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Research Article

Keywords:

Posted Date: November 19th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11559315/v1

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Additional Declarations: No competing interests reported.

The Historical Roots of Invention: Evidence from Migrant Inventors*

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November 2, 2026

Abstract

Does the history of people's ancestors shape how much they invent today? This paper compares skilled migrants of different origins who live and invent under the same institutions in the same destination country. The comparison holds constant the environment in which invention takes place, and thus separates the history that people carry from the history embedded in places. Using a growth model in which an inventive trait passes across generations and travels with migrants, I test its predictions on international patent applications matched with data on skilled migration. Migrants whose ancestors used more advanced technology in 1500 invent more. The advantage follows migrants' ancestry more closely than the territory they come from, so deep history shapes invention through people, not only through places. Individualism at origin is the characteristic most strongly associated with the gap, on a common sample of 48 origins, whereas school quality is not. Taken together, the results show that the legacy of deep history in innovation travels with people across borders. This legacy is cultural, not innate. In the model, children acquire it from their parents and from the society in which they grow up.

Keywords: Deep roots; historical technology; state history; migrant inventors; innovation; culture.
JEL codes: O31; O33; F22; N10; Z10.

*Declaration of competing interest: The author has no competing interests to declare.

1 Introduction

Countries whose populations descend from societies that adopted advanced technologies early or built states early are richer today (Comin et al., 2010; Putterman and Weil, 2010), and such deep roots have become central to explanations of comparative development (Nunn, 2009; Spolaore and Wacziarg, 2013). Yet it remains unclear whether these historical advantages persist because they are embedded in places and institutions or because they are transmitted across generations and carried by people. Cross-country comparisons cannot easily separate the two, because each population is observed under institutions that it or its ancestors built. This paper instead compares skilled migrants of different origins who live and invent under the same destination-country institutions, and asks whether differences in ancestral history explain differences in invention.

The distinction between people and places is at the heart of a long debate about why some countries are rich. One view holds that history matters through the institutions it leaves on a territory (Acemoglu et al., 2001). Another holds that it matters through the human capital of populations, which settlers and migrants carry from one territory to another (Glaeser et al., 2004; Easterly and Levine, 2016). Putterman and Weil (2010) sharpen the question by showing that the history of a population's ancestors predicts income better than the history of its territory. The United States is rich not because its land had early states, but because most of its people descend from societies that did. This finding suggests that part of the historical advantage is carried by people. Yet the descendants of European settlers also live under institutions their ancestors built, so the comparison cannot tell whether the advantage lies in what people carry or in the institutions they create. It also does not establish which dimension of history matters. Answering these questions requires observing people with different ancestral histories within the same institutional environment.

I study these questions by comparing inventors from different origins who live in the same destination countries. I combine inventor records from the World Intellectual Property Organization (WIPO) database of Patent Cooperation Treaty (PCT) applications, the only large patent source that reports both the nationality and the residence of inventors (Miguelez and Fink, 2013), with OECD data on tertiary-educated migrants by origin and destination (Arslan et al., 2015). I measure inventive activity as the number of inventor records of a given origin in a destination relative to the skilled migrant population from that origin in the same destination. I relate inventors per skilled migrant to ancestral technology in 1500 (Comin et al., 2010) and compare this measure with three other indicators of deep historical roots, all adjusted for ancestry: state history (Borcan et al., 2018), technology in 0 AD and the timing of the Neolithic transition (Putterman, 2008).[1] The main estimates cover 97 origin countries and 26 destinations, with destination fixed effects absorbing differences in the institutional and economic environments in which migrants invent.

Migrant inventors provide a particularly informative setting for this comparison. Argentine and Mexican migrants in the United States illustrate why. The two origins share a language and a Spanish

[1]Technology in 1500 is an index, from zero to one, of the adoption of basic technologies in agriculture, transportation, communications, industry and the military. Technology in 0 AD is the same index at an earlier date. State history measures how long, and over what share of their territory, people lived under a state between 3500 BCE and 2000 CE. The timing of the Neolithic transition is the number of millennia since the transition from hunting and gathering to agriculture. Each measure is adjusted for ancestry. It averages the history of the countries from which a country's current population descends, weighted by their share of its ancestors (Putterman and Weil, 2010). The territorial version records instead the history of the land within the country's current borders. The two differ mainly for the Americas, Oceania and South Africa.

colonial heritage and, by the 1990s, had similar income levels and similar shares of adults with tertiary education. Yet they differ in ancestry.[2] Argentines descend mainly from European immigrants (Droller, 2018), whereas many Mexicans descend from populations living in the Americas in 1500. In the United States, both groups operate under the same patent system, labor market and institutions. Nevertheless, during 2001–2010, Argentine migrants produced 26.7 inventor records per thousand skilled nationals, compared with only 2.7 among Mexican migrants. The migrants in the data are first generation, raised and usually educated in their origin countries. If historical differences associated with their origins remain visible after migration, they cannot come from the institutions, markets or patent system of the place where they now work. The design therefore asks which part of the legacy of history is portable rather than fixed to a territory. Invention is a demanding outcome for this test because it requires capabilities at the technological frontier (Jones, 2009), where historians of technology locate the advantage of historically advanced societies (Mokyr, 1990, 2016). Migrants are also central to invention. Immigrants account for about a quarter of patenting in the United States (Bernstein et al., 2022), and migrant inventors shape the technological specialization of the countries they move to (Bahar et al., 2020).

I organize the analysis around a model of how history affects invention. Children acquire an inventive trait from their parents and from the inventors around them. The trait therefore reflects the technological history of a population's ancestors, which the technologies they used also record, and people carry it when they move. Migrants with different traits then choose between production and research in an economy that grows through invention. Within a destination, every group faces the same return to research, so comparing origins in the same destination isolates the trait.

The main empirical challenge is that migrants who share a destination may still differ for reasons other than their history. Patent records count inventors by nationality while migration records count people by birthplace, so I measure the migrant pool by nationality and account for dual-citizenship rules. I also account for graduate-school pipelines (Stuen et al., 2012), migrant selection (Borjas, 1987; Grogger and Hanson, 2011), fields of training, religion, colonial history, genetic distance, origin-country innovation systems and engineers posted abroad by home-country firms. Because deep-roots variables are spatially correlated, conventional standard errors can overstate precision, and even random noise with the same spatial pattern can appear to predict outcomes (Kelly, 2020). I therefore use standard errors that allow for spatial correlation across origins, and a placebo that replaces ancestral technology with simulated noise of the same spatial correlation to check how often such noise predicts migrant invention as strongly.

I find that the deep history of migrants' origins predicts their invention abroad. Skilled migrants whose ancestors, in 1500, lived in societies that used more advanced technology invent more in their destination. Origins whose ancestral technology is 0.1 higher on the zero-to-one index of Comin et al. (2010), about the difference between India and Poland in 1500, have 33 percent more inventor records per skilled migrant, with controls for migrant selection, religion and genetic distance. The relationship remains when China and India are excluded as origins and when the United States is excluded as a destination. It also holds with controls for the origin's modern income, education and innovation system. The estimate remains significant with standard errors that allow for spatial correlation across origins and, as a further check, with the seven world regions as the units of inference.[3]

[2] Argentina and Mexico had ancestral technology levels of 0.87 and 0.48 in 1500, respectively. During 1990–1999, GDP per capita (PPP) averaged $20,947 in Argentina and $18,178 in Mexico, while 6.1 and 6.0 percent of adults, respectively, had completed tertiary education in 1990.

[3] World regions are the seven regions of the World Bank classification: East Asia and Pacific, Europe and Central Asia, Latin

The relationship is stronger between world regions than within them. Different deep roots predict migrant invention at different geographic scales. Technology in 1500 predicts which world regions send more inventive migrants. Within regions, technology in 1500 and the history of statehood both predict which origins send more inventive migrants, with coefficients of similar size.[4]

Two results shed light on what travels with migrants. First, the history of migrants' ancestors matters more than the history of the territory they come from. When the ancestry-adjusted and territorial measures enter together, the ancestry coefficient is about seven times as large with all origins, and still nearly twice as large when the neo-Europes—where the two measures differ most—are excluded. Among origins in the same world region and with the same colonizer, only the ancestry measure predicts migrant invention. Unlike Putterman and Weil (2010), this paper holds destination institutions fixed. The ancestral advantage therefore persists under the institutions of the destination. Second, the evidence points to culture as a more plausible channel than school quality. Ancestral technology predicts both higher test scores and greater individualism at origin. Yet, on a common sample of 48 origins, individualism is the characteristic most strongly associated with the gap in migrant invention across origins, whereas test scores are not.[5] For the same origin, the advantage does not vary with how much destinations discount foreign degrees.

Related literature. This paper contributes to four strands of research: the deep roots of comparative development, the role of migrants in innovation, the economics of culture and innovation, and, more broadly, the measurement of human capital through migrants.

First, pre-modern history predicts modern development, through the timing of the Neolithic transition (Diamond, 1997; Olsson and Hibbs, 2005; Putterman, 2008), state history (Bockstette et al., 2002; Borcan et al., 2018, 2021), past technology (Comin et al., 2010), genetic diversity (Ashraf and Galor, 2013), and traits transmitted across generations (Spolaore and Wacziarg, 2009, 2013; Giuliano and Nunn, 2021). These relationships are often stronger when historical characteristics are assigned to the ancestors of today's population rather than to the territory it inhabits (Putterman and Weil, 2010; Chanda et al., 2014). Yet much of this evidence concerns income or the adoption of existing technologies, outcomes that reflect both the characteristics of a population and the institutions and markets in which it operates. Since populations and institutions have evolved together, it is difficult to distinguish the legacy people carry from the influence of the places where they live (Acemoglu et al., 2001; Glaeser et al., 2004). This paper approaches this difficulty through migrants, whose origins differ while their destination institutions are shared, and through invention, a central driver of long-run growth (Romer, 1990). This combination makes it possible to examine whether ancestral history shapes the capacity to produce new knowledge beyond the institutional environment in which that history formed. It also shifts attention from whether history predicts income to which dimensions of ancestral history shape invention, and at what geographic scale they do so.

Second, immigrants contribute substantially to invention (Hunt and Gauthier-Loiselle, 2010; Stuen et al., 2012; Moser et al., 2014; Akcigit et al., 2017; Bernstein et al., 2022; Terry et al., 2026), and migrant

America and the Caribbean, the Middle East and North Africa (including Afghanistan and Pakistan), North America, South Asia and Sub-Saharan Africa.

[4]Across all origins, state history, the timing of the Neolithic transition and technology in 0 AD add nothing once technology in 1500 is controlled for.

[5]Test scores are the harmonized learning outcomes of Angrist et al. (2021). Individualism is the cultural dimension score of Hofstede et al. (2010), which measures how far a society values individual initiative over loyalty to the group.

inventors respond to visa policy (Kerr and Lincoln, 2010), transfer knowledge to their countries of origin (Kerr, 2008), although modestly in some settings (Breschi et al., 2017), and shape the technological specialization of their destinations (Bahar et al., 2020). Kerr et al. (2016) and Docquier and Rapoport (2012) review the broader evidence. These studies establish the importance of migrants to innovation, but pay less attention to differences in inventive activity across migrants from different origins. Such differences may reflect the selection of skilled migrants (Borjas, 1987; Grogger and Hanson, 2011; Akcigit et al., 2016) and where they received their training (Stuen et al., 2012). This paper examines an additional source of variation, the technological history of the societies from which migrants descend. The results suggest that the contribution of skilled immigrants to innovation depends not only on who migrates and where they are trained, but also on the historical experiences of the populations they come from.

Third, culture shapes economic behavior (Guiso et al., 2006; Alesina and Giuliano, 2015; Tabellini, 2010; Falk et al., 2018; Bazzi et al., 2020). Individualist societies innovate more (Gorodnichenko and Roland, 2011, 2017), and Mokyr (2016) argues that a culture of growth contributed to Europe's take-off in innovation. The epidemiological approach uses migrants and their descendants to examine whether cultural traits persist across different institutional environments (Fernández and Fogli, 2009; Fernández, 2011; Giuliano, 2007; Algan and Cahuc, 2010; Fulford et al., 2020). This approach has been applied to outcomes such as labor supply, fertility, family structure, and trust. Cultural traits themselves can be shaped by historical technologies (Alesina et al., 2013). This paper brings the epidemiological approach to invention by examining first-generation migrants and relates differences in their inventive activity to the technological history of their ancestors. It thus connects two questions, how historical technologies shape cultural traits and whether these historical legacies help explain differences in invention.

Fourth, the outcomes of migrants show how human capital differs across countries, a central input in accounting for differences in income. Returns to education among US immigrants reveal differences in the quality of schooling across origin countries (Schoellman, 2012), while wage gains at migration indicate the magnitude of these differences (Hendricks and Schoellman, 2018). Educated immigrants from some origins are also more likely to work in jobs below their qualifications (Mattoo et al., 2008). Related work emphasizes cognitive skills rather than years of schooling (Hanushek and Woessmann, 2012). These studies measure human capital through educational outcomes, earnings, and job placement. This paper uses invention as a complementary measure of the capacity to produce new knowledge. Comparing inventive activity across origins with test scores, the usual measure of school quality, shows that differences in invention track individualism at origin rather than test scores. Invention therefore reveals a dimension of human capital, rooted in culture, that measures of schooling miss.

Outline. The remainder of the paper is organized as follows. Section 2 develops the model and derives its predictions. Section 3 presents the empirical framework. Section 4 reports the main results, including the comparison of ancestry and territory, the horse race among deep roots and the robustness checks. Section 5 examines the mechanisms. Section 6 concludes.

2 Theoretical Framework

The model builds on the expanding-variety growth framework of Romer (1990), in the form presented by Acemoglu (2009), with generations as in Galor and Weil (2000). Time is discrete, and each period is a generation. Every individual lives two periods, as a child and as an adult, and has one child. In each

country, a competitive sector produces a final good from labor and a range of intermediate varieties. New varieties come from research, which is the source of growth. Countries are linked only through migration. They do not trade, and a variety enters a country only through research there. Adults choose to work in production or in research according to their talents. An inventive trait raises their talent for research. Children acquire the trait from their parents and from the inventors of the society in which they grow up. The trait therefore records the inventive history of a lineage, and individuals carry it when they move, whereas the research productivity belongs to the country in which they work. I first describe the economy of a country in a given period, taking the traits of its adults as given, and then describe how the traits evolve from one generation to the next.

2.1 Production and Research

Consider a country j in which adults of several ancestries live.[6] The final good serves as the numeraire and is produced from production labor and intermediate varieties,

$$Y_{jt} = \frac{1}{1-\chi}\left(\int_0^{N_{jt}} q_{jt}(\nu)^{1-\chi}\, d\nu\right) L_{jt}^{\chi}, \qquad 0<\chi<1, \tag{1}$$

where N_{jt} is the number of varieties, $q_{jt}(\nu)$ the quantity of variety ν and L_{jt} the labor employed in production, in efficiency units. Each variety is produced at a marginal cost of $1-\chi$ units of the final good by a producer that holds monopoly rights over it for one period. As in Aghion et al. (2005), the research firm that invents a new variety holds these rights in the period of the invention, so it earns profit from the variety only in that period. In each later period, the rights pass to a producer owned in equal shares by all adults who live in the country, whatever their ancestry, so that every variety remains under monopoly. These shares belong to the adults of each period, and they are neither inherited nor traded. Each variety then sells at a price of one, in quantity L_{jt}, and earns the profit $\Pi_{jt} = \chi L_{jt}$, and the wage per efficiency unit of production labor is $w_{jt}^{P} = \chi N_{jt}/(1-\chi)$ (Appendix A.2). Given production labor, output rises in proportion to the number of varieties, and so does the production wage. I therefore measure the growth of the economy by the growth of N_{jt}.

Research builds on the varieties of the previous generation. With R_{jt} efficiency units of research labor, it produces $\eta_j N_{jt-1} R_{jt}$ new varieties, so that

$$N_{jt} = N_{jt-1}\left(1+\eta_j R_{jt}\right). \tag{2}$$

The term N_{jt-1} captures the spillover from the existing stock of knowledge to research productivity, as in Romer (1990).[7] The parameter η_j is the research productivity in the country. It reflects the institutions and infrastructure of the territory and is the same for all who work there. Research firms enter freely, so the wage per efficiency unit of research labor equals the value of what it produces,

$$w_{jt}^{R} = \eta_j N_{jt-1}\Pi_{jt}. \tag{3}$$

[6] An ancestry is a group of lineages with a common history, and a lineage is a line of descent from parent to child. Section 2.4 describes how this history forms the inventive trait.

[7] New varieties need not originate in the societies that use them. Adopting technologies developed elsewhere also requires research labor to understand and adapt them to local conditions (Cohen and Levinthal, 1989; Barro and Sala-i-Martin, 1997). Accordingly, R_{jt} represents labor devoted to inventing or adapting technologies, while N_{jt} captures a society's technological activity, regardless of where its technologies originate.

2.2 Occupational Choice

Production and research draw on the same adults. An adult of ancestry i has a talent z_{ijt}^P for production and a talent z_{ijt}^R for research, measured in efficiency units, earns $w_{jt}^P z_{ijt}^P$ in production or $w_{jt}^R z_{ijt}^R$ in research, and chooses the occupation that pays more. I assume that talents are drawn independently across occupations and adults from Fréchet distributions,

$$\Pr(z_{ijt}^o \leq z) = \exp\big(-T_{ijt}^o z^{-\theta}\big), \qquad o \in \{P,R\}, \;\; \theta > 1, \tag{4}$$

where $T_{ijt}^o > 0$ is the scale parameter of talent in occupation o for adults of ancestry i in country j in period t. A higher T_{ijt}^o shifts the distribution of talent in occupation o upward. The shape parameter θ governs the dispersion of talent, which falls as θ rises. The scale parameters depend on two characteristics of the ancestry, its inventive trait x_{ijt} and its general skill s_i,

$$\ln T_{ijt}^R = b\, x_{ijt} + s_i, \qquad \ln T_{ijt}^P = s_i. \tag{5}$$

General skill, such as the quality of schooling, raises talent in both occupations by the same proportion. The inventive trait raises talent for research alone, with $b > 0$, and therefore gives a comparative advantage in research. Section 2.4 describes how the trait is formed.

Adults who work in research are the inventors of the model. Let $\omega_{jt} \equiv w_{jt}^R / w_{jt}^P$ denote the relative return to research. With Fréchet talents, the share of adults of ancestry i who work in research is

$$\pi_{ijt} = \frac{T_{ijt}^R\, \omega_{jt}^\theta}{T_{ijt}^R\, \omega_{jt}^\theta + T_{ijt}^P}, \tag{6}$$

and the M_{ijt} adults of ancestry i who live in country j supply

$$R_{ijt} = \Gamma_\theta M_{ijt}\, (T_{ijt}^R)^{1/\theta}\, \pi_{ijt}^{1-1/\theta}, \qquad L_{ijt} = \Gamma_\theta M_{ijt}\, (T_{ijt}^P)^{1/\theta}\, (1-\pi_{ijt})^{1-1/\theta} \tag{7}$$

efficiency units to research and to production, where $\Gamma_\theta \equiv \Gamma(1-1/\theta)$ and $\Gamma(\cdot)$ is the gamma function. The number of adults is large, so shares and supplies equal their expected values. The share of the workforce of country j that works in research is $\rho_{jt} \equiv \sum_i M_{ijt}\pi_{ijt} / \sum_i M_{ijt}$.

2.3 Equilibrium

An individual is a child in period $t-1$ and an adult in period t. A household consists of one adult and the adult's child, so ancestry i in country j has M_{ijt} households. Only the adult works and makes economic decisions. The household has logarithmic utility over its consumption, does not save and leaves no bequest, so it consumes all its income. Income consists of the adult's earnings and an equal share of the profits from existing varieties. The equal share does not depend on occupation, so the only decision is the adult's occupation, and the adult chooses the one that pays more. Consumption therefore varies across households with earnings, and c_{ijt} denotes the average consumption of households of ancestry i in country j.

Definition 1 (Equilibrium)**.** Given the number of varieties N_{jt-1}, the traits of adults $[x_{ijt}]_i$ and the workforce $[M_{ijt}]_i$, an equilibrium of country j in period t consists of prices $\{w_{jt}^P, w_{jt}^R, [p_{jt}(\nu)]_{\nu\in[0,N_{jt}]}\}$, allocations $\{[q_{jt}(\nu)]_{\nu\in[0,N_{jt}]}, [c_{ijt}]_i, L_{jt}, R_{jt}, N_{jt}\}$ and occupational choices such that the final-good firm,

each monopolist and each research firm maximize profits, research firms earn zero profit, N_{jt} satisfies Equation (2), each adult chooses the occupation that pays more, each household consumes its income, and markets clear,

$$L_{jt} = \sum_i L_{ijt}, \qquad R_{jt} = \sum_i R_{ijt}, \qquad Y_{jt} = \sum_i M_{ijt}\, c_{ijt} + (1-\chi) \int_0^{N_{jt}} q_{jt}(\nu)\, d\nu. \tag{8}$$

A dynamic equilibrium is a sequence of period equilibria linked by the number of varieties and by the transmission of traits in Section 2.4.

Proposition 1 (Return to research and growth)**.** *Given the traits of adults and the workforce, there exists a unique equilibrium in each period. The relative return to research, $\omega_{jt} \equiv w^R_{jt}/w^P_{jt}$, solves*

$$\omega_{jt} \cdot \big(1 + \eta_j \cdot R_{jt}(\omega_{jt})\big) = \eta_j \cdot (1-\chi) \cdot L_{jt}(\omega_{jt}), \tag{9}$$

where $R_{jt}(\cdot)$ and $L_{jt}(\cdot)$ are the supplies implied by Equations (6), (7) and (8) at a given relative return, and the economy grows at $g_{jt} \equiv N_{jt}/N_{jt-1} - 1 = \eta_j R_{jt}(\omega_{jt})$. The equilibrium does not depend on N_{jt-1}, so the economy grows at a constant rate whenever traits and the workforce are constant.

Proof. See Appendix A.2. □

Equation (9) balances the supply of and the demand for research. A higher relative return draws adults into research. More research creates more varieties, which raises the production wage relative to the profit of each new variety. Fewer workers in production also lower that profit. Both forces reduce the relative return to research, which pins down a unique ω_{jt}. The relative return to research depends on research productivity and on the traits of every ancestry in the workforce.

2.4 Transmission of the Inventive Trait

Children acquire the inventive trait through two channels, following the literature on cultural transmission (Bisin and Verdier, 2001).[8] They inherit part of their parents' trait, and they acquire more of it when they grow up among inventors. Neither channel involves a decision by parents. The second channel follows the evidence of Bell et al. (2019) that children who grow up among inventors are more likely to become inventors. Each individual belongs to a lineage ℓ, a line of descent from parent to child, which may remain in the same society across generations or move to another. I take migration as given. An individual who moves does so on becoming an adult, after the trait is formed. The trait of a child of lineage ℓ born in period t is

$$x_{\ell t+1} = \xi\, x_{\ell t} + \phi\, \rho_{j_t t}, \qquad 0 < \xi < 1, \;\; \phi > 0, \tag{10}$$

where $x_{\ell t}$ is the trait of the parent and j_t is the country in which the child grows up. The parameter ξ is the share of the parent's trait that the child inherits, and ϕ measures how strongly exposure to inventors shapes the trait. Iterating Equation (10) gives the trait of an adult of lineage ℓ in period t,

$$x_{\ell t} = \xi^t x_{\ell 0} + \phi \sum_{s=0}^{t-1} \xi^{t-1-s} \rho_{j_s s}, \tag{11}$$

[8] The trait stands for any characteristic that gives a comparative advantage in research, such as values, attitudes toward novelty or practical know-how. The model does not require it to be one of these in particular.

where $x_{\ell 0} \geq 0$ and j_s is the country in which lineage ℓ lives in period s, so that the sequence $j_0, j_1, \ldots, j_{t-1}$ traces the migration path of the lineage.

An individual's trait therefore summarizes the technological history of their lineage. Three features of this history matter. First, the history that counts is that of the societies in which the lineage lived, not that of the territory on which the individual lives today. For a lineage that never moved, the two coincide. Second, history is discounted. Exposure in period s carries the weight ξ^{t-1-s}, so recent history weighs more than distant history. Third, the trait adjusts slowly. Each generation inherits a share ξ of its parents' trait, so a change in a society's inventive activity affects a lineage for many generations after it occurs. I assume that all lineages of ancestry i in country j have the same trait, so that $x_{\ell t} = x_{ijt}$ for each of them, and x_{ijt} is the trait that enters talents in Equation (5).

The technology of a society records the same history. By Equation (2), the number of varieties accumulates all past research,

$$\ln N_{jt} = \ln N_{j0} + \sum_{s=1}^{t} \ln\left(1 + \eta_j R_{js}\right). \tag{12}$$

The technology of a society and the traits of the lineages that lived in it are thus two records of one history of technological activity. Technology accumulates past research without discount, whereas the trait accumulates past exposure to inventors with the weights ξ^{t-1-s}.

2.5 Ancestry and Invention

History forms the trait that individuals carry, and the country in which they live sets the relative return to research that they face. I first consider an ancestry that is small relative to the workforce of the country in which it lives, so that the choices of its members have no effect on the relative return to research there.

Proposition 2 (Ancestry and the choice to invent)**.** *In country j, the share π_{ijt} of adults of ancestry i who work in research satisfies*

$$\ln \frac{\pi_{ijt}}{1 - \pi_{ijt}} = b x_{ijt} + \theta \ln \omega_{jt}. \tag{13}$$

As the share of ancestry i in the workforce of country j goes to zero, the effect of its trait on ω_{jt} goes to zero. For such an ancestry, a characteristic that raises talent in research and in production by the same proportion does not affect π_{ijt}.

Proof. See Appendix A.4. □

Proposition 2 separates what individuals bring with them from what the country offers. The relative return to research ω_{jt} is the same for every resident of country j. Adults of different ancestries who live in the same country therefore differ in their propensity to invent only through their traits (Figure 1).[9] The last part of the proposition is the distinction between comparative and absolute advantage. Schooling that raises productivity in every occupation raises earnings, but not the share of an ancestry that invents. A characteristic affects that share only to the extent that it raises talent for research more than talent for other

[9]The same holds for migrants selected on their earnings. With Fréchet talents, the highest earnings an individual can obtain in a country are independent of the occupation that yields them. Individuals who migrate to country j because of their potential earnings there therefore work in research in the same share as their ancestry (Appendix A.4).

work. By Equation (13), the expected number of inventors I_{ijt} among the M_{ijt} adults of ancestry i who live in country j is

$$E[I_{ijt}] = M_{ijt} \exp\left(b x_{ijt} + \theta \ln \omega_{jt}\right)(1 - \pi_{ijt}). \tag{14}$$

The number of inventors rises in proportion to the size of the ancestry and with its trait.

The situation differs for a population that lives in the country of its ancestors. Its trait then shapes the relative return to research that it faces.

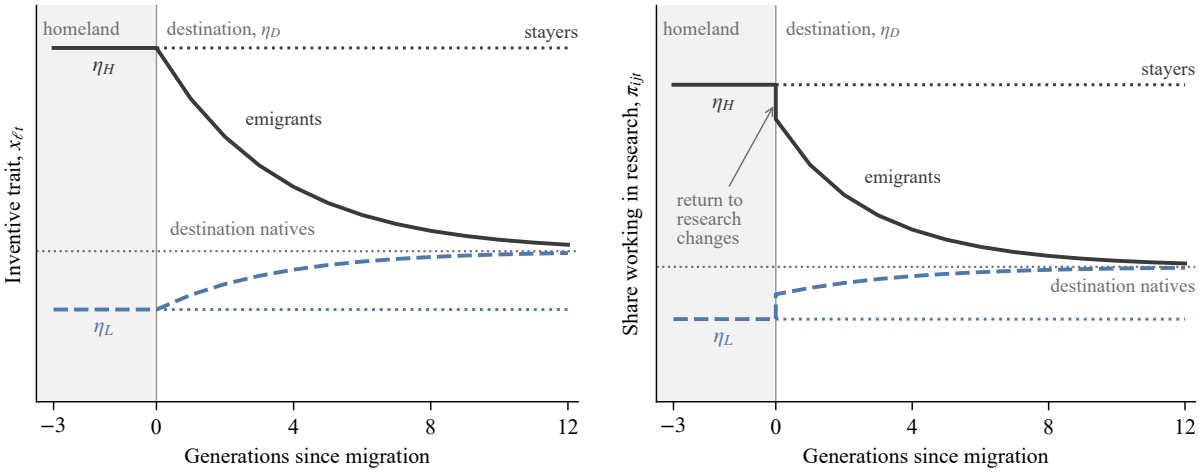
Proposition 3 (Invention at home and abroad)**.** *Consider a country j whose whole workforce is of ancestry i.*

(i) A stronger trait raises the share of the workforce that works in research, but by less than for a small ancestry. The effect of the trait on the log odds, $d \ln\left(\pi_{ijt}/(1-\pi_{ijt})\right)/d(b x_{ijt})$, lies between 0 and 1, whereas it equals 1 for a small ancestry.

(ii) The share of the workforce that works in research, π_{ijt}, increases with η_j.

Proof. See Appendix A.5. □

The trait has a larger effect on invention abroad than at home. At home, the entire workforce shares the trait. A stronger trait draws more workers into research, but the resulting increase in new varieties raises the production wage relative to the profit earned by each variety. This lowers the relative return to research and offsets part of the trait's effect on invention. Abroad, by contrast, the population carrying the trait is too small to affect the relative return to research in its destination country, so the trait has its full effect. Research productivity, however, remains tied to place. Those who stay benefit from the country's research productivity, so they invent more where η_j is higher. Those who leave face the research productivity of their destination instead. Figure 1 illustrates these two results.



(a) Inventive trait

(b) Share working in research

Figure 1: The Inventive Trait and Research Share of Emigrants and Stayers

Notes: This figure simulates the model for three countries that differ only in research productivity: two homelands, H and L, and one destination, D, with $\eta_L < \eta_D < \eta_H$. Each homeland starts in its steady state. At generation 0, members of both ancestries move to D as a first generation of migrants. Dotted lines are stayers, in the color of their homeland, and the grey dotted line is the natives of D. Emigrants are the solid line for ancestry H and the dashed line for ancestry L. Emigrants keep their trait on arrival in D (Panel a), but their share in research jumps to the level set by D's return to research (arrow in Panel b). Parameters, illustrative: $\theta = 2.5$, $\chi = 0.6$, $b = 2$, $\xi = 0.75$, $\phi = 0.8$, $\eta_H = 3$, $\eta_L = 0.6$, $\eta_D = 0.8$.

The trait persists in a society whose population stays in place. Its children grow up among its own inventors, so by Equation (10) the trait follows

$$x_{ijt+1} = \xi\, x_{ijt} + \phi\, \rho_{jt}, \tag{15}$$

where $\rho_{jt} = \pi_{ijt}$, because the whole workforce of country j is of ancestry i. By Proposition 3, ρ_{jt} increases with the trait x_{ijt} and with the research productivity η_j. The right side of Equation (15) is therefore increasing in x_{ijt}, and the trait converges monotonically to a steady state. Among societies that stay in place and start from the same technology, a society with more productive research and an initial trait at least as strong has in every later generation both a stronger trait and more technology (Appendix A.6). Technology and the trait therefore rank societies in the same order, so the technology that a lineage's ancestors used reveals the trait that its members carry. The model thus offers an explanation for the persistence of technological differences documented by Comin et al. (2010).[10]

The same mechanism carries institutional history into the trait. Research productivity η_j reflects the institutions of a territory, which a long history of statehood helped build (Bockstette et al., 2002; Borcan et al., 2018). Where institutions made research more productive, a larger share of workers became inventors, strengthening the trait transmitted to children who grew up there. Mokyr (2016) describes a related process in early modern Europe, where competition among states sustained a market for ideas and fostered a culture that valued useful knowledge. Lineages that later left these territories carried the resulting trait with them. The history of statehood in the societies of a lineage's ancestors therefore enters its trait through η_j, alongside the technology those societies used.

The model distinguishes two legacies of history and shows how migration separates them. Research productivity belongs to a country. It shapes the relative return to research ω_{jt} in Equation (9). The trait belongs to a lineage and, by Equation (11), records its technological and institutional history. Unlike the human capital of Glaeser et al. (2004), what people carry across borders is a comparative advantage in research. Individuals who leave the territory of their ancestors take the trait with them but leave the research productivity of that territory behind (Propositions 2 and 3). A Chinese inventor in the United States, for example, carries a trait shaped by China's technological and institutional history but works under the research productivity of the United States.

3 Empirical Framework

The model predicts that, within the same destination, migrants whose ancestors used more advanced technology invent more. Migrants carry the trait formed by their ancestors' technological history but face the research productivity of their destination, so comparing migrants within the same destination removes the influence of the place where they invent. I test this prediction by relating the number of inventors per skilled migrant of each origin to its ancestral technology. I combine inventor records that report inventors' nationality and residence with data on skilled migrants by origin and destination. Section 3.1 describes the data, and Section 3.2 presents the empirical strategy.

[10] Another explanation for this persistence appears in Aghion et al. (2005), Comin and Nanda (2019) and Avoumatsodo (2025), where financial constraints slow the adoption of new technologies and delay convergence to the frontier.

3.1 Data and Measurement

Appendix B describes each variable in detail, including how it is constructed, its source and the choices behind it.

I measure migrant invention with the database of the World Intellectual Property Organization (WIPO) on the international mobility of inventors (Miguelez and Fink, 2013), built from applications filed under the Patent Cooperation Treaty (PCT). To my knowledge, it is the only large patent source that systematically records both the nationality and country of residence of each inventor. My outcome is the number of inventor records by nationals of an origin country residing in a destination country over 2001–2010, the last full decade in which PCT filings generally had to report inventors' nationality. An inventor listed on several applications is counted on each, and PCT filings cover inventions for which applicants seek protection in several countries. The outcome therefore measures internationally patented invention, not the quality of inventions or inventive activity that is never patented. I use it as a proxy for the number of inventors in the model, the adults who work in research.[11] The model counts inventors among the adults of an ancestry in a country, so I relate inventor records to the pool of skilled migrants, measured with the OECD Database on Immigrants in OECD and non-OECD Countries (DIOC) for 2010/11 (Arslan et al., 2015).[12] Because WIPO counts inventors by nationality whereas censuses count people by country of birth, I construct the pool as the number of tertiary-educated foreign nationals born in the origin and living in the destination. This restricts the analysis to the 26 destinations that report nationality, including the United States, Germany, the United Kingdom, France, Canada and Japan.

My main measure of deep history is the technology adoption index of Comin et al. (2010), which records the technologies a society used in 1500, whether invented there or adopted, and ranges from zero to one. Following Putterman and Weil (2010), I use the version adjusted for migration since 1500, which assigns to each country the technology of the places from which its current population descends.[13] I use technology in 1500 as the main measure for three reasons. First, it is the most recent of the technology measures, and in Equation (11) the model assigns greater weight to recent history than to more distant history. Second, the migration matrix of Putterman and Weil (2010) traces each population to the places where its ancestors lived in 1500. The index therefore describes the societies in which those ancestors actually lived, whereas ancestry-adjusted measures for earlier dates assume that they lived in the same places before 1500. Third, 1500 predates European colonization and thus avoids measuring historical conditions shaped by the institutions colonial rule later imposed on modern territories. The index nevertheless captures a broad historical legacy, of which technology is one component, and I interpret it as a measure of that legacy.

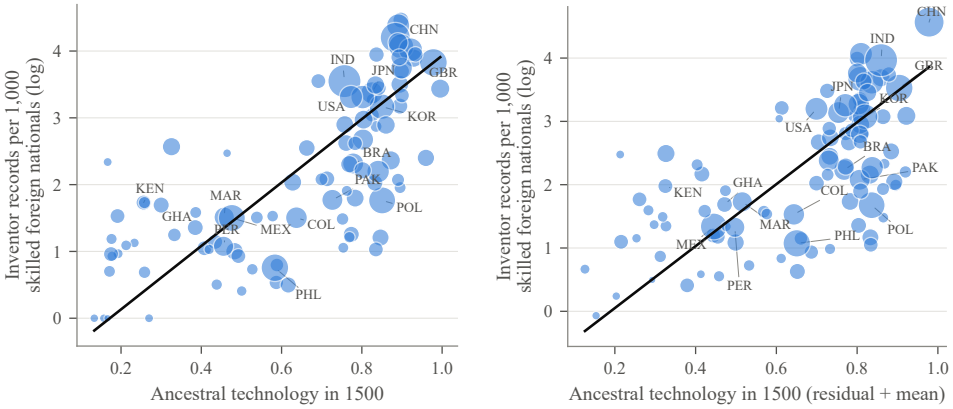
I compare it with three other deep roots, all adjusted for ancestry: state history (Borcan et al., 2018), which scores the presence, autonomy and territorial reach of states from 3500 BCE to 2000 CE, technology in 0 AD (Comin et al., 2010) and the number of millennia since the Neolithic transition (Putterman, 2008).

[11] The proxy assumes that inventor records rise in proportion to inventors within a destination. If records rise instead with research labor in efficiency units, as new varieties do in Equation (2), the effect of the trait is unchanged. By Equations (7) and (13), when inventors are a small share of the ancestry, $\ln R_{ijt} \approx \ln M_{ijt} + b x_{ijt} + s_i/\theta + (\theta - 1)\ln \omega_{jt} + \ln \Gamma_\theta$, so general skill also raises records.

[12] DIOC is built from population censuses and registers. The 2010/11 edition counts migrants at the census held in each destination in 2010 or 2011, so the pool is a stock measured around 2010, not a flow.

[13] The ancestry-adjusted index matches what the trait depends on. A child's trait follows the technological history of its lineage rather than that of the territory where it lives today, and the technology of the societies in which the lineage lived records that same history. Section 2.4 derives both.

I complement these data with further variables on corridors, origins and destinations. They include the number of master's and doctoral students from the origin enrolled in the destination in 2013–2015, the earliest years available, the origin's outbound student mobility ratio over 1999–2005, measured before and early in the inventor flows, gravity variables, origin income and education, relative migrant selection, religion, genetic distance, fields of training and dual-citizenship rules. For the mechanisms, I add measures of skills and values at origin and characteristics of destinations.



(a) Unconditional **(b)** Net of origin income and education

Figure 2: Inventor Intensity and Ancestral Technology in 1500

Notes: This figure plots inventor intensity against ancestral technology in 1500 for the 97 origins of the baseline sample. Each marker is an origin country, and marker area is proportional to the number of skilled (tertiary-educated) foreign nationals of that origin in the 26 destinations. The vertical axis is the logarithm of one plus the number of migrant inventor records (2001–2010) per thousand skilled foreign nationals, pooled across destinations. The horizontal axis is technology adoption in 1500, adjusted for ancestry. Panel (a) plots the two variables as measured. Panel (b) plots their residuals from a regression on origin log GDP per capita and tertiary share, weighted by skilled foreign nationals, with the mean of each variable added back. Lines are linear fits with the same weights. Labels are the ISO codes of selected origins. The estimates in the tables add destination fixed effects and the other controls.

The baseline sample contains every corridor between a destination that reports nationality and an origin with measures of technology in 1500, state history, income, education, relative selection, religion shares, genetic distance and colonizer, provided that at least one tertiary-educated foreign national from the origin lives in the destination. It covers 2,195 corridors between 97 origins and 26 destinations. Hong Kong, which lacks religion shares, and Tanzania, which lacks genetic distance, are not included. Table B.1 in Appendix B reports summary statistics. The distribution of migrant inventors is highly skewed (Figure B.2 in Appendix B). Half of the corridors have no inventor record and the median corridor has one, whereas the China–United States corridor has 44,450. The ten largest corridors account for 55 percent of all inventor records, and all of them lead to the United States. This skewness and the large number of small corridors motivate the Poisson estimator described in Section 3.2.

Figure 2 plots inventor intensity against ancestral technology for each origin. Panel (a) shows the raw relationship. Panel (b) shows the same relationship after controlling for origin income and tertiary education, by plotting the part of each variable that income and education do not explain. The relationship is strong in both panels and is not driven by a few large origins. It extends across the full range of ancestral technology. Origins whose ancestors used more advanced technologies in 1500, particularly in Europe and East Asia and among countries settled from Europe, have higher inventor intensity, while origins in Sub-Saharan Africa and parts of Latin America have lower intensity. Figure B.1 in Appendix B maps the

two variables.

3.2 Empirical Strategy

The estimation design holds constant the institutional and economic environment in which migrants invent. The main identification challenge is that origins with a long history of advanced technology differ from other origins in many ways that could affect both who emigrates and what they do abroad. I therefore measure the skilled migrant pool on the same basis as the inventor count, and I account for migrant selection and for other origin characteristics that may be correlated with deep history.

Estimating equation. The estimating equation follows from Equation (14), which gives the expected number of inventors of ancestry i in destination country j.[14] I take three steps to bring the model to the data. First, ancestral technology in 1500, H_i, proxies for the unobserved trait x_i. Second, a destination fixed effect α_j absorbs $\theta \ln \omega_j$, the return to research shared by everyone working in destination country j. Third, the skilled migrant pool M_{ij} enters with coefficient λ, which the model predicts should equal one. Let I_{ij} denote the number of inventor records for nationals of origin country i residing in destination country j over 2001–2010. I estimate

$$I_{ij} = \exp\left(\beta H_i + \lambda \ln M_{ij} + \mathbf{P}'_{ij}\psi + \mathbf{G}'_{ij}\delta + \mathbf{X}'_i\gamma + \alpha_j\right)\varepsilon_{ij}, \tag{16}$$

where H_i is the ancestry-adjusted technology adoption index of origin country i in 1500, M_{ij} is the number of tertiary-educated nationals of country i living in country j, $\mathbf{P}_{ij}$ contains the logarithm of graduate students from country i in country j, the logarithm of the origin's outbound student mobility ratio over 1999–2005 and an indicator for origins where this ratio is missing,[15] $\mathbf{G}_{ij}$ contains the logarithm of distance and indicators for contiguity, a common official language and a colonial link (Mayer and Zignago, 2011), and $\mathbf{X}_i$ contains the logarithm of the origin's GDP per capita at purchasing power parity, averaged over 1990–1999, and the share of its adults with tertiary education in 1990 (Barro and Lee, 2013). The destination fixed effects α_j absorb everything specific to the host country: its patent system, its research universities, its labor-market institutions and its overall propensity to attract foreign inventors.

This specification is a gravity equation of the kind that Fink et al. (2017) estimate for bilateral inventor flows on the same data, and that Beine et al. (2016) review for migration. It differs in two ways. Invention is measured per skilled migrant, and the regressor of interest is a characteristic of the origin, identified from variation across origins within destinations, as in the epidemiological approach (Fernández and Fogli, 2009).

The coefficient β measures how the number of inventor records per skilled migrant changes with ancestral technology, holding the destination fixed. Because the specification is exponential and $\ln M_{ij}$ enters on the right-hand side, $\exp(0.1\beta) - 1$ is the proportional change in inventor records per skilled migrant associated with a 0.1 increase in the technology index. I estimate Equation (16) by Poisson pseudo-maximum likelihood (Santos Silva and Tenreyro, 2006; Correia et al., 2020). The estimator has two advantages over a linear regression of log inventor counts. It retains the 50 percent of corridors with

[14] The data cover a single period, 2001–2010, so I omit the time subscript. Migrants grow up at origin, so their trait does not vary across destinations. Because inventors are a small share of skilled migrants, $1 - \pi_{ij} \approx 1$ (Appendix A.4).

[15] UNESCO does not report the ratio for 1999–2005 for some origins, including Germany, Australia and Austria. For these origins I set the ratio to the geometric mean of the other origins.

no inventor record, which a logarithm would drop or force to an arbitrary value, and it remains consistent when the variance of the error depends on the regressors, whereas log-linearizing a multiplicative model then biases the coefficients (Santos Silva and Tenreyro, 2006). It also weights corridors by their size, so that large corridors, where inventor counts are measured precisely, carry more information. The coefficient λ is estimated rather than fixed at one, so that the number of inventors can rise more or less than proportionally with the pool of skilled migrants.

The baseline specification adds controls for migrant selection and competing characteristics of the origin, and the full specification adds fixed effects for the world region and the colonizer of the origin,

$$I_{ij} = \exp\left(\beta H_i + \lambda \ln M_{ij} + \mathbf{P}'_{ij}\psi + \mathbf{G}'_{ij}\delta + \mathbf{X}'_i\gamma + \mathbf{Z}'_{ij}\kappa + \alpha_j + \alpha_{r(i)} + \alpha_{c(i)}\right)\varepsilon_{ij}, \tag{17}$$

where $\mathbf{Z}_{ij}$ contains the log of relative migrant selection from country i in country j, measured as the ratio of the tertiary-educated share among migrants from country i in country j to that in the origin population, the shares of the origin population by religion in 2000 and the genetic distance between the populations of countries i and j. The terms $\alpha_{r(i)}$ and $\alpha_{c(i)}$ denote fixed effects for the world region and the colonizer of the origin; the baseline specification omits them. Thus, in the full specification, β is identified by differences in ancestral technology among origins within the same destination, world region and colonial history.

Technology in 1500 is correlated with other measures of deep history, including state history (0.59) and the timing of the Neolithic transition (0.68). I therefore estimate a horse race in which technology in 1500 enters with state history, technology in 0 AD and the timing of the Neolithic transition, all adjusted for ancestry. Each coefficient then captures the association between a historical measure and invention conditional on the other three.

Technology in 1500 varies mainly across world regions. To distinguish differences between regions from differences among origins within the same region, I decompose it into its regional mean and the deviation of each origin from that mean. Region fixed effects would absorb the regional means, so I estimate this specification without them.

I then ask whether the relationship varies across destinations, by interacting ancestral technology with characteristics of the destination,

$$I_{ij} = \exp\left(\mu H_i \times S_j + \lambda \ln M_{ij} + \mathbf{P}'_{ij}\psi + \mathbf{G}'_{ij}\delta + \alpha_i + \alpha_j\right)\varepsilon_{ij}, \tag{18}$$

where S_j is a standardized characteristic of destination country j, such as the discount applied to foreign degrees or the power distance of its organizations. The origin fixed effects α_i absorb every characteristic of the origin, including H_i and the characteristics correlated with it, so only the interaction coefficient μ is identified. It measures how the relationship between ancestral technology and invention varies across destinations for the same set of origins.

Identification. Because H_i varies only across origins and destination fixed effects absorb characteristics common to a destination, β is identified by comparing origins within the same destination. For example, a corridor from India to the United States is compared with one from Poland to the United States, not with one from India to Germany. The identifying variation comes from 97 origins in the baseline specification, observed in up to 26 destinations.

The identifying assumption is that, conditional on the controls and destination fixed effects, no omitted factor correlated with ancestral technology independently explains differences in migrant invention. With $\mathbf{W}_{ij}$ collecting the controls of Equation (17),

$$E\left[\varepsilon_{ij} \,\middle|\, H_i, \mathbf{W}_{ij}, \alpha_j\right] = 1. \tag{19}$$

This condition is all that Poisson pseudo-maximum likelihood requires for consistency, and it gives each robustness test a precise target. An alternative explanation is a factor that sits in ε_{ij} and is correlated with H_i. Each test in Section 4.2 moves such a factor into $\mathbf{W}_{ij}$, or drops the corridors it affects, and asks whether β changes. This assumption is strong, because technology in 1500 was not assigned at random and records a broad history that also includes state formation, population density and economic organization. The design nevertheless supports two claims. First, the gradient travels with people. Destination fixed effects absorb the patent system, labor market and institutions that all residents of a destination share, so a gradient within destinations cannot come from them. Second, the gradient is not explained by the specific alternatives listed below, which the tests of Section 4.2 address one at a time. The destination interactions of Equation (18) require a weaker assumption. Origin fixed effects absorb every characteristic of the origin, so omitted origin characteristics cannot bias μ.

Because migrants were raised in their origins, the relationship may reflect other characteristics of the origin that are correlated with deep history. Where the origin allows dual citizenship, naturalized migrants may leave the pool of foreign nationals but stay in the inventor count, and graduate-study pipelines and migrant selection may differ across origins. Ancestral technology may proxy for religion, colonial history or genetic distance. Migrants may differ in their fields of training, and some inventors may be engineers posted abroad by home-country firms. Section 4.2 summarizes the tests of each explanation, and Appendix C reports them.

Ancestral technology varies across origins and smoothly over space, so conventional standard errors may overstate precision (Kelly, 2020). I cluster standard errors by origin throughout, and by origin and destination for the destination interactions. I assess the estimates with Conley standard errors, a spatial-noise placebo, randomization inference and inference at the level of the seven world regions (Appendix C.4).

4 Results

The results show that skilled migrants whose ancestors used more advanced technology invent more, and that invention is more closely associated with ancestral history than with the history of the territory from which they originate. Ancestral technology in 1500 predicts which world regions send more inventive migrants, while within a region state history and technology both predict differences among origins. Section 4.1 presents the main estimates and two comparisons: ancestry-adjusted against territorial technology, and technology in 1500 against other deep roots. Section 4.2 examines the robustness of the results.

4.1 Main Results

Skilled migrants from origins with more advanced ancestral technology invent more in their destination countries. Table 1 reports the estimates. Column (1) measures the skilled migrant pool by nationality, on the same basis as the inventor count, and yields a coefficient of 7.20. Column (2) measures it by birthplace instead, the way census data count migrants, and the coefficient is 8.10. Column (3) adds graduate-pipeline controls to column (1), and the coefficient falls to 5.04.

Table 1: Ancestral Technology and Migrant Inventors

	(1)	(2)	(3)	(4)	(5)
Technology in 1500	7.201***	8.096***	5.038***	2.824***	2.313***
	(0.975)	(1.436)	(0.674)	(0.596)	(0.772)
Log skilled foreign nationals	0.985***		0.505***	0.550***	0.537***
	(0.057)		(0.094)	(0.066)	(0.065)
Log skilled foreign-born		0.922***			
		(0.055)			
Log graduate students			0.492***	0.377***	0.403***
			(0.074)	(0.056)	(0.061)
Log outbound student mobility			-0.057	-0.041	-0.062
			(0.114)	(0.082)	(0.087)
Log relative selection				0.427***	0.385***
				(0.122)	(0.122)
Origin log GDP per capita	-0.040	-0.155	0.117	0.581***	0.478***
	(0.153)	(0.181)	(0.105)	(0.111)	(0.121)
Origin tertiary share	-0.006	0.002	0.015	0.032*	0.029
	(0.031)	(0.033)	(0.016)	(0.017)	(0.018)
Controls				Baseline	Full
Religion and genetic distance	No	No	No	Yes	Yes
Region and colonizer FE	No	No	No	No	Yes
Pseudo R^2	0.940	0.919	0.959	0.973	0.976
Corridors	2,195	2,195	2,195	2,195	2,179
Origins	97	97	97	97	96
Destinations	26	26	26	26	26

Notes: This table reports estimates of the relationship between ancestral technology in 1500 and migrant invention. The estimates are Poisson pseudo-maximum likelihood estimates of Equation (16) in columns (1)–(3), without the graduate-pipeline controls in columns (1)–(2), of Equation (17) without region and colonizer fixed effects in column (4), and of Equation (17) in column (5). The dependent variable is the number of inventor records on PCT applications, 2001–2010, by nationals of the origin residing in the destination. Technology in 1500 is the ancestry-adjusted index of Comin et al. (2010). Column (2) measures the migrant pool by birthplace; the other columns by nationality. Column (4) is the baseline specification. All columns use the baseline sample. Column (5) loses one origin to its fixed effects. All columns include destination fixed effects, log distance, contiguity, common official language and colonial link. Columns (4)–(5) add relative selection, religion shares in 2000 (Protestant, Catholic, Orthodox, Muslim, Hindu, Buddhist) and genetic distance between origin and destination populations; column (5) adds origin-region and colonizer fixed effects. Standard errors clustered by origin in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The relationship remains, although smaller, with the most demanding controls. Column (4), my baseline specification, adds relative selection, religion shares and genetic distance. The coefficient

falls to 2.82 but remains precisely estimated. It implies that origins whose ancestral technology is 0.1 higher, approximately the difference between India (0.76) and Poland (0.85), have 33 percent more inventor records per skilled migrant ($\exp(0.282) - 1$). The baseline includes the controls for selection and competing origin characteristics but uses the variation across world regions. Column (5), which corresponds to Equation (17), adds origin-region and colonizer fixed effects, so that the comparison is between origins in the same world region with the same colonial history. The coefficient is 2.31 and significant at the one percent level, which implies a 26 percent increase per 0.1 of the index.

Each set of controls reduces the coefficient, which shows that part of the raw relationship reflects graduate pipelines, migrant selection and other origin characteristics. None eliminates it.

Ancestry versus territory. The estimates so far do not say whether the advantage follows people or places. Technology in 1500 can be measured for each origin in two ways (Putterman and Weil, 2010). The territorial index records the technology used in 1500 on the land within the country's current borders. The ancestry-adjusted index, used in all estimates so far, averages the technology in 1500 of the places from which the country's current population descends, weighted by their share of its ancestors. For the United States, the territorial index reflects the technology of indigenous societies in 1500, and the ancestry-adjusted index mainly that of Europe. If the advantage is carried by people, the ancestry-adjusted index should be the stronger predictor of migrant invention.

The advantage follows the history of migrants' ancestors more closely than the history of the territory they come from. The two indices are nearly identical in the Old World, where most of the population descends from people who lived in the same place in 1500. They differ mainly for countries settled by Europeans after 1500. Restricting the sample to Old World origins, that is, excluding origins in the Americas, Australia, New Zealand, South Africa and Namibia, leaves the coefficient with the baseline controls at 3.31 (Table C.1, column 5). The result therefore does not come from the countries where the two indices differ. When both indices enter together with the baseline controls (Table 2), the ancestry-adjusted coefficient is about seven times as large as the territorial one (column 1). This comparison draws largely on the United States, Canada, Australia and New Zealand, whose high ancestral and low territorial technology coincide with very inventive emigrants. Without these four neo-Europes, the ancestry-adjusted coefficient is still nearly twice as large (column 2). With the baseline controls, the territorial coefficient is also positive and significant, so the land retains some predictive power. With the full controls, which compare origins in the same world region and with the same colonizer, only the ancestry-adjusted coefficient is significant, with or without the neo-Europes (columns 3 and 4). The history that predicts migrant invention is nonetheless more closely the history of the people than that of the land they now live on.

Horse race among deep roots. Technology in 1500 is one of several measures of a population's deep history, and it is correlated with state history and the timing of the Neolithic transition (Section 3.2). Its coefficient may therefore capture other aspects of that history, such as long experience with statehood or an early transition to agriculture. The model gives more weight to recent than to distant history, but it does not say whether technology or statehood matters more, because the trait reflects the inventive history of a lineage as a whole.[16] I therefore enter technology in 1500 and state history separately and then together, and, in Table C.12, add technology in 0 AD and the timing of the Neolithic transition, all adjusted for

[16] Statehood shapes the trait only through the inventors it helped produce. A state that raised research productivity drew more workers into research and so strengthened the trait that Equation (11) passes on to later generations.

Table 2: Ancestry versus Territory

	(1)	(2)	(3)	(4)
Ancestry-adjusted technology in 1500	2.433***	1.725**	2.555***	1.866**
	(0.583)	(0.773)	(0.734)	(0.878)
Territorial technology in 1500	0.350**	1.024***	-0.550	0.609
	(0.151)	(0.277)	(0.557)	(0.850)
Origins included	All	No neo-Europes	All	No neo-Europes
Controls	Baseline	Baseline	Full	Full
Pseudo R^2	0.974	0.974	0.977	0.976
Corridors	2,101	2,004	2,085	1,988
Origins	93	89	92	88
Destinations	26	26	26	26

Notes: This table compares the ancestry-adjusted and territorial measures of technology in 1500, with and without the neo-Europes. The estimates are Poisson pseudo-maximum likelihood estimates with both the ancestry-adjusted (first row) and the territorial index of technology in 1500 (second row). Columns (1)–(2) use the baseline controls of Table 1, column (4); columns (3)–(4) the full controls of column (5), with region and colonizer fixed effects. The neo-Europes are the United States, Canada, Australia and New Zealand. Standard errors clustered by origin in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

ancestry, to assess which best predicts migrant invention. Since technology in 1500 varies mainly across world regions, I also examine whether its predictive power differs between comparisons across and within regions.

Table 3: Technology in 1500 and State History

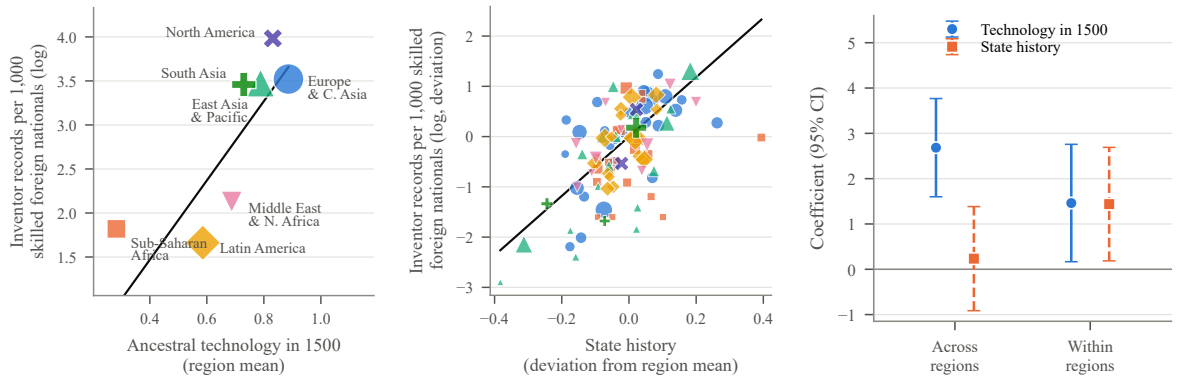
	(1)	(2)	(3)	(4)	(5)	(6)
Technology in 1500		2.798***	2.684***	3.188***	1.462**	1.531**
		(0.595)	(0.553)	(0.831)	(0.661)	(0.697)
State history	1.876**		0.235	0.269	1.438**	1.623**
	(0.729)		(0.586)	(0.698)	(0.639)	(0.754)
Region FE	No	No	No	No	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Origins included	All	All	All	Non-African	All	Non-African
Pseudo R^2	0.971	0.974	0.974	0.973	0.976	0.976
Corridors	2,155	2,155	2,155	1,642	2,155	1,642
Origins	95	95	95	70	95	70
Destinations	26	26	26	26	26	26

Notes: This table compares technology in 1500 and state history as predictors of migrant invention, across and within world regions. The estimates are Poisson pseudo-maximum likelihood estimates with destination fixed effects and the baseline controls of Table 1, column (4), on the 95 baseline origins with all four deep roots. Both measures are adjusted for ancestry with the migration matrix of Putterman and Weil (2010); state history is the index of Borcan et al. (2018). Columns (5) and (6) add fixed effects for the seven World Bank regions, so that origins are compared within regions. Columns (4) and (6) exclude African origins. Standard errors clustered by origin in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3 compares technology in 1500 and state history in more detail, with the baseline controls, first across and then within world regions. Each predicts migrant invention on its own (1.88 for state history and 2.80 for technology; columns 1 and 2). When both enter, technology keeps its size (2.68)

and state history falls to 0.24 (column 3). The same holds without African origins (column 4). With region fixed effects, which compare origins of the same world region, the two deep roots predict migrant invention equally. Technology in 1500 is 1.46 and state history 1.44, both significant at the five percent level (column 5). Excluding African origins gives the same result (column 6). With the baseline controls, technology in 1500 also dominates the three other deep roots. Adding technology in 0 AD and the Neolithic transition lowers it to 2.19, still significant at the one percent level, while neither added deep root is significant (Table C.12, column 4).

Figure 3 illustrates this pattern. Panel (a) shows that, across the seven world regions, those with more advanced technology in 1500 send more inventive migrants. Panel (b) compares origins within the same region, measuring each origin's state history relative to its regional mean. Within regions, origins with a longer history of statehood send more inventive migrants. Panel (c) reports the coefficients from columns (3) and (5) of Table 3. Across regions, technology in 1500 is the stronger predictor and the coefficient on state history is close to zero. Within regions, state history gains and technology in 1500 falls, and the two coefficients are of similar size.



(a) Across regions: technology **(b)** Within regions: state history **(c)** Coefficients

Figure 3: Ancestral Technology and State History Across and Within World Regions

Notes: The figure shows how ancestral technology in 1500 and state history relate to migrant invention across and within world regions. Panel (a) plots one marker per world region. The horizontal axis shows the region's average ancestral technology in 1500, and the vertical axis shows the logarithm of one plus inventor records per thousand skilled foreign nationals. Both variables are weighted by skilled foreign nationals, marker area is proportional to their number, and the line is a weighted linear fit. Panel (b) plots one marker per origin country, using the colors and shapes assigned to regions in Panel (a). The horizontal and vertical axes show deviations from the corresponding regional means of state history and the logarithm of one plus inventor records per thousand skilled foreign nationals, respectively. Regional means are weighted by skilled foreign nationals. Marker area and the fitted line are defined as in Panel (a). Panel (c) reports the coefficients on technology in 1500 (blue, solid) and state history (orange, dashed) from Table 3, with 95 percent confidence intervals based on standard errors clustered by origin. "Across regions" refers to column (3), which excludes region fixed effects, and "Within regions" refers to column (5), which includes them.

Splitting technology in 1500 into its regional mean and the origin's deviation from that mean gives the same pattern (Table C.13). The between-region component is significant in every specification, also with the seven regions as the units of inference. The within-region component is smaller and falls to marginal significance once state history enters as a quadratic.

Technology in 1500 therefore accounts for the large differences in migrant invention between world regions, such as those between European and East Asian origins on one side and African and Latin American origins on the other. State history adds to it within regions. Among origins of the same region, a longer history of statehood goes with more migrant invention, and so does more advanced technology in 1500. The horse race therefore does not single out one deep root. The history of technology predicts

which world regions send inventive migrants, and both histories predict which origins within a region do.

This pattern admits two interpretations. First, the two deep roots may capture distinct aspects of history that operate at different scales. Technology accounts primarily for broad differences across world regions, whereas political organization accounts for differences among neighboring societies within those regions. Second, the pattern may reflect measurement. Technology in 1500 varies mainly across regions and is measured coarsely within them. State history may therefore capture within-region variation that a more finely measured technology index would also explain. Both interpretations are consistent with the model, in which statehood influences the trait through the research productivity of the institutions it created. Under either view, migrants carry a single legacy of technological activity. Technology in 1500 captures this legacy across world regions, while state history captures finer differences among societies within them.

4.2 Robustness

The results are robust to changes in the sample, the timing of the data and the estimator, to other characteristics of migrants, to competing explanations and to alternative methods of inference. I summarize the main checks here and report the details in Appendix C.

First, I vary the sample and estimator. With the baseline controls, the estimate remains significant at the one percent level when China and India are excluded as origins and when the United States is excluded as a destination (Table C.1). The result therefore does not depend on the two largest origins or on the US graduate-school system. Removing the weighting by corridor size or dropping the ten largest corridors leaves the estimate significant at the one percent level (Table C.1, columns 6 and 7). These results also hold with the full controls, where the estimate is significant at the five percent level or better in every column (Table C.2). Dropping one origin at a time leaves the estimate significant at the one percent level with the baseline controls and at the five percent level with the full controls (Figure C.1).

Second, I change the timing of the data. The estimate remains significant at the one percent level when inventor flows are measured in the 1990s, a decade before the skilled migrant pool and graduate students are measured (Table C.1, column 3). Measuring the skilled migrant pool in 2000/01 rather than 2010/11 also reduces the concern that the migrant pool responds to the success of earlier migrant inventors. The estimate then remains significant at the one percent level with both the baseline and the full controls (Tables C.1, column 8, and C.2, column 7).

Third, migrants from origins with a long technological history may differ in other ways that matter for invention (Table C.3). The first difference is education. Controlling for the share of doctorate holders among skilled foreign nationals lowers the baseline estimate from 2.33 to 1.77 on the same corridors. Replacing the skilled pool with doctorate holders lowers it from 2.26 to 1.22, which remains significant at the five percent level. Degrees therefore explain part of the gradient, but not all of it. An official English language at origin leaves it at 2.80. The gap in overqualification between migrants and natives lowers it from 2.13 to 1.67, genetic distance to the United States from 3.06 to 2.17, and the share of migrants with a long stay from 2.02 to 1.88. Technology in 1500 remains significant with each of these controls, at the one percent level in every case except the doctorate pool, where it is significant at the five percent level.

Fourth, I examine whether factors correlated with technology in 1500, rather than technology itself, could explain migrant invention and so violate the identifying assumption of Equation (19). Controlling for migrants' fields of study or origin rules on dual citizenship, or dropping the control measured after the

inventor flows, leaves the estimate significant at the one percent level (Table C.4). Nor is the result driven by engineers posted abroad by home-country firms (Table C.5). It remains significant when I control for origin patenting over 1990–2000 and when I exclude Japan, Korea and Germany, the main sources of posted engineers. Similarly, the origin's foreign direct investment (FDI) in the destination, a measure of the presence of home-country firms that may hire migrants from their own origin, does not account for the gradient (Table C.6), and the gradient is significant in each of the five technology fields (Table C.7). Nor is it smaller where anti-discrimination policy is stronger, as would be expected if discrimination explained the result; if anything, it is larger (Table C.8).

Fifth, I assess whether inference is sensitive to spatial correlation or the small number of origins (Table C.9). Clustering by both origin and destination leaves the estimate significant at the one percent level. Conley standard errors (Conley, 1999), using cutoffs from 1,000 to 5,000 km, are within 5 percent of the clustered standard errors. In a spatial-noise placebo following Kelly (2020), 2.1 percent of noise draws produce a t-statistic at least as large as that for technology, so the estimate is significant at the five percent level by this benchmark. When technology in 1500 is randomly reassigned across origins, 0.3 percent of permutations produce a t-statistic at least as large as that of the actual variable.

Sixth, because technology in 1500 predicts migrant invention mainly across world regions, I assess inference using the seven World Bank regions as the units of inference (Table C.10). The wild score bootstrap gives $p = 0.037$ for the baseline specification, and the cluster jackknife gives $p = 0.009$.

Finally, I examine four features of the data that could affect the estimates (Table C.11). The model predicts that the number of inventors rises in proportion to the skilled pool, but the estimated coefficient on the pool, λ, is about 0.5 (Table 1). Fixing it at one leaves the baseline estimate essentially unchanged at 2.83, so the result still holds per skilled migrant. The low coefficient appears to come from the graduate-student control, which also measures the size of a corridor. Without that control, λ rises to 0.92 and is not statistically different from one, as the model predicts. In addition, the data record inventors' nationality best from 2004 onward. Restricting them to 2004–2010 gives 2.87 in the baseline, so weaker coverage in earlier years does not drive the result. The outbound mobility ratio is imputed for ten origins, and dropping them gives 3.07, so the imputation does not drive it either. Last, Hong Kong has almost no inventor records. It is not in the baseline sample, which lacks its religion shares, and merging its migrants and inventor records into China's leaves the baseline estimate at 2.81, so its coding does not matter.

5 Mechanisms

Why do skilled migrants from historically advanced origins invent more? The answer matters for what ancestral technology captures. It could travel with migrants as skills learned at origin, as values that shape how they work, or as credentials that destinations recognize. This section examines each possibility. I first relate ancestral technology to skills and values at origin and ask which of these characteristics are associated with the gap in migrant invention between origins with more and less advanced ancestral technology. I then compare migrant inventors with inventors of the same nationality who stayed at home, to see how much the gap falls when I control for the inventive activity of the origin. Next, I compare the same origin across destinations, which holds every origin characteristic fixed, and ask whether the gap depends on how destinations treat foreign degrees and on how hierarchical they are. Finally, I examine whether the gap depends on having an employer. The evidence suggests a cultural explanation rather than

one based on school quality at origin or credentials. The gap is associated with individualism and with invention at origin, and it is larger for inventors hired by organizations.

Table 4: Origin Skills and Values

Panel A: Ancestral technology and origin skills and values						
	Test scores	Numeracy 1850–1900	Trust	Autonomy	Confidence in civil service	Individ-ualism
	(1)	(2)	(3)	(4)	(5)	(6)
Technology in 1500	1.259***	0.268	1.185*	1.623***	1.245	2.152**
	(0.321)	(0.649)	(0.696)	(0.586)	(0.881)	(0.891)
Origin controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.701	0.389	0.391	0.485	0.081	0.566
Origins	94	80	72	67	71	55
Panel B: Migrant invention, controlling for origin characteristics (common sample)						
	(1)	(2)	(3)	(4)	(5)	(6)
Technology in 1500	2.423***	0.991*	2.221***	2.163***	2.823***	1.396**
	(0.792)	(0.526)	(0.751)	(0.769)	(0.839)	(0.573)
Individualism (Hofstede)		0.022***				0.017***
		(0.003)				(0.002)
Autonomy (WVS)			1.607***			0.923***
			(0.456)			(0.269)
Trust (WVS)				1.474***		0.552
				(0.564)		(0.371)
Test scores (HLO)					-0.004	-0.003**
					(0.002)	(0.001)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.976	0.980	0.977	0.977	0.976	0.981
Corridors	1,155	1,155	1,155	1,155	1,155	1,155
Origins	48	48	48	48	48	48
Destinations	26	26	26	26	26	26

Notes: This table reports how ancestral technology relates to skills and values at origin (Panel A) and how controlling for these characteristics changes the technology coefficient (Panel B). Panel A: OLS regressions with one observation per origin of the standardized variable in the column heading on ancestral technology in 1500, origin log GDP per capita and origin tertiary share; robust standard errors. Test scores are the harmonized learning outcomes of Angrist et al. (2021); numeracy is the ABCC age-heaping index for birth cohorts 1850–1900 (A'Hearn et al., 2009); trust, autonomy and confidence in the civil service are World Values Survey averages over all waves; individualism is from Hofstede et al. (2010). Panel B: Poisson pseudo-maximum likelihood estimates of Equation (17) without region and colonizer fixed effects, that is, with the baseline controls of Table 1, column (4), on the 48 origins for which all four characteristics are observed. Standard errors clustered by origin. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.1 Origin Skills and Values

Because historically advanced societies accumulated knowledge over centuries, one should expect that ancestral technology predicts school quality at origin, and that controlling for school quality absorbs the gap. Cultural traits could play the same role. I test both in two steps. Panel A of Table 4 regresses standardized measures of origin skills and values on ancestral technology, controlling for origin income and education. Panel B adds each characteristic to the migrant-inventor regression and records how much

the technology coefficient falls. Ancestral technology predicts both school quality and cultural traits, but only culture lowers the gap.

Ancestral technology predicts higher harmonized test scores (Angrist et al., 2021), more autonomy, measured as the preference for independence over obedience in the World Values Survey, and more individualism (Hofstede et al., 2010). It does not predict historical numeracy (A'Hearn et al., 2009) or confidence in the civil service, and it predicts generalized trust only at the ten percent level. Test scores are an imperfect measure of the human capital that matters for invention. They cover primary and secondary schooling of recent cohorts rather than the tertiary training of the migrants I observe. I therefore also control for the gross tertiary enrollment ratio at origin over 1990–2000. It does not absorb the technology gradient, which rises from 3.15 to 3.94 on the 68 origins with enrollment data (Table C.6, column 3).

Panel B estimates every comparison on the same 48 origins with the baseline controls, so that differences between columns reflect the characteristics rather than changes in the sample. Controlling for individualism lowers the technology coefficient from 2.42 to 0.99, a reduction of 59 percent. Autonomy and trust also predict migrant invention, but they lower the coefficient by only 8 and 11 percent. Test scores do not lower it at all. The coefficient rises to 2.82.[17] When all four characteristics enter together, the coefficient falls by 42 percent. Individualism and autonomy remain significant at the one percent level, and test scores enter with a negative sign. The school quality of the origin, as measured today, therefore does not lower the gap. What is most strongly associated with it is individualism, the characteristic that Gorodnichenko and Roland (2011, 2017) link to innovation across countries and that ancestral technology predicts.

5.2 Invention at Home and Abroad

If ancestral technology captures something people carry with them, it should predict invention among those who stayed at origin as well as among migrants. And if migrants carry part of their origin's inventive activity, origins that invented more before the migrant flows should send more inventive migrants. The WIPO data allow both comparisons, because they also record the inventors who hold the nationality of an origin and live there. Table 5 relates their number in 2001–2010 to ancestral technology, with the population, income and education of the origin as controls.

Among home inventors, the coefficient on ancestral technology is 4.00 (standard error 1.55; column 1). For migrant inventors pooled across destinations, with the pool of skilled foreign nationals in place of population, it is 5.41 (1.05; column 2). The history that predicts invention at home also predicts it among people who work under the institutions of another country, with a larger point estimate.

Migrant invention also follows home invention. Origins with more inventors per head at home in 1991–2000, before the migrant flows I study, have more migrant inventors in 2001–2010, with an elasticity of 0.33 (column 6).[18] Adding this control lowers the technology coefficient from 2.82 to 1.69 with the baseline controls and from 2.31 to 1.60 with the full controls (columns 3–6). It remains significant at the one percent level. Controlling for the inventive activity of the origin, in which migrants were trained, therefore lowers the migrant advantage by 31 to 40 percent.

[17] Schooling raises talent in research and in production alike, so it need not change who chooses to invent. Proposition 2 shows that a characteristic raising both by the same proportion leaves the share of a group in research unchanged.

[18] Home invention in the 1990s captures the recent history of a lineage, which weighs more in the trait than its distant history. Technology in 1500 captures the distant part.

Table 5: Invention at Home and Abroad

	(1)	(2)	(3)	(4)	(5)	(6)
Technology in 1500	4.001***	5.413***	2.824***	1.693***	2.313***	1.600***
	(1.546)	(1.047)	(0.596)	(0.405)	(0.772)	(0.554)
Log home inventors per head, 1991–2000				0.334***		0.353***
				(0.041)		(0.054)
Inventors	Home	Migrants	Migrants	Migrants	Migrants	Migrants
Unit of observation	Origins	Origins	Corridors	Corridors	Corridors	Corridors
Origin size, income and education	Yes	Yes				
Baseline controls			Yes	Yes		
Full controls					Yes	Yes
Observations	97	97	2,195	2,195	2,179	2,179

Notes: This table compares invention at home and abroad. The estimates are Poisson pseudo-maximum likelihood estimates. Column (1): inventor records on PCT applications, 2001–2010, by nationals of the origin residing in the origin, one observation per origin, with log population, log GDP per capita and the tertiary share of the origin as controls. Column (2): migrant inventor records pooled over the 26 destinations, one observation per origin, with the log pool of skilled foreign nationals in place of log population. Columns (3)–(6): corridors, with destination fixed effects and the controls of Table 1, column (4) ("Baseline"), or with the controls and region and colonizer fixed effects of column (5) ("Full"). Home inventors per head are the inventor records of 1991–2000 by nationals residing in the origin, divided by its population. Robust standard errors in columns (1)–(2), clustered by origin in columns (3)–(6). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.3 Destination Characteristics and Employer Type

The advantage of migrants from historically advanced origins depends on who employs them, not on where they live. It is no larger where foreign degrees are discounted, where organizations are more hierarchical or where there is more research to do, but it is larger for inventors hired by firms and public research organizations than for independent inventors. This subsection reaches this result by changing the comparison. It asks where the advantage is larger, holding the origin fixed. The question matters because the channels predict different places. If ancestral technology travels as credentials, the advantage should depend on how destinations value foreign degrees. If it travels as habits of work, such as individualism, it should depend on whether invention is organized by an employer. I first compare the same origin across destinations and then compare hired and independent inventors from the same corridors.

Destination characteristics. Comparing the same origin across destinations holds every origin characteristic fixed, observed or not, including the schooling migrants received at origin. I use this comparison to ask in which destinations the advantage is larger. I estimate Equation (18), which interacts ancestral technology with destination characteristics, each standardized to mean zero and standard deviation one across destinations, and includes origin and destination fixed effects, and report the results in Table D.1. The omitted-variable concerns of Section 3.2 therefore do not apply to the interaction. The advantage depends neither on how destinations treat foreign degrees nor on how hierarchical they are.

If migrants from historically advanced origins invent more because their degrees are better recognized, the advantage should be largest where foreign degrees are most discounted. Column (1) shows no such pattern. The interaction with the foreign-degree penalty is small and insignificant, and it is also insignificant for hired inventors, whose degrees are judged by employers (column 4). Credential recognition is therefore not the main channel. The interaction with power distance, which measures how far people accept a more

unequal distribution of authority in organizations, is negative but not significant (column 2). Because the interaction rests on 22 destinations, I also assess it by randomization inference, reassigning power distance at random across destinations 1,000 times. The share of reassignments with a t-statistic at least as large in absolute value as the actual one is 10.4 percent. The advantage does not vary with the destination's R&D intensity either (column 3), so it is not simply larger where there is more research to do.

Hired and independent inventors. If the advantage reflects how migrants work inside organizations, it should be larger for inventors hired by firms and public research organizations than for independent inventors who file on their own behalf. Table D.2 splits inventor records by applicant type. The advantage is larger inside organizations. The coefficient is 2.87 for hired inventors and 1.70 for independent inventors, both significant at the one percent level. A stacked regression that allows every coefficient to differ by applicant type rejects equality of the two at the one percent level ($p < 0.001$).

In sum, the comparison across origins suggests a role for culture. Ancestral technology does not travel as school quality, as measured by test scores, or as credentials, as measured by the foreign-degree penalty at the destination level. It moves with individualism at origin, the characteristic most strongly associated with the gap on a common sample of 48 origins. Separately, controlling for the inventive activity of the origin lowers the gap by 31 to 40 percent on the full sample. The advantage is larger inside organizations.

6 Conclusion

Deep-roots research has shown that the history of a population's ancestors predicts income better than the history of its territory. Migration research has shown that migrants account for a large share of invention. These findings leave a question open. Does the technological history of a population predict how much its members invent once they work under the same institutions as migrants from other origins? Comparing skilled migrants of different origins within the same destination, I find that it does. Part of deep history travels with people. Skilled migrants whose ancestors used more advanced technology in 1500 produce 33 percent more inventor records per skilled migrant for each 0.1 of the technology index. The advantage follows ancestry more closely than territory, and it survives checks on the sample, the timing of the data and competing explanations.

Which history travels depends on the comparison. Migrants from regions that used advanced technology in 1500 invent far more than migrants from other regions, and technology in 1500 predicts these differences better than state history, the timing of the Neolithic transition or technology in 0 AD. The model explains why technology in 1500 should predict better than technology in 0 AD. Each generation passes on only part of the trait it inherited, so a lineage carries its recent history more strongly than its distant past. Within a region, statehood joins technology. Migrants from origins with a longer history of statehood, or with more advanced technology in 1500, invent more than migrants from neighboring origins, as expected if the trait also records the institutions under which a lineage invented.

The evidence points to culture rather than school quality. Ancestral technology predicts individualism at origin, the characteristic most strongly associated with the gap, whereas origin test scores are not associated with it. This is the distinction the model draws. Schooling raises productivity in every occupation and so leaves the choice to invent unchanged, whereas what migrants carry is a comparative advantage in research. For the same origin, the advantage does not depend on how destinations treat foreign degrees. Controlling for the origin's own inventive activity before the migrant flows lowers the

gradient among migrants by 31 to 40 percent. The advantage is also larger for inventors inside firms and public research organizations.

Argentine and Mexican migrants in the United States come from origins with similar incomes, schooling and colonial histories, yet Argentines produce about ten times as many inventor records per skilled migrant. Two skilled migrants living under the same institutions do not invent at the same rate, and part of the difference reflects influences that long predate migration. In the model, these influences are not innate. Children acquire the trait from their parents and from the society in which they grow up. Data following migrants' children would reveal whether these differences persist in a generation raised under the destination's institutions.

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Online Appendix

The Historical Roots of Invention: Evidence from Migrant Inventors

A Mathematical Appendix

This appendix derives the occupational choices, the equilibrium in each period, the transmission and dynamics of the trait and the effect of the trait on growth, and proves Propositions 1 to 3. I write $\Gamma_\theta \equiv \Gamma(1-1/\theta)$, where $\Gamma(\cdot)$ is the gamma function, defined by $\Gamma(a) = \int_0^\infty r^{a-1}e^{-r}\,dr$.

A.1 Occupational Choice

An adult of ancestry i chooses research if $w_{jt}^R z_{ijt}^R > w_{jt}^P z_{ijt}^P$. With independent Fréchet talents, this occurs with probability $T_{ijt}^R (w_{jt}^R)^\theta / \Phi_{ijt}$, where $\Phi_{ijt} \equiv T_{ijt}^R (w_{jt}^R)^\theta + T_{ijt}^P (w_{jt}^P)^\theta$. Dividing the numerator and the denominator by $(w_{jt}^P)^\theta$ gives Equation (6).

Earnings, $\max\{w_{jt}^R z_{ijt}^R, w_{jt}^P z_{ijt}^P\}$, follow a Fréchet distribution with scale Φ_{ijt} and shape θ, and this distribution is the same conditional on either choice. Mean earnings in research are therefore $\Gamma_\theta \Phi_{ijt}^{1/\theta}$, and the efficiency units supplied to research are $R_{ijt} = M_{ijt}\pi_{ijt}\Gamma_\theta \Phi_{ijt}^{1/\theta}/w_{jt}^R$. Since $\Phi_{ijt} = T_{ijt}^R (w_{jt}^R)^\theta/\pi_{ijt}$, this equals $\Gamma_\theta M_{ijt} (T_{ijt}^R)^{1/\theta} \pi_{ijt}^{1-1/\theta}$. The expression for L_{ijt} in Equation (7) follows in the same way from $\Phi_{ijt} = T_{ijt}^P (w_{jt}^P)^\theta/(1-\pi_{ijt})$.

The ratio of the two supplies gives $L_{ijt}\pi_{ijt}/\big(R_{ijt}(1-\pi_{ijt})\big) = (T_{ijt}^P/T_{ijt}^R)^{1/\theta}\big(\pi_{ijt}/(1-\pi_{ijt})\big)^{1/\theta}$, and Equation (6) gives $\pi_{ijt}/(1-\pi_{ijt}) = (T_{ijt}^R/T_{ijt}^P)\,\omega_{jt}^\theta$. Hence

$$L_{ijt}\,\pi_{ijt} = \omega_{jt}\,R_{ijt}\,(1-\pi_{ijt}). \tag{A.1}$$

From Equation (6), $\partial\pi_{ijt}/\partial \ln \omega_{jt} = \theta\pi_{ijt}(1-\pi_{ijt})$ and $\partial\pi_{ijt}/\partial \ln T_{ijt}^R = \pi_{ijt}(1-\pi_{ijt})$. Together with Equation (7), these give

$$\frac{\partial R_{ijt}}{\partial \ln \omega_{jt}} = (\theta-1)(1-\pi_{ijt})\,R_{ijt}, \qquad \frac{\partial L_{ijt}}{\partial \ln \omega_{jt}} = -(\theta-1)\,\pi_{ijt}\,L_{ijt}, \tag{A.2}$$

$$\frac{\partial R_{ijt}}{\partial \ln T_{ijt}^R} = \tfrac{1}{\theta}\big[1+(\theta-1)(1-\pi_{ijt})\big]R_{ijt}, \qquad \frac{\partial L_{ijt}}{\partial \ln T_{ijt}^R} = -\tfrac{\theta-1}{\theta}\,\pi_{ijt}\,L_{ijt}. \tag{A.3}$$

Because $\theta > 1$, R_{ijt} increases and L_{ijt} decreases with ω_{jt}.

A.2 Equilibrium and Proof of Proposition 1

Firms. The representative final-good firm takes prices as given and solves

$$\max_{L_{jt},\,[q_{jt}(\nu)]_{\nu\in[0,N_{jt}]}} \; Y_{jt} - \int_0^{N_{jt}} p_{jt}(\nu)\,q_{jt}(\nu)\,d\nu - w_{jt}^P L_{jt}, \tag{A.4}$$

where $p_{jt}(\nu)$ is the price of variety ν. The first-order conditions give the demand for each variety and the production wage,

$$q_{jt}(\nu) = p_{jt}(\nu)^{-1/\chi} L_{jt}, \tag{A.5}$$

$$w_{jt}^P = \frac{\chi}{1-\chi} \left(\int_0^{N_{jt}} q_{jt}(\nu)^{1-\chi} \, d\nu \right) L_{jt}^{\chi-1}. \tag{A.6}$$

Facing this demand, each monopolist solves

$$\max_{p_{jt}(\nu)} \; \big(p_{jt}(\nu) - (1-\chi)\big) \, p_{jt}(\nu)^{-1/\chi} L_{jt}. \tag{A.7}$$

A research firm hires R_{jt} efficiency units of research labor at the wage w_{jt}^R and, by Equation (2), invents $\eta_j N_{jt-1} R_{jt}$ new varieties, each of which earns the profit Π_{jt} in the period of the invention. It solves

$$\max_{R_{jt}} \; \eta_j N_{jt-1} R_{jt} \Pi_{jt} - w_{jt}^R R_{jt}. \tag{A.8}$$

The payoff is linear in R_{jt}, so with free entry and positive research the firm earns zero profit, which gives Equation (3). The firm problems in Equations (A.4), (A.7) and (A.8) are those of Definition 1.

Prices and profits. The first-order condition of the final-good firm with respect to $q_{jt}(\nu)$ is $q_{jt}(\nu)^{-\chi} L_{jt}^{\chi} = p_{jt}(\nu)$, which gives Equation (A.5). The demand has a constant price elasticity $1/\chi$, so each monopolist sets the price at a markup $1/(1-\chi)$ over the marginal cost $1-\chi$, that is, $p_{jt}(\nu) = 1$. Then $q_{jt}(\nu) = L_{jt}$ and $\Pi_{jt} = \chi L_{jt}$. Substituting $q_{jt}(\nu) = L_{jt}$ into Equations (1) and (A.6) gives $Y_{jt} = N_{jt} L_{jt}/(1-\chi)$ and $w_{jt}^P = \chi N_{jt}/(1-\chi)$.

Return to research. Free entry gives $w_{jt}^R = \eta_j N_{jt-1} \chi L_{jt}$. Dividing by w_{jt}^P and using Equation (2),

$$\omega_{jt} = \frac{\eta_j (1-\chi) L_{jt}}{N_{jt}/N_{jt-1}} = \frac{\eta_j (1-\chi) L_{jt}}{1 + \eta_j R_{jt}},$$

which is Equation (9). Growth is $g_{jt} = N_{jt}/N_{jt-1} - 1 = \eta_j R_{jt}$.

Goods market. The final-good firm has constant returns to scale and earns no profit. New varieties number $N_{jt} - N_{jt-1} = \eta_j N_{jt-1} R_{jt}$, so their profits equal $w_{jt}^R R_{jt}$ and are paid to inventors as research earnings. Producers of the N_{jt-1} existing varieties are owned by adults in equal shares, so adults of ancestry i together receive the share M_{ijt}/M_{jt} of their profits, where $M_{jt} \equiv \sum_i M_{ijt}$ is the workforce of country j. Summing the budgets of their households gives

$$M_{ijt} \, c_{ijt} = w_{jt}^P L_{ijt} + w_{jt}^R R_{ijt} + \frac{M_{ijt}}{M_{jt}} N_{jt-1} \Pi_{jt}.$$

Summing over ancestries, total income is $w_{jt}^P L_{jt} + N_{jt} \Pi_{jt} = \chi(2-\chi) N_{jt} L_{jt}/(1-\chi)$, which equals $Y_{jt} - (1-\chi) N_{jt} L_{jt}$. The goods market in Equation (8) therefore clears.

Existence and uniqueness. Define

$$G_{jt}(\omega) \equiv \omega \cdot \left(1 + \eta_j \cdot R_{jt}(\omega)\right) - \eta_j \cdot (1-\chi) \cdot L_{jt}(\omega).$$

By Equation (A.2), R_{jt} is increasing and L_{jt} is decreasing in ω, so G_{jt} is continuous and strictly increasing, with $G'_{jt}(\omega) \geq 1$. As $\omega \to 0$, $\pi_{ijt} \to 0$ for every ancestry, so $R_{jt} \to 0$ and $L_{jt} \to \Gamma_\theta \sum_i M_{ijt} (T^P_{ijt})^{1/\theta} > 0$, and G_{jt} tends to a negative number. As $\omega \to \infty$, $\pi_{ijt} \to 1$, so $L_{jt} \to 0$ and $G_{jt} \to \infty$. Hence G_{jt} has a unique root, which determines the remaining equilibrium objects. G_{jt} depends on the traits through R_{jt} and L_{jt} but not on N_{jt-1}, so with constant traits and a constant workforce, ω_{jt}, R_{jt} and g_{jt} are constant. □

Scale effect. As in Romer (1990), the growth rate rises with the size of the workforce, M_{jt}. Dividing the research productivity by the size of the workforce removes this scale effect (Jones, 1995) and leaves the results unchanged, with η_j / M_{jt} in place of η_j.

A.3 Transmission of the Trait

Iterating Equation (10) from $t = 0$, with the country j_s in which lineage ℓ lives in each period s, gives Equation (11). Taking logarithms of Equation (2) for country j and summing from period 1 to period t gives Equation (12).

A.4 Proof of Proposition 2

By Equation (6), $\ln\left(\pi_{ijt}/(1-\pi_{ijt})\right) = \ln T^R_{ijt} - \ln T^P_{ijt} + \theta \ln \omega_{jt}$. By Equation (5), $\ln T^R_{ijt} - \ln T^P_{ijt} = b x_{ijt}$, in which s_i cancels. This gives Equation (13).

Ancestry i affects ω_{jt} only through its supplies R_{ijt} and L_{ijt} in Equation (9). By Equation (7), both are proportional to M_{ijt}. By the implicit function theorem, $d\omega_{jt}/dx_{ijt} = -(\partial G_{jt}/\partial x_{ijt})/G'_{jt}(\omega_{jt})$, where $\partial G_{jt}/\partial x_{ijt}$ is proportional to M_{ijt} and $G'_{jt}(\omega_{jt}) \geq 1$. Hence $d\omega_{jt}/dx_{ijt} \to 0$ as the share of ancestry i in the workforce goes to zero.

A characteristic that multiplies T^R_{ijt} and T^P_{ijt} by the same factor leaves T^R_{ijt}/T^P_{ijt} unchanged and, by Equation (6), leaves π_{ijt} unchanged at every ω_{jt}. For a small ancestry, ω_{jt} is also unchanged. □

Selection on earnings. Let $y_{ijt} \equiv \max\{w^R_{jt} z^R_{ijt}, w^P_{jt} z^P_{ijt}\}$ denote the highest earnings of an adult of ancestry i in country j. With independent Fréchet talents,

$$\Pr\left(y_{ijt} \leq v,\ w^R_{jt} z^R_{ijt} > w^P_{jt} z^P_{ijt}\right) = \int_0^v e^{-T^P_{ijt}(w^P_{jt})^\theta r^{-\theta}}\, d\, e^{-T^R_{ijt}(w^R_{jt})^\theta r^{-\theta}} = \pi_{ijt}\, e^{-\Phi_{ijt} v^{-\theta}} = \pi_{ijt} \Pr(y_{ijt} \leq v),$$

so the highest earnings and the occupation that yields them are independent. Any selection of migrants that depends only on y_{ijt} therefore leaves the share in research among them equal to π_{ijt}.

Number of inventors. The expected number of inventors is $M_{ijt}\pi_{ijt}$. Writing $\zeta_{ijt} \equiv b x_{ijt} + \theta \ln \omega_{jt}$, Equation (13) gives $\pi_{ijt} = e^{\zeta_{ijt}}(1-\pi_{ijt})$, so $E[I_{ijt}] = M_{ijt} e^{\zeta_{ijt}}(1-\pi_{ijt})$ exactly (Equation (14)). In logarithms, $\ln E[I_{ijt}] = \ln M_{ijt} + \zeta_{ijt} + \ln(1-\pi_{ijt})$. When π_{ijt} is small, the odds $e^{\zeta_{ijt}}$ are close to the share π_{ijt}, because $\ln(1-\pi_{ijt}) \approx -\pi_{ijt}$ is close to zero, so this term can be dropped. This gives

$$E[I_{ijt}] \approx M_{ijt} \exp\left(b x_{ijt} + \theta \ln \omega_{jt}\right),$$

with an error in logarithms of about π_{ijt}, the share of inventors in the ancestry. This is the form estimated in Equation (16).

A.5 Proof of Proposition 3

Consider country j, whose workforce is of the single ancestry i, so that $R_{jt} = R_{ijt}$ and $L_{jt} = L_{ijt}$. The trait enters through $u_{ijt} \equiv \ln T_{ijt}^R$, with $\ln T_{ijt}^P$ fixed, so $d(bx_{ijt}) = du_{ijt}$. Write G_{jt}, defined in Appendix A.2, as a function of $\ln \omega_{jt}$ and u_{ijt}, let $D_{jt} \equiv 1 + \eta_j R_{jt}$, and note that $\eta_j(1-\chi)L_{jt} = \omega_{jt} D_{jt}$ at the equilibrium. Superscripts ω and u denote partial derivatives with respect to $\ln \omega_{jt}$ and u_{ijt}.

Part (i). Using Equations (A.2) and (A.3) and this equality,

$$G_{jt}^{\omega} = \omega_{jt}\Big[D_{jt} + (\theta-1)\big(\eta_j R_{jt}(1-\pi_{ijt}) + D_{jt}\pi_{ijt}\big)\Big],$$
$$\theta\, G_{jt}^{u} = \omega_{jt}\Big[\eta_j R_{jt}\big(1 + (\theta-1)(1-\pi_{ijt})\big) + (\theta-1)D_{jt}\pi_{ijt}\Big].$$

The log odds equal $u_{ijt} - \ln T_{ijt}^P + \theta \ln \omega_{jt}$, so their derivative with respect to u_{ijt} is

$$1 - \theta\frac{G_{jt}^u}{G_{jt}^\omega} = \frac{G_{jt}^\omega - \theta G_{jt}^u}{G_{jt}^\omega} = \frac{\omega_{jt}(D_{jt} - \eta_j R_{jt})}{G_{jt}^\omega} = \frac{1}{D_{jt} + (\theta-1)\big(\eta_j R_{jt}(1-\pi_{ijt}) + D_{jt}\pi_{ijt}\big)}. \tag{A.9}$$

The numerator equals one and the denominator exceeds one, so the derivative lies in $(0,1)$.

Part (ii). Holding ω_{jt} fixed, $\partial G_{jt}/\partial \eta_j = \omega_{jt} R_{jt} - (1-\chi)L_{jt}$. At the equilibrium, $(1-\chi)L_{jt} = \omega_{jt} D_{jt}/\eta_j$, so

$$\frac{\partial G_{jt}}{\partial \eta_j} = \frac{\omega_{jt}(\eta_j R_{jt} - D_{jt})}{\eta_j} = -\frac{\omega_{jt}}{\eta_j} < 0.$$

Hence $d\omega_{jt}/d\eta_j = -(\partial G_{jt}/\partial \eta_j)/G'_{jt}(\omega_{jt}) > 0$, and π_{ijt} rises with ω_{jt} by Equation (6). □

A.6 Dynamics of the Trait

The population stays in place and each adult has one child, so M_{ijt} is constant. By Proposition 1, the trait x_{ijt} and η_j then determine the equilibrium share ρ_{jt}. Let f denote the map from x_{ijt} to x_{ijt+1} in Equation (15), which does not depend on t. By Proposition 3, ρ_{jt} increases with x_{ijt} and with η_j, so f is continuous, strictly increasing in the trait and increasing in η_j. Because $0 < \rho_{jt} < 1$, f maps the interval $[0, \bar{x}]$, with $\bar{x} \equiv \phi/(1-\xi)$, into itself, and $f(x) < x$ for $x \geq \bar{x}$.

For an increasing map, the sequence $x_{ijt+1} = f(x_{ijt})$ is monotone. If $x_{ij1} \geq x_{ij0}$, then $f(x_{ij1}) \geq f(x_{ij0})$, that is, $x_{ij2} \geq x_{ij1}$, and by induction the sequence is nondecreasing; the same argument applies if $x_{ij1} \leq x_{ij0}$. A monotone sequence that remains in a bounded interval converges, and by continuity its limit x_{ij}^* satisfies $x_{ij}^* = f(x_{ij}^*)$. Because f is strictly increasing in the trait and increasing in η_j, a society with a higher η_j and an initial trait at least as strong has a higher trait in every later period.

Research labor increases with the trait by Appendix A.7. It also increases with η_j for a given trait, because ω_{jt} increases with η_j (Appendix A.5) and R_{jt} increases with ω_{jt} by Equation (A.2). Growth, $\eta_j R_{jt}$, is therefore higher in every later period in the society with the higher η_j and an initial trait at least as strong. By Equation (12), starting from the same N_{j0}, that society has more technology in every later period.

A.7 Ancestry and Growth

A stronger trait in any ancestry raises the growth of the country in which it lives. It lowers the relative return to research ω_{jt} and, with it, the share in research of every other ancestry, but total research labor rises, so the growth rate g_{jt} increases. This movement of other ancestries out of research resembles the displacement that Borjas and Doran (2012) document for inflows of foreign scientists, although Moser et al. (2014) find that such inflows drew new domestic inventors into research. Through Equation (11), the growth of a country rises with the technological history of the lineages that make up its population, which is the counterpart for innovation of the relationship between ancestral history and income documented by Putterman and Weil (2010).

Consider country j. Let $u_{ijt} \equiv \ln T^R_{ijt}$ for the ancestry i whose trait rises, and use the notation of Appendix A.5, with all ancestries k of country j in the sums of Equation (8).

Return to research. By Equation (A.3), $R^u_{jt} > 0$ and $L^u_{jt} < 0$, so $G^u_{jt} = \omega_{jt}\eta_j R^u_{jt} - \eta_j(1-\chi)L^u_{jt} > 0$. Since $G^\omega_{jt} > 0$, $d\ln\omega_{jt}/du_{ijt} = -G^u_{jt}/G^\omega_{jt} < 0$.

Other ancestries. For every other ancestry k, T^R_{kjt} and T^P_{kjt} are unchanged, and π_{kjt} increases with ω_{jt} by Equation (6), so π_{kjt} falls.

Growth. The total change in research labor is

$$\frac{dR_{jt}}{du_{ijt}} = R^u_{jt} + R^\omega_{jt}\frac{d\ln\omega_{jt}}{du_{ijt}} = \frac{R^u_{jt}G^\omega_{jt} - R^\omega_{jt}G^u_{jt}}{G^\omega_{jt}}.$$

With $G^\omega_{jt} = \omega_{jt}D_{jt} + \omega_{jt}\eta_j R^\omega_{jt} - \eta_j(1-\chi)L^\omega_{jt}$ and $G^u_{jt} = \omega_{jt}\eta_j R^u_{jt} - \eta_j(1-\chi)L^u_{jt}$, the numerator equals

$$R^u_{jt}\,\omega_{jt}D_{jt} + \eta_j(1-\chi)\left[R^\omega_{jt}L^u_{jt} - R^u_{jt}L^\omega_{jt}\right].$$

Let $Q_{jt} \equiv \sum_k R_{kjt}(1-\pi_{kjt})$. By Equations (A.1) and (A.2), $R^\omega_{jt} = (\theta-1)Q_{jt}$ and

$$L^\omega_{jt} = -(\theta-1)\sum_k \pi_{kjt}L_{kjt} = -(\theta-1)\,\omega_{jt}Q_{jt}.$$

By Equations (A.1) and (A.3), $L^u_{jt} = -\frac{\theta-1}{\theta}\,\omega_{jt}R_{ijt}(1-\pi_{ijt})$. Substituting,

$$R^\omega_{jt}L^u_{jt} - R^u_{jt}L^\omega_{jt} = \frac{(\theta-1)\,\omega_{jt}Q_{jt}R_{ijt}}{\theta}\left[\big(1+(\theta-1)(1-\pi_{ijt})\big) - (\theta-1)(1-\pi_{ijt})\right] = \frac{(\theta-1)\,\omega_{jt}Q_{jt}R_{ijt}}{\theta} > 0.$$

Both terms of the numerator are positive, so $dR_{jt}/du_{ijt} > 0$, and the growth rate $g_{jt} = \eta_j R_{jt}$ rises.

B Data Appendix

This appendix describes the variables used in the paper. Tables B.2 and B.3 list every source, Table B.1 reports summary statistics, Figure B.2 shows the distribution of inventor records across corridors and Figure B.1 maps the two main variables.

Migrant inventors. I measure migrant invention with the database of the World Intellectual Property Organization (WIPO) on the international mobility of inventors (Miguelez and Fink, 2013). The database is built from applications filed under the Patent Cooperation Treaty (PCT), the only large patent source that systematically records both the nationality and the country of residence of each inventor. Until September 2012, inventors named on PCT applications that designated the United States had to be listed as applicants, and applicants report both to establish eligibility. Coverage of inventors' nationality is good before 2004 and excellent from 2004 to 2011 (Miguelez and Fink, 2013). For each pair of origin (nationality) and destination (residence), the database counts inventor names on PCT applications by priority year. My outcome is the sum over 2001–2010, the last full decade before the nationality field ceased to be mandatory. A record is an inventor on a patent, so an inventor who appears on three applications counts three times; the outcome therefore measures inventive output rather than the number of distinct people. PCT applications are, on average, of higher value than purely national filings, because applicants pay to seek protection in several countries. The database also reports inventor records by type of applicant (firms, public research organizations and individuals) and by technology field, and I use the records of 1991–2000 as an alternative outcome.

Skilled migrants and the graduate pipeline. The number of migrant inventors depends mechanically on the number of migrants who could become inventors. I measure this pool with the OECD Database on Immigrants in OECD and non-OECD Countries (DIOC) for 2010/11 (Arslan et al., 2015), which reports, from censuses and population registers, the number of people born in each origin and living in each destination, by educational attainment.

Two features of the data require care. First, DIOC counts people by country of birth, whereas WIPO counts inventors by nationality. A migrant who becomes a citizen of the destination no longer appears among the inventors of the origin, but still counts among the migrants born there. Because naturalization rates differ widely by origin, comparing the two counts would understate invention for origins whose migrants naturalize more often. In the United States in 2010, 56 percent of tertiary-educated migrants born in India were still Indian nationals, compared with 23 percent of those born in Germany. Because DIOC also reports nationality for most destinations, I measure the pool as the number of tertiary-educated foreign nationals born in the origin and living in the destination, so that the inventors and the pool count the same people. This restricts the analysis to the 26 destinations that report nationality, including the United States, Germany, the United Kingdom, France, Canada and Japan.

Second, many skilled migrants enter destination labor markets through graduate school. I measure each corridor's graduate pipeline with the number of master's and doctoral students from the origin enrolled in the destination, averaged over 2013–2015, the earliest years available in the OECD data on international students.[19] Because these data postdate the inventor flows, I also use each origin's outbound student mobility ratio over 1999–2005 from UNESCO, which predates or overlaps the early years of the inventor flows. The series has broad country coverage only from 1999, and many origins report it in some years only, which is why I average it over seven years. UNESCO does not report the ratio for 1999–2005 for some origins, including Germany, Australia, Austria, New Zealand, South Africa and Singapore. For these origins I set the ratio to the geometric mean of the other origins and add an indicator for the missing ratio to every specification.

[19]The United States does not report doctoral students separately; they are included in its master's count. I therefore define graduate students as master's plus doctoral students throughout.

Ancestral technology and statehood. My main measure of history is the technology adoption index of Comin et al. (2010) in 1500. The index averages the adoption of basic technologies in agriculture, transportation, communications, industry and the military, and ranges from zero to one. Following Putterman and Weil (2010), I use the version adjusted for migration since 1500, which assigns to each country the technology of the places its current population descends from. The distinction matters for the Americas and Oceania. The territorial index for the United States reflects the technology of its indigenous societies in 1500, whereas the ancestry-adjusted index reflects mainly that of Europe.

I compare this measure with three other deep roots. State history comes from Borcan et al. (2018), who score the presence, autonomy and territorial reach of states over every half-century from 3500 BCE to 2000 CE; I use the normalized index with a one percent discount per half-century, adjusted for ancestry with the migration matrix of Putterman and Weil (2010). I also use technology adoption in 0 AD (Comin et al., 2010) and the number of millennia since the Neolithic transition (Putterman, 2008), both adjusted for ancestry. The four deep roots are positively but imperfectly correlated. Technology in 1500 has a correlation of 0.59 with state history and 0.68 with the Neolithic transition.

Control variables. The gravity variables and origin income and education are standard controls in the analysis of bilateral flows. The gravity variables are the logarithm of distance and indicators for contiguity, a common official language and a colonial link (Mayer and Zignago, 2011). Origin income is GDP per capita at purchasing power parity, averaged over 1990–1999, from the World Development Indicators, and origin education is the share of adults aged 25 and over with completed tertiary education in 1990 (Barro and Lee, 2013). Both are measured before the inventor flows.

The baseline controls address the selection of migrants and competing origin characteristics. Relative selection is the ratio of the tertiary share among migrants from the origin in the destination to the tertiary share in the origin population. Religion is measured by the shares of the origin population that were Protestant, Catholic, Orthodox, Muslim, Hindu and Buddhist in 2000, from the World Religion Project. Genetic distance is the population-weighted genetic distance between the populations of origin and destination (Spolaore and Wacziarg, 2018). Origins are grouped into the seven World Bank regions and by colonizer.

Two further variables address how migrants were trained and how they are counted. First, inventors are concentrated among graduates in science and engineering, and origins differ in how many of their skilled emigrants hold such degrees. DIOC 2010/11 does not report field of study, but DIOC 2000/01 does for 15 destinations, including Canada, Australia and Spain. Pooling these destinations, I measure for each origin the share of tertiary-educated emigrants with a degree in science or in engineering, manufacturing and construction in 2000/01, before the inventor flows I study. The share is available for 99 of the 115 origins with technology data, including China (46 percent) and India (35 percent), and it is almost uncorrelated with ancestral technology (0.02). Because the 15 destinations exclude the United States, the United Kingdom, Germany and France, the share measures the field composition of each origin's skilled diaspora as a whole, not of each corridor; it cannot capture, for instance, the selection of engineers into the United States through temporary work visas. As an alternative, I use the share of science and engineering graduates among all tertiary graduates at origin, 1998–2012 (UNESCO).

Second, dual citizenship can break the match between the two counts. A migrant who naturalizes in the destination leaves the pool of foreign nationals. If the origin allows dual citizenship, the migrant keeps the origin nationality and can still report it on a PCT application, so the inventor stays in the count while

leaving the pool. Origins that allow dual citizenship would then show more invention per skilled migrant, which biases the estimate if they also differ in ancestral technology. I measure, for each origin, the share of years 2001–2010 in which a national who voluntarily acquired a foreign citizenship automatically lost the origin one, coded from nationality laws in the MACIMIDE Global Expatriate Dual Citizenship Dataset (Vink et al., 2015). China, India, Germany and Japan, for instance, did not allow dual citizenship over the period.

Further robustness checks use the origin's innovation system before the inventor flows, measured by resident patent applications per million people over 1990–2000 and by R&D spending as a share of GDP over 1996–2000, and its human capital at the tertiary level, measured by the gross tertiary enrollment ratio, all from the World Development Indicators. They also use the inward foreign direct investment (FDI) position of the origin in the destination, averaged over 2005–2010, from the OECD.

Origin and destination characteristics. To study what migrants carry, I use measures of skills and values at origin. School quality is measured by the harmonized test scores of Angrist et al. (2021), which place national and international student assessments on a common scale. Historical numeracy is measured by the ABCC index of A'Hearn et al. (2009) for the birth cohorts of 1850–1900. People who cannot count well tend to report rounded ages, ending in 0 or 5, and the index uses this age heaping in censuses to estimate the share of a cohort that reported its exact age, from 0 to 100. Individualism is the score of Hofstede et al. (2010), built from surveys of employees, and measures how far people see themselves as independent individuals rather than as members of close-knit groups. Three further values are averages over all waves of the World Values Survey. Autonomy contrasts the qualities that respondents want children to learn, independence and determination against obedience and religious faith. Trust records whether respondents think most people can be trusted, and confidence in the civil service how much they trust public administration.

To study where the advantage pays off, I use characteristics of destinations. Power distance, also from Hofstede et al. (2010), measures how far people accept that authority in organizations is distributed unequally, and thus how hierarchical workplaces are. The foreign-degree penalty is the difference between the overqualification rates of tertiary-educated immigrants and natives in the destination, from DIOC 2010/11, and R&D intensity is gross domestic expenditure on R&D as a share of GDP over 2010–2019, from the World Development Indicators. Finally, the anti-discrimination and labor-market-mobility strands of the Migrant Integration Policy Index for 2010 measure destination policy toward migrants (Huddleston et al., 2011).

Table B.1: Summary Statistics

Panel A: Corridors (origin × destination)	Mean	SD	Median	Min	Max	N
Migrant inventors, 2001–10	125.3	1,377.2	1.0	0.0	44,450	2,195
Skilled foreign nationals, 2010/11	4,742.2	24,862.0	196.0	1.0	705,644	2,195
Inventors per 1,000 skilled foreign nationals	25.4	117.6	0.4	0.0	3,000	2,195
Graduate students, 2013–15	475.6	3,557.4	24.3	0.0	121,614	2,195
Distance (km)	6,660.4	4,406.8	6,400.4	81.0	19,586	2,195
Panel B: Origins						
Technology in 1500 (ancestry-adjusted)	0.64	0.26	0.76	0.13	1.00	97
Technology in 1500 (territorial)	0.50	0.33	0.48	0.00	1.00	93
State history (ancestry-adjusted)	0.30	0.15	0.30	0.02	0.73	97
GDP per capita, 1990s (PPP)	17,032.36	16,782.58	10,774.16	946.67	65,437.58	97
Tertiary share of adults, 1990 (%)	6.17	5.33	4.48	0.23	28.01	97
Outbound student mobility, 1999–2005 (%)	7.28	10.86	2.69	0.27	52.14	87

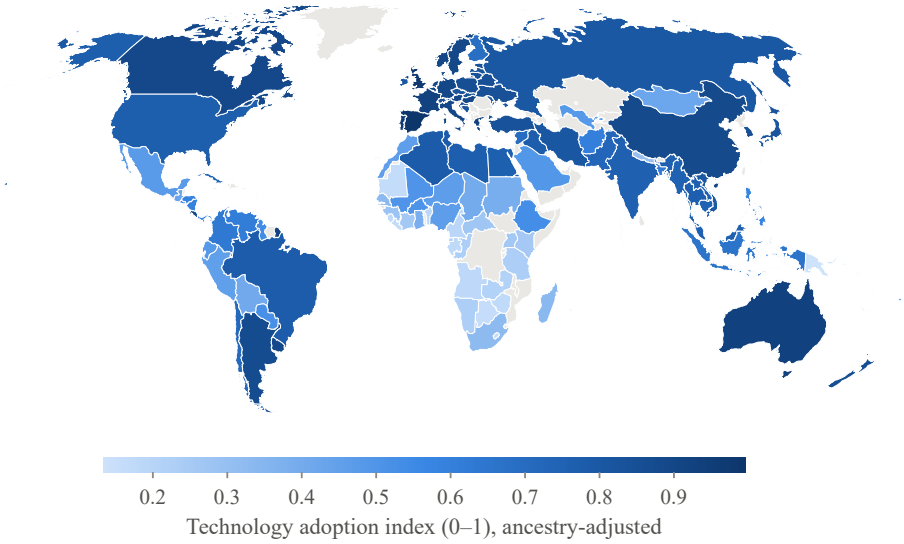
Notes: This table reports summary statistics for the baseline sample. Panel A reports statistics across its 2,195 corridors. Migrant inventors are inventor records on PCT applications by nationals of the origin residing in the destination, summed over priority years 2001–2010 (Miguelez and Fink, 2013). Skilled foreign nationals are tertiary-educated persons born in the origin who hold its nationality and live in the destination (Arslan et al., 2015). Graduate students are master's and doctoral students from the origin enrolled in the destination, averaged over 2013–2015 (OECD). Panel B reports statistics across the 97 origins. Technology in 1500 is the index of Comin et al. (2010); state history is the index of Borcan et al. (2018); ancestry-adjusted versions use the migration matrix of Putterman and Weil (2010). The territorial technology index is missing for four origins.

Table B.2: Data Sources: Inventors, Migrants and Controls

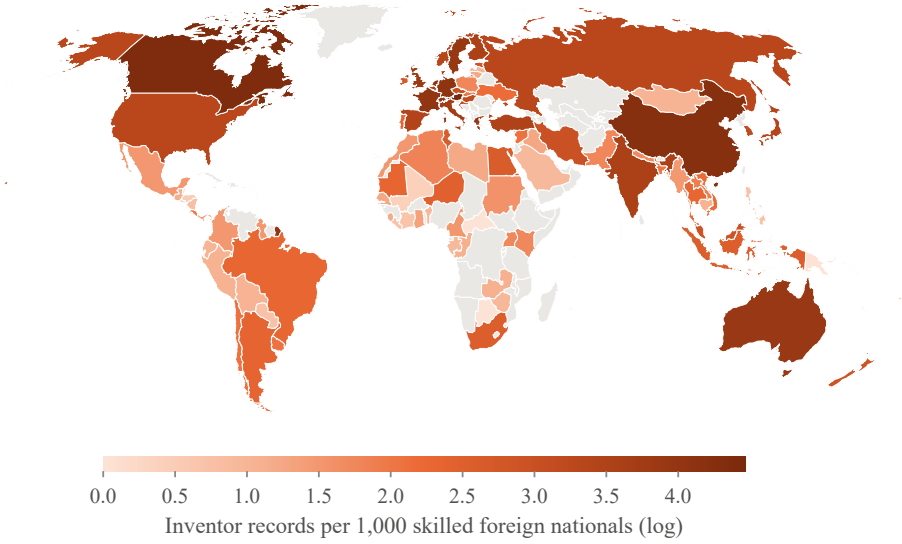
Variable	Definition	Source
Migrant inventors	Inventor records on PCT applications by nationals of the origin residing in the destination, priority years 2001–2010 (and 1991–2000)	WIPO; Miguelez and Fink (2013)
Inventors by applicant type	Same, by corporate, public research and individual applicants	WIPO; Miguelez and Fink (2013)
Inventors by technology field	Same, by technology field of the application	WIPO; Miguelez and Fink (2013)
Home inventors	Inventor records on PCT applications by nationals of the origin residing in the origin, priority years 1991–2000 and 2001–2010	WIPO; Miguelez and Fink (2013)
Relative selection	Tertiary share among migrants born in the origin living in the destination, 2010/11, divided by the tertiary share of adults in the origin, 1990	OECD DIOC 2010/11; Barro and Lee (2013)
Skilled foreign nationals	Tertiary-educated persons born in the origin, holding its nationality, living in the destination, 2010/11 (and 2000/01)	OECD DIOC 2010/11 (Arslan et al., 2015) and 2000/01
Skilled foreign-born	Tertiary-educated persons born in the origin living in the destination, 2010/11	OECD DIOC 2010/11
Graduate students	Master's and doctoral students from the origin enrolled in the destination, mean 2013–2015	OECD Education Database
Outbound student mobility	Tertiary students of the origin studying abroad, % of tertiary enrollment, mean 1999–2005	UNESCO, via World Bank EdStats
Gravity variables	Distance, contiguity, common official language, colonial link	CEPII GeoDist (Mayer and Zignago, 2011)
Genetic distance	Population-weighted genetic distance between the origin and the destination	Spolaore and Wacziarg (2018)
Origin income	GDP per capita (PPP), mean 1990–1999	World Bank WDI
Origin population	Population, mean 1990–1999	World Bank WDI
Origin education	Share of adults 25+ with completed tertiary education, 1990	Barro and Lee (2013)
Religion	Population shares by religion, 2000	Correlates of War, World Religion Project
Region, colonizer	World Bank region; colonial origin	World Bank; QoG (Hadenius–Teorell)
STEM share of skilled emigrants	Tertiary-educated emigrants of the origin with a degree in science or engineering, % of those with a known field, pooled over 15 destinations, 2000/01	OECD DIOC 2000/01, File G
STEM share of origin graduates	Tertiary graduates in science or engineering, % of all graduates, mean 1998–2012	UNESCO, via World Bank WDI
No dual citizenship	Share of years 2001–2010 in which naturalizing abroad cost the origin citizenship	MACIMIDE v5 (Vink et al., 2015)
Origin location	Label point of the country, for Conley standard errors	Natural Earth admin-0
Origin innovation system	Resident patent applications per million people, 1990–2000; R&D, % of GDP, 1996–2000	World Bank WDI
Origin tertiary human capital	Gross tertiary enrollment, 1990–2000	World Bank WDI
Inward FDI	Directional inward FDI position of the origin in the destination, USD million, mean 2005–2010	OECD FDI statistics by counterpart area
Free movement	Origin and destination both in the EU, EEA or Switzerland (2007)	EU and EEA membership in 2007

Table B.3: Data Sources: Deep Roots, Culture, Destination and Corridor Characteristics

Variable	Definition	Source
Technology in 1500, 0 AD	Average adoption of sectoral technologies, ancestry-adjusted and territorial	Comin et al. (2010)
State history	Discounted, normalized state presence 3500 BCE–2000 CE, ancestry-adjusted	Borcan et al. (2018)
Neolithic transition	Millennia since the transition to agriculture, ancestry-adjusted	Putterman (2008)
Ancestry adjustment	Shares of current population descended from each 1500 population	Putterman and Weil (2010)
Test scores	Harmonized learning outcomes	Angrist et al. (2021), World Bank HCI
Numeracy	ABCC age-heaping index, birth cohorts 1850–1900	A'Hearn et al. (2009), Clio-Infra
Trust, autonomy, confidence	World Values Survey averages over all waves	QoG time-series dataset
Individualism, power distance	Cultural dimension scores	Hofstede et al. (2010)
Foreign-degree penalty	Overqualification rate of tertiary-educated immigrants minus that of natives in the destination	OECD DIOC 2010/11, File D
Anti-discrimination, labor-market mobility	Policy strands of the Migrant Integration Policy Index for the destination, 2010	MIPEX III (Huddleston et al., 2011)
R&D intensity	Gross domestic expenditure on R&D, % of GDP, mean 2010–2019	World Bank WDI
Doctorate holders	Skilled foreign nationals with a doctorate, 2010/11; also as a share of skilled foreign nationals	OECD DIOC 2010/11
English at origin	English is an official language of the origin	CEPII GeoDist
Overqualification gap	Overqualification rate of tertiary-educated migrants of the corridor minus that of natives	OECD DIOC 2010/11, File D
Genetic distance to the US	Population-weighted genetic distance between the origin and the United States	Spolaore and Wacziarg (2018)
Long-stay share	Share of tertiary-educated migrants of the corridor in residence for more than ten years	OECD DIOC 2010/11, File B



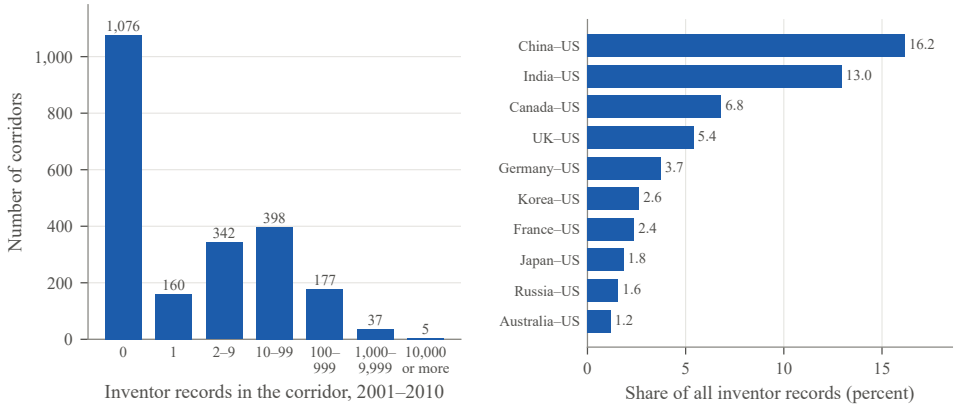
(a) Ancestral technology in 1500



(b) Migrant inventors per skilled migrant, 2001–2010

Figure B.1: Ancestral Technology and Migrant Invention by Origin Country

Notes: This figure maps ancestral technology in 1500 and migrant invention by origin country. Panel (a): technology adoption in 1500, adjusted for ancestry (Comin et al., 2010; Putterman and Weil, 2010), for every country with data. Panel (b): logarithm of one plus the number of migrant inventor records (2001–2010) per thousand tertiary-educated foreign nationals of each origin, pooled across the 26 destinations, for the 97 origins of the baseline sample. Gray: no data. Robinson projection.



(a) Corridors by number of inventor records

(b) Ten largest corridors

Figure B.2: Distribution of Migrant Inventor Records Across Corridors

Notes: This figure shows the distribution of migrant inventor records across the 2,195 corridors of the baseline sample. A corridor is a pair of origin (nationality) and destination (residence), and an inventor record is an inventor listed on a PCT application over 2001–2010. Panel (a) groups corridors by their number of inventor records. Panel (b) shows the ten corridors with the most inventor records and the share of each in the 275,048 records of the sample. US: United States; UK: United Kingdom.

C Robustness

This appendix reports the robustness checks summarized in Section 4.2. Section C.1 asks whether the estimate depends on particular corridors, on the weighting of corridors or on when the data are measured. Section C.2 asks whether education and other traits of migrants account for the gradient. Section C.3 tests explanations other than ancestral technology that could produce the same gradient. Section C.4 asks whether the estimate is statistically significant once spatial correlation and the small number of origins are taken into account. Section C.5 reports checks on features of the data. Section C.6 reports the additional horse races of Section 4.

C.1 Sample, Timing and Estimator

Two corridors, China–United States and India–United States, account for a large share of all migrant inventors, and the United States receives most skilled migrants. The estimate could therefore reflect these two origins or the American graduate-school system rather than a general relationship. Table C.1 shows that it does not. With the baseline controls, excluding China and India as origins gives 2.39 (column 1), and excluding the United States as a destination gives 1.97 (column 2). Both remain significant at the one percent level.

Table C.1: Robustness to Sample, Timing and Estimator

	No CHN, IND	No USA	1991–2000	OLS intensity	Old World only	Inventor rate	No ten largest corridors	Migrant pool 2000/01
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technology in 1500	2.385***	1.973***	3.156***	1.516***	3.310***	2.701***	2.517***	2.529***
	(0.718)	(0.583)	(0.557)	(0.411)	(0.831)	(0.990)	(0.646)	(0.451)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.966	0.933	0.941		0.973	0.493	0.934	0.985
R^2				0.515				
Corridors	2,144	2,114	2,195	2,195	1,678	2,195	2,185	1,412
Origins	95	97	97	97	75	97	97	88
Destinations	26	25	26	26	26	26	26	20

Notes: This table reports robustness checks of the estimate with the baseline controls. Columns (1)–(3) and (5)–(8) are Poisson pseudo-maximum likelihood estimates with the baseline controls of Table 1, column (4). Column (1) excludes China and India as origins; column (2) excludes the United States as a destination; column (3) uses inventor records over 1991–2000 as the dependent variable. Column (4) is an OLS regression of $\ln(1 + \text{inventors per 1,000 skilled foreign nationals})$ on the same controls except the log of skilled foreign nationals. Column (5) excludes origins in the Americas, Australia, New Zealand, South Africa and Namibia, where ancestry-adjusted and territorial measures differ most. Column (6) uses inventors per 1,000 skilled foreign nationals as the dependent variable, without the log of skilled foreign nationals as a control. Column (7) drops the ten corridors with the most inventor records, from Australia, Canada, China, France, Germany, India, Japan, Korea, Russia and the United Kingdom to the United States. Column (8) replaces the 2010/11 pool of skilled foreign nationals with the 2000/01 pool (DIOC 2000/01), available for 20 of the 26 destinations. Standard errors clustered by origin in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The Poisson estimator gives more weight to corridors with more expected inventors, so a few large corridors could drive the result even after these exclusions. I therefore re-estimate the model with estimators that do not weight corridors by their size. An OLS regression of the logarithm of one plus inventors per thousand skilled foreign nationals yields a positive coefficient, significant at the one percent level (column 4). Its size is not comparable to the Poisson estimates, because the logarithm compresses

differences between corridors. A Poisson regression of the inventor rate itself, which also removes that weighting and keeps the scale of the main estimates, gives 2.70 with the baseline controls (column 6) and 3.33 with the full controls (Table C.2, column 5), both significant at the five percent level or better. Dropping the ten largest corridors, all of which lead to the United States, gives 2.52 (column 7) and 2.36 (Table C.2, column 6), both significant at the one percent level.

A single origin could also drive the result. Dropping one origin at a time gives coefficients between 2.16 (without Saudi Arabia) and 3.08 (without Spain) with the baseline controls, all significant at the one percent level (Figure C.1), and between 1.55 and 2.72 with the full controls, all significant at the five percent level.

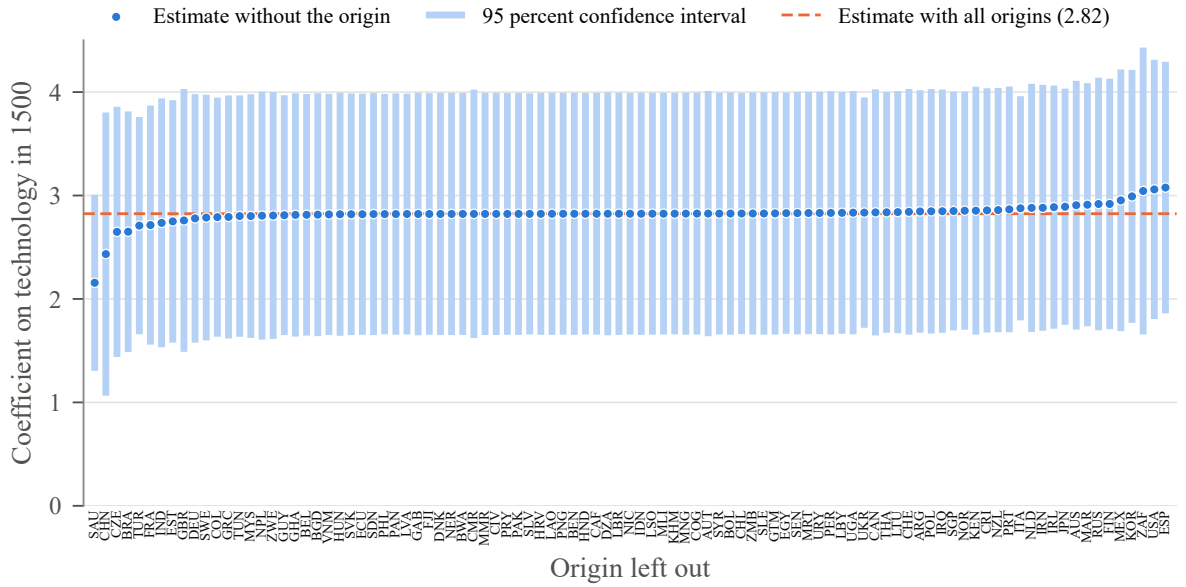


Figure C.1: Estimates Leaving Out One Origin at a Time

Notes: This figure shows the coefficient on technology in 1500 when one origin is left out of the sample, with the baseline controls of Table 1, column (4). Each dot is the estimate without one of the 97 origins, labeled by its ISO code and sorted by the estimate. Bands show 95 percent confidence intervals, with standard errors clustered by origin. The dashed line is the estimate with all origins.

The inventor flows of 2001–2010 are measured after some of the controls and at the same time as the migrant pool, which could itself respond to the success of earlier migrant inventors. Two checks address this timing. First, with inventor flows of 1991–2000, a decade before the migrant pool and graduate students are measured, the coefficient is 3.16 (Table C.1, column 3). Second, I replace the 2010/11 migrant pool with the 2000/01 pool, measured at the start of the inventor flows, which DIOC reports for 20 of the 26 destinations, including the United States, France, Canada and Japan but not Germany or the United Kingdom. The coefficient is then 2.53 with the baseline controls, against 2.91 with the 2010/11 pool on the same destinations, and 1.99 with the full controls, against 2.40 (Tables C.1, column 8, and C.2, column 7).

These checks also hold under the full controls of Table 1, column (5). Table C.2 gives 2.56 without China and India, 1.76 without the United States, 2.51 for the inventor flows of the 1990s and 2.80 among Old World origins (columns 1–4).

Table C.2: Robustness Under the Full Controls

	No CHN, IND	No USA	1991–2000	Old World only	Inventor rate	No ten largest corridors	Migrant pool 2000/01
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Technology in 1500	2.562***	1.755**	2.513***	2.795***	3.329**	2.364***	1.986***
	(0.821)	(0.745)	(0.934)	(0.978)	(1.396)	(0.763)	(0.577)
Full controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.969	0.936	0.946	0.975	0.528	0.939	0.986
Corridors	2,128	2,098	2,179	1,662	2,179	2,169	1,406
Origins	94	96	96	74	96	96	87
Destinations	26	25	26	26	26	26	20

Notes: This table repeats the robustness checks of Table C.1 with the full controls. The estimates are Poisson pseudo-maximum likelihood estimates of Equation (17), with the full controls of Table 1, column (5), including region and colonizer fixed effects. Columns (1)–(3) correspond to columns (1)–(3) of Table C.1, and columns (4)–(7) to its columns (5)–(8). Standard errors clustered by origin in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.2 Other Characteristics of Migrants

Table C.3 adds education and other traits of migrants and origins, one at a time, to the baseline specification. Section 4.2 summarizes the results.

Table C.3: Other Characteristics of Migrants

	(1)	(2)	(3)	(4)	(5)	(6)
Technology in 1500	1.773***	1.216**	2.796***	1.672***	2.171***	1.881***
	(0.548)	(0.520)	(0.603)	(0.599)	(0.805)	(0.609)
Log skilled foreign nationals	0.761***		0.551***	0.761***	0.598***	0.603***
	(0.055)		(0.065)	(0.060)	(0.060)	(0.058)
Log doctorate holders		0.780***				
		(0.045)				
Doctorate share	6.368***					
	(0.763)					
English at origin			0.071			
			(0.122)			
Overqualification gap				-3.697***		
				(0.492)		
Genetic distance to the US					-33.886***	
					(10.894)	
Long-stay share						1.457***
						(0.319)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.983	0.984	0.973	0.982	0.975	0.977
Corridors	1,991	1,376	2,195	1,923	2,170	1,899
Origins	97	97	97	97	96	97
Destinations	23	23	26	24	26	25

Notes: This table reports Poisson pseudo-maximum likelihood estimates with the baseline controls and destination fixed effects of Table 1, column (4), with the variables listed. Standard errors clustered by origin in parentheses. Samples vary across columns with data coverage. Columns (1) and (2) cover the 23 destinations that report a doctorate category. Column (2) replaces the log of skilled foreign nationals with the log of doctorate holders, for corridors with at least one. Inventor records cannot be split by degree, so only the pool changes. The doctorate share is the share of doctorate holders among skilled foreign nationals of the corridor. English at origin indicates English as an official language. The overqualification gap is the overqualification rate of skilled migrants of the corridor minus that of natives. Genetic distance is measured between the origin and the United States. The long-stay share is the share of skilled migrants of the corridor who have stayed more than ten years. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.3 Alternative Explanations

The identifying assumption of Equation (19) fails if a characteristic correlated with ancestral technology raises migrant invention through another channel. This section tests the main candidates.

The controls of the main specifications include graduate students of 2013–2015, measured after the inventor flows. If later student flows responded to earlier invention, this control could bias the estimate. Dropping it raises the baseline coefficient to 3.68, against 2.82 in Table 1, column (4) (Table C.4, column 1).

Origins with high ancestral technology may send migrants trained in science and engineering, who are more likely to patent. Controlling for the share of each origin's skilled emigrants with a science or engineering degree in 2000/01 leaves the coefficient at 3.05, against 2.79 on the same sample with the baseline controls, and at 2.25 with the full controls, against 2.38 (column 2). The share of science and engineering graduates at origin lowers the coefficient from 2.84 to 2.72 on its sample (column 3).

Table C.4: Field of Study, Dual Citizenship and Graduate Students

	(1)	(2)	(3)	(4)	(5)
Technology in 1500	3.684***	3.053***	2.722***	2.820***	4.273***
	(0.476)	(0.629)	(0.829)	(0.597)	(1.238)
STEM share, emigrants 2000		-0.030***			
		(0.011)			
STEM share, origin graduates			0.018*		
			(0.011)		
No dual citizenship				-0.074	
				(0.119)	
Baseline controls	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.966	0.979	0.968	0.973	0.970
Corridors	2,195	1,936	1,548	2,195	1,178
Origins	97	85	67	97	51
Destinations	26	26	26	26	26

Notes: This table reports tests of three concerns about the estimates: the fields in which migrants were trained, dual citizenship and the timing of the controls. The estimates are Poisson pseudo-maximum likelihood estimates with the baseline controls of Table 1, column (4). Column (1) drops the graduate students of 2013–2015, the one control measured after the inventor flows. The STEM share of skilled emigrants is the percentage of tertiary-educated emigrants of the origin with a degree in science or engineering, pooled over the 15 destinations of DIOC 2000/01. The STEM share of origin graduates is the percentage of tertiary graduates in science or engineering at origin, 1998–2012 (UNESCO). "No dual citizenship" is the share of years 2001–2010 in which naturalizing abroad cost the origin citizenship (Vink et al., 2015); column (5) keeps origins that allowed dual citizenship throughout. Standard errors clustered by origin in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A migrant who naturalizes leaves the pool of foreign nationals, but stays in the inventor count if the origin allows dual citizenship. If origins that allow dual citizenship also differ in ancestral technology, the gradient would be biased. Controlling for the origin's rule leaves the coefficient unchanged at 2.82 (column 4). Among the 51 origins that allowed dual citizenship throughout 2001–2010, which all share the same rule, the coefficient is 4.27 (column 5).

The result could reflect origin firms rather than people. Some foreign-national inventors are engineers posted abroad by home-country firms, such as Japanese engineers at the American subsidiaries of Japanese firms. They come disproportionately from origins with high ancestral technology and keep their nationality. The corridor data do not identify the applicant's country, so Table C.5 tests this channel indirectly. Controlling for origin patenting per capita over 1990–2000 lowers the coefficient only from 2.80 to 2.61 (column 1), and from 2.32 to 2.22 with the full controls. Because origin patenting may itself reflect ancestral technology, this is a conservative bound. Origin R&D intensity, available for 60 origins, raises the coefficient on that sample from 2.00 to 2.12 (column 2), and controlling for both patenting and R&D gives 2.17 (column 3). The result holds for inventors hired by firms and public research organizations (2.66; column 5) and rises to 2.94 when Japan, Korea and Germany, the main origins of posted engineers, are excluded (column 6).

Free movement within the EU and EEA lets nationals of member states work in other member states without a visa, which could change who migrates among European origins. Controlling for corridors within this area leaves the coefficient at 2.79 (Table C.5, column 4).

Table C.5: Origin Innovation Systems, Free Movement and Corporate Expatriates

	Origin innovation system					
				Free movement	Hired inventors	Without JPN, KOR, DEU
	(1)	(2)	(3)	(4)	(5)	(6)
Technology in 1500	2.614***	2.123***	2.167***	2.789***	2.660***	2.938***
	(0.582)	(0.533)	(0.570)	(0.604)	(0.586)	(0.633)
Patents per capita, 1990–2000 (log)	0.083		-0.029		0.085	
	(0.078)		(0.097)		(0.078)	
Origin R&D, % of GDP, 1996–2000		0.242**	0.271**			
		(0.100)	(0.124)			
Free movement (EU/EEA)				0.166		
				(0.192)		
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.973	0.976	0.975	0.973	0.973	0.975
Corridors	1,817	1,430	1,412	2,195	1,817	2,122
Origins	77	60	59	97	77	94
Destinations	26	26	26	26	26	26

Notes: This table reports estimates that control for the origin's innovation system, free movement and corporate expatriates. The estimates are Poisson pseudo-maximum likelihood estimates with the baseline controls of Table 1, column (4). Origin patents per capita are resident patent applications per million people, averaged over 1990–2000; origin R&D is gross expenditure on R&D as a share of GDP, averaged over 1996–2000, the first years available (World Bank WDI). Both are measured before the inventor flows. Free movement equals one when both origin and destination belong to the EU, the EEA or Switzerland (2007 membership). Column (5) uses inventor records on applications filed by firms and public research organizations as the dependent variable. Column (6) excludes Japan, Korea and Germany, the main origins of engineers posted abroad by home-country firms. Standard errors clustered by origin in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Home-country firms in the destination could hire migrants from their own origin (Burchardi et al., 2019), and these firms come mainly from origins with high ancestral technology. The origin's inward foreign direct investment (FDI) position in the destination in 2005–2010 strongly predicts migrant invention, but it does not absorb the gradient. On the corridors with FDI data, which account for 95 percent of inventor records, the coefficient moves from 1.87 to 1.55 for all inventors and from 1.91 to 1.59 for hired inventors, and remains significant at the one percent level (Table C.6, columns 1 and 2).

Inventor teams are larger in some technology fields than in others. If origins with high ancestral technology specialize in such fields, the gradient would reflect team size rather than inventiveness. Estimating the model field by field gives coefficients between 1.57 and 2.75, significant in each of five fields (Table C.7).

Finally, destination fixed effects absorb treatment common to all migrants in a destination, but not treatment that differs by origin. Hiring discrimination against migrants from Africa, Latin America, South Asia and the Middle East would produce a gradient along similar lines. If the gradient reflected discrimination, it should be smaller in destinations with stronger anti-discrimination policy and more equal access of migrants to jobs. With origin and destination fixed effects, the gradient is, if anything, larger where anti-discrimination policy is stronger, and its interaction with labor-market access is negative. Neither interaction is significant (Table C.8).

Table C.6: Bilateral FDI and Origin Human Capital at the Tertiary Level

	(1)	(2)	(3)
Technology in 1500	1.554***	1.591***	3.939***
	(0.547)	(0.550)	(0.797)
Inward FDI from origin, 2005–10 (log)	0.111***	0.112***	
	(0.024)	(0.024)	
Origin tertiary enrollment, 1990–2000			-0.017***
			(0.004)
Controls	Full	Full	Baseline
Pseudo R^2	0.980	0.981	0.985
Corridors	1,653	1,653	1,502
Origins	96	96	68
Destinations	22	22	26

Notes: This table reports estimates that control for bilateral FDI and for the origin's human capital at the tertiary level. The estimates are Poisson pseudo-maximum likelihood estimates, with the full controls of Equation (17) in columns (1)–(2) and the baseline controls of Table 1, column (4), in column (3). Inward FDI is the directional inward FDI position of the origin in the destination, USD million, averaged over 2005–2010 (OECD FDI statistics by counterpart area, historical series; reported for 22 of the 26 sample destinations, covering 95 percent of inventor records). Because FDI is measured over the same years as the inventor flows, columns (1) and (2) are bounds rather than clean controls. Tertiary enrollment is the gross tertiary enrollment ratio, 1990–2000 (World Bank WDI). Column (2) uses inventor records on applications filed by firms and public research organizations as the dependent variable. Standard errors clustered by origin in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.7: Estimates by Technology Field

	Electrical engineering (1)	Instruments (2)	Chemistry (3)	Mechanical engineering (4)	Other fields (5)
Technology in 1500	2.431***	1.573**	2.342***	2.408***	2.754***
	(0.887)	(0.756)	(0.842)	(0.752)	(0.920)
Full controls	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.970	0.964	0.973	0.942	0.899
Corridors	2,179	2,179	2,179	2,179	2,101
Origins	96	96	96	96	96
Destinations	26	26	26	26	25

Notes: This table reports estimates by technology field. The estimates are Poisson pseudo-maximum likelihood estimates of Equation (17). The dependent variable is the number of inventor records on PCT applications in the technology field of the column heading, 2001–2010 (Miguelez and Fink, 2013). Because team size differs across fields, estimating the model field by field checks that the result does not reflect a concentration of some origins in fields with large inventor teams. Standard errors clustered by origin in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.8: Discrimination in Destination Labor Markets

	(1)	(2)	(3)
Tech. 1500 × anti-discrimination	0.375		0.371
	(0.292)		(0.300)
Tech. 1500 × labor access		-0.175	-0.153
		(0.224)	(0.213)
Corridor controls	Yes	Yes	Yes
Origin FE	Yes	Yes	Yes
Pseudo R^2	0.985	0.985	0.985
Corridors	1,974	1,974	1,974
Origins	95	95	95
Destinations	23	23	23

Notes: This table reports tests of discrimination in destination labor markets. The estimates are Poisson pseudo-maximum likelihood estimates of Equation (18) with origin and destination fixed effects. The anti-discrimination and labor-market-mobility strands of the Migrant Integration Policy Index 2010 are standardized across destinations and interacted with ancestral technology, with the controls of Table D.1. Standard errors clustered by origin and destination. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.4 Standard Errors and Statistical Significance

The main tables cluster standard errors by origin, so that errors may be correlated across the destinations of the same origin. Two concerns remain. Ancestral technology varies smoothly across space, so unobserved origin characteristics may be correlated across neighboring origins, and spatially correlated noise can then produce apparently significant estimates (Kelly, 2020). In addition, the number of origins is small and a few large corridors carry much of the weight. This section addresses each concern.

Clustering by origin also ignores correlation across origins within the same destination. Clustering by both origin and destination does not widen the confidence interval. The standard error is 0.58, against 0.60 when clustering by origin alone on the same sample (Table C.9).

To allow for correlation between neighboring origins, I compute Conley (1999) standard errors, which let the errors of origins up to a given distance apart be correlated. Table C.9 reports them for cutoffs of 1,000 to 5,000 km. They are within 5 percent of the clustered standard errors at every cutoff, and the estimate remains significant at the one percent level.

Table C.9: Spatial Correlation and Randomization Inference

	Baseline controls
Technology in 1500	2.824
Standard errors	
Clustered by origin	(0.596)***
Clustered by origin and destination	(0.576)***
Conley, 1,000 km	(0.590)***
Conley, 2,000 km	(0.582)***
Conley, 3,000 km	(0.584)***
Conley, 5,000 km	(0.593)***
Spatial-noise placebo	
Share of draws with $\|t\|$ at least that of technology	0.021
Moran's I: variable / noise	0.79 / 0.65
Randomization inference	
Share of permutations with $\|t\|$ at least that of technology	0.003
Corridors	2,195
Origins	97
Destinations	26

Notes: This table reports inference under spatial correlation and randomization inference. The estimate is the Poisson pseudo-maximum likelihood estimate with the baseline controls of Table 1, column (4). Conley standard errors use a Bartlett kernel in the great-circle distance between origin countries; corridors of the same origin are at distance zero, so the estimator nests clustering by origin. In the placebo, technology in 1500 is replaced by draws of a Gaussian process across origins with an exponential or Gaussian covariance; the kernel and its range are chosen on a grid so that the noise comes closest to the Moran's I of technology in 1500 (neighbors within 2,000 km). The noise is rescaled to the mean and standard deviation of technology in 1500; 1,000 draws. t-statistics in the placebo use standard errors clustered by origin. In the randomization inference, technology in 1500 is reassigned at random across origins 1,000 times, and the table reports the share of permutations whose t-statistic, with standard errors clustered by origin, is at least as large in absolute value as that of technology in 1500. Significance stars refer to each standard error. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Standard errors may still understate uncertainty when the variable of interest is spatially clustered.

Following Kelly (2020), I replace technology in 1500 with simulated noise with spatial clustering chosen to come as close as possible to that of technology, and re-estimate the model 1,000 times. The benchmark is how often noise does as well as technology in 1500 (Table C.9, spatial-noise placebo rows). Only 2.1 percent of draws produce a t-statistic as large as that of technology, so by this benchmark the estimate is significant at the five percent level.

Randomization inference does not rely on the large-sample distribution of the estimator, which may be poor with few origins and a few dominant corridors. I reassign technology in 1500 at random across origins 1,000 times, re-estimate the model each time and count how often the reassigned variable has a t-statistic at least as large as that of technology in 1500. This happens in 0.3 percent of permutations (Table C.9, randomization inference rows).

Section 4 shows that technology in 1500 predicts migrant invention mainly across world regions. Its coefficient falls with region fixed effects (Table 3, column 5), and its within-region component becomes marginal once state history enters as a quadratic (Table C.13). If the signal is regional, the effective number of independent observations may be closer to seven than to the number of origins. I therefore treat the seven World Bank regions as clusters (Table C.10). With so few clusters, conventional cluster-robust standard errors are too small and reject too often, so I use the wild score bootstrap of Kline and Santos (2012), with the null hypothesis imposed. The baseline estimate has a bootstrap p-value of 0.037.

Table C.10: Inference with World Regions as Units

	(1)	(2) Wild score	(3) Cluster	(4) Jackknife	(5) Leave one region out	(6)
	Estimate	bootstrap p-value	jackknife s.e.	p-value	Smallest	Largest
Technology in 1500	2.824	0.037	0.736	0.009	2.247	3.171

Notes: This table reports inference with the seven world regions as the units of inference. The estimate is the Poisson pseudo-maximum likelihood estimate of Table 1, column (4), with the seven World Bank regions as clusters (2,195 corridors, 97 origins). The full controls of column (5) are not used, because their region fixed effects absorb the variation across regions that this table tests. The bootstrap p-value comes from the wild score bootstrap of Kline and Santos (2012) with Webb's six-point weights and 9,999 draws, with the null hypothesis imposed (scores evaluated at the model estimated without technology in 1500). The cluster jackknife standard error is computed from the seven estimates obtained by dropping one region at a time, and its p-value uses a t distribution with six degrees of freedom. The smallest leave-one-region-out estimate is obtained without the Middle East and North Africa, and the largest without Sub-Saharan Africa.

The wild bootstrap is less reliable when clusters are very unequal in size (MacKinnon and Webb, 2017), as here, since China and India dominate East and South Asia. Two checks do not depend on it. Dropping one region at a time leaves the baseline estimate between 2.25 and 3.17, so no single region drives it. The cluster jackknife, which uses the spread of these seven estimates as the standard error, gives $p = 0.009$. Finally, a regression across the seven regions of log inventor intensity on average ancestral technology, the raw regional gradient that Figure 3(a) illustrates, gives a slope of 4.86 ($p = 0.023$).

C.5 Features of the Data

Table C.11 reports the estimates summarized in the last paragraph of Section 4.2.

Table C.11: Features of the Data

	(1) Pool coefficient set to one	(2) No graduate students	(3) Records, 2004–2010	(4) No imputed ratio	(5) Hong Kong merged into China
Technology in 1500	2.826***	3.684***	2.869***	3.068***	2.813***
	(0.520)	(0.476)	(0.615)	(0.804)	(0.594)
Log skilled foreign nationals		0.919***	0.531***	0.499***	0.558***
		(0.048)	(0.064)	(0.070)	(0.065)
Baseline controls	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.967	0.966	0.973	0.973	0.974
Corridors	2,195	2,195	2,195	1,953	2,195
Origins	97	97	97	87	97
Destinations	26	26	26	26	26

Notes: This table reports Poisson pseudo-maximum likelihood estimates with the baseline controls and destination fixed effects of Table 1, column (4). Standard errors clustered by origin in parentheses. Column (1) enters the log of skilled foreign nationals as an offset. Column (2) drops the log of graduate students, measured in 2013–2015. Column (3) counts inventor records from 2004–2010. Column (4) drops Australia, Austria, Bolivia, Ecuador, Germany, New Zealand, Singapore, South Africa, Sudan and Zimbabwe, whose outbound mobility ratio is imputed. Column (5) adds the inventor records, skilled foreign nationals and graduate students of Hong Kong, which is not in the baseline sample, to those of China. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.6 Additional Horse Races

Table C.12 compares technology in 1500 with three other deep roots, and Table C.13 splits technology in 1500 into its regional mean and the origin's deviation from it. Section 4 discusses both.

Table C.12: Technology in 1500 and Three Other Deep Roots

	(1)	(2)	(3)	(4)	(5)
Technology in 1500		2.798***	2.684***	2.187***	3.188***
		(0.595)	(0.553)	(0.671)	(0.831)
State history	1.876**		0.235	-0.548	0.269
	(0.729)		(0.586)	(0.802)	(0.698)
Technology in 0 AD				0.584	
				(0.848)	
Millennia since Neolithic				0.124	
				(0.077)	
Baseline controls	Yes	Yes	Yes	Yes	Yes
Origins included	All	All	All	All	Non-African
Pseudo R^2	0.971	0.974	0.974	0.974	0.973
Corridors	2,155	2,155	2,155	2,155	1,642
Origins	95	95	95	95	70
Destinations	26	26	26	26	26

Notes: This table reports a horse race among four deep roots as predictors of migrant invention. The estimates are Poisson pseudo-maximum likelihood estimates with the baseline controls of Table 1, column (4), on the origins with all four deep roots. All deep roots are adjusted for ancestry with the migration matrix of Putterman and Weil (2010). State history is the index of Borcan et al. (2018); technology in 0 AD is from Comin et al. (2010); millennia since the Neolithic transition are from Putterman (2008). Column (5) excludes African origins. Standard errors clustered by origin in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.13: Technology Between and Within World Regions, and State History

	(1)	(2)	(3)	(4)
Technology in 1500, regional mean	4.177***	3.933***	2.987***	
	(0.800)	(0.821)	(1.037)	
Technology in 1500, within-region deviation	1.779**	1.208*	1.096*	
	(0.702)	(0.648)	(0.650)	
Technology in 1500				1.307*
				(0.701)
State history		3.345	5.188**	4.294*
		(2.062)	(2.541)	(2.403)
State history squared		-3.338	-5.744*	-3.779
		(2.585)	(3.364)	(3.167)
Effect of state history at 25th percentile		2.208*	3.230**	3.007**
		(1.238)	(1.452)	(1.389)
at the median		1.371*	1.791**	2.060***
		(0.723)	(0.765)	(0.764)
at 75th percentile		0.733	0.693	1.338**
		(0.562)	(0.615)	(0.637)
State history terms jointly zero (p)		0.164	0.062	0.024
Controls	Baseline	Baseline	+ Colonizer FE	+ Region FE
Pseudo R^2	0.975	0.975	0.976	0.977
Corridors	2,155	2,155	2,139	2,155
Origins	95	95	94	95
Destinations	26	26	26	26

Notes: This table reports the between-region and within-region coefficients of technology in 1500, and the relationship between state history and migrant invention. The estimates are Poisson pseudo-maximum likelihood estimates with destination fixed effects, with the baseline controls of Table 1, column (4), on the 95 baseline origins with all four deep roots (94 in column (3), which loses one origin to its fixed effects). Technology in 1500 is split into its mean across the origins of a World Bank region and the origin's deviation from that mean; column (4) uses the index itself with region fixed effects. Columns (3) and (4) add colonizer and region fixed effects to the baseline controls. State history enters as a quadratic, estimated on these origins. Its effect is the slope of the estimated curve for an origin whose state history is at the 25th percentile, the median or the 75th percentile across origins (0.17, 0.29 and 0.39), with its standard error in parentheses. Because the regional means take seven values, the between-region coefficient of technology is also tested with regions as clusters (wild score bootstrap, null imposed): $p = 0.006$ in column (1) and $p = 0.007$ in column (2). Standard errors clustered by origin in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Destination Characteristics and Employer Type

This appendix reports the estimates by destination characteristics and by employer type discussed in Section 5.

Table D.1: Destination Characteristics and the Technology Gradient

	(1)	(2)	(3)	(4)
Technology 1500 × foreign-degree penalty	0.395			0.440
	(0.581)			(0.607)
Technology 1500 × power distance		-0.313		
		(0.212)		
Technology 1500 × R&D intensity			0.061	
			(0.751)	
Inventors	All	All	All	Hired
Corridor controls	Yes	Yes	Yes	Yes
Origin FE	Yes	Yes	Yes	Yes
Pseudo R^2	0.986	0.986	0.986	0.986
Corridors	1,819	1,819	1,819	1,819
Origins	95	95	95	95
Destinations	22	22	22	22

Notes: This table reports how the technology gradient varies with destination characteristics. The estimates are Poisson pseudo-maximum likelihood estimates with origin and destination fixed effects; only the interaction with ancestral technology is identified. Corridor controls are the log of skilled foreign nationals, the log of graduate students and the gravity variables of Table 1. Destination characteristics are standardized across destinations. The foreign-degree penalty is the difference between the overqualification rates of tertiary-educated immigrants and natives in the destination (DIOC 2010/11); power distance is from Hofstede et al. (2010); R&D intensity is gross domestic expenditure on R&D as a share of GDP, 2010–2019. Column (4) uses inventor records on applications filed by firms and public research organizations as the dependent variable. Standard errors clustered by origin and destination. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.2: Hired and Independent Inventors

	Hired inventors		Independent inventors	
	(1)	(2)	(3)	(4)
Technology in 1500	2.873***	2.357***	1.704***	1.278*
	(0.602)	(0.779)	(0.577)	(0.758)
Controls	Baseline	Full	Baseline	Full
Destination FE	Yes	Yes	Yes	Yes
Region and colonizer FE	No	Yes	No	Yes
Pseudo R^2	0.974	0.976	0.892	0.896
Corridors	2,195	2,179	2,195	2,179
Origins	97	96	97	96
Destinations	26	26	26	26

Notes: This table compares hired and independent inventors. Poisson pseudo-maximum likelihood estimates with the baseline and full controls of Table 1, columns (4) and (5). The dependent variable counts inventor records on applications filed by firms and public research organizations in columns (1)–(2) and by individuals in columns (3)–(4). Standard errors clustered by origin. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.