Migrants, Ancestors, and Foreign Investments*

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Abstract

We use 130 years of data on historical migrations to the United States to show a causal effect of the ancestry composition of US counties on foreign direct investment (FDI) sent and received by local firms. To isolate the causal effect of ancestry on FDI, we build a simple reduced-form model of migrations: Migrations from a foreign country to a US county at a given time depend on (i) a push factor, causing emigration from that foreign country to the entire United States, and (ii) a pull factor, causing immigration from all origins into that US county. The interaction between time-series variation in origin-specific push factors and destination-specific pull factors generates quasi-random variation in the allocation of migrants across US counties. We find that a doubling of the number of residents with ancestry from a given foreign country relative to the mean increases by 4 percentage points the probability that at least one local firm engages in FDI with that country. We present evidence this effect is primarily driven by a reduction in information frictions, and not by better contract enforcement, taste similarities, or a convergence in factor endowments.

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Over the past decades, international migrations have reached unprecedented levels,[1] shaping an increasingly ethnically diverse and socially connected world. The economic consequences of these migrations are at the heart of fierce political debates on immigration policy, yet our understanding of the economic effects of migrations remains incomplete. At the same time, foreign direct investment (FDI) undertaken by multinational firms has become a defining feature of international production.[2] Local policymakers see attracting and retaining FDI as a major goal, and technology transfers through FDI are both a conduit for technological progress abroad and a source of revenue for US firms.[3] Migrations and FDI create two parallel global networks, one of ethnic connections, one of parent-subsidiary linkages. How do these two networks affect each other? In this paper, we estimate the long-term effect of immigration on the patterns of FDI sent and received by US firms, and shed light on the mechanism behind this effect. We show that immigration and FDI are intimately related: The ethnic diversity created by migrations reaching back more than a century has a large positive causal effect on the propensity of US firms to engage in FDI with the historical migrants' countries of origin; and this effect appears to transmit itself primarily through a reduction of information frictions.

Evaluating the causal impact of migrations on FDI requires a rigorous identification strategy, as unobserved factors may simultaneously affect migrations, ancestry, and FDI, creating a spurious correlation between them. We construct a set of instrumental variables (IV) for the present-day ancestry composition of US counties, best explained by the examples of migrations from Germany and Italy. German migrations peaked at the end of the nineteenth century when the Midwest was booming and attracting large numbers of migrants. We observe a large population with German ancestry in the Midwest today. Italian migrations peaked a few decades later, at the beginning of the twentieth century when the West was attracting large numbers of migrants. We observe a large population with Italian ancestry in the West. We use this interaction of time-series variation in the relative attractiveness of different destinations within the United States (e.g. end of nineteenth century Midwest versus early twentieth century West) with the staggered arrival of migrants from different origins (e.g. end of nineteenth century Germany versus early twentieth century Italy) to instrument for the present-day distribution of ancestries. This formal IV strategy is essential. For instance, while the effect of ancestry on FDI is positive in both ordinary least squares (OLS) and IV specifications, its effect on international trade drops

[1]The number of international migrants worldwide reached 232 million in 2013, an all time high (UN Population Facts No. 2013/2).

[2]In 2009, 55% of all US exports emanated from US multinationals that operated subsidiaries abroad. These firms employ 23 million Americans, while US subsidiaries of foreign firms employ another 5 million. Source: Office of the United States Trade Representative, Fact Sheet on International Investment.

[3]See McGrattan and Prescott (2010) and Holmes et al. (2015).

and becomes insignificant when we instrument for ancestry, suggesting that unobservable factors indeed confound simple OLS estimates of these effects.

Our paper makes three main contributions: (i) historical migrations and the ethnic diversity they created have a quantitatively large causal effect on FDI; (ii) this ethnic determinant of FDI operates mainly through a long-lasting (and causal) effect of common ancestry on the flow of information between the origin and the destination; and (iii) we propose a general method for instrumenting the composition of ancestry and for measuring the flow of information between foreign countries across US metro areas.

Before describing the related literature, we summarize our main empirical results.

We find that, for an average US county, doubling the number of individuals with ancestry from a given origin country increases by 4 percentage points the probability that at least one firm from this US county engages in FDI with that origin country, and increases by 7% the number of local jobs at subsidiaries of firms headquartered in that origin country. These effects persist over generations: Even the earliest migrations in the nineteenth century for which we have data significantly affect the patterns of FDI today.

To arrive at those findings on the *causal* impact of foreign ancestry on the patterns of FDI, we follow an IV strategy. We motivate our approach using a simple reduced-form dynamic model of migrations. Migrations from a given origin country o to a given US destination county d in period t depend on the total number of migrants arriving in the United States from o (a push factor), the relative economic attractiveness of d to migrants arriving in t (a pull factor), and the size of the pre-existing local population of ancestry o in d at t, allowing for the fact that migrants tend to prefer settling near others of their own ethnicity (a recursive factor). Solving the model shows that the number of residents in d today who are descendants of migrants from o is a function of simple and higher-order interactions of the sequence of pull and push factors.

To construct valid instruments from this sequence of interactions, we isolate variation in the pull and push factors that is plausibly independent of any unobservables that may make a given destination within the US differentially more attractive for both settlement and FDI from a given origin country. To that end, we measure the pull factor from country o to county d as the fraction of migrants coming from anywhere in the world who settle in d at time t, excluding migrants from the same continent as o. The pull from o towards d thus depends only on the destination choices of migrants arriving at the same time from other continents. Similarly, we measure the push factor as the total number of migrants arriving in the United States from o at time t, excluding migrants from o who settled in the same region as d. We then instrument for the present-day number of residents in county d with ancestry from country o using the full set of simple and higher-order interactions of these pull and push factors. Using the entire series of interactions going back to 1880 maximizes the statistical power of our IV strategy.

A major advantage of this approach is that it yields a specific instrument for migrations from each origin to each destination at each point in time, uniquely allowing us to guard against a wide range of potentially confounding factors, corroborate our approach in various ways, and probe the mechanism linking ancestry to FDI. Most immediately, it enables us to simultaneously control for both origin and destination fixed effects, thus controlling for all origin- and destination-specific factors, such as differences in size, market access, and productivity.

In addition, we conduct a number of falsification exercises and robustness checks. For example, we obtain quantitatively very similar effects of ancestry on FDI when we combine our IV strategy with a natural experiment surrounding the rise and fall of communism. Making use of the periods of economic isolation between the United States and communist countries, these specifications (similar to a difference-in-difference) measure how cross sectional variations in ancestry driven only by the inflow of defectors from communist countries explain changes in FDI, from zero in 1989 to its current level in 2014. Similarly, our results remain largely unchanged when we confine our set of instruments only to migrations pre or post World War II or apply it only to subsets of countries.

The flexibility of this set of instruments also delivers the statistical power to isolate specific channels linking ancestry to FDI: Theory suggests that common ancestry may have a positive impact on FDI because it (i) induces similarities in tastes for consumption, (ii) causes a convergence in factor endowments, facilitating horizontal FDI, (iii) provides social collateral for contract enforcement, substituting for poor institutions, or (iv) reduces information frictions. We find no evidence in support of the first three channels: Common ancestry does not affect FDI in the final goods sector more than in the intermediate goods sector, does not appear to cause a convergence the sectoral distribution of employment, and has a significantly weaker impact on FDI for countries with weak institutions.

To provide a direct test for the remaining hypothesis that common ancestry affects FDI by reducing information frictions, we construct a novel measure of information demand about foreign countries using data from Google internet searches. Our index reflects variation across US metro areas in the relative frequency of search terms containing the names of each countries' most prominent politicians, actors, athletes, and musicians. We find a large causal effect of common ancestry on this index: Residents of US metro areas that received relatively more migration from a given origin country in the past systematically acquire more information about the politics, culture, and language of that country. This fact fully accounts for the effect of ancestry on FDI, in the sense that controlling for our index of information demand drives out the significance of common ancestry in predicting FDI.

Further exploring the mechanism linking ancestry to FDI, we find additional evidence consistent with the view that information is transmitted internationally through networks created by common ancestry (Arkolakis, 2010; Chaney, 2014). Consistent with these models, we find that the effect of ancestry on FDI is highly concave (as all the relevant information is gradually exhausted), weaker if many people from the same or neighboring origins live in the surrounding area (as relevant information is more likely to have already percolated), and stronger for destinations that are more ethnically diverse (indicative of a hub-effect, where for example Poland and Venezuela do not communicate directly but through a hub in New York). Also consistent with this view, the effect of ancestry is stronger for more distant and ethnically diverse countries (where information is plausibly harder to acquire); and stronger for FDI than trade flows, where information frictions are arguably less severe than for foreign investments.

We also find that the effects of ancestry on FDI and information flow continue to operate long after migration from the origin country ceases, suggesting that immigrants pass traits to their descendants that facilitate economic exchange with their origin countries, such as social ties to family and friends or knowledge of the origin country's language and culture. As one example of such a trait, we show a positive effect of ancestry on the use of the origin country's language by US-born individuals.

To illustrate the quantitative implications of our results, we conduct two thought experiments. In the first, we calculate the effect of Chinese exclusion – the effective ban on Chinese immigration between 1882 and 1965. Absent this ban, we predict the fraction of counties in the Northeast with FDI links to China would have increased substantially (e.g. doubled in New York state). In the second, we calculate the effect of a hypothetical "L.A. gold rush" – an early population growth in Los Angeles before 1880 similar to the experience of San Francisco. We predict there would have been 60,000 more individuals with German and Irish ancestry in Los Angeles, and FDI between Los Angeles and Germany and Ireland would have increased by around 60%. The effect of ancestry on FDI is thus large and economically important.

Finally, we note one important limitation to our analysis: Our results rely purely on variation in the composition of FDI within the United States, not between countries. Although we believe that, in light of our results, the ethnic diversity of the United States likely also raises FDI for the country as a whole, we cannot exclude the possibility that increases in FDI in one state are partially or fully offset by decreases in others.

Existing literature. A large literature shows that measures of affinity between regions, such as common ancestry, social ties, trust, and telephone volume, correlate strongly with aggregate economic outcomes, such as foreign direct investment (Guiso, Sapienza, and Zingales, 2009; Leblang, 2010), international asset flows (Portes and Rey, 2005), and trade flows (Gould, 1994; Rauch and Trindade, 2002).[4] How much of this association should be interpreted as causal, however, remains an open question because these measures of affinity are likely to be nonrandom.

Three recent papers make attempts at identifying a causal impact of migrations on FDI and trade. Javorcik et al. (2011) use the cost of acquiring a passport and the existing stock of migrants from different countries in the United States to instrument for the impact of migrations between foreign countries and the United States on FDI. However, these instruments are most likely correlated with both migrations to the United States *and* FDI flows (e.g. a passport facilitates migration to the U.S., but it also facilitates traveling to the U.S. to set up a subsidiary, and traveling back and forth between a parent firm and its subsidiary), and thus likely violate the exclusion restriction. Cohen et al. (2015) use the location of Japanese internment camps during World War II, and Parsons and Vezina (2016) the placement of Vietnamese refugees after the Vietnam War to identify a causal effect of concentrations of descendants of these migrants on contemporary trade flows between locations within the United States and Japan and Vietnam, respectively. While the exclusion restriction for the instruments in those two papers is plausible, instrumenting for migrations from only one country makes it impossible to control for destination fixed effects, that is, unobserved characteristics making a US state both a large recipient of migrants and a large importer and exporter.[5]

Burchardi and Hassan (2013) use variation in wartime destruction across West German regions in 1945, a time when millions of refugees were arriving from East Germany, as an instrument for the share of the population with social ties to the East, and show evidence of a causal effect of these social ties on changes in GDP growth rates and FDI in East Germany after the fall of the Berlin Wall.[6] Other papers studying the effect of historical shocks on economic interactions across borders include Redding and Sturm (2008), Juhász (2014), and Steinwender (2014).

We contribute to this literature in several ways. First, we identify a causal effect of ancestry on FDI in a setting with a high degree of external validity directly relevant for assessing, for

[4] Also see Head and Ries (1998), Combes, Lafourcade, and Mayer (2005), Garmendia, Llano, Minondo, and Requena (2012), and Aleksynska and Peri (2014) for the relationship between common ancestry and trade and Bhattacharya and Groznik (2008) for its relationship with FDI.

[5] Similarly, focusing on migrations and FDI flows to the United States as a whole, Javorcik et al. cannot control for an origin country fixed effect, making it likely that unobserved characteristics make a country both a larger sender of migrants, and a large sender of FDI flows.

[6] See Fuchs-Schündeln and Hassan (2015) and Chaney (2016) for surveys of this literature.

example, the long-term effects of immigration policy. Second, because our identification strategy can be applied to all origin countries and destination US counties, we are able to guard against a wide range of possible confounding factors and to relate to the previous literature by employing a gravity equation with both destination and origin fixed effects. Third, we show that ancestry affects FDI most likely due to its effects on information flow.

Our paper also contributes to the debate on the costs and benefits of immigration. Much of the existing literature has focused on the effects of migration on local labor markets, mostly in the short run.[7] A more recent literature focuses on the effect of cultural, ethnic, and birthplace diversity on economic development and growth.[8] Most closely related are Nunn, Qian, and Sequeira (2015) who study the effect of immigration from all origins during the Age of Mass Migration on present-day outcomes. Fulford, Petkov, and Schiantarelli (2015) study the effect of historical ancestry composition of US counties on local economic growth. We add to this literature by examining the effect of migration on the pattern of international economic exchanges and local employment. Our results show a long-term effect of migration on the absolute advantage in conducting FDI of different regions that may explain part of the association between diversity and long-term growth found in other studies.

Our approach to identification is related to Card (2001) who instruments immigration flows from origin o to destination d with the interaction of the total immigration from o to the United States (the push factor) and the spatial distribution of previous migrants from o in the United States (the recursive factor). This strategy has been widely used in the literature to instrument for changes in labour supply caused by immigration. However, it is not appropriate in our context, where unobserved and persistent origin-destination specific characteristics (such as the local climate) may drive both the spatial distribution of previous migrants and FDI. Our approach instead combines a push-pull model similar to that of Card (2001) with a two-dimensional version of the leave-out approach of Bartik (1991) and Katz and Murphy (1992), and uses multiple subsequent waves of historical migrations going back to the 19th century to instrument for the current stock of ancestry. This hybrid approach can easily be replicated for other countries, other time periods, or variables other than migrations where cumulated flows matter, without the need for a rare or even unique historical accident.

The remainder of this paper is structured as follows. Section 1 introduces our data. Section

[7] See for example Card (1990), Card and Di Nardo (2000), Friedberg (2001), Borjas (2003), and Cortes (2008). Borjas (1994) provides an early survey.

[8] See Ottaviano and Peri (2006), Putterman and Weil (2010), Peri (2012), Ashraf and Galor (2013), Ager and Brückner (2013), Alesina, Harnoss, and Rapoport (2015a), and Alesina, Michalopoulos, and Papaioannou (2015b).

2 gives a brief overview of the history of migration to the United States. Section 3 identifies the causal effect of ancestry composition on FDI at the extensive margin, discusses various challenges to our identifying assumption, illustrates the quantitative implications of our findings using two thought experiments, and conducts a range of robustness checks and falsification exercises. Section 4 examines the mechanism underlying the effect of ancestry on FDI.

1 Data

We collect data on migrations and ancestry, on foreign direct investment and trade, and on origin and destination characteristics. Below is a description of our data, along with their source. Further details on the construction of all data are given in Appendix A.

Migrations and Ancestry. Our migration and ancestry data are constructed from the individual files of the Integrated Public Use Microdata Series (IPUMS) samples of the 1880, 1900, 1910, 1920, 1930, 1970, 1980, 1990, and 2000 waves of the US census, and the 2006-2010 five-year sample of the American Community Survey. We weigh observations using the personal weights provided by these data sources. Appendix Table 1 summarizes specific samples and weights used. We cannot use data from the 1940, 1950 and 1960 censuses, because these did not collect information on the year of immigration. The original 1890 census files were lost in a fire.

Throughout the paper, we use $t-1$ and t to denote two consecutive census waves, o for the foreign country of origin, and d for the US destination county. We construct the number of migrants from origin o to destination d at time t, $I^t_{o,d}$, by counting the number of respondents who live in d, were born in o, and emigrated to the United States between $t-1$ and t. The exception to this rule is 1880 census (the first in our sample), which also did not record the year of immigration. The variable $I^{1880}_{o,d}$ instead measures the number of residents who were either born in o or whose parents were born in o, thus covering the two generations of immigrants arriving prior to 1880.[9] Since 1980, respondents have also been asked about their primary ancestry in both the US Census and the American Community Survey, with the option to provide multiple answers. $Ancestry^t_{o,d}$ corresponds to the number of individuals residing in d at time t who report o as first ancestry. Note that this measure captures self-reported (recalled) ancestry, which may potentially be more relevant for economic exchange than genetic (factual) ancestry.[10]

The respondents' residence is recorded at the level of historic counties, and at the level of historic county groups or PUMAs from 1970 onwards. Whenever necessary we use contempo-

[9] If the own birthplace is in the United States, imprecisely specific (e.g., a continent), or missing, we instead use the parents' birthplace, assigning equal weights to each parent' birthplace.

[10] See Duncan and Trejo (2016) for recent evidence on recalled versus factual ancestry in CPS data.

raneous population weights to transition data from the historic county group or PUMA level to the historic county, and then use area weights to transition data from the historic county level to the 1990 US county level.[11] The respondents' stated ancestry (birthplace) often, but not always, directly corresponds to foreign countries in their 1990 borders (for example, "Spanish" and "Denmark"). However, in other cases no direct mapping exists (for example, "Basque" or "Lapland"). For these cases, we construct transition matrices that map data from the answer level to the 1990 foreign country level, using approximate population weights where possible and approximate area weights otherwise. In the few cases when answers are imprecisely specific or such a mapping cannot be constructed (for example, "European" or "born at sea"), we omit the data. Appendix Tables 2 and 3 report summary statistics on these data transitions, including the share of affected respondents and Appendix A.1 provides a detailed description of the data transformation. The resulting dyadic dataset covers 3,141 US counties, 195 foreign countries, and 10 census waves.

Foreign Direct Investment. Our data on FDI is from the US file of the 2014 edition of the Bureau van Dijk ORBIS data set.[12] For each US firm, the database lists the location of its (operational) headquarters, the addresses of its foreign parent entities, and the addresses of its partially or fully owned international subsidiaries and branches. In our main specification, we treat all equity stakes of any size as constituting a parent-subsidiary link.[13] Altogether, we have information on 36,108 US firms that have at least one foreign parent or subsidiary. Collectively, these firms have 102,618 foreign parents and 176,332 foreign subsidiaries in 142 countries (in their 1990 borders).[14] We then aggregate this information to the county level. Our main outcome variable, *FDI Dummy*, is 1 if at least one firm within a given destination county has at least one parent or subsidiary in the origin country. The variable *FDI dummy* therefore captures both outward FDI (US firms with foreign subsidiaries) and inward FDI (foreign firms with US subsidiaries). For each destination county, we also count the total number of FDI linkages (the total number of foreign parents and subsidiaries of all firms within the county), and the total number of unique parents and subsidiaries in both the origin and the destination. We also count the total number of employees working at firms with a foreign parent in a given destination (#

[11] We also aggregate our data to the PUMA level and show that our results are robust.

[12] In robustness checks we show that our results do not change when we instead use data from the 2007 file.

[13] Appendix Table 11 shows that our results are almost completely unchanged when we restrict ourselves to links with an ownership stake larger than 5%, 25% or 50%.

[14] Although Bureau van Dijk cross checks the data on international subsidiaries and branches using both US and foreign data sources, we cannot exclude the possibility that coverage may be better for some countries than for others. However, all of our specifications control for country fixed effects such that any such variation in coverage at the country level would not affect our results.

of Employees at Subsidiaries in Destination).[15] The ORBIS database also gives the 2007 NAICS code of the sector of the US firm, allowing us to disaggregate these data by 2-digit sector.[16] See Appendix A.2 for details. The resulting dataset covers the same 3,141 US counties and 195 foreign countries as above, yielding 612,495 origin-destination pairs.

Other Data. To streamline the exposition, we discuss our measure of information demand in section 4.2. In addition, we use data on aggregate trade flows between US states and foreign countries for the year 2012 from the US Census Bureau.[17] We construct bilateral distances and absolute latitude differences between US counties and foreign countries, and collect information on a number of characteristics for countries, counties, and sectors. See Appendix A.3 for details.

Summary Statistics. Panel A of Table 1 gives summary statistics on our sample of 3,141 $\times$ 195 origin-destination pairs.[18] Column 1 shows means and standard deviations for all observations. Columns 3-4 show the same statistics for the subsamples of origin-destination pairs containing only observations with non-zero ancestry, and ancestry in the bottom and top quintile, respectively. The table shows that a lot of the variation both in ancestry and FDI is at the extensive margin. Only 1.8% of origin-destination pairs have an FDI link. Conditional on the US county having any population with origins in the foreign country, 3.1% have an FDI link. The larger this population, the larger the probability of finding an FDI link, with 12.8% of the origin-destination pairs in the top quintile having an FDI link. Similarly, about half of the origin-destination pairs have ancestry of zero: most destinations in the United States do not have populations with ancestry from all 195 origin countries. The mean number of individuals with ancestry from a given origin is 316, but is highly skewed, with a mean in the top quintile of 2,852 individuals. Compared to this stock of ancestry, the flow of immigrants between 1990 and 2000 is relatively small, with 23 on average across the sample. The summary statistics also show that the number of first-generation immigrants (foreign born) measured in the 2010 American Communities Survey appears somewhat understated (69 on average). This fact is known in the literature and appears to affect only the measurement of immigration flows but not the stock

[15] When information on the number of employees is missing (which is the case for 95% and 58% of subsidiaries in the destination and origin, respectively), we assume the subsidiary employs one person.

[16] Appendix Table 4 provides a list of sectors and sector groups.

[17] When we aggregate our dataset across US states, the correlation with aggregate trade between the entire US and foreign countries from the NBER bilateral trade dataset is 99.9% for imports and 99.7% for exports respectively (in 2008). When we aggregate our data across foreign countries, the correlation between state level aggregate trade and state population is 93% for imports and 88% for exports respectively. We are therefore confident our trade dataset disaggregated at the US state $\times$ foreign country level is not subject to severe measurement error. To further guard against measurement error, we also use data for the manufacturing sector only, final goods only, or intermediate inputs only.

[18] 53 countries have no FDI links with US firms in our sample.

of ancestry (Jensen et al., 2015). For this reason, we exclude the 2000-2010 wave of migrations from our standard specification (its inclusion however has no effect on any of our main results).

Panels B and C show summary statistics following the same format for destination counties and origin countries for variables used in our estimation of heterogenous effects. Appendix Table 5 gives summary statistics on the intensive margin of FDI.

2 Historical Background

The 1880 US census counted 50 million residents, 10 million of which were first- or second-generation immigrants from 195 countries. The censuses taken since 1880 counted an additional 67 million immigrants. Our sample period thus covers the vast majority of migrations.[19]

During the first part of this period, up until World War I, migration to the United States was largely unregulated. European migrants in particular faced few or no restrictions to entry and came in large numbers. Figure 1 shows the extent and the changing composition of migration over time. Although the peak of British migration was passed before the beginning of our sample, the numbers for 1880 clearly show the effect of the potato famines and the subsequently large inflow of Irish migrants. The second big wave of migration in our sample is that of Germans in the aftermath of the failed revolutions of 1848 and the consolidation of the German empire under Prussian control in 1871. Similarly disrupted by political changes and an economic crisis in the South, Italian migrants began flocking to the United States in large numbers around 1910, followed by a peak in migrations from Eastern Europe, and in particular from Russia, in the years after the October Revolution. The inflow of migrants overall dropped dramatically during World War I, falling below 4 million during the period between 1910 and 1930.

Although economic and political factors in the origin countries dominated the timing of these earlier European migrations, US immigration policies became relatively more important during the 1920s. The first important step toward regulating the inflow of migrants was the Chinese Exclusion Act of 1882 that ended the migration of laborers, first from China, and then in following incarnations from almost all of Asia. These restrictions were followed by literacy and various other requirements that came into effect after 1917, culminating in the establishment of a quota system in 1921. The quota system limited the overall number of immigrants, reduced the flow of migrants from Southern and Eastern Europe, and effectively shut out Africans, Asians, and Arabs. Combined with the effects of the Great Depression, these new regulations led to

[19] The historical information in this section is from Daniels (2002) and Thernstrom (1980). Also see Goldin (1994) for the political economy of US immigration policy.

negative net migration in the early 1930s and then a stabilization at relatively low levels of immigration. The quota system was abolished in 1965 in favor of a system based on skills and family relationships, leading both to a large increase in the total number of migrants and a shift in composition toward migrants from Asia and the Americas, in particular from Mexico.

Figure 2 maps the spatial settlement pattern of newly arrived immigrants in the United States over time. For each census from 1880 to 2010, we project the total number of new migrants from all origins to destination d, I_d^t, on destination and year fixed effects to account for general immigration time trends and persistent destination-specific effects. The figure shows the residuals from this projection, color coded by decile. Migrants initially settled on the East Coast of the United States (in the mid-19th century), and then the frontier for migrants moved to the Midwest (in the late-19th century), to the West (1900-30), and to the South (in the 1980s). Starting in the 1970s, we can also see graphically the increased settlement of migrants in urban centers, with a series of dark dots appearing around large urban areas.

Below we use the interaction of this time-series variation in the relative attractiveness of different destinations within the United States with the staggered arrival of migrants from different origins as the basis of our identification strategy.

3 Ancestry and Foreign Direct Investment

3.1 Identifying the Causal Impact of Migrations

To evaluate the effect of the presence of descendants of migrants from a given origin on the probability that at least one firm within a given destination has an FDI link with a firm based in the origin country (inward or outward), we estimate the structural equation,

$$\mathbf{1}\left[FDI_{o,d} > 0\right] = \delta_o + \delta_d + \beta A_{o,d}^{2010} + X_{o,d}'\gamma + \varepsilon_{o,d}, \tag{1}$$

where $\mathbf{1}\left[FDI_{o,d} > 0\right]$ is a dummy variable equal to 1 if any firm headquartered in destination d is either the parent or the subsidiary of any firm headquartered in origin o in 2014 (thus reflecting both inward and outward FDI). We focus on this combined variable because our main results are largely identical when separately considering inward and outward FDI. However, we report separate results for each direction whenever they are relevant or important for interpretation. $A_{o,d}$ is a measure of common ancestry, usually calculated as the log of 1 plus the number of residents in d that report having ancestors in origin o in 2010, measured in thousands. (We choose this functional form in anticipation of non-parametric results, but also show robustness to a wide range of alternative specifications –see section 3.4). $X'_{o,d}$ is a vector of control variables that always includes the geographic distance between o and d, and the difference in latitude between o and d. δ_o and δ_d represent a full set of origin and destination fixed effects, augmented in most of our specifications by fixed effects for the interaction between destination and continent of origin, and between origin and destination census region.[20] The coefficient of interest is β, which measures the effect of ancestry on the probability that an FDI relationship exists between firms in o and d. The error term $\varepsilon_{o,d}$ captures all omitted influences, including any deviations from linearity.[21] Throughout the main text, we report standard errors clustered at the origin-country level. In the appendix, we report standard errors calculated using alternative methods for all the main results of the paper, and show our results are robust.

Equation (1) takes the form of a gravity equation, widely used in the empirical literature describing the pattern of international trade and FDI. We maintain the same form for consistency with this literature. Moreover, the gravity form is appealing on theoretical grounds because it can be derived in a variety of models.[22] The destination and origin fixed effects absorb all differences in productivity, market size, and market access between origins and destinations that systematically affect prices. We may thus interpret the coefficient β as the effect of ancestry controlling for the large set of conventional economic forces shaping international exchanges.

Equation (1) will consistently estimate the parameter of interest if $Cov\left(A_{o,d}^{2010}, \varepsilon_{o,d}\right) = 0$. This condition is unlikely to hold in our data, despite the inclusion of origin and destination fixed effects. First, past origin-destination specific migration flows might be the result of economic transactions such as FDI or trade, not their driver.[23] Second, origin-destination specific omitted factors might drive both economic transactions and migration flows, affecting both $A_{o,d}$ and $\mathbf{1}\left[FDI_{o,d} > 0\right]$. Third, ancestry might be selectively recalled because of past or present economic interactions. These challenges are not unique to our data, but are likely concerns with any data where ethnic linkages and economic transactions are simultaneously observed.

To address these concerns, we devise an instrumental variables (IV) strategy. This strategy is guided by a simple dynamic model of migration, which helps to identify quasi-random variation in ancestry and relate our approach to the existing literature. The stock of residents of ancestry

[20] A census region is one of nine groupings of adjacent US states listed in Appendix Table 6.

[21] We use a simple linear probability model, which allows for a straight-forward interpretation of the coefficient. As a robustness check, we also report results from a probit estimator; see footnote 26.

[22] See Arkolakis et al. (2012) for a derivation of the gravity structure of international trade in a variety of theoretical settings. See Carr et al. (2001), Razin et al. (2003), Head and Ries (2008), and Ramondo (2014) for an application of the gravity structure to foreign direct investment.

[23] An example of such reverse causality is the strong concentration of Japanese in Scott County, Kentucky, which emerged after Toyota seconded Japanese workers to a newly built manufacturing facility in the 1980s.

o in destination d at time t, $A^t_{o,d}$, depends on the past stock of residents with ancestry o and the newly arrived migrants from o who settle in d. The combination of three forces determines the number of new arrivals: A country-specific *push factor* drives migrants out of country o into the United States; a *pull factor* attracts migrants entering the United States to county d, irrespective of their origin; and a *recursive factor* corresponds to the tendency of newly arrived migrants to settle in communities where people with the same ancestry already live.

Formally, the stock of residents in d with ancestry from o at time t evolves according to

$$A^t_{o,d} = a_t + a_{o,t} + a_{d,t} + b_t A^{t-1}_{o,d} + I^t_o \left(c_t \frac{I^t_d}{I^t} + d_t \frac{A^{t-1}_{o,d}}{A^{t-1}_o} \right) + \nu^t_{o,d}. \tag{2}$$

The constant terms a_t, $a_{o,t}$, and $a_{d,t}$ control for residual forces, such as demographics, which may vary over time, over space, and between different ethnic groups. The term $b_t A^{t-1}_{o,d}$ corresponds to the fact that ancestry is a stock variable that evolves cumulatively, where b_t modulates how ties to one's ancestry are passed from one generation to the next, including attenuation due to internal migrations. The term I^t_o, the total number of migrants from country o entering the United States at time t, measures the strength of the push factor, the fact that migrants are driven out of country o. The fraction of all migrants entering the United States who settle in county d from all origins, I^t_d/I^t, measures the strength of the economic pull factor, the degree to which county d is particularly appealing to migrants at time t. The fraction of people with ancestry from country o who already live in county d, $A^{t-1}_{o,d}/A^{t-1}_o$, measures the strength of the recursive factor, the propensity of migrants to settle near their countrymen. The coefficients c_t and d_t control for the relative importance of the pull and recursive factors. If the pull factor is absent, and only the recursive factor affects the allocation of newly arrived migrants ($c_t = 0$) our model collapses exactly to the Card (2001) model. Finally, $\nu^t_{o,d}$ is a sequence of error terms that are potentially correlated with $\varepsilon_{o,d}$.

Equation (2) is not a suitable first stage because persistent forces are likely to shape both the settlement of migrants and FDI, inducing a correlation between $A^{t-1}_{o,d}$ and $\varepsilon_{o,d}$. Therefore an IV strategy following Card (2001), using variations in I^t_o and $A^{t-1}_{o,d}$ as instruments, would not be suitable in our setting.

We address this challenge by noting that equation (2) is recursive, both because ancestry is passed down from generation to generation (the first $A^{t-1}_{o,d}$ term) and because newly arrived migrants' decision of where to settle depends on where past migrants have settled (the second $A^{t-1}_{o,d}$ term). Given that our data cover the vast majority of migration to the United States (more than 70 million immigrants, including the entire first and second generation of immigrants alive in 1880), we assume the initial condition $A_{o,d}^{1880\text{``}-1\text{''}} = 0, \forall\,(o,d)$ for simplicity. Solving equation (2) recursively, we get,

$$A_{o,d}^{2010} = \sum_{t=1880}^{2010} \left(a_t + a_{o,t} + a_{d,t} + c_t I_o^t \frac{I_d^t}{I^t} + \nu_{o,d}^t \right) \prod_{s=t+1}^{2010} (b_s + d_{o,s} I_o^s), \tag{3}$$

where the constant $d_{o,s}$ only contains information on total migrations from o in previous periods.

Equation (3) highlights that present-day ancestry is the result of a sequence of migration waves and their subsequent cumulative effect. In each period t, the interaction of the contemporaneous push factor (I_o^t) and economic pull factor (I_d^t/I^t) determines the flow of migration from o to d. Demographic factors (the b_s's) and the recursive factor (the $d_{o,s}$'s) then amplify these initial waves of migrants, adding higher-order combinations of the same interactions. This simple specification is flexible, allowing for cases in which no migrants from a given origin country exist at some initial period of time. In the absence of a recursive factor, $d_t = 0$, the higher-order terms drop out and ancestry only depends on the contemporaneous interactions of the push and pull factors.

This specification suggests plausibly exogenous variation in $I_o^t\,(I_d^t/I^t)$ would allow the construction of an instrument for $A_{o,d}^{2010}$. By interacting a push factor, I_o^t, which is not specific to destination d, but common to all destinations in the United States, and a pull factor, I_d^t/I^t, which is not specific to country o but to migrants from all countries, we rule out most plausible sources of endogeneity. However, our exclusion restriction could still be violated since $I_{o,d}^t$ is mechanically a component of I_o^t, I_d^t and I^t and potentially related to $\varepsilon_{o,d}$. This would be a concern if at some point in time, migrants from o to d represent a large fraction of all migrants from o ($I_{o,d}^t$ a large fraction of I_o^t), or a large fraction of all migrants to d ($I_{o,d}^t$ a large fraction of I_d^t), or if migrants from other origins with unobserved similarities to o represent a large fraction of all migrants.

To address these concerns, we exclude from the push factor migrants from o going to all destinations in d's census region, and from the economic pull factor, migrants from all origins in the same continent as o. We replace I_o^t by $I_{o,-r(d)}^t$, the migrants from o who settle in destinations *not* in the same census region as d; and I_d^t/I^t by $I_{-c(o),d}^t/I_{-c(o)}^t$, the fraction of migrants *not* coming from origins in the same continent as o who settle in county d. $-r\,(d)$ stands for all destinations outside of d's census region, and $-c\,(o)$ stands for all origins outside of o's continent.

Replacing the $I_o^t \frac{I_d^t}{I^t}$ terms by $I_{o,-r(d)}^t \frac{I_{-c(o),d}^t}{I_{-c(o)}^t}$ in (3), our first-stage specification is thus

$$A_{o,d}^{2010} = \delta_o + \delta_d + \sum_{t=1880}^{2000} \alpha_t I_{o,-r(d)}^t \frac{I_{-c(o),d}^t}{I_{-c(o)}^t} + \sum_{n=1}^{5} \delta_n PC_n + X'_{o,d}\gamma + \eta_{o,d}, \tag{4}$$

where $\sum_{n=1}^{5} \delta_n PC_n$ stands for the first five principal components summarizing the information contained in the 758 higher-order terms $I^s_{o,-r(d)} \cdots I^t_{o,-r(d)} \frac{I^t_{-c(o),d}}{I^t_{-c(o)}}, \forall t < s \leq 2010$. We prefer summarizing the higher-order interactions in (3) as principle components to avoid an excessive number of highly co-linear instruments.[24] Our results are robust to adding those terms or not.

Our key identifying assumption is

$$Cov\left(I^t_{o,-r(d)} \frac{I^t_{-c(o),d}}{I^t_{-c(o)}}, \varepsilon_{o,d} | controls\right) = 0. \tag{5}$$

It requires that any confounding factors that make a given destination more attractive for both migration and FDI from a given origin country do not simultaneously affect the interaction of the settlement of migrants from other continents with the total number of migrants arriving from the same origin but settling in a different census region.

To further relax this assumption, most of our specifications also control for interactions of fixed effects that are symmetric to the construction of our instruments: the interaction between destination and continent-of-origin fixed effects ($\delta_d \times \delta_{c(o)}$) and the interaction between origin and destination-census-region fixed effects ($\delta_o \times \delta_{r(d)}$). In these regressions we only use variation across origin countries from the same continent, holding the destination constant, and variation across destinations within the same census region, holding the origin constant. These specifications are, by construction, robust to any confounding factors that are origin-census region or continent-destination specific. The main remaining challenge to our approach is that an unobserved, origin-destination specific, factor correlated with FDI today may have induced migrants from that origin to disproportionately migrate to at least two destinations in two different census regions *at the same time* as it caused another group of migrants, large enough to sway averages, *from another continent* to disproportionately migrate to the same destinations across census regions. We show robustness to this and other concerns in section 3.4 with a series of falsification exercises, placebo treatments, and alternative leave-out specifications.

3.2 The First-Stage Relationship

Table 2 shows our basic first-stage regressions, estimates of equation (4). Column 1 is the most parsimonious specification regressing our measure of ancestry on origin and destination fixed

[24] Principal component analysis (eigenvalue decomposition) is simply a means for compactly summarizing the variation contained in the 758 higher-order terms. In our standard specification, the first five components summarize 99.99% of the variation, so that the explained variation in the first stage (4) is almost identical to that using the full set of 758 higher-order terms. To the extent that the higher order terms are valid instruments, the first five principal components are valid instruments as well.

effects and the nine simple interaction terms $\{I^t_{o,-r(d)}(I^t_{-c(o),d}/I^t_{-c(o)})\}_t$. To facilitate the interpretation of the results, we sequentially orthogonalize each of the terms with respect to the interaction terms from the previous censuses. For example, the coefficient marked $I^{1900}_{o,-r(d)}(I^{1900}_{-c(o),d}/I^{1900}_{-c(o)})$ shows the effect of the residual obtained from a regression of $I^{1900}_{o,-r(d)}(I^{1900}_{-c(o),d}/I^{1900}_{-c(o)})$ on the same interaction in 1880, the coefficient marked 1910 shows the effect of the residual from a regression of the 1910 interaction on the interactions from the previous two censuses, and so on. Although this procedure has no effect on the fit and predictive power of the first stage as a whole, we find it useful because it allows us to interpret each coefficient as the marginal effect of the innovation in the migration pattern of the period reported with respect to the previous periods.

All nine coefficients shown in column 1 are positive, and seven are statistically significant at the 1% level. Figure 3 depicts the coefficients graphically. The first main insight from this figure is that even our earliest (pre-1880) snapshot of the cross-sectional variation in economic attractiveness to new migrants has left its imprint on the present-day ancestry composition of US counties: destinations relatively more attractive to the typical migrants pre-1880 continue to the present day to house significantly larger numbers of residents of the ethnic groups that arrived in large numbers pre-1880. The overall pattern of coefficients suggests a hump-shape, where very recent waves of migrants have a smaller impact on current ancestry than migrations a few decades back, but the effect of past migrations eventually fades after about one century (consistent with a model where each immigrant passes her ancestry to more than one offspring and memories of distant ancestries fade over time). An exception to the general pattern is the coefficient for 1920-30, which is smaller and insignificant. A likely explanation is the Great Depression, which induced large reverse migrations from the United States of recently arrived migrants, demonstrating our model is less well suited for periods with negative net migration.

Taken together, the nine simple interactions incrementally increase the R^2 of the regression by 4 percentage points and explain about 9% of the variation in ancestry not explained by origin and destination fixed effects. Column 2 adds controls for distance and latitude difference. Columns 3 and 4 add destination $\times$ continent-of-origin fixed effects and origin $\times$ destination-census-region fixed effects, respectively. Columns 1-4 estimate equation (4) under the restriction that the recursive factor is irrelevant ($d_t = 0$ in (2)). Columns 5-9 relax this restriction and add the principal components of the higher-order interaction terms.

Our standard specification in column 5 includes these additional terms which ensure a strong first stage. However, none of our core results depend on this choice. The Kleibergen-Papp Wald rk-statistic against the null of weak identification is 162.2, well above the Stock and Yogo critical values.[25] Column 6 includes third-order polynomials in the distance and latitude difference between o and d. Columns 7 through 9 successively show variations of our instrumentation strategy: column 7 includes migration data from the 2005-2010 ACS survey, column 8 drops migration prior to 1880, and column 9 estimates our standard specification in levels rather than logs. Throughout all of these variations, we can comfortably reject the null that our instruments are jointly irrelevant in the first stage.

Figure 4 illustrates our first-stage identification using two specific examples: That of migrations from Germany, with a migration peak in the pre-1900 period (corresponding to the failed 1848 revolution and the consolidation of the German empire under Prussian control), and that of Italy, with a migration peak in the 1900-30 period (triggered by the end of feudalism and demographic pressures, and ending with Mussolini's anti-emigration policies). The top-left part shows the relative attractiveness of US destinations for pre-1900 migrants, when German migrations to the United States peaked, where we exclude migrations from Europe – analogously to our regression specification. At that time, most non-European migrants settled in the Midwest. We expect most German migrants from this initial wave to have settled in the Midwest. The top-right part shows the distribution of US residents with German ancestry in 2010, with disproportionately many in the Midwest. The bottom-left part shows the relative attractiveness of US destinations for non-European migrants during the 1900-30 period, when Italian migrations to the United States peaked. At that time, the preferred destination for migrants had shifted to the West and South. We expect many Italians migrants to have settled in the West and South. The bottom-right part shows the distribution of Italian descendants in 2010, with relatively large populations in the West and South.

3.3 Instrumental Variables Results

In our IV estimation, we explicitly test the hypothesis that an increase in the number of descendants from a given origin increases the probability that at least one local firm engages in FDI with that country. The dependent variable is a dummy equal to one if either a parent foreign firm from origin country o owns a US subsidiary in destination US county d (inward FDI), or if a US parent in d owns a foreign subsidiary in o (outward FDI). We present our results for two-way FDI, because the results for inward and outward FDI separately are essentially identical. We separate results only when the difference is relevant or important for interpretation (e.g. for FDI in final goods sectors versus intermediate goods sectors in section 4).

[25] The Hansen J test statistic is 15.891 with a p-value of 0.255. We thus fail to reject the null that our instruments are uncorrelated with the error term and correctly excluded from the second-stage regression.

In column 1 of Table 3, we estimate equation (1) while instrumenting (the log of) ancestry in 2010 with the simple interaction terms $\{I^t_{o,-r(d)}(I^t_{-c(o),d}/I^t_{-c(o)})\}_t$ and controlling for origin and destination fixed effects, distance, and latitude difference. The coefficient estimate on ancestry is 0.231 (s.e.=0.023), statistically significant at the 1% level. The coefficient on distance is not statistically distinguishable from zero, perhaps reflecting the fact that US counties do not differ much in their distance to most foreign countries, and that these smaller differences are irrelevant once we control for the effect of the distance between the United States as a whole and the country in question (absorbed in the country fixed effect). By contrast, the absolute difference in latitude is positive and significant, showing that, all else being equal, firms tend to engage in FDI with origin countries that are climatically different from their own location. Appendix Figure 1 presents the corresponding reduced form results graphically. All nine coefficients are greater than zero, and seven of them are statistically significant at the 5% level. Destinations that received an (exogenous) increase in the number of migrants from a given origin in any of the nine consecutive waves of immigration thus tend to have a significantly higher probability of engaging in FDI with these origin countries today. In column 2 of Table 3, we add the first five principal components of the higher-order interactions to our set of instruments, resulting in a slight fall in the coefficient of interest to 0.190 (s.e.=0.024).

Column 3 shows our standard specification. The estimate, 0.187 (s.e.=0.024), implies that doubling the number of residents with ancestry from a given origin relative to the sample mean (from 316 to 632) increases by 4 percentage points the probability that at least one firm engages in FDI with that origin.[26] This specification includes destination × continent-of-origin fixed effects and origin × destination-census-region fixed effects. For a given origin country, this demanding specification uses only variation across different destinations within the same census region while controlling for the fact that each destination may have a high or low idiosyncratic propensity to interact with the continent containing the origin country, and symmetrically for destinations. Reassuringly, adding these 17,460 fixed effects has almost no effect on our coefficient of interest (0.187, s.e.=0.024 versus 0.190, s.e.=0.024). Comparing this estimate with the same column in panel B shows that it is about 25% larger than the corresponding OLS coefficient. The endogenous assignment of migrants to destinations within the United States thus appears to induce a downward bias in the OLS coefficient, consistent with a simple extension of the Heckscher-Ohlin model: Migrations tend to be driven by differences in factor endowments (creating differences in

[26] Using $\hat{\beta} = 0.187$ from column 3 in Table 3 in equation (1), we have: $\mathbf{1}[FDI_{o,d} > 0 | Ancestry_{o.d} = 632] - \mathbf{1}[FDI_{o,d} > 0 | Ancestry_{o.d} = 316] = 0.187\left(\ln\left(1 + \frac{632}{1000}\right) - \ln\left(1 + \frac{316}{1000}\right)\right) \approx 0.0402$. An IV probit estimate of the same specification yields a marginal effect of Log Ancestry 2010 on $\Pr[FDI > 0]$ of 0.104 (s.e.=0.037).

wages between origin country and destination county), while FDI flows are driven by similarities in factor endowments (as firms use FDI to export their technology to countries with a similar mix of factor endowments).

Another useful way to gauge the relative importance of ancestry is its partial R^2 relative to the controls included in the specification. Taken together, the standard gravity terms, that is, the origin and destination fixed effects, distance, and latitude difference, explain 20.3% of the variation in the FDI Dummy. Adding ancestry to these variables in a simple OLS specification (shown in panel B) raises the R^2 by 9 percentage points, accounting for about about half as much variation as the combined explanatory power of the economic fundamentals reflected in the gravity terms (although this effect is not necessarily causal).[27]

The remaining columns of Table 3 probe the robustness of this result. The coefficient estimate remains remarkably stable and highly statistically significant across specifications. Column 4 adds a third-degree polynomial in distance and latitude difference to capture a potentially non-linear effect of distance; column 5 adds an interaction term for the contemporaneous 2010 migrations in the first stage (as in column 7 of Table 2); and column 6 adds a more stringent set of origin×destination-state fixed effects, exploiting only variation within US states. All of these variations leave our coefficient of interest virtually unchanged.

3.4 The Communist Natural Experiment and Robustness

The main potential challenge to our approach is that, despite our efforts, confounding factors that make a given destination more attractive for both migration and FDI from a given origin country may still, in some complicated way, be correlated with our instruments, although they only use information about migrations from other continents and to other census regions. In this section, we address this challenge using a natural experiment and a set of alternative instrumentation strategies. We then further corroborate our identifying assumption and demonstrate that our results are robust to a wide number of variations in our empirical approach.

Communist Natural Experiment. We begin by combining our instrumental variables with a natural experiment that allows us to focus on changes in FDI and changes in ancestry, similar to a difference-in-difference approach: The periods of economic isolation between the United States and communist countries during parts of the 20th century. These periods are

[27] Instead adding our nine simple interactions to the standard gravity terms, thus running the most parsimonious reduced form, raises the R^2 by 1.5 percentage points, and adding them in combination with the five principal components raises the R^2 by 2 percentage points. These numbers are a lower bound on the importance of common ancestry for FDI, since it only accounts for the part of the causal effect of ancestry which is picked out by our instruments.

1918-90 for the Soviet Union, 1945-80 for China, 1975-96 for Vietnam, and 1945-89 for Eastern Europe (the non-Soviet members of the Warsaw pact). They provide a useful experiment since practically no FDI existed between the United States and each of these countries at the end of each of these periods of isolation,[28] and defectors from communist countries arriving in the United States during the period of isolation would plausibly not have expected to be able to conduct FDI or otherwise interact economically with their countries of origin.

Table 4 shows estimates of (1) for each of these countries or sets of countries, using as excluded instruments only migration waves that occurred during the period of isolation. This specification offers two advantages. First, we can confidently assume the prospect of FDI, outlawed for political reasons, did not drive migrations during those periods (ruling out reverse causality). Second, the specification is similar to a difference-in-difference: It measures how cross-sectional variations in ancestry driven only by the inflow of migrants over a period of exclusion explain changes in FDI, from zero during the exclusion period to its current level in 2014. For all countries, we find a large causal impact of ancestry on FDI: places that (for exogenous reasons) received more defectors from Communism are more likely to take advantage of economic opportunities arising in these countries after the period of isolation. The estimated coefficients are statistically significant for the Soviet Union, China, and Eastern Europe. The coefficient is not statistically significant for Vietnam, most likely because most migration from Vietnam occurred before or after the relatively short 20 year period of isolation. Pooling across all former Communist countries, we find a coefficient very close to that of our standard specification in Table 3 (0.234, s.e.=0.098). The fact that we find similar results in these more restrictive natural experiments suggests that reverse causality does not drive our baseline results and our exclusion restriction is likely valid.

Alternative Instruments. The remaining challenge to our approach is that a common unobserved characteristic of destinations in two different census regions, correlated with FDI today, may still have disproportionately caused large groups of migrants from two origins on two different continents to *simultaneously* migrate to the same destinations across census regions. As a simple way of addressing this concern, we now modify the construction of our instruments to exclude migrations from countries that tended to push migrants towards the United States at the same time as a given origin, thus excluding any variation stemming from such simultaneity in the timing of the push factor.

To that end, we calculate for each pair of origin countries the correlation in the aggregate flow of emigration to the US over time. When calculating the pull factor for origin country o at time

[28] See the UNCTAD time series for the stock of FDI at www.unctadstat.unctad.org.

t in destination d, we then exclude all migrations to d at t from origin countries whose aggregate flow of migrations is correlated with o's at the 5% significance level. Panel A of Table 5 shows the coefficient estimate using this alternative set of instruments, $\{I^t_{o,-r(d)}(I^t_{-s(o),d}/I^t_{-s(o)})\}$. It is 0.197 (s.e.=0.020), and thus almost identical to our standard specification in column Table 3, again bolstering our confidence that no spurious correlations of unobserved factors across continents and census regions are driving our results.

The following row in the same panel also shows an additional variation of our instrument where we remove migrants from all adjacent states, rather than the surrounding census region, when calculating the pull factor as $I^t_{o,-adj(d)}(I^t_{-c(o),d}/I^t_{-c(o)})$. Again the coefficient estimate remains stable at 0.200 (s.e.=0.023). Appendix Table 7 shows additional reasonable variations of our leave-out categories, again yielding results very similar to those in Table 3.

In Panel B of Table 5 we present results using subsets of our instruments. The first row uses as instruments only the simple interactions from the first half of the time period covered by our migration data (1880-1930), the second row only from the second half (1970-2010). The coefficient of interest again remains stable at 0.209 (s.e.=0.037) and 0.175 (s.e.=0.021), respectively. The third row excludes migrations from the first census (1880) from the set of our instruments, as these might be more related to stocks than flows. The estimate of the coefficient of interest remains exactly equal to the coefficient estimate in our standard specification (column 3) in Table 3. Appendix Table 8 replicates our results using data on FDI from 2007 rather than 2014 and data on ancestry from 2000 rather than 2010, again with little effect on our results. We conclude that our results are not driven by specific vintages of migrations and that variations in ancestry have similar effects, regardless of whether they were induced by migrations pre or post World War II.

Ancestry and Immigration. According to our reduced-form model of migration, the number of migrants arriving at a given destination is a function of the economic attractiveness of the destination at the time (measured by the interaction of our pull and push factors) and the stock of descendants of migrants from the same origin (the recursive factor). To provide direct evidence these two forces are at work (the push $\times$ pull and recursive factors), we estimate the specification

$$I^t_{o,d} = \delta_o + \delta_d + \theta \; I^t_{o,-r(d)} \frac{I^t_{-c(o),d}}{I^t_{-c(o)}} + \lambda A^{t-1}_{o,d} + X'_{o,d}\gamma + \vartheta_{o,d} \tag{6}$$

for $t = 2000, 1990$ (the census years for which we have information on lagged ancestry), where we again instrument for $A^{t-1}_{o,d}$ using (4).

Column 1 of Table 6 estimates (6) with immigration $I^t_{o,d}$ in levels, and gives a coefficient on the interaction of the push and pull factors close to 1. This finding is what we would expect if newly arrived migrants were distributed uniformly on average. Columns 2 and 3 estimate (6) in logs for two time periods, 1990 and 2000. Across all specifications, both the coefficient on the push $\times$ pull interaction and on lagged ancestry are positive and significant predictors of current migrations.

Functional Form Exploration. In our main specification, we measure our ancestry variable, $A^t_{o,d}$, as the log of one plus the number of residents with foreign ancestry, measured in thousands. Our results are robust to a wide range of alternative functional form specifications.

In Appendix Table 9, we offer a formal test to justify our choice of functional form $A^{2010}_{o,d} = \ln\left(1 + \frac{1}{1000} Ancestry^{2010}_{o,d}\right)$. To that end, we perform a non-linear least squares estimation of

$$\mathbf{1}\left[FDI_{o,d} > 0\right] = \delta_o + \delta_d + \beta \ln\left(1 + \pi Ancestry^{2010}_{o,d}\right) + X'_{o,d}\gamma + \varepsilon_{o,d}, \tag{7}$$

again including the same covariates as in our simple specification from column 2 in Table 3. We find a point estimate of $\beta = 0.1683$ and $\pi = 0.0010$. This finding forms the basis for our choice of functional form applied throughout the paper. This functional form is convenient because it offers a compact way to model the non-linear impact of ancestry. For small ancestry ($Ancestry_{o,d} \ll 1000$), the function $\ln\left(1 + Ancestry_{o,t}/1000\right)$ is approximately linear in $Ancestry_{o,d}$. For large ancestry ($Ancestry_{o,d} \gg 1000$), it is concave and behaves approximatively like $\ln(Ancestry_{o,d})$. So for a small number of residents with foreign ancestry, the coefficient β in (1) measures the proportional impact of ancestry on the extensive margin of FDI; for a large number of residents with foreign ancestry, β is the elasticity of the extensive margin of FDI with respect to ancestry.

Appendix Figure 2 presents visual evidence the effect of ancestry on FDI is concave. We plot the average number of FDI links across centiles of the distribution of ancestry. The larger the number of residents with ancestry from country o in county d, the more likely an FDI link exists between them, and this positive effect of ancestry on FDI is highly concave.

In Appendix Table 10, we further explore the robustness of our results to alternative functional forms and replicate our results using measures of ancestry from the, 1980, 1990 and 2000 censuses, instead of 2010.

Appendix Table 11 shows our main results on the impact of ancestry on both the extensive and intensive margins of FDI is robust to varying the cutoff for ownership at which we consider a foreign firm to be a subsidiary or parent (from 5% to 50%). Further we replicate our results using a different level of geographic aggregation, Public Use Microdata Areas (PUMAs) instead of US counties, and find similar estimates.

Standard Errors. Appendix Table 12 shows our standard specification from column 3 of Table 3 using alternative standard errors. It reports robust standard errors; standard errors clustered by origin, destination, state, continent, and state-country cells. Among all these simple analytic standard errors, clustering by origin, as we do throughout the paper, is the most conservative choice. Doing so allows for arbitrary correlation in the error term across multiple destinations for a given origin, including for spatial correlation of errors. The specification we use throughout the paper thus allows for more flexible patterns of spatial correlation than for example the standard error correction as proposed by Conley (1999).

A possible concern is that errors may still be correlated across origin countries. However, standard errors designed to adjust for such correlations (clustering by county or state) are narrower, suggesting that any such patterns in the error structure are – if they were present – absorbed by the rich set of fixed effects and controls contained in our standard specification. Consistent with this view, the table also shows that standard errors double clustered at county-plus-country and state-plus-country level, as well as various block-bootstrapped standard errors are either narrower or only very marginally wider than those in our standard specification.

The conclusion that our results are robust to alternative standard error specifications carries over to the other main results of our paper. In Appendix Table 13 we show how alternative standard error specifications affect the results on the communist natural experiment, the intensive margin of FDI, and the effect of ancestry on immigration. For each of these results our inference remains unchanged when we cluster standard errors at the county, state, county-plus-country or state-plus-country level.

An alternative approach to detecting any tendency to over-reject the null is to reassign the "treatment" to a different set of outcome observations, in the spirit of Fisher's randomization inference procedure. We assign the interaction between push and pull factors for country o to randomly selected other countries and calculate the t-statistic on the coefficient of interest. Reassuringly, across 1000 random assignments, the t-statistic rejects the null of no treatment effect in favour of the alternative of a positive treatment effect in only 2.7% of the cases.

Inward and outward FDI. We estimate our standard specification from column 3 of Table 3 separately for inward FDI, where the outcome variable is a dummy equal to 1 if at least one firm in US county d is a subsidiary of a parent in foreign country o, and for outward FDI, where the outcome variable is a dummy equal to 1 if at least one firm in US county d is the parent of a subsidiary in foreign country o. The coefficients for both outward and inward FDI are positive, statistically significant, and close to our baseline estimates. We find a somewhat stronger impact of ancestry on outward FDI, $\beta_{out} \approx 0.2$, than on inward FDI, $\beta_{in} \approx 0.15$, although both coefficients are not statistically distinguishable from each other.

Placebo Test. Our next robustness check uses a placebo treatment to assess whether our instrument reliably isolates push factors that are specific only to one country, or is correlated with omitted variables that affect FDI with other countries in a systematic fashion.

The results are presented in Appendix Table 14. In panel A, we assign the interaction between push and pull factors for a given origin to a quasi-randomly selected other country: Its nearest neighbor in alphabetic order. To further check whether the same push factors might affect two countries in different continents, panel B assigns the interaction between push and pull factors for a given country to its nearest neighbor in alphabetic order in a *different* continent. Across all specifications, our placebo treatment is always statistically insignificant, and the point estimates are near zero. We conclude from this placebo test that our instrument is not picking up any artificial correlation (positive or negative) between the push factors for different countries.

Robustness in Sub-Samples & Heterogeneous Effects. Appendix Table 15 shows results from separate regressions for the five largest origins (by number of descendants, panel A), destinations (in total number of foreign ancestry, panel B), and for six individual sector groups (panel C), flexibly applying our instruments to individual origins, destination, and sectors. The impact of ancestry on FDI is similar across these sixteen specifications, bolstering our confidence that no outliers are driving our results. For example, the effect is 0.216 (s.e.=0.009) for Germany, 0.271 (s.e.=0.009) for Britain, and 0.165 (s.e.=0.024) for the manufacturing sector.

Figure 5 shows the heterogeneity of the effect of ancestry on FDI more broadly by running separate regressions for 112 origin countries (Panel A), the 100 largest US counties (Panel B), and 20 2-digit NAICS sectors (Panel C).[29] Each figure is a funnel plot of the country/country/sector-specific coefficients on ancestry against the reciprocal of their standard errors, where the circles reflect the relative shares in ancestry, US population and firms, respectively. The coefficients are significant at the 5% level for 84 out of 112 countries, 99 out of 100 counties, and 18 out of 20 sectors. This further demonstrates that our results are not driven by any specific subsample or outliers. These results also suggest that there is some heterogeneity in the size of the effect. We will exploit this heterogeneity when probing the mechanisms linking Ancestry to FDI.

3.5 The Intensive Margin of FDI

So far, we have studied the impact of ancestry on the extensive margin of FDI, the probability that at least one firm engages in FDI. We now turn to the impact of ancestry on the intensive

[29] Appendix Tables 16 and 17 show the results from separate regressions for all countries and sectors, respectively.

margin of FDI: Conditional on being positive, how large are FDI flows for a given size of the local population with a given foreign ancestry?

In Table 7, we estimate

$$\ln FDI_{o,d} = \delta_o + \delta_d + \kappa A_{o,d}^{2010} + X_{o,d}' \gamma + \zeta_{o,d}. \tag{8}$$

where $FDI_{o,d}$ corresponds to various measures of the volume of FDI between o and d and where we instrument $A_{o,d}^{2010}$ with the same first-stage equation (4) as earlier. Because of the log specification, cases of zero FDI will automatically be dropped from our sample. This creates a selection problem, as counties with non-zero FDI are likely to be systematically different from those with zero FDI. To correct for this potential selection bias, we implement a simple Heckman (1979) correction. We first estimate an IV probit regression for the extensive margin of FDI

$$\rho_{o,d} = \Pr\left(FDI_{o,d} > 0 | observables\right) = \Phi\left(\delta_o^{pr} + \delta_d^{pr} + \beta^{pr} A_{o,d}^{2010} + X_{o,d}' \gamma^{pr}\right), \tag{9}$$

where $A_{o,d}^{2010}$ is again instrumented as in equation (4). We extract an estimate for $\hat{z}_{o,d} = \Phi^{-1}\left(\hat{\rho}_{o,d}\right)$, the predicted latent variable that determines non-zero FDI. We then include an inverse Mills ratio term, $\hat{\mu}_{o,d} = \varphi\left(\hat{z}_{o,d}\right) / \Phi\left(\hat{z}_{o,d}\right)$, within our set $X_{o,d}$ of controls in the intensive margin equation (8), where φ and Φ denote respectively the p.d.f. and c.d.f. of the normal distribution. This correction for selection, the extensive margin of FDI, is similar to the procedure in Helpman et al. (2008) for international trade.[30]

We use various measures for the volume of FDI. In panel A of Table 7, we count the total number of FDI relationships, that is, the sum of the number of firms in d which are either parent or subsidiary of a firm in o and the number of firms in o which are parent or subsidiary of a firm in d. In panel B, we only count the number of firms in d which are a subsidiary of a firm in o, a measure of inward FDI. In panel C, we measure the total local employment in county d at

[30] We use the Heckman (1979) correction suggested by Helpman et al. (2008) rather than the Poisson pseudo-maximum likelihood method of Silva and Tenreyro (2006) for its more explicit theoretical underpinning, and because running a PPML estimation with a very large number of fixed effects is impractical. Note that in the absence of a plausible excluded instrument for the selection equation, our Heckman (1979) correction is identified primarily off of the functional form of the inverse Mills ratio. Note also that Helpman et al. (2008) correct for both the selected presence of zeros, as well as for the unobserved selection of which firm engages in foreign activities, export in their case. We only correct for the presence of zeros, not for the selection of firms, for three reasons. First, we are not interested in how ancestry affects the volume of FDI of one individual firm but rather in how ancestry affects the *total* volume of FDI between a US county and a foreign country, unlike Helpman et al. (2008) who are interested in how various covariates affect the export of one individual firm. Second, we directly use firm-level data, so that we do not require an explicit correction for firm selection. Finally, at the very fine level of geographic disaggregation we use – US counties versus entire countries in Helpman et al. (2008) – the simple structural model they use to motivate their correction for firm selection is unlikely to be appropriate.

subsidiaries of firms in o, giving us a measure of the impact of inward FDI on local employment.

Across all specifications, we find a positive impact of ancestry on the volume of FDI. The effect of ancestry on the intensive margin of FDI, the coefficient κ in equation (8), is large and significant across most specifications. Furthermore, the size of these effects is economically significant. For example, doubling the number of residents in county d who report ancestry from country o (from the mean, 316, to 632) increases the number of FDI relationships by 6.5% and local employment at subsidiaries of foreign firms by 7.3%.[31]

With all measures of the volume of FDI, correcting for selection using our Heckman type procedure leads to a lower estimated impact of ancestry on the volume of FDI (column 4).[32] In Panel C the impact of ancestry becomes insignificant but remains positive. Overall, the results in this panel are likely prone to measurement error as employment data is missing for many US subsidiaries. However when we re-run the same specification for employment at subsidiaries in the origin (where we have data for half of all firms) the coefficient estimates are very similar, for example, (0.303, s.e.=0.194) in column 3.

Figure 6 illustrates these results graphically by estimating equation (8) using data only for Germany and Britain (top parts), and LA and Cook counties (bottom parts). Each graph shows a conditional scatterplot of the number of subsidiaries as a function of ancestry. They all show a positive and significant slope close to the corresponding full-sample estimate in column 3 of Table 7 and no obvious outliers.

The conclusion from Table 7 is that foreign ancestry affects both the extensive and intensive margins of FDI. More descendants of foreign migrants increases the likelihood that local firms engage in FDI, the number of firms that do so, and the local employment by foreign-owned firms.

3.6 Quantifying the Effect of Ancestry on FDI

Having estimated the impact of ancestry on FDI, we illustrate the quantitative implications of our findings using two thought experiments. First, we estimate how investment relations between US counties and China might have evolved if Chinese migrants had not been effectively barred from entering the United States between 1882 and 1965. Second, we report how FDI relationships between Los Angeles and the world might have evolved if Los Angeles had had an

[31] Using $\hat{\kappa} = 0.326$ in panel C, column 3 of Table 7 in equation (8), we have: $\frac{Employment_{o,d}[Ancestry_{o,d}=2\times 316]}{Employment_{o,d}[Ancestry_{o,d}=316]} - 1 = \exp\left(0.326\left(\ln\left(1+\frac{2\times 316}{1000}\right) - \ln\left(1+\frac{316}{1000}\right)\right)\right) - 1 \approx 0.073$.

[32] The number of interacted fixed effects in column 2 is too large for a probit estimation of the extensive margin of FDI to be computationally feasible. Moreover, Greene et al. (2002) show that that probit regressions tend to give biased estimates in the presence of a large number of fixed effects. For both reasons, in column 4, we implement the Heckman correction in the simple specification with fixed effects only for origins and destinations.

influx of migrants in the 1800s similar to that resulting from the San Francisco Gold Rush. These thought experiments are not meant as formal counterfactuals, but merely as illustrations of the magnitude of the long-term effect of immigration policies on FDI implied by our estimates.

The Effect of Chinese Exclusion. The US government passed the Chinese Exclusion Act into law in 1882 in response to increased immigration from China, essentially closing the United States to legal immigration of laborers from China. In 1943, it was replaced by the Magnuson Act, which allocated a quota of 105 immigrants per year from China, and was in effect until 1965, when the removal of the quota system allowed for large-scale Chinese immigration for the first time. We refer to the entire period from 1882 through to 1965 as the period of "Chinese Exclusion." How different would the ancestry composition and FDI of US counties be today had it not been for Chinese Exclusion?

To answer this question we require an estimate for the impact of Chinese exclusion on the number of immigrants from China. We use our own data to derive a rough estimate. This is by no means a structural estimate, only a rough quantification. We aggregate our immigration data at the time $\times$ census-region $\times$ origin level and run a regression of the form $I_{o,r}^t = \delta_{t,r} + \delta_o - \xi \cdot D_{China}^t + \nu_{t,o,r}$, where D_{China}^t is a dummy equal to 1 if $o = China$ and $t \in [1882, 1965]$, and $\delta_{t,r}$ and δ_o are time$\times$census region and origin fixed effects, respectively. The coefficient ξ can then be interpreted as the average negative impact of the Chinese Exclusion Act on immigration from China. Denoting its estimate as $\hat{\xi}$, we then calculate a hypothetical time path of immigration in the absence of Chinese exclusion as $\tilde{I}_{o,r}^t \equiv I_{o,r}^t + \hat{\xi} \cdot D_{China}^t$. It suggests that the United States would have received 1.8 million additional Chinese immigrants during the period of exclusion.

Given this hypothetical time path of immigration we can then use our estimates from Table 2 to predict the change in ancestry as $dA_{o,d} \equiv \sum_t \hat{\alpha}_t \cdot \left(\tilde{I}_{o,-r(d)}^t - I_{o,-r(d)}^t\right) \frac{I_{-c(o),d}^t}{I_{-c(o)}^t}$, where $\hat{\alpha}_t$ are the estimated first-stage coefficients. The hypothetical change of FDI relations with China at the county level is $d\Pr\left[FDI_{o,d} > 0\right] \equiv \hat{\beta} \cdot dA_{o,d}$, where $\hat{\beta}$ is the estimated second-stage coefficient in a specification as in column 3 in Table 3, excluding the principal components to be consistent with the above described methodology to predict hypothetical levels of ancestry.[33]

These calculations suggest that the increase in Chinese migration would have been highly unequally distributed, translating into heterogenous changes in the incidence of FDI relationships with China. The map in Figure 7 depicts the expected change in the probability of positive FDI with China, $d\Pr\left[FDI_{China,d} > 0\right]$. The absence of Chinese exclusion would have resulted in substantially stronger FDI ties with the Northeast, the Midwest and the Southwest. The bar

[33] Dropping the principal components from this specification has only a negligible effect on the coefficient of interest which rises only sightly from 0.187 (s.e.=0.024) to 0.188 (s.e.=0.023).

graph depicts the fraction of counties within a state which have positive FDI with China in 2014, and the predicted change in this measure of the extensive margin of FDI linkages, i.e. the unweighted average of $d \Pr \left[FDI_{China,d} > 0\right]$ across counties within the state. To save space, the graph shows only the ten states with the highest predicted change. For example, we predict that in the absence of Chinese exclusion, the proportion of counties with an FDI link to China would have doubled in New York, and increased by 60% in Massachusetts and Illinois.

Los Angeles Gold Rush. To similarly gauge the magnitude of the estimated intensive margin effects, we derive predictions on the intensity of FDI relationships between Los Angeles county and the world under the hypothetical scenario that Los Angeles had experienced a Gold Rush similar to that in San Francisco. In particular, we derive predictions on the intensity of FDI relationships with the world if the number of immigrants pre-1880 had been fivefold the actual number of immigrants to Los Angeles. Table 8 presents the results of this thought experiment for the 10 foreign countries with the largest predicted change in their ancestry group in Los Angeles in 2010. Columns 1 and 2 show the actual number of individuals of each ancestry in Los Angeles County in 2010 and the total number of FDI links recorded in our data between Los Angeles County and the respective origin countries. Columns 3 and 4 present the predictions of our thought experiment based on the IV specification corresponding to column 2 of Table 7, again without the principle components as instruments. A Gold Rush in Los Angeles would have resulted in sizeable effects on the intensity of FDI with those countries that were the source of immigration pre-1880: The intensity of FDI between Los Angeles County and Germany and Ireland would have increased by around 60%. Column 4 presents the predicted absolute change in the size of the ancestry groups, based on a reduced form regression analogous to column 9 of Table 2 with *Ancestry 2010* (in levels) as outcome variable, again excluding the principle components. It suggests that the population of Irish and German descent living in Los Angeles County today would each be counting about 60,000 more individuals.

4 Understanding the Effect of Ancestry

So far, we have documented a quantitatively large causal effect of common ancestry on FDI. We now turn our attention to the mechanism linking ancestry to FDI. Existing research suggests that migrations and common ancestry may affect FDI either by making the destination more "similar" to the origin in terms of preferences and skill endowments or by generating social capital that creates an absolute advantage for firms to operate in both the origin and destination country.

In the first category, Atkin (2010) and Bronnenberg et al. (2012) suggest that descendants of migrants may share the same tastes for foods and other products as consumers in their origin country. To the extent that these tastes persist over generations, firms that cater to those tastes may serve both markets. Similarly, we might suspect that migrants may bring with them a specific skill-mix or other factors abundant in their origin country, so that firms can more easily outsource production, using the same skill-mix at home and abroad.

In the second category, common ancestry may create an absolute advantage in conducting FDI for local firms, because social ties between populations in the origin and the destination provide social collateral that helps to enforce contracts when the legal system of o or d is imperfect (Greif, 1993; Besley and Coate, 1995). Alternatively, migrants and descendants of migrants from a given origin may have a privileged access to information (Varian, 1990; Stiglitz, 1990): A more intimate knowledge of the business environment in their origin country and social ties or language skills that provide access to information about business opportunities and practices at a lower cost.

The following section presents evidence testing auxiliary predictions of these distinct channels through which common ancestry may be driving FDI. The collection of these results suggests that ancestry affects FDI primarily because it creates an absolute advantage for local firms by attenuating information frictions. Our most direct evidence in favor of this view comes from a novel measure of information demand constructed from Google Trends data. Using this measure, we show that common ancestry significantly increases the demand for information about the politics and culture of the origin country, and that variation in this demand for information across locations within the United States fully accounts for the effect of ancestry on FDI. We then further probe the mechanism linking the flow of information to FDI and find evidence consistent with the view that information is transmitted internationally through networks created by common ancestry. These links appear to be long-lasting, where the presence of second and third generation descendants of immigrants is as effective as the presence of first-generation immigrants. We also find that descendants of migrants are significantly more likely to use the language spoken in the origin country, suggesting that links to the origin country may be facilitated or maintained by the inter-generational transmission of language and culture.

4.1 Channel Linking Ancestry to FDI

Panels A-C of Table 9 present evidence on the "similarities" hypothesis. Panel A shows the IV coefficient of ancestry on FDI separately for firms producing final goods and for firms producing intermediate inputs.[34] If common tastes were the explanation behind the positive impact of

[34] To separate firms into final-goods producers and intermediate-goods producers, we use the upstreamness index from Antràs et al. (2012). A sector is labelled as final goods (intermediate input) if its upstreamness index

ancestry on FDI, we would expect its impact to be stronger for final goods, for which consumers' tastes matter directly, than for intermediate inputs, for which tastes matter little. We find on the contrary that there is no statistical difference between final goods and intermediate input producers; if anything, the point estimate is slightly larger for intermediate input producers than for final goods producers. Panel B shows similar results for inward FDI only, where the local tastes of descendants from country o may plausibly matter more.

Panel C of Table 9 shows the IV coefficients of a regression of ancestry on measures of sectoral similarity between the origin and the destination. For each origin-destination pair, we compute the rank and cosine correlation of the shares of employees in 127 manufacturing sectors.[35] Both correlations increase with the similarity of the allocation of employees across sectors between the origin and destination. If skill similarities were the explanation behind the positive impact of ancestry on FDI, we would expect common ancestry to cause an increase in these measures. We find, on the contrary, that ancestry has no discernible impact on sectoral similarity. This non-result—migrations do not cause a convergence in the sectoral composition of employment—is robust to using alternative measures of sectoral similarity, as well as alternative data sources.[36]

Panel D of Table 9 examines the contract enforcement channel. If contract enforcement were the explanation behind the positive impact of ancestry on FDI, we would expect the impact to be stronger for countries where the quality of the local judiciary is weaker, as ethnic ties would substitute for weak institutions. We find the opposite result in columns 1 (extensive margin) and 2 (intensive margin), where we add the interaction of ancestry with a measure of the origin country's judicial quality taken from Nunn (2007) to our simple IV specification of column 2 in Table 3. The coefficients show that the effect of ancestry on FDI is significantly larger for countries with good institutions than for countries with bad institutions, suggesting that common ancestry and good institutions are complements rather than substitutes.

We conclude from Table 9 that the data show no evidence for the "similarities" hypothesis and that our results are also not driven by ethnic ties substituting for poor contract enforcement.

is below (above) 2.

[35] We use county and country level industry data from the Bureau of Labor Statistics (BLS) and the UN Industrial Development Organization (UNIDO), respectively. Correlations are calculated for 2006, the year with the largest availability of the data (28 countries). Using this smaller sample of countries, the coefficient on ancestry in our standard specification linking ancestry to FDI is 0.348 (s.e.=0.046).

[36] Results are unchanged whether we use rank or cosine correlation, or when we repeat the same exercise using the OECD Stan country level industry data.

4.2 Information Demand

To directly test the remaining hypothesis that common ancestry affects FDI by reducing information frictions, we require data on the flow of information from foreign countries to US destinations. Because such data is not readily available we construct a simple index of differential information demand using data from internet searches.[37] The Google Trends portal provides data on the relative popularity of different search terms across 210 US metropolitan areas ("media markets" according to the Nielsen DMA definition).[38] For each search term i and US metro area d, the portal returns an index number that is equal to the normalized share of searches conducted in d that contain the search term i:

$$G(i,d) = \left[100 \frac{share(i,d)}{max_\delta\{share(i,\delta)\}} \mathbf{1}[\#(i,d) > T]\right],$$

where $share(i,d)$ is the share of searches in d that contains i and $\mathbf{1}[\#(i,d) > T]$ is an indicator function that is one if the absolute number of searches containing i in d is greater than some threshold number (Stephens-Davidowitz and Varian, 2015; Liang, 2017).[39] Thus, $G(i,d)$ is equal to 100 in the metro area in which the largest share of searches contain i and a positive number smaller than 100 in all other metro areas that have a sufficient number of searches containing i.

To measure the relative demand in a given metro area for information about a given origin country, we compile a list of the five most prominent actors, athletes, musicians, and politicians for each origin country. We automate this process by searching for "notable [country] [category]" and then extracting the five top suggested names from the Google Answer Box, a feature of Google search that automatically suggests the most often clicked names associated with this kind of query.[40] We then calculate our Information Demand Index as

$$IDI(o,d) = \frac{1}{20} \sum_p \sum_{i \in q(o,p)} G(i,d),$$

where $q(o,p)$ is the set of top five names for country o in category $p \in \{$actors, athletes,...$\}$. We

[37] We thank Jack Liang for writing his Bachelor Thesis at the University of Chicago on this topic.

[38] For other recent studies using this data source see Da et al. (2011), Stephens-Davidowitz (2014), Kearney and Levine (2015), and Baker and Fradkin (2016).

[39] As a result of this cutoff, our index tends to assign a value of zero to small origins-destination pairs (38% of our sample). For this reason we focus our attention on the 100 largest origin countries by 2015 population and do not attempt to construct it for all present-day origin countries.

[40] See Appenix Table 21 for the full list of search terms used for Germany and Italy as examples. Liang (2017) shows evidence that search terms with multiple meanings (where for example two prominent politicians from two different countries share the same name) do not impact our results, and gives a detailed account demonstrating that the Google Answer Box generally delivers relevant search terms for each country.

implement this procedure for the 100 largest foreign countries by 2015 population. To facilitate the interpretation of results, we standardize this measure to a unit standard deviation. (See Appendix A.4 for details on our procedures.)

Panel A of Table 10 shows the results of regressions of our differential information demand index on ancestry (instrumented as in (4)), and our standard set of controls at the metropolitan area - country level. Column 1 documents a large causal effect of ancestry on information demand (0.871, s.e.=0.257), where doubling the number of descendants of migrants from a given origin relative to the mean is associated with a 0.19 standard deviation increase in our index of demand for information about prominent actors, athletes, musicians, and politicians in that origin.[41][42] Columns 2 and 3 show that this effect remains positive and statistically highly significant even when we control for the foreign-born population, that is, the demand for information from first-generation immigrants from that origin, and when we condition only on ancestry in 1980 (rather than 2010). Taken together, these results suggest that the differential interest in information about the origin country persists among the US-born descendants of first-generation migrants. (We will show formally below that the effect of ancestry on FDI exhibits a similar persistence over generations and does not require a sustained inflow of new migrants from the origin country.)

The remaining columns show that this persistent interest in the origin country is not limited to politics, but is similar across our four sub-indices for demand for information about actors, athletes, musicians, and politicians. Common ancestry thus engenders a broad-based interest in information about the origin country that may plausibly generate a comparative advantage for local firms to acquire information about the origin country and vice versa.

The longevity of the effect of ancestry on differential information demand suggests that immigrants pass traits to their descendants that facilitate or encourage the exchange of information with their origin countries, such as social ties to family or friends, or knowledge of the origin country's language and culture. Although data on such traits is generally hard to come by at the required level of disaggregation, Panel B shows one additional piece of evidence from the US census: the use of foreign languages. The table again shows systematic evidence that a larger community in county d with ancestry from country o has a positive and significant impact on the number of residents in d who speak o's language at home (column 1). This effect persists if we remove from d's population all foreign-borns, since they 'mechanically' speak the foreign language from their home country (column 2). Columns 4-6 present the results from separate

[41] Following the same calculation as above we have $0.871\left(\ln\left(1+\frac{632}{1000}\right)-\ln\left(1+\frac{316}{1000}\right)\right)=0.19$.

[42] Complimentary evidence to ours is provided in Bailey, Cao, Kuchler, Stroebel, and Wong (2016), who find that recent immigrations from origin country o to US county d, as well as the composition of ancestry across US counties d, are close correlates of a measure of social ties derived from Facebook friendship links.

regressions for large non-English languages: Spanish, Arabic, Chinese and Hindi.[43] The effect of ancestry on foreign languages spoken is positive and statistically significant for all four.

4.3 Ancestry, Information Flow, and FDI

We next ask whether these differences in information flows can account for the the link between ancestry and FDI. We can get a superficial answer to this question by running our standard specification relating ancestry to FDI (column 2 in Table 3), while controlling for our information demand index. We find that the coefficient on ancestry drops to close to zero and becomes statistically insignificant (-0.025, s.e.=0.028), while the coefficient on information demand remains positive and highly statistically significant (0.078, s.e.=0.013). By contrast, similarly controlling for sectoral similarity and the various other channels probed above has no effect on the causally identified coefficient on ancestry (see Appendix Table 20). In this sense, our results suggest that the effect of ancestry on FDI indeed transmits itself through the information channel. To corroborate this finding, we now probe in more detail the mechanisms through which information transmission may generate an absolute advantage in conducting FDI.

Network effects of common ancestry. Theoretical models emphasize the role of networks in facilitating the percolation of information across international borders (Arkolakis, 2010; Chaney, 2014). This class of models tends to predict effects that are concave (as all the relevant information is gradually exhausted), weaker if many people from the same or neighboring origins live in the surrounding area (as relevant information is more likely to have already percolated), and stronger for destinations that are more ethnically diverse (due to a hub-effect, where for example Poland and Venezuela do not communicate directly but through a hub in New York). We test each of these reduced-form predictions.

We have already shown that the relationship between ancestry and FDI is concave as part of our robustness checks in section 3.4 (see Appendix Figure 2). By the same token, information percolation on a network suggests negative spillovers from neighboring regions: If many people with ancestry from o live in locations surrounding d, or if many people in o have an ancestry from countries adjacent to o, it is more likely that relevant information about investment opportunities has already reached the firm, so that the marginal impact of ancestry on FDI is mitigated. In Table 11, panel A, column 1, we use our simple specification from column 2 in Table 3, but add the total number of descendants of ancestry o at the state level. We are able to identify the effect of this spillover at the state level by aggregating our instruments from equation (4)

[43] Appendix Table 19 presents the regression coefficients of ancestry on foreign languages for the 50 largest linguistic groups.

to the state level and including them as a separate set of instruments in the specification, such that both endogenous variables are identified. The coefficient on our measure of ancestry at the state level is -0.020 (s.e.=0.010), suggesting a negative and significant spillover. In column 2 we include a measure of the number of descendants from the closest neighboring country, and we again find a negative and highly significant spillover effect.[44] On balance, our findings are thus consistent with the presence of negative spillovers within co-ethnic networks, so that a large Polish community in a given county has a lower effects on FDI with Poland if the state overall contains a large Polish contingent, or if that county also hosts a large Czech community.

In columns 3 and 4, we repeat the same estimation for the intensive margin of FDI, but in this much smaller sample we lack the statistical power to identify a consistent pattern.

An additional prediction of network-based models is the existence of hubs, where exceptionally well-connected locations also mediate economic activity between distant origins that do not have sufficiently strong direct connections to each other. If such hub-effects were at work, we would expect the effect of ancestry on FDI to be larger in more ethnically diverse destinations. In panel B of Table 11 we explore this possibility by studying the heterogeneity of the effect of ancestry on FDI across US destinations, interacting ancestry with a measure of ethnic diversity (measured as 1 minus the Herfindhal index of ancestry shares). The table shows that the coefficient on this interaction is indeed positive and significant, both at the intensive and the extensive margin (column 2 and 4). By contrast, we find no effect on the interaction between ancestry and the share of the population that are of foreign descent (column 1 and 3). This suggests that the effect in columns 2 and 4 is indeed picking up the role of ethnic diversity, and not simply the effect of a large population share with foreign descent.

Our main conclusion from this set of results is that the patterns by which ancestry affects FDI are consistent with the auxiliary predictions of models of network effects, where information (or other effects of social capital) are transmitted internationally through networks created by common ancestry.

Cost of Information Transmission. If information frictions indeed were the explanation behind the positive impact of ancestry on FDI, we would also expect this effect to be stronger in relationships that suffer from higher costs of information transmission. For example, we might conjecture that information asymmetry is particularly large for distant countries or for countries that are themselves ethnically very diverse.

We confirm this prediction in the Panel C of Table 11. In all specifications, the coefficient on

[44] We determine the nearest adjacent country by creating country pairs, using a standard optimal non-bipartisan matching algorithm, such that the average distance between centroids of country pairs is minimised.

the interaction between ancestry and geographic distance is positive and significant, both for the extensive (columns 1 and 2) and intensive margins of FDI (columns 3 and 4).[45] Columns 2 and 4 also show some evidence that the effect of ancestry on FDI is larger for more ethnically diverse origins (a higher level of ethno-linguistic fractionalization as defined by Alesina et al. (2003)).[46]

Trade versus FDI. Further to the point above, we may expect reducing information frictions between an origin and a destination to have a larger impact on FDI than trade, because FDI (by definition) requires fixed investments in the foreign country and thus better access to local information than shipping goods abroad on a spot market. If common ancestry indeed facilitates FDI by reducing information frictions we would thus expect this effect to be more pronounced for FDI than trade. Table 12 tests this hypothesis, estimating the impact of ancestry separately for FDI (panel A), exports (panel B), and imports (Panel C). Because we do not have access to trade data at the firm level, we use instead data on trade flows between US states and foreign countries sourced from the US Census Bureau. We again instrument for the composition of ancestry as in equation (4), except that all variables are defined at the state, not county, level. To compare our results to the existing literature on migrations and trade, we focus our attention on the intensive margin, and correct for the selection bias due to zero trade using a Heckman correction. As conjectured, the impact of ancestry on FDI at the state-level is positive, significant, and larger than on trade, once we instrument and include both origin and destination effects (column 3).[47]

In fact, the effect of ancestry on trade becomes indistinguishable from zero in our preferred specification. Although we interpret this non-result with due caution due to the limited data available, it contrasts with earlier findings in the literature, started by the seminal contributions of Gould (1994) and Rauch and Trindade (2002) (using OLS), and the recent IV results of Cohen et al. (2015) for trade with Japan, and Parsons and Vezina (2016) for trade with Vietnam, that all find the presence of migrants facilitates exports. Our preferred specification shows no such positive and statistically significant impact of ethnic ties (ancestry) on international trade. A closer look at the data suggests two important features are essential in reaching this negative conclusion: When either a formal identification is missing (OLS in column 1), or no control for destination—US state—fixed effect is included (column 2), we erroneously find a positive and significant estimated impact of ancestry on trade. But when both are present (column 3 panels

[45] Once we account for this interaction, the interaction terms on genetic, linguistic, and religious distance, as defined by Spolaore and Wacziarg (2015), are statistically insignificant, suggesting geographic distance effectively summarizes alternative notions of distance in cultural space.

[46] Results are virtually identical when we consider outward FDI by itself.

[47] In unreported robustness checks, we find similar results for other years, or when restricting our analysis only to trade in manufacturing goods, where determining the final destination (origin) of an import (export) is less subject to measurement error, as well as for separate regressions on final goods and on intermediate inputs.

B and C), we find none.

4.4 Generational Effects

Having already shown in section 3.4 that historical migrations prior to World War II had causal effects on FDI that persist to the present day, and that historical migrations predict future migrations through a recursive factor, we now ask whether the effect of ancestry on FDI requires a sustained inflow of migrants from the same origin—or if it persists even after migration from that origin ceases. Table 13 compares the (causally identified) effect of ancestry to that of foreign born, that is, first-generation immigrants. Column 1 replicates our standard specification for comparison. Column 2 replaces our measure of ancestry in equation (1) with a measure of foreign born from a given origin alive in 2010, instrumenting as in equation (4). As expected, we obtain a positive and statistically significant coefficient on foreign born (the correlation between the two variables is 0.59). When we simultaneously include both endogenous variables in the specification, the coefficient on ancestry remains positive and statistically significant at the 1% level, whereas the coefficient on foreign born in 2010 is close to zero and insignificant in the OLS specification in column 3, the same pattern we observed for relative information demand demand in Table 10. In the IV specification in column 4 the coefficient turns slightly negative and marginally statistically significant.[48] We thus conclude that the presence of the descendants of immigrants continues to predict FDI even after migration from the origin ceases.

If anything, the (marginally negative) coefficient on foreign-born suggests that the effect of ancestry on FDI is slightly smaller for foreign-born than that of their descendants. (Because each foreign born also increase the number of individuals with foreign ancestry, the total marginal effect of foreign-born on FDI is still positive.) Using the number of foreign born in 1970 as a proxy for second-generation immigrants, column 6 repeats the same procedure as column 4, comparing the marginal effect of second-generation immigrants to that of the average descendant with foreign ancestry. This time, the coefficient on second-generation immigrants remains positive (albeit not significant) when we control for descendants of migrants with a foreign ancestry.[49][50] Although these specifications, disentangling the marginal effects of several endogenous variables,

[48]The Kleinbergen-Paap rk LM statistic on the excluded instruments is 18.211 with a p-value of 0.150. We are unable to reject the null that our instruments do not induce differential variation in the two endogenous variables, and therefore interpret any difference in the coefficient estimates with caution.

[49]The Kleinbergen-Paap rk LM statistic on the excluded instruments is 29.04 with a p-value of 0.007. We therefore have sufficient power to detect differences between the coefficient estimates on the two endogenous variables.

[50]These results continue to hold when we drop migrations from Mexico (the largest origin country in recent decades) from the sample.

should be interpreted with caution, they suggest the effect of ancestry on FDI develops over long periods of time, and possibly peaks with the second, but not the first generation of immigrants.

This latter finding is consistent with a set of microeconomic studies that show that only those individuals that advance to managerial or other positions of influence successfully establish business linkages to their origin countries (Aleksynska and Peri, 2014); and that it tends to be the second and third generations of immigrants, that achieve such advancement (Borjas, 2006; Algan et al., 2010). Simply put, to transmit information instrumental for the establishment of foreign investments, one must first have access to this kind of information and be in a position to act on it, which tends to require having reached a sufficiently high hierarchical status within the firm—a feat more likely to be achieved by the second than the first generation.

To conclude, we find a collage of evidence that migrations, and the distribution of ancestry that results from it, has a positive impact on FDI primarily because it reduces information frictions associated with foreign direct investment. We also find evidence consistent with network effects and the inter-generational transmission of traits that facilitate the flow of information between the origin country and the US destination. Two potential channels through which information frictions may be attenuated are differential demand for information about the origin country and the knowledge and use of foreign languages.

Conclusion

The economic effects of migration loom large in public debates about illegal immigration to the U.S. and the ongoing flow of migrants to Europe from places such as Syria, Afghanistan, and the Balkans. Much of the academic debate on the subject has focused on relatively short-term consequences, identifying effects of immigration on local labor markets and consumer prices (Card, 1990; Cortes, 2008). We add to this debate by showing causally identified evidence of an effect of migrations on the propensity of firms based in the areas receiving migrants to interact economically with the migrants' origin countries. This effect of ancestry on FDI explains an economically large share of the variation in patterns of FDI across US counties and states.

Our identification strategy uses 130 years of census data to isolate variation in today's ancestry composition of US counties that derives solely from the interaction of time-series variation in the relative attractiveness of different destinations within the United States with the staggered timing of factors that drove out-migration from the migrants' countries of origin. This approach allows us to generate four main insights.

First, we are able to causally identify and quantify the effect of ancestry on FDI in a setting with a high degree of external validity while guarding against a wide range of possible confounding factors, including unobserved origin and destination effects. We find that a doubling of a US county's residents with ancestry from a given foreign country relative to the mean increases by 4 percentage points the probability that at least one local firm engages in FDI with that country.

Second, the effect of ancestry on FDI is long lasting and appears to unfold over generations rather than years, where even the earliest migrations for which we have data going back to the 19th century significantly affect the pattern of FDI today.

Third, we find a range of results that show a positive effect of ethnic diversity on FDI. The most obvious of these findings is the strong indication of concavity in the number of descendants of migrants from a given origin, such that a more ethnically diverse population, combining many smaller communities from different origins, should generate more FDI than one large community of foreign descent. Further, we find negative spillovers both within states and between migrants from geographically proximate countries, such that a larger community of the same ethnic descent in surrounding counties or a larger community of descent from a neighboring country decreases the effect of ancestry on FDI. In addition, the effect of ancestry on FDI significantly increases with the diversity of the community of residents with foreign ancestry. Ethnic diversity may be a quantitatively important driver of FDI.

Fourth, we present direct evidence in support of the hypothesis that common ancestry affects FDI because it reduces information frictions, but not because it generates similar consumer tastes or factor endowments, or facilitates contract enforcement when legal institutions are poor.

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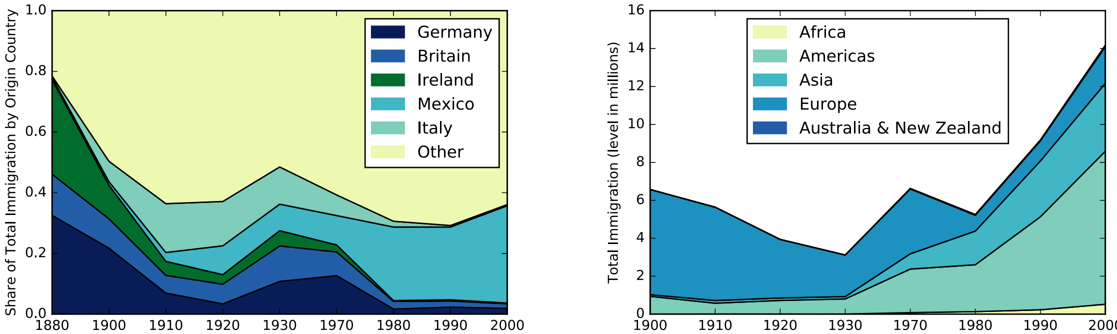
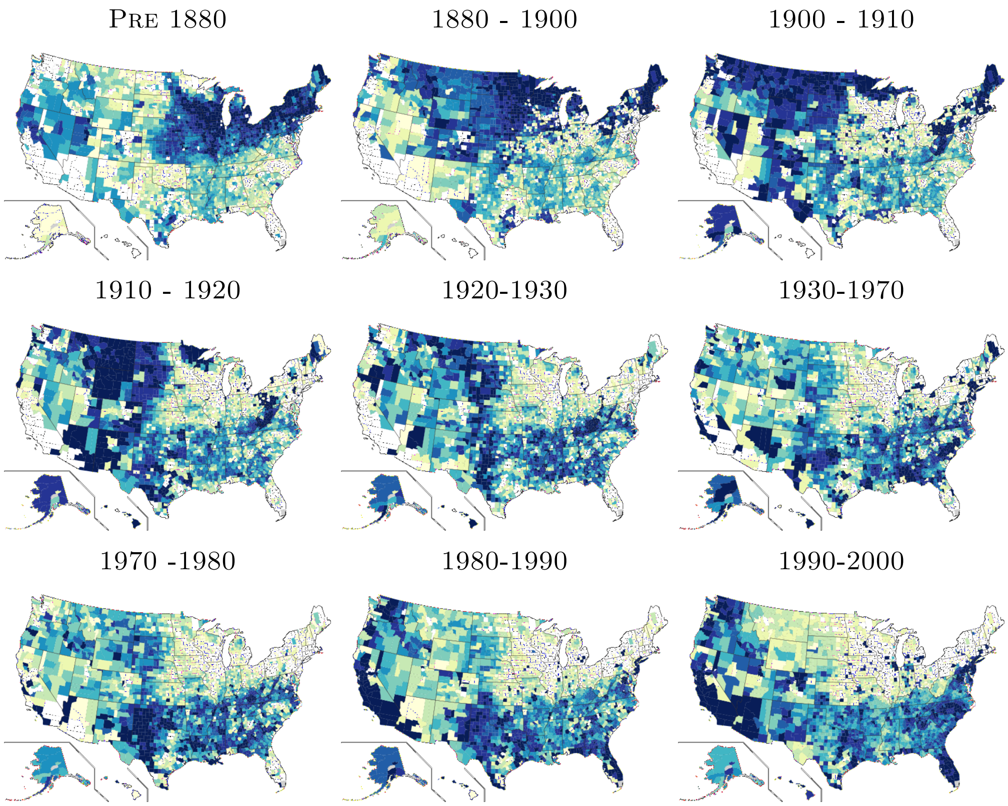
Figure 1: Origins of Immigrants to the United States, pre-1880 to 2000



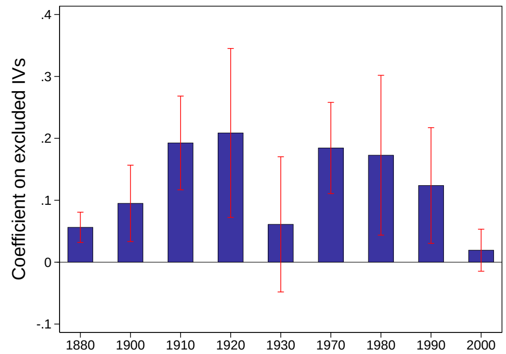
Notes: The left side depicts the share of total immigration to the United States in each census period for the largest five origin countries of US residents that claim foreign ancestry in the 2010 census: Germany, Britain, Ireland, Mexico, and Italy. The right side shows the the number of migrants (in millions) by continent of origin. See section 1 of the main text and appendix A.1 for details.

Figure 2: Destinations of Immigrants to the United States, pre-1880 to 2000



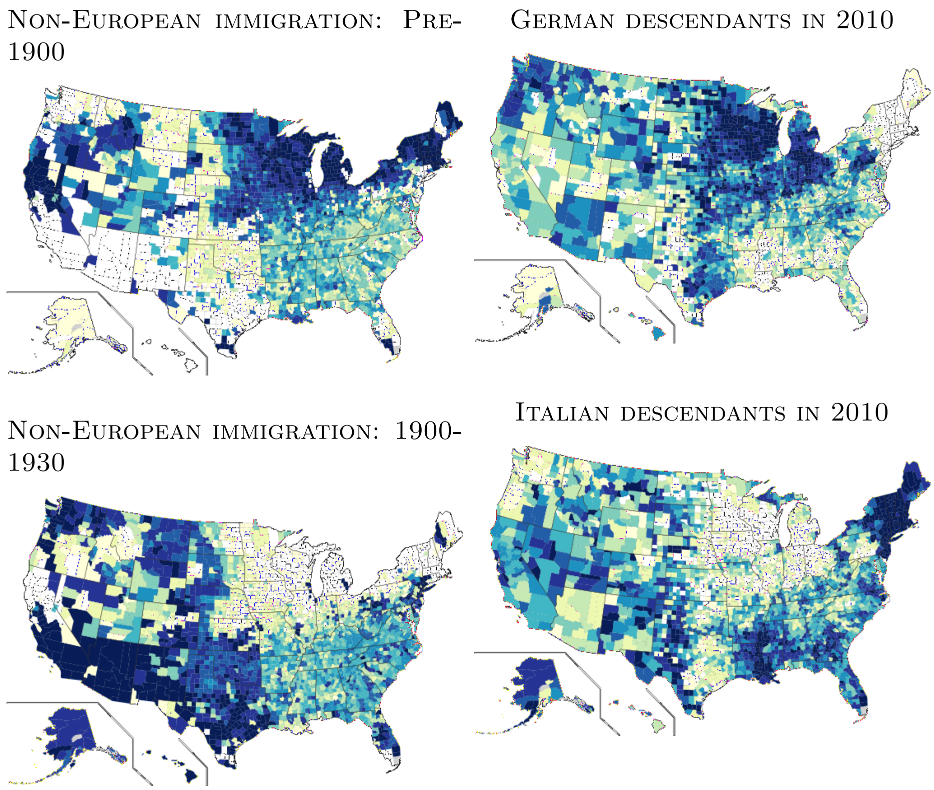
Notes: This figure maps immigration flows into US counties by census period. We regress the number of immigrants into US county d at time t, I_d^t, on destination county d and year t fixed effects, and calculate the residuals. The maps' color coding depicts the residuals' decile in the distribution of residuals across counties and within census periods. Darker colors indicate a higher decile.

Figure 3: First-Stage Coefficients



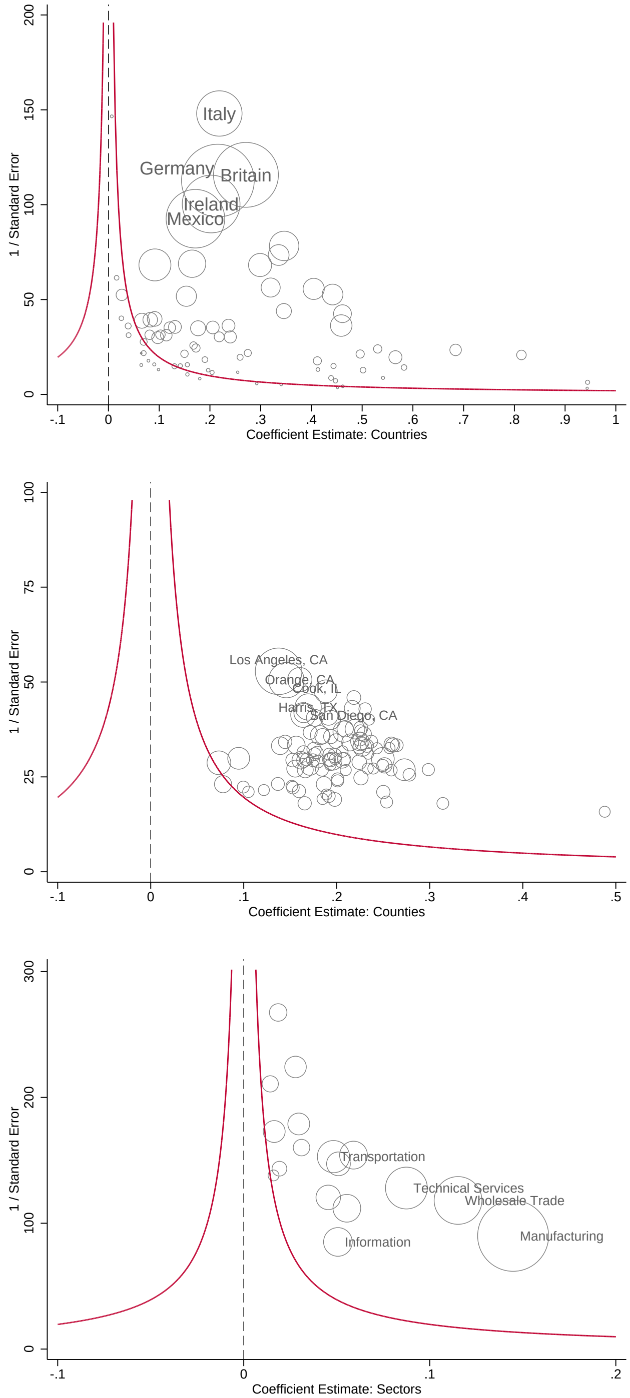
Notes: Coefficient estimates (bars) and 95% confidence intervals (lines) on the excluded instruments $\{I^t_{o,-r(d)}(I^t_{-c(o),d}/I^t_{-c(o)})\}_{t=1880,\ldots,2000}$ from Table 2, column 2. The dependent variable is Log Ancestry 2010. Robust standard errors are clustered at the origin country level.

Figure 4: Migrants and Ancestors:
The Cases of Germany Pre-1900 and Italy 1900-1910



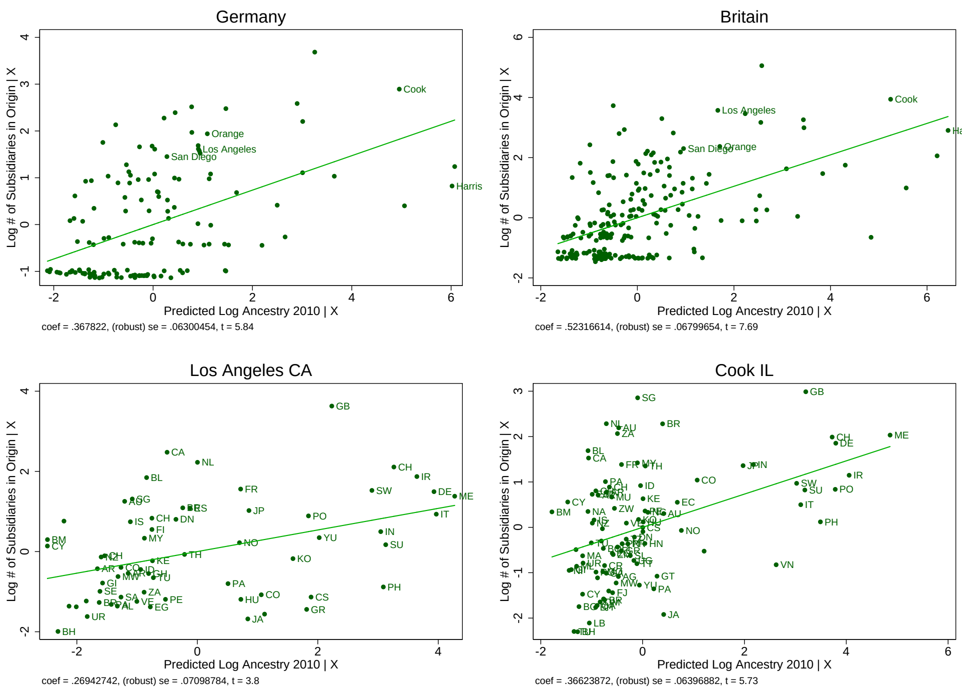
Notes: This figure contrasts Italian and German ancestry in 2010 (right panels), and non-European immigration patterns pre-1900 and 1910-1930 (left panel). The left two panels are created in the same way as the maps in Figure 2, restricted to non-European immigration and the two periods we consider (pre-1900 and 1910-1930). The right two panels plot the county level residuals from a regression of log ancestry in 2010 on county, Italy and Germany fixed effects on the sample of European countries. The maps' color coding depicts the residuals' decile in the distribution of residuals across counties. Darker colors indicate a higher decile.

Figure 5: Heterogeneous Effects across Countries, Counties, and Sectors



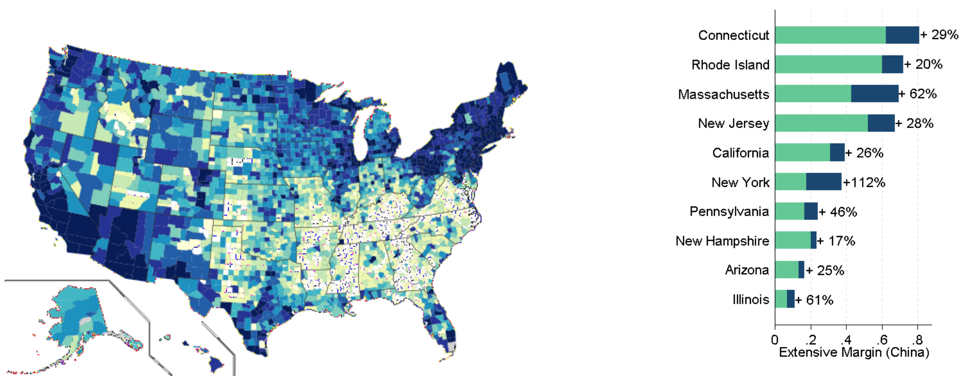
Notes: This figure shows funnel plots of the estimated coefficients and standard errors from separate IV regressions of the FDI dummy on Log 2010 Ancestry for each origin country (top), destination US counties (middle), and sectors (bottom). In all regressions, we use $\{I^t_{o,-r(d)}(I^t_{-c(o),d}/I^t_{-c(o)})\}_{t=1880..2000}$ and principal components as excluded instruments, and control for log distance as well as latitude difference. We plot the estimated coefficients (x axis) against the reciprocal of estimated standard errors on ancestry. The size of the circle is proportional to the size of country ancestry (top), the size of county population (middle), and the size of the sector (bottom). The imposed curve is $y = 1.96/x$ for positive x region and $y = -1.96/x$ for negative x region. Circles above the curve indicate statistically significant coefficients. See section 3.4 for details.

Figure 6: Ancestry and FDI: Germany and Britain; Los Angeles and Cook counties



Notes: The figure shows conditional scatterplots from regressions corresponding to column 3 of Table 7, but restricting the sample to one origin country only (top parts: Germany and Britain) or one destination county only (bottom parts: LA and Cook counties). The solid line depicts the fitted regression line. In each case, the regression controls for distance and latitude difference. The upper-left panel shows a conditional scatterplot from a regression of log # of subsidiaries in Germany for firms in each US county on predicted log 2010 German ancestry. The upper-right panel shows a similar scatterplot for British ancestry and the log # of subsidiaries in Britain. The bottom-left panel shows a conditional scatterplot from the corresponding regression for LA county, CA and the log # of subsidiaries of LA based firms in each origin country. The bottom-right part shows the same plot for Cook county, IL.

Figure 7: Thought Experiment: Removing the Chinese Exclusion Act



Notes: The map on the left depicts for each US county the predicted increase in the probability of having positive FDI relations with China in a counterfactual world where the "Chinese Exclusion" Act of 1882 had never been passed, that is, if Chinese immigration to the United States had not been discriminated against between 1882 and 1965. Darker colors indicate larger increases. The bar graph on the right shows the fraction of counties within each state with FDI relations with China (light color) and the predicted increment in the fraction of counties with FDI relations with China (dark color), which we calculate as the unweighted average of $d\Pr\left[FDI_{China,d} > 0\right]$ across counties in a given state. We also provide the size of this increase relative to the actual fraction in percentage terms. The histogram only depicts the ten US states with the largest change. Interpretation: If Chinese immigration to the United States had not been outlawed, the fraction of counties in Massachusetts with FDI relations to China would have increased from 43% to 69%, a 62% increase. The details of this calculation are section 3.6.

Table 1: Summary Statistics

	All	Ancestry > 0		
		All	Bottom Quintile	Top Quintile
	(1)	(2)	(3)	(4)
Panel A: Origin-destination pairs				
FDI Dummy	0.018	0.031	0.003	0.127
	(0.132)	(0.173)	(0.052)	(0.333)
Ancestry 2010 (in thousands)	0.316	0.575	0.000	2.852
	(5.962)	(8.036)	(0.000)	(17.790)
Immigrants between 1990-2000 (in thousands)	0.023	0.042	0.000	0.199
	(1.070)	(1.443)	(0.001)	(3.221)
Immigrants between 2000-2010 (in thousands)	0.020	0.036	0.000	0.173
	(0.665)	(0.898)	(0.002)	(1.999)
Foreign-born 2010 (in thousands)	0.069	0.125	0.000	0.594
	(2.749)	(3.708)	(0.004)	(8.267)
Geographic Distance (km)	9,122.393	8,397.379	9,142.553	7,463.619
	(3,802.105)	(3,763.718)	(4,299.572)	(2,986.233)
Latitude Difference (degree)	19.440	16.319	18.915	13.750
	(11.312)	(10.902)	(11.388)	(8.807)
# of FDI Relationships	0.196	0.351	0.028	1.620
	(5.486)	(7.396)	(1.461)	(16.294)
# of Subsidiaries in Origin	0.033	0.060	0.003	0.270
	(1.345)	(1.813)	(0.281)	(3.844)
# of Parents in Destination	0.015	0.027	0.001	0.123
	(0.399)	(0.537)	(0.103)	(1.175)
# of Workers Employed at Subsidiary in Origin (in thousands)	0.039	0.069	0.010	0.319
	(4.941)	(6.661)	(1.298)	(14.750)
# of Subsidiaries in Destination	0.068	0.122	0.011	0.562
	(1.903)	(2.565)	(0.546)	(5.667)
# of Parents in Origin	0.079	0.143	0.012	0.664
	(2.282)	(3.077)	(0.580)	(6.811)
# of Workers Employed at Subsidiary in Destination (in thousands)	0.050	0.088	0.027	0.392
	(2.798)	(3.743)	(2.098)	(7.895)
Information Demand Index (standardized)*	0.599	0.741	0.260	1.647
	(1.000)	(1.105)	(0.439)	(1.544)
N	19,110	13,962	2,182	3,677
Panel B: Countries				
Genetic Distance	0.103	0.084	0.106	0.066
	(0.053)	(0.041)	(0.050)	(0.036)
N	155	119	18	25
Linguistic Distance	0.950	0.937	0.990	0.920
	(0.110)	(0.121)	(0.010)	(0.114)
N	132	103	8	26
Religious Distance	0.820	0.807	0.923	0.732
	(0.129)	(0.137)	(0.050)	(0.128)
N	131	101	8	25
Judicial Quality	0.503	0.537	0.546	0.661
	(0.208)	(0.214)	(0.224)	(0.202)
N	144	115	15	26
2010 Country Diversity	0.442	0.405	0.433	0.239
	(0.269)	(0.256)	(0.246)	(0.197)
N	162	122	20	27
Panel C: Counties				
2010 Share of Population with Foreign Ancestry	0.577	0.577	0.560	0.648
	(0.188)	(0.187)	(0.223)	(0.137)
2010 Diversity of Ancestries	0.790	0.789	0.764	0.838
	(0.075)	(0.075)	(0.071)	(0.077)
N	3,141	3,137	628	627

Notes: The table presents means (and standard deviations). Variables in Panel A refer to our sample of (country-county) pairs. Variables in Panel B refer to our sample of countries. Variables in Panel C refer to our sample of counties. Column 1 shows data for all observations. Columns 2 to 4 show all, the bottom quintile, and the top quintile of observations with positive ancestry, respectively. In Panel A, the FDI dummy is a dummy variable equal to 1 if the destination county has either subsidiaries or shareholders in the origin country. The details of variables in Panel B are given in the Data Appendix. The ancestry-diversity variable is computed as 1 minus the Herfindahl index of ancestry group shares in each county. *The data is at the metropolitan area level.

Table 2: First-stage: The Effect of Historical Migrations on Ancestry

	Log ancestry 2010								Ancestry 2010
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$I^{1880}_{o,-r(d)} \times \frac{I^{1880}_{-c(o),d}}{I^{1880}_{-c(o)}}$	0.057***	0.056***	0.045***	0.035***	0.056***	0.056***	0.056***		2.145***
	(0.013)	(0.012)	(0.011)	(0.009)	(0.007)	(0.007)	(0.008)		(0.290)
$I^{1900}_{o,-r(d)} \times \frac{I^{1900}_{-c(o),d}}{I^{1900}_{-c(o)}}$	0.097***	0.095***	0.067**	0.068***	0.099***	0.099***	0.100***	0.106**	3.634**
	(0.032)	(0.031)	(0.028)	(0.019)	(0.033)	(0.033)	(0.036)	(0.043)	(1.425)
$I^{1910}_{o,-r(d)} \times \frac{I^{1910}_{-c(o),d}}{I^{1910}_{-c(o)}}$	0.192***	0.193***	0.145***	0.123***	0.137***	0.137***	0.132**	0.123**	5.646**
	(0.039)	(0.039)	(0.042)	(0.031)	(0.050)	(0.050)	(0.054)	(0.049)	(2.345)
$I^{1920}_{o,-r(d)} \times \frac{I^{1920}_{-c(o),d}}{I^{1920}_{-c(o)}}$	0.205***	0.209***	0.176***	0.174***	0.283***	0.283***	0.249***	0.276***	14.726***
	(0.070)	(0.070)	(0.061)	(0.052)	(0.045)	(0.045)	(0.047)	(0.041)	(3.012)
$I^{1930}_{o,-r(d)} \times \frac{I^{1930}_{-c(o),d}}{I^{1930}_{-c(o)}}$	0.062	0.061	0.061	0.035	0.079	0.079	0.065*	0.078	11.812***
	(0.056)	(0.056)	(0.056)	(0.048)	(0.051)	(0.051)	(0.034)	(0.051)	(2.855)
$I^{1970}_{o,-r(d)} \times \frac{I^{1970}_{-c(o),d}}{I^{1970}_{-c(o)}}$	0.183***	0.184***	0.163***	0.149***	0.149***	0.148***	0.150***	0.151***	6.256***
	(0.038)	(0.038)	(0.036)	(0.031)	(0.028)	(0.029)	(0.027)	(0.029)	(0.669)
$I^{1980}_{o,-r(d)} \times \frac{I^{1980}_{-c(o),d}}{I^{1980}_{-c(o)}}$	0.173***	0.173***	0.174***	0.169***	0.214***	0.214***	0.205**	0.213***	18.694***
	(0.066)	(0.066)	(0.064)	(0.061)	(0.076)	(0.077)	(0.080)	(0.075)	(2.390)
$I^{1990}_{o,-r(d)} \times \frac{I^{1990}_{-c(o),d}}{I^{1990}_{-c(o)}}$	0.123***	0.124***	0.124***	0.111**	0.101**	0.101**	0.115**	0.102**	10.786***
	(0.048)	(0.048)	(0.048)	(0.044)	(0.045)	(0.045)	(0.048)	(0.044)	(3.675)
$I^{2000}_{o,-r(d)} \times \frac{I^{2000}_{-c(o),d}}{I^{2000}_{-c(o)}}$	0.020	0.019	0.026	0.026*	0.046***	0.046***	0.039**	0.046***	5.194***
	(0.017)	(0.017)	(0.016)	(0.015)	(0.017)	(0.017)	(0.016)	(0.017)	(1.148)
$I^{2010}_{o,-r(d)} \times \frac{I^{2010}_{-c(o),d}}{I^{2010}_{-c(o)}}$							0.317***		
							(0.089)		
Kleibergen Wald rk statistic	10.608	10.958	8.327	9.607	162.194	158.125	195.423	142.800	910.331
Stock-Yogo 5% critical values	20.53	20.53	20.53	20.53	21.18	21.18	21.23	21.10	21.18
Stock-Yogo 10% critical values	11.46	11.46	11.46	11.46	11.52	11.52	11.51	11.52	11.52
R^2	0.56	0.56	0.66	0.72	0.73	0.73	0.73	0.73	0.49
N	612,495	612,495	612,495	612,495	612,495	612,495	612,495	612,495	612,495
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Distance	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Latitude Difference	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination × Continent FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin × Census Region FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Principal Components	No	No	No	No	Yes	Yes	Yes	Yes	Yes
3rd order poly in dist and lat	No	No	No	No	No	Yes	No	No	No

Notes: The table presents coefficient estimates of our first stage equation (4) at the country-county level. All specifications control for origin and destination fixed effects. Standard errors are given in parentheses and are clustered at the origin country level. In columns 1-8 the dependent variable is the log of 1 plus the number of residents of the county in 2010 that report having ancestors in the origin country, measured in thousands *(Log Ancestry 2010)*. In column 9 the dependent variable is the level of ancestry in 2010 (again in thousands). The excluded instruments are, for each census period, interactions of pull and push factors in migration, $I^t_{o,-r(d)}(I^t_{-c(o),d}/I^t_{-c(o)})$, where $I^t_{o,-r(d)}$ stands for the number of migrants from o who settle in destinations *not* in the same census region as d in period t and $I^t_{-c(o),d}/I^t_{-c(o)}$ for the fraction of migrants *not* coming from origins in the same continent as o who settle in county d. Columns 3-9 also include the first five principal components of higher-order interactions of these factors. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Second-stage: The effect of Ancestry on FDI

Panel A: IV	*FDI 2014 (Dummy)*					
	(1)	(2)	(3)	(4)	(5)	(6)
Log Ancestry 2010	0.231***	0.190***	0.187***	0.187***	0.198***	0.191***
	(0.023)	(0.024)	(0.024)	(0.024)	(0.023)	(0.024)
Log Distance	0.007	0.004	0.024	0.009	0.026	-0.027
	(0.010)	(0.009)	(0.029)	(0.033)	(0.030)	(0.027)
Latitude Difference	0.006**	0.005**	0.006*	-0.000	0.006*	0.003
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)
N	612495	612495	612495	612495	612495	612300
Panel B: OLS	*FDI 2014 (Dummy)*					
Log Ancestry 2010	0.173***	0.149***	0.149***	0.149***	0.149***	0.161***
	(0.016)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)
R^2	0.2967	0.3635	0.3635	0.3635	0.3635	0.3930
N	612495	612495	612495	612495	612495	612495
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Principal Components	No	Yes	Yes	Yes	Yes	Yes
Destination × Continent FE	No	No	Yes	Yes	Yes	Yes
Origin × Census Region FE	No	No	Yes	Yes	Yes	Yes
3rd order poly in dist and lat	No	No	No	Yes	No	No
$I^{2010}_{o,-r(d)}(I^{2010}_{-c(o),d}/I^{2010}_{-c(o)})$	No	No	No	No	Yes	No
Origin × State FE	No	No	No	No	No	Yes

Notes: The table presents coefficient estimates from IV (Panel A) and OLS (Panel B) regressions of equation (1) at the country-county level. The dependent variable in all panels is a dummy indicating an FDI relationship between origin o and destination d in 2014. The main variable of interest is *Log Ancestry 2010*, instrumented using various specifications of equation (4). In all columns in Panel A, we include $\{I^t_{o,-r(d)}(I^t_{-c(o),d}/I^t_{-c(o)})\}_{t=1880,...,2000}$ as excluded instruments. Columns 3-6 also include the first five principal components of the higher-order interactions of push and pull factors as instruments. Column 5 also includes the interaction of the push and pull factor constructed using data from the 2006-2010 American Community Survey. All specifications control for log distance, latitude difference, origin, and destination fixed effects. Standard errors are given in parentheses. Standard errors are clustered at the origin country level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. (We also run an IV probit regression using the specification in column 2 yielding a marginal effect evaluated at the mean of *Log Ancestry 2010* on FDI equal to 0.104***(0.037).)

Table 4: The Effect of Ancestry on FDI: The Communist Natural Experiment

	FDI 2014 (Dummy)				
	(1)	(2)	(3)	(4)	(5)
Log Ancestry 2010	0.197***	0.380***	0.075	0.242**	0.234**
	(0.066)	(0.053)	(0.054)	(0.104)	(0.098)
N	3,141	3,141	3,141	18,846	28,269
Destination FE	No	No	No	No	Yes
Countries considered	Soviet Union	China	Vietnam	Eastern Europe	All communist countries
Years excluded	1918-1990	1949-1980	1975-1996	1945-1989	

Notes: The table presents coefficient estimates from IV regressions of equation (1) at the country-county level. Each column uses data from a subset of origin countries: Soviet Union (column 1), China (column 2), Vietnam (column 3), as well as Albania, Bulgaria, Czechoslovakia, Hungary, Poland, and Romania (column 4). The dependent variable in all columns is a dummy indicating an FDI relationship between origin country o and destination county d in 2014. All specifications use the same set of instruments as the one in column 3 of Table 3, but only exclude the interaction terms containing measures of pull and push factors in migrations that occur during the years of economic isolation from the United States indicated above; the remaining variables are included as controls. All specifications control for log distance, latitude difference, and origin fixed effects. Standard errors are given in parentheses and are robust. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Alternative Instruments

Panel A: Variations of leave-out categories	*FDI 2014 (Dummy)*
Excluding origins with correlated migration flows: $I^t_{o,-r(d)} \times (I^t_{-s(o),d}/I^t_{-s(o)})$	0.197***
	(0.020)
Excluding states adjacent to the destination: $I^t_{o,-a(d)} \times (I^t_{-c(o),d}/I^t_{-c(o)})$	0.200***
	(0.023)
Panel B: Using subsets of instruments for identification	*FDI 2014 (Dummy)*
Only migrations $1880-1930$	0.209***
	(0.037)
Only migrations $1970-2000$	0.175***
	(0.021)
Only migrations $1900-2000$	0.187***
	(0.024)

Notes: This table presents coefficient estimates from instrumental variable regressions that are variations of our standard specification (column 3 of 3), but not using the principal components of higher-order interactions for identification. The dependent variable in all regressions is *FDI 2014 (Dummy)*. Each row lists the coefficient estimate on *Log Ancestry 2010*. In Panel A we show alternative specifications of our leave-out instrument. First, when calculating the pull-factor of o to d we exclude all countries whose aggregate time path of migrations to the US is correlated with o's migrations to the US. Second, when calculating the push factor of o we exclude migrations to any state adjacent to the state of d. In Panel B we use throughout the interacted instrument of our standard specification. In contrast to the standard specification, each specification in this panel uses as instruments only the simple interaction terms from a subset of the full time period covered by our data. Standard errors are given in parenthesis and clustered at the country level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: The Effect of Ancestry on Immigration

	Immigration 1990-2000	*Log immigration 1990-2000*	*Log immigration 1980-1990*
	(1)	(2)	(3)
Log Ancestry 1990	9.662**	0.556***	
	(4.455)	(0.075)	
Log Ancestry 1980			0.447***
			(0.076)
$I^{2000}_{o,-r(d)} \frac{I^{2000}_{-c(o),d}}{I^{2000}_{-c(o)}}$	1.082***	0.033**	
	(0.358)	(0.015)	
$I^{1990}_{o,-r(d)} \frac{I^{1990}_{-c(o),d}}{I^{1990}_{-c(o)}}$			0.061***
			(0.015)
N	612,495	612,495	612,495

Notes: The table presents the coefficient estimates from IV regressions of equation (6) at the country-county level. The dependent variable is the immigration flow from 1990 to 2000 in columns 1-2 and the immigration flow from 1980 to 1990 in column 3. In all columns, we instrument for *Log Ancestry* with the double-interactions of pull and push factors from prior censuses, $\{I^t_{o,-r(d)}(I^t_{-c(o),d}/I^t_{-c(o)})\}_{t=1880,\ldots,1980}$. All specifications control for log distance, latitude difference, origin$\times$destination-census-region, and destination$\times$continent-of-origin fixed effects. Standard errors are given in parentheses and are clustered at the origin country level.

Table 7: The Effect of Ancestry on the Intensive Margin of FDI

	OLS	IV/GMM	IV/GMM	IV/GMM
	(1)	(2)	(3)	(4)
Panel A	*Log Total # of FDI relationships*			
Log Ancestry 2010	0.245***	0.356***	0.292***	0.147***
	(0.048)	(0.056)	(0.021)	(0.031)
N	10,851	10,851	10,851	10,851
Panel B	*Log # of subsidiaries in destination with shareholders in origin*			
Log Ancestry 2010	0.275***	0.339***	0.288***	0.242***
	(0.050)	(0.059)	(0.016)	(0.045)
N	9,082	9,082	9,082	9,082
Panel C	*Log # of workers employed at subsidiaries in destination*			
Log Ancestry 2010	0.304*	0.077	0.326***	0.192
	(0.175)	(0.236)	(0.051)	(0.139)
N	9,082	9,082	9,082	9,082
Destination FE	Yes	Yes	Yes	Yes
Origin FE	Yes	Yes	Yes	Yes
Destination $\times$ Continent FE	Yes	Yes	No	No
Origin $\times$ Census Region FE	Yes	Yes	No	No
Heckman Correction	No	No	No	Yes

Notes: The table presents OLS (column 1) and IV/GMM (columns 2-4) estimates of equation (8). The dependent variables are specified for each panel in the table. The main variable of interest is *Log Ancestry 2010*. All IV columns use as instruments the same set of variables as column 3 of Table 3. All specifications control for log distance, latitude difference, origin, and destination fixed effects. The coefficient estimates on these controls are not reported in the interest of space. Standard errors are given in parentheses. Standard errors are clustered at the country level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Thought Experiment: A Gold Rush in Los Angeles in 1880

			Predicted Counterfactual Change	
	Ancestry 2010	FDI #	*Ancestry 2010*	*FDI # (in %, IV)*
	(1)	(2)	(3)	(4)
Germany	343,276	241	+65,344	+62.70
Ireland	256,621	40	+61,701	+58.34
UK	396,439	582	+26,645	+21.95
Norway	39,515	55	+4,657	+3.53
Sweden	51,395	71	+4,010	+3.03
France	77,372	278	+3,293	+2.48
Canada	27,722	531	+3,132	+2.36
Switzerland	10,156	162	+2,456	+1.85
Czechoslovakia	17,905	4	+2,140	+1.61
Netherlands	38,392	121	+1,638	+1.23

Notes: The table presents the number of individuals of selected ancestries living in Los Angeles County (column 1), the number of FDI links between Los Angeles County and the countries of origin (column 2), and the predicted changes in these variables under a counterfactual scenario where the pre-1880 pull factor of Los Angeles is 5 times as large as in reality (columns 3 and 4). Column 3 shows the predicted absolute change in ancestry based on a regression analogous to column 9 of Table 2 with *Ancestry 2010* (in levels) as dependent variable, again excluding the principal components. Column 4 shows the predicted change of *Total # of FDI relationships* (in percent) based on the IV regression of *Log Total # of FDI relationships* on *Log Ancestry 2010*, instrumented for by $\{I^t_{o,-r(d)}(I^t_{-c(o),d}/I^t_{-c(o)})\}_{t=1880,...,2000}$, similar to column 2 of Table 7 without the principal components as instruments. All regressions control for log distance and latitude difference and include a origin $\times$ destination-census-region, and destination $\times$ continent-of-origin fixed effects. Only the 10 countries with the highest absolute change in ancestry are shown in the interest of space. The details for the construction of this thought experiment are presented in section 3.6.

TABLE 9: THE "SIMILARITIES" HYPOTHESIS AND CONTRACT ENFORCEMENT

	(1)	(2)
Panel A: Final vs. Intermediate Goods	*FDI 2014 (Dummy)*	
Log Ancestry 2010	0.156***	0.169***
	(0.026)	(0.024)
N	612,495	612,495
Sample	Final goods	Intermediate goods
Panel B: Final vs. Intermediate Goods	*Inward FDI 2014 (Dummy)*	
Log Ancestry 2010	0.108***	0.117***
	(0.033)	(0.032)
N	612,495	612,495
Sample	Final goods	Intermediate goods
Panel C: Sector similarity	*Rank Correlation*	*Cosine correlation*
Log Ancestry 2010	0.011	0.010
	(0.015)	(0.013)
N	21,518	21,518
Panel D: Judicial Quality	*FDI 2014 (Dummy)*	*Log # of FDI relationships*
Log Ancestry × Judicial Quality	0.180*	1.414***
	(0.094)	(0.243)
N	452,304	10,089

Notes: The table presents coefficient estimates from IV regressions at the country-county level. In Panel A, the outcome variable is the FDI dummy; we restrict our sample to firms producing final goods or intermediate inputs, respectively. Final goods and intermediate inputs are defined as 4-digit NAICS sectors with upstreamness index below and above 2, respectively, where we use the upstreamness index from Antràs et al. (2012). The number of country-county pairs that have an (non-zero) FDI link in the corresponding sector is 4,201 and 5,842 in columns 1 and 2, respectively. In Panel B, we replicate the same regressions, except that the outcome variable indicates only the existence of any inward FDI. In Panel C, the outcome variable is the rank and cosine correlation of the share of employees in 127 manufacturing sectors within a given origin-destination pair, respectively. The relatively low number of observations is due to data availability in the industry share of employment: When calculating the correlation between industries' share of employment in county d and country o, the correlation coefficient is missing for those country-county pairs that have at least one missing share of employment. In Panel D, the outcome is the extensive (FDI dummy) and intensive (log # of FDI relationships) margin, and the measure of judicial quality is from Nunn (2007). Throughout we use $\{I^t_{o,-r(d)}(I^t_{-c(o),d}/I^t_{-c(o)})\}_{t=1880,\ldots,2000}$ and principal components as instrumental variables. All specifications control for log distance, latitude difference, and origin and destination fixed effects. In Panels A-C we additionally control for origin×destination-census-region, and destination×continent-of-origin fixed effects. Standard errors are given in parentheses and are clustered by origin country.

Table 10: The Effect of Ancestry on Differential Information Demand and Language

Panel A: Google Trends	Information Demand Index (standardized)			Actors (standardized)	Athletes (standardized)	Musicians (standardized)	Politicians (standardized)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log Ancestry 2010	0.871***	1.717**		0.659**	0.948***	0.531***	0.688***
	(0.257)	(0.783)		(0.257)	(0.359)	(0.076)	(0.183)
Log Foreign-born 2010		-1.108					
		(0.809)					
Log Ancestry 1980			0.801***				
			(0.186)				
N	19,110	19,110	19,110	19,110	19,110	19,110	19,110
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Principal Components	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Language	# of residents in d speaking language of o at home	# of US-born in d that speak the language of o at home					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ancestry 2010	2.226***	0.942***		1.170***	1.257***	0.085***	0.015***
	(0.717)	(0.301)		(0.042)	(0.230)	(0.006)	(0.003)
Ancestry 1980			1.241**				
			(0.504)				
N	454,812	454,813	454,813	65,877	78,376	3,137	3,137
Non-English language	Any	Any	Any	Spanish	Arabic	Chinese	Hindi
Destination FE	Yes	Yes	Yes	No	No	No	No
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents coefficient estimates from IV regressions at the country-DMA (Panel A) and country-county (Panel B) level. In Panel A, all dependent variables are based on a count of Google searches in the category specified above the panel. The Information Demand Index in columns 1-3 is a simple average of the other four categories. Each of the four categories is the average of Google Trends value $G(i,d)$, which measures the (normalized) fraction of queries that include search term i relative to the total number of queries of Designated Market Area (DMA) d. For the search terms i we use the first five terms from Google's Answer Box when we search for "notable [foreign country d] [category]". All outcome variables in Panel A are standardized by their standard deviation. In Panel B, the dependent variable in column 1 is the number of residents in d that speak the language of o at home, excluding English; in column 2 and 3, it is the number of US-born residents in d that speak the language of o at home, excluding English; and in columns 3-6, it is the number of US-born residents in d that speak the language indicated in the respective column. Spanish is the official language in twenty-one countries; Arabic is the official language in twenty-five countries; Chinese and Hindi each are the official language in only one country. Ancestry 2010, Ancestry 1980, Log Ancestry 2010, Log Foreign-born 2010, and Log Ancestry 1980 are instrumented as in column 3 of Table 3. All specifications control for log distance and latitude difference. Standard errors are given in parentheses and clustered at the country level (all of Panel A and columns 1-2 of Panel B) or state level (columns 3-6 of Panel B). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 11: Network Effects

	FDI 2014 (Dummy)		*Log Total # of FDI relationships*	
	(1)	(2)	(3)	(4)
Panel A: Spillovers				
Log Ancestry 2010	0.191***	0.197***	0.359***	0.283***
	(0.024)	(0.020)	(0.132)	(0.099)
Log Ancestry 2010, State Level	-0.020**		-0.159	
	(0.010)		(0.102)	
Log Ancestry 2010 of Nearest Origin Country		-0.056***		0.049
		(0.020)		(0.215)
N	612,495	612,495	10,851	10,851
Panel B: Diversity				
Log Ancestry 2010	0.197***	0.123***	0.661***	0.641***
	(0.061)	(0.030)	(0.245)	(0.089)
Log Ancestry × Foreign Share	1.388		3.548	
	(3.103)		(7.803)	
Log Ancestry × Ethnic Diversity		1.270***		3.692***
		(0.204)		(1.009)
N	611,910	612,495	10,851	10,851
Panel C: Fractionalization				
Log Ancestry 2010	0.269***	0.334***	0.914***	1.247***
	(0.037)	(0.081)	(0.149)	(0.109)
Log Ancestry × Geographic Distance	0.101***	0.170**	0.414***	0.864***
	(0.036)	(0.076)	(0.128)	(0.156)
Log Ancestry × Judicial Quality		0.373**		2.375***
		(0.187)		(0.494)
Log Ancestry × Fractionalization		0.470		3.087***
		(0.324)		(0.831)
N	446,022	446,022	10,089	10,089

Notes: The table presents coefficient estimates from IV regressions at the country-county level. The dependent variable in columns 1 and 2 is the dummy for FDI in 2014. The dependent variable in columns 3 and 4 is the log of the number of FDI links in 2014. We use $\{I^t_{o,-r(d)}(I^t_{-c(o),d}/I^t_{-c(o)})\}_{t=1880,\ldots,2000}$ and principal components as instruments. All specifications control for log distance, latitude difference, origin, and destination fixed effects, as in column 2 of Table 3. Foreign Share, Ethnic Diversity, Distance, Judicial Quality, and Fractionalization are demeaned. Standard errors are given in parentheses and are clustered at the origin country level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Foreign Share is the share of the destination county's population that are of any foreign ancestry in 2010. Diversity of Ancestries is measured as 1 minus the Herfindhal index of ancestry shares in the destination county. Judicial quality in the origin is from Nunn (2007); genetic distance is from Spolaore and Wacziarg (2015); and Ethnic Fractionalization refers to 1 minus the Herfindahl index of ethnicities in the origin country calculated using the data in Alesina et al. (2003).

Table 12: The Effect of Ancestry on the Intensive Margin of Trade (State Level)

	OLS	IV	IV
	(1)	(2)	(3)
Panel A	*Log Total # of FDI relationships*		
Log Ancestry 2010	1.001***	1.374***	0.079***
	(0.077)	(0.183)	(0.025)
R^2	0.659	0.626	0.847
N	2,208	2,202	2,191
Panel B	*Log Aggregate Exports*		
Log Ancestry 2010	1.519***	2.993***	-0.149
	(0.173)	(0.357)	(0.138)
R^2	0.416	0.374	0.665
N	4,799	4,783	4,739
Panel C	*Log Aggregate Imports*		
Log Ancestry 2010	1.927***	3.447***	0.003
	(0.148)	(0.497)	(0.150)
R^2	0.419	0.360	0.576
N	3,823	3,764	3,815
Origin FE	Yes	Yes	Yes
Destination FE	No	No	Yes
Heckman Correction	Yes	Yes	Yes
Panel D	*Log Exports to Vietnam*		
Log Ancestry 2010	1.169***	1.230***	
	(0.124)	(0.124)	
R^2	0.680	0.678	
N	51	51	
Panel E	*Log Exports to Japan*		
Log Ancestry 2010	0.898***	1.107***	
	(0.197)	(0.128)	
R^2	0.442	0.419	
N	51	51	
Origin FE	Yes	Yes	
Destination FE	No	No	

Notes: The table presents OLS and IV estimates of equation (8) at the state level for FDI and trade. The dependent variables are the log number of total FDI links in 2014 (Panel A), the log of aggregate exports (from the US state) (Panel B), aggregate imports (Panel C), exports to Vietnam (Panel D), and exports to Japan (Panel E). Exports and imports are measured in US dollars in 2011. In all columns, we use $\{I^t_{o,-r(d)}(I^t_{-c(o),d}/I^t_{-c(o)})\}_{t=1880,\ldots,2000}$ and principal components as excluded instruments. All specifications control for log distance, latitude difference, and origin fixed effects. Standard errors are given in parentheses and are double clustered at the destination state and origin country. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 13: Generational Effects

	FDI 2014 (Dummy)					
	IV	IV	OLS	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Log Ancestry 2010	0.187***		0.155***	0.242***		0.163***
	(0.024)		(0.022)	(0.043)		(0.014)
Log Foreign-born 2010		0.207***	-0.012	-0.082*		
		(0.014)	(0.031)	(0.049)		
Log Foreign-born 1970					0.286***	0.046
					(0.025)	(0.034)
N	612,495	612,495	612,495	612,495	612,495	612,495

Notes: The table presents the OLS (column 3) and IV (all other columns) estimates of equation (1), contrasting the effect of ancestry and first-generation immigrants (foreign-born) on FDI. The dependent variable is the dummy for FDI in 2014. All IV columns use as instruments the same set of variables as column 3 of Table 3. All specifications control for log distance, latitude difference, origin×destination-census-region, and destination×continent-of-origin fixed effects. The coefficient estimates on these control variables are not reported in the interest of space. Standard errors are given in parentheses and clustered at the origin country level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. For column 4, the Kleibergen-Paap rk LM statistic on the excluded instruments is 18.21 with p-value 0.150. For column 6, the Kleibergen-Paap rk LM statistic on the excluded instruments is 29.04 with p-value 0.007.

Online Appendix
"Migrants, Ancestors, and Foreign Investments"

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A Data Appendix

Overview

To construct the migration and ancestry data up until the year 2000, we download the 1880, 1900, 1910, 1920, 1930, 1970, 1980, and 2000 waves of the Integrated Public Use Microdata Series (IPUMS) from `https://usa.ipums.org/usa-action/samples`. For each wave, we select the largest available sample; for example, if a 1% and 10% sample was available for 1880 data, we used the 10% sample. To construct the 2010 data, we used the 2006-2010 American Community Survey (ACS) sample provided on the IPUMS website. For a more detailed overview on the specific waves used, see Appendix Table 1.

For each sample, we obtain the following variables: year, datanum, serial, hhwt, region, statefip, county, cntygp97, cntygp98, puma, gq, pernum, perwt, bpl, mbpl, fbpl, nativity, ancestr1, yrimmig, mtongue, mmtongue, fmtongue, and language.

We construct the number of migrants from origin country o to destination county d in t, $I^t_{o,d}$, as well as the measure of ancestry $A^t_{o,d}$ from 1980 onward. We first aggregate the individual-level census data to counts of respondents at the level of historic US counties (or country groups from 1970 onwards) and foreign countries, and then transform the data into 1990 country-county level using various transition matrices. Details are given in the following sections.

How we create transition matrices

We create a set of transition matrices that transform non-1990 countries to 1990 countries and non-1990 counties/county groups to 1990 counties.

- Birthplace-to-country: The aim is to construct transition matrices that map all the birthplace answers into 1990 countries. In each wave of the US Census, respondents were asked to report their country of birth. All possible answers (across time) are listed here: `https://usa.ipums.org/usa-action/variables/BPL#codes_section`. The censuses from 1850-2012 contain roughly 550 possible different answers to the question of birthplace. In each census data set, they are saved in the variable "bpld." What follows is our procedure for building those matrices:

    1. We start with a transition matrix of zeros, with all possible answers to the 1990 birthplace question as rows and all 1990 countries as columns. A cell in row r and column c of the transition matrix answers the question, "What is the probability that an individual who claims his/her birthplace as r refers to the area that in 1990 is country c?" So all cells contain values in [0,1], and rows sum up to 1.

2. For each row r in the transition matrix, if r with certainty refers to the area that in 1990 is country c, we simply change the entry in cell (r,c) from 0 to 1; if r does refer to an area that in 1990 is in multiple countries, then we search for the 1990 population of each possible country, and assign probabilities in proportion to the population data. We use the population information from the Worldbank database.[51].

Panel A in Appendix Table 2 lists the distribution of weights that we end up using, and the affected countries and persons.

- Ancestry-to-country: The aim is to construct transition matrices that map all the answers to the ancestry question into 1990 countries. The 1980, 1990, 2000, and 2010 census data provide information on the ancestry (ancestr1, 3-digit version). All possible answers (across time) are listed here: https://usa.ipums.org/usa-action/variables/ANCESTR1/#codes_section. The procedure is the same as in the birthplace-to-country procedure. Panel B in Appendix Table 2 lists the distribution of weights that we end up using, and the affected countries and persons.

- Group-to-county & PUMA-to-county: The aim is to construct transition matrices that map all the county groups/PUMAs into individual counties. For the years 1970 and 1980, the US census data are at the US county group level. A "county group" is an agglomeration of US counties. For the years 2000 and 2010, the census data are at the PUMA level. A "PUMA" is also an agglomeration of US counties.[52] To construct transition matrices from county agglomeration level to county level, we download the corresponding matching files from the IPUMS website. We use data on the population of each county (within each county group/PUMA) to assign a probability that an observation from county group/PUMA g in year t is from county c in year t. This approach gives a transition matrix from year t county groups to year t counties. Appendix Table 3 lists the distribution of weights that we end up using, and the affected counties and persons.

- County-to-county: The aim is to construct transition matrices that map all the non-1990 counties into 1990 counties. This step is necessary because the list and boundaries of US counties changed over time. Similarly to the birthplace-to-country and ancestry-to-country procedure, we use one transition matrix per census year (1880, 1900, 1910, 1920, 1930, 1970, 1980, 2000, 2010). Such a transition matrix has as rows all US counties, indexed c, in year t, and as columns all 1990 US counties, indexed m. Each cell of the transition matrix takes a value that answers the question, "Which fraction of the area of the county c in year t is in 1990 part of county m?" Appendix Table 3 lists the distribution of weights that we end up using, and the affected counties and persons. More specifically, we build these matrices as follows:

  1. We download the year-specific map files. For 1880 us counties, we obtain the 503MB GIS file from Atlas: http://publications.newberry.org/ahcbp/downloads/united_states.html and extract the 1880 part. For 1900, 1910, 1920, and 1930 counties, we obtain the maps from IPUMS: https://usa.ipums.org/usa/volii/ICPSR.shtml.

[51] http://data.worldbank.org/indicator/SP.POP.TOTL

[52] Detailed description of "county group" and "PUMA" can be found here: https://usa.ipums.org/usa/volii/tgeotools.shtml.

Finally, for 1970, 1980, and 1990 counties, we obtain the maps from NHGIS: `https://data2.nhgis.org/main`.

2. We project non-1990 maps onto 1990 counties. We used the intersect command in ArcGIS to map year-specific counties onto 1990 counties based on area. This approach gives a transition matrix from non-1990 counties to 1990 counties.

Appendix Table 1: Description of each IPUMS wave

Wave	Description
1880	We use the 10% sample with oversamples; the sample is weighted, so we use the provided person weights to get to a representative sample; we use the region identifiers statefip and county.
1900	We use the 5% sample; the sample is weighted, so we use the provided person weights to get to a representative sample; we use the region identifiers statefip and county.
1910	We use the 1% sample; the sample is unweighted; we use the region identifiers statefip and county.
1920	We use the 1% sample; the sample is weighted, so we use the provided person weights to get to a representative sample; we use the region identifiers statefip and county.
1930	We use the 5% sample; the sample is weighted, so we use the provided person weights to get to a representative sample; we use the region identifiers statefip and county.
1970	We use the 1% Form 1 Metro sample; the sample is unweighted; we use the region identifiers statefip and cntygp97 (county group 1970); note that only four states can be completely identified because metropolitan areas that straddle state boundaries are not assigned to states; identifies every metropolitan area of 250,000 or more.
1980	We use the 5% State sample; the sample is unweighted; we use the region identifiers statefip and cntygp98 (county group 1980); the sample identifies all states, larger metropolitan areas, and most counties over 100,000 population.
1990	We use the 5% State sample; the sample is weighted, so we use the provided person weights to get to a representative sample; we use the region identifiers statefip and puma; the sample identifies all states, and within states, most counties or parts of counties with 100,000 or more population.
2000	We use the 5% Census sample; the sample is weighted, so we use the provided person weights to get to a representative sample; we use region identifiers statefip and puma; the sample identifies all states, and within states, most counties or parts of counties with 100,000 or more population.
2010	We use the American Community Service (ACS) 5-Year sample; the sample is weighted, so we use the provided person weights to get to a representative sample; we use region identifiers statefip and puma, which contain at least 100,000 persons; the 2006-2010 data contains all households and persons from the 1% ACS samples for 2006, 2007, 2008, 2009 and 2010, identifiable by year.

Appendix Table 2: Historical birthplace to current country: transition matrices

Panel A: Birthplace		weights $\in (0,1)$	weight $= 1$	weights $= 0$
1880	# of answers	22	258	9
	# of persons	26,301	50,177,184	4,933
	% of persons	0.05%	99.94%	.01%
1900	# of answers	15	131	6
	# of persons	23,345	6,555,140	5,339
	% of persons	0.35%	99.56%	.08%
1910	# of answers	20	99	4
	# of persons	31,072	5,613,136	3,105
	% of persons	0.55%	99.39%	.05%
1920	# of answers	13	174	7
	# of persons	36,070	3,905,455	12,559
	% of persons	0.91%	98.77%	.32%
1930	# of answers	25	194	9
	# of persons	35,930	3,086,341	61,462
	% of persons	1.13%	96.94%	1.93%
1970	# of answers	12	77	3
	# of persons	318,800	6,323,100	230,800
	% of persons	4.64%	92.00%	3.36%
1980	# of answers	32	222	7
	# of persons	491,760	4,774,820	313,300
	% of persons	8.81%	85.57%	5.61%
1990	# of answers	24	209	7
	# of persons	721,595	8,532,585	484,433
	% of persons	7.41%	87.62%	4.97%
2000	# of answers	11	136	0
	# of persons	1,122,532	13,144,632	0
	% of persons	7.87%	92.13%	0%
2010	# of answers	14	137	1
	# of persons	1,302,255	11,131,046	17,148
	% of persons	10.46%	89.40%	.14%
2010*	# of answers	14	188	1
	# of persons	3,512,123	300,415,680	37,469
	% of persons	1.16%	98.83%	.01%
Panel B: Ancestry		**weights $\in (0,1)$**	**weight $= 1$**	**weights $= 0$**
1980	# of answers	29	227	143
	# of persons	924,400	198,525,616	27,412,380
	% of persons	0.41%	87.51%	12.08%
1990	# of answers	29	239	9
	# of persons	2,941,941	217,720,512	27,445,182
	% of persons	1.19%	87.75%	11.06%
2000	# of answers	17	137	22
	# of persons	6,000,639	191,300,704	84,120,558
	% of persons	2.13%	67.98%	29.9%
2010	# of answers	19	142	30
	# of persons	8,454,279	229,211,968	66,299,030
	% of persons	2.78%	75.41%	21.81%

The table reports statistics on the transition of data from the 'answer' level to 1990 country level. For each survey wave, and each question – birthplace in Panel A and primary ancestry in Panel B – the table reports the number of answers that can be directly linked to a 1990 country (weight = 1), that are assigned to several 1990 countries using population weights (weights $\in (0,1)$) and that cannot be linked to any modern country with sufficient certainty (weights = 0). The table also reports the number of respondents (scaled from the original data using the person weights provided) in each category. Answers with weights zero essentially consists of "Not Reported" (e.g. 23, 24, 54 and 30 million respondents for the 1980, 1990, 2000 and 2010 ancestry data, respectively) and "African-American" (e.g. 26, 22 and 25 million respondents for the 1990, 2000 and 2010 ancestry data, respectively). The remainders are mostly cases such as "African", "Uncodable", "Bohemian", "Nuevo Mexicano", "Other", etc. In Panel A, all years except 1880 consist of the number of persons that report birthplace since the last Census wave. For the 2010 Census wave the additional entry (denoted by a *) reports the respective numbers for all respondents in that wave.

Appendix Table 3: Historical state-county unit to 1990 state-county unit: transition matrices

Census wave		weights $\in (0,1)$	weight $= 1$	weights $= 0$
1880	# of counties	658	1854	1
	% of persons (birthplace data)	21.54%	78.45%	.01%
1900	# of counties	2211	7	4
	% of persons (birthplace data)	99.09%	0.87%	.05%
1910	# of counties	1517	5	1
	% of persons (birthplace data)	99.00%	0.94%	.05%
1920	# of counties	1355	7	0
	% of persons (birthplace data)	90.80%	9.20%	0%
1930	# of counties	1801	6	0
	% of persons (birthplace data)	90.61%	9.39%	0%
1970	# of countygroups	310	98	0
	% of persons (birthplace data)	34.07%	65.93%	0%
1980	# of countygroups	580	573	0
	% of persons (birthplace data)	17.96%	82.04%	0%
	% of persons (ancestry data)	40.02%	59.98%	0%
1990	# of PUMAs	541	1185	0
	% of persons (birthplace data)	8.97%	91.03%	0%
	% of persons (ancestry data)	32.15%	67.85%	0%
2000	# of PUMAs	620	1451	0
	% of persons (birthplace data)	10.66%	89.34%	0%
	% of persons (ancestry data)	30.36%	69.64%	0%
2010	# of PUMAs	619	1449	1
	% of persons (birthplace data)	12.31%	87.65%	.03%
	% of persons (ancestry data)	30.13%	69.81%	.05%

The table reports statistics on the transition of data from the 'historical spatial area' level to 1990 US county level. For each Census wave the table reports the number of contemporaneous spatial areas that are a subset of a 1990 US county (weight = 1) and the number of contemporaneous spatial areas whose data is transitioned to 1990 US county level using non-degenerate weights (weights $\in (0,1)$). For Census waves 1880 to 1930 the share of their contemporaneous county spatial area in each 1990 US county area is used as weight. For waves 1970 to 2010 there are two steps: In step 1 the share of their contemporaneous countygroup (waves 1970 and 1980) or PUMA (waves 1990 to 2010) population in the contemporaneous county population are used as weights; in step 2 the share of their contemporaneous county spatial area in each 1990 US county area is used as weight. The two-step procedure is necessary because the 1970 to 2010 Census waves do not have a county-level identifier (to protect the privacy of the respondents). The table also reports the share of respondents affected by this transition in the birthplace and ancestry data, respectively.

A.1 Details on the construction of migration and ethnicity data

Details calculation of post-1880 flow of immigrants

For each census wave after 1880, we count the number of individuals in each historic US county d who were born in historic country o (as identified by birthplace variable "bpld" in the raw data) that had immigrated to the United States since the last census wave that contains the immigration variable (not always 10 years earlier). Then we transform these data

- from the non-1990 foreign-country ("bpld") level to the 1990 foreign-country level using bpld-to-country transition matrices.
- from the US-county group/puma level to the US-county level using group/puma-to-county transition matrices.
- from the non-1990 US-county level to the 1990 US-county level using county-to-county transition matrices.
- from the post-1990 US-county level to the 1990 US county level. Based on the information from https://www.census.gov/geo/reference/county-changes.html, a new county is either created from part of ONE 1990 county or assigned a new FIPS code after 1990, so we manually change that county's FIPS code to what it was in 1990. A few counties' boundaries have been changed after 1990 but that only involved a tiny change in population, so we ignore these differences.

Details calculation of pre-1880 stock of immigrants

For the year 1880, we calculate for each historic US county d the number of individuals who were born in a historic foreign country o (no matter when they immigrated). We add to those calculations the number of individuals in county d who were born in the United States, but whose parents were born in historic foreign country o. (If the parents were born in different countries, we count the person as half a person from the mother's place of birth, and half a person from the father's place of birth). Then we transform these data

- from the pre-1880 foreign-country ("bpld") level to the 1990 foreign-country level using the pre-1880 country-to-country transition matrix.
- from the pre-1880 US-county level to the 1990 US-county level using the pre-1880 county-to-county transition matrix.

Details calculation of stock of ancestry (1980, 1990, 2000, and 2010)

For the years 1980, 1990, 2000, and 2010, we calculate for each US county group the number of individuals who state as primary ancestry ("ancestr1" variable) some nationality/area. We transform the data

- from the ancestry-answer ("ancestr1") level to the 1990 foreign-country level using ancestry-to-country transition matrices.

- from the US-county group/puma level to the US county-level using group/puma-to-county transition matrices.
- from the non-1990 US-county level to the 1990 US-county level using county-to-county transition matrices.
- from the post-1990 US-county to the 1990 US-county level. Based on the information from https://www.census.gov/geo/reference/county-changes.html, a new county is either created from part of ONE 1990 county or assigned a new FIPS code after 1990, so we manually change that county's FIPS code to what it was in 1990. A few counties' boundaries have been changed after 1990 but that only involved a tiny change in population, so we ignore the difference.

A.2 Details on the construction of FDI data

Our FDI data are from the US file of the Bureau van Dijk ORBIS dataset. For each US firm, the raw data set lists the location of its (operational) headquarters, the addresses of its foreign parent entities, and the addresses of its international subsidiaries and branches. It also provides the number of employees for both US and foreign firms. The steps for building the data follow below.

Clean postcode information

We use firm's postcode as a unique identifier for the county location of the US firm, and then need to ensure that one county uniquely corresponds to one postcode. Vance, NC; Wakulla, FL; Citrus, FL; Rankin, MS; Union, OH; and Du Page, IL share at least one postcode with a neighboring county. In each case we assign that postcode wholly to the county with the larger population (according to Google 2012 population data). In the last step, we hand-coded missing postcodes that we took from main data set. Only one such case existed: 75427 for Dallas.

Build the parent data

We used the following variables from the parent dataset: "Mark" "Company name" "BvD ID number" "Country ISO Code" "City" "Postcode" "NAICS 2007 Core code (4 digits)" "NAICS, text description" "Number of employees 2013" "Shareholder - Name" "Shareholder - BvD ID number" "Shareholder - City" "Shareholder - Postal code" "Shareholder - NAICS 2007, Core code" "Shareholder - NAICS 2007, text description" "Shareholder - Country ISO code" "Shareholder - Direct %" "Shareholder - Total %" "Shareholder - Number of employees". Here "shareholder" is equivalent to "parent" in our context. The key data-building steps are as follows:

1. Assign numerical values to "Shareholder Direct" and "Shareholder Total":
    - When the stake of a shareholder is described by an acronym rather than a number, we replace it with numerical values as follows: MO, majority owned, is replaced by "75%"; JO, jointly owned, is replaced by "50%"; NG, negligent, is replaced by '0%'; BR, branch and WO, wholly owned are both replaced by "100%".[53]

[53]See http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2407845 for reference.

- When the stake of a shareholder is described by the following expressions, we replace it with a numerical value as follows: Values with a ">", e.g., " > 25.00" were replaced by the original number plus 10; values with a "<", e.g., " < 34.00", were replaced by the original number minus 10; values with a "±", e.g. "±25.00", were replaced by the original number.

2. Postcode matching: We matched both US firms and US parents (foreign parents were ignored in this step), with our postcode data. Besides the original string variable postcode, we generated new variables postcode5digit and postcodeextension and labeled them "Postal code (5 digit)" and "Postal code (extension)." Similarly, shareholders had shareholderpostcodeUS5digit and shareholderpostcodeUSextension (note the spelling postal code in shareholder variables was unified to postcode).

3. Country-code matching: We matched both companies and their parents. Each firm had four country variables: numerical country code, country name, and 2- and 3- digit ISO country code. Then we adjusted those 2014 country codes to 1990 codes based on the information on post-1990 country changes.

Build the subsidiary data

We used the following variables from the subsidiary dataset: "Mark" "Company name" "BvD ID number" "Country ISO Code" "City" "Postcode" "NAICS 2007 Core code (4 digits)" "NAICS, text description" "Number of employees 2007" "Subsidiary - Name" "Subsidiary - BvD ID number" "Subsidiary - Country ISO code" "Subsidiary - City" "Subsidiary - Postal code" "Subsidiary - NAICS 2007, Core code" "Subsidiary - NAICS 2007, text description" "Subsidiary - Number of employees" "Subsidiary - Direct %" "Subsidiary - Total%" "Branch - Name" "Branch - BvD ID number" "Branch - Country ISO code" "Branch - City" "Branch - Postcode" "Branch - NAICS 2007, Core code" "Branch - NAICS 2007, text description" "Branch - Number employees". The data cleaning process is identical to that of the parent data described above, with the exception that we merged subsidiaries with branches and refer to them collectively as "subsidiaries".

A.3 Details on the construction of other data

International trade.— The data on trade between US states and foreign countries, both at the aggregate level and at the sectoral level, are from the Commodity Flow Survey for the year 2012. The data are collected by the US Census Bureau. A representative sample of establishments are surveyed every five years, and information on their shipments collected. The value of all shipments crossing the US international border are recorded as international trade, along with their foreign origin/destination country. We only used thes readily available data aggregated at the US state and foreign country level. Although they do not cover all of the US foreign trade (the data com from a representative survey, not from the universe of foreign transactions), they are the only publicly available source of international data disaggregated at a geographic level below that of the entire United States. For each origin country and destination state, $Import_{o,d}$ are aggregate imports (in dollars) from country o to US state d in 2012, and $Export_{o,d}$ are aggregate exports (in dollars) from US state d to country o in 2012, where we keep the convention of using o for foreign countries and d for US administrative units, states or counties.

Bilateral distances and latitude differences.— To compute the distance between US counties or states and foreign countries, we used the coordinates for all postal codes within a county or state, and the coordinates of the main city for foreign countries.[54] We define the latitude and longitude of a US county as the unweighted average of the latitudes and longitudes of all postal codes within the county. We define the latitude and longitude of a US state as the unweighted average of the latitude and longitude of all counties within the state. The distance between foreign country o and a US county or state d, $Distance_{o,d}$, is computed as the great circle distance between the two, measured in kms. The latitude difference between a foreign country o and a US county or state d, $Latitude\,Difference_{o,d}$, is the absolute difference between the latitudes of the two, measured in degrees.

Country characteristics.— To shed light on the mechanism through which the presence of foreign ancestry affects the patterns for foreign investment, we constructed several measures of foreign country and US county characteristics. *"Genetic Distance"* is a measure of the genetic distance between a given foreign country and the United States, normalized to take values between 0 and 1. *"Linguistic Distance"* is a measure of the linguistic distance between a given foreign country and the United States; it measures the probability that a randomly selected person in the United States speaks the same language as a randomly selected person from that country. *"Religious Distance"* measures the religious distance between a given foreign country and the United States, with a similar construction as the linguistic distance.[55] A higher index for *"Genetic Distance"*, *"Linguistic Distance"*, or *"Religious Distance"* corresponds to a greater distance between the United States and that country. *"Judicial Quality"* is a measure of the judicial quality in a given country.[56] A higher index for *"Judicial Quality"* corresponds to a higher-quality judicial system. *"Ethnic Diversity"* is a measure of a country's ethnolinguistic fractionalization.[57]

US county characteristics.— We define three US-county level measures. *"Diversity of Ancestries"* is a measure of the diversity of communities from different ancestries in a given US county.[58] *"Foreign Share"* measures the share of residents in a given county who claim foreign ancestry.

Sectoral characteristics.— We separated sectors into final consumption goods and intermediate inputs. To do so, we use the measure of upstreamness from Antràs et al. (2012). We classified 4-digit NAICS sectors as "final goods" if their upstreamness index is below 2, and as "intermediates" if their upstreamness index is above 2.

[54]The geo-coordinates are downloaded from www.geonames.organd www.cepii.fr, respectively. When a county has multiple postcodes we randomly select one of them and use the geocoordinates for that randomly selected postcode.

[55]Both genetic and religious distance measures come from Spolaore and Wacziarg (2015).

[56]The measure of judicial quality comes from Kaufmann et al. (2003) and is used in Nunn (2007). It is based on a weighted average of variables measuring perceptions of the effectiveness of the judiciary and the enforcement of contracts.

[57]The measure of fractionalization comes from Alesina et al. (2003). It is equal to 1 minus the Herfindahl index of ethnolinguistic group shares.

[58]It is equal to 1 minus the Herfindahl index of ancestry, measured as the sum of squared fractions of all possible ancestry among people who report foreign ancestry within that US county

A.4 Details on the construction of information demand indices

The Information Demand Index is based on data gathered from Google and created in three steps. In the first step we identify five prominent individuals from country o in category p, where $p \in \{\text{actors, athletes, musicians, politicians}\}$. In the second step we utilise Google Trends to obtain data on the spatial variation in the relative frequency of search queries related to these individuals. In the last step we construct indices of the search intensity related to country o in destination d.

Step 1: To identify the top five prominent individuals from o in each category p, we utilise a tool called Google's featured snippet box. Google's featured snippet box is a response to a search query that is generated by Google and pushed to the top of the result list. Google generates these answers by scraping its top results and using an algorithm to provide what it determines to be the most relevant answer.[59] For our purposes we record the top five names in Google's featured snippet box in response to the query "notable [country] [p]", where [country] is one of the 100 largest countries by 2015 population. For example, searching for "notable Belgium actors" yields Google's featured snippet box with an ordered list of Belgian actors. We save the top five names from left to right as the set of search queries $q(o, p)$. If Google's featured snippet box does not give a response for a country, we record a missing entry.[60]

Step 2: Google Trends provides historical and cross-sectional information about the relative importance of a search query. For the United States, the cross-sectional information with the highest granularity is at the level of a Designated Market Area (DMA).[61] Google Trends expresses the relative importance of a search query in a given DMA as an integer value from 0 to 100. This integer value is calculated as follows. First, find the number of searches for the query at hand relative to the total number of searches, and define the maximum search market share of any DMA to 100. Second, divide each search market share by the maximum, and express it as a rounded percentage. If the result does not exceed an unreported threshold, set it to zero (Liang, 2017; Stephens-Davidowitz and Varian, 2015). Formally,

$$G(i, d) = \left\lfloor 100 \frac{share_{i,d}}{\max_{\delta}\{share_{i,\delta}\}} \mathbf{1}[\#(i, d) \geq T] \right\rceil$$

where $\lfloor x \rceil$ is the integer round function, $share_{i,d}$ is the search market share of search query i in DMA d, and T is the unreported search volume threshold. Note that T is defined on the absolute number of searches, rather than the search market share. This implies that DMAs with a larger population will tend to report more data than those with smaller populations. Note also that in addition to $G(i, d)$ being reported as zero for some i and d, we set its value equal to zero if there is no search result from Google's featured snippet box, or if there is no result from Google Trend.

[59] See https://support.google.com/webmasters/answer/6229325?hl=en

[60] This is the case for about 4-10% of our sample, depending on the category.

[61] Google Trends also breaks the information down by major city; however, we would lose non-city data.

Step 3: We define the p-specific Index for each DMA-country pair as

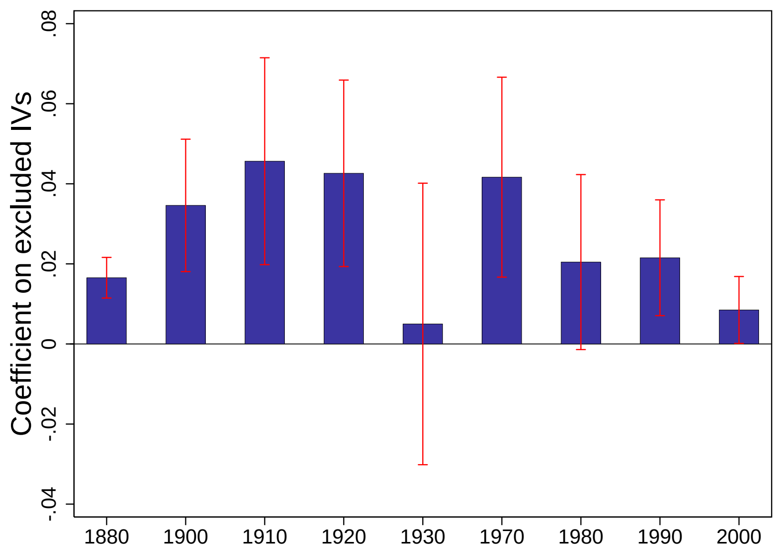
$$I(p,o,d) = \frac{1}{5} \sum_{i \in q(o,p)} G(i,d)$$

We define the Information Demand Index as the average over the p-specific indices:

$$\text{IDI}_{o,d} = \frac{1}{5} \sum_{p} I(p,o,d).$$

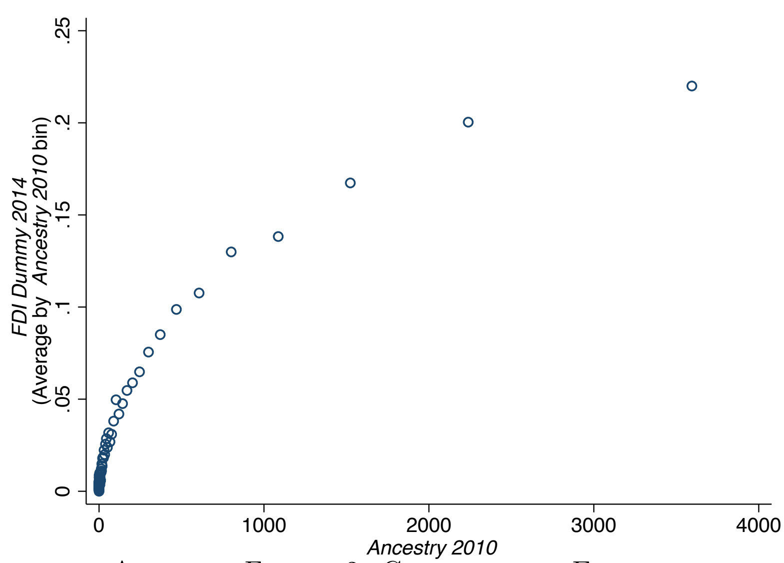
to the query "notable [country] [p]", where [country] is one of the 100

B Additional figures and tables



Appendix Figure 1: Reduced-Form Coefficients

Notes: Coefficient estimates (bars) and 95% confidence intervals (lines) on the excluded instruments $\{I^t_{o,-r(d)}(I^t_{-c(o),d}/I^t_{-c(o)})\}_{t=1880,\ldots,2000}$ from a reduced form regression corresponding to the specification in column 2 of Table 2, using the 2014 FDI dummy as dependent variable. Robust standard errors are clustered at the origin country level. The R^2 of this regression is 0.218.



Appendix Figure 2: Concavity of Effect

Notes: This figure plots of the mean of *FDI Dummy 2014* within bins of *Ancestry 2010*. The *Ancestry 2010* bins are constructed as centiles of the conditional distribution of *Ancestry 2010*$|$*Ancestry 2010*> 0. The lowest bin corresponds to *Ancestry 2010*$= 0$. We do not plot the mean of *FDI Dummy 2014* in the 99th and 100th centile *Ancestry 2010* bin for visual clarity; the overall concave pattern extends to these observations.

Appendix Table 4: Composition of Sector Groups used in Table 17

Group	NAICS Sectors	# of US Firms
Manufacturing	Manufacturing	10009
Trade	Wholesale Trade Retail Trade	7191
Information, Finance, Management, and Other Services	Information Finance and Insurance Professional, Scientific, and Technical Services Management of Companies and Enterprises Administrative and Support and Waste Management and Remediation Services Other Services (Except Public Administration)	10052
Construction, Real Estate, Accomodation, Recreation	Construction Transportation and Warehousing Real Estate and Rental and Leasing Arts, Entertainment, and Recreation Accommodation and Food Services	3039
Health, Education, Utilities, and Other Public Services	Utilities Educational Services Health Care and Social Assistance	1257
Natural Resources	Agriculture, Forestry, Fishing and Hunting Mining, Quarrying, and Oil and Gas Extraction	871

Appendix Table 5: Summary Statistics on the Intensive Margin of FDI

Origin-destination pairs	(1)	(2)	(3)
Ancestry 2010 (in thousands)	10.038	16.502	10.861
	(40.989)	(62.950)	(43.593)
# of FDI Relationships	11.043		
	(39.738)		
# of Parents in Destination		2.282	
		(4.336)	
# of Parents in Origin		8.063	
		(26.132)	
# of Workers Employed at Subsidiary in Destination (in thousands)		6.328	
		(32.695)	
# of Subsidiaries in Origin			1.797
			(10.671)
# of Parents in Destination			0.761
			(3.105)
# of Workers Employed at Subsidiary in Origin (in thousands)			2.435
			(40.360)
N	10851	4065	9082

Notes: The table presents means (and standard deviations). Variables refer to our sample of country-county pairs used in Table 7. Column 1 shows data for observations that have at least one FDI link. Column 2 shows data for observations that have at least one subsidiary in the origin. Column 3 shows data for observations pairs that have at least one subsidiary in the destination.

Appendix Table 6: Assignment of States to Census Regions

Census Region	State Names
New England	Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont
Middle Atlantic	New Jersey, New York, Pennsylvania
East North Central	Illinois, Indiana, Michigan, Ohio, Wisconsin
West North Central	Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota
South Atlantic	Delaware, District Of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia
East South Central	Alabama, Kentucky, Mississippi, Tennessee
West South Central	Arkansas, Louisiana, Oklahoma, Texas
Mountain	Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming
Pacific	Alaska, California, Hawaii, Oregon, Washington

Appendix Table 7: The Effect of Ancestry on FDI: Variations of Leave-Out Instrument

	(1)	(2)	(3)	(4)	(5)	(6)
			FDI Dummy (2014)			
Panel A			$\{I^t_o(I^t_d/I)\}$ excluded			
Log Ancestry 2010	0.204***	0.202***	0.174***	0.174***	0.183***	0.215***
	(0.020)	(0.019)	(0.022)	(0.022)	(0.022)	(0.017)
N	612495	612495	612495	612495	612495	612300
Panel B			$\{I^t_{o,-d}(I^t_{-o,d}/I^t_{-o})\}$ excluded			
Log Ancestry 2010	0.212***	0.204***	0.172***	0.171***	0.185***	0.216***
	(0.020)	(0.019)	(0.024)	(0.024)	(0.024)	(0.017)
N	612495	612495	612495	612495	612495	612300
Panel C			$\{I^t_{o,-d}(I^t_{-c(o),d}/I^t_{-c(o)})\}$ excluded			
Log Ancestry 2010	0.223***	0.217***	0.183***	0.183***	0.200***	0.227***
	(0.022)	(0.021)	(0.024)	(0.024)	(0.024)	(0.018)
N	612495	612495	612495	612495	612495	612300
Panel D			$\{I^t_{o,-adj(d)}(I^t_{-c(o),d}/I^t_{-c(o)})\}$ excluded			
Log Ancestry 2010	0.232***	0.204***	0.192***	0.192***	0.206***	0.237***
	(0.024)	(0.022)	(0.022)	(0.022)	(0.021)	(0.019)
N	640764	640764	640764	640764	640764	640560
Panel E			$\{I^t_{o,-r(d)}(I^t_{-s(o),d})(I^t_{-s(o)})\}$ excluded			
Log Ancestry 2010	0.224***	0.188***	0.193***	0.193***	0.197***	0.197***
	(0.022)	(0.020)	(0.023)	(0.023)	(0.021)	(0.024)
N	612495	612495	612495	612495	612495	612300
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Principal Components	No	Yes	Yes	Yes	Yes	Yes
Destination × Continent FE	No	No	Yes	Yes	Yes	Yes
Origin × Census Region FE	No	No	Yes	Yes	Yes	Yes
3rd order poly in dist and lat	No	No	No	Yes	No	No
$I^{2010}_{o,-r(d)}(I^{2010}_{-c(o),d}/I^{2010}_{-c(o)})$	No	No	No	No	Yes	No
Origin × State FE	No	No	No	No	No	Yes

Notes: The table shows variations of the estimates from Panel A in Table 3, removing or not different sets of migrants from the interaction of pull and push factors. The construction of the interaction is indicated above each panel. In Panel D, *adj* (d) refers to the adjacent states for the state of county d; thus we exclude from the push factor of o migrations to any state adjacent to the state of d, including the state itself. In Panel E, "s" refers to similar countries; that is, we exclude from a given pull factor of o to d all countries for which the time correlation of total migration to the US is significantly (at the 5% level) correlated with o's migration to the US.

Appendix Table 8: The effect of Ancestry in 2000 on FDI in 2007

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: IV			*FDI 2007 (Dummy)*			
Log Ancestry 2000	0.250***	0.184***	0.182***	0.182***	0.188***	0.184***
	(0.018)	(0.020)	(0.020)	(0.020)	(0.019)	(0.021)
KP F-stat on excluded IV's	12.06	10.32	167.32	165.46	156.29	189.21
Stock-Yogo 5% critical values	20.25	20.25	21.10	21.10	21.18	21.18
Stock-Yogo 10% critical values	11.39	11.39	11.52	11.52	11.52	11.52
N	612,495	612,495	612,495	612,495	612,495	612,300
Panel B: OLS			*FDI 2007 (Dummy)*			
Log Ancestry 2000	0.216***	0.184***	0.184***	0.184***	0.184***	0.200***
	(0.015)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)
N	612,495	612,495	612,495	612,495	612,495	612,300
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination × Continent FE	No	Yes	Yes	Yes	Yes	Yes
Origin × Census Region FE	No	Yes	Yes	Yes	Yes	Yes
Principal Components	No	No	Yes	Yes	Yes	Yes
3rd order poly in dist and lat	No	No	No	Yes	No	No
$I^{2000}_{o,-r(d)}(I^{2000}_{-c(o),d}/I^{2000}_{-c(o)})$	No	No	No	No	Yes	No
Origin × State FE	No	No	No	No	No	Yes

Notes: The table presents coefficient estimates from IV (Panel A) and OLS (Panel B) regressions of equation (1) at the country-county level. The dependent variable in all panels is a dummy indicating an FDI relationship between origin o and destination d in 2007. The main variable of interest is *Log Ancestry 2000*, instrumented using various specifications of equation (4). In all columns in Panel A, we include $\{I^t_{o,-r(d)}(I^t_{-c(o),d}/I^t_{-c(o)})\}_{t=1880,\ldots,1990}$ as excluded instruments. Columns 3-6 also include the first five principal components of the higher-order interactions of push and pull factors as instruments. Column 5 also includes the interaction of the push and pull factor constructed using data from the 1990-2010 wave. All specifications control for log distance, latitude difference, origin, and destination fixed effects. Standard errors are given in parentheses. Standard errors are clustered at the origin country level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 9: Nonlinear Least Squares Estimation

β	π
0.1683***	0.0010***
(0.0011)	(0.0003)

Notes: The table presents coefficient estimates from a nonlinear least squares regression at the country-county level. The dependent variable is the dummy for FDI in 2014. It shows (un-adjusted) NLS standard errors. We obtain the optimal β and π by solving the nonlinear least squares problem in equation (7). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 10: Alternative Functional Forms

	FDI 2014 (Dummy)					
	(1)	(2)	(3)	(4)	(5)	(6)
Ancestry 2010	0.002***					
	(0.001)					
Log Ancestry 2010 (-1 for $-\infty$)		0.190**				
		(0.080)				
(Ancestry 2010)$^{1/3}$			0.187***			
			(0.021)			
Log Ancestry 1980				0.127***		
				(0.031)		
Log Ancestry 1990					0.128***	
					(0.036)	
Log Ancestry 2000						0.132***
						(0.038)
N	612495	612495	612495	612495	612495	612495

Notes: The table presents coefficient estimates from IV regressions at the country-county level. The dependent variable is the dummy for FDI in 2014. The main variable of interest in each column is the measure of ancestry indicated by the first column of the table. In the second row, we use Log(Ancestry/1000) instead of Log(1+Ancestry/1000), and replace Log(0) with -1. All specifications are the same as that in Table 3, column 3. Standard errors are given in parentheses and are clustered at the country level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 11: Varying ownership cutoffs

Panel A: FDI dummy on ancestry (IV)	*FDI 2014 (Dummy)*			
	(1)	(2)	(3)	(4)
Log Ancestry 2010	0.189***	0.190***	0.190***	0.157***
	(0.024)	(0.024)	(0.024)	(0.029)
R^2	0.352	0.352	0.352	0.318
N	612495	612495	612495	612495
Panel B: # of FDI relationships on ancestry (IV)	*Log Total # of FDI relationships*			
	(1)	(2)	(3)	(4)
Log Ancestry 2010	0.408***	0.394***	0.402***	0.075
	(0.042)	(0.045)	(0.046)	(0.062)
R^2	0.750	0.749	0.749	0.770
N	10445	10393	10365	6981
Ownership cutoff	keep $\geq$ 5%	keep $\geq$ 25%	keep $\geq$ 50%	keep $<$ 50%
Destination FE	Yes	Yes	Yes	Yes
Origin FE	Yes	Yes	Yes	Yes
Principal Components	Yes	Yes	Yes	Yes
Destination $\times$ Continent FE	Yes	Yes	Yes	Yes
Origin $\times$ Census Region FE	Yes	Yes	Yes	Yes

Notes: This table presents coefficient estimates from variations of the IV regression in column 3 of Table 3 (Panel A) and in column 2 of Table 7 (Panel A). We vary the ownership cutoff across columns: In columns 1, 2, 3, and 4 we keep all shareholder-subsidiary pairs with ownership $\geq$ 5%, $\geq$ 25%, $\geq$ 50%, respectively. The number of origin-destination pairs with any FDI under these cutoffs are 10445, 10393, and 10365. In column 4 we keep all shareholder-subsidiary pairs with ownership $<$ 50%, which results in 6981 origin-destination pairs with any FDI. Standard errors are given in parentheses and are clustered at the origin country level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 12: Alternative Standard Errors: Main Specification

Panel A: Analytical	
Robust	0.0092
Cluster by county	0.0171
Cluster by country†	0.0243
Cluster by county and country	0.0280
Cluster by state and country	0.0285
Cluster by state	0.0189
Cluster by continent	0.0070
Cluster by state×country	0.0114
Panel B: Bootstrap	
Robust	0.0092
Cluster by county	0.0161
Cluster by country	0.0291

Notes: This table shows various standard errors on Log Ancestry 2010 based on our standard specification (column 3 of Table 3). The bootstrapped standard errors in Panel B are obtained using 1,000 draws with replacement. † denotes our standard specification.

Appendix Table 13: Alternative Standard Errors: Other Specifications

	Standard specification	Communist natural experiment	Intensive margin	Immigration 1990-2000
	(1)	(2)	(3)	(4)
Outcome variable	FDI Dummy (2014)		Log total # of FDI Relationships	Immigration 1990-2000
Panel A: Clustered by Country (Standard)				
Log Ancestry 2010	0.187***	0.234**	0.356***	
	(0.024)	(0.098)	(0.056)	
Log Ancestry 1990				9.662**
				(4.455)
$I^{2000}_{o,-r(d)} \frac{I^{2000}_{-c(o),d}}{I^{2000}_{-c(o)}}$				1.082***
				(0.358)
Panel B: S.E. Clustered by County				
Log Ancestry 2010	0.187***	0.234**	0.356***	
	(0.017)	(0.092)	(0.077)	
Log Ancestry 1990				9.662**
				(4.327)
$I^{2000}_{o,-r(d)} \frac{I^{2000}_{-c(o),d}}{I^{2000}_{-c(o)}}$				1.082***
				(0.230)
Panel C: S.E. Clustered by State				
Log Ancestry 2010	0.187***	0.234**	0.356***	
	(0.019)	(0.101)	(0.071)	
Log Ancestry 1990				9.662**
				(3.942)
$I^{2000}_{o,-r(d)} \frac{I^{2000}_{-c(o),d}}{I^{2000}_{-c(o)}}$				1.082***
				(0.267)
Panel D: Clustered by County and Country				
Log Ancestry 2010	0.187***	0.234*	0.356***	
	(0.028)	(0.106)	(0.120)	
Log Ancestry 1990				9.662**
				(4.800)
$I^{2000}_{o,-r(d)} \frac{I^{2000}_{-c(o),d}}{I^{2000}_{-c(o)}}$				1.082***
				(0.105)
Panel E: Clustered by State and Country				
Log Ancestry 2010	0.187***	0.234*	0.356***	
	(0.028)	(0.113)	(0.116)	
Log Ancestry 1990				9.662**
				(4.308)
$I^{2000}_{o,-r(d)} \frac{I^{2000}_{-c(o),d}}{I^{2000}_{-c(o)}}$				1.082***
				(0.044)

Notes: This table shows variations based on four main regressions: standard specification (column 3 in Table 3), communist natural experiment (column 5 in 4), intensive margin (based on column 2 in Panel A of Table 7), and immigration 1990-2000 (column 1 in Table 6). In Panel A, we reproduce the standard error clustering in our main tables; in Panel B, we cluster by county; in Panel C, we cluster by country, in Panel D we double cluster by county and country, and in Panel E we double cluster by state and country.

Appendix Table 14: Placebo Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	FDI 2014 (Dummy)					
Panel A	*Assign to alphabet neighbor*					
Log Ancestry 2010	-0.012	-0.007	0.009	0.009	0.010	0.012
	(0.020)	(0.015)	(0.028)	(0.028)	(0.028)	(0.031)
N	612495	612495	612495	612495	612495	612300
Panel B	*Assign to alphabet neighbor on a different continent*					
Log Ancestry 2010	-0.026	-0.021	0.009	0.009	0.013	0.012
	(0.021)	(0.015)	(0.033)	(0.033)	(0.038)	(0.037)
N	612495	612495	612495	612495	612495	612300
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Principal Components	No	Yes	Yes	Yes	Yes	Yes
Destination × Continent FE	No	No	Yes	Yes	Yes	Yes
Origin × Census Region FE	No	No	Yes	Yes	Yes	Yes
3rd order poly in dist and lat	No	No	No	Yes	No	No
$I^{2010}_{o,-r(d)}(I^{2010}_{-c(o),d}/I^{2010}_{-c(o)})$	No	No	No	No	Yes	No
Origin × State FE	No	No	No	No	No	Yes

Notes: The table presents coefficient estimates from placebo regressions corresponding the the specifications in Table 3. In Panel A, we assign the outcomes (FDI 2014 Dummy) for each origin country to the next country in the alphabet. In Panel B, we assign the outcomes (FDI 2014 Dummy) for each origin country to the next country in the alphabet that is from another continent.

Appendix Table 15: The Effect of Ancestry on FDI: Five Largest Countries and Counties

	FDI 2014 (Dummy)
Panel A: Top 5 Ancestries	*Log Ancestry 2010*
Germany	0.216***
	(0.009)
Britain	0.271***
	(0.009)
Mexico	0.171***
	(0.011)
Ireland	0.202***
	(0.010)
Italy	0.219***
	(0.007)
Panel B: Largest 5 Counties	*Log Ancestry 2010*
Los Angeles, California	0.137***
	(0.019)
Cook, Illinois	0.146***
	(0.020)
Harris, Texas	0.169***
	(0.023)
San Diego, California	0.164***
	(0.024)
Orange, California	0.160***
	(0.020)

Notes: The table presents coefficient estimates from IV regressions at the country-county level. The dependent variable in all panels is the dummy for FDI in 2014. Panel A presents the coefficient on *Log Ancestry 2010* when we run our estimation separately for each of the largest five origin countries. Panel B presents the coefficient on *Log Ancestry 2010* when we run our estimation separately for each of the five US counties with the largest population in 2010. The composition of sector groups in panel A is given in Appendix Table 4. We use $\{I^t_{o,-r(d)}(I^t_{-c(o),d}/I^t_{-c(o)})\}_{t=1880,\ldots,2000}$ and principal components as IVs. All specifications control for log distance and latitude difference. Standard errors are clustered at the country level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 16: The Effect of Ancestry on FDI: Country Specific Effects

	Point Estimate	Standard Error	*FDI 2014 (Dummy)* > 0
United Arab Emirates	11.875***	(2.712)	60
Kuwait	6.098***	(2.120)	22
Finland	4.113***	(0.513)	180
New Zealand	2.980***	(0.511)	107
Oman	2.481	(1.597)	6
British Virgin Islands	2.467***	(0.604)	100
Australia	2.201***	(0.384)	369
Malaysia	2.005***	(0.406)	90
South Africa	1.832***	(0.247)	80
Tunisia	1.438***	(0.345)	9
Iceland	1.359***	(0.276)	25
Saudi Arabia	1.144***	(0.158)	29
Belgium and Luxembourg	1.086***	(0.087)	354
Puerto Rico	1.034***	(0.240)	26
Israel	0.944***	(0.156)	137
Bahamas	0.943***	(0.308)	44
Switzerland	0.814***	(0.048)	371
Denmark	0.684***	(0.043)	278
Thailand	0.583***	(0.070)	68
Japan	0.566***	(0.051)	575
Uruguay	0.541***	(0.115)	21
Austria	0.531***	(0.042)	148
Chile	0.502***	(0.078)	73
Brazil	0.496***	(0.047)	140
Barbados	0.462**	(0.234)	38
Canada	0.461***	(0.024)	809
Norway	0.459***	(0.028)	239
Malta	0.451	(0.281)	11
Costa Rica	0.447***	(0.140)	30
Turkey	0.444***	(0.067)	48
Netherlands	0.442***	(0.019)	398
Panama	0.439***	(0.115)	44
Indonesia	0.413***	(0.076)	29
Argentina	0.412***	(0.056)	64
Sweden	0.405***	(0.018)	323
Senegal	0.383	(0.314)	2
France	0.346***	(0.013)	528
South Korea	0.346***	(0.023)	155
Liberia	0.341*	(0.190)	6
Spain	0.335***	(0.014)	300
India	0.320***	(0.018)	233
China	0.299***	(0.015)	248
Kenya	0.292*	(0.175)	5
Venezuela	0.275***	(0.046)	32
Britain	0.271***	(0.009)	664
Egypt	0.259***	(0.051)	23
Belize	0.255***	(0.086)	14

Hungary	0.240***	(0.033)	52
Colombia	0.237***	(0.028)	45
Italy	0.219***	(0.007)	489
Peru	0.218***	(0.033)	30
Germany	0.216***	(0.009)	608
Portugal	0.206***	(0.028)	85
Samoa	0.204**	(0.086)	5
Ireland	0.202***	(0.010)	247
Morocco	0.197**	(0.078)	11
Nigeria	0.190***	(0.055)	18
Sri Lanka	0.180	(0.120)	6
Czechoslovakia	0.177***	(0.029)	54
Romania	0.173***	(0.041)	23
Mexico	0.171***	(0.011)	259
Pakistan	0.168***	(0.039)	23
USSR	0.165***	(0.015)	97
Ghana	0.156	(0.095)	6
Bulgaria	0.156**	(0.064)	11
Philippines	0.154***	(0.019)	50
Lebanon	0.150***	(0.047)	20
Bolivia	0.142**	(0.066)	8
Greece	0.131***	(0.028)	42
Trinidad and Tobago	0.130*	(0.067)	15
Socialist Yugoslav	0.121***	(0.028)	29
Jamaica	0.114***	(0.032)	15
Honduras	0.103***	(0.032)	14
Algeria	0.099	(0.076)	3
Guatemala	0.097***	(0.033)	14
Poland	0.092***	(0.015)	63
Viet Nam	0.091***	(0.025)	18
Jordan	0.090	(0.063)	7
Cameroon	0.085	(0.065)	2
Dominican Republic	0.082***	(0.025)	16
Ecuador	0.081**	(0.032)	15
Paraguay	0.079	(0.056)	4
Nicaragua	0.069*	(0.036)	7
Albania	0.069	(0.046)	3
North Korea	0.068	(0.072)	1
El Salvador	0.066**	(0.026)	13
Sudan	0.065	(0.065)	1
Fiji	0.065	(0.046)	5
Bangladesh	0.040	(0.032)	2
Cambodia	0.039	(0.028)	3
Haiti	0.026	(0.019)	2
Ethiopia	0.026	(0.025)	1
Syria	0.016	(0.016)	1
Myanmar	0.007	(0.007)	1
Afghanistan	0.003	(0.003)	1
Guyana	0.002	(0.002)	1

Iraq	0.002	(0.002)	1
Cuba	-0.000***	(0.000)	1
Libya	-0.022	(0.024)	1
Nepal	n/a	n/a	0
Grenada	n/a	n/a	0
State of Palestine	n/a	n/a	0
Sierra Leone	n/a	n/a	0
Yemen	n/a	n/a	0
Equatorial Guinea	n/a	n/a	0
Somalia	n/a	n/a	0
Greenland	n/a	n/a	0
Cape Verde	n/a	n/a	0
Mauritania	n/a	n/a	0
Tonga	n/a	n/a	0
Lao	n/a	n/a	0
Mongolia	n/a	n/a	0
Iran	n/a	n/a	0

Notes: The table is an extension of Table 15 Panel A, where we only show the results for top five ancestries. Results are sorted on the point estimate. The last column shows the number of US counties that have an FDI link with the corresponding country. All countries with ancestry < 1 are discarded.

Appendix Table 17: The Effect of Ancestry on FDI: Sector-Specific Effects

20 Sectors Based on 2007 NAICS code	Point Estimate	Standard Error	*FDI 2014 (Dummy)* > 0
Manufacturing	0.165***	(0.024)	5,549
Wholesale Trade	0.141***	(0.026)	2,513
Professional, Scientific, and Technical Services	0.122***	(0.024)	1,925
Retail Trade	0.085***	(0.020)	846
Information	0.084***	(0.018)	906
Transportation and Warehousing	0.084***	(0.016)	620
Administrative and Support and Waste Management and Remediation Services	0.083***	(0.018)	855
Real Estate and Rental and Leasing	0.077***	(0.020)	662
Finance and Insurance	0.071***	(0.019)	1,143
Other Services (except Public Administration)	0.053***	(0.014)	301
Management of Companies and Enterprises	0.049***	(0.014)	524
Construction	0.040**	(0.016)	510
Accommodation and Food Services	0.035***	(0.010)	239
Arts, Entertainment, and Recreation	0.030***	(0.006)	131
Mining, Quarrying, and Oil and Gas Extraction	0.028***	(0.009)	528
Health Care and Social Assistance	0.024**	(0.012)	291
Utilities	0.022*	(0.012)	338
Educational Services	0.009	(0.006)	111
Agriculture, Forestry, Fishing and Hunting	0.007**	(0.003)	149
Public Administration	0.001	(0.001)	10

Notes: The table presents coefficient estimates on *Log Ancestry 2010* from IV regressions for each of the 20 2-digit NAICS sectors at the country-county level. Each row of the table corresponds to one regression. The dependent variable in each row is a dummy variable for FDI in 2014 in the sector indicated. The last column shows the number of country-county pairs that have an FDI link with the corresponding country. We use $\{I^t_{o,-r(d)}(I^t_{-c(o),d}/I^t_{-c(o)})\}_{t=1880,\ldots,2000}$ and principal components as IVs. All specifications control for log distance, latitude difference, origin×destination-census-region, and destination×continent-of-origin fixed effects. Standard errors are given in parentheses and are clustered at the origin country level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 18: Heterogeneous Effects across Sectors and Firms

	Log Ancestry 2010	*FDI 2014 (Dummy)* > 0
FDI 2014 (Dummy)	(1)	(2)
Panel A: Individual Sectors		
Manufacturing	0.165***	
	(0.024)	
Trade	0.158***	
	(0.025)	
Information, Finance, Management, and other Services	0.143***	
	(0.024)	
Construction, Real Estate, Accomodation, Recreation	0.125***	
	(0.021)	
Health, Education, Utilities, and other Public Services	0.042**	
	(0.019)	
Natural Resources	0.035***	
	(0.009)	
Panel B: Small vs. Large Firm Size		
Above Median	0.112***	1,840
	(0.018)	
Below Median	0.051***	723
	(0.024)	
p-value of χ^2 test, H_0: equality of coefficients	0.000	

Notes: The table presents coefficient estimates on *Log Ancestry 2010* from IV regressions at the country-county level. Each row of the table corresponds to a separate regression. The dependent variables in all rows are dummy variables that are one if any firm within the indicated subset of firms in destination county d has a parent or subsidiary in origin country o. These subsets of firms are five sector groups (panel A) and for small- versus large firms (panel C). The composition of sector groups in panel A is given in Appendix Table 4. The cutoff value between small and large firms is the median employee number, which is 1380 for US firms that are subsidiaries and 1057 for US firms that are parents. Throughout, we use $\{I^t_{o,-r(d)}(I^t_{-c(o),d}/I^t_{-c(o)})\}_{t=1880,\ldots,2000}$ and principal components as intrumental variables. "*FDI 2014 (Dummy)* $>$ 0" refers to the number of country-county pairs that have an (non-zero) FDI link in the corresponding sector. All specifications control for log distance, latitude difference, origin×destination-census-region, and destination×continent-of-origin fixed effects. Standard errors are given in parentheses and are clustered at the origin country level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 19: The Effect of Ancestry on Language: Language Specific Effects

	Point Estimate	Standard Error	N	# of US-born in d that speak o at home in 2010
Aleut	1.608***	(0.028)	3,137	116
Malay	1.376	(0.897)	9,411	176
Arabic	1.222***	(0.171)	78,376	45,953
Spanish	1.172***	(0.380)	65,877	65,877
French	0.212***	(0.018)	87,836	87,416
Haitian Creole	0.198***	(0.015)	3,137	595
Greek	0.196***	(0.033)	6,273	1,849
Vietnamese	0.188***	(0.006)	3,137	1,739
Portuguese	0.174***	(0.030)	28,233	13,095
Korean	0.170***	(0.041)	6,274	3,040
Mon-Khmer	0.167***	(0.005)	3,136	316
Urdu	0.159***	(0.020)	3,137	499
Bengali	0.153***	(0.015)	3,137	191
Japanese	0.142***	(0.007)	3,137	1,972
Persian	0.102***	(0.005)	3,137	538
Chinese	0.085***	(0.005)	3,137	1,745
Thai	0.077***	(0.010)	3,137	619
Polish	0.061***	(0.015)	3,137	1,670
Filipino	0.059***	(0.002)	3,137	1,229
Laotian	0.050***	(0.009)	3,137	592
Albanian	0.049***	(0.014)	3,137	181
Italian	0.041***	(0.005)	6,274	5,068
Samoan	0.036	(0.031)	3,137	261
Amharic	0.035**	(0.015)	3,137	123
Tongan	0.034	(0.027)	3,137	115
Russian	0.027***	(0.008)	3,137	53
German	0.022***	(0.002)	15,685	15,513
Hindi	0.015***	(0.003)	3,137	558
Rumanian	0.014**	(0.007)	3,137	417
Turkish	0.012**	(0.005)	3,137	263
Croatian	0.012**	(0.006)	3,137	65
Swahili	0.006	(0.005)	6,274	606
Finnish	0.005	(0.012)	3,137	373
Magyar	0.004**	(0.002)	3,137	578
Indonesian	0.002	(0.003)	3,137	130
Swedish	0.002**	(0.001)	3,137	888
Dutch	0.002**	(0.001)	9,411	4,746
Norwegian	0.002**	(0.001)	3,137	965
Pashto	0.002	(0.002)	3,137	26
Czech	0.001***	(0.000)	3,137	367
Burmese	0.001	(0.001)	3,137	19
Sinhalese	0.000	(0.001)	3,137	9
Danish	0.000***	(0.000)	6,274	1,200
Irish	0.000***	(0.000)	3,137	459
Afrikaans	-0.000***	(0.000)	3,137	6
Nepali	-0.000***	(0.000)	3,137	52

Bulgarian	-0.000***	(0.000)	3,137	85
Bantu	n/a	n/a	9,411	432
Creole	n/a	n/a	3,136	2,252

Notes: The table is an extension of Table 10, where we only show the results for a set of selected languages. The table is sorted on the size of the point estimate. The last column shows the # of US-born residents in d that speak the language of o at home.

Appendix Table 20: Accounting For the Effect of Ancestry

	FDI Dummy (2014)				
	(1)	(2)	(3)	(4)	(5)
Log Ancestry 2010	0.222***	0.213***	0.212***	0.213***	-0.025
	(0.021)	(0.068)	(0.068)	(0.025)	(0.028)
Sector Similarity (Rank Correlation)		0.012			
		(0.020)			
Sector Similarity (Cosine Correlation)			0.022		
			(0.023)		
Log # of residents in d that speak language of o at home				0.005	
				(0.006)	
Information Demand Index (standardized)					0.078***
					(0.013)
N	612,495	23,708	23,708	454,812	19,110
Destination FE	Yes	Yes	Yes	Yes	Yes
Origin FE	Yes	Yes	Yes	Yes	Yes
Principal Components	Yes	Yes	Yes	Yes	Yes

Notes: This table shows IV regressions at the county-country (columns 1-4) and DMA-country (column 5) level. Each column is a variation of the simple specification (column 2 in Table 3) that has origin and destination fixed effects. All variables are defined as in the previous tables. The relatively low number of observations in columns 2 and 3 is due to data availability in the industry share of employment: When calculating the correlation between industries' share of employment in county d and country o, the correlation coefficient is missing for those country-county pairs that have at least one missing share of employment. Standard errors are given in parentheses and are clustered at the origin country level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 21: Search terms for Germany and Italy

Germany	Italy
Politicians	
Angela Merkel	Aldo Moro
Helmut Kohl	Benito Mussolini
Willy Brandt	Alessandra Mussolini
Joseph Goebbels	Amintore Fanfani
Karl Marx	Angelino Alfano
Actors	
Jürgen Prochnow	Isabella Rossellini
Til Schweiger	Robert De Niro
Franka Potente	John Turturro
Udo Kier	Roberto Rossellini
Daniel Brühl	Roberto Benigni
Athletes	
Katarina Witt	Mario Andretti
Dirk Nowitzki	Armin Zoggeler
Boris Becker	Roberto Baggio
Steffi Graf	Andrea Barzagli
Franz Beckenbauer	Gerhard Plankensteiner
Musicians	
Ludwig van Beethoven	Antonio Vivaldi
Nena	Gioachino Rossini
Johann Sebastian Bach	Giacomo Puccini
Nina Hagen	Ennio Morricone
Felix Mendelssohn	Luciano Pavarotti

This table shows the top five results from Google's Answer Box for each category for the countries Germany and Italy when typing "notable [country] [category]" into Google.