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

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Abstract

What impact on local development do immigrants and their descendants have in the short and long term? The answer depends on the attributes they bring with them, what they pass on to their children, and how they interact with other groups. We develop the first measures of the country-of-ancestry composition and of GDP per worker for US counties from 1850 to 2010. We show that changes in ancestry composition are associated with changes in lo-

1 Introduction

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

This paper uses the large and diverse migration to and within the United States over a century and a half to study the effect of the changing ancestry mix on local economic development. The United States constitutes an329Fido(the)-’hal0mix on loc a0(the)15locc-lin the full population, not just of first-generation immigrants, and so we are able to capture the long-term impact of groups and their descendants as they come to the US and move within it.[2] Second, we create a more comprehensive measure of the GDP of each county going back to 1850 that includes agriculture, manufacturing, and services. While measures of manufacturing output and intermediate inputs and agricultural output have been available at the county level, we construct measures of value added for both sectors. More importantly, focusing only on manufacturing and agriculture overlooks the large and growing contribution of the service sector, and so undervalues urban areas and misses the important and changing role played by the transportation, distribution, and financial sectors.

We address three central questions: Do ancestry groups have different effects on local development? If so, which characteristics brought from the country of origin explain why groups have different effects? As groups come together and interact, what is the impact of ancestry diversity? Importantly, we focus on whether the mix of ancestries matters, not the impact of increased total population from immigration or internal population growth. Our work shows that (1) groups have different economic impacts, (2) these impacts are closely related to characteristics in the origin country, and (3) that overall diversity has both positive and negative consequences, depending on the form of diversity.

To help separate the economic effects of people and what they bring with them from the economic effects of a place's characteristics we take several approaches that deal with distinct problems. First, our long panel allows us to control for unobservable county characteristics and hence separate out the effects of the evolving ancestry composition from time invariant characteristics of a county. Doing so removes the endogeneity that arises if certain ancestry groups are attracted to places with particular characteristics. We show that not controlling for the these fixed characteristics leads to misleading conclusr15(xpling)-but toefects-246(tf)-274(toe)-2747efdog25(w)etinmigrants,-250(foor

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wants to make causal statements about the effect of ancestry composition on local development. It is also possible that ancestry groups with particular endowments are more willing to move in response to short-term county-specific economic shocks, creating a form of short-term reverse causality. We address this potential additional source of endogeneity using three instrumental variables approaches. The conclusions we arrive at when instrumenting under each approach are similar to each other. They are also similar to the conclusions basedon estimates obtained without instrumenting, suggesting that the biases arising from group-specific endogenous migration in response to shocks are a lesser concern compared to the importance of controlling for time-invariant county characteristics.

First, we create an instrument for each county's share of a given ancestry using the share in the past and growth in that ancestry nationally, excluding the county's state.[3] Doing so removes any county-ancestry specific pull factors.

Second, we build an instrument for ancestry share using the the interaction of immigrant arrival times with the development of the railroad and highway transportation network that builds on Sequeira, Nunn, and Qian (2019). Because immigrant groups arrived at different times, groups were exposed to different transportation networks, so decided to go to different places for reasons that depend in large part on when they moved. We discuss how one can isolate from this information county-ancestry level variation that can be treated as exogenous, as it is unlikely to be related to group characteristics that may lead a particular ancestry to move disproportionately to a given county following a shock to local development opportunities.

Finally, we present dynamic panel GMM results (Holtz-Eakin, Newey, and Rosen, 1988; Arellano and Bond, 1991) that rely on appropriately lagged values of the regressors as instruments and address the potential issue of the Nickell (1981) bias when the time dimension of the panel is short. At their core, both the first approach and the GMM approach rely on the past distribution of ancestries. Because the vast majority of the population does not move from decade to decade,

[3] The use as an instrument of the past spatial distribution of immigrants, often adjusted for the national growth rate, has been a common strategy in the immigration literature. See Card (2001) and more recently Peri (2012), among others. See also Bartik (1991) in the local development literature. For details on our instrumenting strategy see Section 5.3.2.

the ancestry distribution in one decade is highly predictive of the distribution in the next, so these instruments have highly predictive first stages. Of course, the validity of these instruments relies on the past shares being uncorrelated with current shocks. We are thus careful to use this approach only in dynamic models where we can test for—and reject—the presence of serial correlation in the error term. The instrument based on the interaction between immigrant arrival time and the railway and highway network is less dependent on the ancestry shares in the recent past and only uses the shares in 1870. It is comforting that the basic conclusions remain very similar across the three approaches.

We first show that ancestry groups have different effects on county GDP per worker, even after after we control for county-specific fixed effects, race, and other observables. The effects of different groups are correlated with characteristics of the country of origin. As a summary measure of what groups bring with them, we construct the average origin GDP per person in each county by weighting origin country GDP per person by the share of each ancestry in a county. When internal or external migration results in a county's residents coming from 1% higher GDP per person countries on average, county GDP per worker increases by 0.3% in the first decade and 0.6% in the long run. The impact grows over time, reaching its peak only after several decades. These effects do not seem to be related to origin-country inequality, suggestion that a model of self-selection, such as Borjas (1987), is not likely to be driving the results.

The relationship between origin GDP and county GDP per worker shows that there must be something important for economic development that is transportable and inheritable. We examine possible origin characteristics that might explain the relationship. What appears to matter most for local economic development are cultural characteristics that capture the ability of people to productively interact with others (Tabellini, 2010). Moreover, it also matters whether immigrants

immigrants once we control for their experience of a strong state. Over the long-term, the human capital of migrants is not significantly associated with local economic development once other endowments are controlled for, perhaps because public schooling reduces educational differences and schooling policies respond endogenously to immigration flows (Bandiera et al., 2019).

Diversity has both positive and negative effects. Immigrants and their descendants must interact with other groups from different backgrounds, and the full impact of immigration depends on these interactions. When ancestry diversity increases, so does GDP per worker. Despite the often negative views that greet new groups, more diversity is actually good for growth. Yet when groups

e morotuhavieemesd 368ge292(Immig233)a23c6G68ger disentangle the fundamental causes of development. To deal with this problem, an important subset of the literature focuses on the impact of immigrants. In particular, we build on Putterman and Weil (2010) who reconstruct the share of a country's ancestors in 2000 who migrated from each origin since 1500. They conclude that adjusting for migration flows greatly enhances the ability of historical variables, such as the experience of early development or early institutions, to explain differences in current economic performance. Another strand of this literature examines the impact of European colonists and of the institutions or human capital they brought with them (Acemoglu, Johnson, and Robinson, 2001; Glaeser et al., 2004; Albouy, 2012; Easterly and Levine, 2016). The distinguishing feature in our work is the long panel which allows us to cleanly distinguish the effects of immigrants and of the attributes they carried with them from those of the places they move to. In addition, we analyze *which* endowments brought by immigrants affect economic performance in the long run, a difficult yet important task (Easterly and Levine, 2016). Our examination of inherited culture is related to that of Algan and Cahuc (2010), who use the trust of different cohorts and generation of migrants in the United States to instrument for the changing trust in the origin country and assess its effect on economic development.[5] A distinguishing feature of our contribution is that we use the change of ancestry composition over time in US counties to identify the effect on local development of attributes brought from the country of origin. This is the novel source of variation that our instrumenting strategy uses to identify the effect of culture and institutions on economic development, accounting for the endogeneity of their evolution.

Our emphasis on the long-run economic effects of immigrants *and* their descendants distinguishes our work from the many contributions that focus on the experience of first-generation immigrants and their short-run effect on the labor crwkef.

Qian (2019), who analyze how immigration to the United States during the Age of Mass Migration generation immigrants, as, for instance, in Ottaviano and Peri (2006), Ager and Brückner (2013), Alesina, Harnoss, and Rapoport (2016) and Docquier et al. (2018).

3 Ancestry in the United States

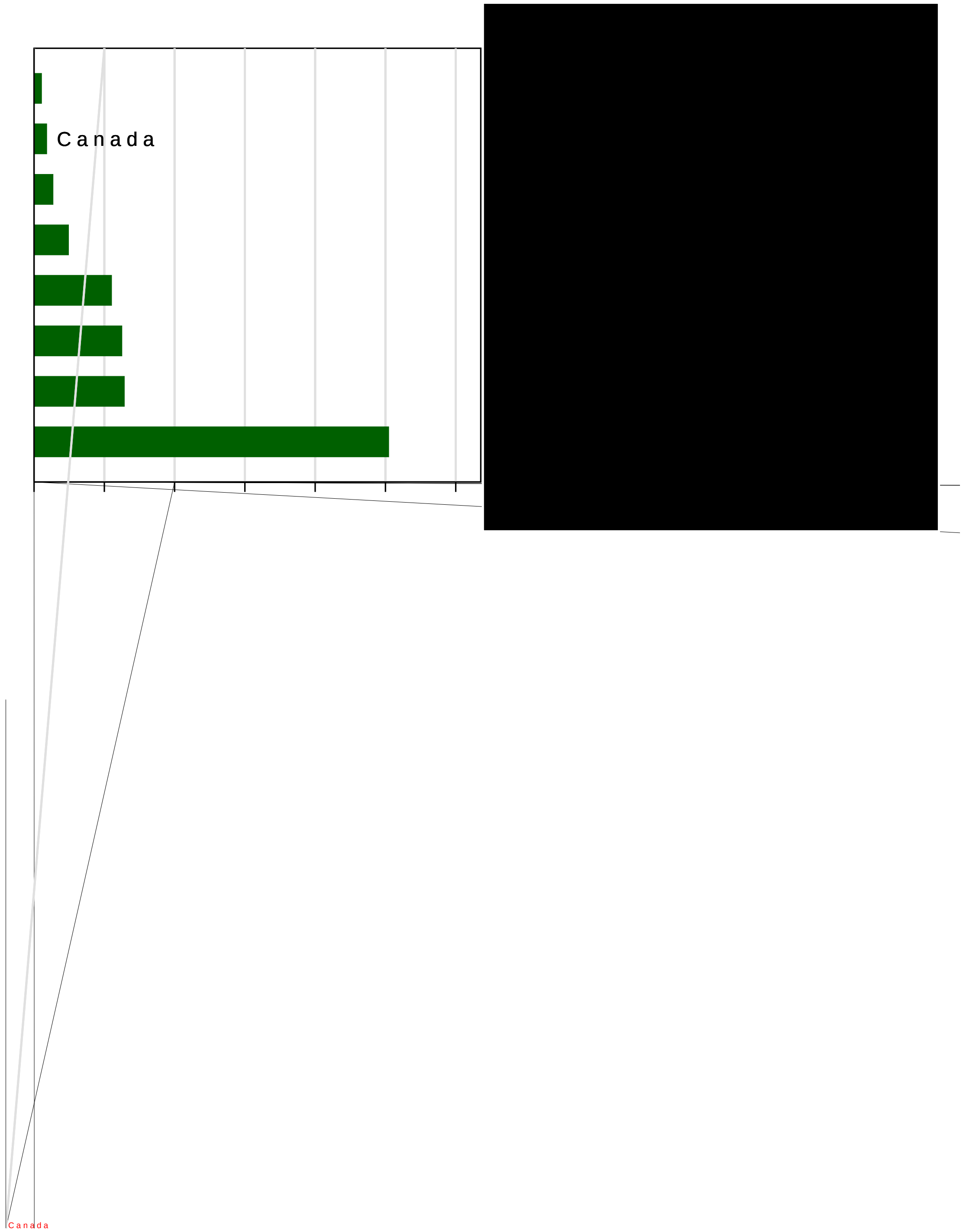
There have been immense changes in overall ancestry and its geographic distribution in the United States since 1850. In this section, we describe how we construct a measure of the geographic distribution of ancestry over time and briefly discuss its evolution. Our estimates are the first consistent estimates of the stock of ancestry over time for the United States at both the national and county level. They are constructed using the census micro-samples and keep track of internal migration and population growth, in addition to new immigrant flows. While previous work has examined racial groups and, in recent decades, some ethnic groups, our work is thus the first to be able to examine the full range of diversity in this nation of immigrants. Finally, our measure of ancestry is distinct from self-reported ethnicity available in the census since 1980, which also reflects the evolving nature of ethnic identity as a social construct.

3.1 Constructing an ancestry measure

We build our estimates of the ancestry shares at the county level and of their evolution over time by aggregating information from questions collected in the decadal census that ask every person to identify the state or country where he or she was born. For every individual, we use the available information to form her expected ancestral origin based on her birth place and, when available, on her parents' birth place. Aggregating over many individuals in given place forms a population estimate of the ancestry composition. For first generation immigrants born outside the United States, the expected ancestry is straightforward since we know exactly where they came from. This is also true for the children born in the US from first generation immigrants from 1880 to birth state, or in the child's residence county if the child has not moved states, in the closest census year to the child's birth. This method allows for some groups to have faster population growth than others past the second generation and keeps track of internal migration. Past the second if ancestry affects individual outcomes, local goods, or has externalities that relate to in-person interactions an analysis at the county level will allow us to capture them.

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

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



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

the self-reported ethnicity or ancestry in the 2000 census very well. For instance, the the overall correlation coefficient for all ancestries across counties in 2000 is 0.966 (see the online appendix A.5and Table A-1 where we also report the cross county correlation for each ancestry separately). In Figure A-1 in the the online appendix we report the share of the total population of the US for each ancestry based on our measure and self-reported ancestry in the 2000 census. We closely match the shares.[10]

3.2 Ancestry since 1850

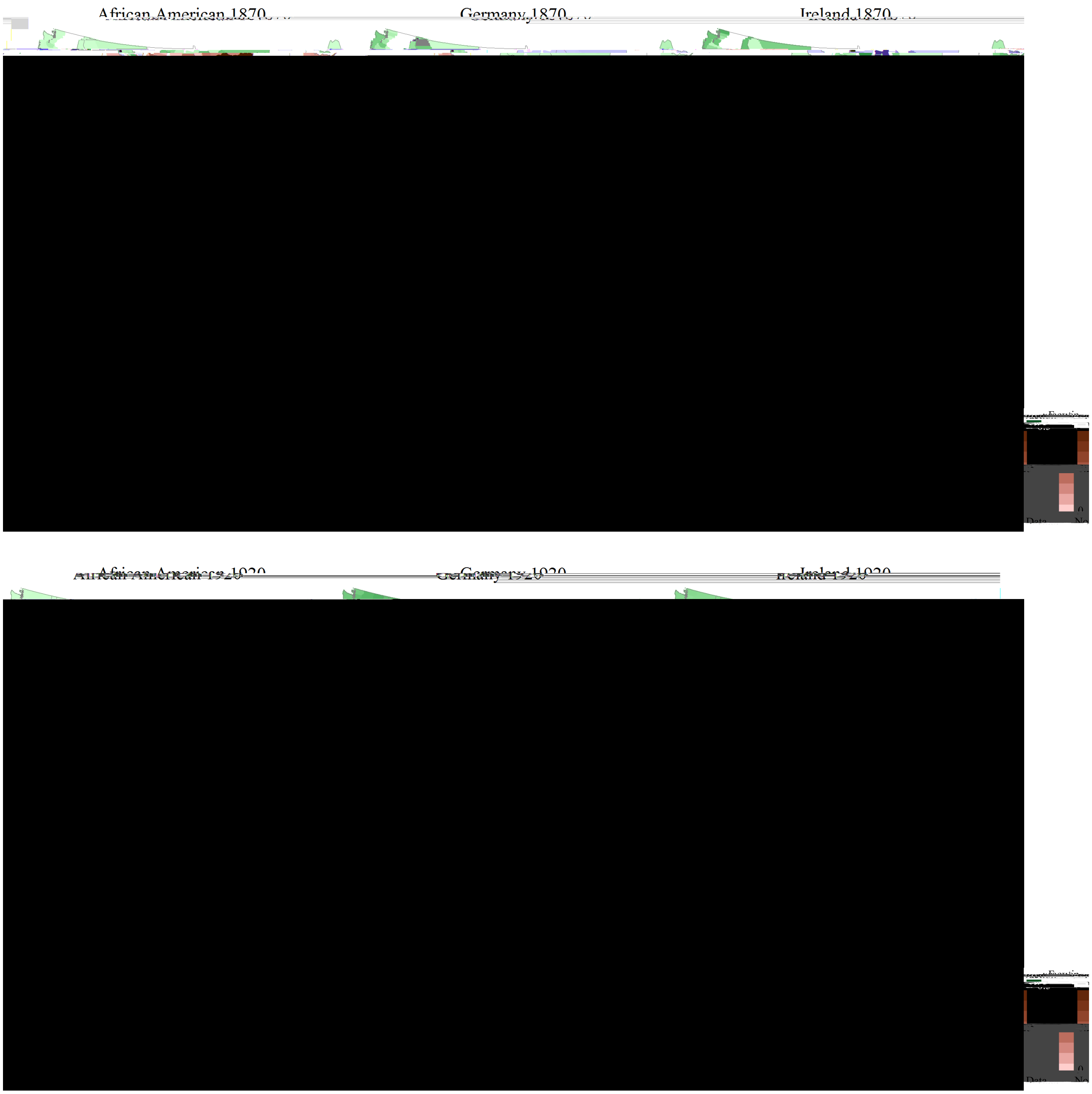
American ancestry has become increasingly diverse over time, and we provide a brief description here of the overall trends in composition necessary to understand our results. Figure 1 illustrates this growing diversity by showing the share of the ancestry stock for all groups that make up more than 0.5%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

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

Immigration restrictions that started in the 1920s severely slowed immigration until the 1960s. These restrictions were only gradually relaxed, and so changes during this period mostly represent internal differences in population growth and demographic structure. Beginning in the 1960s, new groups from Mexico, Central America, and South America started to arrive. The share of

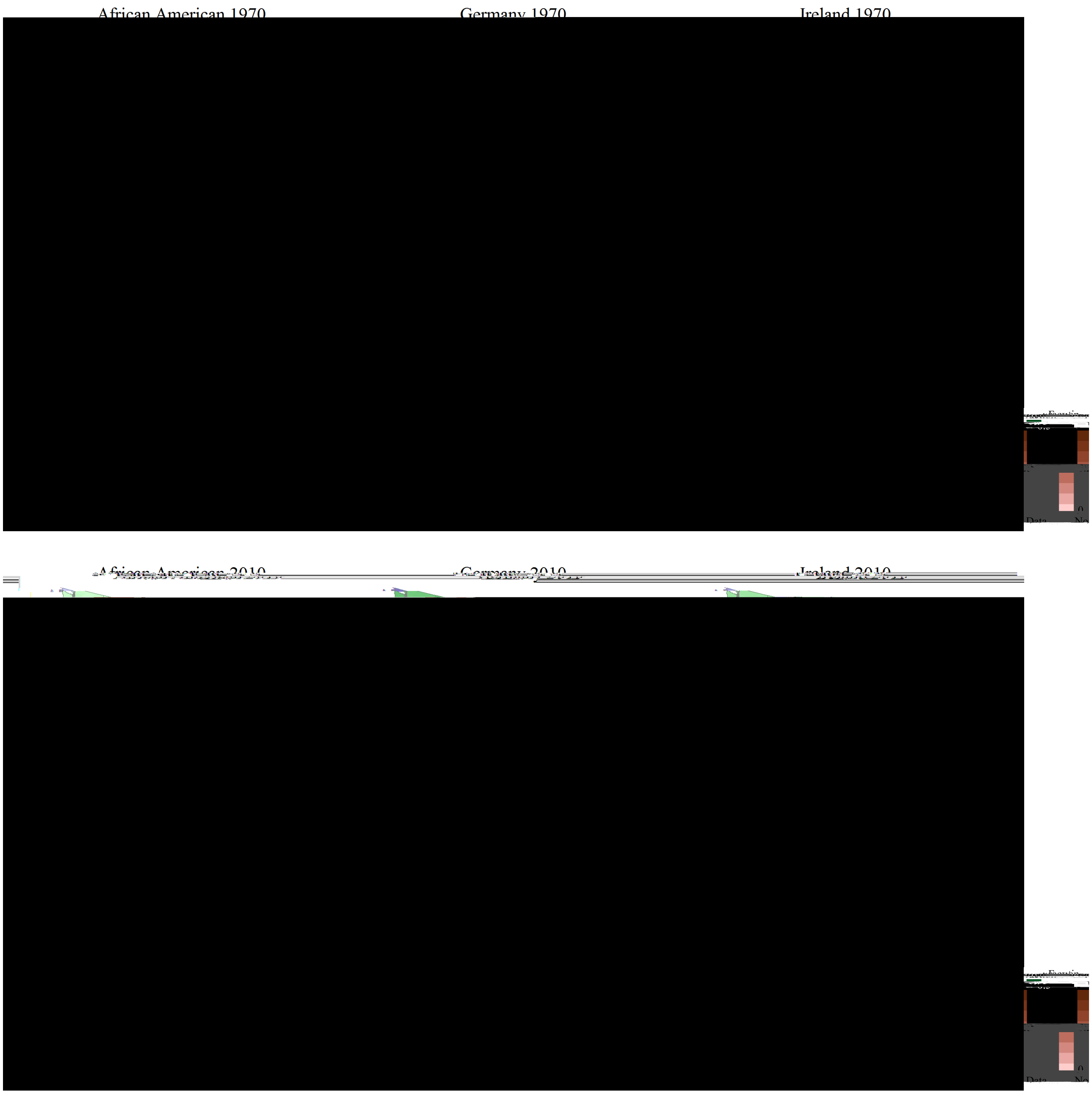
[10]Even the places where we do not match exactly are illuminating. The dots in the upper left are variations of "Southern Europe, Not Specified" or "Baltic States, Not Specified." While these birthplaces have generally been valid responses, because we built up our ancestry measure from the actual birthplace of a migrant or her parents, we are far more likely to classify someone to a particular country, so put a smaller share in these generic ancestries.

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



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

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



level GDP for services, construction, and mining. It is very important to include these components to capture both the geographical distribution and time profile of local GDP. The full details for how we construct our measure of county-level GDP and on the sources used are in the online appendix B, but we describe our procedure briefly below. The basic idea is to combine the geographic distribution of employment in service industries, as reported by individuals in the census micro-samples, with historical wages to form an estimate of county services GDP. We then combine these estimates with estimates of manufacturing value added (equal to the value of output minus intermediate inputs) and agricultural value added (constructed using county agricultural output and a time varying national measure of the value-added-to-output ratio) to form a measure of county GDP.

To obtain county-specific measures of GDP for services, construction and mining, we use the between urban and rural areas.

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 in each county from the census, we construct a ratio of GDP to income at the county level. We use this county-level ratio to get an estimate of GDP from 1960 onward. Effectively, we use the growth rate of income at the county level to approximate the growth rate of county-level GDP. We then calculate GDP for the same county groups used in constructing the distribution of ancestries. We convert nominal GDP to real GDP using the price deflator from Sutch (2006). In our analysis, we generally allow for census division specific year effects that absorb any census division differences in the evolution of the GDP deflator. Then we divide real GDP by the number of workers in each county, calculated by summing all persons who indicate an occupation in the census micro-samples.

Ours is the first measure of GDP at the county level that goes beyond a combined measure of manufacturing value added and agricultural output. By aggregating at the national level and at the state level, we can compare our measure to other calculations and thus provide some validation of our approach. Both the level and the growth rate at the national level closely track the GDP per capita from Sutch (2006) (see Figure A-2 in the online appendix). Our shares of GDP also

5 Does ancestry matter and why?

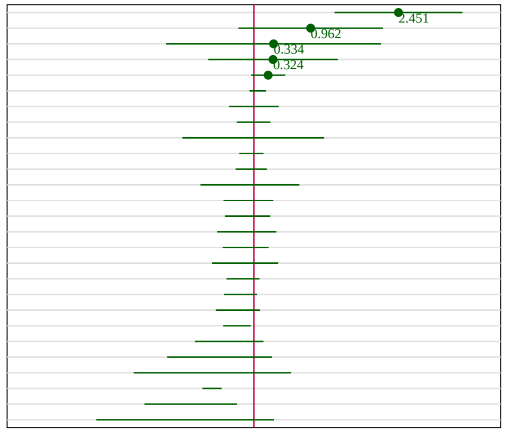
Combining our measure of the ancestry makeup of each county with our measure of county GDP, we ask whether ancestry matters for local economic development and, if so, which attributes

Table 1: County GDP per worker and individual ancestries

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

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

Figure 4: Individual ancestry coefficients



Notes: This figure shows effects on log county GDP per person for ancestry groups composing more than 0.5% of the population in 2010 (bars represent 95% confidence intervals). The excluded group is England, which has an implied coefficient of 0 with a standard error equal to the one of the constant. The regression includes two lags of log county GDP and division by year fixed effects and is based on the results for column 5 of Table 1.

English ancestry) from column 5 of Table 1. A coefficient of 0.24 for Norway means that replacing one percentage point of residents with English ancestry with 1 percentage point of those with Norwegian ancestry increases GDP per person by 0.24 percent within 10 years and approximately double that over the long term (the sum of the two lagged GDP coefficients is approximately 0.5). [13] These results raise the obvious question of what can explain such differences, which we turn to next. Yet these results should be treated with some caution as they do not consider the importance of diversity which we address later in the paper (see Section 5.4).

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

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

The main limiting factor in the analysis of origin attributes is the availability of information for a broad range of countries over long time periods. Unlike our data on ancestry and county GDP, which we have carefully constructed based on micro data to be as consistent as possible across time and space, the cross-country data is not always available or reliable, particularly in the distant past. The full details of the construction of and sources for the origin variables are in the online appendix D.[14]

To reflect the changing nature of what immigrants could bring with them, when the characteristics of the origin country are time varying, we weight them by the time of arrival of immigrant groups (see the online appendix C for our creation of the conditional arrival density for all groups).

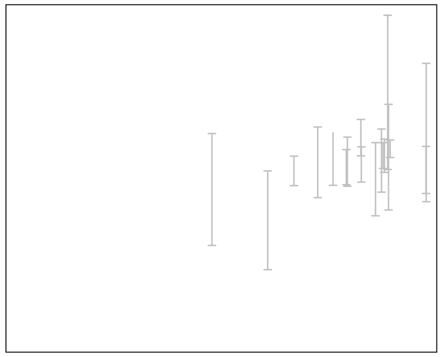
origin measure $\hat{z}^a$ for ancestry a at the time of arrival and $\hat{z}^{US}$ measure in the US, we form the arrival-weighted origin attribute Z_t^a at time t:

$$Z_t^a = \sum_{=0}^{t} (\hat{z}^a \quad \hat{z}^{US})(1 \quad)^t \quad F_t^a(\;); \tag{2}$$

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

As a summary variable for positive economic attributes, we form the Arrival-Weighted Origin GDP as the difference in log GDP per person in the country of origin and the log GDP per person in the United States at the time of immigration, depreciated at 0.5% per year, which implies that 40% of the difference between the origin country and the US disappears in 100 years. The particular rate of depreciation does not affect our results. Origin GDP is a useful summary variable, since it captures whether an ancestry has been exposed to the mix of characteristics that led to economic (updating Bockstette, Chanda, and Putterman (2002)) that reflects for how long before 1500 a particular area had a centralized government above the local level and the extent that government was locally based (State History). Because State History is fixed at a point in time, it does not vary by time of arrival. Some modern states, such as Canada, are largely composed of migrants, so we adjust State History to reflect the state history experience of the population living there using the migration matrix of Putterman and Weil (2010). Other than Canada, few large in-migration countries also had substantial out-migrations to the United States, so this adjustment does not affect our results. We also measure the constraints on the executive power in the country of origin at the time of arrival of various immigrant waves (Executive Constraints at arrival). Finally, we

Figure 5: Ancestry and endowments from the country of origin



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

5.3 A parsimonious representation of origin characteristics

In this section, we introduce a more parsimonious representation of the origin characteristics by constructing an ancestry-weighted average of origin endowments. We start by examining origin country GDP per person in Section 5.3.1, and then we turn to more specific origin characteristics in Section 5.3.3. We define the county average endowment as:

$$z_{ct} = \sum_{a=1}^{A} {}^{a}_{ct} Z^{a}_{t} \tag{3}$$

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

Our typical regression takes the general form:

$$y_{ct} = {}_{c} + {}_{dt} + z_{ct} + X_{ct} + {}_{ct}. \tag{4}$$

In some specifications z_{ct} will be a vector of the ancestry-weighted values of the endowment of several characteristics and in most specifications X_{ct} will include two lagged values of y_{ct}. Note that, implicitly, we are imposing the restriction that the ancestry coefficients in the unrestricted model of equation (1) are proportional to one or more elements of the immigrant endowment vector. The basic idea is that such endowments determine the effect of each ancestry group on local GDP per worker. The inclusion of lagged values of GDP per worker is meant to capture the fact that the impact of such endowments on local development is distributed over time. There are multiple reasons for this to be the case, such as the presence of autocorrelated shocks to technology or learning by doings effects.

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

	Dependent variable: Log(county GDP per worker)							
	Static		Dynamic					
	FE	OLS	FE	FE with Race	FE with Neighbor	IV1 FE	IV2 FE	IV3 GMM
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Origin GDP	0.310***	-0.172***	0.331***	0.152***	0.319***	0.354***	0.319***	0.197***
(ancestry weighted)	(0.0431)	(0.0409)	(0.0253)	(0.0290)	(0.0340)	(0.0172)	(0.0426)	(0.0357)
Decade lag			0.445***	0.436***	0.444***	0.442***	0.456***	0.555***
log county GDP			(0.0161)	(0.0163)	(0.0169)	(0.00777)	(0.0170)	(0.0181)
Two decade lag			0.0286*	0.0270*	0.0281*	0.0307***	0.0513***	0.0993***
log county GDP			(0.0167)	(0.0160)	(0.0166)	(0.00687)	(0.0125)	(0.0185)
Division X Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County group FE	Yes		Yes	Yes	Yes	Yes	Yes	Yes
Long-run effect	0.310	-0.172	0.629	0.283	0.604	0.671	0.647	0.570
Observations	16,713	16,713	14,415	14,415	14,415	14,415	13,232	14,415
County groups	1149		1146	1146	1146	1146	1023	1146
R^2 (within)	0.950	0.887	0.968	0.968	0.968			
R^2 (between)	0.113		0.472	0.486	0.446			
AB test serial corr.	6.01e-07		0.309	0.269		0.370	0.727	0.203
First Stage						Dep. var: *Origin GDP*		
proj. *Origin GDP*						0.849***	1.217***	
						(0.00410)	(0.0129)	
First stage R^2						0.887	0.735	
Kleibergen-Paap F						5660	1441	

Notes: In this table we examine whether *Origin GDP* (the ancestry-weighted log difference between origin GDP per person and US GDP per person at the time of arrival, depreciated at a rate of 0.5% per year) matters for log county GDP per worker in variations of equation (4). In the dynamic specification columns, the long-run effect is the the coefficient on *Origin GDP* divided by (1 $_1$ $_2$), with the 's denoting the coefficients on the lag dependent variable. Column 4 includes the fraction African American and Native American separately (the coefficients are not reported). Column 5 includes the average of the county's neighbors' *Origin GDP* and county GDP in the previous decade. Column 6 instruments for *Origin GDP* using the *Origin GDP* constructed using ancestry in the previous decade (Approach 1; see Section 5.3.2). Column 7 instruments using the interaction between the transportation network and total ancestry migration (Approach 2). Distance to transportation is included in both first and second stages, in addition to lags of log county GDP per worker. Column 8 contains the GMM esimates (Approach 3), using orthogonal deviations and and and0d4(andagona7Yn)-286(v)25(ariations)-2860columns,and an00(es.)-264(an00(es.)-264(an00(es.)-26dandagona7Y7-261)rella

5.3.1 Origin development and county development

Table 2 shows a series of estimates of equation (4) for ancestry-weighted *Origin GDP per capita* used as a summary measure of the endowment brought by immigrants and partly passed down to their descendants. We address questions of reverse causality due to endogenous migration following local shocks in the next section. All of the estimates include census-division-specific year effects. Because much of the variation in the effect of ancestry is likely to be felt across regions, including census-division-year effects removes some variation but ensures that the estimates are not driven purely by differential regional trends.[16]

When we use fixed effects to control for all of the time invariant aspects that may affect economic development in column 1 of Table 2, the coefficient on *Origin GDP* is positive and significant at the 1% level. The estimates imply that when the people who make up a county come from places that are 1% richer, county GDP per worker is 0.3% higher. While the association of *Origin GDP* worker.[18] There is evidence of severe serial correlation in column 1, according to the Arellano and Bond (1991) test.[19] By including previous periods of the dependent variable county GDP per worker, we can remove the serial correlation as well as examine how the impact of ancestry evolves. The dynamic model suggests that the effects of a permanent change in the ancestry mix are felt about half within a decade, and half over the long term.[20] The long-term effect is now quite large: if the people who make up a county come from places that are 1% richer, county GDP per worker is 0.6% higher.

Columns 4 and 5 examine possible variations by including race and allowing for neighbors to have an effect. We permit African Americans and Native Americans to have an unrestricted coefficient, because the information on the "original" level of GDP for African Americans and Native Americans is necessarily speculative and does not capture fully the legacy of slavery, oppression and discrimination for these groups.[21] The coefficient on variable has no additional effect.

In the online appendix Table A-6, we examine whether these results are robust to some other specifications. We first show that our results do not change when we allow the difference on arrival to depreciate faster or slower. When we allow the effect of ancestry to differ between metropolitan and non-metropolitan areas, there is some statistically weak evidence that the effect is slightly smaller in a metropolitan county. When we allow the coefficients to differ before and after 1940, the coefficient of *Origin GDP* does not differ economically and statistically between the two sub-periods. Clustering errors at the state-year level does not affect the significance of our results. The with greater incentives to move, in which case the effect of ancestry may be under-estimated. A counterargument is that the most mobile people may be those from richer countries as they may be the ones with characteristics that allow them to take advantage of new opportunities, and so the effect of ancestry may be over-estimated. We introduce three approaches with different identification assumptions and show that this form of endogeneity does not affect our main conclusions.

Approach 1: Immigrants tend to go where there are already immigrants from their country (Bartel, 1989). Growth of native groups similarly occurs in places where there are already populations of that ancestry. We build on these observations to create an instrument for ancestry based on the past stock of ancestry, in the spirit of Card (2001) and others in the immigration literature, such as Peri (2012).

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

To meet the exclusion restriction, the instrument must be uncorrelated with the error term at t in equation (4). By construction, $\bar{z}_{ct}$ does not use any county specific information from decade t and, by using the growth rate excluding a county's state, does not use any information from surrounding counties either. However, $P^a_{c,t-1}$ could potentially be correlated with the error term in $t-1$, ϵ_{ct-1}. This would invalidate the instrument if there is serial correlation ($\text{Cov}(\epsilon_{ct}, \epsilon_{ct-1}) \neq 0$). We will show that when we include two lags of the dependent variable, there is no evidence of serial correlation in the errors using the Arellano and Bod4(there)-3151ua2t7hak(the)-J/Ft2nf:-7p4(there)-3151ua the fact that, because immigrant groups arrived at different times, groups were exposed to different transportation networks and different geographic opportunities, so tended to go to different places. When a group is migrating, however, is unlikely to be related to county specific shocks in the destination county. Therefore, using the interaction between the transportation network and migration

Using the relative access to transportation means that sum over all counties and ancestries gives the total population in a given year: $\sum_{c,a} \hat{P}^a_{ct} = P_t$, so that we are allocating every mover to some county. Then the transportation-predicted ancestry share is:

$$\hat{\lambda}^a_{ct} = \frac{\hat{P}^a_{ct}}{\sum_a \hat{P}^a_{ct}}.$$

We use the transportation-predicted ancestry share to form $\hat{z}_{ct} = \sum_a \hat{\lambda}^a_{ct} Z^a_t$ and use $\hat{z}_{ct}$ as an instrument for z_{ct}. Note that, by construction, the only county specific component of $\hat{\lambda}^a_{ct}$ is from the relative access to transportation and the only ancestry specific component is from national time-varying ancestry migration.

A potential concern is that the transportation network is likely related to county shocks, for example, if a new railroad line is built to access a booming county. This might invalidate using $\hat{z}_{ct}$ as an instrument for z

may lead a particular ancestry to move disproportionately to a given county in response to shocks to local development opportunities.

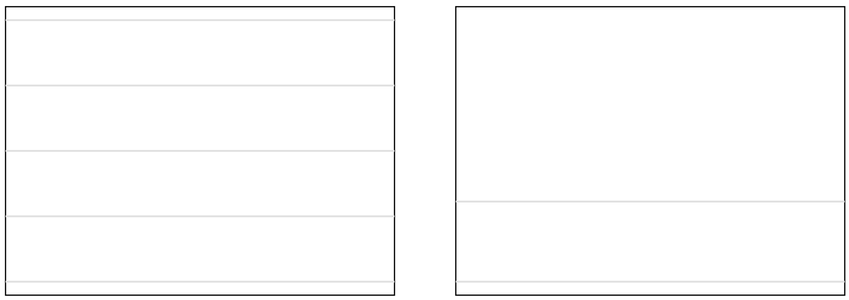
Approach 3: Both approach 1 and 2 instrument the weighted endowments after applying the within transformation. A well developed literature starting with Holtz-Eakin, Newey, and Rosen (1988) and Arellano and Bond (1991) provides GMM estimates of dynamic panels containing endogenous variables using alternative transformations, such as first differencing or deviations from the forward mean (orthogonal deviations). Similar to Approach 1, appropriately lagged values of endogenous variables are used as instruments, so the GMM approach also requires the error term short-term endogenous migration. The first stage regression reported at the bottom of the Table 2 suggests that both instruments are highly correlated with *Origin GDP* (the p value of the t statistic is 0 to at least five decimal places and the same is true for the Kleibergen-Paap F statistics). In all cases, the Arellano and Bond (1991) test rejects the presence of serial correlation in the residuals. Note that when using Approach 2 we also include our index of closeness to the transportation network in the first and second stage, besides the other usual regressors. Doing so removes the concern that transportation-predicted ancestry is just picking up the importance of transportation, rather than ancestry.

The conclusions obtained when using GMM for dynamic panels are also similar and lead to the same general conclusions.[23] In column 8, the sum of the coefficients of the lagged dependent variables is somewhat larger as we would expect in the presence of a Nickell (1981) bias, but the difference is relatively small. The impact effect of ancestry is smaller, but it remains highly significant and the long run effect is similar. Again, there is no evidence of serial correlation in the residuals according to the Arellano and Bond test. Moreover the test of over-identifying restrictions (Hansen test) does not suggest model mis-specification. In the online appendix E and Table A-5, we show additional variations using GMM.

We can go further and estimate the reduced form of a bivariate vector autoregression in which we allow ancestry to affect county GDP and county GDP to affect *Origin GDP*. The results are reported in Figure 6 under two opposite identification assumptions: either county-level GDP per worker affects *Origin GDP* with a lag, or the converse is true (see the online appendix Table A-5for the coefficients). Either assumption generates a recursive system and allows one to recover the impulse response function to structural shocks. Innovations in *Origin GDP* have a significant and sizable initial effect on county GDP, which grows until about the third decade. County GDP has an inconsequentially small effect on *Origin GDP*, suggesting that differential ancestry migration because of shocks is not a concern, as our instrumental results suggested. These results suggest some of the ancestry effect must be relatively immediate, but more than half of the effect shows up

[23]We have used the Roodman (2009) Stata routine xtabond2 for single equation GMM estimation and the Abrigo and Love (2015) routine for VAR GMM estimation.

Figure 6: Impulse responses from VAR for log county GDP per worker and ancestry-weighted *Origin GDP*



Notes: This figure shows impulse responses of a panel vector autoregression examining the co-evolution of ancestry weighted *Origin GDP* and county GDP. See the online appendix E and Table A-5 for the VAR coefficients. The impulses are calculated using two different identification assumptions: (1) No immediate effect of shocks to log county GDP per worker on ancestry weighted *Origin GDP*, but shocks to *Origin GDP* can immediately affect county GDP, (2) No immediate effect of shocks to *Origin GDP* on log county GDP per worker, but county GDP shocks can immediately affect *Origin GDP*. The size of the impulse is the standard deviations of the residuals in each equation. Shaded areas are the 95% confidence intervals based on Monte Carlo simulation.

only after several decades.

5.3.3 Origin characteristics and county development

Which specific attributes and characteristics brought from the origin country help explain the association between ancestry and development? Table 3 takes a selection of the endowment measures and examines which measures are significant by themselves and in combination with each other. Given the significance of lagged values of county GDP, we focus only on the dynamic specification and always include county fixed effects and census-division-year effects. Each of the culture, institution, and human-capital variables are significant when included one at the time in Table 3 (columns 1 through 6). When we include the ancestry-weighted measures of culture, institutions, and human capital together, the coefficients on *Principal component of culture* and *State history in 1500* remain highly significant, while the *Migrant education* coefficient is not significant (column 7). This may be because public schooling reduces educational differences and schooling policies respond endogenously to immigration flows (Bandiera et al., 2019). When we include the fraction of African American and of Native Americans as additional controls the coefficient of the *Principal component of culture* is not significant, but the one for *State History in 1500* remains significant, although its size its now smaller (column 8). The coefficients of *Executive constraint at arrival* and *Political Participation* have small and not significant coefficients when added to the specification with *State history in 1500.* These variables represent political institutions that may change more rapidly and with which immigrants may have more limited experience, and so it makes sense that they have little effect in the United States. The importance of early political centralization for development is consistent with the results obtained by Michalopoulos and Papaioannou (2013) and Gennaioli and Rainer (2007).[24]

These results suggest that multiple endowments play a role in development, although we should

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

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

	Dependent variable: Log(County group income per worker)										
	FE	FE	FE	FE	FE	FE	FE	FE+Race	FE	FE	IV1-FE
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
Principal Component	0.818***						0.362***	0.214	0.358**	0.262	0.308*
of culture	(0.0645)						(0.139)	(0.149)	(0.157)	(0.175)	(0.176)
State history		3.022***					1.945***	1.021***	1.958***	1.867***	1.526***
		(0.235)					(0.260)	(0.380)	(0.264)	(0.272)	(0.383)
Migrant education			0.132***				0.0149	0.0225	0.0154	0.0113	0.0456
at arrival			(0.0117)				(0.0251)	(0.0254)	(0.0247)	(0.0246)	(0.0301)
Executive constraint				0.117***					-0.00582		
at arrival				(0.0125)					(0.0160)		
Political participation					0.0329***				0.00120		
at arrival					(0.00282)				(0.00511)		
Trust						2.039***					
						(0.164)					
Origin GDP										0.0591	
										(0.0490)	
Decade lag	0.444***	0.443***	0.448***	0.453***	0.450***	0.445***	0.439***	0.436***	0.440***	0.440***	0.439***
log county GDP	(0.0162)	(0.0163)	(0.0162)	(0.0163)	(0.0159)	(0.0161)	(0.0163)	(0.0164)	(0.0163)	(0.0163)	(0.0165)
Two decade lag	0.0302*	0.0279*	0.0308*	0.0301*	0.0297*	0.0304*	0.0290*	0.0274*	0.0292*	0.0294*	0.0318**
log county GDP	(0.0167)	(0.0162)	(0.0169)	(0.0168)	(0.0170)	(0.0167)	(0.0162)	(0.0160)	(0.0163)	(0.0163)	(0.0160)
Observations	14,415	14,415	14,415	14,415	14,415	14,415	14,415	14,415	14,415	14,415	14,398
County groups	1146	1146	1146	1146	1146	1146	1146	1146	1146	1146	1146
R^2 (within)	0.968	0.968	0.967	0.967	0.967	0.968	0.968	0.968	0.968	0.968	
R^2 (between)	0.492	0.532	0.529	0.495	0.506	0.494	0.501	0.502	0.502	0.495	
AB test serial corr.	0.322	0.312	0.416	0.540	0.573	0.317	0.695	0.679	0.321	0.695	0.227
Kleibergen-Paap F											307.7

Notes: This table examines which of multiple possible endowments from the origin country matter for county GDP. Column 8 includes the fraction African American and Native American separately (the coefficients are not reported). IV1-FE in column 10 uses instruments constructed using ancestry in the previous decade growing at the national growth rate excluding the county's state (Approach 1 in Section 5.3.2). The AB test is the p-value for the Arellano and Bond (1991) test for second order serial correlation of the errors in difference. All regressions include census division by year fixed effects, county-group fixed effects, and standard errors are clustered at the county group level. Sources for origin variables are in the online appendix D. *** p<0.01, ** p<0.05, * p<0.1.

$$frac^{w}_{c;t} = 1 \sum_{j=1} \sum_{k=1} {}^{j}_{ct}\,{}^{k}_{ct} s^{jk}_{t}; \tag{7}$$

where the w stands for a “weighted” fractionalization and s^{jk} is a measure of similarity between countries of origin. [25] 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 $i \neq j$). While race is part of ancestry, race may have an independent effect. We emphasize again that while ancestry has an objective definition, race is a social construct, so the appropriate way to include race is not obvious. We create two variables that capture the racial component of fraction-

Table 4: County GDP per worker and diversity

	Dep. Variable: Log(County group income per worker)

ment variable, fractionalization, and origin-GDP-weighted fractionalization using either Approach 1 or 2 (see columns 2 and 3). Fractionalization seems to be the relevant measure of diversity. When we include polarization, it does not seem to have an independent effect, so we do not show this regression separately.[28]

We replace ancestry-weighted *Origin GDP* with our deep endowment variables and Origin-GDP-weighted fractionalization with attribute-weighted fractionalization created from the distinct endowment variables in Table 4 columns 4 through 6. The *Principal component of culture* and *State history* remain positive and significant. The coefficients on culture-weighted fractionalization and *State history* fractionalization are negative and significant at the 1% level. The negative sign suggests that fractionalization of these attributes is particularly problematic. Ancestry fractionalization continues to have a positive effect on local development, and its coefficient is highly significant. Education-weighted fractionalization is also positive. We explore whether these effects are capturing skill diversity in the next section.

In column 5 of Table 4, we include as additional regressors the fraction of African Americans and the fraction of Native Americans, as well as racial fractionalization and attribute-weighted race fractionalization for our three origin attributes. The additional fractionalization variables represents the extra effect of diversity that comes along these two racial lines (see footnote 26). The results suggest that our main results still largely hold. The ancestry fractionalization coefficient is still positive, significant, and nearly the same size. Meanwhile, the extra component of race fractionalization is not significant or large. The coefficient on the ancestry-weighted culture and *State history* remain positive and significantat the 10% level. Similarly, the coefficients on culture-weighted fractionalization and *State history*-weighted fractionalization are negative, significant, and the same size. The additional racial fractionalization component for education is positive and gesting that an important component of education and culture fractionalization is coming through race. This suggests that the diversity due to race has an additional impact on local development beyond differences in ancestry, but that the effect of racial diversity as well as of ancestry diversity is not necessarily negative.

Instrumenting the separate endowments and their diversity when they are all included together leads to much less precise results, especially for Approach 2. Approach 1, still yields significant coefficients for fractionalization culture-weighted fractionalization and *State history*-weighted fractionalization, as well as for weighted migrant education, that for the first time is significant when included with all the other endowments. It is not a surprise that the instruments do not capture second moments well. Even small differences between the instrument and the actual ancestry are magnified by squaring to form fractionalization, so the instrument caries far less information about the second moment.

through human capital formation; voter participation as a proxy for social capital; and an index of occupational variety that gives us insight into the diversity of skills present in a county.

The results in Table 5 suggest that origin characteristics, summarized by *Origin GDP*, are strongly positively related to county education (see column 1, which shows the results for the basic related to county GDP per worker (column 6), although the decrease in the coefficient of *Origin GDP* when both are included is small (column 7). Therefore, this particular proxy for social capital appears to play a relatively minor role in the transmission of the origin country attributes.

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

Table 5: Ancestry and county GDP per worker: Mechanisms

Dependent variable:	County Education	Log(county GDP per worker)			County voter participation	Log(county GDP per worker)	
	FE	FE	FE	FE	FE	FE	FE
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Origin GDP	0.727***		0.309***	0.285***	0.0736***		0.309***
	(0.0550)		(0.0272)	(0.0444)	(0.00452)		(0.0241)
County education		0.0302***	0.00973*				
		(0.00750)	(0.00514)				
County literacy (before 1940)				0.280***			
				(0.0984)			
County years educ. (1940 and after)				-0.00644			
				(0.00780)			
Decade lag County voter participation						0.237***	0.153***
						(0.0406)	(0.0389)

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As shown in Table 6, for a reasonable range of elasticities of substitution and for both the broad and narrow occupational classifications, ancestry fractionalization is positively correlated with occupational variety and negatively correlated with origin-GDP-weighted fractionalization, controlling for *Origin GDP* (columns 1 and 3). Moreover, the index of occupational variety is positively and significantly related to county GDP when we include it in our standard equation containing *Origin GDP* and fractionalization (columns 2 and 4). The coefficient of ancestry fractionalization is smaller and less significant relative to its value in the basic specification of Table 4, column 1. The results suggest that the positive effect of ancestry fractionalization reflects, at least in part, the richer mix of skills associated with a county's increasing degree of ancestry diversity. The positive sign of the coefficient of education weighted fractionalization may also capture this effect.

7 Conclusion

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

The complex mosaic of ancestry in the United States has changed profoundly over time, and it is still evolving as new immigrants come and people move internally. Our results provide novel evidence also on the fundamental and recurring question of whether the United States acts as a "melting pot," quickly absorbing new immigrant groups, or whether immigrant groups maintain

Table 6: Ancestry, occupational mix, and county GDP per worker

Dependent variable:	Occ. Mix (broad, = 1:5)	Log(GDP p.w.)	Occ. Mix (narrow, = 2)	Log(GDP p.w.)
	[1]	[2]	[3]	[4]
Origin GDP	0.00488***	0.274***	0.00101***	0.260***
	(0.00123)	(0.0478)	(0.000222)	(0.0376)
Fractionalization	0.00864**	0.179**	0.00212***	0.0761
	(0.00356)	(0.0823)	(0.000787)	(0.0787)
Origin GDP weighted	-0.0203**	0.251	-0.00509**	0.427*
fractionalization	(0.00963)	(0.210)	(0.00190)	(0.235)
Occupation Mix		5.370***		
(broad, = 1:5		(0.412)		
Occupation Mix				27.22***
(narrow, = 2)				(2.436)
Decade lag	0.741***	0.397***	0.707***	0.390***
dependent variable	(0.0252)	(0.0251)	(0.0225)	(0.0283)
Two Decade lag	0.0285	0.0369*	0.0487**	0.0345
dependent variable	(0.0206)	(0.0207)	(0.0183)	(0.0212)
Observations	14,179	14,250	14,250	14,216
Division X Year	Yes	Yes	Yes	Yes
County group FE	Yes	Yes	Yes	Yes
County groups	1145	1145	1145	1145
R^2 (within)	0.835	0.968	0.969	0.968
R^2 (between)	0.625	0.324	0.139	0.259
AB test serial corr.	0.332	0.514	0.166	0.144

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

distinct identities in at least some dimensions. The significance and persistence of our ancestry measure's effect are difficult to explain in a pure assimilationist view and are more consistent with approaches that emphasize a degree of persistence of traits across generations. Our results show that this process generates important long-run consequences for local economic development.

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