil.

1 Introduction

Over its history, the United States of America has absorbed more immigrants than all other nations combined (Barde, Carter, and Sutch, 2006). Unlike most countries composed largely of the descendants of immigrants, such as Australia or Argentina, the United States absorbed immigrants in significant numbers from a wide variety of countries (Daniels, 2002, pp. 24-25). These immigrants came to the United States from different parts of the world with diverse histories and cultures. Some were brought against their will as slaves; others decided to come for economic reasons, or seeking religious or political freedom. Once here, the immigrants and their descendants had to negotiate economic, cultural, and institutional relationships with other groups who were there before them or settled after them.

The United States thus provides a unique laboratory for understanding how the cultural, institutional, and human capital endowments brought by immigrants from their country of origin and passed on to their offspring shape economic outcomes. To understand the importance and role of different groups, we build two unique new data sets. First, we create the geographical country-of-ancestry distribution for the United States from 1850 to 2010. Using micro samples from the census and building iteratively from previous censuses, we construct the fraction of every county's population that has descended from ancestors who migrated from a particular country or region.[1] Crucially, we produce a measure of the stock of ancestry, not of the flow of recent immigrants, and so we can provide objective measures of diversity and quantitatively consider the lasting legacy on economic outcomes of immigrant groups and their descendants beyond the first generation.

The United States has become increasingly diverse in the last 160 years, both in terms of where people live and who they interact with. By 2010 the likelihood that two people drawn from the US population would be from the same ancestry was less than 10%. Indeed, our results show that, based on country of origin, the United States has not had a majority from one group since 1870

[1]Since after 1940 the data are reported only for groups of counties, we aggregate the data at that level to maintain consistency over the entire time period and use such county groups as the unit of analysis. We continue to use "county" for short. There are 1154 county groups as opposed to 3143 counties. Our county groupings approximately correspond to 1980 Public Use Microdata Areas (PUMAs), as defined by the census. See Appendix Afor details.

when the large Irish and German migration waves pushed the English below the majority. Despite the focus on recent migrants from Central America, South America, and Asia, these migrants are entering an already very diverse nation, and so overall diversity has barely increased since 1960. Yet the average American is increasingly exposed to other ancestries, which perhaps explains the attention devoted to recent migrants. Using measures of dispersion and segregation for different ancestry groups, our analysis shows that as groups enter they tend be highly geographically concentrated initially and then slowly disperse. As a result, many previously homogeneous areas are experiencing substantial diversity for the first time.

Second, we construct a measure of county-level GDP per worker that is consistently measured over the entire period and includes services. While manufacturing and agricultural output have been available at the county level, such measures miss the large and growing service sector, and so undervalue urban areas and miss the important and changing role played by the transportation, distribution, and financial sectors.

Using this novel county-level panel data set, we investigate whether changes in the composition of ancestral origin matter for local economic development, and the channels through which the historical characteristics of the country of origin affect current outcomes in US counties. It is always a challenge to cleanly identify the effects of institutions, culture, or other social factors on economic development because such factors typically evolve endogenously. This problem is particularly acute when only a single cross-section is available, since it is then impossible to fully control for the unobservable characteristics of a place. An advantage of our approach is that, by creating a long and consistently measured panel, we can remove the fixed effect of a place and examine whether and how what people brought with them is related to economic development. Moreover, the panel allows us to address possible endogeneity issues due to ancestry-specific movements in response to economic shocks.

We start by documenting that the ancestral composition of a county is significantly associated with county GDP, even after controlling for unobservable time-invariant county-level effects, census-division period effects, and even county specific trends, lagged county GDP, race, population density, and county education. This suggests that what immigrants brought with them and passed on to their children matters for economic development.

To examine the mechanism through which ancestry affects economic development in the US, we build measures of the endowments that immigrants might have brought with them. Since immigrants necessarily leave the geography of their home country behind, such attributes might include their culture, their institutional experience, or the human capital they had and may pass on to their children. When consistent and comparable historical data is available, such as for country-of-origin GDP or institutions, we are careful to associate to each group of immigrants the historical characteristics of the country of origin at the time of emigration. Moreover, for human capital we use the education of the migrant groups themselves.

Different ancestries have distinct effects on county GDP and these effects are correlated with measures of origin culture such as trust and thrift, with measures of origin institutions such as state centralization in 1500 (Putterman and Weil, 2010) and constraints on the executive, and with the human capital that immigrants brought with them. We then construct a weighted average for each county of the endowments brought by immigrants, using the fraction of people from each ancestry as weights. Changes in these ancestry-weighted measures of culture, institutions, and human capital are all significantly related to changes in county GDP per worker when controlling for county fixed effects, both in static and dynamic specifications. Many of theses results are reversed when we do not control for fixed county differences, which illustrates the importance of having a panel. This reversal reflects the fact that over the broad sweep of US history, people from high-income countries settled both in urban and rural areas while later migrants from poorer countries went predominantly to cities.

While these results establish that the endowment that people bring with them is related to local economic development, such a relationship may have different explanations. It could be that as people move, they bring a set of attributes with them which they then pass on to their children and these attributes affect the economic performance of a county. If these characteristics are time invariant, then we already control for them by including fixed effects in our estimation. However, ancestries with certain endowments may be more willing to move in response to economic shocks. For example, more trusting groups may be more willing to move to a new area or away from family to pursue new economic opportunities. We employ an identification strategy which uses ancestry in the past as an instrument for the present, as in the immigration (Card (2001), Cortes (2008), and Peri (2012)) and local development literature (Bartik, 1991). We concentrate on a dynamic model of county GDP per worker to recognize that the effects of ancestry are likely to be distributed over time and to remove serial correlation from the residuals. When the residuals are not autocorrelated, the past distribution of ancestries, possibly augmented by their growth at the national level, is not related to county level contemporary shocks to GDP and can be used as an instrument for the ancestry composition today. We also present estimates based on the dynamic panel GMM literature (Holtz-Eakin, Newey, and Rosen, 1988; Arellano and Bond, 1991). Our results are quite similar to those obtained when we do not instrument.

Finally, we provide evidence that suggests that the groups immigrants and their descendants encounter matter as well. Fractionalization, a measure of the diversity of ancestries, is positively associated with local development, whereas origin attribute weighted fractionalization is negatively associated with it. Increases in origin diversity are good for growth as long as the overall economic experiences or cultural attitudes are similar. We also investigate some of the mechanisms through which the attributes brought by immigrants affect local economic development, either through education, voter participation, or by increasing occupational variety. It appears that fractionalization works partly by increasing occupational variety which in turn increases county GDP.

The structure of the paper is as follows. In the next section we review the related literature. In Section 3, we describe how we build up the stock measure of ancestry by county from 1850 to 2010 based on census micro-samples. We also discuss the evolution of the distribution of the stock of ancestry by county for major immigrant groups. In Section 4, we outline the construction of GDP per worker at the county level. More details on the construction of our ancestry mapping and our measure of county GDP are contained in detailed data appendices. Section 5 contains the basic econometric results, while Section 6 explores the role of diversity and Section 7 contains robustness and extensions. Section 8 concludes the paper.

2 Related literature

Our results provide novel evidence on the fundamental and recurring question of whether the US acts as a "melting pot," quickly absorbing new immigrant groups, or whether immigrant groups maintain distinct identities in at least some dimensions.[2] The significance of our measure of ancestry in explaining local economic development provides further evidence against a pure assimilationist view and in favor of approaches that emphasize the persistence, at least in part, of cultural, institutional, or human capital traits across generations. If immigrants were quickly and fully integrated and homogenized into the United States, then it would be very difficult to make sense of the importance of the ancestry composition of a county, especially with regard to groups that arrived long ago.

Our work is closely related to the growing literature on the importance of history for contemporary economic development, as well as studies on migration and its consequences. Recent work has emphasized the importance of institutions and culture in shaping economic outcomes over the long run.[3] As we have argued, there are serious challenges in identifying the causal effects of culture

[2]Following the seminal contribution by Glazer and Moynihan (1963), many authors have argued that the view of the immigration experience as a process of quick assimilation into the US society is inadequate. For a review of the theoretical contributions see Bisin and Verdier (2010). For recent empirical evidence on the persistence of cultural traits beyond the first generation see Borjas (1992), Antecol (2000), Giuliano (2007), Fernández (2007), Fogli and Fernández (2009), and Giavazzi, Petkov, and Schiantarelli (2014). On whether immigrants assimilate as individuals or communities, see Hatton and Leigh (2011).

[3]See the comprehensive review by Spolaore and Wacziarg (2013) of the evidence on the role of history in economic development, on the fundamental causes of growth and on the relative importance of institutions, culture, and human capital. On the importance of of the ancestral composition of current populations see Spolaore and Wacziarg (2009), Putterman and Weil (2010), Comin, Easterly, and Gong (2010), and Ashraf and Galor (2013). On the importance of culture see Putnam, Leonardi, and Nanetti (1993), Guiso, Sapienza, and Zingales (2006), Guiso, Zingales, and Sapienza (2008), Guiso, Sapienza, and Zingales (2016), Nunn and Wantchekon (2011), Alesina, Giuliano, and Nunn (2013) and the review by Fernández (2010). On the role of institutions across countries see Knack and Keefer (1995) and Acemoglu, Johnson, and Robinson (2005a) (and the references therein to their own and other work); see Michalopoulos and Papaioannou (2013) and Michalopoulos and Papaioannou (2014) for the role of institutions at the ethnic level; and Banerjee and Iyer (2005) and Dell (2010) for the impact of within country institutions in the past. For the relationship between culture, institutions and economic performance see Tabellini (2008), Tabellini (2010), and the review by Alesina and Giuliano (2013). On human capital see Barro and Lee (1993) and Barro and Lee (1994), Gennaioli et al. (2013) and Glaeser et al. (2004) on the relative role of human capital versus other factors. A separate literature has argued for the importance of geography see Diamond (1998) and Bloom and Sachs (1998).

or institutions on economic outcomes since they are likely to be co-determined.[4] The availability of panel data is a distinguishing feature of our work since it allows us to better separate the characteristics of a place from the attributes of the people who live there and to address the potential endogeneity of ancestry composition in a dynamic context. Algan and Cahuc (2010) use changes in the inherited trust of descendants of US immigrants as a time varying instrument for inherited trust in their country of origin in order to identify the effect of changing trust on the change in country level GDP between 1935 and 2000, controlling, therefore, for country fixed effects. Our work also controls for location fixed effects, but differs from Algan and Cahuc (2010) because we use changes in ancestry composition as our key source of variation and instrument it with its past values. Burchardi, Chaney, and Hassan (2016) use a similar strategy by using past immigration flows to build an instrument for the current stock of ancestry in order to determine the effect of ancestry on foreign direct investment.

Our paper is also related to the rich literature on the effect of migration on economic outcomes in the United States, as well as work examining the determinants and importance of ethnicity and ethnic diversity.[5] Since ethnicity in the United States generally reflects a belief about shared ancestry (Waters, 1990), ancestry and ethnicity are closely related. The immigration literature typically focuses either on the characteristics and outcomes for the *flow* of immigrants or on their effects on labor market outcomes of the residents in the short term. Our focus is instead on the *stock* of ancestry and whether the attributes that immigrants brought with them and may pass on to their children affect general economic outcomes such as GDP per worker.

[4]A recent literature has examined regions within many countries to help control for unobservable country-specific effects. See, for instance, Tabellini (2010) and Gennaioli et al. (2013).

[5]The literature on the effect of immigration is very large. Goldin (1994) and Hatton and Williamson (1998) provide evidence from the age of mass migration. On later migrations, see Borjas (1994) for an early review. See also Card (1990), Altonji and Card (1991), Card (2001), Borjas (2003), Ottaviano and Peri (2012), Ottaviano and Peri (2006), and Peri (2012). On the relationship between ethnic diversity, on the one hand, and outcomes such as growth, public goods provision, education, employment, political participation, or conflict see Easterly and Levine (1997) for cross country evidence; Alesina, Baqir, and Easterly (1999) Cutler and Glaeser (1997), and Alesina and La Ferrara (2000) for evidence within the US; and Miguel and Gugerty (2005) for Kenya. Ashraf and Galor (2013) focus on the relationship between genetic diversity and economic development at the cross country level, while Alesina, Harnoss, and Rapoport (2013) present cross country evidence on the effect of birthplace diversity. Ager and Brückner (2013) examine the effect of first generation immigrant flows on fractionalization and polarization within the US. Putterman and Weil (2010) are the only ones that focus on diversity of attributes (as opposed to ethnic diversity) in a cross country setting.

In many ways, our work builds on the work of Putterman and Weil (2010) who show that not accounting for the large population movements across countries since 1500 undervalues the importance of culture and institutions. Putterman and Weil (2010) reconstruct the shares of a given country's ancestors today who came from other countries since 1500 and examine the importance of past history, as modified by migration flows, on current outcomes. Taking into account these flows enhances the ability of measures of early technological or institutional development to explain present outcomes. Our work differs from Putterman and Weil (2010) because of our focus on local as opposed to country-level development, and for our use of panel data.

3 Ancestry in the United States

There have been immense changes in the United States 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. We then examine the evolution of ancestry in the US since 1850, how it has become more diverse, and the segregation and isolation of particular groups. Our ancestry measure is representative at the county level and can be combined to give a representation of ancestry in the US as a whole or any sub-region. 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 since they start with the census micro-samples and keep track of internal migration and population growth, in addition to new immigrant flows. While previous work has examined racial groups and, in recent decades, some ethnic groups, our work is thus the first to be able to examine the full range of diversity in this nation of immigrants.

Our approach is to build an estimate of the ancestry share in each county using census questions that ask every person the state or country where she was 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 among 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 individual census information in 1850 and using the 1790 census updated with immigration records as the initial distribution. Appendix Agives 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 capture not just the fraction of first generation immigrants as in Ager and Brückner (2013), 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.

We can construct ancestry at the county level until 1940. Starting in 1950, the census only reports data for somewhat larger county groups, whose definition changes slightly over time. Because of this aggregation, our analysis centers on the 1154 county groups which allows 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.

Since both the contributions of African Americans and the legacy of slavery are so central to understanding ancestry in the United States, our analysis includes race. The census 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 before the Civil War, and the cultural, economic, and political repression that continued for more than a century following Reconstruction.

While nativity was a central concern in the early censuses, other distinctions within country of origin, such as religion or regional origin within a country, 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 migrants were Jewish, but since we cannot distinguish these migrants, all Russians are recorded as a single group. Similarly, the census does not distinguish among the African countries of origin of the slave population in 1850.

Our effort has been to reconstruct the fraction of the people in a county who come from or are descendants of people who came from a given country of origin. 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 need not be the same concept across the country even at a given time. The social construction of ethnicity does not make it any less powerful, but is necessarily an endogenous measure, responding to circumstances, rather than something than can explain other outcomes on its own. Ancestry appears to be the primary input in forming ethnicity (Waters, 1990) and so we would expect them to be highly related. Our measure of ancestry is highly correlated with self-reported ethnicity or ancestry in the 2000 census.[6]

3.1 Ancestry in the US since 1850

The narratives around migration, ancestry, and ethnicity in the United States have focused almost entirely on the immigrant experience (Daniels, 2002) and the effects of migration in the first generation (Borjas, 1990; Card, 2001) and sometimes in the second (Borjas, 1992). What is missing from most of these narratives is how later generations move and interact with other groups. Moreover, modern accounts often discuss the "white majority" as if it were monolithic, when it is instead

[6] Across counties in 2000, the correlation between the fraction that say they are of Irish ancestry in the census and the ancestry share is 0.79; for Italians it is 0.91; for Germans 0.89; for Mexicans (who are often first generation) 0.98; for Norwegians 0.95; and for Swedish 0.92 (combined, Swedish and Norwegian have a correlation of 0.96 with the combined ancestry share). For African-American the correlation is 0.99. English ethnicity is the most complicated since there is no longer much self-identification of English ethnicity, but when we include those who report themselves to be "American" the correlation is 0.93.

composed of groups, such as the Irish or Italians, that would not have been considered part of the majority when they arrived. Our work challenges this narrative by using an objective measure of ancestry, rather than the socially constructed measures of ethnicity or race that dominate the discussion in the United States. The other distinctive feature of our analysis is that we focus on the stock of people from a given country of origin, as opposed to the flow of new immigrants.

American ancestry has become increasingly diverse over time. Figure 1 illustrates this growing diversity by showing the shares of the groups that make up more than 0.5% of the population for 1870, 1920, 1970, and 2010. 1870 is the last decade that the descendants of the original English settlers still composed a majority. African Americans represented a little over 10% of the population, and recent waves of Irish and Germans migrants had increased these ancestries as well. Descendants of immigrants from Scotland and the Netherlands made up most of the remaining population.

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 when the borders were largely shut for a generation. Similarly the share of African Americans fell, not because their overall numbers declined, but because other groups entered. The new migrants were very diverse, with large groups from southern Europe (particularly Italy), from eastern Europe (particularly Poland and Russia), from northern and central Europe including the Austrians and Germans, and from Scandinavian countries.

Our work shows that there has not been a majority group in the United States since 1870. Our focus on ancestry challenges Census Bureau calculations that the United States will be a "majority-minority" in 2044 (Colby and Ortman, 2015). These calculations, which have been widely discussed, assume that the only relevant differences between groups are skin color and so ask when the "whites" will no longer be in a majority. Yet the Italians and Eastern Europeans were considered members of a different race than northern Europeans when they arrived Ripley

(1899). Similarly, the Irish faced intense discrimination, and the Germans chose to form separate communities that continued to speak German for generations rather than integrate (Daniels (2002) pp. 126 –164). None of these groups would have been considered part of the majority for a number of generations.

Immigration restrictions starting in the 1920s substantially 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. Starting in the 1960s, new groups from Mexico, Central America, and South America started to arrive. The share of Mexicans in Figure 1 grew substantially between 1970 and 2010. 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. The Mexico share of the population more than doubled from 1970 to 2010, pushing it above Italy and Ireland as the fourth largest ancestry.

In 2010 descendants from England represented just under 25% of the population, followed by the German (12.6%), African American (11.4%), Mexican (7.4%), Irish (6%), and Italian (3.8%) ancestries. In the following discussion, we show the distribution of these groups, which comprise two thirds of the total population, and their describe their experiences in more detail. Of course, each group has its own story, but these groups together capture many of the important facets of the US experience. While the Irish and Germans were the largest groups from the first wave of mass migration, the Italians were the largest group from the second wave from southern and eastern Europe that also included Greeks, Poles, and Russians, and the Mexicans are the largest group among the most recent waves of migration that have included other groups from the Americas, as well from Asia and Africa.

One way to characterize the growing diversity of the United States is by calculating how fractionalized it has become. Overall fractionalization measures the probability that two people chosen at random from the entire country will be from different groups and so gives a sense of possible interactions.[7] The top dashed line in Figure 2 shows how overall fractionalization in the US has changed over time. In 1850, the probability of two people being from different groups was approximately 60%, while the large waves of migration over the next 50 years pushed the probability over 80% by 1900. Following the slowdown in migration after 1924, fractionalization stabilized, but began increasing slowly again in the 1970s and was nearly 90% in 2010. These calculations emphasize just how diverse the United States has become from the massive waves of migration that took place at different points in time.

The overall diversity of the United States hides large differences within it. A different way to calculate overall fractionalization is to start from fractionalization at the county level and then take the population weighted average across counties. Formally, this approach captures the probability that in a county chosen randomly according to population weight, two randomly chosen people are of different ancestries. As shown in the lower solid line in Figure 2, this measure is always about 10% lower than the overall fractionalization, which shows that people are far more likely to live within counties composed more of their own group that the non-county based fractionalization would suggest. The difference between the lines shows that groups have tended to cluster, a topic we will explore more in the the next section.

Figure 2 illustrates another important dimension in which our focus on ancestry differs from the preoccupation with race and ethnicity that dominates American discourse. Despite the influx of Asian and Central American immigrants since 1970 that have been the primary focus of the recent the immigration literature, compared to the overall population of the United States these groups are still relatively small. The recent waves of migration have thus not increased overall US fractionalization by much. However, the average American county continues to become increasingly diverse, and so the average American is experiencing greater diversity. Groups have been spreading out and the new migrants are going to more varied places, and so county level fractionalization has increased at a faster pace compared to US fractionalization over the last sixty years.

[7] Fractionalization is defined as $frac_t = 1 - \sum_{a=1}^{A} (\pi_t^a)^2$. where π_t^a denotes the fraction of the US population belonging to ancestry a at time t.

3.2 The geographic distribution of ancestry in the US

Although the overall evolution of diversity of the United States is notable, its geographic diversity is even more interesting. In this section, we start with the simplest form of geographic diversity by considering which groups settled primarily in cities. Then we show the full geographic diversity in a series of maps that help us tell the stories of the largest ancestral groups.

Groups differ substantially in how urban they are and these patterns have shifted over time. For illustration, we show urbanization based on the fraction of an ancestry that lives in a county group containing a metropolitan area as defined by the BEA in 2016. Figure 3 shows the fraction of each ancestry living in an urban county over time. The US population becomes much more concentrated towards large cities from 1850 to 1970, a trend that has continued, although at a slower pace. The Great Migration of African Americans to cities in the North and Midwest is clearly evident. From 1850 to 1900, only 20% of African Americans lived close to metro areas, by 2010 they had become among the most urbanized of the major groups. The Irish and Germans arrived at the same time, but nearly 80% of Irish settled in or close to cities compared to only 70% the Germans. Finally, over 80% of the Italians in 1900 lived in or close to cities. This high rate of urbanization is characteristic of other groups in the second wave of migration as well which we do not show separately in the figure or maps to come: in 1920, 81% of Greeks lived close to metro areas, as did 81% of Poles, and 82% of Russians. The migrations since 1970 have been predominantly to cities as well. While Mexicans used to live predominantly in rural border areas, they are now much more urbanized than the average. Similarly, 78% of immigrants from India and 81% of Chinese are living in a county group with a metro area.

Figures 4 and 5 show the ancestry shares across the United States for select groups in 1870, 1920, 1970, and 2010. We concentrate on briefly telling the stories of the five largest groups in 2010 other than the English: African American, German, Mexican, Irish, and Italian, as well as the Scandinavians whose settlement patterns provide a useful comparison. Of course, it is possible to construct such maps for all groups in every decade, but some groups are too small or too concentrated to appear on a map. The maps tend to visually emphasize large and sparsely populated areas, and therefore, miss the rich diversity of the coastal cities where many more recent migrants live. Our new data are the first that can fully describe the changing geographical distributions of ancestries.[8]

Groups tend to settle together and then slowly spread out. For example, the German started in a few areas around Milwaukee, Pennsylvania, and Texas, and they subsequently spread to the entire Midwest and West. The original settlement and diffusion of Scandinavian immigrants in the upper Midwest and West is also notable. The Irish, initially concentrated in the cities of the Northeast, dispersed widely throughout the entire US. Italians, who initially settled in New York and Boston, spread to the Northeast but not far beyond, although they retain a presence in California, and a smaller one around New Orleans. Curiously, in 1870 the Italians and Irish made up a large fraction of some counties in the West which had very low populations, implying that relatively small shifts in immigrants can produce large changes in an area's ancestry composition.

The Great Migration of African Americans from the South to the cities throughout the country can be clearly seen by comparing 1920 in Figure 4 to 1970 in Figure 5, although since the maps do not depict cities well, the importance of the Great Migration is less obvious than it is in Figure 3. African Americans are still highly concentrated geographically, and have not experienced the slow diffusion that characterizes the descendants of the Germans and Irish.

The experience of the Scandinavians (combined Norwegian and Swedish) and the Germans is useful to understand how groups differ, and how important it is to keep track of internal migration in constructing a measure of ancestry. The Scandinavians and Germans settled different parts of the upper Midwest, with the Germans, who arrived earlier, dominating the eastern side along Lake Michigan and the city of Milwaukee. However, while the Germans maintained a strong presence in their initial areas of settlement, the Scandinavians have become increasingly diffuse and no longer dominate the areas where in 1920 they were the majority (see the maps in Figures 4 and

[8] An alternate way of examining the ancestry distribution across the U.S. is in appendix Table A-1which shows in the same years the share of each census region composed of the six largest groups, and Table A-2which shows what fraction of the total population of an ancestry lives in each census region. In 2010, for example, nearly 30% of Italians still lived in the Middle Atlantic, down from 56% in 1920 (Table A-2), but they accounted for only around 10% of the Middle Atlantic population in either year.

5). Since immigration from Germany and Norway or Sweden had largely ended by 1900, all the changes come from internal migration as Scandinavians moved away or other groups entered, while Germans continued to maintain a concentrated presence.

3.3 Group dispersion and measures of segregation

How dispersed or concentrated groups are is important for understanding the effects of where people live. Most studies focus on whether the residents of urban areas group together by race (Cutler, Glaeser, and Vigdor, 1999), although it is also possible to examine recent migrants or self-reported ethnicity (Borjas, 1995). Since our paper is the first to measure ancestry, our calculations are also the first to examine segregation at the county level across the US and over time.

There are several common measures of segregation or separation which measure slightly different aspects of group dispersion (Massey and Denton, 1988). We focus on the two most widely used measures that are relevant for dispersion of groups across counties. Dissimilarity measures how much of a group would have to move to equalize its share across all counties. If a group is highly geographically concentrated, then most of its members would need to move to equalize its geographical distribution. An alternate measure of segregation is how exposed or isolated a group is from other groups (Massey and Denton, 1988). Isolation is the opposite of exposure to other groups. Isolation measures the probability that a randomly chosen person from a given ancestry will be of the same ancestry as someone else chosen at random from the same county.[9]

Figures 6 and 7 show how these measures of ancestry segregation have evolved over time

[9] The dissimilarity of an ancestry a with share $\pi^a_{c,t}$ in county c with population $Pop_{c,t}$ at t, and overall share of the US population π^a_t, is the fraction of that ancestry that would need to move compared to the maximum that would need to move if segregation is as large as it could be, and so gives the dissimilarity index:

$$D^a_t = \frac{1}{2(1-\pi^a_t)Pop^a_t} \sum_{c=1}^{C} Pop_{c,t} |\pi^a_{c,t} - \pi^a_t|.$$

The isolation measure is just the weighted average across all counties of the share of ancestry a. Since the probability that someone else chosen from county c at time t will be of ancestry a is $\pi^a_{c,t}$, its definition is:

$$I^a_t = \sum_{c=1}^{C} \frac{Pop^a_{c,t}}{Pop^a_{US,t}} \pi^a_{c,t}.$$

for the major groups. The English were initially relatively evenly distributed and have continued to be so. The Irish and Germans, on the other hand, were initially more concentrated than the English, although they concentrated in different areas, and have since become even more evenly spread than the English. Italians were initially very highly concentrated—around 60% would have had to move in 1900 to equalize their share—but have slowly spread out. African Americans have become somewhat less segregated by county over time during the Great Migration. Until 1920, African Americans were highly concentrated in rural areas of the South. The Great Migration brought them to cities around the country, but not much beyond the cities, leaving them still highly concentrated. Importantly, after the decrease in segregation during the Great Migration, African American segregation has not changed much since the 1950s. Of course, within-county segregation may have been increasing or decreasing, even while across-county segregation was constant. Mexicans were once almost entirely living in areas that had been part of Mexico before the Mexican-American War (1846-1847) and the Gadsden Purchase (1854). Later migrations have been mostly to major cities, leaving Mexicans the most concentrated of the major groups.

Figure 7 shows that most groups are far less isolated than they once were, and so are increasingly exposed to other groups.[10] Dissimilarity and isolation capture different elements of segregation. Perhaps the best illustration is the different starting points of the English and Italians and how they have evolved. Large numbers of Italians came and settled mostly in cities along the East Coast making their geographic dispersion very compressed and so highly dissimilar. Even though they were gathered together, because they were in large cities, they were typically a small fraction of the total population, and so were necessarily exposed to many other groups and showed low isolation. As the original settlers, the English were quite dispersed, and so show low geographic dissimilarity. In spite of their dispersion, given their numbers they were typically the largest group in an area, and so the average person of English ancestry did not necessarily encounter people from other ancestries frequently. The English were therefore not dissimilar, but generally isolated, while the Italians were highly dissimilar, but not isolated at all.

[10] Changes in 1850 and 1860 are largely driven by changes in the covered county groups and so are not particularly meaningful.

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, measures of income are available at a county level. Prior to 1950, however, the census only recorded information at the county level on manufacturing and agriculture. The main challenge is to provide an estimate of GDP for services, construction, and mining. Adjusting for these components is very important 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 from 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 construct 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 in order to allow the productivity of a worker in each sector to vary by location.[11] 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 full 1940 census and we use the same allocation for the adjacent decades of 1950 and 1930 when there is much sparser wage information. For the earlier decades, for which we have some information on wages within each sector only at the state level (or for the major city within a state), we combine this historical information with the detailed wage distribution available for the full sample in 1940

[11]We show in Appendix Bthat 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 US.

to obtain a wage distribution that is specific to a given state and allows for difference 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 a 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 Ancestry Vector. We convert nominal GDP to real GDP using the price deflator from Sutch (2006). In our analysis, we will allow in most specifications for year effects that are census division specific which absorb any census division differences in the evolution of the GDP deflator. We finally 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.

5 Does ancestry matter and why?

Combining our measure of the ancestry makeup of each county with our measure of county income, we ask whether ancestry matters for local economic development and which attributes brought by the immigrants from the country of origin play an important role. What is crucial about this exercise 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 the association between ancestry composition and economic development controlling for time invariant county characteristics. The omission of unobservable time invariant county characteristics is a key source of omitted variable bias that prevents one from deriving any causal conclusions on the effect of ancestry on local development from the existence of a cross sectional correlation. We start, therefore, by asking whether the evolution in ancestry composition is significantly related to changes in county GDP, controlling for county fixed effects. We do this first in an unrestricted model in which the fraction of each ancestry enters with a separate coefficient. We then examine which attributes brought from the country of origin help to explain this association by relating the ancestry-specific coefficients to a set of economic, institutional, and cultural characteristics of the country of origin and to the human capital of the immigrants. We then develop summary measures of the endowments brought by immigrants and assess their correlation with local economic development in our panel.

Even after controlling for fixed county effects, there remains the potential for endogeneity issues in assessing the effect of ancestry on development if people move in response to economic shocks in addition to the time-invariant county characteristics for which we control. To address this concern, we use an instrumental variable strategy based on the past distribution of ancestries. The absence of auto-correlation in the error process of the GDP equation is essential for this strategy to be justified and this motivates the importance of allowing for a rich dynamic specification and of testing for serial correlation.

In this section we are primarily concerned with how the attributes brought by each immigrant group from the country of origin contribute to the *average* endowment of a county. In section 6 we also consider how *diversity* in ancestry composition is related to local economic development. Section 7 contains additional robustness exercises and further evidence on the possible mechanisms through which the various characteristics brought by immigrants can affect local development. 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 period difficult; and (2) the iterative construction means that in 1870 the ancestry shares are based on more decades of micro-sample information.

5.1 Is ancestry composition associated with economic development?

We begin by investigating whether ancestry is correlated with local economic development in the context of an unrestricted econometric model that allows the effect of each ancestry to be captured by a different coefficient and so test whether ancestries are different along any economically relevant dimension. Our ancestry share π^a_{ct} gives the share of the population of county c at time t

whose ancestors came from a particular ancestral country-of-origin a out of all possible ancestries A. Note that the sum of all shares in county is one by definition. In the text, we continue to use "county" for the county groups that are our unit of analysis. We start with a series of estimates of the effect of ancestry on log county GDP per worker y_{ct} of the form:

$$y_{ct} = \theta_c + \lambda_t + \sum_{a=1}^{A} \alpha_a \pi_{ct}^a + \gamma X_{ct} + \epsilon_{ct}, \tag{1}$$

where each ancestry is allowed to have a separate coefficient, α_a. All specification include county fixed effects θ_c and year effects that can be either common (λ_t), census division specific (λ_{dt}), or state specific (λ_{st}).[12] Some specifications include additional controls X_{ct} such as population density to reflect time-varying urbanization rates, lags of the dependent variable, and measures of education.

The results for many variations of equation (1) are shown in Table 1. The first set of regressions in columns 1 through 3 of Table 1 do not have variables other than the fraction of each ancestry and different combinations of county effects, year, year-division, or year-state effects. The remaining four columns add to the specification with division-year fixed effects different combinations of county trends, two lags of county GDP, education, and population density. The table shows the F-statistic for the joint test that all α_a are equal (each ancestry matters equally for GDP).[13] We also separately test the hypothesis that all ancestries other than African American and Native American have equal coefficients to examine whether the results are purely driven by race. Below each F-statistic we report its p-value. They are all zero to more decimal places than can fit in the table.

Every specification, therefore, strongly rejects 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 can also ask whether regional trends—which might reflect evolving

[12] The nine census divisions are: New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, Pacific.

[13] Since individual effects for very small ancestries 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 tests, therefore, is whether the coefficients for the other ethnicities are jointly zero.

factors, such as industrial structure, that may be related both to county GDP and ancestry composition—may affect our answer. However, the inclusion of division or state-specific period effects or county-specific trends leaves the significance of the ancestry composition intact. Our conclusion that ancestry composition matters is also robust to the adding two lags of county GDP as a regressor. The last column also include 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 why ancestry may be related with economic development. For example, some groups may tend to put more emphasis on education than others. Similarly, an increase in density may reflect a higher level of urbanization of the county, resulting in a differential attraction for different immigrant groups. The ancestry coefficients continue to be significantly different from from one another even after including these controls, and so ancestry composition seems to matter beyond its relationship to education or urbanization.

5.2 Why is the association significant? Correlating the ancestry coefficients with country-of-origin characteristics

Which attributes and characteristics brought from the origin country help explain the association between ancestry and development? We divide the endowment brought by immigrants into four broad categories: summary measures of past economic development, institutions, social capital or culture, and human capital. Together with geography, these categories encompass the main drivers of economic growth that have been proposed in the literature. Geography of the country of origin is necessarily left behind when migrating, and so can only express itself indirectly through what immigrants bring with them. The main limiting factor in the analysis is the availability of information for a broad range of countries over different 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, particularly in the distant past, is not always available or reliable. Where necessary we attribute some characteristics from one origin country to a nearby one to attain full coverage. The full details are in the appendix. We only show results for origin variables that cover over 99% of the population in every county. Summary statistics for these variables appear in Table A-3in the appendix.

Immigrants arrived at different times and we would like to capture what immigrants brought with them by the conditions in their country of origin at the time of immigration. Doing so requires knowledge of the conditional density of immigration over time so that, for example, we can account for the fact that the Irish coming in the 1850s reflect a different experience than the Irish in the 1890s. Changes in our ancestry measure or in the number of first generation migrants reflect both increases from migration and natural changes from births and deaths, and so are not an accurate measure of the flow of migrants. We therefore turn to immigration records that contain the number of migrants arriving from different countries at the national level. The full procedure is described in Appendix C.

With a density of arrival times, we can construct country-of-origin measures that take into account the distribution over time of migration flows and so associate to groups what they could have brought with them. Of course, this procedure is only possible if we observe country-of-origin measures that change over time. For arrival-weighted variables we consider the endowment of the country of origin relative to its value in the United States on arrival. For example, we want to take into account that the original English settlers came from a country that was poorer in real terms in the 1700s than the countries of some of later immigrants, but the English were much closer to the production frontier at that time. For education, we can go even further and examine the education levels of the immigrants themselves.[14]

The ancestry effects appear to be closely related to economic conditions in the country of origin as measured by historical GDP of the country of origin, weighted by the arrival density, as can be seen in Figure 8. The relationship between the ancestry coefficients and country-of-origin GDP is

[14]Given a country-of origin measure z^a_τ for ancestry a at the time τ of arrival, the arrival weighted version of this variable is:

$$\hat{z}^a_t = \sum_{\tau=0}^{t} z^a_\tau (1-\delta)^{t-\tau} F^a_t(\tau) \quad (2)$$

where $F^a_t(\tau)$ is the arrival density of group a up to time τ, which is is 0 for $\tau > t$, and δ is the rate of depreciation of the importance of the origin. For example, $\hat{z}^a_\tau$ for arrival weighted GDP is the difference in log GDP per worker in the origin and the US, and for education it is the ratio of immigrant's education to US education at the time of arrival.

positive and significant.[15] We think of GDP in the country of origin as a summary measure of all of the cultural, institutional, and human capital elements that lead to economic success at a given time. Migrants from an origin where these elements are present appear to have brought with them whatever mix is important for economic success.

However, we want to go beyond GDP of the country of origin as a synthetic measure of the endowment brought by immigrants to the US. In the second panel of the Figure 8, we show the relationship between the ancestry coefficients and the arrival density weighted ratio of the immigrants' average education to the overall education in the United States at the time of arrival, based on information on literacy and, later, on years of education contained in the census (see Appendix D.3for the construction of the migrants' education, and Appendix C for how it is combined with arrival density). The migrants' education has a positive and significant relationship with ancestry, suggesting that the human capital endowment of immigrants matters.

In the third panel of Figure 8, we plot the relationship between the ancestry coefficients and a possible measure of institutions at the national level, namely the State History variable from Putterman and Weil (2010). State History reflects how long a particular state has had centralized government in 1500 and shows a strong positive and significant association with the ancestry coefficients.

Immigrants also brought with them a set of cultural attributes that can affect their ability to function productively in the area where they settle. If those attributes are passed down, at least in part, to their descendants, this would contribute to explaining the significance of ancestry. To measure cultural attributes we use the World Value Survey which asks a representative sample of respondents in numerous countries a wide variety of questions about their attitudes and beliefs. Optimally, we would want a measure of the culture at the time of departure, but these surveys are available for a large number of countries only starting in the 1980s or 1990s. For recent surveys to tell us something about past culture, one needs to assume that the relative ranking of countries in

[15] The slope coefficients are estimated using Weighted Least Squares to down-weight the ancestries that are less precisely estimated. We use analytic weights defined as the inverse of the estimated standard deviation for each ancestry coefficient. The relationship is similar using other measures of country-of-origin GDP, such as 1870 GDP or GDP in 2010, and when we allow some degree of depreciation of arrival GDP.

more recent decades captures, albeit imperfectly, their relative position in earlier times. This would be true, for example, if some cultural attitudes are fixed or very slow changing, or if they responded to common factors that made them move at a similar pace in different countries. Moreover, one may also want to allow for regional differences in cultural attitudes within countries. However, the census does not provide information on immigrants' region of origin. Appendix D.2discusses our construction of several of the variables Guiso, Zingales, and Sapienza (2008), Tabellini (2010), and others have proposed might be important for economic development.

The last panels of Figure 8 report the results for Trust; for the the principal component at the individual level of Trust, Obedience, Respect, and Control as a summary measure of cultural values important for cooperating with others suggested by Tabellini (2010); and for Thrift. The coefficients are positively and strongly significantly associated with Trust and with the principal component of culture. The association is also positive for Thrift, but it is not significant at conventional levels.

While our choice of variables is constrained by data in the country of origin, other possible variables suggest a similar relationship. Appendix Figure 8 shows that 1870 GDP, origin country education levels, political participation at arrival, and constraints on executive at arrival are all positively and significantly related to the coefficient of each ancestry.

5.3 A parsimonious representation of ancestry endowments and county GDP

Having identified a set of origin country attributes that are correlated with the ancestry specific coefficients, we examine the association between ancestry composition and economic development in a more parsimonious manner by assuming that each ancestry coefficient is proportional to such attributes. Some characteristics, such as the origin GDP at the time of arrival vary both with time and ancestry. For these characteristics, we define the county average endowment as:

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

We can think of z_{ct} as the average or predicted value, across origin countries, of the endowment of a given characteristic z_t^a for county *c* at year *t,* where the italics denote the endowment variable weighted by the ancestry share, and upright case letters the endowment characteristic itself. For variables for which we do not observe changes over time in the origin country endowment, such as culture and state history, z^a is constant over time, and so the county endowment changes only from changes in ancestry composition.[16]

While we focus on the following variables that appear particularly significant in Figure 8, we have examined other variables defined in the same way that appear in the tables and appendix. *Origin GDP* is the ancestry weighted log difference between GDP at the time of arrival and United States GDP, weighted by the density of arrival times up to time *t* (see footnote 14). *Migrant Education to US ratio at arrival* is the ancestry weighted ratio of immigrants' to US education at the time of arrival, also weighted by arrival density. More straightforwardly, *Trust* and *State History in 1500* are the county ancestry weighted versions of these variables since they vary only by ancestry, not time.

Our typical regression asks how well we can predict county GDP per worker using the ancestry composition and country-of-origin characteristics, and so takes the general form:

$$y_{ct} = \theta_c + \lambda_{dt} + \beta z_{ct} + \gamma X_{ct} + \epsilon_{ct}, \tag{4}$$

where we include county group (θ_c) and division-year effects (λ_{dt}). In some specification, z_{ct} will be a vector of the ancestry-weighted values of the endowment of several characteristics. 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.

Our analysis proceeds by introducing progressively more complicated versions of equation (4). We will start by using origin GDP at the time of arrival as a summary measure of the endowment of attributes brought by immigrants and then analyze the role of culture, institutions, and human

[16]Putterman and Weil (2010) form a similar construct at the country level in 2000 for state centralization in 1500 and years since the introduction of agriculture, using population shares adjusted for migration flows since 1500.

capital. We begin by comparing fixed effects to OLS results in a static model to demonstrate the importance of having a panel, but quickly move to a dynamic specification. In this context we we will also address the problem of endogeneity and Nickell (1981) bias.

5.3.1 Changes in ancestry composition and economic development

Table 2 shows a series of regressions of the form of equation (4) for ancestry-weighted *Origin GDP per capita*. Table 3 repeats the same exercise for cultural, institutional, and human capital attributes when they are included one at a time and Table 4 when they are included all together. For each ancestry-weighted variable we present a series of specifications all of which include census-division-specific year effects. Since much of the variation in the effect of ancestry is likely to be felt across regions, including cesus-divisions-year effects removes some of the variation, but ensures that the estimates are not driven purely by differential regional trends.[17] In some specifications, we allow African Americans and Native Americans to have an unrestricted coefficient since 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] In all specifications except one, we include county fixed effects (denoted FE in the tables). Standard errors are clustered at the county level, except in the last column of Table 2 where they are clustered at the state-year level.

Using 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 (*the ancestry-weighted log origin GDP per capita relative to the US weighted by arrival density) is positive and significant at the 1% level. The effect is rather large, since the estimates imply that if 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

[17] 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.

[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 as well.

effects, the association is negative and significant in column 2 without county county fixed effects.

What explains this negative correlation when we do not control for county fixed effects, which is not what one would expect if prosperous areas attract prosperous people? 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 US, they are disproportionately present in rural areas in the poor South and Appalachian states which received little migration after their first settlement. Later migrants, such as the Italians or Irish, while poor 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. The differences between the estimates that use the variation over time within each county and those that rely mostly on the cross-sectional variation suggest that the availability of panel data is very important for understanding the effects of ancestry on development. Much empirical work on culture or ancestry cannot distinguish between the effect of the place and of the people that live there. The negative cross-sectional relationship between *Origin GDP* and county GDP reflects the settlement patterns specific to the United States and what part of the frontier was open when a large migration occurred or where a group was forcibly resettled. However, the point that estimates based on cross-sectional variation do not allow one to disentangle the effects of ancestry composition on development from that of factors inherent in a place is more general.

Since the effect of changes in ancestry may take some time to be fully felt, in the last three columns of Table 2 we show a dynamic specification including two lags of county GDP per worker. Since our specification includes fixed effects, there is a possibility of Nickell (1981) bias when we introduce lags of the dependent variable. We will address this issue later and show that our conclusions remain mostly unchanged (see Section 5.3.2). When we include two lags of county GDP in column 3 of Table 2, the impact of changes in *Origin GDP* within one decade is significant and nearly the same size as the static estimate in coefficient in column 1. Because we have introduced dynamics, the full effect of a change in ancestry takes some time to be felt.[19] In the dynamic spec-

[19]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,

ification, given the sum of the coefficients of the lagged dependent variable, the long run effect of a permanent change in *Origin GDP* is approximately twice the size of the impact effect. Since the estimates include county fixed effects, this estimate is identified as the composition changes over time, not just from the cross-section.[20] Finally, since the country-of-origin endowments used for African-American and Native Americans are speculative, column 4 shows the the results obtained when the fraction of each of these groups are included as additional regressors. 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.

The basic conclusions reached using *Origin GDP* also hold using endowments based on measures of culture, institutions, or human capital in Table 3. More specifically*, Trust,* the *Principal Component of Culture, Thrift, State History in 1500* from Putterman and Weil (2010), *Executive constraints at arrival* (obtained combining Polity IV and Acemoglu, Johnson, and Robinson (2005b)), and *Migrant education-to-US ratio at arrival*, are all positively and strongly associated with county GDP in both the static and dynamic specification with fixed effects.[21] Moreover, the coefficients in the OLS specification without county effects are always very different from those obtained including fixed effects, and in all cases but one, they are negative. Finally, including the fraction of African Americans and Native Americans reduces the size of the endowment coefficients, but leaves them significant at least at the 1% level with the exception of *Executive constraints at arrival* and *Thrift,* which are now significant only at the 10% level.[22]

Table 4 (see columns 1 through 4) combines a selection of the endowment measures used so

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.

[20]The results are similar in terms of significance when using the ancestry-weighted 1870 GDP.

[21]*State History in 1500* is constructed as an index varying from 0 to 1. So a 1 percentage point (0.01) increase in the index brings approximately the same increase as a 1% (0.01) increase in county GDP per worker. We use the Putterman and Weil (2010) measure version 3 with a depreciation of 5% of state history in the past.

[22]The values for historical GDP, culture and institutions we assign in constructing the endowments for these groups are necessarily imprecise, and it is important to point out that the results are not coming just from these groups. With regard to trust, note also that West Africans today have low trust as measured by the World Values Survey, at least partially as a consequence of the slave trade (Nunn and Wantchekon, 2011). The long-term consequences for trust on the descendants of those actually enslaved may be even worse.

far to examine which measures remain significant once they are included together as explanatory variables. Given the significance of lagged values of county GDP, we focus on the dynamic specification only and always include fixed effects. Column 1 repeats our preferred specification for *Origin GDP* for reference (column 3 in Table 2). When we include together measures of culture, human capital, and institutions, the coefficients on *Trust, Migrant education,* and *State History in 1500* remain significant at the 1% level.[23]

These results suggest that multiple endowments play a role in development, although we should not over-interpret them to conclude that these endowments are the only ones that might matter. When our summary measure, *Origin GDP,* is also included with measures of culture, human capital and institutions in column 3, it is not significant and small, and the results do not change for *Trust* and *State history in 1500*, but now the coefficient of *Migrant education* is significant only at the 10% level. It appears that these imperfect measures of endowments capture the different dimensions of economically significant endowments fairly well. Another possible measure of institutions, *Executive constraints at arrival* is not significant at conventional levels (and has a negative coefficient) when included together with *State History in 1500*, while the latter remains positive and significant at the 1% level.

The size of the coefficients matters as well as their statistical significance; all of the variables have a large effect both in the short and long term. Using the interquartile ranges in appendix Table A-3and the coefficients in column 2, moving from the 25th percentile to the 75th percentile county in *Trust* raises GDP per worker by 5.5%, on impact. A similar change for migrant education is associated approximately with a 3.5% increase in county GDP per worker, while the figure for S*tate History* is 4.6%. Given that the sum of the coefficients of the lagged dependent variables is close to 0.5, the long run effect of a permanent change in any of the endowments is approximately twice their impact effect.

[23]We obtained very similar results using the principal component of culture instead of *Trust*, but report the results for *Trust* since it is more straightforward to interpret. *Thrift* did not play a significant role when included.

5.3.2 Sorting, endogeneity and instrumental variables estimates

So far, we have documented a robust association between ancestry composition and county GDP controlling for county specific effects. The association could come from two sources: (1) when people with certain characteristics move to a county, its GDP changes, or (2) people with certain characteristics are attracted to a county whose GDP is changing. It is worth noting that there is only a reverse causality problem if people move immediately in response to shocks. If it takes a decade for them to move then, provided the error term in the GDP equation is not serially correlated, there is no simultaneity bias. Moreover, even if people move immediately, the direction of any bias in estimating the effect of ancestry on GDP is ambiguous. For example, it could be that a booming county disproportionately attracts immigrants who are poorer, since they are the ones with greater incentives to move, in which case the effect of ancestry may be under-estimated. The cross-section results shown in the second column of Table 2 supports this observation that people from poorer countries end up in richer counties on average. A counter argument is that the most mobile people may be those with the highest education and most geographically diverse social networks, and so the effect of ancestry may be over-estimated.[24]

The fixed effects remove and control for all fixed unobserved characteristics of a place that may induce a person to move. In trying to identify the effect of ancestry composition on local GDP, it is not a problem, for example, if the immigrants from a poor country tend to go to cities with ports that require manual laborers, as the presence of a port is largely fixed. Similarly, if Norwegians go to places in the Upper-Midwest whose cold ecology they are familiar with, the fixed effect removes climate and geography. As we have shown in section 5.3.1, it is extremely important to control for county fixed effects since people from richer countries tended to settle in relatively poorer counties. Yet the fixed effect estimates do not address the possible contemporaneous correlation

[24]Note that the problem with selection is not that the poor, or rich, within each ancestry are the ones that are more likely to move if ancestries are equally affected. Instead, the problem is that ancestries with specific characteristics may be more mobile on average. For example, suppose ancestries with low trust are more willing to move since they have lower attachment to a local community. Since trust is likely to have a positive effect on local development, but low trust ancestries are more likely to move to booming counties, the within estimates will tend to underestimate the impact of trust on local development.

between *shocks* to county level GDP per worker and ancestry composition.

A simple instrumenting strategy is to use the lagged value of the endowment variables z_{ct-1} as an instrument for their contemporaneous value in the dynamic model. 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 since it takes Germans to make Germans. Therefore the lagged value of each endowment variable is likely to be an informative instrument for its contemporaneous value because past ancestry shares are informative about their present value. When the country of origin characteristic is fixed, using the lagged ancestry shares is actually exactly equivalent to lagging the endowment variable. A variant of this strategy is to build an instrument of the endowment variable using past ancestry shares, adjusted by the national growth rates for each ancestry, building on the basic instrumenting strategies of the recent immigration literature.[25]

The absence of autocorrelated residuals is essential for our identification strategy. If the shock in one period is correlated with shocks in previous periods, then it will also be correlated with lagged values of the regressors. For this reason, we are careful to instrument only in dynamic models and we test for the absence of serial correlation in the estimating equation.[26] We first instrument for the ancestry-weighted endowment variables in the model with fixed effects, including two lags of the dependent variable. Finally, we examine endogeneity issues in the context of short panels that can also deal with Nickell (1981) bias (Holtz-Eakin, Newey, and Rosen, 1988; Arellano

[25]More specifically, in the latter case we start with the population $P^a_{c,t-1}$of ancestry a in county *c* at time *t-1* and construct its predicted value at time t if in each county the population grew at the national rate for each ancestry, g^a_t, to obtain $\tilde{P}^a_{c,t} = P^a_{c,t-1}(1+g^a_t)$. Summing over all the ancestries we can obtain the predicted growth rate of the total population in each county, $\tilde{P}_{c,t}$. The projected share of ancestry a 's population in each county,$\tilde{\pi}^a_{c,t}$, is then $\tilde{\pi}^a_{c,t} = \frac{\tilde{P}^a_{c,t}}{\tilde{P}_{c,t}} = \pi^a_{c,t-1}\frac{1+g^a_t}{\sum_{a=1}^{A}(1+g^a_t)\pi^a_{c,t-1}}$. Note that $\tilde{\pi}^a_{c,t}$ does not use any county specific information from decade t and will be used (instead of $\pi^a_{c,t}$) in the construction of an instrument for expected endowments. To use these shares to construct instruments, we also make the very reasonable assumption that no single county plays a dominant role in attracting people of a given ancestry. For examples of constructing instruments for the contemporaneous stock of immigrants, see, for example, Cortes (2008) and Peri (2012). Peri (2012) allows for a dynamic specification of the estimating equation by including the lagged dependent variables. They build on Card (2001), who estimates a static model, although he briefly discusses the importance of lack of serial correlation in the estimating equation. A related strategy is also used in the local development literature to instrument for labor demand shocks, see Bartik (1991) and Blanchard and Katz (1992).

[26]In spite of the centrality of lack of serial correlation, the literature often fails to conduct such tests or include lags.

and Bond, 1991).

In columns 5 through 8 of Table 4 we report the instrumental variable estimates of the dynamic fixed effect model. IV-FE denotes the estimator that uses one lag of the endowment variable as instrument, while Bartik IV-FE denotes the estimator based on the lagged ancestry shares augmented by the national growth rate of each ancestry. The two estimators produce nearly identical results and the first stage regressions in both cases suggest that our instruments have strong explanatory power for the corresponding ancestry-weighted endowment variables.[27] In other terms, there is no gain in adding information about the national growth rates of ancestries and most information is contained in the lagged ancestry shares. For this reason, from now on we will only report the the estimates that use the lagged value of the endowment variables z_{ct-1} as an instrument, which are based on lagged values of ancestry shares.

Most importantly, the instrumental variable estimates yield coefficients on the endowment variables that are in most cases quite similar to those obtained using the fixed effects estimator.[28] If anything, the instrumental variable estimates are slightly larger which is compatible with the presence of measurement errors that create an attenuation bias or with a small negative geographical sorting effect in which booming counties attract ancestries with slightly worse attributes. The coefficient of *State History in 1500* is now smaller and significant only at the 10% level. In all cases, including two lags is sufficient to remove serial correlation using the Arellano and Bond (1991) test based on differences of the residuals.[29] This is important because the absence of serial correlation of the residuals is essential for our instrumenting strategy.

With a relatively short panel (T=15), including the lagged dependent variable with fixed effects may generate estimates with a downward bias (Nickell, 1981). The within transformation removes the mean from each county, and so introduces the error from all periods into every period. For

[27]In the first stage, the t statistic on the additional instrument in both cases has P-values that equal zero to the fourth decimal point.

[28]Including a one decade lag of the average neighboring counties' log GDP as an additional regressor leaves the results unchanged. Its coefficient is minuscule and not significant.

[29] In first differences one expects first order serial correlation if the error term in the level equation is white noise, but not second-order serial correlation. Second order serial correlation would invalidate the use of once-lagged variables as instruments.

a short panel, the within transformation introduces bias in the estimate of the coefficients of the lagged dependent variables and of weighted endowments, since it invalidates the exclusion restriction of our lagged instruments. When T is large, these problems disappear, but while our panel covers a long time, it has only an intermediate number of periods, and so there may still be a problem. In the last columns of Table 4 we address both these issues by using the GMM approach to the estimation of short dynamic panels with large N proposed by Holtz-Eakin, Newey, and Rosen (1988) and Arellano and Bond (1991). The basic idea is to use transformations other than the within transformation, such as first differencing or forward orthogonal deviations, that allow one to use appropriately lagged values of the regressors as instruments.[30] We present results based on the forward orthogonal deviations.

Most of the conclusions we have reached so far remain unchanged using GMM. The estimate of the coefficient on the lagged dependent variable are now slightly larger, compatibly with the existence of a small-T bias. The coefficients of the endowment variables are sometimes smaller, but their significance level remains very similar to that of the IV-FE estimates, with the exception of the one of migrants' educational endowment.[31] Moreover, across all of the specifications the long run effect of a permanent change in expected endowments is nearly identical. For instance, for *Origin GDP* the long run effect is 0.59 in column 1 with fixed effects, 0.63 in column 5 with the instrument, and 0.56 for the GMM-FOD estimates of column 8. Again, in all cases the Arellano and Bond (1991) test for serial correlation of the residuals in differences suggests absence of serial correlation. With two lags of county GDP, we do not find evidence of second order serial correlation, which is necessary for the validity of our instruments.[32] Moreover, the test of

[30]The forward orthogonal deviation transformation subtracts from the value of a variable the forward mean (and rescales the results appropriately). This transformation has the property that if the original errors are i.i.d., they maintain this characteristic after the transformation. Twice or more lagged values of z_t^a and y_{ct} are legitimate instruments in this context.

[31]The non-fully-robust result for education may be related to the results in Bandiera et al. (2015). They find that the introduction of compulsory schooling laws in the US in the period from 852 to 1920 occurs earlier in states with more migrants from European countries without compulsory schooling. The level of education of migrants may have therefore a complex effect on local development. However, in Sectionon 7.2 (see Table A-8) we show that an increase of the stock of descendants from richer countries (likely to have higher levels of education) lead to an increase in county level education, using the dynamic fixed effect specification. This issue deserves further investigation.

[32]Note that our instrumenting strategy can also deal with the issue of measurement error in the ancestry-weighted variables. The lack of second order serial correlation in differences suggests that there is no substantial measure-

over-identifying restrictions (Hansen test) does not suggest model mis-specification in any of the equations, supporting the use of lagged values as instruments.

6 Ancestry and diversity

Until now we have examined the average of the attributes people in a county might have received from their ancestors. However the *diversity* of ancestries may be as important as the weighted average of those attributes. In this section, we conduct an initial exploration of this issue in the context of the dynamic model with fixed effects. 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:

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

Recent work has generalized this index by allowing it to incorporate measures of distance between groups (Bossert, D'Ambrosio, and La Ferrara, 2011). We define a measure of similarity based on the difference of some country-of-origin measure z between group j and group k as $s_{ct}^{jk} = 1 - |z^j - z^k|/r$ 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 one. Then a generalized fractionalization index is:

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

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 ($s^{jk} = 0$ for $i \neq j$).

ment error component in county GDP or a moving average component in the ancestry variable. Had we found such components, they could have been dealt with by further lagging the instruments.

Table 5 reports the results when we include measures of fractionalization in the dynamic model. Column 1 shows the fixed effects estimates including fractionalization, and origin-GDP-weighted fractionalization and *Origin GDP*, column 2 the estimates with instrumental variables, and column 3 the GMM estimates. In all of the approaches, the coefficient of fractionalization is positive and significant, while the coefficient of origin-GDP-weighted fractionalization is negative and significant. Going from the 25th to the 75th percentile for fractionalization is associated with a rise in GDP per worker on impact of almost 10% while going from the 25th to the 75th percentile of origin-GDP-weighted fractionalization reduces GDP per worker by almost 5% (see the summary statistics in appendix Table A-3). The long run effects are approximately twice as large.

In the remaining columns of Table 5, we include the expected endowments for *Trust*, *State History* and for *Migrant-education-to-US ratio at arrival* together with fractionalization (column 4) and with both fractionalization and each attribute-weighted fractionalization (column 5). The coefficients of *Migrant-education-to-US ratio at arrival* remains positive and significant in both cases, while the significance of the coefficient of *Trust* and *State History* depends upon the exact specification. In the more general model with fractionalization and attribute-weighted fractionalization, the coefficient of *Trust* is significant, while the one of *State History* is not. Of the attribute-weighted fractionalization measures, only the one constructed using Trust is significant with a negative coefficient. All of the measures of ancestry endowment, and particularly their fractionalizations, are strongly correlated, as shown in appendix Table A-4, and so it is not clear that the effects of the weighted fractionalizations are cleanly separately identified. In all cases, fractionalization has a positive effect on local development.

These results capture two 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 trust this may create conflict and lead to a decrease in the ability to agree on growth enhancing policies at the local level. We explore some of the mechanisms for these effects in the next section.

These results help make sense of a tension in the literature that examines ethnic diversity. In the cross-section, both across countries (Easterly and Levine, 1997) and within them (Alesina, Baqir, and Easterly, 1999; Miguel and Gugerty, 2005; Cutler and Glaeser, 1997) ethnic diversity is related to lower output growth or investment in public goods. Yet diversity can have positive consequences. For example, Alesina, Harnoss, and Rapoport (2013) present cross country evidence of a positive relationship between birthplace diversity and output, TFP per capita and innovation. Ashraf and Galor (2013) find that the relationship between genetic diversity and country-level economic development is first increasing, then decreasing, resulting in an interior optimum level of diversity.[33] Putterman and Weil (2010) find that the standard deviation of state history generated by the post-1500 population flows is positively related to the income of countries today. More recent work has suggested that it is less the existence of different ethnicities that matters, but whether those ethnicities are sufficiently different from each other, supporting our finding that fractionalization is generally positive, while weighted fractionalization is negative. Alesina, Michalopoulos, and Papaioannou (2016) show the more unequal ethnic groups are from each other, the less developed a country is. In a similar finding to ours, Desmet, Ortuño-Ortín, and Wacziarg (2015) show that within countries when cultural diversity and ethnic diversity overlap, violent conflict is more likely, but otherwise cultural diversity by itself is neutral or even positive.

Finally, in the last column of Table 5 we provide additional evidence on the role of diversity by adding an index of polarization. Polarization measures how far a county is from being composed of only two equally sized groups. Ager and Brückner (2013) have found that polarization is negatively related to economic growth across counties in the US from 1870 to 1920, while fractionalization is positively related to growth. Their measures of polarization and fractionalization are calculated by dividing the population into first generation migrants from different countries, African Americans, and all second or higher generation whites together as one group. Our calcula-

[33]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.

tions treat ancestry groups as distinct even past the first generation. The fact that both approaches find that fractionalization is positively related to growth suggests that this finding is quite robust. The coefficient on polarization in the last column of Table 5 is small and insignificant in our case; therefore, we do not find evidence that changes in polarization of ancestry groups is related to county GDP, once one controls for fractionalization and origin GDP weighted fractionalization.

7 Additional robustness and possible mechanisms

In this section we conduct a few more robustness exercises, explore some extensions, and provide additional evidence on some of the mechanisms through which ancestry and its diversity may affect county GDP per worker. The full tables are in the appendix, but we discuss the results in the text.

7.1 Robustness

We start by investigating whether the estimated parameters are constant across type of counties and through time (see Table A-5 for details). When we allow the effect of ancestry to differ between metropolitan and non metropolitan areas, there is some evidence that the effect is smaller in a metropolitan county, but only at the 10% significance level. Moreover, the quantitative difference is rather small. When we allow the coefficients to differ before and after 1940, the coefficient of *Origin GDP* and of the first lag of county GDP do not differ economically and statistically between the two sub-periods and the only difference is in the second lag of county GDP, but it is not large. Splitting the sample at 1920 has nearly identical results. The overall conclusion is that the coefficients appear to be largely stable, both cross-sectionally and over time.

In an additional robustness exercise, we examine whether the coefficients of migrant human capital, culture, and institutions of the countries of origin change when origin geographical characteristics are included (see Table A-6). Since immigrants necessarily leave behind their geography, the only role it can play is indirect through changing their culture, institutional experience, or human capital. However, as our measures of these variables at the country-of-origin level may well be imperfect, we view including geography as a test for whether there are important aspects of immigrant endowments that we have not fully captured. The results suggest that some measures of geography do still seem to have an effect beyond what we capture in migrant education, ancestry trust, or state history.[34] However, the significance of the coefficients of *Migrant education at arrival, Trust*, and *State History in 1500*, does not change when we include ancestry-weighted geographical attributes, with very few interesting exceptions: when measures of latitude or subtropical and tropical location are used, *Trus*t looses its significance, as does *State History in 1500* when including the fraction of a country in subtropical and tropical climate zones. These measures of geography are highly correlated with measures of trust or institutions in a country. For instance, the correlation coefficient between *Trust* and absolute latitude is 0.95 across county groups. This high correlation likely captures the lower trust and institutional quality of African and other tropical and subtropical countries and the increase in both going from southern to northern Europe. We conclude from this exercise that our basic conclusions hold, but there are likely important dimensions that matter for growth that are correlated with country geography, but that are not fully measured by the endowment variables we include.

Another concern is that immigrants may be a selected group, for example with greater willingness to take risks. The work of Abramitzky, Boustan, and Eriksson (2012), for example, suggests that there is likely to be a strong selection effect of which immigrants come and stay. 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 countries of origin at the time of arrival (weighted by arrival density) in our standard regressions (see Table A-7). The idea is that selection issues may be more important for origins that have a more unequal income distribution. A higher *Origin Gini* is associated with a lower county GDP, holding *Origin GDP* constant although the magnitude of the effect is very small and it leaves the coefficient on

[34]We have used the measures of land quality (mean and variation), elevation (mean and variation), arable land, distance to waterways, precipitation absolute latitude, fraction in subtropical and tropical climate zones in Ashraf and Galor (2013).

Origin GDP largely unchanged. When we include our measures of ancestry fractionalization, the *Origin Gini* is no longer significant, and the other coefficients in the regression are nearly identical to when it is not included, a conclusion that also holds when instrumenting. *Origin Gini* is significant when we include *Arrival Education*, *State History*, and *Trust*, but leaves the coefficients of *Arrival Education* and *State History* and their significance largely unchanged relative to those in Table 5. The coefficient on *Trust* becomes insignificant as inequality and trust of the country of origin are strongly negatively correlated (the correlation coefficient is -0.66).[35] We conclude from this exercise that since our results are mostly similar even when including inequality in the country of origin—the dimension on which differential selection is most likely to occur—differential selection is not a key issue for our results and does not alter our fundamental conclusions.

7.2 Some mechanisms

We have documented that summary measures of the attributes brought by the country of origin, such as ancestry weighted *Origin GDP*, or measures that focus on human capital, culture, and institutions bear a significant relationship with local economic development. It is interesting to ask what are the possible mechanisms that could generate an effect of such attributes on county GDP. For instance, is it through an improvement of the local stock of human capital or through an improvement in the level of social capital in a county? Moreover, why does diversity of ancestry positively affect local GDP per worker? Is it because ancestry diversity enhances the availability of skills in a county? In search for answers one is hampered by the limited availability of panel data for the needed variables over long periods of time. However, we can make some progress using information on the level of education in a county, voter participation in presidential elections, and by building an index of county occupational variety. County education helps us understand whether ancestry works through human capital formation; voter participation is a proxy for social capital and we have collected both at the county level for long periods. The census data allow us

[35]The negative relationship between trust (and social capital) and inequality has been highlighted by several authors, using cross-country or within-country evidence. See for instance,Knack and Keefer (1997), Alesina and La Ferrara (2000), Alesina and La Ferrara (2002), and Gustavsson and Jordahl (2008).

to construct an index of occupational variety which gives us insight into the diverse skills present in a county.

Origin characteristics, summarized by *Origin GDP*, are strongly positively related to county education (see Table A-8 in the appendix which shows the results for the basic dynamic model estimated with fixed effects). The effect of origin characteristics on local education is likely to be both direct and indirect: people from richer countries are likely both to be more educated and more likely to be interested in and willing to support local education. Moreover, we show that having a more educated population improves county GDP per worker. Including both *Origin GDP* and education at the county level in the same regression helps us understand how much ancestry operates through the mechanism of improving education. If ancestry, summarized by *Origin GDP,* operates through improved education, then its coefficient should be smaller since we are controlling for the education channel. Instead, the estimated effect of *Origin GDP* is nearly identical whether county education is included or not, while the effect of county education is only marginally significant. The results suggest that while *Origin GDP* does indeed improve county education, education is not the main channel through which it affects county GDP.

Increases in *Origin GDP* are also positively related to county voter participation which may be a proxy for social capital or civic engagement. Yet increases in voter turnout are not significantly related to increases in county GDP per worker (see Table A-8), and so even though changes in ancestry matter for voter participation, this particular proxy for social capital does not appear to play a crucial role in the transmission of the effects of attributes of the country of origin.

On the issue of why diversity of ancestry may matter, we construct a measure of skill variety by using the occupational data from IPUMS which coded the occupation listed in the census records into 269 occupations as classified in 1950. Detailed occupational classifications may be problematic when applied to long spans of time and this should be taken into account in interpreting the results. To minimize this problem, we use broader classifications of either 10 or 82 categories. One possible way to capture the variety of skills available in a county is to construct a Constant Elasticity of Substitution (CES) aggregate of the occupations in each county. In doing so, one needs to impute the distributional share parameter and the elasticity of substitution between different skills. It is easily shown that if the production function is separable in capital and skills, under profit maximization the distributional parameter for each skill reflects essentially the product of its wage and the elasticity-adjusted number of workers in each skill relative to the sum of this term over all occupations.[36]

Across a broad range of elasticities of substitution and both the broad and narrow occupational classifications, ancestry fractionalization is positively correlated with occupational variety (see Table A-9) and negatively correlated with origin-GDP-weighted fractionalization. These results are robust to the inclusion of *Origin GDP* which enters with a positive coefficient in the regression. Moreover, the index of occupational variety is positively and significantly related to county GDP. When we include our index of occupational variety, the coefficient of ancestry fractionalization is smaller relative to its value in the basic specification of Table 5, column 1. The coefficient on origin-GDP-weighted fractionalization is also smaller and only marginally significant. The results suggest that the positive effect of ancestry fractionalization reflects, at least in part, the increasing skill variety associated with an increasing degree of ancestry diversity in a county.

[36]More precisely, assume GDP per worker in county c at time t depends, in a separable fashion, on capital per worker and a CES aggregate of occupations j:

$$\frac{Y_{c,t}}{L_{c,t}} = F\left(\frac{K_{c,t}}{L_{c,t}}, \left[\sum_{j=1}^{J} a_{c,j,t}(s_{c,j,t}/L_{c,t})^{\epsilon}\right]^{1/\epsilon}\right).$$

Profit maximization then implies that the weights in the CES aggregate of occupations are given by:

$$a_{c,j,t} = \frac{w_{c,j,t}s_{c,j,t}^{1-\epsilon}}{\sum_j w_{c,j,t}s_{c,j,t}^{1-\epsilon}}.$$

We have used data for the year 1940, for which the full sample is available, to calculate $a_{c,j}$. Note that if different occupations are assumed to exhibit differential complementarity with capital, matters become more complex and it is not possible to summarize occupational variety in a single index. Exploring this option goes beyond the purpose of this paper and is left for future research.

8 Conclusion

The complex mosaic of ancestry in the United States has changed profoundly over time and it is still evolving as new migrants enter and people move internally. Using micro-samples from the US census since 1850, we provide the first quantitative mapping of the ancestry distribution of US counties over a long period of time. When we combine it with our new consistent estimates of county level GDP per worker, the resulting panel allows us to assess whether the endowments brought by each ancestry are related to local economic outcomes. The changing ancestry composition of US counties is significantly associated with their economic success, even after controlling for county fixed effects. The cultural, institutional, and human capital endowments that migrants brought from their country of origin explain this association. We address the potential endogeneity of ancestry due to geographical sorting through an instrumental variable strategy in a dynamic setting and find that changes in ancestry-weighted characteristics of the country of origin affect local economic development. The effects are sizable, significant, and long lasting.

The diversity of the characteristics of the country of origin are important as well. Our results suggest that ancestry fractionalization is positively related to economic development. However, measures of the fractionalization in the endowments brought by immigrants are negatively related to county level GDP. Part of the effect of ancestry fractionalization is due to the fact that ancestry diversity is positively related to skill variety. It matters not only where you came from, but also whom you came in contact with once you arrived.

Our novel panel data set allows us to provide new evidence on the relationship between ancestry composition and economic development. However, the multifaceted role of ancestry diversity and its relationship with economic outcomes deserves a deeper look, and many more issues can be investigated using our data. For instance, how are inherited values and beliefs modified by surrounding groups? How are group identities such as ethnicity formed from the building block of ancestry? What else can we discover about the mechanisms through which the cultural, institutional, and human capital endowments of immigrants affect social and economic development? We leave the answer to these and other questions to future work.

References

Abramitzky, Ran, Leah Platt Boustan, and Katherine Eriksson. 2012. "Europe's Tired, Poor, Huddled Masses: Self-Selection and Economic Outcomes in the Age of Mass Migration." *American Economic Review* 102 (5):1832–56.

Acemoglu, Daron, Simon Johnson, and James Robinson. 2005a. "Institutions as the Fundamental Cause of Long-Run Growth." In *Handbook of Economic Growth*, vol. 1A, edited by Philippe Aghion and Steven Durlauf. Elsevier, 385–472.

Acemoglu, Daron, Simon Johnson, and James A. Robinson. 2005b. "The Rise of Europe: Atlantic Trade, Institutional Change, and Economic Growth." *American Economic Review* 95 (3):546–579.

Ager, Philipp and Markus Brückner. 2013. "Cultural diversity and economic growth: Evidence from the US during the age of mass migration." *European Economic Review* 64:76 – 97.

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

Alesina, Alberto and Paola Giuliano. 2013. "Culture and Institutions." Working Paper 19750, NBER.

Alesina, Alberto, Paola Giuliano, and Nathan Nunn. 2013. "On the Origins of Gender Roles: Women and the Plough." *The Quarterly Journal of Economics* 128 (2):469–530.

Alesina, Alberto, Johann Harnoss, and Hillel Rapoport. 2013. "Birthplace Diversity and Economic Prosperity." Working Paper 18699, NBER.

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

———. 2002. "Who trusts others?" *Journal of Public Economics* 85 (2):207–234.

Alesina, Alberto, Stelios Michalopoulos, and Elias Papaioannou. 2016. "Ethnic Inequality." *Journal of Political Economy* 124 (2):428–488.

Algan, Yann and Pierre Cahuc. 2010. "Inherited Trust and Growth." *The American Economic Review* 100 (5):2060–2092.

Altonji, Joseph G. and David Card. 1991. "The Effects of Immigration on the Labor Market Outcomes of Less-skilled Natives." In *Immigration, Trade, and the Labor Market*, edited by John M. Abowd and Richard B. Freeman. Chicago: University of Chicago Press, 201–234.

Antecol, Heather. 2000. "An examination of cross-country differences in the gender gap in labor force participation rates." *Labour Economics* 7 (4):409 – 426.

Arellano, Manuel and Stephen Bond. 1991. "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations." *The Review of Economic Studies* 58 (2):277–297.

Ashraf, Quamrul and Oded Galor. 2013. "The 'Out of Africa' Hypothesis, Human Genetic Diversity, and Comparative Economic Development." *American Economic Review* 103 (1):1–46.

Bandiera, Oriana, Myra Mohnen, Imran Rasul, and Martina Viarengo. 2015. "Nation-Building Through Compulsory Schooling During the Age of Mass Migration." STICERD Discussion Paper 057.

Banerjee, Abhijit and Lakshmi Iyer. 2005. "History, Institutions, and Economic Performance: The Legacy of Colonial Land Tenure Systems in India." *The American Economic Review* 95 (4):1190–1213.

Barde, Robert, Susan B. Carter, and Richard Sutch. 2006. *Historical Statistics of the United States, Earliest Times to the Present: Millennial Edition*, chap. International Migration. Cambridge University Press, 523–540.

Barro, Robert J. and Jong-Wha Lee. 1993. "International comparisons of educational attainment." *Journal of Monetary Economics* 32 (3):363–394.

———. 1994. "Sources of economic growth." *Carnegie-Rochester Conference Series on Public Policy* 40 (0):1–46.

Bartel, Ann P. 1989. "Where Do the New U.S. Immigrants Live?" *Journal of Labor Economics* 7 (4):371–91.

Bartik, Timothy J. 1991. *Who Benefits from State and Local Economic Development Policies?* Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

Bisin, Alberto and Thierry Verdier. 2010. "The Economics of Cultural Transmission and Socialization." In *Handbook of Social Economics*, vol. 1A, edited by Matthew O. Jackson and Alberto Bisin. Elsevier, 339–416.

Blanchard, Olivier Jean and Lawrence F. Katz. 1992. "Regional Evolutions." *Brookings Papers on Economic Activity* 23 (1):1–76.

Bloom, David E. and Jeffrey D. Sachs. 1998. "Geography, Demography, and Economic Growth in Africa." *Brookings Papers on Economic Activity* 1998 (2):207–295.

Borjas, George. 1990. *Friends or Strangers: The Impact of Immigrants on the U.S. Economy*. New York: Basic Books.

Borjas, George J. 1992. "Ethnic Capital and Intergenerational Mobility." *The Quarterly Journal of Economics* 107 (1):123–150.

———. 1994. "The Economics of Immigration." *Journal of Economic Literature* 32 (4):1667–1717.

———. 1995. "Ethnicity, Neighborhoods, and Human-Capital Externalities." *The American Economic Review* 85 (3):365–390.

———. 2003. "The Labor Demand Curve Is Downward Sloping: Reexamining The Impact Of Immigration On The Labor Market." *The Quarterly Journal of Economics* 118 (4):1335–1374.

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

Burchardi, Konrad B., Thomas Chaney, and Tarek A. Hassan. 2016. "Migrants, Ancestors, and Investments." Working Paper 21847, NBER.

Card, David. 1990. "The Impact of the Mariel Boatlift on the Miami Labor Market." *Industrial and Labor Relations Review* 43 (2):pp. 245–257.

———. 2001. "Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration." *Journal of Labor Economics* 19 (1):22–64.

Colby, Sandra L. and Jennifer M. Ortman. 2015. "Projections of the Size and Composition of the U.S. Population: 2014 to 2060." CB15-TPS 16, U.S. Census Bureau.

Comin, Diego, William Easterly, and Erick Gong. 2010. "Was the Wealth of Nations Determined in 1000 BC?" *American Economic Journal: Macroeconomics* 2 (3):65–97.

Cortes, Patricia. 2008. "The Effect of Low-Skilled Immigration on U.S. Prices: Evidence from CPI Data." *Journal of Political Economy* 116 (3):381–422.

Cutler, David M. and Edward L. Glaeser. 1997. "Are Ghettos Good or Bad?" *The Quarterly Journal of Economics* 112 (3):pp. 827–872.

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.

Daniels, Roger. 2002. *Coming to America*. New York: HarperPerennial.

Dell, Melissa. 2010. "The Persistent Effects of Peru's Mining Mita." *Econometrica* 78 (6):1863–1903.

Desmet, Klaus, Ignacio Ortuño-Ortín, and Romain Wacziarg. 2015. "Culture, Ethnicity and Diversity." Working Paper 20989, NBER.

Diamond, Jared. 1998. *Guns, Germs, and Steel*. New York: W. W. Norton & Company.

Easterly, William and Ross Levine. 1997. "Africa's Growth Tragedy: Policies and Ethnic Divisions." *The Quarterly Journal of Economics* 112 (4):1203–1250.

Fernández, Raquel. 2007. "Alfred Marshal Lecture: Women, Work, and Culture." *Journal of the European Economic Association* 5 (2-3):305–332.

———. 2010. "Does Culture Matter?" In *Handbook of Social Economics*, vol. 1A, edited by Matthew O. Jackson and Alberto Bisin. North Holland, The Netherlands: Elsevier, 481–510.

Fogli, Alessandra and Raquel Fernández. 2009. "Culture: An Empirical Investigation of Beliefs, Work, and Fertility." *American Economic Journal: Macroeconomics* 1 (1):146–177.

Gennaioli, Nicola, Rafael La Porta, Florencio Lopez-de Silanes, and Andrei Shleifer. 2013. "Human Capital and Regional Development." *The Quarterly Journal of Economics* 128 (1):105–164.

Giavazzi, Francesco, Ivan Petkov, and Fabio Schiantarelli. 2014. "Culture: Persistence and Evolution." Working Paper 853, Boston College.

Giuliano, Paola. 2007. "Living Arrangements in Western Europe: Does Cultural Origin Matter?" *Journal of the European Economic Association* 5 (5):927–952.

Glaeser, Edward L., Rafael La Porta, Florencio Lopez de Silanes, and Andrei Shleifer. 2004. "Do Institutions Cause Growth?" *Journal of Economic Growth* 9 (3):271–303.

Glazer, Nathan and Daniel P Moynihan. 1963. *Beyond the Melting Pot: The Negroes, Puerto Ricans, Jews, Italians and Irish of New York City*. Cambridge, MA: MIT Press.

Goldin, Claudia. 1994. "The Political Economy of Immigration Restriction in the United States, 1890 to 1921." In *The Regulated Economy: A Historical Approach to Political Economy*. University of Chicago Press, 223–258.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales. 2006. "Does Culture Affect Economic Outcomes?" *Journal of Economic Perspectives* 20 (2):23–48.

———. 2016. "Long-term Persistence." *Journal of the European Economic Association* 14 (6):1401–1436.

Guiso, Luigi, Luigi Zingales, and Paola Sapienza. 2008. "Alfred Marshall Lecture: Social Capital as Good Culture." *Journal of the European Economic Association* 6 (2/3):295–320.

Gustavsson, Magnus and Henrik Jordahl. 2008. "Inequality and trust in Sweden: Some inequalities are more harmful than others." *Journal of Public Economics* 92 (1-2):348–365.

Hatton, Timothy J. and Andrew Leigh. 2011. "Immigrants assimilate as communities, not just as individuals." *Journal of Population Economics* 24:389–419.

Hatton, Timothy James and Jeffrey G. Williamson. 1998. *The Age of Mass Migration: Causes and Economic Impact*. Oxford University Press.

Holtz-Eakin, Douglas, Whitney Newey, and Harvey S. Rosen. 1988. "Estimating Vector Autoregressions with Panel Data." *Econometrica* 56 (6):1371–1395.

Knack, Stephen and Philip Keefer. 1995. "Institutions and Economic Performance: Cross-Country Tests Using Alternative Institutional Measures." *Economics & Politics* 7 (3):207–227.

———. 1997. "Does Social Capital Have an Economic Payoff? A Cross-Country Investigation." *The Quarterly Journal of Economics* 112 (4):1251–1288.

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

Michalopoulos, Stelios and Elias Papaioannou. 2013. "Pre-Colonial Ethnic Institutions and Contemporary African Development." *Econometrica* 81 (1):113–152.

———. 2014. "National Institutions and Subnational Development in Africa." *The Quarterly Journal of Economics* 129 (1):151–213.

Miguel, Edward and Mary Kay Gugerty. 2005. "Ethnic diversity, social sanctions, and public goods in Kenya." *Journal of Public Economics* 89 (11-12):2325–2368.

Nagel, Joane. 1994. "Constructing Ethnicity: Creating and Recreating Ethnic Identity and Culture." *Social Problems* 41 (1):pp. 152–176.

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

Nunn, Nathan and Leonard Wantchekon. 2011. "The Slave Trade and the Origins of Mistrust in Africa." *The American Economic Review* 101 (7):pp. 3221–3252.

Ottaviano, Gianmarco I. P. and Giovanni Peri. 2006. "The economic value of cultural diversity: evidence from US cities." *Journal of Economic Geography* 6 (1):9–44.

———. 2012. "Rethinking the Effect of Immigration on Wages." *Journal of the European Economic Association* 10 (1):152–197.

Peri, Giovanni. 2012. "The Effect of Immigration on Productivity: Evidence from U.S. States." *Review of Economics and Statistics* 94 (1):348–358.

Putnam, Robert D., Robert Leonardi, and Raffaella Y. Nanetti. 1993. *Making Democracy Work: Civic Traditions in Modern Italy*. Princeton: Princeton University Press.

Putterman, Louis and David N. Weil. 2010. "Post-1500 Population Flows and The Long-Run Determinants of Economic Growth and Inequality." *The Quarterly Journal of Economics* 125 (4):1627–1682.

Ripley, Willam Z. 1899. *The Races of Europe: A Sociological Study*. D. Appleton and Company.

Roodman, David. 2009. "How to do xtabond2: An introduction to difference and system GMM in Stata." *Stata Journal* 9 (1):86–136(51).

Spolaore, Enrico and Romain Wacziarg. 2009. "The Diffusion of Development." *The Quarterly Journal of Economics* 124 (2):469–529.

———. 2013. "How Deep Are the Roots of Economic Development?" *Journal of Economic Literature* 51 (2):325–69.

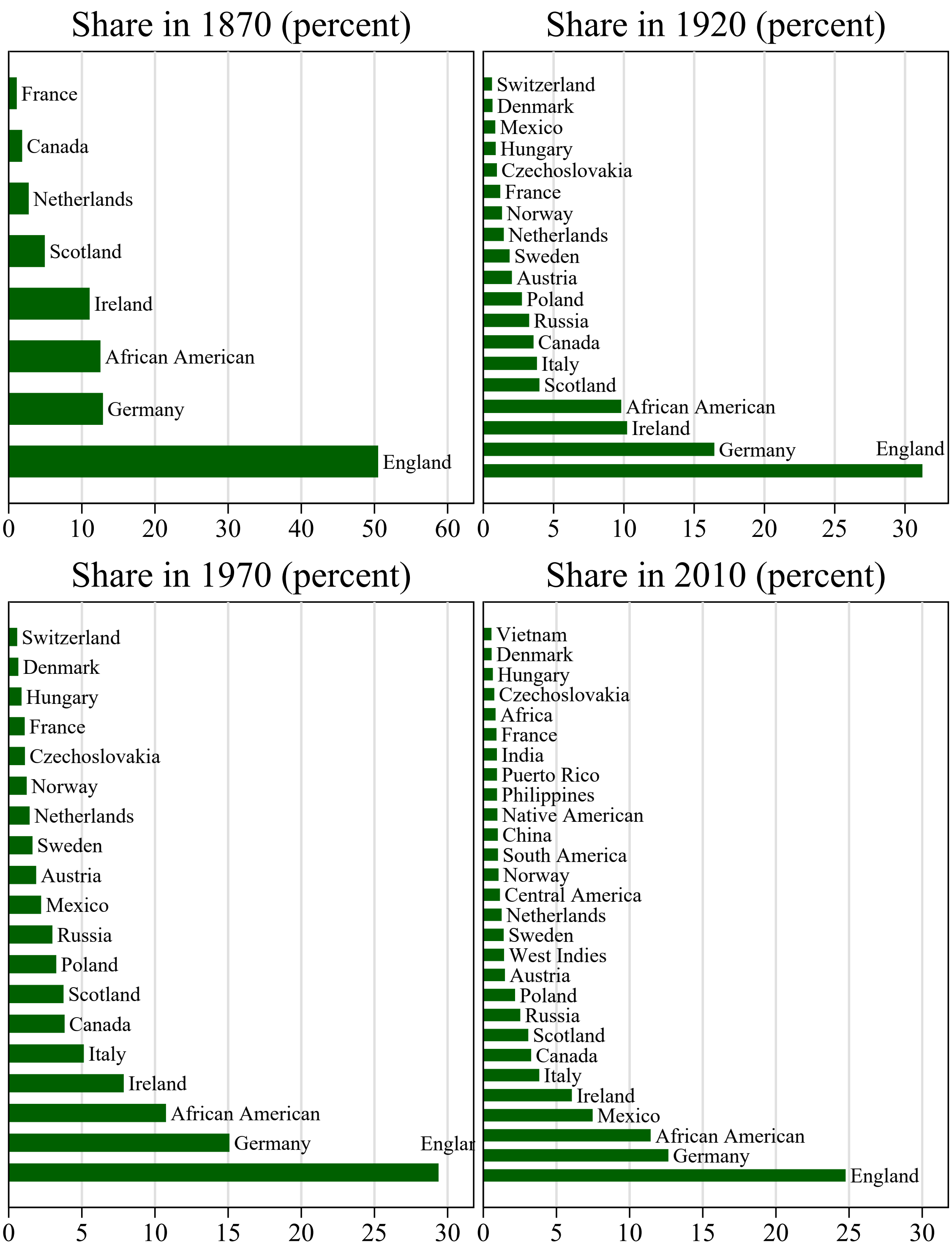
Sutch, Richard. 2006. *Historical Statistics of the United States, Earliest Times to the Present: Millennial Edition*, chap. Gross domestic product: 1790-2002 [Continuous annual series]. Cambridge University Press, Table Ca9–19.

Tabellini, Guido. 2008. "Presidential Address: Institutions and Culture." *Journal of the European Economic Association* 6 (2-3):255–294.

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

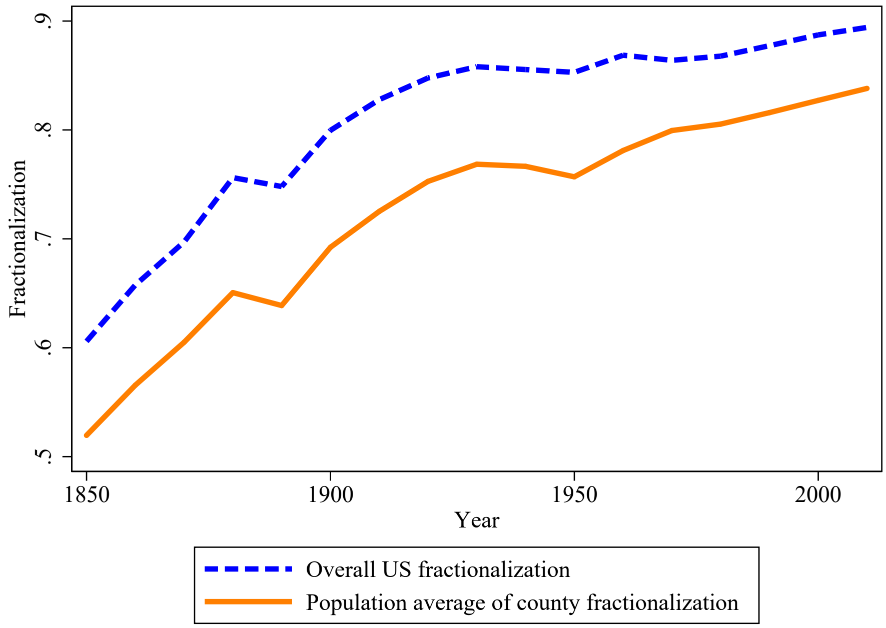
Waters, Mary C. 1990. *Ethnic Options: Choosing Identities in America*. Berkeley, CA: University of California Press.

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



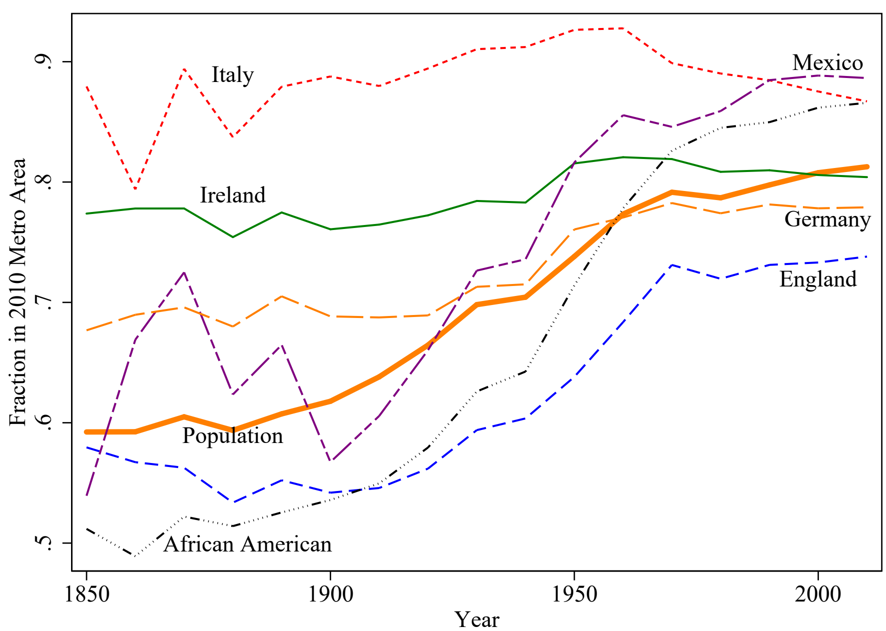
Notes: Aggregate ancestry shares in the US for ancestries with greater that 0.5% of the population. Ancestry shares are created by summing the share in each county weighted by county population in each year. See Section 3 and Appendix A for the ancestry construction.

Figure 2: Ancestry fractionalization in the United States



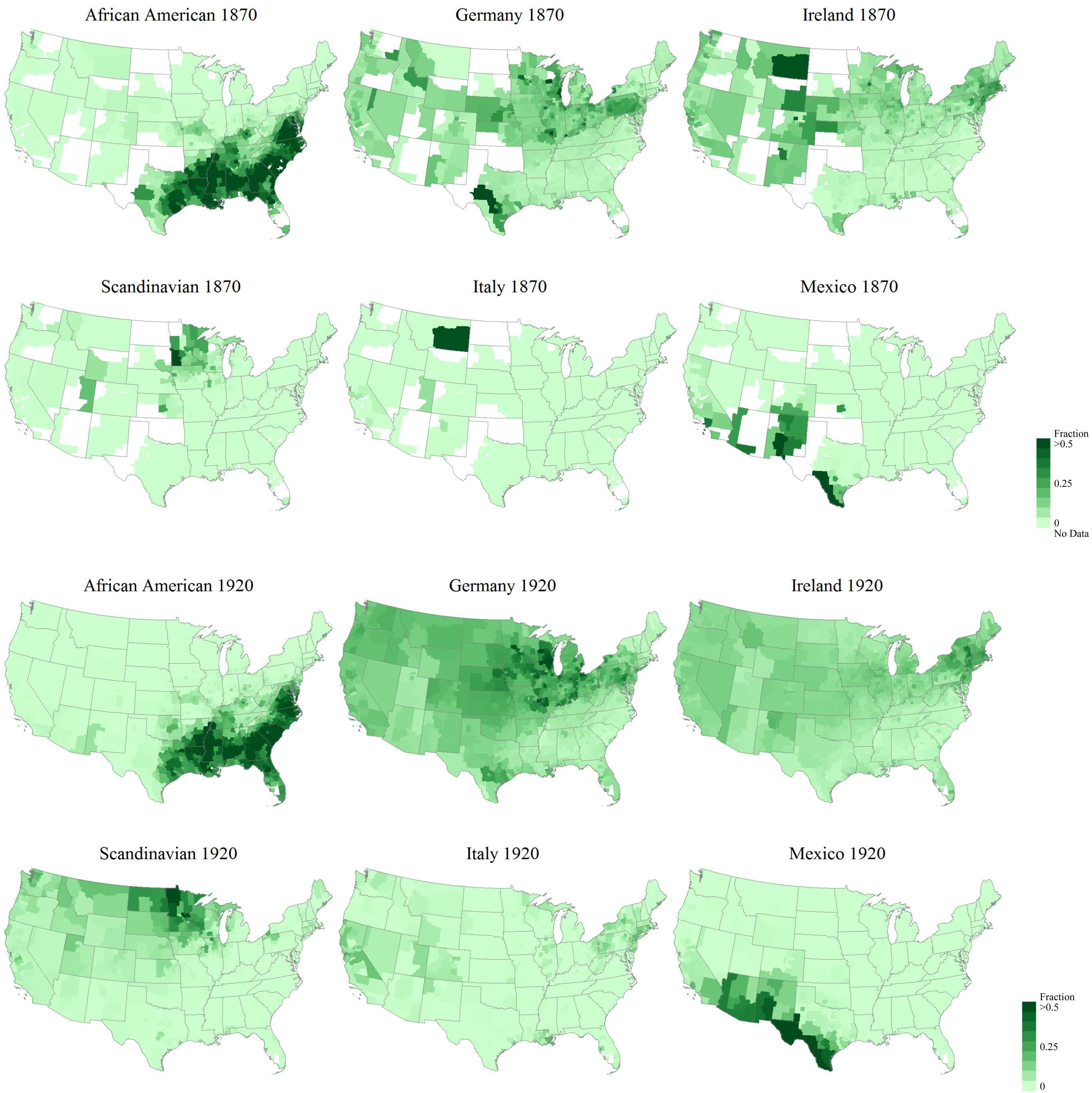
Notes: Overall US Fractionalization is the probability that two people chosen at random from the US will be from different groups: $frac_t = 1 - \sum_{a=1}^{A}(\pi_t^a)^2$ while the population average of county fractionalization is the probability that two people chosen at random from a randomly chosen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

Figure 3: Urbanization by ancestry in the United States



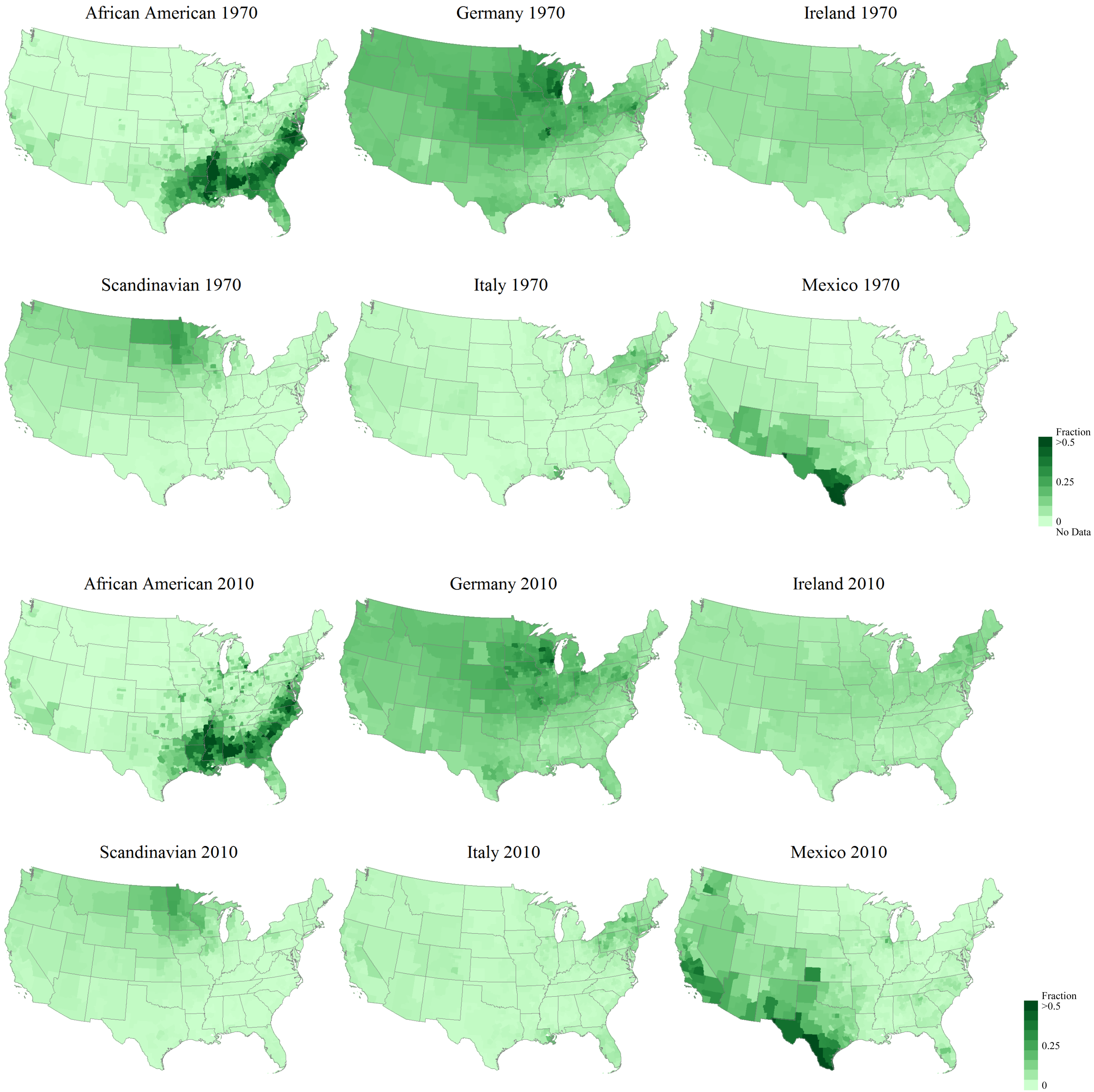
Notes: Fraction of each ancestry living in county groups containing a metropolitan area as defined by the BEA in 2016. The thick solid line is the population average.

Figure 4: Select ancestries in the United States: 1870 and 1920



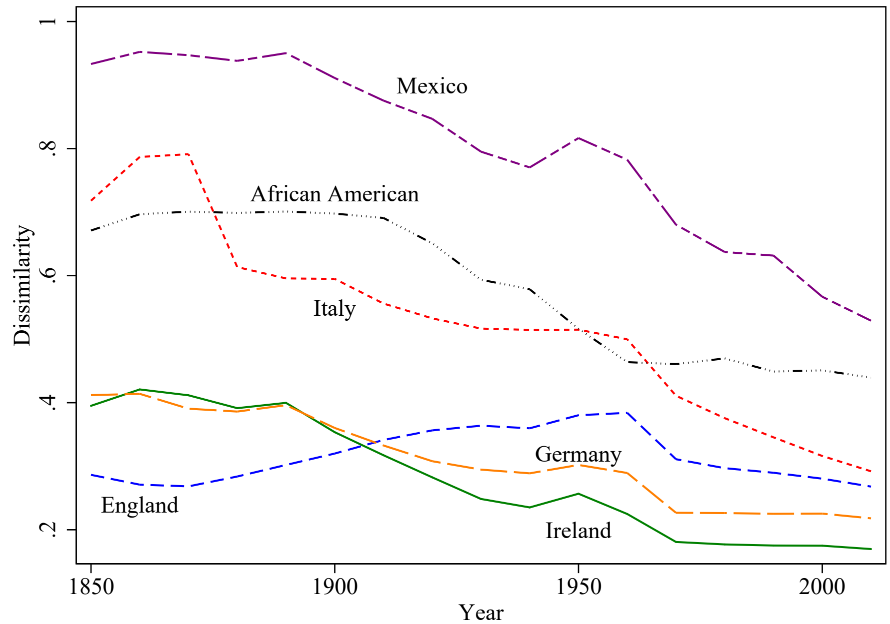
Notes: This figure shows the geographic distribution of select groups. Scandinavian is the combined Norway and Swedish ancestries. See Section 3 and Appendix A for the ancestry construction.

Figure 5: Select ancestries in the United States: 1970 and 2010



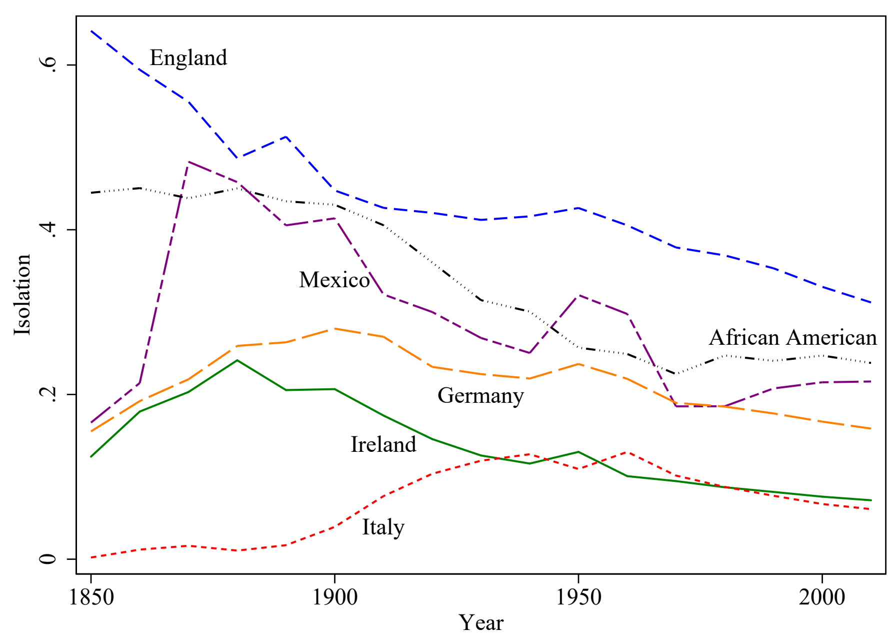
Notes: This figure shows the geographic distribution of select groups. Scandinavian is the combined Norway and Swedish ancestries. See Section 3 and Appendix A for the ancestry construction.

Figure 6: Segregation by ancestry: Dissimilarity



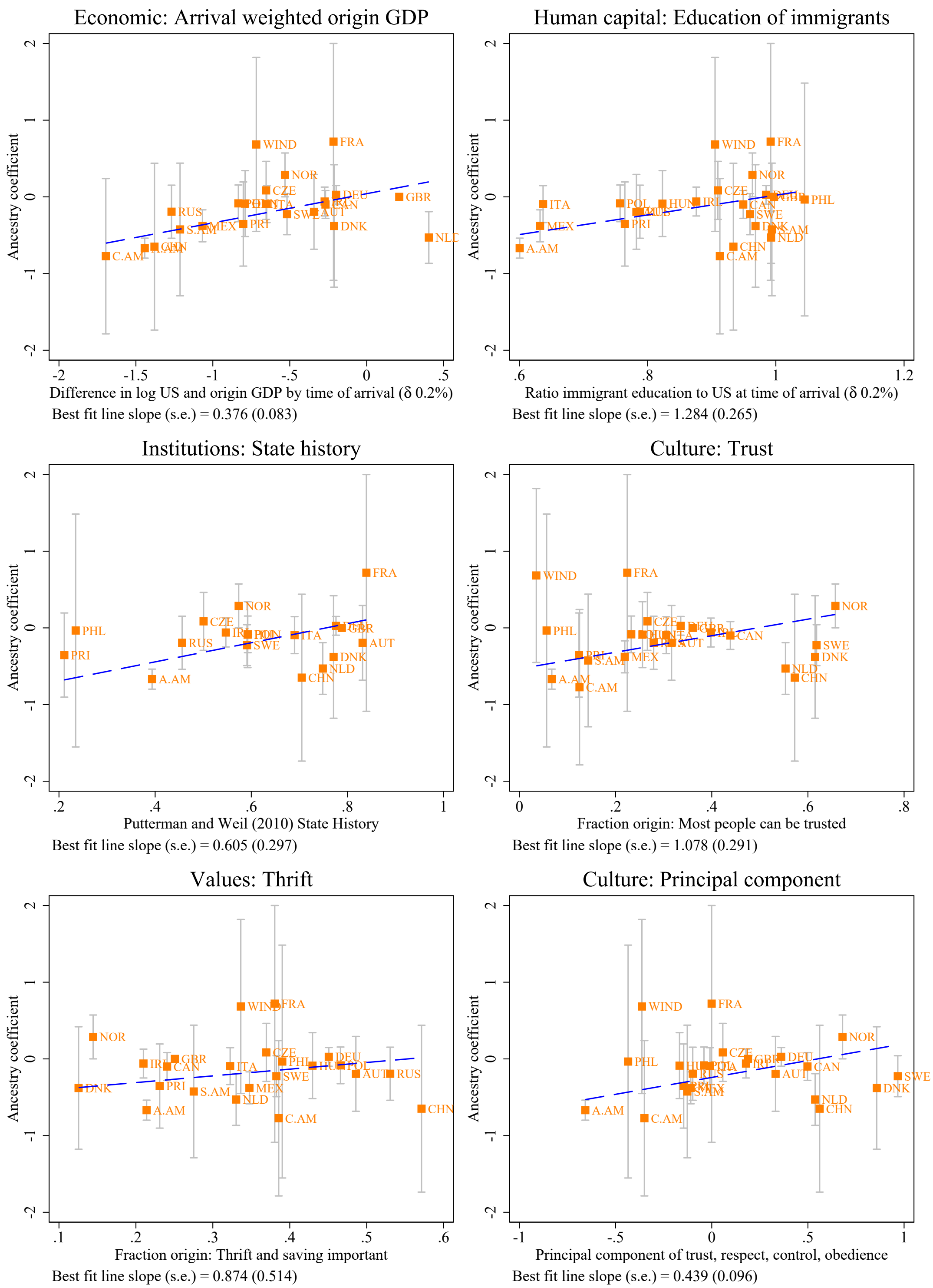
Notes: Dissimilarity is the fraction of each ancestry that would need to move to equalize the share of that ancestry across county groups.

Figure 7: Segregation by ancestry: Isolation



Notes: Isolation is the probability that a member of a given ancestry and another person chosen randomly from the same county group will be from the same ancestry.

Figure 8: 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, including county group fixed effects, census division by year effects, and two lags of county GDP per worker in equation (1) (column 5 in table 1). Time varying origin country measures are constructed as the immigrant arrival weighted density of that country. See Appendix C for sources and calculation of arrival density.

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: 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 regression 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
	[1]	[2]	[3]	[4]	[5]
Origin GDP	0.298***	-0.173***	0.310***	0.144***	0.310***
(ancestry weighted)	(0.0409)	(0.0348)	(0.0231)	(0.0274)	(0.0675)
Decade lag			0.443***	0.436***	0.443***
log county GDP			(0.0161)	(0.0163)	(0.0682)
Two decade lag			0.0279*	0.0267*	0.0279
log county GDP			(0.0164)	(0.0159)	(0.0291)
Division X Year FE	Yes	Yes	Yes	Yes	Yes
County group FE	Yes		Yes	Yes	Yes
Clustering	County	County	County	County	State X Year
Race				Yes	
Long-run effect			0.586	0.268	0.586
Observations	16,713	16,713	14,415	14,415	14,415
County groups	1149		1146	1146	1146
R^2 (within)	0.950	0.887	0.968	0.968	0.968
R^2 (between)	0.109		0.446	0.476	0.446
AB test serial corr.	5.21e-07		0.301	0.264	

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) 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, 4, and 5 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). The last column shows the results double clustering at the state and year level instead of the county group level. 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 3: County GDP per worker and country-of-origin characteristics

	Dependent variable: Log(county GDP per worker)			
	Static		Dynamic	
One variable	FE	OLS	FE	FE with Race
at a time	[1]	[2]	[3]	[4]
Origin GDP	0.298***	-0.173***	0.310***	0.144***
	(0.0409)	(0.0348)	(0.0231)	(0.0274)
Migrant educ./US ratio at arrival	0.531***	-0.416***	1.195***	0.415***
	(0.118)	(0.120)	(0.108)	(0.137)
Trust	1.894***	-0.594***	1.831***	0.559***
	(0.263)	(0.200)	(0.141)	(0.185)
State history in 1500	1.042***	-0.191	1.139***	0.414***
	(0.166)	(0.129)	(0.0953)	(0.104)
Executive constraint at arrival	0.0914***	-0.0462***	0.100***	0.0244*
	(0.0161)	(0.0118)	(0.00974)	(0.0135)
Principal Component of Culture	0.712***	-0.131*	0.653***	0.213***
	(0.0913)	(0.0722)	(0.0486)	(0.0777)
Thrift	1.744***	3.402***	1.316***	-0.375*
	(0.300)	(0.349)	(0.181)	(0.197)
Division X Year FE	Yes	Yes	Yes	Yes
County group FE	Yes		Yes	Yes
Race				Yes

Notes: This table examines which of multiple possible endowments from the origin country matters for county GDP in variations of equation (4). Each cell is from a separate regression and only the coefficient on the ancestry weighted country-of-origin characteristic is shown. Column 1 includes county group fixed effects, while column 2 does not. Columns 3 and higher include two lags of the dependent variable (log county GDP per worker). Column 4 includes the fraction African American and Native American. All regressions include census division by year fixed effects and standard errors are clustered at the county group level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: County GDP per worker and combined country-of-origin characteristics

	Dep. Variable: Log(County group income per worker)								
	FE	FE	FE	FE	IV-FE	Bartik IV-FE	IV-FE	GMM FOD	GMM FOD
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Origin GDP	0.310***		0.0733		0.335***	0.330***		0.208***	
	(0.0231)		(0.0486)		(0.0285)	(0.0278)		(0.0429)	
Migrant educ./US		0.384***	0.288*	0.516***			0.548***		0.202
ratio at arrival		(0.138)	(0.160)	(0.144)			(0.196)		(0.254)
Trust		0.893***	0.781***	0.918***			0.973***		1.358***
		(0.189)	(0.197)	(0.191)			(0.278)		(0.388)
State history		0.489***	0.357***	0.540***			0.326*		0.730**
in 1500		(0.105)	(0.134)	(0.102)			(0.168)		(0.320)
Executive constraint				-0.0173*					
at arrival				(0.00951)					
Decade lag	0.443***	0.439***	0.439***	0.438***	0.440***	0.440***	0.436***	0.545***	0.489***
log county GDP	(0.0161)	(0.0164)	(0.0164)	(0.0164)	(0.0163)	(0.0163)	(0.0167)	(0.0198)	(0.0298)
Two decade lag	0.0279*	0.0279*	0.0278*	0.0276*	0.0299*	0.0299*	0.0302*	0.0940***	0.0739***
log county GDP	(0.0164)	(0.0161)	(0.0161)	(0.0160)	(0.0158)	(0.0159)	(0.0157)	(0.0186)	(0.0206)
Observations	14,415	14,415	14,398	14,398	13,252	13,252	14,398	13,269	13,269
Division X Year	Yes	Yes	Yes	Yes	1146	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County groups	1146	1146	1146	1146	1146	1146	1146	1146	1146
AB test serial corr.	0.301	0.296	0.299	0.290	0.362	0.360	0.312	0.254	0.318
Hansen over-id.								0.719	0.135

Notes: This table examines which of multiple possible endowments from the origin country matters for county GDP when included together and in columns 5 through 9 includes instrumental variables and GMM results. FE refers to fixed effects, IV-FE uses the the lagged values of the explanatory variables as instruments, Bartik IV-FE uses the lagged values adjusted by the national growth rate of that ancestry (see footnote 25), and GMM-FOD estimates using the Forward Orthogonal Differences transformation and lags 2 through 4 as instruments (Roodman, 2009). 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 and standard errors are clustered at the county group level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: County GDP per worker and diversity

	Dep. Variable: Log(County group income per worker)					
	FE	IV-FE	GMM-FOD	FE	FE	FE
	[1]	[2]	[3]	[4]	[5]	[6]
Fractionalization	0.474***	0.433***	0.817***	0.430***	0.331***	0.494***
	(0.0777)	(0.107)	(0.112)	(0.0901)	(0.0988)	(0.0845)
Origin GDP weighted	-0.597***	-0.638***	-0.921***	-0.683***		-0.635***
fractionalization	(0.189)	(0.234)	(0.262)	(0.203)		(0.194)
Origin GDP	0.267***	0.277***	0.269***			0.261***
	(0.0294)	(0.0375)	(0.0411)			(0.0318)
Migrant educ./US				0.477***	0.679***	
ratio at arrival ($\delta = 0$)				(0.145)	(0.204)	
Trust				0.264	0.618***	
				(0.222)	(0.210)	
State history				0.527***	0.211	
in 1500				(0.106)	(0.188)	
Education weighted					0.645	
fractionalization					(0.420)	
Trust weighted					-0.426***	
fractionalization					(0.162)	
State history weighted					-0.388	
fractionalization					(0.243)	
Polarization						0.0305
						(0.0448)
Decade lag	0.437***	0.435***	0.436***	0.435***	0.435***	0.436***
log county GDP	(0.0165)	(0.0167)	(0.0197)	(0.0166)	(0.0165)	(0.0165)
Two decade lag	0.0273*	0.0293*	0.0928***	0.0275*	0.0274*	0.0273*
log county GDP	(0.0158)	(0.0155)	(0.0151)	(0.0158)	(0.0157)	(0.0158)
Observations	14,415	14,398	14,998	14,415	14,415	14,415
Division X Year	Yes	Yes	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes	Yes	Yes
County groups	1146	1146	1146	1146	1146	1146
R^2 (within)	0.968			0.968	0.968	0.968
R^2 (between)	0.513			0.529	0.514	0.509
AB test serial corr.	0.258	0.907	0.00526	0.369	0.353	0.617

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 6. 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.

Appendix for:

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

Scott L. Fulford, Ivan Petkov, and Fabio Schiantarelli

January 2017

For online publication only

A Constructing the ancestry shares

In this section we describe our construction of the ancestry shares. Since each county are composed of many ancestries, we record the information on all of the shares in a single ancestry vector (AV) which describes the full distribution of ancestries in each county.

A.1 The Ancestry Vector for those who are not African American or indigenous

Approach for 1790-1840 when information is limited. The first census in 1790 collected some information by state on "nationality" but none of the censuses until 1850 collected such information. We use the 1790 census to create the initial state level nationality vector. The census did not collect nationality information again until 1850, so for the initial step we simply allocate the AV for each year between 1800 and 1820 based on the nationality in 1790. One nationality in 1790 is "Hebrew" although it is very small in all cases. We combine Hebrew with German.

From 1820 to 1830 and 1830 to 1840 the government started collecting information on immigrants, their country of origin and the state where they moved (Barde, Carter, and Sutch, 2006). We use these values to update the 1790 ancestry vector to account for the immigration flows during these two decades.

Approach for 1850, 1860, 1870, 1980, 1990, and 2000 when no parent data exists, but we have individual data on nativity. Starting in 1850 the census asked the country of birth for those born outside the United States and the state of birth for those born within. Samples from the records have been collected and digitized and are stored in the Integrated Public Use Microdata Series (IPUMS) collected by Ruggles et al. (2010). For most years the sample was 1 in 100 but larger samples (5%) exist for some years and we use those where possible. We further utilized the full census results when available.

For each person in the microsample, we create an ancestry vector. The person receives a one for the place of birth if he or she is from that foreign country. Starting in 1880 the census also recorded the place of an individuals' parents. We describe how we use this information below. Without the parent information, for non-immigrants we attribute to an individual the AV for the group of respondents who have children five years or younger in the place of birth at the time of her birth. In other words, we attribute to a person the AV of the group who are most likely to be her parents. For a non-immigrant who lives in the same state as she was born, we attribute to her the AV for the parent group in the county where she lives now as of the closest census to her birth. We give non-immigrants who have moved the AV for the parent group from their state of birth as of the closest census to their birth. The AV for the parent group reflects differences of the fertility rate across families with different origin. We incorporate these differences by weighing the AVs of parents by the number of children five-or-younger that they have. This means that the AV of the parent group in a county where parents of Irish origin, for example, produce disproportionately more children will properly capture the higher likelihood that the children from this county are also of Irish descent.

During a period of rapid immigration keeping track of the changing demographics matters. For example, consider someone who was 30 years old in the 1870 census and was born in Suffolk county, Massachusetts which contains Boston. We would not want to give a large probability that she had an Irish ancestry, since there was not yet a large Irish presence in 1840. On the other hand, a 10 year old in 1870 would be much more likely to have an Irish ancestry The combination of more Irish, more Irish in the parent group, and potentially more Irish children makes Irish ancestry more likely. We create the county average over all individuals to give AV for county and state in that year, as well as the the AV for those respondents with children fiver years or younger (the "parent" AV). Since we have only state level variation until 1850, 1860 is the first year where the parent AV will differ by county. In later years as we move forward with additional microdata, counties become increasingly diverse.

Approach for 1880 to 1970 using parent nativity. From 1880 to 1970 the census also collected information on the birthplace of the parents of each person in the census. We use the same procedure when only the individual birth place is known for the parents, and then give the individual one half of each parent's AV, so $AV_i = 0.5AV(Mother_i) + 0.5AV(Father_i)$. For the foreign born parents we assign them an AV with 1 for the country of birth and zero elsewhere. For native parents, we assign the parent the AV for the parent group in each parent's state of birth in the closest census of birth. If the parent is born in the same state the individual is living in now, we assign the parents the county AV for the parent group in the birth year. It is common for both parents to be from the same country, in which case the AV is just 1 in the country of origin of both parents.

Approach for 1890 when no individual data exists. Because a fire wiped out all of the individual level 1890 records, we have to use aggregate data published by the census for this year. The NHGIS (Minnesota Population Center, 2011) has collected county level information for a wide range of variables in a number of census years, including 1890, from the published census volumes. These record the place of birth of the foreign born population. For each county the AV is: $AV(\text{County}) = (\text{Fraction Foreign}) * AV(\text{Foreign Born}) + (\text{Fraction Native}) * AV(\text{Natives})$.

Forming the non-immigrant AV is more difficult, since the place of birth is only available at the state level. We use the demographic structure by state in 1880 aged by 10 years to assign weights for birth years—the fraction of the native population born closest to the 1880 census, the 1870 census and so on. Then we assign the native AV over all states as the double sum over state s birthplace (BPL) and year of birth for each age group d:

$$AV(\text{Native born in state}_j) = \sum_{s=1}^{S} \sum_{d=0}^{D} f_{s,j} f_{d,j} AV(s, \text{birthyear of } d)$$

where $f_{s,j}$ is the fraction of the native population in state j born in state s and $f_{d,j}$ is the fraction of birth group d in state j as constructed from 1880.

Approach for 1940. The 1940 census introduced for what appears to be the first time supplemental questions that were asked to only a subset of the population. We use the question about ancestry in the supplement. The Public Use Microdata Sample then took a sample from the people who answered the supplemental question and their households. Since that would tend to over-sample large households, they first sampled people who had been selected to answer the supplemental question, and then selected the households of that person with probability equal to the inverse of household size. It is an elegant solution since it gave a representative sample of the entire population and ensured that every household had one person who had answered the supplemental questions. The procedure means that selecting only those who have answered the supplemental questions is no longer representative. We use the sample weights to adjust for the sampling procedure.

A.2 African Americans and indigenous peoples

Race is a very important and sensitive issue in the US, and the evidence suggests that it is not nearly as fixed a concept as is sometimes believed. Since we are primarily interested in the relationship that culture and institutions have with economic outcomes, forced migration and slavery are one potential source of a particular set of culture and institutions. We therefore treat self-identified "black" and "white" as non-mixing groups which contains separate ancestries within them. Within "blacks" we then distinguish between the descendants of ancestors who were brought from Africa as slaves—whom we refer to as African American—and later African migrants from countries such as Nigeria or "black" migrants from the Caribbean. African Americans represent by far the largest group.

Treating the combined African ancestries as a separate non-mixing group ignores many complexities of race in America, but we think it is closer to capturing the experience of race in US history. In the long and racist history of the United States, the societal rules have tended to make "black" an absorbing state and actively worked to prevent intermarriage. The rape of slave women was widespread (Kolchin, 2003, pp. 124-5), and so many African Americans are the partially descendants of slave holders. Yet children of "black" mothers were still considered "black" and were still slaves (Higginbothham and Kopytoff, 2000). After the Civil War, interracial marriage was still illegal in 17 states in 1967 when the US Supreme Court struck down anti-miscegenation laws (Kennedy, 2000, p. 62). Such laws had the unseemly consequence that made it legally necessary to define who was prohibited from marrying whom by virtue of their "blood" (Saks, 2000). The strictest rule held that "one drop" of blood of African ancestry made someone "black," although the enforcement was not universal and less strict rules also existed (Kennedy, 2000). Partly as a consequence of this history, intermarriage between "blacks" and "whites" were uncommon until very recently. Intermarriage among all races represented just 3.2% of marriages in 1980 and 8.4% in 2010 (Wang, 2012). Further, intermarriage is not necessarily a problem in constructing aggregate county ancestry if the children of mixed race couples do not systematically report themselves as one race or the other.

Similar to African Americans, we treat Native Americans as their own ancestry group. Partly due to the legacy of forced settlement into reservations, some counties have a large presence of Native Americans. They are not always recorded well in the early censuses. Where possible, we take self-identified natives as their own ancestry group and assume no mixing. Except for counties with reservations, they are typically a small portion of the population, so this assumption is not particularly important.

A.3 On mixing

Our procedure does not distinguish between complete ancestry mixing and the full separation of ancestries that share the same geography. For example, in a population half German and half Irish, the second generation will have an AV half German and half Irish whether or not all of the Germans marry Germans and all of the Irish marry Irish or there is inter-marriage between Irish and Germans. The AV is thus the appropriate estimate of the expected ancestry of any individual from that population, but does not provide a measure of cultural mixing, only of co-location. For African Americans the use of race assumes that they are fully African American.

A.4 Aggregation and PUMAs

To protect anonymity, from 1950 onwards the microdata does not typically give counties for the individual records. Usually there is some geographic identifier that combines several counties, although in 1960 only state level information is available. We therefore use the somewhat larger units available in each year to update the county level, but maintain the county as the basic unit of observation. The basic idea is that counties within a group will have a different history and different AV from when we can fully identify them from 1940 and earlier. The new information from each post-1940 census is the same within each group but is applied to an already existing AV. Finally, we aggregate the constructed county level data up to the 1980 Public Use Micro Areas (PUMAs) since these are the most consistently used areas after 1950. In keeping with the terminology starting in 1950, we refer to these somewhat larger aggregates as county groups.[1]

[1] See `https://usa.ipums.org/usa/volii/tgeotools.shtml` for a description of the geographic identifiers used over time.

B Constructing county GDP

B.1 County manufacturing and agricultural value added 1850-1940

The census recorded for each county the total value of agricultural output and the value of manufacturing output and costs of inputs. We construct nominal value added of manufacturing by subtracting the cost of inputs from the total output. In 1850, the census did not collect manufacturing inputs. We use the average of the 1860 and 1870 county level ratio of outputs to inputs in manufacturing to create inputs for 1850,1860 and 1870.

For agriculture during this period the only local measures that exist are of output, not value added. No good measure at the county level exists of the costs of inputs in agriculture over a long period. Agriculture does have intermediate inputs such as fertilizers as well as agriculture inputs used in the production of other agricultural outputs such a feed corn for cattle and seed. To account for these inputs, we construct a national measure of the ratio of value added to total output by subtracting intermediate inputs from total agricultural output using series K 220 -250 from United States Census Bureau (1975). While intermediate inputs were small early on at about 6% in 1850, increasing to nearly 12% by 1900, by 1940 they were nearly 40%. Adjusting for intermediate inputs hastens the relative decline of agriculture after 1900. We apply the ratio between nominal value added and output at the national level to the value of county level agricultural output to obtain an estimate of agricultural value added at the county level.

The census did not collect manufacturing data in 1910, although estimates of it exist at a national level. To create county level manufacturing, we interpolate between 1900 and 1920 using the national growth in manufacturing value added and allocating growth to each decade in the same way we allocated growth in services so that manufacturing value added grows in each decade in each county at the same rate it does at the national level.

B.2 Using county employment 1850-1940 to construct value added in services, mining and construction

The micro-samples of the decadal census collect information on the occupation of the individuals. We allocate the occupations to correspond to the following broad NIPA categories: trade, transportation and public utilities, finance, professional services, personal services, government, mining and construction. We then create the total workers employed in each of these industries in each county according to the occupation listed by the respondents to the census. We also collect estimates of nominal value added per worker in each industry at the national level. When we have information on both employment and wages at the county level so that we can construct the wage bill for each county, we calculate nominal value added per worker in each each county and industry, using the county level wage relative to the weighted average wage across counties multiplied by the national value added per worker. We then use the employment from the micro-samples to estimate nominal GDP in each county and industry. We have this information for the full 1940 census and we use the same allocation for the adjacent decades of 1950 (where there is much sparser wage information) and 1930. For the earlier decades, for which we have some information on wages within each sector only at the state level (or for the major city within a state), 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 difference between urban and rural areas that replicate their ratio in 1940. In the former case, we allow nominal GDP per worker to differ by county. In the latter case, we allow nominal GDP per worker to be state specif (according to the historical wage information) and to vary between urban and rural counties the way it did in 1940.

Allocating occupations to industrial sectors involves difficulties and judgment calls. For instance, some occupations such as legal services that we classify as a professional service for an individual, may be part of manufacturing value added when performed for a manufacturing firm.

We use the 1950 occupations definitions from IPUMS and their corresponding industries using their 1950 definitions of industries. We make some slight changes to the codes to follow the divisions used in the early national accounting measurements.

In addition, the sexism and racism inherent in the early censuses poses additional difficulties. In 1850 women were not coded as having an occupation. While many women did work solely in domestic production, some women were employed outside the home. Similarly, in 1850 and 1860, slaves were not listed as having an occupation. While both slaves and women were enumerated for political purposes, we do not have information on their occupation. Many, but not all, of the slaves would have been employed in agricultural production, either directly or indirectly so we are not missing their output entirely, only undervaluing the skilled services they did provide. Finally, since the physical census records from 1890 were largely destroyed by fire, there is no micro-sample from 1890. We linearly interpolate for each county the employment by industry category in 1890 using 1880 and 1900, but otherwise calculate county value added per worker in the same way.

B.2.1 Using wages to infer relative productivity

Assuming that factors are paid their marginal product, wages are informative about relative productivity. This is the basic reason to use the relative wage bill in allocating national value added in a sector to an area. More specifically, under perfect competition and a constant returns to scale Cobb Douglas production function (with the same factor elasticities but different levels of productivity across counties) the share of nominal value added of a county out of national value added equals the county wage bill relative to the national wage bill.

More precisely, if the United States is divided into C counties with nominal GDP in a particular industry and year equal to Y_c^N (where we do not show the industry and year subscripts) so that U.S.

GDP in an industry is:

$$Y_{US}^N = \sum_{c=1}^{C} Y_c^N.$$

Production takes the simple Cobb-Douglas form within each county:

$$Y_c = A_c K_c^{\alpha} L_c^{1-\alpha}.$$

where Y_c denotes real GDP, A_c productivity, K_c capital, and L_c labor. Under perfect competition in the output market, if labor is paid its marginal revenue product, the wage is proportional to the GDP per worker in c:

$$w_c = MRPL_c = P(1-\alpha)A_c K_c^{\alpha} L_c^{-\alpha} = P(1-\alpha)Y_c/L_c,$$

where P denotes the common output price. Then it is easy to show that:

$$Y_c^N = PY_c = \frac{w_c L_c}{\sum_c w_c L_c} Y_{US}^N. \tag{1}$$

Focusing on nominal GDP per worker:

$$\frac{Y_c^N}{L_c} = \frac{w_c}{\sum_c w_c (L_c/L_{US})} \frac{Y_{US}^N}{L_{US}}. \tag{2}$$

so we can recover nominal GDP per worker in each industry and county c using national GDP per worker and the relative wage.[2] Note that we make no assumptions about the equalization of marginal products across regions or about migration. Note also that the result above holds even if the output market is monopolistically competitive, provided the markup is common across the US.

When wage data is not available at the county level, but at the state level, we follow the same

[2]We use equation (2) to calculate county GDP rather than (1) because national value added includes some areas that are not covered well by the census micro-samples. These areas include Hawaii, Alaska, and Puerto Rico for which the census has incomplete coverage, and US overseas possessions.

approach. When we do not have complete wage information, we assume that we can observe a wage $\tilde{w}_c = \theta w_c$ which is proportional to the average wage in the industry across all states.

Finally, for Finance, Insurance, and Real Estate, wages or income that is comparable across states is not available. Instead, we use the amount of banking capital in a state to infer productivity differences in FIRE. The basic idea is nearly identical to the approach used above for wages, except that we observe something proportional to total capital rather than a price. To the approach for wages we add the assumption that capital is mobile and so the user cost of capital, uc, is equalized across all counties. We also observe capital that is some constant share of the total capital in a state: $\tilde{K}_s = \theta K_s$. Then if capital is paid its marginal revenue product:

$$MRPK_s = P(1-\alpha)A_s K_s^{\alpha} L_s^{-\alpha} = P\alpha Y_s/K_s = uc$$

and so $Y_s = \frac{uc}{\alpha}\theta\tilde{K}_s$. Then in each state the value added for FIRE is obtained as:

$$Y_s^N = \frac{\tilde{K}_s}{\sum_j \tilde{K}_j} Y_{US}^N$$

which allows us to calculate value added per worker in FIRE in each state by dividing by labor and using the relative capital output ratio:

$$\frac{Y_s^N}{L_s} = \frac{\tilde{K}_s/L_s}{\sum_j \frac{\tilde{K}_j}{L_j}\frac{L_j}{L}} \frac{Y_{US}^N}{L_{US}}.$$

B.2.2 Distribution of wages by period and industry

For most of the period we only observe wages at the state level, but we use the distribution of wage across counties in 1940 to allow counties within a state to differ. The 1940 census was the first to ask about income or wages and has a complete sample. We detail below the particular assumptions we make to obtain county level nominal GDP for each year and industry. When county level wage data is not available, for decades up to 1920, we use state level information for wages (or for the major city in a state). The sources we use typically do not have coverage for all states in all years. We use the average wage in the state's census division to fill in the wage for missing states in each year. There are nine census divisions which correspond to the broad economic and climatic zones of the United States. Moreover, the state wage for particular occupation can be either a (weighted) average across urban and non urban areas or represent an urban or rural wage. We use the state level information and the ratio between urban and rural wages in 1940 to construct estimates of the state-urban/rural specific wages in an industry in the decades up to 1920. Urban and rural wages are constructed as total wage compensation divided by total employment in urban and rural in each year. Urban and rural are defined using the 1950 allocation to metropolitan and non-metropolitan areas, the first year such an allocation is available.

1940. The 1940 census asks for wages or income and we use the same classification system for employment to find the average wage within each county and industry. We then apply formula (1) directly at the county level to find the value added in each county.

1950. The 1950 census has only a 1% sample, and asked questions about income and wages to only one in five respondents (not all of whom had any income). We therefore use the 1940 wage distribution at the county level for 1950 as well, but use the 1950 employment from the County Books described above which was originally calculated from the full census. See section B.4 for the calculation of employment.

1930. We apply the 1940 distribution of wages across counties and industries to the 1930 employment by county and industry.

Wages by state for Trade 1850-1920. We use the wage in each state for bakers (1880-1898 across states, 1907-1928 for select cities) and dress makers (1875- 1898 across states) from the United States Department of Labor (1934), page 148 and 219. Since the coverage is fragmentary for different states we take the average wage over several years to form the decade distribution across states. For bakers: 1880 is the average from 1880 to 1887; 1890 the average from 1886 to 1895; 1900 the average from 1891-1898; 1910 the average from 1907-1916; 1920 the average from

1917-1926 we assume the distribution for 1850, 1860, and 1870 follows 1880. For dressmakers: 1880 is the average from 1875 to 1886; 1890 the average from 1886 to 1895; 1900 the average from 1891-1898; we assume the distribution for 1850, 1860, and 1870 follows 1880; and the distribution in 1910 and 1920 follows 1900. Both wages are from urban areas. To form the wage for Trade we take the average of bakers and dress makers.

Wages by state for Transportation. We use the wage in each state for teamsters (male one horse teamsters from 1875-1900 across states, male two horse teamsters from 1913-1928 for select cities) and engineers (male in locomotive railroad from 1875-1898) from the United States Department of Labor (1934), starting on pages 449, 438 and 453. We convert both series into dollars per day, and we exclude the engineers in states which report only in per mile terms. Since the coverage is fragmentary for different states we take the average wage over several years to form the decade distribution across states. For both occupations we take averages over several years. For teamsters: 1870 is the average of 1875-1880; 1880 the average of 1876-1885; 1890 the average of 1886-1895; 1900 the average of 1891-1900; 1910 the average of 1913-1917; 1920 the average of 1916-1925; we assume the distribution for 1850 and 1860 follows 1870. For engineers: 1870 is the average of 1875-1880; 1880 the average of 1876-1885; 1890 the average of 1886-1895; 1900 the average of 1891-1900; we assume the distribution for 1850 and 1860 follows 1870; and the distribution in 1910 and 1920 follows 1900. We take both wages to be an average from urban and rural areas. To form the wage for Transportation we take the average of teamsters and engineers.

Wages by state for Education. We use the average monthly salaries of teachers in public schools as recorded in the Report of the Commissioner of Education for 1880 (Table 1, Part1, page 408), 1900 (volume 1, Tables 9-10, page 72), and 1915-16 (volume 2, Table 11, page 77). We use the average wage across all male and female teachers, and where the average is not reported for a state compute it as the weighted average of male and female teacher's salaries using the share of male and female teachers in the total. We assume 1850 through 1870 follow the 1880 distribution; 1890 follows the 1900 distribution; and 1910 and 1920 come from the salaries in 1915-1916. These are the average wages for the state.

Wages by state for Mining. We use the wage in each state for coal miners (male coal miners from 1875-1898) and iron miners (male, 1875-1899) from the United States Department of Labor (1934), page 330 and 333. In 1919 we use male hand miners of bituminous coal across states from the United States Bureau of Labor Statistics (1919), Table 3, page 9. Few wages exist early on, and so we use the average of 1880-1889 for the wage distribution in 1880, the average of 1880 to 1889 for 1890, and the average of 1890-1899 for 1900. We assume 1850 through 1870 follow the 1880 distribution; and 1910 and 1920 follows the 1919 distribution. The mining wage is the average of coal and iron mining wages in each year. Both mining wages are for rural areas.

Wages by state for Construction. We use the wages of bricklayers, carpenters, and masons from 1875 to 1928 first for states until 1900 and then select cities from the United States Department of Labor (1934), pages 155, 161, and 190. We assign the city wages to the state, and assume that all wages are urban wages. For each occupation we form 1870 using the average of 1875-1880; 1880 average of 1876-1885, 1890 average of 1886-1896; 1900 average from 1891-1900 since the series change in 1901; 1910 average from 1906-1915; and 1920 average 1916-1925. We take the average of the three occupations in each year to form a construction wage.

Wages by state for Government. The Annual Reports of the Postmaster General (1900) recorded the average compensation of fourth class postmasters by state. It is unclear from the text what frequency the salary is paid, but based on the maximum salary ($4000 to the postmaster general himself), the reported salaries appear to be quarterly. We were unable to find another report that gives a similar breakdown by state. We assume the distribution is the same as 1900 from 1850-1900. We also use the wages of male municipal laborers in sanitation and sewage from 1890-1903 from the Nineteenth Annual Report of the Commisisioner of Labor (1905), page 470. We form 1890 using the average of 1890-1895, and 1900 using the average of 1896-1903. We assume that 1850-1880 follows 1890. We form 1850 through 1890 by combining the wages of municipal laborers and postmasters Municipal wages are per hour, and so we combine them with postmasters assuming a 50 hour week and 52 week year. Finally, we form the 1910 and 1920 distribution of wages using the wages paid to police detectives as collected by the Bureau of Municipal Research of Philadelphia (1916). We treat all of these wages as urban wages.

Wages by state for Communication and Miscellaneous Transportation, Professional Services, and Personal Services. We use Transportation for Communication, Education wages for Professional Services, and Trade for Personal Services. These services have a reasonably close approximation to the skill mix in the services for which good wages are difficult to find.

Value added by state for Finance, Insurance, and Real Estate. For FIRE we instead use the banking capital by state to allocate national value added. For for 1880-1910 we use the total assets in national banks in each state collected from the annual report of the Comptroller of the Currency by Weber (2000). For 1870, we use the capital of individual banks aggregated to the state level collected by Fulford (2015). We assume that the distribution of capital in 1850 and 1860 is the same as in 1870 and 1920 is the same as 1910. The 1870 assumption is problematic since the banking capital of the south was largely destroyed by the Civil War, and there were few national banks in the south by 1870. We allocate urban versus non-urban GDP using the same approach we have used when we know wages. Within each state in rural areas $Y_i^{Nr} = \frac{uc}{\alpha}\theta \tilde{K^r}_i = w_i^r L_i^r/(1-\alpha)$. Then since $\tilde{K}_i = \tilde{K}_i^r + \tilde{K}_i^u$ and $\tilde{K}_i^r/\tilde{K}_i^u = (w_i^r L_i^r)/(w_i^u L_i^u)$, we can use the 1940 distribution of wage compensation in each state between urban and rural in FIRE, the labor in FIRE in urban and rural in each year, and the total capital in each state to allocate the state capital between urban and rural counties.

B.2.3 Measures of services, mining, and construction at the national level 1850-1960

The construction of value added for services, mining and construction at the national level varies by sub-period depending on the information available.

Value added per worker by services category 1840-1900. Gallman and Weiss (1969) construct measures of services value added and employment for eight categories at a national level from

1840 to 1900: trade; transportation and public utilities; finance professional services, personal services, government, education, and "hand trades." Hand trades are composed of smithing, shoe repair, and tailoring. These activities are technically manufacturing (they are constructed by hand or *manus*), but by the time formal national accounts were constructed in the 1950s had become part of services. Since the census includes output from the hand trades as manufacturing, we exclude them to avoid double counting. Combined with the Gallman and Weiss (1969) estimates of the labor force in each category, we create a measure of the value added per worker.

Value added per worker by services category 1930-1960. The National Income and Product Accounts (United States Department of Commerce, 1993) break down by industry the product (p. 104) and "persons engaged in production" (p. 122) which includes full time employees, part-time employees, and the self-employed. Since the census samples we use at the county level do not distinguish between full and part-time work or self-employment, the broad measure best matches the county data we use. We use the equivalent tables in United States Department of Commerce (2001) to construct nominal value added per worker engaged in production for the post-war period.

Constructing value added for services in 1910 and 1920. No estimates connect the Gallman and Weiss (1969) and United States Department of Commerce (1993) estimates of services value added by category. Since our goal is to correctly capture the relative value of different services, and their relationship to other productive activities, we interpolate the national value added of service categories in 1910 and 1920 based on 1900 and 1930. Since both prices and real activity increased rapidly over the period, the interpolation method matters. Linear interpolation, for example, is not a good choice because overall growth rates differ by decade. Linear interpolation of current dollar values between 1900 and 1930 tends to overstate growth from 1910 to 1920 since overall real GDP grew faster from 1900 to 1910 than 1910 to 1920 while prices grew faster from 1910 to 1920. So we first convert value added by each service category to real values using the GDP price deflator from Sutch (2006). Then we allocate growth in each decade in each service category from 1900 to 1930 to match the growth of real GDP per capita 1900 to 1930.[3] Note that we do not require the growth in service categories to be the same (some categories had almost no real growth over the period), only that where there is growth the proportion that takes place between 1900 and 1910 be the same as for overall growth. We finally obtain nominal quantities of (national) service value added for 1910 and 1920 by multiplying by the GDP price deflator from Sutch (2006).

Value added for construction and mining. We use the values of mining and contract construction from the National Income and Product Accounts in 1930 and 1940 to construct national value added per worker. From 1880 to 1920 we also use the estimates of Wright (2006) for mining. From 1850 to 1870 we use the ratio of the value added per worker in mining to the value added in transportation in 1880 times the value added per worker in transportation in 1850, 1860, and 1870. This approach assumes that the value added in transportation and mining grow at the same rate from 1850 to 1870. An important part of the value of mineral and fuel extraction comes from transporting it to populated areas. Transportation value added per worker grew at close to the same rate as overall national product per person during the period. Our approach for construction is similar but involves even stronger assumptions. Construction value added per worker before 1930 is simply its ratio to national income per person in 1930 and 1940. This approach assumes that construction value added grows at the same rate as the national economy, and that employment in construction is a good measure of the distribution of construction activity. Construction is a relatively small component of GDP—it composed only 5% of national product in 1950 and our estimates suggest it was smaller before that—and this approach puts a reasonable value on construction.

[3]Let y_{1900} be real national GDP per capita in 1900. Then a fraction $f^y_{1910-1900} = (y_{1910} - y_{1900})/(y_{1930} - y_{1900})$ of that growth took place between 1900 and 1910. We assume the same fraction of growth in each service category took place between 1900 and 1910. So for some service category s we observe value added per person y^s_{1900} and y^s_{1930} then we calculate $y^s_{1910} - y^s_{1900} = f^y_{1910-1900} * (y^s_{1930} - y^s_{1900})$.

B.3 Income 1950-2010

Starting in 1950 official statistics report measures of personal income per capita at the county level. We combine the county level income data from the County Data Books (United States Census Bureau, 2012) with the county income from the census in 1980, 1990, 2000, and the combined 2008-2012 American Community Survey collected by Minnesota Population Center (2011). In 1950, the census only reported median household income at the county level, while in other years we have mean income per person. To account for this discrepancy we multiply the 1950 median household income by the mean income to median income ratio in 1960 for each county. This approach is exactly correct if growth from 1950 to 1960 was entirely mean shifting, leaving the distribution unchanged, and family sizes did not change.

B.4 County output for 1950

Starting in 1950, the census micro-samples no longer report the current county of residence so it is no longer possible to construct county employment shares by industry. The City and County Databooks (United States Census Bureau, 2012) provide measures of employment in 1950 and 1960, as well as manufacturing and agricultural products sold.

The manufacturing values in the the Databooks are reported as value added in 1947, 1954, 1958, and 1963. Rather than taking the linear average, which misses the rapid growth during the period, we take the average growth rate in each county from 1947 to 1954, and use the county specific growth rate for three years starting in 1947. We use the same method to update 1958.

The agriculture values in the Databooks give the total value of farm products sold in 1950 and 1959 which we use to construct agriculture in 1960 by multiplying the county value by the nominal national increase in the total output in agriculture from 1959 to 1960 in series K 220-239 in United States Census Bureau (1975). Since these values do not include farm products consumed by farm households, we adjust both for value added and consumption using series K 220-239 in United

States Census Bureau (1975). Own consumption was slightly more than 6% of total farm output in 1950. Of much larger importance is the value of intermediate inputs which were close to 40% of total output in 1950.

The Databooks report "Mining Industries Employees" in 1939 which we use for 1940 without adjustment, and 1958 and 1963 which we apply to 1960 by taking the county specific linear average. The Databooks report a value added measure of mining in 1963, but we continue to use the employment based measure for consistency with earlier estimates.

In 1950 and 1960, the Databooks report the employees in construction; manufacturing; transportation and public utilities; wholesale and retail trade; finance, insurance, and real estate; and overall employment. The reporting in the Databooks for some counties is problematic, since some counties have more employment listed in a given category than overall. To create a less error filled employment variable, we take the larger of civilian and total employment (total employment is not always larger). Personal and professional employees are only reported in 1950, and government employees only in 1970. We use overall employment to construct a residual government and personal employment in 1950 and 1960 by subtracting out the other categories and setting the residual to zero if it would be negative. The residual in 1960 contains both government and personal services, we divide between them using the fraction of personal in personal and government services in 1950.

With employment totals we find a value added of services using the same method as for 1940 and earlier. Using Tables 6.1B for national income by industry and 6.8B "Persons engaged in production" in United States Department of Commerce (2001) gives an average product per employee per industry which combine with employment by industry in each county to create a measure of value added by county by industry.

B.5 Aggregate output and its composition

Although our goal is for each decade to create a measure that correctly captures the relative GDP across counties, we can also construct an estimate of the national GDP by summing across counties. Figure A-1 shows real GDP per capita as constructed by Sutch (2006), which includes services, and our measure of county GDP summed over all counties and divided by population. Figure A-1 suggests that our measure is a good approximation of the level of aggregate output and captures the change over time. Part of the reason for this close relationship is that the construction of the historical GDP at the national level relies on many of the same sources we have used at the county level such as the national estimates of manufacturing and agriculture output.

B.6 Combining income and output measures

From 1850 to 1960 we have created something close to GDP per worker for each county. Starting in 1950 we have an income based measure from the census. These two measures are not the same; in each decade from 1950 to 2010, the sum of county aggregate incomes from the census is less than GDP from the national accounts. Income leaves out a number of categories such as owner occupied rent that are included in GDP. A a county level, moreover, income, which can include profits from activities elsewhere, need not be the same as a measure of the gross domestic product produced in a county. We use the overlap of our income measure and GDP measure in 1950 to combine the two series to create a measure of GDP over the entire time period. More specifically, we assume that GDP and income grow at the same rate from 1950 onward and use the growth rate of income to create a measure of county level nominal GDP. Once we have GDP, we can convert to GDP per worker using population and employment measures. Some counties have GDP-to-income ratios that are extreme because the constructed value of county GDP is low.

Finally, we deflate our constructed measure of county level nominal GDP by the GDP deflator in Sutch (2006), updated using Bureau of Economic Analysis tables on GDP and the GDP deflator.

C Creating a density of arrival times

Immigrants arrived at different times and we would like to reflect what immigrants brought with them by the conditions in their country of origin at the time of immigration. Doing so requires knowledge of the conditional density of immigration over time so that, for example, the Irish coming in the 1850s reflect different experiences than the Irish in the 1890s, both of whom are different from the Italians in the 1910s. Our ancestry measure captures very well the stock of people whose ancestors came from a country of origin. Since it is a stock, however, changes in it reflect both increases from migration, but also natural changes from births and deaths. We therefore turn to immigration records that contain the number of migrants arriving from different countries starting in the 1820s (Department of Homeland Security, 2013) at a national level. In 1850 we create a density of arrival times for the stock of migrants in 1850 based on Daniels (2002). The division is appropriately coarse given the limited information, and so only divides between arrivals in 1650, 1700, 1750, 1800, and 1850. For example, we allocate all of the Netherlands arrivals to 1700, and divide the English migrants to between 1650 and 1750 to reflect the later migration of lowland Scots and Scotch-Irish. Using our ancestry vector and county population, we create a stock of total population of ancestry a in time t: P_t^a. The immigration records then record the number of migrants I_{t+1}^a from country a over the decade from t to $t+1$. The density $F_t^a(\tau)$ gives the density of arrival times τ of the descendants of the population of ancestry a at time t (which is by definition 0 for all $\tau > t$ since it is a conditional density). Given this definition, the size of the population in year t descended from people who migrated in year τ is $(P_{t+1}^a - I_{t+1}^a)F_t^a(\tau)$. Starting from an initial $F_t^a(1600) = 0$, we update the conditional density based on immigration records using:

$$F_{t+1}^a(\tau) = \frac{(P_{t+1}^a - I_{t+1}^a)F_t^a(\tau) + I_{t+1}^a 1(\tau = t+1)}{P_{t+1}^a}, \tag{3}$$

where $1(\tau = t+1)$ is an indicator which is one if $\tau = t+1$. It is useful to see how this formula works. If $\tau = t+1$ and so we want to know the share of the population in year t+1 descended from people who came in year $\tau = t+1$, then since $F_t^a(t+1) = 0$ (the conditional arrival for the future is zero), the share of the population is just the new migrants share of the total stock: I_{t+1}^a / P_{t+1}^a. On the other hand, if $\tau < t+1$ is in the past, $1(\tau = t+1) = 0$, then updating the density is simply adjusting the fraction of the current population that migrated in τ: $(P_{t+1}^a - I_{t+1}^a) F_t^a(\tau) / P_{t+1}^a$ since new migrants dilute the share of old migrants in the total stock. Since this formula updates the density at t by the fraction of new migrants between t and $t+1$ compared to the total stock. For example, the density changes only slightly for the English between 1880 and 1890, despite more than 800,000 migrants because the stock is so large, while the 1.4 million German immigrants significantly shift the arrival density of Germans because of the smaller stock.

We modify this approach slightly for smaller immigrant groups. Immigration records group some countries together and information is not available for all countries. We assign the density of arrival times to similar countries, or from the overall group. For example, we assign the arrival times of "Other Europe" in the immigration records to Iceland. However, the total migration from all of "Other Europe" is larger than our estimates of the population descended from Iceland migrants in most years. We assume that the arrival of migrants is proportional to the larger group (or similar country), and scale the number of migrants so that the population implied by the immigrant records is no larger than the population implied by the census records. In particular, define a projected population that would come from immigration and natural increase from growth rate g:

$$\hat{P}_t^a = \sum_{\tau=t}^{-\infty} (1+g)^{t-\tau} I_\tau^a.$$

$\hat{P}_t^a$ is the population that would occur if all immigrants came and then grew in population at growth rate g. Then define:

$$\omega^a = \max_t \frac{\hat{P}_t^a}{P_t^a}$$

as the maximum ratio of the projected population based on the (too large) immigration records and the population descended from group a. We then define the scaled immigration of the particular group as $\hat{I}^a_t = I^a_t/\omega^a$ which scales the number of migrants to the overall population of that group.[4]

Austria-Hungary and its constituent countries pose a special problem. At least some Czech and Slovak migration (which are record together as Czechoslovakia) appears to be part of the Austrian migration in the immigration records since our ancestry calculations suggest a substantial Czechoslovakia presence from 1900 to 1920, while the immigration records show few migrants. Similarly, Poland was divided among Austria, Hungary, Germany, and Russia in the decades ending in 1900, 1910, and 1920 during a period of peak migration. We assign a fraction of Austrian migration to Czechoslovakia, and a portion of German, Hungarian, and Russian migration to Poland. The fractions are approximate based on the relative populations in 1910.

Several groups have a special set of arrival times that are more or less by assumption. We assign African Americans an arrival of 1750. Significant groups of Native Americans are first counted in the census or forced to move to new areas after 1850. We assign them an "arrival" of 1840, acknowledging that giving an indigenous group an arrival time is problematic, but think of it as representing an approximate density of the start of substantial contact with other groups, with all of its many, often negative, consequences. Puerto Rico similarly represents a complicated situation since Puerto Rican's have been US. citizens since 1917, but the data used to track Puerto Rico the same way as the rest of the US counties is only sporadically available. We allocate a small mainland migration in 1910 and a much larger one in 1960 to match the ancestry population totals.

While the density is approximate it still provides very useful information that matches immigration narratives. For example, the 2010 density gives the average decade of arrival for each ancestry living in 2010. Most Irish are descended from immigrants who arrived in the 1840s, with substantial populations in the 1850s and 1860s, but few afterwards compared to the large population. Based on these calculations, more people of Chinese ancestry are descended from people

[4] The procedure is slightly more complicated for small countries where measurement error in either our measure based on samples from the census, or immigration statistics can produce very large ω^a. We define ω^a as the maximum ratio of projected to census population when the census population is at least 100,000. If the ancestry never reaches 100,000, we still use the overall maximum. Finally, if this procedure produces an immigration flow larger than our projected population, we set the density equal to 1 in that year.

who migrated from 1860 - 1880 than the second wave of Chinese migration from 1970-2010. Far more migrants came later, but the early migrants had already established a population which grew over time and which we track geographically with the census calculations. Other Asian migrants have come mostly since 1970, except the Japanese who are mostly descended from early migrants.

We use the density to weight country-of-origin characteristics by the time of arrival. For example, we calculate the difference between log GDP per capita in the country of origin and log GDP in the US at the time of arrival ($y^a_\tau - y^{US}_\tau$). For a given ancestry, the arrival weighted log GDP (relative to US GDP) is then:

$$\tilde{y}^a_t = \sum_{\tau=0}^{t} (y^a_\tau - y^{US}_\tau)(1-\delta)^{t-\tau} F^a_t(\tau) \tag{4}$$

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

For the migrant education variable, we instead for it as the ratio to US education: $\mathrm{z}^a_t = \sum_{\tau=0}^{t} (\mathrm{z}^a_\tau / \mathrm{z}^{US}_\tau)^{(1-\delta)^{t-\tau}} F^a_t(\tau)$ where z^a_τdenotes the average immigrants' from country *a* education, z^{US}_τ the average education in the US, $F^a_t(\tau)$ is the arrival density of group a up to time τ, and δ is the rate of depreciation of the importance of that characteristic. When the depreciation rate is greater than zero, as the time of arrival gets further away, the immigrant group characteristic converges to the US characteristics. See Appendix D.3 for a detailed discussion of how we construct immigrant education.

D Constructing country of origin measures

D.1 Origin Country GDP

This section briefly details how we fill in the gaps left in origin country GDP per capita in the Bolt and van Zanden (2013) update of Maddison (1995). Some crucial countries of origin are not available for all dates going back although some information is available. We fill in missing data by making reasonable assumptions about the likely relationship within other countries or the same country on surrounding dates. The most important of these is Ireland which did not obtain independence until 1921, and has only spotty estimates of income separate from the United Kingdom. We use the ratio of Irish to UK GDP in 1921 to fill in dates from 1880 to 1920, and the ratio of Irish to UK in 1870 to fill in dates before that. While this approach will clearly miss Irish specific events such as the potato blight, our goal is to get the relative incomes appropriately.

Little information is available for countries in Africa. Ghana, a British colony, has estimates in 1913 and 1870 and yearly starting in 1950 (Ghana was the first African country to achieve independence in 1957). We linearly interpolate between 1870, 1913, and 1950, but since the value in 1870 is close to subsistence (439 in 1990 $) we set 1850 and 1860 to 439.

The West Indies is a birthplace for a substantial portion of the population in some areas early on. We use the post-1950 Maddison numbers for the Caribbean. We take the ratio of the Caribbean to Jamaica between 1913 and 1950 when there are no overall Caribbean numbers listed, interpolate between years 1900 to 1913, and again use the ratio of Caribbean to Jamaica between 1900 and 1870, and again prior to 1870.

Latvia, Lithuania, and Estonia have some early migration (small overall). They are combined where there is data on them separately, but we use the ratio with overall Eastern Europe to go back earlier.

Puerto Rico has a special status. It has been a US possession since 1898, and after 1950 there was significant migration to the mainland. We treat Puerto Rico as a separate ancestry recognizing its distinct culture. The ancestors of Puerto Ricans appear to be a combination of Spanish, Africans brought as slaves, and a mix of other immigrants. We assign Puerto Rico its own GDP after 1950, but before that give it the Caribbean GDP adjusted for the Puerto Rico-to-Caribbean ratio in 1950.

The Pacific Islands (a birthplace in the census) as well as American Somoa represent a similar problem to Puerto Rico. We create a Pacific Islands (including Somoa) GDP per capita by taking the ratio of Fiji and Indonesia in 2010 (source: World Bank, 2010 International $PPP) and using the Indonesian GDP going back in time.

We create Latin America GDP before 1870 as the ratio of Argentina, Brazil, and Colombia in 1870 times their average before that. Mexico is always separate, so Latin America excludes Mexico as an ancestry.

Israel is complicated in the past since it had substantial migration to create the modern state. We assign the Lebanon GDP to Israel/Palestine before 1950. Note that Jewish migration from Europe to the US is measured as the country of origin in Europe.

Afghanistan has the India GDP in 1870, and its own after 1950.

For smaller countries (with comparably small migrations) where information is missing we assign them to a comparable larger country. We assign Lichtenstein, Monaco, and Andorra the French GDP; San Marino, Vatican City, Malta, and Cyprus the Italian GDP; Gibraltar the Spain GDP; Lapland n.s. the Finland GDP. All of Eastern Europe n.s., Central Europe n.s., Eastern Europe n.s., and Southern Europe n.s. get the Eastern Europe overall GDP.

D.2 Culture Measures from the World Values Survey

We construct measures of several cultural attitudes from the European Values Survey and the World Values Survey. We use an integrated version of the survey that combines both sources and utilized each of the six waves available between 1981 and 2014. The cultural endowment is inferred from the answers to six survey questions:

Trust: A measure of generalized trust is estimated from the responses to the question: "Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?" We calculate the proportion of the total respondents from a given nationality that answer that "most people can be trusted." An alternative response to this question is that one "can't be too careful."

Control: As a measure of the attitude towards one's control over personal circumstances we use the answer to the question: "Some people feel they have completely free choice and control over their lives, while other people feel that what they do has no real effect on what happens to them. Please use this scale where 1 means "none at all" and 10 means "a great deal" to indicate how much freedom of choice and control you feel you have over the way your life turns out." In particular, we take the average response by nationality for all countries in our dataset.

Respect, Obedience, and Thrift: To measure the attitude toward authority and towards saving behavior we use the following question from the survey: "Here is a list of qualities that children can be encouraged to learn at home. Which, if any, do you consider to be especially important? Please choose up to five." There are 17 possible qualities listed. We estimate the proportion of people by nationality that respond that "tolerance and respect for other people" is important to measure Respect and the proportion of people that respond that "obedience" is important to measure Obedience. To measure the importance of saving we estimate the proportion of people that respond that "thrift saving money and things" is important.

Holiday: To measure the attitude towards leisure we use the response to the question: "Here are some more aspects of a job that people say are important. Please look at them and tell me which ones you personally think are important in a job?" Similarly to the questions regarding important qualities in children this question has 18 different aspects. We use the fraction of people that respond that "generous holidays" is an important aspect in a job to proxy for the attitude towards leisure.

Following Tabellini (2010) we also form the first principal component of the combined attitudes Trust, Control, Respect, and Obedience at the individual level, and then take the average of the principal component for each country.

D.3 Immigrant Education

In this section we describe how we measure immigrant education, attempting to capture the human capital compared to the United States at the time, of the immigrants when they arrive. Combined with the density of arrival times, the measure of new immigrant education gives an average arrival weighted education.

The census records the birthplace, so we know the education of immigrants, but does not record the year of arrival. For example, although the census records the Italians who were in the US. in 1910, we do not know which of them arrived between 1900 and 1910. We make the assumption that recent migrants are those who were born in a foreign country and are between 20 and 30 as of the age census. Most of the large waves of migration were primarily among young people, although some migrants brought their families and so came as children. Taking the 20-30 year olds thus mixes some people who came recently with some who may have come as children and so received an their education in the United States. In 1850 we assign the literacy of the 30-40 years olds migrants to the 20-30 year olds migrating in 1830-1840. For 1890 when the census micro-samples were destroyed we assign the literacy of the 30-40 year olds in 1900. For African Americans we use the education level as of 1900 since there were rapid gains in literacy after the civil war which slowed after 1900. For Native Americans we use the literacy levels as of 1900 which is the first year that Native Americans are recorded extensively.

The micro-samples from the census record the education as well as the birthplace. Before 1940 the census only records literacy, while after that it records years of education. Since we want to create a measure that captures the average relative education of migrants, we must combine these disparate measures so that we can compare the relative education of later migrants with early ones. We take the ratio of the 20-30 migrant literacy for each ancestry to the non-migrant US education of 20-30 year olds before 1940, and use years of education starting in 1940.

With no adjustment this procedure assumes that the ratio of years of education is the same as the ratio of literacy. Rather than make this strong assumption, we instead adjust the literacy ratio so that it gives the linear prediction of the years of education ratio. To do this we take the demographic groups that are age 30-40, 40-50, and 50-60 in 1940 for whom we observe their education, and compare the literacy of the same ancestry groups who were 20-30, 30-40, and 40-50 in 1930. Regressing the ratio of each age-ancestry groups years of education to the US (measured in 1940) on the same ratio for literacy (measured in 1930) then gives a prediction of how the ratio to US literacy converts to the ratio to US years of education on average. We use this prediction to adjust the literacy ratios before 1940.

D.4 Executive Constraint

We build a comparable measure of executive constraint on arrival by combining the measure of executive constraint from POLITY IV and Acemoglu, Johnson, and Robinson (2005). Since not all important countries are covered in years of migration, we fill in some values based on nearby years or comparable countries.

References

Acemoglu, Daron, Simon Johnson, and James A. Robinson. 2005. "The Rise of Europe: Atlantic Trade, Institutional Change, and Economic Growth." *American Economic Review* 95 (3):546–579.

Annual Reports of the Postmaster General. 1900. *Report of the Postmaster General*. Washington, D.C.: Government Printing Office.

Ashraf, Quamrul and Oded Galor. 2013. "Genetic Diversity and the Origins of Cultural Fragmentation." *The American Economic Review* 103 (3):528–533.

Barde, Robert, Susan B. Carter, and Richard Sutch. 2006. *Historical Statistics of the United States, Earliest Times to the Present: Millennial Edition*, chap. Immigrants, by country of last residence. Cambridge University Press, Table Ad90–221.

Bolt, Jutta and Jan Luiten van Zanden. 2013. "The First Update of the Maddison Project; Re-estimating Growth Before 1820." Working Paper 4, Maddison Project. Available `http://www.ggdc.net/maddison/maddison-project/data.htm`, accessed 2 October 2014.

Bureau of Municipal Research of Philadelphia. 1916. *Comparative Salary Data*.

Daniels, Roger. 2002. *Coming to America*. New York: HarperPerennial.

Department of Homeland Security. 2013. "Yearbook of Immigration Statistics: 2013." In *Table 2: Persons Obtaining Lawful Permanent Resident Status by Region and Selected Country of Last Residence: Fiscal Years 1820 to 2013*.

Fulford, Scott L. 2015. "How important are banks for development? National banks in the United States 1870–1900." *Review of Economics and Statistics* 97 (5):921–938.

Gallman, Robert E. and Thomas J. Weiss. 1969. *The Service Industries in the Nineteenth Century*. National Bureau of Economic Research and UMI, 287–381.

Higginbothham, A. Leon, Jr. and Barbara K. Kopytoff. 2000. *Interracialism: Black-White Intermarriage in American History, Literature, and Law*, chap. Racial Purity and Interracial Sex in the Law of Colonial and Antebellum Virginia. Oxford: Oxford University Press, 81–139.

Kennedy, Randall. 2000. *Interracialism: Black-White Intermarriage in American History, Literature, and Law*, chap. The Enforcement of Anti-Miscegenation Laws. Oxford: Oxford University Press, 140–162.

Kolchin, Peter. 2003. *American Slavery: 1619-1877*. New York: Hill and Wang.

Maddison, Angus. 1995. *Monitoring the World Economy 1820-1992*. Paris: OECD Development Centre Studies.

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.

Nineteenth Annual Report of the Commisisioner of Labor. 1905. *Wages and Hours of Labor 1904*. Government Printing Office.

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]."

Saks, Eva. 2000. *Interracialism: Black-White Intermarriage in American History, Literature, and Law*, chap. Representing Miscegenation Law. Oxford: Oxford University Press, 61–81.

Sutch, Richard. 2006. *Historical Statistics of the United States, Earliest Times to the Present: Millennial Edition*, chap. Gross domestic product: 1790-2002 [Continuous annual series]. Cambridge University Press, Table Ca9–19.

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

United States Bureau of Labor Statistics. 1919. *Wages and Hours in the Coal Mining Industry in 1919*. Goverment Printing Office.

United States Census Bureau. 1975. *Historical Statistics of the United States, Colonial Times to 1970, Bicentenial Edition, Part 1*. Washington, D.C.: U.S. Government Printing Office.

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

United States Department of Commerce. 1993. *National Income and Product Accounts of the United States*, vol. Volume 1, 1929-58. Washington, D.C.: U.S. Government Printing Office.

———. 2001. *National Income and Product Accounts of the United States, 1929-1997*, vol. Volume 2. Washington, D.C.: U.S. Government Printing Office.

United States Department of Labor. 1934. *History of Wages in the US from Colonial Times to 1928*. Washington, D.C.: Goverment Printing Office, republished by gale research company, detroit, 1966. ed.

van Leeuwen, Bas and Jieli van Leeuwen-Li. 2013. "Average Years of Education." https://www.clio-infra.eu/datasets/select/indicator/362. Accessed 11 February 2015.

Van Zanden, Jan Luiten, Joerg Baten, Peter Foldvari, and Bas van Leeuwen. 2014. "The Changing Shape of Global Inequality 1820–2000: Exploring a New Dataset." *Review of Income and Wealth* 60 (2):279–297.

Vanhanen, Tatu. 2012. "Political Participation." https://www.clio-infra.eu/datasets/select/indicator/384. Accessed 11 February 2015.

Wang, Wendy. 2012. "The Rise of Intermarriage." Tech. rep., Pew Research Center. URL http://www.pewsocialtrends.org/files/2012/02/SDT-Intermarriage-II.pdf.

Weber, Warren E. 2000. "Disaggregated Call Reports for U.S. National Banks, 1880-1910. Research Department, Federal Reserve Bank of Minneapolis." Research Department, Federal Reserve Bank of Minneapolis. Available: http://research.mpls.frb.fed.us/research/economists/wewproj.html, accessed 30 April 2013.

Wright, Gavin. 2006. *Historical Statistics of the United States, Earliest Times to the Present: Millennial Edition*, chap. Mineral operations - establishments, receipts, value added, employment, and expenses: 1880-1997. Cambridge University Press, Table Db1–11.

Table A-1: Ancestry share of the population by census division and year (percent)

Year	Ancestry	Northeast		Midwest		South			West	
		New England	Middle Atlantic	East North Central	West North Central	South Atlantic	East South Central	West South Central	Mountain	Pacific
1870	England	62.7	45.0	53.9	53.2	46.9	50.9	41.9	56.7	45.2
	Germany	2.8	18.6	19.5	16.8	4.8	5.4	7.4	8.0	10.5
	African Am.	0.9	1.7	1.4	3.7	37.7	33.3	36.1	0.6	0.7
	Mexico	0.0	0.0	0.0	0.0	0.0	0.0	1.6	2.9	2.1
	Ireland	21.5	19.9	9.0	9.7	3.5	3.0	3.7	7.8	14.0
	Italy	0.1	0.1	0.0	0.0	0.0	0.0	0.1	0.2	1.0
1920	England	20.6	18.6	26.5	28.5	46.1	51.0	43.8	35.2	26.6
	Germany	4.5	17.7	26.0	25.6	7.4	7.4	11.5	15.2	16.4
	African Am.	1.0	2.6	2.4	2.2	30.8	28.4	20.1	0.9	0.8
	Mexico	0.0	0.0	0.0	0.2	0.0	0.0	5.1	5.1	2.5
	Ireland	22.0	16.4	9.4	9.1	4.5	3.9	4.9	8.3	10.6
	Italy	7.4	10.2	2.3	0.9	0.8	0.4	1.4	2.4	4.1
1970	England	15.3	15.9	25.2	26.2	43.5	52.5	39.2	33.7	25.4
	Germany	5.4	14.0	21.5	25.4	9.2	8.9	12.7	16.4	15.2
	African Am.	3.0	10.0	9.6	4.4	18.8	20.1	15.6	2.2	5.6
	Mexico	0.1	0.1	0.5	0.7	0.2	0.2	9.5	5.4	6.5
	Ireland	15.0	11.5	7.3	7.8	5.3	4.7	5.0	6.9	7.0
	Italy	12.0	12.5	3.5	1.6	2.3	1.0	2.2	2.8	4.1
2010	England	14.9	15.2	24.2	24.5	30.8	43.6	29.0	26.0	17.8
	Germany	6.7	11.3	19.0	22.7	9.1	10.2	10.8	14.3	10.6
	African Am.	4.2	10.4	11.6	6.0	19.8	20.2	13.9	3.2	5.0
	Mexico	0.9	1.4	3.6	2.9	2.6	1.9	17.1	12.4	18.0
	Ireland	11.5	8.4	6.4	6.8	5.1	4.8	4.2	5.9	4.7
	Italy	9.3	8.5	2.9	1.9	3.2	1.6	2.2	3.2	2.8

Notes: This table shows the share of the population within each census region that is composed of the six largest ancestries in 2010. It helps to understand which ancestry is the largest within each region.

Table A-2: Share of select ancestries across census divisions by year (percent)

		Northeast		Midwest		South			West	
Year	Ancestry	New England	Middle Atlantic	East North Central	West North Central	South Atlantic	East South Central	West South Central	Mountain	Pacific
1870	England	11.3	20.5	25.5	10.6	13.7	11.6	4.4	0.7	1.6
	Germany	2.0	33.4	36.1	13.2	5.5	4.9	3.1	0.4	1.4
	African Am.	0.7	3.1	2.7	3.0	44.5	30.6	15.3	0.0	0.1
	Mexico	0.0	0.9	0.7	0.9	0.1	0.2	58.5	12.6	26.1
	Ireland	17.7	41.6	19.6	8.9	4.6	3.2	1.8	0.4	2.2
	Italy	7.7	24.7	11.1	5.4	3.0	5.9	11.8	1.9	28.5
1920	England	4.6	12.5	17.2	10.8	19.3	13.7	13.6	3.6	4.7
	Germany	1.9	22.7	32.1	18.4	5.9	3.8	6.8	2.9	5.5
	African Am.	0.7	5.5	4.9	2.7	41.2	24.3	19.9	0.3	0.5
	Mexico	0.1	0.5	1.1	3.3	0.3	0.2	59.2	19.3	16.1
	Ireland	15.1	33.8	18.7	10.6	5.8	3.2	4.6	2.6	5.7
	Italy	13.6	56.2	12.2	2.9	2.9	0.8	3.4	2.0	6.0
1970	England	3.1	10.0	17.1	7.2	22.5	11.3	12.8	4.7	11.4
	Germany	2.1	17.2	28.4	13.6	9.3	3.7	8.1	4.5	13.2
	African Am.	1.6	17.2	17.8	3.3	26.6	11.9	13.9	0.8	6.9
	Mexico	0.4	1.0	4.5	2.5	1.6	0.6	41.0	10.0	38.4
	Ireland	11.2	26.9	18.5	8.0	10.3	3.8	6.1	3.6	11.6
	Italy	13.8	45.1	13.8	2.5	6.7	1.2	4.2	2.3	10.4
2010	England	2.8	8.2	14.9	6.7	23.4	10.7	14.0	7.6	11.8
	Germany	2.5	12.0	22.9	12.1	13.6	4.9	10.2	8.1	13.8
	African Am.	1.7	12.2	15.5	3.5	32.6	10.7	14.5	2.0	7.2
	Mexico	0.6	2.5	7.4	2.6	6.5	1.5	27.4	12.0	39.5
	Ireland	9.0	18.6	16.1	7.5	15.9	4.8	8.4	7.1	12.6
	Italy	11.5	29.8	11.8	3.4	16.0	2.6	6.8	6.0	12.2

Notes: This table shows the share of each of the six largest ancestries that live in each census division by year. It helps to understand where the largest portion of each ancestry resides (but it may still be a small share of the population in a given region as shown in Table A-1).

Table A-3: Descriptive statistics

Year	1870	1890	1910	1930	1950	1970	1990	2010	1870-2010
					Overall US				
Number of countygroups	988	1047	1130	1143	1146	1146	1146	1136	
Population covered (millions)	38.21	61.79	92.01	122.65	150.43	201.83	246.47	303.41	
Ancestries >1% of population	8	10	18	19	19	19	25	26	
Ancestries >5% of population	4	4	4	4	4	5	4	5	
Overal US fractionalization	0.697	0.748	0.828	0.858	0.853	0.864	0.877	0.894	
US isolation	0.394	0.356	0.275	0.231	0.236	0.195	0.181	0.158	
US dissimilarity	0.402	0.425	0.427	0.411	0.410	0.336	0.333	0.322	
					County group averages				
Real GDP per capita	1915	3154	4741	5507	8782	16576	25955	33518	12340
Log Real GDP per capita	7.426	7.888	8.337	8.483	8.999	9.660	10.106	10.370	8.926
S.D.	0.534	0.604	0.546	0.538	0.422	0.340	0.343	0.315	1.060
Inter-quartile	0.761	0.952	0.807	0.799	0.576	0.484	0.478	0.406	1.707
Origin 1870 GDP per capita	2419	2332	2161	2104	2146	2086	1998	1877	2124
S.D.	441	416	370	355	362	325	361	362	398
Inter-quartile	464	496	465	497	519	418	471	480	556
Log(Origin -US GDP per capita)	-0.091	-0.158	-0.261	-0.303	-0.265	-0.299	-0.355	-0.435	-0.282
S.D.	0.344	0.324	0.282	0.236	0.217	0.193	0.228	0.239	0.274
Inter-quartile	0.300	0.315	0.279	0.312	0.298	0.247	0.286	0.322	0.364
Arrival ratio U.S. education	0.852	0.896	0.887	0.882	0.894	0.890	0.890	0.888	0.885
S.D.	0.180	0.097	0.077	0.064	0.061	0.052	0.051	0.048	0.085
Inter-quartile	0.153	0.085	0.091	0.096	0.092	0.075	0.075	0.067	0.091
Origin Trust	0.333	0.335	0.335	0.331	0.336	0.331	0.324	0.314	0.330
S.D.	0.064	0.065	0.062	0.053	0.049	0.041	0.045	0.047	0.054
Inter-quartile	0.065	0.064	0.063	0.056	0.056	0.050	0.055	0.060	0.062
Origin Thrift	0.272	0.278	0.295	0.301	0.300	0.305	0.307	0.310	0.297
S.D.	0.028	0.032	0.037	0.036	0.036	0.029	0.027	0.024	0.034
Inter-quartile	0.038	0.049	0.056	0.059	0.056	0.041	0.037	0.032	0.052
Origin State history	0.630	0.621	0.607	0.601	0.606	0.600	0.587	0.572	0.601
S.D.	0.082	0.078	0.073	0.067	0.068	0.060	0.068	0.065	0.072
Inter-quartile	0.085	0.097	0.097	0.088	0.088	0.071	0.083	0.086	0.095
Ancestry fractionalization	0.606	0.644	0.717	0.749	0.738	0.782	0.800	0.826	0.740
S.D.	0.112	0.112	0.121	0.125	0.130	0.106	0.101	0.088	0.129
Inter-quartile	0.148	0.150	0.173	0.189	0.191	0.153	0.141	0.117	0.193
Origin GDP weighted fract.	0.123	0.128	0.137	0.144	0.134	0.140	0.147	0.160	0.140
S.D.	0.064	0.060	0.056	0.048	0.045	0.037	0.037	0.036	0.050
Inter-quartile	0.082	0.073	0.069	0.061	0.060	0.051	0.059	0.058	0.073

Notes: This table shows descriptive statistics for the US overall (the top panel) and the average for county groups (the bottom panel). Origin variables are ancestry weighted within each county group using the ancestry fractions as weights. County group averages are not weighted by population since the regressions treat each county group as its own observation. Inter-quartile is the range from the 75th percentile to the 25th percentile. See the text for the construction and definition of indices and ancestry and sources of the country of origin variables.

Table A-4: Covariance and correlation matrix of important variables

	Origin GDP	Migrant educ.	Trust	State History	Fract.	Weight. Fract.	Exec. Const.
	Covariance						
Origin GDP at arrival	0.1106						
Migrant educ./US at arrival	0.0240	0.0077					
Trust	0.0124	0.0038	0.0030				
State History in 1500	0.0204	0.0044	0.0020	0.0055			
Fractionalization	-0.0184	-0.0006	0.0017	-0.0030	0.0194		
Origin GDP weighted fract.	-0.0131	-0.0032	-0.0022	-0.0023	0.0018	0.0028	
Origin executive constraint	0.1403	0.0376	0.0265	0.0207	0.0066	-0.0198	0.3955
	Correlation						
Origin GDP at arrival	1.000						
Migrant educ./US at arrival	0.826	1.000					
Trust	0.677	0.781	1.000				
State History in 1500	0.827	0.684	0.500	1.000			
Fractionalization	-0.396	-0.049	0.222	-0.289	1.000		
Origin GDP weighted fract.	-0.744	-0.688	-0.757	-0.583	0.243	1.000	
Origin executive constraint	0.671	0.683	0.763	0.443	0.075	-0.595	1.000

	Origin GDP	Fract.	Weight. Fract.	Ed. Fract.	Trust. Fract.	St. Hist. Fract.	
	Correlation						
Origin GDP at arrival	1.000						
Fractionalization	-0.396	1.000					
Origin GDP weighted fract.	-0.744	0.243	1.000				
Education weighted fract.	-0.729	0.166	0.840	1.000			
Trust weighted fract.	-0.800	0.403	0.847	0.712	1.000		
State Hist. weighted fract.	-0.734	0.520	0.665	0.596	0.769	1.000	
Polarization	0.267	-0.701	0.054	0.046	-0.175	-0.259	1.000

Notes: This table shows the correlation and variance-covariance matrix of important variables across county groups. Italicized variables are ancestry weighted at the county-group level. The largest possible sample is included for each cell and so the sample sizes may vary. No adjustments for year are made in calculating the correlations.

Table A-5: County GDP per worker and country-of-origin GDP: Robustness

Dependent variable:	Log(county GDP per worker)		
	[1]	[2]	[3]
Origin GDP per capita	0.310***	0.373***	0.290***
(ancestry weighted)	(0.0244)	(0.0482)	(0.0272)
Decade lag	0.444***	0.460***	0.444***
log county GDP	(0.0162)	(0.0204)	(0.0171)
Two decade lag	0.0278*	0.0300*	0.0525**
log county GDP	(0.0164)	(0.0164)	(0.0211)
Origin GDP		-0.0922*	
× In an MSA		(0.0500)	
Decade lag county GDP		-0.0299	
× In an MSA		(0.0195)	
Two decade lag		-0.00304	
× In an MSA		(0.0190)	
Indicator after 1940			2.045***
			(0.212)
Origin GDP			0.00149
× After 1940			(0.0195)
Decade lag county GDP			-0.0206
× After 1940			(0.0303)
Two decade lag			-0.0721***
× After 1940			(0.0246)
Observations	14,415	14,415	14,415
Division X Year FE	Yes	Yes	Yes
County group FE	Yes	Yes	Yes
Cluster	Countygroup	Countygroup	Countygroup

Notes: This table shows a number of robustness variations on our main specification in Table 2 which shows the effect of changing ancestry weighted *Origin GDP* per capita on log county GDP per worker. For comparison purposes the first column reproduces column 3 in Table 2. The second column interacts all variables with an indicator for the fraction of counties in a county group that contain a Metropolitan Statistical Area using the most recent definition. The third column interacts the variables with an indicator that is 1 after 1940 and zero before. Splitting the sample at 1920 produces nearly identical results.

Table A-6: Ancestry and origin geography

	Dependent variable: Log(county GDP per worker)								
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Migrant educ./US	0.324**	0.386***	0.519***	0.457***	0.340**	0.441***	0.606***	0.358**	0.535***
ratio at arrival	(0.147)	(0.138)	(0.135)	(0.130)	(0.139)	(0.142)	(0.161)	(0.140)	(0.143)
Trust	1.177***	0.901***	0.776***	0.808***	1.059***	0.746***	0.473**	0.147	0.116
	(0.298)	(0.201)	(0.178)	(0.177)	(0.203)	(0.200)	(0.229)	(0.307)	(0.274)
State history	0.382***	0.448***	0.506***	0.551***	0.297**	0.589***	0.465***	0.300**	0.163
in 1500	(0.128)	(0.173)	(0.106)	(0.109)	(0.138)	(0.119)	(0.106)	(0.118)	(0.145)
Mean land quality	0.281								
	(0.203)								
Variation in land quality		0.137							
		(0.485)							
Mean elevation			0.195**						
			(0.0899)						
Variation in elevation				0.285***					
				(0.0967)					
Percentage of arable land					0.676***				
					(0.248)				
Distance to waterways						0.122*			
						(0.0660)			
Precipitation							-0.282***		
							(0.0947)		
Absolute latitude								0.00689***	
								(0.00214)	
Frac. in tropical and									-0.375***
subtropical climate zones									(0.114)
Decade lag	0.439***	0.439***	0.438***	0.438***	0.438***	0.439***	0.438***	0.438***	0.438***
log county GDP	(0.0164)	(0.0164)	(0.0164)	(0.0164)	(0.0164)	(0.0164)	(0.0165)	(0.0165)	(0.0165)
Two decade lag	0.0277*	0.0278*	0.0277*	0.0276*	0.0274*	0.0276*	0.0272*	0.0269*	0.0265*
log county GDP	(0.0160)	(0.0161)	(0.0160)	(0.0160)	(0.0160)	(0.0161)	(0.0160)	(0.0160)	(0.0160)
Observations	14,415	14,415	14,415	14,415	14,415	14,415	14,415	14,415	14,415
County groups	1146	1146	1146	1146	1146	1146	1146	1146	1146

Notes: This table shows the relationship between ancestry weighted country-of-origin geography variables and county GDP per worker. The geography variables are from Ashraf and Galor (2013) and are weighted by county ancestry. All regressions include county-group fixed effects, census division X year effects, and standard errors are clustered at the county group level.

Table A-7: County GDP per worker and country-of-origin inequality

Dependent variable:	Log(county GDP per worker)			
	FE	FE	IV	FE
	[1]	[2]	[3]	[4]
Origin Gini	-1.344***	-0.626	-0.104	-0.887**
ancestry weighted	(0.361)	(0.440)	(0.529)	(0.420)
Fractionalization		0.399***	0.418**	0.360***
		(0.127)	(0.166)	(0.130)
Origin GDP weighted		-0.488**	-0.615**	-0.576**
fractionalization		(0.226)	(0.283)	(0.220)
Origin GDP	0.257***	0.250***	0.274***	
	(0.0512)	(0.0493)	(0.0583)	
Migrant educ./US				0.535**
ratio at arrival				(0.215)
Trust				0.00999
				(0.340)
State history				0.521***
in 1500				(0.178)
Decade lag	0.440***	0.436***	0.435***	0.434***
dependent variable	(0.0237)	(0.0229)	(0.0230)	(0.0232)
Two Decade lag	0.0275	0.0272	0.0293	0.0275
dependent variable	(0.0200)	(0.0197)	(0.0193)	(0.0194)
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	0.968
R^2 (between)	0.0414	0.0686	0.223	0.176
AB test serial corr.	0.345	0.272	0.213	0.236

Notes: This table shows relationship between county GDP per worker and the ancestry weighted Gini coefficients in the countries of origin at the time of arrival (and is denoted by *Origin Gini*). *Origin Gini* has a county-group mean of 0.46 and S.D. of 0.0268. The country-of-origin Gini coefficients are from Van Zanden et al. (2014) and are arrival density weighted using the approach in equation (4) with no discounting.

Table A-8: Ancestry and county GDP: Mechanisms

Dependent variable:	County Education	Log(county GDP per worker)		County voter participation	Log(county GDP per worker)	
	[1]	[2]	[3]	[4]	[5]	[6]
Origin GDP	0.582***		0.291***	0.0577***		0.302***
	(0.127)		(0.0440)	(0.0144)		(0.0439)
County education		0.0305***	0.0125*			
		(0.00753)	(0.00651)			
County voter participation					0.0681	-0.00348
					(0.0520)	(0.0355)
Decade lag dependent variable	0.706***	0.452***	0.438***	0.610***	0.465***	0.443***
	(0.0164)	(0.0243)	(0.0242)	(0.0780)	(0.0247)	(0.0241)
Two Decade lag dependent variable	-0.0411**	0.0267	0.0263	0.0404	0.0494***	0.0461***
	(0.0193)	(0.0221)	(0.0201)	(0.0247)	(0.0177)	(0.0168)
Observations	14,321	14,194	14,187	14,206	14,327	14,325
Division X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes	Yes	Yes
County groups	1149	1146	1146	1145	1145	1145
R^2 (within)	0.969	0.966	0.967	0.835	0.968	0.969
R^2 (between)	0.850	0.410	0.217	0.625	0.324	0.139
AB test serial corr.	0.00542	0.550	0.321	0.332	0.514	0.166

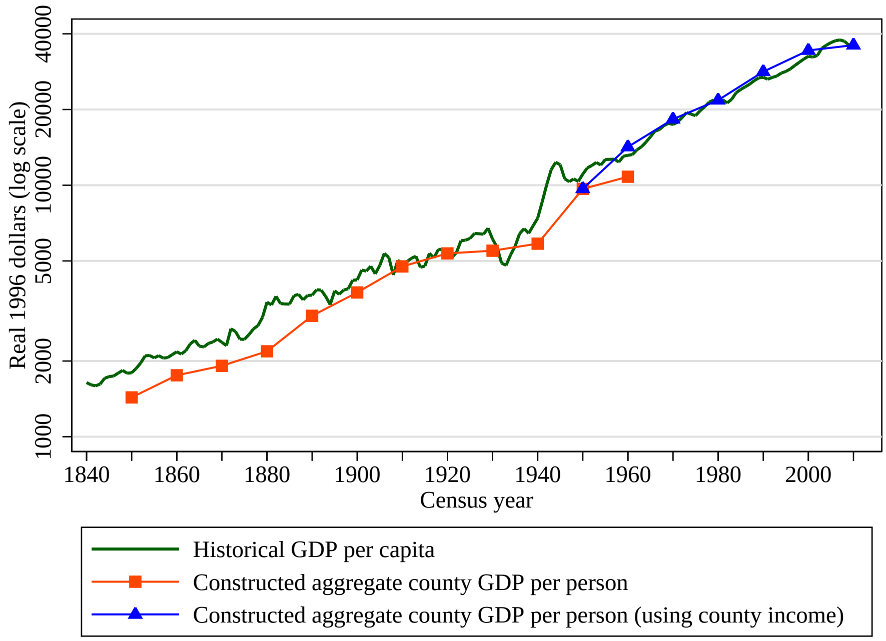
Notes: This table shows other possible outcomes that may explain the relationship between ancestry and county GDP. County education is a variable constructed from county literacy before 1940 and years of education after. We use a regression of county literacy in 1940 on years of education in 1950 to convert pre-1940 literacy into projected years of education, and so county education is in units of years of education. Voter participation is the share of vote in the most recent presidential election relative to the entire population (including women and African Americans who were disenfranchised for much of the period). County voter participation is compiled from IPUMS study 1 and 13, and CQ Press Voting and Elections Data. All regressions are estimated using county-group fixed effects, have census division X year fixed effects, and allow the standard errors to be clustered at the county-group level.

Table A-9: Ancestry, occupational variety, and county GDP

Dependent variable:	Occ. Var. (broad, $\sigma = 1.25$)	Log(GDP p.w.)	Occ. Var. (narrow, $\sigma = 2$)	Log(GDP p.w.)
	[1]	[2]	[3]	[4]
Origin GDP	0.00340***	0.252***	0.00101***	0.226***
	(0.000975)	(0.0442)	(0.000185)	(0.0369)
Fractionalization	0.00884**	0.217**	0.00266***	0.0588
	(0.00336)	(0.0841)	(0.000834)	(0.0784)
Origin GDP weighted	-0.0255**	0.214	-0.00670***	0.485*
fractionalization	(0.00986)	(0.225)	(0.00206)	(0.242)
Occupation variety		5.454***		
(broad, $\sigma = 1.25$		(0.460)		
Occupation variety				27.04***
(narrow, $\sigma = 2$)				(2.348)
Decade lag	0.735***	0.402***	0.701***	0.391***
dependent variable	(0.0253)	(0.0253)	(0.0219)	(0.0285)
Two Decade lag	0.0367*	0.0367*	0.0425**	0.0341
dependent variable	(0.0214)	(0.0206)	(0.0188)	(0.0210)
Observations	12,827	13,240	12,020	14,396
Division X Year	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes
County groups	1146	1146	1146	1146
R^2 (within)	0.943	0.973	0.931	0.969
R^2 (between)	0.959	0.564	0.849	0.143
Mean(Occ. Diversity)	0.0575		0.0152	
	(0.0185)		(0.0040)	

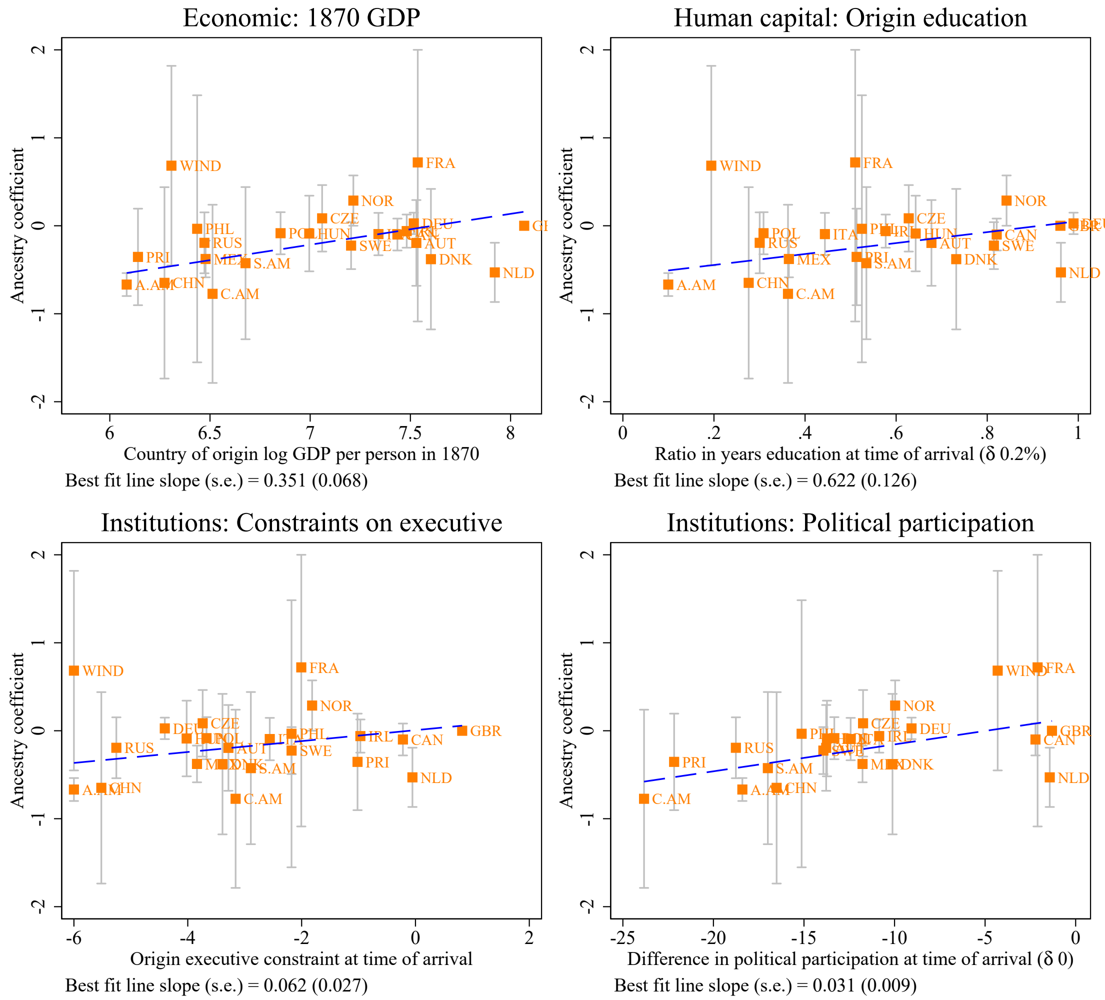
Notes: This table shows the relationship between the occupational variety in a county (measured as the Constant Elasticity of Substitution Aggregator with the elasticity σ and weights determined by the relative wages within occupations in 1940), and county GDP per worker. Broad occupations are the first digit of the IPUMS codes, resulting in 10 categories, while narrow occupations are more detailed taking the first two digits of the IPUMS code, resulting in 82 occupational categories after dropping the non-occupational response.

Figure A-1: GDP and aggregate county GDP per capita: 1840-2010



Notes: This figure shows the relationship between our calculation of US GDP per person constructed by aggregating our county group measures and historical GDP per capita from Sutch (2006). The constructed aggregate GDP per capita and aggregate county income per capita are created by totaling the county measures for each year then dividing by population. Our measure never includes Alaska or Hawaii.

Figure A-2: Ancestry and other 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 equation for log county GDP per worker including county group fixed effects, census division X year effects, and two lags of county GDP per worker in equation GDP per worker in equation 1 (column 5 in Table 1). Each country of origin measure is constructed as the immigrant arrival weighted density of that country. See Appendix C for sources and calculation of arrival density. Origin education is the ratio of years of education in the origin country and in the US at the time of arrival. Years of education are from van Leeuwen and van Leeuwen-Li (2013). Constraints on the executive are described in Appendix D.4. Political participation is the percent that could vote in national elections (Vanhanen, 2012), taken as the difference between each country and the US political participation, weighted by the time of arrival with a depreciation rate of 0.2%.