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

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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 US counties from 1850 to 2010. We also develop a county-level measure of GDP per capita over the same period. Using this novel panel data set, we show that the evolution of the country-of-origin composition of a county is significantly associated with changes in county-level GDP. The cultural, institutional, and human capital endowments from the country of origin drive this association. Particularly important are attitudes towards cooperation with others. Using an instrumental variable strategy, we identify a significant effect of changes in the ancestry-weighted endowments on economic development. Finally, our results suggest that while the fractionalization of ancestry groups is positively related to county GDP, fractionalization in attributes such as trust is negatively related to local economic performance.

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1 Introduction

Over its history, the United States of America has absorbed more immigrants than all other nations combined (Barde, Carter, and Sutch, 2006a). 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 descendents 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 is descended from ancestors who migrated from a particular country or region.[1] Crucially, we produce a stock measure of ancestry, not of the flow of recent immigrants, and so we can consider the lasting legacy of immigrant groups and their descendents beyond the first generation. Our measure is highly correlated with ethnic mappings based on questions from recent censuses, but unlike such subjective questions, our mapping goes back in time and does not change based on the prevailing cultural attitudes towards ethnicity.

Second, we construct a measure of county-level GDP per capita that is consistently measured over the entire period and includes services. While manufacturing and agricultural output have

[1]Since after 1940 the data are reported only for groups of counties, we aggregate the data somewhat to maintain consistency over the entire time period and use such groups as the unit of analysis. We continue to use "county" for short. There are 1154 such 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 A for details.

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 history of the country of origin affects current outcomes in US counties. It 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 is particularly true when only a single cross-section is available, since it is then impossible to fully control for the unobservable characteristics of a place. The clear advantage of our approach is that, by creating a long and consistently measured panel, we can remove the fixed effect of a place, and so we can examine unambiguously whether and how what people bring with them is related to economic development. Moreover, a panel allows us to address possible endogeneity issues due to ancestry specific movements in response to economic shocks.

We start by documenting that the country-of-origin composition of a county is significantly associated with county GDP, even after controlling for unobservable time-invariant county-level effects, state-period effects, county specific trends, race, population density, and county education. The estimated effects of individual ancestries are highly correlated with summary measures of economic development of the country of ancestry, both today and in the past. Whatever qualities make some countries more productive are correlated with the impact the descendants of immigrants from those countries have in the US. Since immigrants necessarily leave the geography of their home country behind, these qualities might include their culture, their institutional experience, or the human capital they brought with them and pass on to their children. The estimated ancestry effects are positively correlated with measures of culture such as trust in others and thrift, and negatively with the importance given to obedience in children, as measured in recent surveys. They are positively correlated as well with measures of state centralization in 1500 (Putterman and Weil, 2010), although we find little evidence that political participation at the time of migration has an impact. The ancestry effects are also positively associated with the human capital that immigrants brought with them.

These general conclusions also hold in more parsimonious representations of the relationship between ancestry and local economic development. For each of the variables capturing the endowment immigrants brought with them, we construct a weighted average value for each county using the fraction of people from each country of ancestry as weights. Changes in ancestry-weighted measures of the culture, institutions, and human capital are all significantly related to changes in county GDP per capita. Combining measures, our results suggest that ancestry-weighted cultural attitudes towards cooperation are those more strongly and robustly associated with local development.[2] These results do not necessarily show that other endowments are not relevant, but that attitudes towards cooperation appear to be more important at the local level.[3]

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. For example, the English are disproportionally present in rural areas in the poor South and Appalachian states, while the Italians and Irish settled and stayed in metropolitan areas, especially in the Northeast.

While these results establish that the endowment that people bring with them matters, they do not show the mechanism behind the association. There are two reasons why changes in ancestry and economic development could be related. The first is 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. The second is that groups with specific attributes are more

[2]Where we have historical data that is comparable over time, such as for country-of-origin GDP and and human capital, we are careful to associate to each group of immigrants the historical characteristics of the country of origin at the time of emigration. Moreover, in some specifications we allow for the importance of the ancestral characteristics to decay over time to reflect the changes that occur during the process of social and economic integration in the US.

[3]For example, immigrants' experience of political institutions in the country of origin may matter at the state or federal level. Furthermore, cultural attitudes, such as trust, may impact development both directly and indirectly through their effect on the functioning of local institutions and the choice of growth enhancing public goods such as education. In addition, cultural attitudes themselves may be the results of the development of historical institutions in the country of origin (Tabellini, 2010).

willing to move to a county with given characteristics. If these characteristics are time invariant, then we already control for them by including fixed effects in our estimation. However, it could also be that 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 following the opening up of new economic opportunities.

To make progress understanding the mechanism through which changes in ancestry may affect economic development, one needs to isolate variation in ancestry that is not caused by contemporary shocks to economic output. To do so we move to a dynamic model of county per capita GDP 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 auto-correlated, 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. Given the centrality of the assumption of the nature of the residuals, it is essential to test for serial correlation in the estimating equation.[4]

We pursue an identification strategy based on this idea, both by instrumenting our ancestry-weighted endowment variables in dynamic models with fixed county effects and also by relying on GMM approaches to deal with endogeneity issues in short dynamic panels (Holtz-Eakin, Newey, and Rosen, 1988; Arellano and Bond, 1991) both in a single and bivariate equation context. Our results suggest that the evolution of ancestry composition has a significant effect on county per capita GDP. Moreover, while there is evidence that shocks to county GDP help to predict ancestry composition, the effect is quantitatively small. Instead, it appears that the dominant mechanism is for changes in ancestry to have large effects on economic development that peak after two to three decades, and are long lasting. The rich time pattern of the effect of ancestry composition reinforces the value of having a panel at our disposal.

Finally, we provide evidence that suggests that the groups immigrants and their descendents

[4]Our approach builds on the strategy used in the immigration literature (see, for instance, Card (2001), Cortes (2008), and Peri (2012)), but with greater attention paid to the serial correlation properties of the residuals, mostly overlooked in this literature. See section 5.5 for a full discussion.

encounter matter as well. Fractionalization, a measure of the diversity of ancestries, is positively associated with local development, whereas cultural fractionalization is negatively associated with it. Increases in the diversity of origin are good for growth as long as the overall cultural attitudes are similar.

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 capita at the county level. More details on the construction of our ancestry mapping and our measure of county GDP is contained in detailed data appendices. Section 5 contains the econometric results, while Section 6 concludes.

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.[5] 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 contem-

[5]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).

porary 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.[6] As we have argued, there are serious challenges in identifying the causal effects of culture or institutions on economic outcomes since they are likely to be co-determined.[7] The availability of panel data is a distinguishing feature of our work since it allows us to better distinguish 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.

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.[8] 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

[6]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 (2013), 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), Acemoglu, Johnson, and Robinson (2001), Acemoglu, Johnson, and Robinson (2002), Acemoglu, Johnson, and Robinson (2005), and Albouy (2012); see Michalopoulos and Papaioannou (2013) 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).

[7]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).

[8]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.

stock of ancestry and whether the attributes that immigrants brought with them and may pass on to their children affects outcomes for all residents.

In many ways, our work builds on 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. They conclude that in the cross-section of countries today what matters is not only the characteristics of the country, but also the characteristics of the populations that inhabit it. 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

The variable at the center of our analysis is an Ancestry Vector (AV), which records our estimate of the countries of origin of the ancestors of a given county's population. We build the AV based on census questions which 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. We construct the AV iteratively using the more detailed information that is available from the census, and starting as far back as possible. For first generation immigrants or their children, the ancestry is straightforward since we know exactly where they came from. If the parents come from two different countries or states, we assume that they contribute equally to the ancestry of their children. For example, the child of German and Irish parents is half German, half Irish. If the parents are born in the US, we assign the child the common ancestry vector among 20-30 years olds in the child's birth year in the state of birth of the parents. The AV for each period therefore depends on the AV 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. Accumulating this information over time for a geographic area, the AV gives, in expectation, the fraction of the people in a given area whose ancestors come from a given country. Therefore, the AV is not just the fraction of first generation immigrants as in Ager and Brückner (2013), but instead keeps track of the ancestry of everyone, accounting for internal migration, age structure of the population, and local variations in where people from different countries originally settled. We give details for how we construct ancestry in the US in Appendix A.

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 that allows us to maintain a consistent geographical unit of analysis from 1850 to 2010. The Data Appendix provides additional details. 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. We allow for distinct ancestries within racial groups, and so recent Nigerian immigrants or immigrants from the West Indies, for instance, are distinct from African Americans who are descendents 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 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.

3.1 Ancestry in the US over space and time

There have been immense changes in the United States in overall ancestry and its geographic distribution since 1850. 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. Since any attempt to construct ancestry at a national level that did not start with the micro-samples and did not keep track of the internal migration and local population growth would be deeply flawed, we believe 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.

American ancestry has become increasingly diverse. 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. The descendents of the original English settlers still made up more than half of the population in 1870, but 1870 is the last decade that they were in the majority. African Americans represented a little over 10% of the population. The Irish population had swelled from a recent wave of migrants, and a large wave of new German immigrants had increased the already substantial German population from colonial migrations. Descendants of immigrants from Scotland and the Netherlands made up most of the remaining population.

Successive waves of immigration, starting particularly in the 1870s, 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. 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 more diverse than is commonly recognized, 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 such as Sweden, Norway, and Denmark.

After 1920, immigration slowed substantially until the 1960s, and so changes 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. Immigrants from Asia arrived as well. By 2010 the United States had become much more diverse with substantial populations from countries in Asia, Europe, Africa, and Central and South America. Of particular note, the share of Irish ancestry in 2010 implies that there was more than three times the number of people of Irish descent in the United States than in Ireland in 2010. Despite the relatively small total migration from England, due to relatively rapid population growth there are around the same number of people of English descent in the United States as there are people in England.

Although the overall evolution of diversity of the United States is notable, its geographic diversity is even more interesting. Figures 2 and 3 show the ancestry shares across the United States for select groups in 1870, 1920, 1970 and 2010. 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. We show six groups that are historically important or that can be seen visually on a map: African Americans, Germans, Irish, Scandinavians, Italians, and Mexicans. The maps tend to visually emphasize large and sparsely populated areas, and therefore, miss the rich diversity of the East Coast and its cities. We combine Norway and Sweden, whose inhabitants settled distinct areas, in order to make the Scandinavian homeland more visible.

Groups tend to settle together and then slowly spread out. Internal migration has continuously reshaped the ancestral geography of the United States. For example, one can observe the German presence in New York, around Milwaukee and Pennsylvania, and the subsequent spread to the entire Midwest and West, as well as the the heavy German migration to Texas. 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 2 to 1970 in Figure 3, although since the maps do not depict cities well, the importance of the Great Migration is less obvious. African Americans are still highly concentrated geographically, and have not experienced the slow diffusion that characterizes the descendants of the Germans and Irish.

By construction, our Ancestry Vector (AV) is an attempt to measure something that could in principle be measured and known exactly: the fraction of the people in a county who come from or are descended from people who came from a given country of origin. While ancestry, as we define it, is objective, ethnicity and race are generally considered 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 is not the same as ethnicity, although the two are clearly linked. Instead, we view ancestry as one of the inputs used to construct ethnicity. Indeed, in the United States, it appears to be the primary input (Waters, 1990). Our measure of ancestry is highly correlated with self-reported ethnicity or ancestry in the 2000 census. Across counties in 2000, the correlation between the fraction that say they are of Irish ancestry in the census and the AV 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 AV). 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.[9]

[9] In the 2000 census, only 5.9% self-report an English ethnicity, while 7.2% give their ethnicity as "American," 19.1% do not report, and 1.4% report "White/Caucasian." Combining all of these other categories with the English and British self-reported ethnicities, there is a 0.93 correlation between our measure of English in the AV and the ethnicities reported in the census. One interpretation of this evidence, consistent with the constructivist approach to ethnicity, is that the dominant ethnicity is English and so all other ethnicities are defined as different from English. Then many whose ancestry is English do not think of themselves as having an ethnicity since they have the dominant

4 County GDP from 1850-2010

To understand the impact of ancestry on economic performance, we construct a county-level measure of GDP per capita. Starting in 1950 measures of income per person are available at a county level. Prior to 1950, however, the census only recorded limited information on manufacturing and agriculture output at a county level. While these measures may be useful for comparing rural counties, as in the study of national banks from 1870-1900 in Fulford (2015), they are inadequate for comparing urban areas where many immigrants settled. The problem is that if some groups disproportionally settled in urban areas where physical output measures systematically underestimate output by ignoring services, then we will underestimate the contribution of these groups. We therefore need to engage in *county* income accounting to recreate a measure of gross domestic product at a county level. To our knowledge this measure is unique in including services as well as manufacturing and agriculture at a county level. The full details for how we construct this measure of county-level GDP are in appendix B, but we describe it briefly below.

Using information on manufacturing inputs in each county, we construct the nominal value added in manufacturing. The census recorded agricultural output at a county level, but not intermediate inputs. We use historical aggregate statistics at the national level on total output, intermediates and value added in agriculture to obtain a measure of value added in agriculture at the county level, assuming that the ratio of value added to total output in agriculture is the same in each county.

Services are the most difficult to value. We use the employment and occupation information collected by the micro-samples from the census for each year to construct employment by broad service category (trade, transportation and public utilities, finance, professional services, personal services, and government). We then calculate nominal valued added per worker in each service category based on national accounts. Our choice of the broad service categories is driven by the availability of value-added estimates that are comparable for long periods. We then multiply nominal value added per worker at the national level by the county-level employment in each

ethnicity.

category. This approach allows New York City, with a substantial service sector composed of finance, to have a much higher income from services than a small rural county where services might be mostly employed servants. Since we are using national value added, however, a lawyer in New York City has the same value added as a lawyer in the rural county. We follow the same procedure used for services to obtain value added in mining and construction. Excluded from our measure is any value from the existing housing stock, although new housing is captured through construction employment.

The census reports personal 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 per capita in each county from the census, we construct a ratio of GDP to income at a county level. We apply this county-level ratio to the income series from 1960 to get an estimate of GDP. Effectively, we use the growth rate of personal 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. Finally, we convert nominal GDP to real GDP using the price deflator from Sutch (2006). In our analysis we will always allow for common year effects which absorb any common changes such as in national prices, but we include state-year effects in some specifications which absorb any state-specific changes in the GDP deflator.

Our goal is for each decade to create a measure that correctly captures the relative GDP per capita of different counties for the period of 1850-2010. Throughout this analysis we include time effects to absorb overall temporal variation. Yet our measure does surprisingly well at capturing aggregate changes. Figure 4 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 4 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.

Figure 5 illustrates the importance of including services rather than simply using the more readily available output numbers for manufacturing and agriculture. The figure shows the share of value added using our measure for each industry. Even in 1850, services represented around 20% of value added and its share grew rapidly. Moreover, the value added from services tended to be highly concentrated. When we map the share of services in the local economy the share is frequently above 70% for a highly urban area, which can be surrounded by rural areas where the share is less than 30%. Figure 5 also shows that by 1950 our measure matches the sectoral shares in the National Income and Product Accounts nearly exactly (and shows similar trends before that).

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. We start by asking whether the evolution in ancestry composition is significantly related to changes in county GDP. We then examine which characteristics of the country of origin help to explain this association, develop summary measures of the endowments brought by immigrants from the country of origin, and assess their correlation with local economic development.

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 time-invariant county characteristics. To address this concern, we propose an instrumental variable strategy based on the past distribution of ancestries. The absence of autocorrelation 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.

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 vector is 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 a fairly unrestricted econometric model that allows the effect of each ancestry to be captured by a different coefficient. Our Ancestry Vector (AV) for a given county c and time t, is an estimate of the share of that place's population whose ancestors came from a particular country-of-origin ancestry a out of all possible ancestries A. Denote these shares by π^a_{ct} and note that they sum to one in each county 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 capita y_{ct} of the form:

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

which include county fixed effects θ_c and year effects, λ_t, and allow each ancestry to have its own effect α_a. Some specifications include additional controls X_{ct} such as population density to reflect time-varying urbanization rates, the lagged dependent variable, and measures of education. In more general specifications we will also allow for state-specific period effects λ_{st}, for county-specific trends, and for the lagged dependent variable. We normalize the ancestry effects by setting the coefficient on the English to zero.[10] The remaining coefficients can then be interpreted as whether replacing the English with that ancestry is associated with a change in GDP per capita. Our basic question is whether, even after controlling for observables and unobservables, the individual

[10]Since 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.

ancestry coefficients are different from zero.

The results of 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, year, state effects, and county trends. The table shows the F-statistic for the joint test that all α_a are zero (each ancestry matters equally for GDP). We also separately test the hypothesis that all ancestries other than African American and Native American are zero 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 form of the estimation, therefore, strongly rejects that ancestry does not matter, in the sense of not being associated with economic development. 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 factors, such as industrial structure, that may be related both to county GDP and ancestry composition—may affect our answer. However, the inclusion of state-specific period effects or county-specific trends leaves the significance of the ancestry composition intact. Our conclusion that ancestry matters is also robust to the adding county GDP in the previous period $y_{c,t-1}$ as a regressor. One might be concerned that ancestry matters only because it reacts to current shocks, yet ancestry matters even when we include it only at a decade lag. We will address this issue more at length in Section 4.5. The last several columns 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 significant even after including these controls, and so ancestry matters beyond its relationship to education or urbanization.

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

We next examine whether the coefficients on the ancestry shares are related to characteristics of the country of origin. We divide the analysis into four broad categories: past economic development, institutions, social capital or culture, and human capital. Together with geography, these categories are the fundamental 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.

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, the Irish coming in the 1850s reflect a different experience 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 (external and internal), and 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. Before that, we create an approximate density of arrival times for the stock of migrants based on Daniels (2002). The full procedure is described in Appendix C. With a density of arrival times, we can construct country-of-origin measures that are weighted 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 ($y_\tau^a - y_\tau^{US}$). For a given ancestry, the arrival weighted log GDP is then:

$$\tilde{y}_t^a = \sum_{\tau=0}^{t} (y_\tau^a - y_\tau^{US})(1-\delta)^{t-\tau} F_t^a(\tau) \tag{2}$$

where $F_t^a(\tau)$ 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. 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. We use the relative value because, 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 the time.

The ancestry effects appear to be closely related to economic conditions in the country of origin as measured by GDP per capita in 1870, or historical GDP weighted by the arrival density in Figure 6. The relationship between the ancestry effect and measures of country-of-origin GDP is positive both for the mainly European ancestries that were important sources of immigration flows before 1924 (see Figure 1) and for all large ancestry groups.[11] 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 may have brought whatever mix is important for success with them.

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 bottom row of Figure 6 we plot the relationship between the ancestry coefficients and different measures of institutions at the national level. For institutions we use state history from Putterman and Weil (2010) and the difference in political participation from the United States, weighted by time of arrival, using the measures of historical

[11] 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 including GDP in 2010 and by allowing some degree of depreciation of arrival GDP.

political participation created by Vanhanen (2012).[12] State history reflects how long a particular state has had centralized government in 1500 and shows a strong positive association with the ancestry coefficients. Political participation is only positive for the mainly European ancestries before 1924. Political participation, however, may not reflect the differing experiences of immigrants. Political participation was low for most countries with large migrations before 1924, and the institutional experience of Italian peasants from its south might have been very different from the Swedish immigrants, even if neither group could vote. Moreover, while country-of-origin institutions may affect the design and functioning of federal or state institutions, which we control for in the regression through time and county fixed effects, national institutions in the country of origin may be a poor proxy for the ability to develop local institutions and make them work effectively.

Immigrants also brought with them a set of cultural attributes from the mother country 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 descendents, this would contribute to explaining the significance of the ancestry vector. We focus on those values and beliefs that facilitate cooperation, which are often referred to as "social capital" and have been at the center of previous investigations (Guiso, Zingales, and Sapienza, 2008; Tabellini, 2010). 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 anything about past culture, one needs to assume that the relative ranking of countries in 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 county-of-origin regional differences in cultural attitudes. However, the census does not provide information

[12]Our choice of institutional variables is largely driven by availability. Measures of executive constraints from Polity IV do not have coverage for key countries going far enough back. The version produced by Acemoglu, Johnson, and Robinson (2005) only covers select European countries.

on immigrants' region of origin. We combine the surveys since 1981 and use the answer to several questions that Tabellini (2010) and others have proposed might be important for economic development: generalized trust (Trust), tolerance and respect for others as an important quality that children should have (Respect), obedience as an important quality in children (and possibly a negative characteristic in a world requiring independence (Obedience), and a feel of control over one's life as an inverse proxy for a fatalism (Control). We will also experiment with measures of thriftiness (Thrift).[13] Following Tabellini (2010), we construct 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.

We plot the relationship of the coefficients of the Ancestry Vector with Trust, Obedience, the principal component of culture, and Thrift in Figure 7. The coefficients are positively and significantly associated with Trust, the principal component of culture, and Thrift, and negatively and significantly associated with Obedience. The correlation with Respect and Control is weak, and so we do not show them separately, but will include them later in a more parsimonious approach.

Figure 7 also shows the ancestry coefficients' relationship with two measures of education: (1) the ratio of the immigrants' 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.3 for a detailed discussion); and (2) the ratio of the average years of education in the country of origin relative to the United States at the time of arrival using the data in van Leeuwen and van Leeuwen-Li (2013). The education of migrants weighted by arrival density has a positive relationship with ancestry. The ratio of the years of education in the country of origin relative to that of the US is positively related to the ancestry coefficients for the ancestries before 1924, but shows only a small relationship for all ancestries. The relatively weak relationship with average years of education in a country of origin may be because the human capital of the immigrants is different from the average, or because differences in human capital rapidly disappear in a new setting. Of particular note is the difference between the education level

[13] The World Values Survey data and variable construction are described in details in the data appendix section D.2.

of recent immigrants, such as Indians, and the lower average level of education of their countries of origin.

5.3 A parsimonious parametrization of ancestry composition

In this section we examine the association between ancestry composition and economic development in a more parsimonious manner by assuming that the effect of each ancestry is proportional to some attribute of the country of origin. More specifically, we take some characteristic z^a for country-of-origin a and define:

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

We can think of z_{ct} as the expected or predicted value, across countries of origin, of the endowment of a given characteristic z_{τ}^{a} for county *c* at year *t,* where the italics denote the endowment variable weighted by the ancestry vector, and upright case letters the endowment characteristic itself.[14] For example, take the simplest form of country-of-origin level of development, the Log GDP per capita in 1870 and form its ancestry-weighted value *Log GDP per capita in 1870.* Since the GDP in 1870 is constant for any given country, its ancestry weighted value varies only because the ancestry composition varies over counties and over time. We can think of it as offering a prediction of county income based on the incomes in 1870 of the country of origin of the county's population. Similarly, our measures of culture, which come only from recent surveys, vary only because of the ancestry composition in a county.

Some characteristics, such as the GDP in the country of origin at the time of arrival, vary both with time and ancestral composition. In this case, we form the z_{ct} variable using the ancestry-weighted average in equation 3, but allow the country-of-origin characteristic z_{t}^{a} to vary over time. We construct z_{t}^{a} by weighting the difference between the country-of-origin characteristic and the United States using the density of arrival times up to time *t* as in equation 2. We also construct

[14]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.

some variables as ratios of the country-of-origin and the United States at the time of arrival.[15]

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

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

where we include county group (θ_c) and state-year effects (λ_{st}) or common year effects. 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 coefficient in the unrestricted model is proportional to one or more elements of the endowment vector. Given the more parsimonious representation of the effects of ancestry, we will be able to experiment more fully with the dynamic specification of the equation by including a richer lag structure for the dependent variable and for the ancestry-weighted endowment z_{ct}. Moreover, since the ancestry vector contains multiple elements, we can construct more complex functions that reflect other aspects of the endowment distribution, such as fractionalization in the characteristics of the country of origin.

5.3.1 Changes in ancestry composition and economic development

Table 2 shows a series of regressions of the form of equation 4 where each estimate is from a separate regression. For each ancestry-weighted variable we present three specifications, each of which include county fixed effects: (1) with year effects, (2) with state-year effects, (3) with state-year effects and including the fraction African-American, Native American, and the log population density. Including state-year effects allows each state to evolve independently over time and so only relies on variation within state. Since much of the variation in the effect of ancestry is likely to be felt across regions, including state-year effects removes much of the variation, but ensures that

[15] We form the migrant-education to US-education ratio, and country-of-origin education to US education ratio in this way. The formula for ratios is: $z_t^a = \sum_{\tau=0}^{t}(z_\tau^a/z_\tau^{US})^{(1-\delta)^{t-\tau}} F_t^a(\tau)$ where $F_t^a(\tau)$ is the arrival density of group a up to time τ, and δ is the rate of depreciation of the importance of that characteristic. This formula gives the average ratio of country-of-origin characteristic by time of arrival. When the depreciation rate is greater than zero, the ratio converges to one as the time of arrival gets further away, and so the immigrant group converges to the US.

the estimates are not driven purely by differential regional trends. We allow African Americans and Native Americans to have an unrestricted coefficient since the information at the country-of-origin level for African Americans and Native Americans is necessarily speculative.[16] We include population density to allow the urban-rural composition of a county to change over time. Of course, if density grows at the same rate for all counties then its effect is completely captured by the county fixed effects and common year effects. We discuss the last three columns of Table 2 later.

The coefficient on the ancestry-weighted *Log origin GDP/US on arrival* is positive and significant at the 1% level in column 1 with just fixed effects, as well as in column 2 with both fixed effects and state-year effects, but is insignificant in column 3 with the additional controls. Using the estimate in column 2, a change in the composition of a county so that the *Log origin GDP/US on arrival* is one percent higher is associated with a 0.53% increase in the county's current GDP per capita. Since the estimates include county fixed effects, this estimate is identified as the composition changes over time, not just from the cross-section. The results are similar in terms of significance when using the ancestry-weighted *Origin-GDP-to-US ratio* or *1870 GDP*.

Ancestry-weighted *State History in 1500* from Putterman and Weil (2010) captures the familiarity with centralized state institutions and shows a pattern of effects on county GDP similar to those of the origin GDP measures. The effect is significant and positive in all specifications, except the one with state-year effects and the additional controls.[17] Ancestry-weighted *Political participation* as of the time of arrival (measured as the difference between the fraction eligible to vote in the country-of-origin and the US weighted by the arrival density) does not predict county GDP, except in the specification with only common year effects, and has a negative coefficient in some specifications. Since few large origin countries had a widespread franchise at the time of migration in the nineteenth and early twentieth century, the fraction of people voting may not well capture differences in institutions or political participation. The role of the endowment of human capital is

[16] 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.

[17] The state history variable 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 1870 GDP. We use the Putterman and Weil (2010) measure version 3 with a depreciation of 5% of state history in the past.

less robust and it depends upon how it is measured and upon the exact specification, although it is mostly positive when included without controls.

Measures of cultural attitudes towards working with others, such as the ancestry-weighted variable *Trust*, are strongly related to higher county income. *Trust* is positive and significant at the 1% level in all specifications. Since our measure of trust from the World Values Survey is the fraction of the population in a country of origin who report that other people can generally be trusted, the coefficient suggests that an increase in the mix of ancestries that increases *Trust* by one percentage point (0.01) is associated with an increase in the income of a county by 2.6%.

The important role of generalized *Trust* is possibly due to its ability to capture and summarize those cultural characteristics that enhance the capacity to cooperate, sometimes called social capital. These characteristics affect the functioning of local institutions, but may also capture the experience of good institutions in the mother country and the ability to transport them to the areas where immigrants settle, as good and effective institutions may foster the creation of trust. For this reason, Trust is likely to capture the effect on economic development of both good culture and good local institutions of the country of origin.

Ancestry-weighted *Obedience* has a precisely estimated and negative effect in three out of the four specifications. *Respect* and *Control* display positive coefficients that are marginally less precisely estimated. *Thrift* is positively and very significantly related to local development in three out of four specifications. Following Tabellini (2010), we have formed the principal component of Trust, Control, Respect, and Obedience from the individual data, and then taken the average across the respondents of the principal component for each country. The ancestry-weighted principal component is positively and significantly associated with county GDP in all specifications.

5.3.2 Rich ancestries in poor places

Perhaps surprisingly, over the broad sweep of US history since 1850, people from high-income countries tend to live in lower income counties on average. Column 4 in Table 2 show that the coefficients on our ancestry-weighted variables most often take the opposite sign when fixed effects are not included. This pattern holds for *Log origin GDP on arrival*, for example, which is positive in column 1 with fixed effects and negative in column 4 without them (state-year effects are included to sweep out time varying state differences).

What explains this negative correlation, 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, particularly among the English. While the English are a large portion of much of the US, they are disproportionally 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 on the cross-sectional variation suggest that the availability of panel data is very important for understanding the effects of ancestry. 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 *Trust* or *Log origin GDP* and county GDP is likely specific to the settlement patterns in 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 disentangle the effects of factors inherent in a place is more general.

5.4 What matters most?

In Section 5.3, we examined country-of-origin characteristics in isolation, with the goal of showing several elements of the endowment vector brought by immigrants are associated with per capita county level GDP. But which component of the endowmentis most strongly associated with local economic development? As we have discussed, the panel nature of our data allows us to address this issue controlling for a rich set of unobservables by including county fixed effects and state-year effects. Doing so necessarily removes any effect of national or state institutions and of their evolution. Similarly, we cannot directly estimate whether there is a "founder" effect of the groups who first settled a county since such an effect is absorbed by the fixed effect.

With these caveats in mind, Table 3 combines a selection of the most important measures from Table 2 to examine which measures remain significant once they are included together as explanatory variables. We use the ancestry-weighted variables *Trust*, *State History*, the *Migrant Education-to-US* ratio at time of arrival created by census records, and *Thrift*.[18] Since many important differences appear across states rather than within them, we show the results both with common year effects, and with state-specific year effects. Finally, since the country-of-origin endowments used for African-American and Native Americans are speculative, we included in some specifications the fraction of each of these groups, as well as the population density to allow for differences between urban and rural areas.

The effect of culture, as measured by ancestry-weighted *Trust*, is robustly significant and about the same size across all columns, while the other possibly important variables are not. *Thrift* is also significant, but only in the specification with state-period effects. *State History* is significant without state effects, but not with them. Culture may summarize the role of both social capital and the quality of local institutions in the country of origin, as we have argued before. Conversely, the experience of a centralized state represented by *State History* may be less relevant in capturing the development and functioning of local institutions, and any effect it has on state or national institutions is absorbed by the state-year and fixed effects.

Puzzlingly, the ratio of education of the migrants to the US education at the time of arrival has either an insignificant or negative and significant coefficient when including state-year effects. This relationship does not depend on the speed of depreciation of the difference (δ), and also holds using the country-of-origin years of education as well. By itself, arrival education is mostly positively related to county GDP in Table 2. The negative relationship may come from colinearity between the education and the other included endowment variables.

[18]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.

Including the fraction of African Americans and Native Americans still leaves the coefficient of ancestry-weighted *Trust* significant and of about the same size. The values 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. 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 descendents of those actually enslaved may be even worse. While we report the coefficients on the fraction African Americans and Native Americans, since the groups also appear within each of the ancestry-weighted variables the coefficients are not informative about the groups themselves.

The size of the coefficients matters as well as their statistical significance. The interquartile range across counties for *Trust* is 0.064, for *State History* it is 0.095, and for the ancestry-weighted migrant education ratio at the time of arrival it is 0.081. Moving from the 25th percentile to the 75th percentile county in *Trust* raises GDP per capita by nearly 25.5%, using the estimated coefficients reported in column 1. The effect is of similar size across all specifications. A similar change for *State History* is associated with a 6.9% increase in county GDP per capita. For migrant education, a change from the 25th percentile to the 75th is associated with an statistically insignificant increase in GDP per capita of 2.3%, using the results in column 1, or a decrease of 15%, using the results in in column 2. *Trust*, therefore, is the most robust, statistically significant, and economically important correlate of local economic development.[19]

5.5 Sorting and endogeneity

The previous sections have documented a robust association between ancestry and income. In this section we examine the possible mechanisms underlying this relationship. The association could

[19] In the next section, we will construct instruments for these variables and consider the importance of allowing for a dynamic specification by including lags of county GDP. While we mostly focus on examining just one variable at a time, when we include multiple endowment variables we reach the same overall conclusions in the dynamic model with instruments and fixed effects as in this section: *Trust* is highly significant with a sizable coefficient, *State History* is less significant but still matters, while the *Migrant Education-to-US* ratio at the time of arrival is insignificant and with a coefficient close to zero.

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, if 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. The cross-section results shown in the fourth 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 geographically diverse social networks.[20]

The estimates in the previous sections allow for county fixed effects. The fixed effects removes and controls for all fixed unobserved characteristics of a place. In trying to identify the effect of ancestry composition on local GDP, it is not a problem, for example, if the poor immigrants tend 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 5.3.2, 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 correlation between shocks to county level per capita GDP and ancestry composition.

In this section, we propose possible strategies to identify the effect of ancestry composition on economic development. We construct an instrument for the Ancestry Vector and the ancestry-weighted endowment variables using the past distribution of ancestries, augmented by the national

[20] 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, for instance, because they have the same income distribution.. 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 positively correlated with 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.

growth rates, building on the basic strategies of the recent immigration literature.[21] We first instrument for the ancestry-weighted endowment variables in the model with fixed effects, including two lags of the dependent variable. Then we examine more fully the issue of the dynamic specification of the model and address the endogeneity issues in the context of short panels (Holtz-Eakin, Newey, and Rosen, 1988; Arellano and Bond, 1991), starting from a single equation framework. Finally, we model explicitly both county GDP and ancestry-weighted endowment variables in a bivariate panel vector auto-regression and present estimates of the impulse response functions, based on a Cholesky decomposition of the residuals, under different assumptions on the ordering of the variables. The absence of autocorrelated residuals is essential for our identification strategy and this requires the specification of rich enough dynamic models and testing for serial correlation in the estimating equation.

We conclude that, while there is some evidence that there is an attraction that draws people of certain characteristics to booming counties, the ancestry composition matters in a causal sense for local economic development even after accounting for this attraction. The effect is significant, sizable, and long lasting. We focus on the effects of ancestry-weighted *Trust*, since it appears to have the most robust role, but also show results for the *Log origin GDP/US on arrival* in the appendix as a summary measure of the potential economic endowment of immigrants.

5.5.1 Instrumenting for ancestry and expected endowments

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. We build on these observations to create an instrument for ancestry based on the stock of ancestry in the past. This approach is similar to using lags of the ancestry-weighted variables as instruments, but brings in information for the overall

[21] 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). Although the absence of serial correlation in the residuals is an essential condition for the use of the past distribution of immigrants as an instrument, this literature often fails to conduct such tests.

growth of ancestries at the national level.

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:

$$\tilde{\pi}^a_{c,t} = \frac{\tilde{P}^a_{c,t}}{\tilde{P}_{c,t}} = \pi^a_{c,t-1}\frac{1+g^a_t}{\sum_{a=1}^{A}(1+g^a_t)\pi^a_{c,t-1}}. \tag{5}$$

Note that $\tilde{\pi}^a_{c,t}$ does not use any county specific information from decade *t*. If there is no serial correlation in the error term of the GDP equation, then $\tilde{\pi}^a_{c,t}$, or simply $\pi^a_{c,t-1}$, can be used instead of $\pi^a_{c,t}$ to construct an instrument for the ancestry-weighted endowment variables. The absence of serial correlation in the local GDP equation is essential for this identification strategy to be valid. We therefore include past values of GDP and test whether there is any evidence of residual serial correlation. We also make the very reasonable assumption that no single county plays a dominant role in attracting people of a given ancestry.

As an intermediate step, we first show the effect of including two lags of county GDP in the second to last column of Table 2 (marked DYN FE for dynamic fixed effects). Since the regression now includes lags of county GDP, the reported coefficients are the effect of a change in the endowment within a decade. The sum of the lags of county GDP are generally around 0.6, indicating that the long-run effect of a permanent increase in *Trust,* for example, is around 2.5 times larger than the short-run effect.[22]

The last column of Table 2 (denoted IV DYN FE) shows the results of using the predicted shares $\tilde{\pi}^a_{c,t}$ to construct an instrument for each expected endowment variable in equation 3 in the dynamic equation that includes two lags of the log county income to remove serial correlation. In

[22]The long-run effect, in a single equation context, is $\alpha/(1-\rho_1-\rho_2)$ where α is the coefficient of each ancestry-weighted endowment variable, and ρ_1 and ρ_2 are the coefficients on the lags of county GDP. Column 6 in Table 4 shows the full estimates for *Trust*, while column 6 in in Table A-1 show the same results for *Log origin GDP/US on arrival*. The coefficients of the lagged dependent variables in each regression are typically very similar. Using the values for *Trust*, to get the long-run effect multiply the coefficients in the DYN FE column by 2.4=1/ (1-0.525-0.054).

all cases, including two lags is sufficient to remove serial correlation using the Arellano and Bond (1991) test based on differences of the residuals. For reasons of space, we report only the tests for the specifications using *Trust* in columns 6 and 7 of Table 4, and using *Log origin GDP/US on arrival* in columns 6 and 7 of Table A-1. The first stage regressions suggest that our instrument has strong explanatory power for the corresponding ancestry-weighted endowment variables.[23]

In all cases in which it was significant in the static specification, the coefficient of the ancestry-weighted endowment variables remains significant in the dynamic specifications, whether it is instrumented or not. The estimates of the impact effect with the instrument are in general slightly larger than those for the dynamic fixed effect results. The long-term effects of a permanent change are again around 2.5 times larger than the short-term effects. Some of the anomalies observed before disappear; in particular, now ancestry-weighted *Migrant education/US* at arrival has a positive and significant sign as does *Arrival political participation*. We will discuss further the dynamic effects of changes in ancestry-weighted endowments in the next section.

We have also examined the effect of including the average log GDP of each county's neighbors in the preceding decade in a specification that is otherwise the same as the IV dynamic fixed effects results in column 6 to allow for possible spatial correlation. The results are essentially identical, and therefore we do not report them separately. The coefficient on the past neighbor's GDP is generally small, typically below 0.01, and mostly statistically insignificant.

5.5.2 Instrumenting for ancestry in short dynamic panels

The instrumental variable results presented in the previous section rely on including the lagged dependent variable to remove serial correlation. With a relatively short panel (T=15), including the lagged dependent variable with fixed effects can generate inconsistent estimates (Nickell, 1981). In this section, we address both this issue and the problem of endogenous migration by using the GMM approach to the estimation of short dynamic panels with large N proposed by Holtz-

[23]For instance, the t-statistic for the first stage instruments constructed using $\tilde{\pi}^a_{c,t}$ has P-values that equal zero to the fourth decimal point. Most of the explanatory power is due to the variation in $\pi^a_{c,t-1}$ since replacing $\tilde{\pi}^a_{c,t}$ with $\pi^a_{c,t-1}$ in constructing the instruments has nearly the same first stage significance and very similar second stage results.

Eakin, Newey, and Rosen (1988) and Arellano and Bond (1991). The basic idea is not to use the within transformation, but other transformations, such as first differencing or forward orthogonal deviations, that allow one to use lagged values of the regressors or other variables as instruments.[24] Note that using lagged values of the ancestry-weighted variable as instruments is identical to using lagged ancestries in the construction of the instrument when the country-of-origin characteristic is not time varying, like Trust. In addition, we estimate a bivariate panel vector auto-regression (VAR) for log county GDP and ancestry-weighted *Trust* that allows us to examine the extent that shocks to county GDP attract migrants of a certain type. We continue to focus on ancestry-weighted *Trust* as an example because it seems to be the variable most robustly correlated with county GDP, but include the results for *Log origin GDP/US on arrival* as a useful summary measure of the endowments brought by immigrants in the appendix.

Table 4 shows a series of GMM estimates of the effect of the ancestry-weighted *Trust* on county GDP per capita (Table A-1 in the appendix shows the same table for *Log origin GDP/US on arrival*). Column 1 estimates the effect using orthogonal deviations to remove the county fixed effect, while column 2 uses the first difference transformation. Appropriately lagged values of the regressors are used as instruments with the precise lags used indicated in the table. In both cases we test for serial correlation in the first differences in the error term using the Arellano and Bond (1991) test for serial correlation of the residuals in differences. 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 with orthogonal deviations or twice-lagged variables as instruments with first differences. 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.[25] Moreover, the test

[24]The forward orthogonal deviation transformation subtracts from the value of a variable at time t 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.

[25]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 measurement 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.

of overidentifying restrictions (Hansen test) does not suggest model misspecification in any of the equations. In column 3, we include multiple lags of *Trust* as well. While the individual coefficients change size, their sum is nearly identical, and so the long-run effect of a change in *Trust* is nearly the same. In column 4 we include as an additional instrument the one constructed in the previous section based on the past stock of ancestry and the growth rate of each ancestry at the national level in equation 5. The results are nearly identical to column 1 which means that the constructed instrument does not add much additional information relative to simply using a lag of the *Trust* as an instrument.[26]

For comparison, columns 6 and 7 show the results of estimating the same dynamic model with two lags of county GDP, using the within transformation but no instruments in column 6, and our constructed instrument in column 7. The sum of the coefficients on the lagged dependent variables is somewhat larger in the GMM estimates that with the fixed effects, as one would expect in relatively short panels (Nickell, 1981), but the difference is small. More importantly, the coefficients on the effect of ancestry-weighted *Trust* remain highly significant. Note that, although the impact effects differ, the long-run effect of a permanent change in *Trust* (defined as 5.14=1.347/(1-0.624-0.114)), using the GMM results of column 1 of Table 4 is very similar to the long run effect of a permanent change in *Trust* in the fixed effects estimation with two lags of county GDP in column 6 (5.20), and in the fixed effect estimation of the same model when *Trust* is instrumented in column 7 (5.63) using the past distribution of ancestries from Section 5.5.1. The estimated coefficient of *Trust* in the static fixed effect model of Table 2 (2.5) is in-between the GMM estimates of the short and long-run effects in the dynamic model, and is closer to the impact effect. It is also very close to the estimated impact effect of the dynamic fixed effect model, with or without instruments.

Finally, we examine the co-evolution of county GDP per capita and ancestry-weighted *Trust* in columns 8 and 9 of Table 4 using a bivariate panel vector auto-regression. This approach allows county GDP to affect *Trust* as well as for *Trust* to affect county GDP and makes no structural assumptions beyond the number of lags. While the previous columns deal appropriately with the

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

potential endogeneity of *Trust*, they do not explicitly model its evolution. Instead of estimating the structural model for county GDP, as in columns 1-7 of Table 4, we now estimate the reduced form of the model for both log county GDP and *Trust*. The coefficient of the first lag of *Trust* is again highly significant in the GDP equation. County GDP also has an effect on *Trust* in column 9. Indeed, when we test for Granger Causality we strongly reject both that *Trust* does not Granger cause GDP and that GDP does not Granger cause *Trust*, with p-values very close to zero. However, the effect of GDP on *Trust* is very small.

We consider the co-evolution explicitly by calculating the impulse responses functions of log county GDP and *Trust* obtained from a Cholesky decomposition under two different assumptions about the ordering of the variables: (1) that county GDP affects *Trust* only with a lag, and (2) that *Trust* affects county GDP only with a lag. Since it takes people time to move in response to a boom, we think that the first assumption may be more reasonable. The impulse responses for a one standard deviation shock to log county GDP and *Trust* are shown in Figure 8 (for *Log origin GDP* see appendix Figure A-1). The overall shape of the impulse responses are very similar for both decompositions. The short-run response is sizable and significant (either immediately or after one period), peaks after four periods and then slowly declines. For instance, when *Trust* is assumed to respond to GDP only with a lag, a one standard deviation shock to *Trust* leads to an increase in GDP of 1.5 percentage points on impact, peaking at somewhat above two percentage points after four decades.. The effect is significant and large (around 1.5 percentage points) even after ten decades. The reverse effect of a shock to county GDP on *Trust* is statistically significant but it is always small (note the different scale of the vertical axes for the *Trust* and GDP responses). For instance, it peaks at 0.002 or 0.004 (depending upon the ordering of the variables), which is a rather small number given that 90% of the observations of *Trust* vary between 0.22 and 0.40.

5.6 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 static 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 (for reference, see Bossert, D'Ambrosio, and La Ferrara (2011), who generalize early work and provide an axiomatic treatment). 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.[27] 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 $i \neq j$). We show results based on fractionalization weighted by country-of-origin Trust, but obtain similar results using fractionalization of origin GDP.

In Table 5 we report the results obtained when we include measures of fractionalization and Trust weighted fractionalization using the fixed effects estimates of the static equation 4 when ancestry-weighted *Trust*, *State History* and the *Migrant-education-to-US* ratio are all included. An increases in county diversity of country-of-origin as captured by fractionalization is associated

[27] Note that the fractionalization index could also be defined using measures of dissimilarity between groups j and k. If $d_{ct}^{jk} = |z^j - z^k|/r$ then $frac_{c,t}^{w} = \sum_{j=1}^{A}\sum_{k=1}^{A} \pi_{ct}^{j}\pi_{ct}^{k}d_{ct}^{jk}$ since the sum over the AV is 1. Although the discussion assumes a fixed x^j for each ancestry, the country-of-origin measure can change over time as well. For example, it is possible to use the density of arrival weighted country-of-origin GDP to calculate the fractionalization at any given time. The double sum over ancestry makes weighted fractionalization somewhat complicated and computationally intensive to calculate weighted fractionalization over the full county-decade panel.

with an increase in county GDP per capita. An increases in Trust weighted fractionalization is associated, instead, with a decrease in GDP. The coefficient on the level of ancestry-weighted *Trust* is very similar to the estimates without fractionalization (see column 1 of Table 3). Since fractionalization and weighted fractionalization are both indices that vary from 0 to 1, the estimated effects are large: an increase in the Trust fractionalization by one percentage point (0.01) decreases county income by 2.7%.[28] The estimated effects of *Trust*, fractionalization, and Trust fractionalization are robust to many different specifications such as including state-year effects, the fraction of Native Americans and African Americans, population density, and county education levels. The positive impact of fractionalization and negative impact of Trust fractionalization does not come just from diverse and high income cities and is not just a racial effect.

These results capture two different views of diversity. The positive effect of fractionalization is consistent with the notion that it is beneficial for people with new skills and ideas to come into a county, particularly if these complement the skills and ideas of the existing population. 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 trust, this may create conflict and lead to a decrease in the ability to agree on growth enhancing policies at the local level. One can imagine, for example, that a low-trust group moving into a high-trust area may not only bring down the average trust level (as captured by the ancestry-weighted *Trust*), but also make the high-trust group less willing to cooperate.

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.

[28]The mean fractionalization across all county groups is 0.73, with an interquartile range of 0.215, while for the fractionalization of Trust the mean is 0.155 and the interquartile range is 0.105. Going from the 25th to the 75th percentile for fractionalization is associated with a rise in GDP per capita of 25%, while going from the 25th to the 75th percentile of Trust fractionalization reduces GDP per capita by 29%.

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. Ager and Brückner (2013) demonstrate that increased fractionalization of first generation migrants in the United States is positively associated with output, while a tendency towards polarization—when there is an even division between two groups—is negatively associated with output. 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.

Given the evidence that fractionalization has both positive and negative effects, and that its effects overall may be non-linear (Ashraf and Galor, 2013), in columns 5-8 of Table 5 we include the square of fractionalization and Trust weighted fractionalization, allowing the effect to be non-linear. The square of fractionalization has a consistently negative effect, indicating that the positive marginal effect of increased fractionalization is decreasing. Increasing diversity in an already diverse place has a smaller positive effect than in a homogenous place. The square of Trust fractionalization has a positive effect, suggesting that the negative marginal effect of Trust fractionalization gets smaller the more diversity in Trust there is. Increasing the diversity of Trust has a larger negative effect in more uniform societies. The quadratic form implies that there is potentially an optimal level of diversity and worst level of Trust diversity. The maximum and minimum, however, fall very close to the limits of the range of diversity of our counties; while diversity has a non-linear effect, we do not find that it has u-shaped effect within the very diverse United States.[29]

6 Conclusion

Using micro-samples from the US census since 1850, we have mapped the ancestral distribution of population of US counties, and combined it with consistent estimates of county level GDP per capita. This panel has allowed us to assess whether the endowments of people's ancestors

[29]For a quadratic $ax + bx^2$ the maximum or minimum occurs when $x = -a/(2b)$. The optimal fractionalization (using column 5) is 0.99, while the least valuable Trust fractionalization is 0.37. The 90th percentile of our county groups is 0.88 for fractionalization and 0.26 for Trust fractionalization, and so the maximum and minimum fall at the very top end of possible values.

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, common or state-specific year effects and other time varying observable county level factors. The cultural, institutional, and human capital endowments that migrants brought from their country of origin explain this association. We find that cultural variables reflecting values and beliefs about cooperation tend to play the most robust role relative to other factors. 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 sizeable, 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 of the cultural endowment brought by immigrants is negatively related to county level GDP. It matters not only where you came from, but also whom you came in contact with once you arrived.

The complex mosaic of ancestry in the United States has changed profoundly over the past and it is still evolving as new migrants enter and people move internally. Our novel data set on the stock of ancestry and GDP has allowed us to provide new evidence on the relationship between ancestry composition and economic development. However, this is just the start; 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? And what are 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

Abrigo, Michael R.M. and Inessa Love. 2015. "Estimation of panel vector autoregression in Stata: A package of programs." Working paper, University of Hawaii. Available: https://sites.google.com/a/hawaii.edu/inessalove/home/pvar, accessed 24 July 2015.

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

Acemoglu, Daron, Simon Johnson, and James A. Robinson. 2001. "The Colonial Origins of Comparative Development: An Empirical Investigation." *American Economic Review* 91 (5):1369–1401.

———. 2002. "Reversal of Fortune: Geography and Institutions in the Making of the Modern World Income Distribution." *The Quarterly Journal of Economics* 117 (4):1231–1294.

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.

Albouy, David Y. 2012. "The Colonial Origins of Comparative Development: An Empirical Investigation: Comment." *American Economic Review* 102 (6):3059–3076.

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, National Bureau of Economic Research. URL http://www.nber.org/papers/w19750.

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, National Bureau of Economic Research. URL http://www.nber.org/papers/w18699.

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

Altonji, Joseph G. and David Card. 1991. *Immigration, Trade, and the Labor Market*, chap. The Effects of Immigration on the Labor Market Outcomes of Less-skilled Natives. 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.

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):pp. 1190–1213.

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

———. 2006b. *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.

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. *Handbook of Social Economics*, vol. 1A, chap. The Economics of Cultural Transmission and Socialization. North Holland, The Netherlands: 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.

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.

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.

———. 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.

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.

Carter, Susan B. 2006. *Historical Statistics of the United States, Earliest Times to the Present: Millennial Edition*, chap. National income, by industry group: 1929–2002. Cambridge University Press, Table Ca35–53.

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.

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.

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*.

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. *Handbook of Social Economics*, vol. 1A, chap. Does Culture Matter? 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.

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

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

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. URL `http://www.bc.edu/content/dam/files/schools/cas_sites/economics/pdf/workingpapers/wp853.pdf`.

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 Regulated Economy: A Historical Approach to Political Economy*, chap. The Political Economy of Immigration Restriction in the United States, 1890 to 1921. 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.

———. 2013. "Long-term Persistence." Working Paper 23/13, Einaudi Institute for Economics and Finance.

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.

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.

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.

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

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.

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

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.

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

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.

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.

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

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.

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.

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

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.

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.

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 Commerce Bureau of the Census. 2012. “County and City Data Book Consolidated File: County Data, 1947-1977 (ICPSR07736-v2).” Inter-university Consortium for Political and Social Research [distributor].

U.S. 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.

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.

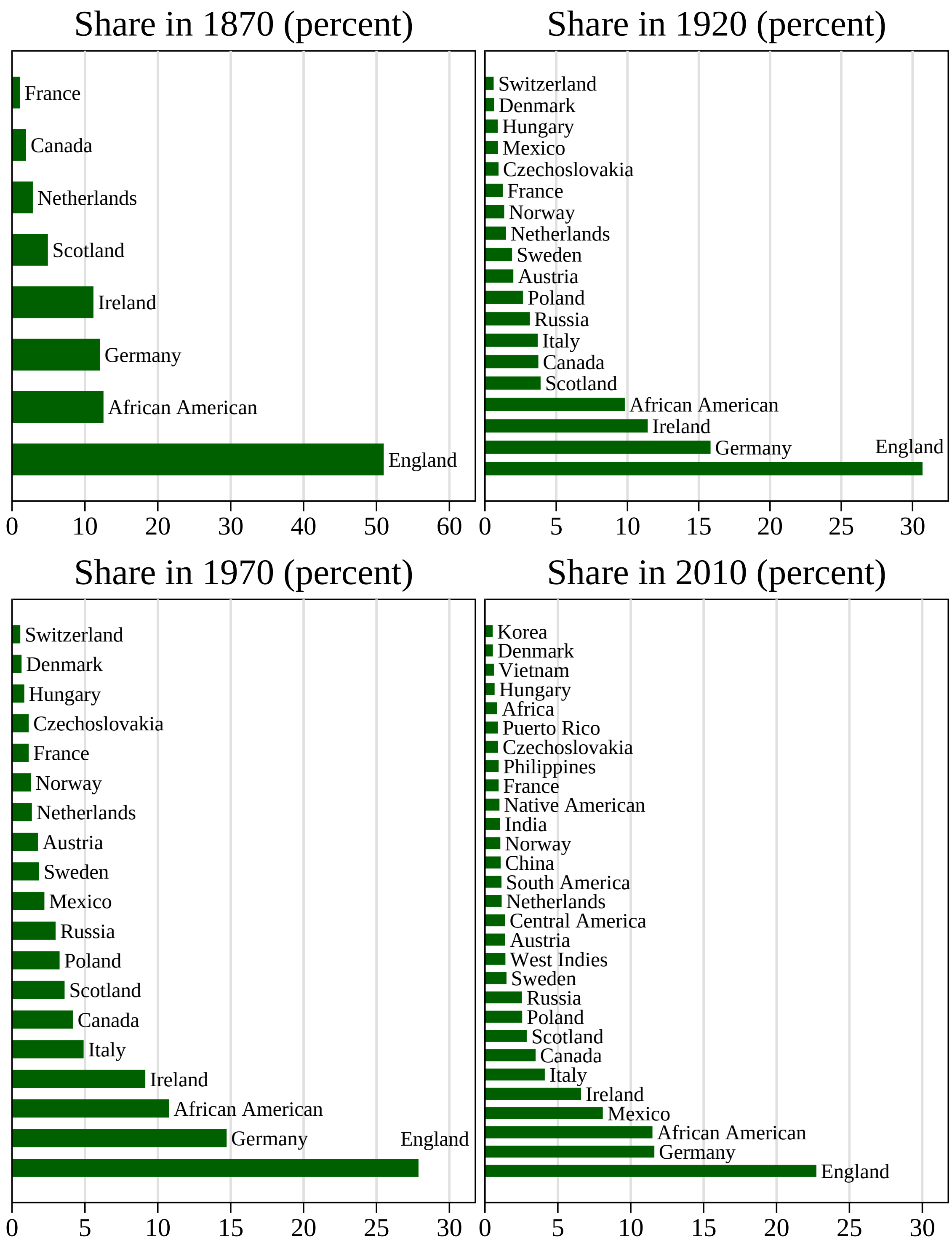
Vanhanen, Tatu. 2012. “Political Participation.” https://www.clio-infra.eu/datasets/select/indicator/384. Accessed 11 February 2015.

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

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

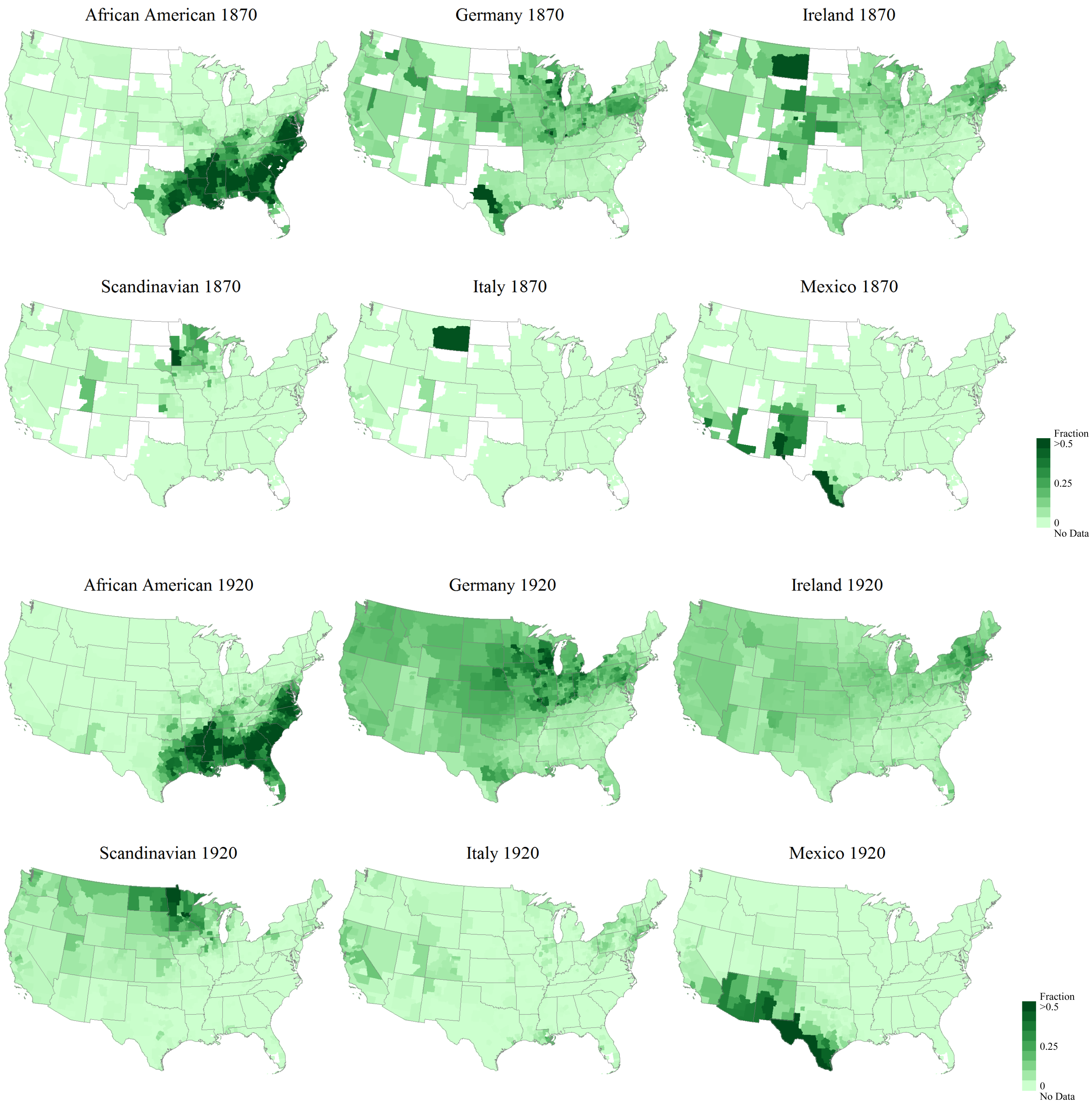
Wright, Gavin. 2006. *Historical Statistics of the United States, Earliest Times to the Present: Millennial Edition*, chap. Mineral operations - establishments, receipts, value added, employment, and expenses: 1880-1997. Cambridge University Press, Table Db1–11.

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



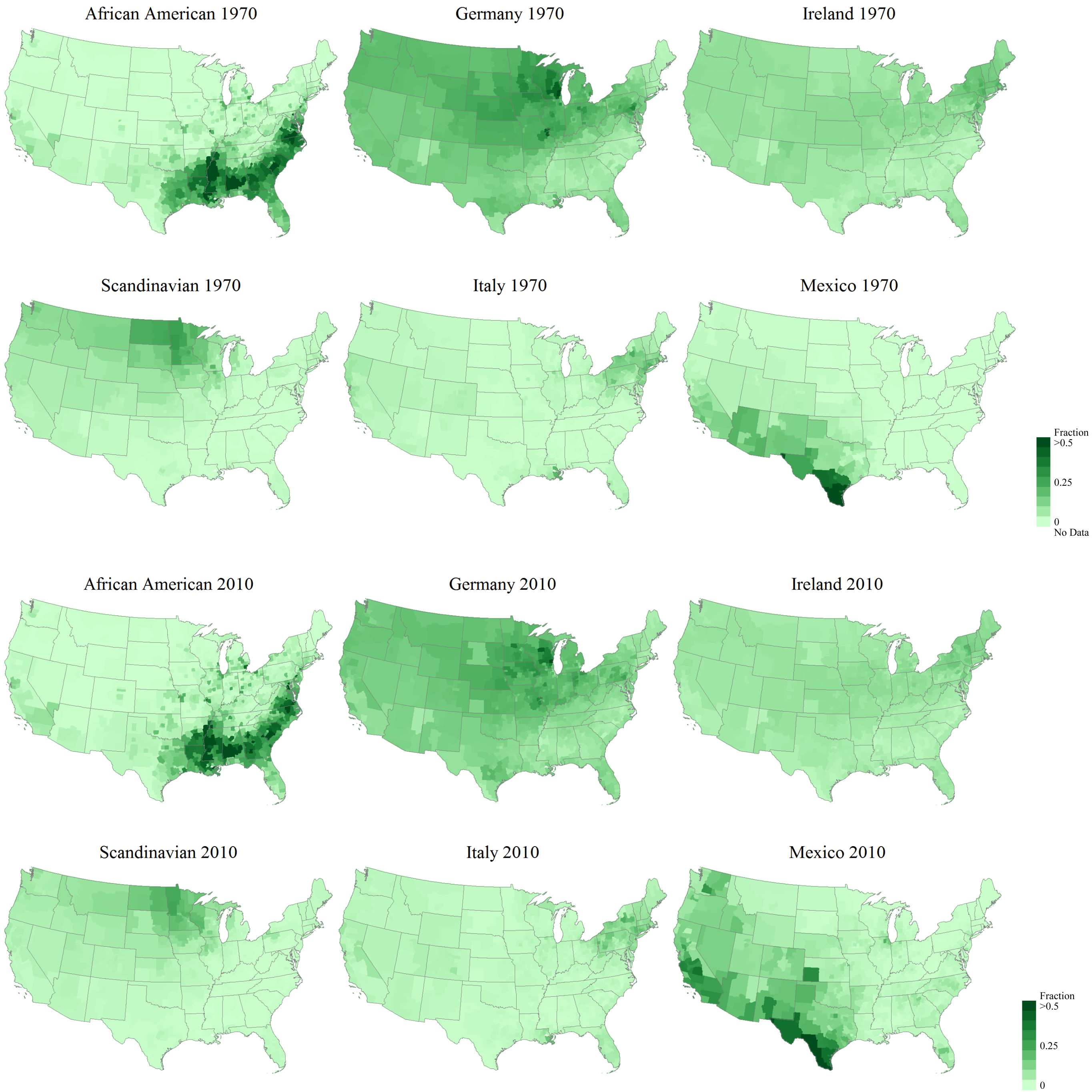
Notes: Shows the aggregate ancestry shares in the US for ancestries with greater that 0.5% of the population. Ancestry shares are created by summing the share in each county weighted by county population in each year. See Section 3 and Appendix A for the ancestry construction.

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



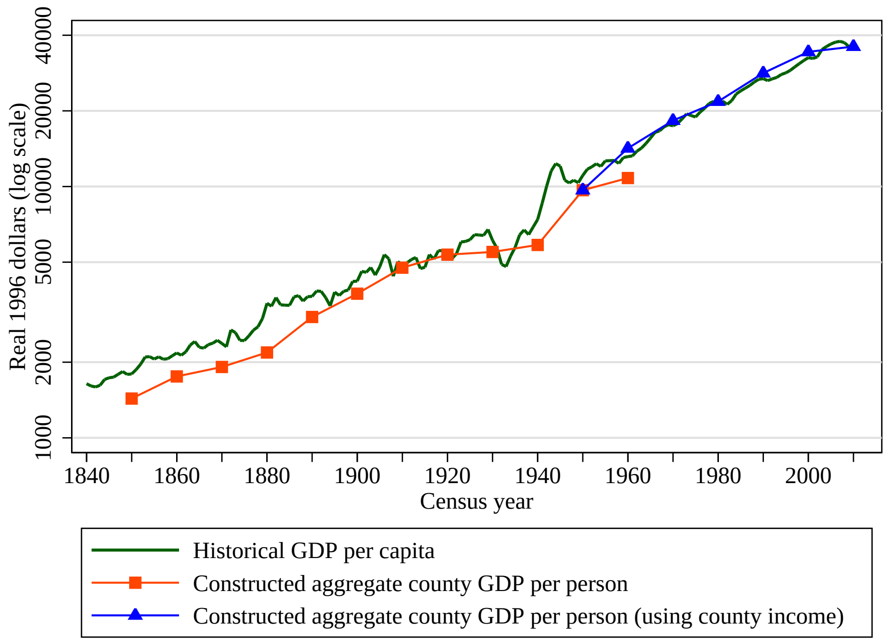
Notes: Scandinavian is the combined Norway and Swedish ancestries. See Section 3 and Appendix A for the ancestry construction.

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



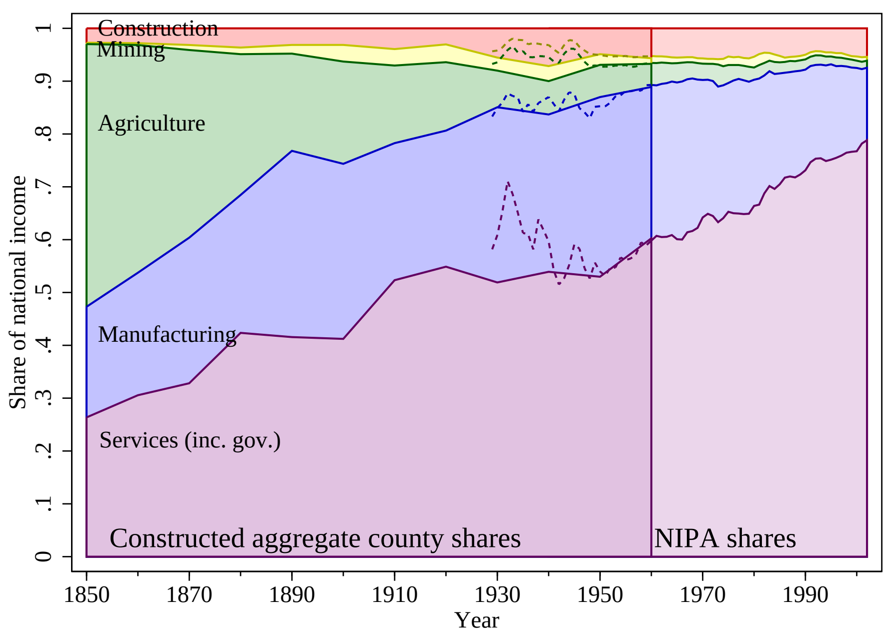
Notes: Scandinavian is the combined Norway and Swedish ancestries. See Section 3 and Appendix A for the ancestry construction.

Figure 4: GDP and aggregate county GDP per capita: 1840-2010



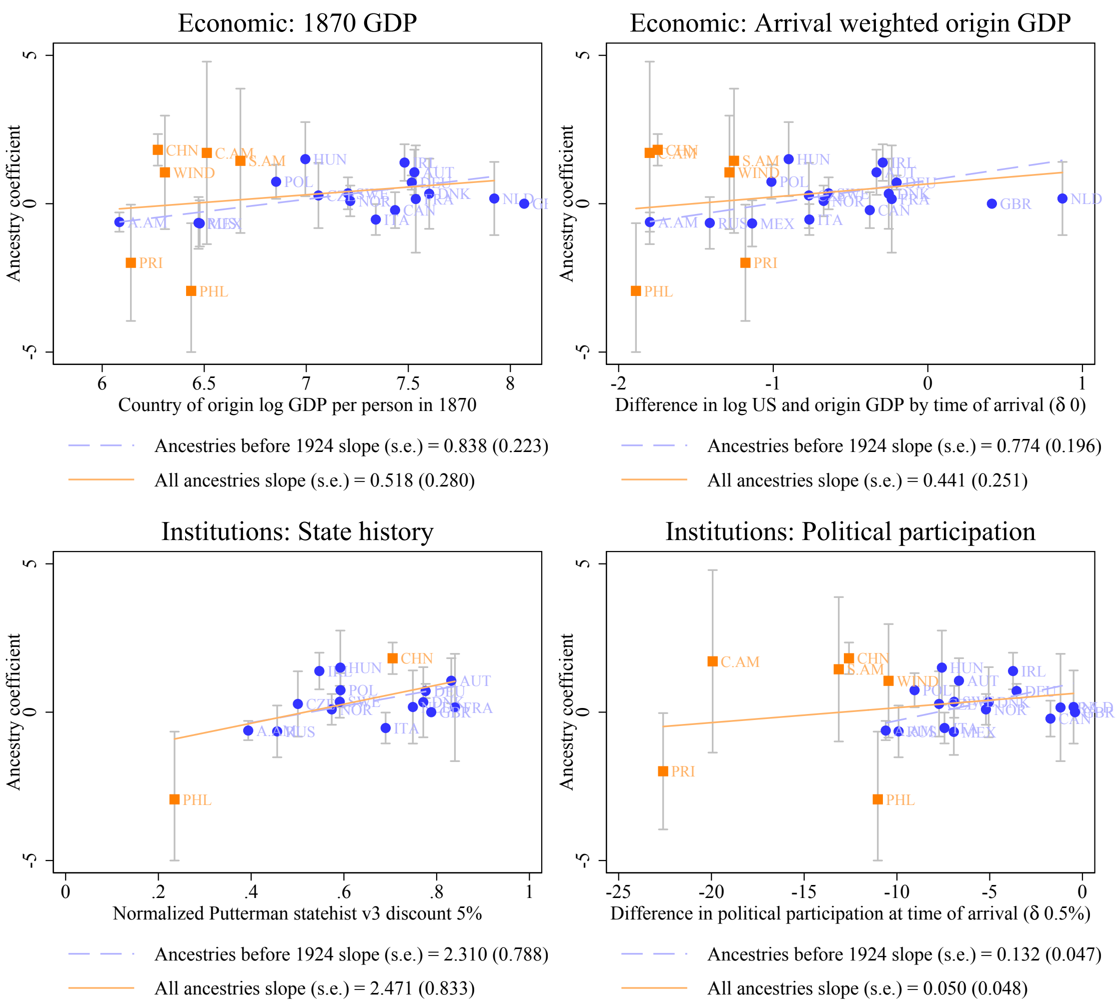
Notes and sources: Historical GDP per capita from Sutch (2006). The constructed aggregate GDP per capita and aggregate county income per capita are created by totaling the county measures for each year then dividing by population.

Figure 5: Constructed sectoral shares 1850-2010



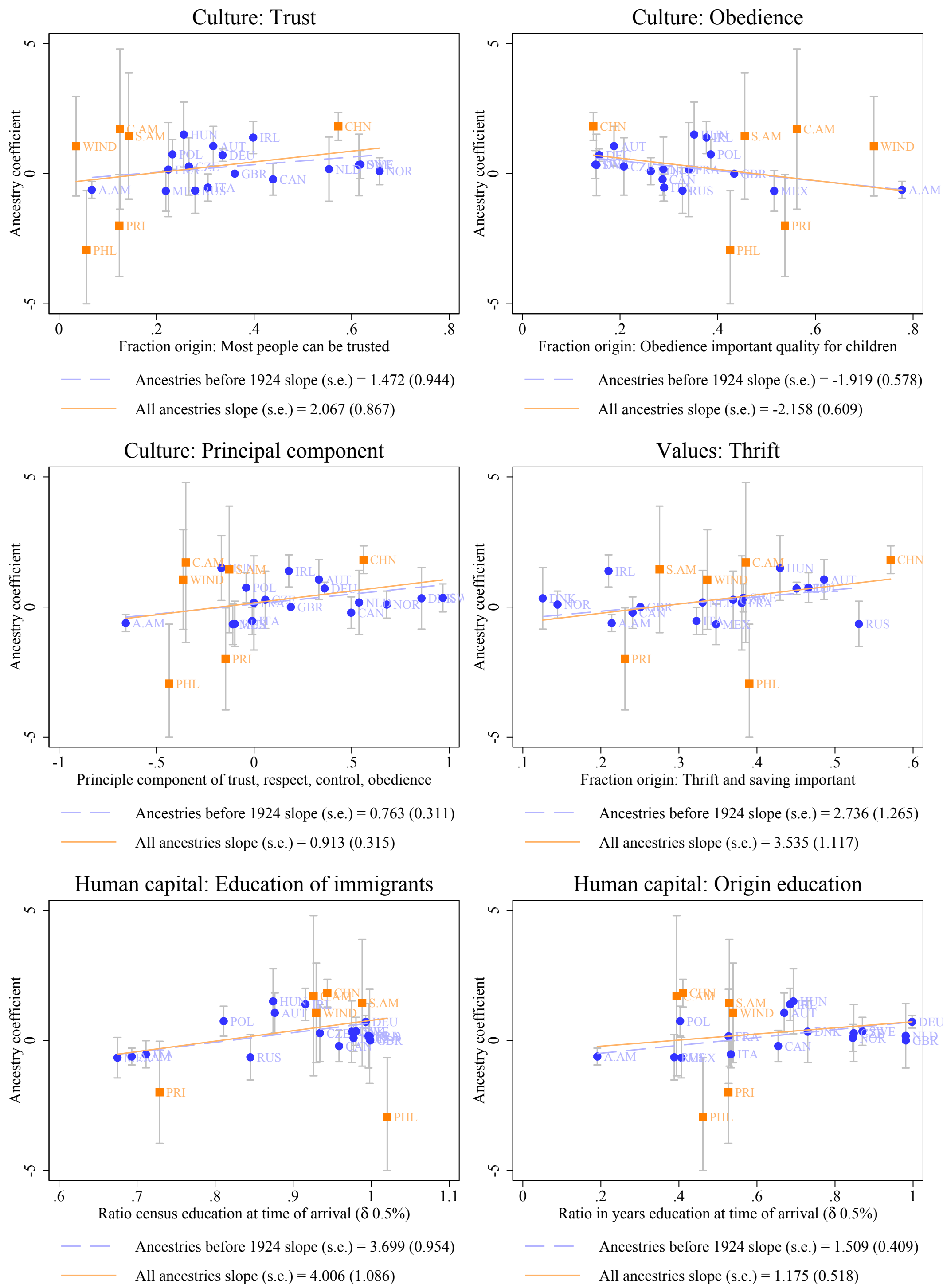
Notes: The shares from 1850 to 1960 are based on our estimates of county GDP totaled over all counties. The National Income and Product (NIPA) shares on the right are the dashed lines in 1929 and the overall shares after 1960 and are based on Carter (2006).

Figure 6: Ancestry and country of origin: Economic and Institutions



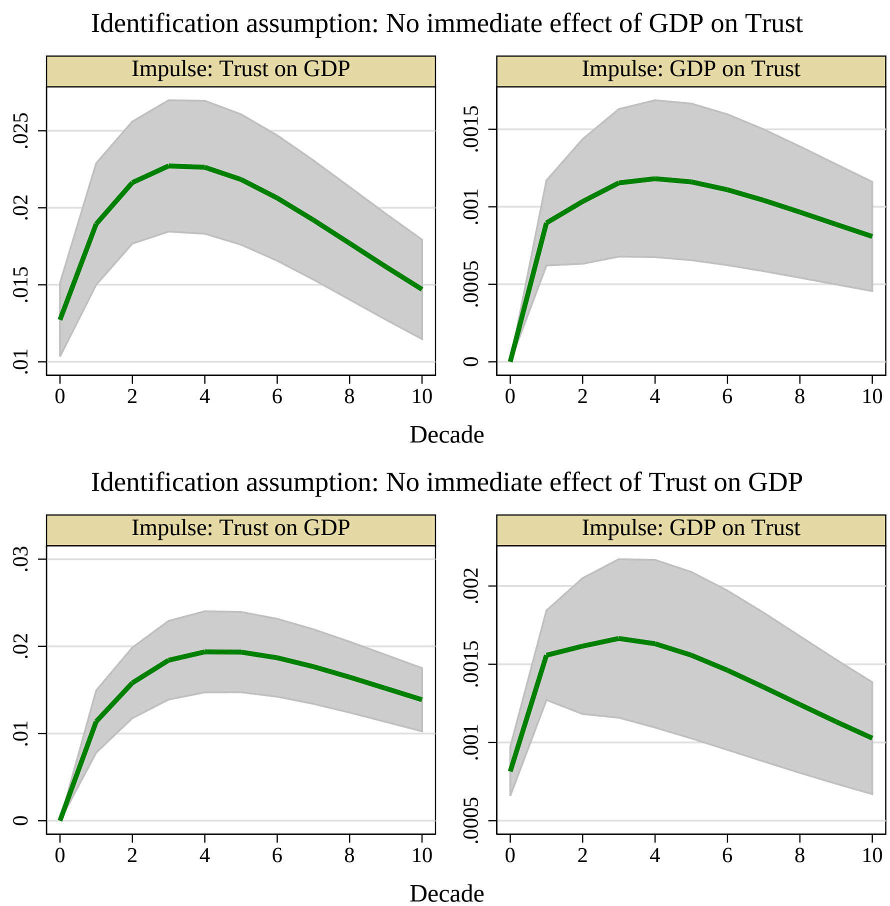
Notes: Shows the relationship between economic variables in the country of origin and the coefficients estimated for large ancestry groups on log county GDP per capita including fixed effects in equation 1. The construction of origin GDP is described in Appendix D.1. Arrival density is based on author calculations from Department of Homeland Security (2013). State History is from Putterman and Weil (2010) and excludes origins that were heavily settled by migrants (the Americas). We use their version 3 with a discount of 5%. Political participation is the percent that could vote in national elections (Vanhanen, 2012), taken as the difference between that group and the US political participation, weighted by the time of arrival with a depreciation rate of 0.2%.

Figure 7: Ancestry and country of origin: Social capital, culture, and human capital



Notes: Shows the relationship between cultural variables in the country of origin and the coefficients estimated for large ancestry groups on log county GDP per capita including fixed effects in equation 1. The questions are based on the World Values Survey, see appendix D.2. Human capital is the difference between years of education in origin and US at the time of arrival. Years of education from van Leeuwen and van Leeuwen-Li (2013). Arrival density is based on author calculations from Department of Homeland Security (2013).

Figure 8: Impulse response of log county income and ancestry weighted trust



Notes: Shows impulse responses corresponding to columns 8-9 in Table 4 estimated together as a panel VAR using pvar (Abrigo and Love, 2015). The impulses are calculated using two Cholesky decompositions: (1) No immediate effect of GDP on TRUST, but TRUST can immediately affect GDP, (2) No immediate effect of TRUST on GDP, but GDP can immediately affect TRUST. The size of the impulse is the standard deviations of the residuals in each equation. Shaded areas are the 95% confidence intervals based on Monte Carlo simulation.

Table 1: County GDP per capita and individual ancestries

Dependent	Log(County group GDP per capita)								
variable	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Log(GDP p.c.)				0.401***	0.254***				0.381***
at t-1				(0.00653)	(0.00700)				(0.00674)
Literacy							0.555***	0.463***	0.321***
							(0.0335)	(0.0332)	(0.0342)
Years education							0.0718***	0.0314***	0.0234***
							(0.00454)	(0.00481)	(0.00421)
Log(density)								0.0896***	0.0292***
								(0.00395)	(0.00382)
F(All ancestry =0)	136.5	53.86	26.14	33.85	13.27	14.52	46.47	51.91	30.54
p-value	0	0	0	0	0	0	0	0	0
F(non-AA anc. =0)	80.27	45.12	23.62	20.78	12.04	12.07	42.98	43.15	20.96
p-value	0	0	0	0	0	0	0	0	0
State X Year	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County group trends	No	No	Yes	No	Yes	Yes	No	No	No
Lag Ancestry	No	No	No	No	No	Yes	No	No	No
R^2 (within)	0.962	0.972	0.979	0.980	0.984	0.981	0.972	0.973	0.980
R^2 (between)	0.517	0.632	0.00872	0.831	0.0446	0.0265	0.703	0.769	0.881
Observations	18,444	18,444	18,444	17,295	17,295	17,404	18,216	18,207	17,061
County groups	1,151	1,151	1,151	1,151	1,151	1,151	1,151	1,148	1,148

Notes: The F-tests test the joint hypothesis that all ancestries (except English, the excluded group) are jointly zero. The Non-AA F tests whether all ancestries except African Americans and Native Americans are jointly insignificant. All regression contain fixed effects for year and county group. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: County GDP per capita and country-of-origin characteristics

Ancestry weighted	Log(County group GDP per capita)					
Variables	Each cell from a separate estimation					
One at a time	FE	FE	FE	NO FE	DYN FE	IV DYN FE
Log origin GDP/US	0.223***	0.532***	-0.101	-0.255***	0.279***	0.327***
on arrival	(0.0547)	(0.0478)	(0.0683)	(0.0714)	(0.0220)	(0.0116)
Origin GDP/US ratio	0.113**	0.646***	-0.328***	-0.441***	0.343***	0.428***
on arrival	(0.0555)	(0.0728)	(0.0888)	(0.121)	(0.0322)	(0.0186)
1870 GDP weighted	0.304***	0.735***	-0.111	-0.343**	0.363***	0.430***
by county AV	(0.0817)	(0.0745)	(0.116)	(0.143)	(0.0315)	(0.0177)
Migrant education/US	-0.151	1.215***	-1.676***	-0.784*	1.170***	1.305***
ratio at arrival	(0.195)	(0.169)	(0.296)	(0.397)	(0.103)	(0.0501)
Origin education/US	0.411***	1.144***	-0.462**	-0.484**	0.646***	0.743***
ratio at arrival	(0.120)	(0.141)	(0.184)	(0.188)	(0.0627)	(0.0304)
State history in 1500	0.968***	2.281***	-0.474	-0.870***	1.183***	1.482***
	(0.234)	(0.248)	(0.310)	(0.272)	(0.118)	(0.0601)
Arrival political	0.0104	0.0631***	-0.0371***	-0.0419***	0.0310***	0.0356***
participation	(0.00720)	(0.00673)	(0.0126)	(0.00898)	(0.00224)	(0.00146)
Trust	2.524***	4.254***	1.573***	-0.801**	2.190***	2.425***
	(0.430)	(0.394)	(0.538)	(0.398)	(0.186)	(0.0792)
Obedience	-2.175***	-2.944***	-2.894***	-0.607**	-1.522***	-1.584***
	(0.216)	(0.293)	(0.391)	(0.269)	(0.129)	(0.0541)
Respect	-0.532	4.379***	-2.474***	-5.196***	2.538***	3.568***
	(0.543)	(0.961)	(0.683)	(1.927)	(0.469)	(0.235)
Control	-0.687***	-0.289	-0.275**	-0.779***	-0.249***	-0.203***
	(0.139)	(0.206)	(0.129)	(0.101)	(0.0701)	(0.0356)
Principal comp.	0.946***	1.505***	1.035***	-0.230*	0.787***	0.860***
culture	(0.137)	(0.134)	(0.194)	(0.129)	(0.0564)	(0.0271)
Thrift	3.781***	1.935**	2.113***	3.449***	1.401***	1.414***
	(0.506)	(0.868)	(0.426)	(0.892)	(0.291)	(0.146)
Observations	16,713	16,713	16,704	16,713	14,419	14,393
Year X State FE		Yes	Yes	Yes		
Other controls			Yes			
Lags of county GDP					Yes	Yes
Count group FE	Yes	Yes	Yes	Yes	Yes	Yes
County groups	1151	1151	1151	1151	1151	1151

Notes: Other controls include the fraction African American, the fraction Native American, and the log population density. All regressions include county group effects and either state-year or state and year effects and errors are allowed to cluster at the state level (except in the IV regressions). All independent variables are constructed at the county group level by weighted country-of-origin characteristics by the ancestry vector as in equation 3. The Dynamic Fixed Effects column includes two lags of Log county GDP. In the IV column, the instrument is the variable constructed using ancestry based on settlement patterns in the past, and each regression includes two lags of the dependent variable. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: County GDP per capita and combined country-of-origin characteristics

Dependent	Log(County group GDP per capita)								
variable	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Trust	3.980***	4.303***	3.259***	2.636***	3.842***	4.005***	3.370***	2.951***	5.420***
	(0.500)	(0.655)	(0.746)	(0.798)	(0.476)	(0.590)	(0.788)	(0.825)	(0.519)
State history	0.724**	0.540	0.626*	0.136	0.634*	0.124	0.632*	0.0579	0.351
in 1500	(0.325)	(0.352)	(0.350)	(0.263)	(0.340)	(0.319)	(0.346)	(0.261)	(0.332)
Migrant educ./US	-0.283	-1.883***	-0.337	-1.908***	-0.181	-1.676***	-0.286	-1.748***	-0.979***
ratio at arrival ($\delta = 0$)	(0.206)	(0.243)	(0.203)	(0.239)	(0.223)	(0.251)	(0.215)	(0.243)	(0.294)
Thrift					0.946	2.514***	0.396	1.573***	-2.081
					(0.620)	(0.389)	(0.627)	(0.396)	(1.944)
Log pop. density			0.0343*	0.0589***			0.0340*	0.0556***	
			(0.0179)	(0.0113)			(0.0182)	(0.0112)	
Frac. African American			-0.411	-0.969***			-0.313	-0.656**	
			(0.323)	(0.309)			(0.317)	(0.325)	
Frac. Native American			0.586***	0.524**			0.603***	0.616***	
			(0.214)	(0.215)			(0.219)	(0.216)	
Observations	16,713	16,713	16,704	16,704	16,713	16,713	16,704	16,704	16,536
R-squared	0.962	0.973	0.962	0.974	0.962	0.974	0.962	0.974	
State X Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No
Instrument	No	No	No	No	No	No	No	No	Yes
County groups	1151	1151	1148	1148	1151	1151	1148	1148	1151

Notes: Italics indicate the variable is ancestry weighted at the county group level as in equation 3. All regressions include county group effects and and standard errors are allowed to cluster at the state level.. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: GMM estimates of the dynamic effects of ancestry weighted Trust

	Single equation GMM					FE	IV	Bivariate VAR	
Dependent	Log(County group GDP per capita)							GDP	*Trust*
Variable	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Trust	1.347***	1.630***	4.552**	1.387***		2.190***	2.425***		
	(0.204)	(0.390)	(2.204)	(0.198)		(0.0680)	(0.0792)		
Decade lag			-2.609		1.271***			1.276***	0.807***
Trust			(1.832)		(0.222)			(0.226)	(0.0258)
Two decade lag			-0.182		0.0225			-0.0108	0.0486**
Trust			(0.200)		(0.168)			(0.152)	(0.0218)
Decade lag	0.624***	0.608***	0.595***	0.626***	0.637***	0.525***	0.520***	0.591***	0.00643***
log county GDP	(0.0178)	(0.0273)	(0.0305)	(0.0179)	(0.0165)	(0.00767)	(0.00786)	(0.0192)	(0.00105)
Two decade lag	0.114***	0.0705***	0.112***	0.110***	0.110***	0.0540***	0.0493***	0.0943***	-0.00157**
log county GDP	(0.0122)	(0.0154)	(0.0116)	(0.0116)	(0.0118)	(0.00700)	(0.00707)	(0.0115)	(0.000698)
Long-run effect	5.14	5.07	6.01	5.25	5.11	5.20	5.63		
Observations	13,268	13,257	13,211	13,268	13,227	13,268	13,242	13,223	13,223
County groups	1,147	1,147	1,147	1,147	1,147	1,147	1,147	1,147	1,147
Add. Inst				Past			Past		
Transform	FOD	FD	FOD	FOD	FOD	FE	FE	FOD	FOD
GMM instruments	1/2	2/3	1/3	1/2	1/2			1/2	1/2
AB AR(1) in diff.	0	0	0	0	0	0	0		
AB AR(2) in diff.	0.146	0.240	0.207	0.233	0.291	0.134	0.0748		
Hansen over id.	0.938	0.889	0.892	0.491	0.323				

Notes: Italics indicate the variable is ancestry weighted at the county group level as in equation 3. All regressions include year effects and remove county group fixed effect either by Forward Orthogonal Deviations (FOD), First Difference (FD) or Fixed Effect (FE). The lags of the instruments are reported in the table under GMM instruments. All endogenous variables have the same instruments. AB AR(1) and AR(2) report the p-values of the Arellano and Bond (1991) test for serial correlation in first and second differences. The Hansen over id. reports the p-value for the Hansen test of over-identifying restrictions when the equation is over-identified. The Additional Instrument is the past ancestry augment with national level ancestry growth as discussed in Section 5.5.1. Columns 1-5 are estimated in Stata as single equation GMM using xtabond2 with the collapse option (Roodman, 2009), column 6 is estimated using the within estimator, column 7 the within estimator and two stage IV, while columns 8-9 are estimated together as a panel VAR using pvar (Abrigo and Love, 2015). *** p<0.01, ** p<0.05, * p<0.1.

Table 5: County GDP per capita and diversity

Dependent variable	Log(County group income per capita) [1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Trust	2.075***	2.832***	3.126***	2.758***	2.154***	2.821***	2.504***	2.238***
	(0.442)	(0.452)	(0.598)	(0.579)	(0.407)	(0.454)	(0.687)	(0.590)
Fractionalization	1.153***	1.350***	1.402***	1.242***	3.718***	2.453***	3.927***	3.246***
	(0.185)	(0.180)	(0.248)	(0.248)	(0.762)	(0.638)	(0.727)	(0.556)
Trust weighted	-2.791***	-2.304***	-3.286***	-2.295***	-4.979***	-1.546*	-4.751***	-1.424
fractionalization	(0.481)	(0.357)	(0.503)	(0.410)	(1.168)	(0.858)	(1.246)	(0.879)
State history	0.227	0.000957	0.632*	0.125	0.174	-0.0398	0.378	-0.156
in 1500	(0.321)	(0.281)	(0.356)	(0.263)	(0.343)	(0.286)	(0.372)	(0.256)
Migrant educ./US	-0.161	-1.645***	-0.0746	-1.567***	-0.446**	-1.672***	-0.434*	-1.735***
ratio at arrival ($\delta = 0$)	(0.190)	(0.212)	(0.222)	(0.199)	(0.204)	(0.225)	(0.220)	(0.219)
Fractionalization^2					-1.882***	-0.905**	-2.038***	-1.735***
					(0.558)	(0.426)	(0.583)	(0.431)
(Trust weighted					6.793**	-2.130	5.788**	-1.623
fractionalization)^2					(2.673)	(2.294)	(2.810)	(2.245)
Observations	16,713	16,713	16,704	16,704	16,713	16,713	16,704	16,704
R-squared	0.964	0.974	0.965	0.975	0.965	0.975	0.965	0.975
State X Year	No	Yes	No	Yes	No	Yes	No	Yes
County group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	No	No	Yes	Yes	No	No	Yes	Yes
County groups	1151	1151	1148	1148	1151	1151	1148	1148

Notes: Italics indicate the variable is ancestry weighted at the county group level as in equation 3. All regressions include county group effects and standard errors are allowed to cluster at the state level. The creation of fractionalization and weighted fractionalization is described in section 5.6. Other controls include the fraction African American, Native American, and log population density. *** 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

Not for publication

A Constructing the Ancestry Vector (AV)

A.1 The AV 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, 2006b). 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.

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 use the demographic structure attributing to an individual the AV for the age group between 20 or 30 in the place of birth at the time of her birth. Using those who are 20-30 year older means we attribute to a person the AV of the age group 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 those who were 20-30 in the county where she lives now as of the closest census to her birth. This age group is in their most fertile years and so are the most likely to be her parents. We give non-immigrants who have moved the AV for 20-30 year olds from their state of birth as of the closest census to their birth.

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, and more Irish in the 20-30 age group 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 age 20-30 (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 age group 20-30 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 those 20-30 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 will 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.[30]

[30]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. This approach assumes that at a county level the same ratio of inputs to outputs is used in 1850 as in 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 U.S. 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 codes of the individuals. We allocate the occupations to correspond to the broad NIPA categories, and so create a measure of the total workers employed in a give industry in each decade. Then we create county level measures of services value added by multiplying county level employment for each service category (trade, transportation and public utilities, finance, professional services, personal services, and government) by the national measure of value added per employee,the construction of which is detailed below. We follow the same procedure for construction and mining.

There are several important difficulties with creating county employment: occupations change over time and some occupations such as legal services that may be classified as a service for an individual are part of manufacturing value added when performed for a manufacturing firm.

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.

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.

B.3 Measures of services, mining, and construction at the national level 1850-1960

The construction of value added for services, mining and construction 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 person 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.[31] 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.

[31] 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 $y^{s}_{1910} = f^{y}_{1910-1900} * (y^{s}_{1930} - y^{s}_{1910})$.

B.4 Income per capita 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 Department of Commerce Bureau of the Census, 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.5 County output 1950 and 1960

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 Department of Commerce Bureau of the Census, 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 U.S. 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 U.S. 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.6 Combining income and output measures

From 1850 to 1960 we have created something close to GDP per capita 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 per capita over the entire time period. We use the ratio of GDP to income in 1950 and update using the county income after that. Effectively, we use the growth rate of personal income at the county level to approximate the growth rate of county level GDP after 1950. Some counties have GDP-to-income ratios that are extreme because the constructed value of county GDP is low. We replace the five counties with a GDP-to-income ratio less that 0.3 with their state average ratio.

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 descendents of the population of ancestry a at time t (which is by definition 0 for all $\tau > t$ since it is a conditional density). We update it based on immigration records using:

$$F_{t+1}^a(\tau) = \frac{(P_{t+1}^a - I_{t+1}^a)F_{t+1}^a(\tau) + I_{t+1}^a 1(\tau = t+1)}{P_{t+1}^a}, \tag{6}$$

where $1(\tau = t+1)$ is an indicator which is one if $\tau = t+1$. 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 $\hat{I}_t^a = I_t^a / \omega^a$ which scales the number of migrants to the overall population of that group.[32]

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 Aus-

[32] 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.

trian 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 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.

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.

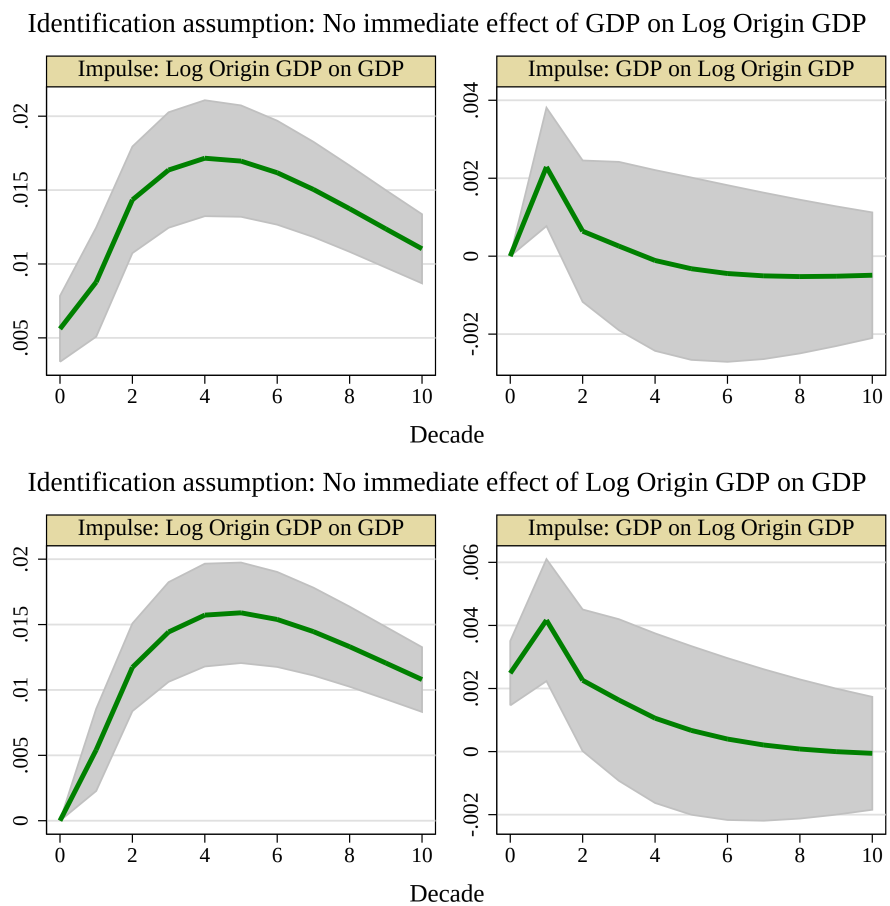
With no adjustment this procedure assumes that the ratio of years of education is the same as the ratio of literacy. Rather than make this strong assumption, we instead adjust the literacy ratio so that it gives the linear prediction of the years of education ratio. To do this we take the demographic 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.

Table A-1: GMM estimates of the dynamic effect of ancestry weighted arrival origin GDP

	Single equation GMM					FE	IV	Bivariate VAR	
Dependent	Log(County group GDP per capita)							GDP	*Origin GDP*
Variable	[1]	[2]	[3]	[4]	[5]	[7]	[7]	[8]	[9]
Log origin GDP/US	0.226***	0.159***	0.107	0.225***		0.279***	0.327***		
on arrival	(0.0244)	(0.0390)	(0.137)	(0.0243)		(0.00995)	(0.0116)		
Decade lag			0.0286		0.106***			0.0869***	0.755***
Log origin GDP			(0.108)		(0.0286)			(0.0282)	(0.0203)
Two decade lag			0.0729***		0.0860***			0.0706***	0.0802***
Log origin GDP			(0.0242)		(0.0226)			(0.0212)	(0.0167)
Decade lag	0.622***	0.644***	0.632***	0.626***	0.633***	0.548***	0.541***	0.598***	0.0163***
log county GDP	(0.0165)	(0.0230)	(0.0166)	(0.0163)	(0.0152)	(0.00760)	(0.00775)	(0.0172)	(0.00586)
Two decade lag	0.126***	0.0828***	0.116***	0.123***	0.116***	0.0701***	0.0669***	0.105***	-0.0175***
log county GDP	(0.0114)	(0.0139)	(0.0113)	(0.0110)	(0.0111)	(0.00702)	(0.00709)	(0.0111)	(0.00463)
Long-run effect	0.90	0.58	0.83	0.90	0.76	0.73	0.83		
Observations	13,268	13,257	13,211	13,268	13,227	13,268	13,242	13,223	13,223
County groups	1,147	1,147	1,147	1,147	1,147	1,147	1,147	1,147	1,147
Add. Inst				Past			Past		
Transform	FOD	FD	FOD	FOD	FOD	FE	FE	FOD	FOD
GMM instruments	1/2	2/3	1/3	1/2	1/2			1/2	1/2
AB AR(1) in diff.	0	0	0	0	0	0	0		
AB AR(2) in diff.	0.0215	0.535	0.122	0.0346	0.138	0.680	0.608		
Hansen over id.	0.00828	0.0345	0.752	0.0206	0.510				

Notes: Italics indicate the variable is ancestry weighted at the county group level as in equation 3. All regressions include year effects and remove county group fixed effect either by Forward Orthogonal Deviations (FOD) or First Difference (FD). The lags of the instruments are reported in the table under GMM instruments. All endogenous variables have the same instruments. AB AR(1) and AR(2) report the p-values of the Arellano and Bond (1991) test for serial correlation in first and second differences. The Hansen over id. reports the p-value for the Hansen test of over-identifying restrictions when the equation is over-identified. The Additional Instrument is the past ancestry augment with national level ancestry growth as disused in Section 5.5.1. Columns 1-5 are estimated in Stata as single equation GMM using xtabond2 with the collapse option (Roodman, 2009), column 6 is estimated using the within estimator, column 7 the within estimator and two stage IV, while columns 8-9 are estimated together as a panel VAR using pvar (Abrigo and Love, 2015).

Figure A-1: Impulse response of log county income and ancestry weighted trust



Notes: Shows impulse responses corresponding to columns 8-9 in table A-1 estimated together as a panel VAR using pvar (Abrigo and Love, 2015). The impulses are calculated using two Cholesky decompositions: (1) No immediate effect of GDP on GDP1870, but GDP1870 can immediately affect GDP, (2) No immediate effect of GDP1870 on GDP, but GDP can immediately affect GDP1870. The size of the impulse is the standard deviations of the residuals in each equation. Shaded areas are the 95% confidence intervals based on Monte Carlo simulation.