Birthplace Diversity and Economic Prosperity

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Abstract

We propose an index of population diversity based on people's birthplaces and decompose it into a size (share of immigrants) and a variety (diversity of immigrants) component. We show that birthplace diversity is largely uncorrelated with ethnic, linguistic or genetic diversity and that the diversity of immigration relates positively to measures of economic prosperity. This holds especially for skilled immigrants in richer countries at intermediate levels of cultural proximity. We address endogeneity by specifying a pseudo-gravity model predicting the size and diversity of immigration. The results are robust across specifications and suggestive of skill-complementarities between immigrants and native workers.

Keywords: birthplace diversity, immigration, culture, economic development

JEL Classification: O1, O4, F22, F43.

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1 Introduction

Population heterogeneity is increasing in virtually all advanced economies due to immigration. Foreign-born individuals now represent about ten percent of the workforce in OECD countries, a threefold increase since 1960 and a twofold increase since 1990. High-skill migration is growing even faster, with a twofold increase during the 1990s alone.[1] As a result, the diversity of the skilled workforce (measured as the likelihood that two randomly-drawn skilled workers have different countries of birth) in a typical OECD country has increased by more than three percentage points (from .19 to .22) within just ten years.[2]

What are the economic implications of such higher diversity? Theory suggests that diversity has positive and negative economic effects. The former are due to complementarities in production, diversity of skills, experiences and ideas (think of a Dixit Stiglitz production function). The latter arise from potential conflicts, disagreements about public policies, and animosity between different groups. A vast literature has investigated these issues. The empirical literature has so far focused on ethnic and linguistic fractionalization, which were shown to exert negative effects on economic growth in cross-country comparisons (Easterly and Levine, 1997, Collier, 2001, Alesina et al., 2003, 2012), with the possible exception of very rich countries (see Alesina and La Ferrara, 2005, for a discussion of these issues). Ashraf and Galor (2013a,b) focus on genetic diversity and show that it exhibits an inverse u-shaped relationship with income per capita. On balance the negative effects of diversity seem to dominate empirically, or to put it differently, it has been hard to document the positive economic effects of diversity. This is the key objective of this paper.

We examine the relationship between intrapopulation diversity in birthplaces and economic prosperity. More specifically, we make four contributions. First, we construct and discuss the properties of a new index of birthplace diversity. We build indicators of diversity for the workforce of 195 countries in 1990 and 2000, disaggregated by skill/education level, and computed both for the workforce as a whole and for its foreign-born component. Empirically, ethno-linguistic and birthplace diversity are - somewhat surprisingly - almost completely uncorrelated. Conceptually, ethnic, genetic and birthplace diversity also differ as people born in different countries are likely to have been educated in different school systems, learned different skills, and developed different cognitive abilities. That may not be the case for people of different ethnic origins born, raised and educated in the same country.

[1] See Ozden et al. (2011) for a picture of the evolution of international migration over the last fifty years, and Docquier and Rapoport (2012) for a focus on high-skill migration and its effects on source and host countries.

[2] That is, a 17-percent increase. 22 out of 27 OECD countries saw increases in the diversity of their skilled workforce between 1990 and 2000 (the only exceptions being Estonia, Greece, New Zealand, Poland and Slovakia).

Second, we investigate the relationship between birthplace diversity and economic development. We find that unlike ethnic/linguistic fractionalization, birthplace diversity remains positively related to long-run income after controlling for many covariates. This positive relationship is stronger for skilled migrants (workers with college education) in richer countries. In terms of magnitudes, increasing the diversity of skilled immigrants by one percentage point raises long-run output by about two percent.

Third, we make progress towards addressing endogeneity issues arising from selection on unobservables and reverse causality. We show that our results are unlikely to be explained by positive selection on unobservables. To address reverse causality, we specify a gravity model to predict the size and diversity of a country's immigration using bilateral geographic/cultural variables. We confirm the robustness of our OLS findings in 2SLS models.

Fourth, we allow the effect of diversity to vary with bilateral distance between immigrants and natives along two dimensions: genetic/cultural distance, and income at origin. The productive effect of birthplace diversity is largest for immigrants from richer origin countries and for immigrants from countries at intermediate levels of cultural proximity. That is, the effect of diversity is inversely u-shaped in terms of cultural distance between immigrant and native workers. This suggests an optimal level of birthplace diversity in terms of cultural proximity.[3]

The current empirical evidence linking income and productivity differences to birthplace diversity is growing rapidly but is still limited when it comes to cross-country evidence. Existing studies have focused mainly on the United States. Ottaviano and Peri (2006) construct a measure of cultural diversity for the period 1970-1990 using migration data on US metropolitan areas and find positive effects on the productivity of native workers as measured by their wages.[4] Peri (2012) finds positive effects of the diversity coming from immigration on the productivity of US states, a result he attributes to unskilled migrants promoting efficient task-specialization and adoption of unskilled-efficient technologies, and more so when immigration is diverse. Ager and Brückner (2013) study the link between immigration, diversity and economic growth in the context of the United States about a century ago, at a time now commonly referred to as "the age of mass migration" (Hatton and Williamson, 1998).[5] They find that fractionalization increases output while polarization decreases it in US counties during the period 1870-1920. Cross-country comparisons include

[3]This inverted u-curve for cultural proximity mirrors the results of Ashraf and Galor (2013a) on genetic diversity.

[4]Bellini et al. (2013) apply the same methodology to European regions and find broadly consistent results for Europe as well.

[5]See also Bandiera, Rasul and Viarengo (2013) and Abramitzky, Boustan and Eriksson (2012, 2013), respectively, on the measurement of entry and return flows and on migrants' self-selection.

Andersen and Dalgaard (2011), who find positive effects of travel intensity on total factor productivity which they attribute to knowledge diffusion of temporary migrants, and Ortega and Peri (2014), who analyze the connection between income per capita and migration in a cross-section of countries. They focus on the growth effects of openness and diversity of trade vs. migration and find the share of immigration to be a stronger determinant of long run output than trade. In contrast, we focus on the effect of intrapopulation diversity, comparing birthplace to other dimensions of diversity (ethnic, linguistic, genetic) and demonstrate the positive effect of the diversity arising from immigration (especially its high-skill component) on income per capita.

The rest of this paper proceeds as follows. Section 2 briefly discusses theoretical channels and related literature on diversity and economic performance. Section 3 explains the construction and analytical decomposition of our birthplace diversity index; we also explore its descriptive features and patterns of correlation with other diversity/fractionalization indices. In Section 4 we provide data sources, develop our empirical model, and describe OLS results for birthplace diversity in a range of empirical specifications. In Section 5, we discuss unobserved heterogeneity and reverse causality, showing that they are unlikely to explain our results. In Section 6, we augment our birthplace diversity index to include bilateral economic and cultural group distance between the native population and each immigrant group. Section 7 concludes.

2 The literature

People born in different countries are likely to have different productive skills because they have been exposed to different life experiences, different school and value systems, and thus have developed different perspectives that allow them to interpret and solve problems differently. We use the term "birthplace diversity" to designate the dimension of intrapopulation diversity arising from the heterogeneity in people's birthplaces and posit that this source of diversity is more likely to capture skill complementarity effects than alternative dimensions of diversity (e.g., ethnic or linguistic fractionalization). Alesina et al. (2000) formalize the idea of skill complementarities using a Dixit-Stiglitz type production function where output increases in the variety of inputs and inputs can be interpreted as different type of workers. Their model thus allows for diversity to increase output without any counterbalancing costs. Lazear (1999a,b) proposes a model of teams of workers where diversity brings benefits via production complementarities from relevant disjoint information sets and also costs via barriers to communication; with decreasing marginal benefits and increasing marginal costs, this suggests that there is an optimal degree of diversity. A related argument, also brought forward by Lazear (1999b), is that diverse groups of immigrants tend to assimilate more quickly (in terms of learning the language of the majority) since they have stronger incentives to do so. Hong and Page (2001) see two sources for the heterogeneity of people's minds: cognitive differences between people's internal perspectives (their interpretation of a complex problem) as well as their heuristics (their algorithms to solve these problems). They show theoretically that, under certain conditions, a group of cognitively diverse but skill-limited workers can outperform a homogenous group of highly skilled workers. Fershtman, Hvide and Weiss (2006) reach similar conclusions in a model where workers are heterogeneous in terms of status concerns.[6]

Empirically, diversity is commonly measured by ethno-linguistic fractionalization (Easterly and Levine 1997, Alesina et al., 2003, Fearon, 2003, Desmet et al., 2012) and ethno-linguistic polarization indices (Esteban and Ray, 1994, Reynal-Querol, 2002 and Montalvo and Reynal-Querol, 2005). At a macro level, the costs of fractionalization have been established empirically in particular for ethno-linguistic diversity. These studies began with Easterly and Levine (1997), who show that ethnic fragmentation is associated with lower economic growth, especially in Africa. Collier (1999, 2001) adds that ethnic fractionalization is less detrimental in the presence of democratic institutions that mediate ethnic conflict, It is, however, unclear if this observation is not a corollary of higher income as shown in Alesina and La Ferrara (2005). Fearon and Laitin (2003) add that ethnic diversity alone is not sufficient to explain the outbreak of civil war. Putnam (1995), and Alesina and La Ferrara (2000, 2002) stress the role of trust, showing that individuals in racially diverse cities in the US participate less frequently in social activities and trust their neighbors to a lesser degree. The authors also find evidence that preferences for redistribution are lower in racially diverse communities. This also extends to the provision of productive public goods (Alesina, Baqir and Easterly, 1999). Alesina and Zhuravskaya (2011) stress the negative effect of ethnic segregation on the quality of government, while Alesina, Michalopoulos and Papaioannou (2015) highlight the detrimental effects of "ethnic inequality" (i.e., when economic inequality and ethnic diversity go hand-in-hand). Esteban, Mayoral and Ray (2012) distinguish conflicts over public and private goods and find polarization to correlate positively with conflict on the former, and fractionalization to correlate positively with the latter (see also Esteban and Ray, 2011). Ashraf and Galor (2013a) introduce a new dimension of diversity, intrapopulation genetic heterozygosity. Genetic diversity is found to have a long-lasting effect on population density in the pre-colonial era as well as on contemporary levels of development. More specifically, the authors find an inverted u-shaped relationship between genetic diversity and income/productivity. Ashraf and Galor (2011) find that cultural diversity (based on World Values Survey data) is positively correlated with contemporary development and suggest that cultural diversity facilitated the transition from

[6] See Laitin and Jeon (2013) for a recent overview of social psychology research on the effects of diversity.

agricultural to industrial societies,suggestive of the trade-off between beneficial forces of diversity expanding the production possibility frontier and detrimental ones leading to higher inefficiency and conflict.

At the micro level, empirical studies of diverse teams in the management and organization literature also find diversity to be a double-edged sword, with diversity (in terms of gender, education, tenure, nationality) being often beneficial for performance but also decreasing team cohesion and increasing coordination costs (see O'Reilly et al., 1989, and Milliken and Martins, 1996 . A study in the airline industry by Hambrick et al. (1996) finds that management teams heterogeneous in terms of education, tenure and functional background react more slowly to a competitor's actions, but also obtain higher market shares and profits than their homogeneous competitors. In an experimental study, Hoogendoorn and van Praag (2012) set up a randomized experiment in which business school students were assigned to manage a fictitious business and increase outcome metrics like market share, sales and profits of their business. The authors find that more diverse teams (defined by parents' countries of birth) outperform more homogeneous ones, but only if the majority of team members is foreign. Finally, Kahane et al. (2013) use data on team composition of NHL teams in the U.S. and find that teams with higher share of foreign (European) players tend to perform better. They attribute this finding both to skill effects (better access to foreign talent) and to skill complementarities among the group of foreign players; however, when players come from too large a pool of European countries, team performance starts decreasing.

Hjort (2014) analyzes productivity at a flower production plant in Kenya and uses quasi-random variation in ethnic team composition as well as natural experiments in this setting to identify productivity effects from ethnic diversity in joint production. He finds evidence for taste-based discrimination between ethnic groups, suggesting that ethnic diversity, in the context of a poor society with deep ethnic cleavages, affects productivity negatively. Brunow et al. (2015) analyze the impact of birthplace diversity on firm productivity in Germany. They find that the share of immigrants has no effect on firm productivity while the diversity of foreign workers does impact firm performance positively (as does workers' diversity at the regional level). These effects appear to be stronger for manufacturing and high-tech industries, suggesting the presence of skill complementarities at the firm level as well as regional spillovers from workforce diversity. Parrotta et al. (2014) use a firm level dataset of matched employee-employer records in Denmark to analyze the effects of diversity in terms of skills, age and ethnicity on firm productivity. They find that while diversity in skills increases productivity, diversity in ethnicity and age decreases it. They interpret this as showing that the costs of ethnic diversity outweigh its benefits. Interestingly, they also find suggestive evidence that diversity is more valuable in problem-solving oriented tasks and in innovative industries. Ozgen et al. (2013) match Dutch firm level innovation survey data with employer/employee records and find that the diversity of immigrant workers increases the likelihood of product and process innovations. Boeheim et al. (2012) find further micro level evidence for the presence of production function complementarities using a linked dataset of Austrian firms and their workers during the period 1994-2005. Workers' wages increase with diversity and the effect is stronger for white-collar workers and workers with recent tenure.

3 An index of birthplace diversity

We base our birthplace diversity measure on the Herfindahl-Hirschmann concentration index. Let s_i refer to the share in the total population of individuals born in country i with $i = 1, \ldots, I$. In particular, $i = 1$ refers to natives.

The fractionalization index Div_{pop} may be expressed as:

$$Div_{pop} = \sum_{i=1}^{I} s_i * (1 - s_i) = 1 - \sum_{i=1}^{I} (s_i)^2 \tag{1}$$

This index measures the probability that two individuals drawn randomly from the entire population have two different countries of birth. It uses information on relative group sizes within a population to construct measures of diversity for the entire national population as well as by skill category; in particular, in the empirical analysis we distinguish between high-skill (for college educated workers) and low-skill diversity. It is important to stress that a key characteristic of the birthplace-diversity measures introduced in this paper is that they treat immigrants from the same country of origin as being identical to one another. The same problem characterizes other group-based measures like ethnic or linguistic fractionalization in which intragroup homogeneity is assumed for any given ethnic or linguistic group in a national population. In particular, unlike the genetic diversity measure of Ashraf and Galor (2013a), group-based fractionalization indices only pick up diversity that arises from intergroup rather than intragroup heterogeneity in individual traits. In particular, the index assumes that: i) all groups are culturally equidistant one from another; and ii) within a skill group, immigrants have the same characteristics as the average native of their origin country. We discuss these potentially important limitations in Section 5.1 on immigrants' selection and Section 6 on group distance.

Our measure of Div_{pop} has two potentially independent margins that we intend to investigate empirically. First, the share of immigrants $(1 - s_1)$, irrespective of their country of origin; and second, the diversity arising from the variety and relative size of immigrant groups (irrespective of their sizes relative to natives). We therefore decompose our diversity index into a component that we call $Div_{between}$ (for "between natives and all immigrants"), which captures the first margin, and a Div_{within} component (for "within immigrant groups only"), which captures the second margin.

If all immigrants were born in one country $i = 2$ so that $s_1 + s_2 = 1$, then using (1) we can define:

$$Div_{between} = s_1 * (1 - s_1) + (1 - s_1) * s_1 \tag{2}$$

This essentially calculates the Div_{pop} index assuming that all migrants can be grouped into one category $(1-s_1)$ - thus excluding all diversity contributed by the fact that migrants tend to come from more than one origin country.

We rewrite (2) to include $Div_{between}$ as follows:

$$Div_{pop} = 2 * s_1 * (1 - s_1) + \sum_{i=2}^{I} [s_i * ((1 - s_i) - s_1)] \tag{3}$$

We can now define

$$Div_{within} = \sum_{i=2}^{I} [s_i * ((1 - s_i) - s_1)] \tag{4}$$

so that Div_{pop} is composed of two parts, $Div_{between}$ and Div_{within} :

$$Div_{pop} = Div_{between} + Div_{within} \tag{5}$$

This decomposition does not separate clearly between size and variety effects: Div_{within} still depends on s_1 - the share of natives -, since $\sum_{i=2}^{I} s_i = (1 - s_1)$. We thus rewrite the Div_{within} component so that it does not depend on s_1. We achieve this by defining s_j as the share of immigrants from country j in the total population of immigrants. It follows that $s_j = \frac{s_i}{(1-s_1)}$ where s_1 is the share of natives ($i = 1$).

We thus re-scale Div_{within} using (4):

$$Div_{within} = \sum_{i=2}^{I} \left[\frac{s_i}{(1 - s_1)} * \frac{((1 - s_i) - s_1)}{(1 - s_1)} \right] * (1 - s_1)^2 \tag{6}$$

and simplify to:

$$Div_{within} = \sum_{j=1}^{J} \left[s_j * (1 - s_j) \right] * (1 - s_1)^2 \tag{7}$$

Our result has a very intuitive interpretation: since $\sum_{j=1}^{J} \left[s_j * (1 - s_j) \right]$ is basically (1) but applied to the population of immigrants, it is essentially a diversity index of immigrants only, irrespective of the natives. We thus define:

$$Div_{mig} = \sum_{j=1}^{J} \left[s_j * (1 - s_j) \right] \tag{8}$$

And rewrite (5)

$$Div_{pop} = Div_{between} + (1 - s_1)^2 * Div_{mig} \tag{9}$$

where $(1 - s_1)^2$ has an intuitive interpretation as scale parameter for Div_{mig}.

We can then rewrite (9) in terms of s_{mig}, the share of immigrants (defined as foreign-born) and define $s_{mig} = (1 - s_1)$:

$$Div_{pop} = 2 * s_{mig} * (1 - s_{mig}) + (s_{mig})^2 * Div_{mig} \tag{10}$$

We have thus an expression of Div_{pop} purely as a function of the size and diversity of immigration.

4 Empirical analysis

4.1 Birthplace diversity data

Our computation of birthplace diversity indices relies on the Artuc, Docquier, Ozden and Parsons (henceforth ADOP, 2015) data set which provides a comprehensive 195x195 matrix of bilateral migration stocks disaggregated by skill category (with or without college education) and gender for the years 1990 and 2000. Immigrants are defined as foreign-born individuals aged 25+ at census or survey date. The dataset is based on a comprehensive data collection effort in the host countries. For few destinations (and even fewer in our sample), official census information is not available. ADOP (2015) thus rely on a gravity model-based estimation of these cells.[7] In our sample, only 10% of skilled immigrants are estimated based on this methodology.[8]

Three caveats are in order. First, illegal immigration is not accounted for in most censuses, although in some cases (like in the US census) it is estimated. However, this limitation is mitigated by the fact that we use data on immigration stocks, not flows: most illegal migrants eventually become legalized or return to their country of origin. Second, immigrants who came as children are subsequently treated fully as immigrant workers (when aged 25+). However, these children then grow up, socialize and go to school in the host country, which puts a limit on the extent of variety in skills that they can contribute when they integrate the labor force. We address this issue in a robustness check. Third, a migrant is considered skilled independently of the location of college education, meaning that skilled migrants may be heterogeneous in terms of human capital quality. We partly

[7] See ADOP (2015) for more details.

[8] We conduct a robustness check restricting our OLS and IV models to non-estimated observations only. The results (available upon request) remain virtually unchanged.

address this issue by controlling for what we call "origin-effects" and review implications for our identification in Section 5.

4.2 Descriptive statistics and correlations

Table 1a shows the weak bilateral correlations between ethnic, genetic and birthplace diversity measures. The correlation between ethnic fractionalization and Div_{mig} (all) is negative at -.11 and close to zero for Div_{mig} (skilled).[9] Table 1b shows summary statistics, Table 1c presents our data sources.

There is ample variation in country level birthplace diversity: Canada, Italy, Israel, Germany, Australia and the UK have high birthplace diversity of immigrants (Div_{mig}). The United States rank only 18th in a list of countries with the highest immigration diversity (at .92) due to relatively low diversity for unskilled immigration (0.84). Similarly low ranks can be observed for Germany (rank 27, at .90) and Australia (rank 28, at .90). In terms of Div_{mig} (skilled), however, the USA is very near the top (at .97). Countries with lowest overall immigration diversity are Pakistan, Bangladesh, Nepal, Syria and Iran (all lower than .5). Neighboring country effects seem to play a role: Ireland's Div_{mig} (.54 overall, .44 for the unskilled and .67 for the skilled) is still quite low due to dominant immigration from the UK. Switzerland, Austria or Australia follow similar patterns. Generally, such effects are more prevalent for Div_{mig} (unskilled). As a result, Div_{mig} (skilled) tends to be higher than Div_{mig} (unskilled). This is consistent with migrants' self-selection being driven by net-of-migration-costs wage differentials, where low migration costs (due to short distances and high networks) mostly affect low-skill migration.[10]

Table 2 shows some multivariate correlations between ethnic, linguistic and genetic diversity (ancestry-corrected), birthplace diversity and income per capita. Unlike all other dimensions of diversity, Div_{pop} is positively correlated with income per capita (at PPP), while ethnic and linguistic fractionalization are negatively correlated. Genetic diversity's effect on income follows an inverted u-shape (Ashraf and Galor, 2013a). When we include population birthplace diversity (Div_{pop}), coefficients on the other diversity variables change insignificantly. The inclusion of birthplace diversity, however, adds considerably to the predictive power of the model. We interpret this as indication that Div_{pop} is correlated with and jointly determined by many other factors, such as geography or the quality of institutions. Interestingly, this seems to be more an issue for the diversity of the unskilled population, and generally this is driven to a lower extent by the variety than by the size of immigration.

[9] This also holds in first differences: the correlation between changes in size and diversity of skilled immigration 1990-2000 is low and even negative at -.14.

[10] See McKenzie and Rapoport (2010) and Bertoli (2010) for micro evidence on the role of migrant networks in determining self-selection patterns, and Beine, Docquier and Ozden (2011) for macro evidence.

This point is further illustrated in models (6)-(8) where we use our decomposition analysis and separate Div_{pop} into $Div_{between}$ and Div_{within}. The productive effects of Div_{pop} clearly vary by skill level: Div_{pop} (unskilled) is mostly driven by $Div_{between}$, but the association of Div_{pop} (skilled) with income per capita runs mostly through Div_{within}. Still, $Div_{between}$ and Div_{within} are not independent from each other, as both depend on s_{mig} (see equations 2 and 4 above). We thus proceed with a model that includes a large range of co-determinants of birthplace diversity and income. We also clearly separate the size (s_{mig}) and the variety (Div_{mig}) dimensions of birthplace diversity.

4.3 Model specification

To empirically investigate the relationship between birthplace diversity and economic development, we specify the following model where our dependent variable y is a country's income per capita (GDP) at real PPP from the Penn World Tables 8.0 (Feenstra et al., 2013):[11]

$$\begin{aligned}\ln y_{kt} \quad = \quad & \alpha + \beta_1 * Div_{mig\ kst} + \beta_2 * s_{mig\ kst} \\ & + \beta_3 * \Delta_k + \beta_4 * \Phi_k + \beta_5 * X_k \\ & + \beta_6 * \Psi_{kt} + \beta_7 * \Omega_{kt} + \beta_8 * \Gamma_{kt} + \eta_t + e\end{aligned}$$

where Δ_k is a vector of fractionalization/diversity measures, Φ_k is a vector of climate and geography characteristics, X_k is a vector of disease environment indices, Ψ_{kt} is a vector of controls for institutional development, Ω_{kt} is a vector of trade and origin effects, Γ_{kt} is a vector containing the country's population size and schooling level, and η_t is a period fixed effect. We use indices s for skill groups (s=overall, skilled, unskilled), t for time periods (1990, 2000) and k for countries.

The results from our decomposition analysis as well as our initial correlation analyses point to the need to separate $Div_{between}$ and Div_{within} further into their components, the share of immigrants, s_{mig}, and the diversity of immigrants, Div_{mig}. Thus we include the share and the diversity of immigrants evaluated at the means of the respective variables. To facilitate the interpretation we standardize both variables with a mean of zero and standard deviation of one. In the appendix we also test for interaction effects between size and variety.

Our baseline specification starts with a parsimonious model based upon Table 2 where we control for fractionalization/diversity indices (Δ_k) only. We specifically include both ethnic and linguistic fractionalization (from Alesina et al., 2003) and genetic diversity (ancestry-adjusted) from Ashraf and Galor (2013a) since all three indices capture a potentially different productive margin of diversity.[12]

[11] See the online appendix for details on the definitions and sources for all variables.

[12] Following Ashraf and Galor (2013a) we also include a squared term for genetic diversity.

We add more controls, going for increasingly stringent specifications incorporating first exogenous geographic/climatic controls only (our vector Φ_k); we follow the literature on the geographical determinants of income[13] in including a landlockedness dummy (from CEPII, 2010), absolute latitude and share of population living within 100km of an ice-free coast (both from Gallup et al., 1998), average temperature and precipitation (World Bank, 2013), as well as a set of regional fixed effects for Latin America, Asia, Middle East and Northern Africa (MENA), and Sub-Saharan Africa. We then add the semi-exogenous geographical controls for the disease environment (X_k), which include malaria, yellow fever and tuberculosis incidence (all from World Bank, 2013).

We further extend the model to account for endogenous variables that co-determine income and migration patterns. For institutional quality (Ψ_{kt}), we use the revised combined Polity-2 score from the Polity IV database (Marshall and Jaggers, 2012). This index measures the degree of political competition and participation, the degree of openness of political executives' recruitment and the extent of executives' constraints (Glaeser et al., 2004). We also add dummies for British, French and Spanish ex-colonies as proxies for the origins of the legal system (CEPII, 2010).

Then comes our "trade and origin effects" vector, (Ω_{kt}), which contains controls for the volume and structure of trade (namely real trade openness from PWT 8.0),[14] measures of trade diversity in imports and exports (based on Feenstra et al., 2005),[15] and also includes a weighted average of the GDP per capita (in PPP) of immigrants' origin countries. The trade diversity indices are the goods market equivalents of Div_{mig}, since import diversity is a proxy for variety in (imported) intermediary goods. Controlling for trade is also necessary since trade is determined by similar factors as migration (Ortega and Peri, 2014). Surprisingly however, Div_{mig} and variables of trade openness/diversity are not much correlated (+.08 for trade openness, +0.12 for trade diversity). Last, the "origin-effects" variable captures the income at origin of the average representative immigrant and - while not a proxy for the selection of immigrants from each country of origin - correlates with immigrant groups' ability to cover migration costs. Richer destination countries that draw on (relatively) richer source countries should be able to attract a wider range of immigrant groups and have higher immigrant diversity. Controlling for such origin-effects allows us to account for differences in migrant backgrounds (and skills) and focus on the pure (birthplace) diversity effect of immigration. Finally, we include a vector (Γ_{kt}) containing education as captured by years

[13] See, e.g., Hall and Jones (1999), Gallup et al. (1998), Rodriguez and Rodrik (2001), Sachs (2003), Rodrik et al. (2004).

[14] We use the standard measure of trade volume: real trade openness (exports+imports) in percentage of GDP in real PPP prices. This indicator correlates most robustly with GDP growth (Yanikkaya, 2003).

[15] This definition follows the literature on trade concentration. See, e.g., Kali et al. (2007) for the effect of trade concentration on income or Frankel et al. (1995) on transportation costs.

of education (Barro and Lee, 2013) and population size (U.N. Population Division, 2013).

We end up with a highly structured model and a short panel of 120 countries with data for 1990 and 2000. We made a significant effort to broaden our sample. The 120 countries reflect the intersection of the ADOP (2015) data, which is available for 190 countries and territories (195 origins, but no immigration data for five destinations), the PWT 8.0 data, which does not contain GDP data for 26 of those, the education data (Barro and Lee, 2013) which is not available for 25 remaining countries and other data sources (primarily Alesina et al. 2003 and Ashraf and Galor, 2013a) where missing data drops another 19 countries.[16] Our full sample does not differ systematically from a broader sample at the intersection of PWT 8.0 and ADOP (2015). Differences in sample means are small (not statistically significant) for most variables, with two exceptions: the sample mean for s_{mig} of skilled people is actually lower in our full sample than in the broader sample, and the sample mean for Div_{mig} is slightly higher (see the appendix for details). This reflects the fact that we drop mainly small island states and territories that have very few skilled natives and correspondingly higher s_{mig} (skilled) as well as experience immigration from few large neighboring countries (leading to a lower Div_{mig}). Still, after these slight reductions of the sample size, our full sample still covers 90% of all global migrants and 93.7% of all skilled migrants.

4.4 OLS results

We estimate our model using an OLS estimator with standard errors clustered at the country level to account for serial correlation of standard errors. Our results are presented in Tables 3-5. Table 3 shows the full model estimated in a sample of 120 countries. In Table 4, we split our sample into two sub-samples of rich vs. poor countries and establish our main results. In Table 5 we analyze the stability of our main coefficients of interest by introducing groups of controls sequentially as described above.

Table 3 shows the full model results for our two margins of birthplace diversity, s_{mig} and Div_{mig}, and does so separately for each skill level (overall, high- and low-skill). Both the size of immigration and its diversity correlate positively with income at the 1% statistical significance level. We report standardized coefficients for our key variables of interest to facilitate interpretation. Coefficients for Div_{mig} (skilled) are somewhat higher than those for Div_{mig} (unskilled), but this difference is not statistically significant. Once we control for geographic variables (Michalopoulos 2012) ethnic and linguistic fractionalization converge towards zero. Genetic diversity shows the expected inverted u-shaped pattern (Ashraf and Galor, 2013a). Trade openness (Frankel and Romer, 1999), the quality of institutions

[16] Typical countries that drop out of this sample are small island states or territories.

(Acemoglu et al. 2001, Glaeser et al., 2004) and the level of education correlate positively with economic development. These findings are consistent with the argument that both the birthplace diversity of migrants as well as the share of immigrants relate positively to economic development.

Table 4 shows sub-sample results for rich and poor countries (above or below median GDP/capita in 1990). Given the theoretical arguments outlined in Section 2, we expect the birthplace diversity (Div_{mig}) of skilled workers to capture production function complementarities to a higher degree than other diversity indices. These complementarities should also be larger in countries closer to the technology frontier. Hence, our estimates for Div_{mig} (skilled) should be larger and more significant in a subset of rich economies relative to Div_{mig} (unskilled) and relative to estimates in a poor country subsample. This is exactly what we find. In the rich country subsample (column 2), our estimates for the standardized Div_{mig} (skilled) are now considerably magnified vis-a-vis the full sample and remain significant at the 1% level. When we conduct a horse-race of skilled and unskilled Div_{mig} (column 4), we find that our results for Div_{mig} (skilled) continue to hold whereas the effect of Div_{mig} (unskilled) are close to zero. In the poor country subsample (columns 5-8) we find no statistically significant results for birthplace diversity. These results are consistent with the view that the economic value of birthplace diversity for countries closer to the technology frontier, particularly that arising from the diversity of skilled immigrants.[17] Interestingly, neither ethnic fractionalization nor linguistic or genetic diversity correlate robustly with income for these countries.

Our identification strategy is potentially exposed to omitted variables bias, since within-country variation in Div_{mig} is very low and is thus an insufficient basis for identification.[18] To address this concern at least partially, we specify in Table 5 a range of models that sequentially introduce our controls. We analyze the stability of our main coefficients of interest (on birthplace diversity of skilled immigrants) for rich countries (based on Table 4). Our estimates for Div_{mig} (skilled) are stable across specifications. The coefficient increases when going from model (1) to model (2), where we add a host of geography controls (including, most importantly, our set of regional fixed-effects). All subsequent model expansions do not substantially affect our coefficient estimates. In the last model (column 6) we add population size and education controls, two variables that are positively related to income and diversity. This slightly decreases the point-estimate for Div_{mig} as this likely takes out a small residual positive omitted variables bias. Interestingly, the relative stability of our Div_{mig} coefficient is not mirrored in our results for s_{mig} (skilled). Here, the

[17] The difference in Div_{mig} (skilled) between the rich and poor country subsample is significant at the 1% level (unlike the diversity of unskilled migrants).

[18] Still, we obtain qualitatively similar results in our rich country subsample when using country fixed effects (see Appendix).

coefficient varies substantially across specifications. This suggests that - as we discuss below - Div_{mig} is less likely to be affected by endogeneity issues than s_{mig}.

To add more structure to the analysis, we follow Oster (2013) who proposes a simple heuristic to calculate bounding values for unbiased coefficients.[19] The results following this procedure indicate that any remaining omitted variables bias in our rich country subsample model is negative but relatively small, as Oster's bounding values for unbiased coefficients are higher but in close proximity to our OLS estimates (see Table 5, column 6).

4.5 Robustness

4.5.1 Patenting activity

We extend our model to patent data in order to shed more light on the productivity effects of Div_{mig} (see Table 6). We define average patent intensity as the average number of patent applications per capita filed by country nationals and registered by national patent offices. We obtain this data from the World Intellectual Property Organization (2010) for the period 1995-2005 and construct this measure for 117 countries.[20] We apply our baseline model using all covariates on a year 2000 cross section. We find that the diversity of immigrants - in particular that of skilled immigrants - is robustly positively related to scientific innovation as measured by patenting activity. This holds both for measures of patent applications and patents granted per capita. These results hold also in our subsample of richer countries. We do not find similar effects for the diversity of unskilled workers. We take this as indication that the productivity-enhancing effect of variety in backgrounds and problem solving heuristics embedded in Div_{mig} partly works through innovation.

4.5.2 Total factor productivity

GDP/capita at PPP is our main dependent variable and we interpret the results for birthplace diversity as indicative of skill complementarities. Our interpretation implies that the effect of birthplace diversity should affect GDP/capita through total factor productivity (TFP). To test this proposition, we replace our measure of GDP by a measure of TFP per capita from the Penn World Tables 8.0 (Feenstra et al., 2013). Table 7 shows the results. In both the full sample as well as the rich country subsample, birthplace diversity of skilled immigrants remains positive and highly robust (at 1%). This suggests that, consistently with an interpretation of the results in terms of skill complementarities, birthplace diversity

[19] This test relies on the assumption that selection on observables from a basic model towards a full model is proportional to selection on unobservables.

[20] The sample thus includes all countries with patenting activity as covered by WIPO (2010). Hence, our estimates are best interpreted as effect on the intensive margin of patenting.

affects income via total factor productivity.

4.5.3 Second-generation effects

Immigration flows are highly time persistent due to network effects. This means that our first-generation measure Div_{mig} could capture also second/third-generation effects of immigration, biasing our results. We thus construct a measure of Div_{mig} in 1960 based on data from Ozden et al. (2011) to obtain a lagged birthplace diversity index and add this new index and a lagged share of immigration to our model (see Table 8).[21] As can be seen in Column 2, the birthplace diversity of immigration in 1960 is positive but not significant while the size of immigration in 1960 is positive and significant when these lagged variables are entered independently of their contemporaneous values. Importantly, our main results for first-generation birthplace diversity and for immigration size remain positive and highly significant when past and present immigration size and diversity are entered jointly, with point-estimates which are barely affected. In particular, the magnitude of Div_{mig} remains virtually unchanged, despite the high positive correlation between Div_{mig} today and in the past (+0.66). This suggests that skilled diversity's productive effects in high income countries - our main finding - operate primarily through first-generation effects. This finding is fully consistent with the theoretical arguments outlined in Section 2. The lack of significance of past diversity, on the other hand, is consistent with an interpretation in terms of compensating effects of birthplace and ethnic diversity (second-generation immigration being a mix of the two).

4.5.4 Children immigrants

Our measure of Div_{mig} counts all foreign-born workers as immigrants irrespective of the duration of their stay in their host country. Immigrants arriving in the destination country as children are - in terms of education and exposure to the destination country - probably closer to being native than foreign. We thus compute Div_{mig} and s_{mig} (skilled) at different age-of-entry thresholds, using data for a subset of 29 OECD destination countries from Beine, Docquier and Rapoport (2007). We find that our estimates for birthplace diversity are robust to the exclusion of such special immigrant groups. We find somewhat lower estimates for these corrected birthplace diversity measures (the difference is not statistically significant), a fact that may be driven by attenuation bias due to counterfactual re-classification of young immigrants as natives.

[21] Note that Ozden et al. (2011) do not provide a skill decomposition of immigration in 1960, we hence rely on diversity of immigrants of all skill groups.

4.5.5 Outliers and alternative fixed effects

In a last step, we test the robustness of our results to the introduction of alternative regional fixed effects as well as to excluding outliers (see Table 10). More specifically, Australia, Canada and New Zealand have points-based immigration systems that select skilled immigrants according to labor market needs. The United States attracts a huge part of all skilled migrants in the world thanks to its large (pre and post tax) premium for skilled labor (Grogger and Hanson, 2011). Controlling for these countries (in Column 3) or simply dropping them from the sample (in Column 4) does not affect our results. Likewise, this also holds for OPEC countries. In addition, we test robustness to alternative sets of fixed effects to establish robustness for our within-geographic region estimator.[22] Our results are fully robust to these modifications.

5 Identification

5.1 Unobserved heterogeneity

Our measures of Div_{pop} and Div_{mig} rely on the assumption that we cover representative individuals for the respective emigrant populations at different origins, and that immigrants across destinations are homogenous. Since we lack detailed information on these migrants (apart from education, gender and age-of-entry), we cannot exclude the possibility that migrants are positively self-selected from the home-country pool of skilled workers and also positively sort themselves to high-income destinations.[23]

In a first step, we use the ADOP (2015) dataset to calculate the relative degree of selection per country of origin and destination based on observable skills. We calculate the distribution of educational attainment (% of skilled) for the natives of any origin country i from Barro and Lee (2013) and ADOP (2015) before emigration and immigration take place. We then calculate the share of skilled emigrants from origin i to any destination k and define:

$$skill\ selection_k \ = \ \sum_{j=1}^{J} \left[\frac{\frac{skilled\ migrants_{jk}}{total\ migrants_{jk}}}{\frac{skilled\ native\ born_j}{total\ native\ born_j}} * s_{mig\ jk} \right] \tag{11}$$

where k is an index for destination country, j for origin country, and $s_{mig\ jk}$ is the share of immigrants from origin j over all immigrants to destination k in year t. This index is a weighted average of immigrants' skills relative to the skill distribution of their home countries' native population. A value of 1 indicates that migrants from j to k are identical in terms of observed skills to non-migrants, a value above 1 signals positive selection. The

[22] In particular, we test for robustness to continental fixed effects as employed by Ashraf and Galor (2013a).

[23] See Grogger and Hanson (2011) for a deeper discussion on such sorting across destinations.

index may reflect skill-selective policies in destination countries as much as it reflects the relative attractiveness of a destination country to skilled workers. Both aspects should be correlated with selection on unobservables, since both are proxies for the relative return to high skill, effort and risk taking attitudes. Clearly, our index of skill selection is at best an imperfect and noisy measure of the true degree of positive selection. Still, *skill selection* is positively correlated with income/capita at destination (+.34), even more than our origin effects variable (+0.17) that accounts for destination countries' over-sampling of immigrants from richer origins.

We proceed by adding the index of *skill selection* to our full model (Table 11, columns 2 and 3). The index and our origin effects variable both possess independent explanatory power in a parsimonious model (column 2). This serves as indicative evidence that the inclusion of these indices indeed mitigates the issue of migrant selection to some degree. Column 3 shows full model results, indicating that once we condition on the full set of controls, both indices lose their predictive power, while the coefficient on our key variable of interest Div_{mig} remains robustly estimated and statistically significant at the 1% level. The estimate is slightly lower than in our base model, indicating the removal of a small positive bias in our estimate.

We test the robustness of our findings further by dropping countries with the highest *skill selection* from our sample. These are Australia, Belgium, Canada, Singapore, United Kingdom and the USA. Their relative attractiveness reveals a preference of highly skilled (and, presumably, highly motivated) workers towards destinations with higher returns to skill and effort. Table 11, column (4) shows that our estimation does not depend on these countries.

In a second step, we employ an alternative indirect measure of selection. We use data collected by Gallup market research reported in Espinova et al. (2011). These authors report an index of net migration potential that is based on surveys of close to 348.000 adults between 2007 and 2010 and available for 148 countries. The index is based on answers to the question "Ideally, if you had the opportunity, would you like to move permanently to another country, or would you prefer to continue living in this country?" and is defined as the potential percentage increase in the destination country population. The index is thus effectively an indicator of attractiveness as it gives the potential share of immigration if there were no constraints on migration. Besides the "usual suspects", countries like Botswana and Malaysia make the TOP 20 due to their relative regional attractiveness. In addition to controlling for this index (Table 11, column 5), we regress it on actual immigration (s_{mig}) and birthplace diversity (Div_{mig}) and add the residuals from these regressions to our full model (columns 6 and 7). These residuals can be interpreted as the degree to which existing constraints to immigration both at origin and destination countries are binding.[24] Constraints to emigration in the origin countries and constraints in destination countries both serve to increase the extent of migrants' skill-selection. Throughout models (5) to (7), we find our estimates for Div_{mig} to remain robust at the 1% level, albeit at slightly lower magnitudes. This suggests that our main OLS findings are robust to alternative indirect measures of selection.

In a third step, we use data provided by the OECD (2009) that capture the quality of education in a range of OECD and non-OECD countries based on standardized (PISA) test scores.[25] Figure A3 in the appendix shows the distribution of countries' mean overall PISA score for high school students at age 15. We re-compute our Div_{mig} indices and exclude countries of origin with scores exceeding the OECD average (e.g. Finland, Hong Kong, Singapore). Countries that draw most heavily on such origins are - on average - more likely to attract above average talent and thus have a higher chance to benefit from "superstar" effects. Table 11, model (8) shows that the exclusion of these immigrants does not change our results.

Next, we use the full distribution of highly-skilled math- and science students (namely, the share of pupils per country in the highest sextile bracket of math and science skills worldwide - see appendix for more details). The quality of education around the world, especially outside the OECD, is remarkably poor.[26] Thus, very few countries have a deep pool of highly skilled individuals. We formalize this insight by calculating the maximum population in each country of origin that could theoretically be classified as "highly-skilled" in terms of mathematical skills. In essence, we apply the share of pupils in the top sextile of math skills today to the entire population born in a given country (before emigration and immigration), make very conservative assumptions (e.g., that the gap between rich and poor countries' educational quality is stable over time) where we encounter missing data and compare that theoretical maximum of highly (math-) skilled people in each country with the stock of actual (subsequent) emigration. The appendix provides more details on the calculation. Given the very low numbers of highly skilled students outside the OECD, the emigrant stock of skilled workers of many countries in the world greatly exceeds even an optimistic hypothetical stock of highly math-skilled workers in these countries.[27] In other

[24] In line with our priors, in a basic model as in Table 11, column (2), both indices hold independent explanatory power and correlate highly positively with income (available upon request).

[25] See www.oecd-ilibrary.org (PISA 2009 results at a glance).

[26] See Filmer, Hasan and Pritchett (2006), for an illustrative review of test score results. They report, among many other examples, that *"the average science score among students in Peru [is] equivalent to that of the lowest scoring 5 percent of US students"*.

[27] See the appendix for a simulation. The figures show that the vast majority of countries – even under the assumption that all high-ability math/science students had left – mostly sent non- highly math-skilled people abroad.

words, it is very unlikely for a rich country (with the possible exception of the mentioned top few destinations) to attract highly-skilled migrants without specializing on just a few countries with deep talent pools. Thus, for any not highly sought-after destination, more Div_{mig} necessarily implies less – not more – skill selection.

We test the robustness of our estimates for Div_{mig} by dropping all immigrants from origins with large pools of highly talented workers (i.e., with a ratio of math/science-talented workers / skilled emigrants > 1) from our calculation of Div_{mig}. We thus obtain a counterfactual index of birthplace diversity that disregards potential "high quality" immigrant groups (see Table 11, columns 9 and 10). Our estimates are very comparable in terms of magnitude and significance to our baseline Div_{mig} index. This suggests that the inclusion of immigrant groups with the highest likelihood for "superstar" backgrounds in our diversity index does not observably drive our results.

Overall, our baseline specification remains fairly robust to empirical and conceptual challenges to identification arising from the issue of selection on unobservables. Our main result for the diversity of skilled immigrants survives the introduction of an index of skill-selection based on observable skills as well as various adjustments to exclude immigrants from source countries that either possess deep "talent pools" (i.e., where the national average score on the standardized PISA test exceeds the cross-country OECD average) or that are not "highly-skilled constrained" (i.e., where the ratio of an imputed number of highly-talented workers in math/sciences skills to the overall number of skilled emigrants is larger than unity). It is therefore plausible that only a minor fraction of our overall effect can be explained by such selection. To the contrary, given that the pools of extra-ordinary high achievers (with high cognitive abilities in science and math fields) are relatively shallow, it seems that drawing skilled immigrants from a wide range of countries (and thus attaining a high Div_{mig}) is likely even correlated with a lower degree of selection of the best and the brightest.

5.2 Reverse causality

Richer countries could attract a larger flow of immigrants (resulting in a higher s_{mig}) coming from a wider range of origin countries (Div_{mig}) simply because they are richer. An initial descriptive analysis shows that the pure bilateral correlation with income, particularly for skilled immigrants, is higher for s_{mig} (+0.32) than for Div_{mig} (+0.23). This is even more prevalent in first differences: changes in s_{mig} between 1990 and 2000 are clearly positively associated with changes in income per capita (at 1% level), but changes in diversity are not (the effect is close to zero and is not estimated precisely). Indirect effects from growth via s_{mig} to Div_{mig} appear also unlikely, since the correlation between a change in s_{mig} and a change in Div_{mig} is clearly negative (-0.36, significant at 5%).

5.2.1 A gravity model of migration and diversity

We construct instruments for the share and diversity of immigration on the basis of a gravity model.[28] In order to mitigate the problem of violation of the exclusion restriction, we use only a very small subset of bilateral cultural and geographic variables. We thus specify a parsimonious gravity model for bilateral migration:

$$\begin{aligned} m_{jkst} &= \alpha + \beta_1 * POPULATION\ 1960_k + \beta_2 * DISTANCE_{jkt} \\ &+ \beta_3 * BORDER_{jkt} + \beta_4 * OFF.LANGUAGE_{jkt} \\ &+ \beta_5 * ETH.LANGUAGE_{jkt} + \beta_6 * COLONY_{jkt} \\ &+ \beta_7 * TIME\ ZONE_{jkt} + \chi_{jt} + \eta_t + e \end{aligned} \quad (12)$$

m_{jkst} is the bilateral immigration rate from origin country j to destination country k for immigrants of skill level s in year t expressed in terms of the population of destination country k. The choice of our model determinants follows the standard in the literature,[29] with destination population size in 1960 as a lagged measure (we also run and report a model excluding this variable), bilateral (geodesic) distance, common border, common official and ethnic minority languages (if language spoken by at least 9% of population in both countries), time zone differences and common colonial history (all from CEPII, available from Head et al. 2010). We also add a vector of year (η_t) and origin-year fixed effects (χ_{jt}) to account for multilateral resistance (Anderson and Van Wincoop, 2003) that arises from time varying common origin shocks to migration which influence migrants' locations decisions (Bertoli and Fernández-Huertas, 2013).[30] We then predict bilateral migration using an OLS estimator following Frankel and Romer (1999) for the canonical log-transformation of the gravity equation and a PPML (pseudo-poisson maximum likelihood) estimator following Santos Silva and Tenreyro (2006) to avoid the bias arising from this log-transformation.[31]

[28] We build on the trade (e.g., Tinbergen, 1962, Frankel and Romer, 1999) and migration (e.g., Grogger and Hanson, 2011, Beine et al., 2011) gravity literatures.

[29] See, Lewer and van den Berg 2008, Felbermayr et al. 2010, Mayda 2010, Grogger and Hanson 2011, Beine, Docquier and Schiff, 2013, Ortega and Peri, 2009 and 2013.

[30] While the use of origin FE largely suffices to account for multilateral resistance in trade, Bertoli and Fernández-Huertas (2013) show this to hold for migration only under more restrictive distributional assumptions.

[31] This bias is particularly salient with data that are heteroskedastic (e.g., due to many zero cells). Overall, the degree of OLS bias relative to PPML depends on the underlying features of the data.

5.2.2 Instrumentation and identification

Table 12a/b shows results for our gravity models. Generally, the models have sufficiently high explanatory power and seem appropriately specified (keeping in mind that they are purposefully excluding potential determinants of destination countries' productivity). All estimates on the migration determinants have the expected sign: destination country population in 1960 and bilateral distance enter negatively. Skilled migration is less constrained by migratory distance, as theory would predict, and is less affected by border-effects. The cultural proximity variables (common colonial relationship and common official/ethnic minority languages) both enter positively, as expected.

We construct instruments for our two main variables of interest, skilled birthplace diversity and the share of skilled immigration, using the predicted bilateral migration shares estimated from our PPML and OLS gravity models.[32] We turn to comparing our instruments for predicted diversity with actual Div_{mig} (see Appendix Figure 2a). The correlation between actual and predicted diversity is strong, suggesting a priori a strong instrument. Furthermore, the instrument should be lower (higher) than actual diversity in richer (poorer) countries. This is exactly what we find (see Appendix Figure 2b): a negative link between GDP per capita at destination and the difference between actual and predicted Div_{mig}. We take this as indication that our gravity model yields an instrument which takes out at least a part of any small but endogenous component in the diversity-income relationship.

Table 13 shows the first-stage results corresponding to our 2SLS models in Table 14. Throughout the models (which start with one instrumented variable and extend to up to three) we reject the null hypothesis of weak instruments both jointly (Kleibergen-Paap F-test) and individually (Angrist-Pischke F-tests), as these statistics exceed the strictest or (in model 3) second strictest Stock and Yogo (2005) critical values.[33]

There are two issues that could affect the validity of our identification. First, bilateral omitted variables could be correlated with bilateral migration and also with destination country GDP/capita; for example bilateral trade with a rapidly growing trade partner such as China could affect the GDP (via TFP) of China's neighboring trade partners. However, Hsieh and Ossa (2011) find that China's productivity growth has only very small positive effects on neighbor countries' TFP. We also account for such effects econometrically by including origin-year fixed effects. Our trade controls should adequately capture any residual aggregate bias. Second, relative bilateral geography variables (such as distance, common

[32] To avoid violating the exclusion restriction via inclusion of a lagged measure of population size, we fully rely on the more parsimonious model excluding this variable.

[33] As is well known, the Stock and Yogo (2002) critical values are are appropriate under homoskedasticity only. We report heteroskedasticity-robust clustered standard errors, which tend to be higher than those obtained under the assumption of homoskedasticity.

language or border contiguity) may be correlated with absolute (unilateral) geography variables, a point first raised in the context of trade gravity models by Rodriguez and Rodrik (2001). We account for that by including a very broad set of geography and disease variables into our second-stage baseline model, including the geographical fixed effects as suggested by these authors and conducting many robustness exercises on our geography variables. The inclusion of geography variables in our main model also served to remove an apparent negative omitted variables bias (see Table 5, column 2), suggesting that such an (unlikely) remaining bias from geography variables if any, may increase (not decrease) our Div_{mig} estimates.

5.2.3 2SLS results

Table 14 shows results from our full model using the 2SLS estimator. We compare our baseline OLS specification in model (1) with alternative IV-specifications in models (2)-(4). In (2), we first instrument solely our main variable of interest, Div_{mig}, assuming that any remaining endogeneity in our model (e.g., from s_{mig}) is negligible. Then in (3), we relax this assumption and also instrument for s_{mig}. We confirm our prior OLS findings on skilled Div_{mig} at the 5% level in both models.[34] The IV estimates appear very stable and somewhat lower than our OLS estimates. This is closely in line with our expectation, namely that first, the OLS model suffers (if at all) from a low negative omitted variables bias, and second, that our OLS estimates may only mildly suffer from a positive bias due to selection or reverse causality. Our IV estimates confirm these inferences to a large extent. The slightly lower IV estimates suggest that the net effect of these two biases was positive and relatively small (less than 10% of the estimate). In other words, the positive bias from selection/reverse causality exceeded the negative bias from omitted variables and (if at all) measurement error. When instrumenting for the share of immigration (model 3), our estimates for s_{mig} remain similar in magnitude but lose significance. This suggests - in line with our discussion of omitted variables and selection - that establishing causality for s_{mig} is a bigger challenge than for Div_{mig}.

In model (4), we go one step further and also instrument for $Div_{imports}$. We thus apply our gravity model of migration determinants to trade, following Frankel and Romer (1999). The strategy to obtain instruments from similar models is valid to the extent that the model determinants for migration and trade are estimated differentially. Table 12b shows that this is indeed the case. Our Div_{mig} estimate remains remarkably robust, but the overall model is weakly identified since the instruments for the diversity of trade and migration are correlated. Needless to say, this approach is very demanding given the few degrees of freedom

[34] F-Tests on the excluded instruments and the joint instruments are well above the respective Stock and Yogo (2002) critical values.

in our model and correlation structure between instruments. Remarkably, our estimate for Div_{mig} remains similar in magnitude but - as expected - loses some statistical significance (it remains significant at the 10% level). This serves as indication that any endogeneity bias in our OLS model is small and unlikely to drive our main results.

6 Does cultural distance matter?

Is birthplace diversity more valuable if immigrants are culturally similar or come from richer origin countries? So far, our index does not capture such characteristics and assumes all groups to be equidistant from each other. We now expand this well-established but restrictive notion of diversity to shed more light on the transmission channels.

6.1 An augmented birthplace diversity index

To incorporate group distance, we rely on Greenberg (1956) and expand our index in order to include group distance by adding two group weights d_{jk} and e_{jk}:

$$Div_{mig,augmented,k} = \sum_{j=1}^{J} s_j * (1 - s_j) * d_{jk} * e_{jk} \tag{13}$$

j is an index of immigrant groups and d_{jk} and e_{jk} are bilateral distance variables between immigrants j and natives k. The augmented diversity index reduces to Div_{mig} when all groups are equidistant at $d_{jk} = 1$ and $e_{jk} = 1$. Finding a distance variable for our index of birthplace diversity requires two building blocks: first, input data for bilateral group characteristics, and second, a mapping of these group characteristics to d_{jk}. As inputs, we use bilateral population-weighted genetic distance (Spolaore and Wacziarg, 2009 and Cavalli-Sforza et al., 1994) and a unilateral measure of GDP per capita (PPP) at origin (PWT 8.0). We standardize these inputs for each destination and obtain vectors of genetic distance as well as GDP at origin that range from 0 (min) to 1 (max).

We specify a range of alternative functional forms for d_{jk} and e_{jk}. This allows us to create a limited set of alternative $Div_{mig,augmented}$ indices that model different hypotheses (e.g., an index that over-weights immigrants from richer vs. poorer origins). We then let these alternative indices run a "horse-race" by replacing our initial Div_{mig} index with these alternative specifications in our baseline model. The results from this horse race are indicative of the productive role played by these distance vectors in the relationship between Div_{mig} and income/capita.

To model the different functional forms of genetic distance into d_{jk} and GDP/capita into

e_{jk} we use a standard logistic function

$$d_{jk} = \frac{2}{\left(1 + e^{-(\theta * x_{jk})}\right)} \tag{14}$$

where θ is a parameter that ranges from -10 to +10 and x_{jk} takes on standardized values of genetic distance (for d_{jk}) and GDP/capita (for e_{jk}). [35] The logistic function is convenient for our purpose. It can be centered easily on $d_{jk} = 1$ for groups at average genetic proximity (income) from the natives of a given per country and set to converge to two bounds 0 and 2. In addition, by varying a single parameter θ, we can vary both the slope of the function and the spread between genetically closer (poorer) and more distant (richer) groups. It assigns d_{jk} and e_{jk} values between 0 and 2 (centered on 1 for the theoretical case that all immigrant groups are equidistant to natives). d_{jk} and e_{jk} then act as group weights in the calculation of $Div_{mig,augmented}$. Larger absolute values of θ indicate a higher degree of relative over/under-weighting. Augmented diversity indices based on $\theta > 0$ overweight groups with higher genetic distance (richer origins), those based on $\theta < 0$ overweight closer groups (poorer origins).The intuition is the following: if, say, genetically more distant (richer) groups were more valuable in terms of explaining productivity differences, weighting these groups with $d_{jk} > 1$ and correspondingly giving a lower weight of $d_{jk} < 1$ to genetically closer (poorer) groups should result in an augmented birthplace diversity index that has higher explanatory power in our model than its inverse index, one where we overweight closer (poorer) groups.

6.2 Results

Table 15 shows coefficients for Div_{mig} (skilled) on a full range of alternative birthplace diversity indices at different combinations of θ_1 and θ_2. First, we interpret unilateral effects. When holding GDP/capita constant (at $\theta_2 = 0$), giving more weight to culturally closer immigrants ($\theta_1 < 0$) increases the predictive power of Div_{mig} slightly - but excessively overweighting those diminishes the predictive power. In turn, overweighting culturally distant groups (and thus relatively underweighting closer groups) clearly diminishes the effect of Div_{mig} on income. This nonlinear, concave pattern for genetic/cultural distance appears to be very stable (even to a large extent when varying income at origin). It suggests a trade-off between the productive costs and benefits of cultural distance. When holding genetic distance constant at ($\theta_2 = 0$), the effect of Div_{mig} increases somewhat linearly in income at origin, but with a very small gradient than that of cultural proximity and also not monotonically. This may suggest that the productive effects of Div_{mig} (skilled) are driven to a larger extent by culture than by income. We however cannot conclude this with certainty since this interpretation is based on marginal, not average effects.

[35] We use GDP/capita in origin countries only (not economic distance) to avoid including our dependent variable in our regressor.

Second, we look at interaction effects. Moving from the center of Table 15 towards the lower left corner (thus overweighting culturally closer immigrant groups and also overweighting those from richer origins), the estimate on e.g., $Div_{mig,augmented}$ $(\theta_1 = -2.5; \theta_2 = 10)$ increases significantly (at 5% level) vs. the simple baseline index Div_{mig}. This increase is larger than any individual increase in either dimension (holding constant either θ_1 or θ_2 at zero). This suggests that a combination of culturally closer immigrants and richer origins (potentially a proxy for higher skills) can be particularly valuable.

7 Conclusion

We construct an index of population diversity based on people's birthplaces. This new index, which we decompose into a *size* (share of foreign born) and a *variety* (diversity of immigrants) component, is available for 195 countries in 1990 and 2000 disaggregated by skill level. Our birthplace diversity measures are conceptually and empirically orthogonal to the various measures of diversity previously explored in the literature (such as ethnic, linguistic or genetic diversity). We find that the diversity of (and arising from) immigration relates positively to measures of economic prosperity. This holds especially for skilled immigrants in richer countries. Increasing the diversity of skilled immigration by one percentage point increases long run economic output by about two percent.[36] These results are robust to our attempts to account for potential reverse causality and unobserved heterogeneity among skilled immigrants. They are also robust to using various sub-samples (and definitions of countries), to accounting for immigrants' age of entry or to second-generation effects.

Lastly, we extend our index of birthplace diversity and account for cultural and economic distance between immigrants and natives. The productive effects of birthplace diversity appear to be largest for immigrants originating from richer countries and from countries at intermediate levels of cultural proximity. We interpret these findings as suggestive of the trade-offs between communication and social costs of diversity and benefits in terms of production function effects that arise from skill complementarities. Hence, birthplace diversity is an important determinant of economic prosperity that is conceptually, empirically and economically different from other (e.g., ethnic, linguistic or genetic) dimensions of intrapopulation diversity.

[36] For a one standard deviation increase in birthplace diversity (skilled immigrants), this equals an increase of about 25% in economic output.

8 References

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Table 1a: Bilateral correlations

	Variables, (n= 240, full sample)	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
(1)	Ethnic fractionalization	1,00								
(2)	Linguistic fractionalization	0,76	1,00							
(3)	Genetic diversity	0,12	0,22	1,00						
(4)	Birthplace diversity, population	0,12	0,11	0,23	1,00					
(5)	Share of immigration	0,14	0,12	0,21	0,98	1,00				
(6)	Birthplace diversity, immigrants	-0,11	-0,12	-0,03	0,10	0,09	1,00			
(7)	Birthplace diversity, population, skilled	0,11	0,10	0,23	0,90	0,86	0,10	1,00		
(8)	Share of immigration, skilled	0,12	0,08	0,21	0,88	0,86	0,09	0,97	1,00	
(9)	Birthplace diversity, immigrants, skilled	-0,04	-0,10	-0,06	0,08	0,08	0,86	0,01	0,00	1,00

Table 1b: Summary statistics

Variable	*n*	*mean*	*std. dev.*	*min*	*max*
GDP/capita, PPP (log)	240	8,55	1,25	5,39	11,04
TFP, 1=USA (log)	206	-0,60	0,58	-2,51	0,68
Patent applications/capita	117	0,0002	0,0006	0,0000	0,0038
Patents granted/capita	112	0,0001	0,0003	0,0000	0,0016
Birthplace diversity, population, all	240	0,14	0,18	0,00	0,88
Birthplace diversity, population, skilled	240	0,17	0,20	0,00	0,94
Birthplace diversity, population, unskilled	240	0,14	0,18	0,00	0,86
Share of immigrants, all	240	0,09	0,13	0,00	0,73
Share of immigrants, skilled	240	0,11	0,15	0,00	0,94
Share of immigrants, unskilled	240	0,08	0,13	0,00	0,74
Birthplace diversity, immigrants, all	240	0,73	0,20	0,02	0,96
Birthplace diversity, immigrants, skilled	240	0,80	0,18	0,08	0,97
Birthplace diversity, immigrants, unskilled	240	0,72	0,21	0,02	0,96
Birthplace diversity, immigrants, all, 1989 borders	240	0,71	0,25	0,00	1,00
Birthplace diversity, immigrants, skilled, 1989 borders	240	0,78	0,23	0,00	1,00
Birthplace diversity, immigrants, unskilled, 1989 borders	240	0,70	0,25	0,00	1,00
Share of immigrants, skilled, > age 12	58	0,08	0,08	0,00	0,28
Share of immigrants, skilled, > age 18	58	0,07	0,06	0,00	0,23
Share of immigrants, skilled, > age 22	58	0,06	0,05	0,00	0,22
Birthplace diversity, immigrants, skilled, > age 12	58	0,87	0,11	0,47	0,97
Birthplace diversity, immigrants, skilled, > age 18	58	0,87	0,11	0,47	0,97
Birthplace diversity, immigrants, skilled, > age 22	58	0,87	0,11	0,48	0,97
GDP/capita PPP (log), weighted av., all immigrants	240	8,41	0,95	6,32	9,95
GDP/capita PPP (log), weighted av., skilled immigrants	240	8,72	0,78	6,32	10,13
GDP/capita PPP (log), weighted av., unskilled immigrants	240	8,36	0.95	6,32	10,01
Population size (log)	240	9,26	1,53	5,95	14,05
Land area (log)	240	12,22	1,91	6,47	16,65
Landlocked (dummy)	240	0,22	0,41	0	1
Ethnic fractionalization	240	0,44	0,25	0,00	0,93
Linguistic fractionalization	240	0,40	0,29	0,00	0,92
Genetic diversity (ancestry-adjusted)	240	0,73	0,03	0,63	0,77
Genetic diversity (a-a, squared)	240	0,53	0,04	0,39	0,59
Years of schooling (log)	240	1,84	0,51	-0,10	2,54
Absolute latitude	240	0,31	0,20	0,00	0,71
Coastal population (%)	240	0,43	0,37	0,00	1,00
Mean temperature (log)	240	2,65	0,81	-0,93	3,35
Mean precipitation (log)	240	6,71	0,87	3,93	7,98
Malaria incidence (%)	240	0,31	0,41	0,00	1,00
Yellow fever presence (dummy)	240	0,43	0,50	0	1
Tuberculosis incidence ('1000 %)	240	149,20	199,00	4	1407
South East Asia (dummy) (World Bank)	240	0,08	0,28	0	1
Sub-Saharan Africa (dummy) (World Bank)	240	0,25	0,43	0	1
Latin America (dummy) (World Bank)	240	0,13	0,34	0	1
Trade openness in % of GDP, PPP	240	0,47	0,44	0,00	3,36
Diversity of exports	240	0,81	0,15	0,20	0,96
Diversity of imports	240	0,84	0,12	0,40	0,96
Polity2 combined institutional quality	240	3,12	6,84	-10,00	10,00
British colony (dummy)	240	0,30	0,46	0	1
French colony (dummy)	240	0,18	0,38	0	1
Spanish colony (dummy)	240	0,14	0,35	0	1
Land area in tropics (%)	222	0,43	0,47	0,00	1,00
Agricultural suitability (mean)	222	0,46	0,24	0,00	0,96
Agricultural suitability (standard deviation)	222	0,19	0,09	0,00	0,41
Elevation (mean)	222	0,58	0,50	0,03	2,52
Elevation (standard deviation)	222	0,37	0,38	0,01	1,91
Property rights index	240	4,79	2,11	1	7
Civil liberties index	240	4,57	1,68	1	7

Table 1c: Data sources

Variable Name	*Definition*	*Source*
Income/Productivity (Y)		
GDP/capita	log of GDP/capita in int. USD, PPP	Penn World Tables 8.0, Feenstra, Inklaar, Timmer (2013)
TFP	log of total factor productivity/capita, 1=USA	Penn World Tables 8.0, Feenstra, Inklaar, Timmer (2013)
Migration & Diversity		
Birthplace diversity(population)	Herfindahl index of population (above age 24) based on country of origin (including native born population). By skill level	Own calculations, ADOP (2013)
Birthplace diversity(immigrants)	Herfindahl index of population (above age 24) based on country of origin (excluding native born population). By skill level	Own calculations, UN Pop. Division (2013), ADOP (2013)
Share of immigration	Sum of all immigrants / total population (above age 24), by skill level	UN Pop. Division (2013), ADOP (2013)
Age-of-entry cut off data	Definition of native extended to immigrants at ages of entry below age of 12, 18, 22, respectively, indices recomputed	Own calculations based on Beine, Docquier, Rapoport (2007)
Market size controls		
Population size	Population size, log	UN Pop. Division (2013)
Area size	Country area size in square kilometers, log	CEPII (2010), Head et al. (2010)
Landlockedness	Dummy = 1 if country is landlocked	CEPII (2010), Head et al. (2010)
Education		
Years of schooling	Years of schooling, population > 25 years, log	Barro and Lee (2013)
Origin effects		
GDP/capita of immigrants	Weighted average of immigrants GDP/ capita at origin	Own calculations based on Penn World Tables 8.0, Feenstra, Inklaar, Timmer (2013)
Trade openness		
Trade openness	Exports and imports in % of GDP, at PPP	Penn World Tables 8.0, Feenstra, Inklaar, Timmer (2013)
Diversity of trade (exports)	Herfindahl index of export shares with all trade partners, in nominal USD. Missing data in 1990 for ex-soviet countries interpolated from next available year (usually 1992). Missing data for 3 African countries (BWA, NAM, SWZ) from Comtrade for 2000.	Own calculations, Feenstra (2005) and COMTRADE (2013)
Diversity of trade (imports)		
Fractionalization		
Ethnic fractionalization	Herfindahl index of ethnic group shares	Alesina et al. (2003)
Linguistic fractionalization	Herfindahl index of linguistic group shares	Alesina et al. (2003)
(Predicted) genetic diversity	Expected heterozygosity of a country's population, predicted by migratory distances from East Africa and predicted pairwise genetic distance between ethnic groups within a country for population in 2000, ancestry-adjusted	Ashraf and Galor (2013)
Geography		
Absolute latitude	Absolute latitude of capital/90	Gallup, Sachs, Mellinger (1998)
Coastal population (%)	% Population within 100km from ice-free coast, 1995	Gallup, Sachs, Mellinger (1998)
Mean temperature (log)	Average temperature in celsius, 1961-1990, log	World Bank (2013)
Mean precipitation (log)	Average precipitation in mm/year, 1961-1990, log	World Bank (2013)
Malaria incidence (%)	% of population with Malaria in 1994	Gallup, Sachs, Mellinger (1998)
Yellow fever presence (dummy)	Dummy, 1 if Yellow fever present in country	World Bank (2013)
Tuberculosis incidence ('1000 %)	# of Tuberculosis cases per 100,000 population	World Bank (2013)
Institutions		
Quality of institutions	Combined Polity2- score -10: Most repressive, +10: Most democratic. Missing value for Kazakstan 1990 from 1991, for Kuweit in 1990 due to interregnum as average 1989-1991	PolityIV database, Marshall Jaggers (2012)
Property rights index	Index inverted, 7= most, 1=least rights	Freedom House (2011)
Civil liberties index	Index inverted, 7= most, 1=least liberties	Freedom House (2011)
Colony dummy	Equals 1 if country former british, french or spanish colony, respectively	CEPII (2010), Head et al. (2010)
Other variables		
Agricultural suitability (mean)	Mean of indicators for agricultural suitability across regions within country	Michalopoulos (2012)
Agricultural suitability (st. deviatio	Standard deviation of indicators for agricultural suitability across regions within country	Michalopoulos (2012)
Elevation (mean)	Mean elevation across regions within country	Michalopoulos (2012)
Elevation (standard deviation)	Standard deviation of elevation across regions within country	Michalopoulos (2012)
Land area in tropics (%)	% land area in geographical tropics	Gallup, Sachs, Mellinger (1998)
Continent fixed effects	Latin America, South-Saharan Africa and South-East Asia	World Bank (2013)
Patent intensity	Average of patents granted and applied for (1995-2005) per capita, respectively, in %	WIPO (2010)
Gravity model parameters		
Population size, 1960	Population size, log	UN Pop. Division (2013)
Bilateral distance	Geodesic distance in km, log	CEPII (2010), Head et al. (2010)
Common official language	Dummy = 1 for pair with same official language	CEPII (2010), Head et al. (2010)
Common ethnic language	Dummy = 1 for pair with language shared by at least 9% of populations	CEPII (2010), Head et al. (2010)
Common border	Dummy = 1 for pair with common land border	CEPII (2010), Head et al. (2010)
Colonial history	Dummy = 1 for pair ever in colonial relationship	CEPII (2010), Head et al. (2010)
Horizontal time diffence	Difference in time zones in hours	CEPII (2010), Head et al. (2010)

Table 2: Dimensions of diversity: Ethnic/linguistic, genetic, birthplace diversity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample				*Full sample, year 2000*				
Dependent variable (log)				*GDP/capita*				
Birthplace diversity (pop), all			**3.327*** (0.419)**					
Birthplace diversity (pop), skilled				**2.307*** (0.373)**				
Birthplace diversity (pop), unskilled					**3.471*** (0.446)**			
Birthplace diversity (within), all						**2.108 (1.844)**		
Birthplace diversity (between), all						3.783*** (0.772)		
Birthplace diversity (within), skilled							**3.336*** (0.479)**	
Birthplace diversity (between), skilled							1.688*** (0.619)	
Birthplace diversity (within), unskilled								**1.583 (2.293)**
Birthplace diversity (between), unskilled								4.127*** (0.821)
Ethnic fractionalization	-1.913*** (0.535)	-1.435** (0.561)	-1.531*** (0.417)	-1.441*** (0.462)	-1.559*** (0.417)	-1.470*** (0.437)	-1.547*** (0.466)	-1.476*** (0.438)
Linguistic fractionalization	-1.112*** (0.421)	-1.199*** (0.427)	-1.166*** (0.311)	-1.218*** (0.349)	-1.164*** (0.309)	-1.199*** (0.323)	-1.129*** (0.344)	-1.206*** (0.322)
Genetic diversity		448.8*** (131.1)	292.2*** (102.8)	356.0*** (110.7)	288.0*** (102.9)	280.2*** (102.8)	367.9*** (113.3)	270.8*** (102.4)
Genetic diversity (squared)		-319.6*** (93.02)	-211.5*** (73.23)	-256.3*** (78.78)	-208.6*** (73.32)	-203.1*** (73.25)	-264.7*** (80.55)	-196.5*** (72.99)
Observations	142	142	142	142	142	142	142	142
Adjusted R-squared	0.325	0.367	0.563	0.487	0.567	0.561	0.489	0.567

Birthplace Diversity (Population) is a Herfindahl index of the population's intrapopulation diversity (including group of natives). Birthplace Diversity (between) denotes the same index assuming all immigrant groups hail from one country of origin. Birthplace Diversity (within) is the additional birthplace diversity derived from the variety of immigrants' origins. Between (between natives and immigrants)- and within-diversity (within groups of immigrants only) add up to the overall birthplace diversity index of the population. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Birthplace diversity and economic development

	(1)	(2)	(3)
Sample		*Full sample*	
Dependent variable (log)		*GDP/capita*	
Birthplace diversity, immigrants	**0.105*** **		
	(0.0317)		
Share of immigration	0.158***		
	(0.0450)		
Birthplace diversity, immigrants, skilled		**0.160*** **	
		(0.0505)	
Share of immigration, skilled		0.186***	
		(0.0660)	
Birthplace diversity, immigrants, unskilled			**0.145*** **
			(0.0436)
Share of immigration, unskilled			0.230***
			(0.0692)
Ethnic fractionalization	0.0735	0.0591	0.0694
	(0.303)	(0.321)	(0.300)
Linguistic fractionalization	-0.155	-0.0172	-0.169
	(0.274)	(0.285)	(0.272)
Genetic diversity	239.1***	242.2***	236.6***
	(87.34)	(88.41)	(87.30)
Genetic diversity (squared)	-171.6***	-173.8***	-169.9***
	(62.53)	(63.33)	(62.46)
Land area (log)	0.0523	0.0335	0.0584
	(0.0462)	(0.0481)	(0.0457)
Landlocked country	0.344**	0.354**	0.349**
	(0.162)	(0.166)	(0.160)
Absolute latitude	1.083	0.958	1.049
	(0.727)	(0.786)	(0.731)
Population within 100km from icefree coast (%)	0.558**	0.541**	0.582***
	(0.214)	(0.238)	(0.208)
Mean temperature (log)	0.0745	0.0450	0.0757
	(0.0941)	(0.0968)	(0.0951)
Mean precipitation (log)	0.0281	0.0149	0.0208
	(0.0994)	(0.106)	(0.0992)
FE South-Saharan Africa	-0.396	-0.386	-0.399
	(0.313)	(0.297)	(0.317)
FE Latin America	-0.378	-0.372	-0.386*
	(0.232)	(0.246)	(0.231)
FE Asia	-0.671***	-0.693***	-0.690***
	(0.223)	(0.224)	(0.222)
FE North Africa / Middle East	-0.0300	0.0580	-0.0668
	(0.267)	(0.255)	(0.273)
Malaria incidence (%)	-0.485**	-0.500**	-0.482**
	(0.221)	(0.230)	(0.220)
Yellow fever incidence (dummy if present)	0.152	0.181	0.136
	(0.148)	(0.151)	(0.148)
Tuberculosis incidence (%)	-0.000411	-0.000399	-0.000425
	(0.000288)	(0.000290)	(0.000288)
Polity2 institutional quality index	0.0164*	0.0183**	0.0160*
	(0.00837)	(0.00809)	(0.00843)
FE French colonizer	-0.0476	-0.0711	-0.0333
	(0.115)	(0.120)	(0.113)
FE British colonizer	0.0140	0.0667	0.0189
	(0.140)	(0.146)	(0.140)
FE Spanish colonizer	-0.0196	-0.0523	-0.0124
	(0.141)	(0.154)	(0.142)
Trade openness (% of GDP at PPP)	0.515***	0.551***	0.518***
	(0.102)	(0.112)	(0.103)
Trade diversity of exports	0.0718	0.196	0.0533
	(0.358)	(0.370)	(0.359)
Trade diversity of imports	0.136	0.0247	0.127
	(0.394)	(0.414)	(0.396)
Average GDP/capita at immigrants' origin	-0.107	-0.0810	-0.103
	(0.0793)	(0.0957)	(0.0758)
Years of schooling (log)	0.945***	0.972***	0.953***
	(0.123)	(0.133)	(0.122)
Population size (log)	0.0789	0.103*	0.0763
	(0.0572)	(0.0570)	(0.0569)
Oster (2013)'s non-biased Div(Mig) coefficients			
at R(max) = 0.9	0.074	0.115	0.063
at R(max) = 1	0.140	0.147	0.127
Observations	240	240	240
Adjusted R-squared	0.854	0.842	0.854

Standard errors clustered on the country level. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Birthplace diversity and economic development – rich/poor country split samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample		> median GDP/capita				< median GDP/capita		
Dependent variable (log)		GDP/capita				GDP/capita		
Birthplace diversity, immigrants	0.138***				0.0182			
	(0.0401)				(0.0669)			
Share of immigration	0.430***				0.0699**			
	(0.0827)				(0.0287)			
Birthplace diversity, immigrants, skilled		**0.260*** **		**0.227** **		**0.00765**		**-0.0741**
		(0.0560)		**(0.0865)**		**(0.0608)**		**(0.117)**
Share of immigration, skilled		0.291***		0.00787		-0.0539		-0.144**
		(0.0980)		(0.145)		(0.0692)		(0.0693)
Birthplace diversity, immigrants, unskilled			**0.108*** **	**-0.0278**			**0.0160**	**0.0885**
			(0.0377)	**(0.0751)**			**(0.0646)**	**(0.128)**
Share of immigration, unskilled			0.423***	0.389***			0.0713**	0.143***
			(0.0873)	(0.136)			(0.0273)	(0.0371)
Observations	120	120	120	120	120	120	120	120
Adjusted R-squared	0.717	0.700	0.713	0.747	0.724	0.713	0.727	0.738

All models include the full vector of controls (not shown). Standard errors clustered on the country level. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Birthplace diversity (skilled) and economic development – rich country subsample

	(1)	(2)	(3)	(4)	(5)	(6)
Sample			> median GDP/capita			
Dependent variable (log)			GDP/capita			
Birthplace diversity, immigrants, skilled	**0.239*** **	**0.269*** **	**0.278*** **	**0.277*** **	**0.278*** **	**0.260*** **
	(0.0667)	**(0.0605)**	**(0.0573)**	**(0.0537)**	**(0.0492)**	**(0.0560)**
Share of immigration, skilled	0.225***	0.168**	0.193***	0.178*	0.229**	0.291***
	(0.0694)	(0.0743)	(0.0715)	(0.0919)	(0.0887)	(0.0980)
Controls						
Fractionalization	x	x	x	x	x	x
Climate & geography		x	x	x	x	x
Disease environment			x	x	x	x
Institutions				x	x	x
Trade and openness					x	x
Education and population						x
Oster (2013)'s non-biased Div(Mig) coefficients						
at R(max) = 0.9						0.2674
at R(max) = 1						0.2730
Observations	120	120	120	120	120	120
Adjusted R-squared	0.344	0.569	0.617	0.619	0.697	0.700

Standard errors clustered on the country level. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Birthplace diversity and patent intensity

	(1)	(2)	(3)	(4)
Sample	*Full sample, 2000*		*> median GDP/capita*	
Dependent variable (log)	*# patent applications/capita*	*# patent grants/capita*	*# patent applications/capita*	*# patent grants/capita*
Birthplace diversity, immigrants, skilled	**0.490***	**0.468**	**0.493**	**0.606**
	(0.173)	**(0.215)**	**(0.205)**	**(0.228)**
Share of immigration, skilled	0.244	0.241	1.196***	1.277***
	(0.212)	(0.218)	(0.368)	(0.370)
Ethnic fractionalization	-0.621	-0.279	-0.833	-0.570
	(0.934)	(1.111)	(1.040)	(1.113)
Linguistic fractionalization	0.171	-0.283	-0.225	-0.316
	(0.820)	(0.990)	(1.106)	(1.085)
Genetic diversity	2.300	5.921	3.501	10.97
	(9.318)	(9.347)	(16.18)	(18.77)
Years of schooling (log)	1.308**	1.227*	1.808	2.136
	(0.536)	(0.620)	(1.612)	(1.796)
Quality of institutions	0.0604	0.0551	0.131	0.115
	(0.0383)	(0.0407)	(0.103)	(0.108)
Observations	117	112	60	60
Adjusted R-squared	0.813	0.793	0.794	0.763

Patents: Average number of patents applied for (or granted, respectively) at national patent bureaus by the respective country's nationals in the years 1995-2005 per capita (*1000, in logs), respectively, from WIPO (2010). All models include the full vector of controls. Heteroskedasticity-robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7: Birthplace diversity and total factor productivity

	(1)	(2)
Sample	*Full sample*	*> median GDP/capita*
Dependent variable (log)	*TFP/capita*	*TFP/capita*
Birthplace diversity, immigrants, skilled	**0.107**	**0.144***
	(0.0427)	**(0.0416)**
Share of immigration, skilled	0.0232	0.109
	(0.0428)	(0.0671)
Observations		
Adjusted R-squared	206	120

All models include the full vector of controls (not shown). Standard errors clustered on the country level.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: Robustness to second-generation effects

	(1)	(2)	(3)
Sample		*> median GDP/capita*	
Dependent variable (log)		*GDP/capita*	
Birthplace diversity, immigrants, skilled	**0.260***** **(0.0560)**		**0.247***** **(0.0619)**
Share of immigration, skilled	0.291*** (0.0980)		0.273** (0.115)
Birthplace diversity, immigrants, 1960		0.0952 (0.0821)	0.0392 (0.0776)
Share of immigration, 1960		0.0114** (0.0557)	0.0611 (0.0592)
Observations	120	120	120
Adjusted R-squared	0.700	0.600	0.699

Birthplace diversity of immigrants and share of immigration calculated for 1960. All models include the full vector of controls (not shown). Standard errors clustered on the country level.
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Robustness to children immigrants

	(1)	(2)	(3)	(4)
Sample		*> median GDP/capita*		
Dependent variable (log)		*GDP/capita*		
Birthplace diversity, immigrants, skilled (no adjustment)	**0.230****			
	(0.0855)			
Share of immigration, skilled	-0.0960			
	(0.189)			
Birthplace diversity, immigrants, skilled (above age 12)		**0.192****		
		(0.0710)		
Share of immigration, skilled (above age 12)		-0.0526		
		(0.0887)		
Birthplace diversity, immigrants, skilled (above age 18)			**0.187****	
			(0.0701)	
Share of immigration, skilled (above age 18)			-0.0284	
			(0.0756)	
Birthplace diversity, immigrants, skilled (above age 22)				**0.186****
				(0.0684)
Share of immigration, skilled (above age 22)				-0.0134
				(0.0668)
Observations	58	58	58	58
Adjusted R-squared	0.848	0.851	0.850	0.849

Birthplace diversity and share of immigration adjusted for migrants' age at entry into destination country. Modified variables regard immigrants below thresholds as natives. Age-of-entry data available only for subset of countries (mostly OECD), thus sample restricted to these. All models include the full set of controls (not shown). Standard errors clustered on the country level.

*** p<0.01, ** p<0.05, * p<0.1

Table 10: Robustness to alternative fixed effects structures

	(1)	(2)	(3)	(4)	(5)	(6)
Sample			*> median GDP/capita*			
Dependent variable (log)			*GDP/capita*			
Birthplace diversity, immigrants, skilled	**0.260*** **	**0.259*** **	**0.257*** **	**0.247*** **	**0.261*** **	**0.257*** **
	(0.0560)	**(0.0559)**	**(0.0578)**	**(0.0553)**	**(0.0494)**	**(0.0591)**
Share of immigration, skilled	0.291***	0.290***	0.284***	0.296***	0.285***	0.298***
	(0.0980)	(0.0980)	(0.0966)	(0.104)	(0.0803)	(0.0888)
FE South-Saharan Africa	-0.0620	-0.0721	-0.0337	0.447		
	(0.382)	(0.384)	(0.405)	(0.594)		
FE Latin America	-0.575	-0.567	-0.538	-0.0891		
	(0.384)	(0.388)	(0.401)	(0.338)		
FE Asia	-0.199	-0.206	-0.209	-0.154		
	(0.180)	(0.180)	(0.185)	(0.211)		
FE North Africa / Middle East	-0.0708	-0.0595	-0.0409	-0.0406		
	(0.246)	(0.252)	(0.258)	(0.307)		
FE OPEC		0.0619	0.0740	0.122		
		(0.184)	(0.186)	(0.203)		
FE USA, CAN, AUS, NZL			0.108			
			(0.345)			
FE Americas continent						-0.155
						(0.375)
FE Africa continent						-0.214
						(0.411)
FE Asia continent						-0.131
						(0.173)
FE Oceania continent						-0.219
						(0.361)
Observations	120	120	120	112	120	120
Adjusted R-squared	0.700	0.697	0.694	0.689	0.703	0.693

Column (1) shows our baseline results for comparison. Column (2) includes additional FE for OPEC countries. Column (3) adds a FE for countries with skill selective policies and the US. Column (4) drops these countries from the sample. Column (5) excludes all fixed effects. Column (6) shows robustness to an alternative specification of fixed effects using continents instread of geographic regions. Standard errors clustered on the country level.

*** p<0.01, ** p<0.05, * p<0.1

Table 11: Robustness to unobserved heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sample					*> median GDP/capita*					
Dependent variable (log)					*GDP/capita*					
Birthplace diversity, immigrants, skilled	**0.260******	**0.229****	**0.249*****	**0.301*****	**0.201*****	**0.240*****	**0.242*****			
	(0.0560)	**(0.0885)**	**(0.0585)**	**(0.0579)**	**(0.0546)**	**(0.0588)**	**(0.0529)**			
Index of positive selection (based on observable skills)		0.273**	0.0511							
		(0.128)	(0.0934)							
Weighted average GDP per capita at PPP at immigrant origins		0.574***	0.191							
		(0.137)	(0.171)							
Index of net migration intentions (Gallup index)					0.00277***					
					(0.000992)					
Index of positive selection (based on residuals from regression of Gallup on share of immigration)						0.000905				
						(0.00113)				
Index of positive selection (based on residuals from regression of Gallup on birthplace diversity, migrants)							0.00298***			
							(0.00103)			
Birthplace diversity, immigrants, skilled, ex PISA > OECD mean score								**0.226*****		
								(0.0587)		
Birthplace diversity, immigrants, skilled, ex PISA science skills in global top 16% > OECD									**0.253*****	
									(0.0543)	
Birthplace diversity, immigrants, skilled, ex PISA math skills in global top 16% > OECD										**0.269*****
										(0.0564)
Share of immigration, skilled	0.291***	0.240***	0.278***	0.285**	0.174**	0.248***	0.167**	0.248**	0.297***	0.239*
	(0.0980)	(0.0693)	(0.0935)	(0.109)	(0.0711)	(0.0817)	(0.0747)	(0.0996)	(0.103)	(0.128)
Full set of controls	x		x	x	x	x	x	x	x	x
Observations	120	120	120	108	114	114	114	120	120	120
Adjusted R-squared	0.700	0.306	0.698	0.699	0.741	0.723	0.746	0.679	0.696	0.728

Column (1) shows baseline results for comparison. Column (2) shows a model including an index of positive selection calculated as weighted average of immigrants' degree of positive selection on observables. The degree of positive selection is calculated as share of skilled immigrants to a destination country over share of skilled natives (those left behind plus emigrated, minus immigrants to that country). Value of 1 indicates that immigrants are drawn randomly from distribution of skills at home, higher value denotes positive selection on observable skill. Column (3) repeats the same exercise but conditions on the full vector of controls. Column (4) drops 6 countries that rank highest (above value of 5) in terms of positive selection. Column (5) adds Gallup (2012) index of "potential net migration" as control. Columns (6) and (7) add two indices based on regression residuals (regressions of the Gallup 2011 index on the Share of immigration and birthplace diversity of immigrants, respectively) as alternative controls. Column (8) excludes all immigrants from countries with higher mean PISA score than OECD average. Columns (9) and (10) exclude all immigrants from countries which are not "highly skilled constrained", meaning that the potential pool of extremely skilled people (highest sextile of PISA score for math and science, respectively) is larger than the sum of emigrants from this country. All models excl. (2) include the full vector of all covariates (not shown). Standard errors clustered on the country level.
*** p<0.01, ** p<0.05, * p<0.1

Table 12a: Gravity model determinants

Variable n = 69936	*Definition & source*	*mean*	*std. dev.*	*min*	*max*
Bilateral migration, all skill levels	ADOP (2013)	2792	48435	0	6319139
Bilateral migration, skilled	ADOP (2013)	642	10292	0	919139
Bilateral migration, unskilled	ADOP (2013)	2150	41790	0	5400000
Bilateral migration, all skill levels, predicte		3294	52744	0	9144851
Bilateral migration, skilled, predicted	based on PPML gravity model	755	9010	0	1147379
Bilateral migration, unskilled, predicted		2539	44271	0	7626276
Population size, 1960, thousands	Population in 1960, CEPII (2010)	16200	61000	15	658000
Distance (km)	Geodesic distance in km between country centoids, CEPII (2010)	7827	4491	2	19781
Time difference (hours)	Difference in time zone hours between country capitals, CEPII (2	5	3	0	12
Border contiguity	dummy=1 if common land border	0	0	0	1
Colonial history	dummy=1 if ever in colonial relationship	0	0	0	1
Common official language	dummy=1 if common offical langue	0	0	0	1
Common ethnic minority language	dummy=1 if common language spoken by > 7% of population	0	0	0	1

Table 12b: Gravity model results

	(1)	(2)	(3)	(4)	(5)	(6)
Model	*OLS*	*OLS*	*PPML*	*PPML*	*OLS*	*PPML*
Sample	*SKILLED*	*SKILLED*	*SKILLED*	*SKILLED*	*FULL*	*FULL*
Dependent variable	*Bilateral migration rate (log)*		*Bilateral migration rate*		*Bilateral trade share (log)*	*Bilateral trade share*
1960 population size at destination	-0.313***		-6.95e-09		-0.194***	4.11e-09***
	(0.112)		(7.59e-09)		(0.0503)	(9.64e-10)
Bilateral distance	-1.332***	-1.322***	-0.000342***	-0.000323***	-1.060***	-0.002696***
	(0.233)	(0.235)	(0.000104)	(9.82e-05)	(0.0669)	(0.000485)
Common border	0.796**	2.368***	0.973***	1.007***	0.983***	1.942***
	(0.367)	(0.307)	(0.242)	(0.178)	(0.130)	(0.228)
Colonial relationship	2.767***	1.260***	1.091***	0.772**	1.156***	0.660***
	(0.424)	(0.369)	(0.209)	(0.322)	(0.103)	(0.216)
Common official language	0.371	0.628*	1.234***	1.287***	0.192	0.571
	(0.340)	(0.349)	(0.258)	(0.272)	(0.210)	(0.548)
Common ethnic language	1.297***	0.436	0.799***	0.926***	0.357**	-0.228
	(0.379)	(0.455)	(0.308)	(0.247)	(0.160)	(0.332)
Horizontal time difference	0.523***	0.465**	0.218**	0.189**	0.0259	0.175**
	(0.188)	(0.191)	(0.0895)	(0.0809)	(0.0594)	(0.0790)
Observations	25,244	25,244	69,936	69,936	19,315	42,369
Adjusted R-squared	0.311	0.275	0.300	0.285	0.687	0.308

OLS model in logs, PPML model in levels. All models include period and origin-year fixed effects to account for multilateral resistance terms.
Standard errors clustered by destination country.
*** p<0.01, ** p<0.05, * p<0.1

Table 13: 2SLS - first stage

Panel 1	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Sample				*> median GDP/capita*		
First stage regressions, dependent variable:	*Div(Mig)*	*Div(Mig)*	*S(f)*	*Div(Mig)*	*S(f)*	*Div(trade)*
Corresponds to Table 14:	Model (2)	Model (3)		Model (4)		
PPML-predicted diversity (Mig), skilled	**4.708*** **	**4.761*** **	-0.128	**5.239*** **	0.0212	0.301***
	(0.990)	**(1.007)**	(0.619)	**(1.019)**	(0.516)	(0.0718)
OLS-predicted share of immigration, skilled		4.409	**10.12*** **	5.003	**10.26*** **	0.284
		(3.453)	**(2.428)**	(3.407)	**(2.360)**	(0.267)
OLS-predicted diversity of imports				0.506	0.237	**0.469*** **
				(1.079)	(0.668)	**(0.119)**
Instruments						
Predicted birthplace diversity, PPML	x	x	x	x	x	x
Predicted share of immigration, OLS	.	x	x	x	x	x
Predicted diversity of imports, OLS	.	.	.	x	x	x
Kleibergen-Paap F-Test	**16.62**	6.632	6.632	4.568	4.568	4.568
Angrist-Pischke F-Test, Birthplace diversity		**8.332**	8.332	**7.283**	7.283	7.283
Angrist-Pischke F-Test, Share of immigration		6.786	**6.786**	5.024	**5.024**	5.024
Angrist-Pischke F-Test, Diversity of imports				7.037	7.037	**7.037**
Stock Yogo (10%/15% maximal IV size)	16.36 / 8.96	7.03 / 4.58	7.03 / 4.58	n/a	n/a	n/a
Observations	120	120	120	120	120	120
Adjusted R-squared	0.398	0.398	0.610	0.390	0.620	0.698

All models include the full vector of controls (not shown). Standard errors clustered on the country level. *** p<0.01, ** p<0.05, * p<0.1

Table 14: 2SLS - second stage

Panel 1	*(1)*	*(2)*	*(3)*	*(4)*
Sample		*> median GDP/capita*		
Dependent variable (log)		*GDP/capita*		
Estimator	*OLS*	*2SLS*	*2SLS*	*2SLS*
Birthplace diversity, immigrants, skilled	**0.260*****	**0.233****	**0.235****	**0.242***
	(0.0560)	(0.108)	(0.107)	(0.124)
Share of immigration, skilled	0.291***	0.289***	0.336	0.339
	(0.0980)	(0.0884)	(0.278)	(0.272)
Years of schooling (log)	-0.210	-0.209	-0.245	-0.248
	(0.259)	(0.218)	(0.322)	(0.323)
Quality of institutions	0.0133	0.0150	0.0187	0.0187
	(0.0161)	(0.0155)	(0.0291)	(0.0290)
Instruments				
Predicted birthplace diversity, PPML	.	x	x	x
Predicted share of immigration, OLS	.	.	x	x
Predicted diversity of imports, OLS	.	.	.	x
Observations	120	120	120	120
Adjusted R-squared	0.700	0.493	0.430	0.492
Kleibergen-Paap F-Test	.	16.62	6.632	4.568
Angrist-Pischke F-Test, birthplace diversity			8.332	7.283
Angrist-Pischke F-Test, share of immigration			6.786	5.024
Angrist-Pischke F-Test, diversity of imports				7.037
Stock Yogo (10%/15% maximal IV size)		16.36 / 8.96	7.03 / 4.58	n/a

All models include the full vector of controls. Standard errors clustered on the country level. *** p<0.01, ** p<0.05, * p<0.1

Table 15: Group distance, genetic/cultural distance and income at origin

Dimension 1: Genetic distance

Dimension 2: Income at origin		$\theta 1 < 0$ - higher weight to closer groups					$\theta 1 > 0$ - lower weight to closer groups			
		-10	-7,5	-5	-2,5	0	2,5	5	7,5	10
$\theta 2 < 0$ - lower weight to richer groups	-10	0.0891	0.121	0.167	0.231	0.282	0.216*	**0.143***	**0.120**	**0.116**
		(0.100)	(0.112)	(0.131)	(0.160)	(0.170)	(0.113)	**(0.0841)**	**(0.0737)**	**(0.0704)**
	-7,5	0.130	0.165	0.213	0.278*	0.316**	0.229**	**0.148***	**0.121***	**0.116**
		(0.101)	(0.113)	(0.132)	(0.157)	(0.153)	(0.100)	**(0.0798)**	**(0.0723)**	**(0.0702)**
	-5	0.183*	0.219**	0.267**	0.326**	0.339***	0.236***	**0.154****	**0.124***	**0.118**
		(0.0987)	(0.109)	(0.124)	(0.138)	(0.118)	(0.0837)	**(0.0750)**	**(0.0712)**	**(0.0707)**
	-2,5	0.218***	0.245***	0.281***	0.315***	0.306***	0.226***	**0.158****	**0.128***	**0.120**
		(0.0804)	(0.0848)	(0.0893)	(0.0884)	(0.0737)	(0.0712)	**(0.0723)**	**(0.0719)**	**(0.0731)**
	0	0.226***	0.241***	0.257***	0.270***	0.260***	0.214***	**0.162****	**0.134***	**0.124**
		(0.0600)	(0.0589)	(0.0571)	(0.0545)	(0.0560)	(0.0682)	**(0.0741)**	**(0.0757)**	**(0.0781)**
$\theta 2 > 0$ - higher weight to richer groups	2,5	0.251***	0.260***	0.269***	0.272***	0.258***	0.218***	**0.170****	**0.140***	**0.129**
		(0.0612)	(0.0585)	(0.0557)	(0.0541)	(0.0585)	(0.0709)	**(0.0783)**	**(0.0809)**	**(0.0838)**
	5	0.276***	0.283***	0.288***	0.287***	0.270***	0.228***	0.180**	**0.147***	**0.133**
		(0.0667)	(0.0636)	(0.0605)	(0.0590)	(0.0631)	(0.0743)	(0.0823)	**(0.0853)**	**(0.0882)**
	7,5	0.298***	0.304***	0.308***	0.306***	0.286***	0.242***	0.189**	0.152*	0.135
		(0.0710)	(0.0678)	(0.0646)	(0.0630)	(0.0666)	(0.0771)	(0.0853)	(0.0883)	(0.0910)
	10	0.321***	0.326***	**0.329*****	**0.325*****	0.303***	0.256***	0.198**	0.156*	0.136
		(0.0744)	(0.0711)	**(0.0679)**	**(0.0662)**	(0.0693)	(0.0793)	(0.0874)	(0.0902)	(0.0925)

Table shows coefficients and (country clustered) standard errors for standardized augmented diversity(mig) index in model with GDP/capita as dependent variable. Rich country subsample.

*Coefficients in bold indicate $p< 0.05$** in Wald test for equality of coefficients relative to θ =(0;0), clustered by country.*

ONLINE APPENDIX

Appendix Figure 1: Correlations between ethnic, genetic and birthplace diversity
Appendix Figure 2: Observed and predicted birthplace diversity
Appendix Figure 3: PISA math test scores (mean and top percentiles)
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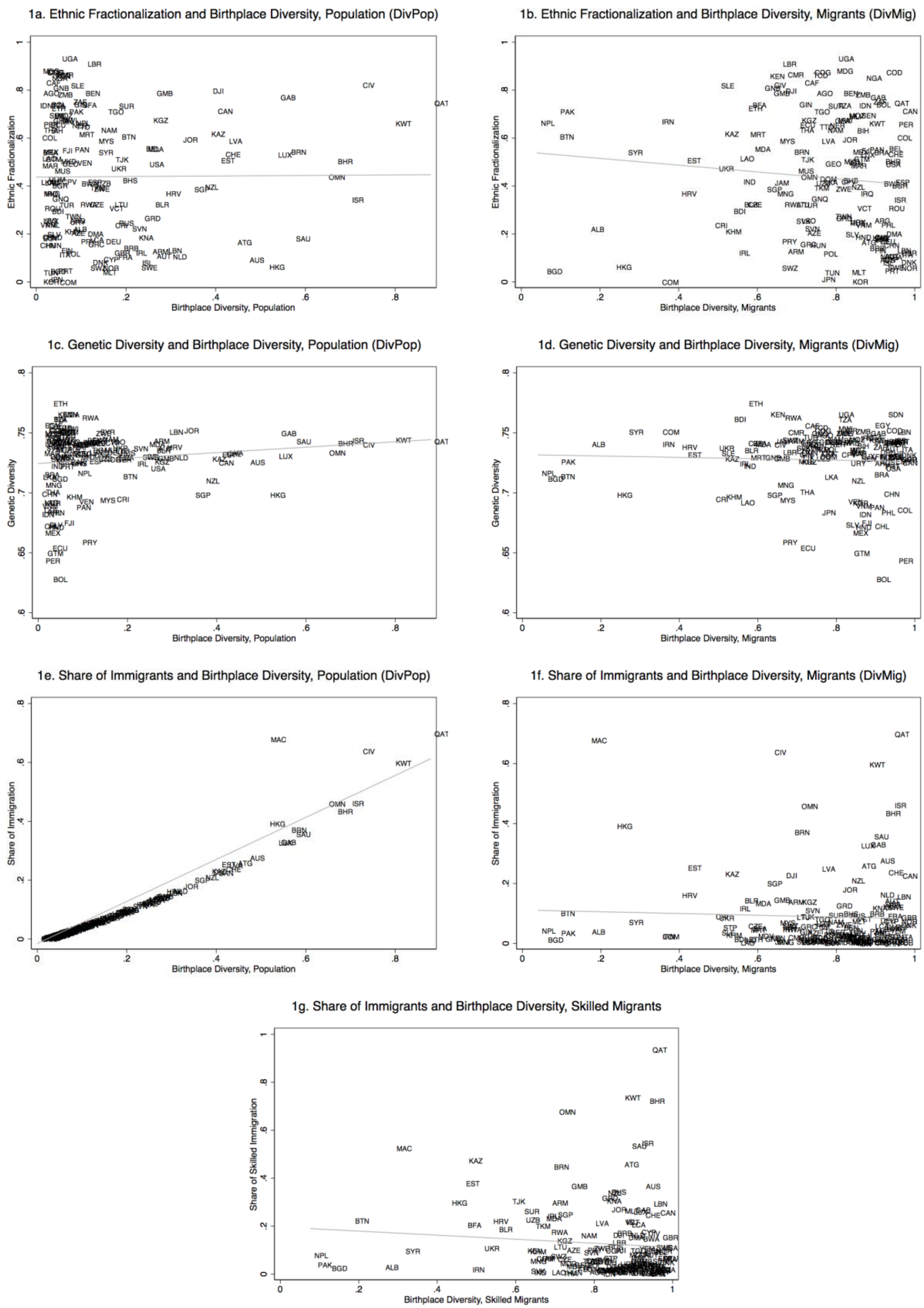
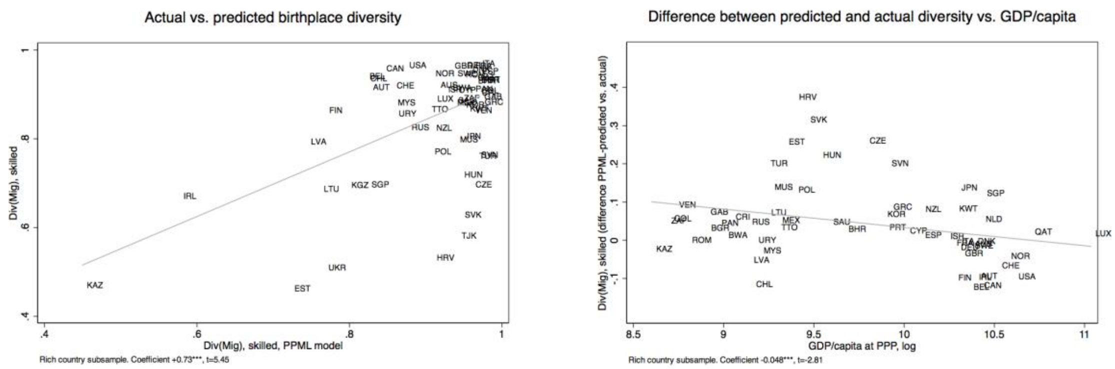
Appendix Table 5: Robustness to alternative fractionalization and polarization controls
Appendix Table 6: Robustness to alternative geography controls
Appendix Table 7: Robustness to alternative institution controls
Appendix Table 8: Robustness to alternative estimators
Appendix Table 9: Robustness to outliers
Appendix Table 10: Split samples: High/low share of immigration and interaction effects

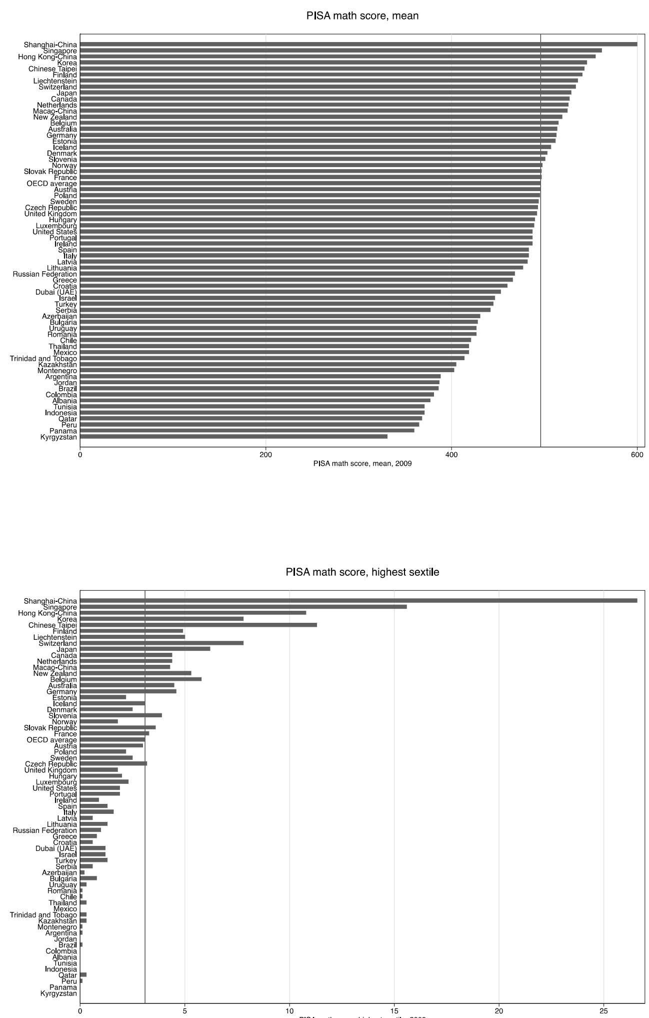
Appendix Figure 1: Correlations between ethnic, genetic and birthplace diversity indices, 2000



Appendix Figure 2: Observed and predicted birthplace diversity



Appendix Figure 3: PISA test scores at mean and mode



Appendix Figure 4: Population 25-65 age, math talent vs. total skilled emigration

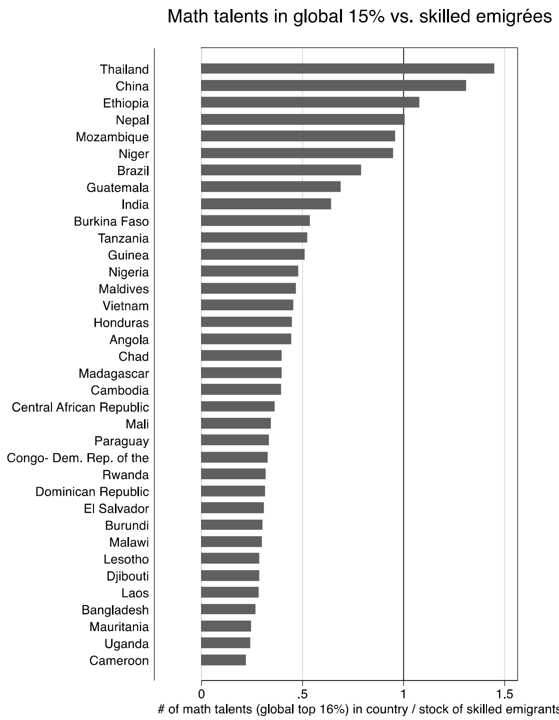
Figures show countries with below median GDP/capita (PPP) in 1990 and ratio of hypothetical math talent (defined as competence at global top standard) to skilled emigration to rich (above median GDP/capita) countries.

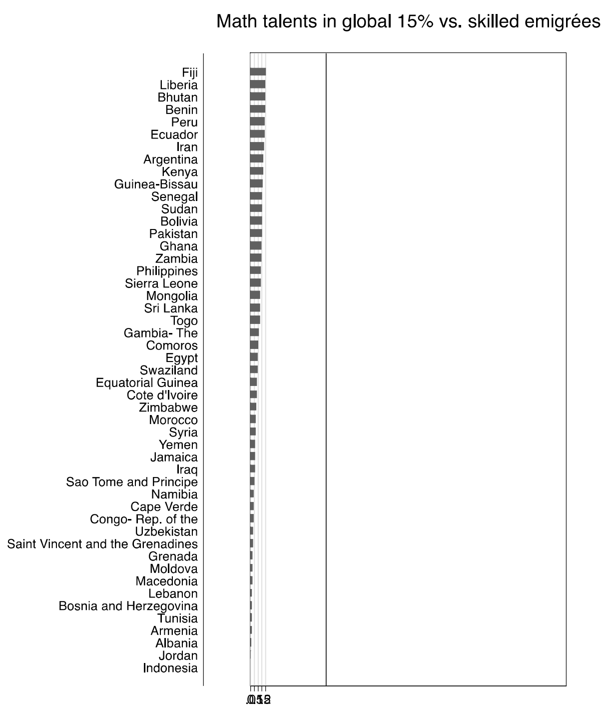
We conduct a simple simulation exercise to compare a country's stock of skill emigrants with the number of potentially highly skilled people in and outside of that country.

We proxy very high skill/talent using PISA test score data from OECD (2009), which is available for OECD and some non-OECD countries. When data for a non-OECD country is not available, we interpolate the share of highly skilled students as an average of the bottom quartile in the overall sample (share of students in top 16%: 0.076%). This interpolation tends to be a rather generous assumption for many developing countries (see e.g. that this number is observed for Indonesia, where it is essentially zero). We then calculate the number of people born in each country in the age group 25-65 (which are eligible to work and covered in the ADOP, 2013) sample and apply the share of highly skilled students to this number. As a result, we obtain the potential native highly (math) skilled population.

This is clearly an upper bound for the true potential since a) the true share of highly skilled in many countries is likely not 0.076% but closer to zero, and b) we implicitly assume that educational quality in developing countries vis-à-vis OECD countries (that define top 16%) has not caught up at least relatively to OECD countries.

In a last step, we divide this talent potential by the number of skilled emigrants from the country. Very intuitively, we thus obtain the maximum share of skilled emigrants per country could hypothetically be talented. We assume that migrants out-select to emigrate with a probability of 1 conditional on being talented, thus ratio is thus obviously an upper bound. Appendix Figure 4 shows the distribution of this ratio across developing countries.


Math talents in global 15% vs. skilled emigrées
Thailand
China
Ethiopia
Nepal
Mozambique
Niger
Brazil
Guatemala
India
Burkina Faso
Tanzania
Guinea
Nigeria
Maldives
Vietnam
Honduras
Angola
Chad
Madagascar
Cambodia
Central African Republic
Mali
Paraguay
Congo- Dem. Rep. of the
Rwanda
Dominican Republic
El Salvador
Burundi
Malawi
Lesotho
Djibouti
Laos
Bangladesh
Mauritania
Uganda
Cameroon
0
.5
1
1.5
# of math talents (global top 16%) in country / stock of skilled emigrants


Math talents in global 15% vs. skilled emigrées
Fiji
Liberia
Bhutan
Benin
Peru
Ecuador
Iran
Argentina
Kenya
Guinea-Bissau
Senegal
Sudan
Bolivia
Pakistan
Ghana
Zambia
Philippines
Sierra Leone
Mongolia
Sri Lanka
Togo
Gambia- The
Comoros
Egypt
Swaziland
Equatorial Guinea
Cote d'Ivoire
Zimbabwe
Morocco
Syria
Yemen
Jamaica
Iraq
Sao Tome and Principe
Namibia
Cape Verde
Congo- Rep. of the
Uzbekistan
Saint Vincent and the Grenadines
Grenada
Moldova
Macedonia
Lebanon
Bosnia and Herzegovina
Tunisia
Armenia
Albania
Jordan
Indonesia
# of math talents (global top 16%) in country / stock of skilled emigrants

Appendix Table 1: Countries in sample

Countries in full sample			
Albania	Ecuador	Latvia	Russian Federation
Argentina	Egypt	Lesotho	Saudi Arabia
Armenia	Estonia	Liberia	Senegal
Australia	Fiji	Lithuania	Sierra Leone
Austria	Finland	Luxembourg	Singapore
Bahrain	France	Malawi	Slovakia
Bangladesh	Gabon	Malaysia	Slovenia
Belgium	Gambia	Mali	South Africa
Benin	Germany	Mauritania	Spain
Bolivia, Plurinational State of	Ghana	Mauritius	Sri Lanka
Botswana	Greece	Mexico	Swaziland
Brazil	Guatemala	Moldova, Republic of	Sweden
Bulgaria	Honduras	Mongolia	Switzerland
Burundi	Hungary	Morocco	Syrian Arab Republic
Cambodia	India	Mozambique	Tajikistan
Cameroon	Indonesia	Namibia	Tanzania, United Republic of
Canada	Iran, Islamic Republic of	Nepal	Thailand
Central African Republic	Iraq	Netherlands	Togo
Chile	Ireland	New Zealand	Trinidad and Tobago
China	Israel	Niger	Tunisia
Colombia	Italy	Norway	Turkey
Congo	Jamaica	Pakistan	Uganda
Congo, the Democratic Republic of the	Japan	Panama	Ukraine
Costa Rica	Jordan	Paraguay	United Kingdom
Croatia	Kazakhstan	Peru	United States
Cyprus	Kenya	Philippines	Uruguay
Czech Republic	Korea, Republic of	Poland	Venezuela, Bolivarian Republic of
Côte d'Ivoire	Kuwait	Portugal	Viet Nam
Denmark	Kyrgyzstan	Qatar	Zambia
Dominican Republic	Lao People's Democratic Republic	Romania	Zimbabwe

Appendix Table 2: Sample means

Variable	*year*	*n*	*mean*	*std. dev.*	*n*	*mean*	*std. dev.*	
		Extended sample (n=164)			Full sample (n=120)			t-test sample mean
GDP/capita								
	1990	44	8,16	1,27	120	8,50	1,18	0,125
	2000	44	8,30	1,30	120	8,61	1,32	0,182
Share of immigration (all)								
	1990	44	0,10	0,15	120	0,09	0,14	0,767
	2000	44	0,10	0,14	120	0,09	0,13	0,499
Share of immigration (skilled)								
	1990	44	0,15	0,16	120	0,10	0,15	0.052*
	2000	44	0,17	0,15	120	0,11	0,16	0.034**
Diversity of immigration (all)								
	1990	44	0,73	0,19	120	0,72	0,21	0,754
	2000	44	0,71	0,20	120	0,75	0,19	0,300
Diversity of immigration (skilled)								
	1990	44	0,76	0,16	120	0,79	0,19	0,235
	2000	44	0,75	0,17	120	0,80	0,18	0.085*

Appendix Table 3: Robustness to borders pre 1989

We also address the potential endogeneity in the definition of migrant groups. For example, we count Slovaks in the Czech Republic as immigrants, although these people have lived jointly together in the same country, Czechoslovakia, until 1993. We proceed by coding these groups as natives in such cases (other cases include, e.g., former Soviet or Yugoslavian Republics). This results in lower birthplace diversity of the population (driven by the now lower share of foreign-born) but higher diversity of immigration in countries where such "virtual" immigration has been substantial. Our results for skilled diversity are robust at somewhat lower magnitudes (reflecting attenuation bias) and similar statistical significance. We restrict this robustness check to the cross section of 2000 data due to substantial measurement error in the immigrant origin data for migrants from the Soviet Republic in 1990. Our results are also robust to grouping all EU countries. This indicates that the size of nations in Europe does not drive our results (available upon request).

	(1)	*(2)*
Sample	*Full sample, 2000*	
Dependent variable (log)	*GDP/capita*	
Birthplace diversity, skilled	**0.270*** **	
	(0.0727)	
Share of immigration, skilled	0.567***	0.681***
	(0.118)	(0.143)
Birthplace diversity, immigrants, skilled (border-adjusted)		0.204**
		(0.0916)
Observations	60	60
Adjusted R-squared	0.777	0.740

Birthplace diversity adjusted for border changes post 1989. All models include the full set of controls (not shown). Year 2000 cross section. Standard errors clustered on the country level.
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 4: Robustness to emigration

Are diversity of emigration and immigration related? We apply equation (8) to data on emigrant groups per country of origin and find that both diversity variables are actually not substantially correlated (at +0.07). Thus, when entering both indices as well as the share of skilled emigrants and immigrants jointly, we find our initial results for skilled immigration diversity to hold at the 1% robustness level. Independently of immigration, the diversity of skilled emigrants also has a positive effect (at 5% significance) on home country incomes (see columns 2 and 3). This result can be driven by benefits of knowledge exchange from a wide set of countries as well as (in a reverse causality argument) by the fact that in richer countries, credit constraints are less binding and allow for diversifying the set of emigration destinations.

	(1)	*(2)*	*(3)*
Sample		*> median GDP/capita*	
Dependent variable (log)		*GDP/capita*	
Birthplace diversity, immigrants, skilled	0.260***		0.240***
	(0.0560)		(0.0572)
Share of immigration, skilled	0.291***		0.318***
	(0.0980)		(0.111)
Birthplace diversity, emigrants, skilled		**0.201****	**0.225****
		(0.0887)	**(0.0861)**
Share of emigration, skilled		-0.228**	-0.0718
		(0.0988)	(0.0812)
Observations	120	120	120
Adjusted R-squared	0.700	0.647	0.742

All models indude the full vector of controls (not shown). Standard errors dustered on the country level.

Appendix Table 5: Robustness to alternative fractionalization and polarization controls

We also check whether our results are stable to alternative specifications of fractionalization and polarization. In a first step, we include a measure of ethnic polarization, a predictor of conflicts (see Section 2). We construct this index of ethnic polarization by applying Alesina et al. (2003)'s ethnic group size data to the polarization index developed in Reynal-Querol (2002) and Montalvo and Reynal-Querol (2005). We re-compute the index from these authors using Alesina et al.'s (2003) data for consistency with the ethnic fractionalization measure and, more importantly, to broaden the available data. Our results for birthplace diversity remain fully robust when accounting for this index while ethnic polarization shows the expected negative sign (column 2). In a second step, we exclude different sets of fractionalization indices from our model to verify robustness to such exclusions. We find our results for birthplace diversity to remain virtually unchanged to any such permutation (columns 3-5).

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Sample			*> Median GDP/capita*		
Dependent variable (log)			*GDP/capita*		
Birthplace diversity, immigrants, skilled	**0.260*** **	**0.227*** **	**0.264*** **	**0.260*** **	**0.259*** **
	(0.0560)	**(0.0527)**	**(0.0527)**	**(0.0536)**	**(0.0527)**
Share of immigration, skilled	0.291***	0.253***	0.289***	0.225**	0.203**
	(0.0980)	(0.0918)	(0.0973)	(0.0899)	(0.0861)
Ethnic polarization		-1.178**			
		(0.526)			
Ethnic fractionalization	-0.158	1.195			
	(0.370)	(0.816)			
Linguistic fractionalization		-1.178**			
		(0.526)			
Genetic diversity	-0.349	-0.301	-0.456*		
	(0.374)	(0.347)	(0.235)		
Genetic diversity, squared	-270.3	-301.0	-287.0	-289.5	
	(196.9)	(196.4)	(175.7)	(180.7)	
Observations	120	120	120	120	120
Adjusted R-squared	0.700	0.720	0.703	0.693	0.693

All models include the full set of additional controls (not shown). Standard errors clustered on the country level.
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 6: Robustness to additional geographic determinants of fractionalization

We add further geography controls to our full model as suggested by Rodriguez and Rodrik (2001) who highlight the importance of robustness to alternative geography specifications in regressions of economic growth or income. This model extends our full model by five additional variables, the share of tropics (in % of land area), indicators of mean and variation in agricultural suitability as well as indicators of elevation and variation in elevation as suggested by Michalopoulos (2012) to account for deeper geographical origins of fractionalization. Our findings (available due to data limitations for 53 out of our 60 rich countries) for skilled diversity of immigrants remain fully robust. We conduct a similar check replacing our Polity IV variable for the quality of institutions with measures from Freedom House (see following table).

	(1)	*(2)*
Sample	*> median GDP/capita*	
Dependent variable (log)	*GDP/capita*	
Birthplace diversity, immigrants, skilled	0.260***	0.216***
	(0.0560)	(0.0582)
Share of immigration, skilled	0.291***	0.154**
	(0.0980)	(0.0766)
Land area in tropics (%)		-0.888**
		(0.417)
Agricultural suitability (mean)		-0.533
		(0.386)
Agricultural suitability (standard deviation)		0.734
		(0.680)
Elevation (mean)		-0.558***
		(0.185)
Elevation (standard deviation)		0.0772
		(0.405)
Observations	120	106
Adjusted R-squared	0.700	0.779

Model (1) for reference only. Model (2) includes - in addition to the full vector of controls - also two indices of average agricultural suitability (mean and standard deviation across regions), a control for % land area in the geographical tropics as well as two indices for elevation across regions (mean and standard deviation). Standard errors clustered on the country level.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix Table 7: Alternative institution controls

	(1)	(2)
Sample	*> median GDP/capita*	
Dependent variable (log)	*GDP/capita*	
Birthplace diversity, immigrants, skilled	**0.260*** **	**0.184*** **
	(0.0560)	**(0.0539)**
Share of immigration, skilled	0.291***	0.258***
	(0.0980)	(0.0748)
Quality of institutions	0.0133	
	(0.0161)	
Civil liberties index		-0.245***
		(0.0821)
Property rights index		0.00824
		(0.0572)
Observations	120	120
Adjusted R-squared	0.700	0.743

All models indude - in addition to the full set of controls - two indices of property rights protection and civil liberties from Freedom House (2011). Standard errors dustered on the country level. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 8: Robustness to alternative estimators

	(1)	(2)	(3)	(4)
Sample	*> median GDP/capita*			
Dependent variable (log)	*GDP/capita*			
Model	*OLS model*	*Cross section 1990*	*Cross section 2000*	*Country fixed effects*
Birthplace diversity, immigrants, skilled	**0.260*** **	**0.198** **	**0.270*** **	**0.107**
	(0.0560)	**(0.0749)**	**(0.0727)**	**(0.150)**
Share of immigration, skilled	0.291***	0.154	0.567***	-0.0501
	(0.0980)	(0.118)	(0.118)	(0.186)
Observations	120	60	60	120
Adjusted R-squared	0.700	0.646	0.777	0.875

All models indude the full set of controls. Model (4) exludes non time varying controls. Standard errors in models (1) and (4) dustered on the country level. Standard errors in models (2) and (3) heteroskedasticity-robust. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 9: Robustness to outliers

	(1)	(2)	(3)	(4)	(5)
Sample			*> median GDP/capita*		
Dependent variable (log)			*GDP/capita*		
Model	*OLS base model*	*excl. highest decile diversity*	*excl. lowest decile diversity*	*excl. highest decile share of immigration*	*excl. lowest decile share of immigration*
Birthplace diversity, immigrants, skilled	**0.260*****	**0.248*****	**0.118****	**0.230*****	**0.277*****
	(0.0560)	**(0.0559)**	**(0.0488)**	**(0.0576)**	**(0.0567)**
Share of immigration, skilled	0.291***	0.319***	0.463***	0.167*	0.290***
	(0.0980)	(0.114)	(0.117)	(0.0888)	(0.0964)
Observations	120	108	108	108	108
Adjusted R-squared	0.700	0.676	0.743	0.701	0.706

Specification (1) shows baseline model for comparison. Models (2) and (4) exclude 10% largest observations, models (3) and (5) 10% of smallest observations on birthplace diversity of immigrants and share of immigrants, respectively. All models include the full set of controls. Standard errors clustered by country. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 10: Split samples: High/low share of immigration, interaction effects

	(1)	(2)	(3)	(4)	(5)
Sample			*> median GDP/capita*		
Dependent variable (log)			*GDP/capita*		
Model	*OLS base model*	*> median share of immigrants*	*< median share of immigrants*	*Interactions*	
Birthplace diversity, immigrants, skilled	**0.260*****	**0.420*****	**0.166***	**0.239*****	
	(0.0560)	**(0.107)**	**(0.0833)**	**(0.0527)**	
Share of immigration, skilled	0.291***	0.252*	-0.0916	0.397***	
	(0.0980)	(0.143)	(0.339)	(0.0960)	
Birthplace diversity, immigrants, unskilled					0.114***
					(0.0369)
Share of immigration, unskilled					0.405***
Birthplace diversity, immigrants, skilled * share of immigration, skilled				**0.107****	
				(0.0409)	
Birthplace diversity, immigrants, unskilled * share of immigration, unskilled					**0.0810**
					(0.0511)
Observations	120	60	60	120	120
Adjusted R-squared	0.700	0.778	0.862	0.715	0.716

All models include the full set of controls (not shown). Standard errors clustered on the country level. *** p<0.01, ** p<0.05, * p<0.1